RISK ASSESSMENT OF GEOLOGICAL DISASTERS TRIGGERED BY HEAVY RAINFALL IN MOUNTAINOUS AREAS: A CASE STUDY IN HEBEI PROVINCE, CHINA

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Abstract. With the increasing frequency of extreme weather events in recent years, geological disasters triggered by heavy rainfall have posed significant threats to the ecological environment and residents' safety. The mountainous areas of Hebei Province, which form part of the Beijing-Tianjin-Hebei ecological barrier, face prominent geological disaster risks due to complex geological conditions and frequent heavy rainfall. This study focused on Hebei's mountainous areas, by establishing a geological disaster susceptibility assessment system to explore the spatial distribution patterns of the geological disaster risks. Historical disaster data were used to calculate the probability of geological disasters triggered by heavy rainfall using a Naive Bayes model. The results indicated that areas of high and moderately high geological disaster susceptibility covered 66,442 km², accounting for 57.75% of the total area, mainly in the western mountains and the hilly regions of Tangshan and Qinhuangdao. High and moderately high-risk areas triggered by heavy rainfall covered 61,214 km², and were not only distributed in high-susceptibility areas but were also concentrated in the northern mountainous regions. These findings provide a scientific basis for policy development for geological disaster prevention in the mountainous areas of Hebei Province, helping to reduce the threats posed by disasters to the ecological environment and residents' lives and property.
Keywords: *heavy rainfall, geological disasters, random forest model, disaster risk management, mountainous areas*

Introduction

Geological disasters are characterized by their hidden nature, complexity, sudden onset, and destructive power (Wang, 2022). Their triggers include both natural and human-induced factors, with heavy rainfall being the primary cause. Nationwide geological disaster surveys indicate that heavy rainfall is the main trigger for 90% of landslides, 81% of collapses, and nearly all debris flows (Li et al., 2004). In recent years, under the influence of global climate change, the impact of localized heavy rainfall on geological disasters has become increasingly significant, with the potential for delayed effects on disaster occurrence (Cao et al., 2018; Guo et al., 2015; Tie et al., 2021). Geological disasters not only threaten residents' lives and property but also cause severe damage to the ecological environment, especially in ecologically sensitive

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mountainous areas. In the field of geological disaster susceptibility assessment, scholars have introduced methods such as the Information Value Method, Fuzzy Mathematics, and Logistic Regression (Fan et al., 2018; Song and Zhang, 2020; Wang et al., 2014; Zhang et al., 2016). Numerous theoretical and applied studies have demonstrated the superior performance of the Random Forest model in evaluating geological disaster susceptibility from various perspectives (Chowdhuri et al., 2020; Huang et al., 2020). Application of the Random Forest model in northwestern and southwestern China has shown promising results in geological disaster susceptibility assessment (Liu et al., 2018a, b; Shen et al., 2022). However, susceptibility assessments of geological disasters in Hebei Province have predominantly focused on geological environments, average annual rainfall, and socioeconomic factors, with limited consideration of triggering factors. Therefore, compared to previous applications of the Random Forest model in other regions of China, this study's integration of heavy rainfall factors and geological conditions offers a more nuanced understanding of disaster risks in Hebei Province. This approach not only improves the model's predictive accuracy but also provides a methodological framework that can be adapted to other regions with similar geological and climatic characteristics.

In recent years, significant progress has been made in studying the risks of geological disasters triggered by heavy rainfall in different regions, both domestically and internationally (Liu et al., 2019; Zhuang and Xing, 2022). Some studies have constructed debris flow risk evaluation indices based on the frequency of heavy rainfall, maximum soil water retention capacity, and cumulative precipitation (Nakai et al., 2006; Yao et al., 2010), but these studies often fail to fully consider the influence of geological conditions. Other researchers have used statistical analyses to investigate the relationship between sudden geological disasters and rainfall intensity or rainfall patterns, thereby exploring the likelihood of geological disasters triggered by heavy rainfall (Chen et al., 2020; Hong et al., 2023; Sun et al., 2018; Zeng and Wu, 2017). Overall, previous research on the risks of geological disasters induced by heavy rainfall has largely focused on constructing rainfall threshold models (Mori and Ono, 2019; Zhou et al., 2024). While these models provide valuable insights into the relationship between rainfall and geological disasters, their applicability and generalizability are constrained by the localized nature of precipitation and the complexity of topographic conditions. Additionally, existing studies have highlighted that the risk of geological disasters triggered by heavy rainfall can be expressed as the product of geological disaster susceptibility and the probability of rainfall-induced triggering (Zhang et al., 2022). These studies further identify factors such as rainfall intensity, duration, cumulative rainfall, and hourly rainfall as critical in geological disaster occurrences (Hu et al., 2021; Wang et al., 2020). These findings provide a theoretical foundation for further research and underscore the importance of integrating rainfall characteristics and geological conditions to develop regional risk assessment models for geological disasters triggered by heavy rainfall. Such models would significantly contribute to targeted disaster prevention, mitigation, and emergency management in specific regions.

In northern China, the occurrence of geological disasters exhibits distinct regional characteristics due to the unique interplay between rainfall (especially heavy rainfall) patterns and disaster-prone geological environments. Between 2005 and 2019, rainfall-triggered geological disasters accounted for 85% of all geological disasters in Hebei Province (*Fig. 1*), with heavy rainfall-induced disasters frequently exhibiting clustered

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occurrences and severe destructive impacts. For instance, the “July 21, 2012” geological disaster in Baoding, as well as the widespread geological disasters triggered by heavy rainfall on July 22, 2021, in Shijiazhuang, Xingtai, and Baoding, caused significant losses to local residents, housing, infrastructure, and the economy (Zhu et al., 2014). This study aims to address an underexplored aspect of incorporating heavy rainfall as a triggering factor to assess the risk of geological disasters in the mountainous areas of Hebei Province, a topic that has not been fully examined in previous studies on geological disaster susceptibility. Therefore, this study employs the Random Forest model to assess the susceptibility of geological disasters in Hebei Province. By combining historical disaster data, it uses a Naive Bayes network to calculate the probability of geological disasters triggered by heavy rainfall and conducts a comprehensive risk assessment. The findings of this study aim to provide precise support for the prevention and management of geological disasters in the mountainous regions of Hebei Province, enhancing regional disaster prevention and mitigation capacity to protect the Beijing-Tianjin-Hebei ecological barrier and safeguard lives and property.

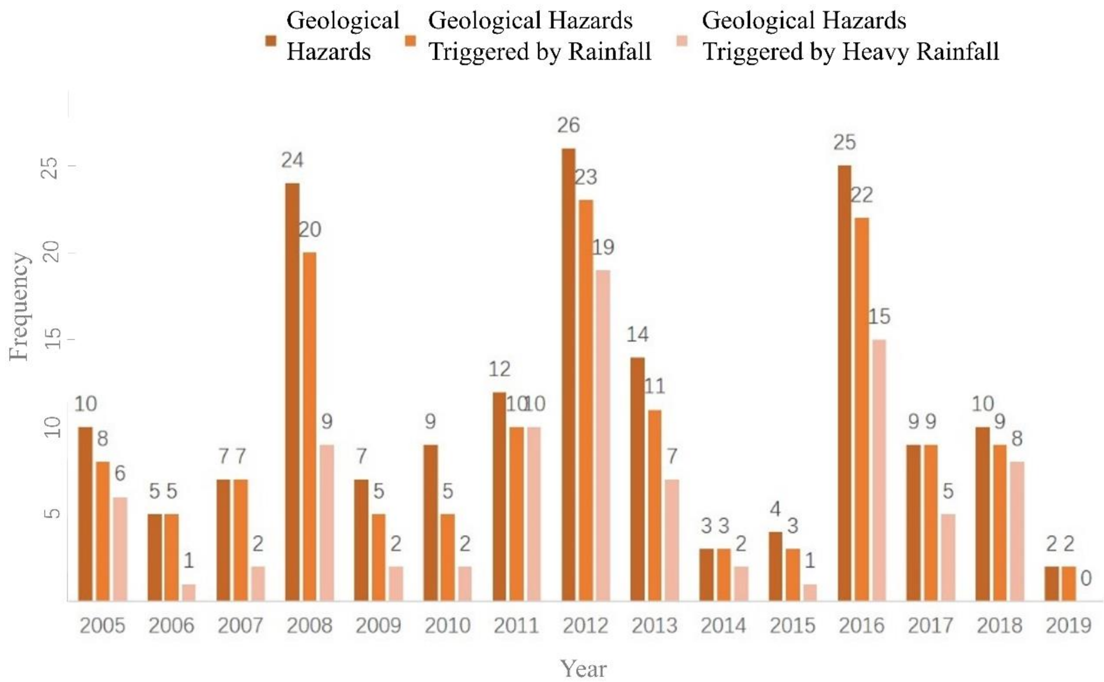

Figure 1. *Occurrence of geological disasters in Hebei Province from 2005 to 2019 (from the Bulletin of Geological and Environmental Conditions of Hebei Province, 2005-2019)*

Material and methods

Study area

This study focuses on geological disasters such as collapses, landslides, and debris flows. Given the significant heterogeneity between the occurrence of geological disasters in the plain and mountainous regions of Hebei Province, the study area is defined based on the “13th Five-Year Plan for Geological Disaster Prevention and Control of Hebei Province,” which divides the province into plain and mountainous areas.

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The mountainous regions of Hebei Province (*Fig. 2*) include the Taihang Mountains and Yanshan Mountain ranges, primarily located in the northeastern, northern, and western parts of the province. Geographically, these regions span 113°00′E to 119°50′E and 36°01′N to 42°37′N, covering eight prefecture-level cities: Qinhuangdao, Tangshan, Chengde, Zhangjiakou, Baoding, Shijiazhuang, Xingtai, and Handan. The mountainous area encompasses 73 county-level cities, with a total area of approximately 115,200 km², accounting for 61.02% of the province's total land area. The terrain in the mountainous regions is complex, dominated by low to mid-altitude mountains and hills, with elevations ranging from several hundred meters to over 2000 m, exhibiting a general west-to-east decline in elevation. The geological conditions are diverse, including granite, sandstone, limestone, and other rock types. The region features fractured strata and well-developed fault structures, leading to numerous geological disaster hazards. Climatically, the mountainous areas of Hebei Province belong to the warm temperate continental monsoon climate zone, with annual precipitation ranging from 400 to 800 mm. Rainfall distribution is influenced by climate and topography, resulting in uneven spatial and temporal rainfall patterns with significant interannual variability. Most rainfall occurs in the summer, when heavy downpours are frequent, often triggering geological disasters such as landslides and debris flows. The vegetation in this region mainly consists of coniferous forests and shrubs. However, some areas have relatively low vegetation coverage, leaving the ecological environment fragile and making the region highly susceptible to geological disasters triggered by heavy rainfall.

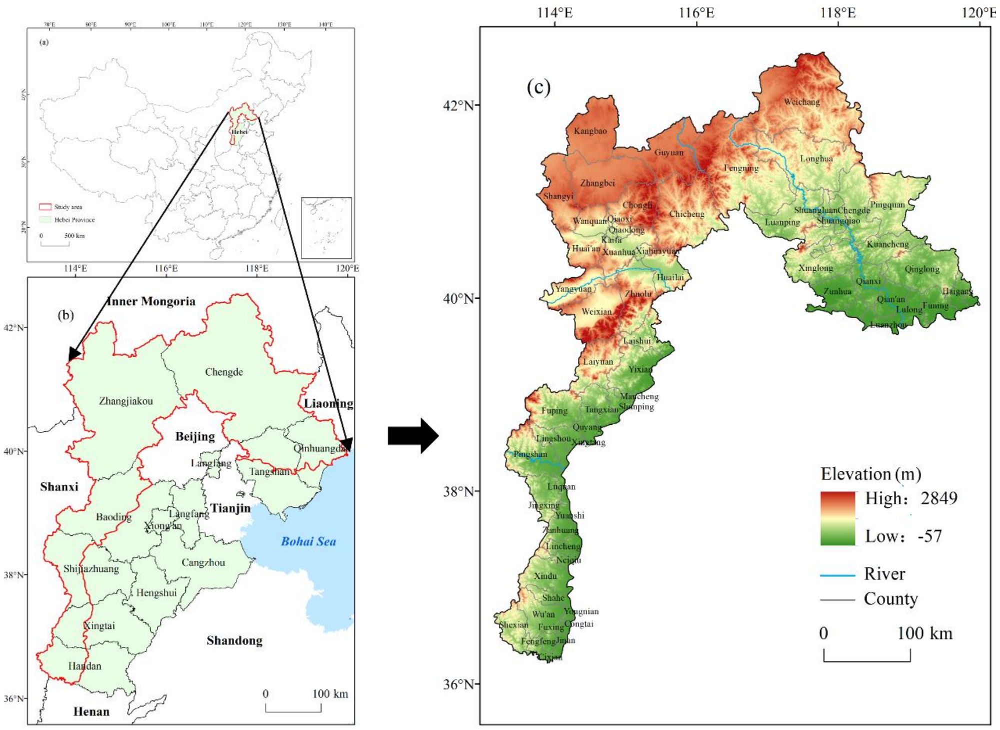

Figure 2. *Location of the study area*

Data sources

The data used in this study include meteorological data, geological disaster data, historical disaster data, geological environment data, and other basic geographic data:

- Meteorological Data: Provided by the Hebei Meteorological Disaster Prevention Center, including daily temperature data, daily rainfall data, and hourly rainfall data.
- Geological disaster Data: Sourced from the Resource and Environment Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn), which includes 3740 geological disaster sites within the study area.
- Historical Disaster Data: Geological disaster data were obtained from the "2005–2021 Hebei Geological Environment Status Bulletin" (http://zrzy.hebei.gov.cn/) and the Hebei Geological Disaster Prevention Information Network (http://www.hedzh.net/). Data on heavy rainfall-related disasters were provided by the Hebei Meteorological Disaster Prevention Center.
- Geological Environment Data: DEM (Digital Elevation Model) data were sourced from the Geospatial Data Cloud (http://www.gscloud/) with a spatial resolution of 30 m. Soil moisture data were obtained from Earth System Science Data (https://www.earth-system-science-data.net/). Topographic and geomorphological data were sourced from the Atlas of Geomorphological Maps of the People's Republic of China (1:1,000,000), which provides spatial distribution data for geomorphological types. Fault and stratigraphic lithology data, as well as NDVI (Normalized Difference Vegetation Index) data, were sourced from the Resource and Environment Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn).
- Other Basic Geographic Information Data: Sourced from the National Geographic Information Resource Catalog Service System (https://www.webmap.cn/).

In this study, all data were unified under the GCS_WGS_1984 coordinate system, and raster data were resampled to a uniform spatial resolution of 90 m.

Methods

Construction of the geological disaster susceptibility evaluation index system

The occurrence of geological disasters is influenced by a combination of factors, including topography, geology, climate, and vegetation cover. Accurately assessing the susceptibility of geological disasters not only helps identify high-risk areas but also provides essential guidance for disaster prevention and resource planning. In constructing the evaluation index system for geological disaster susceptibility, this study comprehensively considers factors related to topography, geological environment, and climatic conditions.

For the selection of evaluation indicators, this study refers to previous research findings (Li et al., 2021; Novellino et al., 2021; Zhang, 2018) and follows the principles of systematicity, scientific rigor, and operational feasibility. The selected indicators include elevation, slope, stratum lithology, soil cohesiveness, land use, NDVI (Normalized Difference Vegetation Index), distance to faults, distance to rivers, and average annual precipitation. Additionally, it is considered that when soil moisture increases to a certain extent, the viscosity of the soil decreases and its density increases, making it more prone to surface runoff during heavy rainfall, which significantly raises the likelihood of geological disasters. Furthermore, the thermal-moisture cycling effects on rock-soil masses can

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damage the internal structure of rocks, increasing porosity and infiltration rates, thereby altering the internal structure and properties of rock-soil masses, ultimately heightening the likelihood of geological disasters (Huang and Ma, 2017; Kalkan, 2011). Based on these considerations, this study introduces two additional influencing factors: soil moisture and average annual temperature. By integrating previous research and expert opinions, a geological disaster susceptibility evaluation index system was developed (*Fig. 3*), and grading criteria for the indicators were established (*Table 1*).

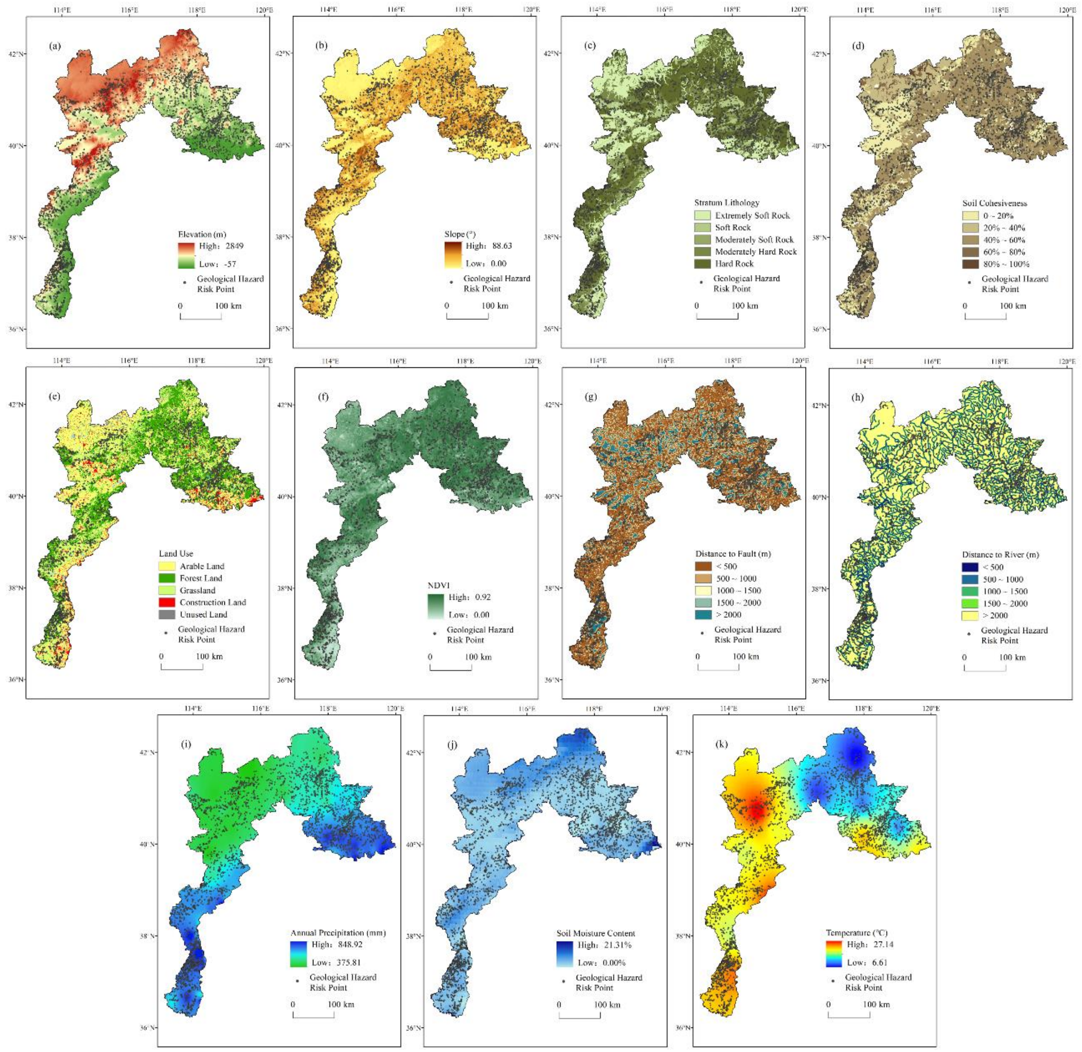

Figure 3. *Spatial distribution of the Evaluation indicators. (a) Elevation, (b) slope, (c) stratum lithology, (d) soil cohesiveness, (e) land use, (f) NDVI, (g) distance to faults, (h) distance to rivers, (i) average annual precipitation, (j) soil moisture content and (k) temperature*

Optimization of indicators

During the selection process of indicators for geological disaster susceptibility evaluation, potential high correlations among certain factors can undermine the accuracy of the model. Therefore, it is essential to optimize the indicators to ensure robustness and reliability. In this study, 3519 geological disaster sites and 7038 non-hazard sites were selected as training samples, and a correlation analysis was conducted using R software.

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The correlation coefficient, along with the associated p-values, was calculated to measure the strength and significance of the relationship between variables. A p-value below 0.05 typically indicates a statistically significant relationship.

Table 1. *Evaluation index system of geological disaster susceptibility in Hebei Province*

Evaluation indicators	Low	Relatively low	Medium	Relatively high	High
Elevation (m)	< 200	200 ~ 500	500 ~ 750	750 ~ 1250	> 1250
Slope (°)	< 6	6 ~ 13	13 ~ 22	22 ~ 33	> 33
Stratum lithology	Hard rock	Moderately hard rock	Moderately soft rock	Soft rock	Extremely soft rock
Soil cohesiveness	0% ~ 20%	20% ~ 40%	40% ~ 60%	60% ~ 80%	80% ~100%
Land use	Unused land	Arable land	Forest land	Grassland	Construction land
NDVI	< 0.3	0.3 ~ 0.5	0.5 ~ 0.6	0.6 ~ 0.8	> 0.8
Distance to faults (m)	< 500	500 ~ 1000	1000 ~ 1500	1500 ~ 2000	> 2000
Distance to rivers (m)	< 500	500 ~ 1000	1000 ~ 1500	1500 ~ 2000	> 2000
Precipitation (mm)	< 400	400 ~ 500	500 ~ 600	600 ~ 800	> 800
Soil moisture content	< 3%	3% ~ 7%	7% ~ 11%	11% ~ 19%	> 19%
Temperature (℃)	< 8	8 ~ 10	10 ~ 12	12 ~ 14	> 14

The results (*Fig. 4a*) show a significant negative correlation between elevation and average annual precipitation (correlation coefficient = -0.76, $p < 0.01$). This relationship is closely related to the topography of the study area, which has higher elevations in the northwest and lower elevations in the southeast. The southeastern coastal regions experience more rainfall compared to the northwest, primarily due to topographical effects. Additionally, since slope is derived from elevation data, and the information conveyed by elevation is already effectively captured by other factors, elevation was excluded as an evaluation indicator. Similarly, NDVI shows moderate correlations with slope (correlation coefficient = 0.62, $p < 0.05$), lithology (correlation coefficient = 0.57, $p < 0.05$), and average annual temperature (correlation coefficient = 0.61, $p < 0.05$), and its influence is adequately represented by these other factors. Therefore, NDVI was also removed.

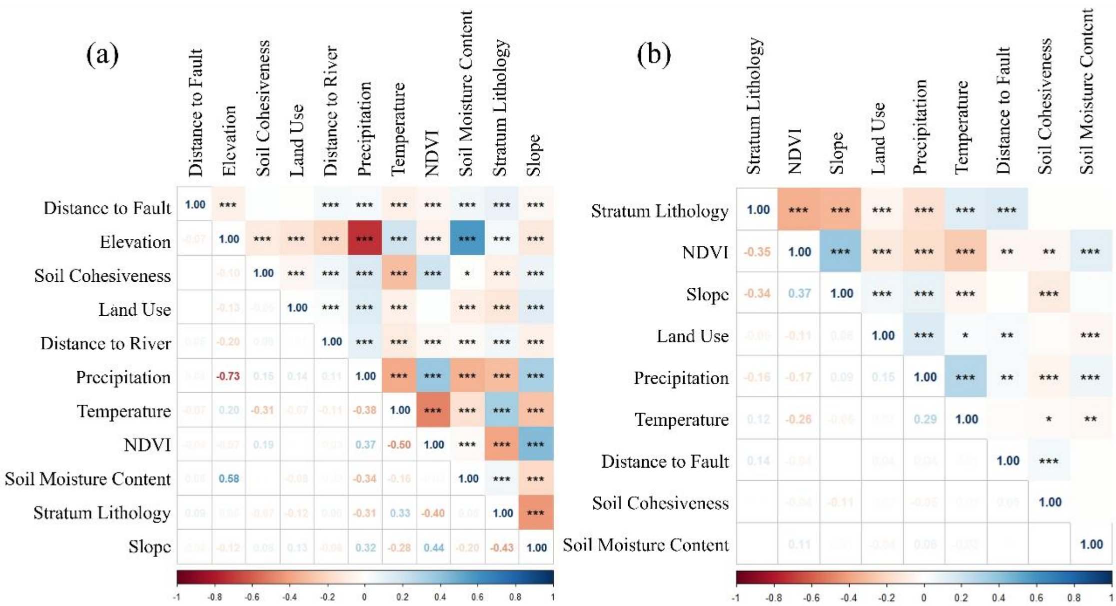

Figure 4. *Correlation analysis of evaluation factors*

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After removing elevation and NDVI, the remaining influencing factors were reanalyzed for correlation, and the results are shown in *Figure 4b*. By eliminating redundant factors, the computational efficiency of the model was improved, and the scientific validity and reliability of the evaluation results were enhanced. This optimization process lays a solid foundation for subsequent modeling of geological disaster susceptibility.

Geological disaster susceptibility assessment using the random forest method

Using the training samples selected during the correlation analysis, 70% of the samples were randomly chosen as training data, while the remaining 30% were used as testing data for input into the Random Forest model. During model construction, cross-validation and grid search were used to determine the optimal parameters for the Random Forest model in this study. Through iterative cycles in R language, it was found that the model achieved the highest accuracy when the number of leaf nodes per classification tree was set to 3. At the same time, when the number of decision trees reached 200, the out-of-bag error stabilized. Therefore, the model was trained and learned with the decision tree count set to 200 and the leaf node count set to 3, yielding the variable importance of each indicator.

In the Random Forest model, multiple decision trees are constructed, and a voting mechanism is used to make the final classification decision. The formula for the Random Forest model's overall prediction is as follows:

$$H(X) = \frac{1}{N}\sum_{i=1}^{N} h_i(X) \quad \text{(Eq.1)}$$

where $H(X)$ is the final prediction result of the Random Forest, N is the total number of decision trees, and $h_i(X)$ represents the prediction result of the i^{th} decision tree. To evaluate the importance of variables, the importance score of each variable is calculated using the following formula:

$$V(X_k) = \frac{1}{N}\sum_{i=1}^{N}(G_i(X_k)) \quad \text{(Eq.2)}$$

where $G_i(X_k)$ represents the contribution of variable X_k to the node split in the i^{th} decision tree.

The ROC (Receiver Operating Characteristic) curve and AUC (Area Under the Curve) are commonly used to evaluate model performance. These metrics have the advantage of being independent of critical thresholds and can accurately reflect the trade-off between specificity and sensitivity of the analysis method, providing excellent experimental accuracy. Consequently, they are widely applied in geological disaster susceptibility evaluations (Liu et al., 2022). During the Random Forest learning process in R, the classification probabilities of the test samples were output, and the ROC curve was plotted to validate the model's accuracy. The area between the ROC curve and the x-axis represents the AUC value, which is used to evaluate the classification model's precision. The AUC value measures the accuracy of the model's predictions, with values ranging from 0.5 to 1. The closer the AUC value is to 1, the higher the model's predictive accuracy. Evaluation metrics for the model are summarized in the accompanying table.

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The ROC curve of the Random Forest model is shown in the figure, where the AUC value for the training set is 0.975, and the AUC value for the testing set is 0.867 (*Fig. 5*). These results indicate that the model demonstrates good predictive accuracy.

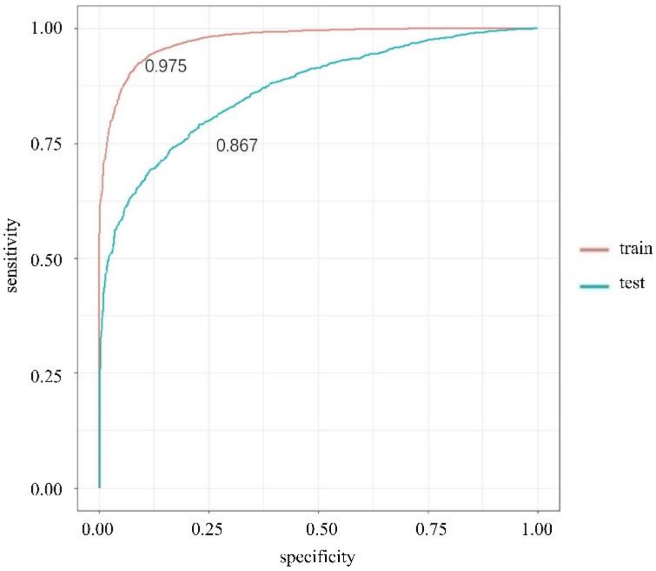

Figure 5. *ROC curve*

The weight values calculated using the Random Forest algorithm are substituted into the following formula:

$$y = \sum_{j=1}^{m} P_j x_j \quad \text{(Eq.3)}$$

where y represents the susceptibility index, m is the number of evaluation factors, P_j is the Random Forest weight coefficient corresponding to the evaluation factor x_j. After weighting the evaluation factor layers, the natural breaks method, commonly used in statistics, is applied to generate the geological disaster susceptibility distribution map based on the Random Forest model.

Probability of geological disaster occurrence

To quantitatively assess the triggering effect of heavy rainfall on geological disasters, this study uses the Naive Bayes model, incorporating heavy rainfall characteristics and historical records of geological disasters to calculate the probability of geological disaster occurrence under different rainfall conditions. Based on historical disaster data recorded in the 2005–2019 Hebei Geological Environment Status Bulletin and heavy rainfall disaster data provided by the Hebei Meteorological Disaster Prevention Center, rainfall characteristic parameters corresponding to each geological disaster were extracted. Referring to previous research on the influence of heavy rainfall on geological disasters, different disaster-causing intensities are characterized by hourly rainfall, cumulative rainfall, and rainfall duration. Hourly rainfall reflects the impact of short-duration high-intensity rainfall, cumulative rainfall captures the saturation effect of accumulated rainfall on the geological environment, and rainfall duration describes the potential influence of prolonged rainfall on geological disasters. After data cleaning

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and standardization, these parameters were combined with geological disaster occurrence records (whether a disaster occurred) to form the training dataset.

The Naive Bayes model assumes that rainfall factors are independent of one another. By learning the conditional probability relationship between rainfall characteristics and geological disaster occurrence in historical data, the model derives the posterior probability of geological disaster occurrence under different rainfall conditions (Mou, 2020). The Naive Bayes model assumes that rainfall factors, such as intensity, duration, and cumulative rainfall, are independent of each other. This simplification is often adopted in similar studies, as each factor can contribute distinctly to the likelihood of a geological disaster. For example, while rainfall intensity may drive immediate risks, duration and cumulative rainfall influence the overall saturation of the ground, each playing a separate role in disaster occurrence. The calculation formula for the model is as follows:

$$p(Z|F) = \frac{p(F|Z) * p(Z)}{p(F)} \tag{Eq.4}$$

where $p(Z|F)$ represents the probability of geological disaster Z occurring under the condition of rainfall characteristics F, $p(F|Z)$ is the probability of rainfall characteristics F occurring given that geological disaster Z has occurred, and $p(Z)$ and $p(F)$ are the prior probabilities of geological disaster occurrence and rainfall characteristics, respectively.

In the model, rainfall characteristics F include the three aforementioned factors. By applying the Naive assumption, their joint probability is decomposed into the product of single-factor probabilities:

$$p(F \mid Z) = p(f_1 \mid Z) * p(f_2 \mid Z) * p(f_3 \mid Z) \tag{Eq.5}$$

where f_1, f_2, and f_3 represent hourly rainfall, cumulative rainfall, and rainfall duration, respectively. Using rainfall characteristic data from 142 meteorological stations across the province during 1980–2020, spatial distribution maps of hourly rainfall, cumulative rainfall, and rainfall duration were generated. Based on these maps and the posterior probabilities calculated by the model, the spatial distribution of the probability of geological disasters triggered by heavy rainfall in different regions was created.

Analysis of heavy rainfall-induced geological disaster risk

The risk of geological disasters triggered by heavy rainfall can be quantified as a functional relationship between the probability of heavy rainfall inducing geological disasters and the susceptibility of geological disasters. The mathematical expression is as follows:

$$H = P \times H_0 \tag{Eq.6}$$

where H represents the risk of geological disasters triggered by heavy rainfall, P is the probability of heavy rainfall inducing geological disasters, and H_0 is the susceptibility of geological disasters.

Using raster calculation tools, the geological disaster susceptibility (H_0) is combined with the probability of heavy rainfall-induced geological disasters (P) to derive the overall risk (H) of geological disasters triggered by heavy rainfall. The resulting risk is

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then classified into five levels—high risk, relatively high risk, moderate risk, relatively low risk, and low risk—using the natural breaks method.

Results

Geological disaster susceptibility assessment

From a spatial distribution perspective (*Fig. 6*), areas with high susceptibility to geological disasters in the mountainous regions of Hebei Province account for 22.92% of the total area, while areas with relatively high susceptibility account for 34.79%. These regions are primarily concentrated in the southeastern parts of Fuping County, Laishui County, and Laiyuan County, and the northwestern part of Yixian County in Baoding; the western mountainous areas of Shijiazhuang, Xingtai, and Handan; and more scattered regions in Zhangjiakou, including southern parts of Xuanhua District, Qiaoxi District, and Zhuolu County. In Chengde and Tangshan, these areas are mainly located in the hilly regions. These regions are characterized by significant topographic variation, hard rock masses, dense fault lines, and intense thermal-moisture cycling, making them prone to geological disasters. Low susceptibility areas account for 15.38% of the total area, while relatively low susceptibility areas account for 26.92%. These regions are primarily distributed around Zhangjiakou and central Chengde, where the terrain is relatively flat with minimal topographic variation, leading to a lower likelihood of geological disasters.

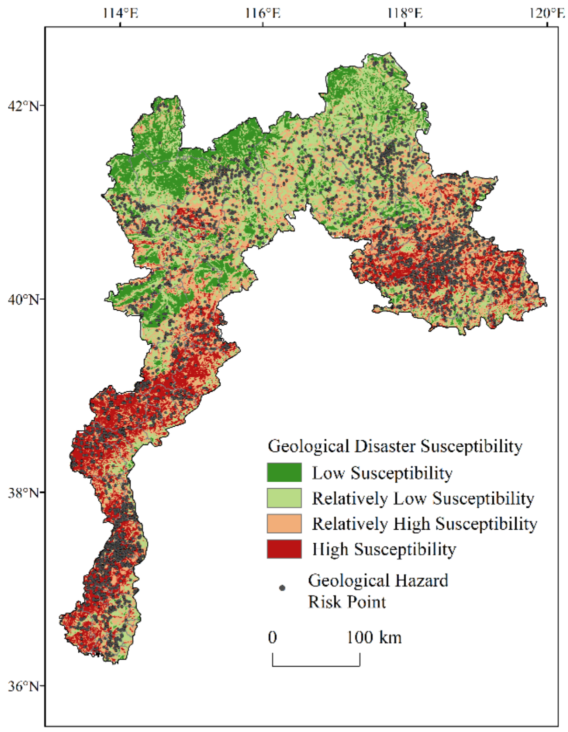

Figure 6. *Susceptibility distribution of geological disasters*

By overlaying geological disaster susceptibility maps with geological disaster points and calculating the density of hazard points in each susceptibility zone (*Table 2*), it was

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observed that the number of geological disaster points is highest in the high-susceptibility zones, with a hazard point density of 0.050052 points/km². As susceptibility decreases, the density of geological disaster points also declines. The density of geological disaster points in high-susceptibility zones is 40 times greater than that in low-susceptibility zones.

Geological disasters risk triggered by heavy rainfall

In the mountainous regions of Hebei Province, areas with high risk of geological disasters triggered by heavy rainfall (*Fig. 7*) account for 21.79% of the total area. These areas are concentrated in the western mountainous regions of Baoding, Shijiazhuang, Xingtai, and Handan, as well as the central areas of Xinglong County, Qianxi County, and Pingquan City. Relatively high-risk areas account for 31.37% of the total area, mainly distributed in the following regions: southern Chongli County, eastern Chicheng County, and Qiaoxi District in Zhangjiakou; northern Laiyuan County in Baoding; most of Chengde City; and the hilly regions of Tangshan.

Compared to geological disaster susceptibility, the overall proportion of high- and relatively high-risk areas has increased, with the distribution of high-risk areas becoming more concentrated. Regions such as the Taihang Mountains, the Bashang Plateau, and the northern parts of Qinhuangdao and Tangshan exhibit both high susceptibility to geological disasters and serve as centers for heavy rainfall, making these areas particularly high-risk. Among these, Chengde City stands out as a region where the risk of geological disasters induced by heavy rainfall has significantly increased. Low-risk and relatively low-risk areas are primarily distributed around Zhangjiakou and in the plains and hilly regions in the eastern parts of Shijiazhuang, Xingtai, Handan, and Qinhuangdao. These areas account for 46.84% of the total area of Hebei Province.

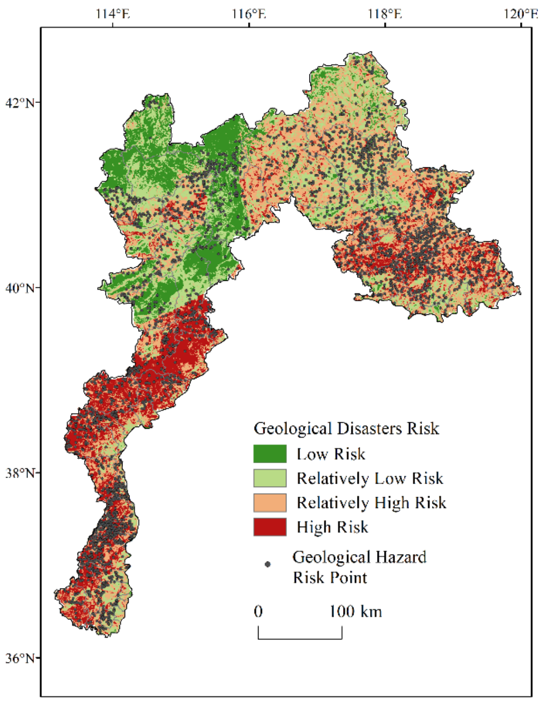

Figure 7. *Risk distribution of geological disasters triggered by heavy rainfall*

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In the risk assessment of geological disasters triggered by heavy rainfall, the distribution density of geological disaster points also increases with the rise in risk levels (*Table 2*). The density of geological disaster points in high-risk areas is 40.5 times that in low-risk areas. Overall, the density of geological disaster points in high- and relatively high-risk zones for disasters triggered by heavy rainfall is higher compared to their density in zones of high and relatively high susceptibility to geological disasters. This distribution aligns more closely with the actual distribution characteristics of hazard points, reflecting the real spatial patterns of disaster occurrence.

Table 2. *Geological disaster points in the mountainous areas of Hebei province*

Geological disasters evaluation	Zone	Number of geological disaster points	Area (km²)	Density (points/km²)
Geological disaster susceptibility	High susceptibility	1321	26,392.34	0.050,052
	Relatively high susceptibility	1229	40,060.23	0.030,679
	Relatively low susceptibility	750	30,994.47	0.024,198
	Low susceptibility	222	17,705.86	0.012,528
Geological disasters triggered by heavy rainfall	High risk	1319	25,095.37	0.052,560
	Relatively high risk	1176	36,119.61	0.032,558
	Relatively low risk	813	35,345.74	0.023,001
	Low risk	241	18,592.18	0.012,962

Conclusions

This study focuses on the mountainous areas of Hebei Province, establishing a geological disaster susceptibility evaluation index system. Using the Random Forest model, geological disaster susceptibility was assessed. Additionally, historical disaster data and the Naive Bayes method were employed to calculate the probability of geological disasters triggered by heavy rainfall. The spatial distribution characteristics and risk levels of heavy rainfall-induced geological disasters were comprehensively analyzed. We find that the susceptibility of geological disasters in the mountainous areas of Hebei Province is primarily influenced by geological and environmental factors such as slope, lithology, soil moisture, and distance to faults. High-susceptibility and relatively high-susceptibility areas account for 22.92% and 34.79%, respectively, and are mainly concentrated in the western mountainous regions of Baoding, Shijiazhuang, Xingtai, and Handan, as well as the hilly areas of Tangshan and Qinhuangdao, which are characterized by significant topographical variation and dense fault lines. Meanwhile, by integrating the probability of rainfall-induced disasters and geological disaster susceptibility, this study constructed a risk assessment model for heavy rainfall-induced geological disasters. The results indicate that high-risk and relatively high-risk areas account for 21.79% and 31.37% of the mountainous areas, respectively. High-risk areas are primarily concentrated in Qiaoxi District, southern Chongli County, and eastern Chicheng County in Zhangjiakou; the northern mountainous regions of Laiyuan County in Baoding; and the hilly regions of Chengde and Tangshan. Moreover, the density of geological disaster points in high-susceptibility and relatively high-susceptibility areas is 0.050,052 points/km² and 0.030,679 points/km², respectively. In the risk distribution of geological disasters triggered by heavy rainfall, the density of hazard points in high-risk and relatively

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high-risk areas increases to 0.052,560 points/km² and 0.032,558 points/km², respectively.

Discussion

This study reveals the spatial distribution patterns and risk classification characteristics of geological disasters triggered by heavy rainfall in the mountainous areas of Hebei Province, providing critical insights for regional disaster prevention, mitigation, and emergency management. Theoretically, this study constructs a risk assessment framework that integrates geological conditions and rainfall characteristics, deepening the understanding of the coupling mechanisms between heavy rainfall and geological disasters. This framework offers valuable methodological references for disaster research in complex geological environments. Practically, the findings can directly inform disaster prevention strategies by identifying high-risk areas and recommending targeted actions. Prioritizing investments in disaster preparedness, improving early warning systems, and enhancing vegetation cover for soil stabilization would be beneficial. Additionally, the results can support ecological preservation efforts, including land-use optimization and the development of ecological barriers to reduce disaster risks. Furthermore, integrating disaster risk management into both urban and rural planning will ensure long-term resilience and sustainability.

The Hebei Provincial Department of Natural Resources classified the geological disaster susceptibility of the province based on the geological environment background, the current development of geological disasters, and the extent of human engineering and economic activities. Comparing the results of this study with their findings shows that the distribution of geological disaster susceptibility obtained in this study is generally consistent with their results, with this study identifying a slightly larger range of susceptible areas. Wang Ruifeng et al. used the AHP (Analytic Hierarchy Process) method to analyze the susceptibility of geological disasters in Chengde City, Hebei Province. Their results indicate higher susceptibility in Kuancheng Manchu Autonomous County, Yingshouyingzi Mining District, and Xinglong County, while the susceptibility in the northwestern region is lower (Wang et al., 2023). These findings are consistent with the results of this study. Similarly, Bai Shufang conducted a susceptibility zoning study on the geological disasters in Shahe City, Hebei Province. The results showed that high-susceptibility areas are primarily distributed in the western region, while the susceptibility in the eastern region is low (Bai, 2013). Overall, the results of this study, which employed the Random Forest model to assess the geological disaster susceptibility of Hebei Province, are in good agreement with previous research findings. Additionally, this study was validated using geological disaster events that occurred in Hebei Province in 2020 and 2021. A total of 38 geological disasters occurred in the province during these two years, of which 34 were triggered by heavy rainfall (*Fig. 8*). The validation process involved comparing the predicted high-risk and relatively high-risk zones identified by the model with the actual locations of these geological disasters. Specifically, the 34 heavy rainfall-induced events were cross-referenced with the geological disaster susceptibility maps generated by the Random Forest model, focusing on the overlap between the disaster sites and the model's high-risk zones. The results showed that 91.2% of the actual disaster sites were located in the high-risk and relatively high-risk zones predicted by the model, while only 8.8%

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occurred in other risk zones. This strong alignment between the model's predictions and the actual disaster occurrences demonstrates the effectiveness and reliability of the study's results and highlights the model's robustness in identifying disaster-prone areas. While the study demonstrates good predictive accuracy for geological disaster risk using the Random Forest and Naive Bayes models, the limitations of these models, including the assumptions of independence in Naive Bayes and the potential for overfitting in Random Forest, should be acknowledged. These limitations could affect the accuracy and generalizability of the findings.

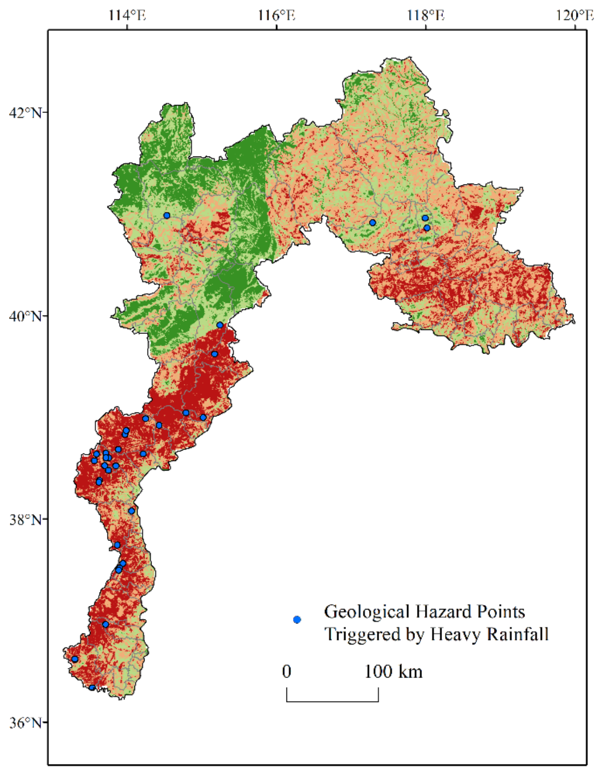

Figure 8. *Spatial distribution map of geological disasters for 2020 and 2021*

Future research could further improve model accuracy and regional applicability by optimizing model factors, conducting spatiotemporal dynamic evaluations, and integrating multi-source data. To enhance model accuracy, further optimization can be achieved by exploring other machine learning methods to capture more complex, nonlinear relationships between variables. These techniques could help fine-tune model parameters and improve feature selection, enabling the model to better adapt to regional variations and enhance prediction accuracy. Meanwhile, future studies could incorporate real-time monitoring data or regional climate models to enhance the accuracy of assessments. The model results in this study are of great significance for disaster forecasting and emergency management in the mountainous areas of Hebei Province, but their applicability needs to be analyzed based on specific regional characteristics. In regions with significantly different geological or climatic conditions, the model may require adjustments to its weights or the introduction of new factors to improve applicability, thereby better balancing ecological protection with disaster risk management.

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REFERENCES

[1] Bai, S. (2013): Shahe City in Hebei Province the Characteristics of Geological Disasters and Regionalization Research. – China University of Geosciences, Beijing.
[2] Cao, M., Zhao, J., Zhang, S. (2018): Research on the suitability evaluation of construction land in southwest mountainous areas of China: a case study of Baoxing County, Sichuan Province, China. – Applied Ecology and Environmental Research 16(5).
[3] Chen, L., Mei, L., Zeng, B., Yin, K., Shrestha, D., Du, J. (2020): Failure probability assessment of landslides triggered by earthquakes and rainfall: a case study in Yadong County, Tibet, China. – Scientific Reports 10(1): 1-12.
[4] Chowdhuri, I., Pal, S., Arabameri, A., Ngo, P. Chakrabortty, R., Malik, S., Das, B., Roy, P. (2020): Ensemble approach to develop landslide susceptibility map in landslide dominated Sikkim Himalayan region, India. – Environmental Earth Sciences 79(20): 1-28.
[5] Fan, Z., Gou, X., Qin, M., Fan, Q., Yu, J., Zhao, J. (2018): Information and logistic regression models based coupling analysis for susceptibility of geological disasters. – Journal of Engineering Geology 26(2): 340-347.
[6] Guo, F., Meng, X., Li, Z., Xie, Z., Chen, G., He, Y. (2015): Characteristics and causes of assembled geo-hazards induced by the rainstorm on 25th July 2013 in Tianshui City, Gansu, China. – Mountain Research 33(1): 100-107.
[7] Hong, B., Shao, B., Wang, B., Zhao, J., Qian, J., Guo, J., Xu, Y., Li, C., Zhu, B. (2023): Using the meteorological early warning model to improve the prediction accuracy of water damage geological disasters around pipelines in mountainous areas. – Science of the Total Environment 889: 164334.
[8] Hu, L., Hu, Y., Sun, P., Zhang, Q., Zhou, Q., Chen, J. (2021): A quantitative analysis of disaster threshold and landslide risk of rainfall-type landslide in southeast Tibet. – Journal of Catastrophology 36(4): 194-199.
[9] Huang, M., Ma, L. (2017): Climatically induced mechanism of geological disasters in Chongqing. – Journal of Chongqing Jiaotong University (Natural Science) 36(11): 66-70.
[10] Huang, P., Peng, L., Pan, H. (2020): Linking the random forests model and GIS to assess geo-hazards risk: a case study in Shifang County, China. – IEEE Access 8: 28033-28042.
[11] Kalkan, E. (2011): Impact of wetting-drying cycles on swelling behavior of clayey soils modified by silica fume. – Applied Clay Science 52(4): 345-352.
[12] Li, Y., Meng, H., Dong, Y., Hu, S. (2004): Main types and characteristics of geo-hazard in China—based on the results of geo-hazard survey in 290 counties. – The Chinese Journal of Geological Disaster and Control (2): 32-37.
[13] Li, Yi., Liu, Y., Liang, L., Li, J. (2021): Assessment on hazard of geological disasters in alpine and canyon landforms of Qinghai-Tibet Plateau-a case study of Yajiang County. – Research of Soil and Water Conservation 28(03): 364-370.
[14] Liu, J., Li, S., Chen, T. (2018a): Landslide susceptibility assessment based on optimized random forest model. – Geomatics and Information Science of Wuhan University 43(7): 1085-1091.
[15] Liu, W., Zhang, Y., Liang, Y., Sun, P., Li, Y., Su, X., Wang, A., Meng, X. (2022): Landslide risk assessment using a combined approach based on InSAR and random forest. – Remote Sensing 14(9): 2131.
[16] Liu, Y., Di, B., Zhan, Y., Constantine, A. (2018b): Debris flows susceptibility assessment in Wenchuan earthquake areas based on random forest algorithm model. – Mountain Research 36(5): 765-773.

© 2025, ALÖKI Kft., Budapest, Hungary

[17] Liu, Y., Gao, Y., Chen, H., Lai, L. (2019): Damage assessment of natural disasters based on cloud model. – Applied Ecology and Environmental Research 17(3): 5723-5735.
[18] Mori, S., Ono, K. (2019): Landslide disasters in Ehime Prefecture resulting from the July 2018 heavy rain event in Japan. – Soils and Foundations 59(6): 2396-2409.
[19] Mou, M. (2020): Study on the Probability Prediction Model of Water Bloom Occurrence in Dianchi Lake Based on Remote Sensing Data and Meteorological Factors. – Nanjing Normal University, Nanjing.
[20] Nakai, S., Sasaki, Y., Kaibori, M., Moriwaki, T. (2006): Rainfall index for warning and evacuation against sediment-related disaster: reexamination of rainfall index Rf, and proposal of R'. – Soils and Foundations 46(4): 465-475.
[21] Novellino, A., Cesarano, M., Cappelletti, P., Di Martire, D., Di Napoli, M., Ramondini, M., Sowter, A., Calcaterra, D. (2021): Slow-moving landslide risk assessment combining machine learning and InSAR techniques. – Catena 203: 105317.
[22] Shen, Z., Zhang, Q., Wu, W., Song, C. (2022): Spatial pattern and attribution analysis of the regions with frequent geological disasters in the Tibetan Plateau and Hengduan Mountains. – Acta Geographica Sinica 77(5): 1211-1224.
[23] Song, Y., Zhang, H. (2020): Study on geological disasters susceptibility assessment based on weighted fuzzy probability exponential model. – Yangtze River 51(11): 109-115.
[24] Sun, L., Cao, X., Li, W., Zhang, T. (2018): A Meteorological Risk Assessment Model for Geological Disasters of Qinhuangdao. – In: 8th Annual Meeting of Risk Analysis Council of China Association for Disaster Prevention (RAC 2018). Atlantis Press, Paris, pp. 278-282.
[25] Tie, Y., Ruan, C., Yang, S., Zeng, B., Zhang, B., Li, F., Sun, J., He, Z. (2021): Characteristics and mechanism of geological disasters induced by '5·25' rainstorm in Gongshan County of Yunnan Province. – Bulletin of Soil and Water Conservation 41(2): 10-15.
[26] Wang, J., Yin, K., Xiao, L. (2014): Landslide susceptibility assessment based on gis and weighted information value: a case study of Wanzhou district, three gorges reservoir. – Chinese Journal of Rock Mechanics and Engineering 33(4): 797-808.
[27] Wang, M. (2022): Some problems of geological disaster prevention and control. – The Chinese Journal of Geological Disaster and Control 33(1): 1-5.
[28] Wang, R., Zhai, Y., Zhang, B., Shen, G., Zeng, Y. (2023): Evaluation of geological disaster in Chengde area based on GIS and AHP coupling technology. – Geoscience 37(4): 1023-1032.
[29] Wang, X., Wang, C., Liao, L., Chen, Z., Tian, Q., Chen, Y. (2020): Rainfall threshold analysis of landslides in red bed areas based on rainfall intensity and duration: Pu'er as an example. – Meteorological Science and Technology 48(5): 758-765.
[30] Yao, X., Pu, J., Tian, G., You, Z., Zhu, E. (2010): Assessment of the risk of debris flow triggered by heavy (torrential) rain along the west section of Baoji-Tianshui expressway. – Journal of Glaciology and Geocryology 32(6): 1270-1275.
[31] Zeng, W., Wu, F. (2017): Risk assessment on geological disaster caused by typhoon and rainstorm in Beibu Gulf economic zone of Guangxi Zhuang autonomous region. – The Chinese Journal of Geological Disaster and Control 28(1):121-127.
[32] Zhang, J., Yin, K., Wang, J., Liu, L., Huang, F. (2016): Evaluation of landslide susceptibility for Wanzhou district of Three Gorges Reservoir. – Chinese Journal of Rock Mechanics and Engineering 35(2): 284-296.
[33] Zhang, J., Rong, G., Li, T., Fang, W. (2022): Comprehensive risk assessment technology of geological disaster chain induced by multiple disaster factors. – Disaster Reduction in China (7): 23-26.
[34] Zhang, X. (2018): Hazard Assessment of Geological Disasters Along Jing-Zhang High-Speed Railway. – Chinese Academy of Geological Sciences, Beijing.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2303_54435460
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[35] Zhou, C., Xia, Z., Chen, D., Miao, L., Hu, S., Yuan, J., Huang, W., Liu, L., Ai, D., Xu, H., Xiao, C. (2024): Extreme Rainfall Events Triggered Loess Collapses and Landslides in Chencang District, Shanxi, China, during June–October 2021. – Water 16(16): 2279.
[36] Zhu, X., Li, Y., Tang, L., Zhang, Y. (2014): The analysis of geological disaster of the '7·21' rainstorm in Baoding in Hebei province. – The Chinese Journal of Geological Disaster and Control 25(1): 90-96.
[37] Zhuang, Y., Xing, A. (2022): History must not repeat itself-urban geological safety assessment is essential. – Natural Hazards 111(2): 2141-2145.

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