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Geologic hazard susceptibility assessment based on statistical optimization and machine learning: A case study of the Loess Plateau, Shaanxi Province, northwestern China

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ABSTRACT

This study developed a modeling methodology for statistical optimization-based geologic hazard susceptibility assessment, aiming to enhance the comprehensive performance and classification accuracy of the assessment models. First, the cumulative probability method revealed that a low probability (15%) of geologic hazards between any two geologic hazard points occurred outside a buffer zone with a radius of 2297 m (i.e., the distance threshold). The training dataset was established, consisting of negative samples (non-hazard points) randomly generated based on the distance threshold, positive samples (i.e., historical hazards), and 13 conditioning factors. Then, models were built using five machine learning algorithms, namely random forest (RF), gradient boosting decision tree (GBDT), naive Bayes (NB), logistic regression (LR), and support vector machine (SVM). The comprehensive performance of the models was assessed using the area under the receiver operating characteristic curve (AUC) and overall accuracy (OA) as indicators, revealing that RF exhibited the best performance, with OA and AUC values of 2.7127 and 0.981, respectively. Furthermore, the machine learning models constructed by considering the distance threshold outperformed those built using the unoptimized dataset. The characteristic factors were ranked using the mutual information method, with their scores decreasing in the order of rainfall (0.1616), altitude (0.06), normalized difference vegetation index (NDVI; 0.04), and distance from roads (0.03). Finally, the geologic hazard susceptibility classification was assessed using the natural breaks method combined with a clustering algorithm. The results indicate that the clustering algorithm exhibited higher classification accuracy than the natural breaks method. The findings of this study demonstrate that the proposed model optimization scheme can provide a scientific basis for the prevention and control of geologic hazards.

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1. Introduction

Geologic hazards are severe natural disasters with a geologic origin (Yu S et al., 2015), including loess collapses, landslides, and debris flows throughout the world (Zhang H and Wang Z, 2022). Fig. 1 presents typical hazard types investigated in this study. Fig. 1a shows the characteristic

landform in the Loess Plateau in China, and Fig. 1b illustrates a common loess collapse from the research database. Loess collapses are typically caused by a sudden detachment of soils from a steep loess slope under the activity of gravity, resulting in soil accumulation at the base of the slope. This process can be triggered by factors such as rainfall, human activities, and biological activities. Fig. 1c depicts a landslide hazard, where soils slide along a weak surface due to gravity, in a high-slope region with thick loess strata. Landslides can be triggered by surface water, groundwater, river erosion, human engineering activities, freeze-thaw cycles, and weathering processes. In the Loess Plateau, loess collapses might trigger landslides. During the formation of loess landslides, collapses may occur first, followed by subsequent landslides along weak structural

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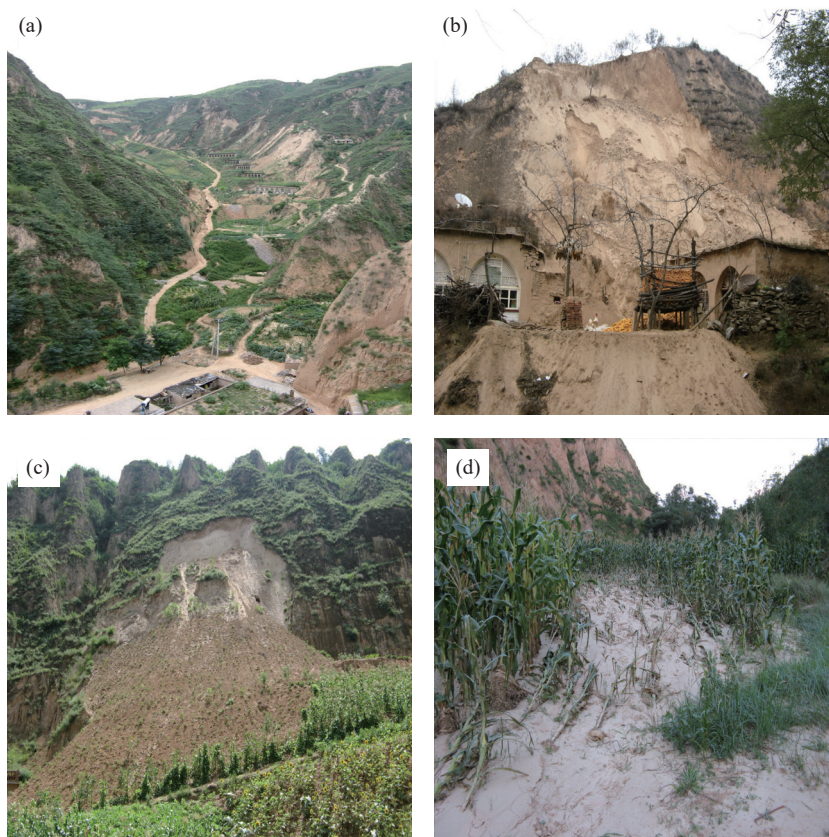


Fig. 1. Geologic hazard types in the Loess Plateau in northwestern China. a–Characteristic landform of the Loess Plateau; b–loess collapse; c–landslide; d–debris flow.

planes within the loess strata, thus forming the collapse-then-landslide model. Fig. 1d represents a debris flow hazard in the study area, which emerges as an engineering-induced dynamic geological phenomenon characterized by torrents of water mixed with sediments and stones. Notably, loess collapses and landslides are closely associated with debris flows. Areas prone to both types of geologic disasters are also susceptible to debris flow outbreaks, though sufficient water is required initially. These hazards pose a serious threat to urban and rural infrastructure, transportation networks, factories, and water conservancy projects (Wang J et al., 2012).

Factors influencing geologic hazards vary with region. Generally, these hazards are caused by natural elements and anthropogenic factors, with the former including abnormal energy release within the Earth, material movements, and rock deformations (e.g., heavy rainfall, earthquakes, and rapid snowmelt) and the latter including road construction and irrigation (Yuan X et al., 2018; Zhang W et al., 2023; Ullah K et al., 2022). The rapid development of technology has greatly improved the efficiency of resource acquisition (He F et al., 2021). However, the excessive exploitation of natural resources has led to numerous natural disasters such as geologic hazards (Abdulwahid WM and Pradhan B, 2017), posing a serious threat and causing irreparable damage to both people and society (Chen C et al., 2018). Therefore, it is essential to develop a model for geological hazard susceptibility assessment by effectively analyzing human

activities, natural and geographical environments, and geological interactions (Andriani GF and Loiotine L, 2020).

The efficiency and reliability of models for geological hazard susceptibility assessment have been greatly improved with the advancement in remote sensing (RS) and geographic information system (GIS) (Hong Y and Abdelkareem M, 2022; Hu Y et al., 2022) since RS-derived data and the spatial analysis tools of a GIS are identified as fundamental components of the models (Zhu J et al., 2011). Geologic hazard conditioning factors and detailed data on historical geologic hazards are crucial to knowledge-based and data-driven spatial modeling approaches (Zhang X 2020). Knowledge-based spatial modeling methods have been extensively applied to map plotting in geological hazard susceptibility assessment (Liang SY et al., 2010), including Analytical Hierarchy Process (AHP) (Abuzied SM and Mansour BMH, 2019), fuzzy logic, frequency ratio, a combination of AHP with GIS-based statistical models (Chen Y et al., 2014; Tazik E et al., 2014), and information value models (Liu Y et al., 2018). The model-derived results are classified using similar classification methods such as the landslide potential index (Kahal AY et al., 2021).

In recent years, machine learning has been increasingly applied to geologic hazard analysis, providing new approaches for addressing geologic hazard challenges, with key algorithms employed including LR (Liu L et al., 2021), boosted regression tree (Alireza A et al., 2019), generalized linear model (Saleh Y et al., 2020), RF (Wang Z et al., 2024),

SVM (Wang W et al., 2020) and multivariate discriminant analysis (MDA; Regina SL et al., 2024). Many models for geological hazard susceptibility assessment have been developed while considering various factors such as topography, geology, meteorology, hydrology, and human activities (Lin J et al., 2021; Youssef AM et al., 2023), proving that advanced machine learning methods are highly effective in the spatial prediction of geologic hazards.

Previous researchers tend to rely on models built using empirical knowledge, which restrict their acquisition of objective and quantitative results. Presently, many researchers have shifted their attention to machine learning methods in geological hazard susceptibility assessment. However, they frequently overlook the rationality of the spatial distribution of samples from a dataset. Furthermore, negative samples are typically constructed through random generation, leading to compromised accuracy and decreased generalizability of models. Regarding the results, the natural breaks method, which is highly sensitive to noise and outliers in large datasets, is commonly used for geological hazard susceptibility classification, resulting in over-segmentation in geologic hazard zoning.

This study aims to address the aforementioned three challenges by advancing quantitative geological hazard susceptibility assessment. By investigating the Loess Plateau in northern Shaanxi, China—a region recognized as one of the most environmentally fragile areas in the country (Zeng L and Huang Y, 2010), this study developed a model for geological hazard susceptibility assessment using RF, GBDT, LR, NB, and SVM algorithms, which were determined based on relevant factors influencing the assessment. First, the probability of the occurrence of geologic hazards between any two geologic hazard points was calculated using the

cumulative probability method. Consequently, the hazard threshold for the training dataset was obtained, using which negative samples were generated, forming the training dataset for the susceptibility evaluation. Finally, the susceptibility probability produced by the model was classified using the clustering algorithm, determining the susceptibility. The results demonstrate that this approach allows for the building of a high-precision model for geological hazard susceptibility assessment, thus contributing to the timely assessments of regional geologic hazards and the minimization of associated losses.

2. Materials and methods

2.1. The study area

The Loess Plateau in northern Shaanxi, emerging as the most representative region of loess deposits and landforms in China, is known for its severe soil erosion and high susceptibility to geologic hazards (Gan Z et al., 2004). This plateau extends from 34.30°N to 39.60°N and from 106.30°E to 111.50°E, covering an area of 79490 km² (Fig. 2). Regarding its landscape, it is generally mountainous in the west and southwest and is dominated by a network of gullies and river valleys in the remaining parts. The Loess Plateau exhibits altitudes ranging from 340 m to 2430 m, slopes from 0° to 80°, and curvatures from −81 to 70. Contemporarily, its gully density is approximately 4–5 km/km², with a ratio between inter-gully and gully areas of 6 : 4. Its surface displays a crack density of about 50%. The crisscrossed gullies lead to fragmented terrain, rendering this region frequently subjected to geologic hazards. (Gan Z et al., 2004; Matsunaga K and Gan Z, 2007; Shi Q et al., 2007).

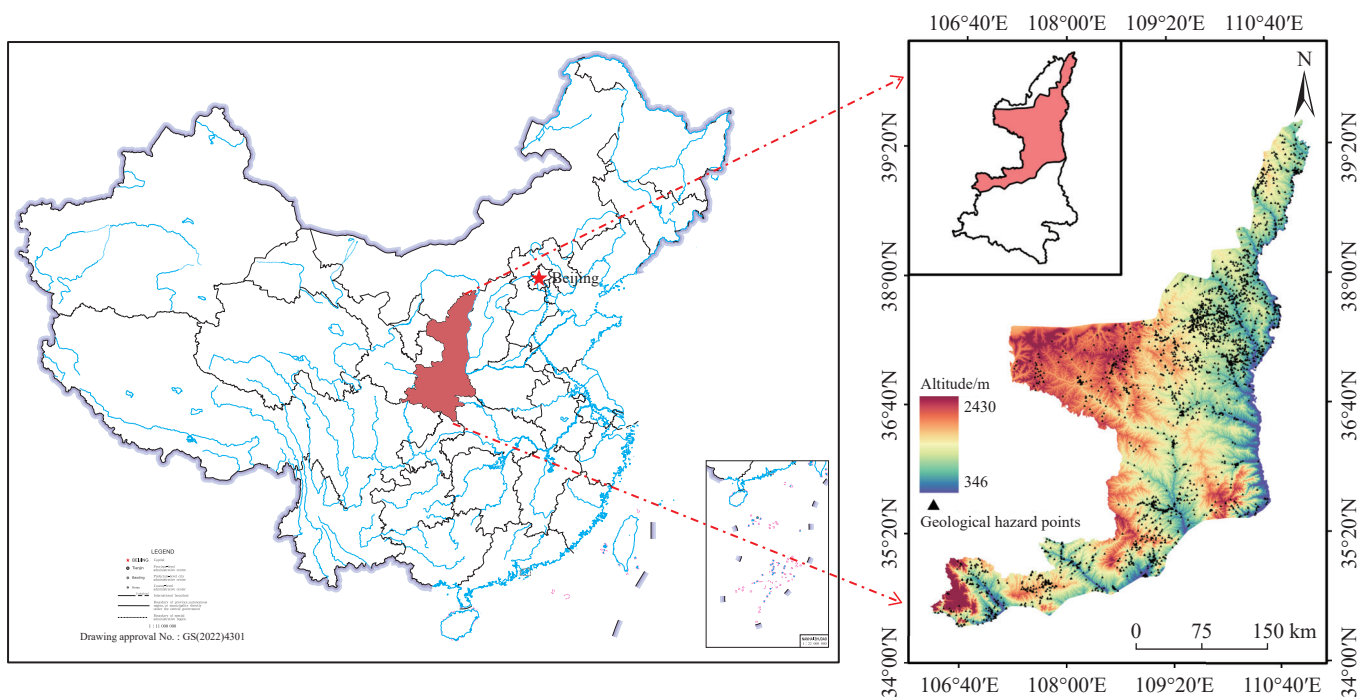


Fig. 2. Location of the Loess Plateau in northwestern China.

2.2. Methodology

In the Loess Plateau in northern Shaanxi, geologic hazards such as loess collapses and landslides are strongly influenced by various geological, climatic, topographic, and human factors. To achieve deeper insights into the causes and enhanced prediction accuracy of these hazards, this study determined the mechanisms behind the correlations between geologic hazards and environmental characteristics using machine learning models. First, the unique geological conditions and topography of the Loess Plateau were analyzed based on a comprehensive literature review, identifying key factors influencing geologic hazards. Next, data on historical geologic hazards and environmental features were transformed into the input variables of the models through feature engineering. A range of machine learning algorithms were then employed to train the models to capture complex relationships between the input variables and geologic hazards. These models can handle multivariate data and detect nonlinear patterns, thus improving the prediction accuracy. During the model training, the models were evaluated and optimized using performance indicators to ensure strong generalization and excellent prediction performance. Additionally, the impacts of different environmental factors on hazard susceptibility were assessed using the mutual information method for feature selection, further optimizing the model structure. Ultimately, the geologic hazard susceptibility in the study area were quantitatively assessed using the models. An overview of the research methodology for quantitative geologic hazard susceptibility assessment is depicted in Fig. 3.

The machine learning-based geologic hazard susceptibility assessment can be divided into four main phases. The first

phase involved data collection and the construction of machine learning datasets. The key innovation in this stage is that the training dataset was divided into positive and negative samples using the cumulative probability method. In the second phase, the dataset was trained using the RF, GBDT, LR, NB, and SVM algorithms, leading to the formation of five models. Additionally, the model accuracy was evaluated using the ROC, Matthews' correlation coefficient (MCC), and OA metrics. In the third phase, the probability values for geologic hazard susceptibility assessment were calculated using the five models and were then used to generate an assessment map. In the fourth stage, a novel method was proposed, using which the assessment models with superior performance were selected. The natural breaks method combined with a clustering algorithm was employed to classify the susceptibility probability results, ultimately forming the optimal classification method.

2.3. Historical geologic hazard data

Historical geologic hazard data, laying the foundation for the modeling process, are essential for geologic hazard susceptibility assessment (Bui DT et al., 2011). To examine the relationships between geologic hazard occurrences and various conditioning factors, as well as identifying common failure mechanisms (Wang C et al., 2021), this study first gathered data on historical geologic hazard events from multiple sources, including the Department of Natural Resources of Shaanxi Province and data from Moderate-resolution Imaging Spectroradiometer (MODIS) and Interferometric Synthetic Aperture Radar (InSAR). The 2850 geologic hazard events recorded consisted of 1666 loess collapses and 1184 landslide events. Geologic hazards in the Loess Plateau are dominated by loess collapses and landslides

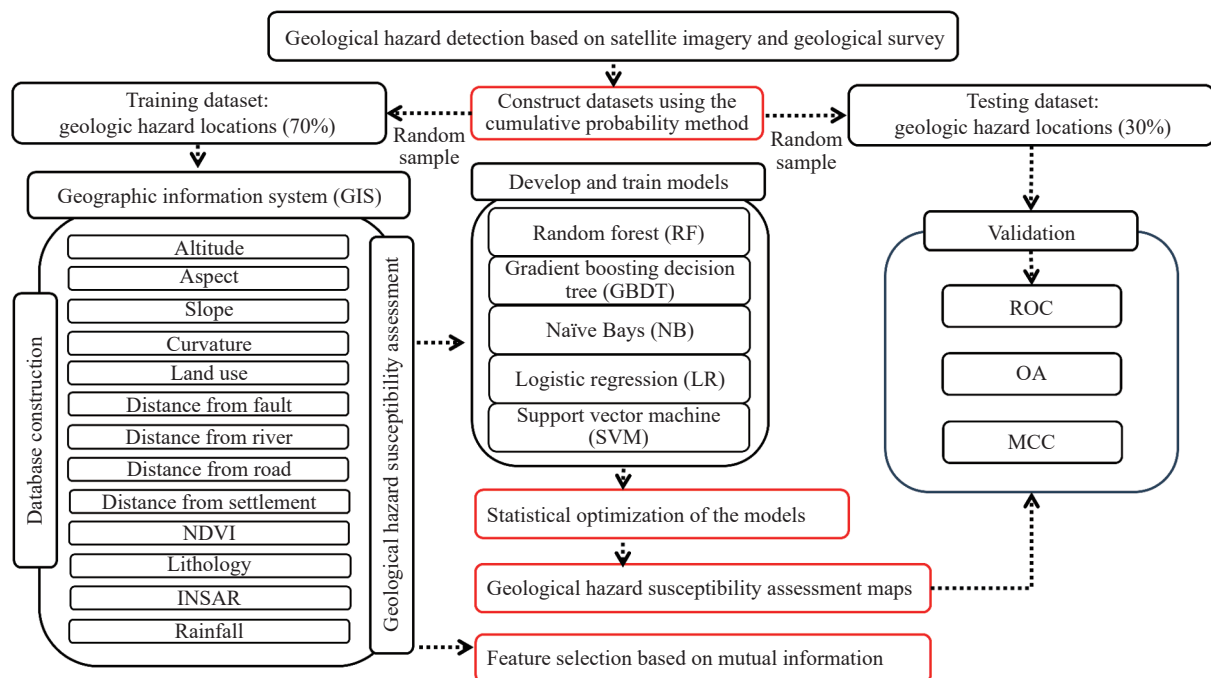


Fig. 3. Geologic hazard susceptibility assessment based on machine learning method.

due to its unique topography (Li Y and Mo P, 2019). Given that loess collapse and landslide events share similarities in mechanisms and occurrence conditions, this study increased the sample size by considering loess collapses and landslides together under a unified ‘collapse-landslide’ model (Xu C et al., 2025).

2.4. Preparation of training and testing datasets

For spatial prediction in machine learning-based geologic hazard susceptibility assessment, it is necessary to divide data into two groups using binary classification: geologic hazard points and non-geologic hazard points. Before selecting negative samples, statistical analysis is required to examine the spatial distribution characteristics of samples. This study investigated the spatial distribution of samples using the cumulative probability method, revealing that the maximum distance between any two adjacent geologic hazard points is 29109.64 m (Fig. 4). The results also indicate that a buffer radius of 2297 m corresponds to an 85% probability that neighboring geologic hazard points fall within the buffer zone. Therefore, a buffer radius of 2297 m was selected. The sampling space outside this buffer zone was designated for negative samples, corresponding to a low geologic hazard probability of 15%. Non-geologic hazard points were then randomly generated using the ArcGIS software. The data was divided into a training dataset (70%) for modeling and a testing dataset (30%) for assessment. Both datasets were converted to the raster format with a pixel size of 90 m, matching the spatial resolution of the digital elevation model (DEM). Geologic hazard points and non-geologic hazard points were denoted by 1 and 0, respectively (Chen W et al.,

2019). Finally, 13 geologic hazard conditioning factors were determined for the training dataset to extract attribute values.

2.5. Preparation of the geologic hazard conditioning factors

Geologic hazard susceptibility assessment assumes that the occurrence of geologic hazards in the future is influenced by environmental parameters linked to past geologic hazards (Catani F et al., 2005). The occurrence of collapses and landslides depends primarily on the local geological conditions of slopes (Broothaerts N et al., 2012), while factors such as terrain and stratigraphic lithology tend to stabilize spatially (Wu Y and Lan H, 2022; Tian H et al., 2023). The analysis of the development and distribution of landslides and collapses, combined with relevant field investigation results, reveals that primary conditioning factors include altitude, curvature, aspect, slope, lithology, distances to faults, rivers, settlement and roads, NDVI, land use, rainfall, and InSAR (Huo A et al., 2019; Huo A et al., 2020; Meng Z et al., 2021; Yi J et al., 2022). These factors reflect the combined influences of topography, lithology, structural features, human engineering activities, and triggering factors on geologic hazards. Additionally, raster data were used as the evaluation units to quantify these factors (Fig. 5).

In this study, the altitude dataset consists of DEM data obtained using the phased array L-band synthetic aperture radar (PALSAR) system on the Advanced Land Observing Satellite (ALOS; Fig. 5a; <https://search.asf.alaska.edu/#/>). Using the ArcGIS Pro software, additional terrain-related parameters such as curvature, slope, and aspect can be computed (Figs. 5b–d). Lithologic data were sourced from the Resource and Environment Science Data Platform

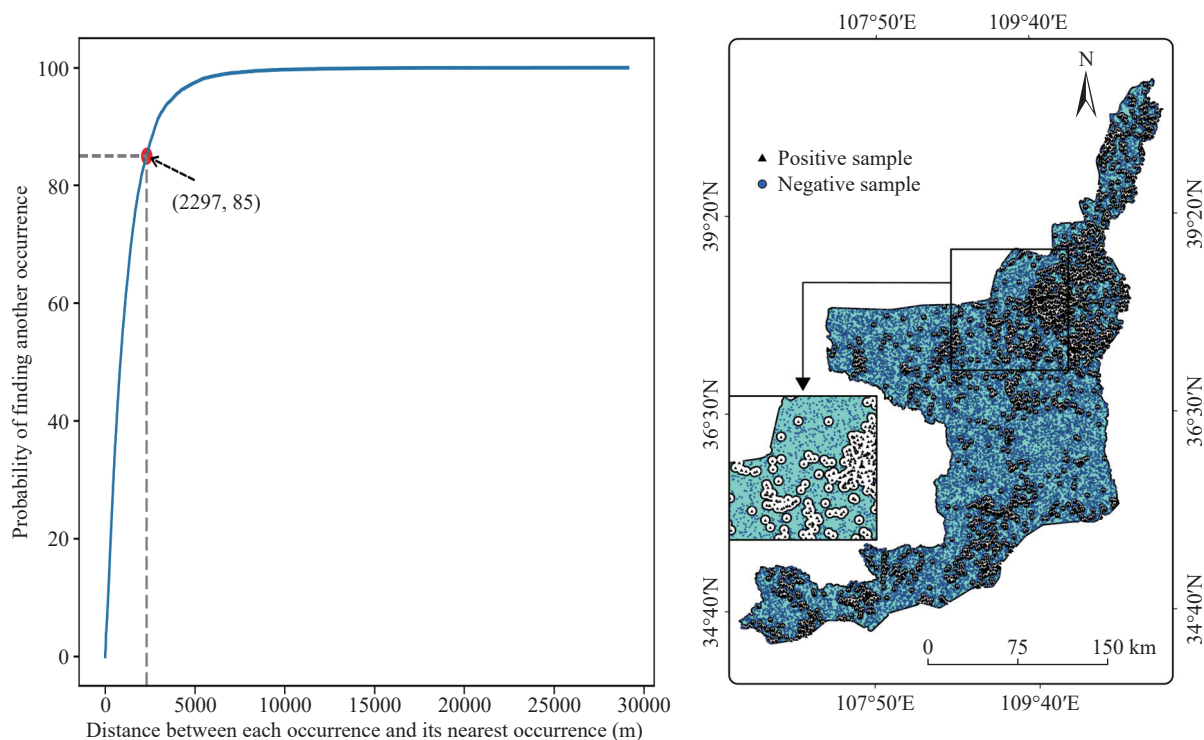
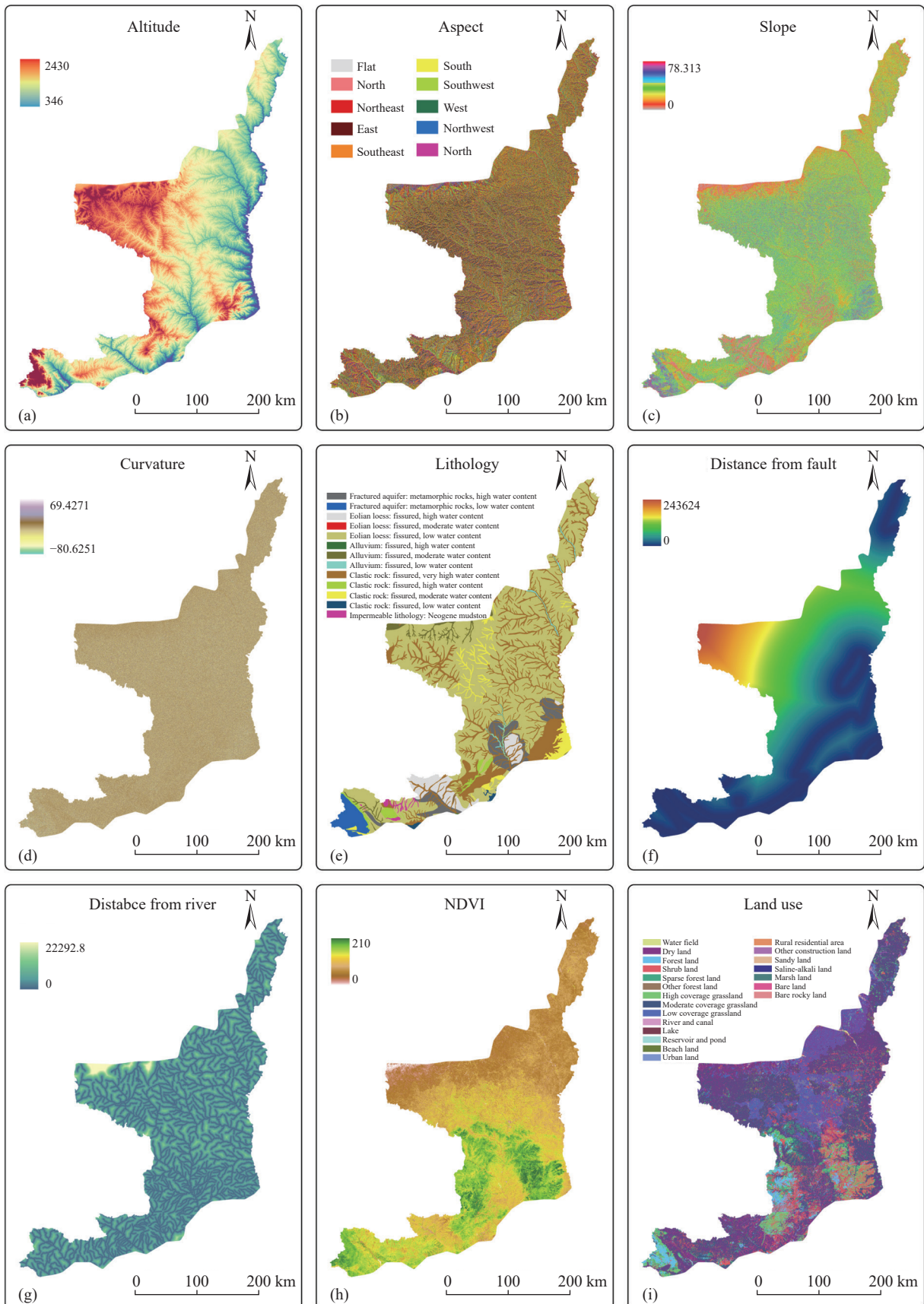


Fig. 4. Negative sample selection.

(<https://www.resdc.cn/>; Fig. 5e). The distance from faults was determined using the Euclidean Distance tool of ArcGIS Pro (Fig. 5f). The distance from rivers was calculated using ArcGIS based on the river data provided by the National

Geomatics Center of China (<https://www.webmap.cn/store.do?method=store&storeId=2>; Fig. 5g). Vegetation coverage was characterized using NDVI (Fig. 5h). To conserve storage space, the NDVI values were first amplified by 10000 times



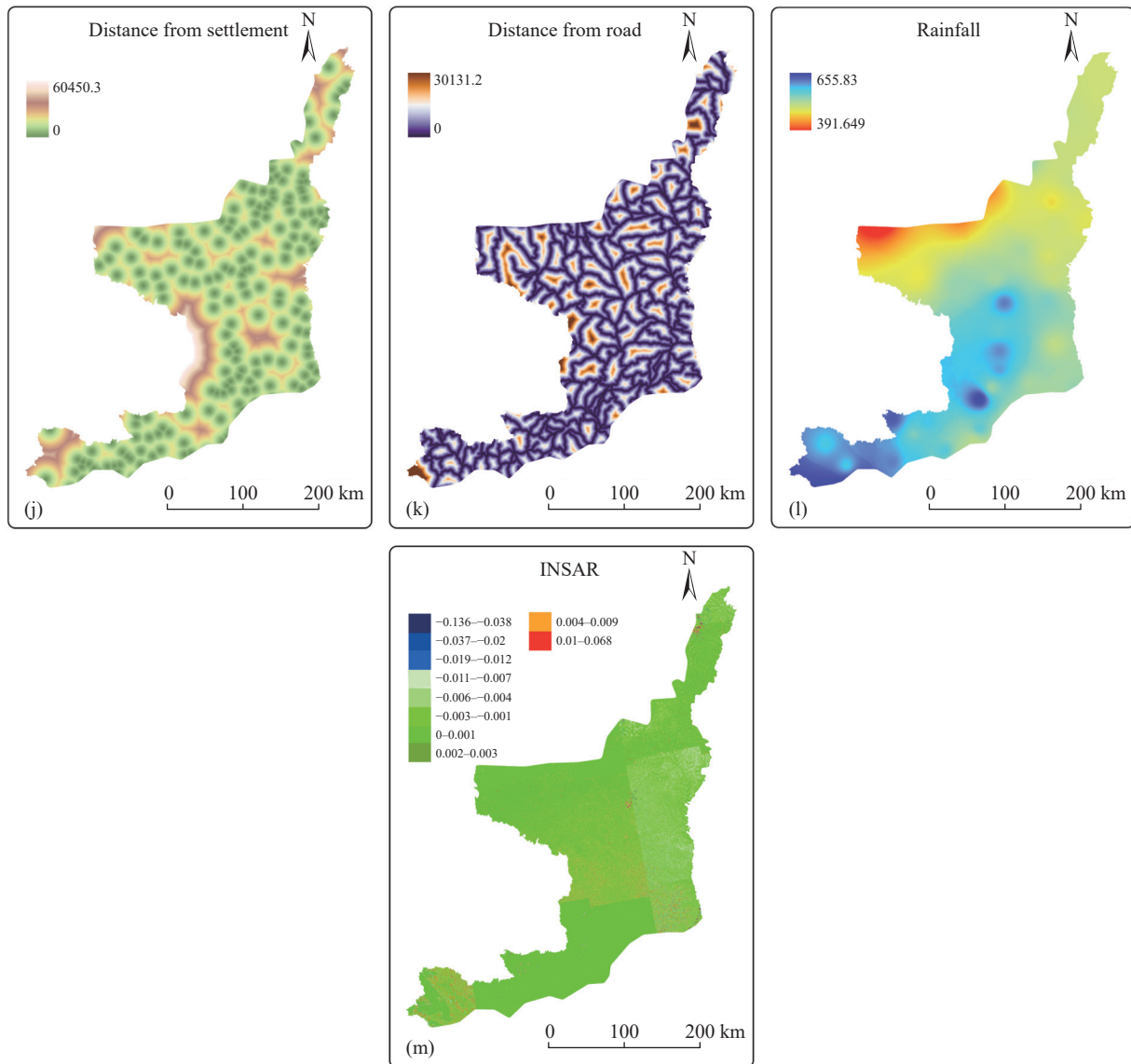


Fig. 5. Geologic hazard conditioning factors. a–Altitude; b–aspect; c–slope; d–curvature; e–lithology; f–distance from faults; g–distance from rivers; h–NDVI; i–land use; j–distance from residential areas; k–distance from roads; l–Rainfall; m–InSAR.

from the range of -0.2 – 1 to -2000 – 10000 and were then compressed to the range of 0 – 255 (Liu J et al., 2005). Land use, changes in land cover, and road data—core components of the human–environment coupling system—are essential variables in research on geologic hazards (Liu J et al., 2010). These datasets were provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (<http://www.resdc.cn>; Figs. 5i, k). In the calculation of the distance from residential areas, the names of towns or streets were obtained from the National Bureau of Statistics (<http://www.stats.gov.cn>). The coordinates of these locations were obtained using the address lookup tool of mapping service software, followed by correction using coordinate correction tools to obtain accurate coordinates. Based on these coordinates, the distance from residential areas was computed (Fig. 5j). The annual average rainfall of the years when geologic hazards occurred was obtained from meteorological stations under the Shaanxi Provincial Department of Natural Resources (Fig. 5l). Raster data were generated using the

Kriging interpolation method. InSAR data were accessed on the website of the European Space Agency's Sentinel dataset (<https://scihub.copernicus.eu/>). Raw radar image data were provided by the Sentinel-1 Synthetic Aperture Radar. After being preprocessed through calibration, filtering, and phase unwrapping, the radar image data were used for interferometric processing to compute the phase differences between them. Ultimately, the surface deformation data of the Loess Plateau were obtained (Hu J et al., 2014; Osmanoglu B et al., 2016; Yu H et al., 2019; Fig. 5m). These conditioning factors are detailed in Table 1.

2.6. Model description

Following the establishment of the training and testing datasets, various models for geologic hazard susceptibility were trained. To determine the feasibility of the assessment, five machine learning algorithms were selected: RF, GBDT, NB, LR, and SVM.

Table 1. Conditioning factors of geologic hazard susceptibility assessment.

Category	Conditioning factor	Source	Data type	Spatial resolution
Terrain and landform	Altitude	DEM	Continuous	90 m×90 m
	Curvature			
	Aspect			
	Slope			
Geotechnical conditions	Lithology	National map	Categorical	1 : 100000
Geological conditions	Distance from faults	National map	Continuous	90 m×90 m
Hydrological conditions	Distance from rivers	National map	Continuous	90 m×90 m
Environmental conditions	NDVI	Official organization	Continuous	30 m×30 m
	Land use			
Human engineering activities	Distance from residential areas	Official organization	Continuous	90 m×90 m
	Distance from roads			
Climate conditions	Rainfall	Sentinel-1	Continuous	90 m×90 m
Surface deformation	InSAR		Continuous	20 m×20 m

RF is a tree-based ensemble learning method widely used for prediction. It works by combining multiple decision trees to generate a single, reliable prediction, exhibiting robust resistance to overfitting and significantly enhanced prediction performance across various applications (Zounemat-Kermani M et al., 2021).

GBDT is a powerful tool for large-scale classification and regression tasks. Based on decision trees, it is well suited to handling heterogeneous data, providing heightened accuracy and robustness in machine learning applications (Hancock JT and Khoshgoftaar TM, 2020; Liu X and Pan R, 2021).

NB classifiers are simple probabilistic models that utilize Bayes' theorem. Assuming strong independence between features, NB is commonly employed in machine learning owing to its simplicity and effectiveness in making predictions (Sugahara S and Ueno M, 2021).

LR is a widely used classification algorithm known for its reliable performance and low computational cost. This algorithm uses a logistic function to model the relationship between multiple variables, effectively reducing confounding effects by analyzing the correlations among all variables (Cyril V et al., 2017).

SVM is renowned for its adaptability and strong performance across various contexts. This algorithm, employing kernel functions to expand the feature space and identify nonlinear decision boundaries, is effective in classification (Su Q et al., 2017).

2.7. Model performance evaluation

Evaluation is essential for probabilistic modeling, determining the reliability of model output. Various performance metrics are available to assess the effectiveness of models for geologic hazard susceptibility assessment. This study employed accuracy, precision, recall, F_1 -score, MCC, OA, and AUC as the evaluation criteria for the models (Nandi A et al., 2016; Davood M et al., 2019). To calculate these metrics, it is necessary to determine four numbers: (1) True Positive (TP), the number of samples that belong to the positive class and are predicted as positive; (2) False Positive (FP), the number of samples that belong to the negative class

but are predicted as positive; (3) True Negative (TN), the number of samples that belong to the negative class and are predicted as negative; and (4) False Negative (FN), the number of samples that belong to the positive class but are predicted as negative.

In this study, accuracy is defined as the proportion of correctly predicted samples ($TP + TN$) within the dataset, precision is the proportion of true positive (TP) predictions among all samples predicted as positive, and recall refers to the proportion of true positive (TP) predictions relative to all actual positive samples ($TP + FN$). Higher precision indicates that a model is more likely to correctly classify positive cases, while recall reflects the sensitivity of a model to positive instances. Given that precision and recall focus on different aspects of model performance, the F_1 -score was employed as a combined metric. This score is defined as the harmonic mean of precision and recall, ranging from 0 to 1. In addition to the F_1 -score, MCC is used as a more comprehensive evaluation metric (Wang H et al., 2021). MCC ranges from -1 to 1, with 1 representing a perfect prediction, 0 indicating no improvement compared to random prediction, and -1 signifying complete disagreement between prediction and observation. Both F_1 -score and MCC are important indicators of model accuracy. To further evaluate the model performance, this study introduced OA as a composite metric incorporating accuracy, F_1 -score, and MCC to evaluate the overall performance of a model (Wang H et al. 2021). The model with the highest OA in the region of interest is considered the best identification model. The five metrics, namely accuracy, precision, recall, F_1 -score, and MCC are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (5)$$

Both F_1 -score and MCC measure model accuracy, while accuracy, F_1 -score, and MCC all act as indicators of model performance. The combined index OA, proposed in this study to comprehensively quantify the overall performance of a model, is defined as follows:

$$OA = \text{Accuracy} + F_1 + MCC \quad (6)$$

2.8. Classification of geologic hazard susceptibility

The models for geologic hazard susceptibility assessment are used to calculate the susceptibility probability value of each evaluation unit, while the natural breaks method and a clustering algorithm are employed to classify the geologic hazard susceptibility. The natural breaks method identifies inflection points or natural boundaries in data based on their distribution characteristics, thus dividing the data into distinct intervals (Thi Ngo PT et al., 2021). The clustering algorithm categorizes similar data points into clusters based on the data's internal structure, allowing for the revealing of potential patterns and groupings. The following equation was defined in this study:

$$P = \frac{N}{S} \quad (7)$$

where P is the geologic hazard density of a susceptibility level and N and S are the number and area of the geologic hazards of the susceptibility level, respectively. This equation is used to quantitatively evaluate the accuracy of a classification

model.

2.9. Importance analysis of conditioning factors

Mutual information-based feature selection (MIFS) emerges as a statistical strategy designed to identify the most informative features for predicting a target variable from a large set of features (Shi Y et al., 2018). This method quantifies the correlation between features and the target variable by calculating the mutual information and then selecting the features with high mutual information. This approach helps identify the most important feature while avoiding selecting features that overlap or contain redundant information. The equation is defined as follows:

$$I(X; Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \quad (8)$$

where $I(X; Y)$ is the mutual information between random variables X and Y , $p(x,y)$ is the joint probability distribution of X and Y , and $p(x)$ and $p(y)$ are the marginal probability distribution of X and Y , respectively. A greater value of the mutual information corresponds to stronger interdependence between X and Y .

3. Results

3.1. Importance of conditioning factors

This study ranked the importance of the 13 conditioning factors using MIFS (Fig. 6). The results indicate that the factors all exhibit mutual information scores exceeding 0, indicating significant interdependence between each of the factors and the geologic hazard susceptibility assessment. The rankings identify rainfall, altitude, NDVI, distance from roads, and land use as the top five influencing factors, highlighting their critical role in the occurrence of geologic

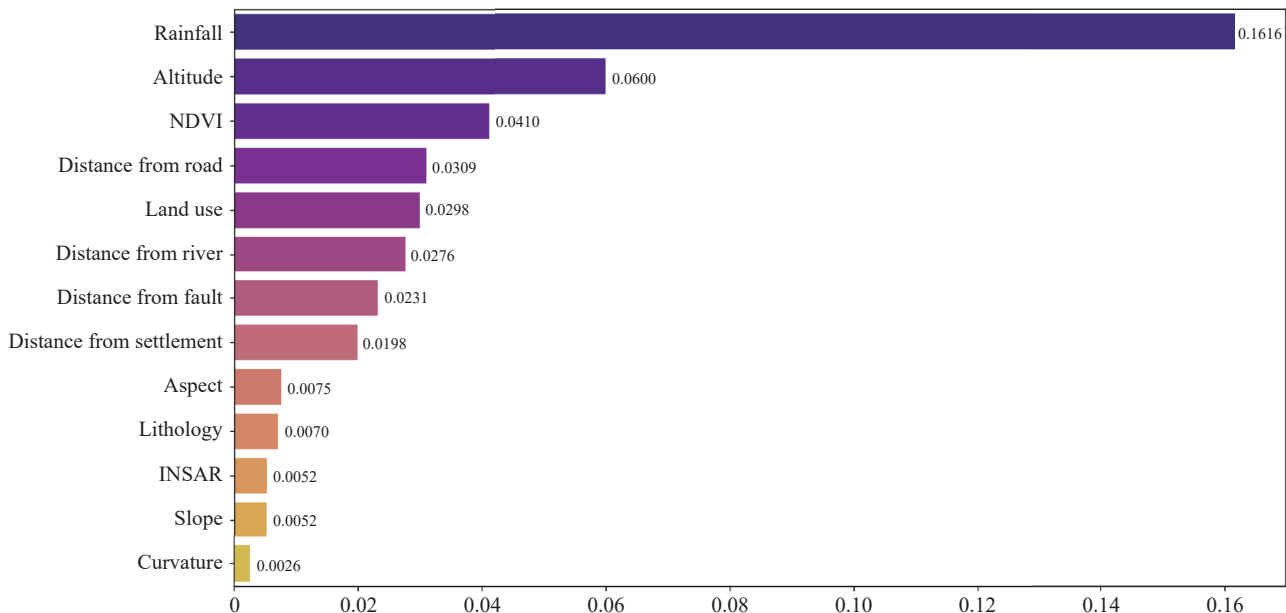


Fig. 6. Importance of conditioning factors.

hazards in the study area. Additionally, the rankings offer valuable insights into the relative influence of these factors and their association with hazard susceptibility.

3.2. Model validation and comparison

The research database, consisting of 981379 samples, were divided into a training dataset and a testing dataset at a ratio of 70/30. Based on the distribution characteristics of samples in the training dataset, the training set was balanced using the Synthetic Minority Oversampling Technique (SMOTE) algorithm to ensure a 50/50 ratio between positive and negative samples (Zuo R and Wang Z, 2020). Five machine learning algorithms, namely RF, GBDT, NB, LR, and SVM, were employed for model training using the training dataset, yielding five models. The geologic hazard susceptibility probability of each pixel was calculated, and the accuracy, precision, recall, F_1 , MCC, and OA of each model were calculated using the testing dataset. The results of various metrics are presented in Table 2.

To quantitatively evaluate the performance of the models, their ROC curves and AUC values were obtained based on both the training and testing datasets (Fig. 7), followed by the evaluation of the models' performance on both known (training dataset) and unknown data (testing dataset). The AUC values derived using the testing dataset are particularly important as they represent the model's generalizability, which is assessed by the prediction accuracy for new data. Additionally, comparing the performance using both datasets

helps determine whether the models suffer from overfitting or underfitting. Similar performance of a model on both datasets typically suggests that the model is stable and can be generalized well.

Fig. 7 shows that the RF and GBDT models exhibited similar high AUC values on both the training and testing datasets, which were 0.981 and 0.977, respectively against the testing dataset and approximately 1.000 and 0.988, respectively against the training dataset. This consistency suggests that both models featured high generalizability across different datasets rather than suffering overfitting. The NB, LR, and SVM models exhibited AUC values of 0.823, 0.779, and 0.752, respectively against the testing dataset. Despite decreased AUC values compared to the RF and GBDT models, these three models demonstrated a certain level of predictive capability. Data in Table 2 show that the RF model featured the highest OA value among all models, further confirming its superior performance in the geologic hazard susceptibility assessment. These results establish the RF model as the best model for the assessment.

To quantify the impacts of dataset construction on model performance, a sample set was created by randomly generating negative training samples using the ArcGIS software, with the sample number matching the quantity of samples produced using the cumulative probability method. Then, the above five machine learning algorithms were used to construct the model for geologic hazard susceptibility assessment. The AUC values of the five algorithms are shown in Fig. 8. The results demonstrate that the models constructed using the optimized dataset (a) exhibited higher AUC values than those derived using the unoptimized dataset (b). Therefore, the statistical optimization of data prior to modeling proves effective in enhancing model accuracy.

3.3. Plotting and classification of maps for geologic hazard susceptibility assessment

In the models for the geologic hazard susceptibility

Table 2. Performance of five machine learning models.

Machine learning model	Accuracy	Precision	Recall	F_1	MCC	OA
RF	0.9286	0.9269	0.9267	0.9268	0.8572	2.7127
GBDT	0.9267	0.9479	0.8991	0.9229	0.8542	2.7038
LR	0.7013	0.6911	0.7014	0.6962	0.4025	1.8001
NB	0.7271	0.6849	0.8160	0.7447	0.4642	1.9360
SVM	0.6704	0.6437	0.7269	0.6827	0.3452	1.6984

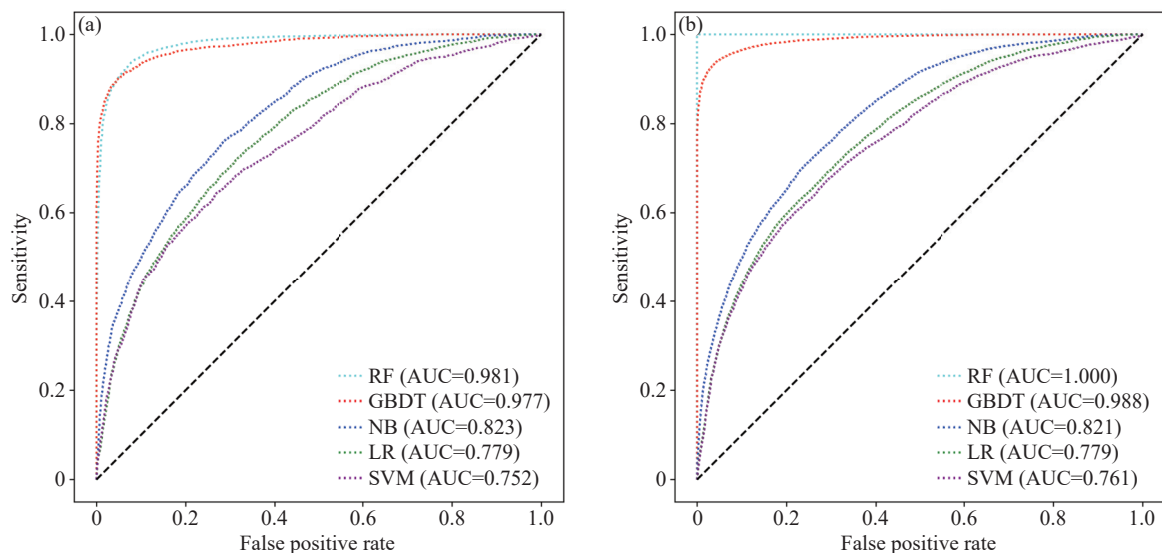


Fig. 7. ROC curves of models for geologic hazard susceptibility assessment derived using testing (a) and training (b) datasets.

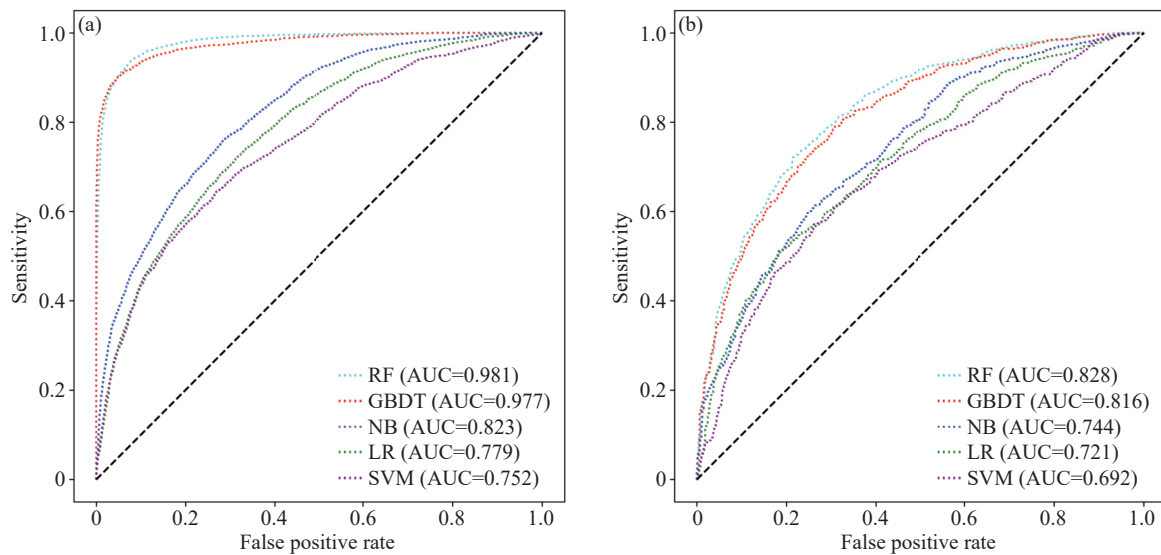


Fig. 8. ROC curves of models for geologic hazard susceptibility assessment (a) after and (b) before statistical optimization.

assessment, a hazard susceptibility probability index was assigned to each raster unit of the study area. Then, using ArcGIS, the assessment maps were plotted by assigning a weight to each hazard susceptibility probability index. To achieve more intuitive maps, the index was further categorized into four levels utilizing the natural breaks method: Very high, high, moderate, and low. Fig. 9 shows the assessment maps produced by various machine learning models. According to this figure, geologic hazards are concentrated in 'very high' and 'high' regions across all models, with the RF and GBDT models yielding very similar assessment results.

To quantify the differences in the classification of geologic hazard susceptibility between the clustering and natural breaks methods, two models with the highest comprehensive performance, i.e., RF and GBDT, were investigated. Their hazard density (P) under specific susceptibility levels was calculated using Eq. 7, and the results are shown in Table 3 and Fig. 10. Given the actual situation, regions with 'very high' and 'high' susceptibility were combined into 'very high to high' regions, of which the P values were calculated. For the RF and GBDT models, their P values obtained using the clustering method were about 1.15 times and 3.15 times higher than those determined using the natural breaks method, respectively. This finding indicates that the clustering algorithm effectively narrowed the regions with specific susceptibility levels while maintaining the geologic hazard number unchanged. Using the clustering method, government departments can prepare strategies for geologic hazard prevention and mitigation.

4. Discussion

Geologic hazards occur frequently in the Loess Plateau in northern Shaanxi, posing a serious threat to the livelihoods and production of local residents. The occurrence of these hazards is influenced by a complex interplay between topographic and environmental factors. Therefore,

constructing a high-accuracy model for geologic hazard susceptibility assessment is crucial to intuitively analyzing geologic hazard-prone areas. Traditional heuristic and statistical models tend to rely on expert assessments, which might introduce subjectivity and uncertainty into the modeling process (Ma Z and Mei G, 2021; Li T et al., 2024). In contrast, machine learning-based susceptibility assessments demonstrate superior performance (Wang Y et al., 2019). This study aims to apply machine learning algorithms to the geologic hazard susceptibility assessment of the Loess Plateau.

Machine learning algorithms RF, LR, SVM, RNN, LSTM, and CNN-1D have been employed to construct models for geologic hazard susceptibility assessment, yielding more precise and objective results (Merghadi A et al., 2020; Zhao Z and Chen J, 2023; Huang F et al., 2024). However, the random generation of negative training samples without considering the mathematical relationships between geographic distance and hazard occurrence during sample division may introduce uncertainty to both the selection of negative training samples and model outcomes. This study introduced a statistical optimization method that utilizes the cumulative probability approach to determine the threshold for selecting negative training samples. The comparison reveals that the assessment models constructed using the statistically optimized dataset significantly outperformed those built using the unoptimized dataset (Fig. 8). This advancement represents an improvement compared to similar studies.

The natural breaks method is typically employed to susceptibility classification in a geologic hazard assessment model (Liu L et al., 2021; Ganesh B et al., 2023; Shahabi H et al., 2023; Huang F et al., 2024). However, the presence of outliers in the data might produce adverse impacts on this method, leading to unstable threshold selection and ineffective identification of demarcation points. To address this issue, this study classified the assessment results using the clustering approach grounded in the statistical characteristics

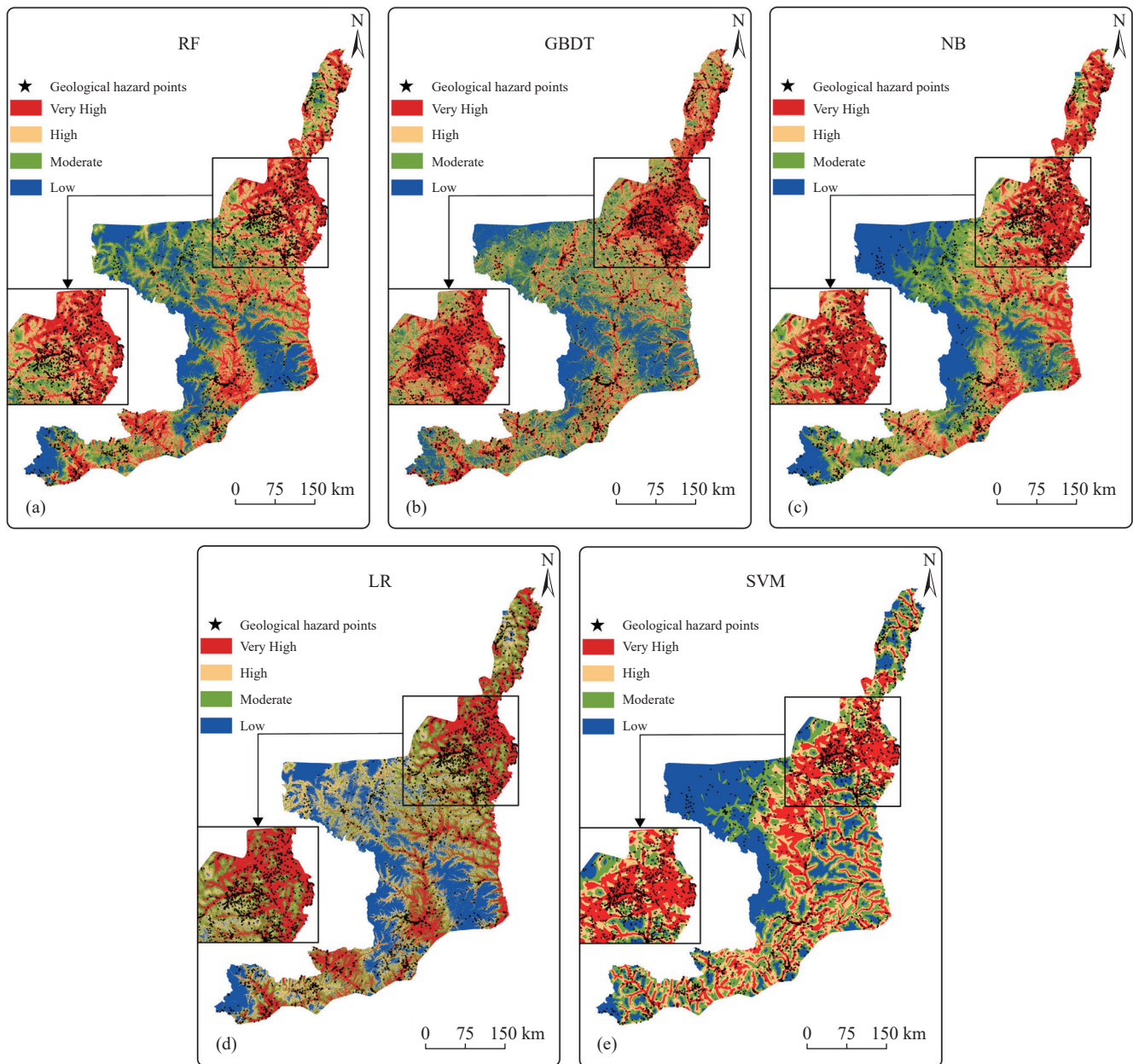


Fig. 9. Geologic hazard susceptibility assessment maps of various models.

Table 3. Hazard density of two models derived using the clustering and natural breaks methods.

Model	Very high	High	Very high-high
RF-clustering	0.001972	0.001477	0.00084
RF-natural breaks	0.001474	0.001474	0.00073
GBDT-clustering	0.005355	0.004038	0.00230
GBDT-natural breaks	0.001477	0.001474	0.00073

of data. The comparison of the classification outcomes derived using the natural breaks method and the clustering approach reveals that the clustering method results in a smaller area for each hazard grade when the hazard number is consistent. This approach enables more detailed and accurate classification, holding great significance for geologic hazard prevention and mitigation efforts.

Despite the fact the proposed method yielded encouraging results on the specific dataset, this study has several

limitations. The data used in this study cover a short time span and merely 13 conditioning factors. A sufficient sample size is crucial to enhancing model learning effectiveness in machine learning. Future studies will benefit from collecting data over a longer time and incorporating a wider range of features. This study employed statistical optimization-based machine learning models for the geologic hazard susceptibility assessment of the Loess Plateau. It is recommended that a more objective and comprehensive assessment model should be established in future research by improving the spatial resolution of the assessment units and exploring deep learning algorithms.

5. Conclusions

Geologic hazard susceptibility assessment is vital for hazard prevention and mitigation in the Loess Plateau,

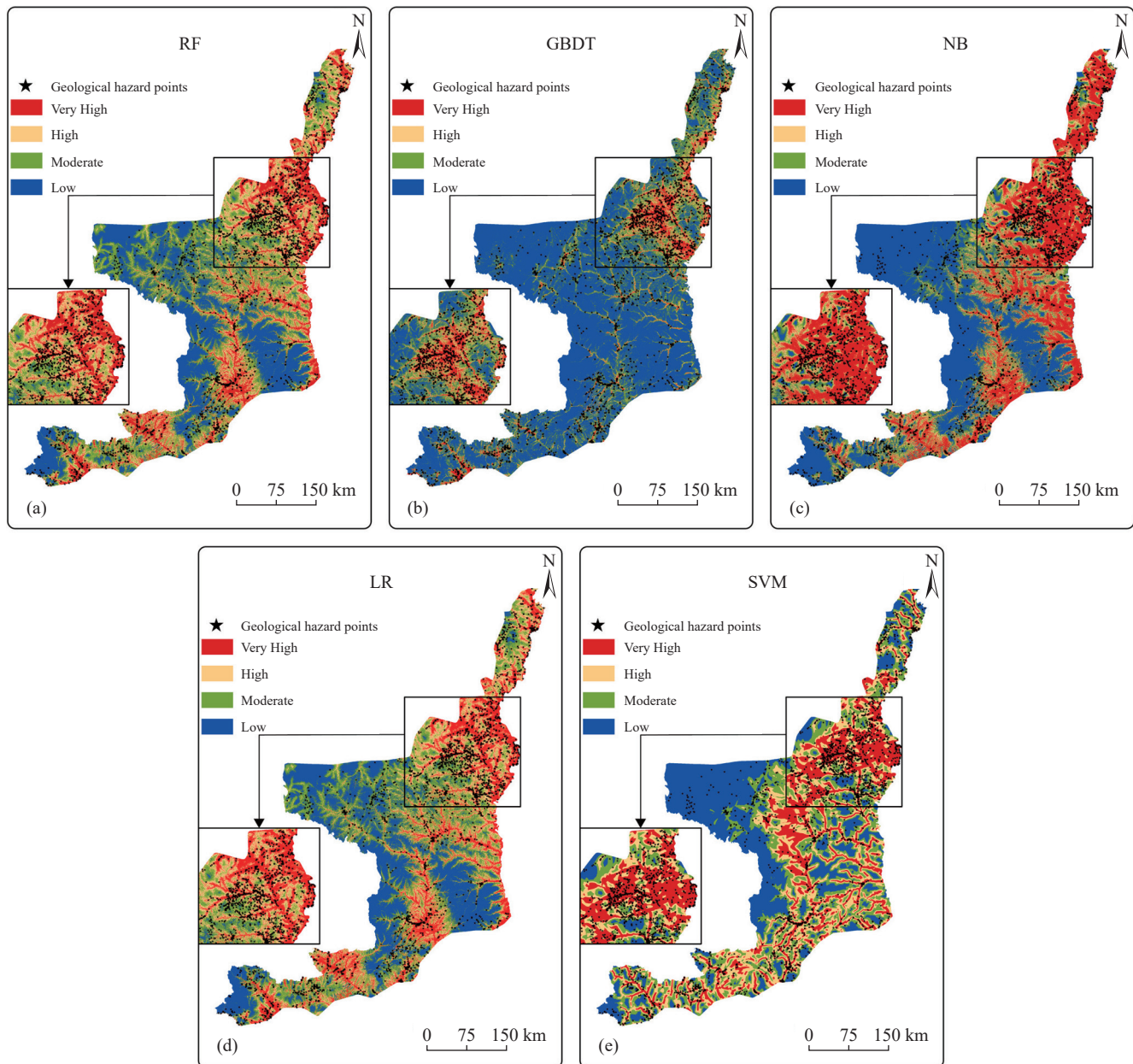


Fig. 10. Different geologic hazard susceptibility assessment maps based on clustering algorithm optimization.

Northern Shaanxi, China. This study demonstrates that the statistical optimization-based assessment exhibits effectively enhanced accuracy. The model-derived assessment results can provide information for forward-looking decisions regarding engineering activities including land planning, resource development, and infrastructure construction in the region. The primary conclusions of this study are as follows:

(i) This study innovatively develops a novel methodology for geologic hazard susceptibility assessment. In this methodology, the cumulative probability method in statistics is employed to accurately determine the distance threshold of geologic hazard points, leading to the generation of more rational negative samples. Thus, innovative concepts are introduced into traditional data construction methods. Five efficient machine learning algorithms, namely RF, GBDT, NB, LR, and SVM, are introduced, with the RF model identified as the optimal model based on the comprehensive

comparison of their performance indicators. The mutual information method is utilized to evaluate the significance of key factors affecting the geologic hazard susceptibility, effectively determining the top five influencing factors: Rainfall, altitude, NDVI, distance from roads, and land use. Additionally, the traditional natural breaks method is improved by using a clustering algorithm to achieve more accurate susceptibility classification, thereby enhancing the accuracy and reliability of the assessment results. These innovations not only enhance the models' predictive capability but also provide scientific decision support for geologic hazard prevention and mitigation.

(ii) The methodology employed in this study is strongly supported by multiple quantitative analyses. The cumulative probability method is utilized to determine the threshold for selecting negative training samples. A geographical distance threshold, i.e., a buffer radius of 2297 m, was determined in

this study, resulting in a more representative number and distribution of negative samples. This provides a scientific basis for sampling in low-probability areas. A comprehensive analysis of the performance metrics of the five machine learning algorithms reveals that the RF model yielded exceptional results on the testing dataset, with an accuracy of 92.86%, precision of 92.69%, recall of 92.67%, F_1 -score of 92.68%, MCC of 0.8572, and OA of 2.7127, all significantly surpassing those of the remaining models. Furthermore, the RF model exhibited an AUC of up to 0.981, further confirming its superior performance in the prediction accuracy and generalizability on unknown data. Compared to the case where the natural breaks method is used alone, the classification effectiveness of the geologic hazard susceptibility is improved by introducing a clustering algorithm. Specifically, the hazard density of regions with very high to high susceptibility increased by 0.15 times and 2.15 times, respectively for the RF and GBDT models. This result indicates that the clustering algorithm can delineate susceptible regions more accurately. These quantitative calculations confirm the effectiveness and reliability of the methods used in this study.

(iii) This study is of great value in several key aspects. First, the methodology employed is highly applicable to the unique regional geological environment of the Loess Plateau in Northern Shaanxi. Besides, it can also be effectively applied to other areas with similar geological conditions. Second, the machine learning algorithms utilized in this study can be widely employed to assess the susceptibility of various types of geologic hazards due to their versatility. Additionally, the model-derived quantitative susceptibility assessment results offer substantial decision support for government agencies and relevant departments in their efforts to prevent and mitigate geologic hazards. Last, this study provides a comprehensive and advanced technical solution for geologic hazard assessment by integrating GIS spatial analysis, geological environment data, RS data, and machine learning technology. This integration enhances the assessment efficiency and accuracy, introducing a new philosophy and methodology for scientific research and practical applications in related fields.

CRedit authorship contribution statement

Hao Cheng, Zhen-kai Zhang, and Zeng-lin Hong conceived of the presented idea. Hao Cheng, Zeng-lin Hong, and Zi-yao Wang organized dataset interpretation. Hao Cheng and Yu-xuan Dong wrote the manuscript. All authors discussed the results and contributed to the final manuscript.

Declaration of competing interest

The authors declare no conflicts of interest.

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References

- Abdulwahid WM, Pradhan B. 2017. Landslide vulnerability and risk assessment for multi-hazard scenarios using airborne laser scanning data (lidar). *Landslides*, 14(3), 1057–1076. doi: [10.1007/s10346-016-0744-0](https://doi.org/10.1007/s10346-016-0744-0).
- Abuzied SM, Mansour B. 2019. Geospatial hazard modeling for the delineation of flash flood-prone zones in wadi dahab basin, egypt. *Journal of Hydroinformatics*, 21(1), 180–206. doi: [10.2166/hydro.2018.043](https://doi.org/10.2166/hydro.2018.043).
- Alireza A, Biswajeet P, Luigi L. 2019. Comparative assessment using boosted regression trees, binary logistic regression, frequency ratio and numerical risk factor for gully erosion susceptibility modelling. *Catena*, 183, 104223. doi: [10.1016/j.catena.2019.104223](https://doi.org/10.1016/j.catena.2019.104223).
- Andriani GF, Loiotine L. 2020. Multidisciplinary approach for assessment of the factors affecting geohazard in karst valley: The case study of gravina di petruscio (apulia, south italy). *Environmental Earth Sciences*, 79(19), 458. doi: [10.1007/s12665-020-09212-y](https://doi.org/10.1007/s12665-020-09212-y).
- Bui DT, Lofman O, Revhaug I, Dick O. 2011. Landslide susceptibility analysis in the Hoa Binh province of Vietnam using statistical index and logistic regression. *Natural Hazards*, 59(3), 1413–1444. doi: [10.1007/s11069-011-9844-2](https://doi.org/10.1007/s11069-011-9844-2).
- Broothaerts N, Kissi E, Poesen J, Van Rompaey A, Getahun K, Van Ranst E, Diels J. 2012. Spatial patterns, causes and consequences of landslides in the gilgel gibe catchment, sw ethiopia. *Catena*, 97, 127–136. doi: [10.1016/j.catena.2012.05.011](https://doi.org/10.1016/j.catena.2012.05.011).
- Catani F, Casagli N, Ermini L, Righini G, Menduni G. 2005. Landslide hazard and risk mapping at catchment scale in the arno river basin. *Landslides*, 2(4), 329–342. doi: [10.1007/s10346-005-0021-0](https://doi.org/10.1007/s10346-005-0021-0).
- Chen C, Oguchi T, Hayakawa YS, Saito H, Chen H, Lin G, Wei L, Chao Y. 2018. Sediment yield during typhoon events in relation to landslides, rainfall, and catchment areas in taiwan. *Geomorphology*, 303, 540–548. doi: [10.1016/j.geomorph.2017.11.007](https://doi.org/10.1016/j.geomorph.2017.11.007).
- Chen W, Zhao X, Shahabi H, Shirzadi A, Khosravi K, Chai HC, Zhang S, Zhang LY, Ma JQ, Chen YT, Wang XJ, Ahmad BB Li R. 2019. Spatial prediction of landslide susceptibility by combining evidential belief function, logistic regression and logistic model tree. *Geocarto International*, 34(11), 1177–1201. doi: [10.1080/10106049.2019.1588393](https://doi.org/10.1080/10106049.2019.1588393).
- Chen Y, Wang QJ, Guo H, Wang C, Jing L, Wang L, Chen F. 2014. A GIS-based statistical model for rapid landslide susceptibility mapping in the Beichuan-Pingwu area, Sichuan, China. *Iop Conference Series. Earth and Environmental Science*, 17(1), 12085–12086. doi: [10.1088/1755-1315/17/1/012085](https://doi.org/10.1088/1755-1315/17/1/012085).
- Cyril V, Gilles N, Soteris K, Marie-Laure N, Christophe P, Fabrice M, Alexis F. 2017. Machine learning methods for solar radiation forecasting: A review. *Renewable Energy*, 105, 569–582. doi: [10.1016/j.renene.2016.12.095](https://doi.org/10.1016/j.renene.2016.12.095).
- Davood MG, Eric KZ, Abolfazl J, Riyahi Bakhtyai HR, Bui DT. 2019. Multi-hazards vulnerability assessment of southern coasts of iran. *Journal of Environmental Management*, 252, 109628. doi: [10.1016/j.jenvman.2019.109628](https://doi.org/10.1016/j.jenvman.2019.109628).

- [10.1016/j.jenvman.2019.109628](https://doi.org/10.1016/j.jenvman.2019.109628).
- Gan ZM, Gan R, Yue D, Liu X, Pei X. 2004. Study on the land use of rural settlements in the loess hill-gully area of yanan and yulin. *Journal of Arid Land Resources and Environment*, 18(4), 101–104 (in Chinese). doi: [10.13448/j.cnki.jalre.2004.04.020](https://doi.org/10.13448/j.cnki.jalre.2004.04.020).
- Ganesh B, Vincent S, Pathan S, Garcia Benitez SR. 2023. Machine learning based landslide susceptibility mapping models and GB-SAR based landslide deformation monitoring systems: Growth and evolution. *Remote Sensing Applications: Society and Environment*, 29, 100905. doi: [10.1016/j.rsase.2022.100905](https://doi.org/10.1016/j.rsase.2022.100905).
- Hancock JT, Khoshgoftaar TM. 2020. Catboost for big data: an interdisciplinary review. *Journal of Big Data*, 7(1), 94. doi: [10.1186/s40537-020-00369-8](https://doi.org/10.1186/s40537-020-00369-8).
- He F, Liu CX, Liu HJ. 2021. Integration and fusion of geologic hazard data under deep learning and big data analysis technology. *Complexity*, 2021, 1–10. doi: [10.1155/2021/2871770](https://doi.org/10.1155/2021/2871770).
- Hong Y, Abdelkareem M. 2022. Integration of remote sensing and a gis-based method for revealing prone areas to flood hazards and predicting optimum areas of groundwater resources. *Arabian Journal of Geosciences*, 15(1). doi: [10.1007/s12517-021-09422-z](https://doi.org/10.1007/s12517-021-09422-z).
- Hu J, Li ZW, Ding XL, Zhu JJ, Zhang L, Sun Q. 2014. Resolving three-dimensional surface displacements from InSAR measurements: A review. *Earth-Science Reviews*, 133, 1–17. doi: [10.1016/j.earscirev.2014.02.005](https://doi.org/10.1016/j.earscirev.2014.02.005).
- Hu YF, Li ZH, Wang L, Chen B, Zhu W, Zhang SC, Du JT, Zhang XS, Yang J, Zhou ML, Liu ZJ, Wang SS, Miao C, Zhang LC, Peng JB. 2022. Rapid interpretation and analysis of the 2022 eruption of hunga tonga-hunga ha'apai volcano with integrated remote sensing techniques. *Geomatics and Information Science of Wuhan University*, 47(2), 242–251. doi: [10.13203/j.whugis20220050](https://doi.org/10.13203/j.whugis20220050).
- Huang F, Xiong H, Zhou X, Catani F, Huang J. 2024. Modelling uncertainties and sensitivity analysis of landslide susceptibility prediction under different environmental factor connection methods and machine learning models. *Ksce Journal of Civil Engineering*, 28(1), 45–62. doi: [10.1007/s12205-023-2430-9](https://doi.org/10.1007/s12205-023-2430-9).
- Huo AD, Peng JB, Cheng YX, Zheng XL, Wen YR. 2019. Temporal characteristics of the rainfall induced landslides in the Chinese loess plateau (China). *Advances in Science Technology & Innovation*, 425–427 (Conference paper). doi: [10.1007/978-3-030-01665-4_98](https://doi.org/10.1007/978-3-030-01665-4_98).
- Huo AD, Yang L, Peng JB, Cheng YX, Jiang C. 2020. Spatial characteristics of the rainfall induced landslides in the Chinese loess plateau. *Human and Ecological Risk Assessment*, 26(9), 2462–2477. doi: [10.1080/10807039.2020.1728517](https://doi.org/10.1080/10807039.2020.1728517).
- Kahal AY, Abdelrahman K, Alfaihi HJ, Yahya MMA. 2021. Landslide hazard assessment of the neom promising city, northwestern Saudi Arabia: An integrated approach. *Journal of King Saud University - Science*, 33(2), 101279. doi: [10.1016/j.jksus.2020.101279](https://doi.org/10.1016/j.jksus.2020.101279).
- Li T, Xie CC, Xu C, Qi WW, Huang YD, Li L. 2024. Automated machine learning for rainfall-induced landslide hazard mapping in luhe county of Guangdong Province, China. *China Geology*, 7(2), 315–329. doi: [10.31035/cg2024064](https://doi.org/10.31035/cg2024064).
- Li YR, Mo P. 2019. A unified landslide classification system for loess slopes: a critical review. *Geomorphology*, 340, 67–83. doi: [10.1016/j.geomorph.2019.04.020](https://doi.org/10.1016/j.geomorph.2019.04.020).
- Liang SY, Wang YX, Wang Y. 2010. Risk assessment of geological hazard in wudu area of Longnan city, China. *Applied Mechanics and Materials*, 39, 232–237. doi: [10.4028/www.scientific.net/AMM.39.232](https://doi.org/10.4028/www.scientific.net/AMM.39.232).
- Lin JH, Chen WH, Qi XH, Hou HR. 2021. Risk assessment and its influencing factors analysis of geological hazards in typical mountain environment. *Journal of Cleaner Production*, 309, 127077. doi: <https://doi.org/10.1016/j.jclepro.2021.127077>.
- Liu JY, Liu ML, Tian HQ, Zhuang DF, Zhang ZX, Zhang W, Tang XM, Deng XZ. 2005. Spatial and temporal patterns of China's cropland during 1990–2000: An analysis based on landsat tm data. *Remote Sensing of Environment*, 98(4), 442–456. doi: [10.1016/j.rse.2005.08.012](https://doi.org/10.1016/j.rse.2005.08.012).
- Liu JY, Zhang ZX, Xu XL, Kuang WH, Zhou WC, Zhang SW, Li RD, Yan CZ, Yu DS, Wu SX, Jiang N. 2010. Spatial patterns and driving forces of land use change in China during the early 21st century. *Journal of Geographical Sciences*, 20(4), 483–494. doi: [10.1007/s11442-010-0483-4](https://doi.org/10.1007/s11442-010-0483-4).
- Liu L, Gao HY, Li Z. 2021. Landslide susceptibility assessment based on coupling of cf model and logistic regression model in yongjia county. *Periodical of Ocean University of China*, 51(10), 121–129 (in Chinese). doi: [10.16441/j.cnki.hdxh.20200247](https://doi.org/10.16441/j.cnki.hdxh.20200247).
- Liu X, Pan R. 2021. Boost-r: gradient boosted trees for recurrence data. *Journal of Quality Technology*, 53(5), 545–565. doi: [10.1080/00224065.2021.1948373](https://doi.org/10.1080/00224065.2021.1948373).
- Liu YR, Sun HL, Gong J. 2018. Geologic hazard susceptibility and disaster risk mapping based on information value model for the Mianchi county, China. *Iop Conference Series. Earth and Environmental Science*, 199(2), 22039. doi: [10.1088/1755-1315/199/2/022039](https://doi.org/10.1088/1755-1315/199/2/022039).
- Ma ZJ, Mei G. 2021. Deep learning for geological hazards analysis: data, models, applications, and opportunities. *Earth-Science Reviews*, 223, 103858. doi: [10.1016/j.earscirev.2021.103858](https://doi.org/10.1016/j.earscirev.2021.103858).
- Matsunaga K, Gan Z. 2007. Geological and geomorphological conditions of mass movements in the loess plateau. *Bulletin of Soil and Water Conservation*, 27(01), 55–57 (in Chinese). doi: [10.13961/j.cnki.stbctb.2007.01.013](https://doi.org/10.13961/j.cnki.stbctb.2007.01.013).
- Meng ZJ, Ma PH, Peng JB. 2021. Characteristics of loess landslides triggered by different factors in the Chinese loess plateau. *Journal of Mountain Science*, 18(12), 3218–3229. doi: [10.1007/s11629-021-6880-6](https://doi.org/10.1007/s11629-021-6880-6).
- Merghadi A, Yunus AP, Dou J, Whiteley J, Thaiphum B, Bui DT, Avtar R, Abderrahmane B. 2020. Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Science Reviews*, 207, 103225. doi: [10.1016/j.earscirev.2020.103225](https://doi.org/10.1016/j.earscirev.2020.103225).
- Nandi A, Mandal A, Wilson M, Smith D. 2016. Flood hazard mapping in jamaica using principal component analysis and logistic regression. *Environmental Earth Sciences*, 75(6), 465. doi: [10.1007/s12665-016-5323-0](https://doi.org/10.1007/s12665-016-5323-0).
- Osmanoglu B, Sunar F, Wdowinski S, Cabral-Cano E. 2016. Time series analysis of insar data: methods and trends. *Isprs Journal of Photogrammetry and Remote Sensing*, 115, 90–102. doi: [10.1016/j.isprsjprs.2015.10.003](https://doi.org/10.1016/j.isprsjprs.2015.10.003).
- Regina SL, Sabino LM, Tatiana DS. 2024. A quantitative rockfall risk analysis system for highway rock slopes. *Geotechnical and Geological Engineering*, 42(2), 1131–1152. doi: [10.1007/s10706-023-02609-z](https://doi.org/10.1007/s10706-023-02609-z).
- Saleh Y, Reza PH, Naeim ES, Soheila P, Saeedeh E, John T. 2020. A machine learning framework for multi-hazards modeling and mapping in a mountainous area. *Scientific Reports*, 10(1), 12144. doi: [10.1038/s41598-020-69233-2](https://doi.org/10.1038/s41598-020-69233-2).
- Shahabi H, Ahmadi R, Alizadeh M, Hashim M, Al-Ansari N, Shirzadi A, Wolf ID, Ariffin EH. 2023. Landslide susceptibility mapping in a mountainous area using machine learning algorithms. *Remote Sensing*, 15(12), 3112. doi: [10.3390/rs15123112](https://doi.org/10.3390/rs15123112).
- Shi QY, Wang M, Gan ZM. 2007. Field survey on water erosion of the rural settlement in the loess hilly-gully area. *Journal of Shaanxi Normal University (Natural Science Edition)*, 35(02), 103–107 (in Chinese). doi: [10.15983/j.cnki.jsnu.2007.02.027](https://doi.org/10.15983/j.cnki.jsnu.2007.02.027).
- Shi YQ, Zhao C, Peng ZQ, Yang HY, He JP. 2018. Analysis of the lag effect of embankment dam seepage based on delayed mutual information. *Engineering Geology*, 234, 132–137. doi: [10.1016/j.enggeo.2018.01.00](https://doi.org/10.1016/j.enggeo.2018.01.00).

- Su QM, Zhang J, Zhao SM, Wang L, Liu J, Guo JL. 2017. Comparative assessment of three nonlinear approaches for landslide susceptibility mapping in a coal mine area. *Isprs International Journal of Geo-Information*, 6(7), 228. doi: [10.3390/ijgi6070228](https://doi.org/10.3390/ijgi6070228).
- Sugahara S, Ueno M. 2021. Exact learning augmented naive bayes classifier. *Entropy (Basel, Switzerland)*, 23(12), 1703. doi: [10.3390/e23121703](https://doi.org/10.3390/e23121703).
- Tazik E, Jahantab Z, Bakhtiari M, Rezaei A, Alavipanah SK. 2014. Landslide susceptibility mapping by combining the three methods fuzzy logic, frequency ratio and analytical hierarchy process in dozain basin. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL-2/W3(2) 267–272 (Conference paper). doi: [10.5194/isprsarchives-XL-2-W3-267-2014](https://doi.org/10.5194/isprsarchives-XL-2-W3-267-2014).
- Thi Ngo PT, Panahi M, Khosravi K, Ghorbanzadeh O, Kariminejad N, Cerda A, Lee S. 2021. Evaluation of deep learning algorithms for national scale landslide susceptibility mapping of iran. *Geoscience Frontiers*, 12(2), 505–519. doi: [10.1016/j.gsf.2020.06.013](https://doi.org/10.1016/j.gsf.2020.06.013).
- Tian HB, Tao YX, Kou PL, Alonso A, Luo XB, Gong CY, Fan YP, Lei CJ, Gou YC. 2023. Monitoring and evaluation of gully erosion in China's largest loess tableland based on sbas-insar. *Natural Hazards*, 117(3), 2435–2454. doi: [10.1007/s11069-023-05950-x](https://doi.org/10.1007/s11069-023-05950-x).
- Ullah K, Wang Y, Fang ZC, Wang LZ, Rahman M. 2022. Multi-hazard susceptibility mapping based on convolutional neural networks. *Geoscience Frontiers*, 13(5), 101425. doi: [10.1016/j.gsf.2022.101425](https://doi.org/10.1016/j.gsf.2022.101425).
- Wang C, Yu Q, Law KH, McKenna F, Yu SX, Taciroglu E, Zsarnóczy A, Elhaddad W, Cetiner B. 2021. Machine learning-based regional scale intelligent modeling of building information for natural hazard risk management. *Automation in Construction*, 122, 103474. doi: [10.1016/j.autcon.2020.103474](https://doi.org/10.1016/j.autcon.2020.103474).
- Wang HJ, Zhang LM, Yin KS, Luo HY, Li JH. 2021. Landslide identification using machine learning. *Geoscience Frontiers*, 12(1), 351–364. doi: [10.1016/j.gsf.2020.02.012](https://doi.org/10.1016/j.gsf.2020.02.012).
- Wang J, Yang S, Ji XJ, Ou GQ. 2012. The review and prospects of the study on Chinese geological disaster. *Applied Mechanics and Materials*, 166–169, 2597–2600. doi: [10.4028/www.scientific.net/AMM.166-169.2597](https://doi.org/10.4028/www.scientific.net/AMM.166-169.2597).
- Wang Y, Fang ZC, Hong HY. 2019. Comparison of convolutional neural networks for landslide susceptibility mapping in Yanshan County, China. *Science of the Total Environment*, 666, 975–993. doi: [10.1016/j.scitotenv.2019.02.263](https://doi.org/10.1016/j.scitotenv.2019.02.263).
- Wang ZP, Chen JP, Lian ZC, Li F, Pang L, Xin YB. 2024. Influence of buffer distance on environmental geological hazard susceptibility assessment. *Environmental Science and Pollution Research*, 31(6), 9582–9595. doi: [10.1007/s11356-023-31739-3](https://doi.org/10.1007/s11356-023-31739-3).
- Wu YM, Lan HX. 2022. Study on the deformation of filling bodies in a loess mountainous area based on insar and monitoring equipment. *Land*, 11(8), 1263. doi: [10.3390/land11081263](https://doi.org/10.3390/land11081263).
- Xu C, Zhang XW, Li L, Feng LY, Yang WT. 2025. Geospatial insights into landslide relics in the northern half of the Taihang Mountains: Topography, geology and beyond. *Geoscience Data Journal*, 12(4), 70028 doi: [10.1002/gdj3.70028](https://doi.org/10.1002/gdj3.70028).
- Yi JS, Wang F, Cheng YJ, Zhang Y. 2022. Study on the risk assessment of geological disasters in alpine valley area: A case study in aba county, sichuan province. *The Chinese Journal of Geological Hazard and Control*, 33(03), 134–142 (in Chinese). doi: [10.16031/j.cnki.issn.1003-8035.2022.03-15](https://doi.org/10.16031/j.cnki.issn.1003-8035.2022.03-15).
- Youssef AM, Mahdi AM, Al-Katheri MM, Pouyan S, Pourghasemi HR. 2023. Multi-hazards (landslides, floods, and gully erosion) modeling and mapping using machine learning algorithms. *Journal of African Earth Sciences*, 197, 104788. doi: [10.1016/j.jafrearsci.2022.104788](https://doi.org/10.1016/j.jafrearsci.2022.104788).
- Yu HW, Lan Y, Yuan ZH, Xu JY, Lee H. 2019. Phase unwrapping in insar. *Ieee Geoscience and Remote Sensing Magazine*, 7(1), 40–58. doi: [10.1109/MGRS.2018.2873644](https://doi.org/10.1109/MGRS.2018.2873644).
- Yu SW, Hou JD, Lv J, Ba GZ. 2015. Economic benefit assessment of the geo-hazard monitoring and warning engineering system in the three gorges reservoir area: A case study of the landslide in zigui. *Natural Hazards*, 75(S2), 219–231. doi: [10.1007/s11069-014-1112-9](https://doi.org/10.1007/s11069-014-1112-9).
- Yuan XF, Ying Y, Wei XD, Hou R, Wang XF, Zhao YH, Shao YJ, Yao YC, Chang JW. 2018. Research status quo and its prevention implication of geological hazards in the central China orogen. *Geological Journal*, 53, 252–265. doi: [10.1002/gj.3039](https://doi.org/10.1002/gj.3039).
- Zeng L, Huang YH. 2010. Valley evolution and geologic hazard occurrences in the loess plateau of China a case study: Zichang County in the northern loess plateau of Shanxi Province. *The Chinese Journal of Geological Hazard and Control*, 21(03), 67–72 (in Chinese). doi: [10.16031/j.cnki.issn.1003-8035.2010.03.024](https://doi.org/10.16031/j.cnki.issn.1003-8035.2010.03.024).
- Zhang HW, Wang ZQ. 2022. Human activities and natural geographical environment and their interactive effects on sudden geologic hazard: A perspective of macro-scale and spatial statistical analysis. *Applied Geography*, 143, 102711. doi: [10.1016/j.apgeog.2022.102711](https://doi.org/10.1016/j.apgeog.2022.102711).
- Zhang WG, Pradhan B, Stuyts B, Xu C. 2023. Application of artificial intelligence in geotechnical and geohazard investigations. *Geological Journal*, 58(6), 2187–2194. doi: [10.1002/gj.4779](https://doi.org/10.1002/gj.4779).
- Zhang XH. 2020. The design and implementation of geologic hazard information management system. *Arabian Journal of Geosciences*, 13(17). doi: [10.1007/s12517-020-05874-x](https://doi.org/10.1007/s12517-020-05874-x).
- Zhao Z, Chen JH. 2023. A robust discretization method of factor screening for landslide susceptibility mapping using convolution neural network, random forest, and logistic regression models. *International Journal of Digital Earth*, 16(1), 408–429. doi: [10.1080/17538947.2023.2174192](https://doi.org/10.1080/17538947.2023.2174192).
- Zhu JX, Zhang LZ, Zhou XY, Wang Q. 2011. Construction of opening regional geological hazards risk assessment system, Proc. SPIE 8205, 2011 International Conference on Photonics, 3D-Imaging, and Visualization, 820520 (28 October 2011), 820520–820525. doi: [10.1117/12.905861](https://doi.org/10.1117/12.905861).
- Zounemat-Kermani M, Okke B, Marzieh F, Reinhard H. 2021. Ensemble machine learning paradigms in hydrology: A review. *Journal of Hydrology*, 598, 126266. doi: [10.1016/j.jhydrol.2021.126266](https://doi.org/10.1016/j.jhydrol.2021.126266).
- Zuo RG, Wang ZY. 2020. Effects of random negative training samples on mineral prospectivity mapping. *Natural Resources Research*, 29(6), 3443–3455. doi: [10.1007/s11053-020-09668-6](https://doi.org/10.1007/s11053-020-09668-6).