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LANDSLIDE SUSCEPTIBILITY ASSESSMENT BASED ON MACHINE LEARNING MODELS INBAILONG RIVER BASIN, CHINA

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AbstractAccuratesusceptibility assessment of geological disaster is crucial for disaster prevention and urban spatial planning. The Bailong River basin, characterized by steep slopes, high relative relief, deep incised valleys, and weak lithologic features, has a complex regional dynamic environment and extreme climatic conditions. In this study, nine evaluation factors were selected, including elevation, lithology, relief, river buffer distance, fault buffer distance, slope, aspect, and slope type. The Weight of Evidence (WOE) model, Support Vector Machine (SVM), WOE-SVM coupled model, Random Forest (RF) model, and WOE-RF coupled model were employed to develop landslidesusceptibility assessment models. The prediction effects of these models were compared and analyzed. The results indicate that the prediction accuracy of the machine learning-based susceptibility models is significantly higher than that of the WOE model. The Area Under the Curve (AUC) of the coupled models reaches a maximum of 0.9999, with 98% of geological disasters occurring in very high and high susceptibility zones. The assessment results are consistent with the spatial distribution of the disasters. The WOE-RF coupled model demonstrates the highest prediction accuracy, exhibiting superior predictive performance and generalization capability. The assessment results are more suitable as references for disaster prevention and long-term major project planning and construction.

Keywords: Susceptibility assessment,Machine learning,The Weight of Evidence model, Support Vector Machine, Random Forest.

1. Introduction

As one of the countries most severely threatened by geological hazards globally, China is characterized by a complete spectrum of geological hazard types, extensive distribution, and high susceptibility. The Bailong River Basin, located in southeastern Gansu Province, is one of the concentrated high-incidence zones for frequent landslides and debris flows.

Numerous methods are currently employed for landslide susceptibility assessment, with each evaluation model exhibiting its unique strengths and weaknesses. However, a definitive consensus has yet to be reached regarding which evaluation model is optimal for different study areas, and the quest for high-precision susceptibility assessment models continues (Chen et al., 2020). While single-algorithm evaluation models have demonstrated promising predictive performance, they still exhibit certain limitations. Statistical models are generally more suitable for linearly separable classification problems, focusing on inferring relationships between data and outcome variables. However, real-world scenarios often involve nonlinear separability, which poses challenges for multivariate statistical analysis (Huang et al., 2020). In contrast, machine learning-based evaluation models are outcome-oriented and have shown more accurate predictive capabilities.Consequently, coupled models that integrate statistical analysis with data-driven machine learning have emerged as a research hotspot in regional susceptibility assessment. These models leverage machine learning methods to extract landslide susceptibility eigenvalues while eliminating feature selection biases, thereby significantly improving prediction accuracy. Moreover, coupled analytical approaches that integrate multiple computational models effectively combine their respective advantages in data analysis and prediction, thus enhancing overall model accuracy and robustness.

2. Data and methods

2.1 Susceptibility assessment system

This study was conducted in Longnan City, Gansu Province, situated in the middle reaches of the Bailongjiang River Basin. Through field investigations and preliminary data collection, we comprehensively assessed the disaster-controlling factors in the study area, including terrain, geomorphology, stratigraphic, landuse, vegetation, and hydrometeorological conditions. A total of ten susceptibility evaluation factors were initially selected to establish a susceptibility evaluation system. These factors included elevation, relief, slope, slope direction, slope type, lithology, land use, normalized difference vegetation index (NDVI), river buffer distance, and fault buffer distance. After conducting a correlation test, it was found that the NDVI coefficient exhibited a strong correlation with both relief and elevation. In contrast, the other selected evaluation factors showed no correlation or only weak correlations. Therefore, the NDVI factor was excluded from the analysis, and the remaining nine evaluation factors were retained for the assessment system.

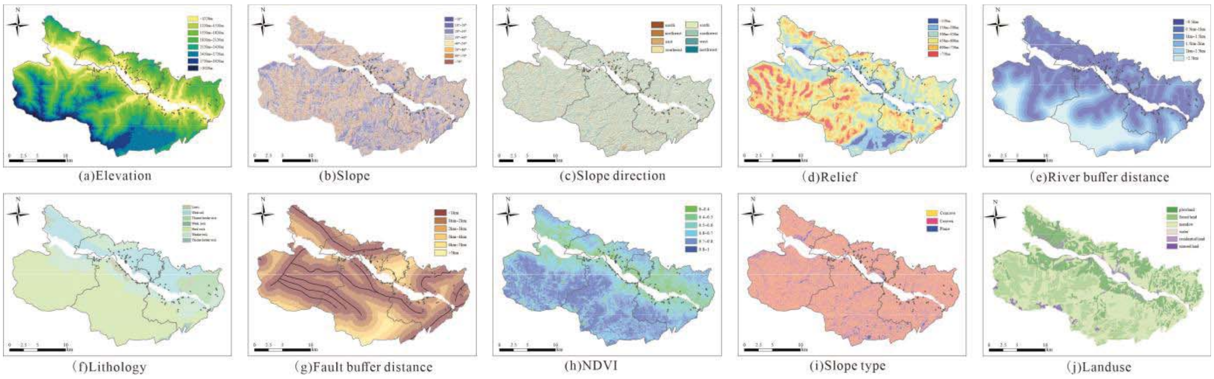


Fig. 1. Susceptibility evaluation system

2.2 Evaluation method

2.2.1 WOE model

The Weight of Evidence (WOE) model is a quantitative calculation method based on Bayes' theorem. It integrates data from the occurrences of geological hazards with the contributions of each evidence factor to hazard occurrence. By conducting sensitivity analysis of geoscientific information, the WOE model calculates the weights of evidence factors and performs superposition composite analysis. This process ultimately derives the susceptibility index for the study area.

2.2.2 SVM model

The Support Vector Machine (SVM) is a supervised machine learning algorithm based on statistical learning theory (Luo et al., 2019). SVM models input data into a high-dimensional feature space using kernel functions. This transformation enables the construction of an optimal hyperplane that maximizes the margin between different classes of samples, thereby facilitating binary classification. The algorithm is particularly suited for predicting binary classification problems, such as the occurrence or non-occurrence of geological disasters. In the SVM model, the optimization algorithm employed was the Sequential Minimal Optimization (SMO), and the kernel function utilized was the Radial Basis Function (RBF). The hyperparameters were set as C=1 and γ=0.5.

2.2.3 RF model

The Random Forest (RF) model utilizes the Bootstrap sampling algorithm to construct multiple decision trees from the sample set, with each tree being independently sampled. These individual decision trees are then aggregated through voting or averaging methods to form a robust and powerful classifier (Goetz et al., 2015).The model employed the Bayesian optimization algorithm to search for the optimal hyperparameter values and outputs the hyperparameters obtained during the iterative process, n_estimators=100, max_depths=none, min_samples_split=3.

2.2.4 Coupled model

The machine learning-based susceptibility assessment model represents a typical binary classification problem. In this context, samples where geological hazards have occurred are designated as positive samples, whereas those where no geological hazards have occurred are labeled as negative samples.When constructing coupled models, negative samples are carefully selected from non-susceptible areas with low Weight of Evidence (WOE) values. This selection process ensures that the probability of geological hazards occurring in the chosen grid units is extremely low. By doing so, the accuracy of negative hazard samples is significantly enhanced.This approach facilitates the development of two coupled models: the Weight of Evidence-Support Vector Machine (WOE-SVM) and the Weight of Evidence-Random Forest (WOE-RF) models.

2.3Evaluation dataset

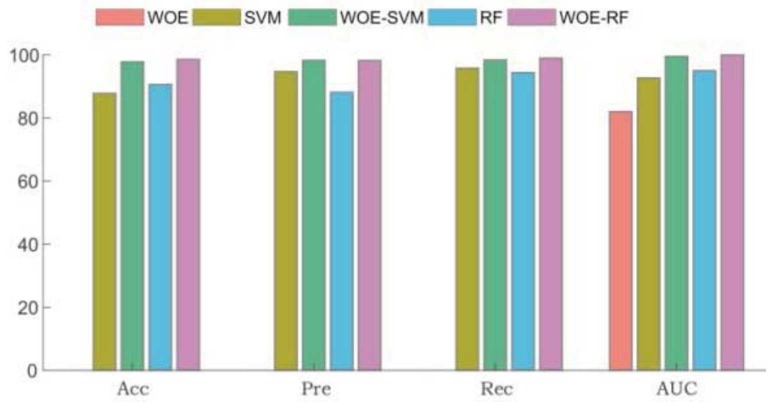
The study area included111 landslide hazards. To generate the sample dataset, random points were created within the manually delineated hazard bodies, resulting in 60,000 positive samples for landslide and collapse hazards, which were labeled as "1". An equivalent number of negative non-hazard samples were randomly selected from non-hazard areas and low susceptibility zones calculated by the Weight of Evidence (WOE) model, labeled as "0". Together, these samples formed the complete dataset.

Given that the selected geological hazard characteristic factors have different dimensions and data continuity, these factors were classified based on the distribution characteristics of geological hazards in the study area to create graded characteristic factor layers. Raster values from these layers were extracted at the sample points and used as input values for model training. The sample dataset was then randomly divided into training and testing datasets at an 8:2 ratio. The evaluation performance of the model was tested by the testing dataset.

3. Results and discussion

3.1 Evaluation accuracy of the models

To verify the effectiveness and reliability of the prediction models for evaluating geological disaster susceptibility, we compared the Accuracy (Acc), Recall (Rec), Precision (Pre), and Area Under the Curve (AUC) values of each model. The results indicate that the AUC value of the WOE model is only 0.82. In contrast, the AUC values of the machine learning-based susceptibility models range from 0.92 to 0.99, representing an increase of 13.0% to 21.94% compared to the WOE model. The prediction success rate of the test set reaches 98.57%.When comparing the Accuracy values of each model, it is evident that the Random Forest (RF) model exhibits slightly better predictive performance than the Support Vector Machine (SVM) model. Additionally, the coupled models demonstrate higher prediction rates than the single prediction models, with prediction accuracies exceeding 98%.



	Acc	Pre	Rec	AUC
WOE				82
SVM	87. 80	94. 70	95. 80	92.67
WOE-SVM	97. 80	98. 30	98. 40	99.52
RF	90. 62	88. 13	94. 40	95.00
WOE-RF	98. 57	98. 22	98. 98	99. 99

Fig.2 Performance comparison of machine-learning based susceptibility models

3.2 Susceptibility zoning

The model evaluation results divided the study area into four susceptibility zones using the natural breaks method: low, moderate, high, and very high. The area proportions of each susceptibility level and the disaster ratios within the corresponding zones were also calculated. The susceptibility zoning results from various evaluation models are shown in Fig. 3.Among the evaluation results from the five susceptibility models (WOE, SVM, WOE-SVM, RF, and WOE-RF), 72.32%, 87.39%, 90.27%, 90.22%, and 94.78% of the landslides were located in the extremely high susceptibility area, respectively.The low susceptibility zone delineate by the WOE model contained 1.79% of the disasters, while the machine learning-based models show less than 0.05% of disasters in the low susceptibility zone. Notably, both the RF model and the WOE-RF model achieve zero disasters in the low susceptibility zone. These results closely align with the actual distribution of landslide disasters, thereby better reflecting real-world conditions.

3.3 Vulnerability assessment analysis

The susceptibility zone classifications reveal that the geological hazard susceptibility patterns of the five evaluation models exhibit similar spatial distributions. The very high and high susceptibility zones are predominantly situated along the Bailong River. This distribution is influenced by the active faults in the region, which compromise the integrity of the rock and promote the development of secondary structures such as small folds, joints, and fissures. The exposed strata primarily consist of loess, loose accumulations, and other weak rock layers, all of which exhibit significant differences in geotechnical properties. These characteristics make these areas highly susceptible to landslide hazards under the cumulative effects of long-term internal and external forces, including weathering and unloading.In the urban fringe areas, human engineering activities have severely disrupted the geological environment of the lower slopes. This disruption has significantly increased the risk of disasters triggered by precipitation and seismic events. In contrast, low susceptibility areas are mainly located in the peripheral regions of the high or very high susceptibility zones, as well as in the middle and upper slopes. These areas benefit from high vegetation cover, minimal influence from faults and rivers, and reduced human activity, all of which contribute to relatively higher slope stability.

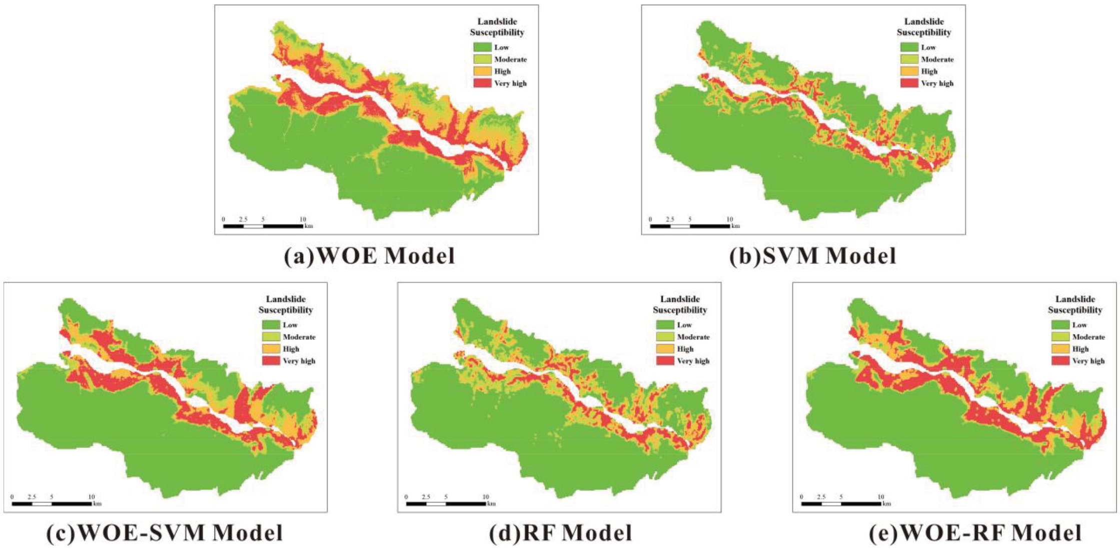


Fig. 3. Susceptibility zoning maps

4. Conclusion

(1) The geological hazard susceptibility assessment system was developed using nine factors (elevation, lithology, relief, etc.). Compared with the WOE model, the machine learning models showed a 13.0%–21.94% increase in AUC values and achieve a prediction success rate of 98.57%, indicating excellent predictive performance.

(2) The machine learning-based susceptibility zoning align closely with the actual landslide distribution, with over 98% of landslides located in very high and high susceptibility zones, reflecting significantly improved model accuracy.

(3) The five evaluation models in the Bailong River Basin show consistent susceptibility trends, with very high susceptibility zones mainly in middle and lower slopes along the river. The coupled models exhibit superior performance and generalization ability, especially the WOE-RF model, which achieve the highest prediction accuracy. The results are valuable for long-term major project planning.

Acknowledgement

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