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SUSCEPTIBILITY ASSESSMENT OF LANDSLIDE IN SOUTHEASTERN TIBETAN PLATEAU

Cong Dai

MOE Key Laboratory of Soft Soils and Geo-Environmental Engineering, Zhejiang University, Hangzhou, Zhejiang, China
E-mail: daicong526@zju.edu.cn

Shuai Zhang

MOE Key Laboratory of Soft Soils and Geo-Environmental Engineering, Zhejiang University, Hangzhou, Zhejiang, China
E-mail: zhangshuaiqj@zju.edu.cn

Jiang Qian

Sun Hung Kai Properties Limited, Hong Kong, China
E-mail: jcqian@shkp.com.cn

The 2008 Wenchuan earthquake triggered large-scale coseismic landslides, which remain a significant challenge for hazard management.This study aims to assess the spatiotemporal evolution of landslide susceptibility from 2010 to 2023 using the Random Forest (RF) algorithm and a hybrid approach combining RF with physical models. The results indicate that RF demonstrates better generalization ability than the hybrid model when predicting future landslide susceptibility.Although the hybrid model, which selects non-landslide points based on the safety factor (FS > 1), improves model performance for training and testing datasets, it tends to overfit current patterns, reducing its generalization ability for future scenarios.External validation from 2021 to 2023 supports this conclusion.Additionally, as landslide data accumulates over time, the accuracy of future susceptibility predictions improves, as reflected by higher area under the curve (AUC) scores.This study highlights the potential of machine learning methods in advancing landslide prediction and offers valuable insights for risk reduction in earthquake-prone regions.
Keywords: Landslide susceptibility, random forest, physical model, Wenchuan earthquake.

1. Introduction

Landslides are among the most destructive geological hazards, often triggered by intense seismic events, prolonged rainfall, and other environmental factors. (Dai et al. 2023).The 2008 Wenchuan earthquake, with a magnitude of 7.9, triggered widespread coseismic landslides, resulting in severe loss of life and property.These landslides not only caused immediate destruction but also left a lasting influence on the region's landscape, posing significant challenges for post-earthquake hazard management and risk mitigation.Even years after the earthquake, the region remains highly susceptible to secondary landslides caused by rainfall, and erosion. (Zhang et al. 2023).Against this backdrop, landslide susceptibility assessment has become a crucial tool for understanding the spatiotemporal evolution of landslide-prone areas.Traditional methods, such as physical models based on slope stability analysis, provide the foundation for landslide risk assessment.However, these models often face limitations in handling complex, multidimensional datasets and generalizing to future scenarios.The emergence of machine learning (ML) methods, such as Random Forest (RF), has revolutionized the field by integrating large-scale spatial data and capturing nonlinear relationships between variables.

This study investigates the spatiotemporal evolution of landslide susceptibility in the Wenchuan region from 2010 to 2023.Specifically, we compared the performance of the RF algorithm with a hybrid model that combines RF with physical model.The aim was to evaluate their effectiveness in predicting future landslide susceptibility and to examine how the growing landslide dataset over time influences prediction accuracy.By bridging physical and data-driven approaches, this study provides insights for improving landslide assessment in earthquake-prone regions.

2. Study area

The study area is in the Sichuan Basin northwest edge of Southwest China, near the Wenchuan earthquake's epicenter, Yingxiu, from the milestone K1 to K19 (Figure 1a). This area marks the transition from the Qinghai-Tibet Plateau to the Western Sichuan Plain. Characterized by towering mountains and deep gorges, the topography features of the study area are steep valleys and slopes, with over 65% of the mountains exceeding a 45° incline. The Yuzixi River, traversing west to east, intersects four faults and runs along the Yingxiu-Beichuan fault's hanging wall. This geological setting contributed to numerous coseismic landslides and subsequent debris flows, particularly on the Beichuan-Yingxiu fault's hanging wall. The primary geological compositions of the study area

are granite and diorite. For a detailed study, 28 watersheds (C1-C28) were delineated based on topography (Figure 1b). Before the earthquake, the hard rocks exposed in the area were deeply fractured and extensively weathered, with varying depths of 10-35 m and a fissure density of 9-27 m^2(Zhang and Zhang 2017). The river is flanked by steep, heavily weathered rock slopes, characterized by outward-inclined joint sets, particularly prevalent in the upper sections of the gullies. The complex geology and seismic history heighten its susceptibility to geological hazards. After the earthquake, a total of 305 landslides, with a combined volume of 54.30 × 10^6 m^3, occurred primarily between elevations of 1000-2500 m and on slopes of 30-50°, within an internal relief range mostly in 200-800 m (Zhang and Zhang 2017).

Climatic data from the Yuzixi River Hydrological Station and post-earthquake monitoring sites over 25 years show an average annual rainfall of 1253.1 mm, with extremes between 836.7 mm and 1688 mm. Most rainfall occurs between June and August, contributing 66%-76% to the annual total(Zhang et al. 2012).

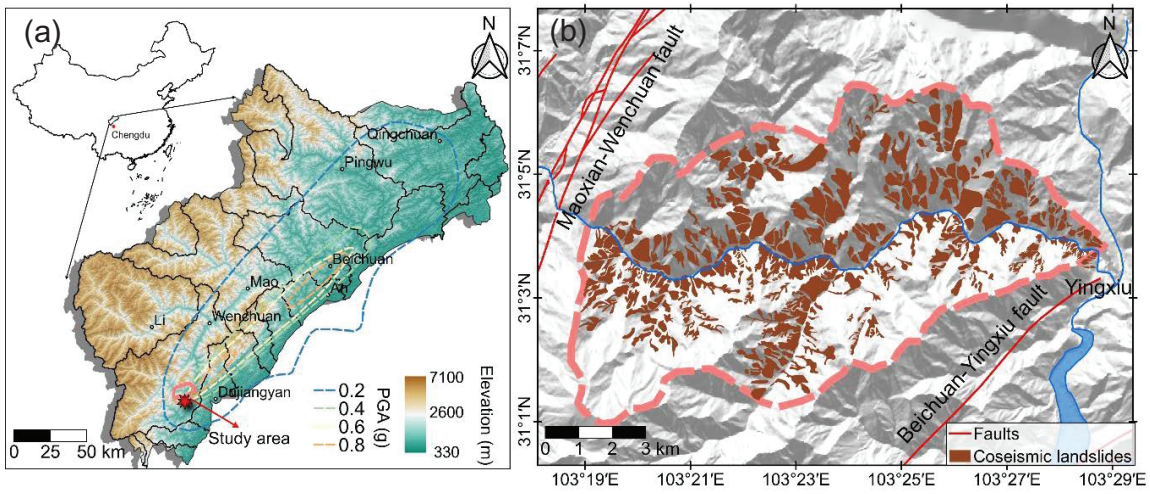

Fig. 1.Location of the study area: (a) the entire earthquake area; (b) coseismic landslides.

3. Data and methods

3.1.*Data*

In this study, landslide susceptibility was assessed using 16 features, including 11 static features and 5 dynamic features. The static features represent spatial and geological characteristics that remain constant over time, while the dynamic features capture temporal variations related to environmental and climatic conditions.The 11 static features include:Elevation, slope,aspect,lithology, topographic wetness index (TWI),topographic position index (TPI),stream power index (SPI),distance to rivers,distance to faults and2008 co-seismic landslides.The 5 dynamic features include:previous year landslides (PYL),maximum monthly rainfall (MMR),annual rainfall (AR),land cover,soil moisture and vegetation index (NDVI).Historical landslides from 2010 to 2023 were identified and interpreted from high-resolution remote sensing imagery.Copernicus DEM serves as the primary source for elevation-related features (elevation, slope, aspect, curvature, SPI, TWI, etc.),accessible at https://panda.copernicus.eu/panda. These features were derived using GIS-based processing tools.Lithology wasobtained from Zhang et al. (2023), representing geological material composition.Soil moistureand rainfall data were extracted from ECMWF Re-Analysis datasets, providing temporal precipitation patterns (Abatzoglou et al. 2018).Land cover classifications were sourced from publicly available datasets.Vegetation indices, were processed using GEE, leveraging historical satellite imagery.

3.2. Methods of landslide susceptibility assessment

Random Forest (RF) (Sun et al., 2020) is an ensemble learning algorithm that performs well in both classification and regression tasks, particularly for high-dimensional nonlinear problems such as landslide susceptibility assessment. The algorithm builds multiple decision trees during training and predicts the output by majority voting for classification or averaging for regression.It is robust against overfitting and well-suited for complex datasets.A common approach for determining the number of predictors subsets is:

$$m' = \sqrt{m}$$

where m' is the subset of predictors considered at each split, and m is the total number of predictors.In this study, to ensure a balanced training dataset and avoid bias toward any class, the number of landslide samples was made equal to the number of non-landslide samples. This balance was achieved by under-sampling the majority class (non-landslide points). The entire dataset was split into a 70:30 ratio, with 70% of the data used for training and 30% for testing. The balanced dataset ensured that the RF algorithm received equal representation of landslide and non-landslide points, enabling the model to better capture complex relationships among features and improve classification accuracy. The physical model used was the Infinite Slope Stability Model (ISSM) under saturated conditions (Wei et al. 2023). This model was only employed to extract non-landslide samples, which were integrated with the RF algorithm and compared to the standalone RF algorithm.Since there is no temporal update of the physical parameters, only the values obtained from field-site testing after the earthquake are used for the safety factor calculation.

4. Discussion and conclusion

Figure 2 shows the results of the landslide susceptibility assessment using both a hybrid model combining physical model and ML, and a model relying solely on ML. The training data consists of landslide records from 2010 to 2020, and accuracy validation conducted based on landslide data from 2021 to 2023. In this study, we chose AUC as the primary evaluation metric because it provides a robust measure of model performance. AUC captures the model's ability to distinguish between landslide-prone and non-prone areas, making it particularly suitable for landslide susceptibility assessments. While other metrics such as precision and recall are important, AUC is considered a comprehensive indicator for this type of geospatial prediction task. Internal validation typically evaluates fitting performance, while external validation assesses predictive performance.

During the internal validation using training data from 2010 to 2020, both models showed high AUCscores, with the hybrid model outperforming the RF model.However, in the external validation for 2021-2023, the RF model demonstrated superior generalization ability, with its AUC consistently exceeding that of the hybrid model.This is due to the enhanced ability of the physical model (ISSM) to emphasize the feature differences between landslide and non-landslide points. By selecting non-landslide points where FS > 1, the non-landslide samples are restricted to a relatively "safe" range. As a result, the feature differences between landslide and non-landslide points become more pronounced. Furthermore, the hybrid model's overreliance on static physical parameters may lead to a decline in its performance on future data, as it tends to overfit the current data distribution.Since the 2024 data has not been updated yet, we used all the landslide data for training to assess future landslides.Consequently, the future landslide susceptibility predictions generated by the RF model trained on data from 2010 to 2023 (Figure 3) provide a detailed spatial distribution of high-risk landslide areas with high accuracy. The susceptibility distribution map clearly illustrates spatial variation, with high-risk areas primarily associated with steep slopes, proximity to fault lines, and regions influenced by heavy rainfall. The AUC distribution box plot, based on 50 experimental runs, further demonstrates the robustness of the RF model, with AUC median value of approximately 0.94 (Figure 3b). This indicates the model's reliability and accuracy in predicting future landslide susceptibility. These results highlight the potential of machine learning-based methods for landslide susceptibility prediction, particularly in enhancing generalization ability for future scenarios. Additionally, the study underscores the importance of incorporating dynamic environmental factors, which can improve the adaptability and accuracy of susceptibility assessments over time.

The hybrid model experiences overfitting due to the static nature of the physical model (ISSM), which overemphasizes certain features, such as FS > 1, limiting the variability in non-landslide data. This overfitting may also be partially influenced by the complexity of the Random Forest (RF) algorithm, which, with many trees or deep decision trees, can lead to excessive fitting to the training data. To mitigate overfitting, future work could explore dynamically adjusting physical model parameters to better reflect changing environmental conditions. Additionally, regularization techniques such as cross-validation, limiting tree depth in RF, or using early stopping during training could help reduce overfitting and improve model generalization. While this study did not explicitly reduce the RF model's complexity, adjusting the number of trees or tree depth in the ensemble could potentially improve the model's ability to generalize to future scenarios and enhance its long-term predictive performance in landslide susceptibility assessments.

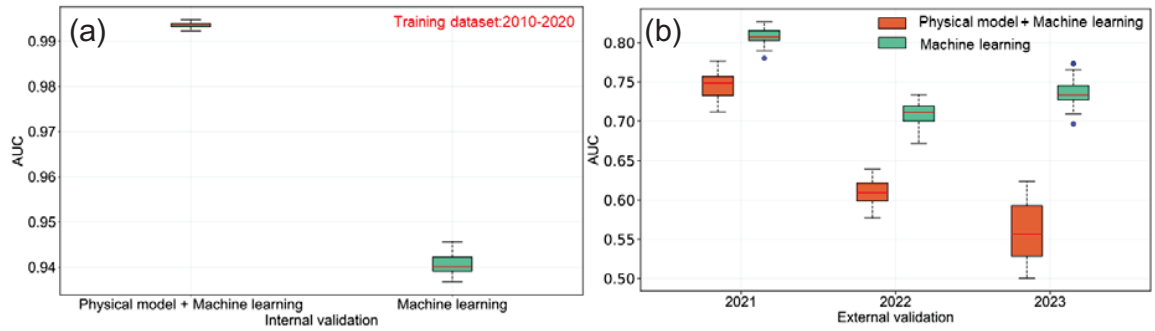

Fig. 2.Comparison of machine learning and hybrid model (machine learning + physical model) for landslide susceptibility assessment. (a) AUC distribution for internal validation with training data from 2010-2020 using machine learning and hybrid model, and external validation in 2021-2023 (b).

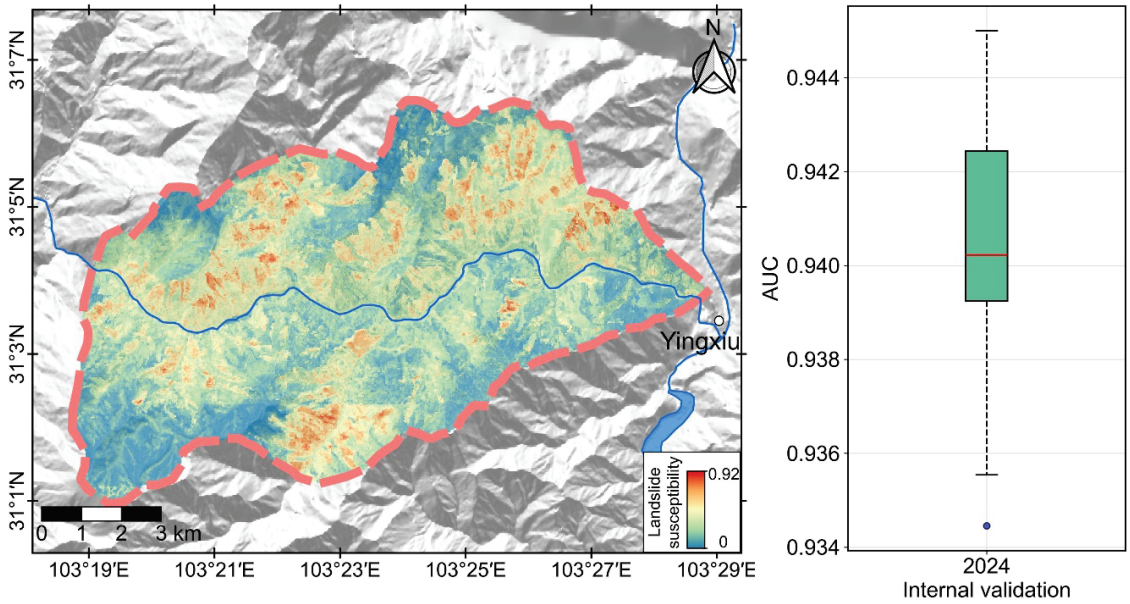

Fig. 3.The landslide susceptibility map of the study area generated using machine learning, along with the corresponding AUC distribution based on testing data from 2010 to 2023.

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