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Dynamic Landslide Susceptibility Mapping Using InSAR and Machine Learning Fusion

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Abstract: Reservoir-induced landslides pose serious hazards in mountainous regions. Landslide susceptibility assessment (LSA) and predicting potential landslide areas (PLA) in reservoir regions play a vital role in disaster prevention and mitigation. This study proposes an integrated framework combining ascending and descending orbit InSAR and machine learning (ML) to generate dynamic LSA. We fuse the susceptibility map with InSAR-derived deformation using threshold intersection method to delineate potential landslide zones. Results show that the Random forest (RF) model with InSAR-sampled negatives achieves the performance (AUC = 0.814). The threshold intersection method predicted a PLA of 7.91 km^2 (including 44 known cataloged areas). This integrated approach provides a robust methodology for LSA in reservoir-affected areas.

Keywords: ***Landslide susceptibility, InSAR, Machine learning, Threshold method, Potential landslide areas.***

Introduction

Landslides are among the most destructive geological hazards, characterized by complex triggering mechanisms and wide-ranging social, environmental, and economic impacts. Accurate landslide susceptibility mapping (LSM) is essential for effective risk mitigation and resilience planning. ML techniques have been increasingly applied to LSM because of their ability to handle complex, nonlinear interactions among terrain, geologic, climatic, and land-cover factors (Dou et al., 2020). However, traditional ML-LSM approaches face several key challenges.

First, the selection of negative samples is often ad hoc, introducing bias and uncertainty. Random or subjective sampling can mislabel potentially unstable areas as negative examples, degrading model performance. Second, relying on single-orbit InSAR provides only one-dimensional (1D) LOS deformation, which can under-represent true slope motion. Multi-orbit InSAR can reconstruct more complete 3D deformation histories, but integrating these measurements into susceptibility models has been underexplored. Third, fusing heterogeneous data (InSAR, geology, hydrology, etc.) in a unified framework is nontrivial, and existing studies often treat deformation and susceptibility mapping separately.

Accordingly, we propose a synergistic susceptibility assessment framework that integrates ascending and descending InSAR and uses an ML approach. Specifically, this study focuses on three main objectives: (1) InSAR deformation rate of the ascent and descent orbit. (2) Tree-based machine learning models. (3) Dynamic potential landslide susceptibility mapping.

Study area and datasets

The Baihetan reservoir area is located on the southeastern margin of the Tibetan Plateau, a region characterized by intense Cenozoic tectonic activity and features a typical plateau-mountain tectonic framework. This study integrates multiple datasets for susceptibility modeling and deformation monitoring, including a landslide inventory, engineering geological data, multi-source remote sensing imagery, and rainfall records.

Methodology

A dynamic LSA framework was developed by integrating multi-source data, ML, and InSAR-derived deformation.

SBAS-InSAR

The spatial complementarity of ascending and descending InSAR data can significantly enhance the completeness of deformation field coverage. To obtain high-precision time-series deformation, ascending and descending Sentinel-1A datasets were processed using the SBAS-InSAR method (Agliardi et al., 2020).

Model construction and evaluation

We constructed three tree-based classifiers: Decision Tree (DT), RF, and Gradient Boosting Decision Tree (GBDT). Model performance was evaluated using Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC), with values of 0.50-0.70, 0.70-0.85, 0.85-0.95, and 0.95-1.00 representing low, moderate, high, and excellent predictive accuracy, respectively. Additional metrics, Accuracy, Precision, Recall, and F1-score, were also calculated.

Dynamic potential landslide zone identification

We set deformation and susceptibility thresholds and flag areas that exceed both. Specifically, after effectively removing the geometrically distorted areas, select the ascending and descending orbit point data. we classify the combined LOS deformation by velocity: areas with rates of -10 mm/yr ~ 10 mm/yr are considered stable. Susceptibility is classified by Jenks natural breaks into five classes—very low to very high. "High" and "Very High" classes serve as the susceptibility threshold. Potential zones are those pixels meeting both the deformation and susceptibility thresholds. We then apply spatial clustering and smoothing to eliminate speckles, delineating more realistic zones.

Results and analyses

Model accuracy evaluation

ROC analysis indicated that all three models achieved AUC values between 0.70 and 0.90, reflecting moderate to good predictive performance (Table 1). RF models consistently outperformed others: RF-InSAR attained an AUC of 0.814. Under the InSAR-based negative sample optimization strategy, the DT model exhibited relatively balanced performance with an F1-score of 0.733. However, its AUC value (0.780) was lower than that of the RF (0.814) and GBDT (0.813) models. The RF model achieved the highest AUC (0.814), indicating strong overall discriminative ability, but its recall (0.561) and F1-score (0.654) were moderate.

Table 1, Landslide susceptibility model accuracy.

Model	AUC	Accuracy	Precision	Recall	F1-score
DT-SAR	0.780	0.749	0.783	0.689	0.733
RF-SAR	0.814	0.703	0.784	0.561	0.654
GBDT-SAR	0.813	0.570	0.872	0.163	0.274

Potential landslide susceptibility

The threshold-based model detected 33 inventory landslides and 11 validation landslides. The threshold model predicted 7.91 km^2 of potential landslide area, of which 1.76 km^2 overlapped with the inventory (Figure 1). The threshold model's ability to identify potential landslide areas highlights the method's ability to effectively delineate landslide hazards by combining deformation information with susceptibility zoning.

Limitations and future outlook

The reliance on a fixed deformation threshold in the threshold method is simplistic and may miss slower precursors or irregular slide dynamics. Future work should explore adaptive or probabilistic thresholding and incorporate additional time-series metrics to capture complex failure patterns.

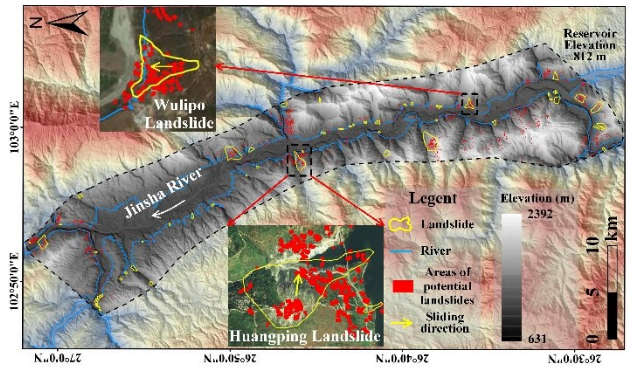

Figure 1, Result map of potential landslide area optimized by threshold model.

Conclusion

This study developed a synergistic framework for dynamic landslide susceptibility evaluation, integrating InSAR-derived deformation, and ML. Key findings include:

(1) Among the three models tested, the RF-InSAR model demonstrated the best predictive performance, with an AUC value of 0.814.

(2) The potential landslide area was optimized by fusing the risk zone and InSAR deformation using a threshold model, with a predicted area of 7.91 km^2.

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