

# High-Precision Landslide Susceptibility Mapping Using CNN-LSTM-Attention Models

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## ABSTRACT

In areas with vulnerable terrain, landslides pose a significant risk to both lives and infrastructure, making precise susceptibility maps essential for effective risk management and planning. This research introduces an advanced Deep Learning (DL) framework that combines multiple models, including Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), Attention U-Net, and their combinations (CNN + LSTM and CNN + Attention), to enhance the landslide susceptibility prediction. The models were trained and validated using 1,580 landslide occurrence data points from the Western Ghats of Karnataka, with 17 geospatial conditioning factors derived from satellite remote sensing and processed through Google Earth Engine (GEE). To verify the reliability of the input features, multicollinearity was evaluated using VIF and TOL. A comparative analysis showed that the LSTM model achieved the highest accuracy at 98.80% and an Area Under the Curve (AUC) of 0.988, with CNN + Attention U-Net performing similarly. The CNN + LSTM hybrid model demonstrated an exceptional spatial detection ability, identifying the highest proportion of landslide risk areas. The generated susceptibility map offers a reliable, data-driven resource for early warning systems, land-use planning, and disaster resilience strategies. This map provides practical insights for the government agencies, urban planners, and disaster response teams to develop proactive hazard mitigation measures.

**Keywords-**landslide susceptibility; deep learning; convolutional neural networks; long short-term memory; google earth engine; remote sensing

## I. INTRODUCTION

Landslides are among the most destructive geological hazards, often resulting in severe casualties, significant infrastructure damage, and environmental harm [1]. Both natural and human factors, such as precipitation, terrain slope, rock type, land use, and proximity to infrastructure, influence their occurrence. The increasing availability of remote sensing data, tools like GEE, and advances in Machine Learning (ML) have revolutionized the methods for creating Landslide Susceptibility Maps (LSM) [2]. Specifically, CNN provides strong methods for identifying the spatial patterns and temporal changes in environmental factors [3]. Authors in [4] assessed the landslide susceptibility in Sichuan Province by combining traditional statistical methods, such as the Certainty Factor (CF) and Information Value (IV), with ML algorithms, including the Decision Tree (DT) and Logistic Regression (LR). The combined IV-LR model achieved the highest AUC of 0.848, outperforming the individual models. Their method categorized susceptibility into five risk levels, highlighting the

eastern and southeastern areas as the most at risk. Similarly, authors in [5] emphasized the subjective nature of decisions in the LSM pipeline and proposed a framework for uncertainty analysis by combining multiple model options at each key step and examining the impact of different Attribute Interval Numbers (AIN). Using Baoji City as an example, they demonstrated that integrating methods, such as the buffer-controlled sampling and Random Forest (RF) with AIN = 12 significantly enhanced performance, achieving an AUC of 0.963.

Ensemble learning has gained increasing popularity for improving the robustness of susceptibility mapping. Authors in [6] evaluated multiple classifiers, both individual and ensemble-based, in Poyang County using Sentinel-2 data, Digital Elevation Model (DEM), and field observations. The stacking classifier outperformed all other methods, achieving an F1 score of 0.846 and an AUC of 0.923, with the voting ensemble closely behind. Explainable AI (XAI) methods help interpret how factors, like the land use and nearby elements

affect the outcome faults. Similarly, authors in [7] used a stacking ensemble of RF, XGBoost, CatBoost, and LR to assess the flood vulnerability, demonstrating its significance for the landslide risks. They found that the ensemble methods outperform the individual models in identifying the high-risk areas influenced by environmental factors, such as rainfall and the Normalized Difference Vegetation Index (NDVI). In Sichuan's Jiuzhaigou region, authors in [8] introduced a combined framework that utilizes LR, SVM, and Gaussian Naive Bayes (GNB) within techniques, such as stacking, Voting, Bagging, and Boosting. SHapley Additive exPlanations (SHAP) - based interpretability verified the models' reliability, demonstrating their effectiveness in the challenging conditions of mountainous regions.

Authors in [9] investigated the landslide susceptibility under projected climate conditions using a physically based model applied to CMIP6 multimodal ensemble data. They predicted that vulnerable areas in Southern Thailand will experience a 29–31% increase under SSP scenarios over the next twenty years, emphasizing the significant impact of rainfall. Authors in [10] introduced a Distributed Deep Learning framework (DDL-CFNN) to address the data silos across different institutions. Applying this framework to the Baijiabao landslide in the Three Gorges Reservoir Area (TGRA) lowered the prediction errors by 62–76% compared to the localized models, showing its effectiveness in enhancing the multi-regional cooperation for displacement forecasting. In regions with rugged terrain and fragile geology, landslides pose serious risks to people's safety, infrastructure, and the natural environment. The increasing effects of the climate change, combined with human activities, such as deforestation, road construction, and uncontrolled urban development, have led to a rise in both the frequency and severity of landslides worldwide. Traditional methods for Landslide Susceptibility Mapping (LSM) are helpful, but they often fail to fully capture the complex, nonlinear relationships among various geo-environmental factors [11]. The use of ML and DL techniques has created new opportunities for hazard prediction because of their strong ability to process high-dimensional data. However, no model consistently outperforms others across different environments and datasets. This has motivated research into hybrid and ensemble DL methods that combine spatial features (such as CNN) with temporal features (like LSTM) to enhance their effectiveness and adaptability in LSM.

Although previous research has highlighted the effectiveness of individual ML and DL models in analyzing THE landslide susceptibility, there is still a considerable lack of understanding of how multi-model DL frameworks can work together synergistically. Many previous studies focus on specific algorithms, like Support Vector Machines (SVM), RF, or CNN, or on traditional ensemble methods, such as boosting or stacking. Authors in [4, 6] have shown the potential for combining statistical methods with ML. However, only a few have successfully integrated spatial-temporal models, such as CNN+LSTM, with real-time earth observation datasets. Additionally, the effects of advanced hybrid models that combine CNNs with attention mechanisms still need further investigation in the LSM domain. This research introduces a multi-model DL framework that combines CNN, LSTM,

Attention U-Net, and their hybrids to enhance the prediction accuracy in the Western Ghats region of Karnataka. By utilizing GEE for large-scale data extraction and hybrid model architectures, this study seeks to create a robust LSM approach that outperforms traditional models in accuracy and spatial scope. This work fills this gap by systematically assessing and comparing different DL configurations, such as hybrid and attention-based models, for landslide susceptibility mapping, using multi-source remote sensing data and features derived from GEE.

Although previous research has examined individual ML and DL approaches for landslide susceptibility mapping, a comprehensive framework incorporating spatial, temporal, and attention mechanisms is still lacking. Most existing studies focus on individual models, such as SVM, RF, or CNNs, without thoroughly evaluating hybrid DL methods. This study specifically addresses the need for a scalable, high-precision, and generalizable DL framework capable of capturing the complex spatial-temporal interactions across various regions, such as the Western Ghats. The proposed hybrid CNN-LSTM-Attention method seeks to bridge this gap by enhancing the prediction accuracy and expanding the range of landslide susceptibility assessments.

## II. PROPOSED METHOD

### A. Data Collection

In this study, the landslide susceptibility modeling relied on a comprehensive and diverse dataset, which included satellite-derived remote sensing variables and additional GIS layers. The GEE was utilized as the primary platform for collecting and processing large-scale geospatial data due to its extensive satellite data archives, cloud-based computing power, and rapid geoprocessing capabilities [12]. Using GEE, 17 Landslide Conditioning Factors (LCFs) were identified and selected based on their significance in evaluating the terrain instability and their frequent application in landslide research. These factors include various topographic, hydrological, vegetation, geological, and human-made elements. Specifically, factors, such as the slope, aspect, elevation, plan and profile curvature, rainfall, NDVI, Stream Power Index (SPI), Topographic Wetness Index (TWI), Fractional Vegetation Cover (FVC), soil type, surface roughness, Land Use/Land Cover (LULC), and proximity to roads and rivers, were represented as raster layers at a 30-m spatial resolution [13].

The dataset included 9,654 spatial records covering both the landslide-affected and stable areas. To train and validate the ML models, a ground-truth inventory of 1,580 landslide points was compiled. These points were collected from historical landslide records, detailed field surveys, and visual assessments of high-resolution satellite images. The confirmed landslide points were randomly split into 70% for training (1,106 points) and 30% for testing (474 points), using stratified sampling. This approach ensured that each subset had a balanced representation of both the landslide and non-landslide classes, thereby preventing the class imbalance issues during model training [14]. A multicollinearity check was conducted using the Variance Inflation Factor (VIF) and Tolerance (TOL) indices to ensure that the predictive modeling process was not

adversely affected by redundancy or collinearity among the features. This diagnostic verified that the selected features remained statistically independent, as indicated by the VIF values below five and TOL values above 0.1, supporting the reliability of the predictor variables [15].

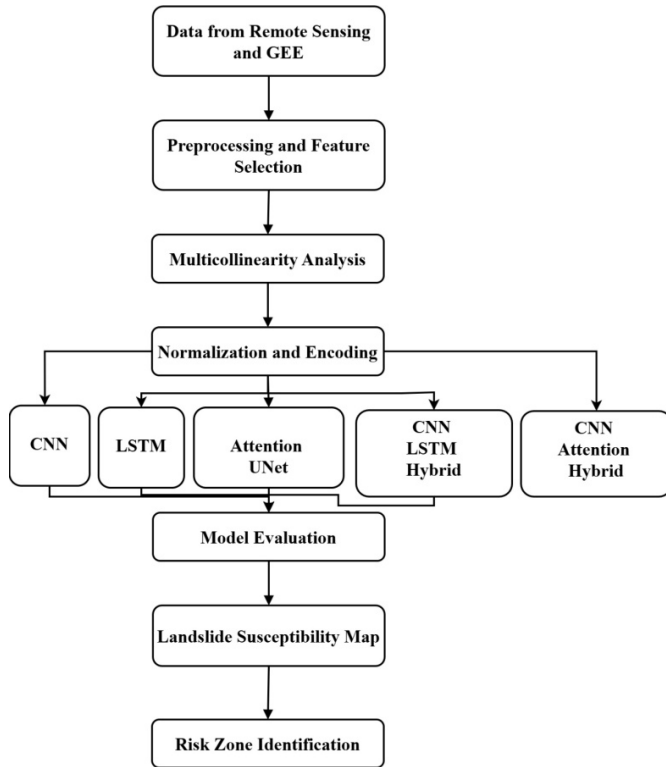


Fig. 1. Workflow of the multi-model DL pipeline for landslide susceptibility mapping.

After performing feature extraction and multicollinearity assessment, the dataset underwent several preparation steps for the DL experiments. Each  $30\text{m} \times 30\text{m}$  pixel was initially assigned a binary label: landslide-prone (1) or stable (0), depending on its overlap with the landslide inventory. The dataset was subsequently balanced to achieve approximately equal counts of landslide and non-landslide samples. Missing data, especially in sensor-derived features, like NDVI, which are vulnerable to the gaps caused by the cloud cover or sensor noise, were later filled using methods, such as spatial interpolation or nearest-neighbor filling [16]. Figure 1 shows the detailed methodological process, beginning with collecting remote sensing data and creating features, then moving on to model training and evaluation, and ending with the production of susceptibility maps. This framework enables the accurate identification of high-risk areas through spatial and temporal DL methods [17].

### B. Multicollinearity Analysis

To verify the independence of the predictor variables, multicollinearity was evaluated with VIF and TOL tests.

These metrics are outlined in (1) and (2):

$$V = \frac{1}{1 - D_i^2} \quad (1)$$

$$T = 1 - D_i^2 \quad (2)$$

where  $D_i^2$  is the coefficient of determination from regressing the  $i$ th predictor against all other predictors. A variable was considered collinear and eligible for removal if  $V > 5$  or  $T < 0.1$ . All LCFs exceeded the threshold, with the highest IF at 4.128 and the lowest T at 0.984, indicating that the collinearity levels are acceptable [17].

The input features used in landslide susceptibility modeling, such as slope, rainfall, NDVI, and TWI, come from various sources and have different units and value ranges. For example, slope is measured in degrees (e.g.,  $0-90^\circ$ ), while NDVI usually ranges from -1 to 1. Feeding such heterogeneously scaled data into ML models—especially DL architectures—can lead to biased training and unstable gradient updates [18]. To handle this, min-max normalization was applied to each feature, scaling its values to a range of 0-1. This process is mathematically represented by:

$$a' = \frac{a - a_{\min}}{a_{\max} - a_{\min}} \quad (3)$$

This maintains the spatial variation while enhancing the model convergence. Categorical variables (e.g., soil type, land use) were converted using One-Hot Encoding, transforming the nominal values into binary feature vectors. The sampling unit was a pixel-level record (e.g.,  $30\text{m} \times 30\text{m}$ ), representing either a landslide-prone or stable area. Samples of both landslide and non-landslide cases were balanced to prevent model bias. For each point, a 17-dimensional feature vector is represented in:

$$A = [\text{Rainfall}_k, \text{Slope}_k, \text{TWI}_k, \dots, \text{LULC}_k] \quad (4)$$

where  $k$  represents the spatial index of the pixel. These features encompass key environmental and topographic characteristics that affect the landslide susceptibility [19]. The binary label for each sample is specified as:

$$\text{Label} = \begin{cases} 1 & \text{if landslide occurred} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

This structured representation allowed DL models to recognize the spatial patterns and distinguish the landslide-prone areas from the stable ones based on geophysical and environmental features.

## III. RESULTS AND DISCUSSION

### A. Experimental Setup

The multi-model DL approach offered insights into the landslide susceptibility patterns throughout Karnataka's Western Ghats. Before training the model, the multicollinearity diagnostics confirmed that all 17 conditioning factors were suitable for modeling, with VIF values between 1.015 and 4.128 and TOL values above 0.1, ensuring no redundant variables. The Frequency Ratio (FR) method was applied to analyze the connection between the environmental factors and landslide occurrences. The FR results indicated that the slope is a key factor in landslide risk; slopes steeper than  $30^\circ$  had  $\text{FR} > 1$ , suggesting a higher likelihood of landslide events. Similarly, areas below 2,600 m in elevation and within 6 km of road

networks exhibited increased susceptibility, highlighting the influence of topography and human activity.

**B. Model Performance Analysis**

Five DL models were trained and evaluated: CNN, Attention U-Net, LSTM, CNN + LSTM, and CNN + Attention. These models were evaluated based on their ability to predict landslide-prone areas using various statistical metrics, including accuracy, precision, recall, F1-score, MCC, Kappa, AUC, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Among them, the LSTM model achieved the highest accuracy (98.80%) and an impressive AUC of 0.9882,

demonstrating excellent model performance in discrimination (Table I). The hybrid CNN + LSTM model also showed strong performance, integrating spatial feature extraction (CNN) with temporal sequence learning (LSTM). While its AUC was slightly lower at 0.9861, it attained a higher accuracy in identifying landslide areas at 23.71%. In contrast, the CNN + Attention model performed poorly across all metrics (AUC = 0.8706, accuracy = 87.12%), suggesting that although the attention mechanism is theoretically promising, it may not be well-suited to the spatial characteristics of landslide data in this region.

TABLE I. PERFORMANCE METRICS OF DIFFERENT MODELS FOR LANDSLIDE SUSCEPTIBILITY PREDICTION

Model	Accuracy	Precision	Recall	F1-score	MCC	Kappa	AUC	RMSE	MAE
CNN	98.62%	0.9912	0.9820	0.9866	0.9724	0.9724	0.9863	0.1175	0.0138
Attention UNet	98.70%	0.9907	0.9841	0.9874	0.9740	0.9739	0.9871	0.1141	0.0130
LSTM	98.80%	0.9933	0.9836	0.9884	0.9761	0.9761	0.9882	0.1093	0.0120
CNN + LSTM	98.59%	0.9927	0.9800	0.9863	0.9719	0.9718	0.9861	0.1186	0.0141
CNN + Attention	87.12%	0.8671	0.8871	0.8770	0.7420	0.7418	0.8706	0.3589	0.1288

**C. Visual Insights and Feature Influence**

Figure 2 presents a comparison of the ROC performance among CNN, LSTM, attention U-Net, and hybrid DL models for landslide susceptibility prediction. The LSTM model achieved the highest predictive performance with an AUC of 0.988, demonstrating its strong ability to capture spatiotemporal landslide patterns.

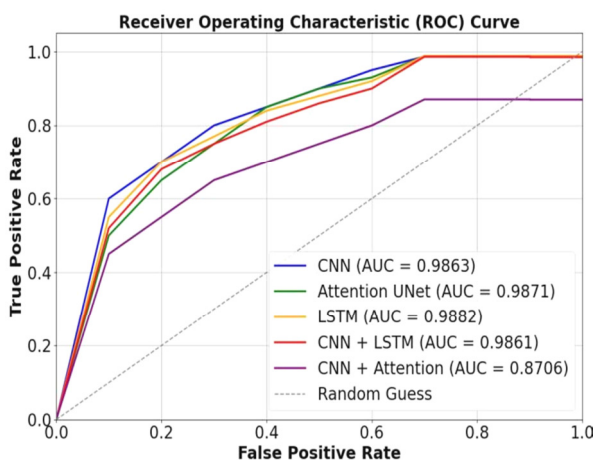


Fig. 2. ROC curve of various DL models applied to landslide susceptibility mapping

To quantitatively evaluate the effect of individual LCFs on susceptibility, a binary LR model was used. The binary dependent variable represented the landslide presence (1) or absence (0), while the 17 geospatial factors served as independent predictors. The regression coefficients ( $\beta$ ) for each factor were calculated using the maximum likelihood estimation method. The resulting model was statistically significant ( $p < 0.01$ ), with a Nagelkerke  $R^2$  of 0.72, indicating a strong explanatory power. The regression results indicated that the slope had the strongest positive standardized coefficient ( $\beta = 0.252$ ), reflecting a significant association with

the landslide occurrence—steeper slopes were more prone to failure. Rainfall was the next most influential factor ( $\beta = 0.110$ ), consistent with its known role in triggering slope failures during the monsoon season. Other variables, such as NDVI ( $\beta = 0.001$ ) and TWI ( $\beta = 0.001$ ), had very low coefficients, suggesting a minimal or negligible impact on the model's predictive performance.

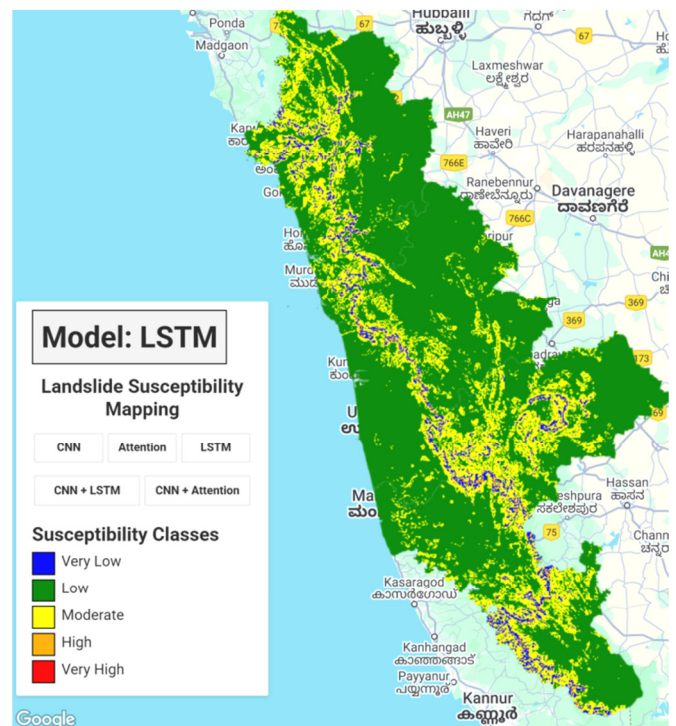


Fig. 3. Landslide susceptibility map of the Western Ghats in Karnataka generated with the LSTM model.

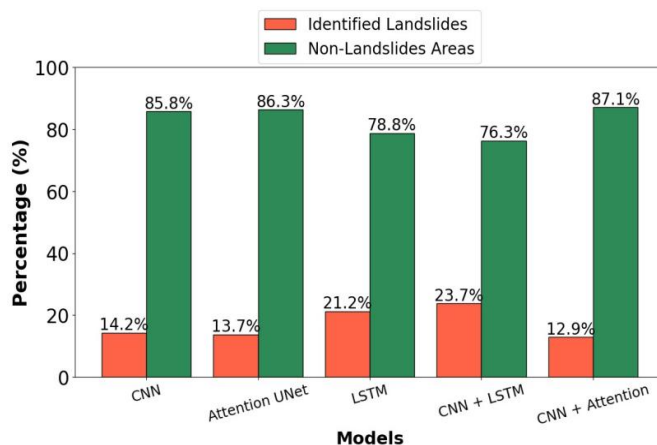


Fig. 4. Percentage of landslide and non-landslide areas using different models.

A landslide susceptibility map of the Western Ghats region in Karnataka was created using the LSTM model in GEE, based on 17 geospatial factors (Figure 3). The spatial distribution of the landslide susceptibility across the Western Ghats region of Karnataka, as forecasted by the LSTM model, showed the highest predictive accuracy (AUC = 0.988) among all tested configurations. These findings suggest that LSTM-based architectures, especially when combined with CNN, are most effective for LSM in diverse terrain environments. The map categorizes areas into five susceptibility levels: very low (blue), low (green), moderate (yellow), high (orange), and very high (red) [20]. The classification reveals that areas with steep slopes, heavy rainfall, and proximity to infrastructure corridors have a moderate to very high susceptibility. Notably, high and very high-risk zones are clustered around Coorg, Chikkamagaluru, and parts of the Malnad region, emphasizing the urgent need for targeted risk mitigation efforts in these areas. This map serves as a vital decision-making resource for regional planners and geohazard mitigation.

Figure 4 compares the percentage of landslide and non-landslide areas identified using different DL models. The CNN + LSTM model demonstrates the highest landslide detection rate, whereas the CNN + Attention model shows the lowest, emphasizing the varied spatial recognition capabilities of these architectures.

While the proposed DL framework showed high predictive accuracy for Karnataka's Western Ghats, its direct scalability to other regions may encounter challenges. The variations in terrain, climate, vegetation, and human activities across different regions may require retraining the model with localized datasets. Additionally, the dependence on remote sensing factors may be limited in areas with persistent cloud cover or limited satellite data availability. Future work may investigate transfer learning and domain adaptation methods to enhance the model portability. Incorporating region-specific features and socioeconomic parameters can further improve the model's flexibility for a wider range of applications. The generated landslide susceptibility maps provide essential tools for real-world decision-making. Government agencies can use these maps in zoning regulations to prevent construction in

high-risk areas. Urban planners can use susceptibility layers when expanding cities and developing infrastructure to minimize landslide hazards. Disaster response teams can use these maps to prioritize monitoring, plan evacuations, and allocate the emergency resources efficiently.

Furthermore, maps can support insurance agencies in evaluating risks and determining pricing strategies. Incorporating susceptibility data into land management policies enables proactive risk mitigation and supports the sustainable development, thereby enhancing the resilience of the vulnerable communities. The landslide susceptibility mapping is crucial for sustainable land management and ecosystem preservation, particularly in fragile regions, such as the Western Ghats. Identifying high-risk areas enables targeted conservation efforts, including restricting deforestation, promoting afforestation, and safeguarding critical zones that maintain the slope stability. It guides infrastructure planning to prevent the ecological disruption and reduces the risk of secondary disasters, such as sediment buildup in rivers and biodiversity loss. By supporting evidence-based decisions, these maps facilitate resilience-building strategies, climate change adaptation, and the safeguarding of ecosystem services essential for long-term regional sustainability.

#### IV. CONCLUSION

This study presents a high-precision Deep Learning (DL) framework that combines Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Attention mechanisms for landslide susceptibility mapping in the Western Ghats region of Karnataka. Among the models tested, the LSTM model achieved the highest predictive accuracy with an AUC of 0.988 and identified the slope and rainfall as the most influential factors. The hybrid CNN + LSTM model demonstrated superior spatial detection abilities, further improving the landslide identification rates. The generated susceptibility maps offer crucial information for land-use planning, disaster preparedness, and environmental protection. By offering a data-driven, systematic approach to hazard prediction, this work addresses the practical challenges in geohazard management and promotes sustainable development strategies. Future research will focus on integrating real-time satellite data for dynamic susceptibility mapping, utilizing transfer learning strategies to expand the regional applications, and incorporating explainable AI techniques to improve the model transparency and foster stakeholder trust. Expanding the framework to other geologically sensitive regions will better show its scalability and operational practicality.

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