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Original Article

Data-driven Forecasting of Landslide Displacement Using Machine Learning and Real-time Monitoring

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Abstract: Landslides pose significant risks to infrastructure and human safety, especially in areas characterized by steep terrain and unstable geological conditions. This study explores the application of machine learning (ML) models for predicting landslides in Lac Duong Town, Lam Dong Province, Vietnam, with a particular focus on the influence of rainfall and pore water pressure (PWP). The dataset comprises hourly rainfall, pore water pressure (PWP), and soil displacement records collected by an automatic monitoring system from 2020 to 2024. Three ML models, Decision Tree (DT), Random Forest (RF), and Long Short-Term Memory (LSTM), were employed to examine the relationship between cumulative rainfall, soil displacement, and landslide occurrence. The analysis identified critical cumulative rainfall thresholds (Rx3d, Rx5d, Rx7d, and Rx10d) as key indicators of landslide events. Among the models, the RF algorithm achieved the highest predictive performance, with an R^2 of 0.6406 and an RMSE of 0.0393, outperforming both DT and LSTM. The findings underscore the importance of cumulative rainfall in landslide forecasting and demonstrate the potential of ML, particularly RF, to enhance early warning systems. The study also proposes data-driven rainfall thresholds validated against historical landslide records. Recommendations include implementing real-time monitoring systems, refining threshold-based models, integrating landslide risk into urban planning, and including additional hydrogeological variables in future research. This work highlights the promise of ML-based approaches in improving landslide prediction and risk mitigation in vulnerable regions.

Keywords: Machine learning (ML), rainfall thresholds, early warning systems, pore water pressure, soil displacement.

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1. Introduction

Landslides are complex phenomena posing significant threats to lives and infrastructure in vulnerable regions [1]. In 2019, the urban area of Lac Duong Town, Lam Dong Province, experienced a major landslide following surface modifications, causing extensive damage and highlighting the need for robust warning systems. Rainfall is a primary landslide trigger, with its impact varying based on intensity and duration. Short, intense rainfall typically triggers shallow landslides, whereas prolonged rainfall promotes deep-seated failures [2].

Current warning systems often rely on generalized rainfall thresholds that fail to account for local geological and topographical specifics, such as soil permeability or PWP, which are critical for accurate risk assessment [3]. The Lac Duong landslide underscored the role of rainfall-induced PWP in triggering events. Advances in sensor technology and ML offer pathways to develop more adaptive, multivariate thresholds by integrating real-time data [4].

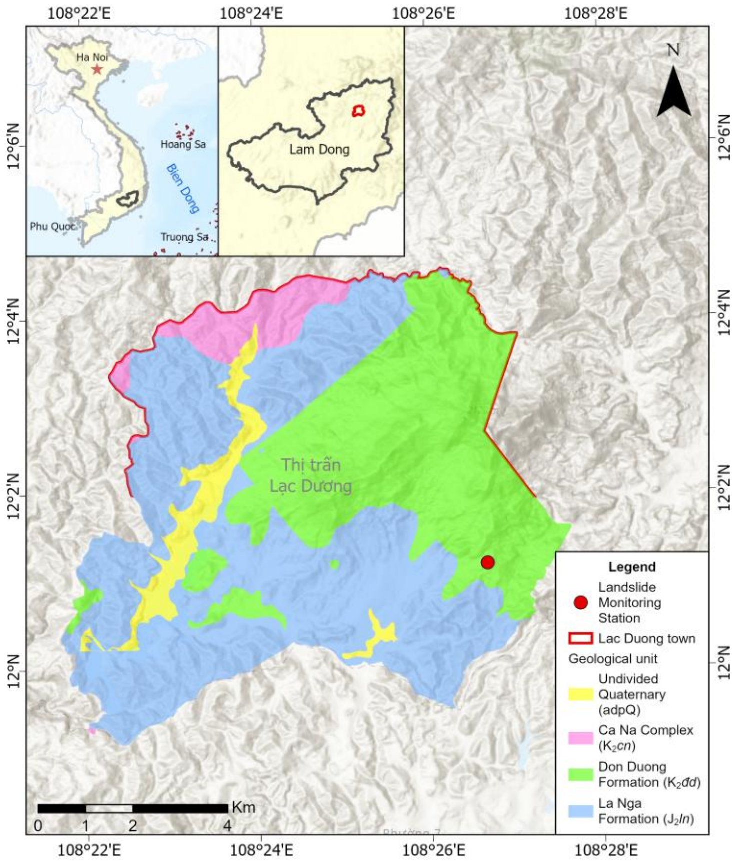

Figure 1. Study area and geological settings.

This study addresses these gaps by analyzing the Lac Duong landslide area (Fig. 1) and proposing an improved monitoring framework. By leveraging automated monitoring systems and machine learning-driven data integration, the research aims to enhance the accuracy of landslide prediction and support more effective risk management strategies. The specific objectives of this study are to: i) Establish quantitative relationships among rainfall, pore water pressure, and displacement; ii) Evaluate the performance of three machine learning models-Decision Tree (DT), Random Forest (RF), and Long Short-Term Memory (LSTM)-in landslide forecasting; and iii) Propose data-driven rainfall thresholds for early warning of deep-seated landslides.

2. Landslide Monitoring and Prediction: A Brief Overview

Landslide early warning systems are crucial for risk mitigation. Monitoring techniques range from ground-based tools like extensometers and tiltmeters to remote sensing methods such as satellite positioning and Interferometric Synthetic Aperture Radar (InSAR) [5]. Meteorological and hydrological monitoring, particularly of rainfall and PWP, is essential for prediction [6].

The concept of rainfall intensity-duration (I-D) thresholds, foundational in landslide forecasting, helps differentiate triggers for shallow versus deep-seated landslides [3]. However, these thresholds vary significantly across regions due to differing meteorological conditions, soil properties, and vegetation. For regional-scale monitoring, landslide inventory maps, enhanced by LiDAR and high-resolution satellite imagery, are indispensable for identifying vulnerable areas [7].

Recently, artificial intelligence (AI) and machine learning (ML) have revolutionized landslide monitoring and prediction. Deep-learning models such as convolutional neural networks (CNNs) can interpret complex, multidimensional sensor data, while ensemble and recurrent frameworks-e.g., Random Forest (RF) and Long Short-Term Memory (LSTM)-have proven effective in modeling non-linear rainfall-displacement relationships [8, 9]. These data-driven methods facilitate the dynamic optimization of rainfall thresholds, thereby enhancing the responsiveness and reliability of landslide early warning systems [10].

3. Study Area, Data, and Monitoring System

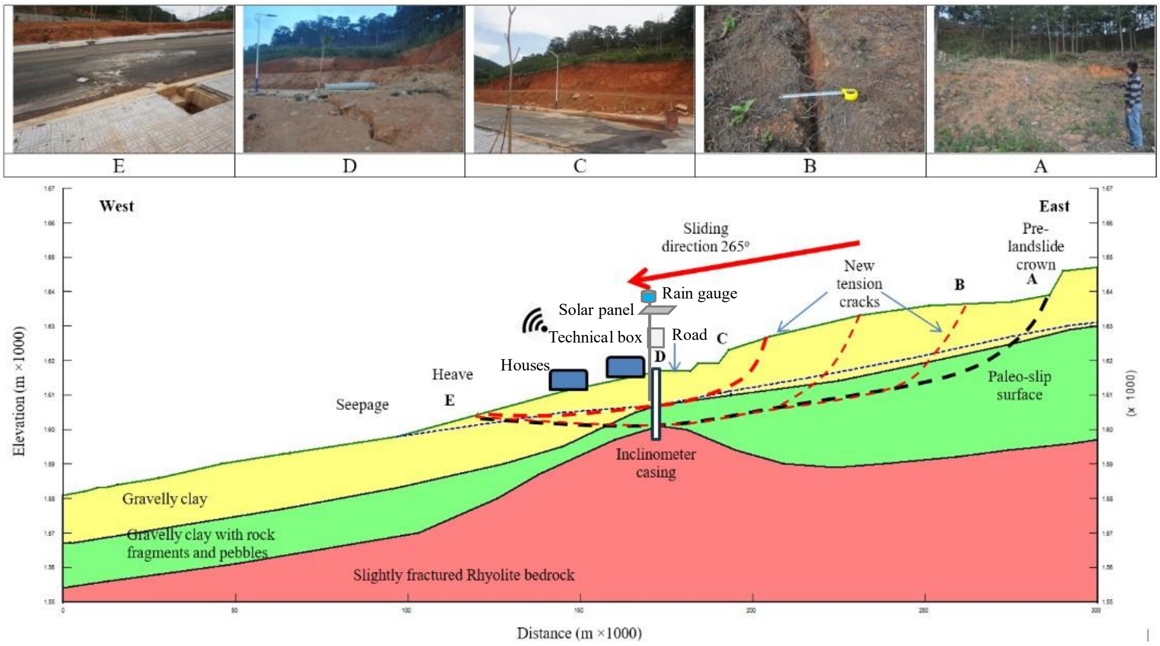

Figure 2. Geological profile of the landslide.

Lac Duong Town (12°2′3″N, 108°25′40″E) is located in a mountainous basin in Lam Dong Province, Vietnam. The area experiences annual rainfall of 1,940-2,000 mm, and rapid urbanization has increased landslide frequency. The geology is dominated by Late Jurassic and Late Cretaceous formations, with a weathering crust of 5-20 m. Large rotational landslides are common in the weathered crust of Cretaceous rhyolite and tuffs (K_2*đd*) (Fig. 1, 2).

An automated monitoring station was installed at a critical landslide site. The system includes:

Rainfall Gauge: A TE525 MM tipping bucket rain gauge measures hourly precipitation.

Displacement Sensors: Five MEMS horizontal displacement sensors (Geokon) installed in a borehole at depths from -6.0 m to -17.5 m to monitor soil movement across different layers (Fig. 3).

Pore Water Pressure Sensors: Two vibrating-wire piezometers (Geokon) installed at depths of -8.0 m and -15.0 m to measure PWP.

Data Logger: A Campbell Scientific CR1000 data logger records all sensor data at one-hour intervals and transmits it to a remote server.

Data was collected from November 2020 to October 2024. Manual displacement measurements were also taken periodically to calibrate and verify the automated sensor readings.

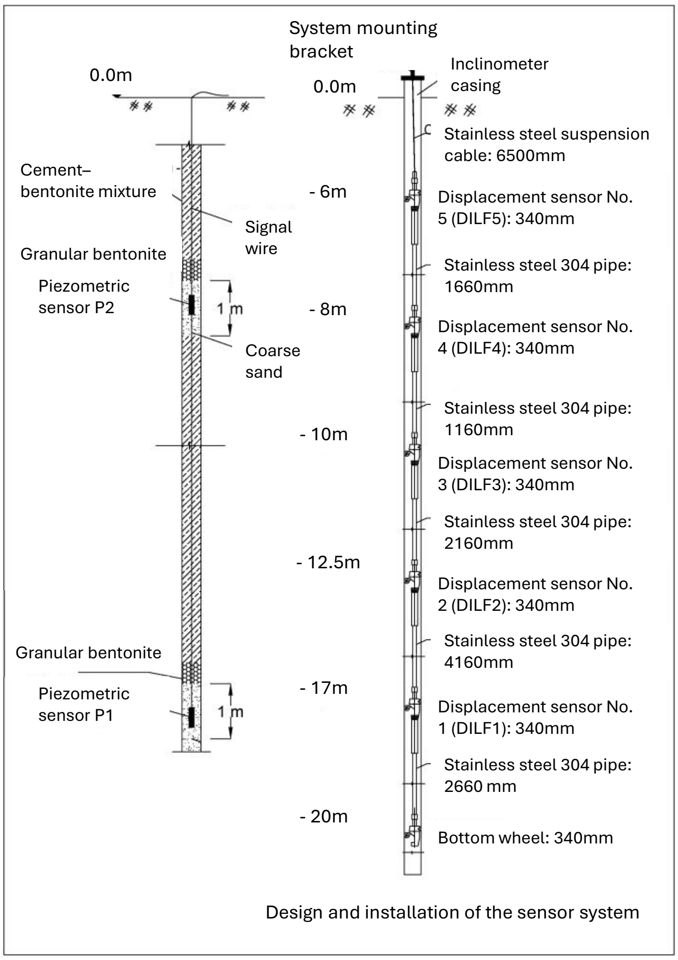

Figure 3. Design and installation of the sensor system.

4. Methodology

This study employed a data-driven approach to develop a landslide prediction framework. The methodology involved data collection, preprocessing, and the development and training of three ML models.

4.1. Data Preprocessing

A wide range of parameters were monitored during this study to capture the complex interactions that influence deep-seated landslides. These parameters included meteorological, hydrological, geotechnical, and environmental variables, as well as device status indicators such as battery voltage, temperature, rainfall, displacement measurements (DIFL1-DIFL5), accumulated displacements (ACCDIFL1-ACCDIFL5), water pressure (P1, P2), soil moisture (VWC), electrical conductivity (EC), and soil temperature (SOILTEMP). For model development, the analysis focused on three key variables directly related to landslide initiation and progression: rainfall (TE525, mm), water pressure (P1, m H_2O), and landslide displacement (DIFL1-DIFL5, mm, and their cumulative values). Rainfall acts as a primary triggering factor, water pressure represents subsurface hydrological response, and displacement serves as a direct indicator of slope deformation. The raw dataset, comprising hourly rainfall, pore water pressure (P1 - measured at a depth of -15 m), and cumulative soil displacement (ACCDIFL4), which reached a maximum of approximately 60mm over the entire 4-year monitoring period, with individual rainfall-triggered events producing 5-25mm displacement increments, underwent rigorous preprocessing. Missing values were imputed using linear interpolation, and outliers were identified and removed through the interquartile range (IQR) method. Time-lagged features were introduced to account for the lag in the hydrological response between rainfall infiltration and slope displacement. Specifically, cumulative rainfall over 3, 5, 7, and 10 days (Rx3d, Rx5d, Rx7d, and Rx10d) was computed to represent short- and long-term precipitation effects. Shorter lags (3-5 days) characterize rapid infiltration influencing near-surface layers, while longer lags (7-10 days) reflect deeper saturation and pore pressure buildup leading to deep-seated slope movements.

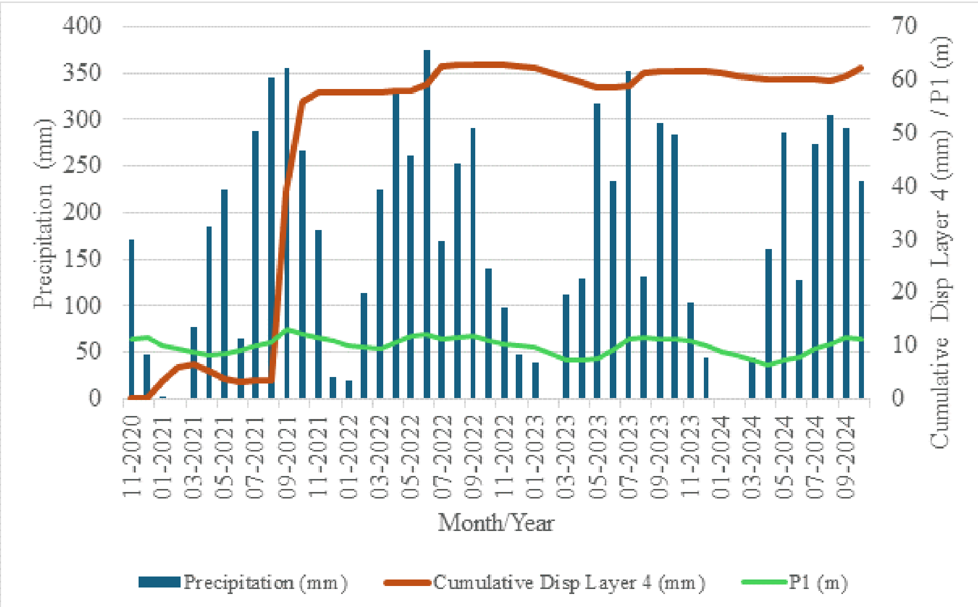

Figure 4. Observed precipitation, cumulative displacement and pore water pressure.

The selection of the 7, 10-day cumulative rainfall windows (Rx7d, Rx10d) is crucial for deep-seated landslide prediction. Unlike shallow landslides that respond to short-duration rainfall (typically 1-3 days), deep-seated failures require prolonged rainfall to infiltrate through thick soil layers and raise pore water pressure at depth. In our study area, the weathering crust extends to depths of 5-20 m, and pore water pressure sensors are installed at -8.0 m and -15.0 m. Water infiltration to these depths requires extended periods, making longer accumulation windows (7-10 days) more relevant for capturing the hydrological processes that trigger deep-seated movements. This approach is consistent with studies of deep-seated landslides that commonly use 7-14 day rainfall accumulation periods (Iverson, 2000; Bordoni et al., 2015).

This approach allows the models to capture the temporal dynamics of rainfall-induced landslide processes. The dataset was then divided into training (80%) and testing (20%) subsets, maintaining temporal continuity to prevent data leakage. The testing subset was manually curated to include both landslide (30%) and non-landslide (70%) periods. The primary datasets-hourly rainfall, pore water pressure, and displacement measurements - are summarized in Supplementary S1 and Fig 4.

4.2. Model Development and Training

Three machine learning models were developed using Python Scikit-learn and TensorFlow/Keras libraries:

DT: A simple, interpretable model that partitions data based on feature thresholds. It was trained to full depth to capture all possible data splits.

RF: An ensemble model that builds multiple DT on bootstrapped data samples and averages their predictions to improve robustness and reduce overfitting. The model used the default of 100 estimators.

LSTM: A recurrent neural network (RNN) designed to model temporal dependencies. The architecture consisted of a single LSTM layer (50 units) and a dense output layer, trained for 50 epochs with the Adam optimizer.

The performance of each model was evaluated using the coefficient of determination (R^2) and Root Mean Squared Error (RMSE).

The DT model (Fig. 5a) demonstrated moderate predictive accuracy, effectively capturing key trends in landslide displacement (RMSE = 0.0438, R^2 = 0.5746). However, its reliance on a single-tree structure limited its ability to generalize complex patterns within the data.

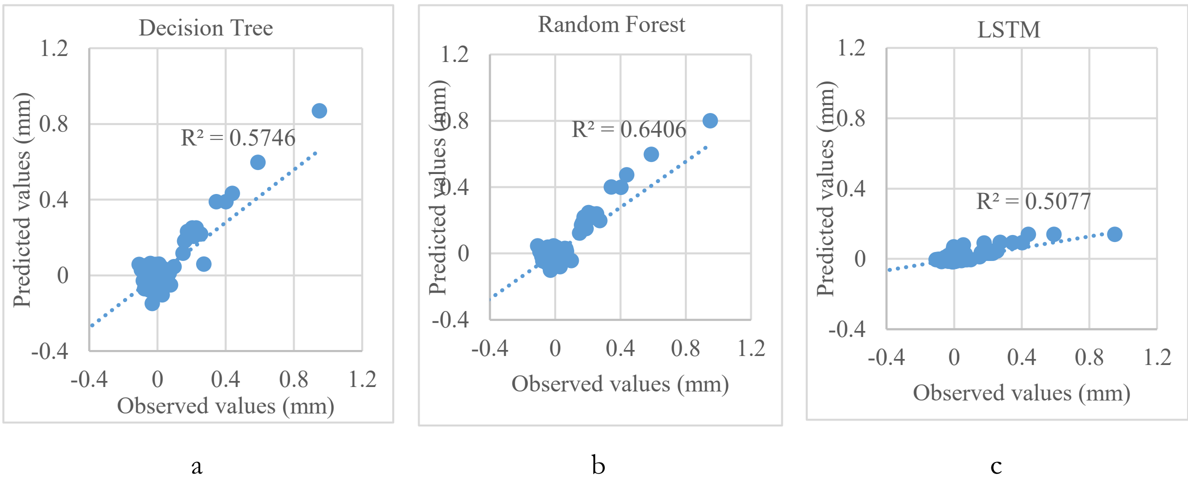

Figure 5. Comparison of Model Performance in Predicting Landslide Displacement.

The LSTM model (Fig. 5c) exhibited higher RMSE and lower R^2 compared to the other models (RMSE = 0.0561, R^2 = 0.5077). While LSTM is adept at modeling temporal dependencies, its performance suggests potential underfitting or limitations in capturing short-term variations in the dataset.

By combining these models, the study aimed to leverage the interpretability of DTs, the ensemble robustness of RFs, and the temporal learning capabilities of LSTM to develop a comprehensive framework for landslide prediction.

5. Results and Discussion

5.1. Application of ML Models for Landslide Prediction

Rainfall is a primary trigger of landslides, particularly in areas with steep slopes and vulnerable geological formations, such as those found in Lac Duong, Lam Dong Province. To establish robust predictive relationships between precipitation and landslide occurrence, we analyzed both hourly rainfall data and cumulative precipitation over multiple time intervals. This study employed three ML models: DT, RF, and LSTM to evaluate the correlation between rainfall patterns and landslide initiation.

The ML models were trained using datasets that incorporated cumulative rainfall metrics (Rx3d, Rx5d, Rx7d, Rx10d) alongside hourly precipitation measurements. Our analysis identified rainfall as the predominant triggering factor for landslides, especially when combined with soil saturation conditions during prolonged wet periods. The investigation of rainfall accumulation thresholds revealed several critical patterns:

\+ Rx3d (3-day cumulative rainfall): Thresholds between 75-100 mm proved crucial to triggering landslides, particularly in areas characterized by thinner weathering crusts where water infiltration rapidly affects slope stability.

\+ Rx5d (5-day cumulative rainfall): Accumulations exceeding 100 mm frequently corresponded with landslide events in zones with moderately saturated soil conditions, indicating the progressive buildup of destabilizing pore pressure.

\+ Rx7d and Rx10d (7- and 10-day cumulative rainfall): Higher thresholds of 130-150 mm were strongly associated with increased landslide susceptibility, especially in areas with deeper soil layers where prolonged infiltration processes gradually compromise slope integrity.

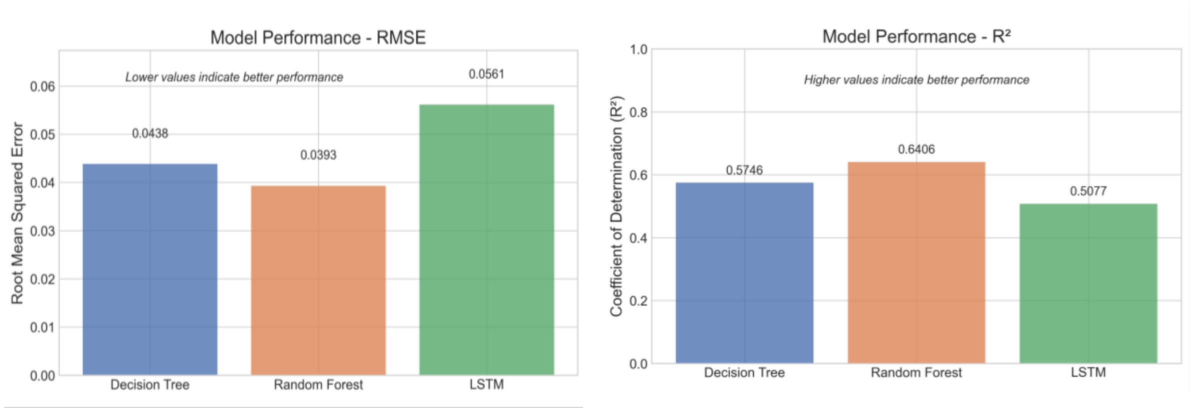

Figure 6. ML models performance.

These findings highlight the critical importance of lag effects in cumulative rainfall for understanding and predicting slope failures. The research demonstrates that gradual precipitation accumulation over extended periods significantly influences pore-water pressure dynamics and overall slope stability, underscoring the necessity of incorporating cumulative rainfall metrics into effective early warning systems.

When comparing model performance, the RF algorithm demonstrated superior predictive performance, with an R^2 of 0.6406 and an RMSE of 0.0393, outperforming both the DT (R^2 = 0.5746, RMSE = 0.0438) and the LSTM (R^2 = 0.5077, RMSE = 0.0561) (Fig. 6). The ensemble-based RF approach effectively captured the complex, non-linear relationships between precipitation patterns and landslide initiation, while maintaining robustness across diverse rainfall scenarios.

The DT model, while offering greater interpretability through explicit threshold identification, showed limitations in generalizing complex rainfall-landslide interactions. Meanwhile, the LSTM network, despite its theoretical advantage in modeling temporal dependencies, exhibited higher error rates, suggesting potential challenges in capturing the short-term variations critical for precise landslide prediction.

These results validate the critical role of cumulative precipitation metrics in landslide forecasting and demonstrate the potential of machine learning, particularly ensemble methods, to enhance the accuracy and reliability of early warning systems in landslide-prone regions.

5.2. Data-driven Warning Thresholds

Based on model insights, new rainfall thresholds were proposed to assess landslide risk. For Alert Level 1, the threshold is exceeded when Rx3d exceeds 75 mm or Rx5d exceeds 100 mm. Alert Level 2 is triggered when Rx7d exceeds 130 mm or Rx10d exceeds 150 mm (Fig. 7).

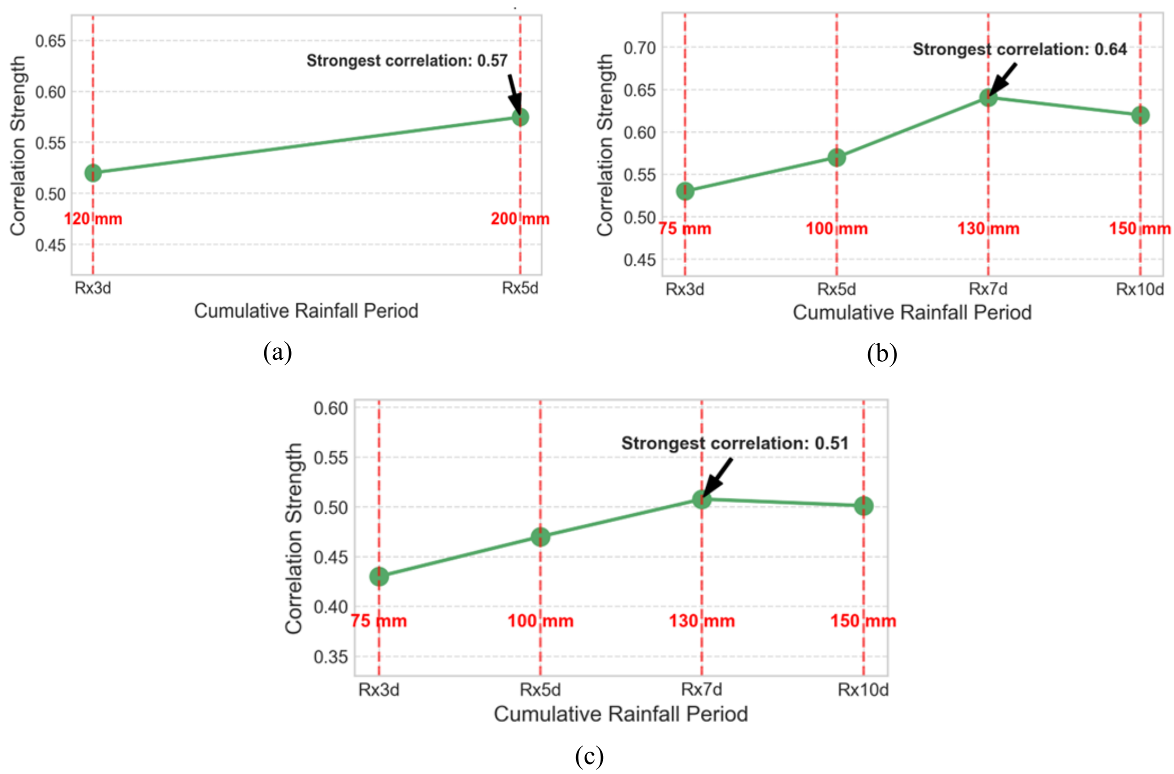

Figure 7. Rainfall Threshold Correlation with Landslide Displacement, (a) DT, (b) RF, (c) LSTM.

A Critical Alert is issued when both Rx3d and Rx10d thresholds are exceeded simultaneously, accompanied by significant cumulative displacement (ACCDIFL4 > 20 mm). These thresholds were validated against observed landslide events, confirming their reliability and practicality in operational settings. The study also investigated seasonal variations and environmental factors influencing landslide susceptibility. Landslide frequency was highest during the monsoon season (June-October), which coincided with periods of heavy rainfall. Areas with fine-grained soils and deep weathering crusts were found to be particularly vulnerable to prolonged rainfall. At the same time, urbanization and slope modifications further increased instability, highlighting the importance of integrated land-use planning.

The selection of rainfall thresholds in this study is grounded in both empirical observations and data-driven analyses derived from AI models performance. The cumulative rainfall metrics (Rx3d, Rx5d, Rx7d, and Rx10d) were selected to capture the lag effects of precipitation on slope stability, reflecting different stages of soil saturation and pore-pressure buildup. Short-term accumulations, such as Rx3d and Rx5d, are particularly sensitive to rapid infiltration processes in areas with thin weathering crusts, often leading to shallow slope failures. In contrast, longer-term accumulations (Rx7d and Rx10d) represent the gradual infiltration of rainfall into deeper soil layers, which can weaken internal structures and induce deep-seated landslides. The proposed threshold values of 75-100 mm for Rx3d, 100 mm for Rx5d, and 130-150 mm for Rx7d-Rx10d were derived from model outputs showing the strongest correlations between cumulative rainfall and displacement data. The superior predictive performance of the RF model further supports the validity of these thresholds, as it effectively captures the non-linear relationships between rainfall patterns and landslide initiation. Thus, the established thresholds not only reflect the physical mechanisms governing slope failure but also provide a scientifically validated framework for operational early warning systems in landslide-prone regions.

5.3. Discussion

Establishing rainfall thresholds for early warning of deep-seated landslides in Lac Duong Town, Lam Dong Province, Vietnam, represents a significant advancement in disaster risk management. The integration of ML models, DT, RF, and LSTM has provided valuable insights into the relationships between rainfall, soil displacement, and landslide susceptibility. This discussion evaluates the effectiveness of these models, the identified thresholds, and their implications for landslide prediction and mitigation strategies.

The comparative analysis of DT, RF, and LSTM models demonstrates distinct advantages and limitations in predicting landslide occurrences. The RF model emerged as the most robust and reliable, achieving the highest coefficient of determination ($R^2 = 0.6406$) and the lowest root mean square error (RMSE = 0.0393). The superior performance of RF can be attributed to its ensemble learning approach, which mitigates overfitting and enhances generalization across diverse rainfall conditions. Moreover, RF effectively identified key predictive variables, including cumulative rainfall over multiple days (Rx3d, Rx5d, Rx7d, and Rx10d), confirming the importance of considering prolonged rainfall in landslide forecasting.

In contrast, the DT model provided practical interpretability, enabling the identification of specific rainfall thresholds associated with landslide events. However, its simplicity led to limited generalization, making it prone to false positives in periods of moderate rainfall. The LSTM model, designed for sequential data, demonstrated promising temporal dependency modeling but underperformed RF ($R^2 = 0.5077$, RMSE = 0.0561). These findings suggest that while LSTM can capture long-term rainfall effects, its application in landslide prediction may require further optimization, such as the incorporation of additional geotechnical and hydrological parameters.

These findings align with global studies on landslide early warning, which emphasize the role of cumulative rainfall in initiating slope failures [11]. The moderate R^2 values (0.51–0.64) reflect the complexity of the landslide system, in which displacement is influenced by numerous factors beyond our three input variables, including spatially variable soil properties, groundwater flow, temperature effects, and limitations of point-based sensors in capturing spatial variability. Similar studies report comparable R^2 values, confirming our results align with current prediction capabilities using limited variables. The gradual accumulation of rainfall over extended periods was pivotal in influencing pore water pressure and slope stability, underscoring the need for cumulative metrics in early warning systems.

These thresholds were validated against historical landslide events in Lac Duong, demonstrating their reliability and practicality in operational settings. The ability to issue timely warnings can significantly reduce the impact of landslides by enabling authorities and communities to take preemptive measures, such as slope reinforcement, evacuation, and infrastructure adjustments.

The integration of ML models demonstrated the potential to improve the accuracy and reliability of landslide prediction by leveraging rainfall thresholds. RF emerged as the most effective model due to its balance of interpretability, robustness, and precision. The findings underscore the importance of considering both the immediate and lagged effects of rainfall, as well as the interaction between surface and subsurface hydrological processes.

The study highlights the need for continued monitoring and model refinement to address limitations such as data sparsity and the dynamic nature of rainfall-landslide relationships. Future research should incorporate additional factors, such as soil moisture and geotechnical properties, to further enhance predictive capabilities.

However, limitations such as data sparsity and the static nature of the thresholds warrant further research. Future research should concentrate on adding additional factors, such as soil moisture and geotechnical characteristics, expanding datasets, and developing dynamic thresholds that adapt to seasonal and geological variability.

Establishing rainfall thresholds for landslide initiation is a complex task, as multiple interacting factors, including geological structure, slope gradient, and land cover, influence landslide occurrences. Notably, rainfall thresholds for landslide initiation are highly site-specific. Therefore, this study aims to propose rainfall thresholds for the Lac Duong area, which features relatively similar geological and topographical conditions. Nevertheless, the proposed approach for determining rainfall thresholds can be applied to other regions, provided that long-term monitoring data are available.

6. Conclusion and Recommendation

6.1. Conclusion

This study has successfully established rainfall thresholds for the early warning of deep-seated landslides in Lac Duong Town, Lam Dong Province, Vietnam. By integrating ML models, including DT, RF, and LSTM, we analyzed the correlation between rainfall accumulation and slope displacement, thereby developing more reliable predictive frameworks. The research findings confirm that cumulative rainfall over various periods (Rx3d, Rx5d, Rx7d, and Rx10d) plays a significant role in landslide initiation, with RF demonstrating the highest predictive accuracy. The proposed warning thresholds have been validated against historical landslide occurrences, demonstrating their practical applicability in real-world disaster mitigation. Key contributions of this study include developing data-driven thresholds for different risk levels that define essential rainfall thresholds and provide a scientific basis for landslide early warning systems. Application of ML Models: The comparative performance analysis shows that RF is the most effective model, balancing interpretability and accuracy.

Implications for Risk Management: The findings emphasize integrating real-time monitoring, remote sensing, and geotechnical data to refine predictions and improve early warning capabilities. Future research should focus on expanding datasets, incorporating additional hydrological and geotechnical parameters (e.g., soil moisture profiles, groundwater levels, and detailed soil properties), and integrating climate variability to improve threshold adaptability and model performance. Implementing these findings into operational monitoring frameworks will enhance disaster preparedness, mitigate landslide risks, and safeguard communities in vulnerable mountainous areas. The integration of machine learning and real-time monitoring represents an important step toward establishing data-driven landslide early warning systems in Vietnam's urbanized highland regions.

6.2. Recommendation

Based on the findings of this study, the following recommendations are proposed to enhance landslide early warning systems in Lac Duong Town and other similar regions: i) Implementation of Real-Time Monitoring Systems: Authorities should invest in automated rainfall and soil displacement monitoring stations, integrating data loggers, remote sensing, and geotechnical sensors for continuous data collection; ii) Refinement of Threshold Models: The established rainfall thresholds should be periodically updated based on new data, climate variations, and improved machine learning models to enhance prediction accuracy; iii) Community-Based Early Warning Systems: Public awareness and preparedness initiatives should be implemented to ensure local communities understand warning alerts and take necessary precautionary measures. iv) Integration with Land-Use Planning: Urban planning authorities should incorporate landslide susceptibility maps into infrastructure development policies to prevent high-risk constructions on unstable slopes; and v) Further Research on Hydrogeological Parameters: Future studies should incorporate groundwater levels, soil moisture content, and vegetation dynamics to develop more comprehensive predictive models for landslide initiation. These recommendations will contribute to the development of a more robust and efficient landslide early warning system, ultimately reducing risks to human lives and infrastructure.

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References

[1] O. Hungr, S. Leroueil, L. Picarelli, The Varnes Classification of Landslide Types, an Update, Landslides, Vol. 11, No. 2, 2014, pp. 167-194, https://doi.org/10.1007/s10346-013-0436-y.

[2] R. M. Iverson, Landslide Triggering by Rain Infiltration, Water Resources Research, Vol. 36, No. 7, 2000, pp. 1897-1910, https://doi.org/10.1029/2000WR900090

[3] F. Guzzetti, S. Peruccacci, M. Rossi, C. P. Stark, The Rainfall Intensity-Duration Control of Shallow

Landslides and Debris Flows: an Update, Landslides, Vol. 5, No. 1, 2008, pp. 3-17, https://doi.org/10.1007/s10346-007-0112-1.

[4] M. Bordoni, C. Meisina, R. Valentino, M. Bittelli, S. Chersich, Hydrological Factors Affecting Rainfall-Induced Shallow Landslides: from the Field Monitoring to a Simplified Slope Stability Analysis, Engineering Geology, Vol. 193, 2015, pp. 19-37, https://doi.org/10.1016/j.enggeo.2015.04.006.

[5] M. Scaioni, L. Longoni, V. Melillo, M. Papini, Remote Sensing for Landslide Investigations: An Overview of Recent Achievements and Perspectives, Remote Sensing, Vol. 6, No. 10, 2014, pp. 9600-9652, https://doi.org/10.3390/rs6109600.

[6] N. Caine, The Rainfall Intensity-Duration Control of Shallow Landslides and Debris Flows, Geografiska Annaler: Series A, Physical Geography, Vol. 62, No. 1-2, 1980, pp. 23-27, https://doi.org/10.1080/04353676.1980.11879996.

[7] F. Guzzetti, A. C. Mondini, M. Cardinali, F. Fiorucci, M. Santangelo, K. T. Chang, Landslide Inventory Maps: New Tools for an Old Problem, Earth-Science Reviews, Vol. 112, No. 1-2, 2012, pp. 42-66, https://doi.org/10.1016/j.earscirev.2012.02.001.

[8] Y. Wang, Z. Fang, H. Hong, Comparison of Convolutional Neural Networks for Landslide Susceptibility Mapping in Yanshan County, China, Science of The Total Environment, Vol. 666, 2019, pp. 975-993, https://doi.org/10.1016/j.scitotenv.2019.02.263.

[9] L. Deng, N. Dixon, H. Yuan, A. Smith, Machine Learning Prediction of Landslide Deformation Behaviour Using Acoustic Emission and Rainfall Measurements, Engineering Geology, Vol. 293, 2021, pp. 106315, https://doi.org/10.1016/j.enggeo.2021.106315.

[10] B. Peng, X. Wu, Optimizing Rainfall-Triggered Landslide Thresholds for Daily Landslide Hazard Warning in the Three Gorges Reservoir Area, Natural Hazards and Earth System Sciences, Vol. 24, No. 11, 2024, pp. 3991-4013, https://doi.org/10.5194/nhess-24-3991-2024.

[11] S. L. Gariano, F. Guzzetti, Landslides in a Changing Climate, Earth-Science Reviews, Vol. 162, 2016, pp. 227-252, https://doi.org/10.1016/j.earscirev.2016.08.011.