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From Empirical Curves to AI-Derived Rainfall Thresholds for Landslide Initiation in Peninsular Malaysia

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Abstract

Rainfall-induced landslides are a persistent hazard in Malaysia, yet existing rainfall thresholds remain largely based on empirical methods and often lack regional adaptability. This study employs machine learning (ML)-based rainfall thresholds for landslide initiation in Peninsular Malaysia. A dataset of rainfall events from 70 rainfall stations across peninsular Malaysia linked with documented 79 landslides was analysed, along with key predictors such as event cumulative rainfall (ECR), maximum and mean intensity, duration, and antecedent rainfall windows (3–20 days). Two state-of-the-art gradient boosting algorithms, CatBoost and XGBoost, were trained to classify rainfall events as landslide- or non-landslide-triggering. Performance of models was evaluated using a confusion matrix, precision, Accuracy, recall, F1-score, and ROC-AUC. Moreover, SHAP explainability analysis was applied to assess the relative importance of rainfall metrics in threshold exceedance. CatBoost shows a superior practical reliability, with a higher accuracy of 0.83 and recall of 0.67 as compared to XGBoost, which showed a higher ROC–AUC of 0.876 but substantially lower recall of 0.33. These findings demonstrate that ML-derived rainfall thresholds for peninsular Malaysia offer a more flexible and reliable basis for early warning systems, supporting landslide risk management in Malaysia.

Keywords: Artificial intelligence, rainfall threshold, landslide prediction, Peninsular Malaysia,

Introduction

Landslides are among one of the most destructive natural hazards, frequently triggered by rainfall in tropical and monsoon-dominated regions[1]. Defining rainfall thresholds is a critical component of landslide early-warning systems across the globe. The pioneering work of Caine and subsequent refinements by Guzzetti [2], [3] and others have underscored the importance of identifying critical rainfall conditions. Accurate and real-time identification of the critical rainfall conditions that initiate slope failures enables effective disaster risk reduction strategies, aligning with the United Nations' Sustainable Development Goal 11 on building resilient and sustainable cities [4]. In tropical environmental regions such as Malaysia, intense and prolonged monsoonal rainfall is very common, and it triggers shallow landslides recurrently, with severe social and economic impacts[5].

Traditional approaches for defining rainfall thresholds, such as intensity–duration (ID) and event-duration (ED) relationships, have been widely used due to their empirical simplicity, and these approaches typically analyse historical landslide and rainfall records to derive functional relationships. These methods, in many cases, often fail to capture the nonlinear interactions between rainfall intensity, cumulative precipitation, antecedent soil moisture, and slope instability. They are also location-specific and may not generalise well under changing climatic conditions or in regions with limited landslide inventory data [6].

In recent times, with the advancement in technology, machine learning (ML) has emerged as a promising technology in rainfall-induced landslide prediction. ML techniques are capable of learning complex, multivariate patterns from historical data and have demonstrated effectiveness in enhancing the accuracy of landslide early-warning systems. Moreover, these Models offer the advantage of being easily updated with new data. Research from Italy demonstrated the value of applying machine learning techniques for rainfall-based threshold evaluation in geologically complex settings. It compared conventional empirical–statistical methods with advanced ML approaches in the Emilia–Romagna region and found that ML models offered superior predictive performance [7].

In this study, we employed Ensemble classifiers such as Extreme Gradient Boosting (XGBoost) and Categorical Boosting (CatBoost), which are particularly suitable because of their ability to handle imbalanced datasets, integrate multiple rainfall predictors, and provide robust performance in small-sample contexts. Despite these advantages, comparative evaluations of such algorithms for rainfall-threshold prediction are rare in Malaysia. This study trains and compares XGBoost and CatBoost classifiers for predicting landslide-triggering rainfall events in Malaysia, using a dataset of 79 rainfall–landslide events from Peninsular Malaysia. Predictors include event cumulative rainfall (ECR), duration, mean rainfall intensity (I mean), and antecedent rainfall (AAR) indices at varying time windows of 3 to 20 days. Model performance is evaluated using accuracy, precision, recall, F1-score, and ROC–AUC, while SHAP (Shapley Additive Explanations) is employed to interpret feature importance and enhance model transparency [8]. The objectives of this study are as follows:

- To evaluate the performance of XGBoost and CatBoost for landslide-triggering rainfall prediction in peninsular Malaysia.
- To interpret the influence of rainfall and antecedent indices using the SHAP-based beeswarm global explainability plot.
- To identify the most suitable model, where minimising false negatives is critical for disaster preparedness.

With the integration of ML with rainfall threshold analysis, this work is contributing to the advancement of data-driven early-warning systems for landslides in tropical, data-scarce regions and offers insights for disaster risk reduction.

Study Area

This study is based on Peninsular Malaysia, a region majorly affected by rainfall-induced landslides due to its tropical climate and intense monsoonal rainfall. Geographically, the peninsula extends approximately between 1°15′N and 6°45′N latitude and 99°35′E and 104°25′E longitude, as shown in Figure 1. Annual precipitation is commonly more than 2,500 mm, with peaks during the Southwest Monsoon (May–September) and the Northeast Monsoon (November–March). Rainfall is a major triggering factor in this region. Rugged highlands, mid-elevation slopes, and coastal plains characterise the physiography of the region. Prominent highland areas such as Cameron Highlands and Genting Highlands are particularly susceptible to slope failures because of their steep terrain. Land cover in Peninsular Malaysia comprises forest, scrubland, grassland, agricultural areas, and ex-mining lands, many of which have undergone anthropogenic changes. Rapid urbanisation in areas such as the Klang Valley further enhances exposure to rainfall-induced landslides [9]. The study aims to derive machine learning-based rainfall thresholds for landslide initiation in Peninsular Malaysia, using landslide inventories and rainfall station records to develop regionally adaptable early warning models focusing on rainfall as a major triggering factor.

Data Used

The landslide inventory for this study is developed from multiple sources, and 79 events are considered in the study, as shown in Figure 1. The primary dataset was the NASA Global Landslide Catalogue (GLC), accessed through the Cooperative Open Online Landslide Repository (COOLR). This dataset was systematically supplemented from local newspapers, governmental reports, and academic research papers. Only events with reliable temporal accuracy and geo-referenced locations were retained, while records with incomplete information were removed. Corresponding rainfall data were obtained from the Malaysian Meteorological Department (MetMalaysia), from a dense network of more than 70 rain gauge stations across Peninsular Malaysia, for every 15 minutes. For each landslide, rainfall records were extracted from stations located within a 10 km radius of the event coordinates, and a 24-hour dry-gap criterion was applied to separate independent landslide-inducing rainfall events, following the procedure adopted in earlier threshold studies, such as Kim's in determining the threshold of South Korea [10].

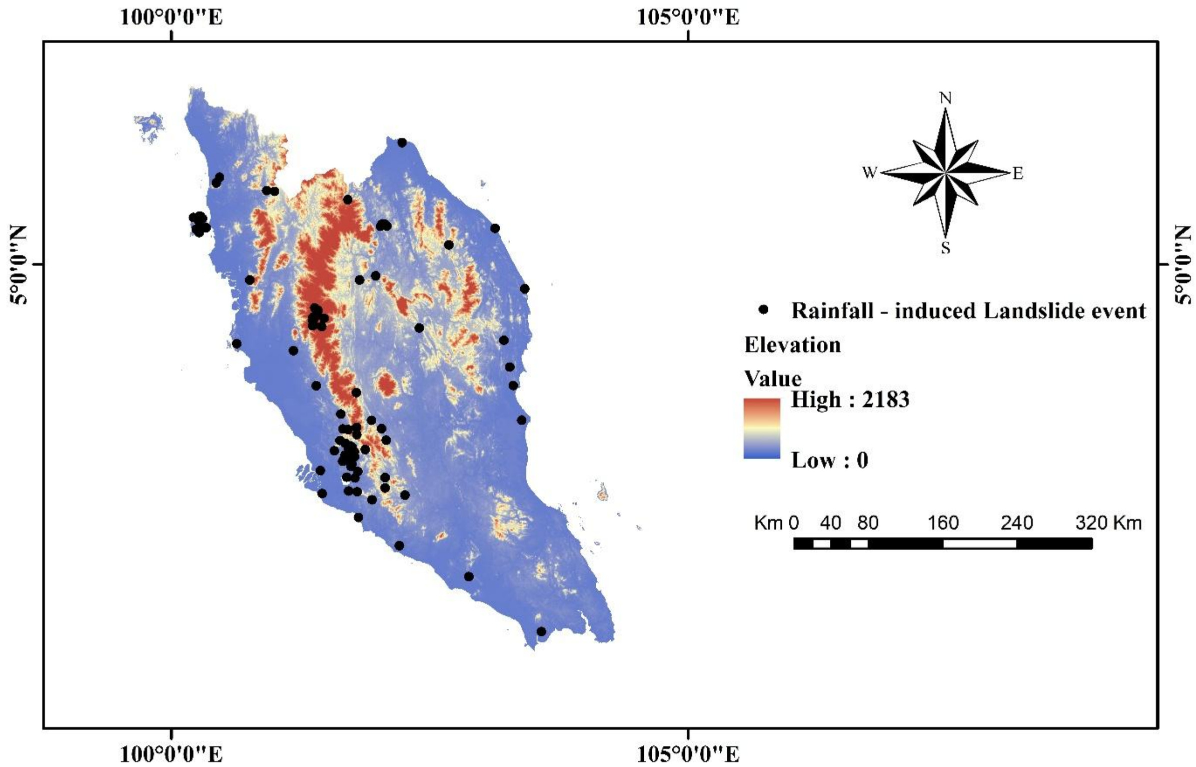

Figure 1: Distribution map of the 79 rainfall-induced landslides analysed in this study

Methodology

Traditionally, rainfall thresholds for slope failure initiation are determined by empirical approaches. The most common method is the development of intensity–duration (I–D) thresholds, which establishes the relationship between mean rainfall intensity and rainfall duration of landslide triggering rainfall. The general form of such a threshold was first introduced by Caine in 1980 [2] is:

$$I = \alpha D^{-\beta} + C \tag{1}$$

Here, I represent rainfall intensity (mm/h), D is rainfall duration (h), α and β are fitting parameters obtained from the regional dataset, and C is a constant ≥ 0. These parameters are important as they offer the customisation of the models at the local and regional level of precipitation patterns. Another event–duration (E–D) threshold-based approach is also widely used, which emphasises cumulative rainfall during an event:

$$E = \alpha D^{-\beta} \tag{2}$$

Here, E is the event rainfall (mm) and D is the duration (h). These curves highlight the critical conditions at which rainfall is likely to initiate landslides. Both I–D and E–D thresholds are calibrated empirically from past landslide records and have been used globally as early warning tools.

In this study, for each landslide triggering rainfall event, a set of hydrological predictors was calculated to characterise triggering conditions. These included the duration (D in h), representing the time from rainfall onset to landslide occurrence, the event cumulative rainfall (ECR, in mm), defined as the total rainfall during the event, and the mean rainfall intensity (Imean, mm/h), calculated as the ratio of ECR to duration [11]. Apart from this, antecedent rainfall (AR, mm) was computed over multiple time windows of 3, 5, 7, 10, and 20 days before the initiation of the landslide event. To reduce class imbalance, the final dataset was balanced into landslide-triggering and non-triggering rainfall events in a 1:2 ratio. This ratio is adopted to fully reflect real-world conditions, where rainfall events that do not trigger landslides occur far more frequently than those that do. This ensures robust model performance, and these non-triggering rainfall events were derived from the rainfall data of the rain gauges, which are included in this study.

Gradient Boosting Machine Learning Algorithms

In this study, we have used two prominent gradient boosting models, XGBoost and CatBoost, and compared them to evaluate their performance for deriving rainfall thresholds for landslide initiation in Peninsular Malaysia. XGBoost was introduced by Chen and Prokhorenkova [12], [13] as an optimised gradient boosting framework, CatBoost was developed by researchers at Yandex.

XGBoost is an advanced gradient boosting algorithm designed for improved efficiency and prediction accuracy. It is tree-based and builds classification trees in a sequential manner, where each new tree corrects the errors of the previous trees. Compared to conventional gradient boosting, XGB integrates regularisation to control overfitting, supports parallel processing for faster training, and uses efficient split-finding methods for handling large datasets. Due to these features, it is highly effective in modelling complex, non-linear relationships, such as those between multiple rainfall parameters and slope failure.

CatBoost (Categorical Boosting, CB) is an advanced gradient boosting algorithm that was developed to address some limitations of existing methods, particularly in handling categorical features and overfitting. It incorporates innovations such as ordered boosting and target statistics, which reduce bias and improve generalisation. Unlike many other boosting algorithms, which rely on encoding methods, CatBoost minimises prediction shift and avoids over-reliance on feature encoding by using its ordered target statistics method, making it more robust when working with heterogeneous data. By combining these properties, CatBoost provides better accuracy along with interpretability and efficiency, which is valuable for applications in landslide threshold modelling. With the integration of SHAP explainability with both XGBoost and CatBoost, this study provides transparent insights into the relative influence of rainfall predictors, thereby bridging the gap between black-box machine learning models and interpretable landslide threshold analysis, which is more practical.

The Dataset is divided into training (70%) and testing (30%) subsets to evaluate the machine learning model's performance. Stratified sampling is employed so that proportional representation of landslide and non-landslide points in both subsets is maintained, to reflect the original dataset balance. The grid-based hyperparameter tuning was done for both models, and details are in Table 1.

Table 1: Hyperparameter Settings of Models

Model	Key Hyperparameters & Values
XGBoost	n_estimators=200, max_depth=3, learning_rate=0.05, subsample=0.9, colsample_bytree=0.9 reg_lambda=1.0, objective=binary:logistic, eval_metric=logloss
CatBoost	iterations=200, depth=3, learning_rate=0.05 , loss_function=Logloss , random_seed=42

SHAP Analysis

SHAP (SHapley Additive exPlanations) was used to interpret the predictions of both models for the rainfall threshold for landslide initiation. The SHAP is a famous and advanced algorithm that is used to explain Machine learning models. This method has its origin in game theory, and it calculates the Shapley value for each input feature by dividing the model's contribution of individual features [14]. It also quantifies the impact and direction of each input feature on the model's output. In the case of a classification model, a positive Shapley value for a feature highlights that the feature increases the predicted value. In contrast, a negative Shapley value highlights that the feature tends to decrease the expected value. While calculating, each feature's Shapley value is determined by taking the weighted average of its marginal contributions across every possible feature subset. The weights are taken by the size of the feature subsets and the feature's position in the subset. At the global level, SHAP summary (beeswarm) plots are employed to rank the predictors according to their overall importance in distinguishing landslide-triggering from non-triggering rainfall events. This enabled the identification of the most influential rainfall metrics, such as event cumulative rainfall (ECR), mean intensity (Imean), and antecedent rainfall windows.

Model Evaluation

The performance of the models is evaluated using the confusion matrix, classification report, and Receiver Operating Characteristic (ROC) curve, along with Area Under the Curve (AUC). All these provide a comprehensive evaluation of the model's performance, particularly focusing on accuracy, precision, recall, and the ability to differentiate between landslide-initiating and non-landslide-initiating rainfall.

Confusion matrix

A confusion matrix is a key tool for the evaluation of classification models by comparing the predicted class labels with the actual labels. It gives a detailed breakdown of the model's predictions into four categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). It summarises predictions into true positives (landslides inducing rainfall identified correctly), true negatives (non-landslides inducing rainfall identified correctly), false positives (non-landslides inducing rainfall misclassified as landslides), and false negatives (landslides inducing rainfall missed by the model).

Classification Report

The classification report metrics are derived from the confusion matrix.

Precision: This is computed as the proportion of rainfall events predicted as landslide-triggering that were actually landslide-triggering events.

Accuracy: It is computed as the proportion of correctly classified instances, including both landslide-triggering and non-triggering events of rainfall, out of the total predictions.

Recall: It represents the proportion of actual landslide-triggering rainfall events that were correctly classified by the model, while low recall shows that many true landslide events were missed.

F1-score: It is basically computed as the harmonic mean of precision and recall, ensuring that both the detection of true landslide-triggering rainfall events and the minimisation of false alarms are considered in the overall performance of the model.

ROC-AUC Curve

The Receiver Operating Characteristic (ROC) curve is a graphical tool used to evaluate the performance of models across different decision thresholds. It plots the True Positive Rate (TPR), or recall, which measures the proportion of correctly identified landslide initiating rainfall, against the False Positive Rate (FPR), which represents the proportion of non-landslide initiating areas that are incorrectly classified. For measuring the overall performance of the model, the Area Under the Curve (AUC) is 1.0 for a perfect classifier. The high AUC value and balanced precision and recall clearly indicate that the model is a robust model for landslide-initiating rainfall predictions. These evaluation metrics reflect the reliability of the model, and they are an essential tool for practical applications in data-driven early warning systems

Results and Discussion

Model Evaluation

The performance of both models in identifying landslide triggering rainfall threshold is evaluated using the Confusion matrix, classification reports and the ROC curves. These metrics will give an in-depth view of the model's ability to identify the landslide triggering rainfall threshold and will also help in identifying the best model.

Confusion matrix

For the XGBoost, 47 instances were correctly classified as no-landslide triggering rainfall (true negatives), and 8 instances were accurately identified as landslide triggering rainfall (true positives), as shown in Figure 2. However, in one case, the model produced 1 false positive, where a non-landslide triggering rainfall threshold was misclassified as a landslide triggering rainfall, and 16 false negatives, where actual landslide triggering rainfall was missed and predicted as no-landslide triggering rainfall. In this case, a large number of false negatives is critical in hazard studies, as failing to detect high-risk rainfall undermines disaster preparedness and mitigation efforts.

On the other hand, the CatBoost model achieved a more balanced performance. It correctly classified 44 instances as no-landslide triggering rainfall (true negatives) and 16 instances as landslide triggering rainfall (true positives) as shown in the Figure. The model produced 4 false positives and 8 false negatives. As compared to XGBoost, CatBoost substantially reduced the false negatives, achieving a better balance between identifying landslide and non-landslide cases.

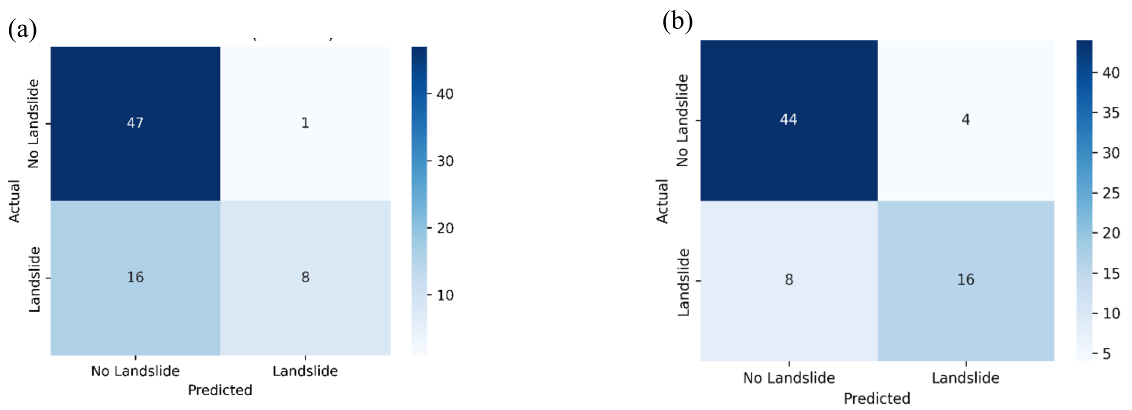

Figure 2 : Confusion matrix illustrating the classification performance of the modes (a) for XGBoost and (b) for CatBoost

Classification report

Table 2: Classification report summarising both models' performance

Model	Class	Precision	Recall	F1-Score
XGBoost	0 (No landslide Triggering rainfall)	0.75	0.98	0.85
	1 (Landslide Triggering Rainfall)	0.89	0.33	0.48
	Overall	Acc = 0.76		
CatBoost	0 (No landslide Triggering Rainfall)	0.85	0.92	0.88
	1 (Landslide Triggering Rainfall)	0.80	0.67	0.73
	Overall	Acc = 0.83		

For the XGBoost model, the overall accuracy turns out to be 76%, showing that the model correctly classified rainfall events as landslide-triggering or non-landslide-triggering in 76% of the cases. In the non-landslide rainfall category, the model achieved a precision of 0.75, meaning that 75% of the events predicted as non-landslide were correct. Its recall is 0.98, showing that almost all actual non-landslide events were correctly identified. Now, the F1-score is 0.85, reflecting strong reliability in detecting stable conditions. While for the landslide rainfall category, the precision is relatively high (0.89), but the recall dropped sharply to 0.33, leading to an F1-score of 0.48. This imbalance shows that XGBoost often failed to capture actual landslide-triggering rainfall.

In Contrast, the CatBoost model outperformed XGBoost in terms of the balance between the classes. It achieved an overall accuracy of 83%, with more consistent performance across both categories. For the non-landslide rainfall class, CatBoost shows a precision of 0.85, a recall of 0.92, and an F1-score of 0.88, confirming its strong capacity to detect stable rainfall events. More importantly, for the landslide class, CatBoost delivered a precision of 0.80, a recall of 0.67, and an F1-score of 0.73. This reflects a significant improvement in sensitivity compared with the XGBoost model, making the model more effective in identifying hazardous landslide-causing rainfall events that may lead to slope failures. In a nutshell, the results highlight that while XGBoost is slightly biased toward non-landslide detection, CatBoost achieves a better balance between precision and recall across both categories, as shown in Table 2. This makes CatBoost more suitable for operational applications where both false negatives and false positives must be minimised for better landslide risk management and an early warning system.

Receiver Operating Characteristic (ROC) Curve

The ROC curve provides an additional graphical evaluation of the predictive performance of the XGBoost and CatBoost models by plotting the true positive rate (TPR) against the false positive rate (FPR) at varying classification thresholds, as shown in Figure 3. The diagonal line shows random guessing, while curves closer to the top-left corner indicate stronger discriminative ability of the model. For the XGBoost model, the ROC curve demonstrates strong classification capability, achieving an Area Under the Curve (ROC–AUC) value of 0.88. It indicates that the model can distinguish between landslide-triggering and non-landslide rainfall events in 88% of cases across threshold settings. The steep rise of the curve at low false positive rates further demonstrates the model's ability to correctly identify non-landslide rainfall events, though its recall for actual landslides remains limited, as also reflected in the confusion matrix.

The CatBoost model indicates a slightly lower ROC–AUC value of 0.86, but its curve also indicates strong discriminative ability. Noticeably, CatBoost offers a better balance between sensitivity and specificity, as it captured truer landslide-causing rainfall events while keeping false alarms at an acceptable level, unlike XGBoost. This balance complements its higher recall for the landslide-inducing rainfall class and makes the model more robust, even after having a slightly lower AUC value compared to XGBoost. After all, both models exhibit good predictive power as indicated by their high AUC values of >0.85. However, the ROC curves confirm that CatBoost achieves a more practical balance between missed detections and false alarms, which is highly required in operational early warning systems.

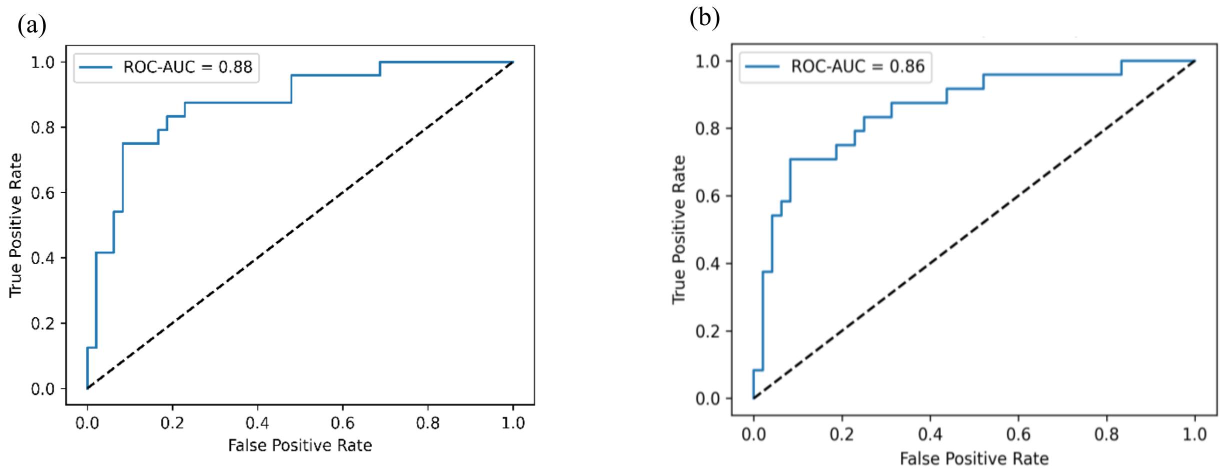

Figure 3: Receiver operating characteristic (ROC) curve illustrating the model's capability to distinguish between landslide-inducing rainfall and non-landslide-inducing rainfall (a) for XGBoost and (b) for CatBoost

SHAP Interpretation

These SHAP beeswarm plots, as shown in Figures 4 for XGBoost and 5 for CatBoost, provide a global interpretation of the landslide triggering rainfall predictors driving landslide threshold classification for both models. For XGBoost prediction, the largest contributors are Event Cumulative Rainfall (ECR) and Duration, with SHAP values ranging between approximately -0.2 to +0.8 and -0.3 to +0.6, respectively. Higher values of these features pushed predictions toward landslide-triggering rainfall events, confirming their role as dominant drivers. Short-term Antecedent Rainfall of 3–5 days also contributed positively up to +0.25, whereas longer windows of rainfall, like 10–20 days, had weaker ranges between -0.1 to +0.2, indicating more diffuse effects of prolonged soil moisture. Mean rainfall intensity I mean showed minor influence around –0.1 to +0.2.

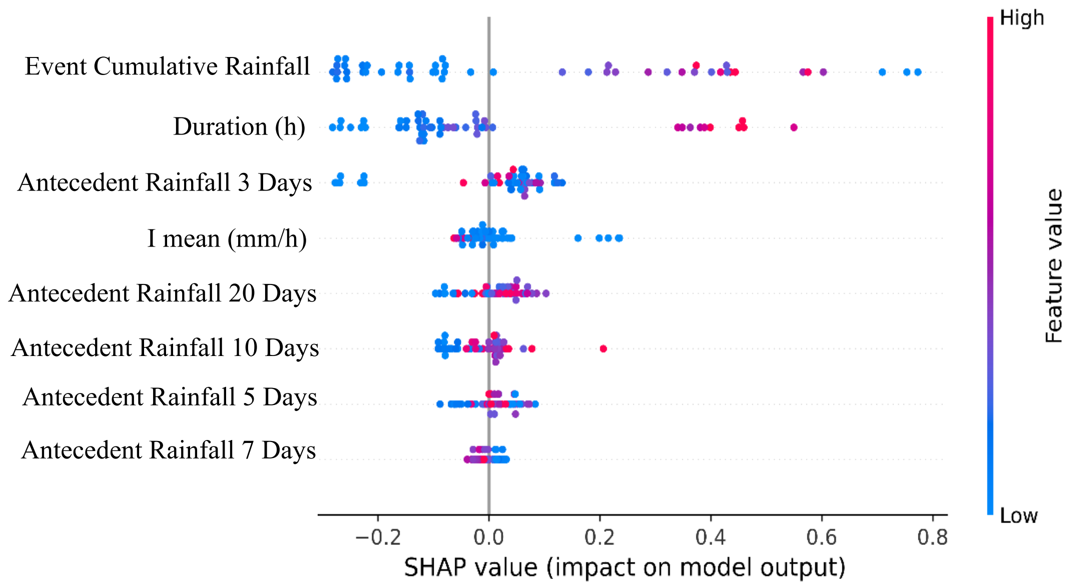

Figure 4: Beeswarm plot showcasing the global impact of features on predictions of the XGBoost model

In the case of the CatBoost model, the same set of predictors dominated, but their influence is more widely spread. ECR exhibited SHAP contributions between -1.0 and more than +1.5, making it the strongest global driver of classification. Duration also played a central role, and it ranges from -0.8 to +1.2, reinforcing the model's sensitivity to prolonged rainfall. Interestingly, Antecedent Rainfall indices, particularly 5-day and 10-day, showed stronger spreads in CatBoost compared to XGBoost, with contributions up to +0.5 or more, highlighting their role in modulating susceptibility through short- to medium-term antecedent wetness. I mean, it ranges from -0.5 to +0.4, and also contributed more prominently in CatBoost, reflecting its ability to capture high-intensity bursts of rainfall within triggering events. In a nutshell, both models confirm that ECR and Duration are the primary rainfall-based determinants of landslide occurrence, while antecedent rainfall indices provide additional discriminatory power to the model. CatBoost shows a broader spread of feature impacts, indicating stronger sensitivity to variations in antecedent rainfall and intensity of rainfall, but XGBoost remains more focused on cumulative rainfall and event duration.

This work could be attributed as a seed for advanced rainfall threshold research in Malaysia by moving beyond traditional empirical intensity–duration and event–duration approaches and demonstrating the potential of machine learning models coupled with SHAP explainability. Consistent with findings from similar studies in India and Italy, our models also indicate Event Cumulative Rainfall (ECR) and Duration as the dominant triggers of landslide initiation by the rainfall events, while short- to medium-term antecedent rainfall indices like 3 days to 10 days, provide additional discriminatory power to machine learning models. CatBoost yields a higher recall and accuracy than XGBoost, suggesting its superiority for operational reliability in practical, real-time operations. XGBoost, however, yielded a slightly higher ROC–AUC, reflecting a stronger ability to rank-order rainfall events by relative risk across all probability thresholds. This means that while CatBoost was proficient at differentiating actual landslides at the chosen cutoff, XGBoost assigned probabilities that more cleanly separated triggering from non-triggering rainfall events, indicating its superior global discrimination capacity as compared to other models. These differences underline the importance of model choice depending on whether reducing false negatives or maximising overall discrimination is prioritised.

The SHAP beeswarm analysis strongly supports these results, indicating that both models consistently rank ECR and Duration as the primary global drivers of landslide thresholds. CatBoost distributed more weight across antecedent rainfall and mean intensity, capturing variability in rainfall regimes that XGBoost ignored in the study. This aligns with recent findings from Kerala India and Italy [7], [15], where cumulative rainfall and short-term wetness were identified as precursors of slope failure. Between these models, CatBoost demonstrates a more balanced sensitivity and specificity, making it more suitable for early-warning applications because missed detections of landslides carry a higher risk of life and property than false alarms. All these suggest that ML-derived thresholds have potential for a more flexible and practically reliable alternative to rigid empirical curves, especially in tropical terrains with the impact of global climate change, which leads to unpredictable, complex rainfall patterns, such as in peninsular Malaysia.

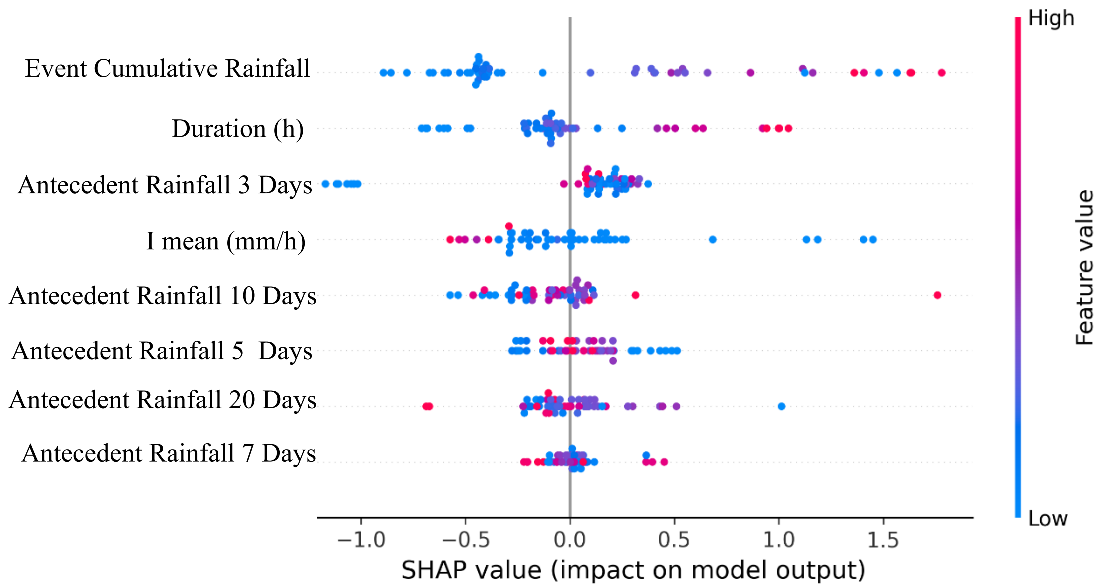

Figure 5: Beeswarm plot showcasing the global impact of features on predictions of the CatBoost model

This study is based on 79 rainfall-induced landslide events in Peninsular Malaysia, which may limit the statistical robustness of the thresholds. A larger inventory would further strengthen the generalizability and reliability of the machine learning models used in landslide triggering rainfall events. The upcoming Sistem Maklumat Geospatial Terain & Cerun (NaTSIS) operated by Jabatan Mineral dan Geosains Malaysia (Department of Minerals and Geoscience Malaysia) will provide a more comprehensive national landslide database, offering an important resource for future studies, and it will enhance the quality of Landslide research in Malaysia.

Conclusion

This work develops a machine learning–based rainfall threshold for landslide initiation in Peninsular Malaysia, moving beyond the limitations of traditional empirical ID and ED threshold curves. Two gradient boosting models are trained and compared, namely XGBoost and CatBoost, with predictors including event cumulative rainfall, duration, mean intensity, and antecedent rainfall indices. Results indicate that event cumulative rainfall and duration are the dominant determinants of landslide-triggering rainfall, while short- to medium-term antecedent rainfall provides complementary discriminatory power to models. SHAP-based beeswarm analysis further confirmed the physical relevance of these predictors, offering global interpretability of model behaviour.

Between the two models, CatBoost shows a superior practical reliability, with a higher accuracy of 0.83 and recall of 0.67 as compared to XGBoost, which showed a higher ROC–AUC of 0.876 but substantially lower recall of 0.33. These findings highlight CatBoost's greater suitable application for early warning systems, in which reducing missed landslide events is more critical than maximising overall accuracy. The integration of explainable AI with hydrological predictors in this study provides a flexible and more interpretable framework for data-driven rainfall thresholds, which could support the development of more reliable landslide early warning systems in peninsular Malaysia.

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