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A multi-variable threshold approach to landslide prediction: integrating rainfall, soil moisture, and soil texture in Indonesia

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Research Article

Keywords: Rainfall thresholds, Soil moisture thresholds, Soil texture, Prediction performance

Posted Date: July 7th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9938553/v1

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A multi-variable threshold approach to landslide prediction: integrating rainfall, soil moisture, and soil texture in Indonesia

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Abstract

Landslides are one of the most devastating hazards globally, including in Indonesia. To reduce casualties, Indonesia has established the Blueprint of Indonesian Landslide Early Warning System (BILEWS). This system currently relies on rainfall-induced landslide thresholds for issuing the warning signals derived from historical landslide occurrences in Java, Sumatra, and Kalimantan Islands. However, landslide occurrence is strongly influenced not only by rainfall but also by antecedent soil moisture conditions and soil characteristics. Therefore, BILEWS still faces technical challenges in accurately predicting landslides, especially in Sulawesi and Papua Islands, where Java's threshold is applied there. This study aims to enhance the existing rainfall thresholds and incorporate soil moisture into a multi-variable threshold framework. Specifically, rainfall thresholds, soil moisture thresholds, and the combination of rainfall-soil moisture thresholds are developed. In addition, the relationship between soil moisture and landslide occurrence is evaluated across different soil textures. The results indicate that the optimal thresholds vary across islands. The existing rainfall thresholds yield the highest performance in Java and the Sumatra Islands with Youden Index of 0.545 and 0.740, respectively. In Sulawesi Island, the best performed threshold is the newly developed rainfall threshold with a Youden Index of 0.477. The rainfall-soil moisture thresholds show optimum performance for Kalimantan (0.465) and Papua (0.458) Islands. Furthermore, soil moisture significantly affects landslide risks in sandy clay loam and loam soil textures. Developing thresholds based on significant soil textures improves the performance of landslide prediction.

Keywords: Rainfall thresholds • Soil moisture thresholds • Soil texture • Prediction performance

1 Introduction

Climate change has intensified the occurrence of global hydrometeorological hazards, including drought, heatwave, floods, storm surges, and landslides (Lu 2024; Ruangpan et al. 2020). Among the hydrometeorological hazards, landslide occurrences have increased relatively higher than seismic disasters, which may relate to the manifestation of climate change (Remondo et al. 2025).

Landslides can cause significant material damage, financial losses, and fatalities worldwide (Lacasse and Nadim 2009). The estimation of annual financial losses from these events is approximately $20 billion (Sim et al. 2023). In terms of fatalities, 73,728 people were killed and 13,064 were injured due to the impact of landslides from 1903 to 2023 (Alcántara-Ayala 2025).

Nevertheless, landslide occurrences are not evenly distributed across the world. The occurrence of landslides in tropical climate regions is more frequent than in high latitude regions (Froude and Petley 2018). As a result, tropical climate countries suffered great casualties in consequence of landslides compared to high latitude countries (Sim et al. 2022). Natural factors, particularly topography and climate, were more dominant in triggering landslides than anthropogenic factors (Fidan et al. 2024). High-intensity rainfall above the seasonal precipitation and steep terrain are key factors behind frequent landslides in the tropical climate region in Asia (Kirschbaum and Stanley 2018).

As a tropical country, Indonesia has experienced numerous landslide events, making them one of the most disastrous natural hazards. According to the Global Landslides Catalogue (GLC) in 2021, Indonesia was the second-ranked country with the highest occurrence of landslides after China (Gómez et al. 2023). The National Disaster Management Agency (BNPB) reported 7,024 landslide incidents from 2015 to 2024 in Indonesia (National Research and Innovation Agency (BRIN) 2024). Risk assessment by BNPB also stated that landslides caused costs of approximately Rp. 515,194 billion (~$31.75 million) during the 2015-2024 period (National Disaster Management Agency (BNPB) n.d.).

Considering the vulnerability of Indonesia to landslide risks, the development of an early warning system is crucial. To help mitigate the risks of landslides in Indonesia, Sabo Engineering Office, under the Ministry of Public Work and Housing, developed the Blueprint of the Indonesia Landslide Early Warning System (BILEWS) in 2019 (Hidayat et al. 2019). The BILEWS model uses daily (1-day) and three-day (3-day) effective antecedent rainfall thresholds as a fundamental reference to generate landslide early warning. A red warning will be issued if both 1-day and 3-day rainfall exceed the thresholds. If one of the 1-day or 3-day rainfall exceeds the thresholds, a yellow warning will be issued. If neither 1-day nor 3-day rainfall exceeds the thresholds, it indicates no landslide potential.

Landslide prediction in Indonesia poses several significant challenges. One of the major challenges is rainfall variability in Indonesia. Indonesia has different rainfall patterns on each island, depending on sea surface temperature, monsoon, intertropical convergence zone and local topography (Aldrian and Dwi Susanto 2003). BILEWS used a single rainfall threshold developed for Java Island to forecast landslides across Indonesia (Hidayat et al. 2019), but this approach did not adequately represent the regional rainfall variability. Previous studies have been conducted to adapt to various rainfall patterns in Indonesia by revising the rainfall thresholds to improve BILEWS performance on Java Island (Yuniawan et al. 2022). Sabo Engineering Office also revised rainfall thresholds on Sumatra and Kalimantan Islands, but the thresholds for Sulawesi and Papua Islands have yet to be established.

Another challenge arises in designing a framework to integrate soil moisture into BILEWS. Research has been carried out to integrate rainfall and soil moisture observation data in Girimulyo District, resulting in an improvement of landslide forecast performance (Yuniawan et al. 2025). However, soil moisture observation data remain spatially limited in Indonesia, which poses a challenge for establishing and integrating soil moisture into BILEWS at the national scale. In

addition, integrating the soil-related parameters into the BILEWS requires consideration of the spatial variability of soil types and textures. Soil textures, such as clay and silt, are related to landslide risks because these soil textures are one of the main factors that contribute to soil water retention and infiltration (Fonseca et al. 2017; Saco et al. 2021).

This study aims to address the accuracy and reliability challenges of BILEWS by developing region-specific rainfall thresholds, soil moisture thresholds, and soil texture studies in forecasting landslides. In particular, this study focuses on establishing missing rainfall thresholds for the Sulawesi and Papua Islands, as well as soil moisture thresholds and the combination of rainfall-soil moisture thresholds for five main islands in Indonesia. This study also provides a performance evaluation to determine the most suitable thresholds to forecast landslides across Indonesia. Additionally, this study examines the relationship between soil moisture, soil texture, and landslide occurrences to provide further insight into the landslide early warning system.

2 Data and Methods

2.1 Study Area

The study area consists of the five major islands in Indonesia, including Sulawesi, Papua, Kalimantan, Java, and Sumatra. Fig 1 visualizes the spatial distribution of the mean annual rainfall and the detailed location of the study area.

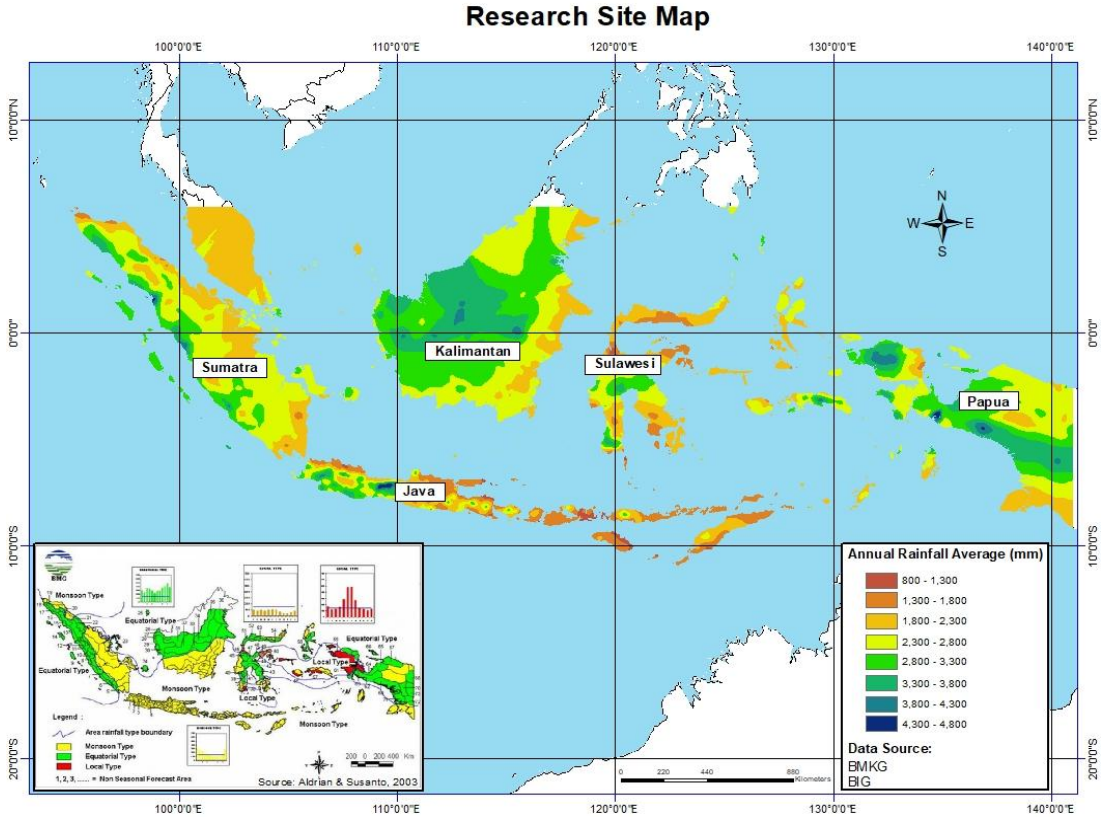


Fig. 1 Study areas map of the main islands, annual mean rainfall and rainfall pattern in Indonesia.

The major islands in Indonesia possess distinctive topographic characteristics. Almost the entire Sulawesi Island is mountainous terrain without major rivers or delta systems and scattered volcanoes in the northern area of the island (Van Gorsel 2022). Papua Island has rugged terrain with multiple peaks over 4000 m above mean sea level, which is surrounded by high mountains (Allison and Peterson 1989). Meanwhile, in the middle and southern areas of Java and Sumatra islands, the volcano arc stretches across the islands (Hamilton 1979). Unlike the other islands, Kalimantan is dominated by lowland with hilly areas making up only 15-25% of its total area (Estiningtyas et al. 2024).

Unique geographical features and warm oceans contribute to diverse rainfall patterns across different regions in Indonesia (Yamanaka 2016). According to the Meteorology, Climatology and Geophysics Agency of Indonesia (BMKG), annual rainfall in a certain region can be up to 4800 mm. There are three types of rainfall patterns in Indonesia, namely monsoonal (region A), equatorial (region B) and local (region C) (Aldrian and Susanto 2003). Most parts of Sumatra and Java are included in the monsoonal rainfall pattern, experiencing a rainy season from November to March (region A). Kalimantan and the eastern area of Papua exhibit an equatorial rainfall pattern marked by two rainy seasons from March to May and October to November (region B). Sulawesi and the western area of Papua are identified as local rainfall patterns that receive the highest rainfall from June to July (region C).

2.2 Data

2.2.1 Landslide data

Recorded landslide event data were used to establish rainfall and soil moisture thresholds and to evaluate the performance of the thresholds. This study collected landslide event data across the main islands of Indonesia from 2014 to 2025. These data were compiled from the BNPB website, regional government website, digital newspapers, blogs, and technical reports, following established data compilation approaches (Brunetti et al. 2015). The dataset should provide information regarding the location, date, number of impacted residents, and material or life losses.

This study focuses on shallow landslides where the depth of unconsolidated soil is less than 3 m (Gullà et al. 2021). Regarding the triggering mechanisms of landslides, this research only focuses on landslide events that were induced by rainfall. Non-landslide event data are also required to generate landslide thresholds. The proportion 1:5 of landslide and non-landslide event data is adopted, following a previous study that identified this 1:5 proportion as optimal for random sampling that aligned with regional character (Li and Tian 2025).

2.2.2 Rainfall data

This study utilizes global satellite precipitation data from the Global Precipitation Measurement (GPM) satellite mission. GPM is a collaborative project between NASA and JAXA, with one of the purposes being to improve the predictive capability of natural hazards and extreme weather events (Skofronick-Jackson et al. 2018). GPM has broad global coverage between latitudes 65°

north and 65° south (Gray, 2013). GPM provides daily precipitation measurement with 0.1° spatial resolution or approximately 10 km (National Aeronautics and Space Administration 2024). GPM precipitation data for the period 2014 to 2025 were used to develop rainfall thresholds and validate forecasting performance. The rainfall data was downloaded from (https://giovanni.gsfc.nasa.gov/).

2.2.3 Soil moisture data

The soil moisture data used in this research were retrieved from European Centre Medium-Range Weather Forecasts (ECMWF) ERA5-Land. ERA5-Land is a reanalysis dataset providing a consistent view of the evolution of land variables, including soil moisture (Copernicus Climate Data Source, 2019). ERA5-Land provides hourly data with a spatial resolution of 0.1° or approximately 10 km (Muñoz Sabater 2019). This research utilizes volumetric soil water content parameters from ERA5-Land for the 2014-2025 period to build soil moisture thresholds and validate the forecast. The amount of volumetric water content in the soil layer can be used to analyse slope instability that leads to landslide risks (Kim and Lee 2023). This study uses multiple soil moisture depths of the volumetric soil moisture (VSW) layer 1 (0-7 cm), 2 (7-28 cm) and 3 (28-100 cm). The source to download the ERA5-Land volumetric soil water data is (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=download).

2.2.4 Soil texture data

This study uses soil texture data from the Harmonized World Soil Database (HWSD) version 2.0 by the Food and Agriculture Organization of the United Nations (FAO) (FAO and IIASA 2025). The HWSD version 2.0 was released in September 2023 as an upgrade of version 1.2. The HWSD version 2.0 comprises soil type and properties data since 1970 and was updated in 2023. The HWSD version 2.0 features a raster file and soil properties database that provides global soil textures. The soil textures database contains clay, silt, loam, sand, and combinations of those textures. HWSD version 1.2 is still used as complementary data for HWSD version 2.0. The soil textures data can be accessed through the FAO platform (https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v20/en/).

2.3 Methods

2.3.1 Rainfall thresholds

In landslide prediction, BILEWS applies 1-day and 3-day rainfall thresholds (Hidayat et al., 2019). The 3-day effective antecedent threshold is used as a proxy for the soil moisture data, which is not widely available yet across Indonesia (Hidayat et al. 2019). This study utilizes rainfall data from 2014 to 2023 to determine 1-day and 3-day thresholds. 1-day cumulative rainfall data is extracted from the GPM satellite dataset at grid locations corresponding to recorded landslide events in Sulawesi and Papua Islands. The same procedure is applied to obtain 3-day rainfall data to determine effective antecedent rainfall using the following formula (Yuniawan et al. 2022):

$$ARx = R_0 + kR_1 + k^2R_2 + \cdots + k^nR_n$$

Where ARx is the effective antecedent rainfall for day x, k is the coefficient of the decay rate of the flood hydrograph curve, R_0 is the daily rainfall on the day of occurrence, R_1 is the daily rainfall for the day before day x and Rn is the daily rainfall n days before day x. The BILEWS assumes that k = 0.9, which refers to a study of flood hydrograph recession in the Central Java Region (Chikalamo et al. 2020). This research uses a similar approach to the existing BILEWS by calculating the value of 1-day and 3-day effective antecedent rainfall in each island (Hidayat et al. 2019). The calculation of 1-day and 3-day effective antecedent rainfall uses statistical averages, minimum, percentiles 30, 40, 50, 60, and minimum rainfall in major landslide events (Gariano et al. 2015; Yuniawan et al. 2022). Major landslide events in this research are landslides that have caused damage to at least 5 houses (National Disaster Management Agency (BNPB) 2023).

2.3.2 Soil moisture thresholds

Soil moisture data is retrieved from the ERA5-Land grid cells corresponding to same spatial locations and dates as recorded landslide events in Sumatra, Java, Kalimantan, Sulawesi, and Papua Islands. This research utilizes the volumetric soil water layer (VSW) 1, 2, and 3 with depths of 0-7, 7-28, and 28-100 cm, respectively. Previous study revealed that shallow soil moisture data with a depth of 0-7 and 7-28 cm yielded a significantly high statistical score in forecasting landslide events in Sicily (Palazzolo et al., 2023). In Indonesia, soil moisture landslide prediction has also demonstrated promising accuracy (Yuniawan et al. 2025). In addition, integrating soil moisture data around 100 cm depth also represents the root hydrological conditions, which are essential for slope stability assessment (Guo et al. 2023).

Soil moisture data, used for landslides forecasting, is extracted from the day before the landslide event (Wicki et al. 2020). Before determining soil moisture thresholds, hourly VSW data need to be converted into daily average data. Soil moisture thresholds are determined by computing the average, minimum, percentile 40, 50, 60, 70, and minimum soil moisture in major landslide events for all VSW layers 1, 2 and 3 in each island. The definition of major landslide events for soil moisture analysis is consistent with that used in the rainfall thresholds calculations, which is a landslide that has caused damage to at least 5 houses.

2.3.3 Evaluation of rainfall, soil moisture and rainfall-soil moisture thresholds performance

Rainfall, soil moisture, and soil moisture-rainfall thresholds are evaluated using a split-sample evaluation and Receiver Operating Characteristic (ROC) (Yuniawan et al. 2022). Split-sample evaluation is the basis for evaluating the true positive rate (TPR), true negative rate (TNR), accuracy, and Youden's index of the thresholds in forecasting landslides. Split-sample evaluation is a method to assess the performance of a prediction by splitting the training dataset and the testing dataset (Joseph and Vakayil 2022). This research uses the landslide events from 2014-2023 as a training set and the landslide events from 2024-2025 as a testing set. The proportion of training set and testing set data is 80:20%. The past research showed that the proper result of the model was obtained using 70-80% training data and 20-30% testing data (Gholamy et al. 2018).

The ROC is a two-dimensional plot that describes classifier system performance, derived from a contingency table and area under the curve (AUC) (Yang and Berdine 2017). The contingency table consists of four conditions based on the model predictions and the occurrences or non-occurrences of a specific event (Table 1). There are four categories inside the contingency table, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN), shown in Table 2. TP and FP can be obtained by validating the rainfall and soil moisture thresholds to the amount of rainfall and soil moisture that trigger landslides. Meanwhile, TN and FN are determined by validating the rainfall and soil moisture thresholds to the amount of rainfall and soil moisture that do not trigger landslides.

Table 1 Contingency table

Model Prediction	**Landslide events**	
	Yes	**No**
≤ Thresholds	TP	FP
≥ Thresholds	FN	TN

Positive and negative refer to the model predictions, while true and false indicate the validity of the model predictions to the real events (Gariano et al. 2015). In summary, TP and TN describe correct prediction, while FP and FN imply incorrect prediction. The value of true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), and accuracy range from 0 to 1. If the value of TPR, TNR, and accuracy is close to or equal to 1, the prediction demonstrates optimum performance in forecasting positive and negative cases of landslides (Santini et al. 2021). In contrast, a FPR value close to or equal to 1 indicates poor prediction performance (Aggarwal and Ranganathan 2018). Meanwhile, the value of the Youden Index ranges from -1 to 1. If the value of the Youden Index is close to or equal to 1, the prediction reflects high performance in forecasting landslides (Youden 1950). The details of the statistical indices of the contingency table are described in Table 2.

Table 2 Statistical indices are used to measure the performance of the thresholds

Statistical Indices	**Description**	**Equation**
Sensitivity/true positive rate (TPR)	The proportion of positive cases of landslide events that are correctly detected by the threshold	$TPR = \frac{TP}{TP + FN}$
Specificity/true negative rate (TNR)	The proportion of negative cases of landslide events that are correctly detected by the threshold	$TNR = \frac{TN}{TN + FP}$
False Positive Rate (FPR)	The proportion of negative cases of landslide events that are incorrectly predicted as positive	$FPR = \frac{FP}{FP + TN}$
Accuracy	The proportion of correct predictions overall	$Acc = \frac{TP + TN}{TP + TN + FP + FN}$

	Youden's Index	The proportion of sensitivity and specificity	$J = Sensitivity + Specificity - 1$

The AUC is used to evaluate the capability of the classifier system to discriminate the real condition of the landslide event in the field (Yang and Berdine 2017). To generate the AUC, one needs to sketch the ROC curve by plotting the TPR on the Y-axis and the false positive rate (FPR) on the X-axis for the thresholds. The ability levels of the classifier system based on the AUC value are presented in Table 3.

Table 3 AUC value classifications

AUC Value	Description
0.5	No discrimination, random guesses
0.5 < AUC ≤ 0.6	Poor discrimination
0.6 < AUC ≤ 0.8	Acceptable discrimination
0.8 < AUC ≤ 0.9	Excellent discrimination
0.9 < AUC	Outstanding discrimination

The rainfall and soil moisture thresholds are evaluated using the training dataset (2014-2023) to assess which thresholds demonstrate appropriate performance in forecasting landslides. To determine the best thresholds to predict landslides in every island, the selected rainfall and soil moisture thresholds were then evaluated to assess the performance using the testing dataset (2024-2025). The evaluation of combination thresholds refers to one of the BILEWS decision frameworks, which does not consider the terrain condition. If both indicators exceed the thresholds, a red alert will be issued. If one of the indicators exceeds the thresholds, a yellow warning will be issued. If neither of the thresholds exceeds the other, it indicates no landslide potential. The performance of the combined thresholds was then evaluated to determine suitability for landslide forecasting across different islands of Indonesia.

2.3.4 Evaluation of soil textures

This step utilises soil moisture data based on landslide events in the 2013-2023 period and soil texture data. Soil texture category in this research refers to 12 soil texture classes published by the USDA (Soil Science Division Staff 2017). Figure 2 illustrates the detailed classes of soil texture.

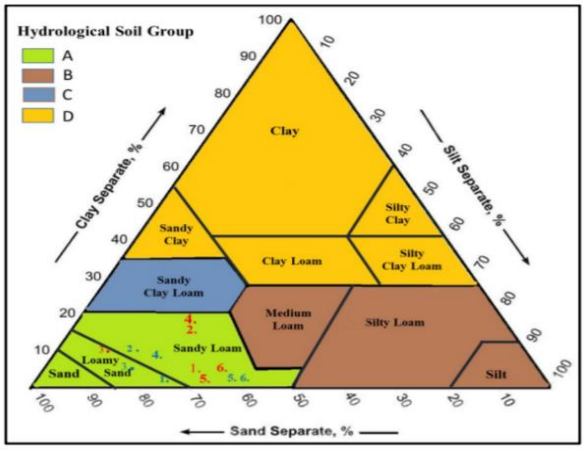


Figure 2 Soil texture classes by the USDA

Logistic regression is used to analyse the relationship between landslide occurrences and soil moisture across different soil texture classes. Logistic regression was chosen as a suitable method to assess the relationship of landslide causal factors by previous studies (e.g., Abolghasem et al. 2014). The formula of logistic regression is expressed by the following formula:

$$P(Y) = \frac{1}{1 + e^{-Z}}$$

P(Y) is the dependent variable, which is the probability of a landslide event happening in a certain place. The logit Z is assumed to contain the independent variables on which landslide occurrence, in this study, is soil moisture data. β is the regression coefficient, indicating a change in VSW which influences the likelihood of landslide occurrence for a specific soil texture. The formula of logit *Z* is shown as follows:

$$Z = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + BnXn$$

X represents the independent variables, which in this study are VSW layer 1, 2, and 3. To evaluate whether the soil moisture has a significant effect on the landslide in each soil texture, a Wald Test is required. The Wald test is fundamentally designed to test the null hypothesis by comparing the magnitude of the coefficient (β) to its standard error (Vakhitova and Alston-Knox 2018). The null hypothesis of this research is that soil moisture does not significantly affect the landslides. The results of the Wald test need to be assessed using the *p*-value. If the *p*-value is less than 0.05, it indicates that soil moisture significantly affects the landslides (null hypothesis is rejected), if the *p*-value is equal to or greater than 0.05, it indicates that soil moisture does not significantly affect the landslides (null hypothesis accepted).

3 Results

3.1 Rainfall thresholds determination and assessment

3.1.1 Rainfall thresholds determination

The rainfall distribution of landslide events and major landslide events from 2013 to 2023 is described in Figure 3. During this period, a total of 228 landslide events were recorded in Sulawesi, of which 30 events were categorized as major events (Fig. 3a). Papua (Fig. 3b), on the other hand, recorded substantially fewer landslide events (40 landslide events in total), including only 8 major events. The relatively low number of recorded landslide events in Papua may not reflect actual landslide occurrence, but rather the limited reporting coverage associated with sparse population distribution in this Island. Disaster databases typically only take into account events that result in causality or significant impacts, which potentially lead to underreporting in remote regions like Papua. In Fig. 3, we only present the results for Sulawesi and Papua since the rainfall thresholds for Java, Sumatra, and Kalimantan were reported in a previous study (Yuniawan et al. 2022) and Sabo Engineering Office report, with details provided in Table S1 of the supplementary materials.

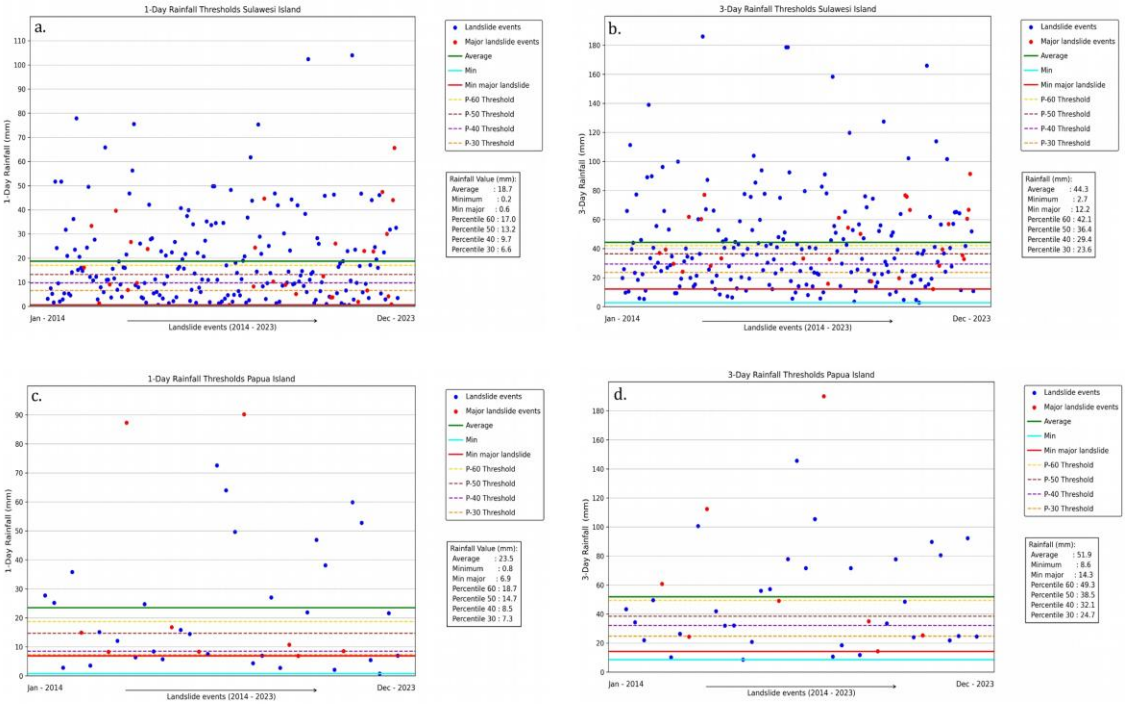


Fig. 3 Rainfall distribution and thresholds of: a) 1-day rainfall thresholds in Sulawesi Island, b) 3-day effective antecedent rainfall in Sulawesi Island, c) 1-day rainfall thresholds in Papua Island, d) 3-day effective antecedent rainfall in Papua Island. The blue and red dots represent the amount of rainfall during the landslide events, with red colour indicating major landslide events. Lines indicate the thresholds derived from statistical analyses.

For Sulawesi Island, the 1-day rainfall thresholds are 18.7 mm (average), 0.2 mm (minimum), 0.6 mm (minimum major landslide), 17.0 mm (p-60), 13.2 mm (p-50), 9.7 mm (p-40), and 6.6 mm (p-30) (Fig. 3a). The 3-day effective antecedent rainfall thresholds are higher, ranging from 2.7 mm (minimum) to 44.3 mm (average), with corresponding percentile values of 12.2 mm (minimum major landslide), 42.1 mm (p-60), 36.4 mm (p-50), 29.4 mm (p-40), and 23.6 mm (p-30) (Fig. 3b). In Papua Island (Fig. 3c), the 1-day rainfall thresholds are 23.5 mm (average), 0.8 mm (minimum), 6.9 mm (minimum major landslide), 18.7 mm (p-60), 14.7 mm (p-50), 8.5 mm (p-40), 7.3 mm (p-30). Similarly, the 3-day effective antecedent rainfall thresholds vary between 8.6 mm (minimum) and 51.9 mm (average), with percentile values of 14.3 mm (minimum major landslide), 49.3 mm (p-60), 38.5 mm (p-50), 32.1 mm (p-40), and 24.7 mm (p-30) (Fig. 3d). Both Papua and Sulawesi Islands exhibit a similar sequence of threshold values, with the average being the largest and the minimum being the smallest. Overall, Papua shows slightly higher rainfall thresholds than Sulawesi for both 1-day and 3-day rainfall, indicating comparatively higher rainfall requirements for landslide initiation.

3.1.2 Rainfall thresholds assessment

All the identified thresholds in Figure 3 were evaluated for their performance using the ROC curve. The ROC analysis yields a value from 0.721 to 0.752, which indicates acceptable performance in discriminating real landslide events in Sulawesi and Papua Islands (supplementary materials Figure S1). An excellent ROC performance means the rainfall data is suitable with the landslide model.

Following the ROC analysis, the selected thresholds are further evaluated using a contingency table and statistical indices. Table 4 summarizes the performance of 1-day and 3-day effective antecedent rainfall thresholds for the Sulawesi and Papua Islands. The Youden Index for 1-day rainfall thresholds in Sulawesi Island ranges from 0.096 (minimum) to 0.346 (p-40). Meanwhile, for the 3-day effective antecedent rainfall in Sulawesi Island, the Youden Index varies between 0.182 (minimum) and 0.382 (p-30). In Papua Island, the Youden Index of 1-day rainfall thresholds range are 0.238 (minimum), to 0.411 (minimum major landslide). As for the 3-day effective antecedent rainfall in Papua Island, the Youden Index varies between 0.299 (minimum) and 0.367 (p-30).

Table 4 Performance of 1-day and 3-day effective antecedent rainfall thresholds in Sulawesi and Papua Islands. The blue colours indicate the selected thresholds based on their performance

		Performance Thresholds	Accuracy	True Positive Rate	True Negative Rate	Youden Index
1-Day	Sulawesi	Average	0.816	0.377	0.904	0.281
		Minimum	0.247	1.000	0.096	0.096
		Minimum Major Landslide	0.331	0.982	0.202	0.184
		P-60	0.805	0.399	0.886	0.285
		P-50	0.734	0.500	0.790	0.290
		P-40	0.721	0.601	0.745	0.346
		P-30	0.645	0.697	0.635	0.332
	Papua	Average	0.847	0.350	0.932	0.282
		Minimum	0.373	1.000	0.238	0.238
		Minimum Major Landslide	0.660	0.769	0.642	0.411
		P-60	0.822	0.400	0.894	0.294
		P-50	0.772	0.500	0.819	0.319
		P-40	0.654	0.600	0.664	0.264
		P-30	0.658	0.700	0.650	0.350
3-day	Sulawesi	Average	0.806	0.373	0.893	0.266
		Minimum	0.317	1.000	0.182	0.182
		Minimum Major Landslide	0.527	0.885	0.456	0.342
		P-60	0.795	0.399	0.875	0.274
		P-50	0.774	0.500	0.829	0.329
		P-40	0.714	0.601	0.737	0.338
		P-30	0.687	0.697	0.685	0.382
	Papua	Average	0.846	0.375	0.925	0.300

	Minimum	0.407	1.000	0.299	0.299
	Minimum Major Landslide	0.496	0.897	0.425	0.322
	P-60	0.827	0.400	0.899	0.299
	P-50	0.768	0.500	0.815	0.315
	P-40	0.729	0.600	0.751	0.351
	P-30	0.672	0.700	0.667	0.367

To assess the threshold performance, this study prioritises the Youden Index over the accuracy because it provides a balanced measure of model performance by combining TPR and TNR. Previous research explained that the Youden Index with a value more than 0.25 is sufficient to consider as a threshold in forecasting landslides (Mercurio et al., 2021). Although most of the thresholds in Table 4 exceed the Youden Index of 0.25 and the accuracy of 0.60, only the thresholds with the highest Youden Index are selected from each of the 1-day and 3-day effective antecedent rainfall in every island (blue color). In Sulawesi Island, the selected 1-day and 3-day effective antecedent rainfall thresholds are P-40 and P-30, respectively. In Papua Island, the selected thresholds for 1-day and 3-day effective antecedent rainfall thresholds are the minimum major landslide and P-30. These results indicate that lower percentile thresholds (e.g., p30-p40) tend to yield better predictive performance across both Islands, although the optimal threshold varies depending on the temporal aggregations.

3.2 Soil moisture thresholds determination and assessment

3.2.1 Soil moisture thresholds determination

The soil moisture distribution of landslide events and major landslide events from 2013 to 2023 in Sulawesi and Papua Islands are described in Fig 4a and 4b, the detailed figures for Sumatra, Java and Kalimantan Islands are attached in supplementary materials Figure S2. During this period, a total of 294 landslide events were recorded in Sumatra, of which 41 events were categorized as major events. In Java, a substantially larger number of landslide events were recorded (315 landslide events in total), including 59 major events. A total of 217 landslide events were recorded in Kalimantan, with 15 identified as major landslide events. The number of landslides and major landslide events for Sulawesi and Papua is identical to that explained in section 3.1.2.

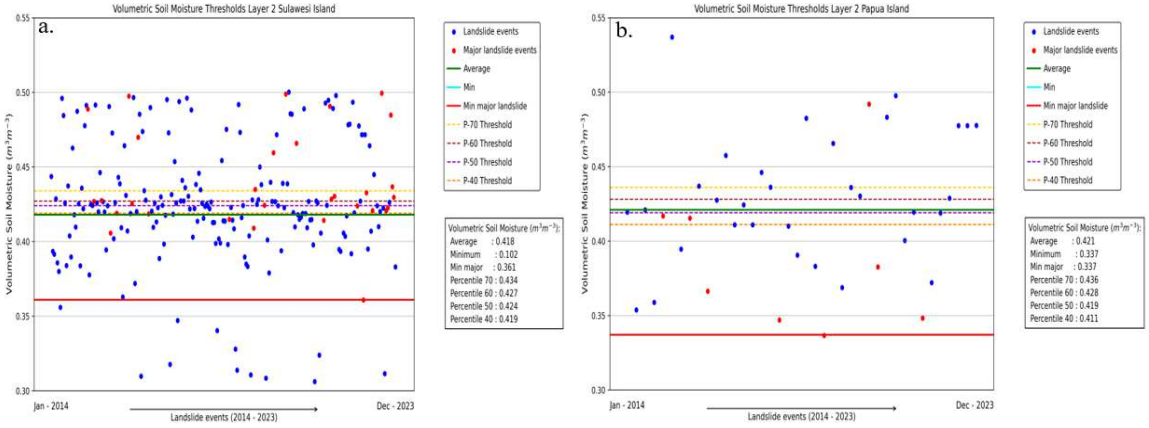


Fig. 4 Selected VSW thresholds with the highest performance of: a) Sulawesi thresholds, b) Papua thresholds. The blue and red dots represent the amount of VSW during the landslide events, with red colour indicating major landslide events. Lines indicate the thresholds derived from statistical analyses.

This paragraph explains the selected soil moisture thresholds from each layer based on soil moisture thresholds assessment, which will be detailed in the sub-chapter 3.2.2. According to supplementary materials Figure S2, the P-40 thresholds of 0.402 and 0.412 provide the highest prediction performance for VSW layers 1 and 2, in Sumatra Island. While average thresholds yield the most reliable prediction with a VSW layer 3 value of 0.403. The result reveals that in Java Island, the average statistical indicator demonstrates the highest predictive capability, with the values for VSW layer 1, 2, and 3 being 0.421, 0.421, and 0.418, respectively. The P-40 thresholds of 0.410, 0.412, and 0.413 provide the most suitable thresholds for landslide forecasting in Kalimantan Island for VSW layers 1, 2, and 3, respectively. In Sulawesi, p-40 becomes the primary benchmark for VSW layer 1 with a value of 0.417. While for the VSW layer 2 (Fig. 4a) and 3, the average value of 0.418 and 0.417 exhibits the highest predictive accuracy. The average of the VSW layer 1 in Papua Island provides the most precise performance, with a value of 0.420. P-50 is selected as the appropriate threshold to forecast the landslide for VSW2 (Fig. 4b) and VSW3 in Papua Island, with values of 0.419 and 0.418.

Each island exhibits distinct characteristics in the range and average values of VSW. In Sumatra Island, the range of VSW is varied from 0.157 to 0.537 with an average of 0.404 to 0.409. Java Island shows a wider range of VSW from 0.091 to 0.604 and an average of 0.418 to 0.421. The range of VSW in Kalimantan Island extends from 0.179 to 0.611, with an average of 0.413 to 0.414. In Sulawesi Island, the range of VSW varies from 0.102 to 0.513 and the average is from 0.414 to 0.418. In Papua Island, the minimum VSW is 0.337, while the maximum VSW is 0.537, with an average value between 0.420 and 0.421.

Among all islands, Papua Island records the highest average of VSW layers 1, 2, and 3, followed by Java, Sulawesi, Kalimantan, and Sumatra, which has the lowest average VSW values. In terms of variability, Java is the Island with the widest range of VSW, followed by Kalimantan, Sulawesi, Sumatra, and Papua Island. Overall, VSW values generally increase from layer 1 to layer 2 and then decrease from layer 2 to layer 3, except for Papua Island.

3.2.2 Soil moisture thresholds assessment

All the identified thresholds were evaluated for their performance using the ROC curve. The ROC analysis scores an AUC from 0.547 to 0.647, which shows poor to acceptable performance in discriminating the observed landslide events in the five main islands in Indonesia (Supplementary materials Figure S3). Although the result demonstrates poor to acceptable performance, the AUC value that is more than or equal to 0.54 can still be used because it performs sufficient discrimination, not just random guessing (Fawcett, 2006).

Following the ROC analysis, the selected thresholds are further evaluated using a contingency table and statistical indices. Table 5 summarizes the performance of VSW layers 1, 2, and 3.

Overall, average thresholds are the most frequently selected thresholds for VSW layers 1, 2, and 3, followed by P-40 and P-50. More specifically, P-40 thresholds of the VSW layer 2 yield the highest performance with a Youden Index of 0.176 in Sumatra Island. In Java Island, average thresholds for the VSW layer 3 exhibit optimal performance with a value of 0.266. P-40 of the VSW layer 2 becomes a threshold with sufficient performance in Kalimantan with a Youden Index of 0.121. Youden index of 0.200 is the primary benchmark resulting from the average thresholds of the VSW layer 2 for Sulawesi Island. Meanwhile, in Papua Island, the P-50 threshold for VSW layer 2 demonstrates the most reliable performance, with a Youden Index of 0.135.

Table 5 Performance of selected thresholds in each layer over the five main Islands. The blue colours indicate the selected thresholds based on their performance

Thresholds/performance			Accuracy	True Positive Rate	True Negative Rate	Youden Index
VSW1	Sumatra	P-40	0.577	0.599	0.573	0.171
	Java	Average	0.638	0.567	0.652	0.219
	Kalimantan	P-40	0.517	0.600	0.500	0.100
	Sulawesi	P-40	0.589	0.601	0.587	0.188
	Papua	Average	0.588	0.500	0.605	0.105
VSW2	Sumatra	P-40	0.581	0.599	0.578	0.176
	Java	Average	0.641	0.589	0.652	0.241
	Kalimantan	P-40	0.534	0.601	0.520	0.121
	Sulawesi	Average	0.591	0.614	0.586	0.200
	Papua	P-50	0.596	0.525	0.610	0.135
VSW3	Sumatra	Average	0.561	0.599	0.553	0.152
	Java	Average	0.668	0.580	0.686	0.266
	Kalimantan	P-40	0.506	0.602	0.487	0.089
	Sulawesi	Average	0.552	0.636	0.535	0.171
	Papua	P-50	0.550	0.500	0.560	0.060

3.3 Evaluation of rainfall and the combination of rainfall-soil moisture performance

3.3.1 Rainfall thresholds evaluation

Fig.5 describes the rainfall thresholds performance in forecasting landslides during the testing period from 2024 to 2025. Sumatra, Java, and Kalimantan Islands use existing thresholds that have been developed by the Sabo Engineering Office, while Sulawesi and Papua Islands use thresholds that have been developed in this research. The existing 1-day rainfall thresholds for Sumatra, Java and Kalimantan Islands are 32.9, 30.0, and 33.5 mm, respectively. Meanwhile, the current 3-day rainfall thresholds for Sumatra, Java and Kalimantan Islands sequentially are 91.3, 64.0 and 113.9 mm.

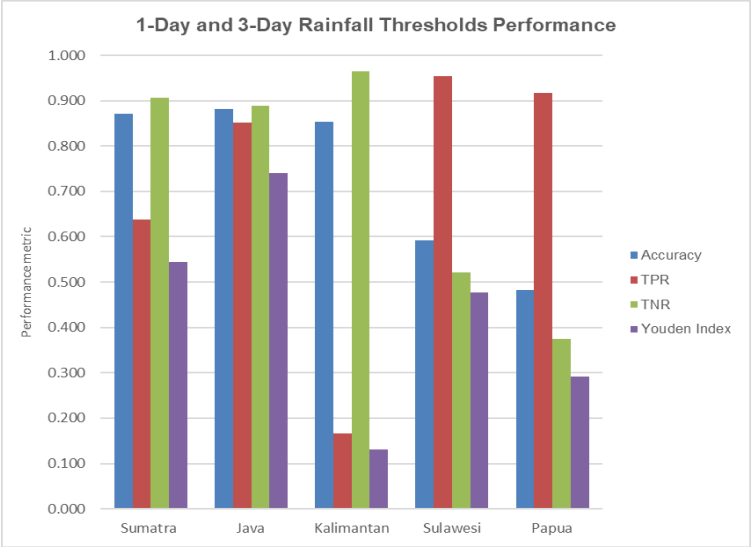


Fig. 5 Performance of 1-day and 3-day effective antecedent rainfall thresholds in forecasting landslides in Sumatra, Java, Kalimantan, Sulawesi and Papua Islands

1-day and 3-day effective antecedent rainfall thresholds in Java and Sumatra simulate high accuracy (0.881 and 0.870, respectively) with a balance between TPR and TNR indicated by the Youden index (0.740 and 0.545, respectively). Kalimantan Island also has high accuracy with a score of 0.854, but the difference between TPR and TNR is too significant, so it does not show a balance between TPR and TNR, indicated by low Youden index of 0.131. Both the Sulawesi and Papua Islands (0.593 and 0.483, respectively) show medium accuracy, with TPR quite higher than TNR. The Youden index values in Sulawesi and Papua Islands (0.477 and 0.292, respectively) are higher than in Kalimantan Island but lower than in Sumatra and Java Islands.

3.3.2 Combination of rainfall-soil moisture thresholds evaluation

The performance of soil moisture-rainfall thresholds combinations for the five major Islands in predicting landslides from 2024 to 2025 is displayed in Fig. 6. The combination of 1-day rainfall and VSW2 shows the highest accuracy (0.611) and Youden index (0.353) than the other combinations in Sumatra. In Java, the combination of 1-day rainfall and VSW3 demonstrates strong performance, with an accuracy of 0.802 and a Youden index of 0.692. The combination of 1-day rainfall and VSW2, in Kalimantan, yields a higher accuracy (0.700) and Youden index (0.465) than the other combination. Similarly, in Sulawesi and Papua, the 1-day rainfall and VSW2 combination reveals best performance, with accuracy (0.537 and 0.617, respectively) and Youden index (0.410 and 0.458, respectively). Overall, the combination of 1-day rainfall and VSW2 provides the most consistent performance among the other combinations, except in Java.

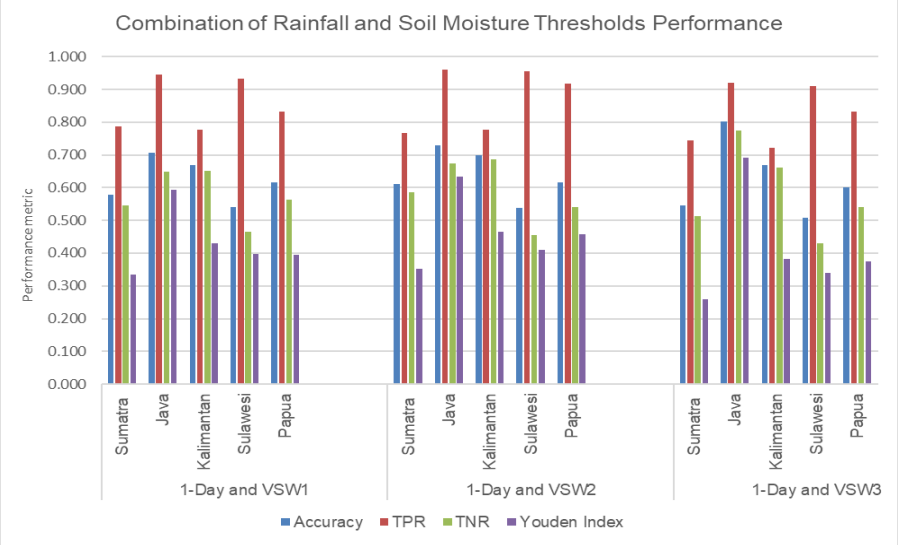


Fig. 6 Performance of combination 1-day and VSW1, VSW2 and VSW3 thresholds in forecasting landslides in Sumatra, Java, Kalimantan, Sulawesi and Papua Islands

Table 6 summarizes the performance of existing rainfall thresholds, newly developed rainfall thresholds, and the selected combination of rainfall-soil moisture thresholds that generate the highest performance in Sumatra, Java, Kalimantan, Sulawesi, and Papua Islands. The blue colour represents thresholds that yield the highest performance, while the red colour indicates thresholds with lower performance. Overall, the existing rainfall thresholds perform best with higher accuracy in Sumatra, Java, Kalimantan, Sulawesi, and Papua Islands than rainfall-soil moisture thresholds and developed rainfall thresholds for Sulawesi and Papua Islands. However, when evaluated using the Youden Index, the optimal threshold combinations vary across regions.

Table 6. Summary performance of existing rainfall thresholds, developed rainfall thresholds, and selected rainfall-soil moisture thresholds in Sumatra, Java, Kalimantan, Sulawesi, and Papua Island. Existing rainfall thresholds for Sulawesi and Papua are derived from Sabo Engineering Office operational thresholds (supplementary materials Table S1).

Thresholds		Combination	Accuracy	True Positive Rate	True Negative Rate	Youden Index
Existing Rainfall Thresholds	**Sumatra**	1-day and 3-day	0.870	0.638	0.907	0.545
	Java	1-day and 3-day	0.881	0.851	0.888	0.740
	Kalimantan	1-day and 3-day	0.854	0.167	0.964	0.131
	Sulawesi	1-day and 3-day	0.830	0.409	0.912	0.321
	Papua	1-day and 3-day	0.733	0.167	0.875	0.042
Developed Rainfall Thresholds	**Sulawesi**	1-day and 3-day	0.593	0.955	0.522	0.477
	Papua	1-day and 3-day	0.483	0.917	0.375	0.292
	Sumatra	1-day and VSW2	0.611	0.766	0.587	0.353

Rainfall-Soil Moisture Thresholds	**Java**	1-day and VSW3	0.802	0.919	0.773	0.692
	Kalimantan	1-day and VSW2	0.700	0.778	0.688	0.465
	Sulawesi	1-day and VSW2	0.537	0.955	0.456	0.410
	Papua	1-day and VSW2	0.617	0.917	0.542	0.458

In detail, the existing rainfall thresholds in Sumatra and Java outperform the other approaches, achieving higher accuracy and Youden Index values (Sumatra: 0.870 and 0.545, respectively; Java: 0.881 and 0.740, respectively) compared to the rainfall-soil moisture combinations. In Kalimantan, the combination of rainfall-soil moisture thresholds yields lower accuracy (0.802) but higher Youden Index (0.692) compared to the existing rainfall thresholds accuracy (0.854) and Youden Index (0.465). A similar trade-off is observed in Papua, where the combined thresholds achieve a higher Youden Index (0.477) but lower accuracy compared to the existing rainfall thresholds (0.733). In contrast, Sulawesi shows a different pattern, where the developed rainfall thresholds score the highest Youden Index (0.477) than the Youden Index of existing rainfall thresholds and the combination of rainfall-soil moisture thresholds (0.321 and 0.410, respectively). For the overview, the best-performing thresholds vary by regions, with existing rainfall thresholds dominating in Sumatra and Java, rainfall-soil moisture thresholds in Kalimantan and Papua, and developed rainfall thresholds in Sulawesi.

3.4 Relationship of landslide and soil texture

3.4.1 Distribution of soil texture in the landslide locations

The distribution of soil textures at landslide locations in five islands from 2013 to 2023 is depicted in the supplementary materials Figure S4. Eight soil textures classes found in landslide locations over Indonesia from 2014-2023, which are from highest to lowest percentage as follow: sandy clay loam (28.70%), loam (26.14%), clay (21.30%), clay loam (16.91%), sandy loam (3.29%), loamy sand (2.38%), sandy clay (0.91%), and sand (0.37%). Regionally, loam becomes the dominant soil texture in landslide locations in Sumatra Island, representing 35.71% of the landslide events. Sandy clay loam is the predominant soil texture in landslide locations in Java and Sulawesi, accounting for 30.16% and 44.74% of events, respectively. In Kalimantan, clay is the most common texture found in landslide locations (42.40%), while in Papua, landslides mostly occur in clay loam soil, with 65% of the total occurrences. In general, landslides mostly occur in soils with rich loam and clay textures.

3.4.2 The relation of soil moisture and landslide in different soil textures

Fig. 7 illustrates the relationship between VSW and landslide occurrences in different soil textures, evaluated using the *p*-value. The dotted red line represents the limit of the *p*-value (0.05) that has a significant relationship to the occurrence of landslides. Even though VSW has various *p*-values across soil textures, a consistent pattern is observed between different depths of the VSW layer 1, 2, and 3. Based on the *p*-value analysis, VSW layers 1, 2, and 3 have a significant relationship with landslide occurrence in loam (p = 0.039, 0.034, and 0.026, respectively) and sandy clay loam soils

(p = 0.017, 0.019, and 0.003, respectively). Our findings suggest that soil moisture plays a significant role in landslide triggering in these dominant soil textures.

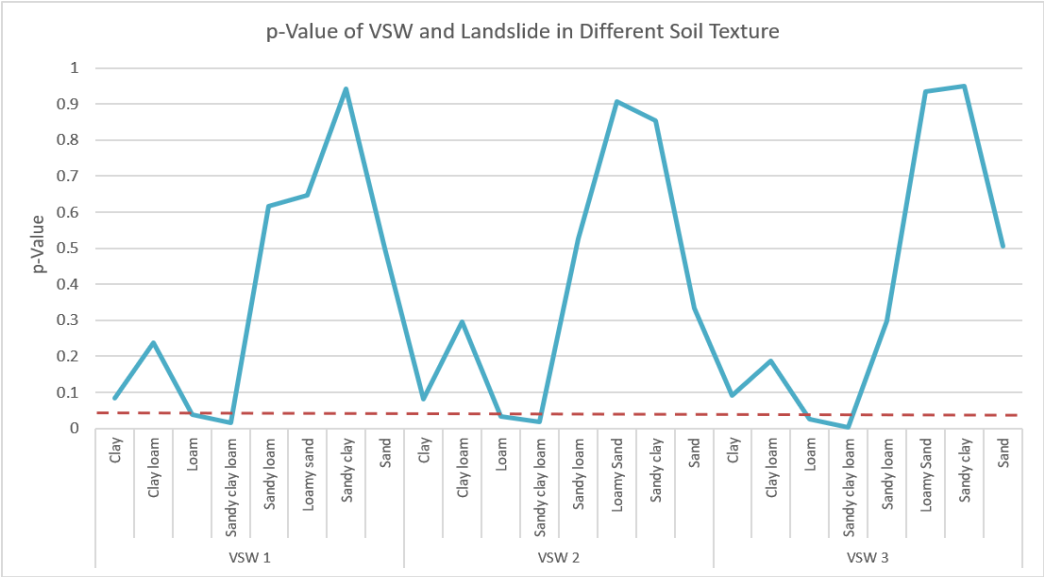


Fig. 7 *P*-value of VSW and landslides in different soil textures over five islands from 2014 to 2023

3.4.3 Developing soil moisture thresholds in susceptible soil textures

The previous section identified sandy clay loam and loam as the soil textures that are significantly associated with landslide occurrence in Indonesia. Based on those findings, this section develops soil moisture thresholds for these types of soils and evaluates their performance in landslide prediction. The VSW thresholds analysis for Papua is excluded due to insufficient data.

In general, P-40 thresholds are most frequently selected across VSW layers 1, 2, and 3, followed by the average and P-50 thresholds (Table S2, Supplementary Material). Performance evaluation indicates that VSW layer 2 yields the highest predicting skill compared to layers 1 and 3. In detail, average thresholds of VSW layer 2 scores the highest performance with a Youden Index of 0.179 in Sumatra and 0.214 in Java. In Kalimantan, the P-50 thresholds of VSW layer 2 demonstrate sufficient performance with the Youden Index 0.142, while in Sulawesi, the average thresholds of VSW layer 2 attain a Youden Index of 0.200.

For the next step, the four best-performing soil moisture thresholds were selected and combined with the 1-day rainfall thresholds. These combined thresholds were then evaluated using the testing dataset to assess the performance of the thresholds in predicting landslides. Fig. 8 below shows the comparison of the performance of the threshold combinations that incorporate soil texture significantly related to landslides (ST) and those that do not consider the soil texture relationship (NST).

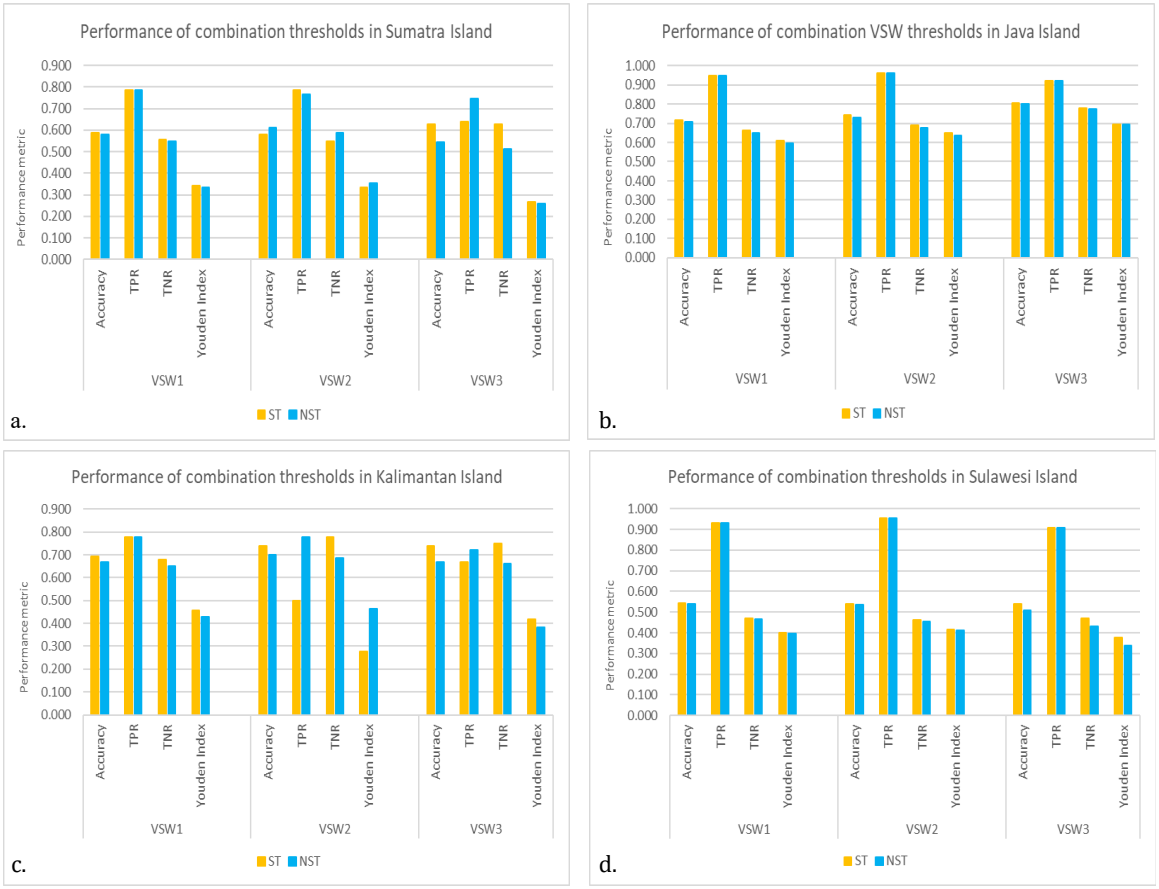


Fig. 8 Comparison of the performance between ST and NST thresholds in: a) Sumatra Island, b) Java Island, c) Kalimantan Island and d) Sulawesi Island

Overall, ST thresholds demonstrate higher performance than NST thresholds in Sumatra, Java, Kalimantan, and Sulawesi Island (Fig. 8). In Sumatra (Fig. 8a), the ST thresholds yield a higher Youden index in VSW layer 1 (0.344) and layer 3 (0.265) than the Youden Index of the NST thresholds in VSW layer 1 (0.334) and VSW layer 3 (0.258). The ST thresholds resulted in more significant performance in Java Island (Fig. 8b), with a Youden Index in VSW layer 1 of 0.607 and a Youden Index in layer 2 of 0.650, compared to NST thresholds (0.594 for VSW 1) and (0.634 for VSW 2). Similarly, in Kalimantan, ST thresholds outperform NST thresholds in VSW layer 1 (0.456 vs. 0.430) and layer 3 (0.417 vs. 0.383) (Fig. 8c). In Sulawesi (Fig. 8d), the ST thresholds generate higher Youden index values in all VSW layers (layer 1 = 0.401 vs. 0.396, layer 2 = 0.415 vs. 0.410, and layer 3 = 0.378 vs. 0.338).

4 Discussion

4.1 The importance of tailoring thresholds for specific regions

Previous research has emphasized the need for regionalisation of landslide thresholds because there are some regions where the climate component had more predominance in the occurrence of

landslides in comparison with other regions where lithology had more influence (Millán-Arancibia & Lavado-Casimiro, 2023). In Indonesia, early implementations by Balai Sabo applied a unified landslide threshold derived from Java to represent the entire country (Hidayat et al., 2019). However, Indonesia is a country with various rainfall patterns and complex geomorphology, so tailoring early warning thresholds for the specific regions is of utmost importance. Subsequent developments in the Indonesian Landslide Early Warning System (BILEWS) employed region-specific thresholds for Sumatra and Kalimantan, but thresholds for Sulawesi and Papua still rely on those derived from Java (Yuniawan et al., 2022). Although the existing rainfall thresholds generally achieve higher accuracy in Sumatra and Java, the newly developed rainfall thresholds perform better in Sulawesi, and the combined rainfall-soil moisture thresholds show improved performance in Papua. These findings highlight that no single threshold approach can be applied across different climate regimes and diverse terrain in Indonesia (Satyaningsih et al. 2023).

4.2 Improving the performance of landslide forecast

This study was conducted based on the previous research on utilizing multiple statistical indicators in determining rainfall thresholds. However, past research only explored the determination of rainfall thresholds using the minimum, average, and the minimum major landslide thresholds (Yuniawan et al., 2022). This research adds percentiles 30, 40, 50, and 60 and combines the minimum, average, and the minimum major landslide rainfall thresholds from previous research. This study reveals that using multiple thresholds yields better predictions. In several areas, the percentile-based thresholds provide the most balanced performance. Previous research has also shown that percentile approaches are effective in managing the trade-offs between false alarms and missed events (Vaz et al., 2018). This ability to manage trade-offs allows for the selection of thresholds that achieve more robust performance across different regions.

This study combines rainfall and soil moisture thresholds, which results in improved landslide forecast performance. Although the combined thresholds decrease overall accuracy, they increase the TPR and Youden Index. High accuracy alone is not sufficient to evaluate the performance of a landslide early warning system. The existing rainfall thresholds perform with higher accuracy because it is primarily driven by a high TNR, while their TPR is relatively low. For a landslide early warning system, maximizing TPR and minimizing FPR are essential, as missed landslide events may potentially lead to casualties (Uwihirwe et al., 2022). Therefore, improving the detection of landslide occurrences and reducing misprediction should be prioritized over only maximizing overall accuracy.

In addition to the TPR, this research also uses the Youden Index to evaluate the landslide thresholds performance. The use of Youden index improve the prediction performance by providing landslide thresholds that have balanced performance between TPR and TNR. Figure S5 of the supplementary materials describes the specific Youden Index values for thresholds derived from the previous studies (Dai et al., 2026; Li et al., 2025; Martinello et al., 2021; Mercurio et al., 2021) and this study (the existing, newly developed, and combined rainfall-soil moisture). Generally, the selected thresholds in this study generate Youden Index values that are comparable to or higher than those reported in previous research. This indicates that the proposed thresholds provide robust and balanced performance in predicting landslides.

4.3 Soil texture and landslide vulnerability

This study found that loam and clay are the dominant soil textures at landslide locations. The past research on soil development and landslide susceptibility indicates that clay-rich soil content can retain up to 40% water, which can increase 15% of its mass (Temme, 2021). The resulting increase in soil weight, especially in mountainous and hilly areas, can reduce slope stability and therefore be prone to slope failure (Wati et al., 2010). On the other hand, loam soils are characterized by a relatively high infiltration rate and a high degree of volumetric shrinkage. Under wet conditions, loam can become highly plastic, while under dry conditions it tends to crack, both of which can affect slope stability (Mazaeva et al., 2013). Due to its characteristics in retaining and absorbing water in wet conditions, soil with clay and loam content is more susceptible to landslides compared to other textures.

Furthermore, *p*-value analysis indicates that soil moisture is significantly associated with landslide occurrence in loam and sandy clay loam soil textures. These significant relationships can be explained by the soil properties. Instead of promoting stability, the mixture of sand, clay, and loam soil texture contributes to slope instability under wet conditions. Sandy clay loam textures allow faster infiltration through the sandy fraction in the surface layer, while the underlying clay-rich layer restricts drainage, causing water accumulation (Kitutu et al., 2009). In addition, sandy clay loam also possesses lower cohesion and shear strength than soils with higher clay content (Xu et al., 2024). The combination of water accumulation and low soil cohesion increases hydrostatic pressure, which increases the risk of landslides.

This study demonstrates that soil texture significantly influences the performance of landslide thresholds in predicting landslides. This study develops soil moisture thresholds in sandy clay loam and loam textures that are significantly related to the landslides. The result reveals that the combination of soil moisture-rainfall thresholds that were developed based on soil texture relationships outperforms purely statistical-based combination thresholds. This finding is consistent with prior research, which indicates that the roughness or smoothness of soil texture plays a key role in controlling the magnitude of landslide triggering thresholds (Luino et al., 2022).

5 Conclusion

The findings of this study highlight that landslide thresholds in Indonesia are highly region-dependent and should be derived using different statistical approaches in determining the best-performing thresholds to predict landslides. Incorporating soil moisture thresholds provides added value for landslide prediction in some regions, but not uniformly across Indonesia. The evaluation using the Youden index shows that the existing 1-day and 3-day rainfall thresholds that have been developed by the Sabo Engineering Office yield the best performance in Sumatra (0.545) and Java (0.740). In Sulawesi, the 1-day and 3-day rainfall thresholds developed in this study provide superior performance (0.477). In contrast, combined rainfall-soil moisture thresholds generate the most balanced performance in predicting landslides in Kalimantan (0.465) and Papua (0.458).

The results emphasize the critical role of soil texture in landslide prediction in Indonesia. This study discovered that most of the landslides in Indonesia occurred in soils that contain clay and

loam textures. Particularly, soil moisture significantly affects the landslides in sandy clay loam and loam soil textures. Developing soil moisture thresholds by incorporating soil texture information that is significantly associated with landslides can improve the predictive performance of thresholds compared to purely statistical approaches.

Overall, this study demonstrates that no universal threshold is suitable across Indonesia. Instead, region-specific and physically informed threshold frameworks significantly improve landslide forecasting performance. These findings provide a strong basis for enhancing not only the Indonesian landslide early warning system but also Landslide early warning in general, by integrating rainfall, soil moisture, and soil texture information to develop the landslide warning thresholds.

Acknowledgements The author would like to thank the Sabo Engineering Office (Balai Sabo) for giving the opportunity to learn and develop the Blueprint of the Indonesian Landslide Early Warning System.

Funding This study is financially supported by the Indonesia Endowment Fund for Education (LPDP).

Declarations

Conflict of Interest The author declares that there is no conflict of interest in this study.

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