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A study of rainfall thresholds for landslides in Badung Regency using satellite-derived rainfall grid datasets

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ABSTRACT

Integrating field rainfall data with satellite data improves data accuracy and overcomes rainfall data limitations for rain thresholds. Integration can involve field rainfall data, satellite rainfall data, or a different satellite dataset. Merging these rainfall data sources provides more spatial coverage of satellite data. To determine how well rainfall thresholds predict rainfall-triggered landslides, the threshold model must be validated. This study will evaluate satellite rainfall data before and after integration in developing a rainfall threshold model for landslide prediction in Badung Regency. To do so, the study used a cumulative rainfall threshold over 3, 7, 15, and 30 days and two rainfall satellite products (integrated merged multi-satellite retrievals (IMERG) and precipitation estimation from remotely sensed information using artificial neural networks (PERSIANN)). Median, first, and third quartiles were used to set thresholds. The area under the curve (AUC) was calculated to validate rainfall threshold outcomes using receiver operating characteristic (ROC) curves. Analysis showed that integrating satellite rainfall data into the rainfall threshold model for landslide prediction yields better results than other methods. An AUC value of 0.903 (90.3%) for the 30-day cumulative rainfall thresholds supports this claim. This model could be a good input for a landslide early warning system in Badung Regency.

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1. INTRODUCTION

Precipitation in a particular geographic area may be the cause of landslides. Rain-induced landslides are a result of the buildup of hydrostatic pressure within the soil [1]. The occurrence of landslides has extensive ramifications, encompassing the loss of human lives, material destruction, and substantial degradation of the environment. To reduce the number of casualties, it is crucial to implement mitigation strategies, which make it necessary to establish an effective early warning system [2]. One method that can be employed is the incorporation of rain thresholds within the context of the early warning system. The accessibility of components related to rainfall predictions is a crucial factor in this system [3]. A multitude of scholars have undertaken endeavors to establish precise thresholds of rainfall in order to effectively predict slope collapse and landslides. The parameters taken into consideration include average rainfall, duration of the rainfall event, the ratio of rainfall to daily rainfall, previous rainfall in relation to the annual average rainfall, and the ratio of daily rainfall to the maximum previous rainfall [1], [4]–[9]. Rainfall is the predominant factor considered in the examination of rainfall thresholds that initiate landslide occurrences.

Therefore, the incorporation of additional rainfall data is imperative in order to complement the existing data obtained from rainfall stations.

The collection and analysis of rainfall data play a crucial role in the identification of changes in climate patterns and the comprehension of the hydrological cycle. However, the collection of rainfall data using rain gauges is subject to limitations and spatial irregularities, which restrict its applicability to a specific geographic area. This phenomenon is especially noteworthy in areas that are distinguished by complex topographical features [10]. An alternative methodology entails utilizing satellite-derived rainfall grid datasets (SRGDs) to produce information that is not only more precise but also by actual environmental circumstances [11]. A number of SRGDs are commonly utilized, including the tropical rainfall measuring mission (TRMM), global satellite mapping of precipitation (GSMaP), global precipitation measurement-integrated merged multi-satellite retrievals (GPM-IMERG), climate hazards group infrared precipitation with station (CHIRPS), climate prediction center morphing method (CMORPH), precipitation estimation from remotely sensed information using artificial neural networks (PERSIANN) [12]–[17].

Numerous scholars have conducted prior research to investigate the utilization of satellite-derived precipitation data in the determination of rainfall thresholds that trigger landslides. Prominent studies have examined the contributions of TRMM [15], [18]–[20], GSMaP [21], [22], IMERG [11], [18], [22]–[24], PERSIANN [12], [22], and CMOPRH [9]. Previous studies have identified variations in the effectiveness of SRGDs, which can be attributed to regional factors. In addition, there is a certain degree of error that remains when comparing this data with measurements obtained from rainfall stations located on the ground. In contrast, the aforementioned studies exclusively utilized a singular dataset obtained from satellites in their examination of the precipitation thresholds that trigger landslides. Therefore, an alternative methodology involves the incorporation of multiple satellite images of rainfall, intending to reduce the inherent uncertainty in determining the rainfall thresholds that lead to landslides.

The amalgamation of earth-based and weather satellite information can be employed to improve the accuracy of early rainfall detection, thereby reducing the potential consequences of landslides. The enhancement of data accuracy and resolution of limitations associated with rainfall data to determine rainfall thresholds can be achieved through the implementation of an integrated approach that combines field rainfall data and satellite information. The integration of rainfall data results in a spatial coverage that is more evenly distributed in comparison to the exclusive reliance on individual satellite datasets [10]. The integration of two separate satellite rainfall datasets to determine rainfall thresholds that trigger landslides is currently subject to significant limitations. Previous studies have explored the integration of satellite-derived rainfall data, with a prominent example being the merging of SM2RAIN and IMERG datasets. The fusion underwent analysis in order to develop a rainfall threshold model within the Indian context. The integration of different satellite data products allows for the utilization of the unique advantages offered by each product, while also addressing the limitations associated with SM2RAIN's tendency to underestimate rainfall or IMERG's tendency to overestimate it, especially in cases of low-intensity rainfall events [24]. The results indicated that, among the products evaluated in India, the IMERG dataset performed the best on an hourly basis, while the SM2RAIN dataset had a comparatively low error rate. Overall, the analysis of rainfall patterns using the combined SM2RAIN and IMERG datasets yielded more accurate results contrasted to the data acquired from traditional rainfall measurement sites. Previous research has identified certain constraints in the utilization of daily precipitation data to establish thresholds that trigger landslides. Therefore, this study employs a methodology that incorporates hourly rainfall data. The successful implementation of a slope instability early detection system relies on the effective application of rainfall thresholds that are derived from the integration of hourly data [25].

Previous scholars analyzed the rainfall events that induce landslides to determine rain threshold values using daily, basic, and monthly rainfall data and using only one rain satellite [1], [4]–[9], [26]. Furthermore, scholars on the utilization of SRGDs such as IMERG in the development of rain thresholds have better performance for hourly rainfall data [24]. Furthermore, the utilization of rainfall thresholds in the advancement of early detection systems has been undertaken in previous research. Several researchers have attempted to establish the threshold for rainfall in accurately predicting slope instability or landslides. This has been achieved by considering parameters such as average rainfall, the duration of rainfall events, the ratio of rainfall to daily rainfall, previous rainfall to average annual rainfall, and daily rainfall to the maximum ratio of previous rainfall [1], [4]–[9], [27]. The utilization of SRGDs in determining rain thresholds for landslide events is still limited, especially in Bali Province [22]. Moreover, previous studies have not analyzed rainfall thresholds based on the integration of high temporal-spatial resolution of SRGDs. Therefore, the novelty of this research involved establishing the precipitation threshold through the integration of datasets with high temporal-spatial resolution, specifically the IMERG and PERSIANN datasets. Conversely, there has been no prior investigation into the examination of rainfall thresholds causing landslides in Badung Regency. Therefore, the recent study would like to evaluate satellite rainfall data before and after integration in developing a rainfall threshold model for landslide prediction in Badung Regency. This investigation aims to enhance the effectiveness of SRGDs, providing another option for identifying rainfall thresholds that lead to landslide events.

2. RESEARCH METHOD

2.1. Study area

This research was conducted in the Badung Regency, located in Bali (Figure 1). Geographically, Badung Regency spans an area of 418.52 km², constituting approximately 7.43% of Bali Province's total land area. The geological conditions of Badung Regency are mostly young volcanic products consisting of volcanic breccia, passive tuff, and lava deposits. Most of the soils in Badung Regency are classified as Inceptisols made from intermediate volcanic ash and tuff. Meanwhile, when viewed from the topographic conditions, the slope of Badung Regency is grouped into 7 (seven), namely slope 0-3%, is a flat area, slope >3-5%, is a gentle area, slope >5-10% is an undulating hilly area, slope >10-15% is a slightly sloping area, slope >15-30% is a sloping area, and slope >30-70% is a very steep area. The further north the slope is the higher [28].

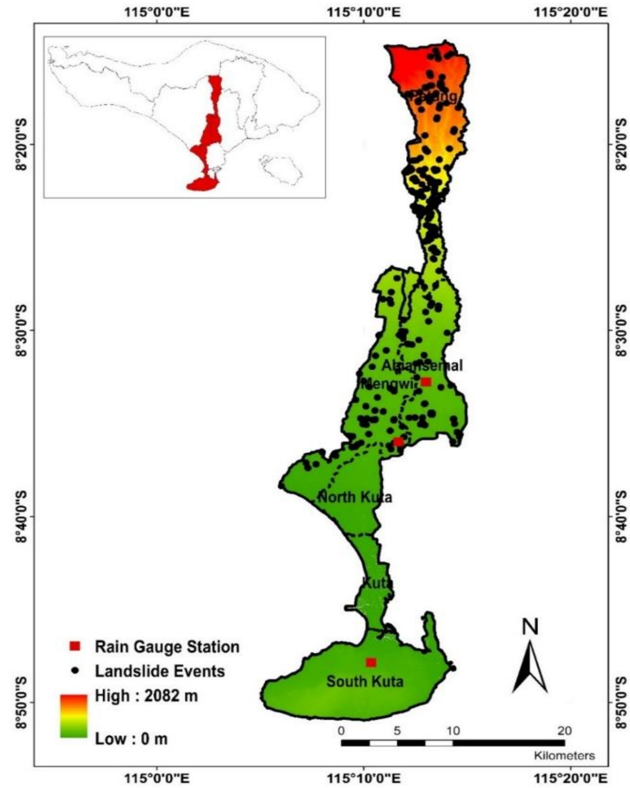


Figure 1. The map of Badung Regency contains the distribution of the landslide events, rain gauge stations, and elevation

2.2. Landslide event

The information utilized in this study comprises landslide data spanning from 2015 to 2022. Landslide data required includes the location of the incident, date of the incident, coordinates of the incident location, area affected, and level of loss. The landslide data was obtained from the report of the Regional Disaster Management Agency of Badung Regency. Landslide data is required to conduct rainfall threshold analysis. Petang District has the highest number of landslide events, amounting to 57% of the total landslide events in Badung Regency. This is indicated because the Petang district which is located in the northernmost area of Badung Regency has an area with a slope above 45% (very steep). Followed by Mengwi District with 20% of landslides, then Abiansemal District with 16% of landslides. Other districts in this regency tend to be dominated by sloping areas (slope 0-8%), namely Kuta, North Kuta, and South Kuta. It also shows that the incidence of landslides in these areas is the lowest among other areas, see Figure 2.

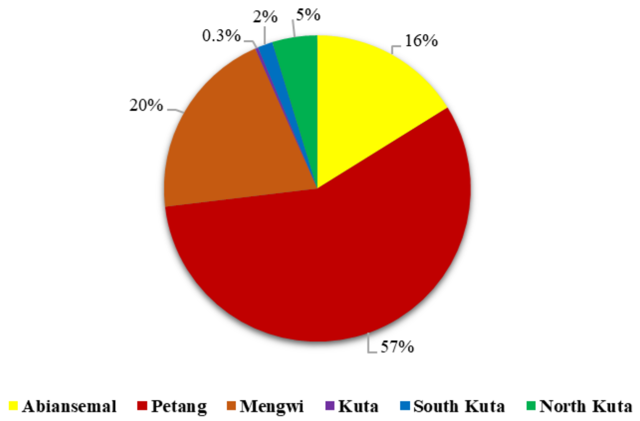


Figure 2. The percentage of landslide occurrences in each district over Badung Regency

2.3. Rainfall dataset

This study uses two rainfall data, namely rainfall data consisting of hourly rainfall measurements obtained from the Balai Wilayah Sungai Bali-Penida (BWSBP), Ministry of Public Works and Human Settlements of Indonesia with selected rainfall stations namely Mambal, Sading, and Unud. Meanwhile, the SRGDs used are IMERG and PERSIANN. IMERG data exhibits a spatiotemporal resolution of 0.1°×0.1° at 30-minute intervals. IMERG satellite rainfall (Integrated Multi-satellite Retrieval for GPM or Global Rainfall Measurement) is the latest replacement for the TRMM satellite. As an earth-orbiting satellite, IMERG data provides a 30-minute, daily, and monthly report of the total rainfall that falls in an area [16], [29], [30]. IMERG data can be downloaded from the GPM National Aeronautics and Space Administration (NASA) website [31]. This study uses the PERSIANN-cloud classification system (CCS) which can estimate global rainfall with a spatial acuity of 0.04° (nearly 4×4 km) [32]. The rainfall data from the PERSIANN satellite was acquired from the website of the Center for Hydrometeorology and Remote Sensing (CHRS) [33].

2.4. Determination of rainfall thresholds

The precipitation threshold for landslide occurrences is characterized as the pivotal limit of rainfall conditions that can either initiate or abstain from causing landslides [34]. The identification of these precipitation conditions involves an examination of the statistical correlation between the intensity and duration of rainfall, as illustrated in a scatter diagram [1]. The probability of the rainfall amount during landslide-triggering events has also served as a basis for establishing thresholds in numerous prior studies aimed at developing an early warning system [1], [20], [35]. This threshold was defined using cumulative rainfall parameters. These thresholds are defined using cumulative rainfall parameters. Cumulative rainfall for precipitation events is computed for various time intervals, such as 3, 7, 15, and 30 days leading up to the occurrence of landslides, see Figure 3. To ascertain the threshold rainfall value, this study employs statistical location measures including the primary quartile (Q1), secondary quartile (Q2), and tertiary quartile (Q3).

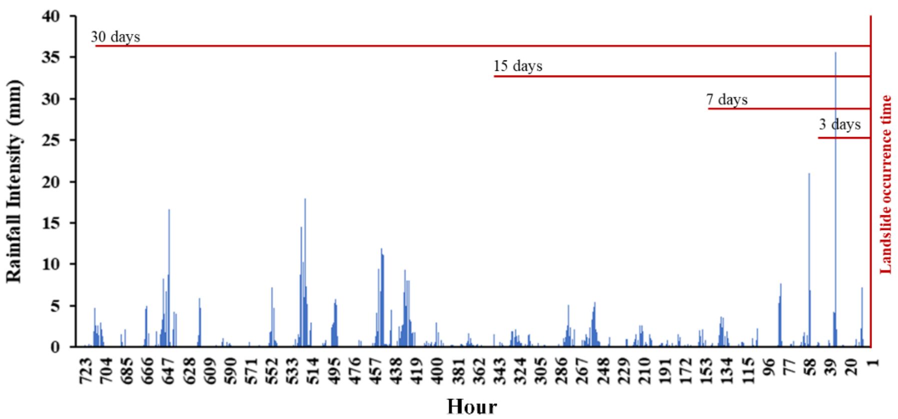


Figure 3. Definition of rainfall conditions before landslide occurrences

2.5. Fusion of rainfall dataset

The combination or fusion of satellite rainfall data involves applying weights determined by the correlation coefficient of each satellite rain data with the rainfall station [24], [36]. In this research, to amalgamate rainfall estimates acquired through various methods for landslide prediction, a composite satellite rainfall product was generated by merging IMERG and PERSIANN data, which was then employed as input for establishing rainfall thresholds. The merging of satellite rainfall data serves to address discrepancies in individual satellite datasets, like PERSIANN underestimating or IMERG overestimating during low-intensity rainfall occurrences [24]. The combination of satellite data is obtained using the (1).

$$S_{fusion} = S_{PERSIANN} + w_i(S_{IMERG} - S_{PERSIANN}) \tag{1}$$

In this context, w_i denotes the integration weight, varying between 0 and 1, and is computed for each pixel according to (2) [36].

$$w_i = \frac{\rho_{PERSIANN.R} - (\rho_{PERSIANN.IMERG} \cdot \rho_{IMERG.R})}{\rho_{IMERG.R} - (\rho_{PERSIANN.IMERG} \cdot \rho_{PERSIANN.R}) + \rho_{PERSIANN.R} - (\rho_{PERSIANN.IMERG} \cdot \rho_{IMERG.R})} \tag{2}$$

2.6. Performance analysis of rainfall thresholds

Threshold performance is calculated by a confusion matrix that contains actual landslide events with predicted landslide events which results in four conditions that can occur. True Positive occurs if rainfall triggers a landslide in both the actual event and the predicted event (1, 1). True Negative is when rainfall does not trigger landslides in the actual or predicted event (0, 0). A false Positive is when rainfall does not trigger landslides in the actual event, but according to the prediction, rainfall can trigger landslides (0, 1). False Negative is when rainfall can trigger landslides in the actual event, but according to prediction, it does not trigger landslides (1, 0) [23]. The evaluation of the thresholds' efficacy was assessed using various statistical quantifiers derived from computations, as outlined in Table 1. Table 2 presents the specific statistical quantifiers used in the analysis.

In this research, ROC analysis is employed to assess the precision of the rainfall threshold model in predicting whether rainfall events will induce landslides or not. The region below the curve, indicating the accuracy of the experimental model, is determined using a calculation method referred to as the area under the curve (AUC), as illustrated in Figure 4. The AUC represents a square-shaped area, with its value consistently falling between 0 and 1. A value of 0.5 is associated with random performance, as it produces a curve in the shape of a diagonal line connecting points (0, 0) and (1, 1). The categorization of AUC levels is detailed in Table 3.

Table 1. Cross-tabulation table [23]

Predictions made by the model	Occurrences of landslides	
	Yes	No
> Criterion	True positive (TP)	False positive (FP)
≤ Criterion	False negative (FN)	True negative (TN)

Table 2. Metrics employed for evaluating the effectiveness of the thresholds [23]

Statistical Indices	Equation
True positive rate (TPR)	$TPR = \frac{TP}{TP + FN}$
False positive rate (FPR)	$FPR = \frac{FP}{FP + TN}$
Accuracy	$Acc = \frac{TP + TN}{TP + TN + FP + FN}$

Table 3. Categorization of AUC values [23]

Value AUC	Description
0.5	No discrimination, random guesses
$0.5 < AUC \leq 0.6$	Poor discrimination
$0.6 < AUC \leq 0.7$	Acceptable discrimination
$0.7 < AUC \leq 0.8$	Excellent discrimination
$0.9 < AUC$	Outstanding discrimination

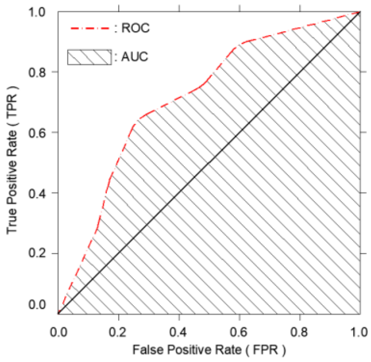
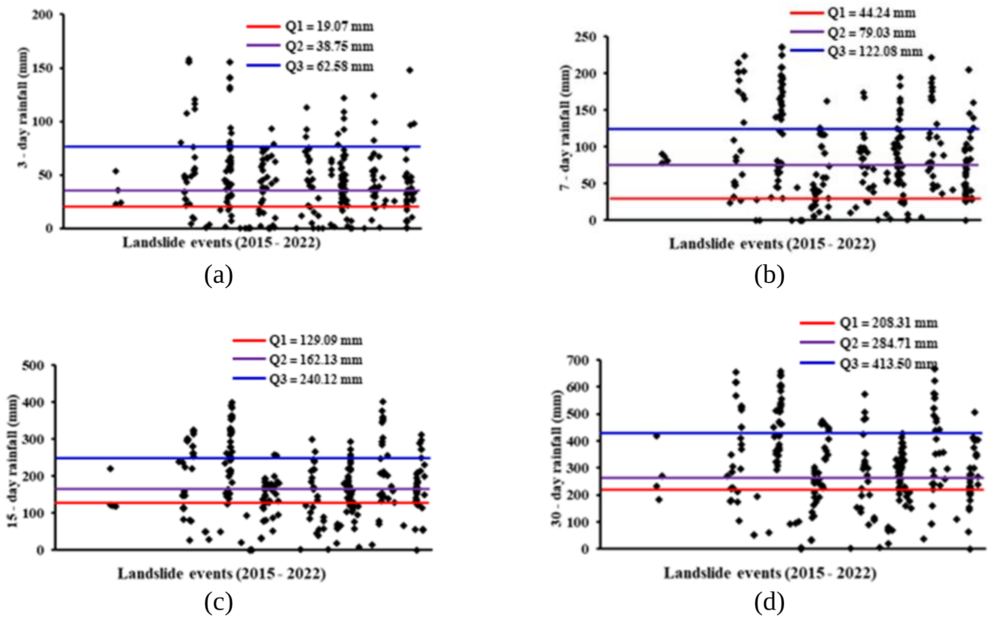


Figure 4. ROC and AOC for rainfall threshold models [37]

3. RESULTS AND DISCUSSION

3.1. Rainfall threshold results

Derived from the approach employed in the analysis of rainfall threshold values in this investigation, it was found that there was an increase in value for each cumulative rainfall variation. The three threshold values have different patterns, the largest threshold is obtained from the 30-day cumulative rainfall for IMERG (Figure 5), PERSIANN (Figure 6), and the integration between IMERG and PERSIANN (Figure 7). The result shows that some landslide events are associated with very low rainfall. However, in general, landslide events occur after heavy rainfall and last for several days. Based on the results of the rainfall threshold analysis for all 3, 7, 15, and 30 days of cumulative rainfall from three satellite rainfall products, the largest threshold value is obtained from the third approach (Q3), subsequently, the second approach (Q2) and finally the first approach (Q1) as shown in Figures 5(a)-(d), Figures 6(a)-(d), and Figures 7(a)-(d). The threshold of the third approach has the largest value in the cumulative 30 days, namely 413.50 mm for IMERG; 437.00 mm for PERSIANN, and 413.95 mm for the integration between IMERG-PERSIANN. Followed by the second method's thresholds of 284.71; 285.50; and 287.66 mm. Last is the lowest threshold of the first method, with threshold values of 208.31; 205.00; and 213.35 mm. Then for the smallest threshold value obtained from the 3-day cumulative rainfall of the three satellite rainfall products IMERG, PERSIANN, and IMERG-PERSIANN integration. The thresholds of the third method are 62.58; 67.75; and 62.44 mm. Then for the second method of 38.75; 32.00; and 38.79 mm. As for the values of 19.07; 18.00; and 17.52 mm for the first method.



(a) (b) (c) (d)

Figure 5. Various accumulation rainfall thresholds of the IMERG dataset: (a) for 3 days period, (b) over 7 days, (c) across 15 days, and (d) within 30 days

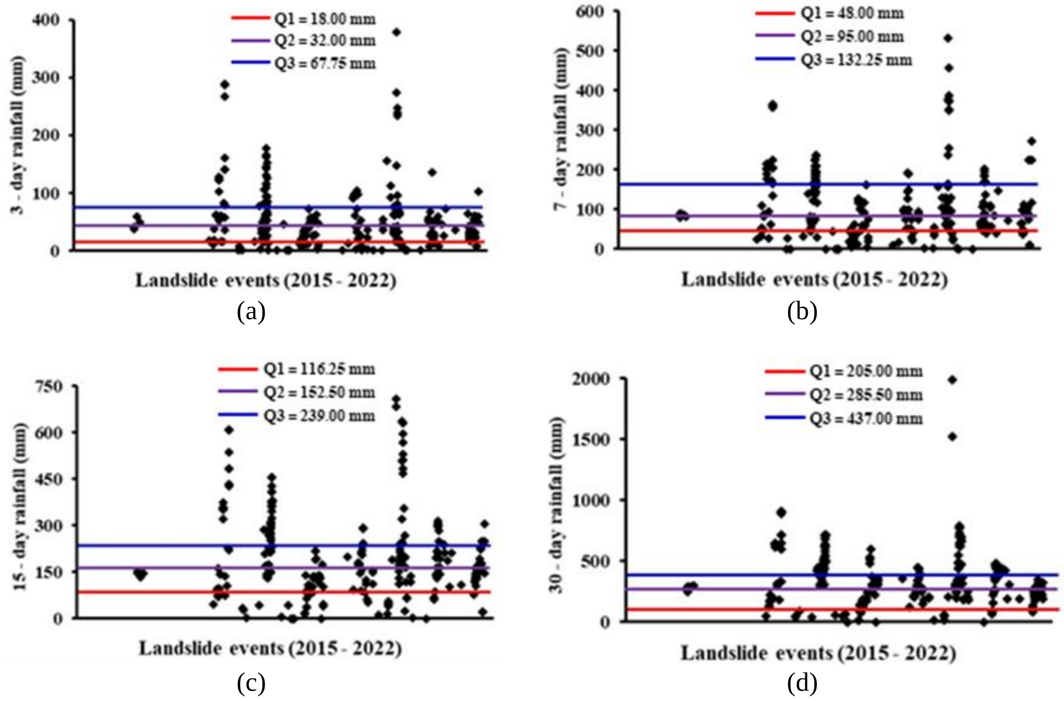


Figure 6. Various accumulation rainfall thresholds of PERSIANN dataset: (a) for a 3-day period, (b) over 7 days, (c) across 15 days, and (d) within 30 days

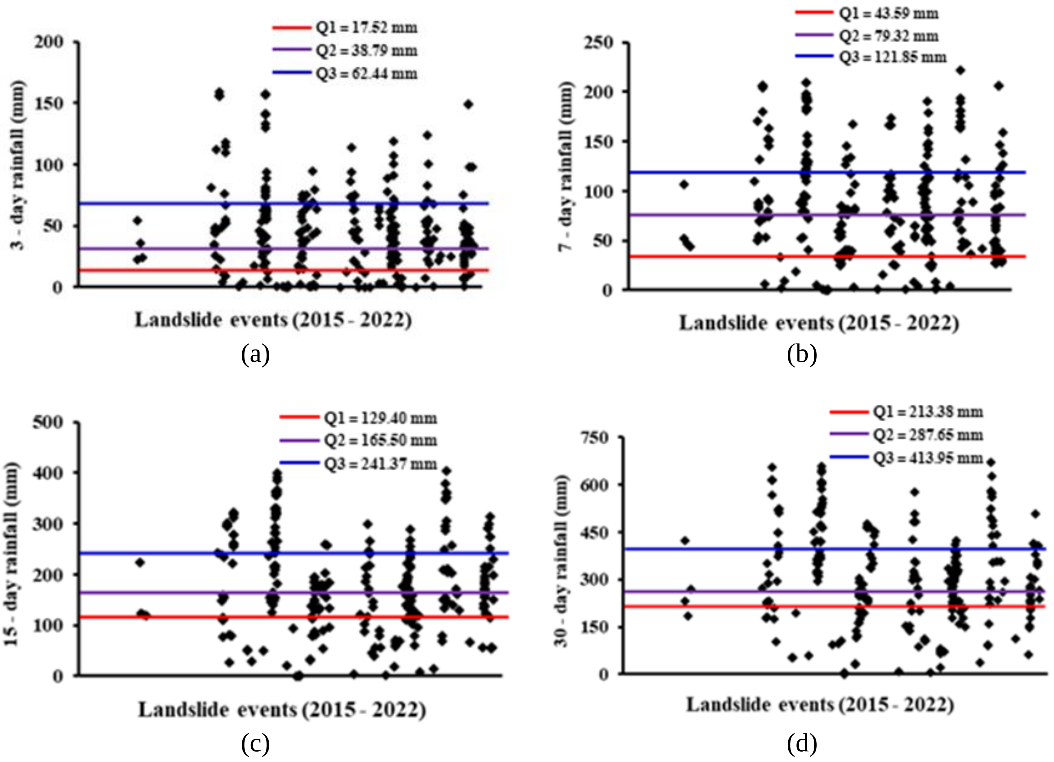
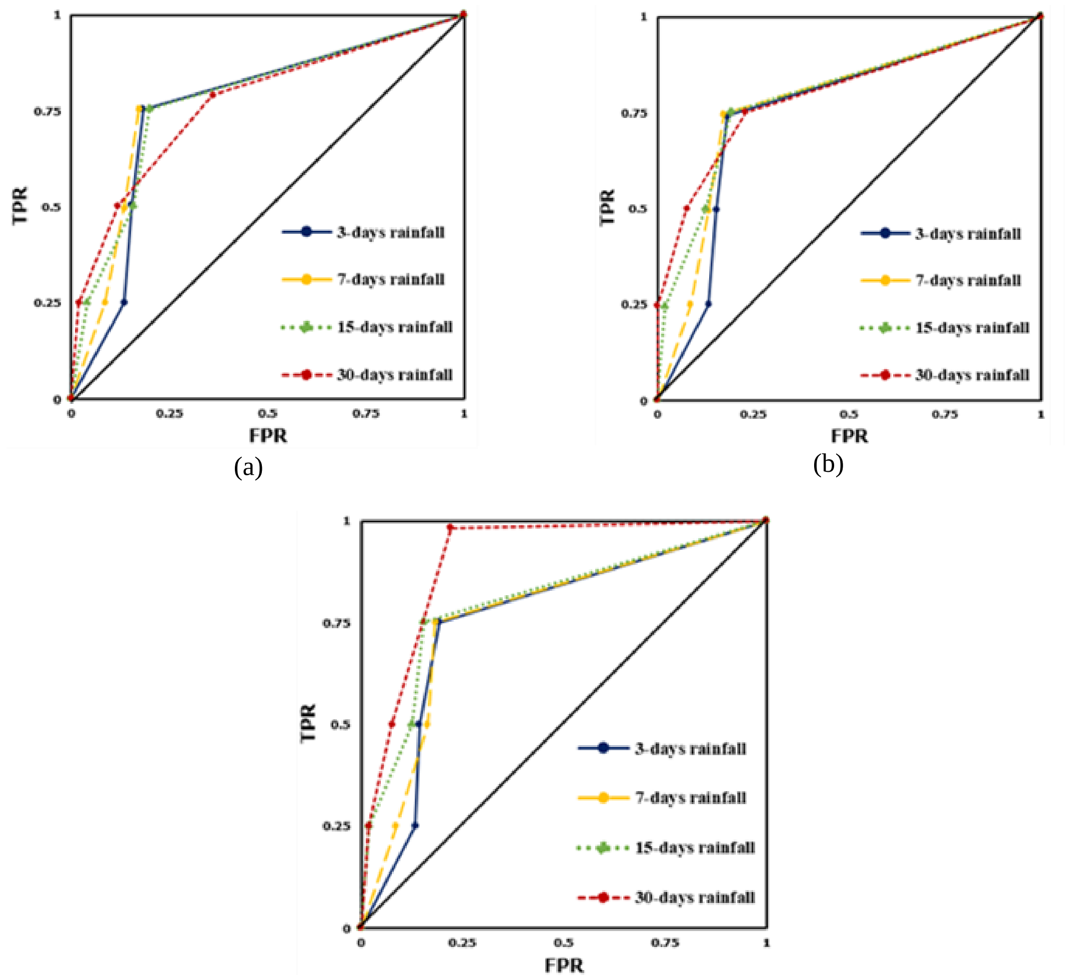


Figure 7. Various accumulation rainfall thresholds of the IMERG and PERSIANN Fusion: (a) for a 3-day period, (b) over 7 days, (c) across 15 days, and (d) within 30 days

Thresholds for landslides, determined from cumulative rainfall, exhibit a wide range, spanning from under 17 mm to over 400 mm. This variability underscores the significant influence of factors such as location and the methodology employed in establishing the threshold line [1]. Regions characterized by elevated terrain featuring steep slopes and low-lying areas with relatively flat slopes will experience distinct rainfall intensities preceding landslides, leading to varied rainfall thresholds. Furthermore, when determining landslide thresholds for a specific location, factors such as seasonal variations, land cover, and soil conditions should be taken into account, contributing to divergent threshold values even when assessing identical locations.

3.2. Performance analysis

Based on 316 landslide events spread across Badung Regency, the number of rainfall events that caused landslides (TP), no landslides (TN), and accuracy (ACC) were obtained. Figure 8 shows the results of ROC analysis showed that for 3,7,15, and 30 days of cumulative rainfall from the IMERG dataset (Figure 8(a)), PERSIANN dataset (Figure 8(b)), and Fusion of IMERG and PERSIANN (Figure 8(c)). The accuracy level of the AUC and rainfall threshold is reasonably high, as indicated by the results lying above the diagonal line. Of the three methods (Q1, Q2, and Q3) used, the first method (Q1) is the best method among the other two methods. The first method shows a "good" TPR value with 0.77 for IMERG; 0.76 for PERSIANN, and 0.78 for the integration of IMERG and PERSIANN.



(c)

Figure 8. ROC for rainfall satellite data: (a) IMERG, (b) PERSIANN, and (c) fusion IMERG-PERSIANN

According to the analysis of the confusion matrix results, among the three approaches employed to establish rainfall thresholds, the initial method proves to be the most accurate in predicting both landslide and non-landslide conditions for each integration of satellite rainfall products. Furthermore, this approach exhibits a low prediction error rate when compared to the actual occurrence of landslide events. In addition, the second approach also gives a good prediction for the integration of IMERG-PERSIANN rainfall data products (Table 4).

The AUC value for the rainfall threshold signifies the accuracy level in identifying rainfall events that either trigger or do not trigger landslides. The cumulative rainfall of 3, 7, 15, and 30 days for IMERG, and PERSIANN satellite data shows that 30 days of rainfall yields better performance. Considering the AUC derived from the ROC, the rainfall threshold demonstrates a reasonably high level of accuracy. The results obtained for each satellite rainfall product are $\mathrm{AUC} = 0.755$ (75.5%) for PERSIANN and $\mathrm{AUC} = 0.769$ (76.9%) for IMERG, as presented in Table 5. However, for this study, it is necessary to optimize rainfall data both in the correction of rain station data and satellite rain products. This is because in previous research that has been done the rainfall threshold 15 days before the landslide event has the highest accuracy (86%) [19]. The findings of this investigation reveal that combining IMERG and PERSIANN satellite data yields superior outcomes compared to not employing the fusion method when establishing the rainfall threshold model for landslides in Badung Regency, indicated by an AUC value of 0.903 (90.3%). A higher accuracy value denotes an improved threshold model. The outcomes of this threshold model are anticipated to be valuable in the establishment of the landslide preemptive notification system for Badung Regency.

Table 4. Threshold model performance

Method	Threshold Line	TPR	TNR	ACC
Q1	IMERG	Good	Good	Good
	PERSIANN	Good	Good	Good
	IMERG-PERSIANN	Good	Good	Good
Q2	IMERG	Not good	Good	Good
	PERSIANN	Not good	Good	Good
	IMERG-PERSIANN	Good	Good	Good
Q3	IMERG	Not good	Good	Not good
	PERSIANN	Not good	Good	Not good
	IMERG-PERSIANN	Not good	Good	Not good

Table 5. AUC values for rainfall thresholds

Satellite rainfall	Cumulative rainfall (days)			
	3	7	15	30
PERSIANN	0.701	0.733	0.754	0.755
IMERG	0.711	0.726	0.777	0.769
IMERG-PERSIANN	0.757	0.766	0.805	0.903

3.3. Discussion

This investigation exclusively examined the thresholds for the entire region of Badung Regency, overlooking variations in local conditions such as seasonal discrepancies, disparities in land cover, and soil conditions. These outcomes are influenced by various factors, including intricate topography and climate, elevated altitudes in mountainous regions, and the limited and uneven distribution of rain stations in these areas. Numerous prior studies have similarly suggested that the accuracy of satellite data may be impacted by the complexity of the terrain [38], [39]. The analysis of satellite data in this research indicates that IMERG satellite data outperforms PERSIANN satellite data. This result stems from IMERG's superior capability in identifying light precipitation. Additionally, IMERG boasts a shorter temporal resolution of 30 minutes, facilitating the recording of short-lived rainfall events. Furthermore, IMERG exhibits a superior spatial resolution of 0.1°, enhancing its ability to detect small-scale rainfall events. This observation aligns with prior studies that utilized IMERG satellite data for analyzing rainfall thresholds in the establishment of a landslide preemptive notification system. The results of this investigation revealed that IMERG satellite data had better performance for hourly rainfall data [24]. In addition, previous researchers also observed that the use of hourly rainfall data has better capabilities compared to daily rainfall data, which causes a decrease in general predictability [25]. However, the assessment of the PERSIANN dataset revealed its inferiority when compared to IMERG and GSMaP in identifying intense rainfall [40].

The threshold defined in this study was applied across the entire Badung Regency during the rainy season. When compared to thresholds that do not incorporate fusion methods, the newly proposed thresholds, which involve the integration of IMERG and PERSIANN rain satellite data, exhibit superior performance, characterized by higher rainfall thresholds. Cumulative rainfall-derived landslide thresholds display a wide range, spanning from 17 to over 400 mm. This variability underscores the strong dependence of landslide thresholds on factors such as location, climate, and the methodology employed to establish the boundary line [1]. Mountainous regions characterized by steep slopes and low-lying areas with relatively gentle gradients will require varying levels of rainfall intensity preceding landslide incidents, resulting in unique rainfall thresholds. Steeper slopes amplify the landslide risk [38], [39], a phenomenon previously noted by researchers who highlight the prevalence of landslides on sloped surfaces influenced by gravitational forces [41]. The new thresholds presented in this study are not applicable for predicting landslides caused by snow, earthquakes, or human activities. In this research, a novel approach is proposed for implementation within the Badung Regency Disaster Management Agency. This approach takes into account the differentiation in rainfall classification as a means of enhancing the landslide preemptive notification system. It is expected that these findings will facilitate decision-makers in formulating landslide disaster mitigation strategies in the Badung Regency.

The evaluation of rainfall threshold-induced landslides was conducted based on the AUC score. The AUC scores suggest that the effectiveness of the thresholds obtained through SRGDs is similar to those obtained from rain gauge station data in Badung Regency. The integration of IMERG and PERSIANN achieved the highest AUC score of 0.903, indicating that the predictive accuracy of integrating SRGDs thresholds surpasses that of individual SRGDs thresholds. Previous research has demonstrated AUC scores for various single SRGDs (TRMM, GSMaP, CMORPH, and IMERG) in determining rainfall thresholds in different locations across Indonesia ranging from 0.64 to 0.893 [23], [42], [43]. Furthermore, these findings align with earlier studies that advocate for the suitability of high-temporal datasets in determining rainfall thresholds for landslide early alert [12], [25]. Hence, the integration of two high-resolution SRGDs can enhance the performance of rainfall thresholds triggering landslides.

4. CONCLUSION

Based on the analysis of the outcomes of the threshold model, a significant conclusion arises. Out of the three methods used, the first approach (using Q_1) shows excellent performance in all statistical measures (TPR, TNR, and ACC). In addition, when the two satellite datasets are combined, the resulting AUC value for a 30-day cumulative rainfall period is 0.903. The threshold mentioned here is a dependable indicator of landslide occurrences, distinguished by a minimal rate of mistakes. Therefore, it is recommended to incorporate this model into the structure of a landslide preemptive notification system for implementation in Badung Regency. Moreover, in future research endeavors, broadening the scope to encompass additional geographical regions could augment the generalizability of these findings and further substantiate the efficacy of the proposed model.

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