



# Development of Landslide Early Warning System Based on the Satellite-Derived Rainfall Threshold in Indonesia

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## Abstract

Landslide is a common natural disaster occurring in Indonesia during the rainy season from November to February. Attempts have been made to develop an early warning system based on the rainfall derived from satellite observation. It is essential to verify the accuracy level of the rainfall threshold in predicting the occurrence of rainfall, causing landslides and non-landslides to model the lower limit that can be used as an early warning device of the landslides. In this analysis, modelling was carried out with an empirical (intensity—duration/ID) approach using 220 data of rainfall that triggered landslide with satellite-based TRMM in Indonesia territory. The intensity and duration of antecedent rainfall were utilized in rainfall threshold modelling. The rainfall threshold was validated with ROC analysis. This method used seven statistics indices and ROC curve to determine the accuracy rate of the rainfall threshold. The results showed empirical equation  $I = 7.83D^{-0.328}$  within the interval time 2–18 days. The results of the analysis of the ROC on the rainfall threshold indicate that the model has

a good accuracy rate and can be used in an early warning system of landslide even though it still has a fairly high error rate.

## Keywords

Rainfall • TRMM • Threshold • Warning system

## Introduction

Landslides are one of the natural disasters that frequently occur in one tropical country in Indonesia. High precipitation can cause unstable soil conditions and cause slope collapse. Rainfall triggering landslides can be predicted using rainfall thresholds used in early warning systems. In this work, rainfall modeling is generated by evaluating rainfall intensity and duration of rain from Tropical Satellite Rainfall Measuring Mission (TRMM) data based on Multi-Satellite Precipitation Analysis (TMPA) (Mathew et al. 2013). Each threshold model created has a different level of accuracy in predicting landslides. Several methods are frequently used to evaluate the empirical threshold models.

Rainfall triggering landslides can be divided into two categories, namely critical and antecedent rainfall. Figure 1 shows the occurrence of rain that can trigger landslides (Aleotti 2004). Critical rainfall is the amount of rainfall that has increased drastically and can trigger landslides. Critical rain can be a trigger for landslides if the rainfall generated is high, and exceeds the maximum limit. Meanwhile, the antecedent rain is a successive rainfall event measured prior to the critical rainfall event until the beginning of the critical rainfall. Both critical and antecedent rainfall can be used as parameters in determining the rainfall threshold model. Measuring antecedent rainfall threshold modeling is simpler than the critical rainfall. The common empirical model of rainfall threshold is determined by intensity—duration curve

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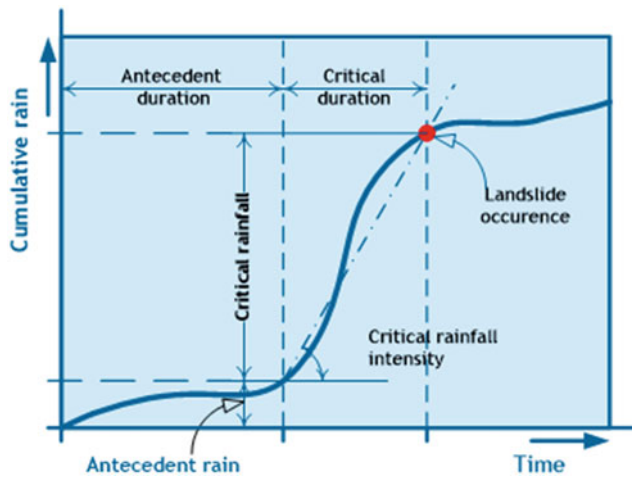
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**Fig. 1** Definition of rainfall parameters for threshold determination (modified after Aleotti 2004)

(I-D curve) (Aleotti 2004; Guzzetti et al. 2007; Reichenbach et al. 1998; Muntohar 2008).

The developed-rainfall threshold models for early warning system must be evaluated to determine the level of accuracy in predicting landslides during the rainy period. This level of accuracy can usually be evaluated by Receiver-Operating Characteristic (ROC) analysis. This method applies statistical index values and ROC curves that represent the level of accuracy of the rainfall threshold model (Fawcett 2006; Zou et al. 2007). The main purpose of this study is to establish the empirical model of the rain threshold based on antecedent rainfall intensity and duration.

The accuracy of the empirical model was evaluated by the ROC method. Thus, the rainfall threshold model can be implemented in a landslide early warning system.

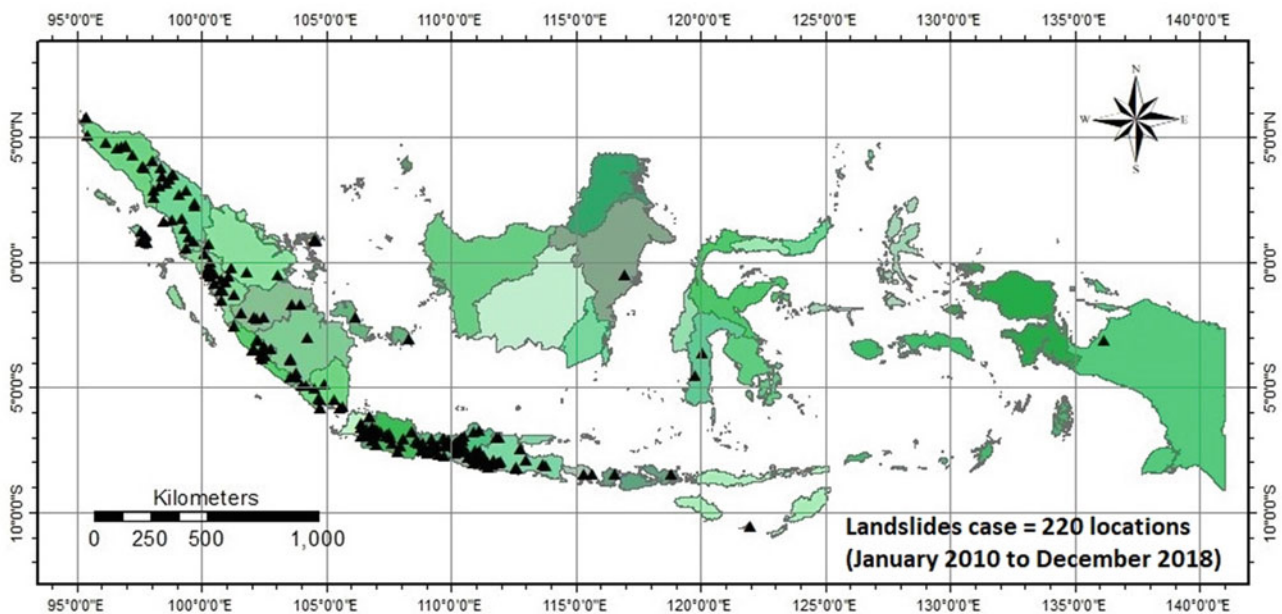
## Research Method

### Landslides Inventory in Indonesia 2010–2018

An empirical model of rainfall threshold to predict landslides requires data such as location, time, and rainfall. Several landslides in Indonesia have been documented through the website of the National Disaster Management Agency (BNPB), the Crisis Centre of the Ministry of Health, and the Geology Agency. However, many landslides were barely well recorded at government agencies but reported by newspapers and online sources. The distribution of landslide locations is shown in Fig. 2. Total landslides that can be recorded are 220 locations. The most recorded locations of landslides were in Java and Sumatra islands, while, in the regions of Kalimantan, Sulawesi, Papua, and Maluku, landslides rarely occur. Therefore, the model developed in this study is valid for the Java and Sumatera islands.

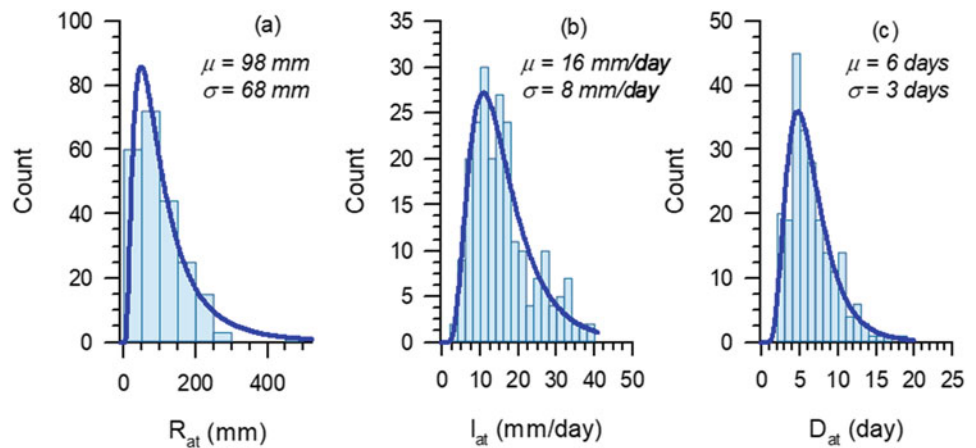
### Rainfall Records

The rainfall records for subsequent landslide location was obtained by the satellite data of the TRMM. Some studies on the validation of TRMM data over Indonesia have been



**Fig. 2** Landslides occurrence in Indonesia during January 2010–December 2018

**Fig. 3** The statistical distribution of antecedent rainfall,  $R_{at}$  (a), average intensity,  $I_{at}$  (b), and duration,  $D_{at}$  (c) from the 220 landslide



conducted by As-Syakur et al. (2011), Sipayung et al. (2014), Pratama et al. (2016), Giarno et al. (2018), and Fatkhuroyan et al. (2018). The studies concluded that the rainfall derived from the satellite was over predicted during the wet season, but the rainfall was applicable for an early warning system. The statistical descriptor (mean  $\mu$ , and deviation standard  $\sigma$ ) and distribution of the antecedent rainfall are shown in Fig. 3. The mean value of the duration of antecedent rainfall is about six days, and the average antecedent rainfall intensity is 16 mm/day, with the mean antecedent rainfall is 99 mm.

## Empirical Model

Empirical models of landslides were analyzed from 220 daily rainfall records at each landslide location. The rainfall threshold model was made based on the relationship between rainfall intensity and duration (I-D). Empirical I-D curve was developed by regression analysis by determining the lowest limit on the curve based on the distribution of data points. Furthermore, empirical equations are approached with power equation models such as Eq. 1 (Guzzetti et al. 2007).

$$I = aD^{-b} \quad (1)$$

where  $I_t$  is rainfall intensity (mm/day),  $D$  is the duration of the rainfall event that triggered each landslides (day),  $a$  and  $b$  are the constants obtained from the best fit.

In this study, a model developed was based on the antecedent rainfall triggering landslides. The definition of antecedent rainfall and respective duration, as explained by Aleotti (2004), is presented in Fig. 1. Parameter  $I$  in Eq. (1) is defined as average antecedent rainfall intensity ( $I_{at}$ ) determined by Eq. (2).

$$I_{at} = \frac{R_{at}}{D_{at}} \quad (2)$$

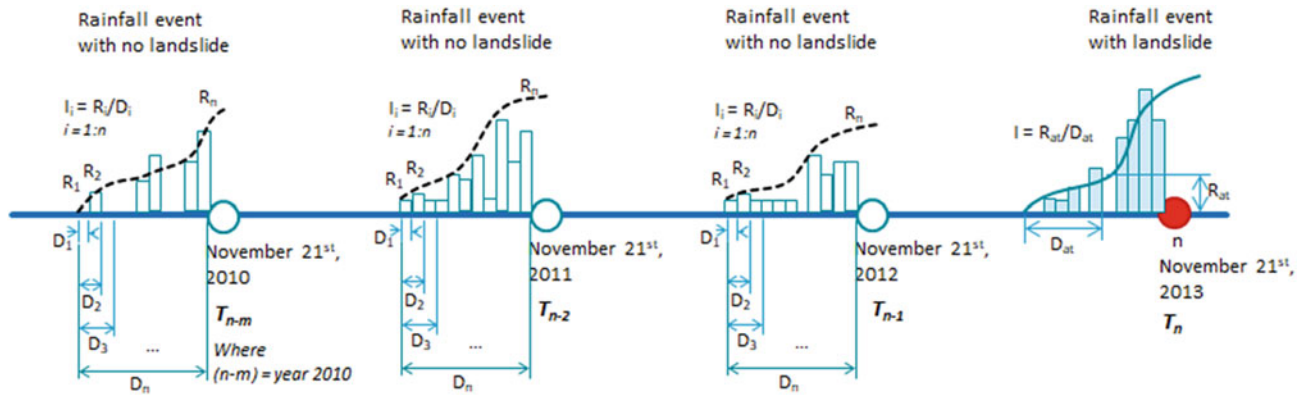
where  $R_{at}$  is the antecedent rain (mm), and  $D_{at}$  is the duration of the antecedent rainfall (days).

## Performance Analysis of the Empirical Model

In this study, the only first-time landslides at a single location was counted. The accuracy of the model was tested by a contingency table, skill scores, and ROC curve. Rainfall events that are not triggering landslide (no-landslide) were also collected to evaluate the empirical model. The rainfall events that are not triggering landslides were defined by the method proposed by Muntohar and Liao (2008). The rainfall events with no-landslide were defined at the same location in previous years, for instance, a landslide occurred at location L1 on November 21st, 2013 ( $T_n$ ) during a rainfall event, which indicates that the slope has not failed on November 21st in previous three years 2012 ( $T_{n-1}$ ), 2011 ( $T_{n-2}$ ), and 2010 ( $T_{n-m}$ ) (see Fig. 4). Thus, the antecedent rainfall and duration in previous years are defined as no-landslide. A total of 5468 rainfall events were observed for performance analysis.

## Contingency Table

The contingency table or confusion matrix considers two classes of a classification model (classifier) and instances (Fawcett 2006; Frattini et al. 2010; Piculio et al. 2016). The classification model and examples used in this study are observed landslide and predicted landslide. The contingency table correlates the observed landslide and predicted landslide. The predicted landslide is positive if a rainfall is positioned at or upper the threshold, whereas the negative is below the threshold. The positive observation is considered



**Fig. 4** A schematic definition of rainfall events with no landslides

**Table 1** Confusion matrix for accuracy analysis of empirical model of rainfall threshold

Predicted	Observed	
	Landslide	No landslide
At or above threshold	True positive, TP	False positive, FP
Below threshold)	False negative, FN	True negative, TN

as true positive (TP), and is considered as false negative (FN) below the threshold. The related definitions for negative results above and below the threshold are false positives (FP) and true negative (TN). As a consequence, there are two main cases of prediction: (1) correct prediction: true positive (TP) and true negative (TN), and (2) wrong prediction: false positive (FP) and false-negative (FN) as presented in Table 1.

**Statistical Indices**

Frattini et al. (2010) used statistical indices to assess the accuracy of empirical models obtained through statistical analysis between the results of the model and the observed data. Seven statistical indices were used to analyze the accuracy of the rainfall threshold model (Fawcett 2006; Frattini et al. 2010), as presented in Table 2. The indices are

- (i) True Positive Rate or hit rate is the ability of the threshold to identify rainfall events that trigger landslides;
- (ii) False Positive Rate states the level of error in identifying rainfall events that do not trigger landslides;
- (iii) True Negative Rate or specificity measures the ability to identify rainfall events that do not trigger landslides;
- (iv) False Negative Rate states the error rate in identifying rainfall events that triggered landslides;
- (v) Positive Prediction Power or precision is to determine the probability of a rainfall event which triggers a landslide;
- (vi) Negative Prediction Power measures the probability of a rainfall event do not trigger a landslide; and
- (vii) True Skill Statistics is the ratio between the True Positive Rate and False Positive Rate.

**Table 2** Statistical indices for measuring the level of accuracy

Index	Equation	Range	Best value
True positive rate or hit rate	$TPR = \frac{TP}{TP+FN}$	(0;1)	1
False positive rate	$FPR = \frac{FP}{FP+TN}$	(0;1)	0
True negative rate or specificity	$TNR = 1 - FPR$	(0;1)	0
False negative rate	$FNR = 1 - TPR$	(0;1)	0
Positive prediction power or precision	$PPP = \frac{TP}{FP+TP}$	(0;1)	1
Negative prediction power	$NPP = \frac{TN}{FN+TN}$	(0;1)	1
True skill score	$TSS = TPR - FPR$	(0;1)	1

(After Fawcett 2006; Frattini et al. 2010; Piciullo et al. 2016)

## ROC Curve

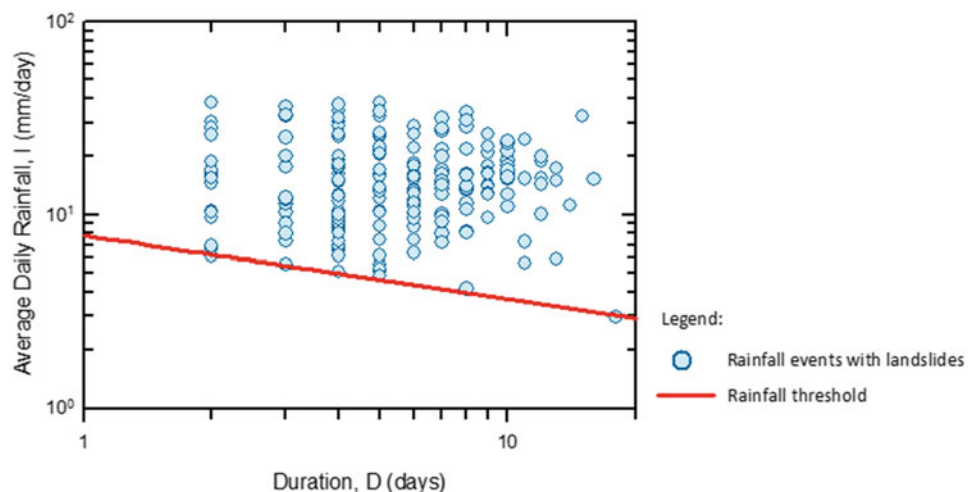
The ROC analysis method can be applied to measure the accuracy of the rainfall threshold. The ROC curve is a relationship between the True Positive Rate and the False Positive Rate indices, which at each point shows the level of the ability of the rainfall threshold to predict landslides. The level of accuracy is high if the ROC curve is close to the perfect classification point; for instance, the point with TPR = 1 and FPR = 0. The area under the curve (AUC) is an area that shows the level of accuracy of the empirical model. AUC is area whose value is always between 0 and 1. Random Performance results in an AUC value of 0.5 since the curve obtained is a diagonal line between point (0,0) and point (1,1). If the AUC is < 0.5, then the statistical model has a deficient level of accuracy and indicates the worst prediction when applied (Fawcett 2006; Zou et al. 2007).

## Result and Discussion

### Empirical Rainfall Threshold

The proposed empirical threshold in this study is presented in Fig. 5. The red line is the best-fit line of threshold. The threshold was defined by Eq. (3). The I-D threshold of this study is compared to the other regional thresholds by Caine (1980), Larsen and Simon (1993), Guzzetti et al. (2007), Mathew et al. (2013), and Rosi et al. (2017) as illustrated in Fig. 6. The figure shows that present threshold is lower than the other empirical equation. The figure also plots the landslides in Indonesia from year 2000 to 2004 that was provided by Muntohar (2008). The rainfall was obtained from the gauge measurement. The plot alludes to show that the established empirical rainfall threshold has a good performance to predict the landslides.

**Fig. 5** The proposed I-D curve as rainfall threshold for landslides warning



$$I = 7.83D^{-0.328} \quad (3)$$

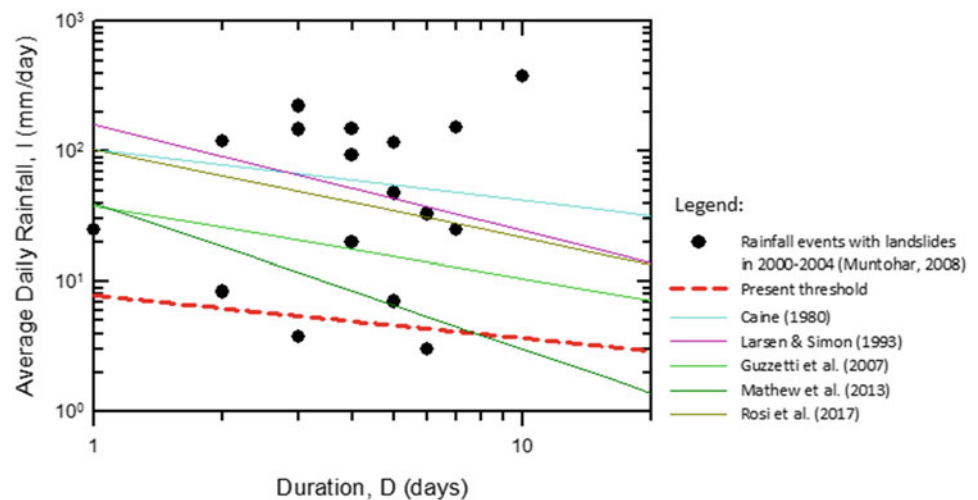
However, Rossi et al. (2017) argued that satellite-derived rainfall could not be used directly in analytical or calibrated hydrogeological models if they were derived from gauge-based data unless the estimating satellite are correctly scaled locally. In terms of locally scale area, Sipayung et al. (2014) and Pratama et al. (2016) found that rainfall from gauge measurement was 0.36–0.44 of the rainfall derived from TRMM. It indicates that the rainfall threshold from satellite-based rainfall estimation can be applied to predict the landslide initiation. Furthermore, Kirschbaum and Stanley (2018) and Guzzetti et al. (2020) stated that satellite rainfall projections might be useful in determining empirical rainfall thresholds for landslides initiation or in general for other hydrogeological models to forecast phenomena of instability over the large territorial area. Therefore, the selection of the empirical threshold model is the key to issuing early warning system (EWS) for rainfall-induced landslides (Monsieurs et al. 2019; Piciullo et al. 2018).

### Performance Evaluation of the Rainfall Threshold Model

Table 3 presents the confusion matrix to evaluate the performance of the empirical rainfall threshold. The total number of events of 5468 was evaluated in the performance analysis. The True Positive was counted as many as 1389 events, while the True Negative, False Positive, and False Negative were 1572, 121, and 2386 events, respectively. Further performance analysis for statistical indices of the model is presented in Table 4.

The empirical model proposed in this study showed a higher True Positive Rate (TPR = 0.92) but a moderate True

**Fig. 6** Comparison the threshold with the worldwide threshold for rainfall events with landslide in 2000–2004



**Table 3** The confusion matrix for performance evaluation of the model

Predicted	Observed	
	Landslide	No landslide
At or above threshold	TP = 1389	FP = 2386
Below threshold)	FN = 121	TN = 1572

Negative Rate (TNR = 0.40). The result implies that the model was right in identifying the occurrence of rainfall-triggered landslides, but it presented low accuracy in predicting not-failure case. Estimated TNR values > 0.90 stated that the rainfall threshold is perfect for avoiding alarm errors in the early warning system (Rosi et al. 2017). However, the TNR value (TNR = 0.40) of the threshold could be categorized as low to a moderate level in identifying rainfall events that did not trigger a landslide, which could cause a high alarm error rate in the warning system. The FPR value of the threshold was highly moderate (FPR = 0.60), indicating that the rainfall threshold was suitable enough to predict the rain event that did not trigger landslides. The FPR is strongly related to the uncertainty of rainfall intensity and causing the condition of FP (Guzzetti et al. 2007).

**Table 4** Statistical indices of the model

Index	Value
True positive rate (TPR)	0.92
False positive rate (FPR)	0.60
True negative rate (TNR)	0.40
False negative rate (FNR)	0.08
Positive prediction power (PPP)	0.37
Negative Prediction power (NPP)	0.93
True skill statistic (TSS)	0.32

The PPP value (PPP = 0.37) was relatively low for an empirical model. The result indicates that the ability to classify precisely the rainfall-triggered landslide was minimal. Furthermore, there was still a high possibility that the rain threshold was incorrect in classifying the occurrence of rainfall-triggered landslides despite having a high TPR value. However, NPP values > 0.90 indicates that the rainfall threshold model has an excellent prediction of rainfall events that do not trigger landslides (Rosi et al. 2017). The NPP value obtained in this study was 0.93, showing that the ability of the rainfall threshold in classifying rainfall events that did not trigger landslides was very high, despite the low TNR value.

The TSS index is expressed as an interval number (0,1), if TSS = 0 then TPR = FPR and TSS = 1 for a perfect prediction level if TPR = 1 and FPR = 0. The high value of False Positive Rate caused the low value of True Skill Statistics (TSS). The analysis of this study revealed a TSS value of 0.32. It means that the rain threshold still has a low predictive level (Peres and Cancelliere 2014). Overall statistical evaluation was considered in ROC analysis. The result is presented in a ROC curve, as in Fig. 7. The diagonal line is a random performance value of 0.50 (AUC = 0.50), assuming the true and false are equal (TPR = FPR). The AUC of the threshold shows that the level of accuracy in detecting rainfall triggering landslides and non-landslides was 0.66. Figure 7 shows the AUC and the rain threshold produce a pretty good level of accuracy since the results obtained exceed the value of random performance.

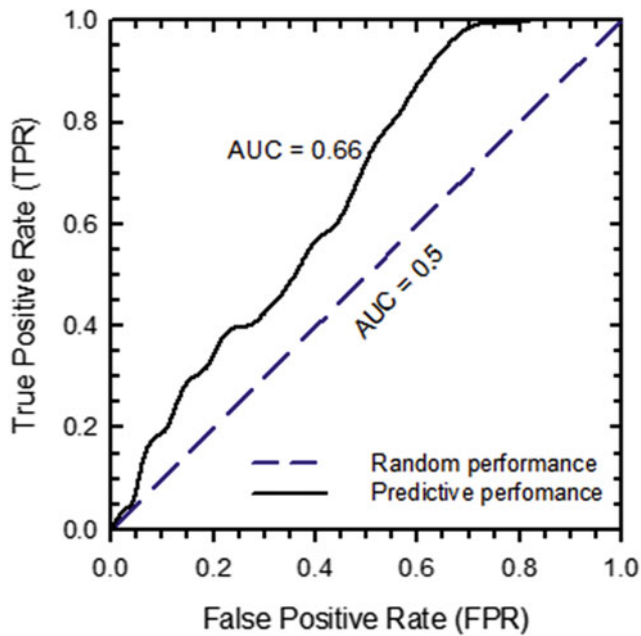


Fig. 7 Calculation for AUC of ROC curve

### Application of the Rainfall Threshold Model

The developed rainfall threshold has been implemented in a prototype of Indonesia Landslides Early Warning System (ILEWS) by Research Centre of Water Resources of the Ministry of Public Works and Housing (PUSAIR 2017). The rainfall threshold model was coupled with the Delft-FEWS platform. The platform was available to manage the forecasting and save the time series data (Werner et al. 2013). The satellite forecasting rainfall data was automatically programmed to download the TRMM precipitation data and forecasting from Weather Agency (BMKG). The territory of analysis was based on water catchment area which provided by Directorate General of Water Resources of the Ministry of Public Works and Housing. The warning scenario is categorized into three levels as presented in Table 5. Figure 8a and b illustrate the forecasting rainfall-derived from TRMM

Table 5 Warning scenario of prototype of ILEWS

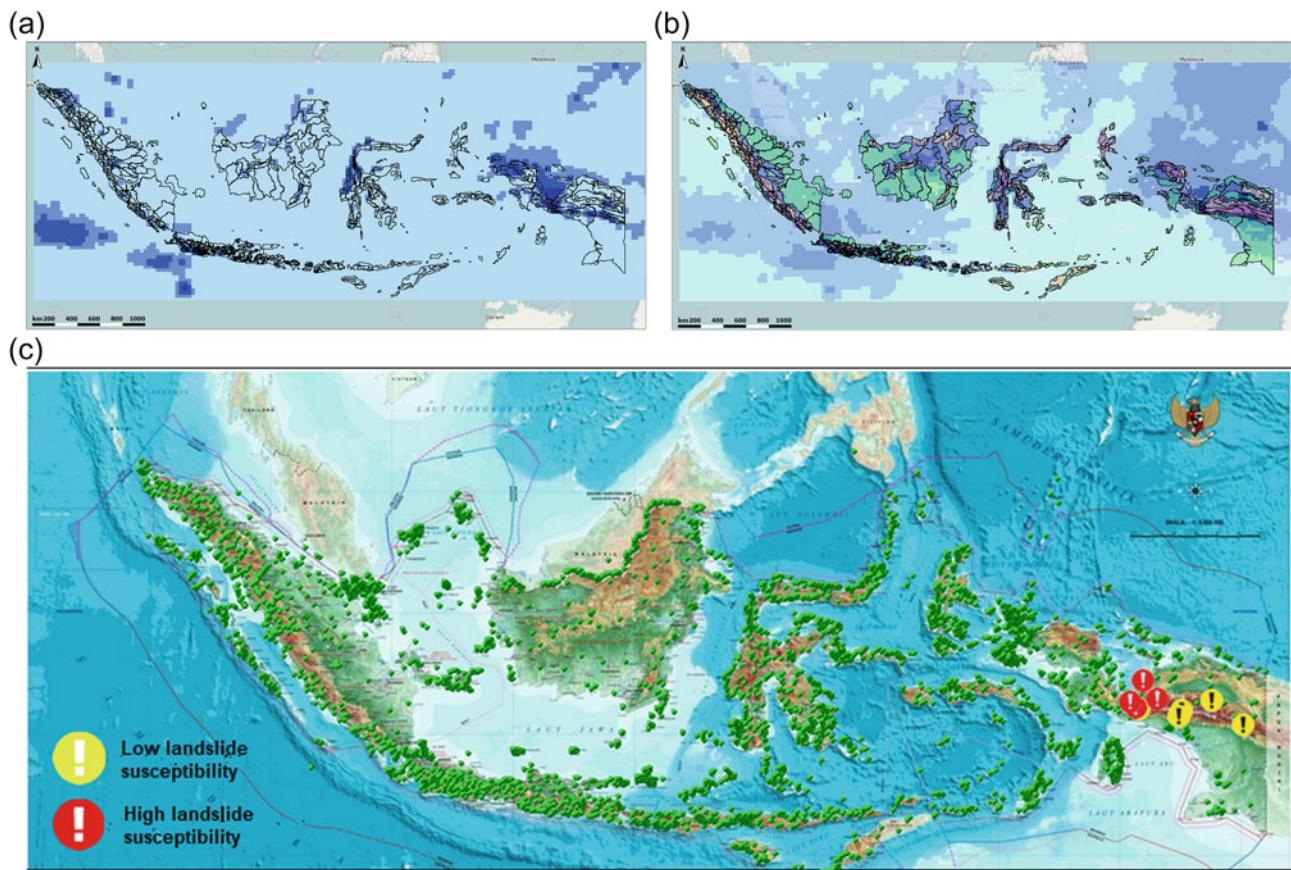
Warning level	Criteria	Remark
Green ●	Daily rainfall and average rainfall for three days is <i>below</i> the threshold	No landslides
Yellow !	Daily rainfall and average rainfall for three days is <i>at</i> the threshold	Potential to landslides (Low susceptibility)
Red !	Daily rainfall and average rainfall for three days <i>exceeds</i> the threshold	Landslides (High susceptibility)

for a day and three days rainfall respectively, while the predicted landslide is shown in Fig. 8c. The warning has been displayed on website of SABO Research Centre ([http://202.173.16.248/status\\_longsor.html](http://202.173.16.248/status_longsor.html)). The warning system can predict landslides with next three days based on the rainfall forecasted by BMKG. However, it should be noticed that the ILEWS prototype has limitation on the resolution. The resolution  $0.25^\circ \times 0.25^\circ$  is quite coarse and covers several river catchment area in one grid (Hidayat et al. 2019).

### Conclusion

The research has successful developed a rainfall threshold based on TRMM satellite observation for landslide prediction. The performance of the empirical threshold model has been evaluated by several accuracy method including statistical confusion matrix, skill scores, and ROC analysis. The application of the model has been also adopted by government authority to develop a prototype of Indonesia Landslide Early Warning System. Thus far, it can be concluded that the empirical rainfall threshold  $I = 7.83D^{-0.328}$  was valid for an interval time 2 to 18 days. The results of the analysis of the AUC on the rainfall threshold indicate that the model has a good accuracy rate and can be used as an early warning system of landslide even though it still has a fairly error rate. The rainfall threshold model showed a good level of accuracy in predicting rainfall triggered landslides and non-landslides events. Thus, it can be implemented in a landslide early warning system.

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**Fig. 8** a A day rainfall forecasting, b three days rainfall forecasting, c prediction of landslides

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