



Utilization climate hazards group infrared precipitation with station data (CHIRPS) to determine rainfall thresholds for early warning landslide in Luwu, South Sulawesi, Indonesia

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सार – रिमोट सेंसिंग का उपयोग करके भूस्खलन की प्रारंभिक चेतावनी ने हाल के दशकों में बढ़ता ध्यान आकर्षित किया है। हालांकि, लुवू राया, दक्षिण सुलावेसी में, सीमित धरातलीय वर्षा डेटा के कारण भूस्खलन को ट्रिगर करने वाली वर्षा की सीमा मान (सीमा) की समझ अभी भी कम है। यह अध्ययन भूस्खलन को ट्रिगर करने वाली सीमा मान निर्धारित करने के लिए 'क्लाइमेट हज़ार्ड्स ग्रुप इन्फ्रारेड प्रेसिपिटेशन विद स्टेशन' (CHIRPS) की उपयुक्तता का मूल्यांकन करता है। इस समझ की कमी से स्थानीय समुदायों और बुनियादी ढांचे को महत्वपूर्ण जोखिम होता है, जिससे भूस्खलन की भविष्यवाणी और जोखिम न्यूनीकरण के लिए विश्वसनीय वर्षा सीमा मान की पहचान करना महत्वपूर्ण हो जाता है। चूंकि सैटेलाइट वर्षा अनुमानों में स्थानिक और कालिक दोनों रूप से भिन्न पूर्वाग्रह होते हैं, इसलिए CHIRPS के विरुद्ध संदर्भ डेटा के रूप में 41 धरातलीय वर्षा अवलोकनों के विवरणात्मक डेटा का उपयोग करके 2019-2024 के लिए सत्यापन किया गया था। परिशुद्धता का आकलन RMSE, एक द्विभाजित मीट्रिक (Dichotomous metric), और चरम वर्षा सूचकांकों का उपयोग करके किया गया था। वर्षा सीमा मान भूस्खलन सूची और CHIRPS वर्षा के बीच घटना-आधारित मिलान द्वारा प्राप्त किए गए थे, जिसके बाद 3, 5, 10, 15, 20 और 30 दिनों में पूर्ववर्ती संचयों के साथ संयुक्त दैनिक वर्षा का वक्र विश्लेषण (Curve analysis) किया गया था। बाढ़ और भूस्खलन की घटनाओं के आधार पर संचित वर्षा (3-30 दिन) के वक्र विश्लेषण से सीमा मान प्राप्त किए गए थे। परिणाम दिखाते हैं कि पर्वतीय क्षेत्रों (>1000 मीटर) में CHIRPS की सटीकता निचले इलाकों की तुलना में कम है। सबसे विश्वसनीय सीमा मान ने दैनिक वर्षा को 15-दिवसीय पूर्ववर्ती वर्षा के साथ जोड़ा, जिससे 67% सटीकता प्राप्त हुई, जबकि कम संचय (10 दिन) का प्रदर्शन खराब (5%) रहा। मध्य लुवू (500-750 मीटर) ने उच्चतम भविष्य कहनेवाला क्षमता प्रदर्शित की। केवल 20 मिमी/दिन की पहचानी गई सीमा मान, जिसे इंडोनेशिया में हल्की वर्षा के रूप में वर्गीकृत किया गया है, यह सुझाव देती है कि हालांकि CHIRPS आशाजनक है, लेकिन सैटेलाइट वर्षा को परिचालन भूस्खलन प्रारंभिक चेतावनी में पूरी तरह से लागू करने से पहले और अधिक शोधन की आवश्यकता है।

ABSTRACT. Early warning of landslides using remote sensing has received increasing attention in recent decades. However, in Luwu Raya, South Sulawesi, rainfall thresholds that trigger landslides remain poorly understood due to limited rainfall ground data. This study evaluates the suitability of the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) to determine landslide-triggering thresholds. This lack of understanding poses significant risks to local communities and infrastructure, making it crucial to identify reliable rainfall thresholds for landslide prediction and risk mitigation. Because satellite rainfall estimates have varying biases, both spatially and temporally, validation was performed

using observational data from 41 ground-based rainfall observation as reference data for 2019–2024 against CHIRPS. Accuracy was assessed using RMSE, a dichotomous metric, and extreme rainfall indices. Rainfall thresholds were derived by event-based matching between the landslide inventory and CHIRPS rainfall, followed by curve analysis of daily rainfall combined with antecedent accumulations over 3, 5, 10, 15, 20, and 30 days. Thresholds were derived from curve analysis of accumulated rainfall (3–30 days) based on flood and landslide events. Results show that CHIRPS accuracy is lower in mountainous areas (>1000 m) than in lowlands. The most reliable threshold combined daily rainfall with 15-day antecedent rainfall, achieving 67% accuracy, while shorter accumulation (10 days) performed poorly (5%). Central Luwu (500–750 m) showed the highest predictive potential. The identified threshold of only 20 mm/day, categorized as light rainfall in Indonesia, suggests that while CHIRPS offers promise, further refinement is needed before satellite rainfall can be fully applied in operational landslide early warning.

Key words – Landslide, Early warning, Extreme, CHIRPS, Luwu Raya.

1. Introduction

Landslides caused by high-intensity rainfall threaten communities throughout the world (Dowling and Santi, 2014; Teja and Dikshit, 2019), whose frequency is increasing due to changing of atmospheric climate (IPCC, 2014). The risk level of landslide impacts can increase due to changes in land use, population density, and urbanization of residents in landslide-prone areas (Gian *et al.*, 2017; Brunetti *et al.*, 2018). The ability to predict the time and site of landslides that triggered by rainfall is a challenge and an effort to reduce the number of fatalities and other destructive impacts. Many efforts have been made to use rainfall threshold determination to mark the potential for landslides, such as rainfall intensity, and duration (Aleotti, 2004).

The mechanisms of soil characteristics and their triggering factors is the main key in predicting landslide events and developing the early warning system for landslides (Uhlemann *et al.*, 2016; Segoni *et al.*, 2018). Identifying changes in soil pore water that can move a land is very important, especially due to rainfall with a certain duration and intensity (Bogaard and Greco, 2016). Some research focuses on relation with the landslide events and rainfall characteristics (intensity and duration) (Rosi *et al.*, 2019; Guzzetti *et al.*, 2019). This method requires much information about material properties on the surface up to a certain depth, which is difficult and expensive to obtain the data (Robbins, 2016), therefore, investigations are typically limited to specific slopes or localized areas (Rossi *et al.* 2017). Meanwhile, empirically, the statistical landslide model only requires real time of data, landslide occurrence sites and total rainfall accumulation. This model requires complete inventory of landslide data, as well as sufficient rainfall temporally and spatially (Robbins, 2016; Tirani and Rabuffetti, 2010).

Generally in developing countries, rainfall data and detailed landslide data are very limited. Apart from being limited in location, temporal data availability is also minimal. Landslide data is only available after the event, and even then if the landslide that occurs becomes the center of attention and causes casualties. Meanwhile, rainfall data is generally only daily data, not hours or even

minutes. The remote sensing observation for rainfall estimates provides data that is wide in coverage, consistent and offers fine resolution (Marra *et al.*, 2014; Robbins, 2016). Generally, verification of satellite rainfall estimates is carried out by comparing pixels versus points where surface rainfall measurements are made and it has been shown that satellite rainfall products exhibit varying levels of accuracy (Liechti *et al.* 2012; Li *et al.* 2014; Moazamia *et al.* 2013; Xue *et al.* 2013; Prasetya *et al.* 2013; Hu *et al.* 2014; Rahmawati and Lubczynski 2018).

Several studies have used satellite rainfall data to examine how precipitation influences landslides, showing its potential for risk assessment. However, before being used for practical applications, satellite products were usually evaluated using statistical analysis with several parameters such as relative bias, root mean error, correlation coefficient or identification using the dichotomous method. Among these, the CMORPH (Climate Prediction Center MORPHing technique), CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), and IMERG (Integrated Multi-satellite Retrievals for Global Precipitation Measurement) datasets have gained prominence due to their widespread use and accessibility. CMORPH is a product of the NOAA Climate Prediction Center, utilizing a technique known as morphing to blend satellite-derived precipitation estimates with ground-based observations. This approach produces high-resolution (0.1°) rainfall estimates with global coverage and a focus on capturing both convective and stratiform precipitation patterns (Joyce *et al.*, 2004). CHIRPS was established at the University of California, Santa Barbara, through the work of the Climate Hazards Group and uses a blend of satellite imagery, station data, and topographic information to generate gridded precipitation estimates. Incorporating gauge-based observations allows CHIRPS aimed at improving rainfall estimates, particularly in data-scarce regions (Funk *et al.*, 2015). The latest remote sensing estimation product in tropical areas, IMERG is originating from NASA's Global Precipitation Measurement (GPM) mission, the product synthesizes data from multiple satellite platforms using advanced algorithms. Near-real-time rainfall estimates are provided by IMERG at a specified spatial resolution of 0.1°, facilitating the monitoring of worldwide precipitation

(Huffman *et al.*, 2010). Despite their widespread use, differences in methodologies and input data sources among CMORPH, CHIRPS, and IMERG can lead to variations in accuracy, particularly in regions with complex terrain or sparse ground observations. A comprehensive comparative analysis of these datasets is essential for understanding their strengths and limitations, thereby improving their utility in various applications and decision-making processes.

As part of the evaluation process, the Global Satellite Mapping of Precipitation Moving Vector employing the Kalman filter (GSMaP_MVK) and its rainfall estimates were found to be underestimated which may significantly affect in estimating heavy rain which results in floods and landslides (Setiawati, and Miura, 2016). Several evaluations of satellite products in Indonesia show that the accuracy of satellite rainfall estimates varies across locations and accumulation periods (Giarno, *et al.*, 2020a; Giarno, *et al.*, 2020b; Satyaningsih, *et al.*, 2023), and patterns need to be identified (Giarno, *et al.*, 2018).

Threshold values for landslides or ID can be done by applying a logistic regression model was applied to evaluate the influence of TRMM satellite estimates of rainfall with surface observation results (Robbins, 2016; Kirschbaum and Stanley, 2018; Brunetti *et al.*, 2010; He *et al.*, 2020; Monsieurs *et al.*, 2019). Rainfall data derived from TMPA (TRMM product) and IMERG (Integrated Multi-satellite Retrievals for GPM, Global Precipitation Measurement) show that this product performs better well in modeling the severe landslide disaster (Thakur *et al.*, 2020).

Landslide identification requires satellites with high spatial resolution because landslide areas are generally narrow and very local. One of the satellite rainfall estimation products that has high spatial resolution is CHIRPS which combines 0.05° spatial resolution of satellite and rainfall surface data. According to validation, this dataset demonstrates higher performance in tropical environments, while its accuracy is lower in dry and semi-arid regions (Bai, *et al.*, 2018; Macharia, *et al.*, 2020). Moreover, CHIRPS estimates are better in lowland areas than in highland areas (Shrestha, *et al.*, 2017). On a temporal scale CHIRPS rainfall estimation works well to estimate monthly and annual rainfall (Gao, *et al.*, 2018; Wu, *et al.*, 2019). CHIRPS data are widely used to analyze changes in rainfall during extreme event (Narulita, and Ningrum, 2018; Cavalcante, *et al.*, 2020; Cullen, *et al.*, 2022; Ayasha, and Bota, 2023). High rainfall is thought to be a key factor in landslide events, where due to the availability of long data, high resolution and its performance in various places is quite good, making CHIRPS an alternative to fill the gaps in surface rainfall

data (Cullen, *et al.*, 2022; Ahmed, *et al.*, 2023; Carmona, *et al.*, 2023). CHIRPS prediction accuracy for landslide events will increase by processing rainfall estimates data from remote sensing products by correcting the data with statistical methods (Gomez, *et al.*, 2023; Fang, *et al.*, 2023).

Landslide events in Indonesia are generally caused by high intensity and continuous rainfall on steep slopes and vulnerable soil (Liao *et al.*, 2010). Identification of landslides is carried out by monitoring land movement accompanied by determining critical rainfall thresholds (Fathani *et al.*, 2011). As part of the tropical maritime continent of Indonesia, South Sulawesi has high rainfall with various patterns (Giarno, *et al.*, 2012). The topography of this province is complex with most of it being mountains so it is prone to landslides (Nasiah, and Invanni, 2013; Sideng, *et al.*, 2018; Rasyid, *et al.*, 2018; Soma, and Kubota, 2018; Nurdin, and Kubota, 2018; Ahmad, *et al.*, 2020; Gawing, *et al.*, 2023). Like other regions in Indonesia, the number of rain measuring equipment in this region is limited and the distribution is not homogeneous, so rain identification using remote sensing products such as satellites is necessary (Giarno, *et al.*, 2019a; Giarno, *et al.*, 2019b). The objective of this study is to identify critical rainfall thresholds in South Sulawesi, a region characterized by diverse rainfall patterns and complex topography.

2. Data and methodology

2.1. Research location and data

Luwu Raya, often referred to as Tana Luwu or Bumi Sawerigading, represents part of the historical legacy of the Luwu Kingdom in South Sulawesi Province. Administratively, the study area covers four regencies and one city. The region is made up of three regencies: Luwu, North Luwu, and East Luwu, and one city, Palopo. Located in the southern region of Sulawesi, Tana Luwu overlooks Bone Bay to the east and borders Poso Regency in Central Sulawesi to the north and Toraja Regency to the east. Mountains more than 3000 meters high protect the Luwu Raya area in the north and east, while in the south it faces Bone Gulf as shown at Fig. 1. The Luwu Raya area covers around 17,791 km², inhabited by more than 700,000 people. Its geographical diversity provides broad economic potential, especially in the agricultural sector with fertile land that produces various superior commodities such as cocoa, coffee, cloves, shrimp, seaweed and nickel ore. As part of South Sulawesi Province, Luwu Raya is prone to floods and landslide which regularly cause heavy rainfall. Typically, flood and landslide events occur due to high rainfall intensity and occur sequentially within a certain period of time. When rain occurs, it is usually preceded by rain with a certain

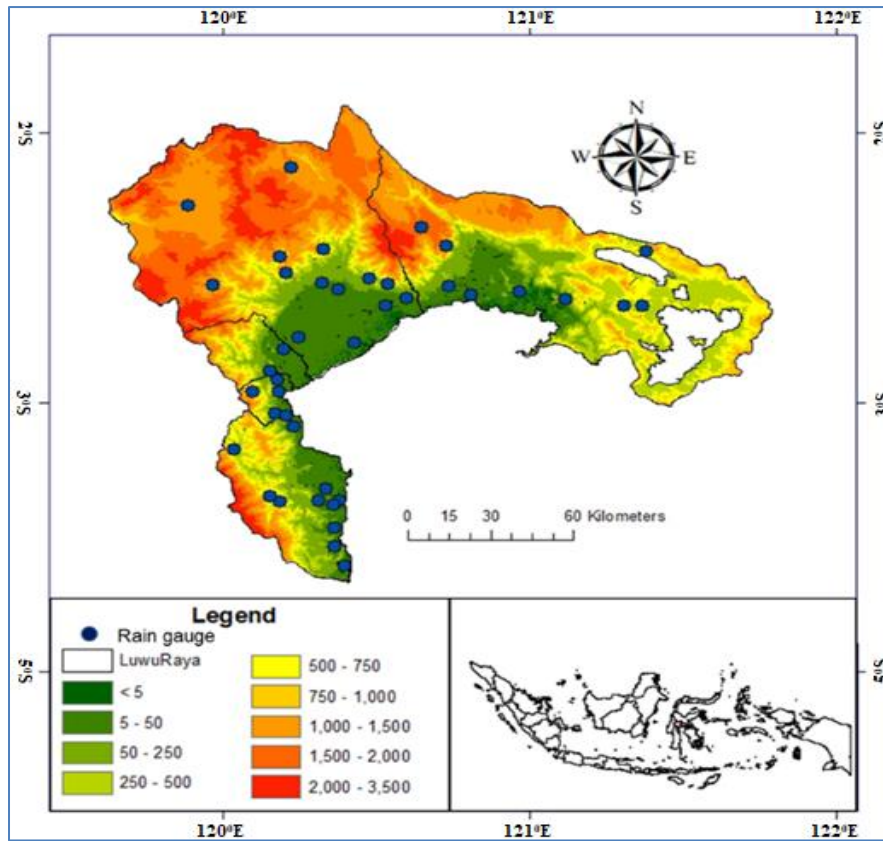


Fig. 1. Rain gauge locations and topography of Luwu Raya

intensity or continuous rainfall over an extended period. Furthermore, flooding and landslide is caused by various factors such as precipitation, geology, distance from faults, vegetation, and topography (Wang *et al.* 2017; Merz *et al.*, 2021). Apart from that, very high rainfall intensity or extreme rainfall is also an important consideration in the analysis of flood variability, and the current study of the frequency and rainfall intensity at flood events are increasing, especially due to affecting all climate regions and seasons (Dey *et al.*, 2019; Myhre *et al.*, 2019; Tabari, 2020).

The analysis was carried out to identify events and the potential for rain to result in landslides, so the data required to use is rainfall data throughout South Sulawesi. However, because in situ data is limited and data availability is not limited in duration, estimated data from satellites is used. This research uses CHIRPS version 2.0 daily rainfall estimates with has 0.05° (± 5.5 km) a spatial resolution (Joyce *et al.* 2004). This data can be accessed from the CHIRPS data set web page, <https://data.chc.ucsb.edu/products/CHIRPS-2.0/>. Meanwhile, the surface rainfall data used is data from 2008 to 2021, both rainfall data taken from data from the Meteorology, Climatology and Geophysics Agency ([https://dataonline.bmkg.](https://dataonline.bmkg.go.id/home)

<https://dibi.bnppb.go.id/>).

2.2. Comparison of CHIRPS rainfall estimates with surface rainfall measurements

Rainfall estimate CHIRPS were compared to surface measurement for assessing their performance with root means square error (RMSE) and mean absolute error (MAE) (Li *et al.*, 2014; Wehbe *et al.*, 2017). The RMSE and MAE were calculated for the period 2019 – 2024, by comparing the rainfall post data with the pixel closest to the rainfall post and calculated using equation (1)-(2)

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (CHIRPS_i - OBS_i)^2}{n}} \quad (1)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |CHIRPS_i - OBS_i| \quad (2)$$

where $CHIRPS_i$ is the rainfall estimate from satellites from CHIRPS, while OBS_i is the rainfall from surface measurements and n is the number of observation. The RMSE parameter is calculated to measure deviation

TABLE 1
Contingency Table Scheme used in the study

		Rainfall observation	
		Yes	No
Satellite	Yes	<i>hit</i> (a)	<i>false alarm</i> (b)
	No	<i>miss</i> (c)	<i>correct negative</i> (d)
	Total	a + c	b + d

satellite rainfall estimate from surface data. Both data has differences types, where surface data is point data and satellite data is in raster.

The comparison of the two values is carried out by selecting the location of the satellite rainfall estimate closest to the observation location. Another method used to measure CHIRPS performance is to use a dichotomous method which uses a contingency table to measure the agreement between CHIRPS rainfall estimates and observation results. There are 4 indicators to fill in Table 1, namely *hit*, *miss*, *false alarm* and *correct negative*.

A *hit* indicates that the CHIRPS estimate states it is raining, and in fact the OBS data also indicates rain, while a *miss* indicates that the CHIRPS estimate states it is not raining, while the OBS data states it is raining. Meanwhile, a *false alarm* indicates that the CHIRPS estimate states it is raining, and in reality the OBS data also shows no rain and *correct negative* if both state it is not raining. Based on the tabulation as in Table 1, it is called the dichotomous method and satellite estimation performance is measured using several indicators. Evaluation of rainfall estimation capability is quantified using the calculation of Proportion Correct (PC), Hit Rate or Probability of Detection (POD), False Alarm Ratio (FAR), Frequency Bias (BIAS), & Critical Success Index (CSI) values using the equations (A1)-(A5).

The presence of rain is identified if the rainfall is more than 0.5 mm/day, while if it is lower it is considered no rain. Obtaining analysis of the distribution of satellite estimation accuracy, the PC, FAR, BIAS, POD and CSI indicators are visualized using a map.

2.3. *Analysis of rainfall causing landslides*

Before calculating the landslide threshold, in each CHIRPS data grid, rainfall is calculated using the 95th or 95th percentile. Many studies use this value to limit rainfall considered extreme (Siswanto, et al., 2016; Gu, et al., 2023; Alexander, et al, 2023; Hariadi, et al., 2024; Li, et al., 2024). In this study, expanded identification of rain that results in floods or landslides based on daily rainfall accumulation (Chikalama, et al., 2020). Rainfall CHIRPS

estimates in daily are calculated into accumulating rainfall values every 1, 3, 15, 20, and 30 days. Accumulated rainfall during landslides or floods is considered based on the percentile of rainfall that is considered significant. Data on flood and landslide events identified location and time.

Based on this event data, the accumulated CHIRPS and OBS rainfall was calculated, the accuracy of which had previously been calculated using CHIRPS data. Based on the accumulated rainfall for 1, 3, 15, 20, and 30 days, graphs were made to obtain a linear equation for the relationship between daily rainfall & accumulated rainfall.

$$RRR_{day} = aRRR_{day-i} + b \tag{3}$$

where RRR_{day} is rainfall during a flood or landslide and RRR_{day-i} is the accumulated rainfall for 1, 3, 15, 20, and 30 days. The evaluation of performance of landslide thresholds was based on positive predictive power (PPP), Negative predictive power (NPP), Sensitivity (true positive rate), & Specificity (true negative rate) (Begueria, 2006; Lagomarsino et al., 2015; Martelloni et al., 2012):

(i) PPP is the proportion of truly positive outcomes formulated by

$$PPP = \frac{TP}{FP+TP} \tag{4}$$

where TP or true positives of phenomenon identified by model, and true negatives (TN) are observations or models where no phenomenon occurs. While false positives (FP) are phenomenon classified by model but not happened and false negatives (FN) are phenomenon occurred but the model not clarified. The perfect score of PPP is 1

(ii) Negative predictive power (NPP) is proportion of predicted negatives that are true negatives.

$$NPP = \frac{TN}{FN+TN} \tag{5}$$

(iii) Sensitivity is the proportion of positives (phenomenon such as flood or landslide) that are correctly classified.

$$Sensitivity = \frac{TP}{TP+TN} \tag{6}$$

(iv) Specificity is the proportion of days without flood or landslides that are correctly classified.

$$Specificity = \frac{TN}{TN+FP} \tag{7}$$

(v) Accuracy is a measure of overall model performance by calculating the proportion of correct predictions in total.

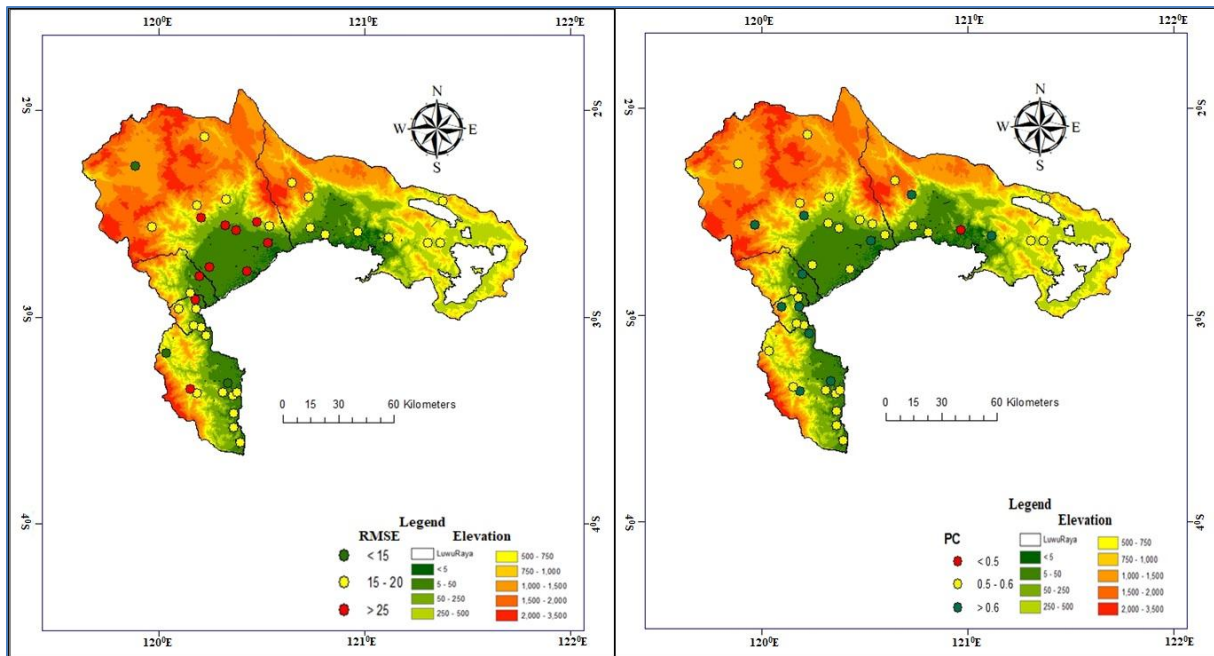


Fig. 2. RMSE and percent correct (PC) of CHIRPS

$$Accuracy = \frac{TP+TN}{FP+TN+TP+TN} \times 10 \quad (8)$$

3. Results and discussion

3.1. CHIRPS accuracy

The average deviation or root mean square error (RMSE) of CHIRPS rainfall estimates against the results of rainfall measurements on the surface of the Luwu Raya area is 18.572. A pattern of RMSE accuracy distribution was found where the lowland area of central Luwu Raya had a higher deviation of satellite rainfall estimates compared to other places. The RMSE value in the area is more than 25 mm, while the surrounding areas have lower accuracy. Interestingly, the smallest RMSE value is in the mountains with an elevation of more than 700 meters as shown in Fig. 2.

The suitability of the rainfall event estimates of CHIRPS data respect to rain surface observations for the research location summarized in percent correct (PC) is shown in Fig. 2. The mountain locations which elevations of more than 1000 meters have lower accuracy compared to lowland areas. PC values in the mountains are generally between less than 0.6 or 60%, while lower elevation areas vary but areas close to the sea are relatively higher.

The suitability of the rainfall estimates for locations in Luwu Raya in lowland areas in adjacent places has a slightly different PC value even though the distance is close. This can happen if the rainfall events are very dynamic. The error in the CHIRPS rainfall estimation due

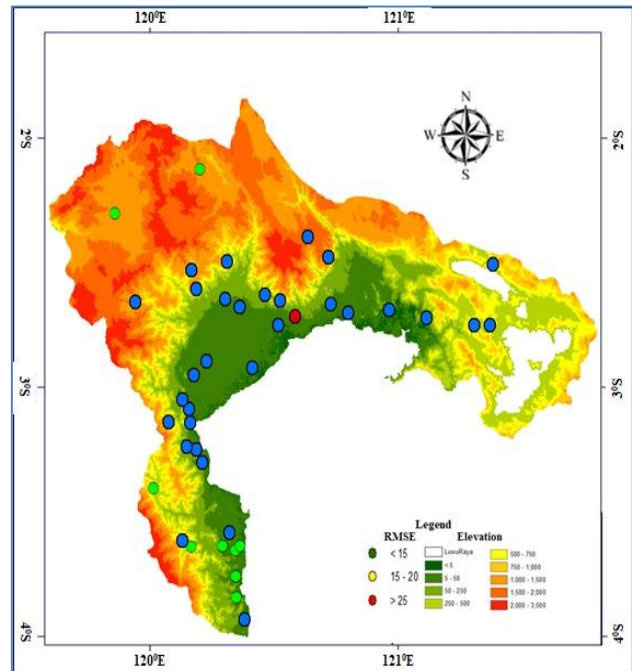


Fig. 3. Distribution MAE of CHIRPS

to the estimate stating rain when it did not rain or false alarms can be seen in the distribution of FAR values which are getting closer to 0 as shown in Fig. 4. Areas with elevations of more than 1000 meters and coastal areas in Bone Bay have FAR values of more than 0.6. Meanwhile, FAR values of less than 0.3 are generally located in the central part of Luwu Raya which has an altitude of 500 - 750 meters above sea level. Compared to the FAR value,

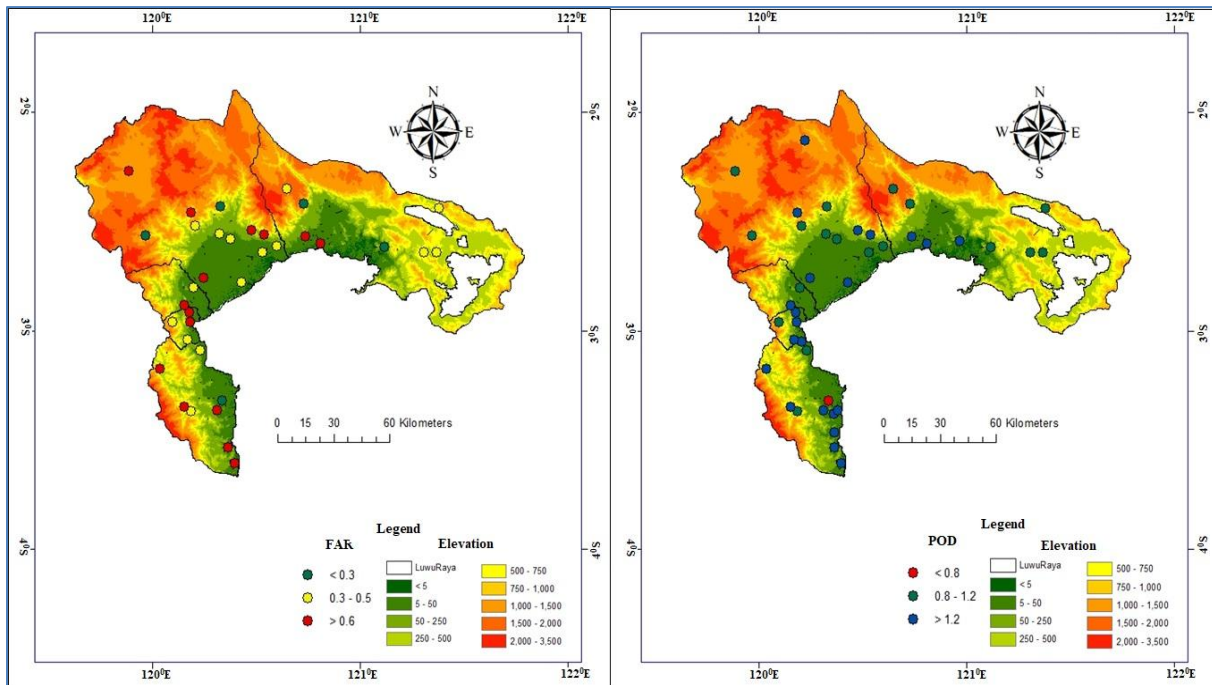


Fig. 4. FAR and POD of CHIRPS

the POD calculation which is a comparison of the number of hits and misses shows a high number of hits in Luwu Raya, especially in areas near the coast as shown in Fig. 3.

The highest RMSE values are mostly found in areas with elevations below 50 meters; however, in the northern part of Luwu Regency, where elevations exceed 1,000 meters, RMSE values also exceed 25. Interestingly, locations with RMSE values greater than 25 are sometimes adjacent to areas with values below 15, indicating that rainfall variability can be very high even over short distances. In contrast, MAE, which represents the average absolute deviation, shows the lowest values in the southern part of Luwu Regency, while areas near Bone Bay have moderate values ranging between 10 and 15 (Fig. 3). This suggests that, although RMSE highlights relatively high CHIRPS estimation errors in Luwu, the errors are still proportional to the actual rainfall amounts.

POD value of more than 1 in the lowlands indicates a greater proportion of hits compared to misses as shown in Fig. 4. In this location, the CHIRPS product is quite capable of being used to estimate rainfall events. While for mountainous areas the value is between 0.8 and 1.2 where the number of hits is slightly more than missing events.

Meanwhile, the distribution of the proportion of the number of errors due to false alarms and missing events can

be seen in the BIAS value in Fig. 4. A fairly contrasting difference was found between the mountains and lowlands, where in locations with low elevations the BIAS value is more than 1.2, which means that the number of false alarms is greater than missing. While in mountainous areas with elevations of more than 1000 meters, the BIAS value is between 0.8 - 1.2, which means that the number of both false alarm and missing errors is balanced.

The ability of CHIRPS to estimate rainfall events compared to two types of errors, namely missing and false alarm, is quite high. Using the CSI indicator shows a value of more than 0.3, with a CSI value of more than 0.5 found in the central part of Luwu Raya as shown in Fig. 5. At least the number of hits for this rainfall estimate is comparable to the number of errors due to false alarms and missing.

3.2. Extreme distribution of CHIRPS rainfall estimates

Rainfall distribution calculations based on the 95th, 96th, 97th, 98th, 99th, and 100th percentiles show higher values in the northern part of the study area. At the 95th percentile, most of the extreme rainfall values range between 20–30 mm/day, which then increase to 30–50 mm/day at the 97th percentile. In Luwu Raya, the highest rainfall values are observed in the lowland areas near Bone Bay, which experience more intense extreme rainfall compared to the northern mountainous region, as illustrated in Fig. 6.

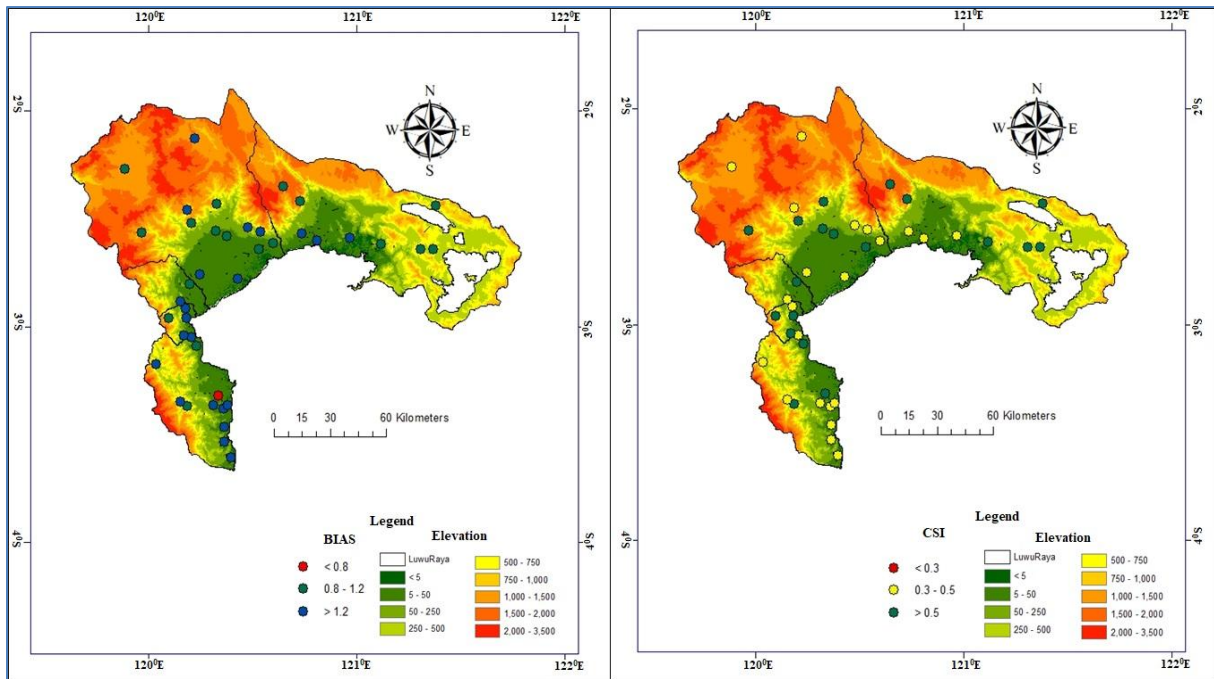


Fig. 5. BIAS and CSI of CHIRPS

Although generally the extreme rainfall values are percentile in the lowland areas south of Luwu Raya, this pattern changed in the 99th. In the central part of the Luwu Raya area and the southern part of this region, extreme rainfall values increase to 50-75 mm/day. A densely populated residential area is located in this location so you need to be wary of high rainfall because it makes this area prone to flooding and landslides.

3.3. Threshold of CHIRPS rainfall estimates for landslide

By utilizing the average daily rainfall, and landslide reports, it is then used to determine the rainfall threshold for the onset of landslides. Landslide data consists of 2 types of reports, namely floods and landslides that occur together and landslide reports alone throughout Greater Luwu. The cumulative rainfall threshold (CT) when a landslide occurs uses data from 2019 to 2024 using a linear formulation on the relationship between accumulated rainfall at the time of the landslide and accumulated rainfall for 3 days, 5 days, 10 days, 15 days, 20 days and 30 days as shown in seen in Fig. 7.

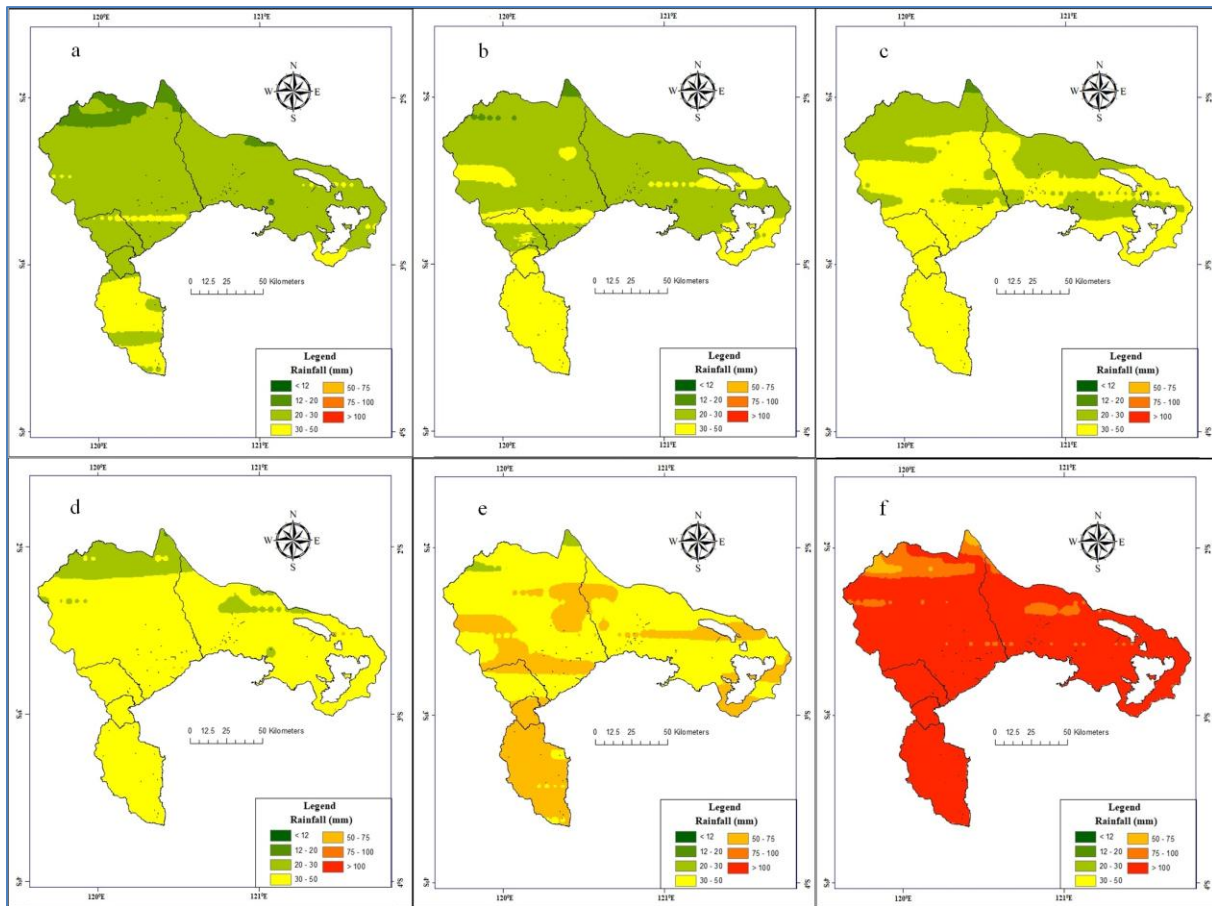
Based on the CT threshold formulation, the rainfall threshold values obtained were 13 mm/day, 15, mm/day 17 mm/day, 20 mm/day, 13 mm/day, and 8 mm/day. Compared with the extreme value percentiles in subsection 3.2, the rainfall threshold below the 95th percentile. Extreme rainfall at the percentile in most of Luwu Raya is

20–30 mm/day and 20 mm/day is the lower limit of the 95th percentile. While the accumulated rainfall in the previous 3 days, 5 days, 10 days, 15 days, 20 days and 30 days before the landslide occurred was 29 mm/day, 35 mm/day, 70 mm/day, 100 mm/day, 150 mm/day and 300 mm/day.

Compared to the CT value limits vary with the duration of the day, where CT at 15 days is the highest compared to other CT limits. While the accumulation of rainfall increases respect to duration of rain as Fig. 6. Based on CHIRPS data on landslides and rainfall, it was found that two landslides occurred below the rainfall threshold in 5 days and 10 days rainfall accumulation and one landslide occurred below the rainfall threshold in 15 days, 20 days and 30 days rainfall accumulation, but there were reported landslides. These landslides were probably not caused by rainfall.

3.4. Evaluation of rainfall thresholds

The trial of CT rainfall thresholds that result in landslides using CHIRPS estimated rainfall data in Luwu Raya using data on the month when the landslide occurred from 2019 to 2024, the results are summarized in Table 1. The best accuracy uses a 15-day rainfall threshold with an accuracy of 67%, while the 30-day threshold accuracy is only 29%. However, the 15-day accuracy is almost the same as the 10-day accuracy with a difference of 5%, which shows that the 10-day CT rainfall threshold can be used for estimating rainfall that results in landslides.



Figs. 6(a-f). The 95th(a), 96th(b), 97th(c), 98th(d), 99th(e), and 100th(f) of rainfall

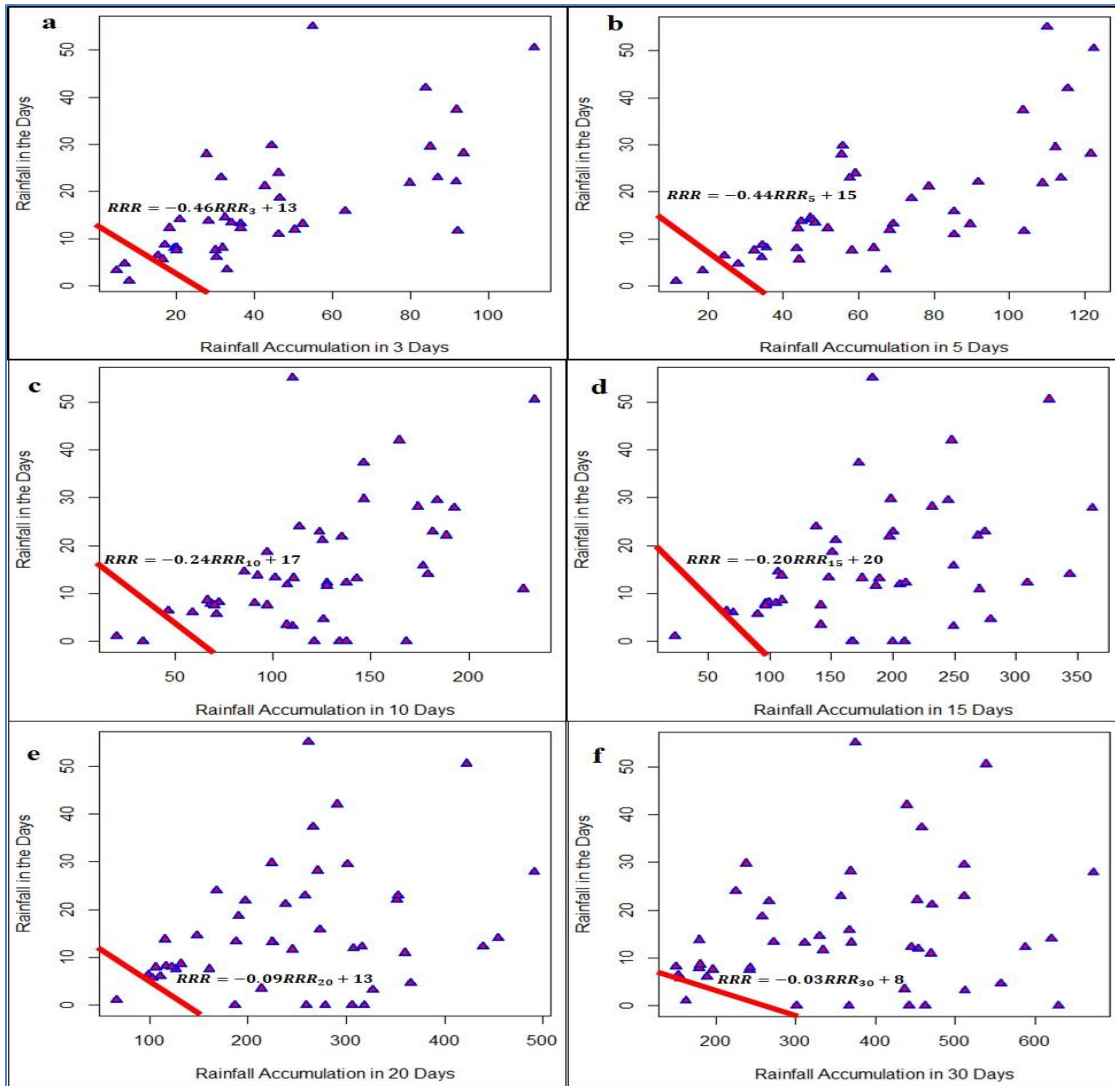
Compared with other rainfall thresholds using other parameters, CT rainfall threshold of 15-day has better accuracy. Based on the PPP, NPP, Sensitivity, and Specificity values, the rainfall threshold of 15-day is closer to 100% compared to the rainfall threshold. The weakness of CT rainfall threshold of 15-day lies in the sensitivity indicator which is only 36% which is the smallest value compared to CT rainfall threshold. Based on the formulation of PPP and sensitivity indicators, CT rainfall threshold of 15-day makes more false alarm and missing errors than hits. Based on the calculations in Table 2, it also shows that the higher the rainfall threshold, the number of hits decreases.

3.5. Discussion

Landslide identification using satellites requires accurate satellite rainfall estimation accuracy. Although Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data in some places has better performance, especially in dry or semi-arid areas (Bai, *et al.*, 2018; Macharia, *et al.*, 2020), however, in highland areas the accuracy decreases (Shrestha, *et al.*, 2017). Based on the results of the CHIRPS accuracy calculation in Luwu Raya,

it shows that the accuracy in mountain areas with elevations of more than 1000 meters has lower accuracy compared to lowland areas. The error in the CHIRPS rainfall estimation occurs in false alarms and missing, where in the study in Luwu Raya, the average FAR and POD values were 0.3 and 0.8, respectively (Giarno, *et al.*, 2018; Fatkhuroyan, *et al.*, 2018). The calculation results of this research detail that the lowest number of errors due to false alarms occurred in the central part of Luwu Raya which has an altitude of 500 - 750 meters above sea level, while in the lowlands the number of hits was greater than the number of misses. Meanwhile, the distribution of the proportion of the number of errors due to false alarms and missing events fairly contrasts the difference between the mountains and lowlands, where in locations with low elevations the number of false alarms is greater than missing. While in mountainous areas with elevations of more than 1000 meters, the number of both false alarms and missed errors is balanced.

Landslide early warning identification can be done by monitoring ground movement and determining critical rainfall thresholds (Fathani *et al.*, 2011; Karnawati *et al.*, 2009). Based on rainfall distribution calculations using the



Figs. 7(a-f). The CT of rainfall on the day of the landslide on 3 days (a), 5 days (b), 10 days (c), 15 days (d), 20 days (e), 30 days (f) rainfall accumulation

TABLE 2

Accuracy rainfall thresholds based on CHIRPS rainfall estimates

Threshold	Predicted	Observed		PPP(%)	NPP(%)	Sensitivity(%)	Specificity(%)	Accuracy(%)
		Landslide	No Landslide					
3 days	Landslide	24	81	23%	80%	57%	47%	49%
	No Landslide	18	71					
5 days	Landslide	17	65	21%	78%	40%	57%	54%
	No Landslide	25	87					
10 days	Landslide	16	47	25%	80%	38%	69%	62%
	No Landslide	26	105					
15 days	Landslide	15	37	29%	81%	36%	76%	67%
	No Landslide	27	115					
20 days	Landslide	24	81	23%	80%	57%	47%	49%
	No Landslide	18	71					
30 days	Landslide	32	128	20%	71%	76%	16%	29%
	No Landslide	10	24					

95th, 96th, 97th, 98th, 99th, & 100th percentiles compared to the accuracy of the cumulative rainfall (CT) threshold, the most realistic threshold is the 95th percentile. However, the experimental values of the CT rainfall threshold were obtained were 13 mm/day, 15, mm/day 17 mm/day, 20 mm/day, 13 mm/day, & 8 mm/day for the accumulation of previous rainfall 3 days, 5 days, 10 days, 15 days, 20 days and 30 days. Compared to the rainfall threshold limit that resulted in landslides in Java with a minimum value of 50 mm/day (Chikalamo, *et al.*, 2020), the CT rainfall threshold in Luwu Raya is lower. Unlike previous studies that only compared it at the time of the landslide, the calculation in Luwu Raya calculates all CHIRPS rainfall estimates whose accumulation meets the limit before the landslide occurred in the same month. For example, rainfall of 20 mm/day often occurs in the Luwu Raya area with an accumulation of 15 previous rainy days of 100 mm.day and not all of them experience landslides. As an area with active convection activity throughout the year, even rain with an intensity of 20-50 mm/day is included in the light rain category. Based on the present correct (PC) value where the highest value of the indicator is at an elevation of less than 700 meters and several places have quite high PC values at elevations of 500-700 meters, the CT rainfall threshold value using CHIRPS can be used in mountainous areas at that elevation.

4. Conclusions

Calculations using CHIRPS data show that this satellite data estimate can be used as input for rainfall thresholds that result in potential landslides. By calculating the accumulation of daily rainfall and rainfall for several days before and the time of landslides in Luwu Raya, it can be concluded that landslides are best predicted using a combination of daily rainfall & previous rainfall for 15 days with an accuracy of 67%, higher than the accuracy of the thresholds of 3, 5, 10, 20 and 30 days. However, the combination of daily rainfall & previous rainfall for 10 days needs to be considered because the accuracy is only 5% different than the combination of daily rainfall and previous rainfall for 15 days. Some inaccuracies that occur may relate to the inventory of landslide event dates, which will not be reported in uninhabited areas. The CHIRPS accuracy in Luwu Raya showed that in mountain areas with elevations of more than 1000 meters had lower accuracy compared to lowland areas. The higher number of missing compared to hits allows landslide events to occur but rainfall cannot predict it needs to be considered. The calculation of CT rainfall thresholds accumulation in the central part of Luwu Raya which has an altitude of 500-750 meters above sea level is very potential because its accuracy is higher. good compared to other areas. The CT rainfall threshold value of only 20 mm/day is very common in Indonesia, where 20-50 mm/day is included in the light rain category.

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Appendix

$$PC = \frac{\text{Hits} + \text{Correct Negatives}}{\text{Total}} \quad (\text{A1})$$

$$POD = \frac{\text{Hits}}{\text{Hits} + \text{Misses}} \quad (\text{A2})$$

$$FAR = \frac{\text{False Alarms}}{\text{Hits} + \text{False Alarms}} \quad (\text{A3})$$

$$BIAS = \frac{\text{Hits} + \text{False Alarms}}{\text{Hits} + \text{Misses}} \quad (\text{A4})$$

$$CSI = \frac{\text{Hits}}{\text{Hits} + \text{False Alarms} + \text{Misses}} \quad (\text{A5})$$