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# Comparison of the accuracy of four satellite rainfall estimates during the rainy season, dry season and transition in South Sulawesi which has complex topography

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**सार** – इंडोनेशिया में वर्षामापी (रेनगेज) स्टेशनों का विरल वितरण उपग्रह-आधारित उत्पादों द्वारा पूरक किया जा सकता है। हालांकि, इस क्षेत्र में वर्षा की अत्यधिक गतिशील और यादृच्छिक प्रकृति के कारण, इन वर्षा आकलन डाटासेट्स की सटीकता का मूल्यांकन करना अत्यंत आवश्यक है। क्लाइमेट हैज़र्ड्स ग्रुप इन्फ्रारेड प्रीसिपिटेशन विद स्टेशन डेटा (CHIRPS), ग्लोबल प्रीसिपिटेशन क्लाइमेटोलॉजी प्रोजेक्ट (GPCP), ग्लोबल सैटेलाइट मैपिंग ऑफ प्रीसिपिटेशन (GSMaP) तथा ग्लोबल प्रीसिपिटेशन मेज़रमेंट हेतु इंटीग्रेटेड मल्टी-सैटेलाइट रिट्रीवल्स (IMERG) ग्रिडेड वर्षा उत्पादों की सटीकता का आकलन करने के लिए रूट मीन स्क्वेयर एरर (RMSE) और द्विविकल्पी प्रदर्शन सूचकांकों–जैसे पोर्शन करेक्ट (PC), फॉल्स अलार्म रेशियो (FAR), बायस स्कोर (BIAS), प्रॉबेबिलिटी ऑफ डिटेक्शन (POD) तथा क्रिटिकल सक्सेस इंडेक्स (CSI)–का उपयोग कर संख्यात्मक तुलना की गई।40 वर्षों के आँकड़ों के विश्लेषण से पता चला कि उपग्रह उत्पादों की सटीकता दक्षिण सुलावेसी प्रांत के दक्षिणी भाग में, विशेष रूप से पश्चिमी तट के साथ, सबसे अधिक थी। दक्षिणी क्षेत्र की सटीकता उत्तरी भाग की तुलना में बेहतर रही, जबकि पश्चिमी क्षेत्र पूर्वी क्षेत्र से अधिक सटीक पाया गया। उपग्रह-आधारित वर्षा आकलनों की सटीकता स्थान और समय दोनों के अनुसार भिन्न पाई गई; अधिक वर्षा की अवधि (जैसे वर्षा ऋतु के चरम पर) में RMSE मान बढ़े और शुष्क ऋतु के दौरान घटे। द्विविकल्पी मेट्रिक्स से यह संकेत मिला कि चूक की तुलना में फॉल्स अलार्म की दर अधिक थी। मूल्यांकित उत्पादों में CHIRPS ने सबसे सुसंगत प्रदर्शन दिखाया और इसकी सटीकता सर्वोत्तम प्रेक्षित मानों के निकट रही। कुल मिलाकर, CHIRPS का प्रदर्शन अन्य उपग्रह उत्पादों से बेहतर रहा, इसके बाद IMERG, GPCP और GSMaP का स्थान रहा। यह प्रदर्शन क्रम उनके स्थानिक विभेदन (स्पैशियल रेज़ोल्यूशन) के अनुरूप था–जहाँ CHIRPS का विभेदन सबसे अधिक (0.05°), IMERG और GSMaP का मध्यम (0.1°) तथा GPCP का सबसे कम (2.5°) था। हालांकि, यह क्रम विभिन्न समयों और स्थानों के अनुसार बदल सकता है, जिससे प्रत्येक विशिष्ट अनुप्रयोग और अवधि के लिए पुनर्मूल्यांकन की आवश्यकता स्पष्ट होती है।

**ABSTRACT.** The sparse distribution of rainfall gauges in Indonesia can be supplemented with satellite-based products. However, due to the highly dynamic and stochastic nature of rainfall in the region, it is essential to evaluate the accuracy of these rainfall estimation datasets. To assess the accuracy of the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Global Precipitation Climatology Project (GPCP), Global Satellite Mapping of Precipitation (GSMaP), and Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG) gridded rainfall products, numerical comparisons using root mean square error (RMSE) and dichotomous performance indicators—such as portion correct (PC), false alarm ratio (FAR), bias score (BIAS), probability of detection (POD), and critical success index (CSI)—were conducted. An analysis of 40 years of data revealed that the accuracy of satellite products was highest in the southern part of South Sulawesi Province, particularly along the west coast. The southern region exhibited better accuracy than the northern part, while the western area outperformed the eastern region. The accuracy of satellite-derived rainfall estimates varied by both location and time, with RMSE values increasing during periods of high rainfall (e.g., at the peak of the rainy season) and decreasing during the dry season. Dichotomous metrics indicated a higher rate of false alarms than missed detections. Among the evaluated products, CHIRPS demonstrated the most consistent performance, maintaining accuracy close to the best observed values. Overall, CHIRPS outperformed the other satellite products, followed by IMERG, GPCP, and GSMaP. This performance ranking corresponded closely to their spatial resolutions, with CHIRPS having the highest resolution (0.05°), followed by IMERG and GSMaP (both 0.1°), and GPCP with the coarsest resolution (2.5°). However, this ranking may vary across different times and locations, highlighting the need for re-evaluation for each specific application and period.

**Key words** – Tropic, Sulawesi, Accuracy, Rainfall, Satellite.

## 1. Introduction

Indonesia is located in a tropical region and consistently receives solar radiation year-round, keeping the area perpetually warm. In addition, the Indonesian Maritime Continent is surrounded by two large oceans and two continents, which causes convection activity to occur throughout the year (Seto *et al.*, 2004; Safril, 2020). Rainfall variability determines the definition of seasons in Indonesia (Tjasyono, 2004). The rainy season is characterized by high rainfall, while the dry season is marked by low rainfall. The uniqueness of Indonesia's geographical location makes it susceptible to global circulation patterns such as the El Niño-Southern Oscillation (ENSO), Madden-Julian Oscillation (MJO), and Indian Ocean Dipole (IOD) (D'Arrigo and Wilson, 2008; Hidayat and Kizu, 2010; As-syakur, 2010; Lee, 2015; Supari *et al.,* 2017; Mulsandi *et al.,* 2021). Local factors, such as the diverse distribution of land and sea and the country's unique topography, also influence rainfall patterns (Giarno *et al.,* 2023).

The number of rainfall gauges in Indonesia remains relatively low and still requires significant augmentation (Giarno *et al.*, 2021; Sunusi and Giarno, 2022; Sunusi and Giarno, 2023). Rainfall estimation using remote sensing technologies, such as satellites, has become an alternative solution to address the gap in rainfall observations (Brunetti *et al.*, 2018; Rahmawati *et al.*, 2021). Advances in satellite technology and sophisticated retrieval algorithms have led to the development of several global rainfall estimation products that are considered fairly reliable in both spatial and temporal dimensions (Joyce *et al.*, 2004; Dinku *et al.*, 2007; Peters-Lidard *et al.,* 2007; Huffman *et al.*, 2007; Skinner *et al.,* 2015; Misnawati, 2019). Among the most widely used and accessible products are CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), Global Satellite Mapping of Precipitation (GSMaP) and IMERG (Integrated Multi-satellite Retrievals for GPM – Global Precipitation Measurement) (Joyce *et al.*, 2004; Huffman *et al.*, 2007; Funk *et al.*, 2015). Variations in methodologies and input data sources can lead to differences in accuracy, especially in regions with complex terrain or sparse ground observations (Giarno, *et al.*, 2018a; Giarno, *et al.*, 2018b; Giarno, *et al.*, 2018c; Giarno, *et al.*, 2020a; Giarno, *et al.*, 2020b).

In tropical regions, comparisons between CHIRPS and other satellite products in Indonesia have demonstrated its notable accuracy in specific provinces such as Yogyakarta (Rahmawati *et al.*, 2021), Bali (Liu *et al.*, 2020), East Java (Faisol *et al.*, 2020; Wiwoho *et al.*, 2021), East Nusa Tenggara (Gerland *et al.,* 2023), and across the Indonesian archipelago (Wati *et al.*, 2021; Asferizal, 2022). The accuracy of CHIRPS has also been evaluated independently-without comparison to other products-in various locations, showing commendable performance (Faisol and Paga, 2021; Budiyono and Faisol, 2021; Saragih *et al.*, 2022; Suryanto *et al.*, 2023; Wahyuni *et al.*, 2021; Hastina *et al.*, 2023; Simanjuntak *et al.*, 2024). The widespread application of CHIRPS for drought monitoring is attributed to its high resolution and extensive data record (Narulita *et al.*, 2021; Faisol *et al.*, 2021; Viddaroini *et al.,* 2023).

Meanwhile, IMERG rainfall estimates have demonstrated low accuracy at daily and annual timescales but have shown improved performance on the monthly scale (Hutagaol *et al.*, 2023). Another validation study indicated that IMERG accuracy was not uniform across locations (Ningsih *et al.*, 2023). Generally, IMERG tends to overestimate rainfall and is influenced by season and topography (Ramadhan *et al.*, 2022a; Ramadhan *et al.*, 2022b). Other satellite products frequently used in Indonesia show that their accuracy varies significantly depending on region, season, and topography. In Bali and Nusa Tenggara, GSMaP demonstrated a strong correlation with observed data, although it tended to underestimate rainfall (Duwanda & Sukarasa, 2021), while in Aceh, accuracy was low during the dry and transitional seasons but improved during the rainy season. Validation across areas with different rainfall patterns indicated that GSMaP was able to capture seasonal variability, such as monsoons and the Madden-Julian Oscillation (MJO), although it generally underestimated observed rainfall (Fitria *et al.*, 2016). In mountainous regions, GSMaP often overestimated rainfall and exhibited lower accuracy compared to lowland areas (Fatkhuroyan & Trinahwati, 2018). Additionally, a flood simulation study in Jakarta found that while GSMaP reliably represented historical rainfall patterns, it was less accurate in near-real-time applications (Sayama *et al.*, 2021). These findings highlight the importance of local validation and the careful temporal application of satellite-based rainfall products such as IMERG and GSMaP in climate and hydrological studies in Indonesia.

National Aeronautics and Space Administration's (NASA) of Mesoscale Atmospheric Processes Laboratory collects monthly rainfall data through the Global Precipitation Climatology Project (GPCP), which combines surface measurements with satellite data into 2.5° × 2.5° gridded datasets, available from 1979 onward. While GPCP data are used for global phenomenon analysis, they require corrections for seasonal and locational variability (Schneider *et al.*, 2014; Fuchs *et al.*, 2001; Becker *et al.*, 2013; Schneider *et al.*, 2016; Schneider *et al.*, 2017). Despite its long temporal coverage and global accessibility, the coarse resolution of GPCP data often limits its applicability and evaluation at regional scales.

Comparative evaluations have shown that all satellite rainfall estimates have limitations, with errors increasing at higher rain rates (Wiwoho *et al.*, 2021). However, CHIRPS performed better than GPM in detecting light rainfall, while GPM was more effective in identifying extreme rainfall events (>40 mm/day). Other studies have shown that estimation accuracy tended to be lower during dry seasons, in overseas and mountainous areas, and in regions with complex topography (Rahmawati *et al.*, 2018; Pratama *et al.*, 2022). Overall, CHIRPS has been considered more reliable for use in Indonesia compared to other products (Wati *et al.*, 2022). During extreme rainfall events such as cyclones, CHIRPS exhibited a lower RMSE compared to GSMaP (Faisol *et al.*, 2020; Gerland *et al.*, 2023), and demonstrated better precision in East Java (Faisol *et al.*, 2020). In contrast to CHIRPS which tends to underestimate light rainfall and has better accuracy on the monthly scale (Wiwoho *et al.*, 2021), GSMaP tends to overestimate during light rainfall events (Ramadhan *et al.*, 2023) and has poor accuracy in mountainous areas ((Fatkhuroyan and Trinahwati, 2018). Although IMERG has higher performance at daily, penta-daily, and seasonal time scales, it overestimates the high altitude Bali Island compared to GSMaP and CHIRPS (Liu *et al.*, 2020). Meanwhile, evaluation of GPCP rainfall estimates was still limited, where the accuracy was low on a daily scale and increased compared to 5 weeks. Rain events above 60 mm/day were often not detected (Jaenicke, *et al.*, 2011).

Several studies have assessed the performance of satellite-based rainfall products in Indonesia (Faisol *et al.*, 2020; Wiwoho *et al.*, 2021; Ramadhan *et al.*, 2023; Fatkhuroyan & Trinahwati, 2018; Liu *et al.*, 2020). However, most of these findings emphasize region-specific characteristics without providing a comprehensive cross-comparison. To address this gap, the present study conducts a detailed comparative analysis of CHIRPS, GSMaP, GPCP, and IMERG, focusing on their relative accuracy in South Sulawesi-a region characterized by highly diverse topography. This region is characterized by multiple distinct rainy season patterns, and the timing of hydrometeorological disaster occurrences varies accordingly (Arifin & Kartikaningrum, 2020; Giarno, *et al.*, 2020b; Bongi, *et al.*, 2020; Zhiddiq, *et al.*, 2023; Oktavianur, 2024). As such, the need for reliable and spatially comprehensive rainfall data can only be met through satellite-derived rainfall estimation products. The findings underscore the importance of validating satellite products across different terrains and temporal scales to support more informed decision-making in climate and water resource management.

## 2. Data and methodology

### 2.1. *Location and data*

This research focused on South Sulawesi Province, which comprises 21 regencies and 3 cities, covering an area of 62,482.54 km². It is bordered to the north by Central Sulawesi and West Sulawesi, to the east by the Gulf of Bone and Southeast Sulawesi, to the west by the Makassar Strait, and to the south by the Flores Sea. According to BPS data, the population of South Sulawesi was 9,312,019 in 2023 (BPS, 2024). Several sectors in South Sulawesi are affected by rainfall conditions, including the cultivation of rice, corn, cocoa, coffee,

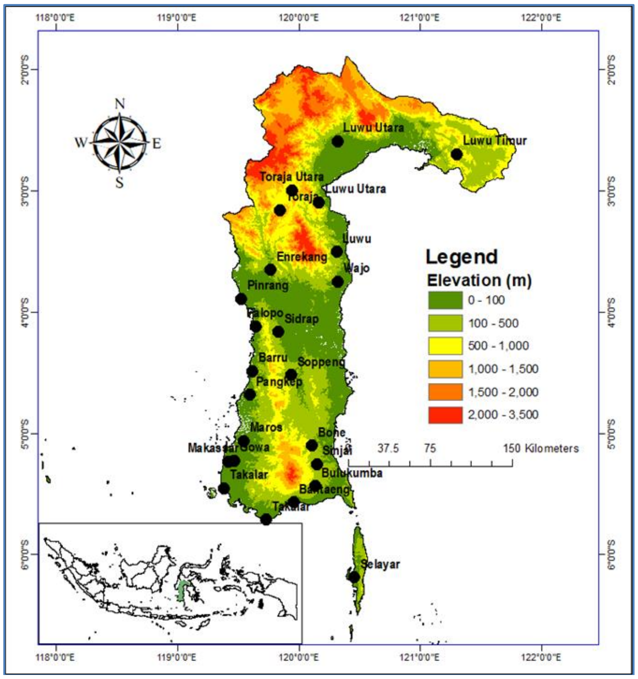



**Fig. 1.** Topography of the study region, South Sulawesi and the black dots represent rain gauge locations

cloves, and nutmeg, as well as livestock, fisheries, and forestry. The tourism sector, promoted through slogans such as "Visit Indonesia" and "Visit South Sulawesi," is also influenced by rainfall variability. Uncertain weather conditions can lead to a decline in tourism productivity, despite the government's efforts to attract foreign visitors (Hariadi & Malau, 2019).

The rainfall data used in this study were collected from 24 locations representing regencies across South Sulawesi Province, as shown in Fig. 1. The regencies in South Sulawesi include Makassar, Palopo, Pare-pare, Selayar, Bulukumba, Bantaeng, Jeneponto, Takalar, Gowa, Maros, Barru, Bone, Sinjai, Pangkajene dan Kepulauan (Pangkep), Soppeng, Wajo, Luwu, Luwu Timur (Lutim / East Luwu), Luwu Utara (Luwut / North Luwu), Sidrap, Tana Toraja (Tator), Toraja Utara (Torut / North Toraja), Enrekang, and Pinrang. Daily rainfall records were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) for the period from January 1, 1993 to December 31, 2022. Each regency is represented by one rainfall gauge station. Missing or problematic data were excluded from the analysis.

Four satellite-based rainfall estimation datasets were used for comparison with ground-based rainfall observations: the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS), Global Satellite Mapping of Precipitation (GSMaP), Integrated Multi-satellite Retrievals for GPM (IMERG), and Global Precipitation Climatology Project (GPCP). The CHIRPS dataset is available at https://www.chc.ucsb.edu/data/chirps, GPCP at https://www.ncei.noaa.gov/data/global-precipitation-climatology-project-gpcp-daily/, GSMaP at https://hokusai.eorc.jaxa.jp, and IMERG at https://gpm.nasa.gov/data/imerg. These four satellite products have unique characteristics and the results vary across locations in Indonesia as shown in Table 1.

In regions like Indonesia, where ground-based rainfall observations are sparse and topographic variation is high, satellite-based rainfall products are essential for hydrological and climate-related applications. However, differences in algorithmic design result in varied accuracy across regions. CHIRPS estimates rainfall using long-term relationships between infrared (IR) cloud-top temperatures and historical rainfall, blended with gauge data via kriging, which improves its performance for monthly totals and extreme events but tends to underestimate light rain (Faisol *et al.,* 2020; Wiwoho *et al.,* 2021). GSMaP combines passive microwave (PMW) and IR data using cloud motion vectors and a Kalman filter, which enhances temporal resolution but often leads to overestimation in light rain and poor accuracy in mountainous terrain (Ramadhan *et al.,* 2023; Fatkhuroyan & Trinahwati, 2018). GPCP merges satellite fields into a global precipitation product and applies bias corrections using gauge data, favoring spatial consistency but offering lower resolution (Jaenicke *et al.*, 2011). IMERG refines PMW data through morphing and Kalman smoothing, yielding higher accuracy at daily to seasonal scales, though it overestimates precipitation in high-altitude areas like Bali (Liu *et al.*, 2020). These differences emphasize the need for region-specific validation and careful product selection, which this study addresses through a comparative assessment of the four products across Indonesia. This study uses the daily temporal resolution produced by the four estimation products, while the comparison with observational data is carried out using the pixel closest to the rain gauge.

### 2.2. *Methodology*

The evaluation involved matching rainfall events recorded from ground-based measurements with estimates derived from satellite data. Rainfall estimates from CHIRPS, GSMaP, IMERG, and GPCP were extracted using the nearest neighbor method at the observation point locations, providing satellite-derived values based on geographic coordinates. These values were then statistically compared with ground observations (Mamenun *et al.*, 2014; Pai *et al.*, 2014; Prakash *et al.*, 2014; Giarno *et al.*, 2018a, 2018b, 2018c, 2020a, 2020b; Rahmawati *et al.*, 2020).

**TABLE 1**

**Comparison of characteristics of CHIRPS, GSMaP, IMERG, GPCP rainfall estimates products**

| Aspect | CHIRPS | GSMaP | GPCP | IMERG |
|---|---|---|---|---|
| **Spatial** | 0.05° (~5 km) | 0.1° (~10 km) | 2.5° (~250 km) | 0.1° (~10 km) |
| **Temporal** | Daily, pentad, monthly | 30 minutes, daily | Daily, monthly | 30 minutes, daily |
| **Latency** | Few days | ~4 hours (near-real time) | ~2 months | ~4, 12, 24 hours |
| **Algorithm** | Based on the relationship cloud temperature IR (infrared) + rainfall data history are obtained rainfall estimates. The estimation results are corrected and blended using kriging. | Rainfall estimates by combining passive microwave (PMW) and infrared (IR) data using cloud motion tracking and Kalman filter-based correction. | Satellite precipitation estimates are first combined into a unified global field, then spatially adjusted by calculating and applying bias corrections based on differences with rainfall data. | Spatial tracking of spatial shifts (morphing) to rainfall estimates from passive microwave (PMW), then using a Kalman smoother to smooth and correct biases. |
| **Data Sources** | Global satellite geostasioner (GOES, Meteosat, Himawari) from National Oceanic and Atmospheric Administration (NOAA), surface rain gauge from Global Precipitation Climatology Centre (GPCC), Global Historical Climatology Network (GHCN), and Famine Early Warning Systems Network (FEWS NET). | Sensor microwave from Tropical Rainfall Measuring Mission (TRMM), Global Precipitation Measurement (GPM), Advanced Microwave Scanning Radiometer 2 (AMSR2), Special Sensor Microwave Imager / Sounder (SSMIS), and limited gauges | Infra Red (IR) + microwave Special Sensor Microwave Imager (SSM/I), Advanced Microwave Scanning Radiometer E (AMSR-E), IR, dan High-Resolution Infrared Radiation Sounder (HIRS), and ground-based gauges | Global Precipitation Measurement (GPM) + satelit partner such as Special Sensor Microwave Imager / Sounder (SSMIS), Advanced Microwave Scanning Radiometer 2 (AMSR2), Microwave Humidity Sounder (MHS), passive microwave, and rain gauges |
| **Strengths** | Long record, gauge integration, ideal for climate studies | High temporal resolution, suitable for nowcasting | Long record, ideal for global climate analysis | High spatial / temporal resolution |
| **Limitations** | Coarse temporal resolution | Lower accuracy in complex terrain and light rain events | Very coarse spatial resolution, not ideal for local analysis | Early & late runs less accurate; final requires ~2 months |
| **Accuracy in Indonesian Region** | Smaller RMSE compared to GPM and GSMaP during extreme rain due to cyclones (Faisol *et al.*, 2020; Gerland *et al.*, 2023), more precise compared to GPM in East Java (Faisol *et al.*, 2020) and tended underestimate at slight rain and better accuracy in monthly (Wiwoho *et al.*, 2021) | Varying correlation strengths across temporal scales and tended overestimate in light rain event (Ramadhan, *et al.*,2023) and has poor accuracy in mountainous area ((Fatkhuroyan and Trinahwati, 2018). | Research was still limited, where the accuracy was low on a daily scale and increases compared to 5 weeks. Rain event above 60 mm/day was often not detected (Jaenicke, *et al.*, 2011) | Higher performance at daily, penta-daily, and seasonal time scales, but overestimated in high altitude Bali Island compared to GSMaP and CHIRPS (Liu *et al.*, 2020) |

Two evaluation approaches were employed: (1) numerical value comparison and (2) presence/absence comparison of rainfall events. A rainfall event was defined as precipitation exceeding 0.5 mm/day; otherwise, it was classified as a no-rain event. The number of correctly estimated rainfall events by satellites was termed as hits, while correct estimations of no-rain events were referred to as correct negatives. Conversely, satellite estimates indicating rain when no rain was observed were labeled as false alarms, and those indicating no rain when rain was observed were categorized as misses, as shown in Table 2. Based on the tabulation in Table 2, the method is referred to as the dichotomous method, and the performance of satellite estimation is measured using several indicators. The evaluation of rainfall estimation capability is quantified through the calculation of Portion Correct (PC), Hit Rate or Probability of Detection (POD), False Alarm Ratio (FAR), Frequency Bias (BIAS), and Critical Success Index (CSI) as defined in equations (1)-(5). This approach enables the assessment of not only how often satellite estimates match ground observations, but also how often they fail to detect rain or incorrectly predict it. These indicators are widely used in satellite validation studies due to their ability to represent different aspects of classification performance in a straightforward and interpretable manner.

$$PC = \frac{Hits + Correct\ Negatives}{Total} \tag{1}$$

$$POD = \frac{Hits}{Hits + Misses} \tag{2}$$

$$FAR = \frac{False\ Alarms}{Hits + False\ Alarms} \tag{3}$$

$$BIAS = \frac{Hits + False\ Alarms}{Hits + Misses} \tag{4}$$

$$CSI = \frac{Hits}{Hits + False\ Alarms + Misses} \tag{5}$$

**TABLE 2**

**Contingency table scheme used in the study**

| | | **Rainfall observation** | | |
|---|---|---|---|---|
| | | Yes | No | Total |
| **Satellite** | Yes | *hit* (a) | *false alarm* (b) | a + b |
| | No | *miss* (c) | *correct negative* (d) | c + d |
| | Total | a + c | b + d | a + b + c + d = n |

Obtaining analysis of the distribution of satellite estimation accuracy, the PC, FAR, BIAS, POD and CSI indicators are visualized using a map. The analysis was carried out by adding elevation in South Sulawesi Province to see how the influence of the dominant winds is divided into the peak of the rainy season, namely December, January and February (DJF), the peak of the dry season, namely June, July and August (JJA), the transition of the rainy season to the dry season is March, April and May (MAM) and the transition from the dry season to the rainy season is September, October and November (SON). This separation is intended to see whether there is an influence of season on satellite accuracy. In addition, we computed the mean values (average) of the daily performance indicators (PC, FAR, BIAS, POD, and CSI) over the period from January 1, 1993 to December 31, 2022, except for IMERG, which has data available only from 2014 onwards.

Apart from using indicators of rain and no rain, this evaluation uses a numerical comparison, namely root mean square error (RMSE), the formulation of which is as follows

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y_i} - y_i)^2}{n}} \qquad (6)$$

where $\hat{y_i}$ is the rainfall estimate from satellites from CHIRPS, GPCP, IMERG, and GSMaP, while $y_i$ is the rainfall resulting from measurements of the earth's surface & n is the number of data series. The RMSE parameter is needed to see the deviation value of satellite rainfall. Because there are differences in data types, where observation data is point data & satellite data is in raster form, a comparison of the two values is carried out by selecting the location of the satellite rainfall estimate closest to the observation location or nearest neighbour algorithm.

## 3. Results and discussion

### 3.1. *Distribution of rainfall event in south sulawesi*

The rainfall climatic variation in South Sulawesi Province exhibits a distinct contrast between its northern and southern regions. In the northern area, which includes the regencies of North Toraja, North Luwu, and the city of Palopo, the frequency of rainfall events is notably higher. The region's geography, particularly the concave shape of Bone Bay contributes to strong atmospheric convergence, resulting in increased precipitation (Furqon *et al.,* 2021). Palopo and North Luwu, located at the northern tip of Bone Bay, are especially affected. North Toraja, situated at a higher elevation northwest of Palopo, experienced rainy days more than 50% of the year. The Latimojong Mountains, located in the northwest and north, serve as a barrier that blocks winds from Bone Bay, further influencing local rainfall patterns.

In contrast, the southern part of the province, including the regencies of Takalar, Bulukumba, and Bantaeng, received significantly less rainfall, with rainy days accounting for less than 30% of the year. The central lowlands, such as Pinrang and Sidrap, are also relatively dry. Other districts across the region experienced a higher proportion of dry days, with 51% to 70% of the days receiving no rainfall. This climatic disparity reflects the complex interplay among geographic features, wind patterns, and atmospheric conditions unique to the region.

In the northern part of South Sulawesi Province, namely the regencies of North Toraja, North Luwu, and the city of Palopo, the proportion of rainfall events was higher than in the southern part. Palopo and North Luwu, located at the northern tip of the concave-shaped Bone Bay, were particularly affected due to potentially high atmospheric convergence (Furqon *et al.,* 2021). Meanwhile, North Toraja Regency, situated at a higher elevation northwest of Palopo, experienced rainy days on more than 70% of the days during the observation period. Winds originating from Bone Bay were blocked by the Latimojong Mountains in the northwest and north, as illustrated in Fig. 2.

### 3.2. *Distribution of deviations rainfall satellite estimates*

The Root Mean Square Error (RMSE) calculations for CHIRPS data indicated that the smallest RMSE values occurred during the transition from the dry season to the rainy season (SON), with RMSEs below 15 mm at 18 locations. Conversely, the highest RMSE values were observed at the peak of the rainy season (DJF), with four locations recording RMSEs above 25 mm and twelve locations recording exactly 25 mm. On average, the RMSE across all months was slightly lower than during the DJF period, as shown in Table 3. Interestingly, the deviation in CHIRPS rainfall estimates during the dry season, when rainfall was minimal, was not always smaller compared to periods of light rain. Notably, the

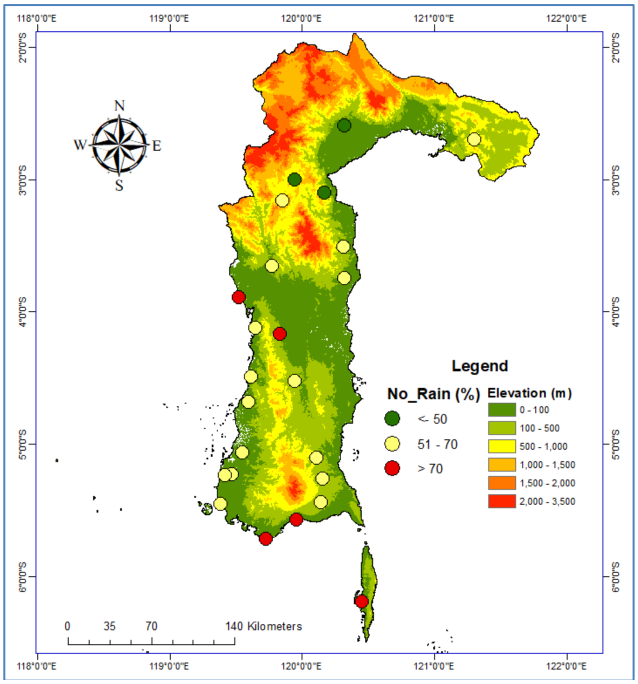



**Fig. 2.** Proportion of the number of rain events at the research location

Torut (North Toraja) area, characterized by high topography exhibited the largest deviation, reaching 59 mm during the peak of the rainy season.

When compared with two other satellite products, GPCP and GSMaP, CHIRPS demonstrated superior performance. More locations had RMSE values below 20 mm and fewer exceeded 25 mm when using CHIRPS. Among the three products, GPCP showed the greatest deviation, particularly during the dry season, with RMSEs exceeding 25 mm in 18 locations and low RMSEs observed at only three rain gauge locations. However, during the transition from the dry to the rainy season (SON), GPCP performed comparably to CHIRPS, with values below 20 mm at 23 locations and only one location exceeding 25 mm. Notably, during the dry season, GPCP even outperformed CHIRPS. Meanwhile, GSMaP performs relatively well during the JJA and SON periods; however, its RMSE values remain higher compared to those of CHIRPS and GPCP.

The IMERG satellite product, which succeeded TRMM, shows RMSE values that are similar or nearly identical to those of CHIRPS. IMERG performed better during the MAM and JJA periods, with RMSE values below 20 mm at 19 locations, compared to 17 for CHIRPS. Additionally, the average RMSE across all periods was lower for IMERG, with smaller RMSE values at 21 locations, compared to 18 for CHIRPS. However, during the rainy season (DJF), CHIRPS outperformed IMERG, with 14 locations having RMSE values below 20 mm, compared to only 11 for IMERG.

In Torut (North Toraja) Regency, the RMSE was very high during the average period, DJF, and MAM. For GPCP, GSMaP, and IMERG estimates, the RMSE exceeded 30 mm, reaching up to 72 mm during the MAM period. The rainfall measurement location in Torut is situated at an altitude of 796 meters above sea level. There are four rainfall measurement locations above 500 meters: Sinjai, Soppeng, Tator, and Torut. The RMSE values varied across these locations, except for Torut, which consistently exhibited high RMSE.

Overall, the IMERG satellite product slightly outperformed CHIRPS in terms of RMSE, with 93 locations showing low RMSE values (< 20 mm) compared to 89 for CHIRPS. IMERG's relative advantage was its more consistent RMSE performance across different elevations. CHIRPS followed IMERG, while GPCP and GSMaP showed considerably higher RMSE values, indicating lower estimation performance compared to both IMERG and CHIRPS.

### 3.3. *Distribution of dichotomous indicators*

Based on RMSE calculations for CHIRPS data show that the smallest RMSE value occurred during the transition from the dry season to the rainy season, namely SON, with an RMSE of less than 15 mm at 18 locations. Meanwhile, the highest RMSE value was observed at the peak of the rainy season, namely DJF, with 4 locations having an RMSE greater than 25 mm and 12 locations having an RMSE of exactly 25 mm. On average, the RMSE across all months is slightly better compared to the DJF period, as shown in Table 3. Interestingly, the deviation in CHIRPS rainfall estimates during the dry season, which experiences little rainfall, is not always smaller than during periods of light rain. The Torut area, characterized by high topography, shows the highest deviation, reaching 59 mm during the peak of the rainy season.

The average performs of satellite rainfall estimates showed that in the southern part of South Sulawesi Province, particularly along the west coast, the accuracy of CHIRPS and GPCP in detecting rain events, as measured by the Portion Correct (PC), was higher compared to GSMaP and IMERG. In the cities of Makassar and Maros, GPCP even recorded PC exceeding 80%. PC values in the western region were generally higher than in other parts of the province, while those in the north were lower. At locations above 500 meters in elevation, CHIRPS showed the highest PC compared to GPCP, GSMaP, and IMERG, as illustrated in Fig. 3.

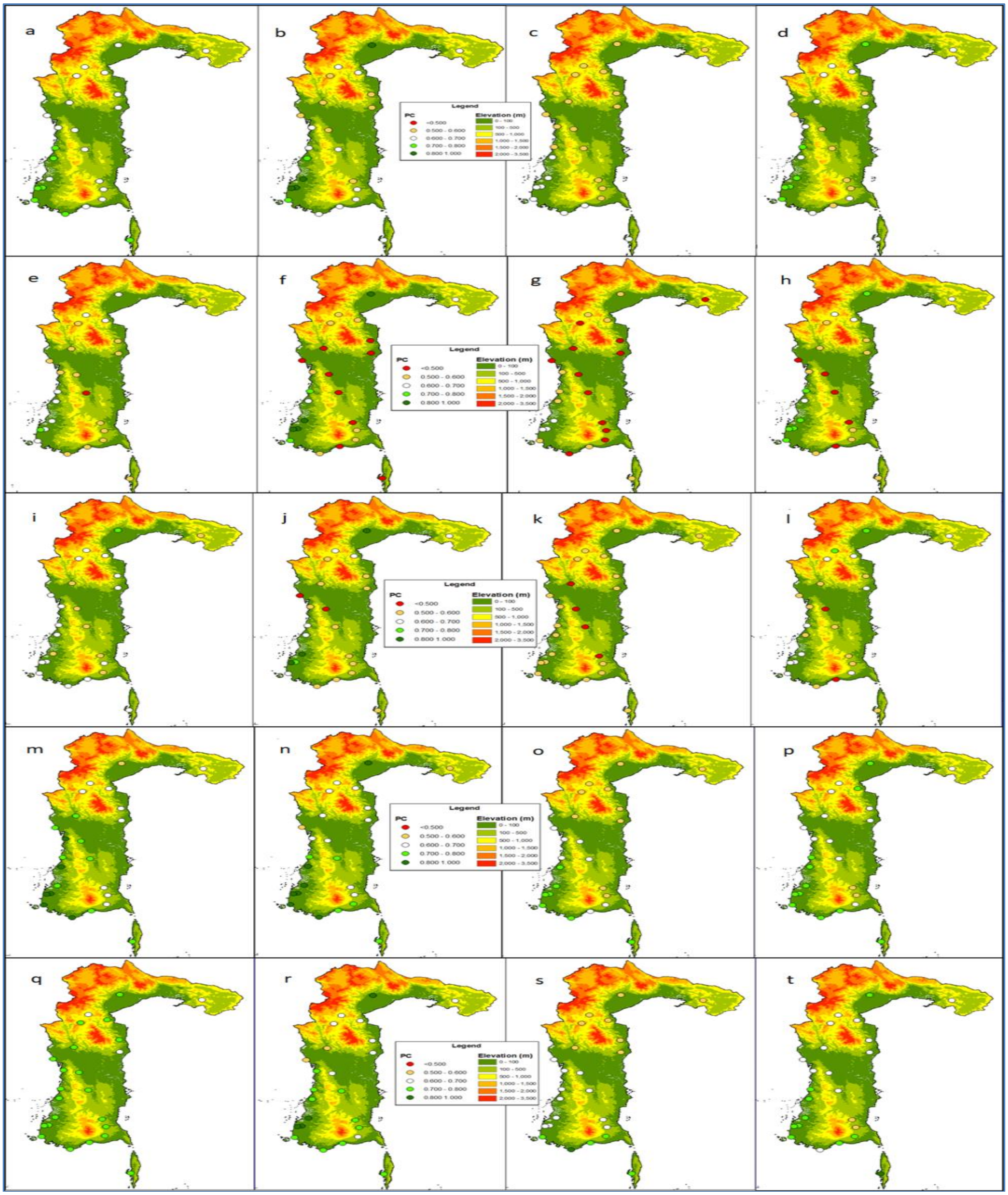
**TABLE 3**.

**Value RMSE of CHIRPS, GPCP, GSMaP and IMERG rainfall estimates**

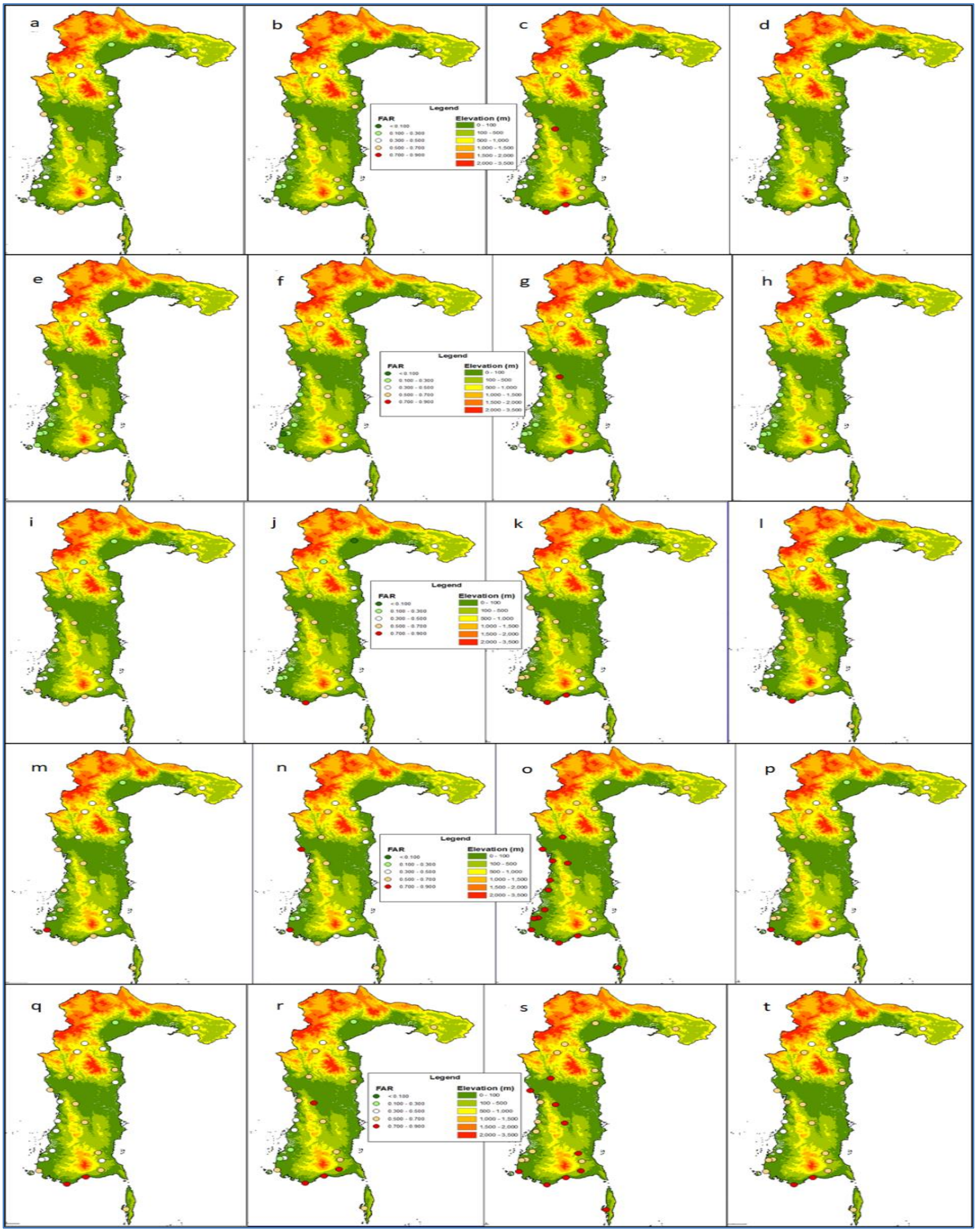
| Estimation | CHIRPS | | | | | GPCP | | | | | GSMaPs | | | | | IMERG | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Season | ALL | DJF | MAM | JJA | SON | ALL | DJF | MAM | JJA | SON | ALL | DJF | MAM | JJA | SON | ALL | DJF | MAM | JJA | SON |
| Bantaeng | 15 | 15 | 17 | 18 | 9 | 19 | 28 | 19 | 14 | 12 | 16 | 15 | 17 | 19 | 10 | 15 | 18 | 17 | 14 | 10 |
| Barru | 20 | 29 | 19 | 11 | 15 | 19 | 30 | 18 | 8 | 15 | 25 | 38 | 23 | 12 | 20 | 17 | 25 | 17 | 9 | 12 |
| Bone | 21 | 14 | 25 | 27 | 14 | 23 | 29 | 26 | 21 | 14 | 21 | 16 | 27 | 24 | 15 | 18 | 17 | 22 | 20 | 13 |
| Bulukumba | 20 | 17 | 25 | 26 | 10 | 23 | 29 | 25 | 21 | 12 | 21 | 18 | 26 | 24 | 11 | 20 | 21 | 24 | 22 | 11 |
| Enrekang | 16 | 17 | 17 | 15 | 14 | 17 | 23 | 18 | 12 | 12 | 18 | 20 | 20 | 14 | 16 | 15 | 18 | 17 | 11 | 12 |
| Gowa | 18 | 28 | 17 | 6 | 11 | 16 | 25 | 15 | 5 | 10 | 28 | 47 | 24 | 10 | 20 | 16 | 24 | 15 | 7 | 11 |
| Jeneponto | 15 | 20 | 16 | 13 | 8 | 18 | 28 | 17 | 9 | 11 | 16 | 24 | 13 | 13 | 7 | 15 | 21 | 16 | 11 | 8 |
| Luwu | 22 | 24 | 17 | 23 | 25 | 23 | 28 | 17 | 22 | 25 | 28 | 30 | 26 | 25 | 33 | 24 | 27 | 16 | 23 | 28 |
| Lutim | 19 | 19 | 22 | 19 | 17 | 21 | 23 | 24 | 19 | 17 | 21 | 24 | 24 | 18 | 17 | 18 | 20 | 22 | 16 | 14 |
| Luwut | 19 | 18 | 21 | 21 | 16 | 7 | 8 | 8 | 7 | 7 | 25 | 24 | 30 | 23 | 21 | 16 | 16 | 19 | 17 | 14 |
| Makassar | 17 | 28 | 16 | 6 | 11 | 14 | 23 | 13 | 4 | 7 | 28 | 46 | 23 | 10 | 21 | 17 | 27 | 16 | 8 | 12 |
| Maros | 23 | 36 | 20 | 15 | 16 | 16 | 25 | 14 | 6 | 11 | 27 | 45 | 23 | 11 | 17 | 16 | 25 | 15 | 7 | 12 |
| Palopo | 17 | 14 | 19 | 17 | 16 | 20 | 20 | 24 | 19 | 18 | 23 | 23 | 29 | 18 | 20 | 16 | 15 | 20 | 13 | 15 |
| Pangkep | 19 | 27 | 18 | 10 | 17 | 18 | 28 | 17 | 7 | 15 | 25 | 39 | 22 | 10 | 21 | 17 | 25 | 17 | 8 | 15 |
| Pare-pare | 17 | 23 | 17 | 9 | 15 | 19 | 28 | 18 | 9 | 13 | 20 | 28 | 20 | 13 | 18 | 16 | 24 | 16 | 9 | 12 |
| Pinrang | 17 | 22 | 17 | 13 | 14 | 18 | 26 | 18 | 12 | 14 | 21 | 28 | 20 | 15 | 19 | 16 | 21 | 17 | 10 | 13 |
| Selayar | 16 | 17 | 18 | 15 | 11 | 18 | 26 | 18 | 11 | 11 | 15 | 18 | 17 | 13 | 11 | 13 | 16 | 16 | 12 | 9 |
| Sidrap | 14 | 15 | 16 | 12 | 11 | 18 | 26 | 17 | 11 | 12 | 16 | 17 | 17 | 16 | 16 | 14 | 16 | 15 | 12 | 11 |
| Sinjai | 22 | 18 | 24 | 30 | 14 | 25 | 29 | 26 | 28 | 15 | 24 | 20 | 27 | 31 | 16 | 18 | 17 | 20 | 21 | 11 |
| Soppeng | 14 | 14 | 16 | 15 | 11 | 18 | 28 | 18 | 10 | 12 | 15 | 16 | 17 | 14 | 12 | 14 | 17 | 15 | 10 | 11 |
| Takalar | 15 | 24 | 13 | 8 | 9 | 16 | 27 | 15 | 6 | 10 | 22 | 38 | 17 | 7 | 11 | 15 | 24 | 14 | 8 | 9 |
| Tator | 15 | 16 | 17 | 13 | 13 | 16 | 20 | 19 | 13 | 13 | 16 | 19 | 20 | 11 | 14 | 14 | 16 | 16 | 10 | 12 |
| Torut | 36 | 28 | 59 | 22 | 16 | 37 | 31 | 61 | 20 | 16 | 40 | 32 | 66 | 22 | 18 | 43 | 33 | 72 | 23 | 14 |
| Wajo | 20 | 13 | 23 | 25 | 15 | 22 | 20 | 26 | 25 | 16 | 28 | 17 | 37 | 31 | 24 | 18 | 13 | 23 | 21 | 13 |

During the rainy season (DJF), the Probability of Detection (PC) values in the southern part, particularly along the west coast, remained higher than in the eastern part. CHIRPS rainfall estimates mostly showed PC values greater than 0.6, indicating that over 60% of predicted rainfall events matched the observations, with only one location recording a PC value below 0.5 (situated between two hills). IMERG followed, with four locations having PC values below 0.5, then GSMaP and GPCP. Overall, PC values during DJF were lower than the multi-period average. In the transition to the dry season (MAM), CHIRPS continued to exhibit the highest detection performance, followed by IMERG, GPCP, and GSMaP. Interestingly, the number of locations with PC values exceeding 0.7 increased, not only in the south but also in the northern part of the region. During the dry season (JJA), a high number of locations, particularly in the western region had PC values above 0.8 for CHIRPS and GPCP, while IMERG and GSMaP did not achieve PC values above 0.8 in any location. Moreover, during the transition from the dry to the rainy season (SON), CHIRPS showed PC values between 0.7 and 0.8 in almost all locations. GPCP also performed relatively well in the southern region-especially along the west coast-but its PC values dropped below 0.7 in the north. GSMaP recorded PC values above 0.7 only in a few scattered locations.

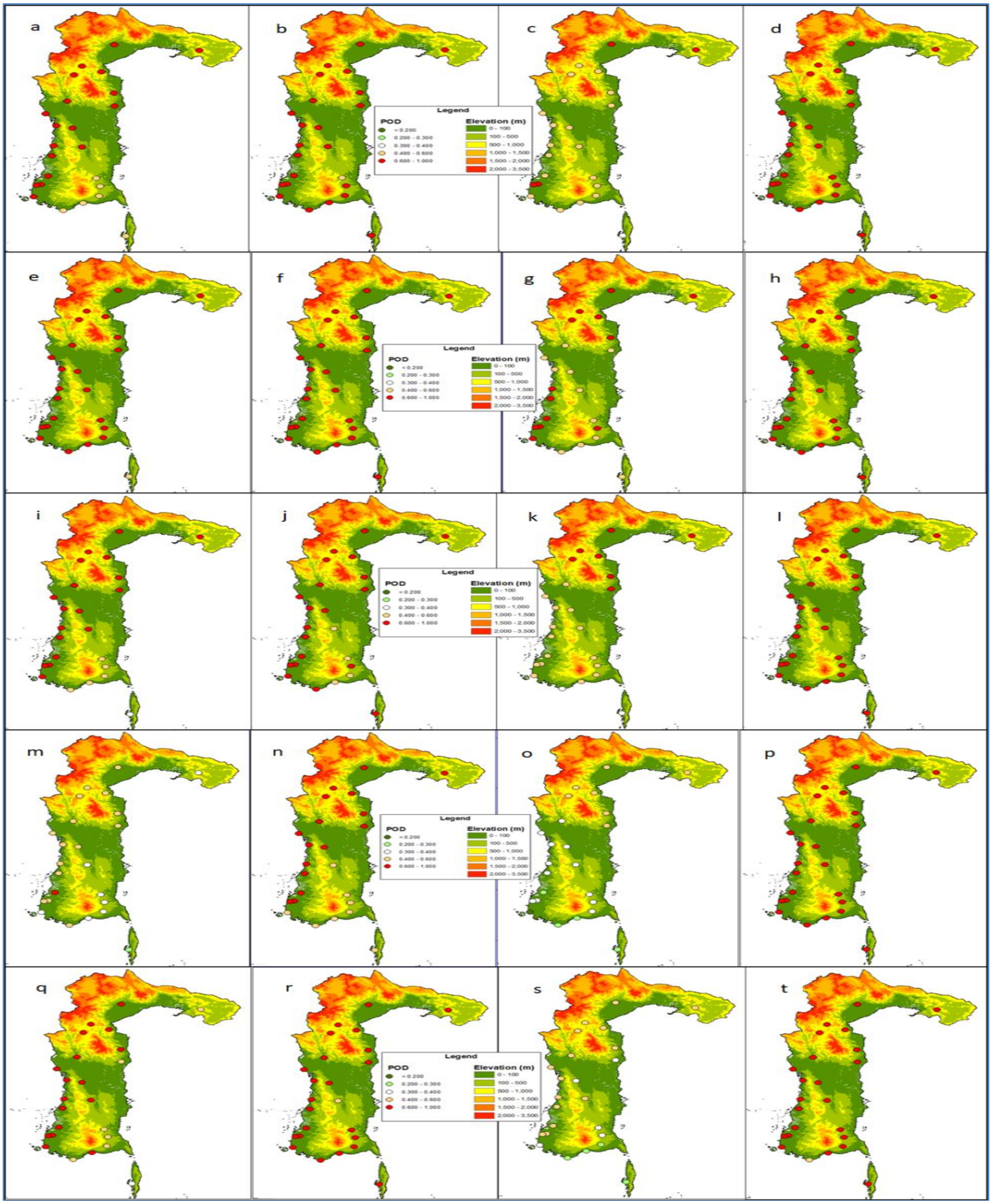
On average across all periods, the False Alarm Ratio (FAR) values for satellite estimates in South Sulawesi were less than 0.7, indicating a considerable number of false alarms where rain was predicted but not observed. Ideally, a FAR value of 0 is preferred, indicating no false alarms. Among all satellite products, CHIRPS and IMERG showed the lowest FAR values, while GPCP and GSMaP had higher false alarm occurrences. GSMaP recorded FAR values approaching 1 in Bulukumba and




**Figs. 3(a-t).** Spatial distribution of portion correct (PC) values for each satellite rainfall product: CHIRPS, GPCP, GSMaP, and IMERG. Each row represents a different seasonal period—Average (a–d), DJF (e–h), MAM (i–l), JJA (m–p), and SON (q–t)—while each column corresponds to a specific satellite product (CHIRPS: a, e, i, m, q; GPCP: b, f, j, n, r; GSMaP: c, g, k, o, s; IMERG: d, h, l, p, t). Labels are also included within each panel for easier identification




**Figs. 4(a-t)**. Spatial distribution of FAR values for each satellite rainfall product: CHIRPS, GPCP, GSMaP, and IMERG. Each row represents a different seasonal period—Average (a–d), DJF (e–h), MAM (i–l), JJA (m–p), and SON (q–t)—while each column corresponds to a specific satellite product (CHIRPS: a, e, i, m, q; GPCP: b, f, j, n, r; GSMaP: c, g, k, o, s; IMERG: d, h, l, p, t). Labels are also included within each panel for easier identification




**Figs. 5(a-t)**. Spatial distribution of POD values for each satellite rainfall product: CHIRPS, GPCP, GSMaP, and IMERG. Each row represents a different seasonal period—Average (a–d), DJF (e–h), MAM (i–l), JJA (m–p), and SON (q–t)—while each column corresponds to a specific satellite product (CHIRPS: a, e, i, m, q; GPCP: b, f, j, n, r; GSMaP: c, g, k, o, s; IMERG: d, h, l, p, t). Labels are also included within each panel for easier identification

Bantaeng (southern region) and Sidrap (an inland area between hills), as shown in Fig. 4. In mountainous areas, satellite-based rainfall estimates tended to produce more false alarms than in coastal regions.

During the rainy season (DJF), the FAR values in the southern part of South Sulawesi, particularly along the west coast, were still higher than in the eastern region. Similarly, in mountainous areas, satellite products generally exhibited higher FAR values compared to coastal regions. A comparison between satellite products showed that false alarm errors did not vary significantly across most products, except at two locations in the GSMaP estimates, where notably higher FAR values were observed. The FAR values increased during the transition from the rainy season to the dry season (MAM: March, April, and May), indicating reduced accuracy in this period. The proportion of locations with FAR values between 0.3-0.5 was nearly equal to those with values between 0.5-0.7. Notably, the CHIRPS product did not record any FAR values close to 1, unlike the GPCP, GSMaP, and IMERG products, which did. Rainfall estimates of CHIRPS continued to outperform the other products during the peak dry season (JJA: June, July, and August) and during the transition to the rainy season (SON: September, October, and November). However, during these periods, the overall FAR values increased, indicating a higher frequency of overestimation or rain was predicted by the satellite but not observed on the ground.

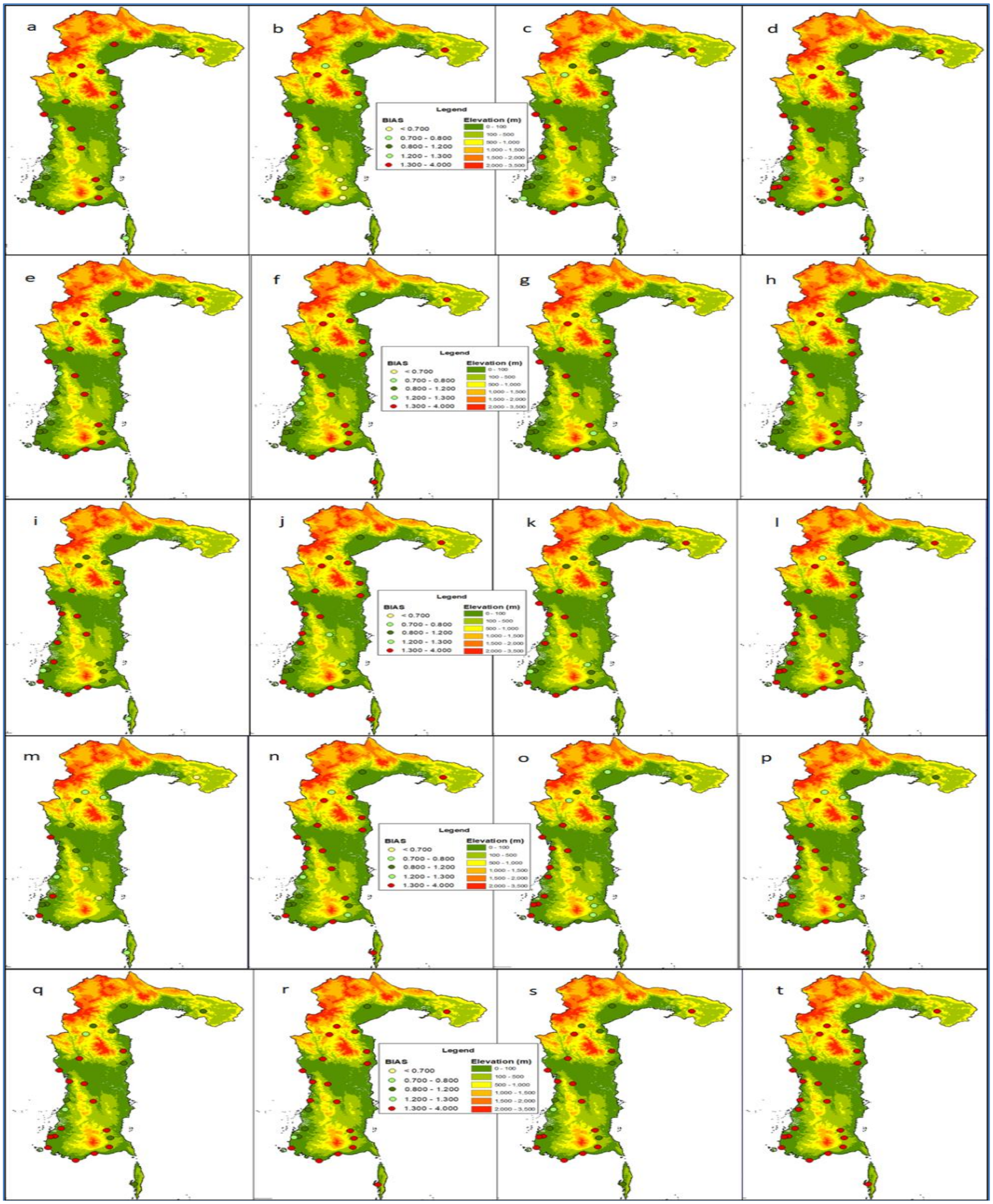
The comparison between errors due to false alarms (predicting rain that did not occur) and misses (failing to predict rain that did occur), relative to the number of correct detections (hits), was assessed using the BIAS metric. Based on the BIAS calculations, the average BIAS value for all months across the satellite estimates in South Sulawesi Province was found to be less than 0.7, as shown in Fig. 5. This means that the number of false alarm errors on satellites is quite high compared to the number of hits or the number of errors due to satellite estimates stating that it is raining, even though the portion of rain that did not occur in the observations is quite high. Among the satellite products, CHIRPS and IMERG showed better performance compared to GPCP and GSMaP. Notably, the GSMaP product recorded FAR values close to 1 at several locations, including Bulukumba and Bantaeng in the southern part of the province, and Sidrap, a region situated between hills (Fig. 5). In general, satellite rainfall estimates tended to produce more false alarms in mountainous areas than in coastal regions.

A comparative analysis of the Probability of Detection (POD) across the four satellite datasets revealed that IMERG consistently performed the best across all periods, with POD values ranging from 0.6 to 1 (Fig. 6). The IMERG data reliably captured actual rainfall occurrences. During the rainy season (DJF), the POD values of IMERG, GPCP, and CHIRPS were comparable, ranging from 0.6 to 1. In contrast, GSMaP exhibited lower POD values, particularly in the southern part of South Sulawesi, along the west coast near Palopo, the mountainous area around Sidrap, and the east coast near Wajo, where POD values ranged from 0.4 to 0.6. During the dry season (JJA), the transition from wet to dry season (MAM), and the transition from dry to wet season (SON), the IMERG dataset consistently achieved the highest POD values, followed by GPCP, CHIRPS, and GSMaP. Overall, the highest POD values were observed during the DJF period, followed by SON, MAM, and JJA. This pattern indicated that satellite products performed better in detecting rainfall during the wet season compared to the dry season or transitional periods.

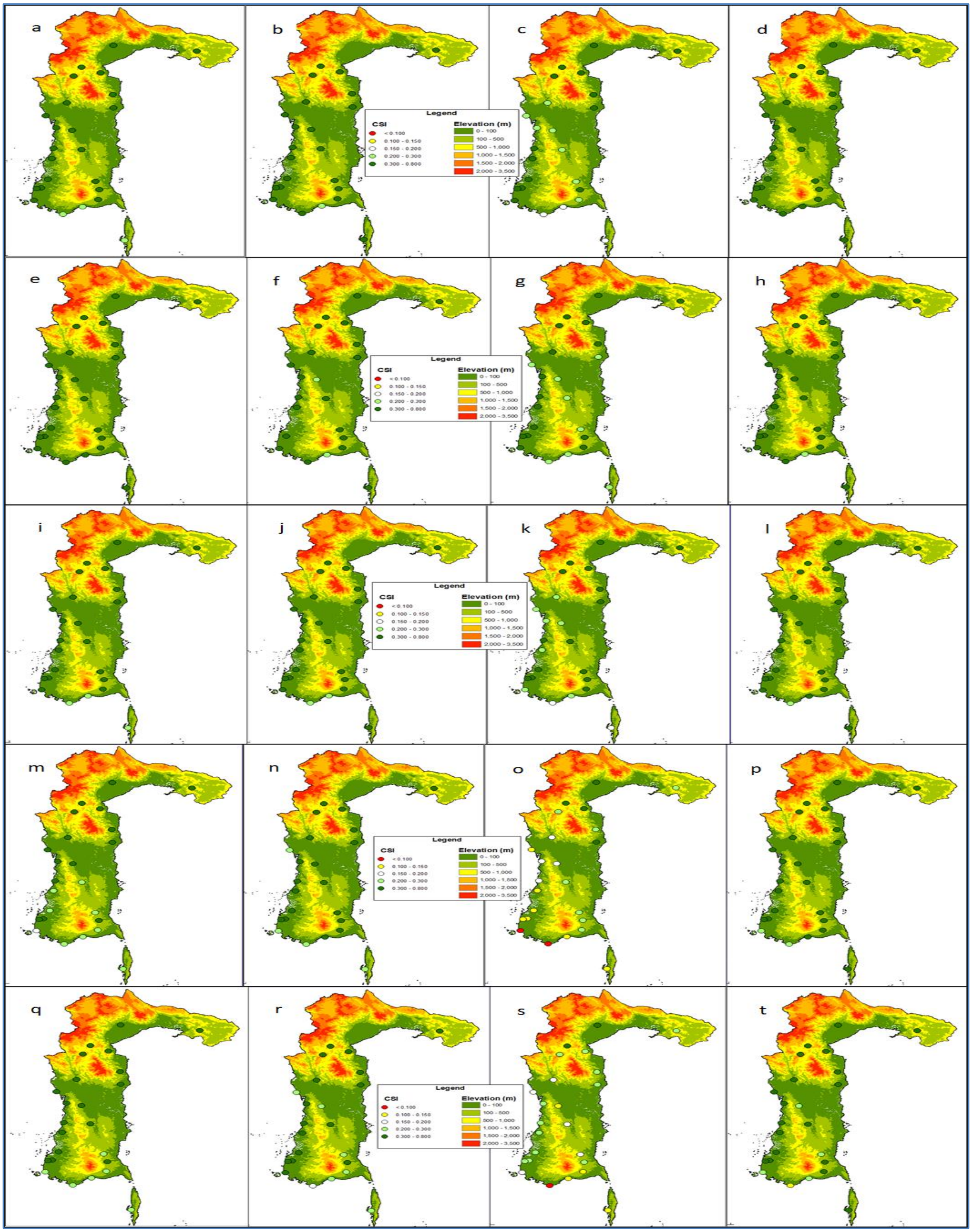
Similar to the POD analysis, a comparative assessment of the Critical Success Index (CSI) among the four satellite datasets showed that IMERG exhibited the highest consistency across all periods, with CSI values ranging from 0.3 to 0.8. However, during the rainy season (DJF), CHIRPS demonstrated more consistent CSI values than IMERG, particularly in Takalar, where the CSI values ranged between 0.3 and 0.8, as illustrated in Fig. 7. Conversely, the GSMaP dataset yielded the lowest CSI values among all products, especially in the southern part of South Sulawesi, the west coast near Pinrang, the mountainous region around Soppeng, and the east coast near Wajo, where CSI values ranged from 0.2 to 0.3. During the transition from the wet to the dry season (MAM), the IMERG dataset consistently achieved the highest CSI values. Meanwhile, CHIRPS and GPCP exhibited comparable CSI distributions, while GSMaP remained the lowest. During the dry season (JJA) and the transition from the dry to the wet season (SON), IMERG continued to show the highest CSI values, followed by GPCP, CHIRPS, and GSMaP. In general, satellite products achieved the highest CSI scores during the DJF period, followed by MAM, SON, and JJA. These findings suggest that satellite-based rainfall detection was more accurate during the wet season compared to the dry or transitional periods, as indicated by higher values of the Critical Success Index (CSI), which reflects a better balance between hits, false alarms, and missed events.

### 3.4. *Discussion*

The availability of several global precipitation datasets allows humans to estimate rainfall over various spatial and temporal scales (Janowiak *et al.*, 1998; Joyce *et al.*, 2004; Dinku *et al.*, 2007; Peters-Lidard *et al.*, 2007; Huffman *et al.*, 2007; Grimes *et al.*, 2012).




**Figs. 6(a-t)**. Spatial distribution of BIAS values for each satellite rainfall product: CHIRPS, GPCP, GSMaP, and IMERG. Each row represents a different seasonal period-Average (a–d), DJF (e–h), MAM (i–l), JJA (m–p), and SON (q–t)-while each column corresponds to a specific satellite product (CHIRPS: a, e, i, m, q; GPCP: b, f, j, n, r; GSMaP: c, g, k, o, s; IMERG: d, h, l, p, t). Labels are also included within each panel for easier identification




**Figs. 7(a-t)**. Spatial distribution of CSI values for each satellite rainfall product: CHIRPS, GPCP, GSMaP, and IMERG. Each row represents a different seasonal period—Average (a–d), DJF (e–h), MAM (i–l), JJA (m–p), and SON (q–t)—while each column corresponds to a specific satellite product (CHIRPS: a, e, i, m, q; GPCP: b, f, j, n, r; GSMaP: c, g, k, o, s; IMERG: d, h, l, p, t). Labels are also included within each panel for easier identification

However, evidence from many studies shows that the accuracy of satellite rainfall estimates varies across different locations and seasonal periods. Comparisons of some satellite products in Indonesia show that, generally, CHIRPS rainfall estimates are notably more accurate than other satellite products, although they vary depending on location (Liu *et al.*, 2020; Faisol *et al.*, 2020; Rahmawati *et al.*, 2021; Wiwoho *et al.*, 2021; Wati *et al.*, 2021; Asferizal, 2022).

The results of the RMSE calculations in this study confirm previous research, where the CHIRPS bias was smallest during the transition from the dry season to the rainy season or SON, with the RMSE value generally being less than 15 mm. Meanwhile, the highest error occurs at the peak of the rainy season or DJF, with 4 locations having an RMSE of more than 25 mm. Compared with GPCP and GSMaP, CHIRPS rainfall estimates are better, with the number of locations having RMSE values less than 20 mm being the highest, and the number of locations with RMSE values greater than 25 mm being fewer. Meanwhile, the performance of CHIRPS is slightly lower than that of IMERG, especially during the MAM and JJA, where there is a smaller number of locations with RMSE values less than 20 mm compared to CHIRPS. However, during the rainy season or DJF, the RMSE value of CHIRPS is smaller compared to IMERG. The RMSE value for satellite products in South Sulawesi Province is slightly better than the evaluation in Bali, where the RMSE value for several satellites such as GSMaP, IMERG, and CHIRPS exceeds 17 mm (Liu *et al.*, 2020). The RMSE variations that occur between seasons are also similar to the TRMM performance in Kolaka, Southeast Sulawesi, which is close to South Sulawesi, with RMSE values of 10.41, 11.92, 7.07, and 3.73 in the DJF, MAM, JJA, and SON, respectively (Satria and Qothrunada, 2022).

Deviations in satellite rainfall estimates, calculated using RMSE values, are almost the same based on monsoonal, equatorial, and local rainfall patterns (Setiyoko *et al.*, 2019). The high RMSE value in Torut in this study, which reached more than 30 mm in the GSMaP product, was also identified by Fatkhuroyan and Wati (2018). This study found that high RMSE values generally occur in the rainy season. Based on RMSE calculations, it was found that Torut Regency's RMSE was very high during DJF, and MAM. In fact, the RMSE value in the GPCP, GSMaP, and IMERG estimates was more than 30 mm and even reached 72 mm during the MAM. The location for measuring rainfall in Torut is situated at an altitude of 796 meters above sea level. There are 4 rainfall measuring locations with elevations above 500 meters, namely Sinjai, Soppeng, Tator, and Torut. Of these, the three locations besides Torut have varying RMSE values. Overall, the IMERG satellite product is slightly better than CHIRPS, with the number of locations with low RMSE values (< 20 mm) being 93, compared to 89 for CHIRPS. The advantage of IMERG is its stable performance across all places, including those with varying elevations. Meanwhile, CHIRPS' performance is slightly below that of IMERG, followed by rainfall estimates from GPCP and GSMaP, whose accuracy lags behind compared to IMERG and CHIRPS. High deviations during the rainy season are caused by high predicted values, which are often comparable to the estimated values and not detected by the RMSE formula, which is sensitive to large values.

The performance of satellite products based on PC, BIAS, POD, FAR, and CSI calculations varies. The accuracy of CHIRPS and GPCP rainfall predictions for rain events, calculated using the portion correct (PC) metric, is higher compared to GSMaP and IMERG. An anomaly occurs in Makassar and Maros, where the accuracy exceeds 80% for GPCP. The western part of the province shows higher accuracy than other areas, while the northern part exhibits lower accuracy. However, at locations with an altitude of 500 meters, CHIRPS performance remains stable with higher accuracy compared to GPCP, GSMaP, and IMERG. If the assessment is based on season, the JJA has the highest PC value compared to other seasons, while during the rainy season or DJF, the PC is the smallest, with many PC values being less than 0.5. Only CHIRPS rainfall estimates exhibit a PC value generally above 0.6, meaning 60% of estimates for rain events are correct. The error in the estimation of false alarms, on average across all months, identified by the FAR value, shows that the South Sulawesi Province area performs better than the northern part, with the western part performing better than the eastern part. The FAR value of CHIRPS and IMERG products is better than that of GPCP and GSMaP rainfall estimation, and it was found that the GSMaP product had a FAR value almost close to 1 in Bulukumba and Bantaeng. In mountainous areas, satellite product estimates generally have more false alarm errors than in coastal areas. In contrast to PC, the performance of satellite products with the FAR indicator is best in the rainy season or DJF, where the value is often less than 0.3. There are two prediction errors using the dichotomous method: errors due to false alarms or failure to predict no rain, and errors due to missing or failure to predict rain, compared to the number of hits or accuracy of predicting rain. The comparison of the number of errors can be seen from the BIAS value. The BIAS calculation results show that, generally, errors are false alarms, characterized by a BIAS value of more than 1. Only on the southwest coast of South Sulawesi Province is the number of false alarms and missing events balanced, with a value of 0.8 to 1.2. The performance of CHIRPS, based on the BIAS value, is clearly visible, as GPCP, GSMaP, and IMERG experienced errors due to high false alarms, while CHIRPS still has many places with a BIAS value of around 1. Compared to other rainy season, the BIAS value of satellite products during the dry season is better. Meanwhile, a comparison between errors due to missing and hit events, represented by the POD parameter, shows that IMERG makes the fewest errors compared to other satellites, followed by GPCP, CHIRPS, and GSMaP. The dry season months experience more missing errors, and the POD values for all satellites are smaller. Meanwhile, the accuracy of rain predictions shows that IMERG data is slightly better than CHIRPS and GPCP, especially in the southern part. Based on the CSI value, almost all satellites have quite high values, namely more than 0.3, except for GSMaP during the dry season. During rainy season shows the highest CSI values for satellite products compared to other seasons.

Compared with other regions, the POD values for GSMaP, IMERG, and CHIRPS products in South Sulawesi are slightly better than in Bali, where the average POD values are 0.73, 0.84, and 0.54, respectively (Liu *et al.,* 2020). Meanwhile, the FAR and CSI values in Bali are around 0.5 and 0.4, respectively. For the Indonesian scale, the average POD value is 0.68, with a maximum of 0.87 and a minimum of 0.29 in Pangkalan Bun, representing monsoonal areas such as the southern part of South Sulawesi Province. In the equatorial region of Indonesia, the average POD value is 0.78, with a maximum of 0.92 in Pontianak and a minimum of 0.29 in Tarempa, as well as local rain patterns, where the average POD value is 0.70, with a maximum of 0.87 in Timika and a minimum of 0.51 in Sanana. The FAR value for equatorial areas averages 0.36, with 0.33 in equatorial areas and 0.39 in areas with local rainfall patterns (Setiyoko *et al.,* 2019).

Future research could explore the effects of satellite product resolution on rainfall accuracy, especially in regions with complex topographies. Additionally, using machine learning techniques to improve rainfall predictions and expand satellite data applications in disaster forecasting could provide valuable insights. The resolution of satellite rainfall estimation products plays a significant role in the accuracy of rainfall predictions. Higher-resolution products, such as CHIRPS (0.05° ~ 5 km) and GSMap (0.1° ~ 10 km), generally provide more accurate estimates, particularly in regions with relatively flat terrain. However, products like IMERG (0.1° ~ 10 km) also demonstrate good performance, even in areas with more complex topographies. In contrast, coarser-resolution products like GPCP (2.5° ~ 250 km) may struggle with accuracy in regions with complex topographies, such as mountainous areas. The larger grid size of lower-resolution products tends to average out local variations in rainfall, leading to a loss of detail and greater errors in rainfall estimates, especially in areas with significant elevation differences. Thus, spatial resolution significantly impacts the performance of satellite products, with higher-resolution datasets being more suitable for finer-scale rainfall prediction in diverse geographical regions

## 4. Conclusions

Based on a comparative study of CHIRPS, GPCP, GSMaP, and IMERG products in South Sulawesi Province, the following conclusions can be drawn:

(*i*) Satellite rainfall estimation products exhibited varying levels of accuracy depending on geographic regions, such as mountainous areas, plains, and coastal regions. Accuracy was generally highest in the southern part of South Sulawesi Province, particularly along the west coast, which consisted mainly of plains and lowland areas. This region showed the best performance compared to the northern part, which featured more mountainous terrain and complex topography. The western part of South Sulawesi consistently outperformed the eastern part, which included both coastal and hilly areas. These variations highlighted the limitations of satellite products in regions with varied elevations. Mountainous areas presented more challenges for accurate rainfall prediction, while flatter plains or coastal regions generally yielded better results.

(*ii*) In addition to geographic variations, accuracy was also influenced by temporal factors. During the rainy season, when rainfall intensity was high, the RMSE tended to increase. Conversely, during the dry season, when rainfall was sparse, the RMSE was lower, reflecting less variation in rainfall predictions.

(*iii*) The accuracy of predicting rain events was also unique to different times of the year. Notably, the transition from the dry season to the rainy season showed the highest accuracy. Among the satellite products, CHIRPS demonstrated the most stable and reliable performance, maintaining a high percent correct value even during the rainy season, which is typically the period with the worst accuracy.

(*iv*) Based on multiple accuracy metrics such as FAR, POD, BIAS, and CSI, CHIRPS showed the most stable performance, with fewer fluctuations compared to other products. This stability ensured that CHIRPS remained consistently reliable across different seasons & locations.

(*v*) Based on RMSE, PC, FAR, BIAS, and CSI values, the CHIRPS product was the best performing satellite rainfall estimation product, followed by IMERG, GPCP, and GSMaP. However, this ranking was dynamic and varied with time and geographical location.

The study's findings were limited by data resolution constraints, which may have impacted rainfall prediction accuracy, particularly in regions with complex topographies. Future research should aim to improve spatial resolution and address potential data biases. Integrating machine learning techniques could also enhance accuracy. It is recommended that meteorological agencies and policymakers account for geographic and temporal variations in satellite product accuracy when making decisions on rainfall estimation and disaster preparedness. Prioritizing improvements in satellite data resolution and calibration will also enhance rainfall prediction reliability in diverse regions.

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