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Giarno^{1*}, Nurtiti Sunusi^{}, Didiharyoni^{***},
Achmad Fahrudin Rais^{****}, Muflihah^{*****},
BonoPranoto^{*****}, Agustina Rachmawardani^{*****},
Hariyanto^{*****}, Muhammad Syamsudin^{*****}, Bagus Satrio
Utomo^{*****}, Irwan Slamet^{*****}, Sayful Amri^{*}**

** Department of Meteorology, School of Meteorology Climatology and Geophysics, Banten, Indonesia*

*** Department of Statistics, FMIPA, Hasanuddin University, Sulawesi Selatan, Indonesia*

**** Research Center for Computing, National Research and Innovation Agency (BRIN), Jawa Barat, Indonesia*

***** Earth and Maritime Research Organization, BRIN, Jawa Barat, Indonesia*

****** Regional Center IV, BMKG, Sulawesi Selatan, Indonesia*

****** Earth and Maritime Research Organization, BMKG, Jawa Barat, Indonesia*

CLUSTERING-BASED EVALUATION OF SATELLITE RAIN-FALL PRODUCTS: A NOVEL PERSPECTIVE

Abstract: Satellite-based rainfall estimation plays a crucial role in regions with limited ground-based observations, such as South Sulawesi. However, the accuracy of these products varies spatially, underscoring the need for localized performance assessment. This study evaluates four widely used satellite rainfall products: 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 GPM (IMERG) by comparing them against station observations using seven statistical accuracy indicators. To capture spatial variability in product performance, a K-Means clustering algorithm was applied to group regions with similar accuracy characteristics. This approach enables the classification of the study area into performance-based zones, facilitating

¹ giarnostmkg@gmail.com (corresponding author)

Giarno (<https://orcid.org/0000-0003-3825-7592>)

Nurtiti Sunusi (<https://orcid.org/0000-0002-6436-831X>)

Didiharyono (<https://orcid.org/0000-0001-8957-2336>)

Achmad Fahrudin Rais (<https://orcid.org/0000-0002-4125-4387>)

Muflihah (<https://orcid.org/0009-0002-6229-4107>)

Bono Pranoto (<https://orcid.org/0000-0002-2772-6528>)

Agustina Rachmawardani (<https://orcid.org/0009-0009-3813-8164>)

Hariyanto (<https://orcid.org/0009-0006-6360-1665>)

Muhammad Syamsudin (<https://orcid.org/0009-0002-9056-1778>)

Bagus Satrio Utomo (<https://orcid.org/0009-0000-8570-3351>)

Irwan Slamet (<https://orcid.org/0009-0006-1881-803x>)

Sayful Amri (<https://orcid.org/0009-0003-0230-0277>)

region-specific recommendations. The results show that no single product consistently outperforms others across all clusters. IMERG performed best in Cluster Type 1 (North Toraja), with a Probability of Detection (POD) of 0.87 and a Critical Success Index (CSI) of 0.89. CHIRPS was most suitable in Cluster Type 2 (Pinrang, Enrekang, Sidrap, Soppeng, Bone) with a Root Mean Square Error (RMSE) of 12.3 mm. GPCP demonstrated the highest accuracy in Cluster Type 3 (Luwu, East Luwu, Palopo, Tanah Toraja, North Toraja, Makassar, Maros, Gowa, Takalar) with an RMSE of 10.5 mm, Pearson Correlation (PC) of 0.92, and BIAS of 0.05. Higher-elevation generally exhibited larger errors and lower detection capability, suggesting that terrain complexity influences satellite rainfall performance. These findings highlight the value of integrating clustering and terrain context into satellite rainfall validation frameworks.

Keywords: rainfall, satellite, accuracy assessment, K-Means clustering, monsoon, South Sulawesi

Introduction

Being located in a tropical region, Indonesia receives solar radiation throughout the year, resulting in consistently warm temperatures. Additionally, its position as a maritime continent, flanked by two large oceans and two continents, promotes convection activity year-round (Seto et al., 2004). In Indonesia, the seasons are determined by rainfall, with the rainy season characterized by substantial rainfall and the dry season marked by little to no rain (Tjasyono, 2004). Due to its unique geographic location, Indonesia is influenced by global circulations such as the El Niño/Southern Oscillation (ENSO), Madden-Julian Oscillation (MJO), and Indian Ocean Dipole (IOD) (D'Arrigo & Wilson, 2008, Hidayat & Kizu, 2010, As-syakur, 2010; Lee, 2015, Supari et al., 2017). Local factors, driven by the diverse distribution of sea and land and the country's unique topography, also affect rainfall patterns (Giarno et al., 2023).

Indonesia's climate variability also responds to a broader set of atmospheric oscillations, including monsoonal shifts and regional-scale circulation anomalies, which interact with topography to produce highly localized rainfall patterns (Aldrian & Susanto, 2003; Hendon, 2003; Chang et al., 2005). Although the Asian and Australian monsoon systems dominate the annual weather cycle, bringing rainfall from November to March and dry conditions from April to October (Giarno et al., 2012), local mechanisms such as wind circulation patterns influenced by land-sea contrasts and topographical features also significantly affect rainfall distribution across the archipelago (Yamanaka, 2016). Sea breezes carry moist air inland, which then rises over mountainous regions where it condenses to form rain clouds. If the moisture content is high enough, rainfall occurs on the windward slopes facing the sea. In areas with complex terrain, variations in elevation play a crucial role in shaping the spatial distribution of rainfall (Juneng et al., 2007; Qian et al., 2010).

Considering the complexity of rainfall dynamics in Indonesia, characterized by highly localized and intense precipitation events, achieving accurate rainfall measurement remains a significant challenge. The limited number of rain gauges in Indonesia (Giarno et al., 2021; Sunusi & Giarno, 2022, 2023) has made satellite-based rainfall estimation crucial for addressing observational data gaps (Brunetti et al., 2018; Rahmawati et al., 2021). With advances in satellite technology and more sophisticated algorithms, global precipitation datasets have been developed to provide reliable rainfall estimates across various spatial and temporal scales (Joyce et al., 2004; Dinku et al., 2007; Peters-Lidard et al., 2007; Huff-

man et al., 2007; Grimes et al., 2012). Despite their widespread use, differences in methodologies and data sources across these products may have led to varying levels of accuracy, especially in regions with complex terrain or limited ground observations.

Among satellite-based rainfall products, CHIRPS (Climate Hazards Center InfraRed Precipitation with Station Data) has demonstrated strong performance in Indonesia's tropical context, as reported in validation studies from Yogyakarta (Rahmawati et al., 2021; Liu et al., 2020), East Java (Faisol et al., 2020; Wiwoho et al., 2021), East Nusa Tenggara (Gerland et al., 2023), and at the national level (Wati et al., 2021; Asferizal 2022) consistently demonstrated its reliability. Additionally, standalone evaluations of CHIRPS in Papua (Faisol & Paga, 2021; Budiyo & Faisol, 2021), North Sumatra (Saragih et al., 2022), West Kalimantan (Suryanto et al., 2023), and East Java (Wahyuni et al., 2021; Hastina et al., 2023) yielded consistently positive results. CHIRPS has also been effectively applied to drought monitoring in Indonesia (Narulita et al., 2021; Faisol et al., 2021; Viddaroini et al., 2023), and this study aimed to use CHIRPS to determine the onset of the rainy and dry seasons in North Sumatra (Mangitua et al., 2024).

Another product, Integrated Multi-satellite Retrievals for GPM (IMERG), showed low accuracy at daily and annual scales but performed better on a monthly scale (Hutagaol et al., 2023). Its accuracy was inconsistent across locations (Ningsih et al., 2023), often overestimating rainfall and being influenced by season and topography (Ramadhan et al., 2022a, 2022b). Similarly, other satellite products, such as Global Satellite Mapping of Precipitation (GSMaP), exhibited varying accuracy depending on region, season, and topography. GSMaP correlated well with observed data in Bali and Nusa Tenggara, though it tended to underestimate rainfall (Duwanda & Sukarasa, 2021). In Aceh, its accuracy improved during the rainy season, but it often overestimated rainfall in mountainous areas (Fatkhuroyan & Trinahwati, 2018). A flood simulation study in Jakarta found GSMaP to be less accurate in near-real-time applications (Sayama et al., 2021). These findings underscore the necessity of locally validated satellite rainfall products for climate and hydrological applications in Indonesia. Meanwhile, Global Precipitation Climatology Project (GPCP) data, while globally accessible and temporally extensive, required corrections for seasonal and locational variability and were limited by their coarse resolution (Schneider et al., 2014; Fuchs et al., 2001; Becker et al., 2013; Schneider et al., 2016; Schneider et al., 2017).

Indonesia experiences periodic changes in wind direction due to its monsoonal climate, which plays a major role in defining the two principal seasons: the rainy season and the dry season (Ramage, 1971). Rainfall in monsoonal regions often exhibits a single peak during the wet season, with a pronounced dry period, forming a wave-like curve over an annual cycle. Indonesia's complex topography results in two main rainfall patterns: a monsoonal pattern, with peaks in December–January–February (DJF), and a local pattern, with peaks outside the DJF period. Some equatorial regions also experience a bimodal pattern, with peaks in March–May and September–November (Aldrian & Susanto, 2003).

Topographic features play a crucial role in shaping precipitation patterns, particularly in regions with complex terrain (Juneng et al., 2007). The study area encompasses a wide range of elevations, from coastal lowlands to mountainous interiors, which influences rainfall through processes such as orographic lifting, terrain-induced wind convergence, and localized convective activity. Given these spatial complexities, satellite remote sensing offers a valuable tool to monitor rainfall patterns consistently across diverse terrains. Infrared and microwave-based satellite imagery enables the detection of convective clouds and

precipitation systems over large and inaccessible areas. These satellite estimates are further refined by integrating ground station observations, resulting in blended products that provide high-resolution and spatially consistent rainfall data. One such product is CHIRPS (Climate Hazards Center InfraRed Precipitation with Station Data), which combines infrared satellite data with in-situ measurements to generate precipitation estimates at a 0.05° resolution (Funk et al., 2015). Its performance has been positively evaluated in various parts of Indonesia, especially in regions with complex topography (Rahmawati et al., 2021; Saragih et al., 2022; Suryanto et al., 2023).

These rainfall patterns are evident in South Sulawesi, a province known for its development and susceptibility to hydrometeorological hazards such as floods and landslides (Arifin & Kartikaningrum, 2020; Putra & Faradilla, 2023; Thahir & Sudin, 2023). South Sulawesi is one of Indonesia's most important agricultural provinces, serving as a major food supplier for the eastern part of the country. In 2023, the province produced approximately 2.3 million tons of rice, with more than 1.4 million tons distributed to other provinces, highlighting its crucial role in national food security and top producers outside of Java (Jannah & Nurbaya, 2017; BPS, 2024). Crop production is concentrated in several regencies, including Sidrap, Soppeng, Bone, Wajo, Jeneponto, Gowa, and North Luwu, which represent key agro-climatic zones across the province. However agricultural productivity in this region is highly sensitive to rainfall variability, with drought and excessive rainfall causing yield losses, erosion, and increasing water stress. This connection highlights the environmental relevance of accurate rainfall estimation (Valjarević et al., 2023; Valjarević, 2025).

Accurate rainfall data is essential for managing such hazards. Satellite-based estimations are often used for this purpose, and the validation of satellite rainfall products has been commonly conducted by classifying regions based on their dominant rainfall pattern (Prasetia et al., 2013; Giarno et al., 2018). However, the association between estimation accuracy and rainfall pattern classification is not always straightforward.

This study aims to evaluate the spatial variations in the accuracy of satellite-based rainfall products by applied multivariate analysis using K-Means clustering to group regions based on seven performance indicators. Cluster analysis has been widely applied in meteorology to classify rainfall patterns and characteristics (Santos et al., 2019; Alam & Paul 2020; Setiawan, 2021; Yanidar & Fatimah, 2022; Sofro et al., 2023), and K-Means, introduced by MacQueen (1967), remains a commonly used method due to its simplicity and computational efficiency.

In this study, K-Means clustering is applied to seven rainfall accuracy indicators to group regions in South Sulawesi based on their similarity in satellite product performance. The spatial grouping is then examined with respect to topographic features, allowing for the identification of terrain-influenced accuracy zones. This method follows a similar spatial approach as Durlević et al. (2025), who integrated satellite rainfall data with elevation models for environmental risk assessment.

By grouping similar temporal patterns, K-Means provides valuable insights into regional rainfall regimes. The centroids of each cluster represent average rainfall profiles, making the results easy to interpret for decision-making in water resource management and disaster risk planning. Several studies have demonstrated that K-Means performs well compared to other clustering methods, especially when dealing with large rainfall datasets.

These studies highlight K-Means' advantages in computational efficiency and simplicity, making it an ideal tool for identifying suitable regions for satellite-based rainfall products based on their accuracy. It is hypothesized that each region may only be accurate for specific satellite products, suggesting that the accuracy of these products varies by region and may be influenced by local factors such as topography, seasonality, and climate patterns.

Materials and Methods

Research location and data

This study was conducted in South Sulawesi Province, which consists of 21 regencies and three cities, covering an area of 62,482.54 km². It is bordered by Central Sulawesi and West Sulawesi to the north, the Gulf of Bone and Southeast Sulawesi to the east, the Makassar Strait to the west, and the Flores Sea to the south. According to BPS data, the population of South Sulawesi Province is projected to be 9,312,019 people in 2023 (BPS, 2024). Several sectors that impact rainfall conditions in South Sulawesi include: (1) the agricultural sector, with rice and corn as leading commodities; (2) the plantation sector, including cocoa, coffee, cloves, and nutmeg; (3) the livestock sector, which includes cattle farming, dairy cattle cultivation, buffalo, goats, and local poultry farming; (4) the fisheries sector, including fish ponds and seaweed cultivation; and (5) the forestry sector, which plays a role in maintaining climate stability. Additionally, the tourism sector is also affected by rainfall conditions. Despite this, the government continues to promote this sector through the "Visit Indonesia" and "Visit South Sulawesi" campaigns, aiming to attract foreign tourists. However, unpredictable weather conditions can lead to a decline in tourism productivity.

The rainfall data used in this study were collected from 24 locations representing districts in South Sulawesi Province, as shown in Figure 1. The data, obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG), cover the period from January 1, 1993, to December 31, 2022. Each district is represented by a single rainfall measurement. Missing or problematic data were removed before analysis.

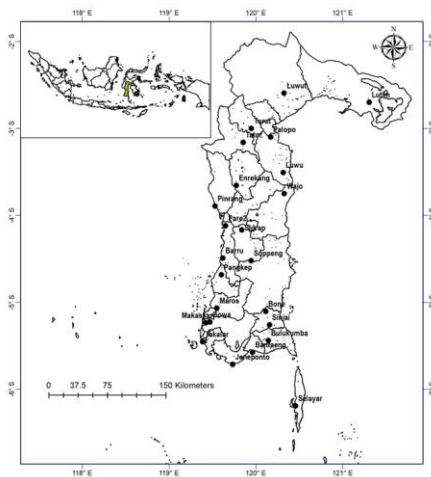


Fig. 1. The research location and rain gauge location is in South Sulawesi

Meanwhile, four satellite-based rainfall estimation datasets were used for comparison with surface rainfall data: 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). CHIRPS data can be accessed at <https://www.chc.ucsb.edu/data/chirps>, GPCP data at <https://www.ncei.noaa.gov/data/global-precipitation-climatology-project-gpcp-daily/>, GSMaP data at <https://hokusai.eorc.jaxa.jp>, and IMERG data at <https://gpm.nasa.gov/data/imerg>. Elevation data were obtained from the 30-m resolution SRTM DEM and used to classify districts into lowland and highland categories for spatial error analysis. The DEM was not validated separately, as it served only as contextual support for interpreting satellite performance over complex terrain.

Research methods

Evaluation satellite products

The evaluation uses matching rainfall events taken from measurements on the earth's surface with the results of satellite rainfall estimates. Two approaches were used: comparing the values numerically and the presence or absence of rain events. 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. The correct estimate of satellite rain events is called a hit, while the correct estimate of satellite no rain events is called a correct negative. Meanwhile, satellite estimates of rain events, while observational data does not rain, are called false alarms, and estimates of no rain events on satellites, while observation data does rain, are called miss, as shown in Table 1.

Table 1. Contingency table scheme used in the study

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

Table 1 shows the dichotomous method for measuring satellite estimation performance 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), and Critical Success Index (CSI) values using the following equations:

$$PC = \frac{Hits + Correct\ Negatives}{Total} \quad (1)$$

$$POD = \frac{Hits}{Hits + Misses} \quad (2)$$

$$FAR = \frac{False\ Alarms}{Hits + False\ Alarms} \quad (3)$$

$$BIAS = \frac{Hits + False\ Alarms}{Hits + Misses} \quad (4)$$

$$CSI = \frac{Hits}{Hits + False\ Alarms + Misses} \quad (5)$$

To analyze the spatial distribution of satellite estimation accuracy, several accuracy indicators such as PC, FAR, BIAS, POD, and CSI were calculated alongside other metrics. The analysis also incorporates elevation data for South Sulawesi Province and considers seasonal monsoonal wind patterns. The data are categorized into four climatological periods: the peak of the rainy season (December–February, DJF), the peak of the dry season (June–August, JJA), the transition from rainy to dry season (March–May, MAM), and the transition from dry to rainy season (September–November, SON). This seasonal breakdown aims to assess whether satellite performance is influenced by seasonal variation.

In addition to binary rain/no-rain indicators, the evaluation also includes a continuous accuracy metric, the root mean square error (RMSE) to provide a more comprehensive assessment of performance.

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

\hat{y}_i is the rainfall estimate from satellites from CHIRPS, GPCP, IMERG, and GSMaP, y_i is the rainfall resulting from the earth's surface measurements, and n is the number of stations. 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 and satellite data is in raster form, the two values are compared by selecting the location of the satellite rainfall estimate closest to the observation location.

Regional grouping using statistical metrics of satellite product performance

Cluster analysis is widely used in various fields, including the classification of weather parameters (Marzban & Sandgathe, 2006; Gokila et al., 2015; Murugesakumar et al., 2017; Komalasari et al. 2017; Kuswanto et al., 2019) or the relationship between weather parameters and pandemics (Giarno, 2021). Variables are grouped into similar objects to form clusters with shared characteristics.

This study uses an unsupervised method to ensure a more objective clustering of the relationship between satellite rainfall estimates and observation locations. Clustering uses K-means to divide the dataset into k groups. K-means was chosen because it is computationally efficient, easy to implement, and particularly effective when the number of clusters is known or can be estimated (Jain, 2010; Ahmad & Dey, 2007). It has also been widely applied in meteorological and climatological studies due to its robustness in handling large datasets and its ability to reveal meaningful spatial or temporal groupings (Unal et al., 2003; DeGaetano, 2001).

In classifying observations, several methods can be used to measure the distance or (dis)similarity between each pair of variables. Suppose there are two elements (x, y) ; in this study, Euclidean distance is used and is calculated as follows:

$$d_{euc}(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (7)$$

The number of clusters used in this study is three, based on the rainfall pattern defined by the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG). The clustering process incorporates dichotomous indicators (e.g., overestimation or underestimation tendency), numerical indicators such as the Root Mean Square Error (RMSE), and local rainfall characteristics represented by average annual rainfall and station elevation. As a result, three regional groups are formed, and the accuracy within each cluster is evaluated using boxplot visualizations, as illustrated in the flowchart in Fig. 2.

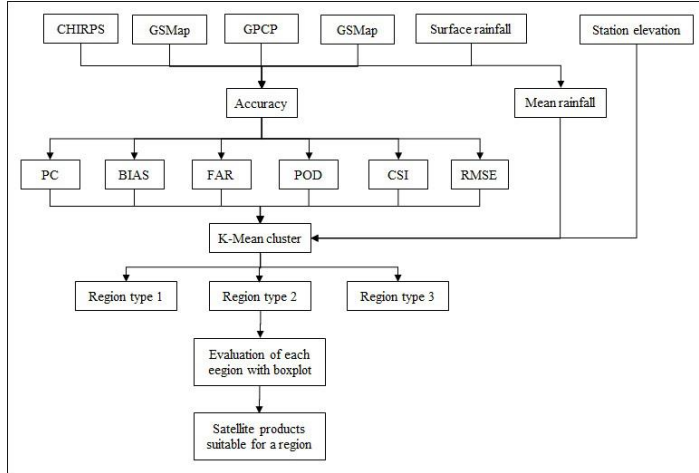


Fig. 2. Clustering process to classify regions and identify the most suitable satellite rainfall product using accuracy indicators and K-Means

The evaluation of the suitability of satellite-based rainfall estimation products results in three recommendation levels: highly recommended ($\checkmark\checkmark$), recommended (\checkmark), and not recommended (\times). These recommendations are determined based on a combination of dichotomous indicators (such as Probability of Detection (POD), False Alarm Ratio (FAR), and Percent Correct (PC)) and RMSE. For dichotomous indicators with ideal reference values (e.g., PC with a perfect score of 100), the following thresholds are applied: scores ≥ 70 are categorized as highly recommended ($\checkmark\checkmark$), scores between 50–69 as recommended (\checkmark), and scores below 50 as not recommended (\times). Likewise, lower RMSE values indicate higher accuracy and contribute to a better recommendation level. This multi-indicator approach offers a more comprehensive basis for evaluating the performance of each satellite product across different clusters.

Results

Distribution of rainfall and no rainfall in South Sulawesi

The spatial distribution of rainy and dry days across South Sulawesi reveals distinct regional rainfall regimes, largely governed by topographic and ocean-atmospheric interactions. The CHIRPS rainfall estimates have a spatial resolution of 0.05° (~ 5 km), and a single representative point was extracted for each district to enable direct comparison with rain gauge observations. This resolution allows CHIRPS to reasonably capture localized rainfall near each station, making the estimates more representative. As shown in Figure 3, the northern region,

encompassing North Toraja, North Luwu, and Palopo shows consistently higher proportions of rainy days, often exceeding 50%. This pattern is closely linked to a combination of orographic influences, mesoscale atmospheric dynamics, and local circulations.

Palopo and North Luwu are situated at the northern tip of Bone Bay, a concave-shaped coastline that enhances low-level convergence and convective uplift due to the funneling of moist maritime air masses (Alfahmi et al., 2021). Further inland, North Toraja is characterized by its elevated terrain, receives substantial rainfall through orographic lifting, particularly when prevailing moist winds from the bay encounter the Latimojong Mountains, which run northwest of Palopo and act as a natural barrier.

Topography also influences local wind systems that may contribute to rainfall distribution across the region. In mountainous areas such as North Toraja, elevated terrain promotes orographic lifting when moist air masses are forced to rise over the slopes, enhancing precipitation. Meanwhile, coastal areas like Palopo and North Luwu may benefit from sea-land breeze circulations that help transport moisture inland. Although the current analysis is based on daily data and does not capture diurnal variability, the general influence of thermally driven local circulations, combined with orographic effects and the concave coastal shape, likely contributes to the higher frequency of rainfall observed in northern South Sulawesi.

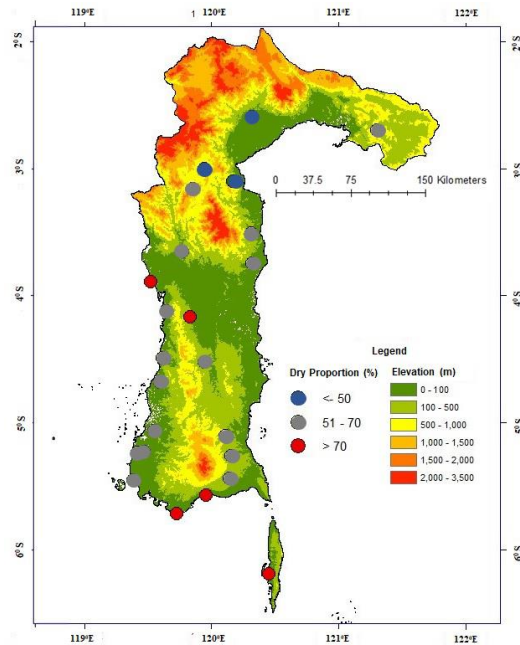


Fig. 3. Proportion of rainfall events in South Sulawesi

In contrast, the southern part of the province, particularly in Takalar, Bulukumba, and Bantaeng Regencies, experiences significantly less rainfall, with fewer than 30% of days classified as rainy. Similarly, lowland areas in the central region, such as Pinrang and Sidrap Regencies, are relatively dry. Other regencies fall into an intermediate category, where dry days outnumber rainy days, with the proportion of dry days ranging from 51% to 70%.

Clustering accuracy of satellite rainfall estimate

The accuracy indicators used in the cluster analysis include average daily rainfall accumulation, root mean square error (RMSE), percent correct (PC), false alarm ratio (FAR), bias score (BIAS), probability of detection (POD), and critical success index (CSI). The clustering process was carried out using the K-Means method, with Euclidean distance as the similarity measure to group locations into three clusters based on the combination of these seven variables. The cluster results for each satellite product are presented in Fig. 4. From this figure, it can be observed that the spatial accuracy patterns of CHIRPS and IMERG show notable similarities, indicating that these two products tend to perform similarly across different regions of the study area.

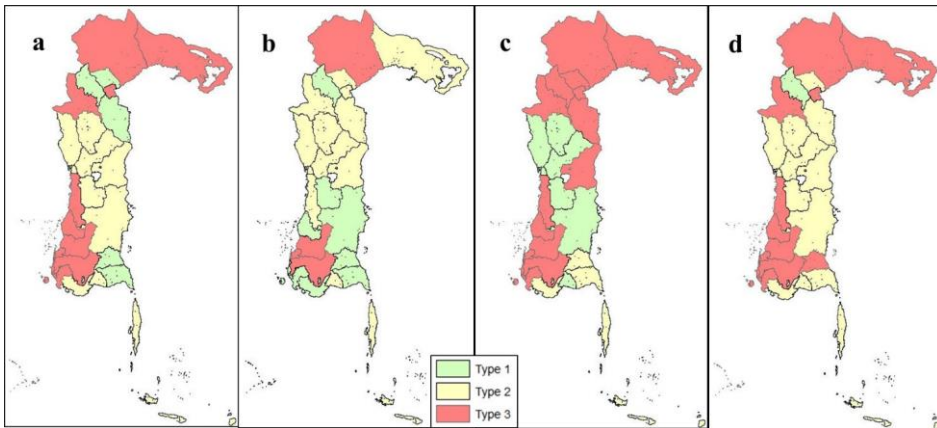


Fig. 4. Clustering area based on accuracy and location characteristics for CHIRPS (a), GPCP (b), GSMaP (c), and IMERG (d)

The accuracy clustering of the four satellite rainfall products: CHIRPS, GPCP, GSMaP, and IMERG reveals broadly similar spatial patterns across South Sulawesi, with certain regional distinctions. In the northern part of the province, particularly in North Toraja, North Luwu, and Palopo, all four products consistently fall into the same accuracy group, identified as Cluster Type 3 in Fig. 4. This consistency suggests that satellite rainfall estimates in these areas perform with relatively similar accuracy profiles, likely influenced by common geographical and meteorological factors such as orographic effects and convergence near Bone Bay. A comparable pattern is observed in the southwestern part of the province, notably in Makassar, Maros, and Gowa. These areas are also assigned to the same accuracy cluster as the northern region, indicating shared performance characteristics despite being geographically distant. This may reflect similarities in elevation, rainfall mechanisms, or observational coverage.

In contrast, the central part of South Sulawesi displays a distinct clustering pattern. For CHIRPS, GPCP, and IMERG, this region is predominantly associated with Cluster Type 2, suggesting an intermediate level of estimation accuracy. Interestingly, GSMaP shows a divergent clustering result in this area, with its Cluster Type 2 covering a much broader portion of the central region and its Cluster Type 3 extending more widely across the north. This divergence implies that GSMaP may respond differently to local rainfall variability compared to the other satellite products.

Furthermore, among the three products (CHIRPS, GPCP, and IMERG), Cluster Type 2 is the least spatially extensive, indicating that the accuracy conditions it represents are relatively uncommon. Cluster Types 1 and 3, by contrast, dominate across most of the province, suggesting that satellite product performance tends to fall into two prevailing accuracy profiles. This highlights the importance of region-specific assessment in determining which satellite product is most appropriate for a given area.

The key differences between Type 1 and Type 3 clusters lie in the performance metrics and spatial patterns. Type 3 generally exhibits better performance across all satellite products, characterized by lower RMSE, higher Probability of Detection (POD), lower False Alarm Ratio (FAR), and higher Critical Success Index (CSI). These areas (colored red in Figure 4) represent regions where the satellite products can more accurately estimate rainfall events. Conversely, Type 1 (green) denotes regions where the satellite rainfall estimates are less reliable, often showing higher error and lower detection skill. Spatially, Type 3 clusters are typically located in more open or lowland areas, while Type 1 tends to appear in mountainous or complex terrain where satellite signals may be affected by orography and persistent cloud cover. This distinction helps in understanding where each satellite product performs optimally within South Sulawesi.

The classification of accuracy into three cluster types requires an examination of the associated accuracy indicators within each group. These indicators include RMSE, PC, FAR, BIAS, POD, and CSI. A comparison of each parameter is presented using box plot diagrams for each satellite rainfall estimation product. The distinctive accuracy characteristics of each cluster type can be observed by examining Figures 5 to 8, which display each accuracy indicator.

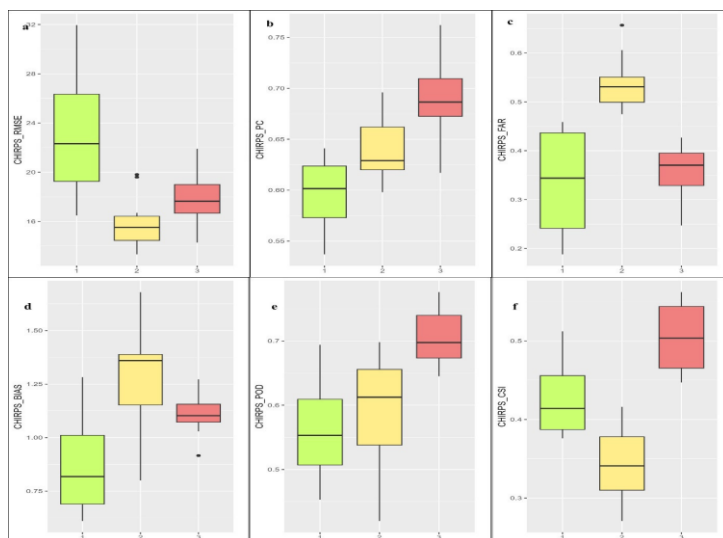


Fig. 5. Evaluation of accuracy indicators for the 3 clusters of CHIRPS (type 1–red, type 2–green, type 3–blue): RMSE (a), PC (b), FAR (c), BIAS (d), POD (e), and CSI (f)

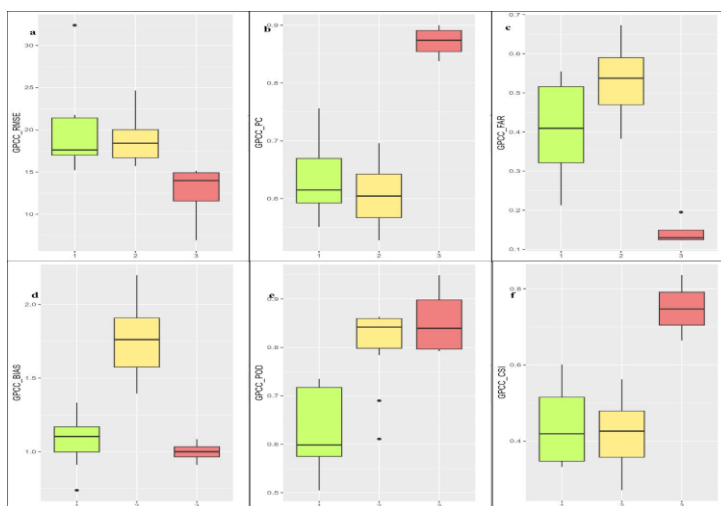


Fig. 6. Evaluation of accuracy indicators for the 3 clusters of GPCP (type 1–red, type 2–green, type 3–blue): RMSE (a), PC (b), FAR (c), BIAS (d), POD (e), and CSI (f)

Cluster Type 1 is characterized by the highest RMSE values compared to Cluster Types 2 and 3, except in the case of GSMaP. For IMERG, Cluster Type 1 only appears in one district (as shown in Fig. 4), yet it exhibits the highest RMSE values with a median exceeding 32 and a wide spread. In CHIRPS, Cluster Type 1 includes Sinjai, Bulukumba, Luwu, Toraja, and North Toraja Regencies, and presents the second-highest RMSE with a median around 22. Interestingly, GSMaP shows the lowest RMSE deviation in this cluster, suggesting it performs best in Type 1 areas based on this metric.

In Cluster Type 2, CHIRPS and GSMaP show similarly low RMSE values, with comparable medians and interquartile ranges, while IMERG has a slightly higher RMSE, especially towards the upper quartile. For Cluster Type 3, GPCP has the lowest RMSE, indicating the highest accuracy, followed by IMERG, CHIRPS, and GSMaP, respectively. These comparisons are illustrated in Fig. 5(a), 6(a), 7(a), and 8(a).

Using the Percent Correct (PC) indicator, IMERG shows the highest PC value in Cluster Type 1, followed by GSMaP, GPCP, and CHIRPS. However, the limited spatial extent of this cluster in IMERG (only Tanah Toraja Regency) restricts its broader applicability. In Cluster Type 2, CHIRPS exhibits the highest PC value, followed by GSMaP, GPCP, and IMERG. Given that this cluster spans six districts in CHIRPS, it underscores CHIRPS' utility as a reliable rainfall estimate in those areas. For Cluster Type 3, GPCP leads in PC value, followed by CHIRPS, IMERG, and GSMaP, as shown in Fig. 5(b), 6(b), 7(b), and 8(b).

The False Alarm Ratio (FAR) is one of the important accuracy indicators because it measures the proportion of false alarms relative to the number of correct detections (hits). The results indicate that the FAR value for the IMERG product is the lowest in the Cluster Type 1 area, followed by CHIRPS, GPCP, and GSMaP. Although IMERG shows a FAR value of only 0.1, which indicates a very low number of hits compared to false alarms, its Cluster Type 1 area covers only one district. Therefore, the second-best product in terms of FAR, CHIRPS, with a median value of 0.344, should be taken into account for broader application.

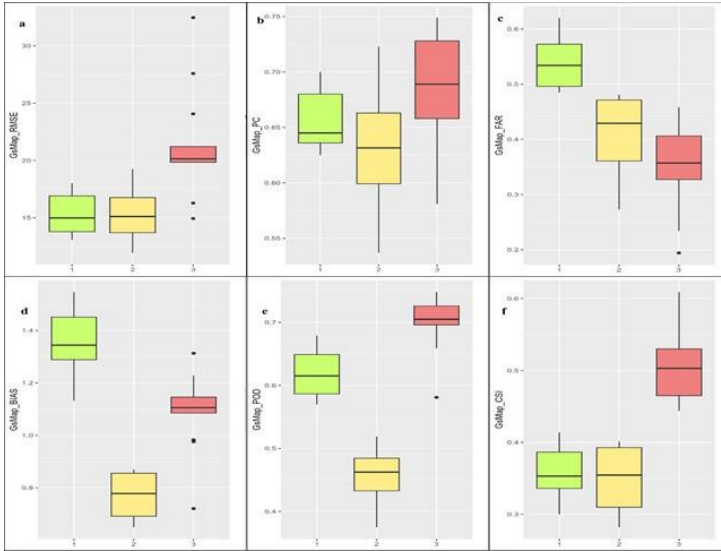


Fig. 7. Evaluation of accuracy indicators for the 3 clusters of GSMaP (type 1–red, type 2–green, type 3–blue): RMSE (a), PC (b), FAR (c), BIAS (d), POD (e), and CSI (f)

In the Cluster Type 2 area, GSMaP demonstrates the lowest FAR value, followed by CHIRPS, GPCP, and IMERG. Although the median FAR for CHIRPS is slightly higher than that of GPCP, the wider range of FAR values in GPCP suggests that CHIRPS offers more consistent performance in this cluster. Moreover, in the Cluster Type 3 area, GPCP performs best with a notably low median FAR value of 0.130 and a narrow interquartile range of 0.024. In comparison, the FAR values of the other three products—CHIRPS, IMERG, and GSMaP—are relatively similar. These results are presented in Fig. 5(c), 6(c), 7(c), and 8(c).

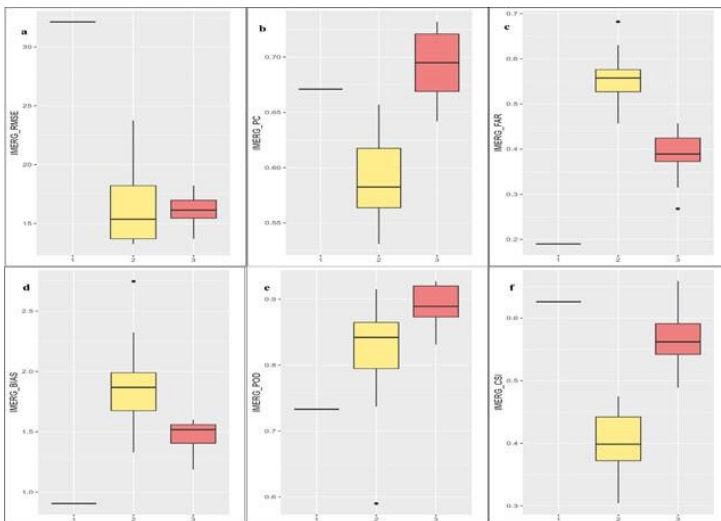


Fig. 8. Evaluation of accuracy indicators for the 3 clusters of CHIRPS (type 1–red, type 2–green, type 3–blue): RMSE (a), PC (b), FAR (c), BIAS (d), POD (e), and CSI (f)

The portion of error due to missing rainfall events, as indicated by the Probability of Detection (POD), shows that the IMERG product has the highest value, with a median of 0.733. However, since this value is derived from only one district, the first and third quartiles are identical to the median. Following IMERG, the products with the next highest POD values are GSMaP, GPCP, and CHIRPS. The Cluster Type 1 area in GSMaP includes six districts in the central part of South Sulawesi Province, namely Pinrang, Enrekang, Sidrap, Soppeng, and Bone, making GSMaP a product worth considering when addressing the issue of missed rainfall detection.

For the Cluster Type 2 and Cluster Type 3 areas, the products that minimize missed events are, respectively, IMERG, GPCP, CHIRPS, and GSMaP, as shown in Fig. 5(d), 6(d), 7(d), and 8(d). In general, the two main types of errors that must be considered in rainfall prediction are missed events and false alarms. In this regard, the BIAS indicator is also important in evaluating satellite-based rainfall estimates. Among all the products, IMERG provides the most balanced estimate with a BIAS value closest to 1, followed by GPCP, CHIRPS, and GSMaP. Although the median BIAS value for CHIRPS is almost equal to that of GSMaP, the interquartile range for GSMaP is wider, indicating greater variability in its accuracy. In the Cluster Type 2 region, GSMaP shows the best BIAS performance compared to the other three products. This comparison can be seen in Fig. 5(e), 6(e), 7(e), and 8(e). The pattern remains similar in Cluster Type 3, although in this case, the BIAS accuracy of CHIRPS closely matches that of GSMaP, both in terms of the median value and the spread between quartiles.

The predictive ability for rare events is assessed using the Critical Success Index (CSI) parameter. This indicator disregards the number of correct negatives and instead compares the number of hits to the total of hits, misses, and false alarms. As a result, CSI is sensitive to these three components, and a perfect CSI value is one that approaches 1.

Based on the results, the IMERG product exhibits a significantly higher CSI value compared to GPCP, CHIRPS, and GSMaP, as illustrated in Fig. 5(f), 6(f), 7(f), and 8(f). However, the region corresponding to Cluster Type 1 in IMERG is limited to Tanah Toraja Regency, making its broad applicability more constrained.

In contrast, the CSI values for GPCP, CHIRPS, and GSMaP in Cluster Type 1 are relatively similar, with median values around 0.34. In Cluster Type 2, all four rainfall estimation products show comparable performance, with median CSI values ranging between 0.35 and 0.4. A notably different pattern emerges in Cluster Type 3, where the GPCP product outperforms the others significantly in terms of the CSI indicator. Its superiority in this cluster is evident when compared to IMERG, CHIRPS, and GSMaP, suggesting that GPCP may be particularly well-suited for areas grouped within this accuracy profile.

Elevation appears to play a significant role in the spatial accuracy of satellite-based rainfall estimates. Our analysis shows that higher-elevation areas, such as Sinjai, Soppeng, and North Toraja, tend to have larger RMSE values and lower correlation (PC), POD, and CSI scores compared to lowland areas such as Jeneponto and Bantaeng. This suggests a decline in satellite performance in mountainous regions. Among the products, CHIRPS and GPCP showed more consistent patterns of increasing error with elevation. GSMaP and IMERG, while more variable, also indicated performance degradation in highland regions. The higher FAR and bias scores in these areas further confirm the challenge of accurately detecting rainfall in complex terrain. These findings support previous studies indicating

that topographic complexity and orographic effects can reduce the accuracy of satellite rainfall retrievals, particularly in regions with strong elevation gradients.

Based on the accuracy clusters for South Sulawesi, this study recommends a guideline for selecting the most suitable rainfall estimation product. Users can choose based on the indicators in Table 2 and their specific needs, as shown in Fig. 2. The suitability evaluation results in three recommendation levels: highly recommended ($\sqrt{\sqrt{}}$), recommended ($\sqrt{}$), and not recommended (x). These levels are based on a combination of indicators like Probability of Detection (POD), False Alarm Ratio (FAR), Percent Correct (PC), and RMSE. For dichotomous indicators, scores ≥ 70 are highly recommended, 50–69 are recommended, and < 50 are not recommended. Lower RMSE values contribute to higher recommendation levels, offering a comprehensive assessment of satellite product performance.

Table 2. Cluster-based recommendations for satellite rainfall estimation products ($\sqrt{\sqrt{}}$ = Highly Recommended, $\sqrt{}$ = Recommended, x = Not Recommended)

Product	Cluster	RMSE	PC	FAR	BIAS	POD	CSI
CHIRPS	Type 1	$\sqrt{}$	x	$\sqrt{\sqrt{}}$	$\sqrt{}$	x	$\sqrt{}$
	Type 2	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{}$	$\sqrt{\sqrt{}}$	$\sqrt{}$	$\sqrt{}$
	Type 3	$\sqrt{}$	$\sqrt{}$	x	$\sqrt{\sqrt{}}$	$\sqrt{}$	$\sqrt{}$
GPCP	Type 1	$\sqrt{}$	x	$\sqrt{}$	$\sqrt{}$	$\sqrt{}$	$\sqrt{}$
	Type 2	x	$\sqrt{}$	$\sqrt{}$	x	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$
	Type 3	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$
GSMaP	Type 1	$\sqrt{\sqrt{}}$	$\sqrt{}$	x	x	$\sqrt{}$	x
	Type 2	$\sqrt{\sqrt{}}$	$\sqrt{}$	$\sqrt{}$	$\sqrt{\sqrt{}}$	x	$\sqrt{}$
	Type 3	x	$\sqrt{}$	$\sqrt{}$	$\sqrt{\sqrt{}}$	$\sqrt{}$	$\sqrt{}$
IMERG	Type 1	x	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$	$\sqrt{\sqrt{}}$
	Type 2	$\sqrt{\sqrt{}}$	x	x	x	$\sqrt{\sqrt{}}$	x
	Type 3	$\sqrt{}$	$\sqrt{}$	x	x	$\sqrt{\sqrt{}}$	x

In Cluster 1, IMERG stands out as the most highly recommended product due to its exceptional performance in POD and CSI, despite being limited to just one district. GSMaP and GPCP are also recommended for this cluster, showing solid performance in RMSE, POD, and CSI. However, GSMaP falls short in PC, while CHIRPS is not recommended due to its poor performance in PC and POD, making it less suitable for use in this cluster.

Moving to Cluster 2, CHIRPS emerges as the top choice, performing exceptionally well across most accuracy indicators, including POD and RMSE. GSMaP is also recommended here, showing good results in RMSE, PC, and POD. However, IMERG is not recommended in this cluster, as its low performance in PC and FAR detracts from its overall reliability in this area.

Finally, in Cluster 3, GPCP proves to be the most highly recommended product, achieving the best performance across all indicators, including RMSE, PC, and BIAS. GSMaP follows as a solid recommendation, performing well in POD and BIAS, but still showing room for improvement in PC and FAR. On the other hand, IMERG is not recommended in this cluster, as it underperforms in PC and FAR, making it less reliable for use here. In conclusion, the selection of the optimal rainfall estimation product depends on the specific cluster

being considered. IMERG is ideal for smaller areas in Cluster 1, CHIRPS performs best in Cluster 2, and GPCC emerges as the top performer for Cluster 3.

Discussion

South Sulawesi experiences a tropical monsoonal climate, with distinct wet and dry seasons influenced by the Australian and Asian monsoons. Orographic rainfall is common in the highlands, contributing to spatially uneven precipitation distribution across the region. The availability of several global precipitation datasets allows for the estimation of rainfall over various spatial and temporal scales (Joyce et al., 2004; Dinku et al., 2007; Peters-Lidard et al. 2007; Huffman et al., 2007; Grimes et al., 2012). However, as many studies have shown, the accuracy of satellite rainfall estimates varies with location and time. Comparisons of several satellite products in Indonesia reveal that CHIRPS rainfall estimates are generally more accurate than other satellite products, although variations occur depending on the region (Liu et al., 2020; Faisol et al., 2020; Rahmawati et al., 2021; Wiwoho et al., 2021; Wati et al., 2021; Asferizal, 2022).

In this context, accuracy assessments using clustering techniques are particularly valuable for regions in Indonesia where rainfall patterns are highly dynamic. Rather than calculating a single aggregate accuracy value for an entire area, clustering provides a more detailed representation of spatial rainfall variation (Fatkhuroyan & Trinahwati, 2018; Setiyoko et al., 2019; Liu et al., 2020; Satria & Qothrunada, 2022). This approach enables more targeted evaluations, helping to identify locations where specific satellite products perform better than others, and is especially relevant for a country like Indonesia where precipitation varies significantly across short distances.

Building on this, the characterization of satellite rainfall estimates also aids in understanding regional rainfall patterns and addresses challenges posed by the limited availability of ground-based data (Kuswanto et al., 2019). Nonetheless, the selection of appropriate rainfall estimates requires careful consideration, as the performance of satellite products differs markedly depending on local conditions (Prasetia et al., 2013; Giarno et al., 2018; Misnawati, 2019; Faisol et al., 2020; Wiwoho et al., 2021; Pratama et al., 2022; Hastina et al., 2023; Viddaroini et al., 2023; Mangitua et al., 2024).

A cluster analysis based on seven accuracy indicators, including RMSE, POD, CSI, and others, was conducted to classify the South Sulawesi region into three cluster types for each satellite product. The spatial clustering patterns of CHIRPS and IMERG exhibited significant similarities, particularly in the northern and southwestern parts of the province. Areas such as Tanah Toraja, North Luwu, and Palopo were consistently categorized as Cluster Type 3, suggesting consistent accuracy driven by geographic factors such as orographic influence and convergence zones. In contrast, the central region showed greater cluster variability. GSMaP, for example, displayed distinct cluster coverage compared to other products, highlighting its sensitivity to local variability. Cluster Type 2 had the most limited spatial extent, reflecting relatively rare accuracy conditions, while Types 1 and 3 were more spatially dominant.

The evaluation of accuracy indicators within each cluster led to specific product recommendations. In Cluster 1, for instance in Tanah Toraja, IMERG was highly recommended due to its superior POD and CSI values, despite covering only one regency. CHIRPS performed best in Cluster 2, corresponding to the central region, based on its strong performance in POD and RMSE. For Cluster 3, encompassing the northern and southwestern areas, GPCC was the most

recommended product due to its high performance in RMSE, PC, and BIAS. These results emphasize the importance of spatially explicit approaches in evaluating the accuracy of satellite-based rainfall estimates and suggest that product selection should be aligned with the specific characteristics of each area.

In line with this, the application of clustering techniques to evaluate satellite-based rainfall products and their assimilated versions demonstrates significant potential for optimizing rainfall data selection based on region-specific requirements. Some areas may be better represented by particular satellite products, and such suitability can be better determined through the use of appropriate accuracy indicators that reflect local climatic and topographic conditions. The clustering method adopted in this study captures the spatial variability and dynamic nature of Indonesia's climate, reinforcing that each cluster exhibits distinct characteristics. Therefore, tailoring the choice of satellite rainfall products to local conditions is essential for improving their reliability and applicability.

Overall, the findings highlight that no single satellite-based rainfall product consistently outperforms others across all regions. Instead, the performance of each product is strongly influenced by geographical and climatological factors. The cluster-based evaluation approach enables a more nuanced and regionally specific selection of satellite rainfall products, which is particularly valuable in areas with complex terrain and sparse rain gauge coverage, such as South Sulawesi. These results underscore the importance of spatially adaptive methodologies when applying remote sensing data in hydrometeorological research and operational decision-making.

Despite these insights, several limitations should be noted. First, the validation relied on rain gauge data at the district level, which may not fully capture sub-regional rainfall variability, particularly in mountainous areas. Second, this study used only one year of daily rainfall data; therefore, product performance may differ across years, especially under different ENSO or IOD phases. Third, although seven accuracy indicators were employed, additional metrics, such as temporal correlation or rainfall intensity classification could provide further insights. Finally, the clustering results are sensitive to the choice and number of indicators, as well as the number of clusters, which may affect the robustness of classification. Future studies should consider incorporating multi-year datasets, additional evaluation metrics, and alternative machine learning approaches to enhance the robustness and generalizability of the results.

Conclusions

This study compared four satellite-based rainfall estimation products (CHIRPS, GPCP, GSMaP, and IMERG) through a clustering approach based on seven accuracy indicators across South Sulawesi. The key findings are summarized as follows:

- Clustering effectively identifies the spatial suitability of rainfall products, allowing for more localized accuracy evaluations and no single product consistently outperformed others across the entire province. Product suitability varied by cluster and region, underscoring the importance of localized assessments.

- IMERG performed well in Cluster Type 1 (North Toraja), with a POD of 0.87 and a CSI of 0.89, though it was slightly less optimal for RMSE (15.2 mm). CHIRPS was most suitable for Cluster Type 2 (Pinrang, Enrekang, Sidrap, Soppeng, Bone), with an RMSE of 12.3 mm, followed closely by IMERG. GPCP showed the best accuracy in Cluster Type 3, which includes areas such

as Luwu, East Luwu, Palopo, Tanah Toraja, North Toraja, Makassar, Maros, Gowa, and Takalar, with an RMSE of 10.5 mm, a PC score of 0.92, and a BIAS of 0.05.

- Product selection should consider the specific needs of users, as different applications prioritize different accuracy indicators (e.g., POD for early warnings, RMSE for hydrological modeling).

- Elevation and terrain complexity appear to influence product performance, with higher-elevation areas generally associated with lower accuracy. This suggests the need to incorporate topographic context into satellite validation efforts.

While the analysis was region-specific, its findings highlight the broader value of spatially explicit evaluation frameworks that integrate both accuracy metrics and terrain features. This is especially relevant for guiding satellite product selection in other topographically complex regions across Indonesia.

However, several limitations remain. District-level averaging may obscure local-scale variability, and only topography was qualitatively assessed among influencing factors. Land cover, seasonality, and extreme rainfall events were not explicitly analyzed. Future studies should address these dimensions, adopt finer spatial and temporal resolutions, and assess performance under more diverse hydroclimatic conditions to better support rainfall-related applications in complex terrain.

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