Performance Analysis of Satellite-Derived Precipitation Data in Aceh, Indonesia

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DOI: https://doi.org/10.52939/ijg.v21i7.4311

Abstract
Accurate precipitation estimation is crucial for effective water resource management, disaster mitigation, and hydrological studies, particularly in regions with limited ground-based observations, such as Aceh Province, Indonesia. This study evaluates the performance of five satellite-based precipitation products (SPPs) by comparing their daily, monthly, and annual estimates against ground-based measurements. The selected products are Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Multi-Source Weighted-Ensemble Precipitation (MSWEP), Climate Prediction Center MORPHing technique (CMORPH), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), and Tropical Rainfall Measuring Mission (TRMM). Performance was evaluated using statistical metrics, including correlation coefficient, root mean square error (RMSE), mean absolute error (MAE), and relative bias (RBS), along with categorical metrics such as probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), and frequency bias (Fbias). At the daily scale, CHIRPS achieved the best performance with an RMSE of 15.03 mm/day, followed by MSWEP (RMSE: 17.34 mm/day). CMORPH and PERSIANN showed moderate performance, while TRMM had the highest RMSE (23.46 mm/day). For categorical metrics, MSWEP excelled at higher precipitation thresholds, indicating its suitability for detecting heavy rainfall events. At monthly and annual scales, MSWEP consistently outperformed other SPPs, exhibiting the highest correlation and lowest error metrics. CHIRPS also demonstrated good performance but with slightly higher RMSE and bias. TRMM and PERSIANN underperformed, especially in capturing heavy rainfall, with notable biases and higher errors. Based on these findings, MSWEP is recommended for hydrological modeling and flood forecasting, while CHIRPS is more suitable for long-term climatological applications. CMORPH and PERSIANN may benefit from calibration to improve their ability to detect heavy rainfall events.

Keywords: Aceh Province, Categorical Metrics, Precipitation Estimation, Satellite-based Precipitation Products, Statistical Metrics

1. Introduction

Precipitation is an essential component of the hydrological cycle, significantly impacting crop yield, water management methods, and disaster mitigation strategies [1]. Precise quantification of precipitation is essential for effective water resource management, particularly in regions prone to extreme weather. Conventional ground-based methods for measuring precipitation, although accurate, are typically limited in their spatial coverage, especially for remote and sparsely gauged areas [2]. Satellite-based precipitation products (SPPs) thus offer critical supplementary data due to their broader spatial-temporal coverage, becoming invaluable tools in hydrological and climatic analyses [3].

SPPs such as Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Multi-Source Weighted-Ensemble Precipitation (MSWEP), Climate Prediction Center MORPHing technique (CMORPH), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), and Tropical Rainfall Measuring Mission (TRMM) data have been widely used in hydrological and climate studies. Each product employs different algorithms and input data, resulting in variable accuracy and reliability depending on regional climatic and topographic conditions [4]. For example, TRMM is noted for effectively measuring light rain events [5], while

MSWEP shows consistency in gauge-scarce highlands [6].

However, biases linked to elevation, terrain complexity, and seasonal variability remain challenging. The performance of SPPs has been extensively studied worldwide due to their significance in hydrological applications and disaster management. Evaluations across various regions reveal notable variations in accuracy, influenced by local climatic and geographical conditions. SPPs generally perform well in capturing monthly precipitation and moderate rainfall but tend to underestimate light and extreme rainfall, particularly in mountainous and orographically complex areas [7] and [8]. Even the most accurate SPPs require ground-based validation and localized assessments, as product performance varies with season and geography [9] and [10]. Overall, the significant variability in performance underscores the need for tailored evaluations that account for specific applications [11].

This need for tailored evaluations is similarly reflected in studies conducted in Southeast Asia, a region characterized by diverse topography and climatic conditions. Research in this area shows significant variability in SPP performance depending on the product and temporal scale. For example, CMORPH often underestimates heavy rainfall in mountainous regions, such as Bali and the Merapi Aquifer System, while CHIRPS, with its finer spatial resolution, more accurately captures rainfall dynamics but may slightly overestimate overall precipitation [12] and [13]. Additionally, climatic factors like the Indian Ocean Dipole (IOD) and El Niño-Southern Oscillation (ENSO) affect seasonal and interannual variability in rainfall, further impacting satellite retrieval accuracy [14] and [15]. No single product consistently outperforms the others, highlighting the importance of considering local terrain and climate when using SPPs for precipitation estimation [16]. Moreover, the limited density of rain gauges and resolution mismatches between ground and satellite data complicate validation efforts [17] and [18], emphasizing the necessity for localized, multi-product validation to identify the most reliable SPPs for complex tropical terrains.

Aceh Province, situated in the northernmost region of Sumatra, Indonesia, faces particular challenges in precipitation monitoring due to its complex topography encompassing coastal plains, highlands, and dense rainforest ecosystems. The region is additionally susceptible to notable climatic fluctuations, which are driven by external factors such as the IOD and the ENSO. These factors pose additional challenges in accurately estimating precipitation rates. The Barisan Mountain range influences spatial variability in rainfall, with higher elevations typically receiving more precipitation. The sparse distribution of meteorological stations limits ground-based observations, complicating comprehensive precipitation assessment. Consequently, SPPs offer a promising alternative for precipitation monitoring in this region, with the potential to improve local water resource management and flood mitigation.

Given the critical need for accurate precipitation data in Aceh, this study evaluates the performance of five widely used SPPs, including CHIRPS, MSWEP, CMORPH, PERSIANN, and TRMM, by comparing them with ground-based observations at various locations throughout the province. The objective is to determine which satellite datasets are most reliable within Aceh's unique meteorological and topographical context. The findings aim to support enhanced decision-making in water resource management, disaster preparedness, and climate resilience planning in the region.

2. Methodology

2.1 Study Area

Aceh Province is bounded by the Malacca Strait to the north and east, the Indian Ocean to the west, and shares its southern boundary with North Sumatra Province (Figure 1). The terrain in Aceh is also diverse, it has coastal flat land with high hills and rough mountains. The province is greatly influenced by climate variations related to SSTA (Sea Surface Temperature Anomalies) in the Indian Ocean [19]. The tropical Indian Ocean shows a dipole mode, characterized by anomalous sea surface temperatures near Sumatra and in the western part of the basin. This dipole mode can significantly affect wind velocity and precipitation patterns in the region [20]. Variability is important, as Aceh is vulnerable to climatic changes triggered by variations in sea surface temperatures because of its close position to the Indian Ocean. The change in climatic conditions is one of the factors leading Aceh to become one of the most disaster-prone provinces in Indonesia [21].

2.2 Data Collection

The study evaluates the accuracy of SPPs by comparing them with ground-based observations from meteorological stations within Aceh Province. Daily precipitation data were obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) and five widely used SPPs: CHIRPS, MSWEP, CMORPH, PERSIANN, and TRMM.

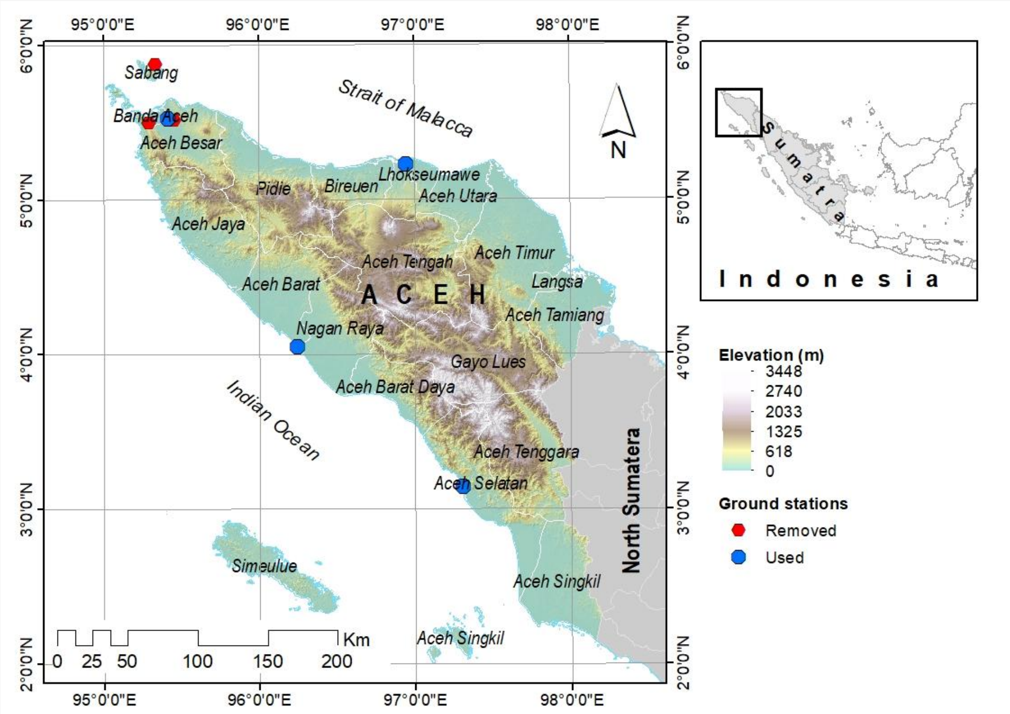

Figure 1: Aceh Province, Indonesia

2.2.1 Ground-Based observation

This study utilizes precipitation data from BMKG meteorological stations in Aceh, covering the period from January 1, 2010, to December 31, 2019. The end date corresponds with the most recent TRMM dataset available at the time of data acquisition. Among the seven available stations, four were selected based on the continuity and reliability of their records. To maintain data integrity, days with missing values from either ground-based observations or satellite products were excluded from the analysis. The limited number of stations with sufficiently long and reliable records, combined with accessibility challenges, constrained the spatial coverage. Similar constraints have been reported in previous studies [22] and [23]. The data are accessible from the official BMKG website (https://dataonline.bmkg.go .id/).

2.2.2 Satellite-Based Precipitation Products (SPPs)

The following five SPPs were selected for this study based on their widespread use in hydrological and meteorological research:

1. CHIRPS combines infrared satellite imagery with ground-based gauge data to provide daily precipitation estimates at a spatial resolution of 0.05° (approximately 5 km). The data can be accessed at the Climate Hazards Center, University of California, Santa Barbara: https://data.chc.ucsb.edu/products/CHIRPS-2.0/. Offering long-term coverage from 1981 to the present, CHIRPS has been extensively used for drought monitoring and rainfall trend analysis in tropical Asia [3] and [24]. Studies in Sumatera and surrounding regions indicate CHIRPS performs well in detecting rain events with a threshold of 1 mm [25]. This makes it particularly suitable for daily rainfall forecasting in the study area.

2. MSWEP is a global dataset that integrates data from rain gauges, satellites, and reanalysis models to produce accurate and reliable precipitation estimates. It has a spatial resolution of 0.1° (approximately 10 km) and a temporal resolution of daily. The dataset spans from 1979 to present and is accessible via https://www.gloh2o.org/mswep/.

MSWEP effectively captures rainfall variability with high accuracy and low bias, outperforming many other satellite precipitation products [26], especially in monsoon-dominated regions like India [27]. Its multi-source weighted-ensemble approach enhances spatial and temporal rainfall representation, making it reliable for hydrological and climate applications such as drought forecasting.

3. CMORPH, developed by the Climate Prediction Center, uses microwave and infrared satellite data combined through a morphing technique to generate high-resolution precipitation estimates. The version used in this study, CMORPH V1.0, has a spatial

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resolution of 0.25° (approximately 25 km) and a temporal resolution of daily. The data is available from 2002 onwards, which can be accessed via the CMORPH V1.0 FTP site (https://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/).

This version aggregates the high-frequency data into daily precipitation estimates, which are widely used for monitoring and analyzing precipitation patterns over extended periods. CMORPH's ability to capture intense convective rainfall events common in the equatorial tropics has been validated in Indonesia, although some studies note a tendency to underestimate rainfall intensity [13].

4. PERSIANN uses artificial neural networks to estimate precipitation from infrared satellite data. The PERSIANN-Climate Data Record (CDR) version provides daily estimates at 0.25° (approximately 25 km) resolution and is available from 1983 to present at the NOAA National Centers for Environmental Information: https://www.ncei.noaa.gov/data/precipitation-persiann/. Despite some underestimation in light rainfall [5] and [9], it remains valuable for regions with sparse gauge coverage [5] and [26].

5. TRMM was a joint mission by NASA and JAXA to measure precipitation in tropical and subtropical regions. This study uses the TRMM 3B42 product, which provides daily precipitation estimates with a spatial resolution of 0.25° (approximately 25 km). The dataset covers the period from 1998 to 2015, after which it was succeeded by the Global Precipitation Measurement (GPM) mission. Data can be downloaded from NASA's GPM website: https://gpm.nasa.gov/data. The TRMM products remain a benchmark for tropical precipitation studies and have been extensively validated in Indonesia, providing reliable monthly and seasonal rainfall estimates that capture convective rainfall and monsoon patterns with good correlation to rain gauge data, especially in lowland areas [18] and [28].

2.3 Statistical Metrics

The accuracy and reliability of the satellite-based precipitation products were evaluated using several statistical metrics. These metrics quantify the differences between the satellite estimates and the ground observations in different aspects of accuracy. These metrics have been widely used in precipitation validation studies [5][11], and [13]. Commonly used variables in these metrics include the satellite precipitation estimates (P_i) and ground observations (G_i) for day i, as well as mean satellite precipitation and mean ground precipitation ($\bar{G}$) calculated over n paired observation days. The metrics considered are:

1. Correlation Coefficient (r) is used to assess how well the satellite precipitation data capture the temporal variability of rainfall compared to ground observations [11] and [13]. The correlation coefficient measures the degree of linear relationship between satellite estimates (P_i) and ground observations (G_i) as expressed in Equation 1. A high r value indicates that the SPP effectively captures temporal precipitation patterns, reflecting consistency in variability over time. The r value is determined from Equation 1.

$$r = \frac{\sum_{i=1}^{n}\left(P_i - \bar{P}\right)\left(G_i - \bar{G}\right)}{\sqrt{\sum_{i=1}^{n}\left(P_i - \bar{P}\right)^2 \sum_{i=1}^{n}\left(G_i - \bar{G}\right)^2}}$$

Equation 1

2. Root Mean Square Error ($RMSE$) measures the average amount of discrepancies between the satellite and ground measurements, offering insight into the overall accuracy of the satellite estimates [5]. Lower $RMSE$ values indicate better performance, as calculated in Equation 2.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_i - G_i\right)^2}$$

Equation 2

3. Mean Absolute Error (MAE) offers a robust measure of average error that is less sensitive to outliers compared to $RMSE$ [11]. It calculates the average absolute discrepancies between satellite estimates and ground observations, shown in Equation 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - G_i\right|$$

Equation 3

4. Relative Bias (RBS) indicates systematic tendencies of the satellite products to overestimate or underestimate precipitation relative to ground data [13]. Values close to zero indicate low bias, which is critical for detecting consistent over- or underestimation in satellite estimates, as formulated in Equation 4.

$$RBS = \frac{\sum_{i=1}^{n}\left(P_i - G_i\right)}{\sum_{i=1}^{n} G_i}$$

Equation 4

2.4 Categorical Metrics

This study employs categorical metrics to assess the proficiency of SPPs in accurately identifying precipitation occurrences. Unlike statistical metrics,

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

which focus on the agreement in precipitation amounts, categorical metrics assess whether the satellite products correctly identify when rainfall happens [13][29] and [30]. This distinction is crucial for hydrological and meteorological applications, such as flood forecasting and drought monitoring, where accurate detection of rainfall events is as important as measuring their intensity [14].

In this context, key terms are defined to evaluate the detection performance of the satellite products. A hit (H) occurs when both the satellite product and ground observations detect precipitation on the same day. A miss (M) happens when precipitation is observed on the ground but not detected by the satellite product. Conversely, a false alarm (F) occurs when the satellite product detects precipitation on a day when no precipitation is observed on the ground. Using these definitions, the following categorical metrics were calculated:

1. Probability of Detection (*POD*) measures the proportion of actual precipitation events correctly detected by the satellite product. A higher *POD* value, closer to 1, indicates better detection skill [14], as calculated using Equation 5.

$$POD = \frac{H}{H+M}$$

Equation 5

2. False Alarm Ratio (*FAR*) quantifies the proportion of precipitation detections by the satellite product that do not correspond to actual precipitation events observed on the ground [31]. It is calculated using Equation 6. Lower *FAR* values indicate fewer false alarms, which suggests better reliability of the satellite product.

$$FAR = \frac{F}{H+F}$$

Equation 6

3. Critical Success Index (*CSI*) combines hits, misses, and false alarms into a single metric that reflects the overall accuracy of event detection [32] as calculated using Equation 7. Values closer to 1 represent better overall detection performance.

$$CSI = \frac{H}{H+M+F}$$

Equation 7

4. Frequency Bias (*Fbias*) indicates whether the satellite product tends to overestimate (*Fbias* > 1) or underestimate (*Fbias* < 1) the frequency of precipitation events compared to ground observations [11]. A value close to 1 suggests an unbiased frequency (Equation 8).

$$Fbias = \frac{H+F}{H+M}$$

Equation 8

These categorical metrics complement the statistical metrics by focusing on event occurrence rather than magnitude, providing a comprehensive evaluation of satellite precipitation product performance.

2.5 Study Procedure

This study adopts a systematic approach to assess the accuracy of SPPs compared to ground observations in Aceh Province. Daily precipitation data were collected from meteorological ground stations managed by BMKG and from five satellite precipitation products for the period from January 2010 to December 2019. The ground-based and satellite data were matched by date to form paired datasets for analysis, ensuring that the data were consistent and comparable. To ensure data quality, days with missing or inconsistent data were excluded during preprocessing. No resampling procedure was employed; the spatial resolution of the satellite data was preserved, and the satellite data were directly compared to the pixel coordinates of the ground stations. The daily precipitation data were then aggregated into monthly and annual sums to analyze temporal trends and performance at multiple scales. Performance evaluation involved the calculation of several statistical metrics (e.g., *r*, *RMSE*, *MAE*, and *RBS*) and categorical metrics, including *POD*, *FAR*, *CSI*, and *Fbias*. In reporting these statistical parameters, standard deviation (*SD*) was used to characterize spatial variability and consistency across all observation stations in the study area. The use of *SD*, calculated using Equation 9, provides information regarding the stability or variability of each metric across different geographic locations.

$$SD = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}{N}}$$

Equation 9

Where N represents the number of ground locations, while x_i denotes the value of the metric for each individual location. The mean value of the metric across all ground stations is represented by $\bar{x}$.

3. Results

3.1 Daily Performance

Table 1 presents the performance of five selected SPPs based on daily data across four ground stations

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in Aceh. Among the evaluated products, CHIRPS exhibits the lowest *RMSE* (15.03 mm/day) and *MAE* (8.20 mm/day), indicating it provides the most accurate daily precipitation estimates compared to other SPPs. Despite MSWEP having the highest correlation coefficient (0.34), its higher *RMSE* (17.34 mm/day) and *MAE* (8.26 mm/day) suggest it is less accurate than CHIRPS in terms of absolute error magnitude. TRMM demonstrates the weakest daily performance, with the highest *RMSE* and *MAE*, reflecting substantial deviation from ground observations. Meanwhile, CMORPH and PERSIANN perform moderately, showing intermediate error values. In terms of bias, most SPPs slightly overestimate or underestimate precipitation.

The *SD* values accompanying each metric further highlight the variability and uncertainty of these models. For instance, CHIRPS has a correlation coefficient of 0.29 ± 0.08, indicating a weak positive correlation with observed precipitation, but with a variability suggesting consistent performance across regions. Similarly, the *RMSE* and *MAE* values for each SPP show significant variability, with MSWEP's *RMSE* of 17.34 ± 5.26 mm/day and *MAE* of 8.26 ± 2.76 mm/day suggesting that its performance can vary widely depending on location. TRMM's higher *RMSE* and *MAE* values also show substantial uncertainty, indicating larger deviations from ground observations.

The *RBS* provides insights into the models' tendencies to overestimate or underestimate precipitation, with considerable variability observed across the SPPs. For example, PERSIANN's *RBS* shows a high *SD* (±3.08), indicating that its bias is not consistent and may fluctuate significantly across different locations. This variability in *RBS* further emphasizes the uncertainty in the SPPs' predictions and the need to assess them in the context of regional calibration and specific precipitation conditions.

The categorical metrics shown in Table 2 illustrate the ability of SPPs to accurately detect precipitation events at various thresholds (0.1, 25, and 50 mm). The thresholds were adopted from BMKG recommendations for daily rainfall intensity thresholds to represent no rain days (<0.1 mm), moderate rain (0.1-20 mm) and heavy rain (>50 mm). They also comply with the World Meteorological Organization (WMO) standard for daily rainfall class [16] and have been used in previous studies in this region [27][30] and [33]. They also comply with the

Table 1: Statistical metrics of daily precipitation estimation by SPPs

Parameters	Unit	CHIRPS	MSWEP	CMORPH	PERSIANN	TRMM
r	-	0.29±0.08	0.34±0.17	0.29±0.15	0.25±0.07	0.25±0.12
RMSE	mm/day	15.03±5.33	17.34±5.26	16.51±5.95	15.15±5.33	17.21±4.75
MAE	mm/day	8.2±2.81	8.26±2.76	8.19±3.09	8.29±2.47	8.56±2.50
RBS	-	-0.04±0.15	0.05±0.12	-0.14±0.3	0.03±3.08	-0.07±0.23

Note: ± indicates the standard deviation

Table 2: Categorical metrics of daily precipitation estimation by SPPs

Parameters	Thresholds (mm)	CHIRPS	MSWEP	CMORPH	PERSIANN	TRMM
POD	0.1	0.67±0.07	0.69±0.08	0.63±0.10	0.87±0.06	0.57±0.08
	25	0.2±0.12	0.32±0.14	0.21±0.05	0.11±0.04	0.22±0.08
	50	0.06±0.08	0.3±0.21	0.1±0.06	0.01±0.01	0.14±0.07
FAR	0.1	0.4±0.11	0.35±0.14	0.35±0.13	0.44±0.11	0.36±0.13
	25	0.73±0.08	0.71±0.14	0.7±0.16	0.72±0.12	0.77±0.14
	50	0.63±0.38	0.79±0.13	0.79±0.19	0.84±0.2	0.84±0.1
CSI	0.1	0.46±0.06	0.51±0.10	0.46±0.08	0.51±0.08	0.42±0.08
	25	0.13±0.06	0.17±0.07	0.14±0.05	0.08±0.01	0.13±0.06
	50	0.04±0.05	0.13±0.08	0.07±0.06	0.01±0.01	0.07±0.03
Fbias	0.1	1.17±0.31	1.1±0.24	1.03±0.31	1.64±0.43	0.94±0.28
	25	0.7±0.32	1.24±0.63	0.86±0.32	0.48±0.26	1.17±0.53
	50	0.26±0.35	1.68±1.40	0.81±0.37	0.12±0.11	1.33±1.19

Note: ± indicates the standard deviation

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Table 3: Statistical metrics of monthly precipitation estimation by SPPs

Parameters	Unit	CHIRPS	MSWEP	CMORPH	PERSIANN	TRMM
r	-	0.73±0.09	0.80±0.10	0.69±0.09	0.67±0.08	0.76±0.11
RMSE	mm/m	89.79±28.40	74.77±17.69	101.08±20.11	108.53±40.55	90.14±27.24
MAE	mm/m	114.66±31.44	116.97±27.62	110.35±27.77	107.74 ±21.70	111.49±26.04
RBS	-	-10.00±26.03	-2.94±24.61	-17.76±21.80	-8.80±24.61	-30.02±36.45

Note: ± indicates the standard deviation

World Meteorological Organization (WMO) standard for daily rainfall class [16] and have been used in previous studies in this region [27][30] and [33]. PERSIANN shows the highest *POD* at the lowest threshold (0.1 mm), followed by MSWEP and CHIRPS. However, as the threshold increases, the detection accuracy of all products decreases, with MSWEP demonstrating the best performance at higher thresholds. Similar to *POD*, *FAR* values increase with the increase in thresholds, with the exception of CHIRPS, which shows better accuracy at heavy rainfall than at moderate rainfall. A high *FAR* value indicates that most of the heavy rainfall detected by the SPPs is a false alarm. This condition indicates difficulties in accurately predicting extreme rainfall events.

The *CSI*, which combines sensitivity (*POD*) and specificity (*FAR*), performs quite well at lower thresholds but significantly decreases at higher thresholds, reaffirming the challenges faced by the products in capturing heavy rainfall. The *Fbias* reveals that while most SPP tends to overestimate light rainfall events and underestimate heavier occurrences, TRMM shows the opposite trend. Meanwhile, all precipitation events were underestimated by MSWEP.

3.2 Monthly Performance

The relationship between ground-observed and SPPs-estimated monthly precipitation reveals a complex picture of variability and error as shown in Table 3. Among the SPPs, MSWEP records the lowest *RMSE* (74.77 mm/month) and the lowest *RBS* (–2.94), indicating that it provides the most accurate and balanced monthly precipitation estimates compared to ground observations. TRMM and CHIRPS follow with slightly higher *RMSE* values, while PERSIANN and CMORPH show greater errors. MSWEP also achieves the highest correlation coefficient (0.80), indicating strong agreement with observed precipitation patterns; when considered alongside its lowest *RMSE*, this underscores both the consistency and accuracy of its monthly estimates. *MAE* values are relatively consistent across all SPPs, with CHIRPS and MSWEP reporting slightly higher *MAE*s (114.66 mm and 116.97 mm, respectively); however, these minor differences do not detract from MSWEP's *RMSE*-based ranking as the most accurate product.

In terms of *RBS*, most SPPs tend to underestimate monthly precipitation, with TRMM exhibiting the largest negative bias (–30.02%). In contrast, MSWEP again performs best, with a bias closest to zero, indicating minimal systematic deviation from ground measurements. Although there are some differences in the *SD* of *RMSE* MSWEP has the lowest variability (±17.69) the overall spread of values across all SPPs is relatively narrow. This consistency suggests that the products demonstrate comparable spatial stability in capturing monthly precipitation patterns across the study area.

To illustrate this point more clearly, the *RMSE* range of the best- and worst performing products is compared. For MSWEP, the *RMSE* is 74.77 ± 17.69 mm/month, yielding an upper range of approximately 92.46 mm/month. For PERSIANN, the *RMSE* is 108.53 ± 40.55 mm/month, yielding a lower range of approximately 67.98 mm/month. Even though the lower bound of PERSIANN overlaps with MSWEP's upper bound, it occurs only at the extreme, while MSWEP consistently maintains lower average *RMSE* and lower variability. This example highlights that even with variability, MSWEP remains the most reliable and accurate product overall.

3.3 Precipitation Intensity and Variability

Figure 2 illustrates the monthly precipitation patterns observed from ground stations compared with five SPPs. The general trend observed across all datasets reflects a semi-annual precipitation variability, which has two peaks, March - May and November - December, and one trough with the lowest monthly precipitation occurs during the driest period, last from June to August. Overall, MSWEP product is the best in ability to replicate the monthly variability, followed closely by TRMM and PERSIANN. However, MSWEP tends to overpredict precipitation during the first peak and underpredict the precipitation during the lowest precipitation period. TRMM demonstrates as the best predictor during the first peak, but consistently underpredict the precipitation for the rest of year.

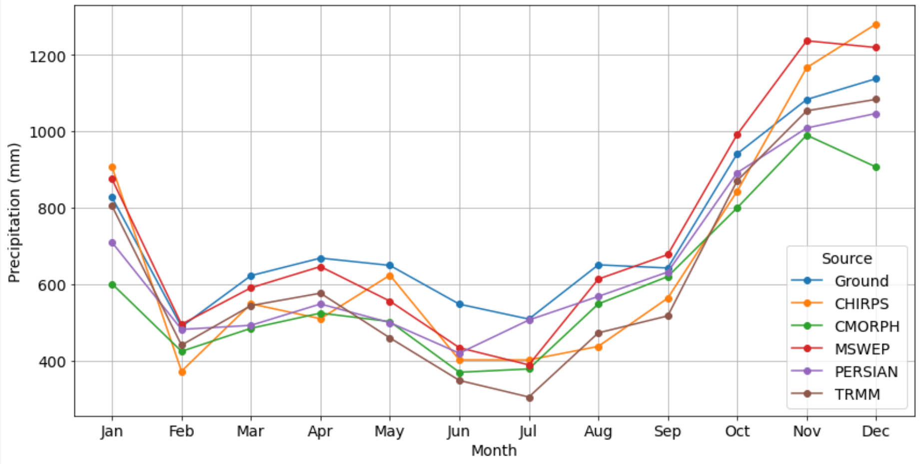

Figure 2: Average monthly precipitation

Table 4: Statistical metrics of annual precipitation estimation by SPPs

Parameters	Unit	CHIRPS	MSWEP	CMORPH	PERSIANN	TRMM
r	-	0.71±0.15	0.75±0.13	0.66±0.14	0.65±0.14	0.64±0.26
RMSE	mm/year	511.9±284.00	407.3±93.60	728.9±117.5	801.7±482.40	643.2±383.1
MAE	mm/year	447.5±287.40	347.9±100.20	662.6±126.1	729.7±490.30	584.2±395
RBS	-	-8.35±9.51	-0.59±7.85	-18.62±4.08	-11.34±8.41	-15.11±6.69

Note: ± indicates the standard deviation

PERSIANN and CHIRPS show relatively well performance during high precipitation months but have significant deviation during low precipitation months. CMORPH have the lowest performance in capturing accurate variability of monthly precipitation.

One of the critical features of is the variability observed during the second peak of precipitation (March – May) and transition period between dry season and first peak period (September and October). The SPPs show different capacity to record these changes. MSWEP and CHIRPS continue to perform better in tracking the observed data, while TRMM and PERSIANN demonstrate more significant variability, sometimes missing or overestimating the observed values. This variability during transition periods can be attributed to the rapid changes in atmospheric conditions which difficult to capture by satellite precipitation algorithms.

3.4 Annual performance

On an annual basis, MSWEP exhibits the best overall performance, characterized by the lowest *RMSE* (407.27 mm), *MAE* (347.94 mm), and *RBS* (–0.59%), as well as the highest *r* (0.75), as shown in Table 4. These results indicate that MSWEP not only provides the most accurate precipitation estimates but also ensures minimal systematic error and strong agreement with ground-based data. Its low *SD*s in *RMSE* and *MAE* further confirm its robustness across varying annual conditions and spatial contexts.

CHIRPS shows reasonable performance with a correlation of 0.71 and a moderate *RBS* of –8.35, indicating some underestimation of precipitation. However, its *RMSE* (511.9 mm/year) and *MAE* (447.5 mm/year) are higher than MSWEP's, suggesting that CHIRPS is less accurate in capturing annual totals, despite its relatively strong correlation with ground data. CMORPH, PERSIANN, and TRMM exhibit poorer performance, with higher *RMSE* and *MAE* values. CMORPH has an *RMSE* of 728.9 mm/year, PERSIANN has 801.7 mm/year, and TRMM has 643.2 mm/year, indicating substantial errors in their estimates. Additionally, all three products show significant negative biases (*RBS* of –18.62, –11.34, and –15.11, respectively), making them less reliable for annual precipitation estimation.

3.5 Annual Variation and Trends

Figure 3 provides annual precipitation data recorded by ground stations and estimated by SPPs from 2010 to 2019.

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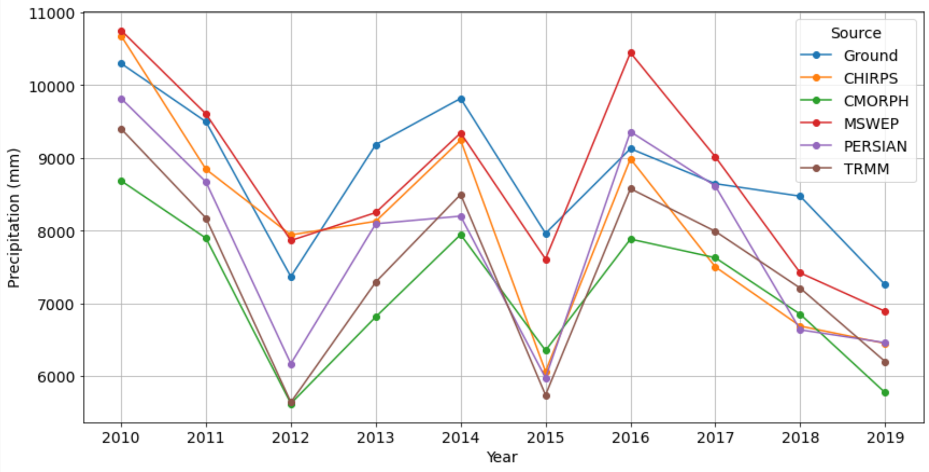

Figure 3: The annual precipitation of ground station and satellite

The data reveals several significant trends and patterns in precipitation over this period. There was a noticeable overall decline in the annual precipitation recorded by the ground stations over the ten years from 2010 to 2019, starting from 10,298.75 mm in 2010 and reaching its lowest point of 7,257.4 mm in 2019. This trend suggests a tendency toward drier condition within the decade, which could indicate changing climatic conditions or variability in weather patterns. The drying trends were also observed in the SPPs, indicating the ability of SPPs to estimate variability in annual precipitation, although with varying degrees of accuracy and bias. MSWEP closely follows the trend in ground data, while CMORPH and TRMM consistently underestimate the amount of annual precipitation throughout the period of observation. The annual precipitation predictions by CHIRPS for the first five years are very close to the ground data, similar to MSWEP. However, the deviation of CHIRPS from the observed values gradually increases in the following years.

4. Discussion

4.1 Performance Across Metrics

The performance of SPPs in Aceh, as assessed using error metrics like *RMSE* and *MAE*, highlights clear differences across the datasets. At the daily scale, CHIRPS achieved the highest accuracy, showing the lowest *RMSE* (15.03 mm/day) and *MAE* (8.20 mm/day), which confirms it offers the most precise daily precipitation estimates. This result is consistent with other studies that found CHIRPS to perform well in regions with high rainfall variability, particularly in tropical and coastal areas [3]. However, while CHIRPS showed reasonable *POD* for light to moderate precipitation, it struggled to accurately detect heavy rainfall, as reflected by higher *FAR* and lower *CSI* values. This suggests that CHIRPS faces challenges at higher thresholds, likely due to the limitations of infrared satellite data, which is less sensitive to smaller droplets and light rainfall [18] and [31]. Despite this, CHIRPS outperformed other products in terms of daily accuracy.

In contrast, MSWEP, while showing a higher correlation coefficient (0.34) at the daily scale, this relatively low value reflects a weak linear relationship and fails to account for the magnitude of errors. Additionally, it exhibited larger *RMSE* and *MAE* values, indicating lower accuracy in absolute error terms. These error metrics, *RMSE* and *MAE*, are more reliable indicators of model accuracy because they directly reflect the magnitude of the discrepancies between predicted and observed values [34]. While the correlation coefficient can provide some insight into the model's behavior, *RMSE* and *MAE* should be prioritized when evaluating the model's performance, especially in this context where understanding the exact magnitude of error is crucial.

However, MSWEP performed better at higher precipitation thresholds, making it more suitable for detecting heavy rainfall events. This finding is consistent with prior studies, which observed MSWEP's strong association with gauge observations, particularly in large urban centers like mainland China, where MSWEP effectively monitored the spatial distributions of heavy rainfall events [7]. Previous studies have also highlighted MSWEP's ability to outperform other products in terms of temporal dynamics and spatial accuracy, particularly in regions with sparse ground observations [7] and [26]. At the monthly and annual scales, MSWEP consistently outperformed other products, showing the highest correlation coefficients (0.80 for monthly and 0.75 for annual) and the lowest *RMSE* values (74.77 mm/month for

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monthly and 407.3 mm/year for annual). A similar result was also found in previous studies in Malaysia [16] and Bali [30], which have similar topographic characteristics, where MSWEP was superior at monthly and annual scales but faced challenges at the daily scale. These results underscore MSWEP's reliability in capturing precipitation patterns over time, confirming its superiority in trend monitoring an important consideration for applications such as hydrological modeling and disaster risk management, where understanding precipitation trends is crucial.

CMORPH and PERSIANN show moderate performance, with greater errors relative to MSWEP and CHIRPS, and show weaker correlations between the monthly precipitation obtained from these datasets and ground-based measurements. CMORPH's tendency to underestimate rainfall, especially during heavy rainstorms, aligns with findings from another study, which notes that CMORPH's morphing technique smooths out the spatio-temporal variations in heavy rainfall events, reducing its effectiveness in regions with complex weather patterns [13][15] and [35]. Similarly, PERSIANN's neural network-based approach, although innovative, appears to be inadequately adaptable across various climatic regions. Previous studies have similarly reported mixed performance of PERSIANN, particularly in capturing extreme precipitation in regions with high variability, such as Southeast Asia [36] and the Middle East [37].

TRMM shows the weakest performance among the products evaluated, despite its historical significance in satellite precipitation estimation. Its lower correlation and higher *RMSE* suggest that it is less reliable in regions characterized by a tropical climate with significant rainfall throughout the year, like Aceh. These limitations are attributed to TRMM's reliance on passive microwave (PMW) sensors and cold surface backgrounds, which interfere with the satellite's accuracy in detecting low-intensity rain and complex weather systems [12] and [38]. However, studies have found that TRMM performs well in subtropical regions, such as Iran, where the climate is more predictable, or in other parts of Southeast Asia with distinct wet and dry seasons [6][15] and [17].

The superior performance of MSWEP can partly be attributed to its multi-source data fusion approach, which integrates gauge, satellite, and reanalysis datasets. This fusion enhances its ability to provide accurate precipitation estimates, especially in regions with sparse ground observations or challenging topography [6] and [39]. By leveraging the strengths of each data source, this fusion improves the model's reliability and makes it more robust in capturing precipitation patterns across various temporal and spatial scales. Satellite products, especially those relying solely on infrared or microwave sensors, often face challenges in detecting such precipitation patterns, where orographic lifting and local convection play a major role in precipitation formation, resulting in underestimation or smoothing of rainfall intensity in mountainous areas [40]. Furthermore, MSWEP's spatial resolution of 10 km enables it to capture localized precipitation more effectively than coarser-resolution products like TRMM, PERSIANN, and CMORPH (25 km resolution).

However, MSWEP's performance is not without limitations. In regions with complex terrain, such as Aceh's mountainous landscapes, MSWEP may still face challenges in detecting fine-scale precipitation variations. While a higher resolution improves the model's ability to capture small-scale precipitation events, 10 km grid cells still represent a 100 km² area. This spatial averaging can lead to smoothed estimates that fail to capture the sharp spatial gradients in precipitation, especially in mountainous regions or areas with localized weather systems. Previous studies have shown that although its spatial resolution limits its precision in localized precipitation detection, MSWEP has been noted for its strong temporal dynamics and ability to capture heavy rainfall events in the Southeast Asia region [16][20] and [30]. Meanwhile, other products with coarser resolutions, such as CMORPH and TRMM, struggle to accurately capture the spatial variability of rainfall, particularly during intense rainfall events or in regions with complex weather dynamics [17] and [41]. Therefore, although MSWEP provides relatively accurate trend estimates at larger scales (monthly and annual), its 10 km grid may fail to capture localized precipitation events, particularly in areas with sharp gradients. This limitation is critical for applications requiring precise precipitation estimates at high spatial resolution, such as flood forecasting and detailed hydrological modeling [10] and [17].

CHIRPS, with its 5 km resolution, provides a finer spatial granularity than MSWEP and performs better in capturing localized precipitation events. However, similar to MSWEP, CHIRPS still faces limitations when it comes to accurately representing the fine-scale precipitation variability in areas with complex terrain. Despite its 5 km resolution, CHIRPS may not fully capture sharp gradients in precipitation over a 100 km² area, especially in mountainous or highly localized weather systems. This highlights the trade-off between higher resolution and the ability to capture small-scale variations within large grid cells, a key consideration when comparing satellite estimates to ground station measurements.

The accuracy of SPPs heavily depends on the availability of ground-based observations for validation. The sparsity of ground-based gauge networks, particularly in regions like Aceh, poses a significant challenge in accurately validating satellite estimates. A limited number of rain gauges, especially in remote or mountainous areas, may fail to capture the full spatial variability of precipitation, leading to biased validation results [42]. This lack of dense coverage can particularly affect the detection of localized events, such as orographic precipitation or heavy rainfall, which may be misrepresented or smoothed out in satellite data. As ground-based networks improve and more gauge stations are established, particularly in data-scarce regions, the validation of SPPs will become more robust. Newer SPPs, which integrate more diverse data sources, could also improve their ability to capture fine-scale precipitation variations and yield more accurate validation results [43]. With an improved ground network and advancements in satellite product algorithms, discrepancies between satellite estimates and actual precipitation data would likely decrease, leading to more reliable model performance across multiple temporal scales of precipitation assessments.

Through analysis at three time scales, the study found that monthly and annual products exhibited much smaller errors and higher correlation coefficients than daily products. This underscores the advantage of aggregating data over longer periods, which reduces fluctuations and provides more stable, reliable estimates [10]. Daily satellite precipitation data, while offering finer temporal resolution, are more sensitive to fluctuations and local factors, leading to higher error margins. This variability can complicate analyses that aim to discern overall trends or patterns. In contrast, monthly and annual data, by smoothing out these fluctuations, allow for more accurate trend analysis and are especially useful in climate studies and hydrological modeling.

4.2 Implications for Practical Applications

The differences in performance among various SPPs have important consequences for their use in a variety of applications. For hydrological modeling, where accurate and timely precipitation data is crucial, MSWEP’s strong performance makes it the preferred choice. Its low bias and high correlation with ground data ensure reliable inputs for models that predict streamflow and flood risks. This is particularly important in disaster-prone areas like Aceh, where accurate precipitation data is essential for effective disaster management. MSWEP's integration of multiple data sources helps to avoid the weaknesses of individual datasets, making it particularly effective in regions with sparse ground-based observations [44] and [45]. In contrast, CHIRPS may be more suitable for climatological studies or drought monitoring, where the slight underestimation of precipitation is less critical, and the focus is on capturing broader trends. A study has shown that CHIRPS performs well in detecting long-term drought conditions, particularly in semi-arid regions, making it a valuable tool for monitoring and early warning systems [3].

For applications that require the detection of heavy rainfall events, such as flood forecasting, both CMORPH and PERSIANN should be used with caution. They exhibit higher *FAR* and lower *CSI* values for heavy precipitation days, implying a tendency toward over- or under-estimating the occurrences of this variable. This finding is consistent with the previous work, which found these products tend to have limitations in accuracy, particularly for extreme mid-latitude precipitation [46]. The results highlight the necessity of combining them with on-ground data or other satellite datasets to improve their reliability.

5. Conclusion

This study presents a comprehensive evaluation of five widely used SPPs in Aceh Province, Indonesia, with the aim of identifying the most reliable satellite products for Aceh’s unique meteorological and topographical context. This approach will help support improved water resource management, disaster response, and climate resilience in the region. Through a systematic comparison across multiple time scales (daily, monthly, and annual), this study contributes significantly to the evaluation of SPPs. We emphasize the importance of spatial variability and consistency in assessing satellite precipitation products. By quantifying spatial variability using *SD*, we provide a deeper understanding of how satellite data performs across different geographic locations, especially in regions like Aceh, where ground stations for validation are sparse.

Our findings highlight the need to prioritize error-based metrics, such as *RMSE*, when evaluating precipitation products, as they provide a more reliable assessment of model accuracy, particularly in tropical regions with diverse weather systems. CHIRPS demonstrates strong performance, especially at the daily time scale, with low *RMSE* values and accurate precipitation estimates. While it slightly underestimates precipitation at higher thresholds, it remains a reliable option for daily precipitation estimates and is well-suited for

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climatological studies and drought monitoring due to its capacity to capture long-term trends.

MSWEP, although performing well at monthly and annual scales, emerges as the most reliable product for these longer time periods, consistently outperforming other products with the lowest *RMSE* and highest accuracy. Its ability to capture precipitation trends over extended periods makes it particularly suitable for hydrological modeling and flood forecasting. CMORPH and PERSIANN, while showing moderate performance, struggle to accurately detect heavy rainfall, which limits their effectiveness in regions with high rainfall variability. TRMM consistently underperforms across all time scales and should be used with caution in applications that require high accuracy.

These results provide actionable recommendations for practitioners in flood forecasting, disaster management, and climatological monitoring. MSWEP is recommended for hydrological modeling and flood forecasting due to its reliability in capturing precipitation trends and its ability to integrate multiple data sources. CHIRPS, despite its slight underestimation, can be effectively used for climatological studies or drought monitoring due to its capability to capture long-term trends. For areas where accurate heavy rainfall detection is critical, we suggest combining CMORPH and PERSIANN with other data sources, such as ground observations or higher-resolution satellite data, to enhance the accuracy of extreme event detection and reduce false alarms.

Although this study provides valuable insights into the performance of satellite precipitation products in Aceh, several limitations must be considered. The scarcity of ground-based rain gauges in the region introduces uncertainty in validating satellite estimates. Additionally, the temporal resolution of satellite data can lead to errors, particularly at the daily scale, and aggregation into monthly or annual data sacrifices finer precipitation details. Product-specific biases also affect the accuracy of the estimates, with different satellite products performing better under different conditions, emphasizing the need for a multi-product approach for reliable precipitation monitoring.

Future research should focus on enhancing the accuracy of satellite precipitation estimates through advanced data fusion techniques, specifically ensemble models and machine learning algorithms. These techniques could combine the strengths of various products, such as MSWEP and CHIRPS, and improve overall precipitation estimation by addressing product-specific biases and uncertainties. Techniques such as Bayesian Model Averaging (BMA), Kalman filtering, and Principal Component Analysis (PCA) could be used to weigh and integrate multiple products based on their performance in different regions. Additionally, machine learning methods like random forests, support vector machines (SVMs), and neural networks can further optimize the combination of satellite products, improving their predictive accuracy across various scales and conditions. Moreover, CMORPH and PERSIANN could benefit from the integration of ground-based data using methods such as quantile mapping or empirical orthogonal function (EOF) analysis to improve heavy rainfall detection and reduce biases in satellite estimates.

Acknowledgments

This research was financially supported by the Ministry of Education, Culture, Research, and Technology of Indonesia through the Research and Community Service Institution (LPPM) at Universitas Syiah Kuala (Grant number: 268/UN11.2.1/PG.01.03/SPK/PTNBH/2024). We would like to express our heartfelt thanks to the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) for granting access to the rainfall data utilized in this research.

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