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Comparison of Correlation, PBIAS and RSR between Monthly, Daily, and Hourly GPM Rainfall Data

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Abstract: Accurate precipitation data is critical for hydrological modeling, flood forecasting, and water resources planning. This study evaluates the performance of satellite-based rainfall estimates from the Integrated Multi-satellite Retrievals for GPM (IMERG) Final Run Version 06 by comparing them with ground-based observations from six stations in the Jatigede Reservoir catchment, West Java, Indonesia. The analysis covers the 2014–2023 period, aligning with the reliable availability of IMERG Final Run products, and examines three temporal resolutions: monthly, daily, and hourly. Statistical evaluation employed Pearson correlation coefficient (r), the ratio of RMSE to observed standard deviation (RSR), and Percent Bias (PBIAS). Results show strong agreement at the monthly scale ($r = 0.84$, $RSR = 0.34$, PBIAS ≈ +24%), suggesting suitability for long-term water resource assessments. However, performance declines at shorter timescales. At the daily scale, IMERG underestimates rainfall (PBIAS ≈ -27%) with moderate correlation ($r = 0.24$). The hourly scale shows the poorest performance ($r = 0.10$, $RSR > 3.0$, PBIAS < -50%), indicating limitations in capturing short-duration, high-intensity rainfall typical in tropical regions. These findings underscore the importance of temporal aggregation and bias correction when applying IMERG data for operational hydrology and flood modeling.

Keywords: Daily; GPM; Hourly; Precipitation

Introduction

Precipitation serves as a fundamental driver in the global hydrological cycle and exerts a profound influence across various domains, including water resources management, infrastructure development, agricultural productivity, and the mitigation of hydrometeorological hazards such as floods and landslides. The availability of accurate, continuous, and spatially distributed rainfall data is essential for supporting robust hydrological modeling, climate impact assessment, and evidence-based decision-making. However, in many regions—particularly in developing countries and remote watersheds—the acquisition of reliable ground-based rainfall data is constrained by sparse observational networks, high maintenance costs, and logistical challenges posed by complex terrain (Sukmadana & Sagita, 2022).

To address these limitations, satellite-based precipitation products have emerged as a viable and widely adopted alternative, offering broad spatial coverage and high revisit frequencies (Mamenun et al., 2014). Among the most advanced products is the Integrated Multi-satellite Retrievals for GPM (IMERG), a core component of the Global Precipitation Measurement (GPM) mission jointly implemented by NASA and JAXA. IMERG integrates observations from multiple satellite platforms operating at varying temporal and spatial resolutions to produce rainfall estimates at a nominal resolution of 0.1° (~11 km) and 30-minute intervals. However, these outputs result from complex merging and interpolation algorithms, rather

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than uniform direct measurements from all sensors (Aksu et al., 2023).

IMERG is available in three processing versions, Early Run, Late Run, and Final Run. Each differing in latency and degree of post-processing. The Final Run product, which incorporates retrospective quality control and calibration using ground-based gauge data, is most suitable for retrospective scientific analyses (Hou et al., 2014; Tang et al., 2016). Numerous studies have evaluated the accuracy of IMERG data against in-situ observations, with performance varying according to geographic region, climatic conditions, topographic complexity, and temporal scale (Sahlu et al., 2016).

In the Indonesian context, rainfall variability and estimation accuracy are particularly critical for hydrological modeling and disaster risk management. For instance, (Mardyansyah et al., 2024) demonstrated the utility of satellite-based rainfall estimation for flood mitigation in Papua using deep learning models, while (Danitasari et al., 2024) improved short-term forecasting accuracy at Soekarno-Hatta International Airport using BiLSTM integrated with SMOTE and ADASYN. At the regional scale, spatial flood modeling using GIS and remote sensing has been applied in Pemangkat (Purwanto & Paiman, 2023) and the Meninting watershed (Virgota et al., 2024), illustrating the growing importance of high-resolution rainfall data in distributed hydrological analysis.

Furthermore, advancements in observational instrumentation support the need for enhanced calibration and monitoring capacity. (Rohmah & Utomo, 2024) developed a portable calibration system for tipping bucket rain gauges, while (Anggana et al., 2024) utilized land vulnerability indices for conservation prioritization. Demonstrated the importance of physical watershed parameters in flood prediction in the Musi Basin. On a broader environmental scale, Safitri et al., (2022) reported significant impacts of land cover change on rainfall dynamics in the area designated for Indonesia's new capital.

Despite the increasing number of validation studies, the majority have focused on monthly and daily temporal resolutions (Habib Muzaki et al., 2022;Abiyyu Putra et al., 2024). Assessments of IMERG performance at finer temporal scales—such as hourly or half-hourly—remain scarce, especially in tropical regions characterized by short-duration, high-intensity convective rainfall events. These events demand higher temporal resolution data for effective flood forecasting, nowcasting, and early warning system development (Veloria et al., 2021; Zhou et al., 2021).

To address this gap, the present study conducts a dual-resolution performance evaluation of the IMERG Final Run Version 06 product at daily and half-hourly scales. The validation employs a consistent set of statistical indicators, including the Pearson correlation coefficient (r), Percent Bias (PBIAS), and the ratio of RMSE to the standard deviation of observations (RSR) (Sharifi et al., 2016).

The analysis is conducted in the Jatigede Reservoir watershed, located in West Java, Indonesia—a hydrologically strategic catchment that supports regional water supply and flood regulation. The selection of this watershed is further justified by the availability of a relatively dense and well-maintained network of Automatic Rainfall Recorder (ARR) stations. These stations provide high-resolution and high-quality rainfall data, enabling rigorous validation of IMERG performance across multiple temporal scales—monthly, daily, and hourly.

Method

This study aims to evaluate and compare the performance of satellite-based rainfall estimates from the GPM IMERG Final Run product with ground-based observations obtained from Automatic Rainfall Recorder (ARR) stations. Two temporal resolutions of IMERG Final Run were used: daily (GPM_3IMERGDF v06) and half-hourly (GPM_3IMERGHH v06). The version designation (v06) ensures consistency across both temporal datasets. All IMERG data were obtained from Giovanni, NASA's GES DISC data portal.

The ground-based rainfall observations were sourced from ARR stations operated by the Hydrology Unit of the Cimanuk–Cisadane River Basin Authority (Balai Besar Wilayah Sungai Cimanuk–Cisadane), a technical unit under Indonesia's Ministry of Public Works and Housing. The specific ARR stations used in this study include Cikajang, Bayongbong, Leuwingitis, Sadawangi, Darmaraja, and Jatigede. The geographic coordinates of each ARR station were used to spatially match with the nearest grid cell of the IMERG dataset. No spatial interpolation was applied; rather, the rainfall value from the IMERG grid cell that spatially coincided with each station location was extracted for direct comparison. The spatial correspondence between the IMERG grids and the ARR locations is illustrated in Figure 1.

Three statistical indicators were used to evaluate the performance of the IMERG data: Pearson correlation coefficient (r), RMSE-to-standard deviation ratio (RSR), and Percent Bias (PBIAS). To interpret these evaluation established (Krisnayanti et al., 2020; Cabrera, 2009; D. N. Moriasi et al., 2007).

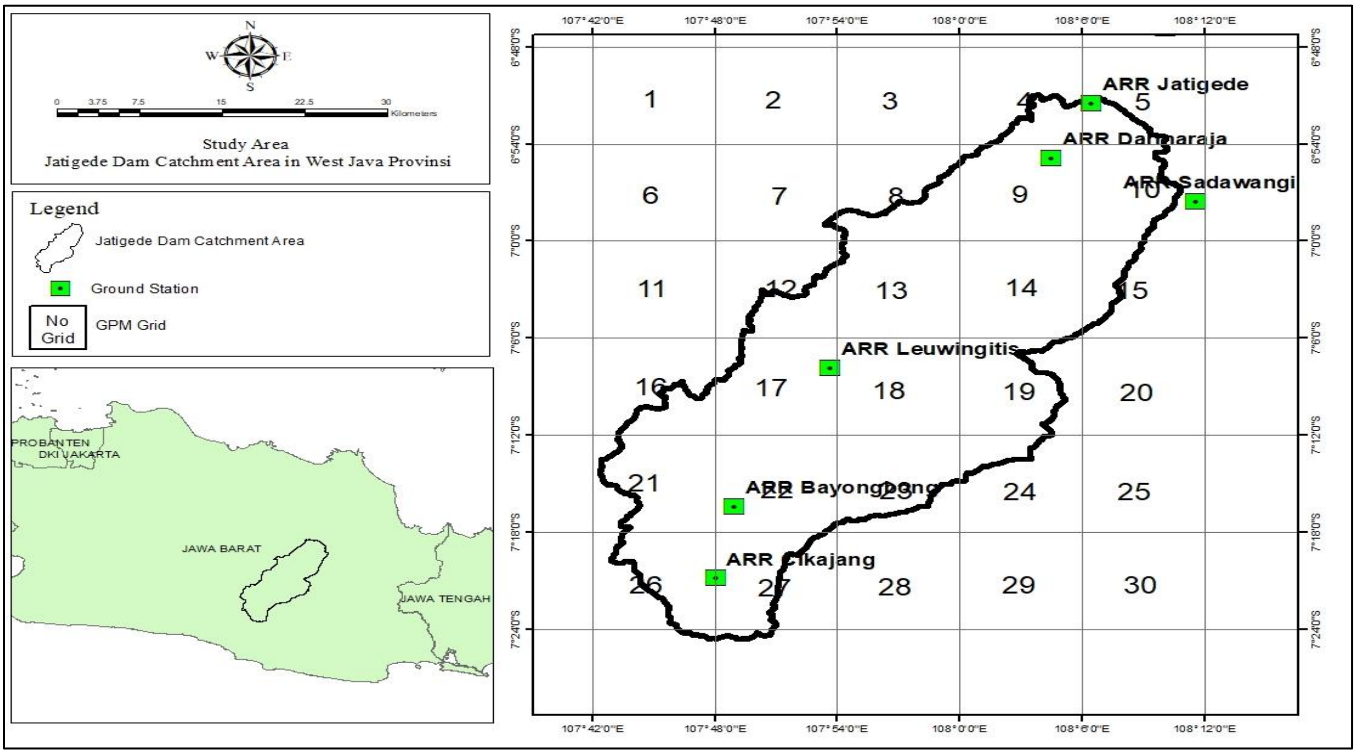

Figure 1. Rain station location and GPM grid

Pearson Correlation Coefficient (r)

Pearson correlation coefficient (r) is used to measure how strong the linear relationship between IMERG data and ground station data is.

The value of (r) ranges from -1 to 1, where r = 1 indicates perfect correlation, r = 0 indicates no correlation, and r = -1 indicates perfect negative correlation. The formula for r is as follows (Daniel S. Wilks, 2011):

$$r = \frac{\Sigma_{i=1}^{N}(xi-\bar{x})(yi-\bar{y})}{\sqrt{\Sigma_{i=1}^{N}(xi-\bar{x})^2}\sqrt{\Sigma_{i=1}^{N}(yi-\bar{y})^2}} \tag{1}$$

Where:
r : correlation between GPM and ARR data
xi : ARR data in period i
yi : GPM data in period i
$\bar{x}$: average ARR rainfall
$\bar{y}$: average GPM rainfall
n : number of data

RMSE-observations standard deviation ratio (RSR)

The RSR is a standardized metric that normalizes the root mean square error (RMSE) by the standard deviation of the observed values. It provides a measure of model error relative to the variability of actual observations. While RMSE indicates the absolute magnitude of error, RSR reflects model performance in the context of observed rainfall variability (D. N. Moriasi et al., 2007). The formulas are as follows:

$$RMSE = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}(xi-yi)^2} \tag{2}$$

$$RSR = \frac{RMSE}{STDEVarr} \tag{3}$$

Where :
xi : ARR data in period i
yi : GPM data in period i
n : number of data
STDEVobs : standard deviation of observed rainfall

Percent Bias (%)

Percent Bias (PBIAS) is used to measure the tendency of IMERG to overestimate or underestimate rainfall. A positive bias value indicates IMERG tends to overestimate rainfall compared to ground station data. A negative bias value indicates IMERG tends to underestimate rainfall. If the bias is close to 0%, then the rainfall value from IMERG is comparable to the ground station observation. The relative bias formula is as follows (Huffman et al., 2020).

$$Bias = \frac{\Sigma_{i=1}^{N}(xi-yi)}{\Sigma_{i=1}^{N} xi}\ x\ 100\% \tag{4}$$

Where:
xi : ARR data in period i
yi : GPM data in period i
n : number of data

Table 1. Proximity Assessment

Performance rating	Correlation coefficient	RSR	Bias relative
Very good	0.75 – 1.00	0.00 – 0.49	< ±10%
Good	0.50 – 0.74	0.50 – 0.60	±10% – ±15%
Satisfactory	0.25 – 0.49	0.60 – 0.69	±16% - ±25%
Unsatisfactory	0.00 – 0.24	>0.70	>±25%

Result and Discussion

After an evaluation process based on the statistical approach described in the previous section, several results were obtained that reflect the accuracy and consistency of IMERG rainfall data with field observations. The analysis was conducted separately for three temporal scales—monthly, daily, and hourly—to assess the effect of resolution on the performance of satellite-based rainfall estimation. The results for each statistical indicator (correlation coefficient, RSR, and PBIAS) are summarized in Table 2 and visualized in Figure 2 (RSR), Figure 3 (Correlation), and Figure 4 (PBIAS).

Table 2. Results

Time Scale	Location	r	RSR	PBIAS (%)	Correlation category	RSR Category	PBIAS Category
Monthly	Jatigede vs Grid 5	0.81	0.32	15.99	Very good	Very good	Satisfactory
Monthly	Darmaraja vs Grid 9	0.86	0.31	12.66	Very good	Very good	Good
Monthly	Sadawangi vs Grid 10	0.84	0.36	17.12	Very good	Very good	Satisfactory
Monthly	Leuwingitis vs Grid 17	0.85	0.34	37.82	Very good	Very good	Unsatisfactory
Monthly	Bayongbong vs Grid 22	0.84	0.38	31.82	Very good	Very good	Unsatisfactory
Monthly	Cikajang vs Grid 27	0.85	0.35	27.57	Very good	Very good	Unsatisfactory
Daily	Jatigede vs Grid 5	0.30	1.33	-10.24	Satisfactory	Unsatisfactory	Good
Daily	Darmaraja vs Grid 9	0.19	1.73	-27.37	Unsatisfactory	Unsatisfactory	Unsatisfactory
Daily	Sadawangi vs Grid 10	0.28	1.37	-12.67	Satisfactory	Unsatisfactory	Good
Daily	Leuwingitis vs Grid 17	0.22	1.51	-34.36	Unsatisfactory	Unsatisfactory	Unsatisfactory
Daily	Bayongbong vs Grid 22	0.25	1.46	-44.09	Satisfactory	Unsatisfactory	Unsatisfactory
Daily	Cikajang vs Grid 27	0.21	1.70	-33.41	Unsatisfactory	Unsatisfactory	Unsatisfactory
Hourly	Jatigede vs Grid 5	0.08	3.73	-44.48	Unsatisfactory	Unsatisfactory	Unsatisfactory
Hourly	Darmaraja vs Grid 9	0.10	3.44	-39.34	Unsatisfactory	Unsatisfactory	Unsatisfactory
Hourly	Sadawangi vs Grid 10	0.11	3.28	-53.75	Unsatisfactory	Unsatisfactory	Unsatisfactory
Hourly	Leuwingitis vs Grid 17	0.10	2.57	-56.07	Unsatisfactory	Unsatisfactory	Unsatisfactory
Hourly	Bayongbong vs Grid 22	0.10	2.62	-68.25	Unsatisfactory	Unsatisfactory	Unsatisfactory
Hourly	Cikajang vs Grid 27	0.12	2.66	-55.43	Unsatisfactory	Unsatisfactory	Unsatisfactory

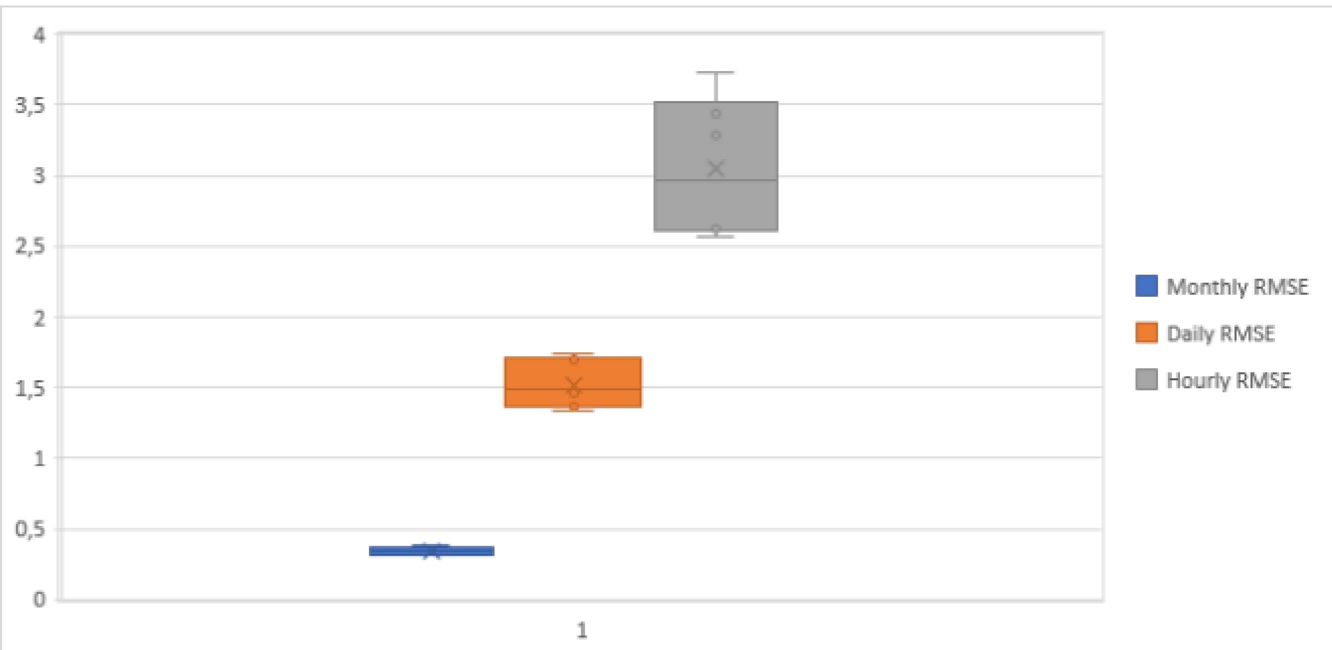

Figure 2 Monthly, daily, and hourly RSR

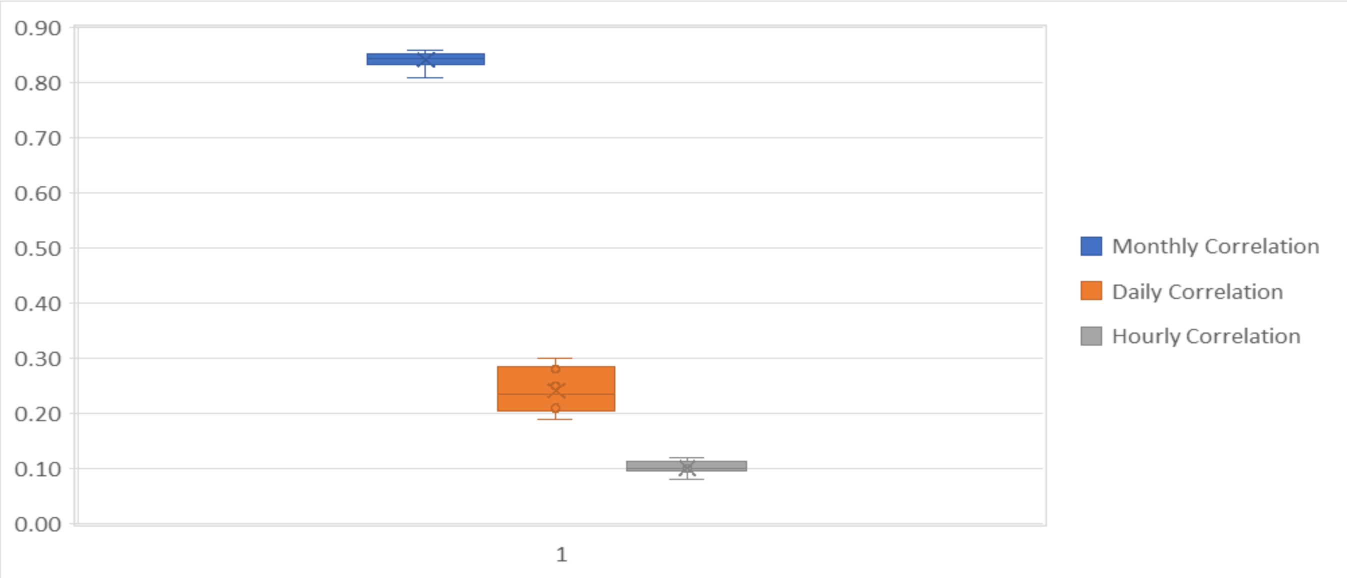

Figure 3. Monthly, daily, and hourly correlation

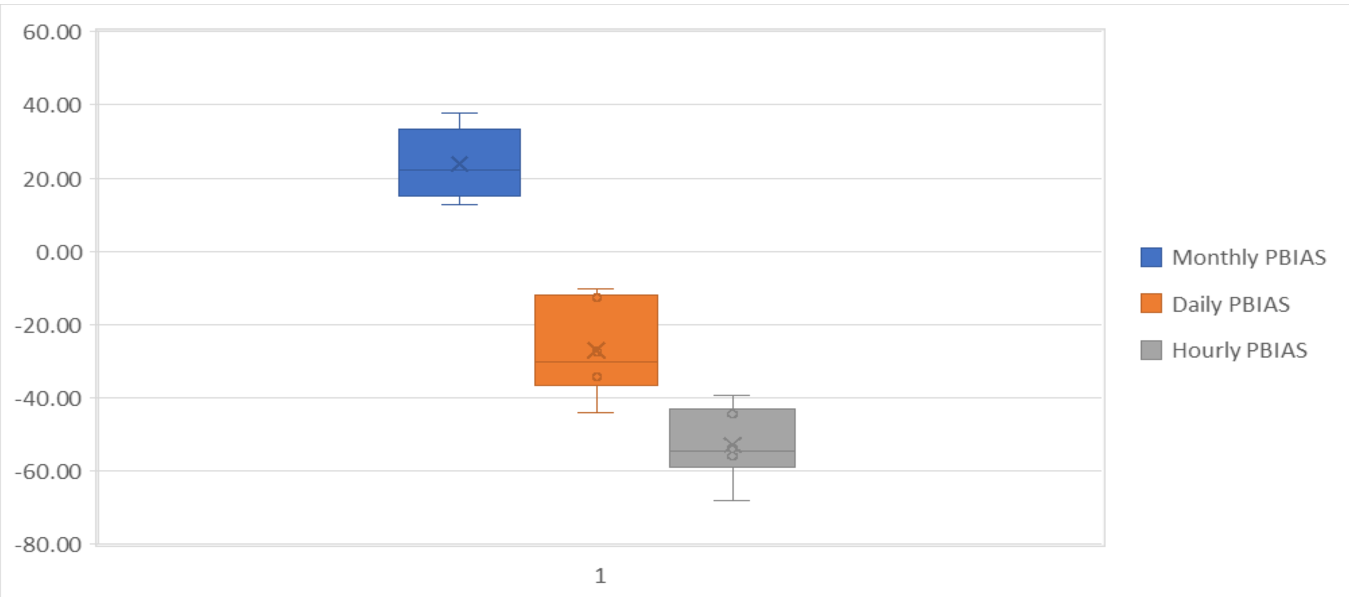

Figure 4. Monthly, daily, and hourly PBIAS

Evaluation on a Monthly Scale

At the monthly scale, IMERG Final Run demonstrated excellent agreement with ground observations. Correlation coefficients ranged from 0.81 to 0.86, with an average of 0.84 ± 0.02. According to performance criteria by Moriasi et al. (2007), these values fall within the "Very good" category, indicating a strong linear relationship between satellite estimates and in-situ rainfall data. This is consistent with findings Tan et al. (2017) in Malaysia and Prakash et al. (2021) in India, which reported enhanced satellite performance at monthly resolutions due to temporal smoothing effects from accumulated short-term errors.

The RSR values, ranging from 0.31 to 0.38 (mean: 0.34 ± 0.03), also support high model accuracy. These low RSR values imply that the RMSE of satellite estimations remains small relative to the natural variability of observed rainfall. Such performance is particularly promising for applications in monthly water balance studies and long-term hydrological modeling (C. Y. Liu et al., 2020).

However, while correlation and RSR were robust, PBIAS analysis revealed a consistent overestimation trend. The average PBIAS was +23.83% ± 10.05%, with the highest value at Leuwingitis station (+37.82%). These results suggest systematic overestimation of monthly rainfall, which could impact hydrological simulations if not adjusted. Prakash et al. (2018) attribute such overestimation to misclassification of light precipitation events and sensor bias in humid tropical regions.

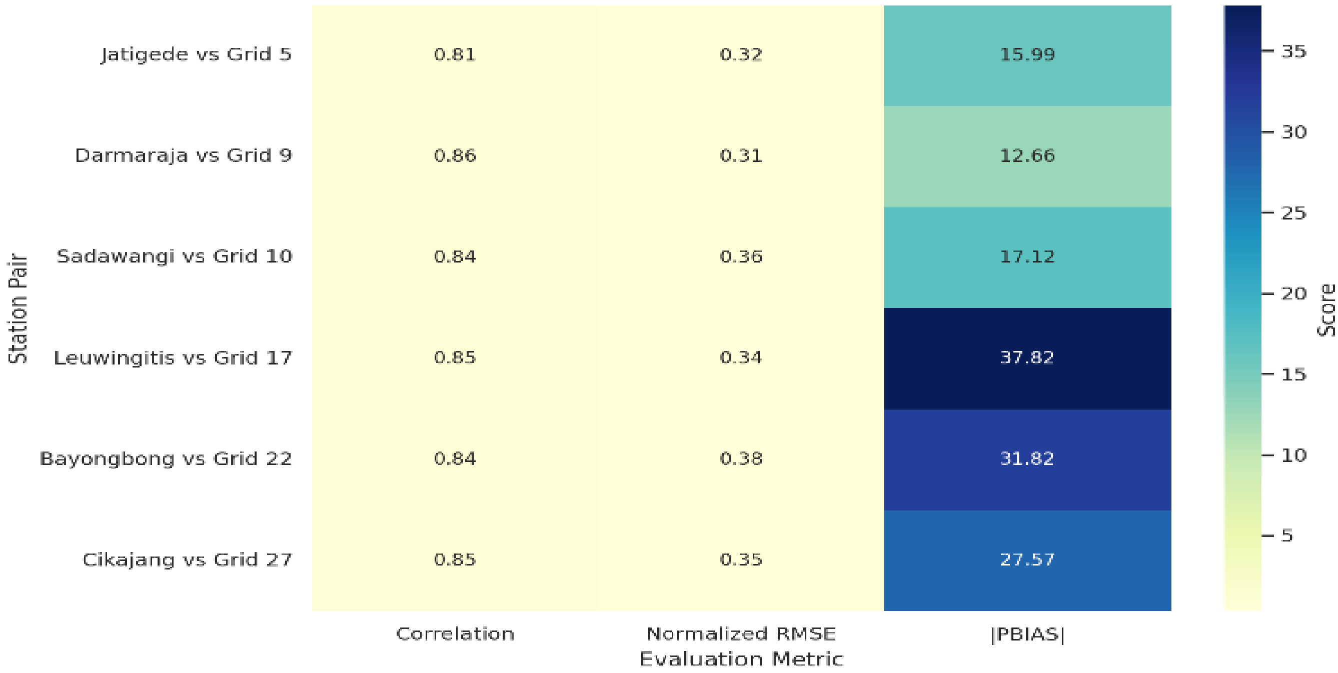

Figure 5. Monthly matplotlib graph

Evaluation on a Daily Scale

On the daily scale, performance declined considerably. Correlation coefficients ranged from 0.19 to 0.30 (mean = 0.24 ± 0.04), corresponding to "Satisfactory" or "Unsatisfactory" categories. This low correlation suggests a weak linear association, potentially due to IMERG's inability to resolve localized, short-duration rainfall typical of tropical convection systems. This is consistent with findings from Hsu et al.(2021) and Tang et al. (2023), who reported degraded performance of satellite rainfall products in complex tropical terrain.

RSR values increased sharply, ranging from 1.33 to 1.73 (mean = 1.52 ± 0.17), exceeding acceptable thresholds and indicating poor predictive accuracy. These values reflect that the root mean square error (RMSE) is more than 1.5 times the standard deviation of observed rainfall, further emphasizing the limitations of satellite data at daily resolutions without post-processing or correction.

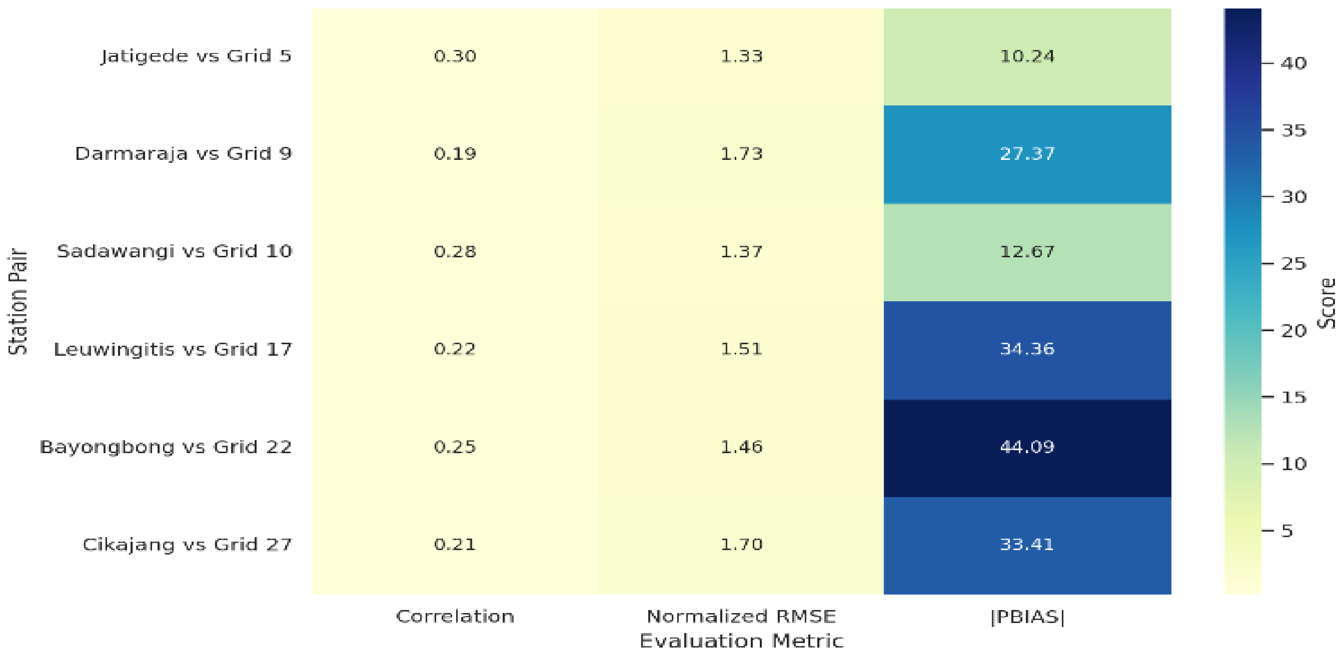

Figure 6. Daily matplotlib graph

PBIAS values also exhibited a consistent underestimation trend, ranging from -44.09% to -10.24% (mean = -27.02%). These biases may stem from IMERG's reduced sensitivity to low-intensity rainfall and detection lags. Furthermore, the complex topography of the study area could amplify retrieval errors, as highlighted by Yuan et al. (2017) and Liu et al. (2020).

Evaluation on an Hourly Scale

At the hourly scale, IMERG performance was markedly limited. Correlation coefficients were extremely low, ranging from 0.08 to 0.12 (mean = 0.10 ± 0.01), indicating a near-absence of linear association between satellite estimates and ground observations. This underscores the challenge of capturing rapidly evolving convective rainfall events in the tropics, where sub-hourly dynamics dominate. These results align with Balogun et al. (2018) and Gehne et al. (2022) who identified similar constraints in the temporal resolution of satellite data products.

RSR values at the hourly scale were extremely high, ranging from 2.57 to 3.73 (mean = 3.05 ± 0.50), with none of the sites achieving acceptable performance. The magnitude of RMSE relative to observed variability confirms the unsuitability of raw IMERG data for sub-daily hydrological applications in the study area. Finally, PBIAS results confirmed a pronounced underestimation trend. All stations recorded negative bias values between -68.25% and -39.34% (mean = -52.89% ± 10.08%). These findings are consistent with Ramadhan et al. (2022), who observed similar underestimations in mountainous Indonesian regions, particularly during afternoon and evening convective rainfall events.

These results collectively emphasize the scale-dependent performance of IMERG Final Run data. While suitable for monthly-scale applications, the product exhibits substantial limitations at daily and especially hourly resolutions. Future work should explore bias correction methods or machine learning approaches to enhance IMERG usability for high-resolution hydrological modeling.

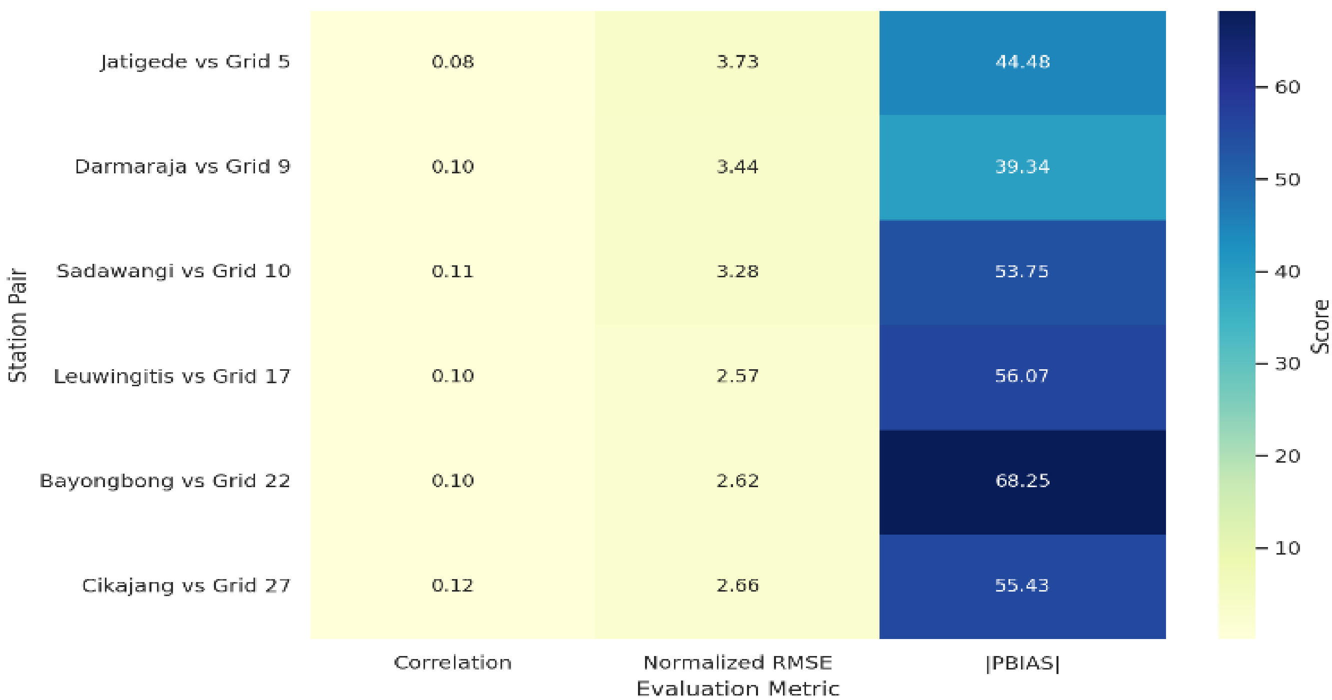

Figure 7. Hourly matplotlib graph

Conclusion

This study evaluated the performance of the Integrated Multi-satellite Retrievals for GPM (IMERG) Final Run Version 06 by comparing its precipitation estimates with ground-based observations across six ARR stations in the Jatigede Reservoir catchment, West Java, Indonesia. The analysis was conducted at three temporal scales—monthly, daily, and hourly—over the 2014–2023 period, aligning with the stable availability of IMERG Final Run V06 data. Three statistical indicators were used: Pearson correlation coefficient (r), the ratio of RMSE to the standard deviation of observations (RSR), and Percent Bias (PBIAS).

The results indicate that IMERG demonstrates the highest performance at the monthly scale, with a strong average correlation (r = 0.84), low RSR values (~0.34), and moderate overestimation reflected by an average PBIAS of +23.83%. Although the bias approaches the upper threshold of the "Satisfactory" classification, the estimates remain acceptable for large-scale water resource assessments, seasonal rainfall trend analysis, and long-term hydrological modeling.

At the daily scale, the IMERG performance declines considerably. The correlation drops to an average of 0.24, while RSR increases to 1.52, indicating significant deviation from observed variability. The average PBIAS shifts to -27.02%, suggesting consistent underestimation. These findings highlight limitations of IMERG in capturing short-duration, localized convective rainfall, particularly in complex topographic settings. Without correction, the dataset is less suitable for applications such as daily flood forecasting or catchment-scale hydrologic response modeling.

At the hourly scale, IMERG exhibits its weakest performance. The correlation is negligible (r ≈ 0.10), RSR exceeds 3.0, and PBIAS shows extreme underestimation (averaging -52.89%). These error magnitudes underscore the inability of IMERG to reliably represent high-intensity, short-duration tropical rainfall events critical for real-time hydrological forecasting.

In summary, the IMERG Final Run (V06) product is reliable for monthly-scale applications, conditionally usable at the daily scale with proper bias correction, and unsuitable in its raw form for hourly-scale modeling. The findings underscore the importance of considering temporal scale in the use of satellite-derived rainfall data and highlight the need for bias correction, data fusion, or statistical downscaling methods to enhance performance at finer resolutions. Future studies are encouraged to incorporate machine learning-based correction frameworks or integrate local gauge data to improve spatial and temporal alignment of satellite estimates with ground-based observations.

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Author Contributions
Conceptualization, Y. A. S. and D. H.; methodology, Y. A. S.; software, Y. A. S.; validation, Y. A. S., D. H., and M. A. S.; formal analysis, Y. A. S.; investigation, Y. A. S.; resources, Y. A. S.; data curation, Y. A. S.; writing—original draft preparation, Y. A. S.; writing—review and editing, Y. A. S. and D. H.; visualization, Y. A. S.; supervision, D. H.; project administration, D. H.; funding acquisition, M. A. S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest.

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