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Performance Evaluation and Calibration of GPM-IMERG Satellite-Based Rainfall Data in Soligi Village

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Abstract

Rainfall is a primary parameter that plays a crucial role in hydrological planning and water resources management. However, several challenges exist in obtaining rainfall data that accurately represent field conditions, including the limited number of rain gauge stations and uneven spatial distribution of data, particularly in developing areas such as Soligi, North Maluku Province. An alternative solution is the use of satellite-based rainfall data such as GPM-IMERG. However, its application in hydrological analysis requires evaluation and calibration to improve its accuracy and reliability. Therefore, this study aims to evaluate and calibrate GPM-IMERG satellite rainfall data against observed rainfall data using statistical parameters: the correlation coefficient (r), bias, Root Mean Square Error (RMSE), and Nash-Sutcliffe Efficiency (NSE). The results indicate that the observed rainfall data are consistent based on the RAPS Method. Calibration of satellite rainfall data against observed rainfall data significantly improves rainfall estimation performance compared to uncalibrated satellite data. During the validation stage, the exponential regression model demonstrated the best performance, with the lowest RMSE value of 96.940 mm and the highest NSE value of 0.770. Therefore, the exponential regression model is considered the most representative in describing the relationship between GPM-IMERG satellite rainfall data and observed rainfall data.

Keywords: *Evaluation, Rainfall, GPM-IMERG, Calibration, Evaluation*

INTRODUCTION

Rainfall is one of the primary parameters in hydrological analysis and plays an important role in water resources planning and management [1], [2]. In the context of water resources planning, rainfall is a key component in water balance analysis used to determine the potential water supply of a region [3]. In addition, rainfall data are used to assess flood potential and mitigation measures, support the planning of flood control infrastructure [3], [5], and analyze drought conditions [6]. As the use of rainfall data in hydrological analysis continues to expand, the availability of accurate and continuous observed rainfall data has become a fundamental requirement. Rainfall records from observation stations provide information that represents actual field conditions. However, the limited number of stations [7], [8], [9], incomplete datasets [7], [10], [11], and uneven spatial distribution of stations [7], [13], [14] remain challenges, particularly in developing regions. In the context of local water resources planning, the accuracy of rainfall data is a crucial factor in hydrological analysis.

One of the hydrological analyses commonly required in rural areas is water balance analysis, including in Soligi Village, North Maluku Province. The increasing demand for clean water in Soligi Village has not been fully matched by the availability of existing water resources, highlighting the need for water resources planning based on reliable hydrological data. However, rainfall data collection in the area faces several challenges. The available rainfall records are very limited, with only one rain gauge station located relatively close to Soligi Village, namely the Bunaken Rainfall Station in Kawasi, Obi Island, South Halmahera Regency. This condition limits the spatial representativeness of rainfall data and may affect the accuracy of water balance analysis, considering that rainfall is a key component in estimating water availability within a region.

A commonly used alternative to overcome the limitations of rainfall observations is the use of satellite-based rainfall data, which provide broad spatial and temporal coverage. The Global Precipitation Measurement–Integrated Multi-satellite Retrievals for GPM (GPM-IMERG) product is one of the satellite rainfall datasets widely applied in hydrological studies. Although satellite-based rainfall products such as GPM-IMERG can effectively capture and detect rainfall patterns, they still require evaluation and calibration to improve their accuracy and performance in hydrological applications [6], [15].

The evaluation and calibration of satellite rainfall data against observed rainfall data are essential to ensure their reliability. The complexity of tropical climate systems and the high spatial variability of rainfall patterns often lead to significant differences between satellite rainfall estimates and ground observations. Uncorrected satellite rainfall data generally show lower agreement with observed data, whereas their performance improves significantly after evaluation and calibration. Several studies have reported that corrected GPM-IMERG data perform well in representing rainfall characteristics, as indicated by high correlations with ground-based measurements and better probability of detection and accuracy scores compared with other satellite rainfall products [9], [16].

The evaluation and calibration of satellite rainfall data are commonly conducted using statistical approaches by directly comparing satellite estimates with observed rainfall records. The statistical parameters employed include the correlation coefficient (r), Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and bias, which describe the level of agreement [9], [11], [12], [14], deviation [19], and uncertainty [13] of satellite rainfall estimates relative to field observations. Such evaluations are particularly relevant in areas with limited ground-based measurements, such as Soligi Village, to obtain rainfall estimates that are representative of local conditions.

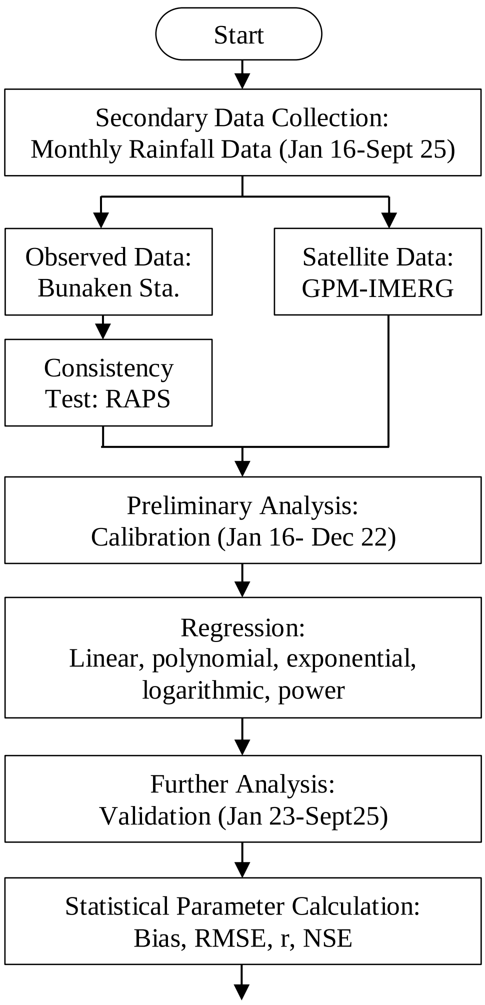
Based on this background, this study aims to evaluate and calibrate GPM-IMERG satellite rainfall data against observed rainfall data in Soligi Village using statistical approaches and performance indicators. The findings of this study are expected to provide representative rainfall data to support water availability planning through water balance analysis in Soligi Village.

METHOD

The case study for this research was conducted in Soligi Village, South Obi District, South Halmahera Regency, North Maluku Province, Indonesia. However, due to the limited number of rain gauge stations, the GPM-IMERG satellite rainfall data were validated using only one rainfall observation station located in Kawasi Village, Obi District, South Halmahera Regency, North Maluku Province. The station is situated at coordinates 127.409° E and 1.537° S. The observed rainfall data used in this study consisted of monthly rainfall records covering a 10-year period from January 2016 to September 2025.

The satellite rainfall data evaluated in this study were obtained from the GPM-IMERG product developed by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA). This product provides rainfall estimates with a spatial resolution of 0.1° × 0.1°. Monthly GPM-IMERG rainfall data from January 2016 to September 2025 were extracted according to the study area and used in the analysis.

The research procedure was carried out in several stages to evaluate and calibrate GPM-IMERG satellite rainfall data against observed rainfall data. All data analyzed in this study were secondary rainfall data. Following data collection, a consistency test of the observed rainfall data was conducted using the Rescaled Adjusted Partial Sums (RAPS) method. The calibration process was then performed by comparing satellite rainfall data with observed rainfall data using records from January 2016 to December 2022 to establish the mathematical relationship between the two datasets. Subsequently, validation was conducted using data from January 2023 to September 2025 to assess the performance and accuracy of the calibration results. The detailed research procedure is presented in Figure 1.



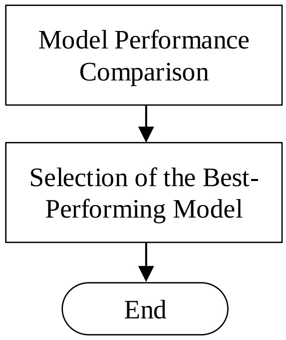


Figure 1. Research flowchart

Rescaled Adjusted Partial Sums (RAPS)

Observed rainfall data used in hydrological analyses should undergo quality and consistency assessments to ensure the absence of systematic deviations in the time series. Consistency testing is an essential step before observed rainfall data are used for analysis, as variations in the data may arise from factors such as manual recording errors [9], [20], incomplete records [9], [19], and environmental influences [19]. The RAPS method is commonly used to evaluate the consistency of rainfall data. This method assesses the stability of rainfall records over an observation period by analyzing cumulative deviations from the mean. The results indicate whether the rainfall data are sufficiently consistent for subsequent hydrological analyses.

The consistency testing procedure using the RAPS method began with the calculation of the mean and standard deviation of the observed rainfall data. Subsequently, cumulative deviations were computed to represent the accumulated differences between each observation and the mean value, which were then normalized. The absolute values of the normalized deviations were used to calculate the Q and R statistics. These statistics were further normalized and compared with critical values at a specified significance level. The mathematical formulations of the statistical parameters used in the RAPS consistency test are presented in Table 1.

Table 1. RAPS test statistics

Parameter	Equation	
Mean rainfall	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$	(1)
Standard deviation	$S_D = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$	(2)
Cumulative deviation	$Sk_i^* = \sum_{j=1}^{i}(x_j - \bar{x})$	(3)
Normalized cumulative deviation	$Sk_i^{**} = \frac{Sk_i^*}{S_D}$	(4)
Q statistic	$Q = \max(\lvert Sk_i^{**}\rvert)$	(5)
R statistic	$R = \max(Sk_i^{**}) - \min(Sk_i^{**})$	(6)
Normalized test statistics	$\frac{Q}{\sqrt{n}}, \frac{R}{\sqrt{n}}$	(7)
Decision criterion	$\frac{Q}{\sqrt{n}} < Q_{critical}$ and $\frac{R}{\sqrt{n}} < R_{critical}$	(8)

Where:

$\bar{x}$ = mean rainfall
x_i = rainfall observation at the (i)-th point
n = total number of rainfall observations
S_D = standard deviation
Sk_i^* = cumulative deviation
Sk_i^{**} = normalized cumulative deviation
$Q_{critical}$ = critical values
$R_{critical}$ = critical values

The $\frac{Q}{\sqrt{n}}$ and $\frac{R}{\sqrt{n}}$ statistics are evaluated by comparing them with their respective critical values at a specified significance level. Significance levels of 1%, 5%, and 10% are commonly adopted in hydrological studies, where lower significance levels correspond to stricter acceptance criteria. The selected significance level is used to determine the critical values in the RAPS reference table, which serve as the basis for assessing rainfall data consistency.

The critical values vary according to the number of observations (n) and the significance level applied in the analysis. If the calculated values of $\frac{Q}{\sqrt{n}}$ and $\frac{R}{\sqrt{n}}$ are lower than their corresponding critical values, the observed rainfall data are considered consistent and suitable for further hydrological analyses.

The critical values of the Q and R statistics employed in the RAPS test are presented in Table 2. These values provide an objective basis for determining whether the observed rainfall records meet the consistency requirements for subsequent hydrological applications.

Table 2. Critical values of RAPS Test Statistics

n	Value of $\frac{Q}{\sqrt{n}}$ (significance level)			Value of $\frac{R}{\sqrt{n}}$ (significance level)		
	$\frac{Q}{\sqrt{n}}$ (90%)	$\frac{\mathbf{Q}}{\sqrt{\mathbf{n}}}$ (95%)	$\frac{Q}{\sqrt{n}}$ (99%)	$\frac{R}{\sqrt{n}}$ (90%)	$\frac{\mathbf{R}}{\sqrt{\mathbf{n}}}$ (95%)	$\frac{R}{\sqrt{n}}$ (99%)
10	1.050	1.140	1.290	1.210	1.280	1.380
20	1.100	1.220	1.420	1.340	1.430	1.600
30	1.120	1.240	1.460	1.400	1.500	1.700
40	1.130	1.260	1.500	1.420	1.530	1.740
50	1.140	1.270	1.520	1.440	1.550	1.780
100	1.170	1.290	1.550	1.500	1.620	1.860
200	1.220	1.360	1.630	1.620	1.750	2.000

Evaluation and Calibration of Satellite Rainfall Data

Satellite rainfall data have been widely used as an alternative to observed rainfall data, including GPM-IMERG. GPM-IMERG is a satellite-based rainfall estimation product developed by the National Aeronautics and Space Administration (NASA). This product integrates observations from multiple satellites to estimate rainfall with a high spatial resolution of 0.1° × 0.1° and a temporal resolution of up to 30 minutes. Owing to its global spatial coverage, GPM-IMERG is frequently used in hydrological analyses, particularly in developing regions where observed rainfall data are limited. Nevertheless, GPM-IMERG, like other satellite rainfall products, is subject to uncertainties in rainfall estimation. Therefore, evaluation and calibration against observed rainfall data are necessary before it can be applied in more detailed hydrological analyses.

Rainfall calibration is the process of adjusting and/or correcting satellite rainfall data using ground-based observations to establish an accurate mathematical relationship, allowing satellite rainfall estimates to better represent actual conditions. Various regression approaches can be used for rainfall calibration, including linear, polynomial, exponential, logarithmic, and other regression models. After the calibration process has been completed, the calibrated rainfall data must undergo validation. Validation is performed using independent datasets that were not involved in the calibration process to evaluate the accuracy and reliability of the resulting model.

Statistical Parameter

In the evaluation and calibration of satellite rainfall data against observed rainfall data, several statistical parameters are used to assess the accuracy of the estimated results. The statistical parameters commonly employed include the correlation coefficient (r), bias, Root Mean Square Error (RMSE), and Nash-Sutcliffe Efficiency (NSE). The mathematical formulations of the statistical parameters used in the evaluation and calibration processes are presented in Table 3.

Table 3. Statistical Parameter for Evaluation

No.	Parameter	Equation		Remarks
1.	Correlation coefficient (r)	$r = \frac{\sum(P_i-\bar{P})(O_i-\bar{O})}{\sqrt{\sum(P_i-\bar{P})^2 \sum(O_i-\bar{O})^2}}$	(9)	P_i= satellite rainfall data O_i= observed rainfall data $\bar{P}$= mean satellite rainfall data $\bar{O}$= mean observed rainfall data n= total number of observations
2.	Bias	$\text{Bias} = \frac{\sum(P_i-O_i)}{\sum O_i} \times 100\%$	(10)	
3.	RMSE	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}$	(11)	
4.	NSE	$\text{NSE} = 1 - \frac{\sum(P_i-O_i)^2}{\sum(O_i-\bar{O})^2}$	(12)	

RESULTS AND DISCUSSIONS

RAPS Consistency Test

The consistency of the observed rainfall data was assessed using the Rescaled Adjusted Partial Sums (RAPS) method to ensure the reliability of the data before they were used in subsequent analyses. Consistency testing is necessary because the observed rainfall data serve as the primary reference in the calibration and validation processes. As these data represent actual field conditions, their quality and consistency must be verified prior to use. The consistency test was conducted using monthly observed rainfall data from January 2016 to September 2025, comprising a total of 117 rainfall observations. The monthly observed rainfall data recorded at the Bunaken Rainfall Station are presented in Figure 2.

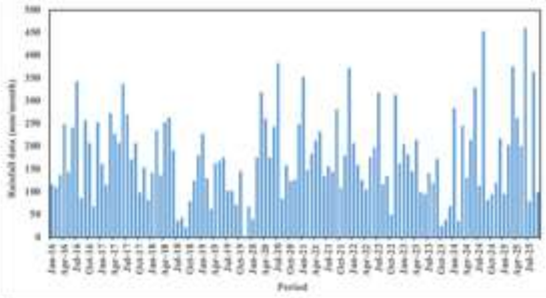


Figure 2. Observed rainfall data from Jan 2016 to Sept 2025

Figure 2 presents the observed rainfall data from January 2016 to September 2025. Although the data show noticeable monthly variability, their consistency cannot be reliably assessed through visual observation alone. Therefore, the RAPS method was applied to evaluate the overall consistency of the observed rainfall data. The results of the RAPS analysis are presented in Table 4.

Table 4. RAPS result

Parameter	Value		Remarks
	Calculated	Critera (95%)	
n	117	-	-
$Q\sqrt{n}$	0,519	1,302	Accepted (consistent)
$R\sqrt{n}$	1,327	1,642	Accepted (consistent)

Based on Table 4, the results of the RAPS consistency test indicate that the observed rainfall data from Bunaken Rainfall Station from January 2016 to September 2025 are consistent. The calculated value of $\mathbf{Q\sqrt{n}}$ and $\mathbf{R\sqrt{n}}$ were lower than their corresponding critical values at the 95% significance level, indicating that no significant inconsistency was detected within the rainfall record. This result suggests that the observed rainfall data exhibit a stable temporal pattern and can therefore be considered reliable for subsequent calibration and validation of the GPM-IMERG satellite rainfall data.

In addition to the statistical indicators presented in Table 4, the temporal behavior of the rainfall data can also be examined through the normalized cumulative deviation values $\mathbf{Sk_i^{**}}$. These values describe the cumulative departures of rainfall observations from the long-term mean and provide a visual representation of the stability of the rainfall record throughout the observation period. As shown in Figure 3, the normalized cumulative deviations fluctuate over time without exhibiting a persistent increasing or decreasing trend, further supporting the conclusion that the observed rainfall data are temporally consistent and suitable for subsequent analysis.

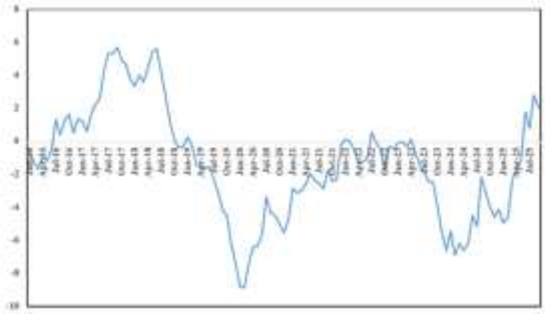


Figure 3. $\mathbf{Sk_i^{**}}$ graph

Based on the visualization of the $\boldsymbol{Sk_i^{**}}$ graph, the normalized cumulative deviations fluctuate throughout the observation period, reflecting the natural temporal variability of rainfall in the study area. Although a noticeable decline occurred from mid-2019 to early 2020, this pattern was primarily associated with several consecutive months of rainfall below the long-term average rather than indicating inconsistencies in the dataset. Following this period, the cumulative deviation gradually returned toward equilibrium, suggesting that the rainfall record remained stable over the long term. The absence of a persistent upward or downward shift indicates that no systematic changes occurred in the observed rainfall series, such as those caused by changes in measurement procedures or station conditions. Therefore, the observed rainfall data can be considered sufficiently representative and reliable for subsequent calibration and validation of the GPM-IMERG satellite rainfall data.

Calibration of Satellite Rainfall Data

After confirming that the observed rainfall data were suitable for further analyses, the calibration of satellite rainfall data was performed. The purpose of the calibration process was to establish the mathematical relationship between GPM-IMERG satellite rainfall data and observed rainfall data. Calibration was conducted using rainfall data from January 2016 to December 2022. This period was considered the calibration dataset and was analyzed using several regression approaches, including linear, polynomial, exponential, logarithmic, and power regression models.

Such fluctuations are expected in tropical regions, where rainfall is strongly influenced by seasonal variability and interannual climate phenomena. Consequently, temporary increases or decreases in cumulative deviations do not necessarily indicate poor data cuality, provided that no persistent systematic shift is observed. The resulting calibration regression equations are presented in Table 5.

Table 5. Calibration model equations

Calibration Model	Regression Equations
Linear	$y = 0{,}197x + 128{,}73$
Polynomial	$y = 0{,}002x^2 - 1{,}098x + 331{,}74$
Exponential	$y = 121{,}98\ e^{0{,}0011x}$
Logarithmic	$y = 51{,}044 \ln(x) - 101{,}12$
Power	$y = 34{,}1\ x^{0{,}285}$

The calibration equations obtained from different regression approaches indicate that the relationship between GPM-IMERG satellite rainfall and observed rainfall is not represented by a single mathematical function. Each regression model characterizes the relationship between the two datasets differently, resulting in variations in their predictive performance. Therefore, statistical evaluation is required to determine which regression model provides the most reliable representation of the observed rainfall data.

To evaluate the suitability of each regression model and identify the most appropriate calibration model, several statistical parameters were calculated, including bias, RMSE, NSE, and the correlation coefficient. These statistical indicators were selected because they provide complementary information regarding model performance, including the magnitude of estimation error, the agreement between simulated and observed rainfall, and the strength of the relationship between two datasets. The performance of the calibration models based on these statistical parameters during the period from January 2016 to December 2022 is presented in Table 6.

Table 6. Performance of calibration models during the 2016-2022 period

No.	Calibration Model	Bias (%)	RMSE (mm)	NSE	r
1.	*Uncalibrated*	*62*	*138.505*	*0.454*	*0.578*
2.	Linear	6	75.409	-2.500	0.578
3.	Polynomial	11	88.334	-1.342	0.107
4.	Exponential	-4	75.345	-3.136	0.575
5.	Logarithmic	5	75.275	-2.559	0.559
6.	Power	-4	75.698	-3.099	0.572

The statistical results of the calibration model performance indicate that the GPM-IMERG satellite rainfall data exhibited relatively large estimation errors prior to calibration, as reflected by a bias value of 62% and an RMSE of 138.505 mm. Following the calibration process, all regression models showed substantial reductions in both bias and RMSE values. Nevertheless, all calibrated models still produced negative NSE values, indicating that the agreement between satellite rainfall estimates and observed rainfall data had not yet reached an optimal level during the calibration period. This condition may be attributed to the high variability of rainfall during the calibration period, resulting in considerable fluctuations in the rainfall data. Despite this limitation, the calibration results still demonstrated considerable improvements compared with the raw satellite rainfall data. Therefore, the regression models obtained from the calibration stage were subsequently applied in the next evaluation stage to assess their ability to represent rainfall data under different periods.

Validation of the Calibration Models

The validation stage was performed to examine whether the regression equations developed during the calibration process could be applied reliably to an independent dataset. Unlike calibration, which establishes the mathematical relationship between satellite rainfall and observed rainfall data, validation evaluates the capability of the developed models to reproduced rainfall conditions outside the calibration period. Monthly rainfall data from January to September 2025, which were not involved in model development, were therefore used as the validation dataset. Model performance was assessed using the same statistical indicators employed during calibration, namely bias, RMSE, NSE, and r. The results of the satellite rainfall validation are presented in Table 7.

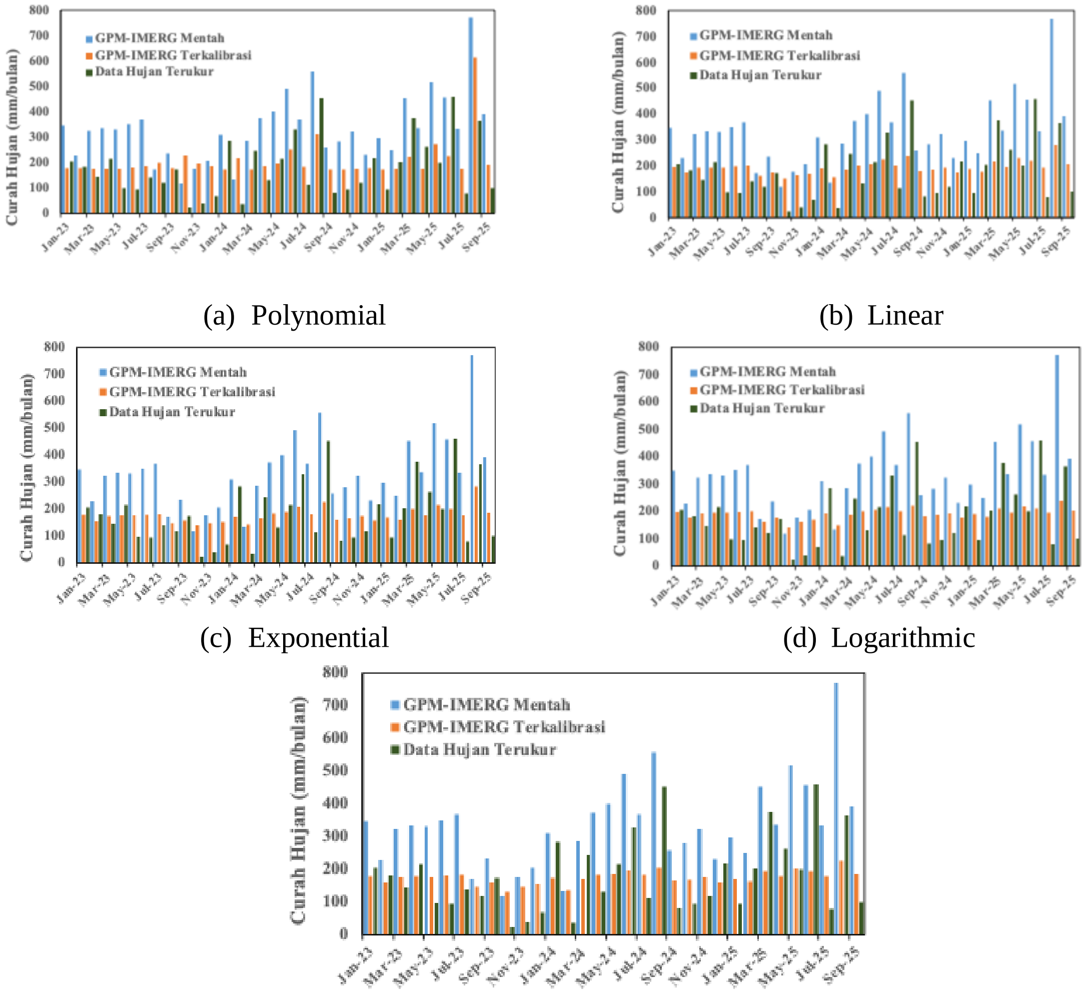
Table 7. Validation results of satellite rainfall data for the Jan 2023-Sept 2025 period

No.	Calibration Model	Bias (%)	RMSE (mm)	NSE	r
1.	*Uncalibrated*	*84*	*180.766*	*-0.977*	*0.690*
2.	Linear	7	98.481	0.731	0.690
3.	Polynomial	15	108.051	0.640	0.452
4.	Exponential	-2	96.940	0.770	0.676
5.	Logarithmic	6	101.618	0.720	0.671
6.	Power	-3	101.361	0.754	0.683

The validation results for the January 2023 to September 2025 period demonstrate a substantial improvement in the performance of calibrated satellite rainfall data compared with the uncalibrated data. During the validation period, the RMSE decreased markedly from 180.766 mm for the uncalibrated data to values ranging from 108.051 mm to 96.940 mm after calibration. Although the RMSE values during the validation period were higher than those obtained during the calibration period, direct comparisons between the two periods should be interpreted with caution due to differences in rainfall characteristics and variability. Nevertheless, both periods consistently indicate that calibration substantially improved the performance of satellite rainfall estimates.

The improvement observed in all calibrated models indicates that the regression-based calibration successfully reduced the systematic differences between the GPM-IMERG satellite rainfall estimates and the observed rainfall data. The uncalibrated satellite rainfall exhibited a substantial overestimation, as reflected by the bias of 84%. After the calibration, the bias decreased considerably to between -3% and 15% indicating that the regression equations effectively corrected the systematic error in the satellite rainfall estimates. This finding demonstrates that a relatively simple statistical calibration can substantially improve the applicability of satellite rainfall data for hydrological analysis in areas with limited rain gauge observations.

In addition to RMSE, the NSE values also improved considerably, increasing from −0.977 for the uncalibrated data to values ranging from 0.640 to 0.770 after calibration. The improvement in these statistical parameters suggests that calibrated satellite rainfall data provide a more accurate representation of rainfall variability during the validation period. Among the evaluated models, the exponential regression model exhibited the best overall performance, as indicated by the lowest RMSE (96.940 mm) and the highest NSE (0.770). A comparison between the observed rainfall data and the calibrated satellite rainfall estimates from each model is presented in Figure 4.



(a) Polynomial (b) Linear

(c) Exponential (d) Logarithmic

(e) Power

Figure 4. Comparison of satellite rainfall estimates before and after calibration

The linear regression model exhibited the highest correlation coefficient, with an (r) value of 0.690. However, the selection of the best calibration model should not be based solely on the correlation coefficient. The correlation coefficient only reflects the strength of the relationship between two variables and indicates how well the temporal variations of satellite rainfall follow those of the observed rainfall. Nevertheless, it does not quantify the value of estimation errors or evaluate how closely predicted rainfall values agree with the observed measurements. Therefore, relying on the correlation coefficient may lead to an overestimation of model performance.

For this reason, the calibration models were evaluated using multiple statistical indicators, including bias, RMSE, NSE, and the correlation coefficient (r), to provide a more comprehensive assessment of model performance. The bias reflects the tendency of the model to overestimate or underestimate rainfall, RMSE measures the magnitude of prediction errors, while NSE evaluates the capability of the model to reproduce the observed rainfall variability. Considering all statistical indicators simultaneously allows a more reliable identification of the optimum calibration model than using a single evaluation metric.

Based on the overall statistical performance, the exponential regression model demonstrated the most satisfactory results among the evaluated models. This model produced the lowest RMSE value (96.940 mm), indicating the smallest prediction error, and the highest NSE value (0.770), suggesting a better agreement between the estimated and observed rainfall data.

Although its correlation coefficient (0.676) was slightly lower than that of the linear regression model, the difference was relatively small and did not outweigh the considerable improvements achieved in RMSE and NSE. These findings suggest that the exponential regression model is the most capable of describing the relationship between satellite rainfall data and observed rainfall data while providing the best representation of actual field conditions.

CONCLUSIONS

The results of this study indicate that the observed rainfall data from Bunaken Rainfall Station are consistent based on the RAPS consistency test, indicating that the data are suitable for subsequent analyses and can be used as a reference in the evaluation and calibration of GPM-IMERG satellite rainfall data. The calibration process was shown to improve the accuracy, reliability, and overall performance of satellite rainfall estimates compared with uncalibrated satellite rainfall data.

During the validation stage, all calibration models demonstrated improved performance relative to the uncalibrated satellite rainfall data. Among the evaluated models, the exponential regression model exhibited the best and most optimal performance based on the calculated statistical parameters, namely bias, correlation coefficient, RMSE, and NSE. These findings demonstrate that a simple regression-based calibration approach can substantially enhance the applicability of GPM-IMERG rainfall data in areas with limited ground-based rainfall observations. Therefore, the exponential regression model can be recommended for subsequent hydrological analysis, including water balance assessment and water resources planning, as it provides the best representation of the relationship between satellite rainfall data and observed rainfall data.

Future studies are encouraged to evaluate a wider range of satellite rainfall products with finer temporal resolutions to strengthen the analysis. In addition, alternative calibration approaches, such as machine learning or hybrid statistical methods, may be explored to further improve the accuracy of satellite rainfall estimates. The proposed calibration framework should also be evaluated in different climatic and geographical settings to assess its transferability and broader applicability.

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