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Assessment of Bias-Correction Methods for CHIRPS Satellite Rainfall Estimates in the Petung Watershed, Indonesia

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Abstract: Satellite-based rainfall products such as CHIRPS are essential in data-scarce tropical regions, but they require bias correction to improve reliability. This study compares five correction techniques—Linear Regression, Linear Scaling, a static Correction Factor, a Genetic Algorithm (GA)-optimized Correction Factor, and a Python-based Temporal Analysis—against gauge observations in the Petung Watershed, East Java, Indonesia. The GA method optimized nonlinear correction coefficient by minimizing RMSE through iterative selection and mutation processes. The Temporal Analysis applied monthly dynamic scaling using Python scripts to account for seasonal rainfall variability. Model performance was assessed using the Nash–Sutcliffe Efficiency (NSE), Pearson correlation (R), and the RMSE–Standard Deviation Ratio (RSR). Linear Scaling achieved the best results (R = 0.857, NSE = 0.724, RSR = 0.547), followed by Linear Regression. The GA-based approach showed marginal improvement over the static factor (NSE = 0.658 versus 0.639). Temporal Analysis improved correlation (R = 0.813) but showed poor performance overall (RSR = 1.425), indicating residual errors exceeding natural data variability. While statistical methods performed best in this case, the poor results of the complex methods reflect implementation limitations—rather than inherent inferiority. This study also highlights the importance of including RSR alongside conventional metrics to expose residual structures often masked by high correlation.

Keywords: Bias correction; Calibration; CHIRPS; Hydrological model; Satellite rainfall; Statistical validation

Introduction

Satellite-based precipitation products such as CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) have emerged as critical tools in hydrology and climate research, particularly in regions with limited in situ rainfall monitoring infrastructure. By combining infrared satellite imagery with ground station data, CHIRPS offers global rainfall estimates at a high spatial and temporal resolution (Funk, Peterson, et al., 2015). Nevertheless, research into CHIRPS remains challenging due to persistent biases in satellite-derived estimates caused by factors such as cloud interference, topographical complexity, and gauge sparsity (Dinku et al., 2018). A specific challenge arises in correcting CHIRPS data for bias, particularly in tropical watersheds like Petung, where high variability in rainfall further complicates the calibration process. These biases, if not properly addressed, can lead to significant errors in hydrological modeling and water resource planning. This research is novel in combining a comparative analysis of both standard and algorithmic bias correction methods in a tropical watershed, while also integrating the underutilized RSR metric to capture error dispersion more comprehensively.

Although CHIRPS is widely used, it consistently underestimates extreme rainfall and overestimates light precipitation, leading to inaccuracies in rainfall

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distribution, especially during seasonal transitions (Supari et al., 2016; Bhattacharyya & Sreekesh, 2021). Correction methods such as linear regression, linear scaling, and optimization-based models (Genetic Algorithms) have been proposed to adjust these discrepancies. Despite the availability of satellite-based rainfall products such as TRMM and GSMaP, comparative assessments with CHIRPS remain limited in tropical catchments like the Petung Watershed, especially in Indonesia. These products sometimes outperform CHIRPS under extreme rainfall conditions due to different retrieval algorithms and calibration strategies (Luo et al., 2019), yet a systematic local-scale evaluation and calibration study remains underexplored. This study is important because accurate satellite rainfall estimation is essential for flood forecasting, drought monitoring, and sustainable water resource planning in tropical regions with limited observation networks like Indonesia. Another underexplored parameter is the Root Mean Square Error Standard Deviation Ratio (RSR), which offers valuable insight into model residual errors but remains overlooked in many validation studies (Zeng et al., 2023; Bayissa et al., 2017). This study attempts to close these gaps by offering a comparative evaluation of five correction methods and incorporating key but underutilized validation metrics.

The central problem of this study is the insufficient accuracy of raw CHIRPS rainfall estimates for reliable hydrological analysis in tropical regions. This leads to the formulation of the following hypothesis: different correction methods will yield significantly different performance levels in reducing CHIRPS bias in rainfall estimation. To address this, five correction approaches are employed—Linear Regression, Linear Scaling, Correction Factor, Correction Factor with Genetic Algorithm, and Temporal Analysis using Python. The Temporal Analysis method utilizes monthly dynamic scaling to adjust for seasonal variability, implemented through Python scripting to iteratively calibrate time-series rainfall data. This research contributes to the literature by providing a systematic performance comparison using statistical indicators such as NSE, R, and RSR, while highlighting the calibration challenges and trade-offs associated with each method.

The primary objective of this study is to compare the performance of five bias correction techniques for CHIRPS satellite rainfall data against ground-based observations in the Petung Watershed, Pasuruan Regency. The methodology includes bias correction using both statistical and optimization techniques, temporal analysis for dynamic variability, and performance validation using key statistical metrics (NSE, R, RSR). By addressing both the lack of local CHIRPS calibration studies and the limited use of RSR in validation, this study fills a unique research gap that links spatial bias correction with improved error structure evaluation. Visual interpretations through scatter plots are also included to highlight data dispersion and correction accuracy. Ultimately, this study seeks to recommend the most effective and practical correction method for improving CHIRPS rainfall estimates in hydrologically complex and data-scarce environments.

Method

This study was conducted in the Petung Watershed (DAS Petung), located in Pasuruan Regency, East Java Province, Indonesia. The Petung Watershed covers an area of 141.729 km² and is equipped with one water level monitoring station, namely the Automatic Water Level Recorder (AWLR) Sekar Putih, as well as three rainfall observation stations: Oro-Oro Pule, Puspo, and Tutur. The observed rainfall data from these stations serve as reference data for calibrating CHIRPS satellite rainfall estimates, allowing for an evaluation of the feasibility and accuracy of using CHIRPS satellite rainfall data in the Petung Watershed.

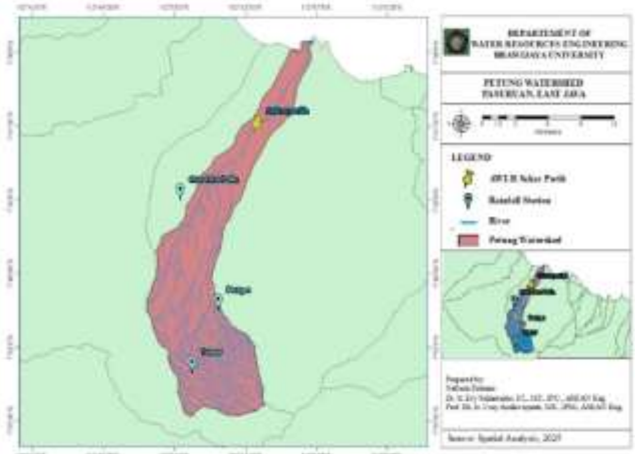

Figure 1. Petung Watershed

Data

The data required for this study consist of rainfall data from ground observation stations, obtained from relevant agencies, and CHIRPS satellite rainfall data, which were acquired from the Google Earth Engine platform. The three rainfall observation stations: Oro-Oro Pule (elevation: 770 m), Puspo (elevation: 960 m), and Tutur (elevation: 1125 m) are present at varying elevations that may influence rainfall intensity. Observational data were available from 2004 to 2023, although some minor data gaps (<3%) were identified and handled through linear interpolation.

Models

This study employed five methods in the correction analysis of CHIRPS satellite rainfall data, namely:

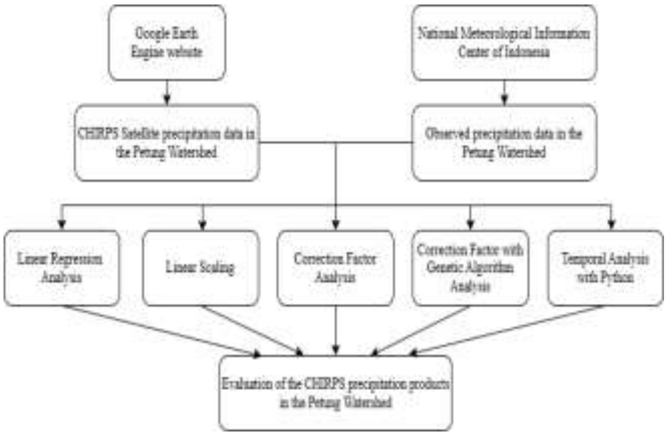

Figure 2. Flowchart of the CHIRPS rainfall data evaluation methodology in the Petung Watershed

Linear Regression

Linear Regression Analysis is a fundamental method for calibrating CHIRPS satellite rainfall data using ground-based observations, especially in areas with sparse measurements like the Petung Watershed. By applying the least squares method, a regression equation is developed to adjust satellite estimates and reduce systematic biases (Funk, Verdin, et al., 2015; Guo et al., 2017). The calibration effectiveness is evaluated through Nash-Sutcliffe Efficiency (NSE), correlation coefficient (R), and Root Mean Square Error Standard Deviation Ratio (RSR), where higher NSE and R, coupled with lower RSR, indicate successful error reduction (Hordofa et al., 2021). This method's simplicity, combined with its ability to capture local climatic relationships, supports its reliability for improving satellite rainfall estimates in hydrological studies.

Linear Scaling

Linear Scaling Analysis is a bias correction technique that adjusts CHIRPS satellite rainfall estimates based on the ratio between observed and satellite mean rainfall, addressing systematic biases while preserving temporal variability (Dlamini et al., 2024). This method proportionally corrects satellite rainfall data without altering the natural sequence of rainfall events. Its effectiveness is validated using NSE, R, and RSR, with results showing improved correlation and predictive accuracy while maintaining rainfall pattern consistency (M. W. Kimani et al., 2018). Linear Scaling is thus recognized as a practical and efficient approach for large-scale bias correction of satellite rainfall datasets.

Correction Factor

Correction Factor Analysis uses a single static coefficient, calculated from the ratio of total observed to CHIRPS rainfall, to uniformly adjust satellite estimates across the study period (Ningrum et al., 2025). While this method effectively corrects systematic biases in total rainfall, its inability to account for temporal variability limits its accuracy in areas with seasonal rainfall fluctuations (Dinku et al., 2018). Although validation through NSE and R indicates performance improvements, static correction often fails during wet or dry seasons, suggesting that dynamic or region-specific methods may be required for more precise calibration (Gumindoga et al., 2019).

Correction Factor with Genetic Algorithm

Correction Factor with Genetic Algorithm Analysis integrates Genetic Algorithm (GA) optimization to determine the most effective correction factor by iteratively exploring possible solutions using selection, crossover, and mutation processes (Kouchi et al., 2017). This approach addresses nonlinear relationships often missed by static methods. Performance evaluation using NSE, R, and RSR confirms that GA optimization improves calibration accuracy and reduces error compared to traditional correction factors, although it requires higher computational resources (Gyawali et al., 2022). This method offers a robust alternative for correcting satellite rainfall data in hydrologically complex regions (Rajkovic et al., 2017).

Temporal Analysis

Temporal Analysis with Python applies dynamic, time-step-based corrections to address seasonal and temporal rainfall variability, with Python's programming flexibility enabling iterative calibration and time-series analysis (Habib et al., 2014). By aggregating data at daily to seasonal scales, this method targets both short-term fluctuations and long-term rainfall trends (Hordofa et al., 2021). Visualization of corrected time series in Python, combined with statistical evaluation using NSE, R, and RSR, supports assessment of calibration improvements (Muthoni et al., 2019). This approach enhances model adaptability to rainfall variability, making it valuable for hydrological forecasting and water resource management (Usman et al., 2018).

Statistical Indicators

Nash-Sutcliffe Efficiency (NSE)

The Nash-Sutcliffe Efficiency (NSE) test is used to evaluate the accuracy of the relationship between observed and modeled data. The NSE can be calculated using the following formula.

Formula:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(P_i - Q_i)^2}{\sum_{i=1}^{N}(P_i - P_l)^2} \quad (1)$$

Description:
Pi = observed data
Qi = estimated (modeled) data
Pl = mean of observed data
N = number of data points

Table 1. Nash-Sutchliffe Efficiency (NSE) Values (Moriasi et al., 2007)

NSE	Properties Value
0.75 < NSE ≤ 1.00	Very Good
0.65 < NSE ≤ 0.75	Good
0.50 < NSE ≤ 0.65	Satisfactory
NSE ≤ 0.50	Unsatisfactory

Correlation Coefficient (R)

The correlation coefficient (R) test determines the strength of the linear relationship between two variables. The value of the correlation coefficient ranges from -1 to 1 (Soewarno, 1995). The correlation coefficient can be calculated using the following equation:

$$R = \frac{N\sum_{i=1}^{N} P_i Q_i - \sum_{i=1}^{N} P_i x \sum_{i=1}^{N} Q_i}{\sqrt{N\sum_{i=1}^{N} {P_i}^2 - (\sum_{i=1}^{N} P_i)^2}\sqrt{N\sum_{i=1}^{N} {Q_i}^2 - (\sum_{i=1}^{N} Q_i)^2}} \quad (2)$$

Description:
P_i = observed data
Q_i = estimated data
N = number of data points

Table 2. Correlation Coefficient Values (Sugiyono, 2021)

Coefficient Interval	Interpretation
0.00 – 0.199	Very Low
0.20 – 0.399	Low
0.40 – 0.599	Moderate
0.60 – 0.799	Strong
0.80 – 1.000	Very Strong

Root Mean Square Error Standard Deviation Ratio (RSR)

The Root Mean Square Error Standard Deviation Ratio (RSR) is a widely used statistical indicator for evaluating the performance of hydrological models and satellite data corrections. RSR integrates the Root Mean Square Error (RMSE) and the standard deviation of observed data, thereby standardizing the RMSE relative to the variability of the observed dataset. The formula for RSR is expressed as:

$$RSR = \frac{RMSE}{STDEV_{obs}} \quad (3)$$

where RMSE is the root mean square error between predicted and observed values, and STDEV_obs is the standard deviation of observed data. The RSR value ranges from 0 (perfect model performance) upward, with lower values indicating better model accuracy and predictive capability. In general, RSR ≤ 0.5 reflects very good performance, while RSR > 0.7 indicates unsatisfactory model performance (Moriasi et al., 2007).

Results and Discussion

Rainfall Data Quality Assessment

The rainfall data used in this study were first subjected to data quality analysis, including consistency tests (RAPS method and double mass curve), stationarity tests (F-test and T-test), and persistence tests. These tests are necessary to assess the suitability of the data for analysis. Based on the results of these analyses, the data were found to be consistent and originating from the same population (homogeneous). Similar rainfall variability patterns in Indonesian tropical basins have also been reported in previous studies, reinforcing the importance of robust data quality evaluation before calibration (Zaini et al., 2023). A bibliometric review of STEM-related environmental data processing indicates an increasing emphasis on dynamic temporal modelling in tropical regions (Laksita et al., 2024).

Bias Correction of CHIRPS Satellite Rainfall Data
Linear Regression Analysis

The evaluation of CHIRPS satellite rainfall using the Linear Regression Method shows a strong correlation with ground observations (R = 0.841) and good predictive accuracy (NSE = 0.702), supported by an acceptable error level (RSR = 0.608). These results confirm CHIRPS's potential for representing rainfall in the Petung Watershed. However, the scatter plot indicates that CHIRPS tends to overestimate during high rainfall events, revealing limitations of the linear regression approach in capturing extreme variability. While more advanced correction techniques could improve accuracy, this method offers a practical and reliable baseline for CHIRPS calibration in data-scarce regions (Kimani et al., 2017; Belay et al., 2019). The consistency of the regression line and the clustering of points along it demonstrate the robustness of the linear model in general rainfall conditions. Yet, discrepancies at the upper tail suggest the model's inadequacy in handling peak rainfall outliers, which may lead to hydrological misinterpretation. Nevertheless, combining this method with temporal or non-linear corrections could enhance performance under dynamic climate variability.

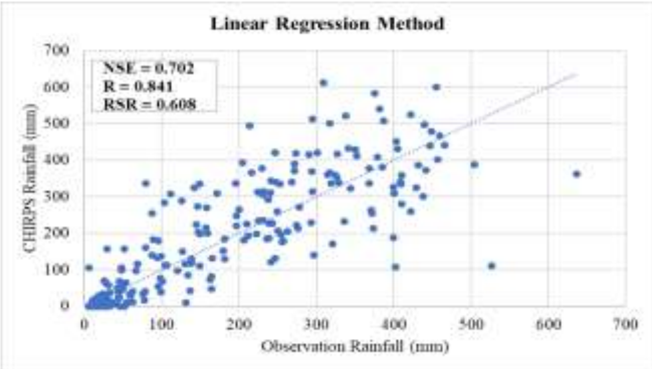

Figure 3. Calibration of CHIRPS satellite rainfall data with linear regression in 20 years (2004–2023)

Linear Scaling Analysis

The application of the Linear Scaling Method significantly improved the calibration of CHIRPS satellite rainfall data, as evidenced by the higher Nash-Sutcliffe Efficiency (NSE = 0.724), strong correlation coefficient (R = 0.857), and reduced residual errors (RSR = 0.547). The scatter plot illustrates a consistent alignment of CHIRPS estimates with ground observations, confirming the method's effectiveness in correcting mean bias while preserving rainfall variability. This performance surpasses typical outcomes from alternative techniques such as quantile mapping, as reported in previous studies (Gumindoga et al., 2019; Goshime et al., 2019). Although some dispersion remains at higher rainfall levels, indicating residual error during extreme events, Linear Scaling maintains a balance between computational simplicity and calibration accuracy, making it a practical solution for semi-tropical regions with limited ground observations (Aadhar et al., 2017). Simpler statistical frameworks have been shown to enhance analytical clarity in applied environmental modelling (Arisa et al., 2021).

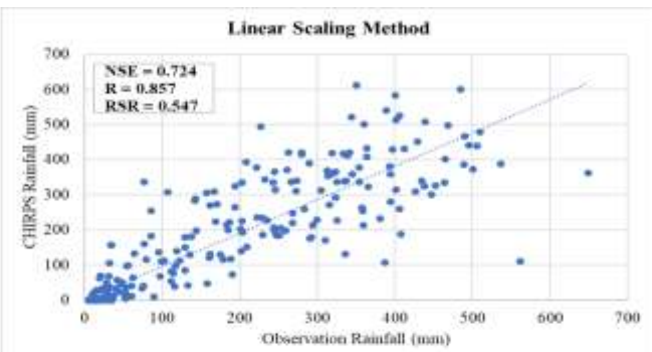

Figure 4. Calibration of CHIRPS satellite rainfall data with linear scaling in 20 years (2004–2023)

Correction Factor Analysis

The scatter plot of the Correction Factor Method shows a strong correlation (R = 0.838) between CHIRPS satellite rainfall and ground observations, yet the moderate NSE (0.639) and relatively high RSR (0.680) indicate that significant residual errors persist, especially at higher rainfall levels. This method's uniform adjustment approach fails to address temporal variability and extremes, as reflected in the increasing data scatter seen in the graph. Although computationally simple and widely used, the Correction Factor Method proves less effective in refining CHIRPS data compared to more adaptive correction techniques, highlighting the need for dynamic or hybrid methods to improve calibration accuracy in regions with complex rainfall patterns.

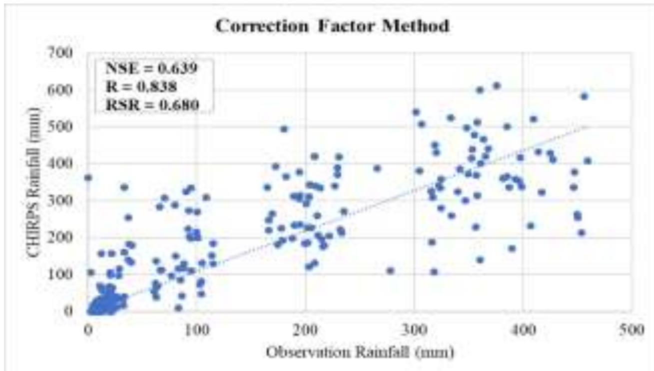

Figure 5. Calibration of CHIRPS satellite rainfall data with correction factor in 20 years (2004–2023)

Correction Factor with Genetic Algorithm Analysis

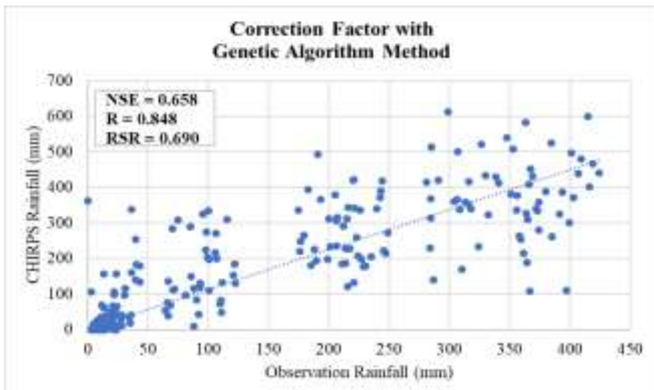

Figure 6. Calibration of CHIRPS satellite rainfall data with correction factor and genetic algorithm in 20 years (2004–2023)

The Correction Factor with Genetic Algorithm (GA) method achieved a modest calibration improvement, with NSE increasing to 0.658 and correlation coefficient (R) reaching 0.848, indicating a strong yet only slightly enhanced relationship compared to the basic correction factor approach. The scatter plot illustrates persistent data dispersion, particularly at mid-to-high rainfall levels, reflected in the relatively high residual error (RSR = 0.690). These results suggest that while GA optimization slightly improves calibration, its standalone effectiveness remains limited, consistent with prior findings that optimization techniques yield incremental gains when not integrated with hybrid approaches (Gu et al., 2024; Talari et al., 2015). Thus, although GA-based optimization contributes to error reduction, its utility in satellite rainfall calibration appears constrained in complex hydrological conditions without additional bias correction or machine learning integration.

Temporal Analysis

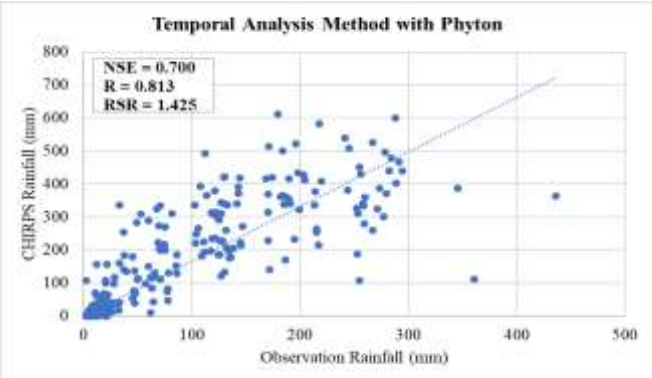

Figure 7. Calibration of CHIRPS satellite rainfall data with temporal analysis in 20 years (2004–2023)

The Temporal Analysis Method using Python produced a moderate calibration improvement, as reflected in an NSE of 0.700 and a correlation coefficient (R) of 0.813, indicating reasonable but sub-optimal predictive accuracy when compared to previous studies such as Zargar et al. (2025) and Khatakho et al. (2024). The scatter plot reveals a positive relationship between CHIRPS rainfall estimates and observed rainfall, but with substantial dispersion at mid-to-high rainfall intensities. This dispersion contributes to the notably high RSR value (1.425), highlighting significant residual errors despite improved correlation. Similar challenges of error persistence have been noted in earlier temporal calibration research, particularly during extreme rainfall events (Bedada, 2025). While Python-based temporal corrections improve data alignment, the method's inability to reduce error variance suggests that integrating temporal analysis with bias correction or machine learning techniques could yield more reliable calibration outcomes (Sriwongsitanon et al., 2023).

Best Results from CHIRPS Satellite Correction

The comparative evaluation of five correction methods reveals that the Linear Scaling Method offers the best calibration performance for CHIRPS satellite rainfall data, as indicated by the highest correlation (R = 0.857) and the lowest residual error (RSR = 0.547), while maintaining good predictive accuracy (NSE = 0.724). Similarly, Linear Regression achieved strong results with R = 0.841 and NSE = 0.702, confirming its effectiveness in reducing bias, though slightly less efficient than Linear Scaling. In contrast, methods such as the Correction Factor and its optimization using the Genetic Algorithm showed only moderate improvements, with NSE values of 0.639 and 0.658 respectively, suggesting limited capacity to correct temporal variability or extreme rainfall. The Temporal Analysis Method, despite reaching R = 0.813 and NSE = 0.700, exhibited the highest residual error (RSR = 1.425), indicating significant dispersion and reduced reliability in minimizing prediction errors. However, the RSR value of 1.425 exceeds the threshold of 1.0, which, according to Moriasi et al. (2007), indicates a statistically unacceptable model. Such a high RSR means the prediction error (RMSE) surpasses the variability of the observed data itself—rendering the model less effective than a baseline mean predictor. This critical outcome underscores that despite moderate R and NSE values, the method cannot be considered reliable for practical calibration without further refinement. These results demonstrate that simple, statistically based methods like Linear Scaling and Linear Regression are more practical and effective for CHIRPS calibration in regions with limited observational data, outperforming more complex optimization and temporal correction techniques. These comparative outcomes are also in line with recent JPPIPA studies indicating that simple statistical approaches frequently outperform algorithmic and temporal corrections in tropical hydrological applications (Virgota et al., 2024). Comparable studies in Indonesian contexts highlight that method adaptation is critical in tropical watershed environments (Istiyati et al., 2023).

Table 3. Summary of CHIRPS Satellite Rainfall Correction Results Using Different Calibration Methods

Method	NSE		R		RSR	
	Value	Interpretation	Value	Interpretation	Value	Interpretation
Linear Regression	0.702	Good	0.841	Very Strong	0.608	Acceptable
Linear Scaling	0.724	Good	0.857	Very Strong	0.547	Acceptable
Correction Factor	0.639	Moderate	0.838	Very Strong	0.680	Marginal
Correction Factor with GA	0.658	Good	0.849	Very Strong	0.690	Marginal
Temporal Analysis	0.700	Good	0.813	Very Strong	1.425	Unacceptable

Conclusion

This study compared five correction methods—Linear Regression, Linear Scaling, a static Correction Factor, a GA-Optimized Correction Factor, and Temporal Analysis—for bias correction of CHIRPS satellite rainfall data in the Petung Watershed. Among these, Linear Scaling showed the highest overall performance (R = 0.857, NSE = 0.724, RSR = 0.547), with the lowest residual error, making it the most accurate and reliable method in this study. Although Linear Regression also demonstrated good predictive accuracy (NSE = 0.702) and strong correlation (R = 0.841), it had a significantly higher residual error (RSR = 0.608) than Linear Scaling, indicating less effective error minimization. The GA-based method provided only marginal improvements over the static correction factor. Temporal Analysis achieved decent correlation (R = 0.813) and NSE (0.700) but failed to meet statistical reliability due to a very poor RSR (1.425), which exceeds the acceptable threshold (> 1.0), indicating that the model performs worse than simply using the observed mean. In summary, simple statistical correction methods proved more practical and effective than optimization-based or temporal approaches in this case. These findings emphasize the importance of considering RSR alongside traditional metrics for a more holistic evaluation. Future research should integrate physical hydrological modeling or machine learning to further improve rainfall calibration accuracy.

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Author Contributions
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Conflicts of Interest
The authors confirm that there are no conflicts of interest related to this publication.

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