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Machine learning-based reconstruction of missing rainfall extremes: a comparative analysis with classical models

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ABSTRACT

The limited availability of daily rainfall data remains a key challenge in rainfall data analysis. This study assesses the effectiveness of spatial interpolation and bias correction techniques using satellite-derived rainfall data to fill missing observations in the Banten and Jakarta regions. Three interpolation methods inverse distance weighting (IDW), kriging, and spline were compared. Nine statistical and machine learning-based bias correction methods were applied to climate hazards group infrared precipitation with station data (CHIRPS), multi-source weighted-ensemble precipitation (MSWEP), and global precipitation measurement integrated multi-satellite retrievals for GPM (GPM IMERG). Performance was evaluated using root mean square error (RMSE), mean absolute error (MAE), bias, Pearson correlation (R), and Kling-Gupta efficiency (KGE) in the expert team on climate change detection and indices (ETCCDI) extreme index. The research findings indicate that CHIRPS with quantile mapping (QM) bias correction delivers the best performance, followed by random forest regression (RFR) as the most accurate machine learning method. In spatial interpolation, IDW stands out as the leading method. Testing the extreme index ETCCDI confirms that CHIRPS-QM consistently outperforms machine learning and interpolation methods. In general, CHIRPS-QM and IDW represent the most effective combination of techniques for reconstructing daily rainfall, particularly extreme events. This study uniquely integrates spatial interpolation and bias correction in a unified evaluation.

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1. INTRODUCTION

Rainfall is crucial in various climate, hydrology, and natural disaster management sectors. The accuracy of rainfall data significantly determines the reliability of long-term climate analysis, including flood modelling, extreme index calculations, and climate trend monitoring. Climate change has increased the frequency and intensity of rainfall anomalies in tropical regions, especially those affected by the El Niño Southern Oscillation (ENSO) phenomenon [1], [2]. However, there are related challenges, as the distribution of rainfall measurements in Indonesia lacks long series, and many locations experience technical disruptions, infrastructure limitations, or missing archives. This poses a significant challenge in hydrological and climate analysis, especially in areas with complex topography and limited observation networks [3].

The Banten and Jakarta regions are strategic areas in the western part of Java Island at high risk of extreme hydrometeorological events. Jakarta, a metropolitan center with a high population density, and Banten, the source of several major river basins such as Ciujung, Cidurian, and Cidanau (C3), often experience flooding due to extreme rainfall. Previous studies have indicated that this area has significant characteristics of extreme daily and seasonal rain [4]-[6], and even record-breaking rainfall events have caused substantial economic losses and flooding disasters in Jakarta [7].

Researchers have developed various methods to address the issue of missing rainfall data. Global-scale research on daily rainfall data imputation has utilized diverse datasets to produce continuous meteorological records by integrating reanalysis products, international station data, and various gap-filling approaches, including interpolation, quantile mapping, and machine learning [8]. Multiple methods for filling missing data continue to evolve from conventional statistical-based approaches, such as interpolation, to machine learning and deep learning-based methods, which can recognize complex patterns in climate data [9]. The performance of each method is greatly influenced by the spatial distribution of stations and the topographical characteristics of the area [10], [11]. Inverse distance weighting (IDW) is known for its computational efficiency and implementation within geographic information system (GIS) systems [12]. It has proven operationally effective in flat regions such as Sydney [13]. Meanwhile, the spline interpolation method tends to be more sensitive to outliers and produces irregularities in locations with extreme data [14].

On the other hand, bias correction approaches are implemented to improve the estimates of satellite products such as climate hazards group infrared precipitation with station data (CHIRPS), multi-source weighted-ensemble precipitation (MSWEP), and global precipitation measurement integrated multi-satellite retrievals for GPM (GPM IMERG) to better align with local conditions. These products are beneficial because they cover large areas and have high spatial resolution, but they contain systematic biases due to sensor estimation limitations. Bias correction has been performed using various approaches, ranging from statistical methods such as quantile mapping (QM) and linear regression (LR) to machine learning methods such as random forest or XGBoost [15]-[17]. The accuracy of daily rainfall estimates can be significantly improved by correcting the CHIRPS data [16], [18]. Previous studies have demonstrated that machine learning approaches can highly capture complex patterns in rainfall data. Research in Indonesia, such as [19] successfully applied machine learning techniques to model daily rainfall in tropical regions with high variability. Similarly, studies conducted in India also showed improved rainfall prediction accuracy in areas characterized by monsoon climates [20].

Although interpolation and bias correction have been widely used, there are still very few studies in Indonesia that integrate both approaches within a single systematic evaluation framework. In extreme climate analysis, additional validation becomes crucial to ensure that the reconstructed data is statistically accurate and suitable for extreme analysis. Therefore, this research adds a feasibility test for the reconstructed data by calculating extreme indices based on the expert team on climate change detection and indices (ETCCDI), which are widely used in global climate studies and disaster risk assessments [2], [21], [22]. The ETCCDI index is susceptible to the quality of input data, necessitating a careful approach to ensure its reliability, including for assessing disaster risk and climate change to avoid misinterpretation of climate change signals [23]-[25]. The effectiveness of imputation methods is significantly influenced by rainfall variability and the spatial characteristics of the area, as demonstrated in [26]. Therefore, method selection should be tailored to the analytical requirements, particularly for extreme events. It was noted in [27] that extensively filled historical data may affect the detection of long-term trends in extreme indices, especially when the proportion of missing data exceeds a certain threshold.

This study contributes to filling the existing research gap by systematically integrating interpolation methods and bias correction across multiple satellite rainfall products, thereby enhancing extreme rainfall analysis using ETCCDI, especially in tropical regions. The uniqueness of this research lies in its comprehensive evaluation framework, which aims not only to compare interpolation methods and bias correction quantitatively but also to test the results of these reconstructions in the context of ETCCDI extreme index analysis. This approach is expected to make methodological contributions to using multi-category rainfall data for extreme climate studies in Indonesia.

2. METHOD

This study focuses on the Banten and Jakarta regions. Observational rainfall data were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG), particularly from the Banten Climatology Station. Initially, rainfall records from 180 stations were collected, and following a quality control (QC) process, 140 stations were deemed valid. Among these, 105 stations were selected for analysis, with 44 having more than 80% daily data availability between 1991 and 2020, while the rest ranged from 41% to 80%, primarily due to data gaps in the early years. The spatial distribution of these stations and data availability is illustrated in Figure 1. Three satellite-based rainfall products were used: CHIRPS, with a 0.05° (~5 km) resolution and data available from 1981 [28]; MSWEP, with a 0.1° (~10 km) resolution and data starting from 1979 [29]; and GPM IMERG, also with a 0.1° resolution, available from 1998 [30]. These datasets were accessed from their respective official sources.

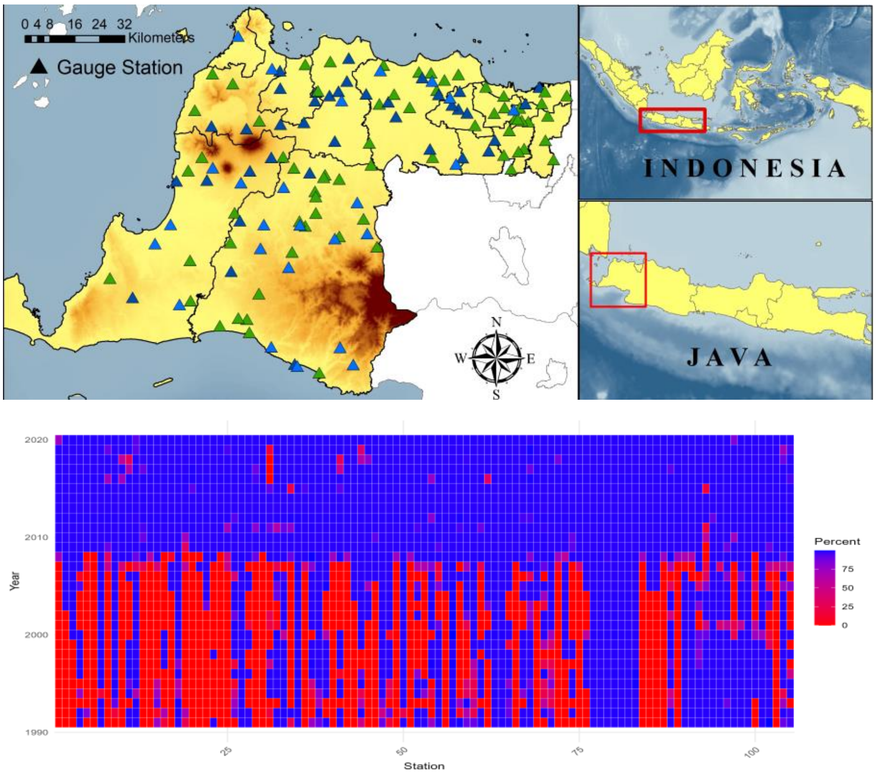

Figure 1. Station locations and rainfall data availability in Banten and Jakarta

The simulation of missing data reconstruction used seven rain stations with complete and homogeneous time series from 1991 to 2020: Kemayoran, Tanjung Priok, Soekarno Hatta, Curug, Tangerang Geophysical, Banten Climatological, and Serang Maritime Meteorological Stations. These stations were the primary reference for testing interpolation and bias correction methods before broader application. In the simulation, rainfall data from 1991–2005 were intentionally removed to evaluate method performance. The missing data were reconstructed using three interpolation methods, six statistical bias correction methods, and three machine learning-based methods. Interpolation utilized data from 105 other stations, while bias correction was based on satellite training data from 2006 to 2020 to estimate rainfall values for 1991 to 2005.

Satellite product data is used for bias correction methods, where the evaluation and bias correction processes are aligned to the same period, specifically data from 1991 to 2020, except for GPM IMERG, whose data is available from 1998. Subsequently, the downloaded data were extracted at locations matching the rain gauge coordinates for evaluation and bias correction purposes. In summary, the flow of the research procedure can be seen in Figure 2. This study employs various interpolation and bias correction methods, with the interpolation methods used including spline, kriging, and IDW. For the CHIRPS, MSWEP, and GPM IMERG satellite products, the statistical bias correction methods used are average ratio (AVG), QM, LR, linear bias correction (LBC), robust regression (RR), and weighted regression (WR), as well as the machine learning methods random forest regression (RFR), XGBoost regression (XG), and isolation forest (IF).

Spline interpolation constructs a smooth surface that minimizes curvature by seeking an interpolation function $f(x_i, y_i)$ that minimizes the square differences between the data and the surface, while controlling the smoothness of the surface through the smoothness parameter λ with (1). The effectiveness of spline interpolation compared to IDW has also been evaluated in previous rainfall studies, which highlight the superior performance of IDW in various climatic conditions [10].

$$J(f) = \sum_{i=1}^{n}[Z_i - f(x_i, y_i)]^2 + \lambda \iint \left[\left(\frac{\partial^2 f}{\partial x^2}\right)^2 + \left(\frac{\partial^2 f}{\partial y^2}\right)^2\right] dx\ dy \quad (1)$$

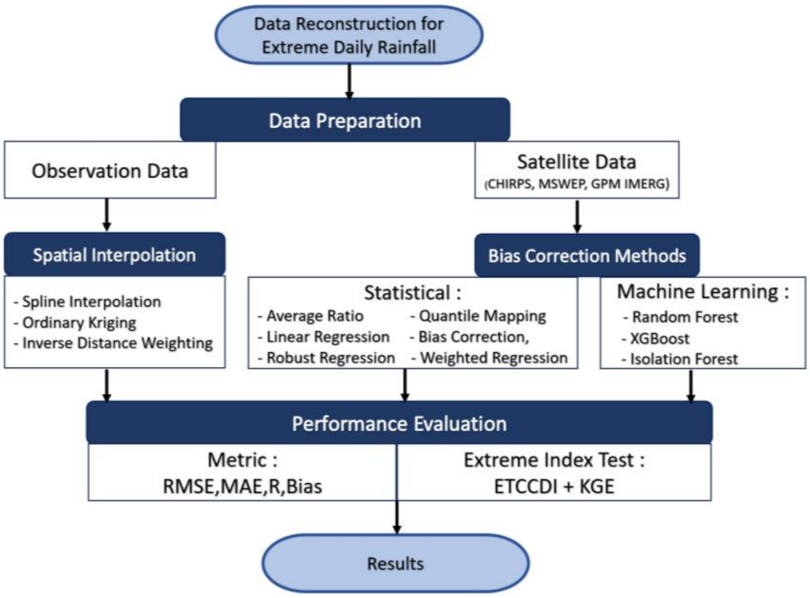

Figure 2. Research flowchart of rainfall data reconstruction methods

The kriging method takes into account the spatial correlation between points. This method uses a semivariogram to estimate spatial autocorrelation with (2). In kriging, $\hat{Z}(x_0)$ is the estimated value at the location x_0, and λ_i is the spatial weight obtained from the semivariogram model. Kriging relies on a semivariogram to estimate spatial autocorrelation, and has been shown to outperform non-geostatistical interpolation methods in tropical regions [31]. The IDW method estimates the value at a specific point based on the distance to observation points using (3). This method estimates the rainfall value at a point x_0 based on the distance to the observation points. Here, $Z(x_i)$ is the rainfall value at the point i, di is the distance from point x_0 to point x_1, and p is the distance weighting parameter ($p = 2$). The value of 2 for the distance weighting parameter provides an optimal balance between the nearest data points' contribution and the interpolation results' spatial stability [32]-[34]. The AVG method is a correction that involves multiplying the satellite value S by the ratio between the average observation $\overline{O}$ and the average satellite $\overline{S}$ during this calibration period in (4). This method can be used as a baseline to compare with other methods [35].

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{2}$$

$$\hat{Z}(x_0) = \frac{\sum_{i=1}^{n} \frac{Z(x_i)}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \tag{3}$$

$$S_{\text{corr}}(t) = S(t) \cdot \frac{\overline{O}}{\overline{S}} \tag{4}$$

The QM method can address bias in averages and extreme quantiles in (5). QM adjusts the quantile distribution of satellite data with observational data. F_S is the cumulative distribution function (CDF) of the satellite data, and F_O^{-1} is the inverse CDF of the observational data. This method has been demonstrated to effectively improve CHIRP/CHIRPS rainfall estimates and support long-term hydrological applications [16]. LR methods, although simple, are still commonly used in correcting climate data bias to form a time series of correction results based on the historical relationship between the observational data and satellite model outputs [17]. This method is found in (6). A simple linear model where a is the intercept and b is the slope determined by regression fitting between observational and satellite data. The Robust linear correction method is used explicitly for upper quantiles (extremes) to avoid overfitting and improve prediction stability [36]. RR is a model resistant to outliers, using an M-estimator approach. The WR method is similar to LR, but weights w_i assigned based on the variance of satellite data at point i, so points with low uncertainty are prioritized. Model resilience to outliers is also an important consideration, although the robustness aspect is not explicitly reflected in (7).

$$S_{\text{corr}}(t) = F_O^{-1}\left(F_S\big(S(t)\big)\right) \tag{5}$$

$$S_{\text{corr}}(t) = a + b \cdot S(t) \tag{6}$$

$$S_{\text{corr}}(t) = a + b \cdot S(t), w_i = \frac{1}{\text{Var}(S_i)} \tag{7}$$

The RFR method is an ensemble model of T decision trees, where the final result is the average output of all trees $h_t(x)$, using (8). This method has been extensively used for GPM IMERG correction [37]. The XG method has been proven to have a high bias correction capability on precipitation data in mountainous areas, with bias values significantly smaller than conventional statistical approaches [38]. The boosting model adjusts the previous prediction $\widehat{y_i^{(t-1)}}$ with a new tree function $f_t(x_i)$, multiplied by the learning rate η (9). Random partitioning is used to detect outliers and rectify extreme values. The IF method has been shown to enhance the accuracy of precipitation data distribution and demonstrate superiority in preserving physically relevant extreme values without compromising model stability [39].

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{8}$$

$$\widehat{y_i^{(t)}} = \widehat{y_i^{(t-1)}} + \eta f_t(x_i) \tag{9}$$

The results of estimating rainfall are compared with actual data from seven BMKG stations that have complete data and are evaluated using error metric indicators, specifically RMSE, MAE, Bias, and correlation coefficient (R). These error metric calculations determine the best method for filling in missing daily rainfall data, especially for high and extreme rainfall events. The equations for these error metrics can be found in (10)-(13). With S_i as the value of the estimated result (interpolated result or bias correction), O_i as the observation value (actual rainfall data), $\bar{S}$ and $\bar{O}$ as the estimated and observed data averages, and n as the total number of daily data points compared.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \tag{10}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|S_i - O_i| \tag{11}$$

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(S_i - O_i) \tag{12}$$

$$R = \frac{\sum_{i=1}^{n}(S_i - \bar{S})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}} \tag{13}$$

An evaluative approach to two types of rainfall data reconstruction methods, namely spatial interpolation and satellite product bias correction, was used in this study. The evaluation is conducted not only on performance based on general statistics but also on its ability to maintain the signal of extreme events, highlighting the importance of selecting imputation methods based on spatial variability and sensitivity to extremes [26]. Then, to ensure the reliability of the filled data in long-term analysis, ETCCDI index calculation tests are conducted. This approach takes into account the findings in [27], which indicates that using in-filled data can significantly affect the detection of extreme trends, especially when the proportion of filled data is significant. Accurate forecasting of the ETCCDI index is heavily influenced by the completeness of daily rainfall data, as incompleteness of data during specific periods will lead to biases in extreme trend calculations, thus requiring effective data reconstruction techniques [40]. Filling in rain data with gridded data or interpolation results can reduce peak values and the frequency of extreme values; hence, strict verification is required before the data is used in climate change analysis [24].

The results of filling in missing data also depend on the quality of the input data, including data derived from interpolation, as it can affect the trends produced in the extreme index [41], [42]. With the previous research, the calculation of the ETCCDI index in this study will be used for climate characterization and as an additional validation testing tool for the interpolation results and bias correction. The extreme ETCCDI indices to be tested include 14 indices based on their intensity, such as maximum 1-day precipitation amount (Rx1day), maximum 5-day precipitation amount (Rx5day), simple daily intensity index (SDII), annual total wet-day precipitation (PRCPTOT), percentage of total precipitation from days exceeding the 90th percentile (P90pTOT), percentage of total precipitation from days exceeding the 95th percentile (P95pTOT), and percentage of total precipitation from days exceeding the 99th percentile (P99pTOT); based on frequency, number of heavy precipitation days (≥10 mm) (R10 mm), number of very heavy precipitation days (≥20 mm) (R20 mm), number of extremely heavy precipitation days (≥50 mm) (R50 mm), number of extremely heavy precipitation days (≥100 mm) (R100 mm), and number of extremely heavy precipitation days (≥150 mm) (R150 mm); and based on duration, consecutive wet days (CWD) and consecutive dry days (CDD). The extreme index results from the best interpolation, and all satellite bias corrections are measured using a combination of four metrics: RMSE, Bias, R, and augmented with kling-gupta efficiency (KGE). One of the new metrics used is the KGE, as proposed in [43], which combines three main evaluation components: correlation, mean bias ratio, and variation ratio, as shown in (14). Where r is the Pearson correlation coefficient, μ is the mean value, $CV = \sigma/\mu$ is the coefficient of variation, and subscripts s and o refer to simulated and observed data, respectively.

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\mu_s}{\mu_o} - 1\right)^2 + \left(\frac{CV_s}{CV_o} - 1\right)^2} \tag{14}$$

Adding KGE complements conventional evaluation metrics, as it can capture the model’s overall accuracy. Nevertheless, RMSE, bias, and R remain retained, as each provides specific insights not always reflected in the aggregate KGE score [43]. In assessing the performance of these four metrics, their values are normalized into a range of 0–1 before the total score is computed. The purpose of applying normalization is to ensure that all metrics contribute equally and do not dominate each other in the evaluation process, thus ensuring transparency in the standardized framework [44]. To consolidate the four metrics into a single performance measure, a normalization process is carried out where the normalization formula for RMSE and bias is described by (15), and the normalization formula for KGE is defined by (16). The absolute sign $|x|$ is used explicitly for metrics sensitive to direction (bias).

$$Metrik_{norm} = 1 - \frac{|X| - |X|_{min}}{|X|_{max} - |X|_{min}} \tag{15}$$

$$Metrik_{norm} = \frac{|X| - |X|_{min}}{|X|_{max} - |X|_{min}} \tag{16}$$

The total score of each method is calculated using the weighted average of the four metrics normalized by (17). For objectivity in the classification of interval scores, the total score intervals in this study are determined based on the quartiles of the overall total score distribution. This allows performance evaluation to be carried out according to the principle of distribution-based classification, which has been widely applied in assessing climate and hydrology model performance [45]. Each category interval will then be assigned a rating, such as ‘low,’ ‘fair,’ ‘high,’ and ‘very high,’ to represent a statistically consistent range of values while being relevant for differentiating methods based on the quality of results.

$$Total\ Score = 0.25 \times (1 - RMSE_{norm}) + 0.25 \times (1 - Bias_{norm}) + 0.25 \times KGE_{norm} + 0.25 \times |r| \tag{17}$$

The use of the ETCCDI index in this study is intended as part of the internal evaluation to assess the consistency of data filling against the characteristics of extreme precipitation. In this study, the RMSE, BIAS, and KGE metrics are first normalized before being used in the composite score weighting system, except for the correlation value, which is only taken in absolute terms as it already has a value range of 0-1. This normalization step is carried out so that each metric is on an equal scale and can be compared fairly. Without normalization, differences in units and value ranges among metrics can lead to the dominance of one metric over another, resulting in biased assessments. This approach aligns with the practices proposed in [26], [45], where a composite evaluation system for climate models was developed by transforming all error metrics into a range of 0–1 to minimize bias caused by differences in scale and sensitivity, ensuring that each indicator contributes proportionally to the final assessment. An important note in this approach is that all calculated performance indices are based solely on the highest and lowest reference values that emerge from this research and are not a globally accepted standard, thus allowing for a consistent and relevant evaluation of the data context and research area. Nevertheless, the final results will not conclude that the method is generally reliable. Instead, the results are the most optimal among the tested methods and are limited to this study.

3. RESULTS AND DISCUSSION

3.1. Data observation, interpolation, and bias correction

This section presents the performance evaluation of daily rainfall estimation using spatial interpolation and bias correction of three satellite products. Table 1 summarizes the results based on four statistical metrics. Among interpolation methods, IDW performed best with the lowest RMSE (12.00 mm), MAE (5.37 mm), bias (–0.71 mm), and the highest correlation (R = 0.47). Kriging showed slightly lower correlation than IDW, while spline yielded unrealistically high errors (RMSE > 100 mm), indicating poor suitability for daily data. Among satellite products, CHIRPS with LR and GPM IMERG with IF produced RMSE values around 12.99 mm, outperforming MSWEP, whose RMSE consistently exceeded 13 mm, reaching 29.93 mm under quantile mapping. However, none of the bias correction methods achieved a higher correlation than IDW; all R values remained below 0.26. These findings align with [18], which highlights CHIRPS's reliability in tropical climates, and with [36], demonstrating the improvement of extreme rainfall accuracy through hybrid quantile mapping. CHIRPS consistently showed low bias and more stable correlation than GPM IMERG, making it the most accurate satellite product in this study. Nevertheless, other studies [37], [38] noted that GPM IMERG, when corrected with Random Forest, performs better in mountainous regions. The selection of CHIRPS here also reflects its longer data availability, which suits the temporal needs of this research.

Table 1. Daily rainfall estimation errors compared to observations (1991–2005)

Method	Type	Product	Error metric value			
			RMSE (mm)	MAE (mm)	BIAS (mm)	R
IDW	Interpolation	Observation	12.0004	5.3729	-0.7116	0.4653
Kriging			14.1497	7.6077	-0.5644	0.4170
Spline			106.2412	44.9541	38.7334	0.1303
Average ratio	Statistical	Chirps	13.7441	6.7364	-0.0751	0.2504
Linear bias corr			12.9958	6.8320	0.0171	0.2504
Linear reg			12.9958	6.8320	0.0171	0.2504
Quantile mapping			16.7705	7.2640	-0.0977	0.2107
Robust reg			13.5638	5.1684	-3.9986	0.2504
Weighted reg			13.4702	6.4409	-0.5812	0.2504
Random forest reg	Machine learning		14.9706	7.3529	-0.0831	0.1372
XGBoost reg			13.2925	6.9041	-0.0274	0.2185
Isolation forest			13.0035	5.9920	-1.8660	0.2504
Average ratio	Statistical	Mswep	17.3636	6.9963	0.4245	0.2022
Linear bias corr			17.0414	7.1052	0.4158	0.2022
Linear reg			17.0414	7.1052	0.4158	0.2022
Quantile mapping			29.9331	9.3495	2.3386	0.1965
Robust reg			13.6425	5.2864	-3.5354	0.2022
Weighted reg			16.5303	6.6879	-0.1028	0.2022
Random forest reg	Machine learning		16.2035	7.0498	0.2020	0.2159
XGBoost reg			14.8524	6.6735	-0.0470	0.2479
Isolation forest			13.9647	5.9262	-1.5668	0.2022
Average ratio	Statistical	GPM imerg	15.0398	6.7375	-0.2585	0.2207
Linear bias corr			13.4163	6.7901	-0.0713	0.2207
Linear reg			13.4163	6.7901	-0.0713	0.2207
Quantile mapping			17.9079	7.2161	-0.2338	0.2057
Robust reg			13.3320	5.1620	-3.6199	0.2207
Weighted reg			14.8270	6.6129	-0.4626	0.2207
Random forest reg	Machine learning		15.0128	7.1553	-0.1792	0.1794
XGBoost reg			13.3961	6.7171	-0.1652	0.2315
Isolation fores			12.9938	5.9476	-1.7239	0.2207

Figure 3 illustrates scatter plots comparing observed and interpolated daily rainfall values using three methods. Spline interpolation shows the weakest agreement with observed data (R=0.12), with a wide spread below the 1:1 line, particularly overestimating high-intensity rainfall. This suggests the spline's smoothing nature is less suited for daily rainfall with substantial local variability, as noted in [10], [14]. Kriging and IDW provide better alignment to observations, especially IDW, with the highest correlation (R=0.61), reflecting stronger consistency across stations and intensities. Both methods show more concentrated clustering around the ideal line, affirming their suitability under sparse station conditions. These findings align with previous research [46] supporting IDW and kriging's strengths in preserving spatial accuracy without extreme deviations. Nevertheless, spline methods remain relevant in seasonal-scale applications due to their smoothing capacity across longer temporal aggregations [13].

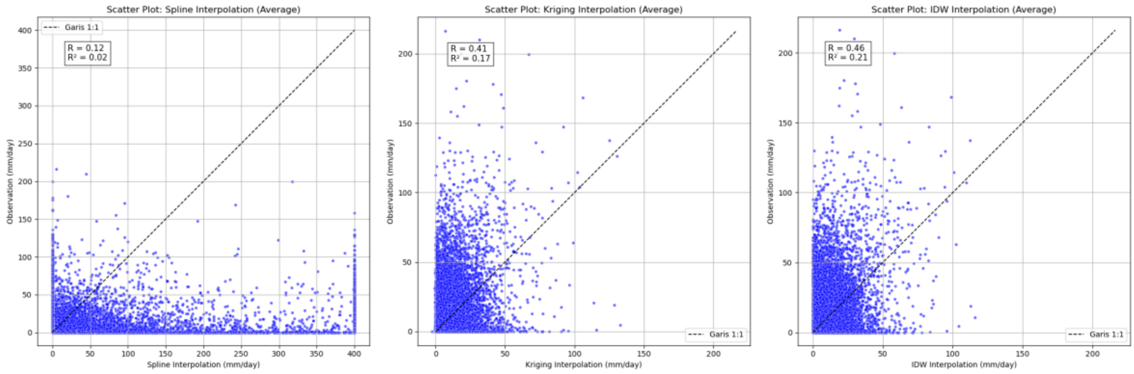

Figure 3. The relationship between observation and interpolated rainfall (spline, kriging, and IDW)

Figure 4 displays the performance of nine bias correction methods applied to CHIRPS satellite data, averaged over seven rain gauge stations. The methods include three statistical approaches AVG, LBC, and LR, and three regression-based techniques QM, RR, and WR, alongside three machine learning-based models IF, RFR, and XG. The RFR, XG, and QM methods visually produce scatter plots with points more concentrated along the 1:1 reference line, suggesting stronger agreement with observed rainfall values. This indicates their superior ability to reduce systematic bias and capture variability, particularly in extreme rainfall cases, consistent with findings in [15], [25], [37], [38]. QM stands out in handling high-intensity rainfall events (>100 mm/day), while simpler methods such as AVG and LBC show more dispersed and biased corrections, often underestimating heavy rainfall. IF and RR are prone to underprediction, especially for extreme events, and tend to produce outputs clustered at lower values. Meanwhile, WR shows a limited distribution range, suggesting low adaptability to the observed variability. These results highlight that machine learning methods and quantile-based corrections offer better flexibility and accuracy than conventional linear methods, as supported by [35], [39].

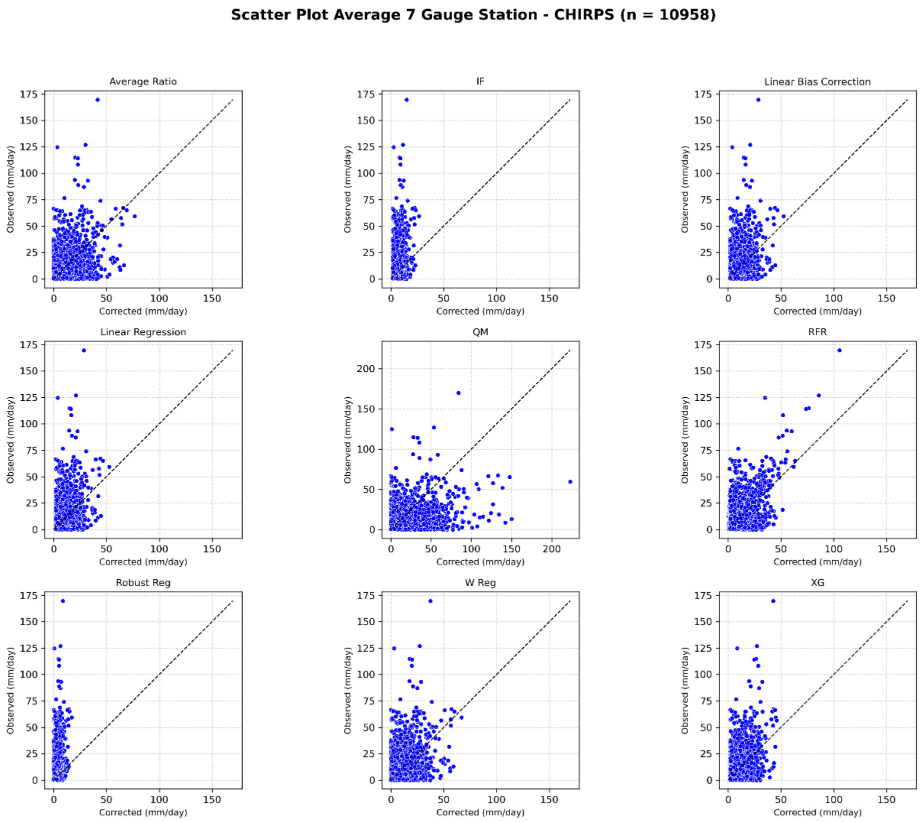

Figure 4. Comparison of rainfall bias correction and observations for CHIRPS

3.2. Evaluation of performance of methods based on the ETCCDI extreme index

Figure 5 presents scatter plots comparing observed values and predicted results from each data-filling method across four ETCCDI indices: intensity (Rx1day, PRCPTOT), frequency (R20 mm), and duration (CWD). The dashed 1:1 line marks the ideal agreement; predictions closer to this line indicate higher accuracy. These indices were selected based on the approach in [40], with a total of 105 data points evaluated per method. For Rx1day, QM provided the highest number of accurate predictions (27 points with ≤10% error), followed by IDW (11 points) and RFR (6 points). This finding supports [15], [25], which emphasizes QM's effectiveness in capturing daily rainfall extremes by aligning predicted and observed quantiles. IDW also showed strong results, reinforcing its reliability for estimating extreme daily rainfall based on spatial interpolation [10].

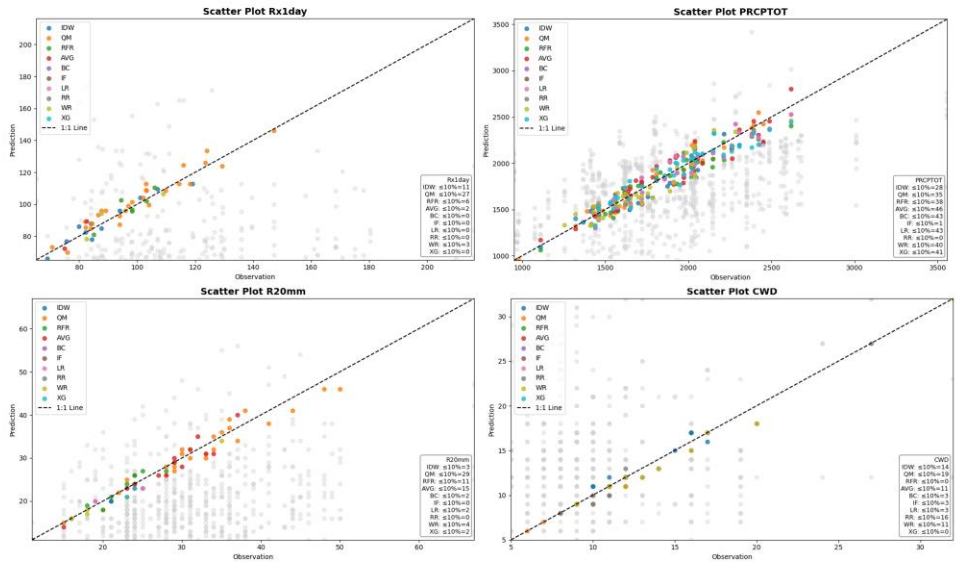

Figure 5. Scatter plot of observation and prediction results for Rx1day, R95pTOT, R20mm, and CWD

For PRCPTOT, most methods performed better than for the other indices. The AVG method recorded the highest number of accurate predictions (46 points), followed by WR (34 points), QM (19 points), and IDW (28 points). Cumulative indices such as PRCPTOT tend to be less sensitive to daily fluctuations, making them more predictable, as confirmed by [23], [35]. For CWD, the top-performing methods were QM (19 points) and IDW (14 points). QM was the most consistent method across intensity, frequency, and duration-based indices. However, IDW remained competitive, particularly for cumulative and duration indices like PRCPTOT and CWD. Its strength is preserving daily sequence patterns, essential for duration analysis [13], and offering reliable performance even with sparse data, as highlighted in [46]. Compared to machine learning methods, IDW offers practical advantages due to its more straightforward implementation and lower resource requirements, as discussed in [36], [40].

Figure 6 presents the total normalized scores (ranging from 0 to 1) based on four error metrics RMSE, Bias, Pearson correlation coefficient (R), and Kling–Gupta efficiency (KGE) to evaluate the performance of various bias correction methods on CHIRPS data for 12 ETCCDI extreme climate indices. The dataset includes nine bias correction methods (statistical and machine learning) and one spatial interpolation method (IDW). Red shades indicate high performance (scores near 1), while blue indicates poor performance (near 0). QM and IDW consistently show high performance across most indices, particularly in intensity-based categories (Rx1day, Rx5day, PRCPTOT, R95pTOT). These findings reinforce previous studies that confirm QM's ability to retain quantile distributions and extreme values [15], [25], [35], while IDW maintains stable performance despite its simplicity and lack of complex statistical modeling [13], [46]. Conversely, RFR and IDW exhibit low performance on very high rainfall frequency indices (R100 mm and R150 mm), likely due to the limited training data in those ranges [37]. This limitation in RFR has also been noted in other studies that recommend hybrid or extreme-specific correction methods [36]. IDW, however, performs better than RFR in the SDII intensity category and duration indices like CDD and CWD, reaffirming its practical advantages even over machine learning approaches.

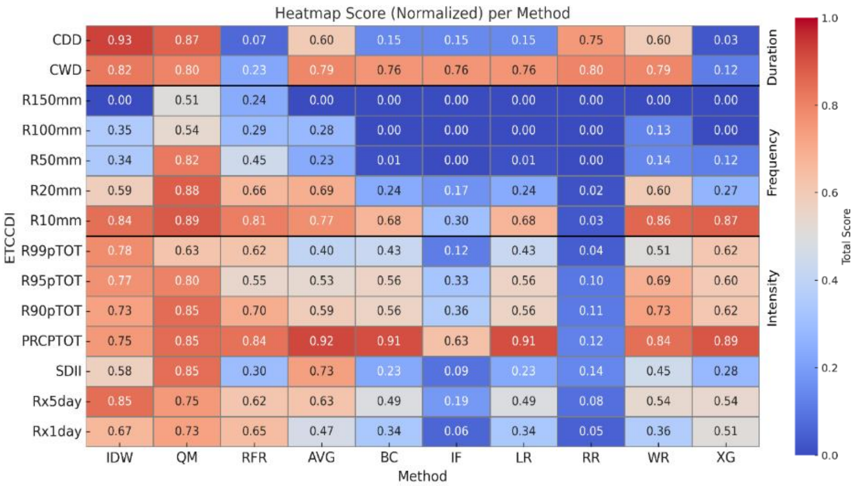

Figure 6. Normalised total score (RMSE, R, Bias, KGE) per method for the ETCCDI index

To aid interpretation, the normalized scores were categorized qualitatively using quartile thresholds from all combinations of methods and indices: quartile 1 (Q1) = 0.25, median = 0.59, and quartile 3 (Q3) = 0.80. Based on these, the categories are defined as low (<0.31), fair (0.31–0.60), high (0.61–0.79), and very high (≥0.80). QM consistently dominated the high and very high categories, with only R100 mm and R150 mm falling into the fair category. IDW followed closely with strong performance in most intensity and duration indices, only scoring low in R150 mm and fair in SDII, R20 mm, R50 mm, and R100 mm. Meanwhile, machine learning-based RFR performed best in PRCPTOT, an annual cumulative rainfall index [44]. Other methods like IF and RR mostly fell in the low-to-fair range, with IF particularly criticized for over-suppressing outliers and failing to represent extremes [39]. IDW outperformed several statistical and machine learning approaches in spatially and temporally variable environments despite not being explicitly designed for bias correction. These results confirm IDW's viability in data-scarce contexts, although all findings shown in Figure 6 remain qualitative and should be interpreted cautiously, as they are not definitive for choosing a universally best method in this study.

4. CONCLUSION

This research presents a comprehensive approach to reconstructing daily rainfall data in tropical regions with limited observational data through an integrative evaluation of statistical and machine learning-based bias correction methods and spatial interpolation. Of the three interpolation methods, IDW was the most accurate and stable for estimating daily rainfall values, based on statistical metric evaluations of simulated missing observational data. Regarding satellite data bias correction, the CHIRPS product appeared more consistent than MSWEP and GPM IMERG. QM achieved the highest predictive accuracy among the six statistical bias correction methods. RFR performed best among the three machine-learning-based methods. Further testing using the extreme climate index ETCCDI reinforces these findings. CHIRPS-QM provides the most representative index results against observational data, superior to the machine learning-based RFR and IDW interpolation. Nevertheless, IDW is still better than most other bias correction methods. Thus, this research concludes that integrating CHIRPS-QM and IDW is a highly effective strategy for reconstructing daily rainfall data, especially for extreme event analysis needs, compared to other methods produced in this research. Considering all evaluation results compared to other methods in this study, the combination of CHIRPS-QM and IDW produces the best results in reconstructing daily rainfall data with limited data. This approach excels in statistical metrics and maintaining the presence of extreme values that are important for disaster risk analysis and climate change in the Banten and Jakarta regions. However, using imputed data for extreme rainfall analysis should be cautiously approached, as most methods show low accuracy in estimating the frequency of rainfall events greater than 150 mm.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available from the first author on reasonable request.

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