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Correction and Validation of GPM-IMERG and CHIRPS Satellite Precipitation Data in the Lahor River Basin

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Abstract. Data availability is one of the challenges, especially for hydraulic data in water resources management. The expansion of satellite precipitation data has provided a solution with advantages in both spatial and temporal dimensions. This research aims to evaluate and validate satellite-based precipitation data such as GPM-IMERG and CHIRPS against observed. Data evaluation is needed to determine the suitability of satellite precipitation data usage. Correcting satellite precipitation data bias is conducted using regression, distribution mapping, and average ratio methods. The validation stage used the Root Mean Squared Error (RMSE) method, Nash-Sutcliffe Efficiency (NSE), Correlation Coefficient (R), and Relative Error Test (RE) as validation methods. The Lahor River basin is used as a case study due to the availability of adequate data. The research is conducted on monthly and daily data for each dataset with three calibration and validation periods, each spanning 19 years. The analysis results indicate that the validation of CHIRPS before and after correction is better than GPM-IMERG. The GPM-IMERG data is best corrected using the distribution mapping method with a linear intercept equation. Meanwhile, the most suitable method for the CHIRPS data is a regression with a polynomial intercept equation.

Keywords: Satellite data, rainfall data, correction, validation

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INTRODUCTION

Water resource development and management depend heavily on hydrological data, especially precipitation data. Precipitation data is used for the transformation to predict weather conditions, floods, and droughts and design hydraulic and water resources management [1]. The qualification of precipitation data should be stationary, consistent, and homogeneous when used for frequency analyses or to simulate a hydrological system [2]. Precipitation gauges are the only instruments used to record the precipitation. It is considered accurate and reliable at regional and global scales due to rainfall's high temporal and spatial variability. However, the temporal and spatial distribution of precipitation gauge is uneven, making it difficult to determine how many precipitations are on the earth, often inadequate for hydrological study, particularly in areas with precipitation heterogeneity [3][4].

Remote sensing technology is starting its expansion for global precipitation observation, helping to overcome the difficulty of precipitation data estimation for water resources. The advantages of satellite-based precipitation estimation include global coverage, enhanced understanding of precipitation systems, and the ability to cover areas where ground-based data are unavailable [5]. This could improve water resource management, especially in areas with limited field observations [6].

Satellites estimate precipitation using a variety of sensors and techniques, providing a global perspective and a complete picture of precipitation systems [7][8][9]. Satellite-derived precipitation data offers extensive synoptic coverage while remaining cost-effective compared to conventional precipitation recorders (Nashwan, M.S.et al., 2019)[11]. Challenges such as errors, uncertainties, and limited verification over oceans exist. Spatial and seasonal characterization of results, along with bias issues, are challenges in using satellite precipitation products [12]. However, addressing challenges related to accuracy and uncertainty is crucial for their effective utilization in water resource management.

The historical developments in satellite technology for precipitation monitoring have significantly advanced our understanding of precipitation patterns and improved the accuracy of precipitation measurements [13]. However, accuracy, uncertainty, and spatial resolution persist, highlighting the need for ongoing research and improvements in satellite-based precipitation estimation [14]. [15] they used the climate prediction center MORPHing technique (CMORPH) and Integrated Multi-SatellitE Retrievals for the Global Precipitation Mission (GPM) algorithm (IMERG) to perceive satellite-based precipitation data performance over the United Arab Emirates. They found that both satellites have great potential to fill spatial gaps in rainfall observations and improve temporal resolution. Performance improvements are needed regarding the overestimation and underestimation of small and large rainfall amounts, respectively.

(Gulakhmadov et al., 2023). tested IMERG and PERSIANN precipitation products for the Mountainous Domain of Tajikistan, Central Asia. The research shows that the IMERG data is recommended for hydro-climatic applications over the mountainous domain of Central Asia. Other research suggested IMERG for use in southeastern South America due to its better performance in representing observed precipitation patterns at annual and seasonal timescales [17]. Geleta & Deressa, 2021 evaluated Climate Hazards Group InfraRedPrecipitation Station (CHIRPS) satellite-based precipitation estimates over Finchaa and Neshe Watersheds, Ethiopia. It indicated that CHIRPS has good performance in maintaining observed measurement patterns at monthly, seasonal, and annual time scales across the watershed. On the other hand, CHIRPS has a high spatial resolution of 0,05°While PERSIANN and TRMM have 0,25° of spatial resolution and 0,1°Or IMERG. The high spatial resolution allows the product to be used in small watersheds, for example, in the case of the current study and reduces uncertainties and errors.

In Indonesia, the research on satellite precipitation has been widely carried out but limited to a few types of data sources, such as TRMM and PERSIANN, which are related to the water resources sector. Other resources, such as GPM-IMERG and CHIRPS, are starting to be used as precipitation data in Indonesia. Partarini et al., 2021 have researched the evaluation of IMERG and CHIRPS satellites in the Selorejo River basin. The research results show that both satellites perform well in precipitation estimation. The performance of IMERG before and after correction is better than CHIRPS. In this research, analysis will be developed related to the evaluation of IMERG and CHIRPS precipitation data in other river basins to perceive the consistency of the results of previous research.

MATERIALS AND METHODS

Description of the Lahor River Basin

The location of this research is the Lahor River basin, which is located in Malang Regency, East Java, with an area of 158.84 km^2. This river basin is the catchment area of the Lahor Reservoir, which is also part of the Brantas watershed. It has flood control, irrigation, hydropower, connectivity, and tourism functions. The boundaries of the Lahor watershed can be seen in **FIGURE 1**.

The upstream is in the form of mountains, and the downstream is in the Lahor Reservoir. The Lahor catchment area is the upstream part of the Brantas watershed, so it has the characteristics of a relatively steep slope and high potential for heavy rainfall and sediment transport.

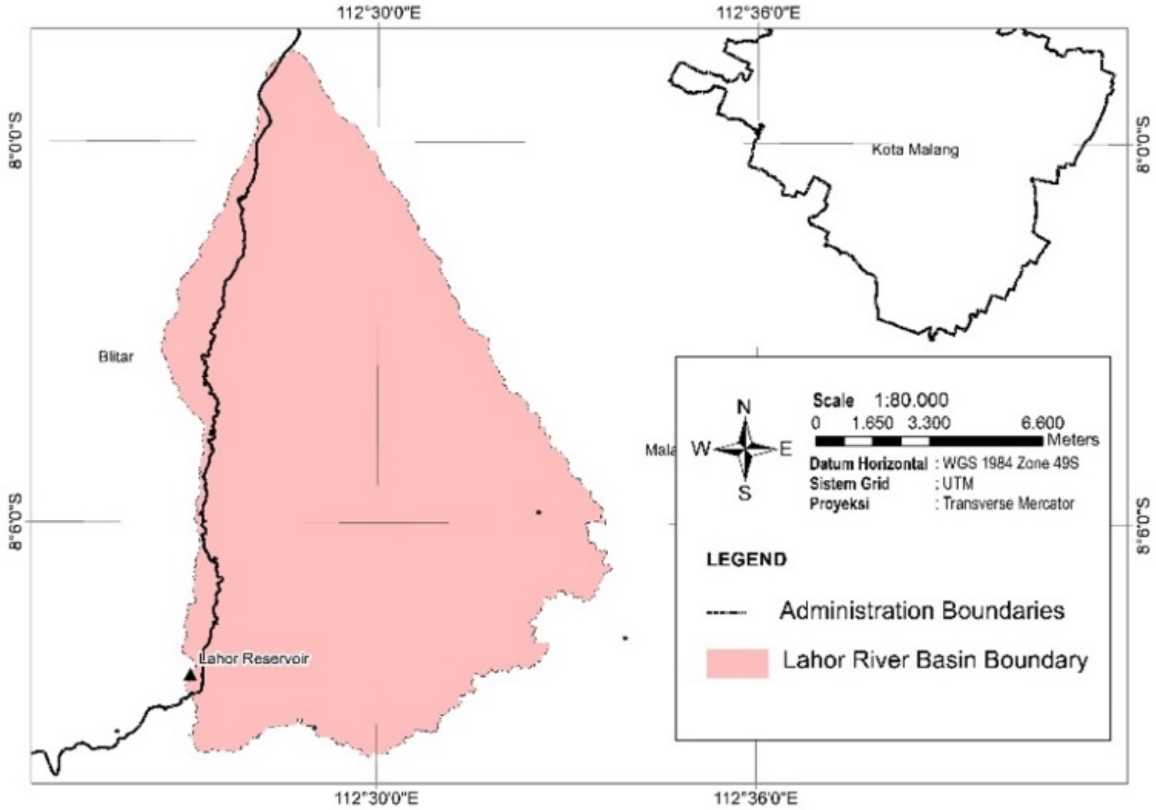

FIGURE 1. Lahor River Basin boundary

Satellite-Based Precipitation Data

This research uses two types of satellite-based precipitation, namely GPM-IMERG and CHIRPS. The selection of this data was based on several considerations, such as data availability and advantages in spatial and temporal resolution, and was a development of previous studies. The data length used is daily data for 19 years, around 2001 – 2019, of the Lahor River basin.

GPM IMERG precipitation data provides precipitation estimates using inter-calibrated data from a constellation of satellites and other sources [20][21]. IMERG computes half-hour, daily, and monthly with 0.1° × 0.1° gridded datasets over 60°N-S, with three "Runs" consisting of Early, Late, and Final, each released at different time intervals after observation. This research uses the final version of daily precipitation data. The data is available on the website https://gpm.nasa.gov/data/imerg. However, it can be downloaded at https://giovanni.gsfc.nasa.gov/giovanni/ to obtain data by downscaling it according to the research area. According to the location of the Lahor River basin boundary, the downloaded grids are six grids, as in **FIGURE 2** (a).

CHIRPS precipitation data is a high-resolution climatic database of precipitation that incorporates satellite imagery, in situ station data, and atmospheric model rainfall fields [22] [23]. CHIRPS provides high-resolution data at 0.05° resolution, making it unique compared to other precipitation databases. It has been extensively evaluated for its performance, utility, and limitations in various regions, making it a valuable tool for monitoring drought and environmental change. Further research is needed to address these limitations and enhance the accuracy of CHIRPS for diverse applications. CHIRPS computes daily, half-monthly, and monthly periods. The CHIRPS-2.0 dataset, which offers global coverage, can be accessed through https://data.chc.ucsb.edu/products/CHIRPS-2.0/. Users can download it for specific research area purposes via Google Earth Engine. The grid structure of each satellite data can be observed in **FIGURE 2** (b) for the Lahor River basin area.

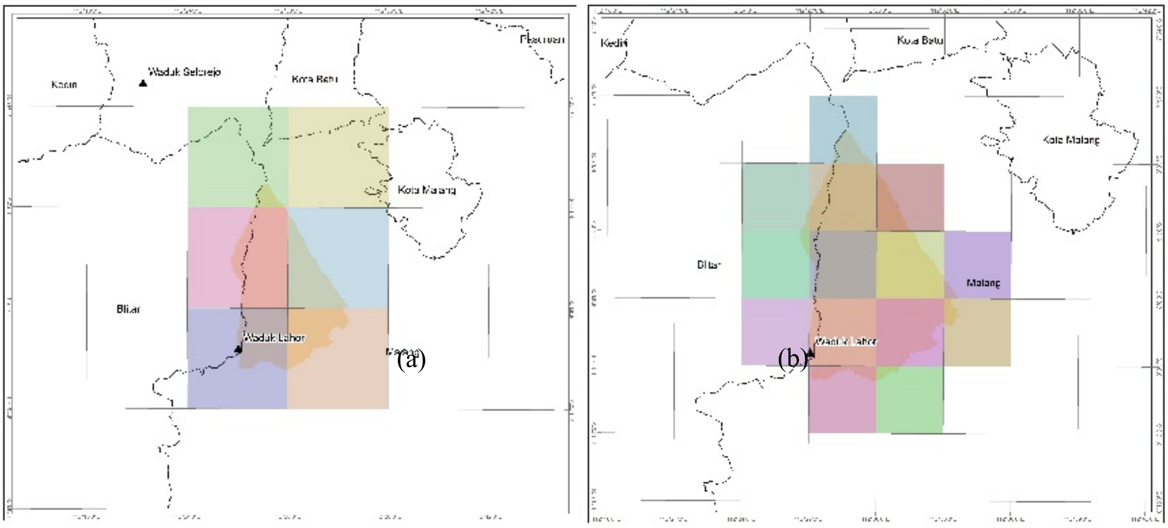

FIGURE 2. Grid of satellite (a) IMERG (b) CHIRPS

Ground Station-based Precipitation Data

Six rain gages/ground stations are located around the Lahor river basin, including Pohgajing, Ngadirenggo, Sumberpucung, Ngajum, CD Office, and Bantaran Station. This data comes from a manual rain gauge owned by the East Java Provincial Government. The selection of these six rain stations was based on the distribution of station locations closest to the Lahor river basin, as in **FIGURE 3**. The data period used in this research is 19 years, namely 2001 - 2019. This data was then tested for consistency using the Rescaled Adjusted Partial Sums (RAPS) method. RAPS results show that the six stations have consistent data.

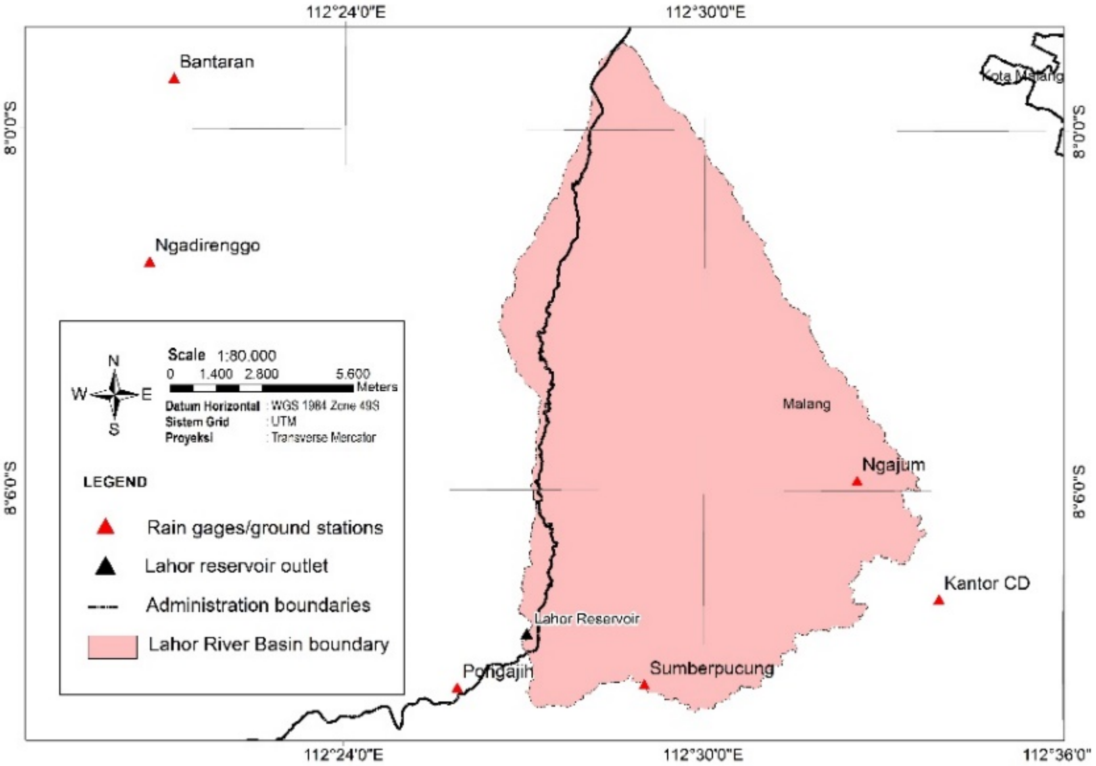

FIGURE 3. Ground stations around the Lahor River basin

Methodology

The researchers opted for a monthly data period for this study, as it is considered the most suitable for validation analysis, as supported by [24]. In this condition, data comparisons use regional average data. The ground stations use the Thiessen polygon to cover the average data, while the satellite uses the average grid method. The research methodology can be broadly divided into calibration and validation. The data was split into three parts or simulations for this purpose. The calibration phase utilized data from 2001 to 2010, while the validation phase employed data from 2011 to 2019. Additionally, calibration was performed using data from 2001 to 2014 and 2001 to 2015, followed by validation from 2015 to 2019 and 2016 to 2019, respectively—this data range segmentation aimed to identify the calibration and validation combinations best aligned with the observational data.

This research will use three calibration methods to obtain correction factors to improve the quality of satellite data performance. The methods used are regression equation, average ratio, and distribution mapping. These three methods will be simulated in 3 different time span scenarios. After calibration step, the analysis stage continues with validation analysis using the following methods:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(Yi-\hat{Y}i)^2}{n}} \tag{1}$$

$$NSE=1-\frac{\sum_{i=1}^{n}(Yi-\hat{Y}i)^2}{\sum_{i=1}^{n}(Yi-\overline{Y}i)^2} \tag{2}$$

$$R=\frac{n\sum_{i=1}^{n}Yi\hat{Y}i-\sum_{l=1}^{n}Yi\sum_{l=1}^{n}\hat{Y}i}{\sqrt{n\sum_{i=1}^{n}Yi^2-(\sum_{i=1}^{n}Yi)^2}\sqrt{n\sum_{i=1}^{n}\hat{Y}i^2-(\sum_{i=1}^{n}\hat{Y}i)^2}} \tag{3}$$

$$RE=\frac{\sum_{i=1}^{n}(Yi-\hat{Y}i)}{\sum Yi}\times 100\% \tag{4}$$

Yi: observation data (ground-based precipitation data), $\hat{Y}i$: approximate data (satellite-based precipitation data), n: the amount of data.

The methods used in this stage are Root Mean Squared Error (RMSE) as equation 1, Nash-Sutcliffe Efficiency (NSE) as equation 2, Correlation Coefficient (R) as equation 3, and Relative Error (KR) as equation 4. This equation is used to validate rainfall data before and after correction to determine the performance of satellite-based precipitation data.

RESULT AND DISCUSSION

Comparison of Ground-based and Satellite-based Precipitation

Precipitation estimates from GPM-IMERG and CHIRPS show discrepancies compared to ground-based precipitation around the Lahor River basin, as illustrated in **FIGURE 4**. According to the results of this comparison, CHIRPS was overestimated in estimating heavy precipitation compared to observed data. However, CHIRPS appears to be able to match values in low conditions. Meanwhile, IMERG performs well in estimating heavy rain and overestimates in low conditions. Overall, both data can provide an overview of fluctuations in precipitation conditions that match observed conditions.

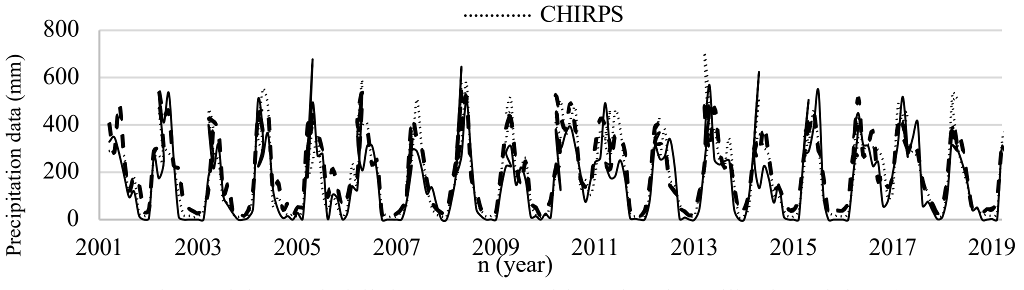

FIGURE 4. Comparison of three rainfall datasets: ground-based and satellite-based data (GPM-IMERG and CHIRPS)

Multiple studies have evaluated the performance of satellite-derived rainfall products, such as CHIRPS and GPM-IMERG, against ground-based precipitation. CHIRPS has been found to slightly outperform GPM-IMERG in terms of accuracy and reliability in various regions and time scales [25](Nashwan, Shahid et al., 2019)[27]. Both CHIRPS and GPM-IMERG datasets have shown good agreement with ground-observed precipitation data, indicating their potential use as a surrogate in the absence of ground-based precipitation data for monthly or seasonal agro-hydrological studies [28]. In this research, further analysis will be carried out regarding the performance of CHIRPS and IMERG to find conclusions.

Calibration and Correction

The calibration of satellite precipitation data is crucial for improving the accuracy and reliability of precipitation estimates, which impacts weather forecasting. Advancements in calibration techniques, such as spatial calibration methods and downscaling calibration schemes using machine learning algorithms, have shown promising results in addressing the challenges and improving the accuracy of satellite precipitation data [29]. In this research, coherence refers to the consistency between ground-based and satellite-based data obtained through satellite weather algorithm modeling. The output of this stage is bias correction, which consists of an equation or correction coefficient to evaluate satellite data.

The comparison of observed and GPM-IMERG satellite rainfall in the Lahor River Basin using monthly scatterplot graphs as calibration stage and bias correction. Bias correction analysis for the Lahor River Basin was conducted using regression, average ratio, and distribution mapping among three comparison ranges/scenarios. The three ranges are 2001 to 2010; 2001 to 2015; and 2001 to 2014. The output of bias correction consists of an equation or correction coefficient. Before obtaining the bias correction coefficient, the most important thing to do is assess the relationship between the dataset using the RMSE, NSE, R, and RE methods.

Specifically for the regression and distribution mapping method, the comparison assessment also employs the coefficient of determination (R^2) to evaluate the data's performance before applying the correction. Among the three comparison ranges/scenarios, the linear intercept equation consistently yielded the highest R^2 values, with an average exceeding 0.80. Meanwhile, the distribution mapping method has a value of 0,98 for all equations. According to **TABLE 1**, the average coefficient of this correlation tends to be overestimated for all months except data in April. This is indicated by the correction factor values being less than 1, suggesting that the estimated satellite data values must be reduced. This coefficient will correct the satellite data for the following data range. While these methods and equations seem promising, we must still validate them using statistical measures such as RMSE, NSE, KR, and R to ensure their performances. This result is relatively similar to the satellite analysis in the Selorejo River basin, according to [19]. It could happen because both river basins are nearby and have similar geographic conditions.

TABLE 1. Correction factor for IMERG data of Lahor river basin

Calibration	**Month**											
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**August**	**Sep**	**Oct**	**Nov**	**Des**
Ten years (2001 - 2010)	0,79	0,78	0,84	1,00	0,54	0,66	0,38	0,43	0,49	0,58	0,90	0,89
15 years (2001 - 2015)	0,80	0,83	0,78	1,09	0,65	0,72	0,32	0,31	0,38	0,54	0,91	0,99
14 years (2001 - 2014)	0,81	0,83	0,78	1,03	0,66	0,73	0,33	0,34	0,40	0,56	0,93	0,97

The calibration of CHIRPS and the ground station have outcomes similar to the IMERG analysis's. According to regression analysis, CHIRPS has a determination factor over 0,85 and 0,9 for the distribution mapping method. The average ratio method results as shown in **TABLE 2**, overall data have overestimated the same as IMERG, although underestimated in April and November. This stage concludes that CHIRPS performs better than IMERG based on the proceeds of three methods.

TABLE 2. Correction factor for CHIRPS data of Lahor River basin

Calibration	**Month**											
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Augst**	**Sep**	**Oct**	**Nov**	**Des**
10 years (2001 - 2010)	0,91	0,85	0,92	1,09	0,65	0,87	0,76	0,73	0,89	0,64	1,02	0,85
15 years (2001 - 2015)	0,83	0,87	0,83	1,10	0,79	0,80	0,56	0,56	0,75	0,65	1,04	0,94
14 years (2001 - 2014)	0,84	0,87	0,83	1,04	0,77	0,83	0,57	0,60	0,77	0,66	1,04	0,92

Validation Analysis

The calibration stage uses three data ranges such as 2001 to 2010; 2001 to 2015; and 2001 to 2014, for the validation stage using data outside these data such as 2011 to 2019; 2016 to 2019; and 2015 to 2019. All data ranges were also analysed using three methods and validated through RMSE, NSE, R, and RE methods. The three data ranges are corrected with correction factors obtained at the calibration stage.

The results of this analysis are submitted to **TABLE 3** of 9 years validation data for IMERG and CHIRPS. Analysis of nine years of uncorrected precipitation data reveals a higher RMSE of 99.81 mm compared to corrected data. However, NSE of 0.76 indicates a good performance between the uncorrected data and satellite. This is further supported by a low error of around 0.02 and a very strong correlation of 0.88.

TABLE 3. Validation proceeds for 2011 - 2019

Bias Correction Methods		GPM-IMERG				CHIRPS			
		RMSE	NSE	RE	R	RMSE	NSE	RE	R
Ground-based data	Uncorrected	99.81	0.76	0.02	0.88	103.78	0.74	0.02	0.86
Regression method	Linear	89.67	0.81	0.05	0.90	88.02	0.81	0.03	0.90
	Linear Intercept	91.43	0.80	0.05	0.90	91.50	0.80	0.03	0.89
	Polynomial	93.51	0.79	0.03	0.88	125.97	0.62	0.01	0.90
	Polynomial Intercept	91.71	0.80	0.04	0.89	97.14	0.77	0.01	0.88
Averaged ratio method		90,08	90.08	0.80	0.05	0.90	89.38	0.81	0.01
Distribution mapping method	Linear	107.70	0.72	0.08	0.85	96.47	0.77	0.03	0.90
	Linear Intercept	89.88	0.80	0.0023	0.90	92.08	0.79	0.03	0.89
	Polynomial	107.01	0.72	0.07	0.85	177.54	0.24	0.18	0.79
	Polynomial Intercept	104.07	0.74	0.07	0.86	100.78	0.75	0.03	0.88

TABLE 4. Validation proceeds for 2016 – 2019

Bias Correction Methods		GPM-IMERG				CHIRPS			
		RMSE	NSE	RE	R	RMSE	NSE	RE	R
Ground-based data	Uncorrected	87.42	0.81	0.03	0.91	117.72	0.66	0.00	0.81
Regression method	Linear	75.32	0.86	0.03	0.93	97.45	0.76	0.05	0.88
	Linear Intercept	78.05	0.85	0.03	0.92	105.20	0.72	0.00	0.86
	Polynomial	138.46	0.52	0.10	0.93	100.47	0.75	0.02	0.90
	Polynomial Intercept	76.35	0.85	0.04	0.93	95.91	0.77	0.04	0.88
Averaged ratio method		90,08	77.03	0.85	0.03	0.92	103.40	0.73	0.03
Distribution mapping method	Linear	89.13	0.80	0.04	0.90	118.26	0.65	0.05	0.86
	Linear Intercept	78.34	0.85	0.10	0.93	109.96	0.70	0.05	0.85
	Polynomial	117.88	0.65	0.19	0.88	121.82	0.63	0.06	0.86
	Polynomial Intercept	89.60	0.80	0.05	0.90	124.84	0.61	0.07	0.82

TABLE 5. Validation proceeds for 2016 - 2019

Bias Correction Methods		GPM-IMERG				CHIRPS			
		RMSE	NSE	RE	R	RMSE	NSE	RE	R
Ground-based data	Uncorrected	87.75	0.79	0.07	0.90	108.53	0.68	0.03	0.83
Regression method	Linear	80.65	0.83	0.09	0.92	93.28	0.77	0.09	0.89
	Linear Intercept	83.14	0.81	0.10	0.91	97.96	0.74	0.04	0.87
	Polynomial	138.05	0.49	0.06	0.90	95.41	0.76	0.07	0.91
	Polynomial Intercept	84.02	0.81	0.10	0.91	91.42	0.78	0.08	0.89
Averaged ratio method		90,08	84.46	0.81	0.10	0.91	97.92	0.74	0.08
Distribution mapping method	Linear	93.86	0.76	0.08	0.88	109.32	0.68	0.09	0.88
	Linear Intercept	84.87	0.81	0.14	0.91	102.78	0.72	0.09	0.86
	Polynomial	97.74	0.74	0.08	0.88	133.63	0.52	0.00	0.79
	Polynomial Intercept	90.93	0.78	0.10	0.89	109.31	0.68	0.10	0.85

This was also shown in other year periods with relatively lower RMSE values, namely 87.42 and 87.75 as in **TABLE 4** and **TABLE 5**. In the 2015-2019 data range, the relative error value tended to be higher, and the RMSE value was lower. Other parameters also show better values, for example NSE = 0.81 and 0.79 and R = 0.91 and 0.90. The analysis for CHIRPS seems like IMERG.

Based on the validation parameters, the uncorrected IMERG and CHIRPS data have good performance, so these data can be used directly without being corrected for bias. The equation that has the best performance as a correction equation for the regression method is the linear equation for both datasets. The validation results of the average ratio method can provide better validation values than uncorrected data. The distribution mapping method shows linear intercept validation in the three data ranges for IMERG and CHIRPS. According to the nominal values produced, the regression method with linear equations is considered the best among other methods for both satellite data. This good performance is also shown in the comparison of IMERG and CHIRPS on observed precipitation in the Selorejo river basin [19].

IMERG data offers high-resolution global precipitation estimates, even with limitations such as overestimating precipitation amount and intensity. IMERG product has demonstrated exemplary performance in various regions and under different rainfall intensities, making it a valuable tool for analyzing precipitation distribution and extremes [30]. While IMERG outperforms other satellite products in some respects, its accuracy is influenced by factors such as atmospheric aerosols and precipitation volume (Tang et al., 2020). CHIRPS satellite data has demonstrated exemplary performance correlating with observed rainfall data, particularly at multiple temporal scales, making it suitable for assessing drought and supporting global drought early warning systems. However, it exhibits limitations in detecting extremely high precipitation events and has a spatially dominating wet bias in certain regions. Further research is needed to address these limitations and fully explore the potential applications of CHIRPS satellite data in environmental monitoring and climate research (Geleta & Deressa, 2021)[32].

CONCLUSION

The three bias correction methods perform well on each calibration and validation data range. In general, the performance of both GPM-IMERG and CHIRPS is good for estimating precipitation. However, the corrected data produces better corrected satellite-based precipitation data than uncorrected data. The IMERG and CHIRPS precipitation data offer high-resolution and high-temporal resolution estimates, making them valuable for various applications in climate research and hydrological modeling. It has limitations in capturing certain types of precipitation and may overestimate precipitation in some regions. The continuous evolution of the product through new versions shows promise for current and future applications, but further research is needed to address its limitations and challenges.

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