

ASSESSMENT OF BIAS CORRECTION FOR SATELLITE PRECIPITATION IN A MONSOON-INFLUENCED BASIN: PHETCHABURI RIVER BASIN, THAILAND

ÉVALUATION DE LA CORRECTION DU BIAIS DES PRÉCIPITATIONS SATELLITAIRES DANS UN BASSIN INFLUENCÉ PAR LA MOUSSON : BASSIN VERSANT DE PHETCHABURI, THAÏLANDE

Jutitthep Vongphet¹, Thirasak Saion², Ketvara Sitichok³, Songsak Puttrawutichai⁴, Chaiyapong Theprasit⁵, Polpech Samanmit⁶, Bancha Kwanyuen⁷ and Sasiwimol Khawkomol^{8,*}

ABSTRACT

Satellite precipitation datasets provide important spatial rainfall information for monsoon-influenced basins, particularly in regions with limited rain gauge coverage and complex terrain-related rainfall variability. However, their applications are often constrained by systematic bias and inconsistencies in seasonal and spatial rainfall representation. This study evaluated the effects of rainfall bias correction on the statistical, seasonal, and spatial characteristics of four satellite precipitation datasets (GSMaP, CMORPH, CHIRPS, and PERSIANN-CCS) in the Phetchaburi River Basin, Thailand. Linear Scaling (LS) and Quantile Mapping (QM) were applied using both long-term and monthly parameterization approaches during calibration (2003–2015) and validation (2016–2022) periods. The results demonstrated that bias correction substantially improved the agreement between satellite precipitation datasets and observed rainfall under monsoon conditions. Monthly parameterization generally provided better representation of temporal rainfall variability, wet-season transitions, and monsoon rainfall peaks compared with long-term parameterization. Among the evaluated approaches, monthly Quantile Mapping (QM_M) showed the strongest capability in preserving seasonal rainfall dynamics across different elevation groups. Spatial analysis further indicated that bias correction improved terrain-related rainfall organization and rainfall gradients across the basin. Overall, the findings demonstrate that rainfall bias correction plays an important role in improving the representation of seasonal and spatial rainfall variability under monsoon conditions. The proposed framework provides useful insights for enhancing the application of satellite precipitation datasets in hydrological modeling, flood and drought assessment, and water resources management in regions with limited rain gauge coverage and complex terrain-related rainfall variability.

Keywords: satellite precipitation; rainfall bias correction; rainfall parameterization; monsoon rainfall variability; spatial rainfall structure.

¹ Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: fengjtv@ku.ac.th

² Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: therasak.s@ku.th

³ Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: fengkrs@ku.ac.th

⁴ Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: songsak.pu@ku.th

⁵ Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: fengcpt@ku.ac.th

⁶ Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: polpech.sa@ku.th

⁷ Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: fengbak@ku.ac.th

^{8,*} Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng, Kasetsart University, 2 Moo 6 Kamphaeng Saen District, Nakhon Pathom 73140, Thailand; Email: fengsmk@ku.ac.th

RESUME

L'ensemble de données de précipitations satellitaires fournissent des informations spatiales importantes sur les précipitations concernant les bassins influencés par la mousson, en particulier dans les régions avec une couverture limitée des pluviomètres et une variabilité complexe des précipitations liée au terrain. Cependant, leurs applications sont souvent limitées par un biais systématique et des incohérences dans la représentation saisonnière et spatiale des précipitations. Cette étude a évalué les effets de la correction du biais pluviométrique sur les caractéristiques statistiques, saisonnières et spatiales de quatre ensembles de données de précipitations satellitaires (GSMaP, CMORPH, CHIRPS et PERSIANN-CCS) recueillies dans le bassin versant de Phetchaburi, en Thaïlande. La mise à l'échelle linéaire (LS) et la cartographie quantile (QM) ont été appliqués en utilisant des approches de paramétrage à long terme et mensuelles pendant les périodes d'étalonnage (2003–2015) et de validation (2016–2022). Les résultats ont démontré que la correction du biais a considérablement amélioré l'accord entre les ensembles de données de précipitations satellitaires et les précipitations observées dans des conditions de mousson. Le paramétrage mensuel a généralement fourni une meilleure représentation de la variabilité temporelle des précipitations, des transitions de la saison des pluies et des précipitations maximum de mousson par rapport au paramétrage à long terme. Parmi les approches évaluées, la cartographie quantile mensuelle (QM_M) a montré la plus grande capacité à préserver la dynamique des précipitations saisonnières dans différents types d'altitudes. L'analyse spatiale a en outre indiqué que la correction du biais améliorerait l'organisation des précipitations liées au terrain et les gradients de précipitations à l'échelle du bassin. Dans l'ensemble, les résultats démontrent que la correction du biais pluviométrique joue un rôle important dans l'amélioration de la représentation de la variabilité saisonnière et spatiale des précipitations en période de mousson. Le cadre offre des perspectives utiles pour améliorer l'application des ensembles de données de précipitations satellitaires dans la modélisation hydrologique, l'évaluation des inondations et des sécheresses, ainsi que la gestion des ressources en eau dans les régions ayant une couverture limitée des pluviomètres et une variabilité complexe des précipitations liée au terrain.

Mots-clés : Précipitations satellitaires; Correction du biais des précipitations; Paramétrage des précipitations; Variabilité des précipitations de mousson; Structure spatiale des précipitations.

1. INTRODUCTION

Strong seasonal variability associated with tropical monsoon climates creates significant uncertainty in satellite-based rainfall estimation (Shah, H.L. and V. Mishra). Rainfall intensity and spatial distribution can vary substantially between wet and dry periods, often leading to inconsistent rainfall representation throughout the year (Cristiano et al., 2016). In regions influenced by complex terrain and convective rainfall systems, rainfall estimation uncertainty becomes more pronounced during seasonal transition periods (Espinoza Villar et al., 2015). Such variability can affect the reliability of rainfall information used in irrigation scheduling, reservoir operation, and seasonal water resources management (Fowler et al., 2003).

Satellite precipitation datasets are increasingly used to complement ground-based observations because they provide continuous spatial coverage over large areas (Kidd & Levizzani, 2011). However, differences in retrieval algorithms, sensor characteristics, and rainfall detection techniques can produce varying levels of uncertainty among satellite products (Guo et al., 2015). Rainfall estimation performance may also vary seasonally, particularly in monsoon regions where rainfall characteristics differ substantially between months (Hoyos and Webster, 2007). As a result, satellite rainfall products that perform reasonably well during one season may exhibit larger discrepancies during another.

Several statistical approaches are commonly applied to reduce bias in satellite rainfall estimation (Yang et al., 2022) (Tian et al., 2010). Among these, Linear Scaling (LS) and Quantile Mapping (QM) are widely adopted because of their relatively simple implementation and ability to improve rainfall agreement with observed data (Wasko & Sharma, 2014). In many applications, however, correction parameters are derived using long-term averaged conditions, which may not sufficiently represent seasonal rainfall behavior under monsoon climates (Falga and Wang, 2022). Monthly parameterization offers an

alternative approach by allowing correction factors to vary throughout the year, potentially improving the representation of intra-annual rainfall variability and seasonal rainfall characteristics (Kim et al., 2013). The Phetchaburi River Basin in western Thailand represents a monsoon-influenced basin characterized by strong wet-season rainfall and complex elevation gradients extending from mountainous upstream regions to downstream agricultural areas (Limsakul et al., 2010). These conditions provide a suitable setting for evaluating seasonal bias correction performance under varying monsoon conditions. In this study, four satellite precipitation datasets (GSMaP, CMORPH, CHIRPS, and PERSIANN-CCS) were evaluated using Linear Scaling and Quantile Mapping under both long-term and monthly parameterization approaches. Rainfall performance was assessed during calibration and validation periods using correlation coefficient, root mean square difference, and standard deviation. Particular attention was given to comparing the influence of parameterization strategy on rainfall representation under monsoon variability.

2. MATERIALS AND METHODS

2.1 Study area

The Phetchaburi River Basin is situated in western Thailand and is influenced by a tropical monsoon climate characterized by distinct wet and dry seasons (Sittichok et al., 2022). The basin covers approximately 6,254 km² and extends from mountainous headwater regions near the western border to lowland agricultural areas downstream. Elevation ranges from approximately sea level in downstream plains to more than 1,600 m above mean sea level in upstream mountainous areas, producing substantial spatial variation in rainfall distribution across the basin.

Annual rainfall is concentrated mainly during the southwest monsoon period from May to October, while rainfall during the dry season is relatively limited. Monsoon rainfall is strongly affected by terrain characteristics, particularly in upstream mountainous areas where orographic effects enhance rainfall accumulation. In contrast, downstream regions generally receive lower annual rainfall and are dominated by agricultural and irrigation activities. Seasonal rainfall variability therefore plays an important role in water availability throughout the basin.

To represent spatial rainfall variability associated with topographic conditions, rain gauge stations within the basin were classified into three elevation groups: low elevation (0–50 m), medium elevation (50–200 m), and high elevation (>200 m). These elevation ranges reflect the transition from downstream lowland irrigation areas to upstream mountainous regions influenced by stronger orographic rainfall effects. The elevation-based grouping was applied to evaluate satellite rainfall correction performance under different terrain and rainfall conditions across the basin. The basin also includes the Kaeng Krachan Reservoir, which supports irrigation and water supply in downstream agricultural areas. Figure 1 shows the location of the Phetchaburi River Basin, elevation distribution, river network, reservoir location, and rain gauge stations used in this study.

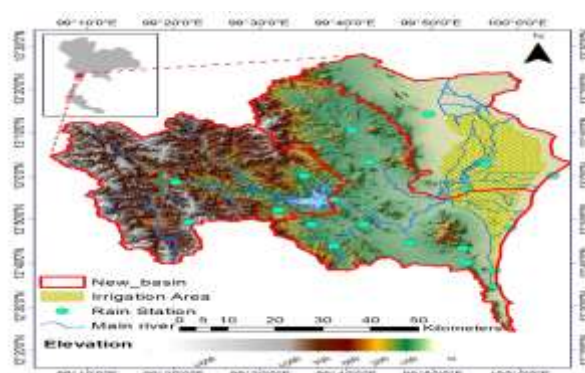


Figure 1. Study area showing the Phetchaburi River Basin, elevation distribution, river network, Kaeng Krachan Reservoir, and rain gauge stations classified into three elevation groups (0–50 m, 50–200 m, and >200 m) used for satellite rainfall correction evaluation.

2.2 Rainfall Observation and Satellite Precipitation Data

2.2.1 Ground-Based Rainfall Observation

Daily rainfall observations from 21 rain gauge stations distributed across the Phetchaburi River Basin were used as reference data for bias correction and performance evaluation during 2003–2022. The station network spans a wide range of terrain conditions, from mountainous upstream regions to downstream agricultural areas, providing representation of rainfall variability associated with monsoon and topographic influences.

To evaluate terrain effects on rainfall correction performance, stations were classified into three elevation groups: low elevation (0–50 m), medium elevation (50–200 m), and high elevation (>200 m). This classification represented the transition from downstream lowland areas to upstream mountainous regions influenced by stronger orographic rainfall processes.

Daily rainfall records were screened for missing and inconsistent observations prior to analysis. Basin-scale rainfall derived from rain gauge observations was subsequently used as reference data for calibration, validation, and evaluation of corrected satellite precipitation datasets.

2.2.2 Satellite Precipitation Datasets

Four satellite precipitation datasets (SPDs), including GSMaP, CMORPH, CHIRPS, and PERSIANN-CCS, were used in this study to evaluate rainfall correction performance under monsoon conditions in the Phetchaburi River Basin (Wild et al., 2021). These products were selected because they represent different precipitation estimation approaches, including microwave-based retrieval, infrared cloud classification, and satellite–gauge blended techniques (Guo et al., 2015). The use of multiple SPDs allowed comparison of correction performance under varying terrain and seasonal rainfall conditions across the basin.

GSMaP employs a microwave–infrared combined approach for precipitation estimation, whereas CMORPH utilizes a microwave-based morphing technique to generate spatial rainfall fields. CHIRPS integrates satellite observations with rain gauge data to improve rainfall representation over land areas, while PERSIANN-CCS applies infrared cloud classification methods for rainfall estimation. Differences in retrieval methodology may influence rainfall estimation performance, particularly under conditions characterized by strong seasonal rainfall variability and complex topography.

Daily satellite precipitation data corresponding to the rain gauge observation period were extracted and processed for basin-scale analysis. All satellite datasets were spatially adjusted to a common analysis framework prior to bias correction and performance evaluation. Characteristics of the satellite precipitation datasets used in this study are summarized in Table 1.

Table 1. Characteristics of satellite precipitation datasets used in this study.

Product	Estimation Technique	Spatial Resolution	Temporal Resolution	Developing Organization
GSMaP	Microwave–IR combined	0.1°	Daily	JAXA
CMORPH	Microwave-based morphing technique	0.25°	Daily	NOAA/CPC
CHIRPS	Satellite–gauge blended	0.05°	Daily	UCSB/CHG
PERSIANN-CCS	Infrared cloud classification	0.04°	Daily	CHRS, University of California, Irvine

Note: JAXA = Japan Aerospace Exploration Agency; NOAA/CPC = National Oceanic and Atmospheric Administration / Climate Prediction Center; UCSB/CHG = University of California, Santa Barbara / Climate Hazards Group; CHRS = Center for Hydrometeorology and Remote Sensing.

2.3 Methodological Framework

Figure 2 illustrates the overall methodological framework applied in this study. Ground-based rainfall observations and four satellite precipitation datasets (GSMaP, CMORPH, CHIRPS, and PERSIANN-CCS) were used as input datasets for rainfall correction analysis. Rainfall stations were classified into low- (0–50 m. msl.), medium- (50–200 m. msl.), and high-elevation (>200 m. msl.) groups to evaluate the influence of terrain conditions on rainfall correction performance.

The rainfall datasets were subsequently separated into long-term and monthly parameterization approaches. In the long-term parameterization approach, rainfall data from the complete calibration period were used to derive correction parameters and cumulative distribution functions. In the monthly parameterization approach, rainfall data were independently grouped into 12 calendar months to represent seasonal rainfall variability under monsoon conditions.

Linear Scaling (LS) and Quantile Mapping (QM) were then applied during the calibration period (2003–2015) to generate rainfall correction relationships for each parameterization approach. The derived correction parameters and distribution relationships were subsequently applied during the validation period (2016–2022) to evaluate correction performance under independent rainfall conditions. Statistical performance evaluation was conducted using the Taylor diagram, correlation coefficient (R), root mean square difference (RMSD), and standard deviation (SD).



Figure 2. Overall methodological framework for satellite rainfall bias correction and performance evaluation under long-term and monthly parameterization approaches.

2.4 Bias Correction Methods

Satellite precipitation datasets were corrected using Linear Scaling (LS) and Quantile Mapping (QM). Both methods were implemented using long-term and monthly parameterization approaches to evaluate the influence of seasonal rainfall variability on correction performance under monsoon conditions.

Correction parameters and cumulative distribution functions were derived from rainfall data during the calibration period and subsequently applied during the validation period. The long-term parameterization approach used a single parameter set for the entire year, whereas the monthly parameterization approach independently derived parameters for each calendar month to account for seasonal rainfall variability.

2.4.1 Linear Scaling (LS)

Linear Scaling (LS) was used to adjust the magnitude of satellite rainfall based on correction factors derived from rain gauge observations. The corrected rainfall (R_c) was estimated from the original satellite rainfall (R_s) using a correction factor as follows:

$$R_c = R_s \times K$$

where R_c is the corrected rainfall, R_s is the original satellite rainfall, and K is the rainfall correction factor. Two parameterization approaches were implemented in this study: long-term parameterization and monthly parameterization. For the long-term parameterization approach, a single correction factor was derived from mean rainfall over the entire calibration period as:

$$K = \frac{\overline{R_g}}{\overline{R_s}}$$

where $\overline{R_g}$ and $\overline{R_s}$ represent the mean observed rainfall and mean satellite rainfall during the calibration period, respectively. For the monthly parameterization approach, independent correction factors were derived for each calendar month to account for seasonal rainfall variability associated with monsoon conditions:

$$K_m = \frac{\overline{R_{g,m}}}{\overline{R_{s,m}}}$$

where K_m is the monthly correction factor, while $\overline{R_{g,m}}$ and $\overline{R_{s,m}}$ denote the monthly mean observed rainfall and monthly mean satellite rainfall for month (m), respectively. The long-term parameterization approach applied a single correction factor throughout the year, whereas the monthly parameterization approach allowed rainfall adjustment to vary according to seasonal rainfall characteristics in each month.

2.4.2 Quantile Mapping (QM)

Quantile Mapping (QM) was used to adjust the statistical distribution of satellite rainfall based on the cumulative distribution relationship between satellite and observed rainfall. The corrected rainfall R_c was estimated as:

$$R_c = F_g^{-1}(F_s(R_s))$$

where R_s is the original satellite rainfall, F_s is the cumulative distribution function (CDF) of satellite rainfall, and F_g^{-1} is the inverse cumulative distribution function of observed rainfall. Similar to Linear Scaling, Quantile Mapping was implemented using both long-term parameterization and monthly parameterization strategies. In the long-term parameterization approach, cumulative distribution functions were derived using rainfall data from the calibration period:

$$R_c = F_{g,LT}^{-1}(F_{s,LT}(R_s))$$

where $F_{g,LT}^{-1}$ and $F_{s,LT}$ represent the inverse observed rainfall distribution and satellite rainfall distribution derived from the entire calibration period, respectively. For the monthly parameterization approach, independent cumulative distribution functions were derived for each calendar month to account for seasonal rainfall variability under monsoon conditions:

$$R_c = F_{g,m}^{-1}(F_{s,m}(R_s))$$

where $F_{g,m}^{-1}$ and $F_{s,m}$ denote the monthly inverse observed rainfall distribution and monthly satellite rainfall distribution for month (m), respectively. The long-term parameterization approach applied a single rainfall distribution relationship throughout the year, whereas the monthly parameterization approach adjusted rainfall distributions according to seasonal rainfall variability throughout the year.

2.5 Performance Evaluation

The study period from 2003–2022 was divided into calibration (2003–2015) and validation (2016–2022) periods for derivation and evaluation of rainfall correction parameters.

Performance evaluation was conducted using the correlation coefficient ((R)), root mean square difference ($RMSD$), and standard deviation (SD). These statistical metrics were used to assess the agreement between corrected satellite rainfall and ground-based rainfall observations in terms of rainfall variability and distribution characteristics. The correlation coefficient was calculated as:

$$R = \frac{\sum_{i=1}^n (R_{c,i} - \overline{R_c})(R_{g,i} - \overline{R_g})}{\sqrt{\sum_{i=1}^n (R_{c,i} - \overline{R_c})^2} \sqrt{\sum_{i=1}^n (R_{g,i} - \overline{R_g})^2}}$$

The root mean square difference was calculated as:

$$RMSD = \sqrt{\frac{1}{n} \sum_{i=1}^n (R_{c,i} - R_{g,i})^2}$$

The standard deviation was calculated as:

$$SD = \sqrt{\frac{1}{n} \sum_{i=1}^n (R_{c,i} - \overline{R_c})^2}$$

where R_c and R_g represent corrected satellite rainfall and observed rainfall, respectively, while (n) denotes the number of rainfall observations. Performance comparisons were conducted for both long-term and monthly parameterization approaches under wet- and dry-season conditions.

3. RESULTS AND DISCUSSIONS

3.1 Statistical Characteristics of Bias Correction Performance

Figure 3 summarizes the statistical performance of satellite precipitation datasets before and after bias correction during calibration and validation periods. Overall, both Linear Scaling (LS) and Quantile Mapping (QM) improved rainfall representation relative to the original satellite precipitation datasets, although the degree of improvement varied among satellite products and parameterization approaches. Before bias correction, the original satellite precipitation datasets showed moderate agreement with observed rainfall under monsoon conditions. During the validation period, correlation coefficients ranged from 0.37 to 0.53, while $RMSD$ values ranged from 8.77 to 11.59 mm/day. CMORPH exhibited the highest overall statistical agreement with observed rainfall, whereas PERSIANN-CCS showed the largest rainfall deviation and variability differences relative to observed rainfall conditions.

The heatmap analysis indicates that long-term parameterization approaches generally reduced overall rainfall deviation compared with the original satellite precipitation datasets. Both LS_T and QM_T produced lower $RMSD$ and SD values during calibration and validation periods, indicating more stable rainfall correction behavior. Validation-period $RMSD$ values were reduced by approximately 1–3 mm/day after correction, depending on satellite product and correction approach. In particular, QM_T substantially reduced rainfall variability differences across all satellite precipitation datasets. For example, the SD value of PERSIANN-CCS decreased from 11.38 mm/day before correction to 3.47 mm/day during the validation period, while similar reductions were also observed for GSMaP and CHIRPS.

Monthly parameterization approaches generally produced higher correlation coefficients than long-term parameterization approaches, particularly during the validation period. QM_M yielded the highest validation-period correlation coefficients for GSMaP ($R = 0.55$), CHIRPS ($R = 0.48$), and PERSIANN-CCS ($R = 0.46$), representing correlation improvements of approximately 0.02–0.09 relative to the original datasets. Both LS_M and QM_M also showed improved temporal rainfall agreement compared with the original satellite precipitation datasets. However, LS_M produced increased SD values for several satellite products, particularly GSMaP and CMORPH, suggesting greater sensitivity of monthly correction relationships to seasonal rainfall fluctuations.

Statistical performance during the validation period was generally consistent with calibration results, indicating stable correction behavior under independent rainfall conditions. Overall, parameterization strategy strongly influenced correction performance, with long-term parameterization reducing overall rainfall deviation and monthly parameterization better preserving seasonal rainfall dynamics. Among the evaluated approaches, QM_M provided the most consistent improvement across satellite precipitation datasets.

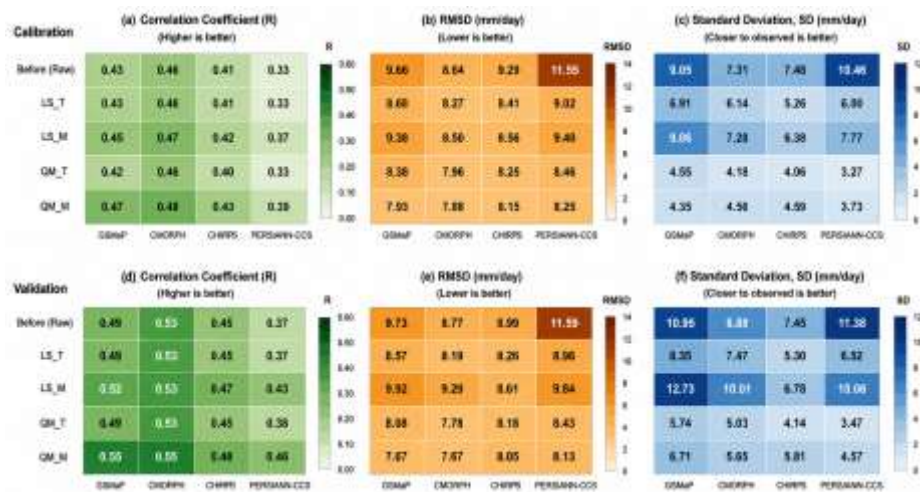


Figure 3. Heatmap of correlation coefficient (R), root mean square difference (RMSD), and standard deviation (SD) for raw and bias-corrected satellite precipitation datasets during calibration (2003–2015) and validation (2016–2022) periods. Observed rainfall SD was 5.68 mm/day and 6.59 mm/day for the calibration and validation periods, respectively.

3.2 Seasonal Rainfall Characteristics under Monthly Parameterization

Figure 4 presents the seasonal rainfall characteristics of satellite precipitation datasets corrected using monthly Quantile Mapping parameterization (QM_M), which exhibited the most consistent statistical performance during the validation period. Similar seasonal patterns were observed for the other correction approaches, although differences among methods were generally less pronounced.

Overall, the corrected satellite precipitation datasets successfully reproduced the seasonal rainfall cycle across all elevation groups, including the transition from the dry season to peak monsoon rainfall during September–October. GSMaP and CMORPH generally showed closer agreement with observed seasonal rainfall patterns, whereas CHIRPS and PERSIANN-CCS tended to underestimate rainfall during peak wet-season conditions, particularly in low- and medium-elevation regions.

Seasonal rainfall variability remained dependent on terrain conditions. Larger differences among corrected satellite precipitation datasets were observed in high-elevation regions, where rainfall peaks were generally underestimated despite the application of monthly parameterization. These results suggest that monthly parameterization effectively preserved seasonal rainfall dynamics across different elevation groups, while the representation of peak monsoon rainfall remained influenced by terrain effects and satellite retrieval characteristics.

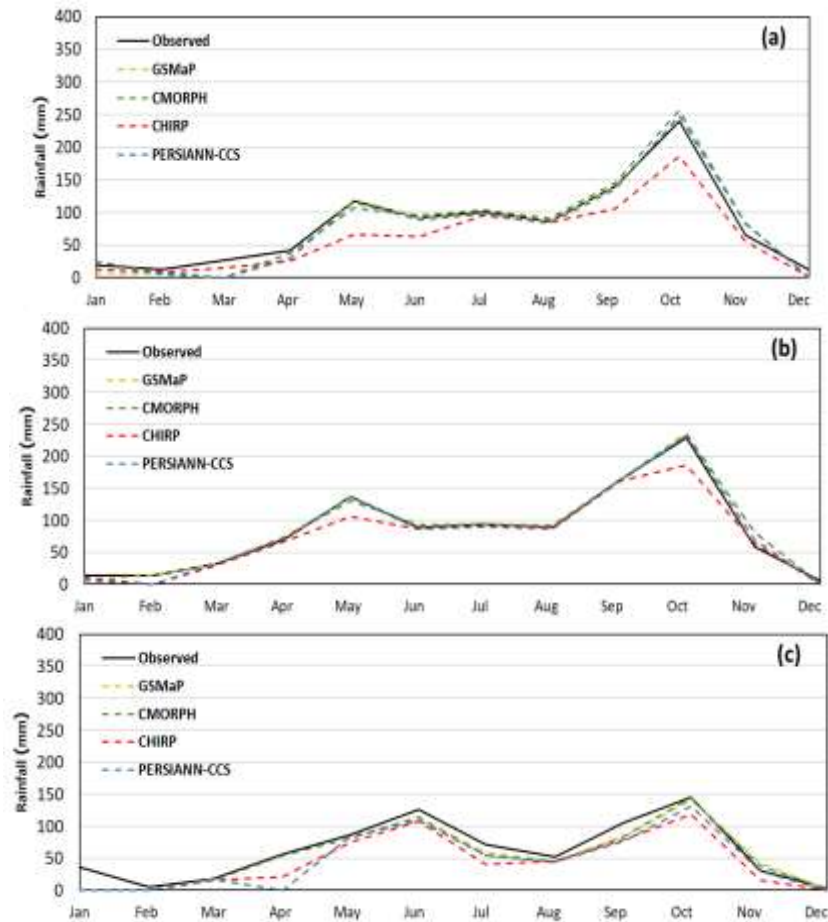


Figure 4. Seasonal rainfall climatology of observed rainfall and satellite precipitation datasets corrected using monthly Quantile Mapping parameterization (QM_M) across different elevation groups: (a) 0–50 m, (b) 50–200 m, and (c) >200 m above mean sea level. The figure illustrates the capability of monthly parameterization to preserve seasonal rainfall variability and monsoon rainfall characteristics under varying terrain conditions.

3.3 Spatial Rainfall Structure under Bias Correction

Figure 5 illustrates the spatial distribution of annual rainfall before and after bias correction using monthly Quantile Mapping parameterization (QM_M). Overall, the original satellite precipitation datasets exhibited relatively smooth rainfall patterns and limited representation of terrain-related rainfall variability across the basin.

After correction, the rainfall fields became more spatially organized and showed clearer rainfall gradients, particularly in mountainous and upstream regions. The corrected rainfall distributions exhibited more organized spatial rainfall patterns and clearer terrain-related rainfall organization under monsoon conditions.

The effects of bias correction became more pronounced in regions with strong spatial rainfall variability. Monthly parameterization redistributed rainfall magnitude across the basin and reduced unrealistic spatial discontinuities observed in several original satellite precipitation datasets. As a result, terrain-related rainfall organization became more apparent after correction, particularly in areas influenced by elevation and monsoon rainfall processes.

Overall, the results demonstrated that spatial bias correction played an important role in improving the representation of terrain-related rainfall structure under monsoon conditions.

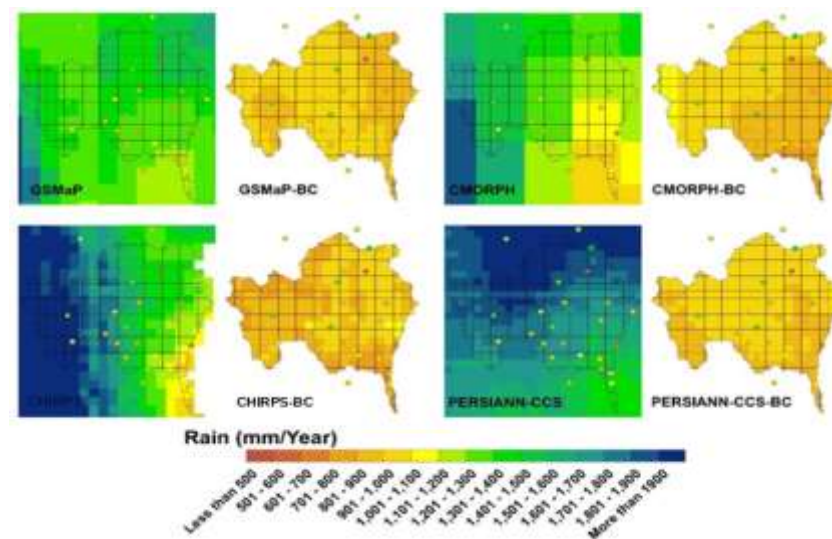


Figure 5. Spatial distribution of annual rainfall before and after bias correction using monthly Quantile Mapping (QM_M) for satellite precipitation datasets in the Phetchaburi River Basin.

4. Conclusions and Suggestions

This study evaluated the effects of rainfall bias correction on the statistical, seasonal, and spatial characteristics of satellite precipitation datasets under monsoon conditions in the Phetchaburi River Basin, Thailand. The main findings are summarized as follows:

- Bias correction substantially improved agreement between satellite precipitation datasets and observed rainfall.
- Monthly parameterization better represented temporal rainfall variability, wet-season transitions, and monsoon rainfall peaks than long-term parameterization.
- Monthly Quantile Mapping (QM_M) showed the most consistent performance in preserving seasonal rainfall dynamics across elevation groups.
- Bias correction improved terrain-related rainfall organization, rainfall gradients, and spatial rainfall continuity across the basin.
- Rainfall bias correction should be interpreted not only as a statistical adjustment process, but also as a mechanism that reshapes seasonal and spatial rainfall structure.
- The proposed framework provides a useful perspective for evaluating satellite rainfall correction in monsoon-influenced basins.

Satellite precipitation datasets offer considerable potential for rainfall monitoring in regions with limited gauge coverage. The findings highlight the value of bias-corrected satellite rainfall products for hydrological modeling, flood and drought assessment, and water resources management. Future studies should further investigate how rainfall structural changes induced by bias correction propagate through hydrological processes under different climatic and topographic conditions.

5. REFERENCES

Cristiano, E., M.-C. ten Veldhuis and N. van de Giesen. 2017. Spatial and temporal variability of rainfall and their effects on hydrological response in urban areas – a review. *Hydrol. Earth Syst. Sci.* 21(7): 3859–3878. DOI: 10.5194/hess-21-3859-2017.

- Espinoza Villar, J.C., S. Chavez, J. Ronchail, C. Junquas, K. Takahashi and W.S. Lavado Casimiro. 2015. Rainfall hotspots over the southern tropical Andes: Spatial distribution, rainfall intensity, and relations with large-scale atmospheric circulation. *Water Resour. Res.* 51(5): 3459–3475. DOI: 10.1002/2014WR016273.
- Falga, R. and C. Wang. 2022. The rise of Indian summer monsoon precipitation extremes and its correlation with long-term changes of climate and anthropogenic factors. *Sci. Rep.* 12(1). DOI: 10.1038/s41598-022-16240-0.
- Fowler, H.J., C. Kilsby and P.E. O'Connell. 2003. Modeling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system. *Water Resour. Res.* 39(8): 1222. DOI: 10.1029/2002WR001778.
- Guo, H., S. Chen, A. Bao, J. Hu, A.S. Gebregiorgis, X. Xue and X. Zhang. 2015. Inter-comparison of high-resolution satellite precipitation products over Central Asia. *Remote Sens.* 7(6): 7181–7211. DOI: 10.3390/rs70607181.
- Hoyos, C.D. and P.J. Webster. 2007. The role of intraseasonal variability in the nature of Asian monsoon precipitation. *J. Clim.* 20(17): 4402–4424. DOI: 10.1175/JCLI4252.1.
- Kidd, C. and V. Levizzani. 2011. Status of satellite precipitation retrievals. *Hydrol. Earth Syst. Sci.* 15(4): 1109–1116. DOI: 10.5194/hess-15-1109-2011.
- Kim, D., F. Olivera and H. Cho. 2013. Effect of the inter-annual variability of rainfall statistics on stochastically generated rainfall time series: Part 1. Impact on peak and extreme rainfall values. *Stoch. Environ. Res. Risk Assess.* 27(7): 1601–1610. DOI: 10.1007/s00477-013-0696-z.
- Limsakul, A., S. Limjirakan and B. Suttamanuswong. 2010. Asian summer monsoon and its associated rainfall variability in Thailand. *APN Sci. Bull.* 3(2): 79–89.
- Shah, H.L. and V. Mishra. 2016. Uncertainty and bias in satellite-based precipitation estimates over Indian subcontinental basins: Implications for real-time streamflow simulation and flood prediction. *J. Hydrometeorol.* 17(2): 615–636. DOI: 10.1175/JHM-D-15-0115.1.
- Sittichok, K., J. Vongphet and O. Seidou. 2022. Predicted rainfall, surface runoff and water yield responses to climate change in the Phetchaburi River Basin, Thailand. *Asian J. Water Environ. Pollut.* 19(3): 1–13. DOI: 10.3233/AJW220033.
- Tian, Y., C.D. Peters-Lidard and J.B. Eylander. 2010. Real-time bias reduction for satellite-based precipitation estimates. *J. Hydrometeorol.* 11(6): 1275–1285. DOI: 10.1175/2010JHM1246.1.
- Wasko, C. and A. Sharma. 2014. Quantile regression for investigating scaling of extreme precipitation with temperature. *Water Resour. Res.* 50(4): 3608–3614. DOI: 10.1002/2013WR015194.
- Wild, A., Z.-W. Chua and Y. Kuleshov. 2021. Evaluation of satellite precipitation estimates over the South West Pacific Region. *Remote Sens.* 13(19): 3929. DOI: 10.3390/rs13193929.
- Yang, X., S. Yang, M.L. Tan, H. Pan, H. Zhang, G. Wang, R. He and Z. Wang. 2022. Correcting the bias of daily satellite precipitation estimates in tropical regions using deep neural network. *J. Hydrol.* 608: 127656. DOI: 10.1016/j.jhydrol.2022.127656.