Error analysis of satellite precipitation estimates over Sungai Sarawak basin by Triple Collocation method

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Abstract: *Satellite precipitation estimate (SPE) provides alternative to ground measurements with synoptic coverage and improving rain estimation accuracy in Malaysia. Validation of rain estimates is necessary to select the most appropriate precipitation repository and to gain confidence in its selection. Conventional validation using gauge becomes ineffective when the quality of this reference degrades especially in the area with less stations and poor coverage. In the critical scenario where the reference is unreliable or low accuracy, equivalent measurement parameters could offer the opportunity to serve as surrogate validation agents based on their similarity to other precipitation estimates. The study presents systematic error estimates in the evaluation of CHIRPS, PERSIANN-CDR and ERA5 with rain-gauge stations for 40-year measurement in Sungai Sarawak basin. Previous studies defined that CHIRPS and PERSIANN-CDR are overestimated and errors by spatial and temporal variability have been less discussed. For this exercise, the Triple Collocation (TC) analysis is introduced. TC employing both multiplicative and additive models to derive error variances and signal-to-noise ratios (SNRs) from monthly precipitation sums over 40 years (1983–2023). Data preprocessing involved merging datasets and cleaning the missing and void data pixel. Regression with in-situ data showed R values of 0.81–0.63 and RMSEs of 125–173 mm/month. Covariance and correlation matrices were computed, followed by TCA metrics and regression against in-situ data for R and RMSE. The multiplicative TCA yielded SNRs of 5.69 dB (CHIRPS), 4.73 dB (PERSIANN-CDR), and 1.98 dB (ERA5), with correlations of 0.77–0.68, indicating strong relative signal coherence but higher noise in ERA5. The additive TCA produced SNRs of 4.84 dB (CHIRPS), 4.38 dB (PERSIANN-CDR), and 2.49 dB (ERA5), with moderate correlations (0.74–0.69). Seasonal standard deviations were highest in the NE Monsoon (~200–300 mm/month), reflecting wet-season variability. The multiplicative model outperformed additive in capturing heteroscedastic errors, identifying CHIRPS as the most reliable SPE for tropical monsoon contexts, with ERA5 limited by noise. Monthly aggregation reduced daily variability, enhancing SNR consistency. These findings support CHIRPS for improved drought monitoring in Sarawak.*

Keywords: Satellite Precipitation Products, CHIRPS, PERSIANN-CDR, ERA5, Accuracy Assessment, Tropical Climate, Sarawak

Introduction

Precipitation measurement is fundamental to hydrological modeling, climate studies, and water resource management, particularly in tropical regions like Malaysia where rainfall patterns are highly variable and influence phenomena such as floods, droughts, and ecosystem dynamics (Beck et al., 2017). Traditional validation of precipitation estimates relies on ground-based rain gauges as a reference; however, these in-situ measurements are not infallible and can introduce biases due to factors such as missing data, instrument malfunctions, and inadequate spatial representation, especially in areas with sparse gauge networks that fail to capture the full heterogeneity of precipitation events (Kidd et al., 2017). In such contexts, advanced error assessment techniques like Triple Collocation (TC), become essential tools for quantifying uncertainties in precipitation datasets without assuming any single source as the absolute truth (Stoffelen, 1998).

TC operates on the principle that errors among independent datasets are uncorrelated, allowing the decomposition of variances into signal and noise components (McColl et al., 2014). By collocating multiple satellite precipitation estimates (SPEs) either from satellite-based estimates such as Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) or reanalysis-based data (ERA5), and in-situ gauges at the same spatial and temporal scales, TC treats each as an equivalent measurement with its own random errors (Alemohammad et al., 2015). This approach reveals hidden noise inherent in the data, including systematic biases and random uncertainties, which are often overlooked in conventional pairwise validations. Since these products are derived independently (e.g., via different satellite sensors, algorithms, or ground observations) but represent the same geophysical variable, TC provides a robust framework for error analysis, enhancing confidence in dataset selection for applications in regions with limited ground truth.

Despite the advantages of SPEs in offering synoptic coverage and improved accuracy over traditional gauges, challenges persist in validating these products, particularly in tropical basins like Sungai Sarawak in Malaysia (Sun et al., 2018). In-situ rain gauges often suffer from sparse distribution, leading to incomplete representation of precipitation variability across the basin; ungauged or sparsely gauged areas introduce significant doubts about the reliability of estimates in those regions. This spatial limitation exacerbates issues during extreme events, where localized heavy rainfall may go undetected, hindering accurate hydrological forecasting and climate impact assessments.

While TC offers a promising solution by leveraging gridded SPEs to surrogate for or complement in-situ data in uncovered areas, there remains a notable research gap in its application to precipitation error analysis in Sarawak specifically. A review of existing literature reveals limited studies employing TC for evaluating precipitation uncertainties in this region, with most prior work focusing on global or other tropical contexts rather than the unique hydroclimatic conditions of Borneo, such as its peat-dominated landscapes and monsoonal influences (Tan et al., 2015). Furthermore, although previous research has identified overestimation in gridded SPEs like CHIRPS and PERSIANN-CDR, discussions on errors attributable to spatial and temporal variability such as seasonal underestimation in reanalysis products like ERA5, have been insufficient (Funk et al., 2015; Hersbach et al., 2020). Regarding error types, while additive and multiplicative models have been explored in some satellite precipitation studies (e.g., showing multiplicative errors as more suitable for daily scales and additive for monthly), their specific characterization and dominance in tropical Malaysian contexts, including interactions with local topography and vegetation, remain underexplored (Tian and Peters-Lidard, 2010). Additional gaps include the lack of long-term (>30-year) error assessments that integrate multiple data sources to inform drought and flood management amid climate change, in which understanding systematic versus random errors could refine predictive models and policy decisions.

The primary objectives of this study are twofold: (1) to derive error variances using Triple Collocation based on long-term (40 years) precipitation measurements for collocated grids in the Sungai Sarawak basin, using CHIRPS, PERSIANN-CDR, ERA5, and in-situ gauges; and (2) to assess these errors through intercomparisons among the sources, and at different error models (additive or multiplicative) that best represent precipitation scenarios in Malaysia, with implications for spatial and temporal variability. TC offers application in sparsely gauged tropics and this could set a precedent for global studies, promoting data fusion techniques that bridge gaps between satellite, reanalysis, and ground observations for more robust environmental monitoring

Methodology

Study Area

Sungai Sarawak Basin is situated at the Southwest region of the Sarawak state, facing South China Sea at its Northwestern direction. The catchment covers 2459 km^2 with the topography consisting of the hilly interior (~300 m) that transitions into the coastal lowlands, influenced by the equatorial climate.

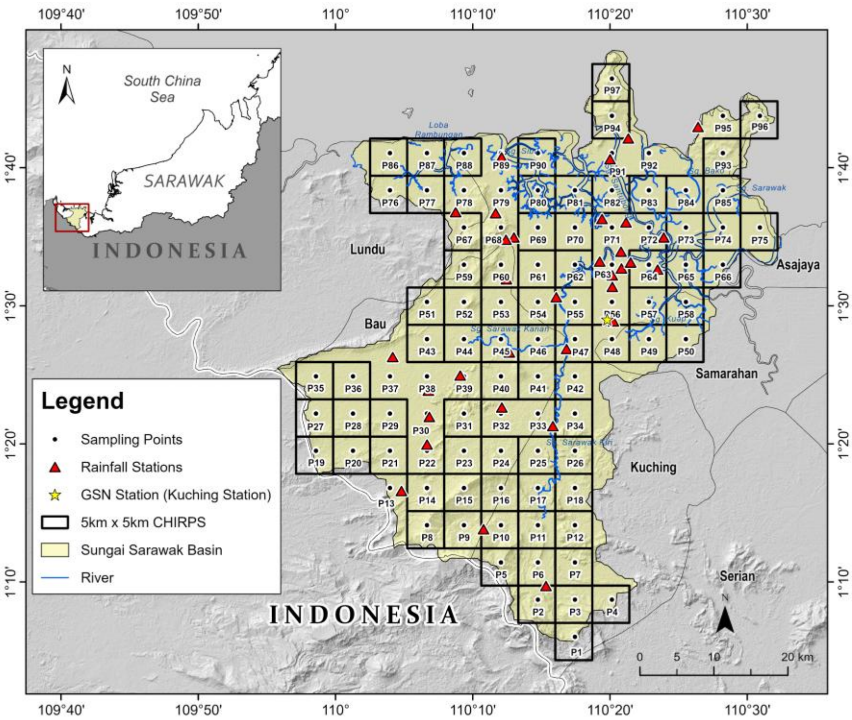


Figure 1: Map of Sungai Sarawak Basin, Sarawak with the geographical location, elevation, rain gauge stations, and grids at the CHIRPS native spatial resolution.

The river's estuary at Muara Tebas is influenced by tidal dynamics. This basin has topography that supports rich biodiversity but also exacerbates flood risks in low-lying areas during monsoons. The geomorphology, as shown in Figure 1, combining mountainous sources and coastal outlets, facilitates sediment transport and nutrient distribution, essential for its ecological and hydrological functions. The main river, known as Sarawak River, flows through the catchment at approximate 120 km through its two main tributaries (Sungai Sarawak Kanan and Sungai Sarawak Kiri), originating near the Kapuas Mountains and serves as the crucial water source and navigations route for Kuching and its surroundings.

Sarawak experiences an equatorial climate, characterized by consistently high temperatures (mean daily range of 21–32°C), high humidity (70–90%), and copious rainfall averaging 2,000–4,000 mm annually. The climate is influenced by two main monsoon seasons: the Northeast (NE) monsoon typically from November to March, which brings heavier rainfall and increased flood risk due to northeasterly winds from the South China Sea, and the Southwest monsoon typically from May to September, which is relatively drier but still features frequent showers. Inter-monsoon periods (April and October) serve as transitions with variable weather, often including thunderstorms.

Pre-processing on datasets of gridded precipitation product

The present study applied various gridded precipitation products – CHIRPS, PERSIANN and ERA5. The CHIRPS combines satellite imagery with in-situ station data to create a quasi-global rainfall product available at a high spatial resolution (0.05°, approximately 5 km) from 1981 to the present (Funk et al., 2015). CHIRPS is widely used for drought monitoring due to its long record and fine resolution, making it suitable for capturing localized drought events. PERSIANN provides global precipitation estimates derived from infrared satellite data, available at a 0.25° (approximately 25 km) resolution from 1983 to the present (Ashouri et al., 2015). The PERSIANN family of products has been extensively used in hydrological and climatological studies. Like other satellite products, PERSIANN data can exhibit systematic biases and may underestimate precipitation, with biases varying regionally and seasonally (Salmani-Dehaghi et al., 2021). ERA5 is the global gridded atmospheric reanalysis precipitation estimates developed by the European Center for Medium- Range Weather Forecasts. The ERA5 offers weather related parameters produced by the numerical weather forecast modeling and data assimilation through the basis of humidity and temperature information. The dataset represents gridded precipitation at daily scale with the spatial resolution at 0.25◦.

Data preprocessing involved merging datasets on id and date, replacing sentinel values (-9999) with NaNs, dropping NaNs, and filtering zero-inflated values (≤0.01 mm) to stabilize log-transformation. Different spatial resolutions require spatial interpolation using the Inverse Distance Weighting (IDW) method to ensure scale consistency in intercomparison and collocation, and thus, 5-km grid is considered in native CHIRPS resolution. Temporal difference between data is minimized by the monthly sum precipitation estimate in the 5-km grids. For this study, the data were compiled from January 1983 to October 2023 and supported by the in-situ data taken at different rain gauge stations (Figure 1).

Triple Collocation Method for error estimation

The standard definition of Triple Collocation is as follows.

$$P_i = \alpha_i + \beta_i P_{true} + \varepsilon_i \tag{1}$$

where P_i and ε_i $(i = 1,2,3)$ is the ith precipitation estimates and the ith observation errors of true value (P_{true}) respectively; coefficients of α_i and β_i represents the intercept and slope of the error model respectively. By using the Eq.(1), the computation of covariance can be obtained in form of 3x3 covariance matrix as shown in Eq.(2).

$$C_{ij} = Cov\left(P_i, P_j\right) = \beta_i \beta_j \sigma_{Ptrue}^2 \qquad (2)$$

Here, the diagonal elements of 3 parameters in the covariance matrix represent the variances of three collocated estimates as presented in Eq.(3).

$$\sigma_{P_i}^2 = D(P_i) = D(\alpha_i + \beta_i P_{true} + \varepsilon_i) = \beta_i^2 \sigma_{P_{true}}^2 + \sigma_{\varepsilon_i}^2 \qquad (3)$$

where C_{ij} is the covariance between two different collocated parameters, $D(.)$ and $Cov(.)$ indicate the variance and covariance, respectively; σ is the standard deviation. Noise variance in the triple collocation can be described either in additive or multiplicative form (Chen et al., 2022).

The multiplicative error model was introduced to present the accuracy of rainfall products. The model is defined as

$$P_i = \alpha_i P_{true}^{\beta_i} e^{\varepsilon_i}. \qquad (4)$$

In the multiplicative error model, the random error (ε) is the multiplicative factor. To compute it, the logarithmic transformation is taking into account by substituting the following; $\alpha_i = \ln(\alpha_i)$, $R_{true} = \ln(P_{true})$ and $R_i = \ln(P_i)$. The Eq.(3) can be simplified in the linear fashion like Eq.(1). Comprehensive explanation on the TC process can be referred in Li et al., (2018) in which the estimation of RMSE (i.e., between each collocated dataset and its true value can be obtained without knowing the true RMSE), error variance, signal variance and signal-to-noise ratio (SNR). For multiplicative noise model, the respective RMSE is calculated using method by Alemohammed et al, (2015) as the RMSE results are in the logarithmic scale and without physical meaning, so that,

$$\sigma_{P_i} = \mu_{P_i} \sigma_{R_i} \qquad (6)$$

where the σ_{R_i} is the RMSE in the logarithmic scale and μ_{P_i} is the estimate of RMSE. The triple collocation was applied on the three ensembles of CHIRPS, PERSIANN-CDR and ERA5 taken during the wet season, dry season and inter-monsoon period of Sungai Sarawak Basin.

Results and Discussion

(a) Variability of CHIRPS, PERSIANN and ERA5 precipitation data

Probability density functions (PDFs) were employed to evaluate the distributional characteristics of monthly precipitation from in-situ observations and SPEs (CHIRPS, PERSIANN, ERA5), and determining the measurement biases, variability, and attributes of extreme event across seasons from January 1983 to October 2024. The analysis of precipitation PDFs reveals distinct characteristics across all SPEs stratified by season as shown in Figure 2. Across the entire database, Figure 2(a), in-situ data have the broadest distribution and thickest tail (extending 1500mm/month) indicating the higher sensitivity to capture extreme events than other SPE products. ERA5 shows the sharpest peak (below 200 mm/month) and it suggests a bias toward central tendencies. The CHIRPS and PERSIANN align approximately and have impact of smoothing from the satellite retrieval algorithms. Figure 2(b), (c) and (d) highlight seasonal stratification impact on PDF where the disparity is evident during the wet season in which in-situ PDF has shift rightward with a dense tail (>1000 mm/month), underscoring its sensitivity to heavy rainfall. Unlike ERA5 and other satellite-based products, narrow spreads and rapid tail decay are presented which implies underestimation of extremes. In dry and inter-monsoon seasons, all SPEs converged toward lower precipitation ranges (<600 mm/month) with minimal tail differences, and this indicates that the SPE has reduced method-specific bias under low-rainfall conditions.

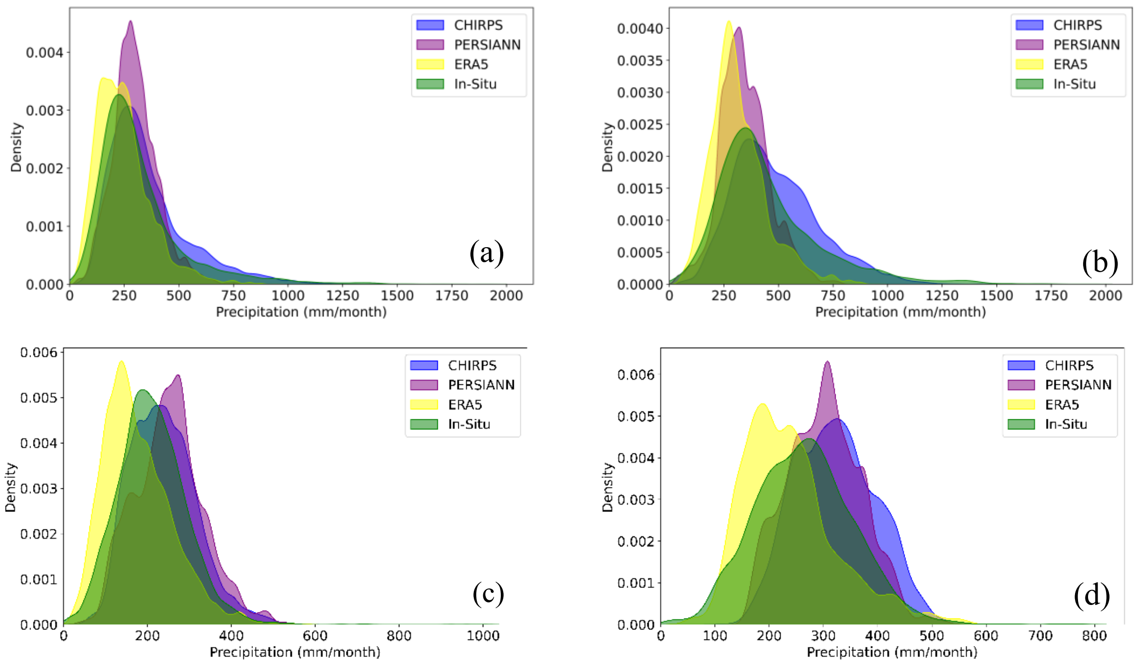


Figure 2: PDF of precipitation estimates from CHIRPS, PERSIANN and ERA5 as compared to the ground gauge measurement for (a) whole dataset, (b) data of wet season, (c) data for dry season and (d) data for inter-monsoon season.

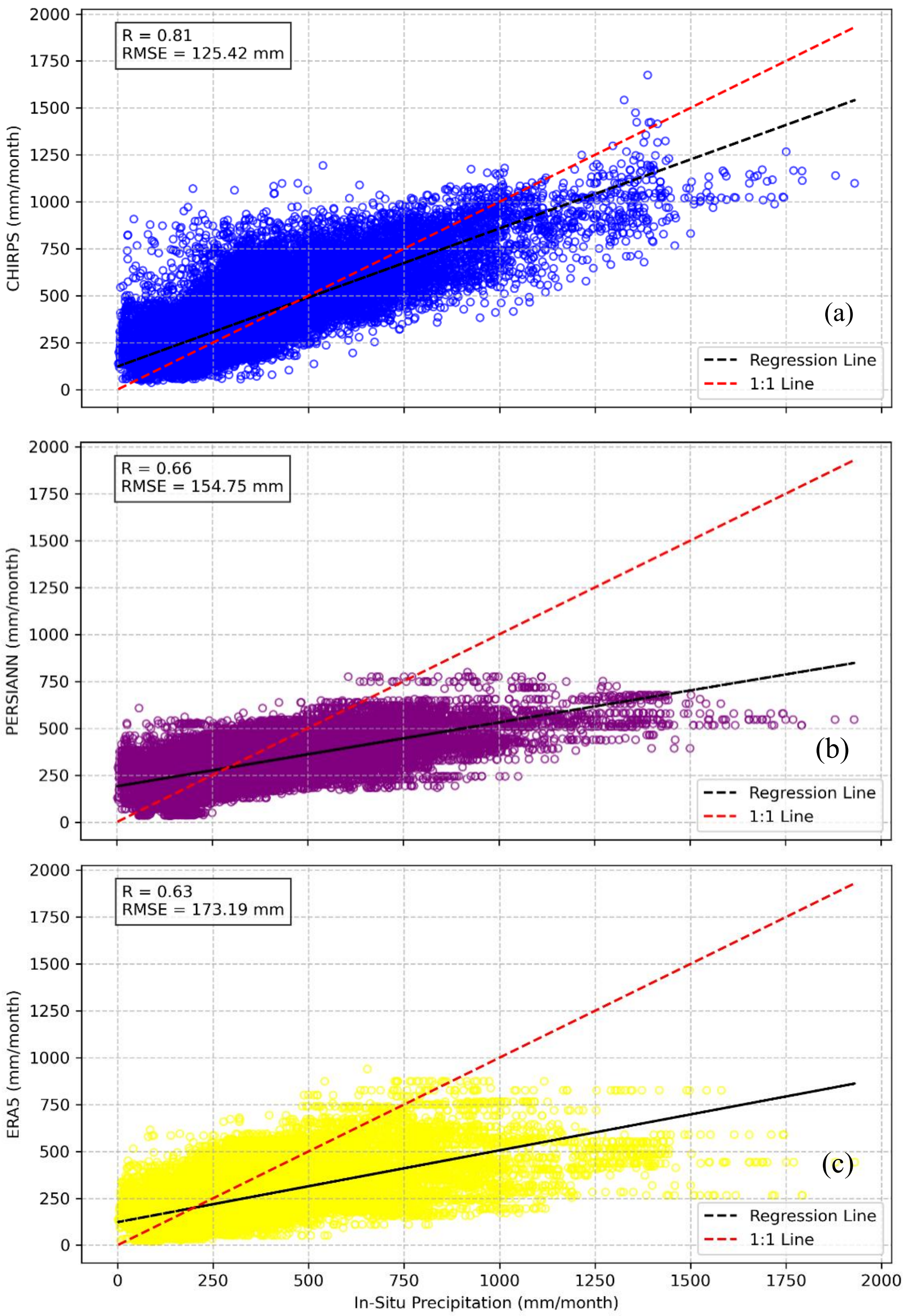


Figure 3: Regression plot of in-situ monthly precipitation measurement against (a) CHIRPS, (b) PERSIANN-CDR and (c) ERA5 satellite precipitation estimates.

To start the TC analysis, linear regression of monthly precipitation sums from CHIRPS, PERSIANN and ERA5 against in-situ measurement (assumed that we have the in-situ first) is presented in Figure 3 (a), (b) and (c) respectively. CHIRPS exhibits the highest correlation (R=0.81) and lowest RMSE (RMSE~125 mm), yet showing cluster of ensembles at higher precipitation of which systematic underestimation of extreme is suggested. PERSIANN and ERA5 presents weaker correlations (<0.66) and higher RMSE and implying higher biases possibly from retrieval algorithms. These regressions highlight limitation of pairwise comparisons in precipitation validation where errors from SPE are defined by spatial mismatches, instrument noise or environmental factors (McColl et al., 2014; Stoffelen, 1998). The regression analysis is limited to identify between random and systematic errors and this motivates the need for advanced error characterization which can be overcame by the Triple Collocation (TC) method. The TC would leverage three independent SPEs to isolate variances into "truth" signal and uncorrelated errors without assuming a "truth" reference.

(b) Triple Collocation (TC) analysis on the independent SPE variants, seasonal types and noise models

Figure 4 shows the standard deviation (SD) of precipitation errors, calculated from the Triple Collocation method for CHIRPS(C), PERSIANN(P), ERA5(E) and their combinations (C+P, C+E and P+E) stratified across wet, dry and inter-monsoon. Standard deviation measures the spread of monthly precipitation sums around their mean, reflecting the dataset's sensitivity to seasonal dynamics in this tropical region. CHIRPS consistently presents the highest SD (around 200 to 300 mm/month in wet season), underscoring its integration of gauge and satellite data at higher spatial resolution which is likely preserves localized variability and introduces a larger random error component. Unlike CHIRPS, the ERA5 and PERSIANN products have SDs of 100 to 150 mm/month and it suggests that their methods exhibit smoother error profiles from the model assimilation biases in ERA5 or smoothing retrieval in PERSIANN, but may underrepresent the extreme events. To experience the impact of data integration, combinations ensemble yields intermediate SD and this reflects that a reduction in random error through the averaging of uncorrelated noise, which is the key strength of the TC approach.

During NE Monsoon, all SPEs exhibit highest deviations due to intense convective rainfall, consistent with monsoon-driven extremes; CHIRPS at approximately 200 mm/month, PERSIAN-CDR at around 125 mm/month and ERA5 around 150 mm/month. The values decrease during the dry season of SW monsoon (~ 50-100 mm/month) implying stable lower precipitation conditions. The inter-monsoon captures the transitional weather patterns with the display of intermediate values from 75-150 mm/month. Similar pattern can be seen in the pairwise combination of CHIRPS-PERSIANN (C+P), CHIRPS-ERA5 (C+E) and

PERSIANN-ERA5 (P+E) albeit the higher deviations in individual datasets. It suggests additive sensitivities from the product combinations for wet-season extremes while the deviations remain low (~50-100 mm/month) for dry seasons.

This result shows the ability of TC to quantify random error variances under assumptions of mutual independence and linear error structures, and this could offer a robust foundation for probabilistic uncertainty analysis. An increase of SD during wet seasons highlights a seasonal modulation of error magnitude which is likely linked to intensified precipitation dynamics. This is not the case for dry season where the SD is lower suggesting significant convergence under stable conditions in the TC method. Combination SDE in TC allows multi-source fusion to reduce random errors and also increase performance by mitigating systematic biases.

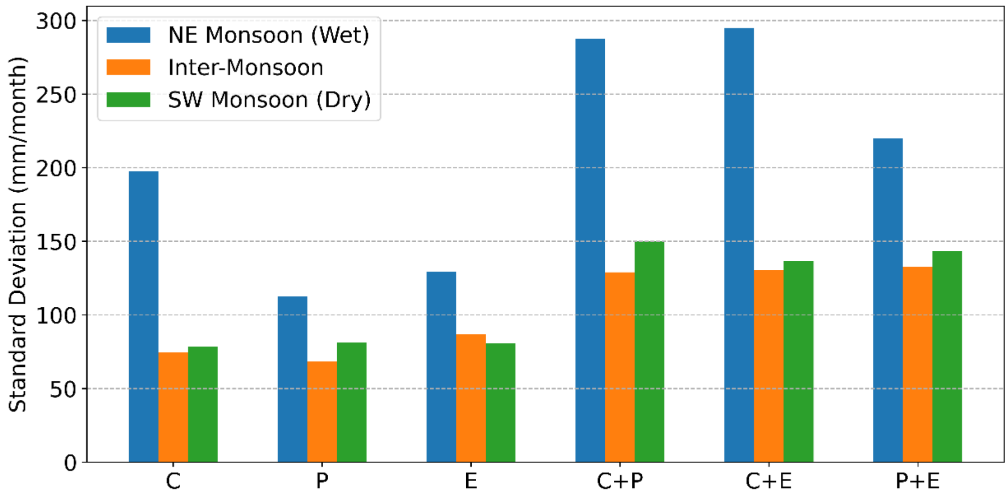
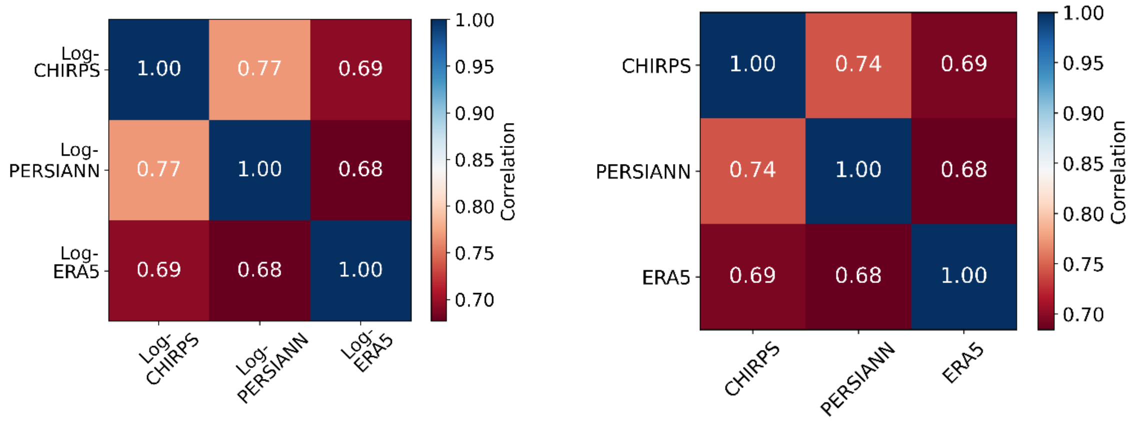


Figure 4: Precipitation variability to annual seasonal changes during the wet, dry and inter-monsoon seasons.

Two noise models in additive and multiplicative forms were demonstrated to examine their influence in the TC analysis. The correlation matrix in TCA contexts represents the linear association between the observed precipitation estimates from the three datasets (CHIRPS, PERSIANN, ERA5) as shown in Figure 5 respectively.



(a) (b)

Figure 5: Correlation Matrix Heatmap for (a) Multiplicative TCA and (b) Additive TCA.

The correlation matrix for Multiplicative TCA shows coefficients of 0.77 (CHIRPS-PERSIANN), 0.69 (CHIRPS-ERA5), and 0.68 (PERSIANN-ERA5), imply a log-transformed signal where relative errors with impact of extreme values are reduced (Figure 5a). The correlation in the Additive TCA reflects the absolute covariability with similar patterns but slightly lower coefficient; 0.74 (CHIRPS-PERSIANN), 0.69 (CHIRPS-ERA5) and 0.69 (PERSIANN-ERA5). Multiplicative TCA correlations imply lower relative error interdependence, while Additive TCA suggest moderate absolute error alignment, but neither indicates direct error correlation.

The 40-year monthly summation likely reduced noise (random errors) that is often more pronounced in daily precipitation data, leading to a smoother distribution and higher SNRs. In the tropical climate context, monthly summation mitigates the short-term variability from events such as the Borneo vortices (Liang et al, 2023). The generally high correlation suggests that summation of daily precipitation has strengthened the composed signal while preserving error uncorrelatedness. TCA assumes errors (ϵ) are independent, zero-mean, and uncorrelated with the signal in Figure 5. However, if correlations exceed 0.8–0.9, it may consider the signal error dependence, and thus, the TCA is unsuitable for noise estimation. In this case, the values are appropriate, and support the application of TCA, though the ERA5 had lower correlations due to partial violation (some missing data), potentially reducing its noise estimation accuracy.

The monsoon impact is not explicitly modelled here because the monthly summation mitigates the effects, transforming seasonal variability into a smoothed signal that TCA handles effectively. This aggregation reduces the need for monsoon-specific adjustments, as demonstrated by Dong et al., (2020) and Wild et al., (2022) in which the signal dominates over seasonal noise.

Table 1: Error variance (equivalent RMSE) and signal-to-noise (SNR) from multiplicative and additive noise model of TCA.

Noise Model	**Metrics**	**CHIRPS**	**PERSIANN-CDR**	**ERA5**
Additive	RMSE	90.58	53.57	73.78
	SNR	4.84	4.38	2.49
Multiplicative	RMSE	79.6	56.71	79.74
	SNR	5.69	4.73	1.98

The error variance in term of equivalent RMSE and signal-to-noise ratio (SNR) of three SPEs (CHIRPS, PERSIANN-CDR, and ERA5) using both additive and multiplicative models are summarized in Table 1. In the additive TCA, which assumes constant absolute errors, RMSE values were 90.58 mm/month (CHIRPS), 53.57 mm/month (PERSIANN-CDR), and 73.78 mm/month (ERA5), with SNRs of 4.84 dB, 4.38 dB, and 2.49 dB, respectively. Lower RMSE and higher SNR for PERSIANN-CDR indicate its superior accuracy and signal dominance, while ERA5's higher RMSE and lower SNR suggest greater noise, potentially due to reanalysis uncertainties in tropical regions.

The multiplicative TCA incorporated log-transformation to account for relative errors proportional to precipitation intensity and yielded RMSE of 79.6 mm/month (CHIRPS), 56.71 mm/month (PERSIANN-CDR), and 79.74 mm/month (ERA5), with the SNRs of 5.69 dB, 4.73 dB, and 1.98 dB. CHIRPS showed the lowest RMSE with highest SNR, reflecting the robustness of signal capture, that is likely being enhanced by the gauge integration, while the ERA5 was underperformed with higher relative noise.

The multiplicative TCA generally produced lower RMSE and higher SNRs for CHIRPS and PERSIANN-CDR, and this suggest that such noise model has better handling the heteroscedastic errors which is commonly evident in daily precipitation data. The additive model has pronounced RMSE for CHIRPS that is the basis of absolute error assumption where the model misrepresents the multiplicative noise in gauge-blended products. The ERA5 showed least performance across models and highlighted systematic biases. Overall, the multiplicative TCA is preferred for determining the best SPE in this tropical context, identifying CHIRPS as superior, consistent with studies showing its efficacy for relative error estimation at monthly scales.

Conclusion and Recommendation

For selecting the optimal Satellite Precipitation Estimate (SPE) dataset (CHIRPS, PERSIANN-CDR, or ERA5) for hydrological analysis, the TCA results favor CHIRPS under both frameworks. In the additive TCA, CHIRPS achieves the highest SNR, coupled with the strongest correlation to in-situ data and lowest RMSE. The multiplicative TCA reinforces this, with CHIRPS exhibiting the highest log-space SNR, alongside minimal RMSE. These metrics indicate that CHIRPS captures the true precipitation signal with the least contamination, making it ideal for calibration in hydrological models where accurate representation of variability is critical.

PERSIANN-CDR and ERA5, while showing reasonable correlations (R = 0.66 and 0.63, respectively), suffer from higher RMSE and lower SNRs, suggesting greater error propagation in downstream applications. For hydrological implementation—such as runoff modelling or water balance assessments—the multiplicative TCA is recommended as the primary selector, given precipitation's multiplicative error structure. This approach minimizes overestimation in dry periods and underestimation in wet events, enhancing model reliability. Thus, CHIRPS should be prioritized for calibration, with potential bias correction using TCA-derived error variances to refine hydrological simulations.

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