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The performance of satellite-based precipitation data to reproduce observed precipitation in Tanzania's Little Ruaha Catchment

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ABSTRACT

Satellite-based precipitation datasets have emerged as promising tools for addressing rainfall data scarcity in regions with limited ground observations, such as Sub-Saharan Africa. This study evaluates the performance of five satellite-based precipitation products CHIRPS, CPC, GPCC, MERRA-2, and ERA5 in capturing rainfall characteristics over the Little Ruaha Catchment in Tanzania. The assessment was carried out at daily, monthly, and seasonal timescales and focused on key rainfall indices including onset and cessation dates, length of the rainy season, total rainfall, and frequency of rainy days. Validation was conducted using statistical indicators such as the correlation coefficient (r), Nash–Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percent Bias (PBIAS). The results indicate that CHIRPS and CPC had strong agreement with observed rainfall at monthly and seasonal scales. CHIRPS, in particular, demonstrated consistent performance with r > 0.85 and NSE > 0.7 across most stations. At the daily scale, although all datasets performed poorly, CHIRPS still outperformed the others, showing moderate correlations around r ≈ 0.65. MERRA-2 and ERA5 showed higher errors and inconsistencies across different locations. The rainfall indices revealed that satellite datasets generally estimated earlier rainfall onset and delayed cessation compared to gauge data, resulting in longer estimated rainy seasons. For instance, CHIRPS overestimated the rainy season length by 31 days at Mafinga Bomani. In addition, satellite data often reported a higher frequency of rainy days, with discrepancies up to 16 days in some locations. These variations are attributed to the satellites' ability to detect light and scattered rainfall events missed by ground gauges. Overall, CHIRPS emerged as the most reliable product, offering a credible alternative for climate monitoring, hydrological modelling, and agricultural planning in data-scarce regions.

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INTRODUCTION

The emergence of satellite and remote sensing technologies has transformed the way global precipitation data is collected, effectively addressing the longstanding issue of data shortages worldwide (Khan & Bhuiyan, 2021). These satellite-based methods have significantly altered hydrological and climate research by allowing for ongoing, high-resolution collection of rainfall data, especially in regions where traditional ground measurements are lacking or unavailable (Khan & Bhuiyan, 2021). Such global precipitation datasets offer viable solutions for filling gaps in rainfall records, providing high spatial resolution and continuous time series data gathered from infrared sensors, microwave sensors, and weather radars (Mbungu & Kashaigili, 2017; Su, Hong, & Lettenmaier, 2008). The capability of satellite-based technologies to monitor precipitation patterns over extensive and remote regions makes them indispensable for a wide range of hydrological, agricultural, and climate-related applications (Kidd & Huffman, 2011; Nguyen et al., 2018).

In regions such as Sub-Saharan Africa, the use of satellite-derived precipitation data is particularly vital, as conventional water monitoring methods are often impractical due to high costs, logistical challenges, and limited spatial coverage, which hinder their widespread implementation (Dinku, Connor, & Ceccato, 2011; Funk et al., 2015; Maidment et al., 2017)Remote sensing technologies provide timely and reasonably accurate data that are critical for a wide range of water resource management applications, including not only water quality monitoring, but also flood risk assessment, drought monitoring, irrigation planning, reservoir management, and surface water mapping. These tools enhance decision-making in both data-rich and data-scarce regions by offering consistent spatial and temporal coverage that complements traditional ground-based measurements (Gao, Birkett, & Lettenmaier, 2012; Schumann, Di Baldassarre, & Bates, 2009; Schumann et al., 2008; Wanders, Wada, & Van Lanen, 2015). However, the adoption of these technologies is still limited in some Sub-Saharan African regions due to high costs and resource constraints (Cattani et al., 2021; Levizzani & Cattani, 2019). Additionally, satellite observations are subject to random and systematic errors, which can affect the accuracy of precipitation estimates essential for climate research and hydrological applications reliant on the water cycle (Khan & Bhuiyan, 2021). The African continent's vulnerability, particularly its population living in drought-prone and flood-affected regions, highlights the critical need for precise and dependable precipitation data (Cattani et al., 2021).

Numerous studies across various geographical and temporal contexts, including Sub-Saharan Africa, have evaluated the effectiveness of satellite-based rainfall estimation at various geographical and temporal scales (Asadullah, McIntyre, & Kigobe, 2008; Cattani et al., 2021; Dinku et al., 2007; Dinku, Connor, & Ceccato, 2011). These assessments have shown that satellite-derived datasets can improve precipitation monitoring while uncovering spatial and temporal inconsistencies between satellite estimates and ground-based observations. However, the accuracy of satellite precipitation data in reflecting ground measurements varies considerably by region and timescale, with discrepancies often influenced by local climate, topography, and the specific algorithms used for satellite retrieval (Su, Hong, & Lettenmaier, 2008). The challenges of obtaining reliable precipitation data in Africa are exacerbated by the sparse distribution of meteorological stations, frequent data gaps, and inconsistencies in historical records (Mbungu, 2016; Mbungu & Kashaigili, 2017; Mbungu et al., 2012). The complex and variable rainfall patterns typical of eastern Africa, shaped by various local, regional, and global factors, result in significant seasonal and inter-annual variability, complicating the establishment of historical trends and hindering climate models' ability to simulate regional rainfall patterns. Therefore, validating and calibrating satellite-derived precipitation data as an alternative or supplement to traditional ground-based measurements is essential, particularly in regions with intricate climatic and geographical features.

Satellite-based precipitation data have increasingly been used to supplement ground observations in basin-scale hydrological studies (e.g., Dinku et al., 2007; Dessu & Melesse, 2013). Prior evaluations show that most satellite precipitation products perform poorly at daily scales but achieve higher skill at monthly and seasonal scales in East Africa (Gebrechorkos et al., 2018). Nonetheless, comprehensive local validation of these products remains important to gauge their accuracy for end-users and model developers. In Tanzania, only a few studies (e.g., Gebrechorkos et al., 2018; Dessu & Melesse, 2013) have attempted to validate satellite-based rainfall products, and those were limited to specific regions. To our knowledge, there is very limited literature evaluating multiple satellite rainfall datasets at a catchment scale while accounting for differing climatic conditions within the basin. This study therefore aims to evaluate the capability of satellite-based precipitation data to reproduce local rainfall characteristics (daily, monthly, and seasonal) at the catchment level, thereby addressing this knowledge gap. Our work also complements the limited existing studies on satellite precipitation product evaluation in Tanzania such as those by Dinku et al. (2007), Mbungu and Kashaigili (2017), and Maidment et al. (2017) by providing a basin-specific analysis under a range of climatic settings, from semi-arid to wetter zones within the Little Ruaha catchment.

STUDY AREA DESCRIPTION

This research was carried out at the Little Ruaha Catchment, which is located within a semi-arid belt from north to south Tanzania, between 33.5° E-36.5° E and 6.5° S-9.3° S, (Figure 1), and covers an area of approximately 69,843.85 km2. The catchment has one rainy season that lasts from November to early May, with the driest months being from June to October.

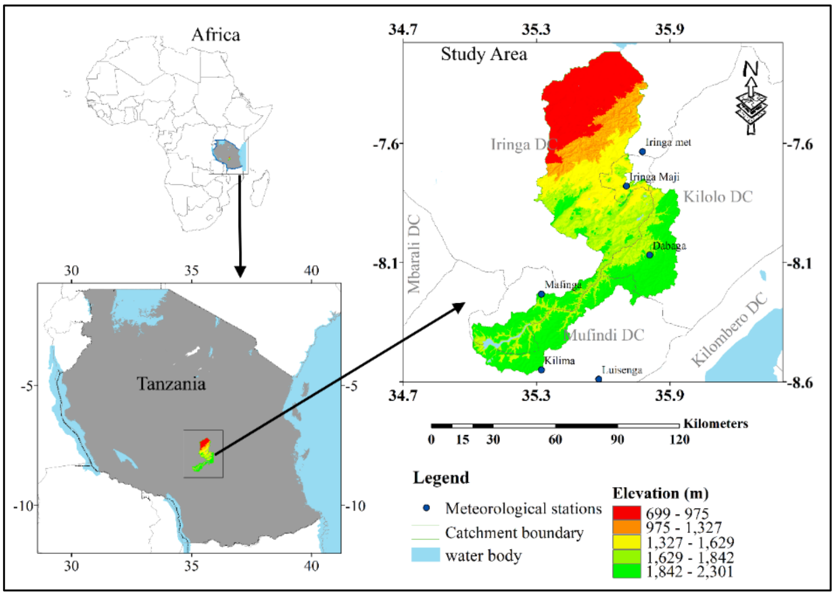

Figure 1: Location map of the study area (source: National Bureau of Statistics GIS administration layer of Tanzania)

In the Ruaha catchment, the average annual rainfall ranges from 400 mm to 1,200 mm, and the average temperature ranges from 22 ^{o}C to 30 ^{o}C. Low humidity characterizes the climate, and potential evaporation (PET) is highly variable, ranging from 1,200 mm, in the south to 2,000 mm in the north. The catchment is critical to the livelihoods of the communities that live in the area, particularly the upper and lower catchments. The catchment supports agriculture (the catchment's dominant activity, employing approximately 90% of the population), fishing, livestock, beekeeping, and tourism. In addition, Ruaha National Park's wildlife habitats and surrounding game reserves rely on the Little Ruaha River for survival. In general, the Little Ruaha basin benefits the region's ecosystem in terms of habitat and food.

DATA

Observed Precipitation data

The Tanzania Meteorological Authority (TMA) provided historical daily precipitation data (1981–2020) for stations in and around the study area. A data quality control screening was applied to retain only stations with no more than 10% missing data over the study period. As a result, four stations Iringa Maji, Iringa Meteorological Office (Nduli), Mafinga Bomani, and Mbeya Meteorological Station met the criteria and were selected for the satellite data performance evaluation at daily, monthly, and seasonal scales. These stations had minimal missing data (0–2%; see Table 1). Small gaps in the daily records were addressed using linear interpolation or monthly climatological averages, given their infrequency, to maintain data continuity and integrity for subsequent comparisons.

Table 1: List of the Meteorological stations used for satellite data evaluation

SN	Station Name	Latitude	Longitude	Available data	Missing data (%)
i.	Iringa Met	-7.63	35.77	1980 - 2000	0
ii.	Iringa Maji	-7.78	35.70	1980 - 2021	0.3
iii.	Mafinga Bomani	-8.25	35.33	1981 - 2020	2
iv.	Mbeya	-8.93	33.47	1981 - 2020	0

Satellite-based precipitation data

As summarized in Table 2, five satellite-based precipitation datasets were obtained from their respective sources at various spatial resolutions: (1) CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) at 0.05° resolution (UCSB/USGS); (2) CPC Global Unified Precipitation at 0.5° (NOAA PSL); (3) GPCC Full Data Reanalysis at 1.0° (Global Precipitation Climatology Centre, NOAA PSL); (4) MERRA-2 reanalysis at 0.5° (NASA/GSFC); and (5) ERA5 reanalysis at 0.25°–0.5° (Copernicus/ECMWF). All data were extracted at the station locations (point-to-pixel) for 2001–2020 using the Climate Data Tool (R). These five products were chosen based on their widespread use, long-term data availability, and representation of different precipitation data sources. In particular, CHIRPS, CPC, and GPCC are gauge-informed products (satellite-gauge blended or gauge-only) that provide long historical records, while MERRA-2 and ERA5 are state-of-the-art reanalysis products that offer model-based estimates. This selection captures a broad spectrum of data generation approaches (ground gauge analysis, satellite estimate, and model reanalysis) for a comprehensive evaluation. Other well-known products (e.g., PERSIANN-CDR, TAMSAT, TRMM, GSMaP, IMERG) were not included in order to focus the study on datasets with longer overlapping record lengths and distinct methodologies. Many of those excluded either have shorter record periods (e.g., TRMM, IMERG) or similar characteristics to the chosen products (for instance, TAMSAT and PERSIANN-CDR are also gauge-corrected infrared estimates like CHIRPS). Thus, the selected five datasets serve as a representative set for comparing satellite and reanalysis precipitation performance over the study area.

Table 2. Satellite-based precipitation data from different data sources

SN	Data	Time interval	Resolution	Source
1	CHIRPS	1981-2020	0.05° *0.05°	Funk et al., 2015
2	CPC	2000-2020	0.5°*0.5°	Chen et al., 2008
3	GPCC	1996-2020	1.0° * 1.0°	Becker et al., 2013
4	MERRA-2	1982-2020	0.5° * 0.5°	GMAO, 2015
5	ERA5	1981-2020	1.0*1.0	Li an Babovic,2019

METHODS

To validate the applicability of satellite-based climate data (CHIRPS, CPC, GPCC, MERRA-2, and ERA5), a comparison was made between satellite-based daily data extracted at a point (station) scale relative to meteorological stations around the study area with observed data. This study uses point to pixel method to compare ground observations with satellite-based rainfall estimates and climate model outputs as it was previously stated as a most appropriate methods to compare observations with satellite datasets (Gebrechorkos et al., 2018).This study chose meteorological stations with less than 10% data gaps (Table 1). It was carried out on a daily, monthly, and seasonal scale for the period 2001-2020, depending on data availability for at least 20 years within that period. To assess how accurately satellite-based precipitation products reflect observed rainfall patterns, we performed statistical comparisons and examined rainfall characteristic indices. This combined methodology allows for evaluating both quantitative performance and climatic authenticity.

Statistical metrics

The performance of satellite data relative to ground-based observations was evaluated using standard statistical measures. The assessment is vital for determining the suitability of satellite products in climate studies, where long-term rainfall patterns and trends are essential for understanding climate variability and change, as well as for developing effective early warning systems that rely on timely and accurate rainfall information to mitigate the impacts of extreme weather events (Nadeem et al., 2022). Furthermore, the evaluation informs agricultural planning by providing data for crop modeling, irrigation management, and drought monitoring, thereby supporting sustainable agricultural practices and food security.

Three standard evaluation indices were used for validation, namely:

(a) Nash–Sutcliffe efficiency (NSE), which compares the magnitude of the residual variance relative to that of the measured data variance using normalized statistics;

$$NSE = 1 - \left[\frac{\sum_{i-1}^{n}\left(Q_i^{obs}-Q_i^{sim}\right)^2}{\sum_{i-1}^{n}\left(Q_i^{obs}-Q^{mean}\right)^2}\right] \ldots\ldots\ldots (1)$$

Where Q_i^{obs} is the ith observed precipitation, Q^{mean} is the mean of observed precipitation data, and Q_i^{sim} is the ith modelled precipitation data.

The NSE can range from -∞ to 1. A value of 1 indicates a perfect fit between simulated and observed data. A value of 0 indicates that the average of the observed data would be a better fit than the model output (Nash and Sutcliffe, 1970). An NSE of 0.5 or higher is accepted as an indicator of satisfactory model performance for a monthly time step (Moriasi et al., 2007).

(b) Percent bias (PBIAS) quantifies whether the average tendency of the simulated data is greater or less than the observed data and is expressed as a percentage, indicating a high or low bias in the modeled data. The PBIAS values were calculated using the following equation:

$$PBIAS = \left[\frac{\sum_{i=1}^{obs}\left(Q_i^{obs}-Q_i^{sim}\right)*100}{\sum_{i=1}^{n}\left(Q_i^{obs}\right)}\right] \ldots\ldots\ldots (2)$$

Positive PBIAS values indicate that the simulated data is lower than the observed data on average, but negative values indicate the reverse: simulated data is higher than the observed data on average. A PBIAS value below 25% is considered satisfactory model performance and a PBIAS value of 0 indicates a perfect simulation for a monthly time step (Moriasi et al., 2007). For example, a PBIAS of –42.8% (as shown in Table 3 for the MERRA-2 product at Mbeya Station) indicates that the satellite product overestimated rainfall by 42.8% compared to the observed station data.

(c) The RMSE observations' standard deviation ratio (RSR), which standardizes the RMSE with regards to the observed records. The RSR values are the ratio of root mean square error (RMSE) to the standard deviation of observed data and were calculated as:

$$RSR = \frac{RMSE}{STDEV_{abs}} = \left[\frac{\sqrt{\sum_{i=1}^{n}\left(Q_i^{obs}-Q_i^{sim}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_i^{obs}-Q^{mean}\right)^2}}\right] \ldots (3)$$

However, the RSR value of 0 indicates a perfect simulation, but values below 0.70 are considered satisfactory for model performance at a monthly time step (Moriasi et al., 2007).

Furthermore, the study applied Taylor diagrams to graphically compare observed time series with satellite-based data using three key statistics: the Pearson correlation coefficient (r), root mean square error (RMSE), and standard deviation. Taylor diagram (Taylor, 2001) is a graphical representation of model performance against observations. It provides a concise visual summary by plotting RMSE and standard deviation in relation to correlation. The X and Y axes represent standard deviations. The formula used to calculate the Pearson correlation coefficient is shown in equation 4:

$$r = \frac{n(\sum XY)-(\sum X)(\sum Y)}{\sqrt{[n\sum X^2-(\sum X)^2]\,[n\sum Y^2-(\sum Y)^2]}} \ldots\ldots\ldots (4)$$

where X = Observed data, Y = Modeled data, and n = number of events.

Note: In the Pearson's coefficient of determination when, r = 0 to 0.30; negligible correlation. r = 0.30 to 0.50; moderate correlation. r = 0.50 to 1 highly correlated.

Calculation of rainfall characteristics indices

In addition to the statistical comparisons, rainfall indices were computed using daily precipitation data to capture seasonal and quantitative rainfall patterns. These included the onset and cessation dates of rainfall, the length of the growing season, total annual rainfall, and the number of rainy days. Each index was calculated for both satellite and gauge data to evaluate rainfall behavior and assess consistency across data sources.

(a) Rainfall Onset days (ROD)

The onset of the rainy season is defined as the first day after a predefined start date when cumulative rainfall over a specified number of days exceeds a threshold, indicating the beginning of effective rainfall. The ROD is calculated using Equation (5):

$$OD = min\left\{d \sum_{i=d}^{d+n} P_i \geq T \; and \; no \; dry \; spell \; of \; \geq 7 \; days \; in \; the \; next \; 30 \; days\right\} \quad \ldots (5)$$

- Pi: Daily rainfall on day i
- n window of consecutive days (typically 3 to 5)
- T rainfall threshold (e.g. : 20-25 mm)
- ROD is validated if no 7-day dry spell occurs within the next 30 days

(b) Rainfall Cessation Date (RCD)

Rainfall Cessation Date (RCD) marks the end of the rainy season. It is defined as the last day within a rainy period after which rainfall ceases for an extended duration. Mathematically, it is determined using Equation (6):

$$RCD = max\left\{d \sum_{i=d}^{d+n} P_i \geq T \; and \; followed \; by \; a \; dry \; spell \; of \; \geq 15 \; days\right\} \quad \ldots\ldots\ldots (6)$$

- T: Similar threshold as ROD.
- Dry spell: Sequence of consecutive days with rainfall < 1 mm.

(c) Length of Growing Season (LGS)

LGS is defined as the number of days between the onset and cessation of rainfall, representing the effective duration of the rainy season, which is crucial for agricultural planning. It is computed using Equation (7):

$$LGS = RCD - ROD \ldots\ldots\ldots (7)$$

This represents the duration of the effective rainfall season, crucial for agricultural planning.

(d) Frequency of rainy days

The frequency of rainy days is defined as the proportion of days with measurable rainfall (typically ≥1 mm) relative to the total number of days in a given period (e.g., annually or seasonally) as expressed in Equation (8):

$$FRD = \frac{N_r}{N_t} \ldots\ldots\ldots (8)$$

- Nr: Number of rainy days (days with rainfall ≥ 1mm)
- Nt: Total number of days in the period (e.g., 365 for a year, or number of days in the season)

(e) Amount of rainfall in the season

The total seasonal rainfall was computed as the cumulative sum of daily rainfall values (Equation. 9).

$$ARA = \sum_{i=1}^{n} P_i \quad \ldots\ldots\ldots (9)$$

where:

- Pi: Rainfall recorded on day i (in mm)
- n: Total number of days in the season)

RESULTS AND DISCUSSIONS

Rainfall amounts

The statistical analysis was done on daily, monthly and seasonal timescales. Table 3, 4 and 5 present the analysis of daily, monthly and seasonal data, respectively for Iringa Maji (9833001), Iringa Meteorological Station (9735013), Mafinga Bomani (9835033) and Mbeya Meteorological Station (9833001). For all objective functions, results shows poor correlation except for the percentage bias of CHIRPS data in the daily time scale (table 3). The poor performance at a daily scale may be attributed to the region's rugged and mountainous terrain, which influences local rainfall through orographic effects, and to the presence of variable rainfall systems that make consistent satellite estimation more difficult. Furthermore, estimating rainfall from satellite data in the mountainous region of East Africa is proven to be challenging (Cattani et al., 2016) as these products certainly do not represent regional rainfall patterns due to the region's rugged, mountainous landscape and sharp elevation changes, which can influence local rainfall patterns and reduce the accuracy of satellite estimates (Romilly and Gebremichael, 2011)

Table 3. Statistical comparison between observed and satellite-based precipitation data at a daily timescale

SN	Station	Satellite data	Statistical tests			
			NSE	RSR	RMSE	Pbias
1	Iringa Maji	CHIRPS	0.06	1.28	8.06	-26.90
		CPC	0.00	1.31	115.12	47.54
		GPCC	-0.03	1.02	-213.2	-102.07
		MERRA-2	-0.69	1.01	10. 21	-58.02
		ERA5	-0.68	1.29	5.52	-30.52
2	Iringa Met	CHIRPS	0.00	1.25	7.04	-27.90
		CPC	0.00	1.00	117.14	48.50
		GPCC	-0.05	1.00	-216.4	-102.07
		MERRA-2	-0.72	1.01	10. 21	-59.00
		ERA5	-0.72	1.31	6.30	-32.50
3	Mafinga Bomani	CHIRPS	-0.80	1.34	7.57	5.10
		CPC	0.00	1.00	117.22	116.4
		GPCC	0.00	1.00	261.25	-103.9
		MERRA-2	-0.25	0.68	11.29	-40.30
		ERA5	-0.40	1.18	8.26	-27.30
4	Mbeya Met	CHIRPS	-0.40	1.18	-14.02	7.01
		CPC	0.00	1.00	117.19	105.9
		GPCC	0.00	1.01	-103.61	-103.6
		MERRA-2	-0.05	1.02	8.92	-42.82
		ERA5	-0.14	1.07	8.90	-52.71

Table 4 presents the analysis of monthly data for Mbeya Met (9833001), Iringa Met (Nduli) (9735013), Iringa Maji (9735014) and Mafinga Bomani (9835033). Results are more promising in that for most data sets, objective functions results show good correlation between observed and satellite data except for the GPCC, MERRA-2 and ERA5 which have a Pbias of > 25%. Other statistical tests have shown good performance where CHIRPS and CPC have performed highly in reproducing the monthly data series at a station level. The monthly results are further supported by the Taylor diagrams (Figure 2) in which the correlation of each rainfall product with station data is summarized for the four (4) stations used for validation. The results indicate that CHIRPS and CPC are correlated with station data in all tested weather stations. However CHIRPS were strongly correlated with station data compared to CPC.

Table 4: Statistical analysis between observed and satellite-based precipitation data at a Monthly timescale

SN	Station	Satellite data	Statistical tests			
			NSE	RSR	RMSE	Pbias
1	Iringa Maji	CHIRPS	0.98	0.15	9.29	6.7
		CPC	0.96	0.18	13.44	-4.5
		GPCC	0.89	0.32	26.28	-25.8
		MERRA-2	0.41	0.74	79.81	-52
		ERA5	0.87	0.35	30.56	-14.4
2	Iringa met	CHIRPS	0.97	0.17	11.03	-12.4
		CPC	0.95	0.21	14.44	-14.2
		GPCC	0.77	0.46	37.51	-36.9
		MERRA-2	0.22	0.85	91.74	-59.5
		ERA5	0.75	0.48	41.95	-37
3	Mafinga Bomani	CHIRPS	0.92	0.28	21.43	27.5
		CPC	0.97	0.17	15.07	4.6
		GPCC	0.86	0.36	25.4	18.9
		MERRA-2	0.71	0.52	55.97	-35
		ERA5	0.89	0.32	38.08	-25.1
4	Mbeya Met	CHIRPS	0.94	0.24	12.52	-14
		CPC	0.98	0.13	10.05	-5.7
		GPCC	0.97	0.17	21.6	3.2
		MERRA-2	0.71	0.57	73.39	-42.8
		ERA5	0.39	0.75	74.8	-55.1

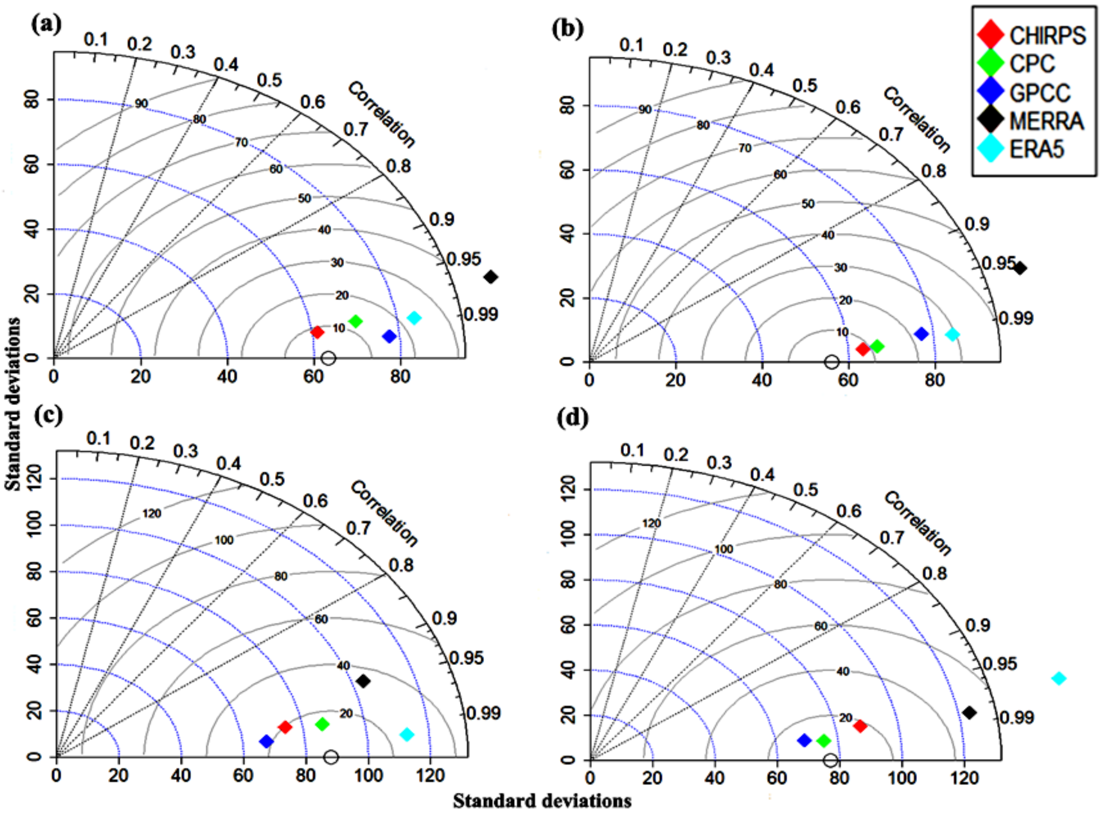

Figure 2: Taylor diagram for comparison between the observed precipitation data and Satellite-based precipitation data at a monthly time scale for (a) Iringa Maji (b) Nduli (c) Mafinga Bomani and (d) Mbeya meteorological stations

Comparison of annual cycles (2000-2020) mean monthly rainfall at the four meteorological stations' point scale to corresponding points datasets for the satellite-based products in the study area shown in Figure 2(a-d) and magnitude of the errors shown in Table 4, shows that satellite-based products were able to capture trends and peaks at all synoptic locations, with error ranging from 0.98 to 91.74 mm.

The results show that all satellite-based data in the study area captured well the observed rainfall peak at all tested station points. However, CHIRPS and CPC produced the lowest RMSE (Table 4), with the values between 9.29 mm and 21.43 mm for CHIRPS, and between 10.05 mm and 15.15 mm for CPC. The results indicate that CHIRPS and CPC are able to capture monthly rainfall better than other satellite-based data.

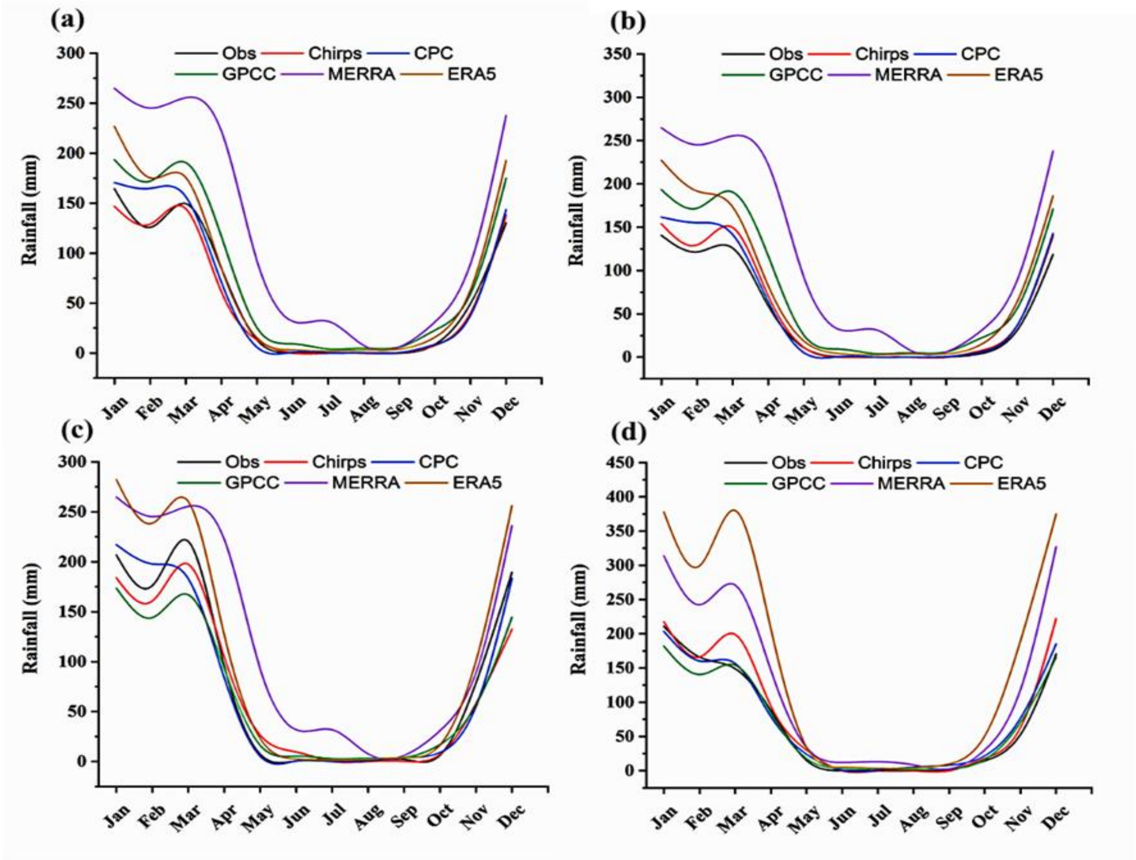

Figure 3: Monthly series for comparison between the observed precipitation data and Satellite-based precipitation data for (a) Iringa Maji (b) Nduli (c) Mafinga Bomani and (d) Mbeya Meteorological Station

Likewise, the study evaluated the average seasonal rainfall for the October–April (ONDJFMA) period, which represents the dominant rainy season across the study area. This evaluation is critical, as approximately 70% of the population relies on rain-fed agriculture for their livelihoods. Seasonal-scale comparisons were conducted using gauge data from 2000 to 2020 and were benchmarked against five satellite rainfall products CHIRPS, CPC, GPCC, MERRA-2, and ERA5 for selected locations (Table 1). The aim was to assess the ability of each product to reproduce seasonal rainfall patterns and identify the most reliable dataset for hydrological and climate-related applications.

As shown in Table 5, CHIRPS and CPC consistently exhibited the best performance across all stations. For example, at Iringa Maji, CHIRPS achieved an NSE of 0.95 and RMSE of 12.17 mm, while CPC had an NSE of 0.92 and RMSE of 17.38 mm. Similarly, at Mbeya, CPC recorded the highest NSE of 0.96 and the lowest RMSE (12.33 mm) among all products. In contrast, MERRA-2 and ERA5 generally showed poor performance, with NSE values below 0.5 and large RMSE and PBIAS magnitudes at most stations. An exception was observed at Mafinga, where ERA5 achieved an NSE of 0.72, indicating relatively better agreement with ground observations.

These performance patterns are further confirmed by the Taylor diagram (Figure 4), which visually illustrates the high correlation of CHIRPS and CPC with the observed station data.

All satellite products generally captured the seasonal rainfall cycle across the study area. Figure 4 presents the mean monthly rainfall distribution for the ONDJFMA period at the four meteorological stations. Among the evaluated datasets, CHIRPS and CPC consistently reproduced the seasonal rainfall peaks with high accuracy, particularly at Iringa Maji and Iringa Met stations, where CHIRPS achieved NSE values of 0.95 and 0.93, respectively, with RMSE values below 15 mm. CPC also showed strong performance at these sites, with NSEs of 0.92 and 0.90, respectively.

At Mbeya Station, however, CPC and GPCC outperformed CHIRPS, with CPC attaining the highest NSE of 0.96 and the lowest RMSE of 12.33 mm among all datasets. This exception can be attributed to the mountainous topography and sharp elevation gradients in the Mbeya region, which complicate satellite-only rainfall retrieval. CHIRPS, which relies primarily on satellite estimates, tends to under-capture localized convective rainfall events in such terrain. In contrast, gauge-blended products like CPC and GPCC benefit from integrating in situ observations, enhancing their accuracy in areas with complex terrain. These findings are consistent with previous studies showing that orographic effects and terrain variability introduce uncertainties in satellite-based rainfall estimates.

Table 5. Statistical comparison between observed and satellite-based precipitation data at seasonal (ONDJFMA) timescale

			Statistical tests			
SN	Station	Satellite data	NSE	RSR	RMSE	Pbias
1	Iringa Maji	CHIRPS	0.95	0.21	12.17	6.70
		CPC	0.92	0.26	17.38	-5.30
		GPCC	0.72	0.49	33.78	-23.30
		MERRA-2	-0.32	1.06	98.63	-47.00
		ERA5	0.70	0.51	39.65	-23.70
2	Iringa met	CHIRPS	0.93	0.24	14.44	-12.70
		CPC	0.90	0.29	18.77	-15.00
		GPCC	0.41	0.71	48.59	-34.80
		MERRA-2	-0.79	1.24	114.83	-55.30
		ERA5	0.45	0.69	54.80	-36.00
3	Mafinga Bomani	CHIRPS	0.82	0.39	26.90	15.30
		CPC	0.93	0.24	19.70	4.80
		GPCC	0.64	0.55	32.99	22.40
		MERRA-2	0.45	0.69	63.56	-27.50
		ERA5	0.72	0.49	49.48	-24.00
4	Mbeya Met	CHIRPS	0.87	0.34	27.72	-13.10
		CPC	0.96	0.18	12.33	-3.60
		GPCC	0.92	0.27	16.27	4.70
		MERRA-2	0.14	0.86	95.55	-41.30
		ERA5	-0.86	1.26	158.19	-54.70

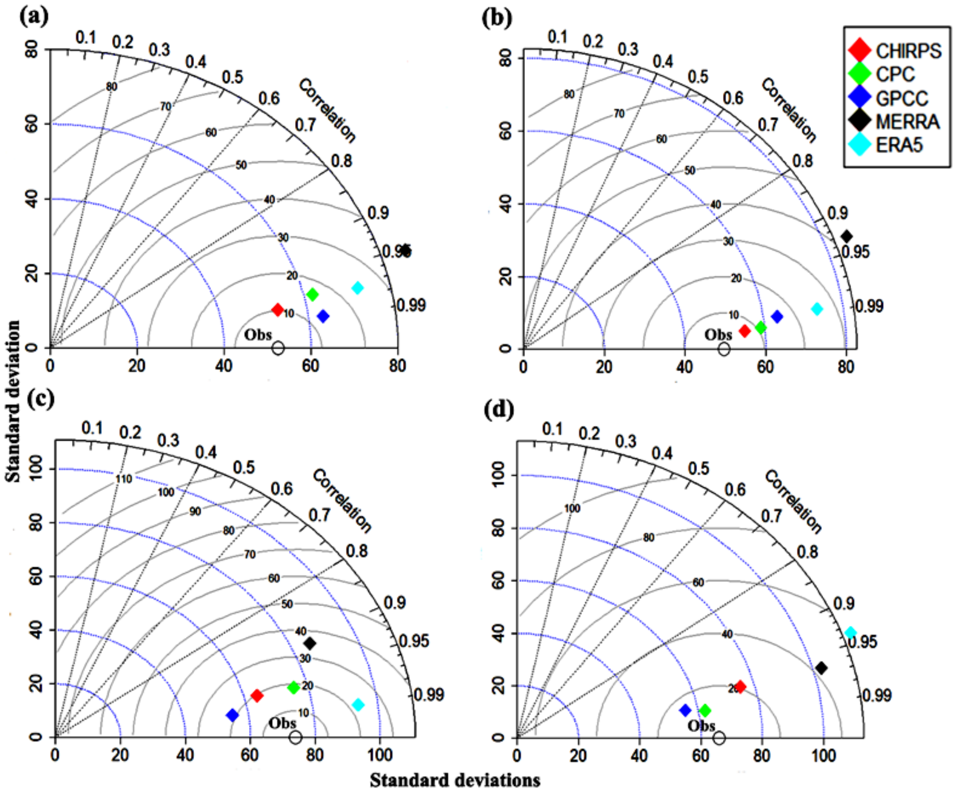

Figure 4: Taylor diagram for comparison between the observed precipitation data and Satellite-based precipitation data at a seasonal time scale for (a) Iringa Maji (b) Nduli (c) Mafinga Bomani and (d) Mbeya meteorological stations.

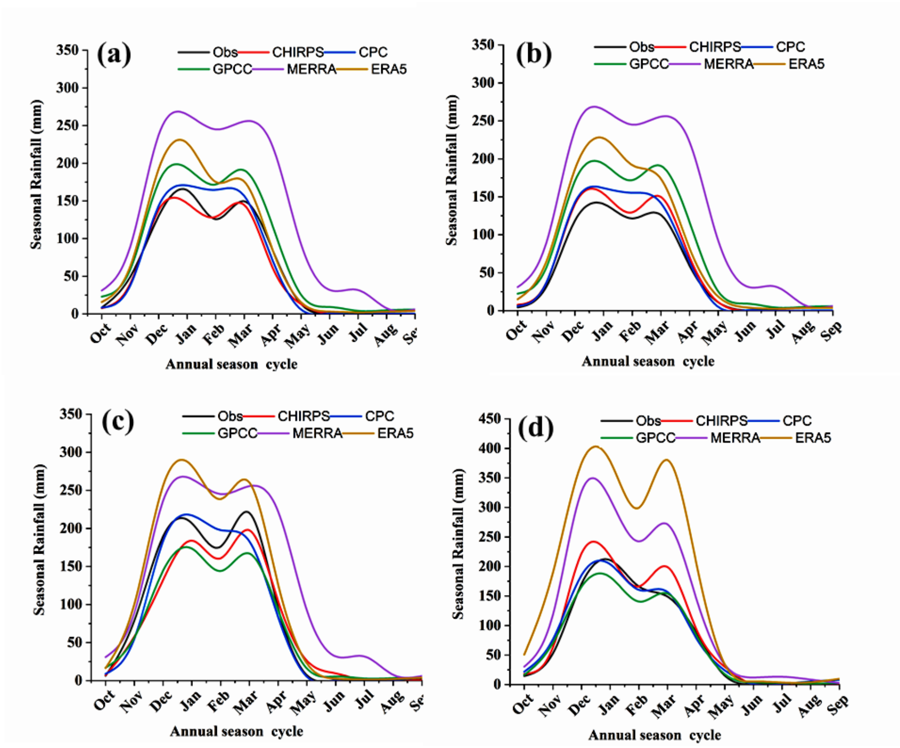

Figure 5: Annual seasonal cycle series for comparison between the observed precipitation data and Satellite-based precipitation data for (a) Iringa Maji (b) Nduli (c) Mafinga Bomani and (d) Mbeya Meteorological Station.

Overall, CHIRPS and CPC exhibited the lowest RMSE values, ranging approximately from 12–28 mm and 12–20 mm, respectively, while other products such as MERRA-2, GPCC, and ERA5 recorded higher errors. At the Mafinga and Mbeya stations, CPC achieved the smallest RMSE (~12.3 mm), outperforming CHIRPS, MERRA-2, GPCC, and ERA5. Conversely, at Iringa Maji and Nduli stations, CHIRPS demonstrated the best performance, with RMSE values between 12.2 and 14.4 mm (see Table 4). These contrasting results across stations can be attributed in part to the heterogeneous topography of the catchment, which significantly influences local rainfall dynamics. CPC, being gauge-driven, performed well in the highland regions (e.g., Mafinga and Mbeya), likely due to its ntegration of local observational data. In contrast, CHIRPS performed better in other areas where its high-resolution satellite estimates aligned more closely with observed rainfall patterns. Despite all datasets exhibiting non-negligible errors (RMSE >10 mm) across stations, they all maintained very high correlation with observed data on monthly and seasonal scales ($r > 0.9$), as demonstrated by the Taylor diagrams (Fig. 4) and seasonal rainfall cycles (Fig. 5). CHIRPS and CPC also consistently captured the unimodal annual rainfall regime dominated by the passage of the ITCZ more accurately than the other products across all stations. The strong performance of CHIRPS is likely due to its hybrid algorithm, which blends satellite observations with station data (Funk et al., 2015), allowing for effective calibration to local conditions. On the other hand, the higher errors and biases observed in MERRA-2 and ERA5 reflect the limitations of reanalysis products in tropical regions, where they often struggle to represent convective rainfall and complex terrain due to the lack of integration with ground-based observations (Ahmed et al., 2024). Similarly, GPCC, which depends entirely on sparse rain gauge networks, may fail to capture spatial rainfall variability between stations (Ahmed et al., 2024). Satellite-only products, while useful in ungauged areas, can also misrepresent rainfall magnitudes in mountainous or transitional zones. In summary, the variation in dataset performance underscores the influence of station density, terrain complexity, and algorithm design gauge-informed datasets tend to perform best where ground data are available, whereas reanalysis and satellite-based products require careful calibration in data-scarce or topographically complex environments.

Since CHIRPS performed better at monthly and seasonal timescales, further analysis was done to assess its performance with regard to the different rainfall indices. The results are presented in figure 6

5.2 Rainfall characteristics indices

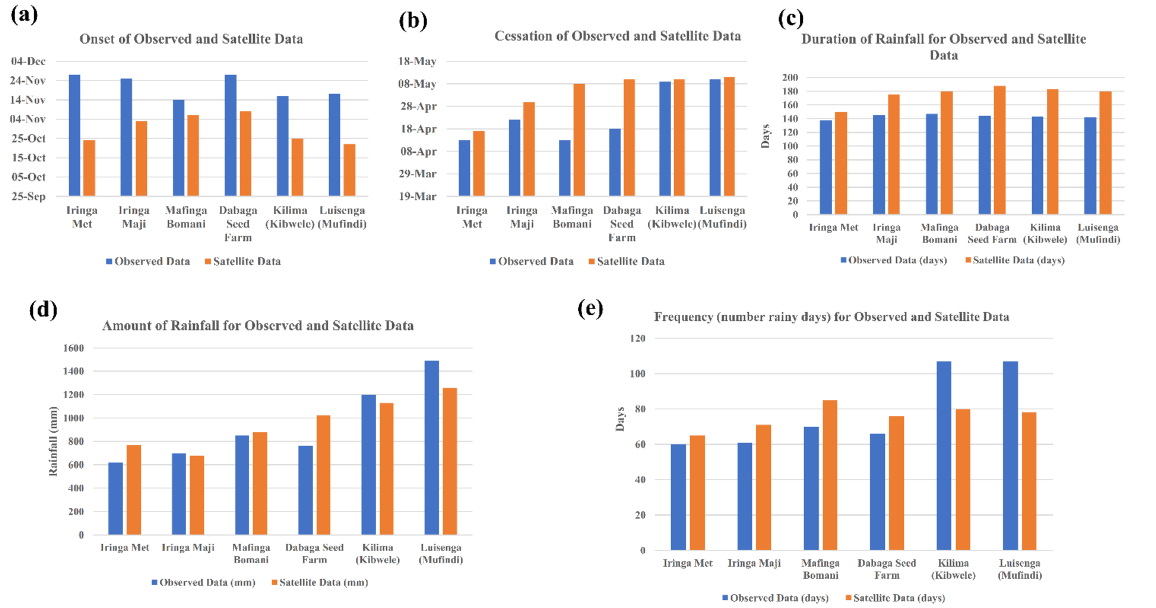

Figure 6: Comparison of rainfall indices between observed and CHIRPS satellite precipitation data (a) Onset of Rainfall (b) Cessation of Rainfall (c) Duration of the Rainfall (d)Amount of Rainfall and (e) Frequency of Rainy Days

(a) Onset and Cessation of Rainfall

As illustrated in Figure 6(a, b), satellite-based precipitation data generally indicate an earlier onset and a delayed cessation of the rainy season when compared to ground-based observations across most stations. This systematic discrepancy can be attributed to the spatial averaging and broader sensing capabilities of satellite products, which enable them to detect light, intermittent, or spatially dispersed rainfall events that point-based rain gauges limited by their fixed locations often fail to capture. A prominent example is found at Iringa Maji, where satellite data estimate the end of the rainy season to be approximately ten days later than recorded by the gauge, highlighting the potential of satellite datasets to capture prolonged or residual rainfall not evident in localized measurements.

These findings are consistent with previous research. For instance, Tan et al. (2015), found that satellite products tend to identify earlier rainfall onset and extended cessation periods due to their sensitivity to pre-season drizzle and post-season light rainfall, particularly in tropical regions like Malaysia. Similarly, Zhang et al. (2017) reported that in the Sahel region, satellite-derived rainfall data captured more extended rainy periods than ground stations, leading to longer perceived rainy seasons. In Ghana's Black Volta Basin, Logah et al. (2021) observed that satellite estimates not only predicted earlier onsets but also overstated the duration of the wet season, aligning closely with the patterns observed in this study.

These consistent findings reinforce the notion that while satellite rainfall products are invaluable for broad-scale climatic assessments, particularly in data-sparse regions, their application at local scales demands careful validation and calibration. The tendency to overestimate rainfall season duration can have implications for agricultural planning, hydrological modeling, and early warning systems, especially in regions where precise rainfall timing is critical.

(b) Duration of the Rainfall Season

As shown in Figure 6(c), the duration of the rainfall season estimated from satellite data is consistently longer than that derived from ground-based observations across all stations. This difference is likely due to the higher sensitivity of satellite sensors, which are capable of detecting light, scattered, or marginal rainfall events that often occur at the beginning or end of the rainy season, but fall below the detection threshold of point-based rain gauges. For instance, at Mafinga Bomani, the satellite-derived rainfall duration exceeds the observed duration by 31 days, suggesting that satellite products can capture prolonged or low-intensity rainfall activity extending beyond the traditionally defined wet season.

This finding aligns with the work of Logah et al. (2021), who found that satellite products such as CHIRPS and TAMSAT often reported longer growing seasons in Ghana's Black Volta Basin, largely due to their ability to detect early-season drizzle and late-season light showers that gauges often miss. Similarly, Tan et al. (2015) observed that satellite-derived rainfall seasons in Malaysia were consistently extended, particularly in humid regions, due to the influence of low-intensity rain events that were below gauge sensitivity. Zhang et al. (2017) also reported longer satellite-estimated rainy seasons in the Sahel, attributing this to the detection of low-frequency rainfall signals that are otherwise underrepresented in ground measurements.

Overall, these comparisons underscore the complementary nature of satellite and ground-based rainfall data. While satellite products offer broader spatial and temporal coverage, their tendency to overestimate rainfall duration especially in complex terrains or transitional climatic zones highlights the importance of calibrating satellite estimates with local observations for applications in agriculture, hydrology, and early warning systems.

(c) Amount of Rainfall

As shown in Figure 6(d), the total rainfall estimated from satellite datasets exhibits noticeable spatial variability when compared to ground-based observations. While some locations show higher totals in satellite-derived rainfall, others display lower estimates. This spatial inconsistency underscores the location-specific accuracy of satellite rainfall products, which can be affected by factors such as topography, microclimatic conditions, and sensor resolution. For example, at Dabaga Seed Farm Station which lies within the study area but was not part of the four stations used for statistical validation satellite estimates exceeded observed rainfall by 267.2 mm. This overestimation may be attributed to the broader spatial coverage of satellite sensors, which can detect rainfall events that point-based rain gauges may miss, particularly in heterogeneous terrain.

These findings are consistent with results reported by Ray et al. (2022) who found that satellite products displayed both under- and overestimations of rainfall depending on the station and landscape characteristics. Similarly, Ghorbanian et al. (2022) observed significant station-level discrepancies, attributing them to the inability of satellite data to resolve fine-scale rainfall patterns. Furthermore, (Logah et al., 2021) and (Sen Roy & Sen Roy, 2014) reported that satellite-based rainfall estimates often diverged from gauge data, especially in topographically diverse or climatically transitional regions. Collectively, these studies affirm that while satellite precipitation products offer valuable spatial coverage, their use in station-level or local-scale applications requires careful calibration and validation against observed data to ensure accuracy and reliability.

(d) Frequency of Rainy Days

As illustrated in Figure 6(e), satellite data generally report a higher number of rainy days compared to ground-based observations. This disparity is likely due to the enhanced sensitivity of satellite sensors, which can detect light and spatially scattered rainfall events that may not register at individual rain gauge stations. For example, at Mafinga Bomani, the satellite dataset recorded 16 additional rainy days relative to the observed data. The results of satellite overreporting are consistent with findings by Zhang et al. (2017), who found that satellite datasets showed increased frequency of low rainfall days (<10 mm) compared to ground data.

(e) Implications

Given the observed discrepancies and correlations between satellite-derived and ground-observed rainfall data, satellite products prove to be a valuable alternative for estimating rainfall patterns, particularly in regions where in-situ observations are sparse or unavailable. However, users should be mindful of systematic tendencies in satellite data, such as predicting earlier rainfall onset, later cessation, longer seasonal duration, and a higher frequency of rainy days. These tendencies reflect the satellite's sensitivity to light and scattered rainfall events and its broader spatial coverage, which, while advantageous, may lead to overestimation in certain localized applications.

The findings emphasize the complementary roles of satellite and ground-based rainfall data in hydrometeorological monitoring. Ground observations offer high-precision, point-specific measurements, whereas satellite data provide spatial continuity and extended coverage, especially in remote or under-monitored areas. However, MERRA-2 and ERA5 consistently underperformed compared to CHIRPS and CPC, particularly at the monthly time scale. This may be due to their reliance on global atmospheric models that are not locally calibrated and their limited ability to resolve convective rainfall patterns and terrain-driven variability common in the study area. For enhanced accuracy and utility, particularly in climate-sensitive sectors like agriculture and water resource management, calibration and validation of satellite data against local observations are essential. Moreover, employing data fusion techniques that integrate both sources can significantly improve the reliability, spatial completeness, and temporal resolution of rainfall assessments, ultimately supporting more informed decision-making in data-scarce environments.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study assessed the performance of five satellite-based precipitation products CHIRPS, CPC, GPCC, MERRA-2, and ERA5 in reproducing observed rainfall over the Little Ruaha Catchment in Tanzania. The results revealed that all datasets showed weak agreement at the daily timescale, with CHIRPS consistently outperforming the others in statistical accuracy and in reproducing rainfall characteristics.

At the monthly and seasonal scales, CHIRPS and CPC exhibited strong correlations with gauge data. CHIRPS particularly demonstrated the highest performance in capturing rainfall onset and cessation, seasonal duration, total rainfall, and number of rainy days. GPCC showed moderate accuracy, while MERRA-2 and ERA5 were the least reliable, particularly in reflecting temporal rainfall dynamics and extreme rainfall events.

The superior performance of CHIRPS is attributed to its finer spatial resolution, long-term record, and station-calibrated estimates, making it highly suitable for use in hydrological modeling, agricultural planning, and climate analysis in data-scarce regions such as the Little Ruaha Catchment.

However, caution is advised when using satellite data at high temporal resolutions due to the influence of topography and potential biases. Local calibration or bias-correction techniques are recommended to improve their performance in operational applications.

Overall, this study confirms that CHIRPS is the most dependable dataset among those evaluated and can serve as a credible alternative to gauge data for supporting water resource management and planning in regions with limited observational infrastructure.

Recommendations

Based on the findings of this study, the following recommendations are proposed to enhance the use of satellite-based precipitation products in hydrological and agricultural applications within data-scarce regions: one, the need to strengthen the ground-based observation network in the Little Ruaha Catchment. Additional rain gauges would improve the calibration and validation of satellite products, enabling more accurate rainfall estimates. Secondly, a need to apply bias correction techniques to satellite precipitation datasets before using them in hydrological and agricultural models. This step can reduce systematic errors and improve model performance. Finally, it is recommended to promote long-term monitoring and trend analysis using validated satellite data to track climate variability and support decision-making in water resource management and agricultural planning.

Based on the results of this study, several recommendations are advanced to improve the application of satellite-based precipitation products in hydrological and agricultural contexts within data-limited regions. First, there is a need to enhance the ground-based observation network in the Little Ruaha Catchment; deploying additional rain gauges would facilitate better calibration and validation of satellite-derived precipitation, thereby increasing the accuracy of rainfall estimates. Second, applying bias correction methods to satellite precipitation datasets prior to their integration into hydrological and agricultural models is advised to reduce systematic errors and improve model reliability. Lastly, it is recommended to encourage long-term monitoring and trend analysis using validated satellite data to effectively assess climate variability and inform decision-making for water resource management and agricultural planning.

Author contributions. All Authors have substantial contribution to this work

Conflict of interests: The Authors declare that they have no any conflict of interest**.**

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Nomenclature

Symbol	Definition	Unit
CHIRPS	Climate Hazards Group InfraRed Precipitation with Stations	— (dataset)
CPC	Climate Prediction Center	— (dataset)
ERA5	ECMWF Reanalysis Version 5	— (dataset)
GPCC	Global Precipitation Climatology Centre	— (dataset)
LGS	Length of Growing Season	days
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications Version 2	— (dataset)
NSE	Nash–Sutcliffe Efficiency	— (dimensionless)

PBIAS	Percent Bias	%
PET	Potential Evapotranspiration	mm/day
RCD	Rainfall Cessation Date	day (calendar date)
ROD	Rainfall Onset Date	day (calendar date)
RMSE	Root Mean Square Error	mm
RSR	RMSE-observations Standard Deviation Ratio	— (dimensionless)

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