Journal of Science and Technology, Vol. 44, No. 3 (2026), pp. 1-15
Kwame Nkrumah University of Science and Technology (KNUST)
https://dx.doi.org/10.4314/just.v44i3.1

EVALUATION OF SATELLITE RAINFALL PRODUCTS FOR WATER-RELATED STUDIES ACROSS BORNO STATE, NIGERIA

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ABSTRACT

Understanding rainfall variability is essential for sustainable rain-fed agriculture, optimised water resources management, and improved drought early warning systems in semi-arid regions such as Borno State, Nigeria. However, the scarcity of rain gauge networks limits accurate rainfall monitoring and drought assessment. With comprehensive spatial and temporal coverage, satellite rainfall products (SRPs) offer a viable alternative, but their accuracy requires local validation. The study evaluates the performance of the three SRPs, Precipitation from Remotely Sensed Information Using Artificial Neural Networks- Climate Data Record (PERSIANN-CDR), Climate Hazard Group InfraRed Precipitation with Station Data (CHIRPS), and Climate Research Unit Time Series (CRU TS), against rainfall data from the Nigeria Meteorological Agency (NiMet) from 1993 to 2021. Statistical techniques, including the correlation coefficient (r), mean absolute error (MAE), root mean square error (RMSE), and Bland-Altman analysis, were used for validation. Among the evaluated SRPs, PERSIANN-CDR exhibited the strongest agreement with the NiMet rainfall dataset (r = 0.85), and the lowest error metrics (MAE = 29.7 mm; RMSE = 50.2 mm). CHIRPS and CRU TS showed moderate correlation (r = 0.81- 0.82), and slightly higher error metrics (MAE = 29.5 - 33.3 mm, RMSE = 55.7 - 55.9 mm). Bias analysis revealed slight underestimation by PERSIANN-CDR (-5.1 mm) and CHIRPS (-5.5 mm), while showing slight overestimation by CRU TS (+6.5 mm). The results suggest that optimal planting periods should align with the onset of rainfall in late April to early May to maximise crop yield. These findings demonstrate that PERSIANN-CDR enhances localised drought monitoring, supports improved planting schedules, and strengthens agricultural planning and water management decision-making across Borno State, thereby contributing to food security, sustainable water use, and climate resilience in line with (SDG 2, 6, and 13).

Keywords: Satellite Rainfall Products, PERSIANN-CDR, CHIRPS, CRU TS, Rainfall validation, Borno State, NiMet

INTRODUCTION

Rainfall plays a vital role in water availability, agricultural productivity, and socio-economic stability in semi-arid regions (Rindap, 2020). In Borno State, Nigeria, declining and erratic rainfall patterns intensify drought risk, undermine rain-fed agriculture, and thereby threaten livelihoods (Mustapha and Arshad, 2014). Rising temperatures further compound these issues, with projections estimating a 6-10% decline in crop yields per degree Celsius increase, placing rain-fed agricultural systems at risk (Mustapha and Arshad, 2014). The near disappearance of Lake Chad is a stark example of the ecological consequences of these climate shifts (Mohammed *et al*., 2019). Accurate and consistent rainfall observations are essential for effective water management, drought preparedness, and climate resilience. In Borno State, Nigeria, the sparse rain gauge network, security challenges, and inconsistent data collection limit the ability to monitor rainfall accurately at scale (Dieulin *et al*., 2019). Conventional ground-based rainfall measurement techniques, such as rain gauges and radar, provide accurate localised data but lack the spatial coverage needed to capture large-scale hydrological patterns. The increasing variability of rainfall due to climate change further underscores the need for high-resolution continuous datasets (Akhtar *et al*., 2021; Liu *et al*., 2018; Zhang *et al*., 2020).

Satellite rainfall products (SRPs) have emerged as a transformative tool, offering high-resolution spatiotemporal coverage, particularly in data-scarce regions. This study focused on three widely used satellite rainfall products (SRPs) that have extensive temporal coverage and relatively fine spatial resolution, especially in data-scarce regions.

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record (PERSIANN-CDR) (Ashouri *et al*., 2015), provides daily global precipitation at a 0.25º resolution from 1983 onward. Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (Funk *et al*., 2015), dataset blends satellite infrared imagery with station data at 0.05º resolution from 1981 onward. Climatic Research Unit Time Series (CRU TS) (Beck *et al*., 2017) offers a long-term, gauge-based gridded precipitation data at 0.5º resolution extending back to 1901. Collectively, these products provide daily to monthly time steps, gauge-calibrated satellite estimates, and multi-decadal records, making them valuable datasets for predicting drought, floods, and long-term climate trends (Alijanian *et al*., 2019; Funk *et al*., 2015; Khatibi *et al*., 2019; Miao *et al*., 2015; Zhong *et al*., 2019)however their performance varies with respect to gauged precipitation data in different climatic regions. A limited number of studies investigated the performance of SREs for spatio-temporal (regional. Despite their potential, these products often exhibit biases and uncertainties due to their reliance on indirect measurements, necessitating local validation to ensure their reliability in water-related studies (Tang *et al*., 2016).

While global validation studies of SRPs are well documented, localised assessments tailored to semi-arid regions such as Borno State are notably limited (Le Coz *et al*., 2020; Shamkhi *et al*., 2019)which causes a paucity in the rainfall data, and these are regarded as the basic inputs for the models of water resources. Therefore, a good alternative information source is required. This paper gives a report on the applicability of using satellite derived precipitation data. Given the critical role of rainfall data in supporting water resource management, agricultural development, and climate adaptation, it is vital to evaluate the performance of SRPs under the specific hydrological and climatic conditions of Borno State. Localised validation not only enhances the precision of rainfall estimates but also improves their applicability in decision-making processes aimed at supporting drought resilience and sustainable water management.

This study addresses these gaps by evaluating the performance of three widely used SRPs, PERSIANN-CDR, CHIRPS, and CRU TS, against rainfall data from the Nigeria Meteorological Agency (NiMet) station, over 29 years (1993 to 2021). Statistical metrics, including Bland-Altman analysis, correlation coefficient (r), root mean square error (RMSE), and mean absolute error (MAE), were employed for a comprehensive assessment. By identifying the most reliable SRP for Borno State, this research provides practical insights for improving water-related studies, strengthening climate adaptation planning, and enhancing drought risk management. The findings also support progress toward Sustainable Development Goals (SDGs) related to food security (SDG 2) through better agricultural planning, strengthening water-resource management (SDG 6) via more reliable precipitation data, and improving climate action strategies (SDG 13) through enhanced drought monitoring and early warning.

MATERIALS AND METHOD (METHODOLOGY)

Study Area Description

Borno State is located in the north-eastern part of Nigeria, lying between approximately 10º00’N and 13º50’ North latitude and 11º30’ and 14º40’ East longitude (Figure 1). Covering an expansive land area of approximately 70,898 km², Borno is Nigeria’s second-largest state by landmass. Despite its vast size, it ranks as the eleventh most populous state, with a population estimated at 5.75 million based on the 2006 census and the 2019 population projections by the National Bureau of Statistics (NBS, 2013).

Borno State shares a boundary with Gombe State to the southwest, Adamawa to the south, and Yobe to the west. It also has international borders with Chad to the northeast, Niger to the north, and Cameroon to the east. The state’s economy is primarily agrarian, producing cash crops grown in the region, including cotton, sesame, and groundnut, which are widely cultivated, alongside food crops, including maize, millet, rice, sorghum, cassava, cowpea, and sweet potato. Livestock farming, particularly Cattle rearing, also holds significant potential for enhancing the agricultural value chain.

The topography of Borno State is predominantly flat plains interspersed with gently undulating terrain, particularly in the southern and southeastern parts, where hillier landscapes are observed, with elevation ranging from 325 m to 775 m above sea level. The climate is predominantly semi-arid, reflecting the Sudano–Sahelian ecological zone of West Africa and heavily influenced by its proximity to the Sahara Desert.. The region experiences an average annual temperature of 21 ℃, though extremes have been recorded, ranging from 47 ℃ (May 28, 1983) to 5 ℃ (December 26, 1979). The Annual rainfall averages around 215 mm, reflecting the semi-arid climate that defines much of the state’s ecological landscape (Babalola, 2014). This combination of climatic, geographic, and socio-economic characteristics underscores the vulnerability of Borno state to rainfall variability, emphasising the need for accurate rainfall data to inform sustainable development and climate resilience strategies.

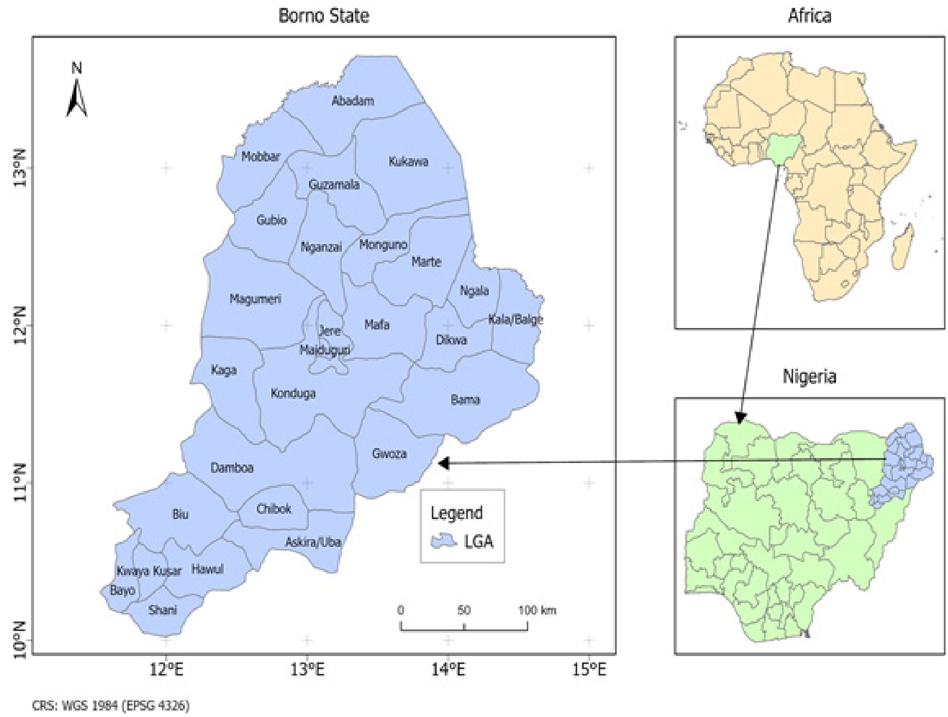

Figure 1: Map of Borno State indicating 27 Local Government Areas

The rainfall in the region is highly seasonal, averaging between 300 mm and 1000 mm annually (Adeaga and Olusegun, 2002). The rainy season is relatively short but intense, typically from June - September, while the rest of the year is marked by prolonged dryness. The spatial variability of rainfall across the state is closely tied to the seasonal movement of the Intertropical Convergent Zone (ITCZ), with the northeast parts of the state experiencing a shorter rainy season and lower annual rainfall compared to the southern parts of the region (Jidauna *et al*., 2012; Mansur *et al*., 2020)latest estimate by the Inter-governmental Panel on Climate Change (IPCC, 2002.

The climate of the region is further categorised into three main seasons based on temperature and moisture conditions: (i) the cold and dry season (November – February), commonly referred as the harmattan, characterized by lower temperatures ranging from 15 ℃ to 25 ℃ and dry northeasterly winds from Sahara Desert; (ii) the hot and dry season (March – May), marked by extreme heat and aridity with temperature occasionally exceeding 40 ℃; and (iii) the warm and moist season (June – September) during which temperature range between 28 ℃ and 34 ℃, which coincides with the main rainy season.

These seasonal variations exert a strong influence on agricultural activities, water resource management, and drought vulnerability across the region (Jajere *et al*., 2021)Maiduguri and Nguru Stations were used. Descriptive and inferential statistical tools were employed in analysing the data. The findings of the study revealed a significant year-to-year variability in rainfall characteristics around 61 years (1957-2017. This climatic variability, influenced by both regional and global atmospheric dynamics, highlights the crucial importance of accurate rainfall monitoring in Borno State. The unpredictable and uneven distribution of rainfall presents significant challenges for water management, agricultural productivity, and sustainable livelihoods. thereby emphasising the need for robust and locally tailored climate resilience strategies.

Rain Gauge (RG) Data

The study utilises rainfall data from rain gauge (RG) obtained from the Nigerian Meteorological Agency (NiMet), which has a limited number of stations across Borno State. The dataset comprised average monthly rainfall data over 29 years, from 1993 to 2021, compiled as a ground truth reference for validating satellite rainfall products. Given the reliability and currency of NiMet rainfall data, but recognising its sparse spatial coverage in Borno state, it was selected as the most dependable ground-based source available.

Before the analysis, both NiMet and SRPs datasets were screened for missing values and outliers. The monthly total of zero rainfall was retained as valid dry-season conditions typical of Borno's semi-arid climate, rather than the missing or erroneous data. Outlier screen confirmed that all values were climatologically reasonable. This ensured that the comparison between satellite rainfall products and gauge observations reflected true rainfall variability rather than artefacts of data gaps and errors.

Satellite Rainfall Products (SRPs)

The three satellite rainfall products were evaluated: PERSIANN-CDR, CHIRPS, and CRU TS. These datasets provide daily to monthly precipitation estimates at varying spatial resolutions and have been widely used in semi-arid climates for hydrological and climate studies. Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record (PERSIANN-CDR) is produced by the University of California, Irvine (UCI) Centre for Hydrometeorology and Remote Sensing, and Estimates rainfall between 60º N and 60º S using an artificial neural network (Fernando *et al*., 2022; Miao *et al*., 2015)the damages caused by flooding has been severe globally, and several research studies indicated extreme precipitations and changes in land-use plays a crucial role.

The hydrological and climate impact studies in data-scarce regions are relatively challenging, and several global dataset products have aided in overcoming them. However, their accuracy and reliability vary from climatic regions to the topography of the land surface. Therefore, this study employed global dataset products for precipitation and land use to identify the major flood driver in tropical, subtropical, and temperate regions where severe flooding had occurred in the past decade. The study evaluated the performances of the PERSIANN-CDR, PERSIANN-CCS and PERSIANN precipitation products, and ESACCI-LC land-use product to develop a statistical relationship among the land-use and extreme precipitation variables using the Multiple Linear Regression technique. The result shows that the PERSIANN-CDR estimates were more accurate than others in the selected study basins. The statistical model showed that the combined contribution of both land-use and precipitation to the flood (R2. The PERSIANN-CDR dataset can be accessed through NOAA's NCDC CDR program website in the atmospheric CDR category at https://chrsdata.eng.uci.edu/.

Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) is jointly produced by the Climate Hazard Group at UCSB and the US. Geological Survey. It blends satellite data with rain gauge records, using infrared Cold Cloud Duration information (Haigen and Yanfei, 2019), and offers data at a spatial resolution of 0.05º x 0.05º per month, with near-real-time and monthly temporal updates (Paredes-trejo *et al*., 2017; Retalis *et al*., 2017; Serrat-capdevila *et al*., 2016). The CHIRPS rainfall dataset, which covers most of the globe, can be accessed through ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0.

Climate Research Unit Time Series version 4.2 (CRU TS) was developed by the University of East Anglia, UK, at a resolution of 0.5º x 0.5º and provides a long-term gauge-based gridded precipitation dataset extending back to 1901 (Harris *et al*., 2020). CRU TS version 4.02 dataset can be accessed through http://www.cru.uea.ac.uk/data/.

Methods

The study adopted a point-to-point comparison method. The geographic coordinates of the NiMet station in the study area are used to extract rainfall estimates from the SRPs. Data extraction and aggregation were performed using Python 3.10.18.

Each satellite dataset was resampled to align with the NiMet station coordinates, ensuring spatial compatibility for direct comparisons. All datasets were aggregated to a consistent monthly time scale for the 1993 – 2021 study.

Several statistical metrics were employed to assess the accuracy of the SRPs, including correlation coefficient (r), mean absolute error (MAE), root mean square error (RMSE), and Bland-Altman plot analysis (Bias). Before the analysis, both NiMet and SRPs datasets were screened for missing values and outliers.

The monthly total of zero rainfall was retained, as it represents true dry-season conditions typical of the Borno semi-arid climate rather than missing or erroneous records. This temporal harmonisation and quality control ensured reliable and consistent comparisons between satellite products and gauge rainfall data. The methodological flowchart is summarised in Figure 2

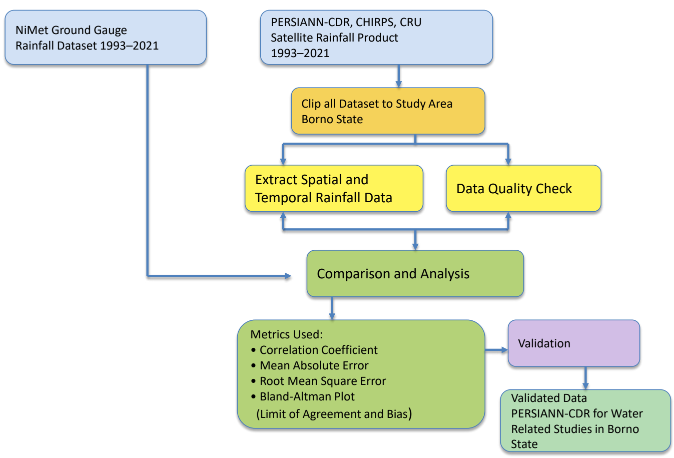

Figure 2: Methodological flowchart of Work Involved

Bland-Altman plot and Bias Analysis

The Bland-Altman plot approach was applied to visually assess the agreement between the satellite rainfall products and NiMet gauge data. This graphical method highlights both the systematic difference (bias) as the central solid line and the 95% limits of agreement as the green dotted lines, thereby revealing both systematic and random discrepancies between paired measurements. Figure 4 presents the Bland Altman plots comparing NiMet rainfall data with (a) PERSIANN-CDR, (b) CHIRPS, and (c) CRUS TS satellite rainfall products for Borno State, from 1993 to 2021.

The mean difference (bias) derived from Bland Altman plots quantifies the average deviation of each satellite product from gauge observations.

A bias close to zero indicates minimal error, while positive or negative values indicate overestimation or underestimation (Moucha *et al*., 2021). Equation (1) presents the formula used to compute the bias, as the average difference between the satellite estimates ($X_{sat,i}$) and the observed gauge measurement ($X_{obs,i}$) represents the difference for each observation.

$$\text{Bias} = \frac{1}{n}\sum_{i=1}^{n}\left(X_{Sat,i} - X_{Obs,i}\right) \quad \textbf{eqn 1}$$

where *n* is the number of paired observations, and $\epsilon i = X_{Sat,i} - X_{Obs,i}$ represents the difference for each observation.

Correlation Coefficient

The correlation coefficient (r) quantifies the strength and direction of the linear association between NiMet rainfall data and the satellite rainfall products. two variables. It measures how closely paired values vary together relative to their respective means. The coefficient ranges from -1 to +1. Values approaching ±1 represent stronger correlations. A value of +1 indicates a perfect positive linear relationship, while -1 denotes a perfect negative linear relationship (Moucha *et al*., 2021). Equation (2) presents the formula used for computing the correlation coefficient (r).

$$r = \frac{\sum_{i=1}^{N}(S_i - \bar{S})\,(G_i - \bar{G})}{\sqrt{\sum_{i=1}^{N}(S_i - \bar{S})^2}\sqrt{\sum_{i=1}^{N}(G_i - \bar{G})^2}} \quad \textbf{eqn 2}$$

Where Σ represents the sum of all data, G_i and *Si* are individual data points for the average of measurements and difference, and *Si* and *Gi* are satellite and gauge rainfall at the i-th observation, and and are the means of ground gauge *(G*) and satellite (*S)* respectively.

Mean Absolute Error (MAE)

The mean absolute error (MAE) is used to quantify the average magnitude of the differences between satellite rainfall products and the NiMet rain gauge (RG) measurements. Equation (3) presents the formula used to compute MAE.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Si - Gi| \quad \textbf{eqn 3}$$

where $\sum(|S\_i - G\_i|)$ is the sum of the absolute difference between the corresponding measurements from two methods for each data point; *n* is the overall number of data points; and S_i and *Gi* are satellite and gauge rainfall at the *i-th observation.*

Root Mean Square Error (RMSE)

The RMSE quantifies the average magnitude of the differences between satellite and rain gauge observations. RMSE values are always positive and reflect the amplitude of the error. Consequently, a model may appear accurate based on a Bias close to zero but still show high RMSE values if positive and negative errors cancel each other out. RMSE, therefore, complements Bias by measuring error magnitude, whereas Bias identifies overestimation or underestimation of rainfall amounts (Moucha *et al*., 2021; Salih *et al*., 2022). Equation (4) presents the formula for calculating RMSE.

$$RMSE = \sqrt{\frac{1}{n} + \sum_{i-1}^{N}(S_i - Gi)^2}$$ **eqn 4**

Where $(S_i - Gi)^2$ is the squared difference between satellite and gauge measurements for the i-th observation, and n is the total number of paired observations.

RESULTS AND DISCUSSION

Monthly Rainfall Patterns

Figure 3a - c presents the monthly rainfall patterns of Borno State derived from the Nigeria Meteorological Agency (NiMet) rainfall data, along with three satellite rainfall products (SRPs): PERSIANN-CDR, CHIRPS, and CRU TS, for the period 1993 to 2021. The graphical comparisons reveal consistent seasonal trends across all datasets.

Rainfall typically begins in April, intensifies between June and September (the peak rainy season), and then drops sharply from October to March (the dry season). Among the three SRPs, PERSIANN-CDR aligns closely with NiMet rainfall data, especially during high rainfall months, though it slightly underestimates peak values.

CHIRPS follows the general seasonal trend but shows more notable deviations during the rainy season, underestimating peak rainfall values.

CRU TS displays the highest variability, with occasional overestimation or underestimation in certain years. In critical rainy years such as 1999, 2007, 2014, and 2020, PERSIANN-CDR aligned most closely with NiMet rainfall data, especially during peak months. CHIRPS and CRU TS displayed greater inconsistencies. The overall pattern shows that all SRPs effectively captured the seasonal rainfall cycle of Borno State; however, PERSIANN-CDR exhibited the greatest reliability for hydroclimatic applications.

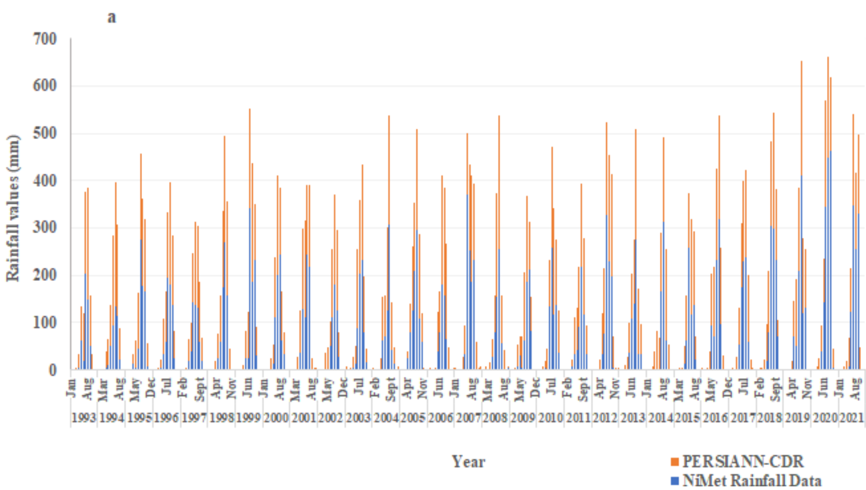

Figure 3a: NiMet Rainfall Data and PERSIANN-CDR Patterns of Borno State 1993–2021

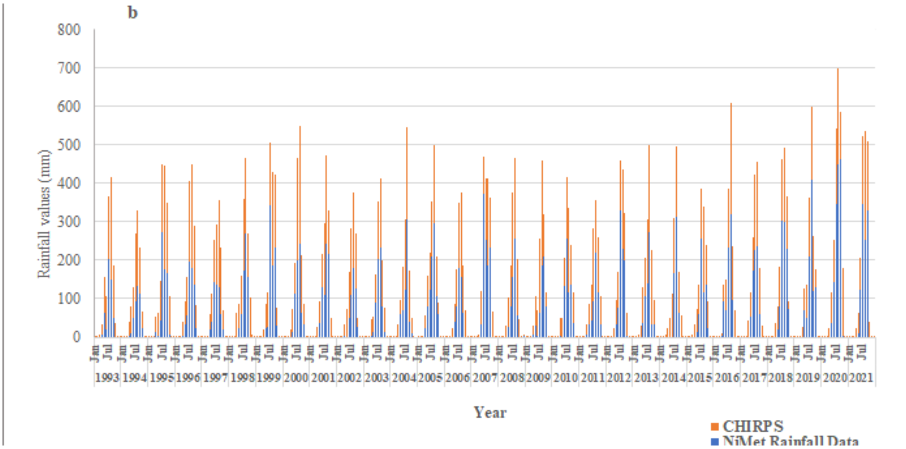

Figure 3b: NiMet Rainfall Data and CHIRP Patterns of Borno State 1993-2021

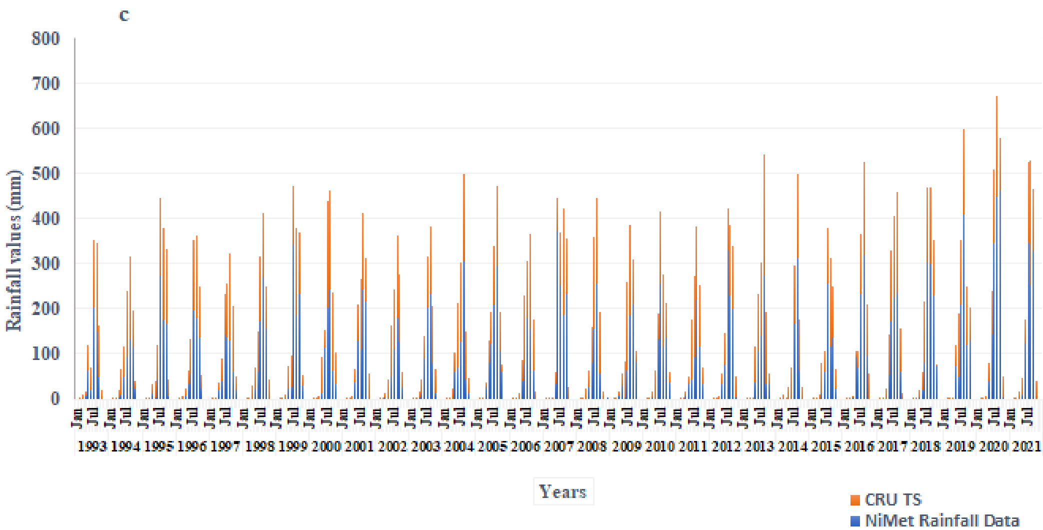

Figure 3c: NiMet Rainfall Data and CRU TS Pattern of Borno State 1993-2021

Statistical Performance of Satellite Rainfall Products Compared with NiMet Rainfall Data

A statistical comparison between NiMet rainfall data and the three satellite rainfall products (SRPs) is presented in Table 1. The evaluation metrics, including the correlation coefficient (r), mean absolute error (MAE), root mean square error (RMSE), and bias, were used to assess the performance and reliability of each dataset in replicating observed rainfall patterns.

Table 1. Statistical Performance Metrics Comparing NiMet Rainfall Data with Satellite Rainfall Products (SRPs: PERSIANN-CDR, CHIRPS, and CRU TS)

Dataset	Correlation	MAE (mm)	RMSE (mm)	Bias (mm)
NiMet versus PERSIANN-CDR	0.85	29.7	50.2	-5.1
NiMet versus CHIRPS	0.81	33.3	55.9	-5.5
NiMet versus CRU TS	0.82	29.5	55.7	6.5

Among the three SRPs, PERSIANN-CDR demonstrated superior performance, recording the highest correlation with NiMet rainfall data (r = 0.85) and the lowest error values (MAE = 29.7 mm, RMSE = 50.2 mm). Its narrow limits of agreement (-103.6 to 92.3 mm) and low bias (-5.1 mm) indicate greater accuracy in estimating rainfall compared to CHIRPS and CRU TS. These results correspond with previous studies, such as (Awange *et al*., 2016), which identified PERSIANN-CDR as a robust tool for monitoring rainfall validation across Africa. The current study strengthens evidence through localised validation specific to Borno State, where the ground gauge network is sparse. By contrast, CHIRPS and CRU TS exhibited moderate correlations (r = 0.81 and 0.82). CHIRPS displayed higher error values (MAE = 33.3 mm, RMSE = 55.9 mm), while CRU TS produced comparable error metrics (MAE = 29.5 mm, RMSE = 55.7 mm), but with greater variability in rainfall estimation. In terms of bias, both PERSIANN-CDR and CHIRPS underestimated rainfall, with biases of -5.1 mm and -5.5 mm, respectively (see Figure 4 and Table 1). Whereas CRU TS tended to overestimate rainfall with positive bias (+6.5 mm), particularly during low-rainfall months and transitional periods (see Figure 3c). The findings align with previous studies, such as (Awange *et al*., 2016), which highlighted the robustness of PERSIANN-CDR for rainfall monitoring across Africa. The current validation strengthens this evidence within the context of Borno State, providing a region-specific understanding of SRPs reliability where the ground gauge network is sparse.

Bland-Altman Plots Analysis

The Bland-Altman plots Figure 4a-c illustrate the limit of agreement between NiMet rainfall data and the three SRPs datasets (PERSIANN-CDR, CHIRPS, and CRU TS). These plots highlight the mean difference (bias) at 95% limits of agreement, thereby providing insights into both systematic error and variability.

PERSIANN-CDR Figure 4a exhibited the narrowest limits of agreement (-103.6 to 92.3 mm), indicating minimal variability and strong consistency with NiMet data.

The small negative bias (-5.1 mm) suggests a slight underestimation of rainfall. CHIRPS (Figure 4b) displayed wider limits of agreement (-114.1 to 104.2 mm), reflecting greater variability. Its negative bias (-5.5 mm) also indicates underestimation, though the deviation is more pronounced than for PERSIANN-CDR. CRU TS Figure 4c showed the limit of agreement (- 102.05 to 115.1 mm), comparable to CHIRPS but exhibited a positive bias (+6.5 mm), suggesting a tendency to overestimate rainfall relative to NiMet rainfall data.

Overall, the Bland-Altman analysis Figure 4a-c confirms that PERSIANN-CDR provides the closest agreement and the lowest variability, reinforcing its reliability for rainfall estimation across Borno State. CHIRPS and CRU TS showed moderate agreement but greater fluctuations, limiting precision for fine-scale hydrological assessment

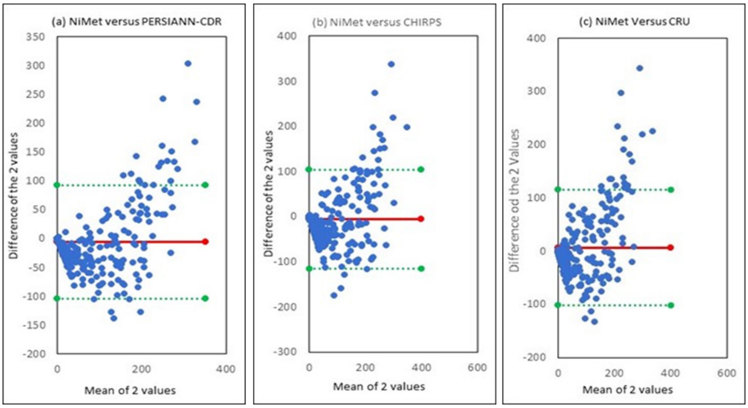

Figure 4a-c: Bland Altman Plot of Rainfall: (a) NiMet Rainfall Data versus PASIANN-CDR: (b) NiMet Rainfall Data versus CHIRPS: and (c) NiMet Rainfall Data versus CRU TS. The Plot Shows the Mean Difference and the Limit of Agreement

Implications of Water and Agricultural Resource Management

The demonstrated accuracy of PERSIANN-CDR suggests its strong potential for enhancing drought early warning systems and improving decision-making in water and agricultural management. Accurate rainfall estimation is crucial in Borno State, where over 70% of the population relies on rain-fed agriculture. Given that rainfall onset typically occurs in April and ceases around October, PERSIANN-CDR reliable replication of seasonal cycles makes it an effective tool for determining optimal planting windows and managing irrigation schedules. Early detection of rainfall deficits can guide timely interventions, mitigate the impacts of drought, and improve the predictability of crop yields.

The datasets' consistency supports reservoir operations, groundwater recharge planning, and flood risk mapping, which are critical for sustainable water resource management in semi-arid regions. The integration of SRPs such as PERSIANN-CDR into climate monitoring frameworks can therefore advance food security, strengthen drought preparedness, and enhance resilience to climate variability across the region.

CONCLUSION

The study highlights the potential of satellite rainfall products (SRPs), particularly PERSIANN-CDR to effectively supplement the limited rain gauge network in Borno State. Among the evaluated datasets, PERSIANN-CDR demonstrated superior performance, achieving the highest correlation with NiMet rainfall data and the lowest error metrics, confirming its reliability for rainfall estimation, drought monitoring, and water resource management. Its strong agreement with observed rainfall patterns reinforces its suitability for supporting sustainable development goals related to food security (SDG 2). clean water and Sanitation (SDG 6), and climate action (SDG 13). Future research should integrate PERSIANN-CDR with other climate datasets and explore hybrid modelling approaches to further enhance rainfall estimation accuracy across diverse climatic and topographical conditions.

FUNDING

Funding for this project was provided by the World Bank through the Africa Centres of Excellence Project, in collaboration with the Regional Water and Environmental Sanitation Centre (RWESCK), at Kwame Nkrumah University of Science and Technology, Ghana, and the Water Resources Institute, Kaduna,

Nigeria. The opinions expressed in this paper are solely those of the authors and do not necessarily reflect the views of the World Bank, the Government of Ghana, NWRI, or KNUST.

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