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# Evaluation of ground-based, daily, gridded precipitation products for Upper Benue River basin, Nigeria

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**Abstract**

In-situ rain gauge stations are not adequately covering the total area of Upper Benue basin in Nigeria. An accurate gridded precipitation dataset is therefore required for climate study, hydrological modelling and water resource management. For this purpose, three candidates of global, gauge-based, daily, gridded precipitation products were evaluated and compared with the monitoring data from eight stations spanning 25 years period from 1982 to 2006. The three products are Climate Research Unit (CRU), the Climate Prediction Centre (CPC), and the Global Precipitation Climatology Centre (GPCC). The evaluations covered spatial analyses and statistical validations for daily, monthly, seasonal, and extreme rainfall data. Results show that all the three datasets captured well the spatial rainfall characteristics and were able to replicate the rainfall gradient and orographic conditions of the study area, though the GPCC dataset outperformed the others. Line plots and scatter plots were used to compare the gridded datasets with the observation data for monthly data. The GPCC and CRU datasets are both better than that of the CPC. We also used the mean absolute error, the mean bias error, the correlation coefficient, and the modified index of agreement to compare daily data, and found that the GPCC set is the most agreeable with the observation and the CPC set is the least. The daily gridded data products were also compared using probability distribution similarity, with the in-situ data by KS and AD tests. We found the distributions of GPCC and CRU datasets to follow the same distribution as that of the rain gauge data but that of the CPC does not. The results of the extreme events namely annual maximum numbers of consecutive dry-, wet-day, and total rainfall depth show that the dataset of GPCC is the most compatible with the observation and the CPC set is again the least. The most suitable daily ground-based gridded precipitation dataset for hydrological study and modelling in the Upper Benue basin is therefore the GPCC.

**Keywords:** Accuracy, Evaluation, Gridded precipitation data, Hydro-climatology, Spatiotemporal, Upper Benue River basin

## 1. Introduction

Accurate and consistent precipitation records are crucial for the analyses of climate variability and trends [1], hydrologic impacts studies, sustainable water resources management, agriculture, and disaster management [2]. Direct measurements from rain gauge networks are conventionally the most reliable source of Earth's surface precipitation records [3-5]. In many parts of the world, including Nigeria, gauge observations are characterized with sparse and uneven distributions [6-10], especially over Upper Benue River basin, Nigeria, which has very steep rainfall gradient and orographic effects. Moreover, rain gauge measurements are prone to errors arising from instrument operations, human operators and data transmission. In some cases, the data qualities are usually not fit for hydro-climatological assessments [9, 11].

In recent years, several large-scale precipitation datasets at different spatiotemporal scales have evolved [1]. They include model reanalysis, satellite-based, radar-based, and ground-based datasets, and their combinations [9, 10, 12, 13]. Reanalysis and gauge-based gridded precipitation datasets have found wide applications among climate scientists, owing to their inherent long-term records, which particularly, made them suitable for climate studies. Satellite-based and radar-based products have limitations in this regard, but have proved useful for weather process and hydrological monitoring [1, 14]. The approach in gauge-based gridded products consists of extensive collection of ground observation measurements, quality control, and rain gauge data analysis across the globe to arrive at the products. Reanalysis products are derived from assimilating models with rain gauge data. Simplification of complex climatic system in modelling together with incomplete observation data always produce erratic datasets [15]. Examples of reanalysis datasets are the Modern-Era Retrospective Analysis for Research and Application version 2 (MERRA -2) [16], the Japanese 55-year Reanalysis (JRA-55) [17], and the Climate Forecast System Reanalysis (CFSR) [18]. These datasets were classed as the least confident [19]. Satellite-based datasets are resulted from interpretation of indirect radiation measurement using complex algorithms rendering large uncertainties [3]. The examples of satellite-based products are the Tropical Rainfall Measuring Mission (TRMM) and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) [6]. Radar-based products can provide very high resolutions but most of them are localized and not existed in the Upper Benue basin.

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We were interested in the global daily ground-based gridded precipitation products with the spatial resolution of half a degree. Three popular datasets covering the Upper Benue basin are (i) the Climate Research Unit (CRU) at the University of East Anglia products [20, 21], (ii) the Climate Prediction Centre (CPC) global unified gauge-based analysis of daily precipitation [22], and (iii) the Global Precipitation Climatology Centre (GPCC) full data daily product version 2018 [23]. The Benue River is the main tributary of the Niger River in Nigeria. Its watershed is divided into Upper and Lower basins, and they are two of the eight hydrological regions of Nigeria, known as HA-3 and HA-4, respectively [24]. The water resource management of the Benue River basin i.e. flood, drought, irrigation, and water supply depend largely on the accurate rainfall data of the basin especially the Upper Benue basin. Due to complex topography and adverse climatic condition of the area, its scarce rain gauge data can be substituted by a daily gridded dataset. The objective of our study was to evaluate the fore mentioned three global daily ground-based gridded precipitation products by comparison with the available rain gauge data of the Upper Benue River basin using spatial distribution and statistical methods to daily, monthly, seasonal, and extreme precipitation data.

## 2. Materials and methods

### *2.1 The study site*

The Upper Benue basin is situated between tropical rain forests of southern Nigeria and the Savannah of the north consisting of Adamawa, Bauchi, Gombe and Taraba states (Figure 1). Its hydrological area is designated as HA-3, representing one of the eight hydrological areas in Nigeria. It is identified as one of the twelve River Basin Development Authorities (RBDA), with its headquarters in Yola. The basin extends over an area of 156,546 km2, bounded by Jos plateau in the west, Cameroon highlands in the south and Biu plateau in the north-eastern region. Thus, the basin has a wide range of topography, with elevation varying between 90 m over Ibi to a maximum of 2367 m above mean sea level over Mambilla Plateau. The elevations at Jos and Biu Plateaus are 1750 m and 900 m respectively. The micro-climate of the region is greatly influenced by its varying topography. Annual rainfall over the basin ranges from 700 mm to over 1800 mm [25] which contributes about 60.2 billion m3 to the total annual flow of River Benue [26]. Ninety per cent of the rain falls during the period of May to October. The mean annual temperature of the basin is 26 0C though it is lower on the plateaus. The basin accommodated 10.866 million people in 2006, and the population is expected to reach 19.40 million by 2030 [25]. The major occupation of the inhabitants is rain-fed agriculture. Thus, agro- as well as hydro-climatic studies for the region are vital to food security and economic growth. Despite these potentials, the rain gauge observation measurements in the region are sparse and unevenly distributed. In view of this, it is crucial to compare gauge-based precipitation products over the basin with available rain gauge observations, to reveal the extent to which gridded precipitation products can be relied upon.

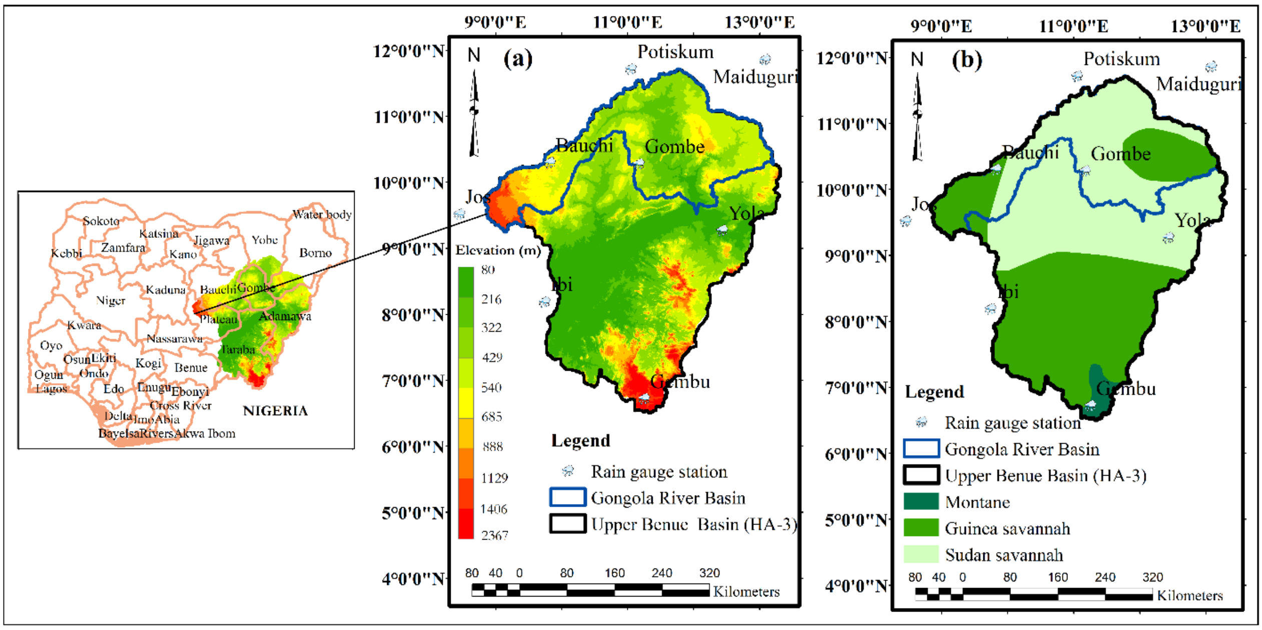


**Figure 1** Upper Benue Basin (HA-3) showing (a) Topography and (b) Climate including the rain gauge stations

### *2.2 Data and data sources*

#### *2.2.1 Rain gauge data*

Rainfall data of the eight stations were acquired from Nigerian Meteorological Agency (NiMET), Abuja, and Upper Benue River Basin Development Authority (UBRBDA), Yola. The data were used as reference for these evaluations, they are of daily temporal resolution for the period of 1982-2006. The distributions of these stations are sparse and uneven over the basin (Figure 1), the number of stations maintained by the agency are in most cases not more than one in each state in the case of NiMET. Although, meteorological data are measured by some other sister organisations, however, the data are in most cases characterised with data gaps, which render such datasets unsuitable for hydrological impact studies. Interestingly, the stations are situated at key locations over the basin, where measurements are most critical. NiMET ensures adequate quality checks before releasing the data. However, the data were thoroughly checked for accuracy and consistency for reliable evaluations.

*2.2.2 Gauge-based precipitation products*

We evaluated three global ground-based gridded datasets which are of daily for temporal resolution, 0.5°x0.5° for spatial resolution and cover the period of 1982 to 2006. These three datasets are CPC-Global, CRU TS3.10, and GPCC v.2018. They are available over the Upper Benue River basin and are briefly described below.

The Climate Prediction Centre gauge-based analysis of global daily precipitation product was initiated by the NOAA Climate Prediction Centre. The mandate is to create a set of unified precipitation datasets with improved quality and inter-product consistency to suite a wide range of applications. In formulating the CPC-Global datasets, gauge reports from over 30,000 stations worldwide including Global Telecommunication System (GTS), COOP and other national and international agencies, consisting of in-situ measurements and satellite estimates were utilised [22]. The product is freely available on 0.5° lat/long grids over the entire global land areas from 1979-present.

The Climate Research Unit (CRU TS3.10) consists of gridded climatological variables at monthly scales covering the entire global land surface, at half-degree spatial resolutions for 1901-2014 [20]. The datasets were developed at the University of East Anglia with major contribution from World Meteorological Organization. The data sources are mainly from CLIMAT, MCDW and WWR consisting of over 4000 stations globally [27]. However, the daily datasets of the CRU are available globally for the period 1970-2006, downloadable from www.2w2e.com [21].

The Global Precipitation Climatology Centre (GPCC) is a gauge-based gridded precipitation product for the global land surface. It was established in 1989 on the request of the World Meteorological Organisation (WMO) with a unique capability of analysing daily and monthly precipitation, based on in-situ rain gauge observations [23]. The Full Data Daily Product V.2018 which is freely available online at spatial resolution of 0.5° lat/long on a period of 1982-2016. The data has received much attention among the scientific communities owing to its improved quantitative accuracy. This version was based on more than 35,000 stations per month.

*2.3 Methods*

The evaluation of the gridded precipitation products in this study considered two approaches i.e. climatological descriptions and statistical analyses. The climatological descriptions were to study and compare the rainfall estimates in four seasons of the year, which are the dry season - December, January, February (DJF); pre-rainy season - March, April, May (MAM); rainy season - June, July, August (JJA); and post-rainy season - September, October, November (SON) [27]. Though, only JJA was reported, the analysis considers a common period of 1982-2006 in eight stations over the basin.

We considered the statistics for the performance evaluations based on insight from literatures. The statistical indicators being chosen were mean bias error (MBE), mean absolute error (MAE), coefficient of correlation (r), and modified index of agreement ($d_{mod}$) as demonstrated by Pereira et al. [28]. Further evaluations, use the test of similarity, using Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests and scatter plots. In addition, few selected climate indices such as, maximum consecutive dry days (CDD), maximum consecutive wet days (CWD) and annual total wet-day precipitation (PRCPTOT) were analysed to determine the suitability of the datasets for hydrologic applications as contained in Gampe and Ludwig [29]. The statistical indices are defined as follows [9, 27].

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(X_{grid} - X_{obs}\right) \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|X_{obs} - X_{grid}\right| \quad (2)$$

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left[\left(\frac{X_{grid}-\bar{X}_{grid}}{\sigma_{grid}}\right)\left(\frac{X_{obs}-\bar{X}_{obs}}{\sigma_{obs}}\right)\right] \quad (3)$$

$$d_{mod} = 1 - \frac{\sum_{i=1}^{n}|X_{grid}-X_{obs}|}{\sum_{i=1}^{n}|X_{grid}-\bar{X}_{obs}|+|X_{obs}-\bar{X}_{obs}|} \quad (4)$$

where $X_{grid}$ and $X_{obs}$ refer to gridded and observed data; n is number of observations; $\bar{X}_{grid}$ and $\bar{X}_{obs}$ are the mean values of gridded and observed data; $\sigma_{grid}$ and $\sigma_{obs}$ are the standard deviations of the gridded and observed data, respectively.

In MBE, a smaller absolute value indicates a better performance, while negative or positive value measures under– or overestimation of model respectively; MAE draws the mean difference between observed and gridded data, r measures the strength of the linear relationship between two variables, r = 1 indicates perfect positive relationship, while r = -1 shows perfect negative relationship and, r = 0 means no relationship whatsoever between the two variables. Similarly, the values of $d_{mod}$ varies from 0 to 1, 1 implies a perfect agreement and 0 shows no agreement between the two sets of variables.

In order to test the similarity between the two sets of samples, KS and AD tests were used to measure the difference of the probability distributions of the rain gauge observations and the gridded precipitation data. A significance level (p-value) of 0.05 was used, which implies that the null hypothesis would be rejected, should the test yields value less than 0.05.

The data quality checks and evaluations of the climate indices considered the use of R ClimDex (1.0) – a source code in R software packages, as contained in Zhang and Feng [30], freely available at (http://etccdi.pacificclimate.org/software.shtml) and as utilised by Zhang et al. [31, 32]. The programme identifies outliers and detects for instance, a precipitation amounts less than 0 mm and exclude them from the dataset prior to analysis. The CDD, CWD and the PRCPTOT were analysed using the same software package.

## 3. Results and discussions

### *3.1 Annual distribution of seasonal variation of rainfall*

The mean quarterly spatial rainfall climatology from GPCC, CRU and CPC were evaluated and compared with the reference ground observation data over Upper Benue Basin for 25 years' period. However, the spatial rainfall patterns for the rainy season (June, July, August) are shown in Figure 2. All the analysed precipitation products are consistent in capturing the general north-south gradient with higher precipitation in the south, around Mambilla Plateau. The GPCC demonstrated the best capability in capturing the localised high rainfall amount around Mambilla Plateau, Jos Plateau and high Bauchi plains, and appeared to be in near perfect agreement with the observed features. Although, the CRU dataset showed good agreement with the reference data, but with less capability. However, the CPC failed to capture the orographic related high rainfall around Jos plateau and it therefore appeared to be the least in representing the spatial rainfall distributions over the basin.

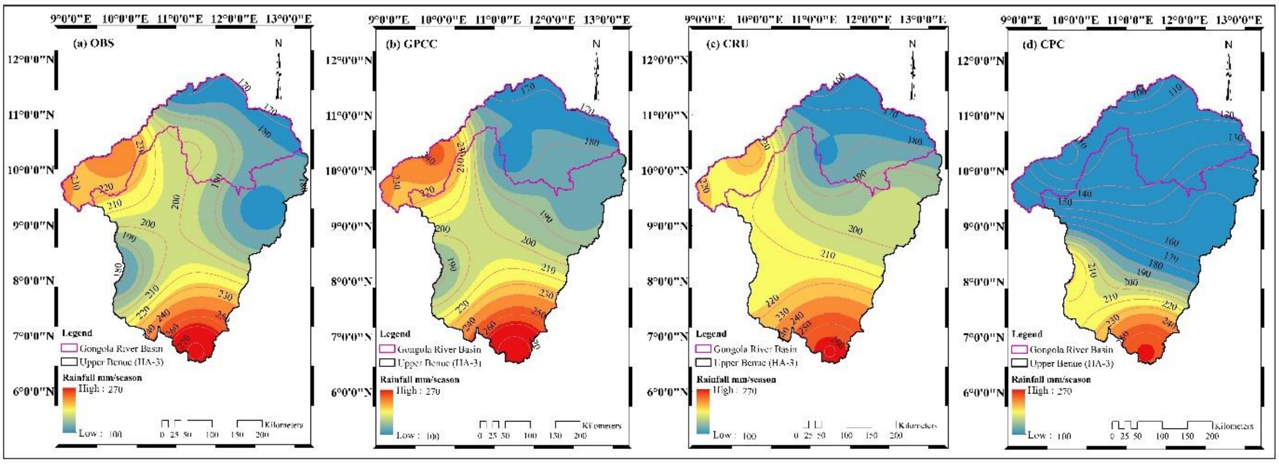


**Figure 2** Spatial rainfall distributions for rainy season (JJA) of different datasets during 1982-2006.

### *3.2 Assessing the mean monthly rainfall*

The skills of the gridded precipitation products in replicating the mean annual cycle of precipitation climatology over the basin was assessed using line charts as shown in Figure 3. It is evident that ninety percent of the rain falls between the period of May to October with a marked peak in August, except for the southern region where the peak occurs in September. However, the rain band in the most northern part mainly occurs from May to September.

It is worth noting that all the datasets captured well the pattern, except CPC which grossly underestimated the rainfall amount in almost all the stations. GPCC and CRU showed better agreement with the ground reference observations over the entire basin, although GPCC is more consistent with superior performance.

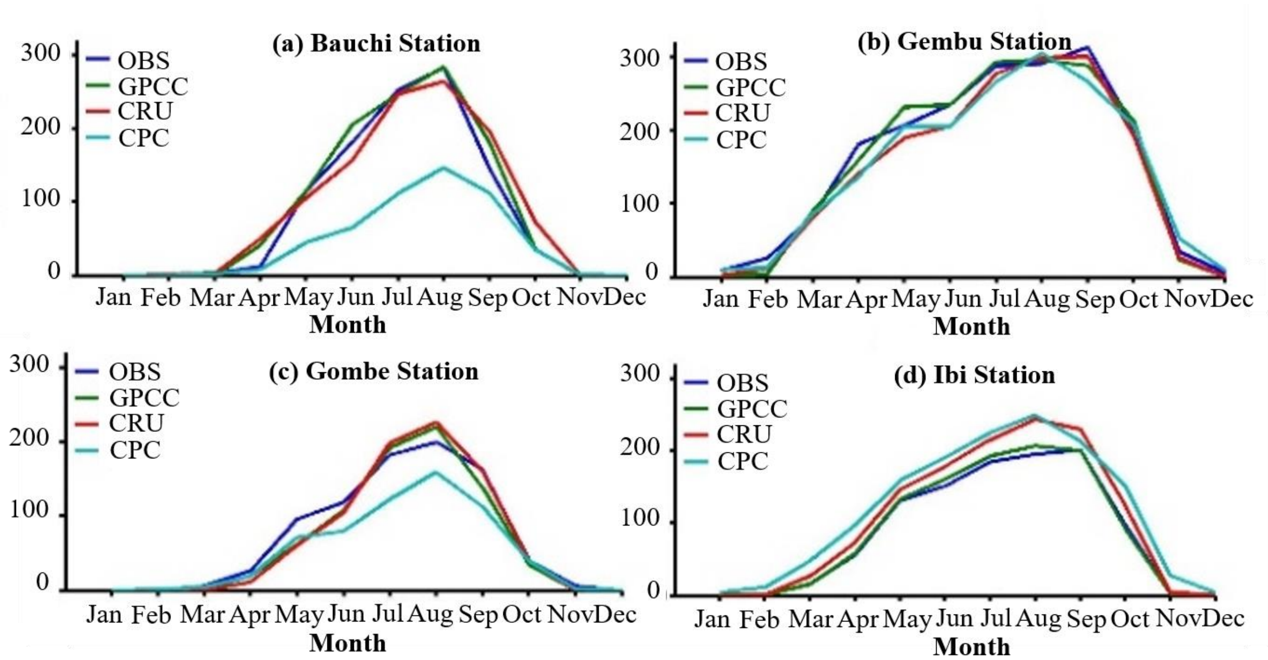


**Figure 3** Mean monthly rainfall comparisons over Upper Benue basin

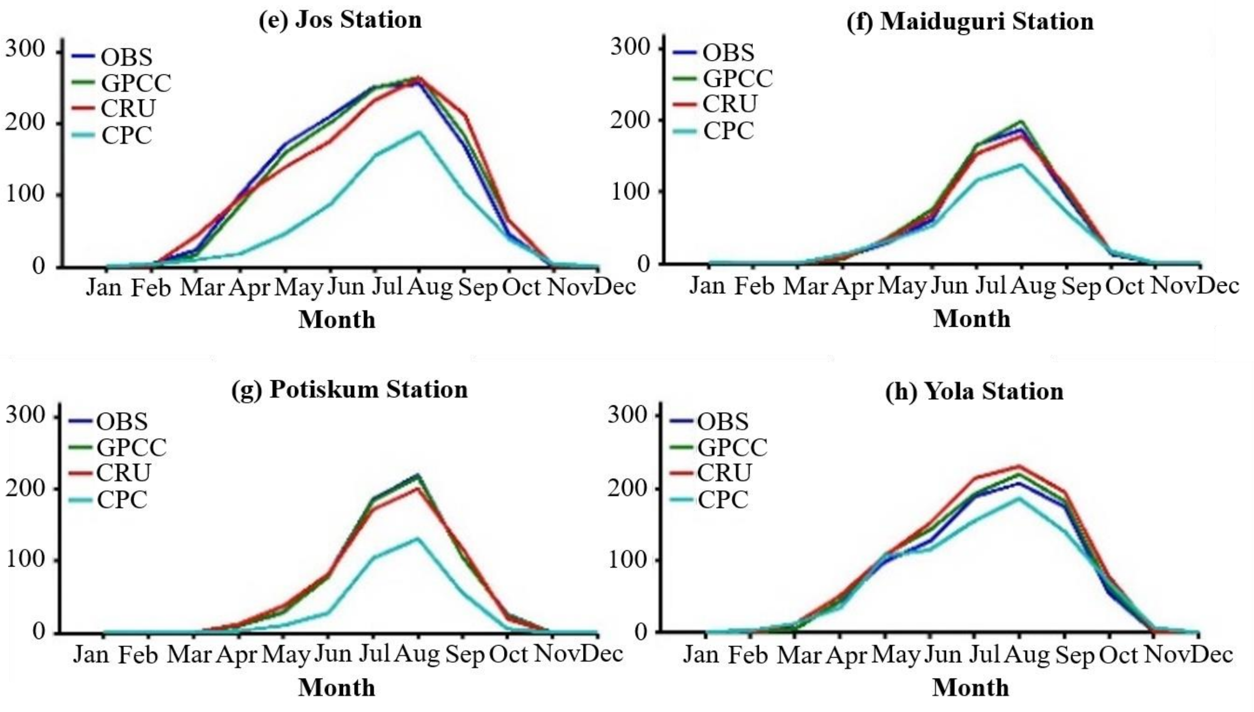


**Figure 3** (continued) Mean monthly rainfall comparisons over Upper Benue basin

Scatter plot was used to assess the degree of association between two datasets. Here, the rain gauge observations were plotted against the gridded datasets in each station. The plots are arranged horizontally for comparison between the different datasets as shown in Figure 4. From the plots, the GPCC data have strong association with the observed data for all stations except for Bauchi and Gembu. The GPCC dataset overestimates for Bauchi and shows higher dispersity around 45° line for Gembu station. Therefore, CRU dataset is better than that of GPCC in representing the observed data for these two stations. The higher level of correspondence of CRU over GPCC in these two stations may be due to the number and quality of datasets available to each organization for generating the gridded products [33]. Moreover, the result is similar to that reported by references [9, 27] over West Africa and some parts of Pakistan where CRU outperformed GPCC in some seasons of the year. Nevertheless, the GPCC dataset is considered to be the best and CPC is the worst.

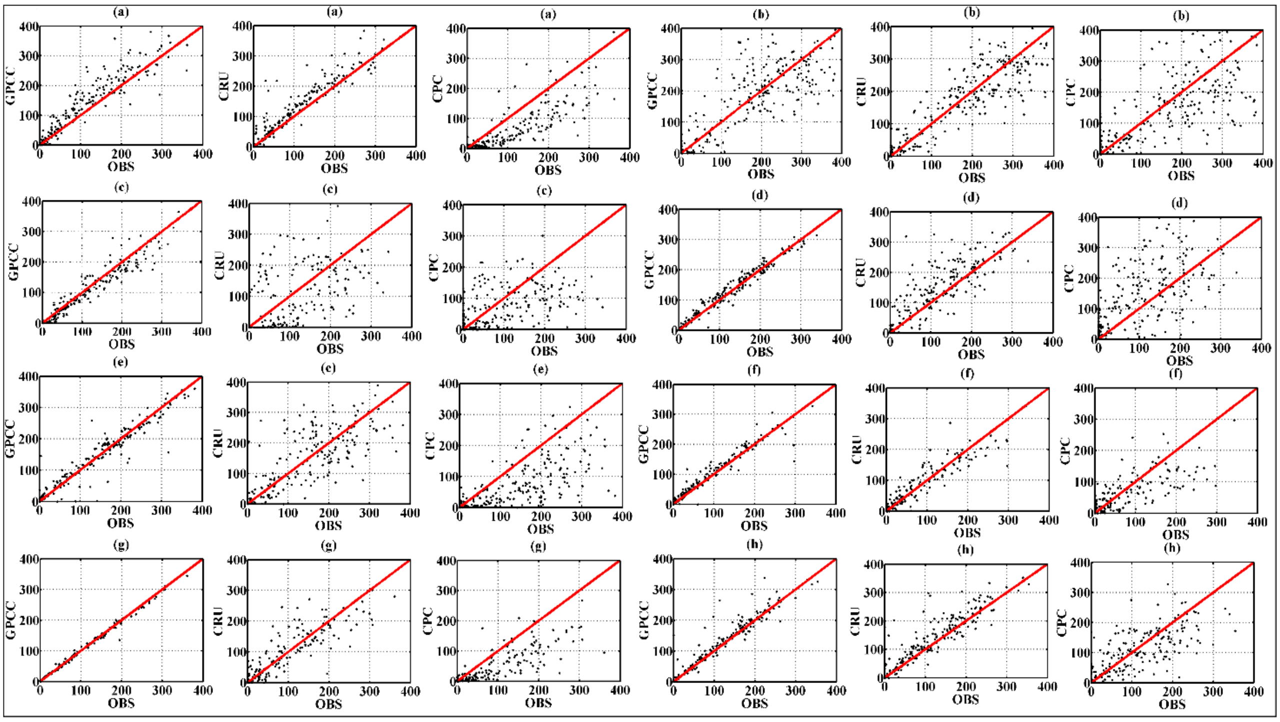


**Figure 4** Scatter plots of observed data against gridded precipitation datasets for (a) Bauchi (b) Gembu (c) Gombe (d) Ibi (e) Jos (f) Maiduguri (g) Potiskum (h) Yola

*3.3 Statistical validation*

The results of the statistical analyses are presented in Figures 5 and 6 in the forms of bar charts and radar plot. Figure 5(a) presents the MAE for all the stations. GPCC dataset is the best owing to its lowest MAE in all the stations, except around Bauchi and Gembu where the CRU has the least error. Similarly, the MBE as shown in Figure 5(b) indicates the GPCC dataset to slightly overestimated the rainfall data in 5 stations and underestimated in 3 others. The lowest errors noted in CRU dataset for the two stations may not be unrelated to the stringent quality control checks it underwent [34] similar to GPCC product, such that anomalies are interpolated rather than the absolute values of the data, which consequently produces high-quality estimates, with less biases [33, 35]. Nonetheless, errors in datasets are directly related to spatial variability of the gauging stations. Incidentally, regions with poor station coverage and high spatial variability are prone to large interpolation errors [33], which are noted to be prevalent in cold, dry and mountainous areas. Moreover, cases where CRU have lower error statistics as compared to GPCC datasets in some seasons of the years relative to ground reference observation is well documented in previous studies e.g. (Ahmed et al. [9] and Akinsanola et al. [27]). The bias is -0.3 mm around Jos plateau and only 0.8 mm around Gembu, Mambilla plateau. The highest error is noted in CPC. It is clear that GPCC perform better than the other two datasets. Further analysis in Figure 6 reveals the datasets to generally have good agreement with the ground observation data. For GPCC dataset, the correlation coefficient, r, varies from 0.82 to 1.0 for Gembu in the south to further north at Potiskum. These indicate near perfect to perfect match. The CRU data records between 0.64 and 0.96. The least correlation is found in CPC dataset with a range of values from 0.62 to 0.85. The GPCC dataset is outstanding in this study and is similar to those reported by references [9] and [27].

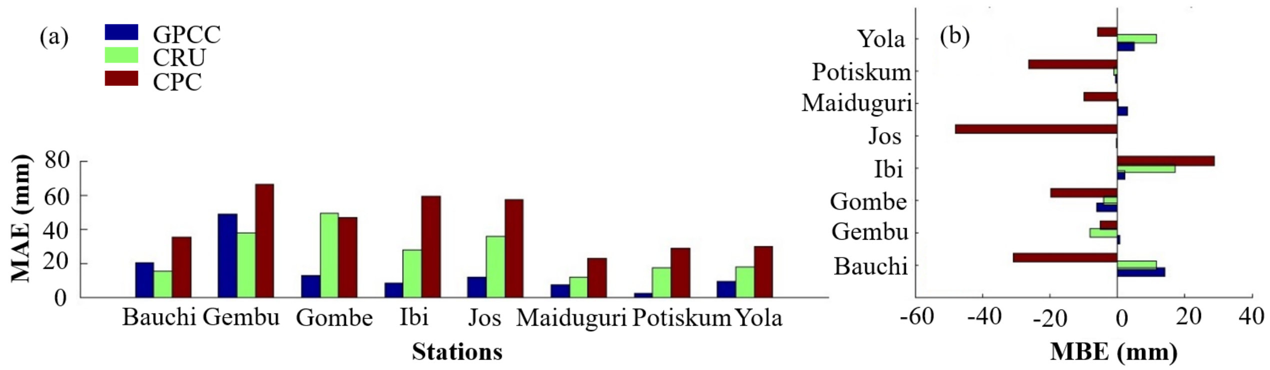


**Figure 5** Error comparisons among gridded datasets (a) MAE, (b) MBE

*3.4 Test of probability distribution similarity*

The results of the probability distribution similarity tests using Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) at 5 % significance level is shown in Table 1 along with the modified index of agreement. The rejection level was set at 0.05 to verify the null hypothesis that the two datasets do not significantly differ. Results indicate that the whole GPCC dataset cannot be rejected for all the stations from both KS and AD. Although, two datasets were rejected from AD test results. Similarly, the KS rejected only two datasets from CRU, while only three were accepted in AD and conversely rejected up to five datasets. The whole CPC datasets failed the similarity tests and are therefore found to be the least in representing the precipitation climatology over the study domain.

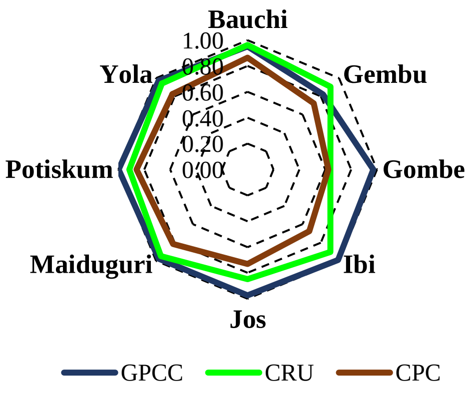


**Figure 6** Correlation Coefficient between observed and gridded precipitation datasets

The modified index of agreement (dmod) proposed by Willmott [36], and demonstrated by Pereira et al. [28] was used to test the level of agreement of the datasets relative to the rain gauge observations. The results obtained from the $d_{mod}$ are similar to those from r. For instance, the GPCC dataset varies from 0.79 to 0.98, and 0.67 to 0.91 for CRU data while CPC spans from 0.64 to 0.79. These ranges of values concur with those obtained from r and therefore reveal the strengths of the precipitation products across the basin. Based on the level of agreement with the rain gauge observations, GPCC was found to be more reliable than the other two products.

**Table 1** Results of KS test, AD test, and modified index of agreement

| Station | KS Test | | | AD Test | | | dmod | | |
|---|---|---|---|---|---|---|---|---|---|
| | GPCC | CRU | CPC | GPCC | CRU | CPC | GPCC | CRU | CPC |
| Bauchi | 0.0530 | 0.3412 | 0.0017 | 0.0302 | 0.3029 | 0.0001 | 0.88 | 0.91 | 0.75 |
| Gembu | 0.2923 | 0.0001 | 0.0023 | 0.2015 | 0.0000 | 0.0002 | 0.79 | 0.82 | 0.70 |
| Gombe | 0.0530 | 0.0002 | 0.0042 | 0.0178 | 0.0001 | 0.0038 | 0.91 | 0.67 | 0.64 |
| Ibi | 0.8475 | 0.0813 | 0.0000 | 0.5897 | 0.0131 | 0.0000 | 0.95 | 0.84 | 0.66 |
| Jos | 0.3412 | 0.0126 | 0.0000 | 0.2089 | 0.0076 | 0.0000 | 0.94 | 0.82 | 0.67 |
| Maiduguri | 0.9700 | 0.9408 | 0.0337 | 0.9764 | 0.9335 | 0.0023 | 0.94 | 0.90 | 0.77 |
| Potiskum | 1.0000 | 0.0530 | 0.0042 | 0.9965 | 0.0184 | 0.0001 | 0.98 | 0.87 | 0.75 |
| Yola | 0.9700 | 0.5842 | 0.0023 | 0.8117 | 0.0885 | 0.0006 | 0.94 | 0.88 | 0.79 |

### *3.5 Analysis of extreme precipitation*

We considered three climate indicators addressing extreme precipitation over the basin as utilized by Gampe and Ludwig [29]. These indices were selected from the 27 core indices adopted by the Expert Team for Climate Change Detection Monitoring and Indices (ETCCDMI). They are the maximum number of consecutive dry days (CDD), maximum number of consecutive wet days (CWD), and the annual total precipitation in wet days (PRCPTOT) by using a threshold of 1.0 mm to define a wet day [37].

Figure 7 presents the statistics for (a) Bauchi, (b) Jos and (c) Ibi. The first, second and third rows show the results for CDD, CWD and PRCPTOT respectively. The ability of the products to capture each extreme index is demonstrated using box and whisker plots. This displays five-number summary of the datasets vis-a-vis the minimum values, the lower quantile Q1, the median Q2, the upper quantile Q3, and the maximum observations. The GPCC dataset provides summaries which have good replica of the observed CDD values for the three stations than the other two datasets. Although, CRU representation is encouraging, while the CPC has least capability in reproducing the observed pattern of the CDD, except in Bauchi station where CPC perform better than the CRU.

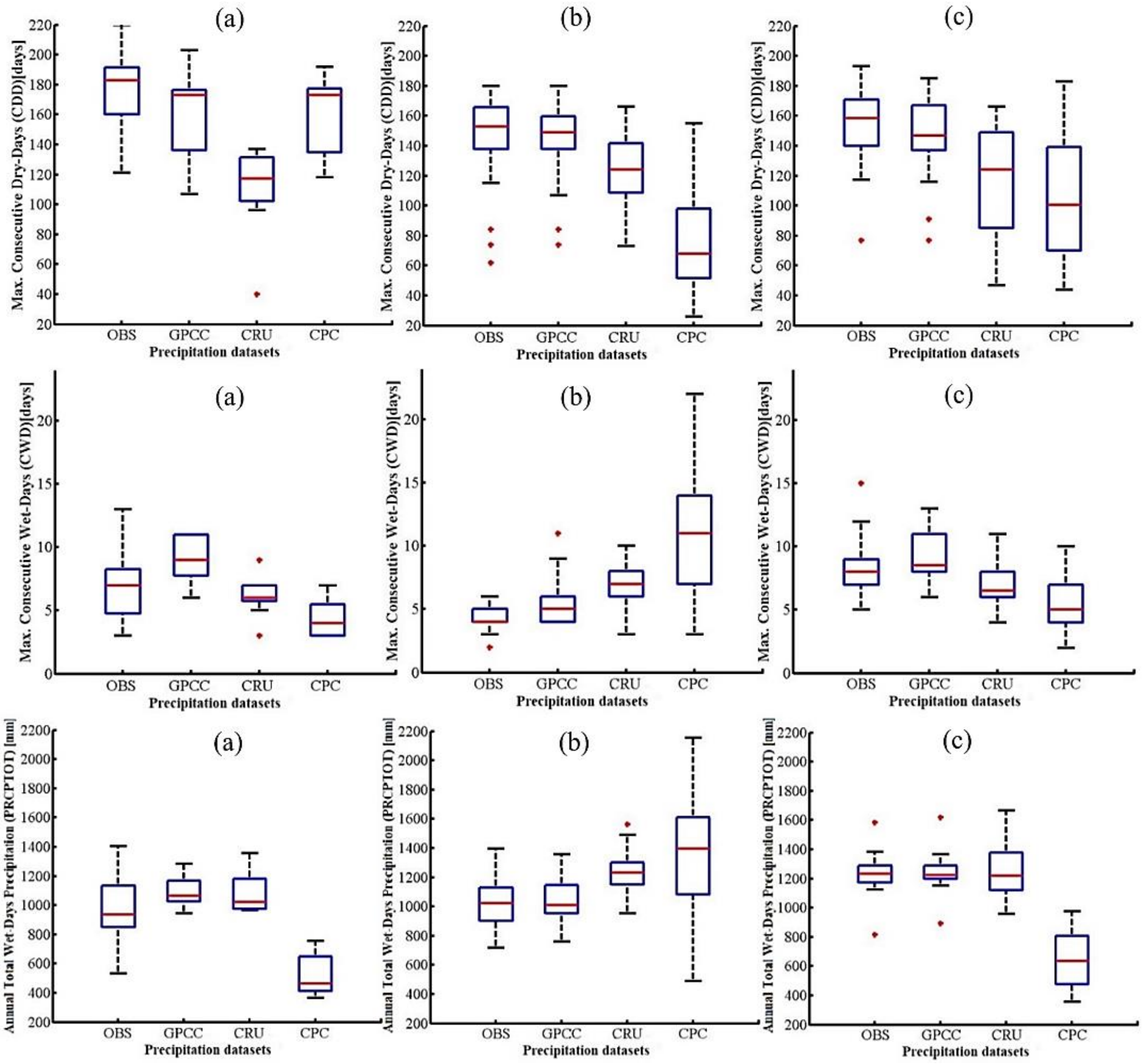


**Figure 7** Comparisons of extreme precipitation indices, CDD (top row), CWD (middle), and PRCPTOT (bottom row) among observation and gridded datasets at (a) Bauchi, (b) Ibi, and (c) Jos.

The median observed values of CWD for Bauchi, Ibi, and Jos are 7, 5, and 8 days, respectively, while the median values of the PRCPTOT indicate 960 mm over Bauchi, 1000 mm over Ibi, and 1200 mm over Jos. These median values confirm the orographic effect of the Jos plateau along the western boundary of the study area. The GPCC dataset almost outperforms those of CRU and CPC in capturing the rainfall extreme events on the entire study domain.

On the whole the performance evaluations revealed the GPCC dataset to be superior to the other two datasets. The results in this study are similar to those reported by [9, 27, 38].

A number of factors contributing to the improved accuracy of GPCC dataset are sufficiently reported in literatures. The number of weather stations used worldwide to develop the monthly database were far above 85,000 [39], although the daily timescale dataset was based on 35,000 stations per month globally [23]. This number is more than 4,000 and 30,000 stations used in the construction of CRU and CPC datasets, respectively. In addition, the GPCC dataset undergoes a rigorous quality control checks, which include: visual and semi-automatic processes [9, 39]. To further uncover the improved accuracy of GPCC dataset, Schneider et al. [39] reported that the construction of gridded datasets utilises modified SHEREMAP interpolation method, and that anomalies are interpolated rather than absolute values. This reduces sampling errors considerably and allows for better prediction as it considers the land surface elevation to account for orographic conditions. They further argued that GPCC dataset has the ability to accurately reproduce precipitation patterns and amounts over rough terrains. This accounts for the reliability and wide acceptability of the data, particularly in the regions with low rain gauge density.

## 4. Conclusions

The degree of accuracy of three daily gauge-based gridded precipitation products including, CRU, CPC and GPCC were quantified using eight metereological stations in Upper Benue basin, to compare their level of reliability for 25 years' period. A point-to-grid-based comparison was carried out at seasonal, monthly and daily scales. The performances were evaluated using climatological descriptions and statistical analyses which include mean bias error, mean absolute error, coefficient of correlation, modified index of agreement, and tests of probability distribution similarity. Further analyses considered three extreme rainfall indicators i.e. CDD, CWD, and PRCPTOT. Results reveal similar spatial distributions of all the rainfall products throughout the basin, and the north-south precipitation gradient are well captured. Although, the pattern was better replicated by the GPCC. It was further observed that the GPCC dataset have strong correlation and near perfect modified index of agreement with the ground observation dataset than the CRU and CPC products with less errors. The similarity tests in probability distribution by KS and AD tests yield good results for GPCC and CRU, but rejected the CPC datasets in totality. The assessments of the extreme precipitation over the basin show that GPCC and CRU are more consistent with the reference ground observation data in capturing both dry and wet conditions in most of the stations. However, this capability was found to be less in Bauchi. CPC to a large extent failed to replicate these conditions and was found to either underestimate or overestimate the rain gauge observations.

The findings from the study indicate GPCC dataset to be most oustanding out of the three precipitation products considered and analysed. However, the performance of CRU was good to a large extent. But, the CPC daily data has the least correlation, index of agreement with higher errors and therefore did not perform acceptably over the basin. Based on superior performances, the GPCC dataset is fit for hydrological and water resource modeling over Upper Benue basin.

## 5. Acknowledgements

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