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Research article

Bias correction and spatial disaggregation of satellite-based data for the detection of rainfall seasonality indices ☆,☆☆

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A R T I C L E I N F O

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A B S T R A C T

Like many other African countries, Ghana's rain gauge networks are rapidly deteriorating, making it challenging to obtain real-time rainfall estimates. In recent years, significant progress has been made in the development and availability of real-time satellite precipitation products (SPPs). SPPs may complement or substitute gauge data, enabling better real-time forecasting of stream flows, among other things. However, SPPs still have significant biases that must be corrected before the rainfall estimates can be used for any hydrologic application, such as real-time or seasonal forecasting. The daily satellite-based rainfall estimate (CHIRPS-v2) data were bias-corrected using the Bias Correction and Spatial Disaggregation (BSCD) approach. The study further investigated how bias correction of daily satellite-based rainfall estimates affects the identification of seasonality and extreme rainfall indices in Ghana. The results revealed that the seasonal and annual rainfall patterns in the region were better represented after the bias correction of the CHIRPS-v2 data. We observed that, before bias correction, the cessation dates in the country's southwest and upper middle regions were slightly different. However, they matched those of the gauge well after bias correction. The novelty of this study is that, in addition to improving rainfall using CHIRPS data, it also enhances the identification of seasonality indices. The paper suggests the BCSD approach for correcting rainfall estimates from other algorithms using long-term historical records indicative of the rainfall variability area under consideration.

1. Introduction

Climatic change affects agricultural productivity and food supply directly. This is owing, in part, to the fact that agriculture is fundamentally vulnerable to climate change and is one of the weakest economic sectors to the risks and repercussions of changing

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weather patterns [32]. Floods, heat waves, droughts, and storms affected hundreds of millions of people in Africa from 2006 to 2015, resulting in billions of dollars in economic losses [31]. In Ghana, rainfall influences agricultural activities, from crop selection and planting to harvesting in Ghana. As such, water scarcity is one of the most significant constraints to agricultural productivity in the region [4].

Besides, significant temporal and spatial variations of rainfall amounts as well as the time of onsets and cessations of rainfall affect agricultural productivity [5]. For instance, the beginning of the rainfall period must be determined at the station level for agro-climatological applications. However, if the overall goal is to predict the onset, it must be defined regionally rather than locally. These differences may impede socioeconomic growth by jeopardizing food security and causing poverty [2]. Therefore, it is essential for the development and sustainability of agricultural operations in Ghana to analyze and predict when the rainy season will begin and end. Besides, random convective events can impact local rainfall, especially daily rainfall, causing heavy rainfall and delayed onset dates by a few days or weeks. However, these circumstances are inherently unpredictable. Delays in onset may result in a later farming season, increasing the nation's need for food. Additionally, earlier cessation dates might result in water stress by crops, which would lower yield [13].

Due to increased pressure from human activity, global warming is currently accelerating at the rate more quickly than ever before [1]. According to Sterling et al. [37], agriculture and settlement have replaced natural vegetation on the Earth's surface due to human influence. Climate change makes humans more vulnerable by increasing temperatures, altering precipitation regimes (such as when the rainy season starts and ends), and altering the risks associated with drought and heavy precipitation. Climate change is anticipated to increase the frequency of short-term solid precipitation events because metropolitan areas contain significant amounts of impermeable surfaces, which lower infiltration capacity [11,20,30]. Tracking and predicting extreme weather conditions, such as wet and dry spells, floods, and drought, among others, for hydrological applications and climate research necessitate high-resolution precipitation observations [33]. However, due to a variety of technological and practical constraints, getting reliable observational precipitation readings with high resolution spatially is challenging due to difficulties in installing and maintaining a dense network of measuring equipment, especially in difficult-to-reach places like mountains, deserts, and primary forests [24,29,33,21]. As a result, majority of rainfall impact studies rely on satellite estimates [6].

Accurate and realistic daily rainfall representation from climate models is essential for impact assessment studies, and bias correction of climate model outputs and satellite rainfall estimations is necessary to ensure relevant runoff simulations from hydrological models [26]. To correct the Regional Climate Model (RCM) simulations, several bias correction approaches with varying degrees of complexities have been developed. Simple mean correction, more complex techniques such as mean and variance correction, and improvements in changing quantile values are all included and developed [39]. While there are several methods for bias correction, most of them use monthly statistics to derive correction factors, which may cause errors in rainfall magnitude when applied on a daily scale [39]. As a result, daily scale corrections are applied to rainfall outputs to improve the quality of data outputs.

In an earlier study, Atiah et al. [9] generated maps for the onset and cessation of rain and the length of growing period (LGP) for the last 40 years from satellite rainfall estimates (CHIRPS V2). These maps were validated with gauge and farmer knowledge. Substantial biases were noted that might affect the reliability of agro-advisories generated from daily CHIRPS-v2 satellite rainfall estimates. Therefore, that study recommended bias correction of the CHIRPS-v2 satellite daily rainfall to reduce the biases when deriving the rainfall indices (onset, cessation, and length of the rain season). Bias correction of satellite rainfall data effectively removes systematic bias in the time series. While there are several approaches for bias correction, most rely on monthly statistics to calculate correction factors, which may result in errors in rainfall amount when applied on daily time series [39].

Three widely used techniques in atmospheric research for bias correction are linear scaling, quantile mapping, and local intensity scaling. Each technique seeks to modify the outputs of climate models at coarse scales to reflect observable data at fine scales. To match the empirical data, linear scaling includes only scaling the mean and standard deviation of the climate model data. This strategy assumes that the climate model and observational data are linearly related, which may not hold for all variables and areas [25]. Contrarily, a non-parametric technique called quantile mapping can adjust for biases in extreme occurrences while maintaining the distribution's form. Unfortunately, this approach might not work well with variables with intricate non-linear correlations [14]. Using a probability density function to be fitted to the observational data, the local intensity scaling technique takes higher-order moments of the distribution into account. In particular, this strategy can deliver more precise results when scaled down for severe occurrences. However, it needs a lot of observational data and might need to work better for variables with much skewness [36]. In earlier work, these three methods and the Bias Correction and Spatial Disaggregation (BSCD) technique were tested to verify which method gives better results. The BCSD method was observed to show superior results for the for point-to-point evaluation. Therefore, the best method, which is the BSCD method, was applied in this study.

The main goal of the current study is to investigate whether bias correction of daily satellite-based rainfall estimates improves the identification of seasonality indices in Ghana. The remaining parts of the study are structured as follows. Section 2 discusses the methodology and datasets employed in this study. The results and discussion are in Section 3, whereas conclusions are presented in Section 4.

2. Study area

Ghana is situated at the western part of the African continent lying a few degrees north of the equator (between latitude 4.5° N and 11.5° N and longitude 3.5°W and 1.5° E) and bordered by Togo, Burkina Faso, and Cote d'Ivoire in the east, north and west respectively and with the Gulf of Guinea in the south (see Fig. 1b). The country is made up of sixteen administrative regions (see Fig. 1a), which have further been classified into four (4) main Agro-ecological zones (Coastal, Forest, Transition, and Savannah

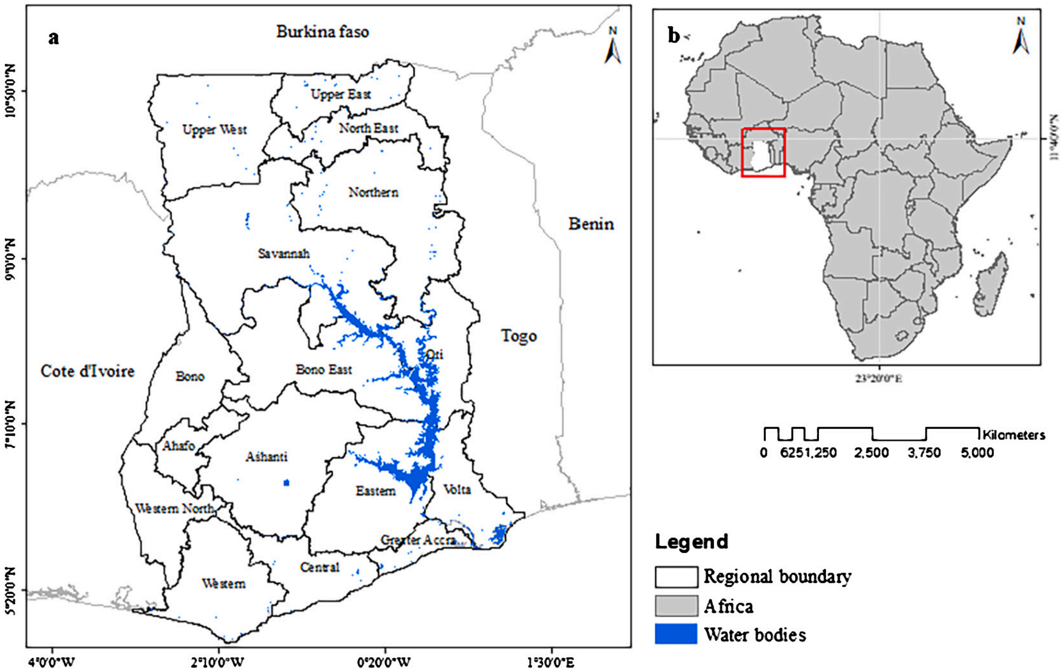

Fig. 1. Map of the study area.

Zones) by the Ghana Meteorological Agency (GMet) [10,2,6].

Ghana is mainly characterized by two major seasons, the wet and the dry seasons (also known as the Harmattan seasons). Previous studies show that rainfall is mostly influenced by the formation and movement of Mesoscale Convective Systems (MCS) and is controlled by the advection of moisture from the Gulf of Guinea at the lower levels of the atmosphere [38,2,8,7]. Temperature and energy variations between the Sahara and the Gulf of Guinea control this system. A maritime tropical air mass from the Atlantic Ocean converges with a dry, frigid tropical continental air mass along the inter-tropical discontinuity (ITD) [3,2].

According to Nicholson [28], three quasi-independent mechanisms-ascent associated with upper-level jet streams, convergence associated with the surface inter-tropical convergence zone (ITCZ), and a coastal circulation cell associated with sea-breeze effects-act as controls to precipitation development over West Africa. These variables drive the creation of a tropical rain belt (rainfall maxima; not related to ITCZ) which migrates periodically between the northern and southern parts of the continent. As a consequence, two rainfall regimes are present in the region. Bi-modal rainfall patterns are prevalent in the coastal and forest zones of the country's south. In contrast, a uni-modal pattern may be seen throughout the northern part of the country, primarily in some areas of the transition zone and the savannah zones.

In addition to the aforementioned rainfall mechanisms, local convective activity caused by vegetation type and terrain or topography has an important impact on the rainfall pattern in the area. Examples include considerable convective activity on the windward side of the Togo-Akwapim ranges, owing to orographic processes [2,18]. Other factors that influence rainfall in the area include dynamic stability, sea surface temperature (SST), land surface feedback, and transitory tropical waves [10]. The southern Forest and coastal zones have their first rains in the second and third dekads of March. Between the second dekad of March and the third dekad of April is when rainy season in the transition zone starts. Beginning in the second dekad of April and ending in the first dekad of May, the savannah experiences rainy weather. The Forest zone experiences its last significant rainfall between the third and first days of November. Between the second and third dekad of October, the coastal zone comes to an end. The transition zone will cease operations between October 2 and October 3. Additionally, the savannah zone experiences a stoppage of precipitation between the third dekad of September and the first dekad of October [2]. Significant late cessations and protracted LGP were seen in the majority of Northern Ghana, according to Atiah et al. [8]. The onset dates were slightly but noticeably later and earlier in the west and east of 1.5 W longitude, respectively, according to CHIRPS-v2 data. Our research indicates that the majority of the region's areas are moving toward later cessation dates. Due to CHIRPS-v2's tendency towards capturing early and late onsets, the LPG was much longer.

3. Datasets

3.1. Gauge data

Daily rainfall data from several weather stations around the nation are used for analysis in this study. The data was acquired from the Ghana Meteorological Agency (GMet) and covered a thirty-five (35) year period from 1981 to 2015. GMet is the primary agency in Ghana responsible for providing weather-related information and services. It adheres to World Meteorological Organization

(WMO) standards in its rainfall and other weather parameter measurements. These readings, however, may contain minor errors. Evaporation, wetness loss, and wind-induced errors are just a few examples of error causes. Concerns about data inhomogeneity may arise as a result. However, evaporation and wetting loss errors were less than 0.45 mm daily. Because all of the rain gauges were wind-protected, wind-induced inaccuracies were infinitesimally small [2].

The potential for data gaps in the extended time series record of the meteorological dataset was a significant concern and one of its key constraints. These data gaps have to be adequately filled and quality-controlled [23] in order to provide a trustworthy, continuous, and uniform reference time series in which divergences are exclusively brought on by weather and climatic fluctuation. Inverse distance weighting (IDW) was used to determine the missing rainfall quantity in the data time series, as described in [15]. Equations (1) and (2) were used to determine the missing data gaps in the reference series using rainfall data from neighboring stations within a radius of no more than 4 km:

$$r_r = \sum_{k=1}^{m} w_i R_k \tag{1}$$

$$w_j = \frac{d_i^{-\alpha}}{\sum_{i=1}^{N} d_i^{-\alpha}} \tag{2}$$

where r_r is the missing rainfall data (mm), R_k is the rainfall value of the neighboring stations, m is the total number of the nearby stations, d_i is the distance of each station from the reference station, w_j represents the weighting of each neighboring station, and α represents the highest power, which takes values between 0 – 1.5 and 4 – 5. This study used a power of 5 to estimate the missing rainfall as described in [15,2].

The Minimum Surface Curvature (MSC) interpolation method was used to grid the gauge data using 190 stations distributed across Ghana at a spatial resolution of $0.25° \times 0.25°$. This data was used as the reference for the bias-corrected satellite rainfall over Ghana.

3.2. CHIRPS-V2

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS-v2) dataset is based on infrared Cold Cloud Duration (CCD) measurements as well as high resolution, long-term precipitation estimates [16]. In-situ precipitation observations, the Tropical Rainfall Measuring Mission (TRMM), the Atmospheric Model Rainfall fields from the NOAA Climate Forecast System, and other data sources were combined to produce the product, which is a reliable satellite-based rainfall dataset. The product is the result of a collaboration between scientists at the Earth Resources Observation and Science (EROS) Center and the United States Geological Survey (USGS), to provide accurate rainfall data for climate-impact studies such as trend analysis and flood and drought monitoring, among other things [16]. In the present study, bias correction was applied to daily CHIRPS data with a spatial resolution of $0.25° \times 0.25°$ during a thirty-five (35) year period, from 1981 to 2015. The ability of the bias-corrected data to represent seasonality indices over Ghana was later determined. Seasonality indices are measurements of the beginning, end, and length of the growth season of rainfall.

3.3. Bias correction and spatial disaggregation method (BCSD)

For the purpose of producing fine-scale land surface meteorological forcing for hydrological modeling, Wood et al. [42] originally suggested the BCSD technique. The three components of the BCSD technique – data preparation, bias correction (BC), and spatial disaggregation (SD) – are a trend-preserving statistical downscaling procedure. The daily rainfall readings are detrended as part of the data pretreatment process in order to protect the climate trends from the BC step. The method applies a quantile-based mapping of some probability density functions for daily precipitation onto gridded observed data, spatially aggregated to the scale of interest. The BC step employed in this work is based on the Vandal et al. [41] approach, which uses observations to rectify model flaws or satellite data biases. Bias-correcting data is frequently done before spatial and temporal disaggregation, which leads to daily predictions. However, Thrasher et al. [40] outlined a method of directly applying BCSD to daily forecasts, skipping the crucial stage of temporal disaggregation. To downscale the satellite precipitation dataset, we take the following actions:

1. Bias correction of satellite daily rainfall using observed precipitation. Observed precipitation is remapped to fit the reanalysis grid. For each day of the year, values are combined from the CHIRPS-V2 and observed gauge datasets to generate a quantile mapping. With the quantile mapping produced, the satellite data points are mapped, bias-adjusted, to the same distribution as the observed data. Using this approach to daily precipitation detrending the data is optional because of the absence of a trend [41].
2. Spatial disaggregation of the bias-corrected satellite-based rainfall. Coarse-resolution rainfall is then bilinearly interpolated to the same grid as the observation dataset. To maintain geographic characteristics of the fine-grained data, the average precipitation of each day of the year is estimated from the observation and set as scaling factors. These scaling variables are then multiplied by the daily interpolated bias-corrected estimates to obtain the downscaled CHIRPS -V2 rainfall [41].

As presented above, BCSD utilizes a relatively simple quantile mapping approach to statistical downscaling followed by interpolation and spatial scaling. A summarized step-by-step procedure of the BCSD method is presented in Fig. 2.

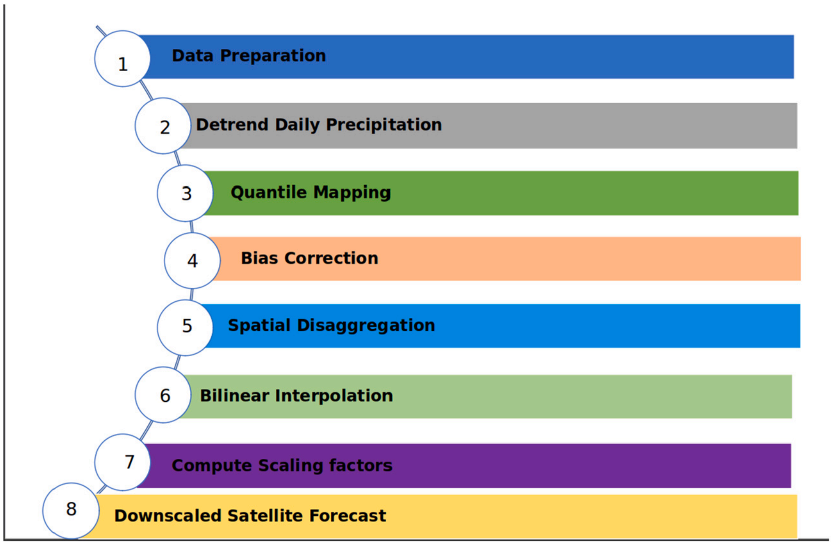

Fig. 2. Schematic diagram showing the summary of the BCSD bias-correction method.

4. Methodology

4.1. Statistical metrics

Equation (3) depicts the Pearson correlation coefficient, which shows the relationship between two variables. This would help us determine the relationship between the two variables. Computing the RMSE and MAE as shown in Equation (4) and (5) can be used to make a comparison between an observed variable and a bias-corrected variable, with low values depicting the closeness of the two and vice versa. The relation is shown in Equation (6).

$$r = \frac{N\sum_{i=0}^{N} O_i P_i - \sum(O_i)\sum(P_i)}{\sqrt{(N\sum O_i^2 - \sum(O_i^2))((N\sum P_i^2 - \sum(P_i^2))}} \tag{3}$$

$$RMSE = \sqrt{\frac{\frac{1}{n}\sum_{i=0}^{N}(O_i - P_i)^2}{O_i}} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n} |P_i - O_i|}{n} \tag{5}$$

$$Bias = \frac{\sum_{i=0}^{n} P_i}{\sum_{i=0}^{n} O_i} \tag{6}$$

5. Results and discussion

5.1. Evaluation of various bias-correction methods

In another study, we assessed the effectiveness of four bias-correction methods. These methods included Linear Scaling (LS), Local Intensity Scaling (LOCI), Quantile Mapping (QM), and Bias Correction and Spatial Disaggregation (BCSD). Here, we present the summary of the results obtained. Fig. 3 shows the FAR (a) and POD (b) results of various bias-correction approaches at selected stations in Northern Ghana. As shown in the results the bias correction method with the highest PoD was the BCSD approach, with values ranging from 98% to 100%, and the lowest FAR was also reported for almost all of the stations. As a result, the BSCD technique delivered the best results for point-to-point evaluation, with rainfall estimates nearly matching the observed datasets. These findings are consistent with those in [35], indicating the method's ability to satisfactorily reproduce the observed trend and variation of average rainfall amount except during heavy rainfall events with a certain degree of spatial and temporal variations. Based on these findings, we employed the best approach to perform spatial bias correction on the data, allowing us to determine whether the method improves the capture of seasonality indices.

5.2. Evaluation of spatial bias correction method: rainfall

The ability of the BCSD method to improve the rainfall patterns of CHIRPS-V2 on seasonal, and annual scales over Ghana with respect to the gauge was evaluated in this section. Figs. 4 a–c depict Ghana's average annual rainfall climatology from 1981 to 2015,

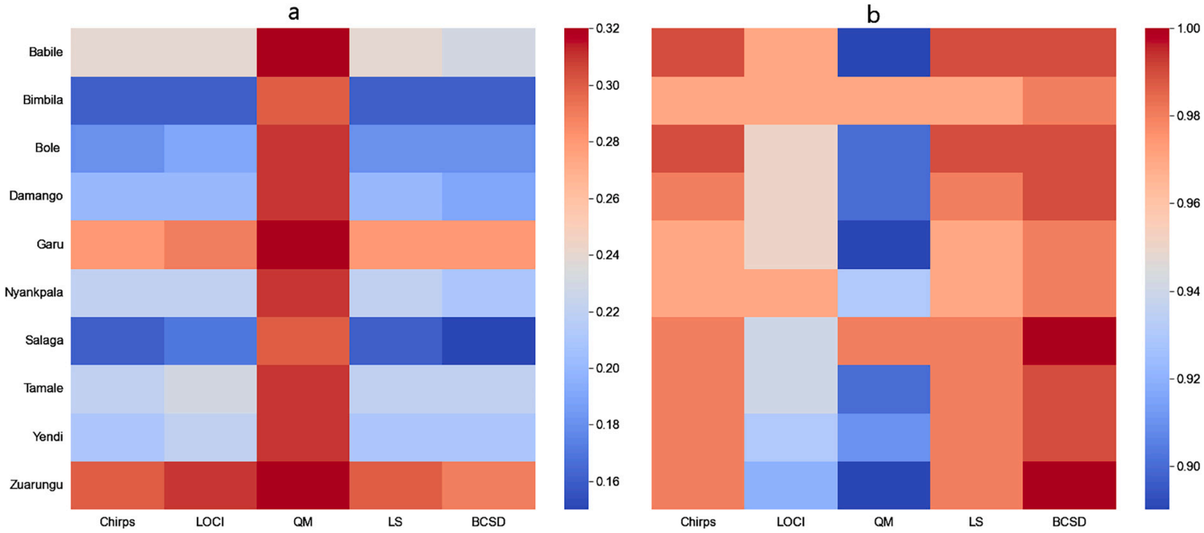

Fig. 3. Heatmap Showing the False Alarm Ratio (a) and the Probability of Detection (b) of Daily Rainfall Values for CHIRPS-v2 and the various Bias Correction Methods.

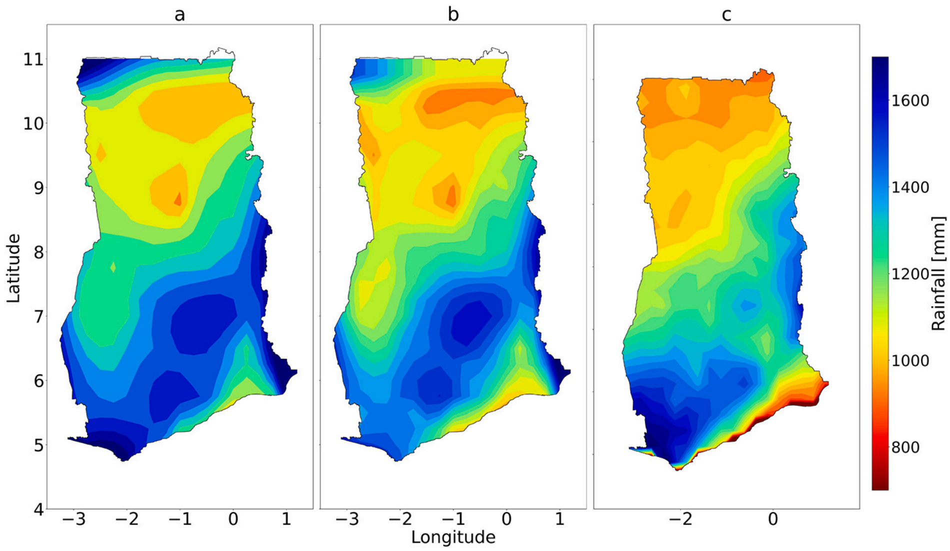

Fig. 4. Annual mean rainfall climatology over Ghana from 1981 – 2015 for GMet gauge (a), CHIRPS V2 (b), and BSCD (c).

as captured by gauge, CHIRPS-V2, and bias-corrected CHIRPS-V2 (BSCD) respectively. The Figure shows that the spatial patterns closely matched the gauge data after bias correction with very few variations compared to the CHIRP-v2 data. This indicates that the rainfall in the region is better represented after the bias correction of the CHIRPS-v2 data. This confirms findings of Xu and Wang [43] who revealed significant improvement of the rainfall data after bias correcting with the BCSD method. Similar findings were seen in Sharma et al. [35], where the bias-correction approach revealed the capacity to reduce frequency and amount biases when compared to the computed frequency and amount at grid nodes based on spatially interpolated observed rainfall data. Furthermore, with the exception of large rainfall events with significant spatial and temporal fluctuations, the spatial disaggregation model adequately represented the observed trend and variance in average rainfall amount.

Furthermore, the seasonal climatological means over the region also showed significant improvement in the dataset as depicted in Figs. 5 a–c for GMet gauge, BSCD, CHIRPS V2 respectively. Visible variations over the entire region were seen to follow patterns of the gauge dataset after bias correction closely. These results are consistent with other findings; for instance, [12] spotted vast improvement in the monthly and seasonal rainfall values after bias correcting seasonal forecasts using BCSD method. [34], recently also recorded similar results in Califonia where seasonal rainfall was well represented post BSCD. During the dry season (DJF), we observed that the BSCD was very good at bias correction, as very high values observed by the raw CHIRPS V2 in the southwestern parts of the country were well corrected to resemble those of the gauge. For the MAM season, we found that the spatial patterns of rainfall in the southern parts of the country for both bias corrected and raw CHIRPS data were similar to those of the gauge;

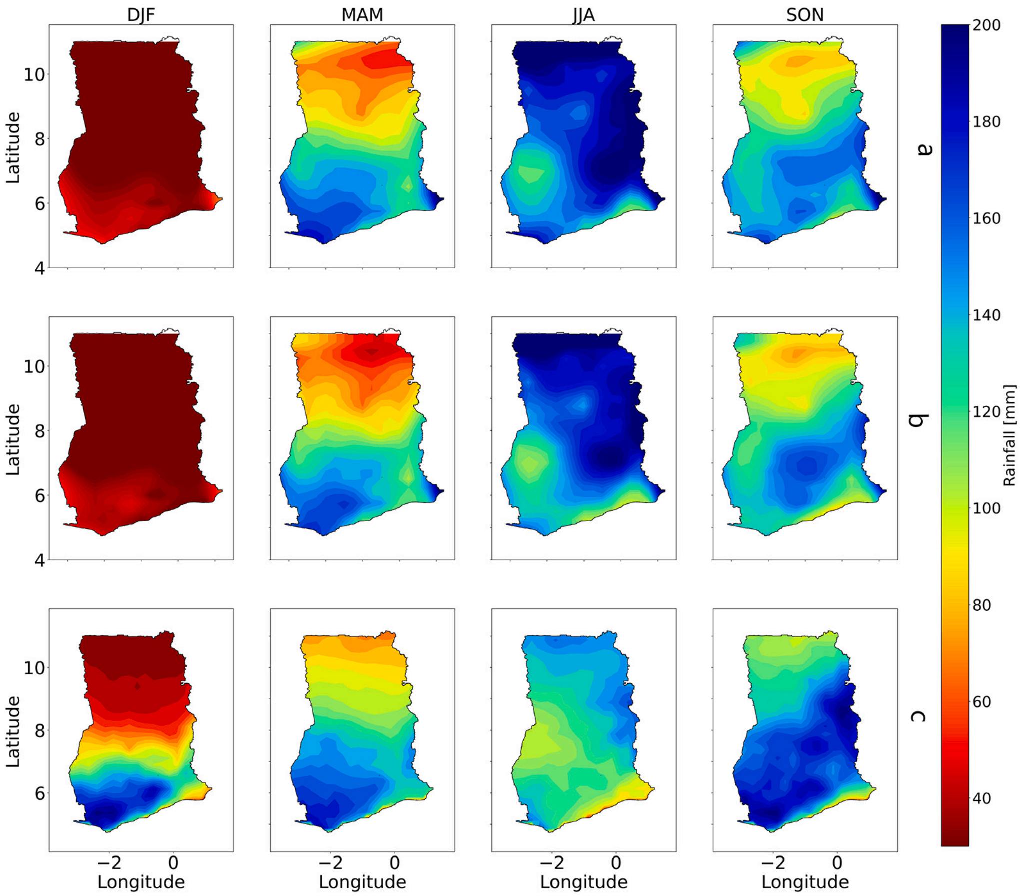

Fig. 5. Seasonal mean climatology of rainfall over Ghana from 1981 – 2015 for GMet gauge (a), BCSD (b), and CHIRPS V2 (c).

however, in the northern parts, CHIRPS captured relatively high values (between 80–120 mm) compared to the gauge (40–100 mm). However, we see that the values match the gauge after bias correction. Compared to gauge observations, the spatial patterns of rainfall captured by CHIRPS during the JJA season were relatively poor. After bias corrections, the spatial rainfall patterns for the season closely matched those of the gauge. Compared to the gauge, rainfall patterns in the country's southwestern and eastern, northern regions for the SON season were significantly overestimated (> 40 mm). After bias correction, we found that the seasonal rainfall patterns were remarkably consistent. Overall, it was found that the BSCD method was very effective at correcting CHIRPS V2 at all seasonal levels. These findings confirm results in Lorenz et al. [22] who used the spatial-disaggregation and bias-correction approaches to bias-correct the seasonal precipitation from SEAS5 data. Their findings showed decreased biases and root means squared errors for most of the study's regions and variables. Additionally, the forecasts' spatial resolution was increased, and the precipitation patterns exhibited much better agreement with the reference data.

Fig. 6 a–d shows the spatial statistics for spatial Correlation, Root Mean Square Error (RMSE), Bias, and Mean Bias Error (MBE) respectively between the gauge and bias-corrected CHIRPS data. The more significant part of the Savannah zone observed a correlation of about 0.8. This decreases to about 0.6 in the eastern part of the zone. The more substantial part of the Transition and the northern part of the Forest zones had a correlation of about 0.55. The western and the extreme northwestern portions of the Transition and Forest zones observed a minor Correlation of about 0.4. The southern part of the Forest zone also correlated by about 0.8. The majority of the Coastal zone also observed a correlation of about 0.6, which decreases to about 0.5 at the eastern part of the zone. The extreme northwestern part of the Savannah zone observed the highest RMSE, about 15 mm. This decreases towards the southern part of the zone. The greater portion of the Savanna zone observed an RMSE of about 8 mm, with the central part having the least RMSE of about 6 mm. The RMSE decreases from the eastern part of the Transition and the Coastal zones to the western parts. This excludes the extreme west and northwestern portions of Transition and Forest zones, which observed an RMSE of about 13 mm. The southern part of the Forest zone and most of the Coastal zone had an RMSE of about 8 mm. This increases to about 14 mm at the eastern part of the Coastal zone. The northernmost part of the Savanna zone observed the highest Bias of about 1 mm. This decreases to about 0.5 mm at the central portion of the zone and over the southwestern part of the Savannah zone. The middle portion of the Transition zone had a bias of approximately 0 mm, which increases to about 0.5 mm at the eastern and western parts of the zone. The middle part of the Forest zone also observed a bias of about 0 mm, which increases to about 0.25 mm at the eastern and western parts of the zone. A greater part of the Coastal zone observed a bias of about 0.2 mm, which decreases to

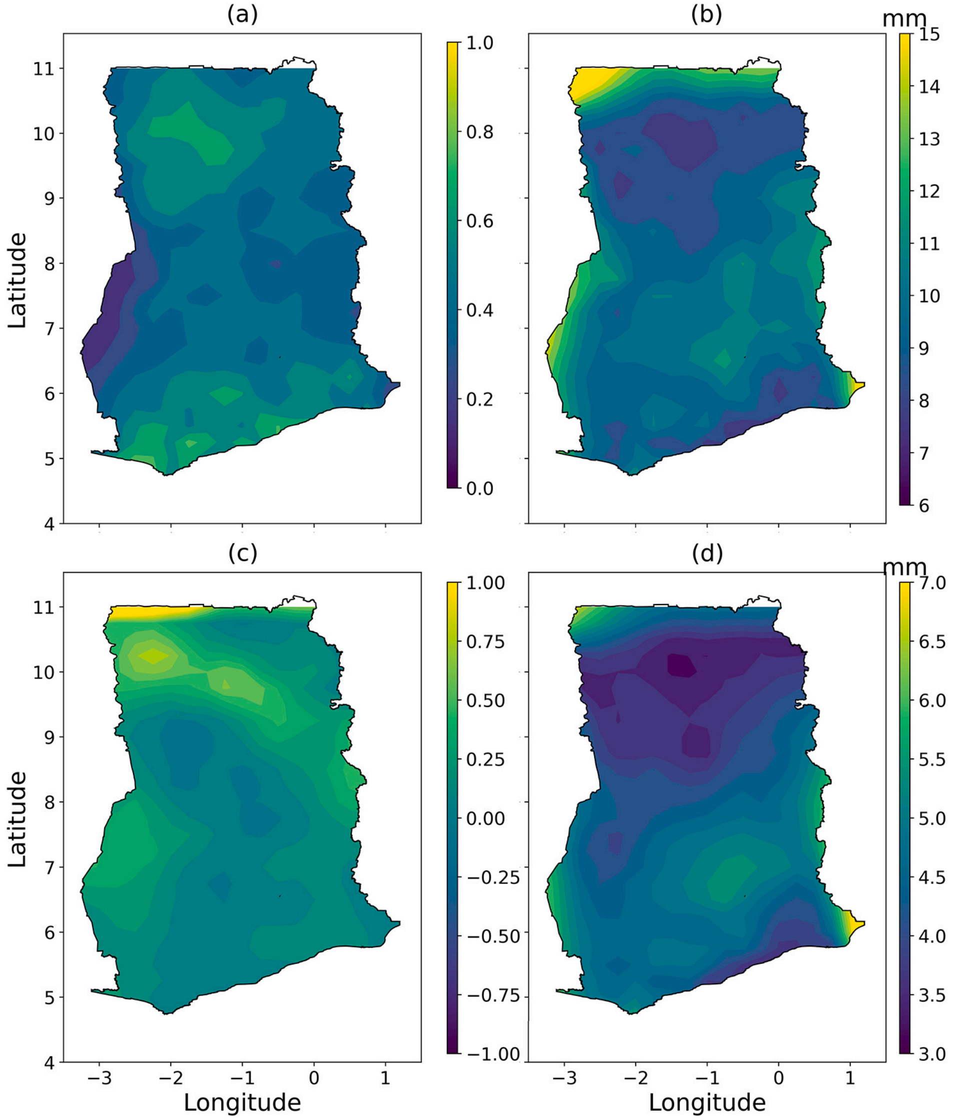

Fig. 6. Spatial distribution of Correlation (a), RMSE (b), Bias (c), and Mean Absolute Error (d) values between Gauge and BCSD data over Ghana.

about 0.1 mm at the eastern part. The extreme northwestern part of the Savannah zone observed the highest MBE of about 6 mm. This decreases to about 3 mm at the middle portion of the zone. The greater portion of the Transition zone also had an MBE of approximately 4 mm, which increases to about 6 mm at the extreme eastern part of the zone. The greater part of the Forest zone also had an MBE of about 4.5 mm. This increases to about 5 mm and 6 mm at the eastern and western parts of the zone. A majority part of the Coastal zone also observed an MBE of about 4 mm, which decreases to about 7 mm at the eastern part of the zone. This clearly demonstrates that the bias-correction strategy is spatiotemporal-location dependent. Similar findings in Gruber et al. [17] confirm our findings that temporal aggregation boosts correlations and conceals mistakes, although spatial aggregation does so only when comparing extremely fine and very coarse granularities. This also implies that the absolute threshold processing used in BCSD, which significantly improves the spatial Correlation of precipitation distributions when compared to uncorrected data, performs better in terms of producing realistic precipitation patterns, as evident in [44].

5.3. Evaluation of spatial bias correction method: seasonality indices

Results from the gauge, CHIRPS V2, and BSCD-based seasonality indices are presented in this section. The spatial distribution of seasonality indices over Ghana as recorded by Gauge, BSCD, and CHIRPS V2 from 1981 to 2015 is shown in Fig. 7 a–c respectively. After bias correction, we can see that the spatial patterns for the onset of rainfall were well captured compared to gauge observations. We can see that the onsets in the country's central were accurately recorded, but there were a few late onset dates in the upper east regions of the nation and a few early onset dates at a few specific locations in the south. Regarding cessation dates, we typically

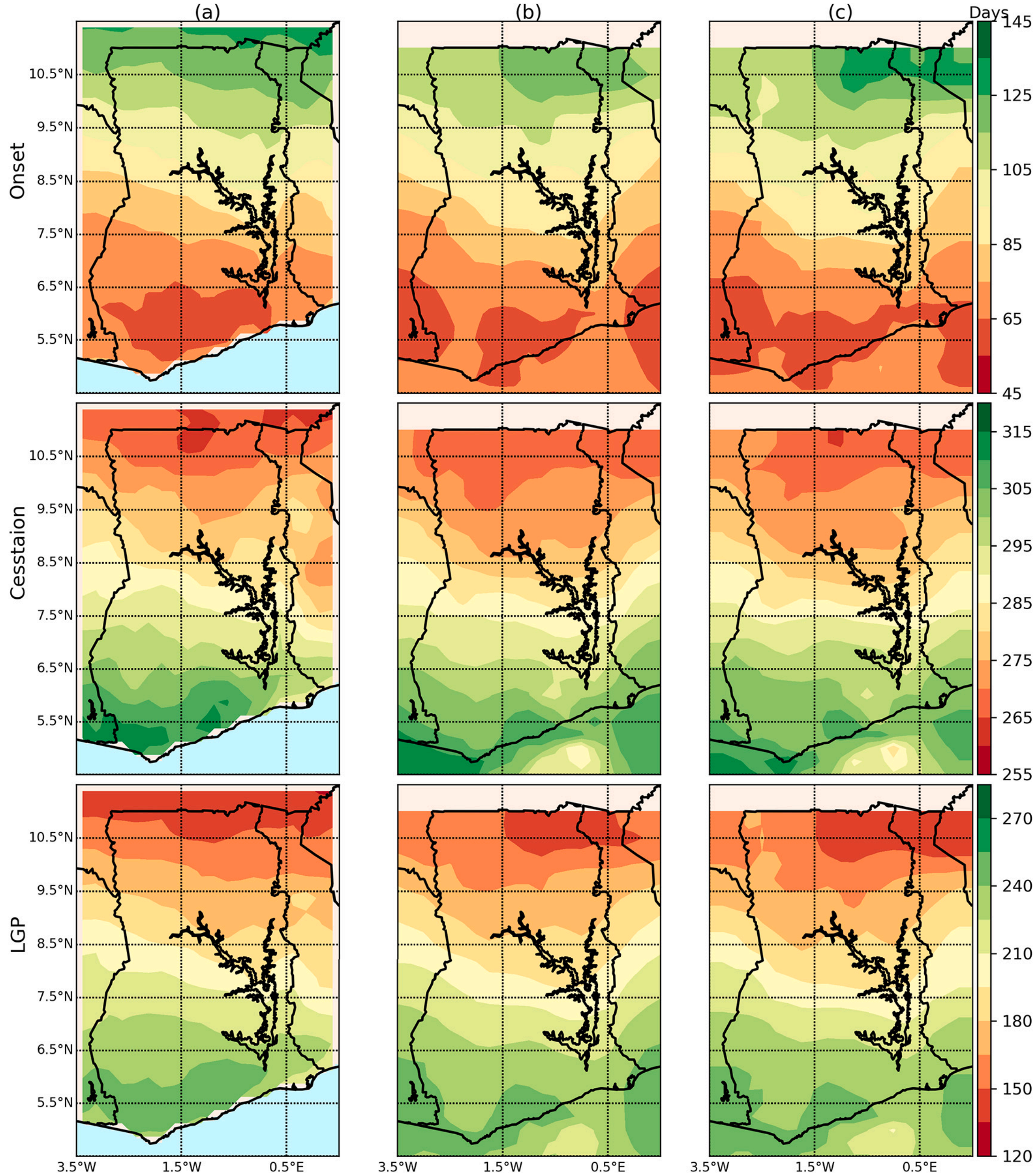

Fig. 7. Spatial distribution of seasonality indices over Ghana as captured by CHIRPS V2 (a), GMet gauge (b), and CHIRPS V2 corrected (c) for the period of 1981–2015.

observe a high level (about 7%) of proficiency with the BSCD method nationwide. Before bias corrections, we noticed that the cessation dates in the country's southwest and upper middle regions were slightly late compared to gauge observations. The variations complement research by Atiah et al. [9] that indicated that nearly all regions in Northern Ghana showed early cessation dates in certain years (2001, 2004, 2005, 2007, 2011, and 2017) and late cessation dates in other years (2009, 2012, 2019). These are a true representation of the significant degree of uncertainty farmers encounter when making crop selections in between growing seasons. Early cessations can stop grain filling, which reduces production; late cessations can delay harvesting, which increases pre-harvest losses and increases the danger of mold infestations, which can cause aflatoxins. However, the spatial patterns at these portions matched those of the gauge well after bias correction. The LGP was accurately captured after bias corrections. In [35], the study concluded that when compared to observed flow data, the bias-corrected downscaled precipitation scenarios exhibit more realistic hydrologic modeling, and this was observed in this study as the seasonality indices were well-simulated because of the uncertainty associated with satellite and model estimations. [19], concluded that such agriculturally orientated climate impact models should be regarded carefully when these datasets are used without bias correction.

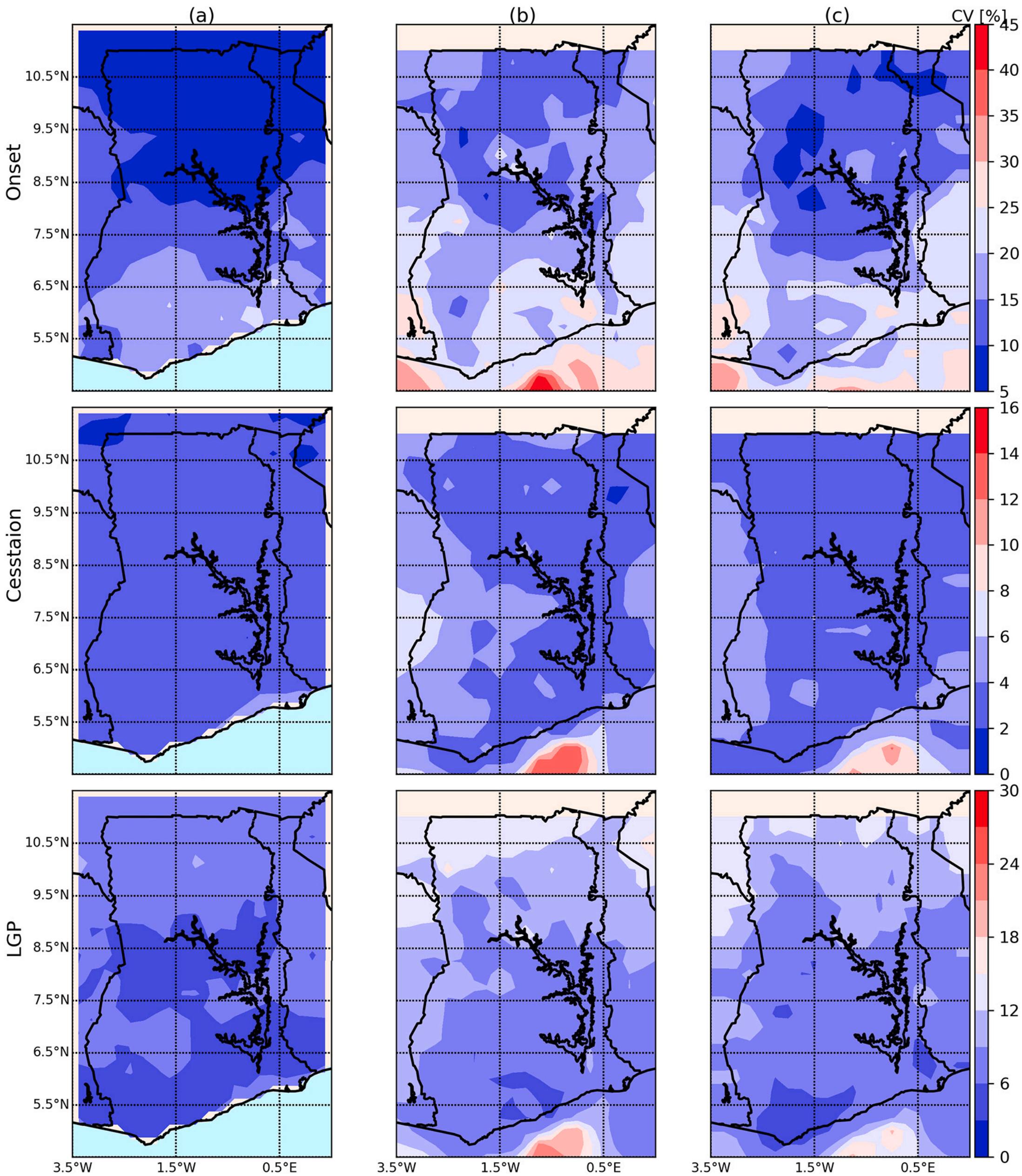

Fig. 8. Variation for the seasonality indices as captured by CHIRPS V2 (a), GMet gauge (b), and BCSD (c) over Ghana during 1981–2015.

The dispersion of data in a time series around the mean is statistically measured by the coefficient of variation (CV). As a result, the CV for the CHIRPS V2 (a), GMet gauge (b), and CHIRPS v2 (c) were computed. Although the CV values (5–10%) for onsets captured by CHIRPSs are relatively lower than gauge, its CV spatial patterns are different from the gauge, as shown in Fig. 8. However, we discovered that the CHIRPS-post-bias V2's correction spatial patterns of CV are comparable to those of the gauge observations, which fall within a similar range (5–26%). Further, the cv values for the cessations of rainfall are generally very low. The cv values for the CHIRPS V2, gauge, and Bias corrected CHIRPS-V2 rainfall cessations were found to be in the range of 0–2%, 2–8%, and 2–8%, respectively. The CV values of the gauge and those after the bias correction exhibit very good spatial correspondence, as seen in Fig. 8 which could be attributed to the fact that one benefit of the BCSD method is that it can bring more realistic variability at finer scales than simpler spatial interpolation systems while also reducing biases in the distribution of precipitation totals [27]. It is important to note that, generally, the CV values for the entire country from all datasets are higher for the length of the growing season and the cessation of rainfall compared to the onset of rains.

The spatial distribution of the mean absolute difference before and after bias correction with the gauge for onsets, cessations and LGP are shown in Figs. 9 a–c. In general, we note a few variations in the onsets of the rain across the nation, as captured from CHIRPS

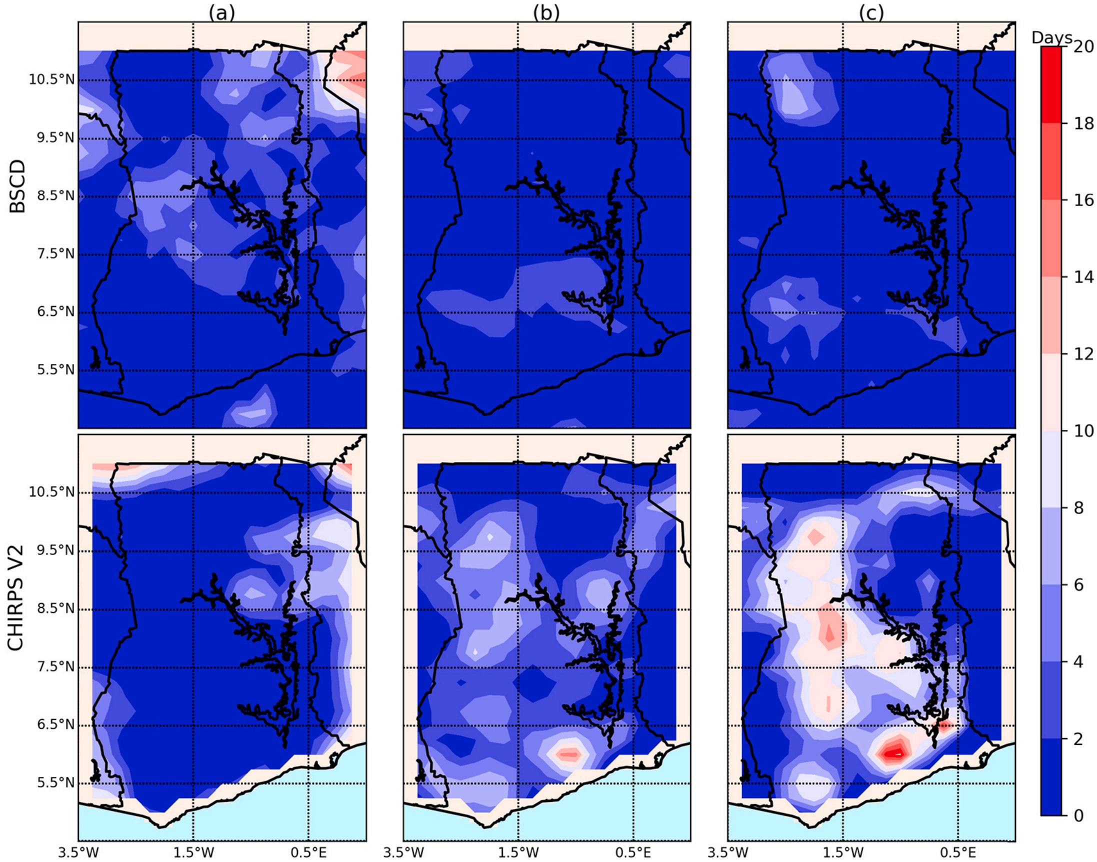

Fig. 9. Spatial distribution mean absolute difference before and after bias correction compared to gauge for onset (a), cessation (b), and LGP (c).

before and after bias correction. We can see that onset for both CHIRPS before and after bias corrections varied from gauge by up to about 6–10 days in some countries. In contrast, for the cessations of rainfall, we note that before bias corrections, the difference between the CHIRPS and gauge was high in a few localized areas of the country (> 10 days), but that after bias correction, the difference was reduced to 6 days with most areas of the country being 2 days.

6. Summary and conclusions

Rain gauge distributions are declining, and satellite rainfall estimates are increasingly being used to supplement the poor gauge networks. On the other hand, rain gauges are still used as reference data to validate existing and incoming satellite products because they provide the most direct information on local rainfall variations. The spatiotemporal variability of rainfall seasonality hampers Ghana's food security and other socioeconomic activities.

Accurate and realistic daily rainfall representation from satellite and climate models is essential for impact assessment studies, and bias correction of their outputs is necessary to ensure meaningful runoff simulations from hydrological models. The BCSD method is used in this study to bias-correct daily satellite-based rainfall estimate (CHIRPS-v2) data. Additionally, the study uses the bias-corrected spatially high-resolution CHIRPS-v2 daily rainfall series in Ghana to analyze the variability of the three rainfall indices thoroughly. In particular, the study examined whether bias correction of daily rainfall estimates derived from satellite data enhanced the ability to identify seasonality indices in Ghana.

Our results support other regional findings by showing that the rainfall in the region is better represented after the bias correction of the CHIRPS-v2 data. Overall, it was discovered that all seasonal levels of CHIRPS V2 could be corrected very successfully using the BSCD method. Our results demonstrated a decline in biases and root mean squared errors for most regions. Regarding the seasonality indices, we note that the spatial patterns for the start of rainfall were well captured when compared to gauge observations post-bias correction. We can see that the onset dates in the middle of the country were accurately recorded, but there were a few late-onset dates in the upper-east regions of the country and a few early onset dates at a few specific locations in the south. We typically observe a high level of BSCD method proficiency across the country concerning cessation dates. Before bias corrections, we observed that cessation dates in the nation's southwest and upper middle regions were marginally late compared to gauge observations. These effectively capture the high level of uncertainty farmers encounter when making crop selections in between growing seasons. Early cessations can stop grain filling, which reduces yield; late cessations can delay harvesting, which increases post-harvest losses and raises the possibility of mold infestations that can produce aflatoxins. Nevertheless, the spatial patterns at these points matched the

gauge's patterns quite well after bias correction. Following bias adjustments, the LGP was successfully captured.
The study, therefore, recommends the BCSD method for adjusting rainfall estimates from other algorithms with long-term historical records that are representative of the area under consideration's rainfall variability. The method is appropriate for reducing systematic errors, particularly in high-elevation regions. However, it is sensitive to sparse rain gauge distributions in deep convective systems due to cirrus effects, which cause overestimation. As a result, the approach works better in those areas with a high-quality rain gauge network. Therefore, we recommend using higher or equal spatial scale reference data for higher rainfall spatial representation.

CRediT authorship contribution statement

Winifred Ayinpogbilla Atiah: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper. Robert Johnson: Performed the experiments; Analyzed and interpreted the data; Wrote the paper. Francis Kamau Muthoni: Conceived and designed the experiments; Contributed analysis tool and data; Proofread paper. Gizaw Tsidu Mengistu: Conceived and designed the experiments; Contributed analysis tool and data, Proofread paper. Leonard Kofitse Amekudzi & Fred Kizito: Conceived and designed the experiments; Contributed analysis tools and data, Proofread paper. Osei Kwabena: Analyzed and interpreted the data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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