

# Is equatorial Africa getting wetter or drier? Insights from an evaluation of long-term, satellite-based rainfall estimates for western Uganda

Jeremy E. Diem<sup>1</sup>  | Bronwen L. Konecky<sup>2</sup> | Jonathan Salerno<sup>3</sup> | Joel Hartter<sup>4</sup>

<sup>1</sup>Department of Geosciences, Georgia State University, Atlanta, Georgia

<sup>2</sup>Department of Earth and Planetary Sciences, Washington University of St. Louis, St. Louis, Missouri

<sup>3</sup>Department of Human Dimensions of Natural Resources, Colorado State University, Fort Collins, Colorado

<sup>4</sup>Environmental Studies Program, University of Colorado Boulder, Boulder, Colorado

## Correspondence

Jeremy E. Diem, Georgia State University, 24 Peachtree Center Avenue, Atlanta, GA 30303. Email: jdiem@gsu.edu

## Funding information

National Science Foundation, Grant/Award Number: 1740201

Long-term trends in equatorial African rainfall have proven difficult to determine because of a dearth in ground-measured rainfall data. Multiple, satellite-based products now provide daily rainfall estimates from 1983 to the present at relatively fine spatial resolutions, but in order to assess trends in rainfall, they must be validated alongside ground-based measurements. The purpose of this paper is twofold: (a) to assess the accuracy of four rainfall products covering the past several decades in western Uganda; and (b) to ascertain recent, multi-decadal trends in annual rainfall for the region. The four products are African Rainfall Climatology Version 2 (ARC2), Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR), and TAMSAT African Rainfall Climatology And Timeseries (TARCAT). The bias and accuracy of 10-day, monthly, and seasonal rainfall totals of the four products were assessed using approximately 10 years of data from 10 rain gauges. The homogeneity of the products over multiple time periods was assessed using change-point analysis. The accuracy of the four products increased with an increase in temporal scale, and CHIRPS was the only product that could be considered sufficiently accurate at estimating seasonal rainfall totals throughout most of the region. TARCAT tended to underestimate totals, and ARC2 and PERSIANN were in general the least accurate products. Only annual rainfall estimates from CHIRPS and TARCAT were significantly correlated with ground-measured rainfall totals. TARCAT was the most homogeneous product, while ARC2, CHIRPS, and PERSIANN had significant negative change points that caused a drying bias over the 1983–2016 period. After adjusting the satellite-based rainfall estimates based on the timing and magnitude of the change points, annual rainfall totals derived from all four products indicated that western Uganda experienced significantly increasing rainfall from 1983 to 2016.

## KEY WORDS

double-mass curve, equatorial Africa, inhomogeneity, rainfall, satellite-based estimates, validation

## 1 | INTRODUCTION

A major environmental conundrum exists in tropical Africa: rainfall variability has an outsized impact on people in the region, but the variability is difficult to determine using past

and present rain-gauge networks. Millions of rural households in the region practice rain-fed agriculture; consequently, their livelihoods depend on the timing and amount of rainfall within rainy seasons (Rosegrant *et al.*, 2002; Cooper *et al.*, 2008). Despite the dire need for a large network of

daily rainfall measurements, tropical Africa has suffered a dramatic loss of rain gauges over the past several decades, with an extreme case being central equatorial Africa (CEA) which has lost over 90% of its gauges since the early 1980s (Washington *et al.*, 2013). The available stations are unevenly distributed across the region; for example, Ethiopia has a relatively high density of gauges (Dinku *et al.*, 2014) and the Democratic Republic of Congo (DRC), which is over twice as large as Ethiopia and is the second-largest country in Africa, has just a few gauges (Washington *et al.*, 2013).

The use of satellite-based rainfall products has been increasingly employed to both supplement and replace ground-measured rainfall data. Rainfall-estimation algorithms use onboard satellite data from thermal infrared (TIR) and passive microwave (PM) sensors. TIR information, which is based on the cloud-top brightness temperature, is useful for distinguishing between raining and non-raining clouds but is relatively poor at estimating rainfall amount (Kidd *et al.*, 2003; Dembélé and Zwart, 2016). PM information, which is sensitive to the concentration of ice crystals or droplets in a cloud associated with precipitation, is better than TIR at estimating rainfall amount, but it is obtained at a coarser spatial resolution (Kidd *et al.*, 2003; Dembélé and Zwart, 2016).

Currently, four satellite-based products provide daily precipitation totals across tropical Africa from 1983–present at relatively fine spatial resolutions, and thus can potentially be used not only to analyse spatial patterns of rainfall in tropical Africa but also to reproduce the inter-annual variability in rainfall over the past several decades. The African Rainfall Climatology Version 2 (ARC2) product has a spatial resolution of  $0.10^\circ$  and is derived from TIR data and Global Telecommunication System (GTS) gauge observations reporting 24-hr rainfall accumulations (Novella and Thiaw, 2013). The Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) product has a spatial resolution of  $0.05^\circ$  and is derived from the following: a gridded precipitation climatology based on topographic variables and monthly means of station data and precipitation-related data from five satellite products, which includes both PM and TIR data, and interpolated station data (Funk *et al.*, 2015). The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR; abbreviated in this paper as PERSIANN) product has a spatial resolution of  $0.25^\circ$  and is derived from both TIR and makes use of the Global Precipitation Climatology Project (GPCP) data set, which estimates precipitation totals at a  $2.5^\circ$  resolution, to adjust biases in monthly precipitation totals (Ashouri *et al.*, 2015). The TAMSAT African Rainfall Climatology And Timeseries (TARCAT) product has a spatial resolution of  $0.0375^\circ$  and is based on TIR data that has been climatologically calibrated using rain-gauge data (Maidment *et al.*, 2014). The

developers of all four products endorse the suitability of the products for multi-decadal time series analyses (Novella and Thiaw, 2013; Maidment *et al.*, 2014; Ashouri *et al.*, 2015; Funk *et al.*, 2015). Nevertheless, satellite-based rainfall products with long time series should have some inhomogeneities (i.e., changes in rainfall estimates not caused by actual changes in rainfall) caused by variations in satellite inputs (Dinku *et al.*, 2018).

All four satellite-based products have varying degrees of suitability for estimating monthly/seasonal rainfall totals for all or parts of tropical Africa. Ethiopia, with its relatively high-density rain-gauge network, has usually been an optimal validation region for the products (Dinku *et al.*, 2007). Most products generally struggle in complex terrain, especially mountainous areas. The products are not designed to capture warm-cloud processes; therefore, they underestimate rainfall in mountainous areas (Dinku *et al.*, 2008). PERSIANN, for example, has performed poorly in complex terrain (e.g., Ethiopia) (Derin *et al.*, 2016; Bayissa *et al.*, 2017). But both CHIRPS and TARCAT performed well in Ethiopia (Bayissa *et al.*, 2017). ARC2, CHIRPS, and PERSIANN have performed well in West Africa, while TARCAT performed poorly there (Dembélé and Zwart, 2016). Despite TARCAT being notorious for underestimating rainfall totals (Young *et al.*, 2014; Dembélé and Zwart, 2016; Maidment *et al.*, 2017), it has performed better than other products in Ethiopia (Abera *et al.*, 2016). CHIRPS has performed better than TARCAT in Mozambique (Toté *et al.*, 2015) and Ethiopia (Dinku *et al.*, 2018) and is more accurate than ARC2, PERSIANN, and TARCAT in East Africa as a whole (Kimani *et al.*, 2017; Dinku *et al.*, 2018). While Ethiopia has served as an excellent proving ground for rainfall products, much less attention has been devoted to equatorial Africa. Previous work showed that ARC2 is reasonably accurate in western Uganda, except at low-elevation locales possibly in a rainshadow (Diem *et al.*, 2014a), but ARC2 has not been compared with CHIRPS, PERSIANN, and TARCAT in the region.

The evaluation of satellite-based rainfall products, especially a multi-decadal assessment, in tropical Africa is becoming more important as findings of a significant drying trend across equatorial Africa become more common and as differing results for CEA and western Uganda emerge. Locales in equatorial Africa typically have a bimodal rainfall regime caused by the Intertropical Convergence Zone traversing the region twice per year, resulting in the equinoctial seasons typically having the highest rainfall totals (Nicholson, 1996). Over the past several decades, decreasing boreal-spring rainfall totals—derived principally from rain-gauge measurements—have been observed for all or parts of eastern equatorial Africa (EEA) (e.g., Kenya, northern Tanzania, and Somalia) (Williams and Funk, 2011; Lyon and DeWitt, 2012; Yang *et al.*, 2014). Western Uganda is climatologically transitional between EEA and CEA (Monaghan

et al., 2012), and significant drying in the region has been found in studies using ARC2 data (Diem et al., 2014b; Ssentongo et al., 2018). Analyses of satellite-based rainfall estimates for CEA also reveals a drying trend there (Asefi-Najafabady and Saatchi, 2013; Diem et al., 2014b; Hua et al., 2016). Nevertheless, rainfall might actually be increasing for CEA and western Uganda: TARCAT data show a wetting trend in annual rainfall (Maidment et al., 2015), and recent research involving ARC2, CHIRPS, and TARCAT has shown that both rainy-season and annual rainfall totals at multiple location in western Uganda has probably increased over the past two decades (Salerno et al., 2019).

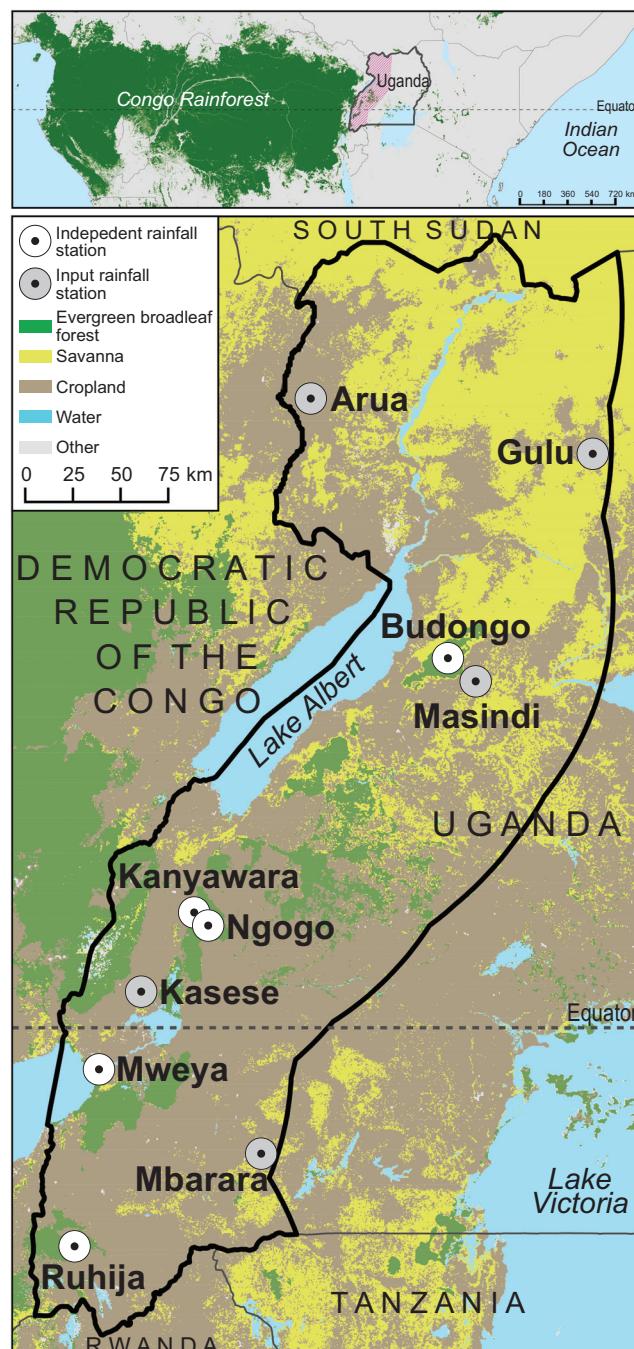
Validation work is greatly needed in western Uganda and CEA in order to better determine the rainfall variability in those regions. As noted previously, CEA is greatly deficient in rain gauges (Washington et al., 2013); therefore, there simply does not exist adequate ground-measured totals to compare with satellite-based estimates. Fortunately, western Uganda contains a sufficient amount of high-quality rainfall data to validate rainfall products, and multiple sites in the region have ground-measured rainfall totals extending back several decades, thereby enabling the potential identification of significant inhomogeneities in satellite-derived time series. While there has been previous validation research in western Uganda (Diem et al., 2014a), it only included one long-term satellite-based product (i.e., ARC2), it involved only five rainfall stations, and it did not assess the homogeneity of rainfall time series.

The purpose of this paper is to validate rainfall estimates from ARC2, CHIRPS, PERSIANN, and TARCAT across western Uganda. We define the western Uganda study region as a zone within 160 km of the Congo watershed boundary (Figure 1). It has over 6 million people (Stevens et al., 2015), the majority of which are in households practicing rain-fed small-scale agriculture (Hartter et al., 2015). Therefore, an enhanced understanding of rainfall is important to those farming households. The two main objectives of the research are as follows: (a) assess the accuracy of satellite-based rainfall estimates over a fixed time (e.g., 2001–2010); and (b) provide the best estimates of trends in rainfall totals for western Uganda from 1983 to 2016.

## 2 | DATA AND METHODS

### 2.1 | Data

Ground-measured rainfall totals, primarily daily rainfall totals, were obtained for 10 sites in the study region (Figure 1 and Table 1). Eight of the stations were missing less than 8% of daily rainfall totals. Among those stations was Kanyawara, which—with uninterrupted measurements occurring since 1976—has the longest record of any station in western Uganda. Most of the missing daily rainfall totals



**FIGURE 1** The western Uganda study region showing the proximity of the region to the Congo rainforest as well as the dominant land-cover types in the region and the locations of the 10 rainfall stations used in the study. Land-cover information is derived from the MODIS land-cover type product (MCD12Q1) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

at Kanyawara occurred from 1993 to 2001; during this period, rainfall totals on days without a recorded total were often added to the totals on subsequent days. Fortunately, the last day of all but 1 month (i.e., May 2013) had rainfall totals; therefore, Kanyawara had a nearly serially complete monthly rainfall record. The serially complete daily (i.e., no missing days) rainfall data at Ngogo, which is located inside Kibale National Park and 10 km southeast of and 70 m

TABLE 1 Locations and data characteristics of the rain gauges

Site	Latitude	Longitude	Elevation (m.a.s.l.)	RE (m) <sup>a</sup>	Data availability	% non-missing daily data	Data source
Arua	3.050°N	30.920°E	1,205	131	Jan 2000–Dec 2012	100.0	Uganda National Meteorological Authority
Budongo	1.794°N	31.583°E	1,029	38	Jan 1993–Oct 2016	98.4	Budongo Conservation Field Station
Gulu	2.783°N	32.283°E	1,078	62	Jan 2000–Dec 2012	96.6 <sup>b</sup>	Uganda National Meteorological Authority
Kanyawara	0.565°N	30.356°E	1,507	200	Jan 1976–Dec 2016	92.7 <sup>c</sup>	Makerere University Biological Field Station
Kasese	0.183°N	30.100°E	964	−323	Jan 2000–Dec 2012	98.0	Uganda National Meteorological Authority
Masindi	1.683°N	31.717°E	1,145	228	Jan 2001–Dec 2010	94.2	Uganda National Meteorological Authority
Mbarara	0.600°S	30.680°E	1,384	−28	Jan 2000–Dec 2012	98.0	Uganda National Meteorological Authority
Mweya	0.193°S	29.896°E	961	−465	Jan 1996–Jun 2011	73.1 <sup>d</sup>	Uganda Wildlife Authority
Ngogo	0.502°N	30.424°E	1,437	45	Jul 1996–Dec 2016	100.0	Ngogo Chimpanzee Project
Ruhija	1.049°S	29.778°E	2,301	452	Jan 1987–Jul 2012	85.3 <sup>e</sup>	Institute of Tropical Forest Conservation

<sup>a</sup>RE (relative elevation) is the elevation of the station minus the mean elevation of a 11,310 km<sup>2</sup> zone centred on the station.

<sup>b</sup>Daily data at Gulu were only available for 2001–2010. Monthly data were available for 2000, 2011, and 2012.

<sup>c</sup>Except for days in May 2013, rainfall totals on days without a recorded total were often added to the totals on subsequent days.

<sup>d</sup>All the days with missing totals existed between 1997 and 2002.

<sup>e</sup>1987–1996 had 95.8% of days with valid totals, while 1997–2012 only had 78.5% of days with valid totals.

lower in elevation than Kanyawara, were used to estimate rainfall at Kanyawara for May 2013. The stations with the largest amounts of missing data were Ruhija (~15%) and Mweya (~27%). Most of the missing data at Ruhija occurred after 1996: the 1987–1996 period was missing less than 5% of daily rainfall totals. All the missing data at Mweya occurred from 1997–2002, with no data available for 1999, 2000, and 2001.

Gridded rainfall estimates for 1983–2016 from the ARC2, CHIRPS, PERSIANN, and TARCAT products were obtained from the International Research Institute for Climate and Society at Columbia University. CHIRPS was serially complete and TARCAT was only missing data for the first 10 days of 1983. ARC2 and PERSIANN were missing 1.7 and 1.0%, respectively, of daily rainfall totals. Nearly all the ARC2 missing data occurred during 1983–1990; 9.3% of the days were missing rainfall totals during these years. Similarly, nearly all the PERSIANN missing data occurred during 1983–1993; 9.5% of the days were missing rainfall totals during these years, with 1984 missing 35% of the daily rainfall totals.

## 2.2 | Validation of rainfall totals

For approximately the 2001–2010 period, rainfall totals at the 10 rainfall stations were compared with rainfall totals estimated by the four satellite-based products. The four products use ground-measured rainfall to varying degrees to produce the gridded rainfall estimates, and the following five stations have been used as input for the products: Arua, Gulu, Kasese, Masindi, and Mbarara. These stations have been classified as “input stations” in this paper and the other five stations (Budongo, Kanyawara, Mweya, Ngogo, and Ruhija) have been classified as “independent stations” (Figure 1 and Table 2). The distinction between input and independent stations matters the least for TARCAT

estimates, since these estimates are not produced from contemporaneous gauge records (Maidment *et al.*, 2017). Due to the relatively large amount of missing daily rainfall totals at Mweya and Ruhija during 2001–2010, the validation periods for those two sites were extended to 1997–2010 and 2000–2012, respectively. Rainfall totals for periods with at least 90% of days with non-missing rainfall totals were upwardly adjusted to represent 100% of the days (e.g., a period with 90% valid days had its rainfall total multiplied by 1.11). Periods with more than 10% of days with missing rainfall totals were excluded from the analyses. The rainfall total for a given product corresponding to a given gauge was calculated two ways. The first estimate was the value for the grid cell in which the station existed. The second estimate was a weighted mean of the gauge cell and the eight cells sharing either an edge or corner with that cell (i.e., Queen’s case contiguity). The weights for the nine cells were based on the distance of the gauge to the centroids of the cells (Figure 2). Therefore, the centre cell always had the highest weight. The range in weights for the nine cells across all gauge/product combinations was 0.032–0.672. The weighting procedure was used to produce the satellite-based totals at additional gauges and time periods presented in subsequent sections of this paper.

The ability of the products to reproduce the intra-seasonal behaviour of rainfall was assessed by comparing measured and estimated monthly rainfall totals. Mann–Whitney *U* tests ( $\alpha = .05$ ; one-tailed) were used to test for significant differences between measured and estimated monthly rainfall totals. For example, a comparison of measured January rainfall and rainfall estimated by CHIRPS involved 10 cases (i.e., 2001–2010).

Percent bias (PB) and the Nash–Sutcliffe coefficient of efficiency (*E*) were calculated for 10-day, monthly, and seasonal (i.e., December–February, March–May, June–August,

**TABLE 2** Mean percent bias (PB) and Nash–Sutcliffe  $E$  values for the four products based on values for the 10 validation sites

	ARC2	CHIRPS	PERSIANN	TARCAT
$ PB $				
Input	11	6	15	13
Independent	19	16	27	20
<i>10-day E</i>				
Input	0.29	0.35	0.24	0.28
Independent	−0.01	0.18	0.04	0.13
<i>Monthly E</i>				
Input	0.38	0.59	0.34	0.40
Independent	0.11	0.32	0.00	0.20
<i>Seasonal E</i>				
Input	0.49	0.73	0.38	0.58
Independent	0.13	0.52	−0.04	0.35

*Note.* Input stations (Arua, Gulu, Kasese, Masindi, and Mbarara) are those stations for which data was available during the development of the four products, and therefore may have been ingested into the products themselves. Independent stations (Budongo, Kanyawara, Mweya, Ngogo, and Ruhija) are stations for which no data were used to produce any of the products. Since the optimal PB value is zero, absolute PB values are used.

<sup>a</sup>The Kanyawara 10-day  $E$  was estimated by multiplying the Ngogo 10-day  $E$  by the ratio of the Kanyawara monthly  $E$  to the Ngogo monthly  $E$ .

and September–November) rainfall totals at the eight stations. PB and  $E$  were calculated for all time steps as follows:

$$PB = 100 \frac{\sqrt{\frac{1}{N} \sum (S - G)^2}}{\bar{G}}, \quad (1)$$

$$E = 1 - \frac{\sum (G - S)^2}{\sum (G - \bar{G})^2}. \quad (2)$$

0.131	0.138	0.069
0.178	•Gauge 0.195	0.074
0.078	0.079	0.057

**FIGURE 2** Example of the nine-cell weighting procedure used with the gridded rainfall estimates. The weights shown are those pertaining to the TARCAT data and the Arua rain gauge

$G$  is a rainfall total at a gauge,  $G$  is the mean observed rainfall total at a gauge,  $S$  is a rainfall total for a satellite product, and  $N$  is the number of data pairs. PB is the average tendency of estimated totals to be larger or smaller than the observed totals. In this paper, a positive (negative) PB indicates overestimation (underestimation).  $E$  ranges from  $-\infty$  to 1, with higher values indicating better agreement between observations and estimates (Nash and Sutcliffe, 1970; Legates and McCabe, 1999). In the case of the satellite-based rainfall products, negative  $E$  values indicate that the mean observed value (i.e., the null model) is a better estimate for all cases than are the estimated values from a product.

## 2.3 | Detection of temporal change points and adjustment of time series

The homogeneity of the satellite-based rainfall records was assessed using change-point analysis, which involved the use of double-mass curves (DMCs). While multiple methods exist for detecting inhomogeneities (i.e., temporal change points) in climatological time series (Buishand, 1982; Easterling and Peterson, 1995), this study used the DMC approach for the following reasons: (a) it is a straight-forward, graphical tool for identifying inhomogeneities; and (b) the curves are created from cumulative rainfall totals and thus—when compared to other inhomogeneity-detection procedures—should be less impacted by the occasional large monthly difference between a ground-measured rainfall total and a satellite-based rainfall estimate. The production of DMCs requires serially complete data; therefore, in this study, a day with a missing rainfall total was given the mean rainfall total for its particular day of the year. The DMCs were cumulative totals of monthly satellite-based rainfall versus cumulative totals of monthly ground-measured rainfall. In a DMC, the relationship between the two variables is a straight line so long as the relation between the variables is a fixed ratio (Searcy and Hardison, 1960). Four periods were analysed using pooled station totals: 1987–1996, 1993–2016, 1997–2016, and 2000–2012. The mean of Kanyawara and Ruhija totals were the measured values for the 1987–1996 analysis. The mean of Budongo and Kanyawara were the measured totals for the 1993–2016 analysis. The mean of Budongo and Kanyawara/Ngogo (i.e., the mean of those two proximate stations) values were the measured totals for the 1997–2016 analysis. The mean of Arua, Budongo, Gulu, Kanyawara/Ngogo, Kasese, and Mbarara values were the measured totals for the 2000–2012 analysis. The pooling of data from multiple gauges was performed to reduce the possibility that a change point was caused by station-specific inhomogeneities (e.g., change in gauge location, change in measurement procedure, etc.) (Easterling and Peterson, 1995); therefore, it is assumed that all significant change points resulted from inhomogeneities in the satellite products. The only time pooled gauge data were not used

was when potential change points were further examined in the late 1980s and early 1990s; DMCs were created for 1983–1996 at Kanyawara and 1987–1996 at Ruhija. Analysis of covariance ( $\alpha = .05$ ) was used to test for significant change points.

Rainfall time series from 1983 to 2016 for the entire western Uganda region and time series from 2000 to 2012 for the mean of the six stations (i.e., Arua, Budongo, Gulu, Kanyawara/Ngogo, Kasese, and Mbarara) were adjusted by multiplying monthly rainfall estimates prior to a significant change point by an adjustment factor. Change points were assumed to exist for the entire region only if they existed in multiple DMCs and occurred within approximately 2 years of each other. Adjustment factors were the ratio of two linear regression slopes: the slope following the change point was divided by the slope preceding the change point (Searcy and Hardison, 1960). The final adjustment factor was a weighted mean of the multiple adjustment factors, with the weighting based on the number of rain-gauge stations used to produce the DMCs (i.e., a DMC based on eight stations was given much more weight than a DMC based on two stations). The month of the change point was also weighted by the number of rain-gauge stations. If two change points of opposite sign existed in a time series, then the monthly values between those points were adjusted upwards (i.e., negative change point followed by positive change point) or downwards (i.e., positive change point followed by negative change point). When significant change points of the same sign existed in different curves at approximately the same year, then a single adjustment factor was produced by using the weighted mean of the adjustment factors. Finally, for the 2000–2012 time series, only the adjustment factors derived from the 2000–2012 DMCs were used.

## 2.4 | Assessment of temporal correlations and multi-decadal trends

Temporal relationships between the measured and estimated annual rainfall totals from 2000 to 2012 were assessed using Spearman's rank correlation coefficient (one-tailed;  $\alpha = .05$ ). The mean of Arua, Budongo, Gulu, Kanyawara/Ngogo, Kasese, and Mbarara rainfall totals (described in section 2.3) was used. Correlations were calculated between both the measured and unadjusted rainfall totals and the measured and adjusted rainfall totals.

Temporal trends in estimated annual and seasonal rainfall totals from 1983 to 2016 were calculated for the entire region. As in other analyses, a missing daily rainfall total was replaced with the mean value for that day of the year over the period. In addition to the unadjusted rainfall totals, adjusted rainfall totals were produced using slope ratios from the DMCs. The Kendall–Theil robust line, the median of the slopes between all combinations of two points in the data (Helsel and Hirsch, 2002), was used to estimate changes over the 34-year period.

## 3 | RESULTS

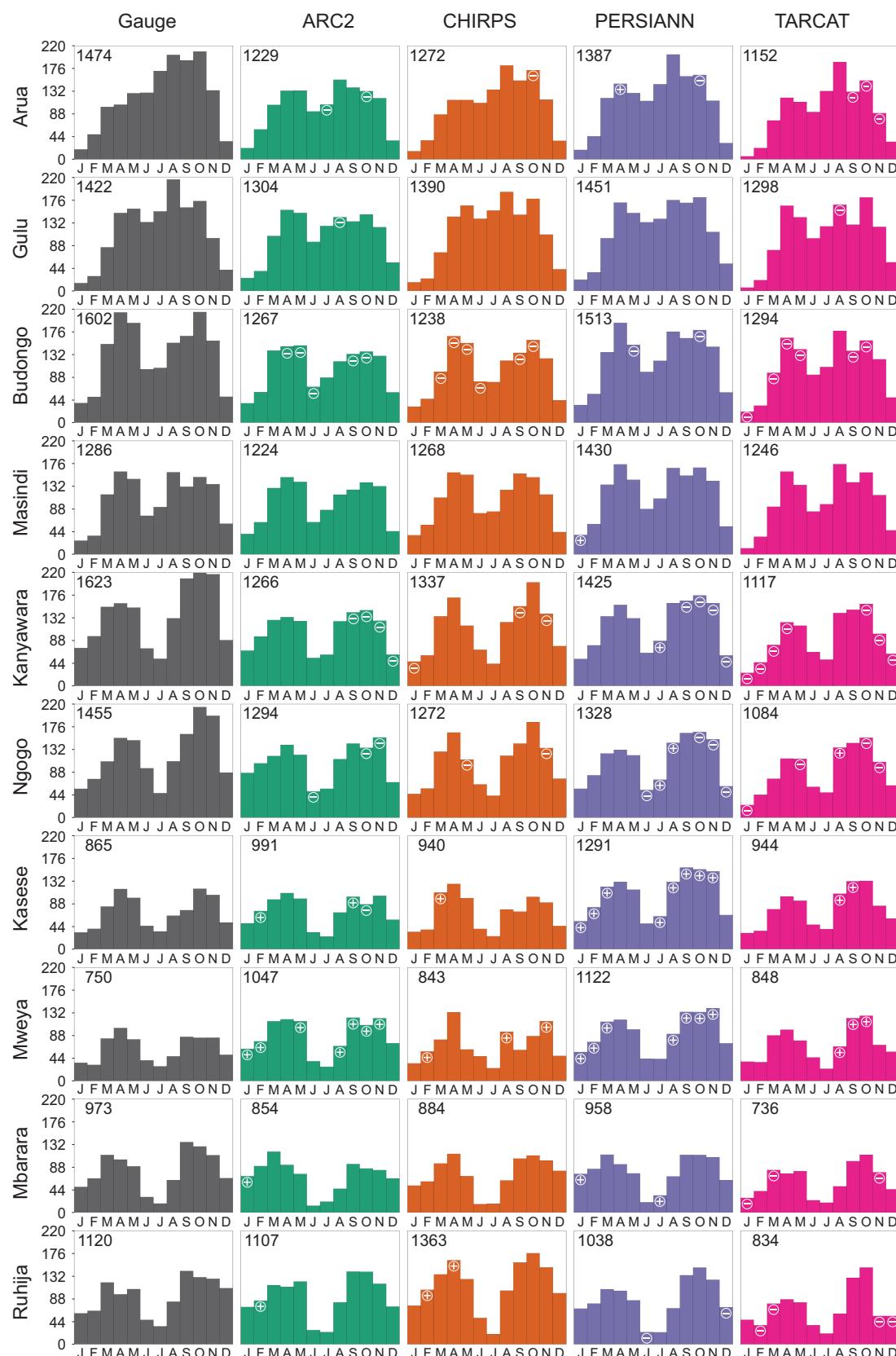
### 3.1 | Bias in rainfall estimates

While all products generally captured the typical intra-annual rainfall variability at the 10 stations, as well as the transition from an annual rainfall regime at the northernmost stations to a biannual regime at the southernmost stations, there were significant underestimates and overestimates of rainfall totals for specific months and seasons (Figure 3). ARC2 tended to underestimate boreal-summer and boreal-autumn rainfall totals at the northern stations and overestimated rainfall totals during all months outside of boreal summer at Kasese and Mweya, which were the two stations located in the rift valley and thus located hundreds of meters below the surrounding terrain (Table 1) (Diem *et al.*, 2014a). ARC2 performed well at Mbarara and Ruhija, with only significant overestimates occurring during boreal winter. CHIRPS replicated monthly rainfall totals extremely well at all five input stations (i.e., Arua, Gulu, Masindi, Kasese, and Mbarara). CHIRPS had significant underestimates and overestimates at the five independent stations: rainfall totals were underestimated throughout the year at Budongo and Kanyawara, rainfall totals were overestimated throughout the year at Mweya, and rainfall totals were overestimated in boreal spring at Ruhija. Except for underpredictions throughout the year at Kasese and Mweya, PERSIANN did not have consistent underpredictions and overpredictions at the other stations. Besides 1 month at Ngogo, TARCAT underpredicted monthly rainfall totals at all non-rift stations. Similar to the other products, TARCAT overpredicted at Kasese and Mweya; however, the overpredictions were confined to boreal summer and autumn.

Irrespective of specific months and seasons, the products tended to underestimate rainfall totals at Arua, Gulu, Budongo, Masindi, Kanyawara, Ngogo, Mbarara, and Ruhija, and all products overestimated rainfall totals at the rift stations (Kasese and Mweya) (Figure 4). These results were nearly identical regardless of which procedure was used to assign rainfall estimates to rainfall stations (i.e., based on a single grid cell vs. a weighted mean of nine; see section 2.2). Previous research has established a PB  $\geq \pm 25\%$  to be unsatisfactory (Moriasi *et al.*, 2007). Therefore, using  $\pm 25\%$  as a PB threshold, CHIRPS was the only product to have satisfactory PB values at all stations. ARC2 only exceeded  $+25\%$  at Mweya, and PERSIANN only exceeded  $+25\%$  at Kasese and Mweya. TARCAT did not have any unsatisfactory overestimates, but it did have underestimates exceeding  $-25\%$  at Kanyawara, Ngogo, and Ruhija.

### 3.2 | Nash–Sutcliffe *E* values

None of the products performed satisfactorily at estimating 10-day rainfall totals, but most products were accurate at estimating monthly and seasonal rainfall totals, especially at

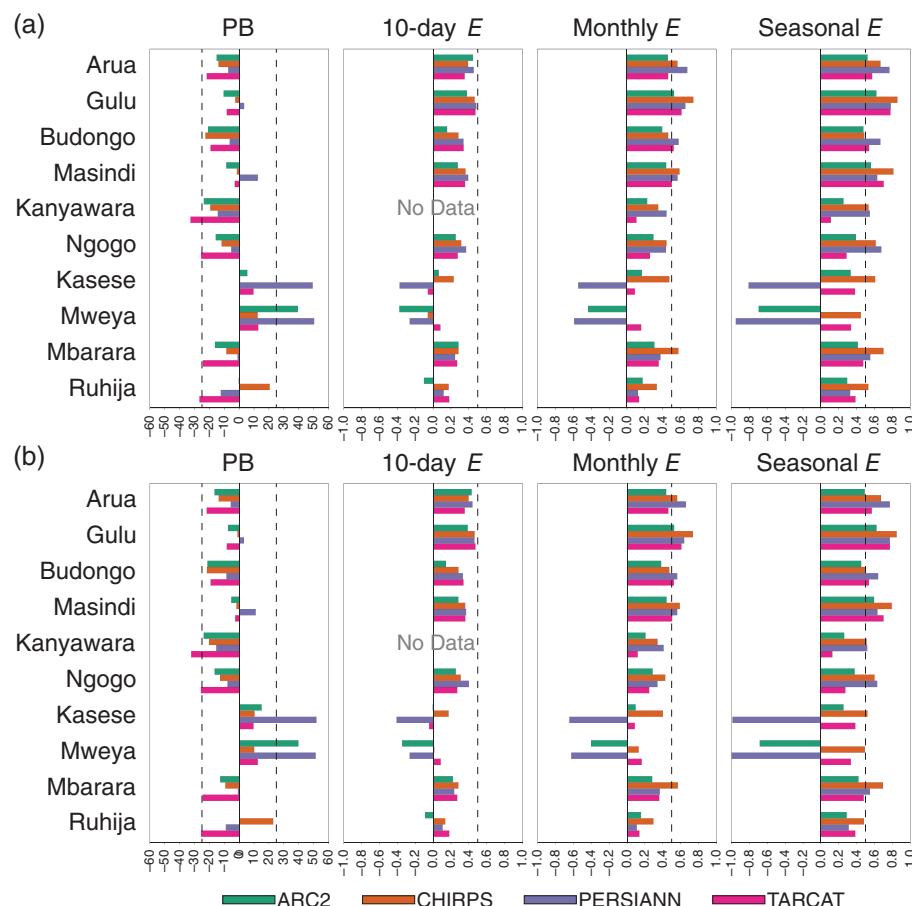


**FIGURE 3** Mean monthly rainfall totals (in mm) at 10 rain-gauge sites for approximately 2001–2010. Measured totals at the gauges and estimated totals by the four products are shown, and significant differences between estimated totals and observed totals are denoted by plus (+) (overestimate) and minus (underestimate) signs. The mean annual rainfall total (in mm) is provided in the upper-left hand corner of each panel. Mweya and Ruhija values pertain to 1997–2010 and 2000–2012, respectively [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

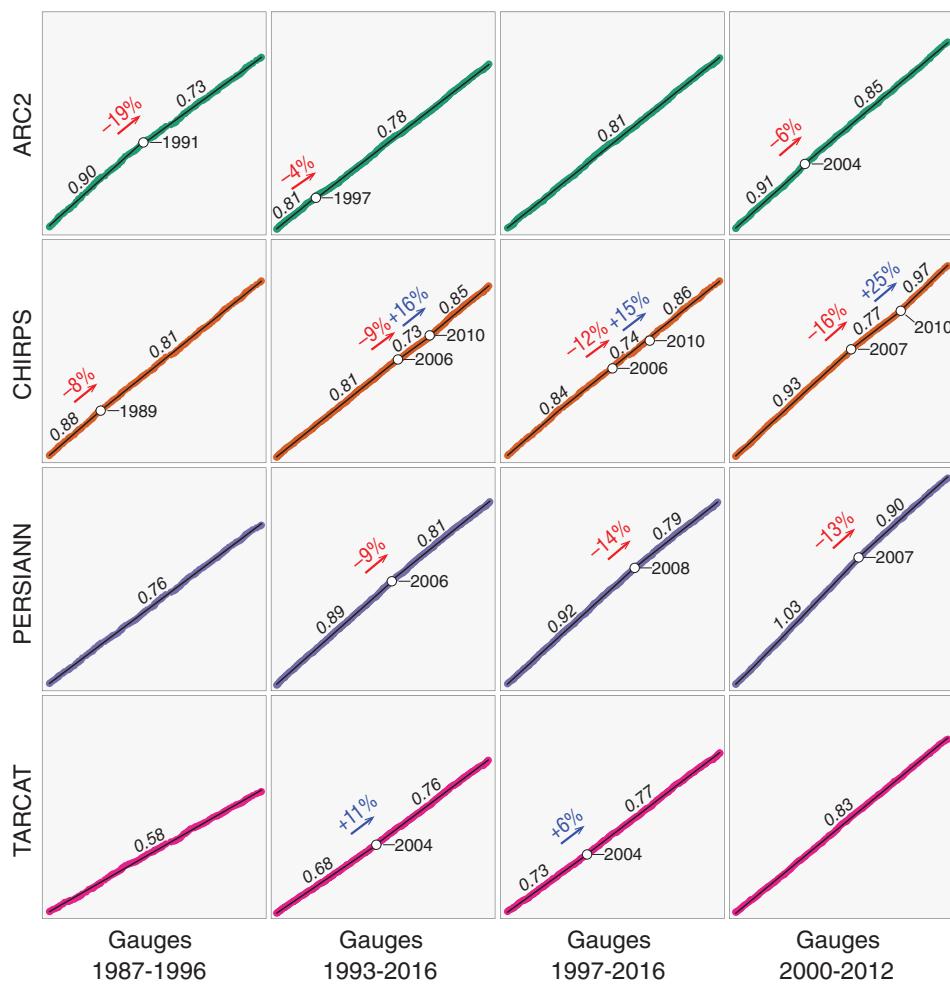
the northern stations (Figure 4). Similar to the PB values, the  $E$  values resulting from the two procedures used to estimate rainfall totals at a gauge were nearly identical. And in general, the larger the absolute PB value (i.e., increased bias) for a product then the lower the  $E$  value; the largest PB values produced negative  $E$  values. A product in this study had satisfactory estimates (i.e., it was accurate) if the  $E$  value was greater than 0.50 (Moriasi *et al.*, 2007; Diem *et al.*, 2014a). ARC2 only accurately estimated seasonal totals, and that occurred only at Arua, Gulu, and Masindi, which as noted earlier were input stations (i.e., gauge data was used to produce satellite-based estimates). ARC2 performed poorly at Mweya, where it consistently had negative  $E$  values. CHIRPS was accurate at four of the 10 stations at the monthly scale and was accurate at all stations but Mweya—where the  $E$  value was 0.47—at the seasonal scale. PERSIANN was accurate at the four northernmost stations at the monthly scale and accurate at seven stations at the seasonal scale. But PERSIANN had extremely large negative  $E$  values at Kasese and Mweya at both the monthly and seasonal scales. TARCAT was accurate at three northern stations (Gulu, Budongo, and

Masindi) at the monthly scale and accurate at the four northernmost stations at the seasonal scale.

CHIRPS was the most accurate product both at the input stations and the independent stations, with the latter stations tending to be located in more challenging environments for rainfall estimation (Table 2). One would expect ARC2, CHIRPS, and PERSIANN to perform better at the input stations, while TARCAT, which as noted previously is not developed from contemporaneous gauge data, should have performed approximately the same at the input and independent stations. But the mean PB and  $E$  values for TARCAT at the independent stations were much higher than and lower than the PB and  $E$  values, respectively, at the input stations. The five independent stations are either located in a tropical forest (Budongo, Kanyawara, Ngogo, and Ruhija) or at the bottom of a rift (Mweya). The products tended to substantially underestimate rainfall totals at Budongo, Kanyawara, and Ngogo and substantially overestimate rainfall totals at Mweya (Figures 3 and 4). Over all, CHIRPS was the only product with an acceptable mean seasonal  $E$  value at the independent stations.



**FIGURE 4** Percent bias (PB) and Nash–Sutcliffe  $E$  values for the four products at 10 rain-gauge sites for 2001–2010 based on rainfall totals for (a) the grid cell in which the rain gauge exists and (b) a weighted mean of nine neighbourhood grid cells.  $E$  values are provided for 10-day totals, monthly totals, and seasonal totals. A positive PB indicates overestimation by a product, while a negative PB indicates underestimation. PB values between  $-20\%$  and  $+20\%$  are indicated by dashed lines in the PB panels.  $E$  ranges from  $-1.0$  to  $1.0$ , with higher values indicating better agreement between observations and estimates.  $E$  values  $\geq 0.5$ , which are indicated by dashed lines in the  $E$  panels, are considered acceptable.  $E$  values  $< 0$  indicate extremely poor performance [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

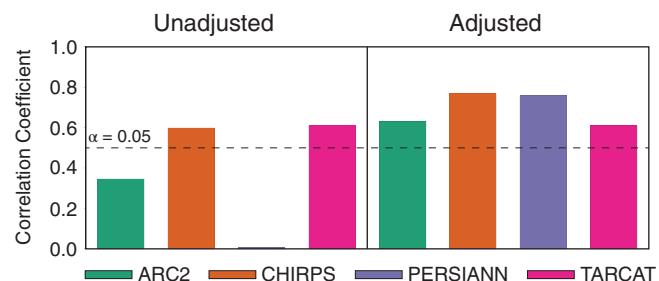


**FIGURE 5** Double-mass curves for the four products over four periods (1987–1996, 1993–2016, 1997–2016, and 2000–2012). Cumulative monthly rainfall measured at gauges is the *x* axis, and cumulative monthly rainfall estimated by a product is the *y* axis. Italicized numbers are the slopes of the lines. Significant break points in the relationship between measured and estimated rainfall are indicated by circles, and the year in which the break occurred is provided. When significant change points exist, the percentage change in estimated totals is indicated by red and blue numbers. Negative changes indicated a bias towards a drying trend, positive changes indicate a bias towards a wetting trend [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

### 3.3 | Homogeneity of the products

All satellite-based products had significant change points in their time series, thereby indicating drying and wetting biases of the products (Figure 5). For the 1987–1996 period, both ARC2 and CHIRPS had change points occurring around 1990: the 1991 change point in the ARC2 data and the 1989 change point in the CHIRPS data produced 19 and 8% decreases in rainfall totals, respectively. Each product had one or more change points during 1993–2016, with ARC2 having a small decrease (−4%) in 1997, PERSIANN

having a moderate decrease (−9%) in 2006, and TARCAT having a moderate increase (+11%) in 2007. CHIRPS had artificially decreased rainfall totals from 2006 to 2010: a negative change point in 2006 was followed by a slightly larger positive change in 2010. Change points during 1997–2016 were similar to those during 1993–2016, with the major differences being the lack of an ARC2 change



**TABLE 3** Adjustments factors for monthly rainfall totals for the entire western Uganda region

Product	Period	Adjustment factor
ARC2	Jan 1983–Jul 1991	0.8151
CHIRPS	Jan 1983–Jul 1989	0.9353
CHIRPS	Mar 2007–Apr 2010	1.1899
PERSIANN	Jan 1983–Jul 2007	0.8782
TARCAT	Jan 1983–Mar 2004	1.0310

**FIGURE 6** Correlations between annual rainfall for the products (both unadjusted and adjusted) and measured rainfall for 2000–2012. Adjustment values for the products are provided in Table 4 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**TABLE 4** Adjustments factors for monthly rainfall totals for the six stations, applying only to the 2000–2012 period

Product	Period	Adjustment factor
ARC2	Jan 2000–May 2004	0.9381
CHIRPS	Jun 2007–Apr 2010	1.2224
PERSIANN	Jan 2000–Sep 2007	0.8741

point and a larger negative change for PERSIANN and a smaller positive change for TARCAT. The change points during 2000–2012 were similar to those during the previous two periods (1993–2016 and 1997–2016), with the following exceptions: the ARC2 change point in 1997 was moved to 2004, and the TARCAT change point disappeared. The adjustment factors based on the above information are shown in Table 3, and the impact of those adjustment factors on rainfall trends is described in section 3.5.

### 3.4 | Inter-annual correlations

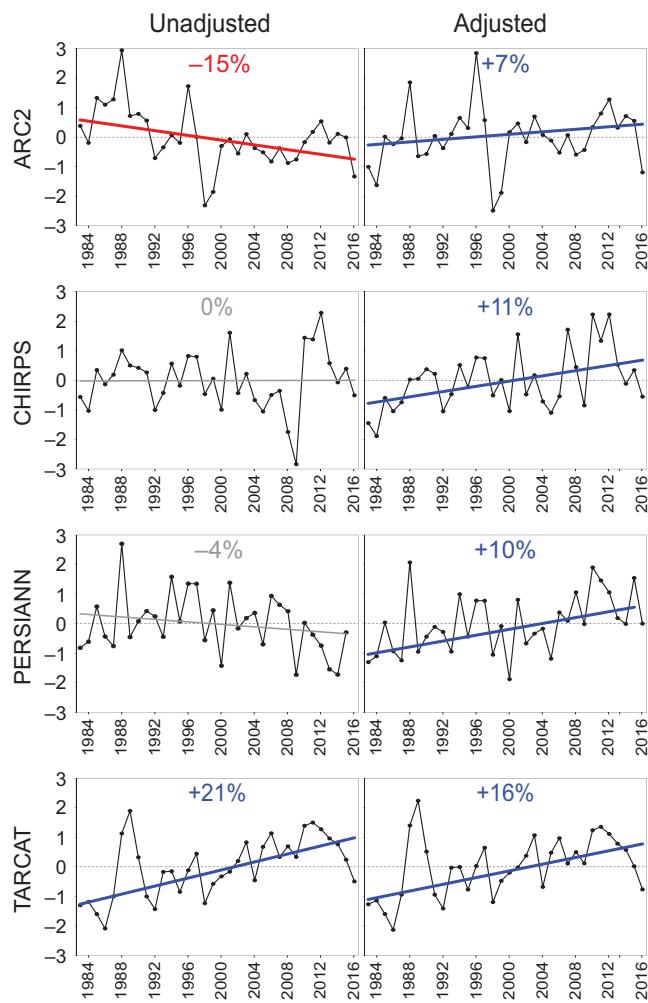
Inter-annual correlations from 2000 to 2012 between gauge totals and estimated totals increased after the change-point adjustments for the four products (Figure 6). Only CHIRPS and TARCAT had significant correlations using the unadjusted totals. The correlation coefficients for ARC2, CHIRPS, and PERSIANN increased by 0.29, 0.17, and 0.75, respectively, when moving from unadjusted to adjusted totals. Adjustment factors are shown in Table 4. All products but ARC2 had significant correlations when using the adjusted totals; therefore, ARC2 was the least accurate product at replicating inter-annual variability in annual rainfall in the region.

### 3.5 | Multi-decadal trends in rainfall

There were dramatic differences among the products for 1983–2016 trends in unadjusted annual rainfall totals for western Uganda (Figure 7). ARC2 had a significant 15% decrease in rainfall. CHIRPS and PERSIAN did not have significant changes. TARCAT had a significant 21% increase in rainfall.

Adjusted annual rainfall totals for the four products show that annual rainfall in western Uganda increased by at least 7% from 1983 to 2016 (Figure 7). The adjustment of ARC2 totals swung the trend from a significant decrease to a significant increase. CHIRPS and PERSIAN had 10 and 11% increases in rainfall, respectively. While the TARCAT increasing trend was reduced to 16% after adjustment, it remained significant.

Based on adjusted seasonal rainfall totals, a significant drying trend did not occur during any season (Figure 8). Boreal winter did not have any significant trends of either sign. Boreal spring and autumn, which coincide with the two rainy seasons throughout much of western Uganda, had wetting trends, with all products but ARC2 having significant rainfall trends in one or both of the seasons. TARCAT had

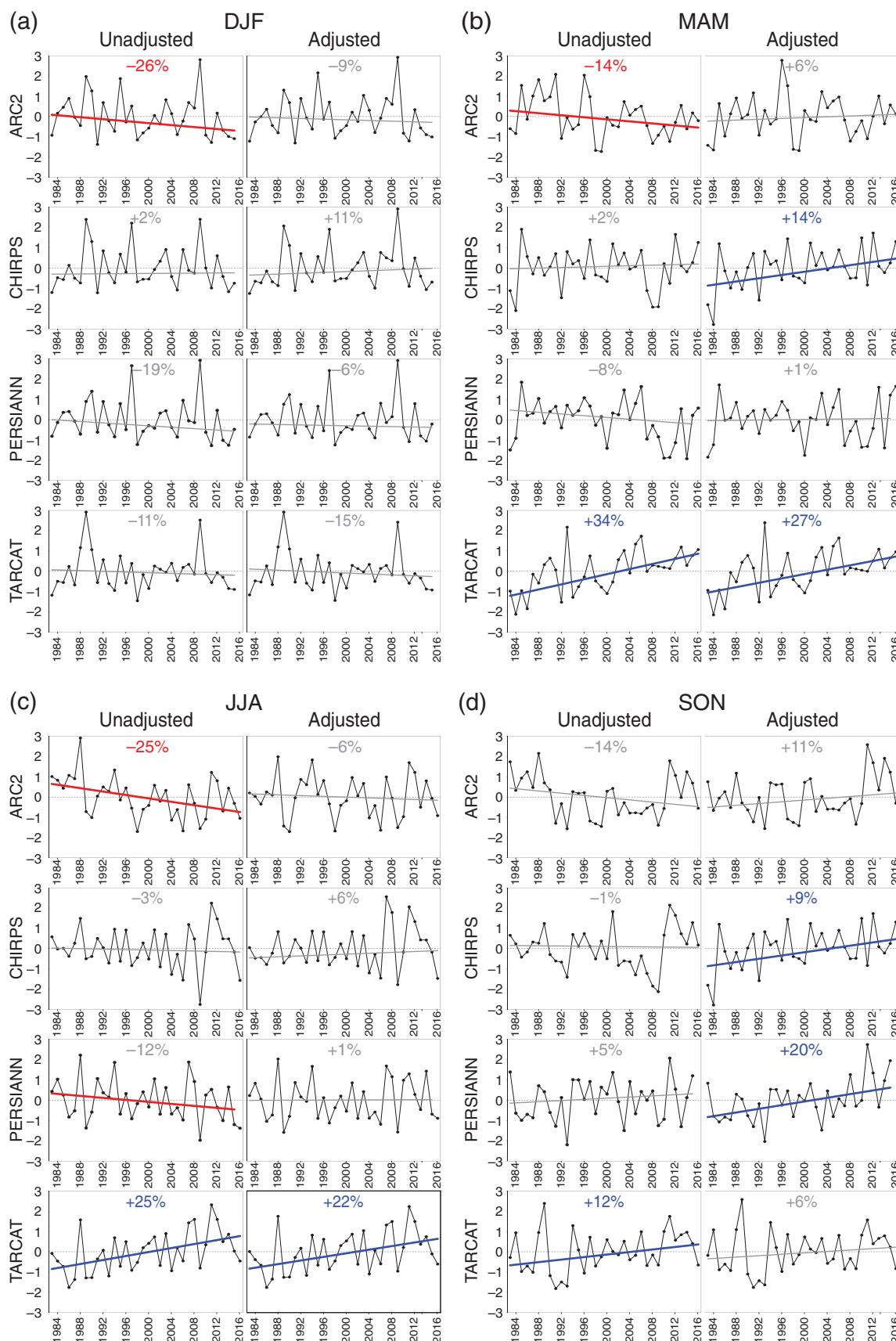


**FIGURE 7** Time series plots of standardized annual rainfall for western Uganda from 1983 to 2016. Significant positive (negative) trends are shown in blue (red); the numbers are the percentage change in rainfall from 1983 to 2016. Adjustment values for the products are provided in Table 3 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

significant wetting trends, either using unadjusted or adjusted totals, during all seasons but boreal winter.

## 4 | DISCUSSION

This study's results concerning the performance of the four products at estimating monthly and seasonal rainfall totals in western Uganda generally matched those from previous studies in tropical Africa. CHIRPS was the least biased and most accurate product, resulting presumably from the inclusion of rain-gauge data and microwave images during the calibration of CHIRPS data (Kimani *et al.*, 2017). TARCAT had the second-largest  $E$  values behind CHIRPS. However, TARCAT was prone to underestimates, likely the result of the product being designed to better capture more frequent, low-intensity rainfall events and thus less able to estimate rainfall during high-intensity events (Maidment *et al.*, 2017). ARC2 performed moderately well but consistently underestimated boreal-summer rainfall, a characteristic of the product

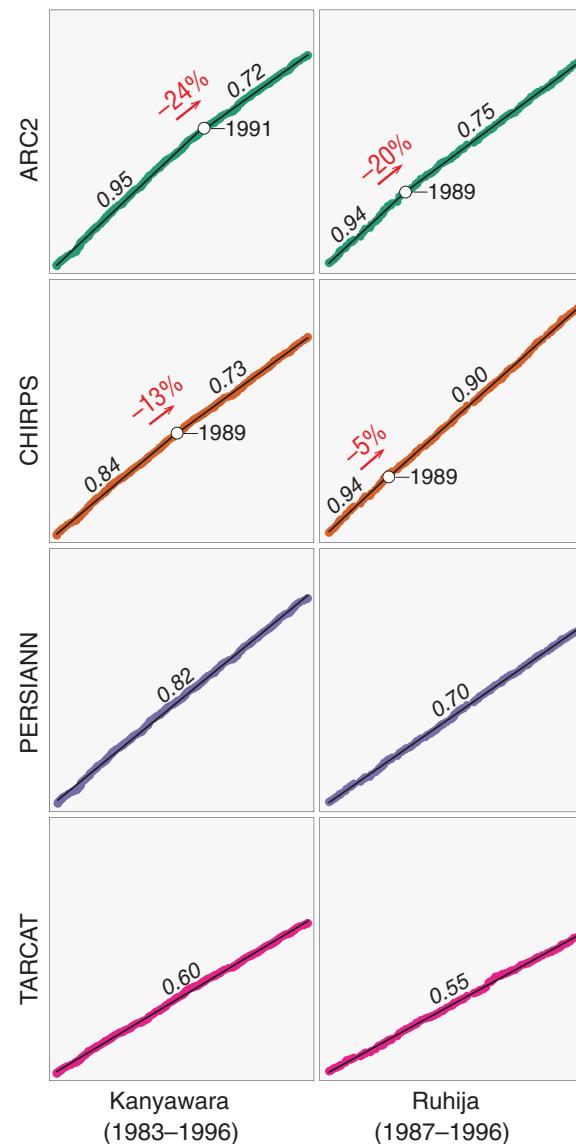


**FIGURE 8** Time series plots of standardized (a) December–February, (b) March–May, (c) June–August, and (d) September–November rainfall for western Uganda from 1983 to 2016. Significant positive (negative) trends are shown in blue (red); the numbers are the percentage change in rainfall from 1983 to 2016. Adjustment values for the products are provided in Table 3 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

across tropical Africa (Novella and Thiaw, 2013). ARC2 also struggled at estimating rainfall at the independent stations. PERSIANN performed well in our study region except at Kasese and Mweya, which were the driest and lowest locations. In fact, all products overestimated rainfall at Kasese and Mweya, with PERSIANN having the largest overpredictions. These overestimates are not unexpected, since increased amounts of sub-cloud evaporation should cause rainfall overestimations (i.e., rainfall is detected aloft but a substantial amount evaporates before reaching the surface), and, in the case of a coarse-resolution product, such as PERSIANN, rainfall overestimates should be larger than those from high-resolution products (Dinku *et al.*, 2011).

With respect to the long-term evaluation of the satellite products, the change points indicate that—unless satellite-based rainfall estimates are adjusted using a standard set of gauge data—multi-decadal trends in rainfall based on data from ARC2, CHIRPS, and PERSIANN will be biased towards drying trends. Of the four products, the unadjusted data for ARC2 showed a significant decrease in annual and seasonal rainfall from 1983 to 2016 in western Uganda, and this artificial decrease was caused by artificially decreased rainfall totals after 1991. Adjusting for the drying bias in the ARC2 data resulted in a significant increase in annual rainfall totals for western Uganda from 1983 to 2016. These findings stand in stark contrast to previous findings of significant drying in the region, which did not sufficiently account for the ARC2 drying bias (Diem *et al.*, 2014b; Ssentongo *et al.*, 2018). Rather, the region most likely has gotten wetter, and the most homogeneous product (i.e., the product with the weakest inhomogeneities), TARCAT, showed a significant wetting trend for the region. Among the four climatological seasons, the wetting trend primarily occurred for March–May and September–October, which coincide with the two rainy seasons. These results are congruent with the previously reported increased satellite-based, rainy-season rainfall totals in western Uganda, which, in turn, were supported by perceptions by farmers in the region (Salerno *et al.*, 2019). Adjusted values for all four products in this study showed an annual wetting trend from 1983 to 2016, with the mean increase being 3.2%/decade. The annual wetting trends were caused by increased rainfall during the rainy seasons, rather than during boreal winter. Therefore, western Uganda has not experienced the boreal-spring drying trend experienced in EEA (Williams and Funk, 2011; Lyon and DeWitt, 2012; Yang *et al.*, 2014).

Temporal changes in rain-gauge data appear to be the most likely culprit of the change points over periods of at least a decade in the satellite-based products. TARCAT is the only product that does not incorporate gauge data in “real time”; thus, inter-annual variations in rainfall are dependent only on satellite observations (Maidment *et al.*, 2017). It seems highly plausible that the lack of reliance on a time series of ground-measured rainfall enabled TARCAT to



**FIGURE 9** Double-mass curves for the four products at Kanyawara during 1983–1996 and at Ruhija during 1987–1996. Cumulative monthly rainfall measured at gauges is the x axis, and cumulative monthly rainfall estimated by a product is the y axis. Italicized numbers are the slopes of the lines. Significant break points in the relationship between measured and estimated rainfall are indicated by circles, and the year in which the break occurred is provided. When significant change points exist, the percentage change in estimated totals is indicated by numbers [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

avoid significant negative change points in western Uganda. Shifts towards a dry bias occurred for ARC2 and CHIRPS in the late 1980s to the early 1990s, and these shifts occurred at both stations (Kanyawara and Ruhija) with data spanning the 1980s and 1990s (Figure 9). Both ARC2 and CHIRPS rely on rain-gauge measurements, and the amount of gauge data in the region has decreased dramatically over the past several decades (Washington *et al.*, 2013). For example, the rapid reduction in gauge coverage in central Africa has been hypothesized to be the cause of decreasing trends in ARC2 rainfall totals from 1983 to 2010 for the region (Maidment *et al.*, 2015).

## 5 | CONCLUSIONS

Western Uganda has a dense human population dependent on rainfed agriculture and highly impacted by rainfall variability. The existing rain-gauge data in the region are insufficient to determine the spatio-temporal variability of rainfall, thereby making it difficult to understand rainfall variability with respect to farming decisions. Satellite-based rainfall estimates are a promising alternative to ground-measured rainfall totals; however, those estimates must be validated. This study has validated rainfall estimates from four products, ARC2, CHIRPS, PERSIANN, and TARCAT, in western Uganda. CHIRPS was the most accurate product at estimating 10-day, monthly, and seasonal rainfall totals and at capturing intra-seasonal rainfall variability. TARCAT was the most reliable product when inter-annual variability was involved: it had the largest correlations with ground-measured rainfall and it did not have any significant negative change points in its time series. ARC2 and PERSIANN were arguably the least reliable products based on consistent disagreements with the validation sites, especially the independent stations, as compared to other products. ARC2 and PERSIANN also are inappropriate for assessing inter-annual variability, especially multi-decadal variability, in rainfall in this region. In addition, after adjusting for inhomogeneities in the rainfall time series of the four products, none of the products showed a drying trend in western Uganda. In fact, it appears highly likely that western Uganda has experienced a wetting trend over the past several decades.

We recommend that future rainfall research in western Uganda, and possibly for CEA in general, should rely only on CHIRPS and TARCAT data. CHIRPS is ideal for fixed-time rainfall-totals analyses and TARCAT is ideal for time series analyses. CHIRPS was sufficiently accurate at estimating seasonal rainfall totals at sites in western Uganda with varying topographic settings and rainfall regimes. While TARCAT has an underestimation bias, its lack of reliance on contemporaneous rain-gauge data makes it a temporally stable product. Consequently, inter-annual analyses involving TARCAT are the least biased, and not plagued by a drying bias like the other products assessed in this study.

## ACKNOWLEDGEMENTS

This research was supported by the National Science Foundation (Award No. 1740201) and approved by the Uganda National Council for Science and Technology. We thank the following: Fred Babweteera for sharing the Budongo rainfall data; Colin Chapman, Patrick Omeja, and Thomas Struhsaker for sharing the Kanyawara rainfall data; David Watts, John Mitani, Kevin Potts, and Jeremiah Lwanga for sharing the Ngogo rainfall data; Margaret Driciru and staff at Queen Elizabeth National Park and Uganda Wildlife Authority for sharing the Mweya rainfall data; Robert Bitariho and Badru

Mugerwa at the Institute of Tropical Forest Conservation for sharing the Ruhija rainfall data; and the Uganda National Meteorological Authority for providing data for the Arua, Gulu, Masindi, Kasese, and Mbarara stations.

## ORCID

Jeremy E. Diem  <https://orcid.org/0000-0003-1949-5245>

## REFERENCES

Abera, W., Brocca, L. and Rigon, R. (2016) Comparative evaluation of different satellite rainfall estimation products and bias correction in the Upper Blue Nile (UBN) basin. *Atmospheric Research*, 178–179, 471–483. <https://doi.org/10.1016/j.atmosres.2016.04.017>.

Asefi-Najafabady, S. and Saatchi, S. (2013) Response of African humid tropical forests to recent rainfall anomalies. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1625), 20120306. <https://doi.org/10.1098/rstb.2012.0306>.

Ashouri, H., Hsu, K.-L., Sorooshian, S., Braithwaite, D.K., Knapp, K.R., Cecil, L.D., Nelson, B.R. and Prat, O.P. (2015) PERSIANN-CDR: daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bulletin of the American Meteorological Society*, 96 (1), 69–83. <https://doi.org/10.1175/BAMS-D-13-00068.1>.

Bayissa, Y., Tadesse, T., Demisse, G. and Shiferaw, A. (2017) Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. *Remote Sensing*, 9(7), 669. <https://doi.org/10.3390/rs9070669>.

Buishand, T.A. (1982) Some methods for testing the homogeneity of rainfall records. *Journal of Hydrology*, 58(1), 11–27. [https://doi.org/10.1016/0022-1694\(82\)90066-X](https://doi.org/10.1016/0022-1694(82)90066-X).

Cooper, P.J.M., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B. and Twomlow, S. (2008) Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? *Agriculture, Ecosystems and Environment*, 126(1–2), 24–35. <https://doi.org/10.1016/j.agee.2008.01.007>.

Dembélé, M. and Zwart, S.J. (2016) Evaluation and comparison of satellite-based rainfall products in Burkina Faso, West Africa. *International Journal of Remote Sensing*, 37(17), 3995–4014. <https://doi.org/10.1080/01431161.2016.1207258>.

Derin, Y., Anagnostou, E., Berne, A., Borga, M., Boudevillain, B., Buytaert, W., Chang, C-H, Delrieu, G., Hong, Y., Hsu, Y.C., Lavado-Casimiro, W., Manz, B., Moges, S., Nikolopoulos, E.I., Sahlu, D., Salerno, F., Rodríguez-Sánchez, J-P., Vergara, H.J. and Yilmaz, K.K. (2016) Multiregional satellite precipitation products evaluation over complex terrain. *Journal of Hydrometeorology*, 17(6), 1817–1836. <https://doi.org/10.1175/JHM-D-15-0197.1>.

Diem, J.E., Harter, J., Ryan, S.J. and Palace, M.W. (2014a) Validation of satellite rainfall products for western Uganda. *Journal of Hydrometeorology*, 15 (5), 2030–2038. <https://doi.org/10.1175/JHM-D-13-0193.1>.

Diem, J.E., Ryan, S.J., Harter, J. and Palace, M.W. (2014b) Satellite-based rainfall data reveal a recent drying trend in central equatorial Africa. *Climatic Change*, 126(1–2), 263–272. <https://doi.org/10.1007/s10584-014-1217-x>.

Dinku, T., Ceccato, P., Grover-Kopec, E., Lemma, M., Connor, S.J. and Ropelewski, C.F. (2007) Validation of satellite rainfall products over East Africa's complex topography. *International Journal of Remote Sensing*, 28 (7), 1503–1526. <https://doi.org/10.1080/01431160600954688>.

Dinku, T., Chidzambwa, S., Ceccato, P., Connor, S.J. and Ropelewski, C.F. (2008) Validation of high-resolution satellite rainfall products over complex terrain. *International Journal of Remote Sensing*, 29(14), 4097–4110. <https://doi.org/10.1080/01431160701772526>.

Dinku, T., Ceccato, P. and Connor, S.J. (2011) Challenges of satellite rainfall estimation over mountainous and arid parts of East Africa. *International Journal of Remote Sensing*, 32(21), 5965–5979. <https://doi.org/10.1080/01431161.2010.499381>.

Dinku, T., Hailemariam, K., Maidment, R., Tarnavsky, E. and Connor, S. (2014) Combined use of satellite estimates and rain gauge observations to generate high-quality historical rainfall time series over Ethiopia. *International Journal of Climatology*, 34(7), 2489–2504. <https://doi.org/10.1002/joc.3855>.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H. and Ceccato, P. (2018) Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, 144, 292–312. <https://doi.org/10.1002/qj.3244>.

Easterling, D.R. and Peterson, T.C. (1995) A new method for detecting undocumented discontinuities in climatological time series. *International Journal of Climatology*, 15(4), 369–377.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J. (2015) The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2, 150066. <https://doi.org/10.1038/sdata.2015.66>.

Hartter, J., Ryan, S.J., MacKenzie, C.A., Goldman, A., Dowhaniuk, N., Palace, M., Diem, J.E and Chapman, C.A. (2015) Now there is no land: a story of ethnic migration in a protected area landscape in western Uganda. *Population and Environment*, 36(4), 452–479. <https://doi.org/10.1007/s11111-014-0227-y>.

Helsel, D.R. and Hirsch, R.M. (2002) Statistical methods in water resources. In: *Hydrologic Analysis and Interpretation*. Washington, DC: U.S. Geological Survey.

Hua, W., Zhou, L., Chen, H., Nicholson, S.E., Raghavendra, A. and Jiang, Y. (2016) Possible causes of the central equatorial African long-term drought. *Environmental Research Letters*, 11(12), 124002. <https://doi.org/10.1088/1748-9326/11/12/124002>.

Kidd, C., Kniveton, D.R., Todd, M.C. and Bellerby, T.J. (2003) Satellite rainfall estimation using combined passive microwave and infrared algorithms. *Journal of Hydrometeorology*, 4(6), 1088–1104.

Kimani, M., Hoedjes, J. and Su, Z. (2017) An assessment of satellite-derived rainfall products relative to ground observations over East Africa. *Remote Sensing*, 9(5), 430. <https://doi.org/10.3390/rs9050430>.

Legates, D.R. and McCabe, G.J. (1999) Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, 35, 233–241. <https://doi.org/10.1029/1998WR900018>.

Lyon, B. and DeWitt, D.G. (2012) A recent and abrupt decline in the East African long rains. *Geophysical Research Letters*, 39(2), 2702. <https://doi.org/10.1029/2011GL050337>.

Maidment, R.I., Grimes, D., Allan, R.P., Tarnavsky, E., Stringer, M., Hewison, T., Roebeling, R. and Black, E. (2014) The 30 year TAMSAT African rainfall climatology and time series (TARCAT) data set. *Journal of Geophysical Research: Atmospheres*, 119(18), 10619–10644. <https://doi.org/10.1002/2014JD021927>.

Maidment, R.I., Allan, R.P. and Black, E. (2015) Recent observed and simulated changes in precipitation over Africa. *Geophysical Research Letters*, 42(19), 8155–8164. <https://doi.org/10.1002/2015GL065765>.

Maidment, R.I., Grimes, D., Black, E., Tarnavsky, E., Young, M., Greatrex, H., Allan, R.P., Stein, T., Nkonde, E., Senkunda, S. and Alcántara, E.M.U. (2017) A new, long-term daily satellite-based rainfall dataset for operational monitoring in Africa. *Scientific Data*, 4, 170063. <https://doi.org/10.1038/sdata.2017.63>.

Monaghan, A.J., MacMillan, K., Moore, S.M., Mead, P.S., Hayden, M.H. and Eisen, R.J. (2012) A regional climatology of West Nile, Uganda, to support human plague modeling. *Journal of Applied Meteorology and Climatology*, 51(7), 1201–1221. <https://doi.org/10.1175/JAMC-D-11-0195.1>.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D. and Veith, T.L. (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, 50(3), 885–900.

Nash, J.E. and Sutcliffe, J.V. (1970) River flow forecasting through conceptual models part I—a discussion of principles. *Journal of Hydrology*, 10(3), 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6).

Nicholson, S.E. (1996) A review of climate dynamics and climate variability in Eastern Africa. In: Johnson, T.C. and Odada, E. (Eds.) *The Limnology, Climatology and Paleoclimatology of the East African Lakes*. Boca Raton, FL: CRC Press.

Novella, N.S. and Thiaw, W.M. (2013) African Rainfall Climatology Version 2 for famine early warning systems. *Journal of Applied Meteorology and Climatology*, 52(3), 588–606. <https://doi.org/10.1175/JAMC-D-11-0238.1>.

Rosegrant, M.W., Cai, X. and Cline, S.A. (2002) *World Water and Food to 2025: Dealing with Scarcity*. Washington, DC: International Food Policy Research Institute.

Salerno, J., Diem, J.E., Konecky, B.L. and Hartter, J. (2019) Recent intensification of the seasonal rainfall cycle in equatorial Africa revealed by farmer observations, satellite-based estimates, and ground-based station measurements. *Climatic Change*. <https://doi.org/10.1007/s10584-019-02370-4>.

Searcy, J.K. and Hardison, C.H. (1960) Double mass curves. In: *Manual of Hydrology: Part 1. General Surface Water Techniques*. Washington, DC: U. S. Geological Survey.

Ssentongo, P., Muwanguzi, A.J.B., Eden, U., Sauer, T., Bwanga, G., Kateregga, G., Aribi, L., Ojara, M., Mugerwa, W.K. and Schiff, S.J. (2018) Changes in Ugandan climate rainfall at the village and forest level. *Scientific Reports*, 8(1), 3551. <https://doi.org/10.1038/s41598-018-21427-5>.

Stevens, F.R., Gaughan, A.E., Linard, C. and Tatem, A.J. (2015) Disaggregating census data for population mapping using random forests with remotely-sensed and ancillary data. *PLOS One*, 10(2), e0107042. <https://doi.org/10.1371/journal.pone.0107042>.

Toté, C., Patrício, D., Boogaard, H., van der Wijngaart, R., Tarnavsky, E. and Funk, C. (2015) Evaluation of satellite rainfall estimates for drought and flood monitoring in Mozambique. *Remote Sensing*, 7(2), 1758–1776. <https://doi.org/10.3390/rs70201758>.

Washington, R., James, R., Pearce, H., Pokam, W.M. and Moufouma-Okia, W. (2013) Congo Basin rainfall climatology: can we believe the climate models? *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368 (1625), 20120296. <https://doi.org/10.1098/rstb.2012.0296>.

Williams, A.P. and Funk, C. (2011) A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. *Climate Dynamics*, 37(11–12), 2417–2435. <https://doi.org/10.1007/s00382-010-0984-y>.

Yang, W., Seager, R., Cane, M.A. and Lyon, B. (2014) The East African long rains in observations and models. *Journal of Climate*, 27(19), 7185–7202. <https://doi.org/10.1175/JCLI-D-13-00447.1>.

Young, M.P., Williams, C.J.R., Chiu, J.C., Maidment, R.I. and Chen, S.-H. (2014) Investigation of discrepancies in satellite rainfall estimates over Ethiopia. *Journal of Hydrometeorology*, 15(6), 2347–2369. <https://doi.org/10.1175/JHM-D-13-0111.1>.

**How to cite this article:** Diem JE, Konecky BL, Salerno J, Hartter J. Is equatorial Africa getting wetter or drier? Insights from an evaluation of long-term, satellite-based rainfall estimates for western Uganda. *Int J Climatol.* 2019;39:3334–3347. <https://doi.org/10.1002/joc.6023>