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Identifying changing precipitation extremes in Sub-Saharan Africa with gauge and satellite products

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Abstract

Sparse gauge networks in Sub-Saharan Africa (SSA) limit our ability to identify changing precipitation extremes with in situ observations. Given the potential for satellite and satellite-gauge precipitation products to help, we investigate how daily gridded gauge and satellite products compare for seven core climate change precipitation indices. According to a new gauge-only product, the Rainfall Estimates on a Gridded Network (REGEN), there were notable changes in SSA precipitation characteristics between 1950 and 2013 in well-gauged areas. We examine these trends and how these vary for wet, intermediate, and dry areas. For a 31 year period of overlap, we compare REGEN data, other gridded products and three satellite products. Then for 1998–2013, we compare a set of 12 satellite products. Finally, we compare spatial patterns of 1983–2013 trends across all of SSA. Robust 1950–2013 trends indicate that in well-gauged areas extreme events became wetter, particularly in wet areas. Annual totals decreased due to fewer rain days. Between 1983 and 2013 there were positive trends in average precipitation intensity and annual maximum 1 d totals. These trends only represent 15% of SSA, however, and only one tenth of the main wet areas. Unfortunately, gauge and satellite products do not provide consensus for wet area trends. A promising result for identifying regional changes is that numerous satellite products do well at interannual variations in precipitation totals and number of rain days, even as some gauge-only products. Products are less accurate for dry spell length and average intensity and least accurate for annual maximum 1 d totals. Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis (3B42-V7) and Climate Hazards center Infrared Precipitation with Stations (CHIRPS v2.0) ranked highest for multiple indices. Several products have seemingly unrealistic trends outside of the well-gauged areas that may be due to influence of non-stationary systematic biases. Social media abstract. Sparse data show increasing Africa rainfall extremes and satellite products fill some missing pieces.

1. Introduction

As the global climate warms, changes to the global distribution of precipitation (Held and Soden 2006, Putnam and Broecker 2017) and increases in precipitation extremes (Allen and Ingram 2002, Trenberth et al 2003) are capable of producing more frequent destructive storms and droughts (Milly et al 2002, Hoegh-Guldberg et al 2018). Wet areas of the globe are generally thought to be those most likely to experience the greatest increases in extreme precipitation. Increases in extreme precipitation have been observed in many regions (Easterling et al 2000, Alexander et al 2006, Min et al 2011, Westra et al 2013, Donat et al 2016), but data gaps in Sub-Saharan Africa (SSA) challenge our ability to monitor both regional and global climate change. Long-term publicly available gauge observations in SSA are not well distributed and compared to other regions of the world there are fewer reliable daily records (Washington et al 2006). The spatial coverage of satellite-based precipitation products and their proven skill in identifying droughts and floods in SSA and in estimating observed rainfall (Brown and Brickley 2012, Toté et al 2015, Dembé and Zwart 2016,
Agutu et al (2017, Ayehu et al 2018) makes them a promising resource for identifying post-1980s change. Helpful reviews of precipitation products are in Sun et al (2018) and for Africa specifically, Maidment et al (2014) and Maggioni et al (2016). For identifying temporal changes, an important difference between satellite products that also incorporate in situ data is how sensitive they are to the temporal changes in SSA’s gauge networks. Products that blend reports based on a background climatology are less sensitive (Tarnovsky et al 2014, Funk et al 2015a, 2015b), but other methodologies can produce spurious trends (Maidment et al 2015).

Here we investigate changing precipitation extremes in SSA and satellite product performance at replicating observed variability and trends. We evaluate seven core climate change precipitation indices from the World Meteorological Organization joint Expert Team on Climate Change Detection and Indices (ETCCDI) (Peterson and Manton 2008). According to the lengthiest gauge-only global daily dataset currently available, the Rainfall estimates on a Gridded Network (REGEN v1.1, 1950–2013) (Contractor et al 2019), there are notable changes in SSA precipitation characteristics at annual and seasonal scales.

Motivated by the Donat et al (2016) assessment of increasing precipitation extremes in global dry versus wet areas, we examine how these extremes vary in REGEN data and some satellite products for dry (<500 mm mean annual rainfall), intermediate (500–1000 mm), and wet areas (>1000 mm). We focus on areas where data are based on quality historical gauge reports, as defined by the REGEN quality mask, and briefly discuss the limitations of sparse coverage in SSA. Then we evaluate the level of agreement between 3 gauge and 12 satellite products in the well-gauged areas during the periods 1983–2013 and 1998–2013, subject to when the products are available. We build on recent studies (Maidment et al 2015, Contractor et al 2019) by comparing additional products and climate change indices and by focusing comparisons where there is well-gauged gridded daily data. We close by discussing which precipitation indices products seem effective at measuring and which of the evaluated satellite products are most promising for this avenue of research.

2. Methods

For each year and dataset, we computed three indices based on January to December daily precipitation: (1) annual total (PRCPTOT), (2) annual maximum 1 d total (R×1day), and (3) annual maximum 5 d total (R×5day). We computed four indices based on daily precipitation for the wettest 3 month season at each pixel: (1) wet season total (WS PRCPTOT), (2) number of rainy days (WS R1 mm), (3) Simple Precipitation Intensity Index (WS SDII, the average rainfall intensity on rainy days), and (4) maximum length of dry spell (WS CDD, consecutive days with <1 mm). Computations followed ETCCDI definitions (online at http://etccdi.pacificclimate.org/list_27_indices.shtml) and used a 1 mm threshold. The local climatological wettest 3 month season was identified from a high quality 0.05° climatology (CHPclim; Funk et al 2015b) that was regridded to 1°. These seasons closely correspond to the map in figure 1 of Funk et al (2015a). Linear time trends were calculated using the Theil-Sen median slope estimator, a nonparametric technique that is insensitive to outliers and heteroscedastic data. Significance was tested using the Mann-Kendall test for a monotonic trend. A modified version that is robust to serial correlation was used for the quality area time series trends (Hamed and Rao 1998). More details can be found in the supplementary material is available online at stacks.iop.org/ERL/14/085007/mmedia.

3. Data

Precipitation data from the Frequent Rainfall Observations on Grids (FROGs) database (Roca et al 2019) was the main data source for this study. FROGs is a compilation of daily continental to global datasets regridded to a common 1° × 1° resolution. All datasets are freely available via an ftp server and identified thanks to the DOI: https://doi.org/10.14768/06337394-73A9-407C-997-0E380DAC598. Gauge products are: REGEN (‘All Stations’ version) (Contractor et al 2019), Global Precipitation Climatology Centre Full Data Daily (GPCC FDD 2018) (Becker et al 2013, Schamm et al 2014, Ziese et al 2018), and Climate Prediction Center Unified Gauge-based Analysis of Global Daily Precipitation (CPC v1.0) (Chen et al 2008). REGEN data in Africa are based on a quality-controlled archive that includes Global Precipitation Climatology Centre (GPCC) stations and additional Global Historical Climatological Network stations (GHCN-Daily). CPC v1.0 has fewer Africa stations than GPCC (Sun et al 2018) and REGEN but all have a broadly similar spatial distribution. REGEN has more Africa stations than GPCC FDD v1 (Contractor et al 2019), but GPCC has noted a substantial increase in global stations in v2018 (Schneider et al 2018, figure 9). CPC v1.0 is a ‘retrospective version’ up to 2005, subsequent data are from a ‘real-time version’ with fewer stations. REGEN, GPCC FDD 2018, and CPC v1.0 interpolate station climatological anomalies using different algorithms; respectively, these are ordinary block kriging, a modified inverse distance weighting scheme (SPHEREMAP), and an optimal interpolation technique for reducing orographic errors. Kriging and SPHEREMAP are relatively similar interpolators in which local anomaly estimates are based on weighted sums of neighboring stations. Optimal interpolation involves fitting a surface through observations. Reductions in
network density are a known problem for CPC quality (Chen et al. 2008).

FROGs satellite products with a 30+ year record are: Climate Hazards center Infrared Precipitation with Stations version 2 (CHIRPS2.0) (Funk et al. 2015a, 2015b), Africa Rainfall Climatology version 2 (ARC2) (Novella and Thiaw 2013), and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Climatic Data Record (PERSIANN CDR V1R1) (Ashouri et al. 2015). Satellite products evaluated for a shorter period (1998–2013) are: Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis 3B42-V7 (Huffman et al. 2007), CPC MORPHing technique bias-corrected (CMORPH CRT V1.0) (Joyce et al. 2004, Xie et al. 2017), Global Precipitation Climatology Project Climate Data Record (GPCP CDR v1.3) (Huffman et al. 2001), Global Satellite Mapping of Precipitation Reanalysis Gauge-calibrated (GSMAP-gauges-RNLv6) (Kubota et al. 2007), African Rainfall Estimation Algorithm v2 (RFE2.0) (Xie and Arkin 1996), European Space Agency Climate Change Initiative (ESA CCI) soil moisture-derived rainfall (SM2RAIN-CCI) (Ciabbata et al. 2018), and Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT v3) (Tarnavsky et al. 2014, Maidment et al. 2014, 2017). We also compare two non-station improved versions of products: the satellite-only version of CHIRPS, CHIRP, and the non-research grade ‘real time’ version of TRMM, 3B42RT. CHIRPS, ARC2, RFE2.0 regularly and directly blend gauge reports. Of these, CHIRPS does so using a quality high resolution background climatology. TAM-SAT does not directly blend gauges but rather uses a gauge-based climatology to calibrate satellite estimates. The GPCP CDR and PERSIANN CDR constrain monthly totals to match the GPCP monthly 2.5° product (which is bias-corrected with GPCP monthly). The SM2RAIN-CCI algorithm is calibrated with GPCCC FDD. GSMAP-gauges-RNLv6 uses GPCCC for unbiasing (Zhao et al. 2018).

4. Results and discussion

4.1. Observed long-term changes in SSA precipitation indices

Trends in area-averaged annual total precipitation (PRCPTOT), highest annual 1 d precipitation (R×1 d), and number of rainy days during the local 3 month wettest season (WS R1 mm) are shown in figure 1. Two time series are shown: the average for quality data areas only and the average for all of SSA.

Figure 1(a) shows a declining trend in 1950–2013 annual PRCPTOT for both the quality data only and the all SSA time series. These show a step change around the 1980s and no clear incline or decline after

![Figure 1](https://example.com/figure1.png)

**Figure 1.** Long-term changes in SSA precipitation from REGEN data. For 1950 to 2013, area-averaged annual total precipitation (PRCPTOT) (a), highest annual 1 d precipitation (R×1 d) (b), and number of rainy days during the local 3 month wettest season (WS R1 mm) (c), based on the REGEN dataset. These time series show the average value for quality data areas only (bold black) and for all of Sub-Saharan Africa (SSA) (blue). Dashed lines show 1950–2013 means. In the upper right of (a)–(c) is Pearson’s correlation coefficient between these time series. (d) shows where quality data pixels are located in compared to SSA’s main precipitation zones. Black outlines surround quality data areas as indicated by the REGEN quality data mask. (e) shows the fractional coverage of SSA by each zone and by quality data pixels (hash). Percentages in (e) are the number of pixels in each category, e.g. in wet (wet and quality), compared to the SSA total.
Table 1. Theil-Sen slope trend for REGEN quality data time series for seven climate change indices, presented in terms of the overall change from 1950 to 2013 (annual trend multiplied by 64 years). For three annual indices: total precipitation (PRCPTOT), highest 1 and 5 day precipitation (R×1day and R×5day); and four wet season indices: total precipitation (WS PRCPTOT), number of rainy days (WS R1mm), average precipitation intensity (WS SDII), and length of longest dry spell (WS CDD). Time series are area-averaged values in quality data areas, first for all SSA, and for dry, intermediate, or wet zone subsets. Quality data areas and climate zones from figure 1(d). Bold values with asterisks are significant at \( p < 0.05 \). Values with crosses have a \( p \) value <0.15. Other values are grayed.

|                | All       | Dry       | Intermediate | Wet       |
|----------------|-----------|-----------|--------------|-----------|
| PRCPTOT (annual) | −91.3±   | 10.0      | −77.6±       | −82.9±    |
| R×1day (annual)   | 2.2±     | 1.0       | 2.1±         | 4.5±      |
| R×5day (annual)   | −3.3     | −5.8      | −3.2±        | 1.7       |
| WS PRCPTOT        | −21.8±   | −10.3     | −34.0±       | −23.0±    |
| WS R1mm           | −3.6±    | 1.2       | −5.8±        | −2.9±     |
| WS SDII           | 0.1      | −0.3      | 0.3          | 0.2       |
| WS CDD            | −1.0     | −4.7±     | 0.5          | 0.2       |

that. Based on dry, intermediate, and wet precipitation area subsets of these data, we find that the declining PRCPTOT trend in the quality REGEN SSA time series is mainly attributed to decreases in intermediate and wet areas (table 1). Time series for these trends show significant declines of about 80 mm in total for 1950–2013. Totals for just the local 3 month wettest season (WS PRCPTOT) also show declines.

Annual R×1day exhibits an increasing trend during 1950–2013 in both the quality area and all SSA time series (figure 1(b)). For this measure of extreme precipitation, wet, intermediate, and dry quality data all have positive trends for 1950–2013 (table 1) and for 1983–2013 when there is a clear steep incline. Only the wet area trend is significant for 1950–2013 and only the dry area trend is significant for 1983–2013. The magnitude of changes in table 1 correspond to increases of 9.5%, 5.3%, and 3.8% compared to 1950–2013 means for wet, intermediate, and dry zones, respectively.

The number of wet season rainy days (WS R1mm) exhibits a declining trend throughout 1950–2013 in the quality area and all SSA time series (figure 1(c)). The quality SSA time series has a significant trend of −3.6 d in total. Negative trends are significant in the intermediate and wet area subsets. An interesting feature is that decreases are largest in intermediate precipitation areas in terms of trend magnitude and impact. The −5.8 d decrease in intermediate quality data areas corresponds to a 11.4% decline in the average number of rainy days, which is typically about 50 d of the 3 month period.

4.2. Important data limitations in SSA
The declines in annual and wet season totals, declines in rainfall frequency, and increases in extreme precipitation observed in the REGEN data indicate important changes in SSA precipitation. However, only a small fraction of the SSA gridded data, about 15% of SSA pixels in this dataset, contains quality long-term daily observations. This is an important limitation for assessment of changing precipitation extremes in SSA.

Quality data coverage is in six SSA areas in REGEN: South Africa, Zambia-Malawi, southern Kenya, central-western Ethiopia, coastal western West Africa (in Senegal, The Gambia, Guinea-Bissau), and southeastern West Africa (in Ghana, Togo, Benin, southern Burkina Faso, and western Nigeria). How this fragmented distribution represents SSA’s major precipitation zones is shown in figures 1(d)–(e). Wet areas cover more than a third of SSA, but only about 10% of these pixels are quality data, and none are located in Central Africa. Underrepresentation of wet areas results in a large negative bias of around 100 mm for annual precipitation (figure 1(a)). Compared to wet areas, fractional representation of dry and intermediate precipitation areas is higher but still low, about 14% and 25%, respectively. Dry area coverage is mainly in Southern Africa; almost none of East Africa or northern Sahel dry areas are included.

4.3. Evaluation of precipitation indices and satellite products
4.3.1. Trends in SDII and R×1day quality area time series
Some of the satellite products overlap REGEN by 31 years (CHIRPS, ARC2, and PERSIANN), so we use that overlap to determine if these products exhibit similar trends in the quality data areas. For this analysis we compute spatial means for each dataset and examine trends in these area-averaged time series, similar to section 4.1. We also evaluate the gauge-based CPC and GPCC datasets. TAMSAT v3 was omitted from this comparison due to gaps in daily data during the 1980s. We focus our analysis on the two most significant 1983–2013 REGEN trends: Wet season SDII and annual R×1day. Other indices did not show clear trends during this period.

Figure 2 shows the Theil-Sen estimated slope for WS SDII and annual R×1day area-averaged time series for each product, first for the all-SSA quality pixels and then for dry, intermediate, and wet area subsets of those data. There is general agreement between the gauge-based REGEN and GPCC and satellite-gauge CHIRPS and ARC2 as to increases in wet season precipitation intensity (figure 2(a)). This is seen for the all-SSA time series and for the dry and intermediate subsets, though only REGEN, ARC2, and CHIRPS trends are significant. All of the products show a positive trend in the dry area subset, though trend magnitudes vary greatly. There are large differences between product trends for the wet area subset. The REGEN trend is negligible, GPCC shows a large increase in WS SDII, and CHIRPS and PERSIANN show significant positive and negative trends, respectively.
Products show comparatively less agreement for annual $R \times 1$ day trends (figure 2(b)). There is some agreement for the dry area subset, but for other subsets the gauge and satellite-gauge products mainly show opposite sign trends. REGEN and several products show positive trends for dry area annual $R \times 1$ day (GPCC, ARC2, and PERSIANN) while others have trends that are near zero (CPC and CHIRPS). Similar to WS SDII, products disagree most for the wet area subset. We have low confidence in the GPCC wet area annual $R \times 1$ day and WS SDII trends. These time series look odd, with very high values in 1983–1986 followed by values ~25% lower and then a steep increasing trend from the early 1990s to 2013. We suspect this is related to low-quality GPCC data in western Ethiopia and northern Zambia, as GPCC and REGEN per-pixel time series are poorly correlated in these areas even for the less challenging index, WS PRCPTOT ($\rho_{1983–2013} < 0.4$). The GPCC intermediate area annual $R \times 1$ d and WS SDII time series also begin with suspiciously high values but data from 1985 to 2013 look reasonable and are similar to the REGEN time series (e.g. WS SDII $\rho_{1983–2013} = 0.6$).

Results thus far have shown that with respect to time trends in area-averaged indices, in quality data areas there is decent agreement between gauge and satellite products for increasing WS SDII. For positive annual $R \times 1$ day time trends, however, gauge and satellite products show agreement only in the dry areas. Disagreement in wetter areas resulted in trends of opposing sign for the SSA average. These variations, differences between the gauge-based products, and the limitations of poor-quality data coverage, highlight wet areas of SSA as being the areas we are seemingly least likely to find convergence with regard to climate change impacts on high precipitation extremes.

4.3.2. Product performance for all indices in quality data areas

Here we examine two questions. First, which products most consistently agree with gridded in situ measurements? Second, which indices are associated with the most interproduct agreement? To address this we compare products and indices to REGEN data using data from all quality area pixels rather than the area-averaged time series. We make this comparison with the five longer record products over 1983–2013 period and with all the products over the 1998–2013 period. For the first comparison we are mainly interested in whether or not the product can recreate the temporal variability in REGEN data. To reduce the influence of spatial biases for each product, time series at each grid cell were first converted into standardized anomalies using the local 1983–2013 mean and standard deviation. Figure 3 shows the per-product correlation with REGEN based on these data. Time series from all pixels in the area of interest were first stacked, for each dataset, then Spearman’s Rho correlation was calculated using these data.
As figure 3 demonstrates, satellite products struggle with correctly identifying extreme precipitation amounts on a daily time scale. The products do most poorly for annual R×1 day and WS CDD. This problem appears related to both accuracy and precision, based on the improved but still relatively weak correlation R×1 day for annual R×1 day totals. Agreement for 1 d extremes would be surprising, however, given that the observation-based products also show weak correlations R×1 day (p < 0.5). For the observation-based products, comparatively higher correlations for annual R×1 d (GPCC ρ ∼ 0.6) are somewhat promising and lead us to infer that, for SSA, more confidence might be placed in climate change assessments of extreme storm totals rather than extreme 1 d precipitation. On the other hand, given the similarities in inputs and methods in the REGEN and GPCC datasets, the modest 0.6 correlation for annual R×5 day time-series underscores the greater uncertainties in estimates of extreme statistics.

The satellite products perform better for the indices based on longer accumulation periods. Two of the products (CHIRPS and PERSIANN) stand out as best performers for annual and wet season precipitation totals, coming close to the agreement seen between REGEN and GPCC (ρ ∼ 0.8). This is promising, given that they may also perform reasonably well in less-gauged regions. CPC and ARC2 have lower correlations but are still around R ∼ 0.65. Compared to the precipitation total indices, correlations for wet season rain days (WS R1mm) and average intensity (WS SDII) are lower for all products and are between ρ ∼ 0.45 and ρ ∼ 0.6. Most of the satellite products perform similarly to GPCC for WS R1mm, as do CHIRPS and PERSIANN for WS SDII. This finding may suggest that satellite-gauge products are good tools for exploring changes in R1 mm and WS SDII.

When based on a shorter time period but more products, satellite product performance remains highest for wet season precipitation totals. This larger set of products shows consistently higher accuracy for number of rain days than for dry spell length or precipitation intensity. These aspects are shown in figure 4, in which Taylor Diagrams are used to compare 1998–2013 data from 14 products (GPCC, CPC, and 12 satellite products) to REGEN wet season indices, again for quality data pixels only. Products were evaluated based on years with complete data. Products with fewer than 16 years evaluated were TAMSAT (2000–2005 and 2007–2013), RFE2 (2001–2004, 2006–2013), and GSMAP and TRMM 3B42 (both 2001–2013). A number of products do well at WS PRCPTOT and WS R1 mm, including TRMM 3B42, CHIRPS, GPCC, TAMSAT, PERSIANN, GPCP, and CMORPH. This again suggests that changes in R1 mm may be a quite tractable target for which the satellites provide valuable information. Correlations (indicated by azimuth angle), are highest for WS PRCPTOT and WS R1 mm for most of the products (R ∼ 0.9), lower for WS CDD (R ∼ 0.7), and lowest for WS SDII (R ∼ 0.6). Correlations shown in figure 4 are higher than in figure 3 because these are based on non-standardized values that contain more spatial covariance. Correlations for all the standardized products were similar to those shown in figure 2, with correlations for WS R1 mm ranging from R ∼ 0.3 to R ∼ 0.7 and correlations for WS PRCPTOT ranging from R ∼ 0.5 to R ∼ 0.8.

It is interesting to see that a number of satellite products perform as well as or better than the gauge-only data. As expected, gauge-only GPCC (orange dot) ranks high for most indices. However, GPCC overestimates REGEN variability in WS SDII and underestimates variability for WS R1 mm. Over or underestimation of REGEN variability is shown by the ratio of product standard deviation to REGEN standard deviation (distance from the standard deviation = 1 curve). Mean square error is proportional to the linear distance between product symbols and the REGEN symbol (black circle) on the x axis. The other gauge-only product, CPC Unified (gray dot), is among the least skillful products for WS PRCPTOT and WS R1 mm. CPC does about as well for WS SDII as CHIRP (purple box), which is the satellite-only version of CHIRPS.

No satellite product scores highest across all four indices, but TRMM 3B42 (light green triangle) and CHIRPS (purple triangle) show the best performance...
overall. PERSIANN (green asterisk) also ranks consistently high but does not do as well recreating the observed variability. For WS PRCPTOT and WS R1mm, TRMM 3B42 and CHIRPS correlations are similar to GPCC and these products closely mimic REGEN variability and means, outperforming GPCC in these measures. For dry spell length (CDD), the best performing products are TRMM 3B42, GSMAP-gauges, ARC2, CPC, SM2RAIN, CMORPH, and RFE2. CHIRPS, PERSIANN, and TAMSAT all struggle with under or overestimating CDD variance. For SDII, CHIRPS, PERSIANN, and TRMM 3B42 do somewhat better than the other products, including CPC and GPCC.

Blending stations usually results in higher performance, as can be seen from lower bias and higher correlations in the CHIRPS compared to CHIRP and TRMM 3B42 compared to TRMM 3B42RT (triangle versus square symbols). An exception is for WS R1mm—both versions of TRMM 3B42 perform well. For CHIRPS, the blended stations are what makes it one of the top performing products in WS PRCPTOT and WS R1mm. The satellite-only CHIRP overestimates the WS R1mm variance and underestimates the WS CDD variance.

4.3.3. Wet season precipitation trends across SSA
We complete our evaluation by comparing spatial patterns of SSA trends for indices well represented by the satellites in quality data areas: precipitation totals, rain days, and SDII for the local wettest season. Figure 5 shows the Theil-Sen slope calculated at each pixel using 1983–2013 data. Slope values that did not pass significance with \( p < 0.10 \) were set to white. WS

Figure 4. Taylor diagram for wet season indices, 1998–2013. Taylor Diagrams for wet season indices (a) total precipitation (WS PRCPTOT), (b) average rainfall intensity WS (SDII), number of rain days (R1 mm), and longest dry spell length WS (CDD). The diagrams show how gauge and satellite products compares to REGEN 1998–2013 data in terms of Pearson’s correlation (azimuth angle), ratio of standard deviations (distance from black curve), and mean square error (distance from black circle on x-axis). To allow for comparison of the four indices values were normalized such that the reference (REGEN) has a standard deviation of 1.
SDII (bottom row) is calculated from the ratio of total precipitation (top row) to the number of rain days (middle row), thus it is these first order variables that are behind trends in SDII. Earlier we showed agreement from multiple gauge-based and satellite-based products as to positive WS SDII trends during 1983–2013 for quality data area-averaged time series (except for in wet areas, figure 2). For all the products, trend maps for annual PRCPTOT (not shown) are similar to WS PRCPTOT maps but are larger in magnitude.

Products show agreement as to increasing 1983–2013 trends in boreal summer wet season rainfall totals, wet days, and SDII in West Africa Sahel (figure 5). In southwestern West Africa there is some agreement as to declines in boreal summer rain days. Agreement is also seen in Southern Africa for increasing totals, rain days, and SDII, though these trends are spatially fragmented. The Sahel wetting trends are strongly influenced by the severe 1980s drought (Dai et al 2004, Nicholson 2013, Nicholson et al 2018), however, several regional studies have reported increases in rainfall intensity that may also be related to a more extreme climate (Giannini et al 2013, Lodoun et al 2013, Panthou et al 2014). In Southern Africa, increases in seasonal and annual totals are also reported in other studies and are thought to be related to intensification of the Walker Circulation (Maidment et al 2015). Products show some agreement as to drying in central equatorial Africa. Based on figure 5 there is more agreement between these products as to decreases in wet season rain days than rainfall totals (these correspond to boreal fall and winter seasons), however, spatial extent and magnitude of trends vary widely. Drying trends, potential drivers, and dataset discrepancies in this region have been a topic of numerous studies (Malhi and Wright 2004, Yin and Gruber 2010, Zhou et al 2014, Diem et al 2015, Hua et al 2016). According to Hua et al (2016) downward GPCC rainfall trends have been confirmed by some gauge records and are most prominent in boreal spring.

The differences between the gauge products are interesting and potentially concerning. REGEN and GPCC trends are broadly similar, though not identical, while CPC has highly pronounced negative trends across large areas of western East Africa and Central Africa. The CPC differs from REGEN and GPCC in that it mainly uses gauges from the Global Telecommunication System station (GTS) network in Africa. We suspect that changes in the GTS network, fewer stations in the post-2005 ‘real time’ product, and interactions with its interpolation algorithm could be responsible for CPC’s spurious trends. The GPCC and REGEN use interpolation algorithms based on distance-weighted sums of neighboring station anomalies. The CPC product uses a surface fitting procedure (optimal interpolation) that may be sensitive to changes in the station distributions over time. The CPC trends also remind us why it is important to thoroughly examine data inputs when working with second order climate change indices. CPC WS SDII trends in western East Africa and Central Africa are not dissimilar from the rest of the products, but trends in the first order variables are.

It is interesting to note large differences between the satellite-gauge products. CHIRPS looks similar to the GPCC and the REGEN, while the ARC2 and PERSIANN show much greater increases in precipitation and the number of rain days in West and Southern Africa. The similarity in the ARC2 and PERSIANN increases in WS PRCPTOT and WS R1 mm is quite striking, given the large differences in how the
products are created and constrained by station data. The ARC2 uses GTS data to correct for bias. The PERSIANN is bias corrected to match the GPCP. Both the GPCP and ARC merging procedures, combined with changing gauge networks, have previously produced spurious trends (Yin and Gruber 2010, Maidment et al 2015). Potentially spurious trends in the ARC2 dataset were recently examined by Maidment et al (2015). Given the similarities between figures 5(e)–(f) and (k)–(l), we hypothesize that the common element driving similarities between the trends in these products may reside in the underlying thermal infrared radiation datasets, and the inter-calibration of these archives between successive geostationary satellites.

Evaluation of trends in WS PRCPTOT, R1mm, and WS SDII in the satellite-only CHIRPS also indicate large increases in precipitation (not shown), although the location of these increases is different than those found in the ARC2 and PERSIANN datasets. It is interesting that the station-adjusted CHIRPS seems to remove these potential discrepancies. The following explains what may be happening. The CHIRPS product is built around a high resolution climatology which makes it much more resilient to changes in network density. When there are large discrepancies between satellite-only estimates and station observations, changes in the station network over time can produce large time-varying systematic errors. Consider, for example, a location with a wet season precipitation average of 300 mm. Large biases in satellite-only estimates are common. If these averaged 200 mm for a location, and stations were only available at that location for the beginning period of record, a large spurious decline would be produced in the blended product. On the other hand, if the satellite estimates have low mean bias, shifts in the frequency of observations would have smaller impacts. The CHIRPS climatology has low bias when compared to stations (Dinku et al 2018). This low bias, combined with the large number of stations used in the CHIRPS, appears to produce trends similar to the REGEN and GPCC products. However, this bias correction may reduce the rainfall variance in the CHIRPS, especially in drier locations, and this may explain why the CHIRPS trends are more muted than in the other products. The CHIRPS is calculated as a percent anomaly multiplied by the climatological mean. When this mean is low the CHIRPS will almost always be low. So, while the CHIRPS seems to be preferable for analyzing long-term trends, our study has also suggested limitations in some other categories.

5. Conclusion

In areas of SSA with quality daily precipitation data, robust trends over 1950–2013 indicate that extreme events have become wetter but that annual totals have decreased due to fewer rain days. The quality area SSA time series showed significant declines in wet season rain days (WS R1 mm change = −3.6 d; \( p < 0.01 \)), and in annual and wet season totals (annual and WS PRCPTOT changes = −51 and −22 mm; \( p = 0.06 \) and \( p = 0.10 \)), and an increase in the annual 1 d maximum (R × 1 day change = 2.2 mm; \( p = 0.12 \)). Part of the increase in extreme rainfall comes from post-1980s trends in dry areas, but the long-term annual R × 1 day trend is significant in wet areas. The largest increases in annual R × 1 day were in wet areas, by about 9.5% over 1950–2013. These trends are based on the longest length gridded gauge-only daily precipitation dataset covering SSA, REGEN (“All Stations” version). Further investigations into REGEN trends across Africa shown here and in Contractor et al (2019) would be worthwhile. ETCCDI studies based on non-publicly available data (Alexander et al 2006), such as Omundi et al (2014) and Gbode et al (2019), could be good resources.

Sparse and time varying gauge networks challenge our ability to identify long-term precipitation changes for much of SSA, and this is most problematic for wet areas of SSA. Only 15% of SSA in REGEN data is supported by long-term quality gauge reports. Only one tenth of SSA’s climatologically wet areas (>1000 mm annual rainfall), which cover nearly 40% of the region, are represented by quality data. In our comparison of trends in 3 gauge and 12 satellite-gauge products for quality data areas, wet areas had least agreement. Comparisons with REGEN (figures 3 and 4) indicated that satellite products overall performed better at indices based on longer accumulation periods (PRCPTOT and R1mm) than short ones like CDD and R × 1 day. For R1mm and PRCPTOT, satellite products performed nearly as well as gauge-based datasets. Satellite products tend to be less accurate for precipitation intensity (SDII), and dry spell duration (CDD). None of the 12 satellite products scored highest across all the indices, but TRMM 3B42 and CHIRPS show best performance overall and PERSIANN also ranked high. Prior research has noted CHIRPS performance in Southern Africa (Toté et al 2015) and East Africa (Aguju et al 2017, Ayehu et al 2018, Dinku et al 2018) and has recommended CHIRPS for climate change and hydrological studies when station data are not available (Gebrechorkos et al 2018).

An analysis of SSA trends in core indices (figures 2 and 5) identified some existing major discrepancies between products. In the quality data region (figure 2), CHIRPS and ARC2 were able to recreate REGEN’s 1983–2013 positive WS SDII trends for SSA, though the ARC2 WS SDII trend was much greater than in REGEN. There was less across-product agreement for annual R × 1 day trends (figure 2). Similar to REGEN, ARC2 and PERSIANN showed positive annual R × 1 d trends in dry areas with quality data. However, data users should be aware of unrealistic, amplified trends (figure 5) in ARC2, PERSIANN, and CPC Unified in West Africa and Southern Africa for annual
and WS PRCPTOT and WS R1 mm, and for ARC2, also WS SDII. Comparison between REGEN and GPCC FDD 2018 (figure 2) revealed extreme wet area annual $R \times 1$ day and WS SDII trends that may be related to low-quality GPCC data in western Ethiopia and northern Zambia.

The satellite-only versions of TRMM 3B42 and CHIRPS perform well at WS PRCPTOT, even outperforming the gauge-only CPC, but it is the blending of stations in research-grade TRMM and CHIRPS that makes these products rank high for multiple indices. In this and prior studies (Yin and Gruber 2010, Funk et al 2015a, 2015b, Maidment et al 2015), better performing products in this regard use a more dense gauge network and interpolate gauge anomalies upon a background climatology.

The main take away points from this study may be summarized as follows. First, nearly all the products recreated interannual variations in precipitation totals and rain days well, but non-stationary systematic biases in some products may influence long-term trends in those products. Second, we found fairly compelling evidence that, in aggregate, wet-day extremes are increasing in the quality data areas, but in wet regions there were discrepancies between the various products. These wet regions also tend to be poorly monitored. Finally, since the early 1980s, we find little evidence suggesting large changes in seasonal precipitation totals (figure 1(a)), but some evidence indicating increases in precipitation intensity (figure 2(a)).

The study of precipitation extremes is a rapidly evolving discipline. Current satellite and observing systems have challenges but new approaches may offer new opportunities for monitoring extremes. For example, the Trans-African HydroMeteorological Observatory aims to install thousands of new hydro-meteorological monitoring stations and low-cost disdrometers across Africa. In the field of computer vision, $R \times 1$ day automated detection of hydrologically relevant spatial features from complex data is improving. This type of information has been used in machine learning systems for hydrologic prediction (Jiang et al 2018) and in opportunistic sensing projects such as for measuring rainfall intensity from ordinary surveillance cameras (Jiang et al 2019). The relationship between large-scale variability, anthropogenic forcing, and precipitation extremes requires more study. El Niño-Southern Oscillation (ENSO) is the main global driver of fluctuations in tropospheric moisture content (Trenberth et al 2005), a key ingredient for extreme rain, and its influence is most pronounced in the tropics (Trenberth 2011). Recent efforts in attributing observed changes in tropical region precipitation extremes to mixed influence from local processes, ENSO, and global change (Li et al 2016, 2018) provide helpful guidance for similar work in SSA.

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