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RESEARCH ARTICLE

Changes in temperature and precipitation extremes in Ethiopia, Kenya, and Tanzania

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East Africa is one of the most vulnerable regions of Africa to extreme weather and climate events. Regional and local information on climate extremes is critical for monitoring and managing the impacts and developing sustainable adaptation measures. However, this type of information is not readily available at the necessary spatial resolution. Therefore, here we test trends and variability of temperature (1979–2010) and precipitation (1981–2016) extremes in East Africa, particularly Ethiopia, Kenya, and Tanzania, at a spatial resolution of 0.1 and 0.05°, respectively, using the indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI). We use gridded data sets with high accuracy and resolution from the Terrestrial Hydrology Research Group, University of Princeton and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Trends of 19 indices are computed by fitting a linear model and using the nonparametric Mann–Kendall test and the magnitude of change is computed using the Sen's slope method. The results show an increasing trend in monthly maximum and minimum values of daily maximum and minimum temperature in large parts of the region. This is accompanied by significant increasing trends in warm nights (TN90p), warm days (TX90p), warm spell duration index (WSDI), and summer days index (SU). In addition, cold days (TX10p) and cold nights (TN10p) showed a significant decreasing trend. In general, the results show an increasing tendency in temperatures extremes, which is in line with rising global mean temperature. In addition, most of the temperature extremes observed after 2000 are warmer than the long-term mean (1979–2010). Precipitation indices, on the other hand, showed increasing and decreasing trends in Ethiopia, Kenya, and Tanzania, but no general pattern. The outcomes enable identifying hot spot areas and planning of adaptation and mitigation measures at much finer spatial scale than previously possible.

KEYWORDS

climate, East Africa, ETCCDI, extremes, precipitation, temperature, trend

1 | INTRODUCTION

Climate extremes, compared to the average climate, drive more significant changes in the human and natural system (Peterson and Manton, 2008; Tierney *et al*., 2013). Extreme climate and weather events cause a wide range of impacts on the society and environment and pose serious challenges to environmental and resources management, particularly in developing countries. Africa is one of the most vulnerable regions to climate variability and extreme events due to limited capacity to adapt (Niang *et al*., 2014). In recent years, East Africa has been facing frequent droughts and excessive rainfall events (Hastenrath *et al*., 2010; Omondi *et al*., 2012; Viste *et al*., 2013) and left millions of people in need of humanitarian assistance. The livelihood of the majority of East Africans (>80%) is dependent on agriculture and will continue to depend on it under the continuing global changes (FAO, 2014). The income from the agriculture sector provides a substantial contribution (30–50%) to the regions gross domestic product (GDP).

According to current global climate projections, a considerable change in climate and warming temperatures will cause more frequent extreme events such as heavy rainstorms, floods, fires, hurricanes, and tropical storms (Bates *et al*., 2008; IPCC, 2013), and widespread droughts (Wara *et al*., 2005). The rise in temperature, leads to an increase in the rates of evapotranspiration, changes in timing, reliability, and intensity of rains, and duration and frequency of floods and droughts (Oguge *et al*., 2011). In Africa, the temperature has increased significantly during the last 50–100 years by more than 0.5 °C (Funk *et al*., 2012; Nicholson *et al*., 2013; IPCC, 2014; Niang *et al*., 2014; Gan *et al*., 2016). During the last decades, maximum and minimum temperature (T-max and T-min) have shown positive trends in Africa (Collins, 2011; Daron, 2014; Mengistu *et al*., 2014; Niang *et al*., 2014; Adhikari *et al*., 2015) and the increase is statistically significant since the 1980s (Anyah and Qiu, 2012). The increase in temperature is accompanied by a steady decline in precipitation in some parts of the region (Lyon and DeWitt, 2012; Mekasha *et al*., 2014) while the observed long-term precipitation trends are not significant (Daron, 2014; Mengistu *et al*., 2014).

Regional and local-scale information on the frequency and magnitude of climate extremes are therefore critical for managing the extremes and developing sustainable adaptation measures. In order to provide a uniform understanding of changes in climate and weather extremes at regional and local scale, climate indices have been developed by the Expert Team on Climate Change Detection and Indices (ETCCDI). These indices, statistically robust, are designed to describe the characteristics such as the amplitude, persistence, and frequency of daily rainfall and temperature extremes and help explain if the climate is more extreme or variable (Klein Tank *et al*., 2009). A single climate extreme may not be directly linked to anthropogenic climate change but rather represent natural variability; however there is evidence that the observed increase in frequency and magnitude can be attributed to anthropogenic climate change (Christidis *et al*., 2005; Klein Tank *et al*., 2009; Stott *et al*., 2010).

General climatic conditions and climate change are well captured by mean monthly observations, but extremes are better reflected by daily observations. During the last decades, daily temperature and precipitation observations have been used for computation of indices (Zhang *et al*., 2011; Kruger and Sekele, 2013; Chaney *et al*., 2014; Mekasha *et al*., 2014; Omondi *et al*., 2014; Panda *et al*., 2014), but only very few studies (e.g., Chaney *et al*., 2014; Mekasha *et al*., 2014; Omondi *et al*., 2014) have been done in East Africa. It can be assumed that this paucity of in-depth investigations is mainly due to the limited availability of high quality observed daily data. In fact, available studies for the region are either based on regionally averaged information from global databases such as the observational-reanalysis hybrid (Chaney *et al*., 2014) or, at a higher spatial resolution, confined to the vicinity of the field based meteorological stations. For example, Mekasha *et al*. (2014) used only 11 stations to identify changes in extremes in different parts of Ethiopia, while Omondi *et al*. (2014) used 23 stations in Ethiopia (10), Kenya (3), and Tanzania (10). Even though these studies provide reliable information around the vicinity of the stations used, they seem less suited to represent the region.

This adds to the imbalance of data needs and data availability since in particular assessments for remote parts of the region with no or sparse meteorological stations are lacking, while these are often the areas where agricultural activities take place. This is true in East Africa where the topography is very complex and the number of stations and of station data is spatially and temporally limited. In addition to the limited number of stations, data accessibility is somewhat restricted. Therefore, for remote and data sparse regions, reanalysis data (Kalnay *et al*., 1996) can be a preferential data source to be used for computation of the ETCCDI indices to monitor long-term changes in extremes (Zhang *et al*., 2011). Rainfall data from reanalysis, however, have some known biases and inhomogeneities and computed precipitation extremes using the reanalysis data should be treated with caution (Zhang *et al*., 2011). According to Zhang *et al*. (2011), extreme indices are better computed using gridded daily data sets to compare with climate model outputs. In the present study, we aimed to assess climate extremes for large parts of East Africa, particularly Ethiopia, Kenya, and Tanzania, at a high spatial and temporal (daily) resolution based on multiple climate data sets. In particular, we used gridded daily precipitation, T-max, and T-min products with high spatial resolution and covering long periods (>30 years), based on a comprehensive data evaluation study for the region (Gebrechorkos *et al*., 2017).

2 | STUDY AREA AND DATA

2.1 | Study area

The study focuses on Ethiopia, Kenya, and Tanzania, (Figure 1) during the periods 1981–2016 and 1979–2010 for precipitation and temperature, respectively. The climate in East Africa is highly variable and ranges from arid in the east to humid in the west. In addition to the very complex topography, the climate is highly influenced by the Rift Valley lakes, monsoon systems, and several convergence zones (Seregina *et al*., 2014). Climate variability in this region is partly influenced by local factors such as the heterogeneity of the land surface and diverse topography and their linkages with global climate forcing mechanisms (Endris *et al*.,

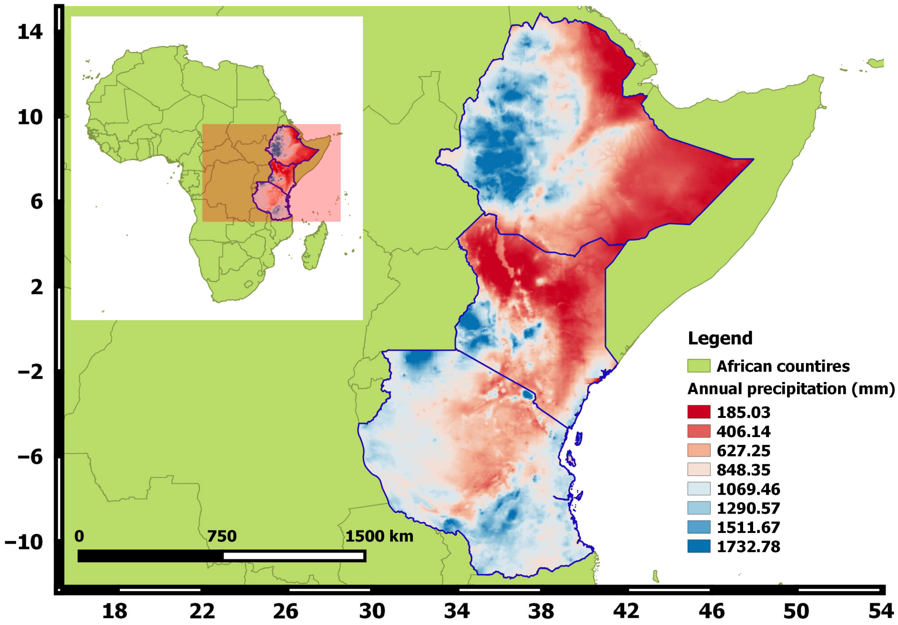

FIGURE 1 Location map and long-term annual average (1981–2016) precipitation (based on CHIRPS) of the study area (Ethiopia, Kenya, and Tanzania) [Colour figure can be viewed at wileyonlinelibrary.com]

2013). The long-term area average annual rainfall in the region during 1981–2016 is 620 mm (Ethiopia), 627 mm (Kenya), and 976 mm (Tanzania) and the maximum amount of rainfall is observed in the western part of Ethiopia and Eastern Tanzania (Figure 1). By contrast, observed long-term average rainfall is low (<500 mm/year) in the eastern part of Ethiopia and Northern Kenya. The long-term area average T-max in Ethiopia, Kenya, and Tanzania ranges from 29 to 31 °C and T-min ranges from 17.5 to 19 °C. Observed area average T-max is higher in the eastern part and T-min is lower in the highlands of the region. The region has four major climatic seasons: January–February (JF), March–May (MAM), June–September (JJAS), and October–December (OND) (Camberlin and Philippon, 2002; Daron, 2014).

MAM and OND are the wettest seasons in much of the equatorial East Africa, where they are known as the long and short rainy seasons, respectively. In addition, JJAS is a main rainy season in the highland parts of the region and receives its highest rainfall during this season. JF and JJAS are the driest seasons with lower rainfall and higher temperature records in Ethiopia and Kenya and Tanzania, respectively.

2.2 | Data sets

For this study, gridded daily precipitation, T-max, and T-min with high spatial resolution and accuracy are used. In East Africa, getting observed data from the field-based meteorological station is limited due to their data sharing policies. Even though some station data is available, its applicability in climate studies is limited due to the missing values and limited lengths of observations. The region is known for its complex topography which implies that the limited number of stations cannot represent the whole region. To overcome the data challenge, we have in an earlier study (Gebrechorkos *et al*., 2017) evaluated multiple climate data sources such as data from remote sensing, reanalysis, and regional climate models (RCMs) by confronting them with an as-comprehensive-as-possible data set comprising meteorological data from more than 200 stations over 21 regions of Ethiopia, Kenya, and Tanzania. We used multiple statistical evaluation methods such as correlation coefficient, root mean square error, bias, and relative biases. In addition, we used multiple rainfall characteristics such as extremes, wet and dry days, daily and total rainfall. The result show that the precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) version 2.0 (Funk *et al*., 2015) and T-max (TX) and T-min (TN) data from the observational reanalysis hybrid (Sheffield *et al*., 2006; Chaney *et al*., 2014) are the most accurate data products for this region.

CHIRPS is a precipitation product, ranging from 50°S to 50°N (and all longitudes), developed for monitoring extreme climate events such as droughts and other global environmental changes (Funk *et al*., 2015). This data source is developed from long-term infrared cold cloud duration (CCD) observations and station data with smart interpolation and novel blending techniques. The process of developing CHIRPS includes multiple ground stations data (e.g., monthly), monthly precipitation Climatology (CHPclim), and CHIRP (satellite only Climate Hazards Group InfraRed Precipitation). CHIRPS is updated regularly (ftp://ftp.chg.ucsb.edu/pub/org/chg/products) and the second version provides an improved daily precipitation product (1981–present). Due to the high quality and spatial resolution (0.05°), CHIRPS is used for assessing and monitoring of extreme weather and climate events and hydrological projections in remote and data scarce regions of Africa (Funk *et al*., 2015; Katsanos *et al*., 2016; Petitta *et al*., 2016; Shiferaw *et al*., 2018).

The observational reanalysis hybrid (Sheffield *et al*., 2006; Chaney *et al*., 2014) is another widely used global (1948–2010) and regional, sub-Saharan Africa (SSA), (1979–2005) meteorological data set. The hybrid data is developed for driving land surface and terrestrial models and for assessing climate extremes in data-sparse regions such as Africa. This data source is developed by a spatial downscaling of the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP-NCAR) reanalysis (Kalnay *et al*., 1996) to a spatial resolution of up to 0.1°. Due to the high number of ground stations used, the hybrid data showed higher accuracy in West and East Africa and has been used for regional analysis of climate extremes using the indices defined by the ETCCDI in SSA (Chaney *et al*., 2014; Sheffield *et al*., 2014). The hybrid data, which is not updated regularly, is available at sub-daily, daily, and monthly time scale from the Terrestrial Hydrology Research Group, University of Princeton (http://hydrology.princeton.edu/data.php).

3 | METHODOLOGY

3.1 | Data management and extreme indices

The gridded daily precipitation, T-max, and T-min are sequentially re-arranged for computation of indices and percentiles using the climate data operator (CDO; Schulzweida *et al*., 2009) and WQ (Jassby, 2013) package of the free R software (R Core Team, 2012). CDO enables to merge data sets, convert units, clip areas of interest, and aggregate multiple time series. The software is consistent with the RClimDex (Zhang and Yang, 2004) with the main focus on daily gridded climate data set. In addition, the NetCDF Operator (NCO; http://nco.sourceforge.net/) is used to modify and rearrange variables and dimensions of the gridded NetCDF data that interferes with the packages of the R software.

The European Climate Assessment (ECA) project has defined 72 climate indices for describing the change in mean and extremes of climate (https://www.ecad.eu//indicesextremes/index.php). Out of the 72 indices, 26 indices follow the definition recommended by the ETCCDI. ETCCDI has defined a core of 27 indices (http://etccdi.pacificclimate.org/index.shtml) based on daily precipitation amount and maximum and minimum temperature values. These ETCCDI indices are designed to provide a uniform understanding of the observed variabilities and change in extreme weather and climate events (Klein Tank *et al*., 2009). In addition, these indices help to monitor the change in extremes and manage the impacts (Alexander *et al*., 2006; Zhang *et al*., 2011; Donat *et al*., 2013). For this study 19 indices, 11 for temperature (Table 1) and 8 for precipitation (Table 2) are used and their definitions are given according to ETCCDI and the ECA project.

To compute the selected indices, the gridded daily precipitation, T-max, and T-min are imported into the CDO software. CDO calculates grid wise extremes for a given time period and spatial resolution. According to the National Meteorological Agency of Ethiopia and ETCCDI, wet (dry) days are days with precipitation amount of greater (less) than 1.0 mm. For daily precipitation, defining a threshold helps avoid artificial trends (Haylock *et al*., 2006; Mekasha *et al*., 2014). The current climate normal (1981–2010) is used as a base period for computation of percentiles of the indices.

TABLE 1 Selected extreme temperature indices and their ETCCDI and ECA definitions

No.	Index name	Definition	Unit
1	TXx	Monthly maximum value of daily maximum temperature	°C
2	TXn	Monthly minimum value of daily maximum temperature	°C
3	TNx	Monthly maximum value of daily minimum temperature	°C
4	TNn	Monthly minimum value of daily minimum temperature	°C
5	SU	Summer days index: annual number of days where daily maximum temperature is >25 °C	Days
6	WSDI	Warm spell days index: annual number of days, in interval of six consecutive days, where daily maximum temperature is >90th percentile of base period	Days
7	CSDI	Cold spell days index: annual number of days, in interval of six consecutive days, where daily minimum temperature is <10th percentile of base period	Days
8	TX90p	Warm days: percentage of days where daily maximum temperature is >90th percentile of base period	%
9	TX10p	Cold days: percentage of days where daily maximum temperature is <10th percentile of base period	%
10	TN90p	Warm nights: percentage of days where daily minimum temperature is >90th percentile of base period	%
11	TN10p	Cold nights: percentage of days where daily minimum temperature is <10th percentile of base period	%

TABLE 2 Selected extreme precipitation indices and their ETCCDI and ECA definitions

No.	Name	Definition	Unit
1	CDD	Consecutive dry day index: maximum number of consecutive days with precipitation below 1 mm	Days
2	CWD	Consecutive wet day index: maximum number of consecutive days with precipitation above 1 mm	Days
3	R20mm	Annual count of very heavy precipitation days where daily precipitation is >20 mm	Days
4	SDII	Simple daily intensity index for a given time period: annual total precipitation divided by number of wet days	mm/day
5	Rx1day	Highest 1-day precipitation amount: monthly maximum 1-day precipitation	mm
6	Rx5day	Highest 5-day precipitation amount: monthly maximum consecutive 5-day precipitation	mm
7	R95p	Very wet days: percentage of wet days exceeding the 95th percentile of the base period	%
8	R99p	Extremely wet days: percentage of wet days exceeding the 99th percentile of the base period	%

3.2 | Trend analysis of extreme climate events

Annual trends of selected precipitation and temperature indices are spatially (grid-wise) computed using the Satellite Application Facility on Climate Monitoring (CMSAF; Kothe, 2016) package of the free R software (R). The trend is computed by fitting a linear model to the time series in each grid cell. To provide regional information, the computed gridded annual indices in Ethiopia, Kenya, and Tanzania are spatially averaged to create a regional time series of indices. Finally, the trend in regional averages is computed using the nonparametric Mann–Kendall test (Mann, 1945; Kendall, 1975) in R using the Trend package (Pohlert, 2016).

The Mann–Kendall test is used to determine the presence of monotonic upward or downward trends in the data. In addition to the Mann–Kendall test, the slope of the trend is computed using the Sen's slope estimator (Sen, 1968) in R using the Trend package (Pohlert, 2016). For a given time period, the slope of the trend is used to describe the magnitude of change in the extremes. In addition to the long-term change, the regional time series are used to assess annual variabilities in selected indices by computing their anomalies from the long-term mean (1979–2010 for temperature and 1981–2016 for precipitation). Anomalies are widely used to accurately show variabilities in climate and allow regional comparisons (Camuffo *et al.*, 2013; NOAA, 2017).

4 | RESULTS

4.1 | Long-term changes in temperature extremes

The long-term (1979–2010) trend analysis of temperature indices in the region reveals statistically significant increasing trends in TXx, TXn, TNx, and TNn in the majority of the region (Figure 2). The trend value in this section provides the change during 1979–2010. TXx shows a significant increasing trend (up to 2.4 °C) in Ethiopia, northern Kenya, and the southwestern part of Tanzania. In addition, in large parts of Ethiopia and Kenya and the northwestern part of Tanzania TXn show a significant increasing trend (up to 1.9 °C), while a significant decreasing trend (up to −1.0 °C) was detected in the eastern part of Tanzania (around Lindi). On the other hand, TNx shows a significant increasing trend (up to 1.6 °C) in Kenya, Tanzania, and the southeastern part of Ethiopia and a decreasing trend (up to −0.8 °C) in the western part of Ethiopia (around western Wellega). TNn in Ethiopia (the western part of Ethiopia, Afar zone 2, and Somalia) and the eastern part of Tanzania (around Pwani and Lindi) showed a significant decreasing trend (up to −2.2 °C). On the other hand, TNn showed a significant increasing trend (up to 1.4 °C) in Kenya and northwestern Tanzania. The monthly area average values of the TX (TXx and TXn) and TN (TNx and TNn) show higher variability (anomalies up to 1.5 and −0.9 °C) in Ethiopia, Kenya, and Tanzania. Compared to Ethiopia and Tanzania, monthly values of TX and TN show higher variability in Ethiopia. Taking the annual average observed values of TXx and TNx after (before) 2000 are warmer (colder) than the long-term mean in Ethiopia, Kenya, and Tanzania (Figure S1, Supporting Information). In addition, the observed annual averages of TXn after 1999 and 1995 are warmer than the long-term mean in Ethiopia and Kenya, respectively.

Observed increasing trends in TX and TN are accompanied by an increasing trend in summer days (SU) in the

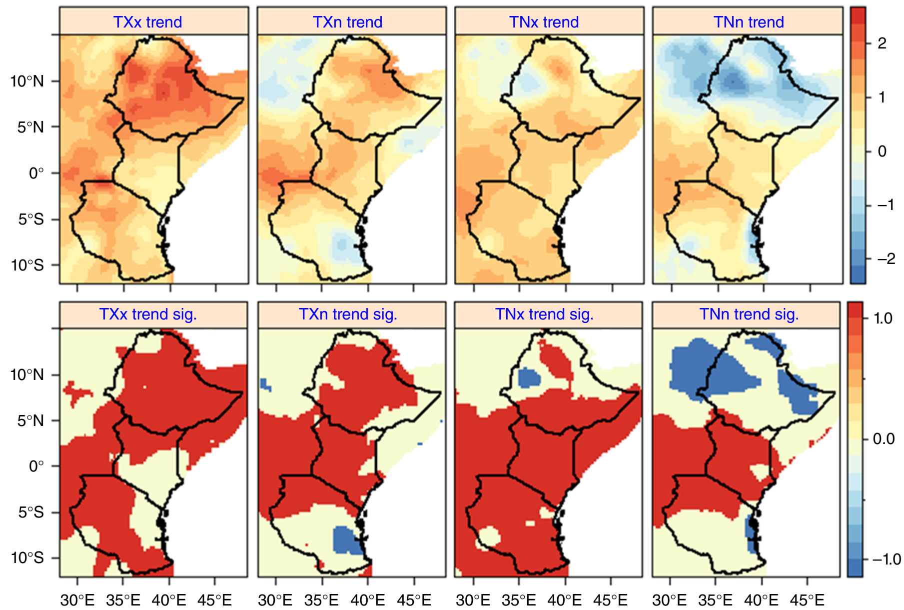

FIGURE 2 Annual trends (upper panels) of TXx, TXn, TNx, and TNn (°C) during the period of 1979–2010 based on the hybrid data. The trend sig. (bottom panels) displays the significance of the trend at $p < .05$ and 1 (dark red) and −1 (dark blue) and 0 show a statistical significant increasing and decreasing trend and not significant change, respectively [Colour figure can be viewed at wileyonlinelibrary.com]

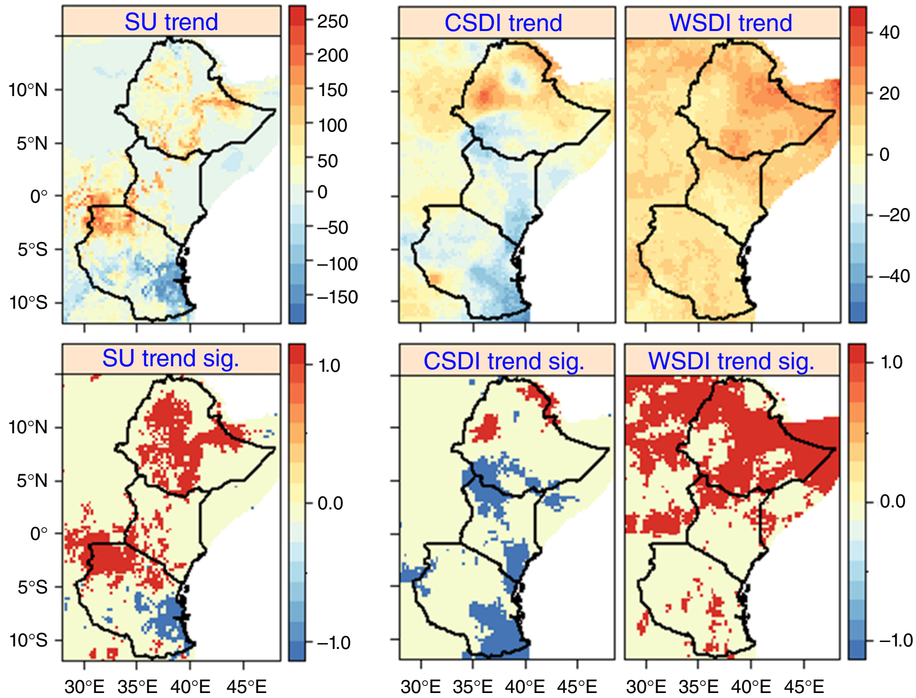

FIGURE 3 Annual trends (upper panels) of SU, CSDI and WSDI (days) during the period of 1979–2010 based on the hybrid data. The trend sig. (bottom panels) displays the significance of the trend at $p < .05$ and 1 (dark red) and −1 (dark blue) and 0 show a statistical significant increasing and decreasing trend and not significant change, respectively [Colour figure can be viewed at wileyonlinelibrary.com]

majority of the region (Figure 3). SU showed a significant increasing trend (up to 241 days) in Ethiopia, northern Tanzania, and some parts of western Kenya. On the other hand, SU only in the eastern part of Tanzania showed a significant decreasing trend (up to −163 days). In Ethiopia and Kenya, on average, the observed numbers of summer days during 1995–2010 are higher (up to 20 days) than the long-term mean (Figure S2).

In addition, the increase in TX and TN is accompanied by an increase in WSDI and decrease in CSDI (Figure 3). A significant decreasing trend (up to −48 days) in CSDI is found in the northwestern and southeastern parts of Kenya, western and eastern parts of Tanzania, and southern parts of Ethiopia. CSDI in the western (Gojam–Welega) and eastern (Afar to the eastern part of Tigray region) parts of Ethiopia showed a significant increasing trend (up to 40 days). The number of WSDI days, on the other hand, showed a significant increasing trend (up to 45 days) in Ethiopia. WSDI in large parts of Kenya and Tanzania showed a non-significant increasing trend. In some parts of the northeastern and northwestern Kenya and central eastern Tanzania, a significant increasing trend (up to 18 days) is observed in WSDI. In general, the observed change in WSDI in Ethiopia, particularly in the eastern part of Ethiopia, is higher than the change in Kenya and Tanzania. Compared to the long-term mean, the average number of days of WSDI in Ethiopia, Kenya, and Tanzania are higher (anomalies up to 15 days) after 2000 and lower (anomalies up to −7.2 days) before 2000 (Figure S2). However, the numbers of days of CSDI in Kenya and Tanzania are lower (anomalies up to −13.5 days) than the long-term mean after 1994. In general, higher annual CSDI and WSDI variability is observed in Kenya and Tanzania compared to Ethiopia.

Similar to CSDI, WSDI, and SU, the increase in TX and TN is accompanied by an increase in the frequency of warm days (TX90p) and nights (TN90p) and decrease in frequency of cold nights (TN10p) and cold days (TX10p) (Figure 4). In the majority of Kenya and some parts of Tanzania (around Kigoma, Arusha, and Lindi) the frequency in TN10p shows a significant decreasing trend (up to 16%). Moreover, the frequency in TN10p shows a significant decreasing trend (up to −15%) in the western (Southern Nations, Nationalities, and Peoples) and increasing trend (up to 10%) in the eastern (Afar zone 2) and western (Wellega) parts of Ethiopia. On the other hand, the frequency in TN90p in Kenya and Tanzania and the southern part of Ethiopia shows a significant increasing trend (up to 20%). In the eastern and western parts of Ethiopia, however, the frequency in TN90p showed a non-significant decreasing trend (up to 9%). Similar to the change in TN10p, the frequency in TX10p shows a significant decreasing trend (up to 22%) in Kenya, large parts of Ethiopia, and the northern and western parts of Tanzania. Compared to the change in Kenya and Tanzania, the observed significant decreasing trend (up to 22%) in the frequency of TX10p is higher in the eastern parts of Ethiopia. The frequency in TX90p, on the other hand, shows a significant increasing trend (up to 20%) in Ethiopia, the northern and western parts of Tanzania, and different parts of Tanzania. Compared to Kenya and Tanzania, the maximum and

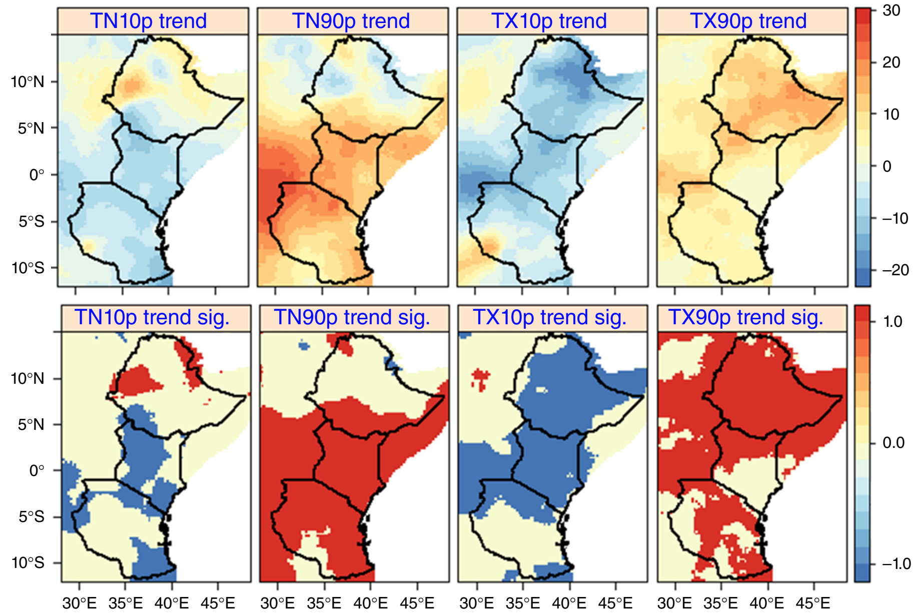

FIGURE 4 Annual trends (upper panels) of TN10p, TN90p, TX10p, and TX90p (%) during the period of 1979–2010 based on the hybrid data. The trend sig. (lower panels) displays the significance of the trend at $p < .05$ and 1 (dark red) and −1 (dark blue) and 0 show a statistical significant increasing and decreasing and not significant change, respectively [Colour figure can be viewed at wileyonlinelibrary.com]

significant change in TX90p is observed in the eastern part of Ethiopia (around Somali region).

During the study period, in addition to the observed change, higher annual variability in TN10p and TN90p in Kenya and Tanzania than in Ethiopia were detected (Figure S3). Observed TX10p before 1995 is higher (anomalies up to 10%), but after 1995 lower (up to −6%) than the long-term mean. Moreover, after 2000 observed values of TN90p are higher (anomalies up to 19%) than during the long-term mean, particularly in Kenya and Tanzania, while the opposite (anomalies up to −10%) is true in these countries before 2000.

4.2 | Long-term changes in precipitation extremes

The long-term (1981–2016) trend analysis in precipitation extremes show a non-significant change in large parts of the region. The trend value in this section provides the change during 1981–2016. The numbers of consecutive dry (CDD) and wet (CWD) days show significant changes only in some parts of the region (Figure 5). CDD showed a significant increasing trend (up to 150 days) in some parts of Eastern Ethiopia, Kenya, and Tanzania. In addition, CWD showed significant decreasing trends (up to −24 days) in the western parts of Ethiopia, Eastern Kenya, and some parts of Tanzania. In large parts of the region, the observed increasing trend in CWD is not significant. Similar to the weak trend, area average annual anomalies in CDD and CWD showed a weak variability (up to ±5.4 days) (Figure S4). CWD is almost regular throughout the study period in Ethiopia and the highest variability (anomalies up to ±3 days) is detected in Tanzania.

In addition to CDD and CWD, Rx1day and Rx5day show very patchy significant changes in small pockets of the region (Figure 5). Rx1day in Southwestern Ethiopia (around Kefa and Gamo Gofa) and the western (around Kisumu) and central-western (around Nakuru) parts of Kenya show a significant increasing trend (up to 27 mm). A significant decreasing trend (up to −17 mm) in Rx1day is observed in Central Ethiopia (around Dessie, northern Addis Abeba, and Goba) and Tanzania (in Bukoba, Tarime, and Mbeya). Rx5day, on the other hand, shows a similar trend to Rx1day in the majority of the region, but the magnitude of change is higher in Rx5day. Significant increasing trends (up to 33 mm) in Rx5day are observed in Southern Ethiopia (around Gamo Gofa) and the western (around Kisumu) and central-western (around Nakuru) parts of Kenya. In addition, a significant decreasing trend (up to −22 mm) in Rx5day is observed in Central Ethiopia (northern Addis Abeba and Goba). Compared to the very patchy trends, higher variability in area average of R1xday (anomalies up to ±15 mm) and Rx5day (anomalies up to 30 mm and −20 mm) is found in Ethiopia, Kenya, and Tanzania (Figure S5).

The number of very wet (R95p) and extremely wet (R99p) days show an increased trend in some parts of the region, particularly in Kenya (Figure 6). Significant increasing trends in R95p (up to 16 days) and R99p (up to 12 days) are observed in different parts of Kenya, southern Ethiopia, and the northern (around Arusha) and central (around Morogoro) parts of Tanzania. Moreover, significant decreasing trends in R95p (up to −9 days) and R99p (up to −6 days) are observed in some parts of Eastern Ethiopia (around Afar zone) and the southern part of Tanzania (around Ruvuma and Mbeya). Compared to the change in R99p, the observed

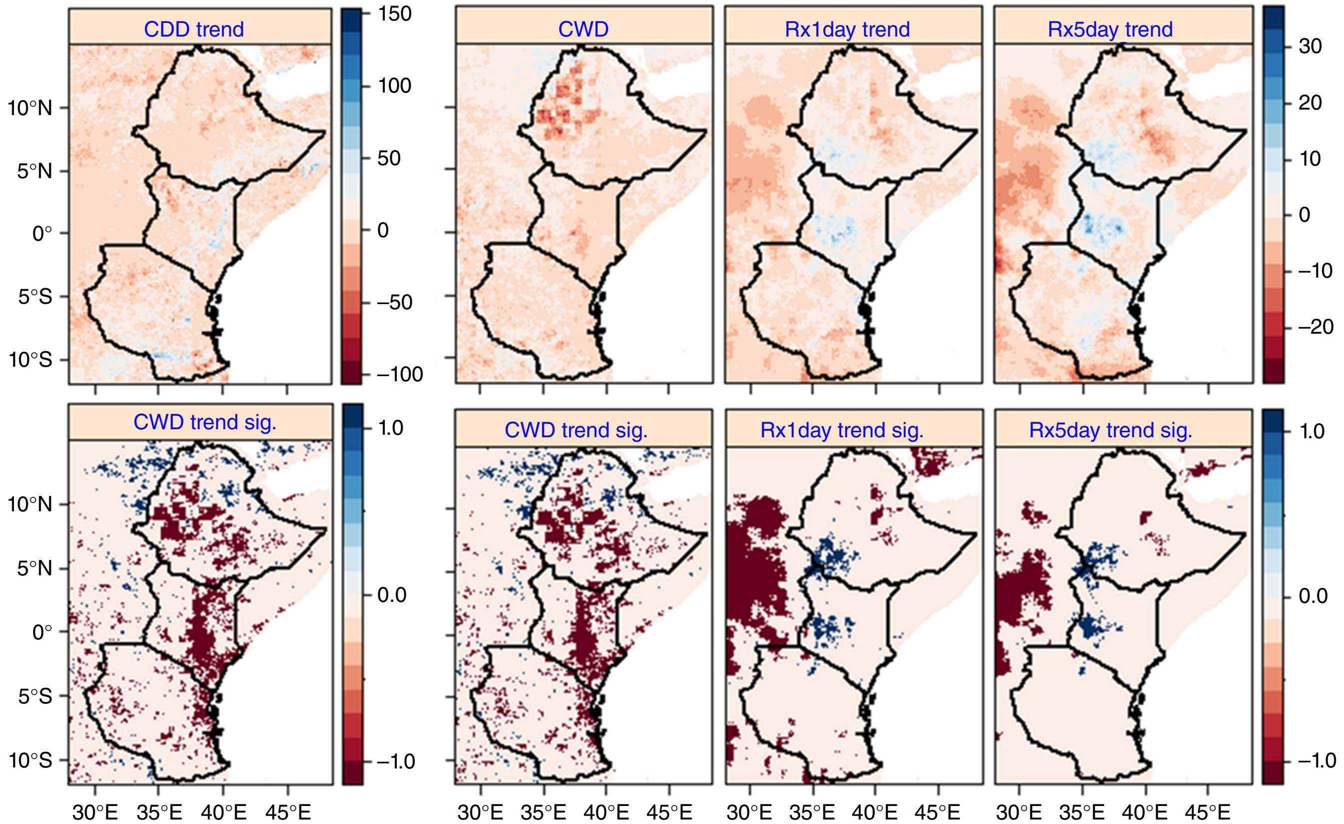

FIGURE 5 Annual trends (upper panels) of CDD, CWD, RX1day, and Rx5day during the period of 1981–2016 based on CHIRPS. CDD and CWD are given in number of days and Rx1day and Rx5day are given in mm. The trend sig. (lower panels) displays the significance of the trend at $p < .05$ and 1 (dark blue) and −1 (dark red) and 0 show a statistical significant increasing and decreasing trend and not significant change, respectively [Colour figure can be viewed at wileyonlinelibrary.com]

change is higher in R95p. However, taking the area average, annual variability (anomalies up to 3.8% and −3.2%) in R95p is higher than R99p and the maximum variability is observed in Kenya (Figure S6). In Kenya, most of the observed numbers of R95p and R99p days before (after) 1990 are lower (higher) than the long-term mean.

The R20mm, on the other hand, shows a significant increasing trend (up to 24 days) in some parts of southwestern Ethiopia, southern Kenya, and over highly localized parts of Tanzania (Figure 6). R20mm in eastern Ethiopia (around Afar zone 3, Harerge and Fik) and the eastern and southern parts of Tanzania (around Iringa and Ruvuma) show a significant decreasing trend (up to −13 days). Annual average numbers of R20mm are higher in Tanzania (11 days) followed by Kenya (8 days) and Ethiopia (7.5 days). Compared to the long-term mean, annual variability in area average of R20mm is higher in Kenya and Tanzania (up to 7.2 and −3.7 days) and it almost regular in Ethiopia (Figure S7). Similar to R20mm, significant SDII trends cover a much larger area than other precipitation indices do (Figure 6). Only in the eastern part of Ethiopia (around the eastern and western Harerge and Afar zone 3), SDII shows a significant decreasing trend up to 6 mm/day. Observed average values of SDII are higher in Kenya (13.6 mm/day) compared to Tanzania (12.3 mm/day) and Ethiopia (11.1 mm/day). Taking the regional average, SDII shows higher variability in Kenya (anomalies up to 4.3 mm/day and −3.1 mm/day) and lower in Tanzania (anomalies up to 1.7 mm/day and −1.9 mm/day) and Ethiopia (anomalies up to 1.41 and −1.9 mm/day) (Figure S8). Summing up, few precipitation indices in few areas of the region show a significant positive change, while in large parts of the region no significant change was detected.

4.3 | Regional average of trends

Regionally, the area average temperature indices show an increasing and decreasing trend and most of the indices are significant. In Ethiopia, significant increasing trends in TXx (0.048 °C/year), TXn (0.026 °C/year), and TNx (0.021 °C/year) and non-significant decreasing trend in TNn (−0.014 °C/year) are observed. The observed increasing trends in TXx (0.023 °C/year), TXn (0.025 °C/year), TNx (0.024 °C/year), and TNn (0.014 °C/year) are significant in Kenya. In Tanzania, significant increasing trends in TXx (0.02 °C/year) and TNx (0.025 °C/year) and non-significant increasing trend in TXn (0.014 °C/year) and TNn (0.02 °C/year) are observed. Overall, the increase in TX and TN in Ethiopia, Kenya, and Tanzania are accompanied by an increase in warm indices (e.g., TX90p, TN90p, and WSDI) and decrease in cold indices (e.g., TX10p, TN10p, and CSDI).

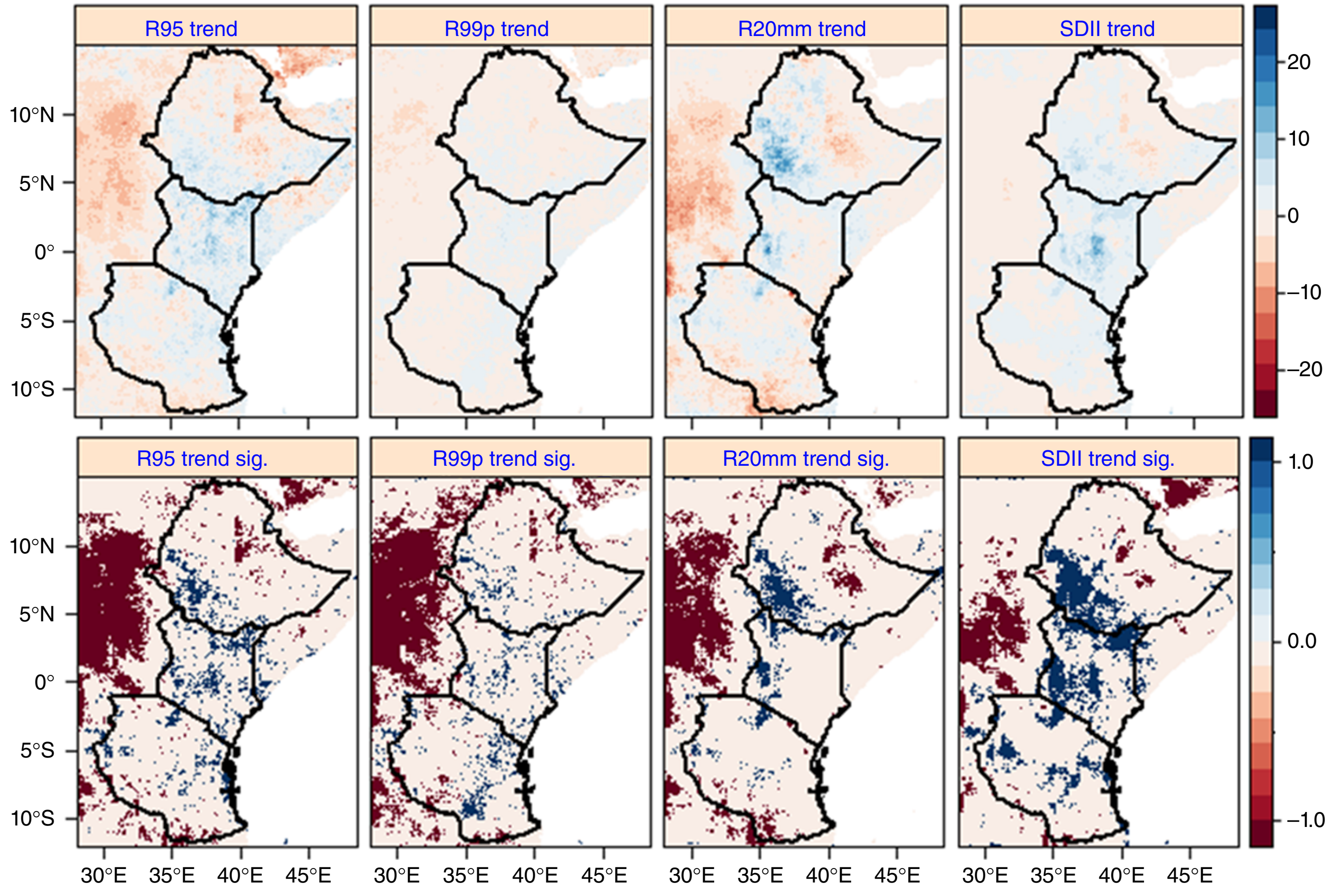

FIGURE 6 Annual trends (upper panels) of R95p, R99p, R20mm, and SDII during the period of 1981–2016 based on CHIRPS. R95p and R99p in percentage of days, R20mm in days, and SDII is given in mm/day. The trend sig. (lower panels) displays the significance of the trend at $p < .05$ and 1 (dark blue) and −1 (dark red) and 0 show a statistical significant increasing and decreasing trend and not significant change, respectively [Colour figure can be viewed at wileyonlinelibrary.com]

Significant changes in the numbers of warm and cold nights and days are observed in Ethiopia, Kenya, and Tanzania. In Ethiopia, a significant increasing trend in annual TN90p (0.19%) and TX90p (0.34%) and a significant decreasing trend in TX10p (0.29%) are observed. Annual TN10p in Ethiopia showed a non-significant decreasing trend (−0.05%). Significant increasing trends in annual TN90p (0.47%) and TX90p (0.2%) and significant decreasing trends in annual TN10p (−0.2%) and TX10p (0.23%) are observed in Kenya. In Tanzania, significant increasing trends in annual TN90p (0.4%) and TX90p (0.17%) are observed. Further, statistically not significant decreasing trends in annual TN10p (−0.2%) and TX10p (−0.08%) are observed in Tanzania.

In line with the increase in TX and TN, the numbers of WSDI days were increased while numbers of CSDI days are decreased in this region. WSDI showed a significant increasing trend in Ethiopia (0.36 days/year), Kenya (0.32 days/year), and Tanzania (0.24 days/year). CSDI, however, showed a non-significant decreasing trend in Ethiopia (−0.14 days/year), Kenya (−0.27 days/year), and Tanzania (−0.38 days/year). The magnitude of change in WSDI is higher than CSDI in Ethiopia and Kenya. The increase in temperature in this region is also associated with an increase in summer days index (SU). SU showed a significant increasing trend in Ethiopia and Kenya and non-significant increasing trend in Tanzania.

Area average precipitation indices, compared to temperature indices, show less significant changes in Ethiopia, Kenya, and Tanzania. In Ethiopia, only CDD shows a significant decreasing trend (−0.023 days/year). However, significant increasing trends in annual SDII (0.08 mm/day), R95p (0.07%), and R99p (0.02%) are observed in Kenya. Unlike to the change in Kenya, none of the indices showed a significant change in Tanzania. Overall, the magnitude of change in precipitation indices is higher in Kenya compared to Ethiopia and Tanzania.

5 | DISCUSSION

Based on best performing gridded climate data products, considerable changes in climate extremes were revealed for East Africa. Our in-depth analysis provides high-resolution visualization (maps) of trends in climate extremes allowing for comparison of changes in different areas of the region. These maps foster communication with and awareness of decision makers and allow identification of hotspot areas for managing the impacts (e.g., agriculture and environmental resources) and developing adaptation and mitigation measures.

In Ethiopia, Kenya, and Tanzania, most of the temperature indices show significant increasing and decreasing trends. Increasing trends in TXx, TXn, and TNx in Ethiopia, Kenya, and Tanzania are consistent with the results of recent studies which did, however, cover limited parts of the region (Mekasha *et al*., 2014; Omondi *et al*., 2014; Camberlin, 2017). The increase in TX and TN in this region are accompanied by increasing trends in warm indices and decreasing trends in cold indices. The number of warm nights (TN90P), warm days (TX90P) and warm spell duration index (WSDI) show significant increasing trends in Ethiopia, Kenya, and Tanzania. On the other hand, decreasing trends inTN10P, TX10P, and CSDI are observed. Taking the general direction of these indices, on regional and global basis, our results are in line with the findings of current studies (King'uy*u et al*., 2011; Zhang *et al*., 2011; Chaney *et al*., 2014; Mekasha *et al*., 2014; Omondi *et al*., 2014; Marigi *et al*., 2016; Mequaninta *et al*., 2016) that showed decreasing tendency in cold indices and increasing tendency in warm indices. The observed changes in temperature extremes could be associated with climate change induced by human activities producing greenhouse gases such as agriculture and deforestation (Meinshausen *et al*., 2009; Zhou *et al*., 2009; Zhang *et al*., 2011).

The observed changes in temperature extremes, in general, are in line with what is expected with the increase in global average temperature. Globally, several studies (Donat and Alexander, 2012; Hansen *et al*., 2012; Chaney *et al*., 2014) showed an increase in global daily temperature. In addition, several studies showed significant increasing trends in minimum and maximum temperature (Christy *et al*., 2009; Omumbo *et al*., 2011; Omondi *et al*., 2014; Camberlin, 2017) and in mean temperature during the last 50–100 years (Nicholson *et al*., 2013; IPCC, 2014; Niang *et al*., 2014; Gan *et al*., 2016). Compared to temperature indices, which showed a significant change in the majority of the region, only few precipitation indices showed significant changes. Observed increasing trends in R95p and R99p are significant in Kenya and not significant in Tanzania. The increase in R95P and R99P in Kenya and Tanzania and decreasing trends in CDD and CWD in Ethiopia are in agreement with the findings of other studies (Chaney *et al*., 2014; Mekasha *et al*., 2014; Mequaninta *et al*., 2016). According to Chaney *et al*. (2014), the increase in R95P and R99P and decreasing trend in CDD is mainly associated with the recovery of the region from the 1970 and 1980s droughts. While our results support this notion, given the overall weak trends in precipitation, we feel it is premature to argue that the increase in R95P, R99P, and R20mm and a decrease in CDD are signals for the region as going from drier towards wetter climate as done by Omondi *et al*. (2014). On the other hand, CDD showed a significant increasing trend (up to 150 days) in some parts of the region. Studies (e.g., Orlowsky and Seneviratne, 2012; Duan *et al*., 2017) concluded that the increase in CDD indicates enhanced dryness and risk of seasonal droughts. Compared to the (largely lacking) trends in precipitation indices, we found higher annual variability of extremes which might be associated with the very complex topography and relief features of the region and large-scale climate variables (Kotir, 2011; Fer *et al*., 2017; Mpelasoka *et al*., 2018).

The changes in climate extremes might induce significant impacts on environmental resources, agriculture and food security, human health, and the overall regional development. In East Africa, agriculture is one of the most important sectors and the change and variability in extremes, example changes in the amount of rainfall and increase in temperature, affect the growth of crops and finally affect the region's food security. In line with changing in climate, projected warming in temperature (1.4–5.5 °C), based on RCMs and global climate models (GCMs), will pose significant impacts such as on agriculture and livestock production (Thornton *et al*., 2011; Adhikari *et al*., 2015; Serdeczny *et al*., 2016). However, the output from both RCMs and GCMs is too coarse and these models face large uncertainties to be used for impact assessment studies. Impact assessment studies, such as in agriculture and water resource, require climate information at higher spatial and temporal resolution, which is equivalent to point information (Gachon and Dibike, 2007; Wilby and Dawson, 2007; Wilby *et al*., 2014). Therefore, for impact assessment studies climate projections need to be much more detailed such as using statistical downscaling models to bridge the resolution gap and minimize uncertainties (Coulibaly *et al*., 2005; Wilby and Dawson, 2007; Khan and Coulibaly, 2009). Our analysis of climate extremes enables an assessment of potential impacts in recent periods at high spatial resolution. Future impact studies should focus on climate projections with a similarly high resolution.

In addition to the impact on crop yield (Fuller *et al*., 2018), the increase in warm days and nights could induce considerable impacts on sectors such as the energy (e.g., high water requirement for cooling), water supply (e.g., increase freshwater need) and transportation (e.g., deformation of roads). According to Hatfield *et al*. (2014), a significant increase in temperature affects the immunity of livestock to diseases and finally reduces the fertility and milk production. Changes in temperature and precipitation have direct (e.g., thermal stress, eye diseases, skin cancer, and water-borne diseases, ultimately affecting mortality and morbidity) and indirect (e.g., malnutrition, diarrhoea and malaria and dengue fever) impacts on human health (Byass, 2009; ACPC, 2013; Mellor *et al*., 2016; Song *et al*., 2017; Wichmann, 2017). Considering the above example and other related impacts of changing in extremes, there is a need to improve the current forecasting system and awareness at different levels, particularly regional-local, and sectors to manage the risks. In addition, countries should make their meteorological data easily accessible for research to develop climate projections and sustainable adaptation and mitigations strategies.

6 | SUMMARY AND CONCLUSION

Annual and long-term variability and trends of 19 temperature and precipitation indices are provided for a better monitoring allowing an improved management of impacts of climate extremes and for developing sustainable adaptation measures even in remote and data sparse parts of East Africa. The results show significant changes in most of the temperature indices in Ethiopia, Kenya, and Tanzania. In Kenya, monthly maximum (TNx) and minimum (TNn) values of daily minimum temperature and minimum values of daily maximum temperature (TXn) showed significant increasing trends. Additionally, monthly maximum values of daily maximum temperature (TXx) in Ethiopia and Tanzania and maximum values of daily minimum temperature (TNx) in Tanzania showed significant increasing trends. In Ethiopia, TXn also showed a significant increasing trend. TNn showed statistically not significant decreasing trend only in Ethiopia with minimum change compared to TXx, TXn, and TNx.

The increases in maximum (TX) and minimum (TN) temperature are accompanied by an increase in warm indices and a decrease in cold indices. In Ethiopia, Kenya, and Tanzania, significant increasing trends in warm nights (TN90P), warm days (TX90P), and WSDI are observed. On the other hand, significant decreasing trends in cold nights (TN10P) and cold days (TX10P) and a non-significant decreasing trend in the cold spell duration index (CSDI) are observed in Ethiopia, Kenya, and Tanzania. Compare to the cold indices (TN10P, TX10P, and CSDI), the magnitude of change in warm indices (TN90I, TX90P, and WSDI) is higher in Ethiopia, Kenya, and Tanzania. Observed values of TXx and TNx after 2000 are warmer than those representing the long-term mean in the region. In addition, observed WSDI (CSDI) after 2000 is higher (lower) than the base period. Compared to Ethiopia and Tanzania, the higher annual variability of WSDI and CSDI are observed in Kenya.

Unlike to the trend in temperature indices, only few precipitation indices show significant increasing and decreasing trends in some parts of Ethiopia, Kenya, and Tanzania. In Kenya, significant increasing trends are found in SDII, R95P, and R99P. On the other hand, none of the precipitation indices showed a significant change in Tanzania. Similar to Tanzania, most of the precipitation indices showed a non-significant change in Ethiopia, where only CDD showed a significant decreasing trend. Similar to temperature indices, the magnitude of change in most of the precipitation indices is higher in Kenya compared to Ethiopia and Tanzania. Considering the observed changes in the extremes, there is a need to improve the region's capacity in weather forecasting and awareness at regional-local levels to manage the risks and adapt to the changes. In contrast to temperature trends, precipitation trends are not robust. Even when moderate extremes (R95P and R99P) are addressed, the overall variability is more pronounced than temporal changes. Adaptation to high variability is, however, no less challenging than adapting to an overall change.

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SUPPORTING INFORMATION

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