Projected Changes in Meteorological Drought Over East Africa Inferred from Bias-Adjusted CMIP6 Models

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Abstract

The ongoing global warming has caused unprecedented changes in the climate system, leading to climate change and increase in drought occurrence, duration, severity and intensity. This research uses the sixth phase of Coupled Model Intercomparison Project (CMIP6) data to investigate the projected changes in drought events over East Africa (EA) under four Shared Socioeconomic Pathway (SSP) emission scenarios (SSP1-2.6, SSP2-4.5, SSP3-4.0 and SSP5-8.5). Drought is quantified using the standardized precipitation index (SPI) considering different measures: drought duration (DD), drought frequency (DF), drought severity (DS) and drought intensity (DI). The CMIP6 data are first bias-corrected using a quantile mapping method, with the Climatic Research Unit (CRU)'s precipitation data as the observation. Evaluating the accuracy and reliability of historical data before and after correction demonstrates the importance of such approach. The projection results show that a drying pattern is expected during the mid future, while the end of the century is projected to get wetter, with a stronger magnitude for the wetting than the drying trend. Moreover, the dry areas of EA are likely to experience more frequent drought events with longer duration and stronger intensity and severity in the far future. In contrast, the highland and lake regions are likely witness a decrease in drought occurrences, affirming the “dry gets drier and wet gets wetter” theory over EA. This study identifies possible drought hotspots over EA, thus enabling early preparation for such events.

1. Introduction

The earth system continues to witness unprecedented changes (Steffen et al. 2019). An observed increase in the concentration of greenhouse gases (GHGs) in the atmosphere has altered the climate feedback mechanisms, posing a significant threat to the survival of both humans and ecosystems. This has led to a “new norm” characterized by the unparalleled occurrence of extreme events such as droughts, floods, and heat waves (Eckstein et al. 2020). The impact of extreme events varies in magnitude, with drought occurrence dominating various sectors (IPCC 2014). The damage caused by drought alone is estimated to affect over 1.5 billion people globally and will likely increase in the future (Jenkins and Warren 2015; Funk et al. 2019; Ukkola et al. 2020). This calls for urgent monitoring of its tendency as a way of identifying the hotspots and vulnerable communities for timely interventions and appropriate adaptation strategies (Wilhite et al. 2000; Lloyd-Hughes 2012).

Research shows that the frequency of drought occurrence will increase significantly in the future (Trenberth et al. 2014; IPCC 2014), mainly as a consequence of climate change. However, unanimity on the extent of the variation and magnitude is yet to be reached (Sheffield et al. 2012). The aforementioned studies utilized global climate model outputs derived from the Coupled Model Intercomparison Project phase three (CMIP3; Meehl et al. 2007) and/or phase five (CMIP5; Taylor et al. 2012). In general, CMIP5 ensembles depict an increase in the intensity and frequency of droughts globally in the 21st century (Sheffield and Wood 2008; Dai 2013; Huang et al. 2016). To illustrate, climate models projected a significant increase in drying patterns in central Europe, particularly in Poland (Osuch et al. 2016), western North America (Ahmadalipour et al. 2017; Wei et al. 2019; Zhao et al. 2020), the Mediterranean

(Trenberth et al. 2014), the Amazon (Duffy et al. 2015), Africa (Masih et al. 2014; Haile et al. 2020), South Asia (Wang et al. 2018; Zhai et al. 2020), and Australia (van Dijk et al. 2013). Despite the robust projections that have been conducted over different parts of the world using the CMIP datasets, there remain some uncertainties and biases in the model results (Burke and Brown 2008). Such biases cast aspersions on the reliability of the projections based on previous model outputs (Ukkola et al. 2018), calling for concerted efforts for improved model parameterization.

The new generation of CMIP outputs (CMIP6; Eyring et al. 2016) provides an opportunity to enhance our apprehension of the future climate. Policymakers, among other users of climate information, need timely information that will enable them to address pertinent climate-related issues. Researchers have conducted preliminary examinations of drought changes using model ensembles at global and regional scales. Ukkola et al. (2020) reported an overall increase in drought occurrence by more than 45% over the world's land area, mainly due to changes in mean precipitation and natural variability. The findings concur with a related study by Cook et al. (2020) that noted a severe drying pattern with an anomalous increase in extreme drought events by up to 200 – 300 % in some locales. Meanwhile, regional studies demonstrate a concomitant tendency to that of global land area analysis. For example, Zhai et al. (2020) reported a significant increase in drought features over the north-west sub-region of the larger south-east Asia domain using a CMIP6 ensemble. While conducting drought changes analysis over regions of India using bias-corrected CMIP6 data, Shrestha et al. (2020) observed that multiple severe-to-extreme drought events would intensify during the 2030s in most climate scenarios.

Africa remains the most vulnerable continent to drought-related impacts compared to other sub-regions of the world (Ahmadalipour et al. 2019). With the largest expanse of drylands exceeding the aridity index of < 0.05 (Huang et al. 2016), the observed and projected drought intensification will negatively impact nearly all spheres of livelihood. Wei et al. (2019) showed that drier and hyper-arid regions would experience higher warming of about 2.4 °C under the worst-case emission scenario (O'Neill et al. 2016). The projected warming will raise the temperature of dryland regions of the Sahara Desert (5.6 °C under the Shared Socioeconomic Pathway (SSP) 5-8.5) and Southern Africa by an extra ~1.4 °C (Almazouri et al. 2020). The escalation in temperature coupled with declining precipitation over most regions of Africa at large is likely to exacerbate the occurrence of drought events.

A few CMIP6-based studies (e.g., Cook et al. 2020; Ukkola et al. 2020) have been conducted over Africa's hydroclimatic sub-regions to examine the drought changes. The existing studies over EA focused on precipitation changes owing to the observed decrease in the March to May (MAM) seasonal rainfall (Funk et al. 2014; Ongoma and Chen 2017; Nicholson 2017). The region's most common extreme weather events are droughts and floods (Lukamba 2010; Nkunzimana et al. 2021). These events cause huge losses, disruption of livelihoods and destruction of property in EA (Otieno and Awange 2006; Lyon and Dewitt 2012; Opiyo et al. 2015), calling for response measures that consume millions of dollars annually (Martey et al. 2020).

The availability of CMIP6 global circulation models (GCMs) provides an opportunity to re-examine the future changes in drought events and map out possible drought hotspots over EA. This will assist in devising effective adaptation and mitigation strategies. This study investigates the future changes in drought occurrences using the Standardized Precipitation Index (SPI) to build an accurate drought map for EA. Ukkola et al. (2020) advocate the use of SPI since other approaches that incorporate potential evapotranspiration (PET), such as Standardized Precipitation Evapotranspiration Index (SPEI), tend to overestimate future drought as compared to climate model outputs. This study thus seeks to answer one main question: What is the spatial and temporal extent of projected drought extremes variations over EA? This information is useful in improving the accuracy and reliability of existing drought early warning systems.

2 Study Area, Data And Methods

2.1 Study area

EA lies in the equatorial region, within 28° E–42° E and 12° S–5° N (Fig. 1). In this study, Rwanda and Burundi are treated as part of Tanzania owing to their relatively small size and having similar climate Tanzania. Generally, the rainfall spatio-temporal distribution across EA is very complex (Indeje et al. 2001), due to the region's complex topography and water bodies. EA's topography varies considerably from the coastal region to the mountain peaks (e.g., Mts. Kilimanjaro and Kenya). The region has Africa's largest lake, Lake Victoria, among other large inland water bodies. The Great Rift Valley divides the study area into nearly two halves. Most parts of the region, especially Kenya, the western part of Uganda and eastern Tanzania, receive a bimodal rainfall distribution during MAM and October–December (OND) (Kabanda and Jury 1999; Ongoma and Chen 2017; Gebrechorkos et al. 2020). The rainfall seasonality is mainly influenced by the migration of the tropical rain belt (TRB; Nicholson 2018). Rainfall interannual variability is mainly influenced by El Niño and La Niña (El Niño-Southern Oscillation, ENSO) and other factors such as the Quasi-Biennial Oscillation (QBO) and the Indian Ocean Dipole (IOD) (Endris et al. 2016). More details on the area of study can be found in Ongoma et al. (2018a) and references therein.

2.2 Datasets

This study utilizes the gridded monthly rainfall data from the University of East Anglia Climatic Research Unit (CRU version TS4.04) spanning 120 years (1901–2020) as observed data. The data has been successfully used in related studies over EA (e.g., Ogwang et al. 2014; Maidment et al. 2015; Ogwang et al. 2015; Ongoma et al. 2015, 2018b; Sagero et al. 2018; Ayugi et al. 2018). The CRU data is preferred over station data because it has a long time series and is quality controlled. Weather records over EA are of low quality and have short records, most of which are less than 50 years and exhibit incompleteness, as reported by several previous studies (e.g., Omondi et al. 2014a; Ongoma et al. 2018c). The CRU data created by interpolating station datasets is on a 0.5 ° × 0.5 ° resolution grid (Harris et al. 2014). A detailed description of the CRU version TS4.04 data is provided by Harris et al. (2020). CRU data is preferred over other datasets of similar time length, such as the Global Precipitation Climatology Centre (GPCC) data

(Schneider et al. 2015), owing to its higher accuracy in reproducing rainfall over EA (Ayugi et al. 2016; Ongoma and Chen 2017).

This study employs a multi-model ensemble (MME) of 16 CMIP6 GCM outputs derived from the first variation run. The datasets are accessed through the Earth Systems Grid Federation (ESGF; <https://esgf-node.llnl.gov/search/cmip6/>) data replication centers (Eyring et al. 2016). The modelled precipitation for historical experiments and four future scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) are used to estimate drought patterns. The SSP denotes an integrated scenario of possible future climate and societal change, which would be employed to assess topics such as the mitigation and adaptation efforts needed to attain a particular climate outcome (O'Neill et al. 2016). The historical experiment starts from 1850 to 2014 whilst projection under the Scenario Model Intercomparison Project (Scenario MIP; O'Neill et al. 2016) run from 2015 to 2100. Table 1 gives the models' description. The drought index used in the present study is computed from the native resolution and then re-gridded to a consistent spatial resolution of $1^{\circ} \times 1^{\circ}$ using a bilinear interpolation technique.

Table 1
List of the CMIP6 GCMs used in this study

S/N	Models	Reporting Institutions	Horizontal Resolution (lat × lon)
1	BCC-CSM2-MR	Beijing Climate Center (BCC) and China Meteorological Administration (CMA), China	1.13° × 1.13°
2	CanESM5	Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada, Victoria, Canada	2.81° × 2.81°
3	CESM2-WACCM	National Center for Atmospheric Research, USA	1.25° × 0.94°
4	CMCC-CM2-SR5	Euro-Mediterranean Centre on Climate Change couple model (CMCC-CM2), Italy	1.3° × 0.9°
5	EC-EARTH3	EC-EARTH consortium, Europe	0.70° × 0.70°
6	EC-EARTH3-Veg	EC-EARTH consortium, Europe	0.70° × 0.70°
7	FGOALS-g3	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	2.25° × 2.0°
8	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory, USA	1.25° × 1.00°
9	HadGEM3-GC31-M	UK Met Office Hadley Centre, UK	1.86° × 1.25°
10	INM-CM4-8	Institute for Numerical Mathematics, Russian Academy of Science, Moscow, Russia	2.00° × 1.50°
11	INM-CM5-0	Institute for Numerical Mathematics, Russian Academy of Science, Russia	2.00° × 1.50°
12	KACE-1-0-G	National Institute of Meteorological Sciences/Korea Meteorological Administration (NIMS-KMA), Republic of Korea	1.92° × 1.44°
13	MPI-ESM1-2-HR	Max Planck Institute, Germany	0.90° × 1.30°
14	MRI-ESM2-0	Meteorological Research Institute (MRI), Japan	1.13° × 1.13°
15	NESM3	Nanjing University of Information Science and Technology, Nanjing, China	1.9° × 1.9°
16	NorESM2-MM	Climate Modeling Consortium, Norway	0.9° × 1.25°

2.3 Methods

2.3.1 Model bias correction and validation

To improve the reliability of CMIP6 data in projecting the changes in drought properties, the study employs the quantile mapping (QM) based on the gamma distribution bias correction technique (Ines and Hansen 2006; Piani et al. 2010) to minimize the biases reported in recent studies over EA (Akinsanola et al. 2021; Ayugi et al. 2021a; Ngoma et al. 2021a). Quantile perturbations adjust the model output values for historical simulation in order to mimic similar features as the observed data. The same distribution is then enforced on the projection datasets, assuming that the bias is similar in the historical and future periods (Maraun 2013). The Climate Data Bias Corrector developed by Gupta et al. (2019) is used to correct the bias. The effectiveness of the technique has been affirmed in previous studies where it was applied on various climatic variables such as precipitation and temperature over different regions (Ayugi et al. 2020a; Tabari et al. 2021). The empirical cumulative distribution function (ECDF) is used to display the model's performance before and after the QM implementation of the QM algorithms.

2.3.2 Drought Index and Event Characteristics

This study examines future meteorological drought evolution over EA using the multi-scale drought technique of Standardized Precipitation Index (SPI; McKee et al. 1993). Compared to other existing drought indices, SPI uses precipitation as an input fit in a gamma distribution. Estimation of SPI values is derived from a transformation of cumulative probability represented by zero as a mean and variance equal to 1. Consequently, negative SPI denotes lower than median precipitation, whereas positive values indicate higher than median precipitation. The computed SPI values highlight the extent of dryness for a given location and period. According to McKee et al. (1993), SPI values denoting dry/wet conditions are represented by -1.0/+1.0 values.

The drought events over EA are quantified on a three-month timescale (SPI-3) to mirror the seasonal precipitation climatology (MAM and OND) of the study domain. The SPI-3 illustrates the influence of precipitation anomalies on short-term water availability, which is important for agricultural activities. Further, three main categories are considered, namely: *moderate* ($1.49 < \text{SPI} < -1.00$), *severe* ($-1.99 < \text{SPI} < 1.50$), and *extreme* ($\text{SPI} \leq -2.00$). The listed classifications are employed to examine four main drought characteristics: frequency, duration, intensity, and severity.

A number of studies have highlighted the necessity of using long-term precipitation time series in evaluating dry conditions using the SPI technique (McKee et al. 1993; Wu et al. 2005; Mishra and Singh 2010). Wu et al. (2005) advocate using datasets with the longest possible time series to examine drought events as short-term data may introduce errors while approximating the values. To investigate the possible changes in drought conditions over the study area, two time slices of 30-year are used. They are the mid future (2041 – 2070) and the far future (2071 – 2100) in comparison to the baseline period of 1985 – 2014.

In order to examine the impact of drought events in the study region, the study considers drought components of drought duration (DD), drought frequency (DF), drought intensity (DI) and drought severity (DS) to detect the possible effects of climate change on drought events in the wake of global warming. Previous works conducted over Kenya (e.g., Ayugi et al. 2020b; Tan et al. 2020) contain detailed explanations and equations. This study employs a boxplot to demonstrate the distribution of DD, DF, DI, and DS over the study area. A box-and-whisker plot is useful in graphically representing the spread and comparison of various drought characteristics. It highlights the distribution of datasets based on five key indicators: minimum value, first quartile (25th percentile), median, third quartile (75th percentile) and maximum value. The interquartile range shows the changes in drought events. This approach has been utilized in various studies (e.g., Sheffield et al. 2012; IPCC 2013; Haile et al. 2020).

3. Results And Discussions

3.1 Model correction and validation

The ability of models to simulate observed precipitation is assessed over the study area since the accuracy of future projected changes depends on their capability to replicate observed values at the historical level (Piani et al. 2010; Tabari et al. 2021). In order to examine their agreement with observations and the effect of quantile mapping, the GCM data before (BC) and after correction (AC), together with their MME, are presented in Figure 2. The results after correction indicate a consistent improvement by all the models. The models before correction over EA (Fig. 2a) remarkably deviate from CRU with an increase in amounts, especially when rainfall exceeds 80 mm. After correction (Fig. 2b), the overall distribution shows a tight agreement with observation. Further statistical analysis of correlation coefficients, RMSEs and standard deviations, the bias-corrected data shows improved skills compared to the original ones (Table S1). For instance, the BC CMIP6-MME shows a correlation coefficient of 0.58, which is improved to 0.8 AC, while the RMSE is reduced from 43.84 (BC) to 39.9 (AC). The standard deviation also denotes an improvement in the individual models and their respective MME after bias correction. The present findings agree with existing studies that highly recommend the correction of inherent GCM biases before employing the data for impact studies (Dosio et al. 2021; Tabari et al. 2021; Ayugi et al. 2021a). In fact, recent studies that employed GCMs in projecting extreme events such as drought, high temperatures and extreme precipitation equally conducted bias correction before using the models in examining the projected changes over various locales (Mondal et al. 2021; Iyakaremye et al. 2021; Dosio et al. 2021).

3.2 Projected change in precipitation

Precipitation is a major factor regulating the occurrence of drought from one region to another (Dai 2018). Other factors include mean surface air temperature, wind speed, humidity, and incoming solar radiation that directly or indirectly affect drought occurrence in terms of enhanced evaporative demand through vapor pressure deficit (IPCC 2014). Thus, it is imperative to understand the projected changes in precipitation in order to relate the changes to drought events. Figures 3 and 4 show the future temporal

and spatial precipitation change over EA relative to the historical period. Generally, all the scenarios depict increasing patterns with differing magnitudes. The SSP5-8.5 scenario shows intensified changes during the far future (15%) relative to the historical period (5%), while minimal changes are predicted to occur under SSP1-2.6 during the mid (3%) and far future (7%) (Fig. 3). Meanwhile, spatial changes in precipitation over EA during the mid and far future depict a homogeneous spread of precipitation with a 100 – 300% increase under high emission scenarios (Fig. 4d, h). However, negative anomalies are projected to occur over most parts of Kenya and the coastal belt in Tanzania at -40% under SSP1-2.6 during the mid and far future (Fig. 4a, e). Interestingly, a persistent dry anomaly is projected to occur over the coastal belt of Tanzania across all scenarios and timescales, with intense dryness at -60% under SSP1-2.6 and subsequent reduction at -10% under SSP5-8.5 (Fig. 4). Generally, the projected increase in precipitation under a high emission scenario demonstrates the impact of anthropogenic GHG emissions. The results of this study agree with existing literature over EA that demonstrated the pronounced increase in precipitation under high emission scenarios as compared to the low forcing sustainability pathways (Onyutha et al. 2021; Ayugi et al. 2021b; Makula and Zhou 2021). The recently released assessment report of the Inter-governmental Panel on Climate Change Working Group 1 (IPCC, 2021) pointed to unprecedented changes that will affect the climate system due to human influence as a result of GHG emissions. For instance, the report projected an increase or decrease in the frequency and intensity of heavy precipitation over most land areas, leading to more drought or flood events over different regions. It is thus necessary to examine the possible changes in EA's drought characteristics that exhibit high interannual precipitation variability (Ongoma and Chen 2017; Ongoma et al. 2018; Tan et al. 2020; Ayugi et al. 2021c).

3.3 Projected Changes in dryness/wetness

To quantify the dryness and/or wetness over EA, the estimated probability distribution functions (PDFs) are shown in Fig. 5. The PDFs are calculated from the regional mean CMIP6 SPI for the baseline period, mid and far future under the selected scenarios. Further, spatial changes in drought patterns based on SPI is presented in Fig. 6. In general, relative to the baseline period, the projected drought changes over EA are characterized by both drying and wetting patterns with average negative SPI anomalies of -0.06, -0.03, -0.13, and -0.14 for the mid future and positive SPI of 0.12, 0.20, 0.41, and 0.54 in the far future. Except for SSP1-2.6 (Fig. 5a), the PDFs of SSP2-4.5, SSP3-7.0 and SSP5-8.5 show left-skewness during the mid future, while this phenomenon is expected to lapse into a distinct wetting trend in the far future as portrayed by the right-skewed PDFs (Fig. 5). Likewise, the spatial changes demonstrate noteworthy drought (wetness) events during the mid future (far future) under the SSP3-7.0 and SSP5-8.5 scenarios (Fig. 6). For instance, severe drought events ($SPI = -1.5$) are projected across the entire domain under SSP3-7.0 and SSP5-8.5 during the mid-century (Fig. 6c, d). Reverse patterns of extreme wetness events of 2.0 to 2.5 are observed towards the end of the twenty-first century (Fig. 6g, h). Obviously, the difference in dryness and wetness is high in the far future and relatively low in the near future.

3.4 Projected Changes in drought event characteristics

The absolute spatial changes of drought characteristics during the mid and far future, relative to the baseline period, are shown in Figs. 7-10. To quantify the changes of drought characteristics, the box plots of regional drought characteristics under the four selected scenarios are shown in Fig. 11. Drought duration is defined as the number of months under drought conditions. The spatial variance and temporal distribution of drought duration are given in Fig. 7a-h and Fig. 11a. Relative to the baseline period, most areas under the four scenarios are projected to experience drought duration in the mid future while wetting patterns are projected in the far future over EA (Fig. 7). The mean drought duration in EA is projected to occur for 3.6, 3.62, 3.8, and 3.85 months under SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios, respectively, during the mid future (Figs. 11a). Mid future shows the lowest occurrence of DD, except under the high emission scenario that shows the likely occurrence of longer drought duration. The emission effect from SSP1-2.6 on DD is not evident in the mid future (Fig. 7a-d) but distinct in the far future (Fig. 7e-h).

Figure 8 and Fig. 11b present spatially-averaged drought frequency over EA that amounts to 15% during the baseline period, 13% (average value from all scenarios) in the mid future (Fig. 8a-d and 11b) and 9% in the far future (Fig. 8e-h and Fig. 11b). The drought frequency in the mid future will be higher than during the baseline period. This suggests that EA may experience more drought frequency in the mid future. Curiously, during the far future, drought frequency decreases from 14% under the low-emission scenario (SSP1-2.6) to 3% under the high-emission scenario (SSP5-8.5). This implies the possibility of a higher DF during the mid future and lower DF in the far future. This is consistent with the dryness changes shown in Figures 5 and 6. Interestingly, DF in the far future is projected to increase considerably (Fig. 8e-h), particularly under average no policy (SSP3-7.0) and worst-case no policy (SSP5-8.5) (Fig. 8g, h) along the coastal belt of the Tanzanian region. The regions dominated by dry changes (e.g., northern Kenya, the northern parts of Uganda and northern tips of Tanzania, as shown in Fig. 6) tend to experience more drought events in the mid future under the four scenarios (Fig. 8a-d). For example, relative to the baseline period with an average drought frequency, Kenya, Uganda, Rwanda, and Burundi are projected to experience more drought events in the mid future (2%, 4%, and 8%) under SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios (Fig. 8b, c, d), respectively.

The examination of DI, computed as the ratio between DS and DD, is presented in Figures 9 and 11c. DI is used to measure the overall intensity of drought events. For example, drought events of similar severity may have very different intensities if their durations are different. The mean values of DI are calculated for the historical and future periods under the different scenarios. The absolute changes in DI during the mid and far future are shown in Fig. 9a-h, and the regional DI statistics are given in Fig. 11c. Generally, relative to the baseline period, EA's DI preserves similar or becomes lower in the far future and becomes higher in the mid future under the different scenarios. DI will likely impact the north-eastern parts of Kenya and Uganda during the mid future under SSP3-7.0 and SSP5-8.5 (Fig. 9c, d). In the mid future, relative to the baseline period, EA will experience higher DI than the baseline period at 10, 22, 21 and 25% under SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5, respectively. Similarly, in the far future, the region is

likely to experience DI at 14%, 10%, 8% and 5% under SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5, respectively.

Lastly, the study assesses the changes in DS, which is defined as the cumulated SPI value during the drought event and is used to measure drought magnitude. The larger the DS value, the more severe the drought. The absolute change in mean drought severity is calculated for each grid in the mid and far future under the four future scenarios (Fig. 10a-h). In addition, the statistics of DS over EA are also shown in Fig. 11d. In general, EA is projected to experience a more severe drought during the mid and far future under the different scenarios. As expected, DS increases much more in the mid future than in the far future, partly contributed to by the great increase in DD as presented in Fig. 7. The coastal region and parts of Tanzania are projected to experience less severe droughts in the far future under SSP5-8.5 scenarios (Fig. 10d). The effect of emission concentration is not apparent in the far future in most regions. In western Kenya and north parts of Tanzania, there is an interesting higher DS for the low emission concentration (Fig. 10e), while in the far future, the emission concentration effects on DS are less significant over the entire region (Fig. 10f, g, h).

The results agree with previous studies conducted over the region based on the Representative Concentration Pathways (RCPs) scenario derived from CMIP5 data and demonstrated an increase in wetness and dryness during the far future (Tan et al. 2020; Spinoni et al. 2020). For instance, related studies (e.g., Nguvava et al. 2019; Haile et al. 2020) showed an increase in drought events, mainly attributed to increased evaporation from higher temperatures. The studies mentioned above were mainly based on the Standardized Precipitation Evapotranspiration Index (SPEI) that accounts for both precipitation and PET. Supportably, Joeng et al. (2014) affirmed that the observed and projected drought extremes are mainly driven by an increase in mean surface temperature and PET. In fact, recent studies based on CMIP6 models (i.e., Almazroui et al. 2021; Ayugi et al. 2021c; Iyakaremye et al. 2021) have all pointed out a steady increase in mean and extreme temperature properties over EA comparative to other sub-regions of the continent. For instance, Almazroui et al. (2020) stated that the increasing trend in temperature over EA under SSP1-2.6, SSP2-4.5, and SSP5-8.5 is projected to be 0.03, 0.22 and 0.49°C decade⁻¹, respectively.

However, other researchers have remarked that the more pronounced drought events projected at a regional level are mainly due to uncoupled modelling approaches that largely overestimate regional drought events due to wrong assumptions under increasing CO₂ emissions (Swan et al. 2016; Yang et al. 2019). Overall, the projected drought changes over EA follow changes in emissions and different periods. The mid future shows persistent drought events under medium forcing middle-of-the-road pathways (+7.0 W m⁻²) and high-end forcing pathways (+8.5 W m⁻²), reflecting a sustained pattern observed since 1992, following intense warming that occurred along the Western Indian Ocean (Lyon and DeWitt 2012; Liebmann et al. 2014) and SST variations over the Indo-Pacific associated with the Walker circulation (Hua et al., 2016) over EA. In contrast, during the far future, the region will likely experience more wetness under SSP3-7.0 and SSP5-8.5 as compared to the low emission scenario of SSP1-2.6 or under low forcing sustainability pathways of SSP2-4.5. The results reaffirm the conclusions of the IPCC (2021)

report that clearly stated the influence of humans in climate change over most parts of the regions around the globe.

4. Conclusion

This study employs bias-corrected data derived from CMIP6 GCMs to assess the future changes in meteorological drought over EA. Four scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), representing different ranges of future GHGs emissions and land use are used to project changes in drought during two time slices: mid-future (2041 – 2070) and far-future (2071 – 2100), relative to a baseline period (1985 – 2014). The study examines changes in precipitation anomaly as a principal component that influences drought and further investigates changes in drought based on SPI-3 to mirror the MAM and OND precipitation climatology of the study domain. In order to examine the impact of climate change over the study region, the study considers drought facets such as drought duration (DD), drought frequency (DF), drought intensity (DI) and drought severity (DS). The main findings of this study are:

- i. The CMIP6 GCMs' ability to capture the multi-year annual precipitation spatial patterns improves when the models are subjected to quantile gamma mapping. The MME shows superiority over individual GCMs. Also, the BC (AC) CMIP6 MME shows a correlation coefficient of 0.58 (0.8). The RMSE is equally reduced from 43.84 before correction to 39.9 after bias correction. The downscaled GCMs and their ensembles, can be used for drought monitoring over EA.
- ii. Large parts of EA are expected to get more precipitation in the future under different scenarios. However, the spatial heterogeneity of the increase in precipitation magnitude is high. In general, dry regions are expected to receive less precipitation increase, whereas highlands and lake regions are expected to receive a large amount of precipitation anomaly. In the late 21st century (2071-2100), the increase in precipitation is projected to be much higher than during the mid future. For instance, the high emission scenario shows intensified changes during the far future (15%) relative to the historical period (5%). In comparison, minimal changes are predicted to occur under SSP1-2.6, during the mid (3%) and far future (7%) over the study area. As a consequence of precipitation change, EA may show a “dry gets drier and wet gets wetter” relation, which is likely to intensify in the distant future. The emission concentration effects on the changes in precipitation and dryness are not obvious in the mid future but will become significant in the far future over the EA region and its enclosing countries.
- iii. The projected drought changes are characterized by an average negative SPI for the mid future and positive SPI in the far future. From the low to the high emission scenarios, the drying pattern is observed in the mid future, while this phenomenon is expected to lapse into a distinct wetting trend in the far future. Obviously, the difference in dryness and wetness is larger in the far future and relatively smaller in the mid future.
- iv. Drought events are likely to occur more frequently over the dry regions (arid and semi-arid) of EA with longer durations, and more significant severity and intensity in the far future under the four different

scenarios. Precipitation and SPI-3 also project a similar trend in the far future.

The findings of this study call for further quantification of drought changes, particularly over dry regions of EA under different warming scenarios of 1.5, 2.0, 3.0 and 4.0°C. The expected population exposure should also be investigated. This will aid in developing effective short- and long-term mitigation and adaptation strategies against drought events.

Declarations

Authors contribution: The following are individual contributions: B.A., Z.W.S., A.C., V.O.: conceptualization. B.A., A.C. and V.O.: formal writing, and original draft preparation. V.I., K.T.C.L.K.S., V.N.D., V.I., and H.B.: Data curation, methodology, visualization. R.M., K.T.C.L.K.S., and V.O.: writing-review and editing, investigation. V.O., Z.W.S., and V.N.D.: Validation.

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Data availability

The CMIP6 data used in this study can be accessed at no cost from the Earth System Federation portal at <https://esgf-node.llnl.gov/search/cmip6>. Precipitation data from the Climatic Research Unit (CRU version TS4.04) is also freely available at https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.04/.

Code availability

The data analysis codes are available from B.A. and H.B., and can be shared on request.

Ethics approval and consent to participate

Not applicable

Consent for publication

Consents for publication from all the co-authors are received.

Conflict of interest

The authors declare no competing interests.

References

1. Ahmadalipour A, Moradkhani H, Castelletti A, Magliocca N (2019) Future drought risk in Africa: Integrating vulnerability, climate change, and population growth. *Sci Total Environ* 662: 672–686. <https://doi.org/10.1016/j.scitotenv.2019.01.278>
2. Ahmadalipour A, Moradkhani H, Svoboda M (2017) Centennial drought outlook over the CONUS using NASA-NEX downscaled climate ensemble. *Int J Climatol* 37: 2477–2491. <https://doi.org/10.1002/joc.4859>
3. Akinsanola AA, Ongoma V, Kooperman GJ (2021) Evaluation of CMIP6 models in simulating the statistics of extreme precipitation over Eastern Africa. *Atmos Res* 254, 105509. <https://doi.org/10.1016/j.atmosres.2021.105509>
4. Almazroui M, Saeed F, Saeed S, Islam MN, Ismail M, Klutse NAB, Siddiqui MH (2020) Projected change in temperature and precipitation over Africa from CMIP6. *Earth Syst Environ* 4: 455–475. <https://doi.org/10.1007/s41748-020-00161-x>
5. Amissah-Arthur A, Jagtap S, Rosenzweig C (2002) Spatio-temporal effects of El Niño events on rainfall and maize yield in Kenya. *Int J Climatol* 22: 1849–1860. <https://doi.org/10.1002/joc.858>
6. Ayugi B, Jiang Z, Zhu H, Ngoma H, Babaousmail H, Karim R, Dike V (2021a) Comparison of CMIP6 and CMIP5 models in simulating mean and extreme precipitation over East Africa. *Int J Climatol*. <https://doi.org/10.1002/joc.7207>
7. Ayugi B, Dike V, Ngoma H, Babaousmail H, Mumo R, Ongoma V (2021b) Future Changes in Precipitation Extremes over East Africa Based on CMIP6 Models. *Water* 13(17), 2358. <https://doi.org/10.3390/w13172358>
8. Ayugi B, Ngoma H, Babaousmail H, Karim R, Iyakaremye V, Liam Kam Sian KTC, Ongoma V (2021c) Evaluation and projection of mean surface temperature using CMIP6 models over East Africa. *J Afr Earth Sci* 181, 104226. <https://doi.org/10.1016/j.jafrearsci.2021.104226>
9. Ayugi B, Tan G, Ruoyun N, Babaousmail H, Ojara M, Wido H, Mumo L, Ngoma NH, Nooni IK, Ongoma V (2020a) Quantile mapping bias correction on rossby centre regional climate models for precipitation analysis over Kenya, East Africa. *Water* 12(3), 801. <https://dio.org/10.3390/w120801>
10. Ayugi B, Tan G, Rouyun N, Zeyao D, Ojara M, Mumo L, Babaousmail H, Ongoma V (2020b) Evaluation of Meteorological Drought and Flood Scenarios over Kenya, East Africa. *Atmosphere* 11, 307. <https://doi.org/10.3390/atmos11030307>
11. Ayugi BO, Tan G, Ongoma V, Mafuru KB (2018) Circulations associated with variations in boreal spring rainfall over Kenya. *Earth Syst Environ* 2: 421–434. <https://doi.org/10.1007/s41748-018-0074-6>
12. Ayugi BO, Wang W, Chepkemai D (2016) Analysis of Spatial and Temporal Patterns of Rainfall Variations over Kenya. *Environ Earth Sci* 6: 69–83.
13. Burke EJ, Brown SJ (2008) Evaluating uncertainties in the projection of future drought. *J Hydrometeorol* 9: 292–299. <https://doi.org/10.1175/2007JHM929.1>

14. Cook BI, Mankin JS, Marvel K, Williams AP, Smerdon JE, Anchukaitis KJ (2020) Twenty-first century drought projections in the CMIP6 forcing scenarios. *Earth's Futur* 8, e2019EF001461. <https://doi.org/10.1029/2019EF001461>
15. Dai A (2013) Increasing drought under global warming in observations and models. *Nat Clim Chang* 3: 52–58. <https://doi.org/10.1038/nclimate1633>
16. Dai A, Zhao T, Chen J (2018) Climate Change and Drought: a Precipitation and Evaporation Perspective. *Curr Clim Chang Reports* 4: 301–312. <https://doi.org/10.1007/s40641-018-0101-6>
17. Dosio A, Jury MW, Almazroui M, Ashfaq M, Diallo I, Engelbrecht FA, Klutse NAB, Lennard C, Pinto I, Sylla MB (2021) Projected future daily characteristics of African precipitation based on global (CMIP5, CMIP6) and regional (CORDEX, CORDEX-CORE) climate models. *Clim Dyn*. <https://doi.org/10.1007/s00382-021-05859-w>
18. Duffy PB, Brando P, Asner GP, Field CB (2015) Projections of future meteorological drought and wet periods in the Amazon. *Proc Natl Acad Sci* 112: 13172–13177. <http://www.pnas.org/lookup/doi/10.1073/pnas.1421010112>.
19. Eckstein D, Künzel V, Schäfer L, Winges M (2019) Global climate risk index 2020. Briefing Paper. Germanwatch e.V. https://germanwatch.org/sites/germanwatch.org/files/20-2-01e%20Global%20Climate%20Risk%20Index%202020_10.pdf (Accessed 20 September 2021)
20. Endris HS, Lennard C, Hewitson B, Dosio A, Nikulin G, Panitz H-J (2016) Teleconnection responses in multi-GCM driven CORDEX RCMs over Eastern Africa. *Clim Dyn* 46: 2821–2846. <https://doi.org/10.1007/s00382-015-2734-7>
21. Eyring V, Bony S, Meehl GA, Senior CA, Stevens B, Stouffer RJ, Taylor KE (2016) Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci Model Dev* 9: 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>
22. Funk C, Hoell A, Shukla S, Bladé I, Liebmann B, Roberts JB, Robertson FR, Husak G (2014) Predicting East African spring droughts using Pacific and Indian Ocean sea surface temperature indices. *Hydrol Earth Syst Sci* 18: 4965–4978. <https://doi.org/10.5194/hess-18-4965-2014>
23. Funk C, Senay G, Asfaw A, Verdin J, Rowland J, Michaelson J, Eilerts G, Korecha D, Choularton R (2005) Recent drought tendencies in Ethiopia and equatorial-subtropical eastern Africa Washingt. DC, FEWS-NET. http://pdf.usaid.gov/pdf_docs/PNADH997.pdf (Accessed 10 June 2021).
24. Funk C, Shukla S, Thiaw WM, et al. (2019) Recognizing the Famine Early Warning Systems Network: Over 30 Years of Drought Early Warning Science Advances and Partnerships Promoting Global Food Security. *Bull Am Meteorol Soc* 100: 1011–1027. <https://doi.org/10.1175/BAMS-D-17-0233.1>
25. Gebrechorkos SH, Hülsmann S, Bernhofer C (2020) Analysis of climate variability and droughts in East Africa using high-resolution climate data products. *Glob Planet Change* 186, 103130. <https://doi.org/10.1016/j.gloplacha.2020.103130>
26. Gupta R, Bhattarai R, Mishra A (2019) Development of Climate Data Bias Corrector (CDBC) Tool and Its Application over the Agro-Ecological Zones of India. *Water* 11(5), 1102. <https://doi.org/10.3390/w11051102>

27. Haile GG, Tang Q, Hosseini-Moghari SM, Liu X, Gebremicael TG, Leng G, Kebede A, Xu X, Yun X (2020) Projected Impacts of Climate Change on Drought Patterns over East Africa. *Earth's Futur* 8(7), e2020EF001502. <https://doi.org/10.1029/2020EF001502>
28. Harris I, Jones PD, Osborn TJ, Lister DH (2014) Updated high-resolution grids of monthly climatic observations—the CRU TS3. 10 Dataset. *Int J Climatol* 34: 623–642. <https://doi.org/10.1038/s41597-020-0453-3>
29. Harris IC, Osborn TJ, Jones P, Lister D (2020) Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Sci Data* 7, 109. <http://doi.org/10.1002/joc.3711>
30. Hua W, Zhou L, Chen H, Nicholson SE, Raghavendra A, Jiang Y (2016) Possible causes of the Central Equatorial African long-term drought. *Environ Res Lett* 11(12), 124002. <https://doi.org/10.1088/1748-9326/11/12/124002>
31. Huang J, Yu H, Guan X, Wang G, Guo R (2016) Accelerated dryland expansion under climate change. *Nat Clim Chang* 6: 166–171. <https://doi.org/10.1038/nclimate2837>
32. Indeje M, Semazzi FHM, Xie L, Ogallo LJ (2001) Mechanistic model simulations of the East African climate using NCAR regional climate model: influence of large-scale orography on the Turkana Low-Level Jet. *J Clim* 14: 2710–2724. [http://doi.org/10.1175/1520-0442\(2001\)014<2710:MMSOTE>2.0.CO;2](http://doi.org/10.1175/1520-0442(2001)014<2710:MMSOTE>2.0.CO;2)
33. IPCC (2013) *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.
34. IPCC (2014) Summary for policymakers, *Climate Change 2014: Impacts, Adaptation, and Vulnerability, Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1–32.
35. IPCC (2021) Summary for Policymakers. In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M, Leitzell K, Lonnoy E, Matthews JBR, Maycock TK, Waterfield T, Yelekçi O, Yu R, Zhou B (eds.)]. Cambridge University Press. In Press.
36. Ines AVM, Hansen JW (2006) Bias correction of daily GCM rainfall for crop simulation studies. *Agric For Meteorol* 138: 44–53. <https://doi.org/10.1016/j.agrformet.2006.03.009>
37. Iyakaremye V, Zeng G, Yang X, Zhang G, Ullah I, Gahigi A, Vuguziga F, Asfaw TG, Ayugi B (2021) Increased high-temperature extremes and associated population exposure in Africa by the mid-21st century. *Sci Total Environ* 148162. <https://doi.org/10.1016/j.scitotenv.2021.148162>

38. Jenkins K, Warren R (2015) Quantifying the impact of climate change on drought regimes using the Standardised Precipitation Index. *Theor Appl Climatol* 120: 41–54. <https://doi.org/10.1007/s00704-014-1143-x>
39. Jeong D II, Sushama L, Khaliq MN (2014) The role of temperature in drought projections over North America. *Clim Change* 127: 289–303. <https://doi.org/10.1007/s10584-014-1248-3>
40. Kabanda TA, Jury MR (1999) Inter-annual variability of short rains over northern Tanzania. *Clim Res* 13: 231–241.
41. Liebmann B, Hoerling MP, Funk C, Bladé I, Dole RM, Allured D, Quan X, Pegion P, Eischeid JK (2014) Understanding recent eastern Horn of Africa rainfall variability and change. *J Clim* 27: 8630–8645. <http://doi.org/10.1175/JCLI-D-13-00714.1>
42. Lloyd-Hughes B (2012) A spatio-temporal structure-based approach to drought characterisation. *Int J Climatol* 32: 406–418. <https://doi.org/10.1002/joc.2280>
43. Lott FC, Christidis N, Stott PA (2013) Can the 2011 East African drought be attributed to human-induced climate change? *Geophys Res Lett* 40: 1177–1181. <http://doi.org/10.1002/grl.50235>
44. Lukamba MT (2010) Natural disasters in African countries: What can we learn about them? *TD J Transdiscipl Res South Africa* 6: 478–495. <https://doi.org/10.4102/td.v6i2.266>
45. Lyon B (2014) Seasonal drought in the Greater Horn of Africa and its recent increase during the March–May long rains. *J Clim* 27: 7953–7975. <http://doi.org/10.1175/JCLI-D-13-00459.1>
46. Lyon B, DeWitt DG (2012) A recent and abrupt decline in the East African long rains. *Geophys Res Lett* 39, L02702. <http://doi.org/10.1029/2011GL050337>
47. Maidment RI, Allan RP, Black E (2015) Recent observed and simulated changes in precipitation over Africa. *Geophys Res Lett* 42: 8155–8164. <http://doi.org/10.1002/2015GL065765>
48. Makula EK, Zhou B (2021) CMIP6 Evaluation and Projection of East African Precipitation. *Int J Climatol*. <https://doi.org/10.1002/joc.7207>
49. Maraun D (2013) Bias correction, quantile mapping, and downscaling: Revisiting the inflation issue. *J Clim* 26: 2137–2143. <https://doi.org/10.1175/JCLI-D-12-00821.1>
50. Martey E, Etwire PM, Kuwornu JKM (2020) Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties. *Land Use Policy* 94, 104524. <https://doi.org/10.1016/j.landusepol.2020.104524>
51. Marthews TR, Otto FEL, Mitchell D, Dadson SJ, Jones RG (2015) 17. The 2014 Drought in the Horn of Africa: Attribution of Meteorological Drivers. *Bull Am Meteorol Soc* 96: S83–S88.
52. Masih I, Maskey S, Mussá FEF, Trambauer P (2014) A review of droughts on the African continent: a geospatial and long-term perspective. *Hydrol Earth Syst Sci* 18: 3635–3649. <https://doi.org/10.1016/j.jhydrol.2010.07.012>
53. McKee TB (1995) Drought monitoring with multiple time scales *Proc. 9th Conf. Appl. Climatol.* Boston, 1995. American Meteorological Society, Boston, MA. 233–236.

54. McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. *Proc 8th Conf Appl Climatol* 17: 179–183.
55. Meehl GA, Covey C, Delworth T, Latif M, McAvaney B, Mitchell JFB, Stouffer RJ, Taylor KE (2007) The WCRP CMIP3 multimodel dataset: A new era in climate change research. *Bull Am Meteorol Soc* 88: 1383–1394. <https://doi.org/10.1175/BAMS-88-9-1383>
56. Mishra Ashok K, Singh Vijay P (2010) A review of drought concepts. *J Hydrol* 39: 202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>.
57. Mondal SK, Huang J, Wang Y, Su B, Zhai J, Tao H, Wang G, Fischer T, Wen S, Jiang T (2021) Doubling of the population exposed to drought over South Asia: CMIP6 multi-model-based analysis. *Sci Total Environ* 771, 145186. <https://doi.org/10.1016/j.scitotenv.2021.145186>
58. Ngoma H, Wen W, Ayugi B, Babaousmail H, Karim R, Ongoma V (2021a) Evaluation of rainfall simulations in CMIP6 models over Uganda. *Int J Climatol* 41: 4743–4768. <https://doi.org/10.1002/joc.7098>
59. Ngoma H, Wen W, Ayugi B, Karim R, Kisesa ME (2021b) Mechanisms associated with September to November (SON) rainfall over Uganda during the recent decades. *Geogr. Pannonica* 25: 10–23. <https://doi.org/10.5937/gp25-29932>
60. Ngoma H, Wen W, Ojara M, Ayugi B (2021a) Assessing current and future spatiotemporal precipitation variability and trends over Uganda, East Africa, based on CHIRPS and regional climate model datasets. *Meteorol Atmos Phys* 133: 823–843. <https://doi.org/10.1007/s00703-021-00784-3>
61. Nguvava M, Abiodun BJ, Otieno F (2019) Projecting drought characteristics over East African basins at specific global warming levels. *Atmos Res* 228: 41–54. <https://doi.org/10.1016/j.atmosres.2019.05.008>.
62. Nicholson SE (2014) A detailed look at the recent drought situation in the Greater Horn of Africa. *J Arid Environ* 103: 71–79. <https://doi.org/10.1016/j.jaridenv.2013.12.003>
63. Nicholson SE (2016) An analysis of recent rainfall conditions in eastern Africa. *Int J Climatol* 36: 526–532. <http://doi.org/10.1002/joc.4358>
64. Nicholson SE (2017) Climate and climatic variability of rainfall over eastern Africa. *Rev Geophys* 55: 590–635. <https://doi.org/10.1002/2016RG000544>
65. Nicholson SE (2018) The ITCZ and the seasonal cycle over equatorial Africa. *Bull Am Meteorol Soc* 99: 337–348. <https://doi.org/10.1175/BAMS-D-16-0287.1>
66. Nkunzimana A, Shuoben B, Guojie W, Alriah MAA, Sarfo I, Zhihui X, Vuguziga F, Ayugi BO (2021) Assessment of drought events, their trend and teleconnection factors over Burundi, East Africa. *Theor Appl Climatol* 145: 1293–1316. <https://doi.org/10.1007/s00704-021-03680-3>
67. O'Neill BC, Kriegler E, Ebi KL, Kemp-Benedict E, Riahi K, Rothman DS, van Ruijven BJ, van Vuuren DP, Birkmann J, Kok K (2017) The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob Environ Chang* 42: 169–180. <https://doi.org/10.1016/j.gloenvcha.2015.01.004>

68. Ogwang BA, Chen H, Li X, Gao C (2014) The influence of topography on East African October to December climate: sensitivity experiments with RegCM4. *Adv Meteorol* 2014, 143917.
<http://dx.doi.org/10.1155/2014/143917>
69. Ogwang BA, Ongoma V, Xing L, Ogou KF (2015) Influence of Mascarene high and Indian Ocean dipole on East African extreme weather events. *Geogr. Pannonica* 19:64–72.
70. Omondi PA, Awange JL, Forootan E, Ogallo LA, Barakiza R, Girmaw GB, Fesseha I, Kululetera V, Kilembe C, Mbatia MM, Kilavi M, King'uyu SM, Omeny PA, Njogu A, Badr EM, Musa TA, Muchiri P, Bamanya D, Komutunga E (2014) Changes in temperature and precipitation extremes over the Greater Horn of Africa region from 1961 to 2010. *Int J Climatol* 34: 1262–1277.
<https://doi.org/10.1002/joc.3763>
71. Ongoma V, Chen H (2017) Temporal and spatial variability of temperature and precipitation over East Africa from 1951 to 2010. *Meteorol Atmos Phys* 129: 131–144. <http://doi.org/10.1007/s00703-016-0462-0>
72. Ongoma V, Chen H, Gao C, Nyongesa AM, Polong F (2018a) Future changes in climate extremes over Equatorial East Africa based on CMIP5 multimodel ensemble. *Nat Hazards* 90: 901–920.
<https://doi.org/10.1007/s11069-017-3079-9>
73. Ongoma V, Chen H, Gao C (2018b) Projected changes in mean rainfall and temperature over East Africa based on CMIP5 models. *Int J Climatol* 38: 1375–1392. <http://doi.org/10.1002/joc.5252>
74. Ongoma V, Chen H, Omony GW (2018c) Variability of extreme weather events over the equatorial East Africa, a case study of rainfall in Kenya and Uganda. *Theor Appl Climatol* 131: 295–308.
<https://doi.org/10.1007/s00704-016-1973-9>
75. Ongoma V, Chen H, Gao C, Sagero PO (2018d) Variability of temperature properties over Kenya based on observed and reanalyzed datasets. *Theor Appl Climatol* 133: 1175–1190.
<http://doi.org/10.1007/s00704-017-2246-y>
76. Ongoma V, Tan G, Ogwang B, Ngarukiyimana J (2015) Diagnosis of seasonal rainfall variability over East Africa: a case study of 2010-2011 drought over Kenya. *Pakistan J Meteorol* 11: 13–21.
77. Onyutha C, Asimwe A, Ayugi B, Ngoma H, Ongoma V, Tabari H (2021) Observed and future precipitation and evapotranspiration in water management zones of Uganda: Cmp6 projections. *Atmosphere* 12(7), 887. <https://doi.org/10.3390/atmos12070887>
78. Opiyo F, Wasonga O, Nyangito M, Schilling J, Munang R (2015) Drought adaptation and coping strategies among the Turkana pastoralists of northern Kenya. *Int J Disaster Risk Sci* 6:b295–309.
<http://doi.org/10.1007/s13753-015-0063-4>
79. Osuch M, Romanowicz RJ, Lawrence D, Wong WK (2016) Trends in projections of standardized precipitation indices in a future climate in Poland. *Hydrol Earth Syst Sci* 20: 1947–1969.
<https://doi.org/10.5194/hess-20-1947-2016>
80. Otieno HO, Awange JL (2006) *Energy resources in East Africa: Opportunities and challenges*. Springer-Verlag, Heidelberg

81. Piani C, Haerter JO, Coppola E (2010) Statistical bias correction for daily precipitation in regional climate models over Europe. *Theor Appl Climatol* 99: 187–192. <https://doi.org/10.1007/s00704-009-0134-9>
82. Sagero PO, Shisanya CA, Makokha GL (2018) Investigation of rainfall variability over Kenya (1950–2012). *J Environ Agric Sci* 14: 1–15.
83. Schneider U, Becker A, Finger P, Meyer-Christoffer A, Rudolf B, Ziese M (2015) GPCC full data reanalysis version 7.0 (at 0.5°, 1.0°, 2.5°): Monthly Land-Surface Precipitation from Rain-Gauges built on GTS-based and Historic Data. http://dx.doi.org/10.5676/DWD_GPCC/FD_M_V7_050
84. Sheffield J, Wood EF (2008) Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. *Clim Dyn* 31: 79–105. <http://link.springer.com/10.1007/s00382-007-0340-z>.
85. Sheffield J, Wood EF, Roderick ML (2012) Little change in global drought over the past 60 years. *Nature* 491: 435–438. <https://doi.org/10.1038/nature11575>
86. Shongwe ME, van Oldenborgh GJ, van den Hurk B, van Aalst M (2011) Projected changes in mean and extreme precipitation in Africa under global warming. Part II: East Africa. *J Clim* 24: 3718–3733. <https://doi.org/10.1175/2010JCLI2883.1>
87. Shrestha A, Rahaman MM, Kalra A, Jogineedi R, Maheshwari P (2020) Climatological drought forecasting using bias corrected CMIP6 climate data: A case study for India. *Forecasting* 2: 59–84. <https://doi.org/10.3390/forecast2020004>
88. Spinoni J, Barbosa P, Buchignani E, Cassano J, Cavazos T, Christensen JH, Christensen OB, Coppola E, Evans J, Geyer B, Giorgi F, Hadjinicolaou P, Jacob D, Katzfey J, Koenigk T, Laprise R, Lennard CJ, Kurnaz ML, Delei LI, Liopart M, McCormicj N, Naumann G, Nikulin G, Ozturk T, Hans-Juergen P, Rocha RPD, Rockel B, Solman SA, Syktus J, Tangang F, Teichmanaa C, Vautrd R, Vogt JV, Winger K, Zittis G, Dosio A (2020) Future global meteorological drought hot spots: A study based on CORDEX data. *J Clim* 33: 3635–3661. <https://doi.org/10.1175/JCLI-D-19-0084.1>
89. Steffen W, Rockström J, Richardson K, Lenton TM, Folke C, Liverman D, Summerhayes CP, Barnosky AD, Cornell SE, Crucifix M, Donges JF, Fetzer I, Lade SJ, Scheffer M, Winkelmann R, Schellnhuber HJ (2018) Trajectories of the Earth System in the Anthropocene. *Proc Natl Acad Sci USA* 115: 8252–8259. <https://doi.org/10.1073/pnas.1810141115>
90. Swann ALS, Hoffman FM, Koven CD, Randerson JT (2016) Plant responses to increasing CO₂ reduce estimates of climate impacts on drought severity. *Proc Natl Acad Sci* 113: 10019–10024. <https://doi.org/10.1073/pnas.1604581113>
91. Tabari H, Paz SM, Buekenhout D, Willems P (2021) Comparison of statistical downscaling methods for climate change impact analysis on precipitation-driven drought. *Hydrol Earth Syst Sci* 25: 3493–3517. <https://doi.org/10.5194/hess-25-3493-2021>
92. Tan G, Ayugi B, Ngoma H, Ongoma V (2020) Projections of future meteorological drought events under representative concentration pathways (RCPs) of CMIP5 over Kenya, East Africa. *Atmos Res* 246, 105112. <https://doi.org/10.1016/j.atmosres.2020.105112>

93. Tayler KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experimental design. *Bull Am Meteorol Soc* 93: 485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
94. Taylor KE (2001) Summarizing multiple aspects of model performance in a single diagram. *J Geophys Res Atmos* 106: 7183–7192. <https://doi.org/10.1029/2000JD900719>
95. Trenberth KE, Dai A, Van Der Schrier G, Jones PD, Barichivich J, Briffa KR, Sheffield J (2014) Global warming and changes in drought. *Nat Clim Chang* 4: 17–22. <https://doi.org/10.1038/nclimate20167>
96. Ukkola AM, De Kauwe MG, Roderick ML, Abramowitz G, Pitman AJ (2020) Robust future changes in meteorological drought in CMIP6 projections despite uncertainty in precipitation. *Geophys Res Lett* 47(11), e2020GL087820.
97. Ukkola AM, Pitman AJ, De Kauwe MG, Abramowitz G, Herger N, Evans JP, Decker M (2018) Evaluating CMIP5 model agreement for multiple drought metrics. *J Hydrometeorol* 19: 969–988. <https://doi.org/10.1175/JHM-D-17-0099.1>
98. van Dijk AIJM, Beck HE, Crosbie RS, de Jeu RAM, Liu YY, Podger GM, Timbal B, Viney NR (2013) The Millennium Drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society. *Water Resour Res* 49: 1040–1057. <https://doi.org/10.1002/wrcr.20123>
99. Wang Z, Zhong R, Lai C, Zeng Z, Lian Y, Bai X (2018) Climate change enhances the severity and variability of drought in the Pearl River Basin in South China in the 21st century. *Agric For Meteorol* 249: 149–162. <https://doi.org/10.1016/j.agrformet.2017.12.077>
100. Wei Y, Yu H, Huang J, Zhou T, Zhang M, Ren Y (2019) Drylands climate response to transient and stabilized 2°C and 1.5°C global warming targets. *Clim Dyn* 53: 2375–2389. <https://doi.org/10.1007/s00382-019-04860-8>
101. Wilhite DA, Svoboda MD (2000) Drought early warning systems in the context of drought preparedness and mitigation. *Early Warn. Syst. Drought Prep. Drought Manag.*, https://www.unisdr.org/files/1882_VL102149.pdf (Accessed 10 September 2021)
102. Williams AP, Funk C (2011) A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. *Clim Dyn* 37: 2417–2435. <https://doi.org/10.1007/s00382-010-0984-y>
103. Wu H, Hayes MJ, Wilhite DA, Svoboda MD (2005) The effect of the length of record on the standardized precipitation index calculation. *Int J Climatol* 25: 505–520. <https://doi.org/10.1002/joc.1142>
104. Yang T, Ding J, Liu D, Wang X, Wang T (2019) Combined use of multiple drought indices for global assessment of dry gets drier and wet gets wetter paradigm. *J Clim* 32: 737–748. <https://doi.org/10.1175/JCLI-D-18-0261.1>
105. Zhai J, Mondal SK, Fischer T, Wang Y, Su B, Huang J, Tao H, Wang G, Ullah W, Uddin MJ (2020) Future drought characteristics through a multi-model ensemble from CMIP6 over South Asia. *Atmos Res* 246, 105111. <https://doi.org/10.1016/j.atmosres.2020.105111>

106. Zhai L, Feng Q (2009) Spatial and temporal pattern of precipitation and drought in Gansu Province, Northwest China. Nat Hazards 49: 1–24. <http://doi.org/10.1007/s11069-008-9274-y>
107. Zhao JT, Su B Da, Mondal SK, Wang YJ, Tao H, Jiang T (2021) Population exposure to precipitation extremes in the Indus River Basin at 1.5°C, 2.0°C and 3.0°C warming levels. Adv Clim Chang Res 12: 199–209. <https://doi.org/10.1016/j.accre.2021.03.005>

Figures

Figure 1

Diagrammatic sketch of the African continent and elevation map (meters) of East Africa, consisting of three countries: Kenya [35°E – 41.5°E, 3°S – 4.5°N], Uganda [29°E – 5°E, 1.5°S – 4°N], and Tanzania [29°E – 40°E, 10°S – 4°S].

Figure 2

Empirical cumulative density function (ECDF; mm/month) of GCMs before (a) and after the bias correction (b), relative to the precipitation observation (CRU) over East Africa.

Figure 3

Time series of mean precipitation anomaly (%) over East Africa during the historical period (1995 – 2014), and mid (2041 – 2070) and far future (2071 – 2100) under four selected scenarios. The black, green, purple, blue, and red lines are the CRU, MME-historical, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios, respectively. The shadings indicate the ensemble spread. The green dashed line separates the observed period from the projected one.

Figure 4

Spatial changes in precipitation anomalies (%) for the mid (2041-2070) and far future (2071-2100) periods under SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios relative to the baseline period (1985-2014).

Figure 5

PDFs of regional SPI during the (a) mid future (2041 – 2070) and (b) far future (2071 – 2100) under SSP1-2.6 (red), SSP2-4.5 (green), SSP3-7.0 (blue), and SSP5-8.5 (orange) scenarios. The baseline period

(1985 – 2014) is plotted in black.

Figure 6

Projected change in SPI-3 for mid (2041 – 2070) and far future (2071 – 2100) under (a, e) SSP1-2.6, (b, f) SSP2-4.5, (c, g) SSP3-7.0, and (d, h) SSP5-8.5 scenarios relative to the baseline period (1985 – 2014).

Figure 7

Spatial change of drought characteristics (a-h) mean drought duration (DD) for the mid future (2041-2070) and far future (2071-2100) under SSP126 (first column), SSP245 (second column), SSP370 (third column) and SSP585 (fourth column) relative to the baseline period (1985-2014) over East Africa.

Figure 8

same as Fig. 7, but for drought frequency (DF).

Figure 9

Same as Fig. 7, but for mean drought intensity.

Figure 10

same as Fig. 6, but for mean drought severity (DS).

Figure 11

Boxplot of drought characteristics during the baseline period, mid future (2041 - 2070) and far future (2071 – 2100) under four selected scenarios over East Africa. (a) DD, (b) DF, (c) DI and (d) DS. The boxes show the interquartile range, the horizontal lines represent the median and the whiskers show the maximum/minimum value of the lower/upper quartile. The circles are outliers.

Supplementary Files

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