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Key Points:

- We examined the impact of changes in precipitation and temperature on drought characteristics over East Africa during 1981–2099
- Precipitation and temperature will increase over East Africa; however, the temperature impact is dominant leading to extreme droughts
- Drought area in East Africa is likely to increase at the end of the 21st century by 16%, 37%, and 54% under RCP 2.6, 4.5, and 8.5, respectively

Supporting Information:

Supporting Information S1

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Projected Impacts of Climate Change on Drought Patterns Over East Africa

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Abstract Investigation of the pressing impacts of climate change on drought is vital for sustainable societal and ecosystem functioning. The magnitude of how much the drought will change and the way how droughts would affect society and the environment are inadequately addressed over East Africa. This study aimed at assessing future drought changes using an ensemble of five Global Climate Models (GCMs) in the Coupled Model Intercomparison Project (CMIP5) over East Africa. To this end, drought characteristics were investigated under the Representative Concentration Pathways (RCPs) 2.6, 4.5, and 8.5 in the near term (the 2020s; 2011–2040), midcentury (2050s; 2041–2070), and end of century (2080s; 2071–2,100). The changes of the Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI) were first compared, and the SPEI was used for measuring future droughts as it showed stronger changes due to its inclusion of temperature effects. Drought area in East Africa is likely to increase at the end of the 21st century by 16%, 36%, and 54% under RCP 2.6, 4.5, and 8.5, respectively, with the areas affected by extreme drought increasing more rapidly than severe and moderate droughts. Spatially, drought event, duration, frequency and intensity would increase in Sudan, Tanzania, Somalia, and South Sudan, but generally decrease in Kenya, Uganda, and Ethiopian highlands. Results also confirm that drought changes over East Africa follow the "dry gets drier and wet gets wetter" paradigm. The findings provide important guidance for improving identification of causes, minimizing the impacts and enhancing the resilience to droughts in East Africa.

1. Introduction

Climate change and the accelerated population growth have become the key limiting factors for sustainable human resources development and natural systems conservation. In the Anthropocene, drought may not be seen as purely "natural hazards" because human has altered drought characteristics (Haile, Tang, Li, et al., 2020; Tang, 2020; Van Loon et al., 2016). As global warming increases, the magnitude of climate change impacts on the environment and society increases (Touma et al., 2015). Notably, greenhouse gases are driving the regional warming and drying conditions leading to increased megadroughts around the world (Ault et al., 2016; Leng et al., 2015). The rapidly increasing population is challenging the food security of 7.6 billion current world's population that is projected to be 9.8 and 11.2 billion in 2050 and 2100, respectively (United Nations, 2017). An increase in food demands due to the rapid population growth may lead to severe food insecurity and may challenge the 2030 United Nations (UN) zero-hunger agenda planned to be achieved through securing sustainable development (FAO, 2017; Fujimori et al., 2019). Furthermore, the rapid population growth has increased water consumption, thereby substantially intensified the frequency of global droughts by 27% (Wada et al., 2013).

Climate change is one of the most pressing challenges the human being and the natural ecosystems are facing (IPCC, 2007, 2013). Under climate change, food and water insecurity are likely to increase unless early adaptations strategies and development programs are applied more efficiently (AghaKouchak, 2015b; Brown & Funk, 2008; Lobell et al., 2008). Since 2008, an average of 22.5 million people displaced annually, due to climate- or weather-related disasters such as droughts and floods (Bower et al., 2015). According to the Intergovernmental Panel on Climate Change (IPCC), more intense and longer droughts have been



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observed over wider areas during the twentieth century dominantly linked to higher temperatures and decreased precipitation (IPCC, 2007). Marvel et al. (2019) suggested that anthropogenic influences have been aggravating drought since the beginning of the twentieth century. However, the previously reported increase in global drought during the twentieth century is overestimated, mainly due to the use of the Palmer Drought Severity Index and the data sets used to determine the evapotranspiration component (Trenberth et al., 2014). These disagreements have made the twentieth century drought trends ambiguous and lack consensus on climate change patterns on drought (Schwalm et al., 2017). Nevertheless, given the projected climate warming in the 21st century and the forcing factor of climate change, drought is likely to set in more quickly, be more intense and last longer (Cook et al., 2015; Dai, 2011, 2013; Sheffield & Wood, 2008; Trenberth et al., 2014). These suggest that more frequent and severe droughts are expected in the 21st century across many regions (Cook et al., 2015; Schwalm et al., 2017; Touma et al., 2015). Moreover, climate models project increased drought areas across many regions in the 21st century, suggesting droughts are intensifying in magnitude and severity globally (Cook et al., 2014a; Sheffield & Wood, 2008). To this end, the growing concern on the impacts of climate change on droughts has made it the "most far-reaching of all-natural disasters' on Earth" (United Nations, 2014).

Dry lands in arid and semiarid regions, for example, East Africa face potential threats due to the effects of climate change and the resultant aridification is gradually exacerbating land degradation and desertification (Huang et al., 2017; Park et al., 2018). Even under limited or lessened global warming, climate change can substantially affect the socioeconomic basis of Africa as the well-being of livelihoods is strongly linked to the climatic conditions (Weber et al., 2018). These effects are more pronounced in the drought-vulnerable East African countries, where aridification and recurrent drought is persisting (AghaKouchak, 2015a; Verschuren et al., 2000). There is also a longe existing feature of reduced interannual rainfall variability that may further intensify drought conditions (Wolff et al., 2011). These suggest that there is an increasing risk of drought-related stresses for natural and human systems, which indicates the pressing need to quantitatively explore the projected changes in drought conditions due to climate change over East Africa.

Therefore, evaluating the magnitude of the projected droughts and their impacts is very important over East Africa. Although some researches have been carried out to address this issue (e.g., Nguvava et al., 2019; Osima et al., 2018; Spinoni et al., 2020), the magnitude of how much the drought is projected and the way how those impacts would affect the society and the environment remain largely unexplored. Therefore, this study was designed to fill this gap by focusing on understanding of future drought severity levels (moderate, severe, and extreme), and characteristics (drought area, event, duration, frequency, and intensity) at different spatiotemporal scales. Moreover, there is a paradigm indicating the climate change impacts on wet/dry regions stating "the dry regions tend to get drier, and wet regions tend to get wetter" (Feng & Zhang, 2015; Moraes Frasson et al., 2019; Yang et al., 2019). This directly links to the phenomena of droughts, which is the centerpiece of this study over East Africa. Therefore, the projected impact of climate change on future East African drought conditions would have great importance for the society and policymakers for effective drought mitigation, adaptation and reduce future drought risks.

This paper has outlined as follows: Following section 1, section 2 provides details of the study area, data sources, GCMs, RCPs, study timeframe, and drought analysis methods. Section 3 presents drought time series results and the major drought characteristics changes, followed by detailed discussions in section 4. Finally, section 5 contains the summary and concluding remarks.

2. Materials and Methods

2.1. Study Area

East Africa also called the Greater Horn of Africa (Anyah & Semazzi, 2006; Nicholson, 2017) comprises 11 countries in Africa, including Kenya, Uganda, Tanzania, Ethiopia, Eritrea, Djibouti, Somalia, South Sudan, Sudan, Rwanda, and Burundi. It is located between the latitudes of 11°S and 23°N, and longitudes of 21°E and 51°E covering an area of 6.22 million km² (Figure 1). East Africa is home to the Great East African Rift Valley, the Nile River basin, and mountains such as Kilimanjaro, Mount Kenya, and Ras Dashan. The hottest and lowest depressions including Lake Assal and Danakil Depression are situated in East Africa (Camberlin, 2018). Moreover, freshwater lakes such as Lake Victoria and Lake Tana are also located in the region (Vanderkelen et al., 2018). East Africa is a tropical region, of which 81% of the region





Figure 1. Map of East African countries.

comprises warm and 19% cool-climate condition and agroecological, the environments in East Africa are categorized as 37% arid, 28% semiarid, 30% subhumid, and 5% humid (Kate, 2009).

The estimated East African population was about 330 million in the year 2015, and it is projected to be more than doubled in 2050 (UNDESA, 2015). The population is mainly dependent on agriculture and nomadism sectors. The mean annual rainfall ranges from less than 100 in some arid and semiarid areas of Sudan, Djibouti, Eritrea, Somalia, and Ethiopia to more than 2,000 mm in the highlands of Ethiopia, Tanzania, and Kenya (Fenta et al., 2017; Gebrechorkos, Hülsmann, & Bernhofer, 2019b). The climate of East Africa consists of three rainy seasons including, long rains (March-May), summer rains (July-September), and short rains (October-November). Generally, the climate and topography range from wet highlands to arid lowlands and coastal areas (Dinku et al., 2011). East Africa is one of the most vulnerable regions to climate change and nonclimate factors threatening the food security of the population (Gebrechorkos, Hülsmann, & Bernhofer, 2019a, 2019b). There is a strong linkage between the livelihood and climate in most countries of East Africa. Food security in most countries is mainly dependent on rainfed agriculture, which provides a living for 80% of East Africans and contributes more than 40% of the regional Gross Domestic Product (Seitz & Nyangena, 2009). However, rainfed agriculture in East African countries is highly vulnerable to climate change where a frequent crop yield failure has been affected the livelihoods of

the region's population in the past few decades (Adhikari et al., 2015). Further details about East Africa can be found in different literature (Haile et al., 2019; Nicholson, 2017, and references therein).

2.2. Data Sets, Models, RCPs, and Study Periods

Investigation of the projected impacts of climate change on drought over East Africa subject to various Coupled Model Intercomparison Project Phase 5 (CMIP5) participating Global Climate Models (GCM) and Representative Concentration Pathways (RCPs) possess noteworthy. The Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP) project was mainly initiated for global and regional climate change impacts and adaptation studies (Warszawski et al., 2014) for the 21st century. Thus, data were extracted from five GCMs provided by ISIMIP Fast Track simulation round (https://www.isimip.org/), namely, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM 2M, and NorESM1-M (Table 1; Warszawski et al., 2014). These data sets were downscaled to a spatial resolution of 0.5° and were bias corrected using a trend-preserving approach (Hempel et al., 2013). The GCMs' ensemble mean was used to detect future drought events in the 21st century.

There are several reasons for choosing CMIP5 from the ISIMIP data set. First, the biased corrected data provided by ISIMIP is more reliable than other data sets provided by other projects like CORDEX for projecting temperature (Ito et al., 2020). As a result, in drought studies at which temperature plays an important role,

Table 1			
List of GCMs of ISIMIP	Used for	This	Study

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GCM	Institute	References
HadGEM2-ES	Met Office Hadley Centre	Collins et al. (2011)
IPSL-CM5A-LR	Institute Pierre-Simon Laplace, Paris, France	Dufresne et al. (2013)
MIROC5	Japan Agency for Marine-Earth Science and Technology	Watanabe et al. (2011)
	(JAMSTEC), Atmosphere and Ocean Research Institute,	
	The University of Tokyo, and National Institute	
	for Environmental Studies, Japan	
MPI-ESM-LR	Max Planck Institute for Meteorology	Giorgetta et al. (2013)
NorESM1-M	Norwegian Climate Centre	Bentsen et al. (2013)

t Indices



Table 2	
Classification Scales of Drought Severity Using SPI/SPEI Dro	ough

Drought severity levels	SPI/SPEI value
No drought Moderate drought Severe drought Extreme drought	SPI/SPEI > -1 -1.0 \ge SPI/SPEI > -1.5 -1.5 \ge SPI/SPEI > -2.0 -2.0 \ge SPI/SPEI

the ISIMIP data would be the best option. Second, the data provided by ISIMIP was biased corrected using observations at the historical period (Hempel et al., 2013). Thus, the data match well with observed precipitation and temperature data sets in the historical period. Third, these GCMs were selected for their long history of development and evaluation, and a preference for higher resolution and above all these GCMs established worldwide performance for undertaking future climate change impacts on drought (Giuntoli et al., 2015; Prudhomme et al., 2014; Wanders et al., 2015).

RCPs of 2.6, 4.5, and 8.5 were considered to analyze the projected changes in drought due to climate change. These climate scenarios (projections) were designed to represent the various possible states of the future climate system (Van Vuuren et al., 2012). The RCPs were selected considering the mitigation scenario leading to medium stabilization scenarios (RCPs 2.6 and 4.5) and a higher stabilization scenario (RCP 8.5) (Moss et al., 2010). The study period covers 1981–2099 partitioned in a reference period and future projections for ease of climate analysis. The experimental setups were historical/reference period (1981–2010), near term (the 2020s; 2011–2040), midcentury (the 2050s, 2041–2070) and end of century (the 2080s, 2071–2099). Since the historical GCM data were simulated until 2005, the data for the time period of 2006–2010 were taken from associated RCPs of each GCM. For this study, the different GCMs were used subject to different future periods in relation to the reference period.

To evaluate the reliability of GCMs simulation over East Africa, we assessed their simulated precipitation and temperature in the historical period (1981–2010) and 8 years of projections (2011–2018) against observed data from the Climatic Research Unit (CRU TS 4.03; Harris et al., 2014, 2020). To this end, we considered validation metrics such relative bias (RBias), correlation coefficient (CC), and root-mean-square error (RMSE) for the simulated and observed precipitation and temperature data sets (supporting information Table S1). Moreover, the error was decomposed into random and systematic part following AghaKouchak et al. (2012) method.

2.3. Drought Analysis Procedures

The widely used drought indices of the Standardized Precipitation Index (SPI; McKee, Doesken, & Kleist, 1993) and Standardized Precipitation-Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010) were used to quantify the future droughts. Both SPI and SPEI are used to assess the future drought conditions over East Africa. The SPI was calculated using gamma distribution fitting to the historical data to estimate the future SPI data sets, whereas the SPEI is estimated based on a log-logistic distribution fitting on historical data to estimate the future SPEI data sets (Hosseini-Moghari et al., 2019). The SPI uses the precipitation data sets under the standardized condition and is mainly recommended for meteorological droughts (Hayes et al., 2011). The SPEI enhances the robustness of the drought projection if PET is incorporated in future drought assessment. The SPEI is typically developed and used to investigate the effects of climate change on drought in the context of global warming. The SPEI is quantified using precipitation (P) and evapotranspiration (PET) as input variables resulted in the water balance (P-PET) outputs with the temperature effect being considered in PET estimates (Vicente-Serrano et al., 2010). The SPI/SPEI is quantified at 12-month (SPI/SPEI12) timescale forced with P and PET ensemble data set (averages of all ISIMIP-GCMs considered). The SPI/SPEI12 is selected as it is mostly useful to detect drought conditions in arid dominated regions such as East Africa. The drought severity status is examined using SPI/SPEI drought index levels (Table 2). PET quantification requires temperature, radiation, humidity, and other near-surface meteorological data as input. Accordingly, the PET was estimated using the Penman-Monteith approach as it gives a better estimate of the true trend in global drought due to its more comprehensive physics (Sheffield et al., 2012).

A threshold value of -1 is usually used to identify the availability of drought conditions for the SPI/SPEI drought index.

Furthermore, droughts were evaluated using drought events, duration, frequency, intensity, and drought area (Table 3). These parameters are usually used to analyses the characteristics of drought conditions under various spatiotemporal conditions. These parameters were used to detect the potential effects of climate change on drought characteristics in the context of global warming. Various parameters such as areal



Drought Parameter Equations Used for Drought Analysis		
Drought parameter	Equation	Symbol and units
Drought area	$D_a = \frac{\sum_{i=1}^n d_a}{n_a} \times 100$	$D_a = \text{drought area } (\%)$ $d_a = \text{number of pixels with SPEI values} \le -1$ n = total number of pixels
Drought duration	$D = \frac{\sum_{i=1}^{n} d_i}{n}$	D = drought duration (months) $d_i =$ duration of <i>i</i> th drought event n = total number of drought events
Drought frequency	$F = \frac{n_m}{N_m} \times 100$	F = drought frequency (%), $n_m = $ number of drought months, $N_m = $ total number of months
Drought intensity	$I = \left \frac{1}{n} \sum_{i=1}^{n} SPEI_i \right $	I = drought intensity (-), n = number of drought occurrences in months with SPEI < -1, $SPEI_i =$ SPEI value below the threshold (-1)

Table 3 Drought Parameter Equations Used for Drought Analysis

extent, events, duration, frequency, and intensity are robust drought measuring parameters (Cook et al., 2014b; Gebrechorkos et al., 2019; Gebrechorkos, Hülsmann, & Bernhofer, 2019b).

In addition, a boxplot was used to show the spread of the projected drought characteristic changes of the drought event, duration, frequency, and intensity. A box-and-whisker plot (i.e., boxplot) is a graphical representation for comparing a large number of observations in a data set using the central value, spread/distribution, and overall range/variability along with outliers (if there is in the data set) (Gebremicael et al., 2019). This graph is typically useful to show the most extreme values (the maximum, minimum values, and the outliers), the lower (25%) and upper (75%) quartiles, and the median ordered from lowest to the highest value in the data set.

The long-term projected drought (2011–2099) was analyzed relative to the baseline period (1981–2010) for each RCP. The drought changes were computed as the percentage of change departure (expressed in percentage changes/magnitude) from the baseline period. The projected droughts show drought events and drought-vulnerable areas throughout the 21st century, which is believed useful to develop sustainable adaptation strategies for the human-natural systems. These help to drive a better understanding of how the drought is being affected by climate change useful for policymakers to put practical solutions.

2.4. Uncertainty Analysis of the Projected Droughts

Future climate change projections and analysis are subject to different sources of uncertainties. To minimize these possible uncertainties, an ensemble-based experiment was applied and the SPEI was calculated from each of the GCM (see Table 1). Considering the minimum value of the SPEI as lower and maximum as the upper bound of the uncertainty range, the uncertainty in the GCM projections was drawn for the period between 1981 and 2099 for each RCP scenarios (RCPs 2.6, 4.5, and 8.5). The mean of the five models was used to show the average trends of the future drought useful to detect possible uncertainty ranges of the GCMs.

The projected drought changes were also compared against the preexisting agroecological and climatic characteristics of East Africa to assess the dry/wet patterns. The information on the agroecological and climate conditions of East Africa was obtained from the Agro-ecological Zones of Africa data set (http://hdl.handle.net/1902.1/22616). According to Kate (2009), the agroecological classification is based on the length of crop growth periods (LGP) conducive for crop growth under the conditions of mean temperature \geq 5°C and P exceed half the PET (P > 0.5PET). Accordingly, the classifications include arid (LGP < 70 days), semiarid (70–180 days of LGP), subhumid (180–270 days of LGP), and humid (LGP > 270 days). Moreover, the climatic condition is classified based on the altitudinal range with areas higher than 1,200 m a.s.l. as cool and if lower is a warm climate. Thus, making decisions on projected drought changes in comparison with the preexisting agroecological and climatic characteristics is important in this regard. The widely known paradigm 'dry gets drier and wet gets wetter' (Cook et al., 2014b; H. Feng & Zhang, 2015; Greve et al., 2014) has been used as a basis to verify whether our results support the argument or otherwise.



3. Results

3.1. Long-Term Drought Projections Using SPI and SPEI

Figure 2 shows the projected SPI and SPEI time series drought values for each RCP scenario during the entire study period (1981-2099). The SPI projection from the ensemble means of the five GCMs shows a decreasing trend of droughts due to increasing trend of precipitation. However, the ensemble mean projects an increase in SPEI compared to SPI time series for each scenario. This suggests that the SPI shows a decrease in drought projection whereas the SPEI projects an increase in droughts. As presented in Figure 2, the difference in the trend of the SPI/SPEI time series increases with time and RCP scenarios (RCP 2.6 to 8.5) attributed to increasing in temperature and precipitation. For that, we have evaluated the reliability of the GCMs using different evaluation metrics for precipitation (supporting information Table S2) and temperature (supporting information Table S3) with observed data. The validation metrics has proved the reliability of the ISIMIP data set used in studying drought conditions over East Africa. Moreover, using ensemble mean from the Coordinated Regional Downscaling EXperiment (CORDEX), Osima et al. (2018) projected an increase in temperature by more than 1°C and 1.5°C over East Africa, under 1.5°C and 2°C warming levels, respectively. These suggest that the temperature is playing a leading role in the future climate system of East Africa. Similarly, due to the greater influence of temperature changes, the projected changes in drought characteristics using the SPEI index are stronger than the changes in SPI (Touma et al., 2015). Thus, the projected increase in PET (mainly due to temperature increase) in the context of global warming has enhanced the severity of future droughts in East Africa. Osima et al. (2018) also indicated that East Africa will warm faster than the global mean which further strengthens the role of temperature in the region.

The projected SPI/SPEI time series data also indicate that the effect of PET is a more important variable in detecting future drought risks than precipitation. Nguvava et al. (2019) analyzed SPI and SPEI time series in East Africa, using CORDEX model setups and RCPs (4.5 and 8.5), and projected an increase in severity and frequency of SPEI as compared to SPI suggesting the magnitude and robustness of SPEI for drought projections. Using four drought indices Jiang et al. (2014) revealed that the effects of climate change in drought conditions showed a temperature increase (2°C) suggesting the importance of the SPEI drought index. This further implies that the SPEI is more robust in revealing future droughts as a result of the increased temperature in the context of global warming. Thus, considering the role of temperature in the PET during SPEI estimation can give an acceptable result, which is essential for policymakers in the region. Furthermore, comparing the SPI/SPEI drought projection can help to show the importance of PET (mainly temperature) for future drought assessments over East Africa. The use of SPEI for understanding future drought characteristics may also help to get evidence of future drought risks that will help to minimize the drought impacts. The calculated SPEI 12 is also consistent in magnitude and direction with SPEI 1, 3, and 6 SPEI timescales (supporting information Figure S1). Accordingly, the SPEI has been used in this study to predict future drought projections over East Africa described in the following sections. The SPEI time series along with their uncertainty bound among the GCMs is presented in Figure 3. These suggests that the projected time series of SPEI for RCPs 2.6, 4.5, and 8.5 scenarios during the period 1981 to 2099 showed an increasing trend in drought conditions over East Africa with uncertainties varying across the time periods and RCPs.

3.2. Long-Term Projected Changes in Drought Magnitude and Extent

Figure 4 shows a time series of the drought area percentage of pixels with SPEI values less than or equal to -1 against the total number of pixels in East Africa during 1981–2099. The average changes in the drought areas between the given periods were calculated in percentage of the drought pixels. Overall, the drought area is likely to increase as time increase over East Africa (Figure 4). For the RCP 2.6 scenario, the projected change in drought area in all future periods is likely to increase in the 2020s (9%), 2050s (17%) and 2080s (16%). The RCPs 4.5 and 8.5 scenarios also showed an increasing change pattern of drought area by 7.7% and 14.5% in the 2020s, 22% and 41.5% in the 2050s, and 36% and 39% 2080s, respectively (Figure 4). The drought area is also calculated for SPEI 1, 3, and 6, which showed consistent direction with SPEI 12 with small differences in magnitude (supporting information Figure S2). In summary, the projected change in the 2080s. The patterns are characterized by increased drying over most of East Africa attributed to increase in temperature. This is also in agreement with Dai (2011) who





Figure 2. Comparison of projected time series of SPI and SPEI for RCPs 2.6, 4.5, and 8.5 scenarios for the period 1981 to 2099. The *x* axis represents time in months. The data used were ensemble mean of the five models given in Table 1 (GFDL-ESM 2 M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M). The dotted gray vertical line is a partition line among the study time periods of the reference period (1981–2010), the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099).

showed that the occurrence of warming since the 1980s has contributed to the upward trend in global drought areas.

3.3. Projected Changes in Drought Severity Levels

To further understand the future drought conditions of East Africa, drought severity levels (moderate, severe and extreme droughts) for the different periods have been analyzed as shown in Figure 5. The change in drought area under moderate drought (SPEI value ranges from -1 to -1.5) was evaluated for each period.



Figure 3. The projected time series of SPEI for RCPs 2.6, 4.5, and 8.5 scenarios for the period 1981 to 2099. The gray filled range corresponds to the uncertainty bound using the minimum (lower bound) and maximum (upper bound) of the GCMs. The *x* axis represents time in months. The mean is calculated using the SPEI values of the GCMs given in Table 1.





Figure 4. The projected time series of drought area (%). The color-filled range corresponds to the uncertainty bound using the minimum (lower bound) and maximum (upper bound) of the GCMs for each RCPs. The horizontal panel shows drought area (%) time series values from each RCP scenario in the period 1981–2099. Drought area was calculated as the number of SPEI values less than or equal to -1 divided by the total number of pixels as proposed by Dai (2011). The dotted gray vertical lines are partition lines among the study time periods of the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099).

The result showed that moderate drought in RCP 2.6 showed an increasing trend during the 2020s by 7.5%, in the 2050s and 2080s by 12% each. Similarly, the moderate drought under RCP 4.5 shows a consistent increase by 6%, 13%, and 17% in the 2020s, 2050s, and 2080s, respectively. The moderate drought areas under RCP 8.5 scenario showed increasing during the near future (the 2020s; 10%) and midcentury (2050s; 17%), and then decreased afterward during the end of century (the 2080s; 11.6%), respectively (Figure 5). This implies the moderate drought areas increases under RCPs 2.6, 4.5, and 8.5 for all periods except during the 2080s (RCP 8.5).

Similarly, the change in the percentage area of severe drought levels (SPEI value of -1.5 to -2) has been investigated for each RCPs and period (Figure 5). The result indicated that severe droughts will consistently increase as time increases for all RCP scenarios (except during the 2080s under RCP 8.5). Thus, the severe drought areas will increase by 1.4% in the 2020s, 3.8% in 2050s, and 3.5% in the 2080s under RCP 2.6. Similarly, the severe drought areas for the RCPs 4.5 and 8.5 projections are likely to increase by 1.4% and 3.4% in the 2020s, 6% and 12.3% in the 2050s, and 11% and 13.5% in the 2080s, respectively (Figure 5).

The future occurrences of change in the percentage areas of pixels under extreme drought (SPEI values less than or equal to -2) were also assessed in a similar approach with the moderate and severe droughts (Figure 5). Under the RCP 2.6 projection, the extreme drought areas have been increased by 0.2%, 1%, and 0.8% during the 2020s, 2050s, and 2080s, respectively. In addition, the extreme drought will increase by 0.2%, 3%, and 8% during the 2020s, 2050s, and 2080s, respectively, under the RCP 4.5 projection. The extreme drought also shows increasing changes by 1%, 12%, and 29% during the 2020s, 2050s, and 2080s, respectively, under RCP 8.5 projection. Generally, all RCP scenarios except RCP 2.6 (which showed little change) the extreme drought area is likely to increase as time increases.

From the above findings, the projected change in moderate, severe and extreme droughts is greater under RCP 8.5 as compared to RCP 4.5 and RCP 2.6 in the 2020s and 2050s. During 2080s, however, the opposite is true. Thus, the future droughts in East Africa are predicted to be under extreme drought followed by severe and moderate droughts, consecutively.

3.4. Temporal Drought Area Change Projections3.4.1. Monthly Drought Area Projection

Figure 6 reveals monthly drought variations for the SPEI ≤ -1 value for each RCP and period of analysis. The drought areas are increasing as the time frame increases from the 2020s to the 2080s for each scenario. The average changes have been quantified for each month in the future comparing to the reference period as





Figure 5. The projected time series drought levels showing the areal extent of different drought severity levels. The dark yellow, purple and red filled range corresponds to the uncertainty bound using the minimum (lower bound) and maximum (upper bound) of the GCMs for moderate, severe and extreme drought levels for each RCPs, respectively. Moderate (SPEI –1 to –1.5), severe (SPEI –1.5 to –2) and extreme drought (SPEI ≤ -2) in the time series. The *x* axis represents time in months.

a baseline. The results indicate that there is a positive change for each future period and RCP scenarios in all months. The higher drought area change under RCP 2.6 is predicted to be August (9.7%), April (17.5%), and May (17.5%) for the near term, midterm, and end of the century, respectively.





Figure 6. Monthly average drought area changes in percentage for the SPEI ≤ -1 for each RCP.

The drought months showing relatively greater drought changes under RCP 4.5 will be October (8.3%), May (23.4%), and May (37.4%) in the 2020s, 2050s, and 2080s, respectively. Similarly, under RCP 8.5, the higher the change in droughts is found in the months of October (15.8%) in the 2020s, August (42.5%) in the 2050s, and April (54.8%) in the 2080s. In summary, August, April, and May will show relatively higher drought month under RCP 2.6 during the study periods, whereas October and May will face bigger drought changes under RCP 4.5 in all periods. Meanwhile, October, August, and April are likely showing higher values of drought months under RCP 8.5 during all periods in East Africa.

3.4.2. Seasonal Drought Area Projection

Figure 7 presents seasonal average drought change variations for the SPEI ≤ -1 value of each RCP. The seasonal average drought change is increasing consistently with an increase of time period from 2020s to 2080s for each scenario. Average seasonal changes in all periods were estimated to identify which season is likely to be most vulnerable to future drought. It was found that under all RCP scenarios, all seasons (winter, spring, summer, and autumn) have shown positive changes for all the three future periods. The higher drought seasons in the RCP 2.6 projection will be in autumn by 9.5% and 17.2% in the 2020s and 2050s, respectively, and Spring by 17% at the end of the 21st century. The higher drought seasons in RCP 4.5 projection will occur during autumn (8%) in the 2020s, and summer and spring by 23% and 37%, in the 2050s and 2080s, respectively. Similarly, the greater seasonal drought changes will occur in autumn by 15.8% in the 2020s, and summer and spring by 42% and 54% seasons during the 2050s and 2080s, respectively, for the RCP 8.5 projection. In summary, the future higher drought change seasons are found to be in autumn and spring (for RCP 2.6), summer and spring (for RCP 4.5), and autumn, summer, and spring (for RCP 8.5). This implies that the East African region is likely to face a relatively greater drought changes in autumn, summer, and spring seasons during all periods under all RCP scenarios, respectively.

3.5. Projected Changes in the Spatial Patterns of Drought

3.5.1. Drought Characteristic Conditions During the Base Period (1981-2010)

Figure 8 presents drought conditions during the base period (1981–2010). The change in drought characteristic conditions in the future periods was quantified with reference to the base period for each RCPs. The average drought event is estimated to have six events with higher values found in Ethiopia, northern Kenya, and western Somalia. The average drought duration is also estimated to be 8 months during the base



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Figure 7. Seasonal average drought area change percentage variations for the SPEI ≤ -1 for each RCP.

period with higher durations occurred at various locations across East Africa. In addition, the average drought frequency during the base period was 17% for which the higher frequencies are concentrated at the central parts of East Africa. For the drought intensity, the average value during the base period is 1.44 having higher values at eastern Somalia and Ethiopia and northern Tanzania (Figure 8).

3.5.2. Drought Events

In this study, the drought event is a period in which the SPEI value is continuously less than or equal to -1 for at least 3 months or more following the definitions given in Schwalm et al. (2017). Figure 9 presents the spatial changes of future drought events (2011–2099) in reference to the baseline period (1981–2010). Under RCP 2.6, drought events have shown an increase during the 2020s followed by similar increasing patterns in 2050s and 2080s. Similarly, the RCPs 4.5 and 8.5 projections have also shown a consistent increasing pattern except RCP 8.5, which showed a positive but slight decrease in the 2080s. However, the magnitude of change follows similar patterns in all RCPs across the time period over East Africa (Figure 9).

The average values of changes in drought event also reveal similar trends. In in the RCP 2.6, the average change in drought event is projected to be three, four, and four events in the 2020s, 2050s, and 2080s, respectively. Similarly, the drought event change in RCP 4.5 and 8.5 were two and three events for the 2020s, four and five events for the 2050s, and five and three events for the 2080s, respectively. With an increase in future time, all RCP scenarios except RCP 8.5 (which showed slight decreases) have shown similar increasing patterns on the spatial drought event changes in majority areas of East Africa. Notwithstanding this, the magnitude of change in the spatial patterns of drought event showed a consistent pattern in all RCP scenarios across all time periods. Particularly, higher change of drought events during all periods is likely to occur in parts of Djibouti, Eritrea, Sudan, South Sudan, and Tanzania under RCPs 2.6 and 4.5, whereas under the RCP 8.5 sce-



Figure 8. Drought characteristic conditions (drought event, duration, frequency, and intensity) during the reference period (1981–2010).

nario the drought events will be less during the middle and end of 21st century. A lower change in the drought events will occur during all periods and scenarios in Kenya, Uganda, and Ethiopian highlands. Similarly, the box-and-whisker diagrams shown in Figure 11a also reveals similar results. The differences between the medians and means of the projected drought vary as the scenarios and time period increases. The drought change is showing a decreasing trend under RCP 8.5 (in the 2080s). The outliers reveal the existence of higher variabilities in future drought events.

3.5.3. Drought Duration

The duration of the drought, the lifespan of droughts in months under climate change, was also quantified for each scenario. Figure 10 presents the spatial changes of future drought durations during 2011–2099 compared to the reference period (1981–2010). Under all RCP scenarios, the drought duration has shown a consistent increase with increasing timeframe. Likewise, the drought duration magnitude has shown a consistent increase with the increasing of RCP scenarios.

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Figure 9. Projected changes in drought events (in number). Drought event is a period in which the SPEI value is continuously less than or equal to -1 for at least 3 months or more as given in Schwalm et al. (2017). The horizontal panel shows spatial drought event change for each RCP scenario across each timeframe. The vertical panel shows the spatial drought event change in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099).

Similarly, the average values of changes in the drought duration exhibited similar patterns. Under RCP 2.6 the average drought duration change is 5, 7, and 7 months for the 2020s, 2050s, and 2080s, respectively. The drought duration changes in RCP 4.5 and 8.5 also showed the same patterns with an average value of 4 and



Figure 10. Projected changes in drought duration in months. The horizontal panel shows spatial drought duration change for each RCP scenario across each timeframe. The vertical panel shows the spatial drought duration change in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099).





Figure 11. Box-and-whisker diagrams showing the spread of the projected drought changes, (a) drought event, (b) duration, (c) frequency, and (d) intensity. The black horizontal line in each box represents the median. The dotted point inside each box represents the mean value. The bottom and top edges of the boxes indicate the 25th and 75th percentiles, respectively; meanwhile, the top and bottom of each whisker represents the most extreme data values. The black dotted points, in some scenarios, above or below of the whisker represent outliers.

7 months for the 2020s, 10 and 32 months for the 2050s, and 29 and 108 months during 2080s, respectively. In summary, all RCP scenarios have shown a similar increasing pattern on spatial change of drought duration as time increases. Moreover, although drought in Eritrea, Sudan, South Sudan and parts of Somalia, Ethiopia, and Tanzania shows a consistently higher duration in all periods and scenarios, it is more pronounced in RCP 8.5 during the mid and end century and RCP4.5 during the end century. In agreement with the drought events, the duration of drought in Kenya, Uganda, and the majority of Ethiopian highlands will continue to be lower in all periods.

The box-and-whisker diagrams shown in Figure 11b also indicated that the projected changes in drought duration have higher variabilities in RCPs 2.6 and 4.5 scenarios. The observed mean and median values, suggesting small variabilities in the magnitude of change in drought durations. On the contrary, the mean and median values under the RCP 8.5 projection showed a large difference in the 2050s and surprisingly large variabilities with higher magnitudes during the 2080s, which explicitly shows large variabilities in the future drought durations. It is worthwhile to mention that some outliers exist under all RCP scenarios during the 2020s and 2050s, which implies that there is a possibility of high variabilities in drought durations.

3.5.4. Drought Frequency

Analysis of the drought frequency of under climate change was also undertaken to further understand how frequent the drought is likely to occur in East Africa. Figure 12 shows the spatial changes of future (2011–2099) drought frequency (%) compared to the reference period (1981–2010). Under the RCP 2.6 projection, drought frequency is likely to increase from the 2020s to 2050s and starts to decrease afterward during the 2080s. Under the RCPs 4.5 and 8.5 scenarios, the drought frequency also showed similar increasing patterns from the 2020s to 2080s. Generally, all RCP scenarios have shown similar increasing patterns with increasing time periods. The magnitude of spatial drought frequency also increases from RCPs 2.6 to 8.5 in each study period (Figure 12).

The average values of the drought frequency changes were also quantified using a similar approach as in the drought duration. Accordingly, the average change in the drought frequency under RCP 2.6 is found to be 9%, 17%, and 16% in the 2020s, 2050s, and 2080s, respectively. Correspondingly, the change in the drought



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Figure 12. Projected changes in drought frequency (%). The horizontal panel shows spatial drought frequency change for each RCP scenario across each timeframe. The vertical panel shows the spatial drought frequency change in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099).

frequency under RCPs 4.5 and 8.5 projections were found to be 8% and 15%, 22% and 41%, and 36% and 54% in the 2020s, 2050s, and 2080s, respectively. The frequency of drought fellows the same pattern with the duration in which Sudan, South Sudan and parts of Somalia, Ethiopia, and Tanzania are likely to have a frequent drought in all periods and scenarios. In contrast, southeastern Ethiopia, Uganda, and Kenya are likely to have a relatively lower drought frequency.

The box-and-whisker diagrams have also shown that the projected change in drought frequency exhibited low differences in the mean and median values under all RCP scenarios (except RCP 8.5 in the 2080s) and time periods (Figure 11c). It is also boldly indicated in Figure 11c that the large data ranges exist in all RCP scenarios and each time period. The box-and-whisker plots with higher 25th and 75th percentile ranges reflect higher variability in future drought frequencies.

3.5.5. Drought Intensity

The drought intensity for all periods and scenarios was also investigated in East Africa. Figure 13 indicates the spatial changes of future drought intensities during 2011–2099, by comparing with the baseline period. Under RCP 2.6, the spatial intensity change in drought has shown an increasing pattern from the 2020s to 2050s and then starts to decrease during the end of the 21st century. The drought intensity under RCP 4.5 decreases in the 2020s and then increases afterward in the 2050s and 2080s. The drought intensity under RCP 8.5 has also shown increasing spatial change patterns with an increase in the time period from the 2020s to 2080s (Figure 13). The change in intensity of drought is consistent with the duration and frequency of droughts where the countries that will receive higher and frequent drought are likely to experience a higher intensity of drought. This is essential to understand how intensified drought is persisting in a specific area per a given period.

Similar trends were observed on the average values of drought intensity changes under all RCP scenarios. For the RCP 2.6 projection, the average change in drought frequency is 0.1%, 11% and 3% in the 2020s, 2050s, and 2080s, respectively. Likewise, the drought intensity changes in the RCPs 4.5 and 8.5 projections were -10% and 5% in the 2020s, 6% and 32% in the 2050s, and 17% and 57% in the 2080s, respectively. All RCP scenarios have shown similar increasing patterns with an increase in time periods except RCP 2.6 in the 2080s and RCP 4.5 in the 2020s. The magnitude of spatial drought intensity also increases in all periods as we go from RCP 2.6 to RCP 8.5 scenarios.



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Figure 13. Projected changes in drought intensity (%). The horizontal panel shows spatial drought intensity change for each RCP scenario across each timeframe. The vertical panel shows the spatial drought intensity change in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099).

Similarly, in the box-and-whisker diagrams, the differences between the medians and means of the projected drought intensities show similar patterns under all RCP scenarios (Figure 11d). The outliers in each RCP scenario in all periods demonstrate large variabilities in the projected changes of drought intensity. This graph also shows a clear sign of an increase in drought intensity in all periods and RCP scenarios except RCP 4.5 in the 2020s. These suggest that the variability of future drought intensity increases as the time increases in the context of global warming.

3.6. Uncertainty Analysis of the Projected Droughts

As indicated in the sections described above, the temporal and spatial drought magnitude is expected to be higher at the end of the 21st century, considering the average value of the RCPs, as compared to the 2020s and 2050s. Figures 3–5 present the uncertainty analysis of the mean SPEI time series values, time series drought area percentage, and drought severity levels percentage area. The ranges of the SPEI values characterize how the drought is accurately projected along with its uncertainty. The observed uncertainty increases with increased future drought projections due to the effect of climate changes. These uncertainties are largely linked to precipitation and temperature (demonstrated in PET), and the associated hydroclimatic governing factors in the region. This finding is in agreement with Orlowsky and Seneviratne (2013) who reported that the dominant source of uncertainties in future drought is due to internal climate variability during the near term and formulation of GCMs by the end of the 21st century. Another factor that drives the observed uncertainties that cause differences in drought projection is the disparities in use of P and PET data sets and roles of natural variabilities attributed to large-scale oscillations such as El Niño–Southern Oscillation (ENSO) and La Niña conditions (Sheffield et al., 2012).

Moreover, climate-related uncertainty is associated with the inability to predict the scale, intensity, and impact of climate change on human and natural environments (Mehata et al 2019). Different sources of uncertainties exist in future climate projections, which include internal climate variability, GCM data sets and future climate scenarios (Lu et al., 2019; Meresa et al., 2016; Meresa & Romanowicz, 2017; Orlowsky & Seneviratne, 2013). By far, climate change projections are inherently uncertain due to assumptions made about the formulation, parameterization, and boundary conditions of the underlying factors in climate (Mackay et al., 2019; Meresa & Romanowicz, 2017). Furthermore, the local factors such as complex terrain, large inland water bodies and land heterogeneity complimented by large-scale climate interactions result in

diverse climate patterns over East Africa (Haile et al., 2019; Osima et al., 2018). Duan and Mei (2014) indicated that GCM initial conditions and scenarios used could also produce large uncertainties in drought responses to climate change. Given the inherent difficulty of drought quantification, the climate change projections on droughts are already inevitably hard.

Despite the fact that large uncertainties are observed in the magnitude of the changes which are more pronounced in the 2020s and 2080s, the projected droughts are expected to increase in multiple countries of East Africa by the end of the 21st century. This suggests that considering specific hydroclimatological, geographical conditions, and climate mitigation measures are indispensable to minimize the concerns associated with the increased future drought projections. To reduce these uncertainties a thorough evaluation of the uncertainties and more rigorous considerations of the different sources of uncertainty could have paramount importance.

4. Discussion

4.1. Comparison of SPI and SPEI in Future Drought Assessments

To understand the future drought characteristics, this study has compared the results of SPI and SPEI drought indices' time series for RCPs 2.6, 4.5, and 8.5 scenarios for the period of 1981 to 2099. The SPEI is shown more drought conditions in the future as compared to the SPI suggesting an increase in PET as compared to precipitation. Various studies (Ahmadalipour et al., 2017; S. Feng et al., 2017; Jeong et al., 2014; Nguvava et al., 2019; Spinoni et al., 2020) assessed drought in East Africa and beyond using SPI and SPEI that resulted in differences in magnitude and direction. For example, Nguvava et al. (2019) revealed that SPEI has simulated higher drought magnitude as compared to SPI in East Africa and suggested an effective land management practices can reduce the amount of water loss through evaporation. Drought projections based on precipitation only would result in decreasing drought over the Horn of Africa from those based on both precipitation and PET (Spinoni et al., 2020). Jeong et al. (2014) assessed drought risks to see the effects of temperature and PET on drought by comparing future drought events, suggesting long-term and extreme drought events would likely occur due to future increases in temperature and PET. Feng et al. (2017) compared multiple drought indices about the future drought risk outcomes in drought-prone regions, and indicated more extreme droughts to occur especially at the end of 21st century. Ahmadalipour et al. (2017) investigated the changes in hydrometeorological drought characteristics, the SPEI results indicate that the frequency and duration of drought events is expected to increase whereas SPI indicates decreasing trends. The differences in drought risk projections, due to use of SPI and SPEI, would highlight the need to consider appropriate drought indices in projecting future drought changes. Furthermore, these studies suggest for considering the role of temperature in future drought assessments. This implies that studying drought using the SPI is insufficient for analyzing the impacts of climate change. Thus, SPEI has become more robust to detect possible future drought risks in the context of global warming. Understanding future drought risks is useful for minimizing the drought impacts via introducing adaptation and mitigation measuring and through building drought resilience over East Africa. According to Meza et al. (2019) and Hagenlocher et al. (2019) drought vulnerability and risk assessments across spatiotemporal scales have shown an increase consistent with increasing droughts suggesting a need for reducing social, environmental, and economic impacts of droughts by creating drought-resilient societies. A study by Nguvava et al. (2019) in East Africa indicated that incorporating PET in quantifying the severity of future drought projections is better than using only precipitation. According to Sheffield and Wood (2008), an increase in drought during the 21st century is primarily driven by increased evaporation from higher temperatures. To this effect, the use of SPEI for drought projection is advantageous to understand future drought changes over East Africa so as to minimize.

4.2. Projected Changes in Drought Characteristics Over East Africa

The projected SPEI drought results show an increase in drought conditions throughout the 21st century under the RCP scenarios considered. The future drought changes have been detected using temporal scales such as drought area, different drought severity levels (moderate, severe, and extreme) and different time-frames using monthly and seasonal timescales. In addition, drought event, duration, frequency, and intensity were used for analyzing the future spatial drought changes.

The projected change in drought area has shown an increase in all RCPs and periods. Specifically, the projected change in drought area is predicted to show a large increase by the end of the 21st century. These suggest that East Africa will face unprecedented increases in drought area by the end of the 21st century under RCP 8.5 scenario if drought mitigation and adaptation mechanisms are inadequate. Similarly, the extreme drought severity level is likely to dominate the future drought followed by severe and moderate drought levels consecutively. It is worth to indicate that all drought severity levels show a positive increasing trend with much higher magnitude suggesting worst droughts in the future. The projected change in drought area is in line with previous studies, which presented an increase in drought area in large parts of East Africa (Dai, 2011; Seitz & Nyangena, 2009). The increased upward trend in global drought areas is due to the occurrence of global warming since the 1980s (Dai, 2011, 2013). It can be concluded that the increased drying over most parts of East Africa is attributed to increased evaporation due to temperature increase but not due to decreased precipitation.

Moreover, future drought changes in seasonal and monthly basis have been reported to show an increasing trend. The projected change monthly patterns have shown a positive increase in all RCPs and time periods. The projected drought months reveals that May and April are likely to show the highest increase in drought occurrence during the end of the 21st century. Similarly, the seasonal analysis reveals that the biggest drought area changes will likely occur in spring by the end of the 21st century. Thus, the spring season will likely face an increased dryness with a relative increase in temperature during the end of the 21st century. In East Africa, the spring season is associated with the long rains season known by the main agricultural season in East Africa. During the long rain season (March–May) the higher drought is likely to occur as greater drought changes are projected across East Africa. As indicated by Haile et al. (2019) and Haile, Tang, Leng, et al. (2020) the long rains season has been reported to have increased drought trends in the past four decades and our results revealed the continued drought increase in the future that needs better drought protection measures.

In addition, the drought characterizing features such as drought event, duration, frequency, and intensity have projected for the future in reference to the baseline period. The drought event, duration, frequency, and intensity have shown a consistently increasing trend, under RCPs 4.5 and 8.5, with the increasing timeframe. However, the drought event has shown a positive, but decreasing trend under RCPs 2.6 and 8.5 during the 2080s. Under RCP 8.5, Touma et al. (2015) found increases in the spatial extent, duration, and occurrence of droughts in subtropical and tropical regions, suggesting the increasing risk of drought-related stress for natural and human systems. Similarly, Gizaw and Gan (2017) suggested that East Africa will experience a drier climate in the 2050s and 2080s with an increase in drought-prone areas calling for actionable policies geared toward adaptation and mitigation. Furthermore, the projected increase in drought over East Africa is in line with previous studies covering similar geographical settings (Cook et al., 2014b; Nguvava et al., 2019; Zhao & Dai, 2017). Using regional model simulations, Nguvava et al. (2019) projected an increase in the intensity and frequency of droughts over large parts of East Africa. For example, during the end of the 21st century, the frequency and intensity of droughts are expected to increase as the climate warms (Cook et al., 2014b). Indeed, this study has shown that drought quantifying parameters such as drought events, duration, frequency, and intensity have become largely a clear indicator of the 21st century climate change impacts in response to drought changes. Generally, the projected changes in drought characterizing parameters are much greater under RCP 8.5. The higher change magnitudes are most pronounced after the 2050s, which is consistent with the projected increase in global warming (IPCC, 2013). Seitz and Nyangena (2009) indicated that millions of people are likely to be adversely affected by climate change in East Africa, particularly arid and semiarid areas, the Great Lakes region and the coastal regions.

4.3. Analysis of Drought Change Patterns on Wetting/Drying Conditions

In this study, we showed how drought may change for the 21st century in the context of continuing global warming. It is still important to demonstrate the projected drought condition in relation to the wetting/drying patterns over East Africa due to climate change effects. Assessment of drying and wetting patterns is largely valid to recommend area-specific drought monitoring and management strategies. The wetting/drying pattern is directly linked to the widely known "dry gets drier and wet gets wetter" paradigm (Cook et al., 2014b; H. Feng & Zhang, 2015; Greve et al., 2014). This pattern is mainly associated with the P and PET, which are the main variables in the calculation of the SPEI. These are further associated with water





Figure 14. Environmental and climatic conditions of East Africa. (a) Agroecological zones and (b) warm/cool climate obtained from the Agro-ecological Zones of Africa data set (http://hdl.handle.net/1902.1/22616).

balance (P-PET) estimations where the humid regions hold wet with positive P-PET value whereas arid regions result in deficit/negative P-PET values (Feng & Zhang, 2015; Kumar et al., 2015; Liu & Allan, 2013; Yang et al., 2019). To cross validate whether the temporal trends of the dry regions tend to get drier, and wet regions tend to get wetter works or otherwise with our results, assessment of the inherited agroclimatic characteristics of East Africa is required for making expert decisions.

The preexisting inherited agroecological and climatic characteristics of East Africa are diverse in nature. By far, East Africa is a tropical region with 81% warm climate and 37% arid agroecology (Figure 14; Kate, 2009). As presented in the spatial drought patterns of East Africa (Figures 8–10, 12, and 13), a decrease in future droughts is expected in Rwanda, Uganda, Kenya, and Ethiopian highlands. These areas are particularly characterized by humid agroecology that represents a wet region (Figure 14). On the contrary, the magnitude and spatial variability of drought patterns in the arid and semiarid countries, including Sudan, South Sudan, Somalia, Djibouti, Eritrea, large parts of Ethiopia, Kenya, and small parts of Tanzania are likely to increase in drought. Greater drought changes over arid and semiarid dry lands highlight for higher risk of future droughts over 65% of the East African landscapes. This increased drought changes are in agreement with the agroecological paradigm and supports the argument "dry will get drier and the wet will get wetter." A comparison of the agroclimatic and drought change projections clearly shows the consistent dry/wet changes in East Africa (Figure 14). From this analysis, it is worthwhile to note that the largest part of East Africa is expected to increase in drying trends suggesting acute mitigation measures on the basis of existing local conditions.

4.4. Mitigation Measures to Impacts of Future Droughts

Drought projection changes relative to the reference period have shown a large-scale increase, particularly toward the end of the 21st century and for the warmer RCP 8.5 emission scenario. Based on the analysis of the projected drought indicators, a recurrent drought is expected to increase in the magnitude, time, and spatial variability over most East Africa countries. Osima et al. (2018) noted that East Africa will warm faster than the global mean temperature, suggesting a greater focus on the impacts of climate on drought responses and drought alleviation strategies. Thus, higher severity and frequency of the drought conditions could create a significant negative impact, particularly in the Horn African countries (Eastern Ethiopia, Djibouti, Eritrea, and Somalia). The combined effects will likely impact the livelihoods of people living in the coastal areas, lake regions, highlands, and arid and semiarid lands of Kenya, Tanzania, Somalia, Ethiopia, and Sudan (Osima et al., 2018). Climate change projections will lead to increasing aridity in East Africa affecting key sectors such as agriculture, water, energy and health (Osima et al., 2018; Serdeczny et al., 2017).



Therefore, understanding of projected spatiotemporal change in future drought patterns over East Africa is critical for taking mitigation measures before the full range of projected drought risks affects the societal setups and the overall environments. These future drought risks/impacts due to future climate change would cause large-scale damages for local to regional to global terrestrial lands and may create intrasocietal and intersocietal inequalities. This is particularly pronounced under the existing increase of the greenhouse gas concentrations and associated warming of the climate system. Thus, it is worth mentioning the acute actions/prevention measures that should be taken in terms of different early warning systems and facilities derived from policies and strategies for the policymakers.

Various mitigation measures, including greater implementation of environmental rehabilitation approaches and water resources management strategies, are essential (Gebrechorkos, Hülsmann, & Bernhofer, 2019a, 2019b; Gebremeskel et al., 2018; Haile et al., 2019). This is particularly important to combat future water shortages and land degradation over East Africa. The solutions put forward should also encompass the wider challenges affecting drought monitoring and management. Thus, efficient drought management and monitoring, designing response policies and strategies at national, regional, and international levels are required for building resiliencies to future droughts (Haile et al., 2019; Sheffield et al., 2014). These activities could further help to minimize the natural climate variabilities and anthropogenic influences in aggravating future drought conditions (Haile et al., 2019). Further, building a drought-resilient economy is needed for drought-vulnerable societies as it can help for better preparedness for coping awareness for early warning of droughts (Sheffield et al., 2014). These could help to reduce the future impacts of droughts on socioeconomic activities and the natural ecosystem functions across East Africa. In addition, considering the impacts of climate changes on droughts, serious attention should be given to particularly vulnerable regions in need of urgent assistance and support. Furthermore, providing efficient drought forecasts and drought early warning facilities should be much strengthened in East Africa (Mwangi et al., 2014; Shukla et al., 2014). Thus, future sustainable drought management is pressing through designing policy, strategies and social infrastructures.

5. Summary and Conclusion

The projected climate change impacts on drought patterns are vital to address the various risks of future droughts. This study takes a particular look at the future droughts over East Africa helpful to address the core challenges of droughts. Five GCMs obtained from the ISIMIP were used to quantify projected droughts in the future (2011–2099) under RCPs 2.6, 4.5, and 8.5 in reference to the baseline period (1981–2010). The future periods were partitioned into the near term (2011–2040), midcentury (2041–2070), and end of the 21st century (2071–2100) for easy of policymaking and infrastructure decisions.

The main findings are summarized as follows.

- 1. The SPEI is showing more drought conditions in the future as compared to the SPI over East Africa. Thus, future drought risks can be minimized by incorporating PET data in drought quantification rather than using only precipitation in the context of global warming.
- 2. The projected change in drought area has shown an increase in all RCPs and periods over East Africa. During the end of the 21st century, the drought area is predicted to increase by 36% and 54% under RCPs 4.5 and 8.5, respectively. Much of the future droughts in East Africa lay under extreme drought followed by consecutively severe and moderate drought severity levels. The projected drought will likely show greater drought changes in May and April and the corresponding spring season.
- 3. The drought event, duration, frequency, and intensity have shown an increasing spatial drought change patterns with increasing time periods under all RCPs with exceptions in drought event changes. Specifically, higher drought changes are likely to occur in Sudan, South Sudan, Djibouti, parts of Eritrea, Somalia, and Tanzania, whereas Uganda, Kenya, and Ethiopian highlands are likely to have shown lower drought changes over East Africa.
- 4. Uncertainty analysis of the climate change impacts on drought patterns shows that projected drought changes are likely to increase under higher uncertainties with increasing timeframe from the near future to the end of the 21st century.
- 5. Results also showed strong agreements with the "drying will get drier and wetting will get wetter" conditions supported by the agroclimatic conditions of East Africa.



The drought projection partitioned in different future periods is important for policymaking, infrastructure decisions and overall monitoring of climate change impacts on drought. The projected drought conditions are key for developing drought adaptation and mitigation policies. This study has created a good insight to understand the likely future drought conditions in East Africa.

Data Availability Statement

Data used for this study were extracted from Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP) Fast Track simulation round (https://www.isimip.org/) and Climatic Research Unit (https://crudata.uea.ac. uk/cru/data/hrg/cru_ts_4.03/).

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