Future changes in precipitation extremes over East Africa based on CMIP6 projections

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Abstract

This paper presents an analysis of precipitation extremes over the East African region. The study employs six extreme precipitation indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) to evaluate possible climate change. Observed datasets and CMIP6 simulations and projections are employed to assess the changes during the two main rainfall seasons of March to May (MAM) and October to December (OND). The study evaluated the capability of CMIP6 simulations in reproducing the observed extreme events during the period 1995 – 2014. Our results show that the multi-model ensemble (herein referred to as MME) of CMIP6 models can depict the observed spatial distribution of precipitation extremes for both seasons, albeit with some noticeable exceptions in some indices. Overall, MME’s assessment yields considerable confidence in CMIP6 to be employed for the projection of extreme events over the study area. Analysis of extreme estimations shows an increase (decrease) in CDD (CWD) during 2081 – 2100 relative to the baseline period in
both seasons. Moreover, SDII, R95p, R20mm, and PRCPTOT demonstrate significant OND estimates compared to the MAM season. The spatial variation for extreme incidences shows likely intensification over Uganda and most parts of Kenya, while reduction is observed over the Tanzania region. The increase in projected extremes during two main rainfall seasons poses a significant threat to the sustainability of societal infrastructure and ecosystem wellbeing. The results from these analyses present an opportunity to understand the emergence of extreme events and the capability of model outputs from CMIP6 in estimating the projected changes. More studies are encouraged to examine the underlying physical features modulating the occurrence of extremes incidences projected for relevant policies.

**Keywords:** CMIP6, extreme precipitation, model evaluation, east Africa

1. Introduction

The frequent occurrence of extreme events such as heatwaves, droughts, pluvial events, and hurricanes over the recent years points to clear evidence of global warming (GW) and climate change (Alexander et al., 2006; Sillmann et al., 2013; IPCC, 2014; Alexander, 2016). The recent IPCC special report on impacts of global warming of 1.5 °C estimate that GW is likely to attain 1.5 °C by 2030 and 2052 if the global community maintain “business as usual” scenario (IPCC, 2018). The resultant response of climate systems will depict features associated with increased intensity of precipitation extremes, a sharp decline in the number of wet spell lengths, and an increase in dry spell lengths (Giorgi et al., 2019). The unprecedented impacts of climate extremes threaten human health, economic stability, and stability of natural and build infrastructure (Aghakouchak et al., 2020). Thus, characterizing the response of the anthropogenic climate change, which results in extreme events such as an increase both the intensity and frequency at the regional or local level is an imperative task. This will aid decision and policymakers and planners in developing future adaptation strategies.

Global and regional changes have been noted with substantial upsurge detected over Europe (Fischer and Knutti, 2016; Paplexious and Monanari, 2019), China (Jiang et al., 2012; Yuan et al., 2015; Chen and Sun, 2018; Zhu et al., 2020) and US (Paplexious and Monanari, 2019; Janssen et al., 2014; Kukel et al., 2008; Akinsanola et al., 2020), among other regions. Consequently, much progress has been made to enhance our understanding of the recent changes and possible attributions that links extreme events to the global warming even though the full scientific is deficient (Fischer and Knutti, 2016; Sillman et al., 2013; Myhre et al., 2017;
Kunkel et al., 2008; Pendegrass, 2018). Overall, an increase in moisture as a result of shifts in the dynamical processes has been noted to drive amplification of precipitation intensity.

Comparable to other regions, Africa stands out as one of the most susceptible areas to climate variability and change (Niang et al., 2014). Numerous studies agree that the region above is experiencing an observed change in climate patterns (Trenberth, 2011; Anguilar et al., 2009; Shongwe et al., 2011; Omondi et al., 2014; Taylor et al., 2017). For instance, many subregions have experienced notable changes in precipitation frequency, intensity, and quantity of occurrence over the recent decades (Trenberth, 2011; Donat et al., 2013; Alexander, 2016). Similarly, positive trajectories in temperature have been observed and projected to increase significantly (Collins, 2011; Senevirante, 2012; Niang et al., 2014; Ongoma et al., 2018a). This will affect the broader population's livelihoods that rely entirely on rainfed agriculture to support the economy (FAO, 2019). Further, the projected increase in temperature will intensify moisture loss through amplified evapotranspiration and strengthen the occurrence of drought hazards (Funk et al., 2012; Van Loon, 2019; Ayugi et al., 2020a; Tan et al., 2020).

Despite the widespread evidence of extreme events occurrences, regional variation is noted due to complex physiographical features and processes, resulting in varying responses to the global-scale change (IPCC, 2013). Using the global climate models outputs derived from Coupled Intercomparison Project Phase five (CMIP5; Taylor, 2012), varying researchers have reported this phenomenon of regional variability in the extent, duration, frequency, and intensity of extreme climate events (Zhang et al., 2011; Jiang et al., 2012, 2015; Fischer et al., 2015). A recent study (Weber et al., 2018) observed that temperature projections in sub-Saharan Africa (SSA) are to be higher than the global mean temperature increase. To illustrate, the region situated between 15ºS and 15ºN is projected to experience an amplification in hot nights, coupled with much longer and more frequent heatwaves (Kharin et al., 2018). Thus, it is paramount to characterize the regional trends and future variations of extreme events for robust adaptation and risk management strategies.

East Africa (EA) witnesses’ unusual occurrences of signature immoderate events such as droughts and floods (Viste et al., 2013; Liebmann et al., 2014; Kilavi et al., 2018; Ayugi et al., 2020a; Ongoma et al., 2018a, b). The region located in the tropics and bound along latitude 12ºS - 5ºN and longitude 28º E - 42ºE will need humanitarian assistance if no proper mechanism is put in place. Several studies based mainly on CMIP5 or regional climate models (RCMs) have been conducted to examine to historical trends and future projections of extremes events of the EA region (Ongoma et al., 2018c; Gebrechorkos et al., 2018; Osima et al., 2018; Onyutha, 2020; Ogega et al., 2020; Tegegne et al., 2020). Undoubtedly, these studies' overall
conclusion shows a varying trend of change, mainly attributed to the data sets employed or period analysed.

Essentially, temperature extremes (i.e., minimum and maximum temperature) show an overall upward tendency in many studies (IPCC, 2014; Ongoma et al., 2018a; Gebrechorkos et al., 2018; Osima et al., 2018). Conversely, projections in precipitation extremes using indices developed by the Expert Team on Climate Change Detection and Indices (ETCCDI; Klein Tank et al., 2009; Zhang et al., 2011) are marred by uncertainty and unclear patterns (Osima et al., 2018; Ogega et al., 2020; Onyutha, 2020). To demonstrate, Onyutha (2020) showed significant biases in RCMs employed in simulating maximum wet spell (MWS) over the EA region. Similar uncertainty in precipitation projections is noted across the Greater Horn of Africa (GHA), in a study that utilized a large 25-member RCMs and employed robust technique for detecting climate change signal (Osima et al., 2018). There remains an urgent need for reliable projections of precipitation extremes over the EA region for appropriate measures to be put in place to cushion the population from the adverse impacts of unforeseeable impacts.

The new generation model outputs of phase six (CMIP6; Eyring et al., 2016) provide an opportunity to improve our understanding of climate change impacts resulting from exacerbated global warming. Policymakers and community workers are in dire need of timely information that will enable them to address pertinent issues such as those that pinpoint exact tendencies of historical changes, the magnitude of the shift, and future projections. Presently, no studies to our understanding have attempted to use the models' outputs from CMIP6 with improved parameterization schemes and higher spatial-temporal resolution (e.g., from ~0.7º to ~2.8º) in assessing the projected changes in precipitation extremes over the EA region. Moreover, the new pathways representing a range of future greenhouse gas emissions and land-use change scenarios promise a robust estimate of future projections of hydroclimate variables. They incorporate various assumptions about socio-economic growth, climate mitigation efforts, and global governance (O’Neill et al., 2016).

Consequently, the present study seeks to add to the concerted efforts being undertaken to enhance our understanding of extreme precipitation events' potential occurrence. In particular, the study assesses CMIP6 models' performance in simulating precipitation extremes over the EA domain and further examines the projected changes of EA's extremes under Shared Socio-economic Pathways (SSP2 – 4.5 and SSP5 – 8.5). This will enable decisions and policymakers to develop robust policies for sustainable development. The rest of the paper is structured as follows: section 2 elaborates more on the data and methods used, while section 3 gives the analyses' results. Lastly, discussion and conclusion are presented in section 4.
Figure 1. The map of Africa delineating different sub-regions. The east Africa region marked as with countries considered for analysis in this study.

2. Data Methods

2.1 Data

The study utilized CMIP6 model outputs from DECK experiment (Eyring et al., 2016) accessed through Earth Systems Grid Federation data centers. The daily precipitation variable ($pr$) for historical experiment and two future SSP2-4.5 and SSP5-8.5 are used in the estimation of extreme precipitation events. The SSP-forcing denotes an integrated scenario of possible future climate and societal change, which would be employed to assess issues such as the mitigation and adaptation efforts needed to attain a particular climate outcome (O’Neill et al., 2016). The choice for the two scenarios from the available five possible framework was informed by the assumption that differences in climate outcomes produced by varying scenarios for the same global pathways are likely small relative to varying features of regional climate or/and inter-model uncertainties (O’Neill et al., 2016). The historical experiment starts from 1850 – 2014 while forcing datasets under Scenario Model Intercomparison Project (Scenario MIP; O’Neill et al., 2016) starts from 2015 – 2100. In this study, we selected a baseline period of 1995 – 2014 whereas two future period referred herein as near-future (2021 – 2040) and far-future
(2081 – 2100), respectively. This study utilized the first realization (r1i1p1f1) from fifteen models that have relatively higher spatial resolution (~ 1°). Due to the inherent uncertainties of individual GCMs, the mean ensemble average was employed for its robust estimates compared to each model. Table 1 denotes the model description, including the spatial resolution, the institute(s) possessing the intellectual property rights, the abbreviate name, and key reference(s) for further detailed information.

For the observed datasets, the current work utilized satellite-derived datasets from Climate Hazards Group InfraRed with Station data version two (CHIRPSv2). The datasets are available on a global scale (i.e., 50ºS - 50ºN) and begin from 1981 to the present day on varying timescales. Developed by a lead scientist from the US Geological Survey, the CHIRPS data integrates satellite imagery with a native horizontal grid increment of approximately ~ 27.75 km. Funk et al. (2015) detailed more information regarding datasets. The dataset’s suitability in reproducing observed climate over the study domain has been proven in previous studies (e.g., Gebrechorkos et al., 2017; Kimani et al., 2017; Ayugi et al., 2019). Because of different grid scales, all datasets were re-gridded to 1° x 1° using a remapping technique conducted in the Climate Data Operator toolkit (CDO). The analyses to examine changes in precipitation extremes was conducted for two seasons, namely, March to May (MAM) and for October to December (OND). The MAM season represent period when the region receives more rainfall and locally referred as ‘long-rains’ while OND show winter precipitation, also known as ‘short-rains’. The regional climatology and influencing factors regulating the occurrence of mean and extreme events are well detailed in previous studies (Ongoma et al., 2017; Nicholson, 2017; Camberlin, 2018).

Table 1. Information of the fifteen CMIP6 climate models used in this study

<table>
<thead>
<tr>
<th>S/N</th>
<th>Models</th>
<th>Institution</th>
<th>Resolution</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BCC-CSM2-MR</td>
<td>Beijing Climate Center and China Meteorological Administration, China</td>
<td>1.13°x1.13°</td>
<td>Wu et al. 2019</td>
</tr>
<tr>
<td>2</td>
<td>EC-EARTH3</td>
<td>EC-EARTH consortium, Sweden</td>
<td>0.70°x0.70°</td>
<td>(E-C Earth, 2019b)</td>
</tr>
<tr>
<td>3</td>
<td>EC-EARTH3-Veg</td>
<td>EC-EARTH consortium, Sweden</td>
<td>0.70°x0.70°</td>
<td>(E-C Earth, 2019a)</td>
</tr>
<tr>
<td>4</td>
<td>GFDL-ESM4</td>
<td>Geophysical Fluid Dynamics Laboratory (GFDL), USA</td>
<td>1.25°x1.00°</td>
<td>(John et al., 2018)</td>
</tr>
<tr>
<td>5</td>
<td>INM-CM4-8</td>
<td>Institute for Numerical Mathematics, Russian Academy of Science, Moscow, Russia</td>
<td>2.00°x1.50°</td>
<td>(Volodin et al., 2019)</td>
</tr>
<tr>
<td>6</td>
<td>INM-CM5-0</td>
<td>Institute for Numerical Mathematics, Russian Academy of Science, Moscow, Russia</td>
<td>2.00°x1.50°</td>
<td>(Volodin et al., 2019)</td>
</tr>
<tr>
<td>7</td>
<td>MPI-ESM1-2-HR</td>
<td>Max Planck Institute, Germany</td>
<td>0.90°x1.30°</td>
<td>(von Storch et al., 2017)</td>
</tr>
</tbody>
</table>
2.2 Methods

2.2.1 Model performance metric

As a first step, models were compared with observational data sets to examine their capability of simulating the observed mean and extreme events over the study area. The comparative analysis was conducted for the period 1995 – 2014, which corresponds to the modern baseline period for upcoming sixth assessment report. The statistical metrics of mean bias error (MBE), the root mean square distance (RMSD), and the pattern correlation (PC) was employed in this study to analyze the seasonal extreme simulation. For instance, the PC is used to check the relationship between the model and CHIRPS with -1 or 1 representing the range of perfect correlation or lack of similarity features in the two data sets. Similarly, the RMSD and MBE cross-examine the spread and accuracy of model data sets. The smaller values of the two metrics denote the best performance, while the more extensive distance denotes higher amplitudes than the observed values. Various studies, i.e., Wilks (2006), Chai and Draxler (2014), Ongoma et al. (2018c), and Ayugi et al. (2020b), highlights mathematical functions and necessary information regarding the approaches employed.

2.2.3 Climate extreme indices definition and calculation

This study used a suite of six precipitation extreme indices (Table 2) recommended by the ETCCDMI for monitoring and detection of climate change (Zhang et al, 2011). The listed indices mainly assess changes in the intensity, frequency, and duration of precipitation events over the study area. The indices can be divided into four main categories. Firstly, the duration
indices, which mainly defines periods of excessive wetness/dryness. Here we used consecutive dry days (CDD) and consecutive wet days (CWD). The CDD represents the length of the most prolonged dry spell in a year, while the CWD index represents the most extended wet spell in a year. Secondly, a percentile-based index that defines very wet days (R95P). The precipitation index used in this category represents the rainfall amount falling about the 95th (R95p). Thirdly, threshold-based indices, defined as the number of days in which precipitation value is above/below a fixed threshold. Here we defined the number of very heavy precipitation days > 20 mm (R20). Lastly, the study employed other indices that delineate the period of seasonal precipitation total (PRCPTOT) and those that defines precipitation intensity, such as the simple daily intensity index (SDII). The listed indices are intended to demonstrate the observed and projected change in extreme climate occurrences (Klein Tank et al., 2009; Zhang et al., 2011). More details regarding the indices are summarized in Table 2.

Table 2. Definitions and Units of Rainfall Indices Used in this study

<table>
<thead>
<tr>
<th>ID</th>
<th>Name</th>
<th>Definitions</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRCPTOT</td>
<td>Wet-day precipitation amount</td>
<td>Total precipitation in wet days (RR ≥ 1 mm), defined as ( P_{ij} ) representing daily precipitation amount on day ( i ) in a period ( j ). If the ( i ) denote the number of days in ( j ), then: ( \text{PRCPTOT}<em>j = \sum</em>{i=1}^{I} P_{ij} ) mm</td>
<td></td>
</tr>
<tr>
<td>R95p</td>
<td>Extremely wet days</td>
<td>Total precipitation when ( PP &gt; 95\text{th} ) percentile. Here, ( PP_{cd} ) be daily precipitation amount on a wet day ( c \text{ (} PP\geq1.0 \text{ mm} ) in a period ( i ) and let ( PP_{cd95} \text{ where 95}\text{th} ) percentile of precipitation on wet days in the baseline/projected period. If ( d ) represent the number of wet days in the period, then ( R95P_j = \sum_{c=1}^{d} PP_{cd} \text{ where } PP_{cd} &gt; PP_{cd95} ) mm</td>
<td></td>
</tr>
<tr>
<td>SDII</td>
<td>Wet-day intensity</td>
<td>Average precipitation from wet-days. This can be defined as ( PP_{wj} ) be the daily precipitation amount on wet days, ( w \text{ (} PP\geq1 \text{ mm} ) in period ( j ). If ( w ) represents number of wet days in ( j ), then ( SDII_j = \frac{\sum_{w=1}^{W} PP_{wj}}{W} ) mm/day</td>
<td></td>
</tr>
<tr>
<td>R20mm</td>
<td>Heavy precipitation days</td>
<td>Number of very heavy precipitation days (RR ≥ 20mm). That is; let ( PP_{ij} ) be the daily precipitation amount where ( PP_{ij} \geq 20 \text{ mm} ) mm/day</td>
<td></td>
</tr>
<tr>
<td>CDD</td>
<td>Consecutive dry days</td>
<td>Maximum number of consecutive dry days (RR ≤ 1 mm). Let ( PP_{ij} ) be the daily precipitation amount on day ( i ) in period ( j ). Count the largest consecutive days where ( PP_{ij} \leq 1 \text{ mm} ) days</td>
<td></td>
</tr>
<tr>
<td>CWD</td>
<td>Consecutive wet days</td>
<td>Maximum number of consecutive dry days (RR ≥ 1 mm). Let ( PP_{ij} ) be the daily precipitation amount on day ( i ) in period ( j ). Count the largest consecutive days where ( PP_{ij} \geq 1 \text{ mm} ) days</td>
<td></td>
</tr>
</tbody>
</table>

3.0 Results and Discussions

3.1 Evaluation of model performance

The first step of the analyses examined the capability of MME to simulate the observed mean and extreme events over the study area. The spatial distribution of the six extreme indices used (listed in table 2) are displayed in Figure 1 (MAM) and Figure 2 (OND). The study employed
CHIRPS as observation datasets to analyze the model performance. Regions where models agree with a statistical significance value of > 70% are marked with sloped black boxes. The CHIRPS datasets have been proven to perform exemplary over the study region following detailed assessment study by various researchers (Kimani et al., 2018, Cattaini et al., 2018; Gebrechorkos et al., 2018; Dinku et al., 2018; Ayugi et al., 2019). To highlight, Dinku et al. (2018) employed > 1200 station datasets to evaluate the CHIRPS and established a higher skill and low or no bias over EA domain.

The results show that MME of CMIP6 can depict the observed spatial distribution of precipitation extremes for both seasons (Figures 2 and 3), albeit some noticeable exceptions in some indices. For instance, the MAM season (Figure 2) underestimates the total precipitation occurrence with ≤ 10% bias while extremely wet days are overestimated in model ensemble. Interestingly, there were also differences in the estimations of consecutive dry days or wet days during the study period. Significant biases are depicted in CWD, with a high magnitude of ≥ 160% covering the whole region. The observed declining trends in the seasonal precipitation over the region is not well captured by the MME, leading to huge biases noted. In agreement with previous studies (i.e., Osima et al., 2018; Ogega et al., 2020), the GCMs show an underestimation of CDD, and R20mm, especially over eastern Kenya and northeastern Tanzania, where model agree significantly. Remarkably, western Uganda shows a substantial bias of overestimating heavy precipitation days despite underestimating in most regions. This could be due to moist westerlies originating from the Congo basin resulting in enhanced rain during this season in the north and southwest when other parts of the country are cold and dry (Mchugh 2004; Kizza et al. 2009).
Figure 2. Spatial distribution of March-April-May (MAM) precipitation extremes, (left)–(right) PRCPTOT, R95p, R20mm, CDD, CWD, and SDII from (top)–(bottom) CHIRPS (OBS), Ensemble Mean (MME), and percentage bias of the MME relative to OBS for the present-day period, 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the changes, are marked with sloped black boxes.

On the other hand, the OND season (Figure 3) demonstrates the incidence of underestimations of CDD, SDII, and R20mm in most regions, except for western Uganda, that depicts significant positive bias of the number of very heavy precipitation days. Conversely, the occurrence of CWD, R95p, and PRCPTOT shows significant overestimations over most regions. Interestingly, similar to the MAM season, the consecutive wet days are strongly overestimated with bias > 160%, which is substantial in most areas. This depicts the inability to models to reflect the recent drying patterns observed over the study region since 1999 (Lyon...
Previous studies have established the causes of observed drying patterns attributed to the western Indian Ocean (William and Funk, 2011).

Overall, the MME of CMIP6 simulates the spatial patterns of daily precipitation extremes reasonably well over the study region. Most models show the higher distribution of precipitation along the western side of the study area and dry bias and the eastern Kenya and parts of Tanzania. Except for CWD, most indices are well represented over the study region, thereby giving the model ensemble confidence to be employed to projection extreme events over the study area.

Figure. 3. Spatial distribution of October–November–December (OND precipitation extremes, (left)–(right) PRCPTOT, R95p, R20mm, CDD, CWD, and SDII from (top)–(bottom) CHIRPS (OBS), Ensemble Mean (MME), and percentage bias of the MME relative to OBS for the present-day period, 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the changes, are marked with sloped black boxes.

3.1 Seasonal precipitation distributions

3.1.1 MAM precipitation extremes
The overarching objective of climate projection is to equip society and local communities with timely and relevant information about future changes in weather and climate. Consequently, the present study considered relevant extreme indices suitable for examining the societal needs that are “user-relevant” for appraising possible future changes in extreme events. Figures 4 and 5 present spatial distribution of the projected changes in MAM precipitation extremes under the SSP2 – 4.5 (SSP5 – 8.5) scenarios for the near future (2021 - 2040) relative to 1995–2014. The region will experience varying changes over the next few decades. For illustration, the results show that the area will experience a significant occurrence of extreme wet days that is projected to occur over the whole region. The projected upsurge range between 0.2 – 0.6 mm in both scenarios.

Further, analysis shows an increase in total PRCPTOT during the SSP5 – 8.5 scenario compared to the SSP2 – 4.5 scenario. The projection for modest mitigation (Figure 4) demonstrate a declining trend over Kenya and Uganda while significant increase tendency is noted over the Tanzania region. Notably, no significant differences are projected to occur in wet-day intensity index (SDII), both in SSP2 – 4.5 or in worst-case, no policy (i.e., SSP5 – 8.5) scenario. The CWD index, CDD, and R20mm equally show no significant changes in the two scenarios projected (Figures 4 and 5). The occurrence of heavy precipitation days is likely to intensify over the Tanzania region during SSP2 – 4.5 and further strengthen to cover other areas such as western Kenya and northwest Uganda. A recent study (Mafuru and Guirong, 2020) noted an increase of heavy rainfall events (HRE) with a total of 822 cases, which were mostly concentrated over the northern section of Tanzania. The study further attributed the upsurge in HREs to several factors such as low-level westerly convergence, intensified advection of moisture from both the Indian Ocean (IO) and Congo basin, and distinct tropospheric warm temperature anomaly. The results of the present study suggest that the region will continue to experience changes in extreme weather and climate events. Most indices demonstrate the reduction in extreme incidences, except for total precipitation and the variability in very wet days (R95p). Such changes will likely affect most sectors, such as agricultural productivity and societal infrastructure.
Figure 4. Spatial distribution of the projected changes in March-April-May (MAM) precipitation extremes under the SSP2-4.5 scenario for the near future (2021-2040) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.
Figure 5. Spatial distribution of the projected changes in March-April-May (MAM) precipitation extremes under the SSP5-8.5 scenario for the near future (2021-2040) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.

Projected changes towards the end of the century (i.e., 2081 – 2100) relative to 1995 – 2014 is for the long rainy season is presented in Figure 6 (SSP2 – 4.5) and Figure 7 (SSP5 – 8.5). Because of the adverse impacts of extreme events, it is essential to examine its evolution both in the near future and towards the end of the century for adequate planning purposes. Moreover, the large-scale climate drivers regulating the interannual and decadal variability of precipitation over the region for the MAM season remains complex (Lyon and DeWitt, 2012; Yang et al., 2014). Assessment of the number of wet days and simple precipitation index are
represented by PRCPTOT and SDII. The results (Figures 6 and 7) show a significant increase in total precipitation in wet days (RR ≥ 1mm) covering the entire area with a substantial magnitude of > 40 mm impacting the southwestern parts of Tanzania, southern Uganda and along parts of western Kenya. Noticeably, during the SSP2 – 4.5 scenario, the spatial patterns of PRCPTOT depict the considerable impact over southwest and southeast Tanzania while during the SSP5 – 8.5, significant shift is noted towards the southwest section only. Conversely, the intensity index depicts no remarkable change in both scenarios towards the end of the century. The spatial distribution shows comparable patterns with Uganda and along the southeast stretch of Kenya and Tanzania, highlighting significant impact with most models agreeing to the projected changes. The projected SDII change under the SSP5 – 4.5 scenario show 0.4 – 1.6 mm, while SSP5 – 8.5 depicts a 0.8 – 1.6 mm increase towards the end of the century.

Further analyses on the duration indices, which mainly defines periods of excessive wetness/dryness such as CDD and CWD, show continuous drying (wetting) patterns during the two scenarios examined. The CDD depicts significant drying patterns over Kenya and few areas along with southern parts of Tanzania during SSP2 – 4.5 and 5 – 8.5 scenarios. Similar patterns are shown for CWD during the study period but for wetting trends. Besides, the study considered R95p and R20mm to examine the evolution of the number of days with heavy precipitation and projected changes in total rainfall with >95th percentile. The two indices' results depicted noteworthy positive trajectories over the whole region with values of 0.2 – 0.4 mm (R95p) and 0.4 – 1.4 mm (R20mm) during the two scenarios.

Overall, the study area will experience varying extremes, such as a reduction in PRCPTOT under 'business as usual' scenario than a modest mitigation policy scenario. A decrease in MAM precipitation could be due to projected earlier onset/cessation dates relative to the baseline period, possibly impacting the long rain season (Ogega et al., 2020). Likewise, the persistent drying patterns are showed in CDD, which is likely to intensify under the SSP5 – 8.5 scenario. The resultant impact will likely to be reduced agricultural production which mainly relies on rainfall and other climatic variables. Precipitation intensity will likely to increase with cases of R95p, R20mm, and CWD, showing significant positive projections. The incidences of concurrent wetness/dryness projected agree with previous studies (Shongwe et al., 2011; Liebman et al., 2014; Maidment et al., 2015). The region is prone to the occurrence of drought/flood incidences, which are mainly a result of anthropogenic influence and changes associated with internal variability, e.g., by ENSO and in Interdecadal Pacific Oscillation (IPO) (Gu et al., 2013; Lyon, 2014; Hua et al., 2016; Dai, 2016).
Figure 6. Spatial distribution of the projected changes in March-April-May (MAM) precipitation extremes under the SSP2-4.5 scenario for the Far future (2081-2100) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.
3.1.2 OND precipitation extremes

Recent studies have shown that EA region is likely to experience a massive increase in precipitation occurrence during OND season as compared to MAM season (Maidment et al., 2015; Ongoma et al., 2019; Tan et al., 2020). Understanding the evolution of extreme events in the wake of the projected increase in precipitation remains a crucial task. This study assessed the changes in extreme during period 2021 – 2040 and towards the end of century 2081 – 2100.
for two scenarios SSP2 – 4.5 and 5 – 8.5. Figures 8 and 9 displays the spatial distribution of the projected changes during OND season under two main scenarios utilized in this study. The results for extreme indices show no significant change in the two scenarios employed. For instance, projections for PRCPTOT (Figure 8) display intensification variations along with western Uganda with > 40 mm while reduction trends (< -10 mm) are observed over Tanzania region. Corresponding patterns are detected during SSP5 – 8.5 scenario (Figure 9). Regarding the projected changes in R95p, the MME demonstrate an agreement of 70 % in likely changes over the entire EA region with reported changes of about 0.2 – 0.4 mm in both figures 8 and 9. Notable increasing trends are recorded in CDD over entire Kenya while southern parts of Tanzania depict likelihood of reduction trends, evidenced by most models agreement. Likewise, the CWD projections exhibit tendencies of intense occurrence around Lake Victoria region whereas no significant changes are observed are over most parts, except for the southern parts of Tanzania where a reduction of up to 4 days in a year is projected. The findings of the present study are in harmony with the recent study that employed large ensemble members from regional climate models (RCMs) models outputs to project changes in extremes precipitation over EA region (Cattaini et al., 2018; Osima et al., 2018; Ogega et al., 2020). Studies above noted an increase(decrease) in CDD (CWD) over the study domain which is mainly associated with the alteration in the Hadley circulations and thermodynamic components such as Indian Ocean Dipole (IOD) (Hastenrath et al., 2011; Endris et al., 2016, 2019).
Figure 8. Spatial distribution of the projected changes in October-November-December (OND) precipitation extremes under the SSP2-4.5 scenario for the near future (2021-2040) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.
Figure 9. Spatial distribution of the projected changes in October-November-December (OND) precipitation extremes under the SSP5-8.5 scenario for the near future (2021-2040) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.

The projections showing probable changes towards the end of the twenty-first century are presented in figures 10 and 11. The figures show likely deviations in OND precipitation extremes under the SSP2-4.5 scenario relative to the baseline period. Undoubtedly, the results show an intense incidence of projected SDII, PRCPTOT and CWD over entire Kenya and Uganda. At the same time, the sharp decline is anticipated over southern parts of Tanzania (Figures 10 and 11). Reverse trends are showed CDD which indicate significant drying scenario over Kenya and Uganda while southern Tanzania exhibits fewer incidences of CDD.
The rise in CDD, the decline in CWD and the general increase in SDII may suggest the likelihood of less rainy days with regular precipitation above average. These findings pose a challenge to farming activities and, thus, to the socio-economic well-being of EA societies whose economy is heavily powered by small-scale rain-fed agriculture production (Adhakari et al., 2015; Mumo et al., 2018).

The tendencies of R95p and R20mm signify percentile-based and threshold indexes showing a remarkable increase in the projected precipitation. The observed rise in both parameters (Figures 10 and 11) are mainly centred around inland lake region with values of 0.2 – 0.4 mm (0.4 – 1.6 days) for R95p (R20mm), respectively. Presence of complex physiographical features has considerable influence on the variation of extreme events and impacted regions (Nicholson and Kim, 1997; Camberlin, 2018). For instance, the presence of large inland water bodies, ie. Lake Victoria, which is the largest freshwater lake in Africa and second in the world covering about 68000 km² and bordering three countries; Uganda (45 %), Tanzania (49 %) and Kenya (6 %) have a significant influence on the incidences of extreme events (Bowden, 2007).

Additionally, high elevation (i.e., Mt. Kenya (5000 m); Mt. Kilimanjaro (5892 m); Mt. Elgon (4321 m) and Mt. Ruwenzori (5109 m)) among others impact hugely on precipitation extreme. Remarkably, the shift in a projected increase in regions of northeastern Kenya, which is predominantly arid and semi-arid (ASAL) presents an excellent opportunity for agricultural activities that have been deprived due to unbearable climatic conditions.
Figure 10. Spatial distribution of the projected changes in October-November-December (OND) precipitation extremes under the SSP2-4.5 scenario for the far future (2081-2100) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.
Figure 11. Spatial distribution of the projected changes in October-November-December (OND) precipitation extremes under the SSP5-8.5 scenario for the far future (2081-2100) relative to 1995–2014. The black dots indicate statistically significant changes at the 95% confidence level while areas, where 70% of models agree on the projected changes, are marked with sloped black boxes.

4. Summary and Conclusion

This study sort to examine the future changes of seasonal precipitation extremes over EA region using MME derived from fifteen models’ outputs of CMIP6. The research employed subset of precipitation indices provided by ETCCDMI to assess extreme incidences during two time slices defined as near future (2021 – 2040) and far future (2081 – 2100). The two main projection utilized is drawn from Tier 1 ScenarioMIP: SSP2 – 4.5 and SSP5 – 8.5. Firstly, the
study examined MME's capability to simulate the observed extreme events over the study area for the period 1995 – 2014 using CHIRPS as the observed datasets. Our results show that MME of CMIP6 models can depict the observed spatial distribution of precipitation extremes for both seasons, albeit some noticeable exceptions in some indices. For instance, the CMIP6 ensemble generally depicted large biases of CWD overestimation during the MAM and OND season, respectively.

In agreement with previous studies (e.g., Ongoma et al., 2018c; Osima et al., 2018; Ayugi et al., 2019), this study's findings yield considerable confidence in CMIP6 to be employed for projection of extreme events over the study area. Analysis of extreme estimations shows an increase (decrease) in CDD(CWD) during 2081 – 2100 relative to the baseline period in both seasons. Moreover, SDII, R95p, R20mm, and PRCPTOT demonstrate significant OND estimates compared to the MAM season. The spatial variation for extreme incidences shows likely intensification over Uganda and most parts of Kenya, while reduction is observed over the Tanzania region. The increase in projected extremes during two main rainfall seasons poses a significant threat to the sustainability of societal infrastructure and ecosystem wellbeing. On the other hand, it is imperative to note that the predominantly ASALs and are estimated to experience wet conditions. This will provide the new opportunity for agricultural and other economic activities. The projected drying patterns over the Tanzanian belt call for a new policy formulation and possible mitigation measures to cushion the community from possible impacts of drought events that are likely to ravage the region. The results from these analyses present an opportunity to understand the emergence of extreme events and the capability of model outputs from CMIP6 in estimating the projected changes. More studies are encouraged to examine the underlying physical features modulating the occurrence of extremes incidences projected for relevant policies.

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investigation. Hassen Babaousmail: methodology, investigation, data curation. Victor Ongoma: Validation, writing-review, and editing.

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