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RESEARCH ARTICLE

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Evolution and copula modelling of drought duration and severity over Africa using CORDEX-CORE regional climate models

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Abstract

This study assessed the dependence of drought severity and duration across four subregions (Southern, Western, Eastern and Central) in Africa using copula modelling. The analysis was carried out for the reference period 1991–2020 and the future period 2071–2099. Simulated daily precipitation at a horizontal resolution of 0.22° were obtained from three regional climate models (RCMs) participating in the Coordinated Output for Regional Evaluations within the Coordinated Regional Downscaling Experiment (CORDEX-CORE). The RCMs were downscaled by three global climate models and validated using three high-resolution gridded daily precipitation products obtained from The Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS), Climate Prediction Center Africa Rainfall Climatology Version 2.0 (CPC-ARC2) and Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT). Comparison of precipitation from the RCMs with the three gridded reference observations shows relatively good performance across the different regions with median value within the range of 3–5 mm·day^{-1} in Central Africa, 1.5–4.5 mm·day^{-1} in Western Africa, 1.8–2.8 mm·day^{-1} in Eastern Africa and 0.5–2.2 mm·day^{-1} in Southern Africa. On the other hand, the correlation values of drought duration–severity from CORDEX-CORE models in the different regions of Africa exhibit predominantly strong values greater than 0.8 for both historical and projected climate. The analysis also considered two families of copulas: Archimedean (Frank, Clayton, Gumbel) and Elliptical (Gaussian, Student's *t*). The performance of the copula functions were estimated using the Akaike information criteria (AIC). Generally, there is a good agreement in the distribution of observed precipitation among the three observational data products across the subregion of Africa, with slight differences attributed to the different processing algorithms of the products. Across West Africa, mean precipitation values from CPC, CHIRPS and TAMSAT was 2.86, 3.16 and 3.07 mm·day^{-1}, respectively. The CCLM-NCC underestimated the mean values of precipitation reported in the observation data, while CCLM-MPI and CCLM-HAD overestimated the mean values of precipitation in the West Africa region.

KEYWORDS
COPULA modelling, CORDEX-CORE, drought severity

1 | INTRODUCTION

Across Africa, especially the Sub-Saharan region, the economy and human livelihoods depend on agriculture and water resources. To a large extent, water resources play a crucial role in the day-to-day living of Africans (Braune & Xu, 2010; Nojiyeza, 2022; Pollard & Du Toit, 2011). In the agricultural sector, which is the largest consumer of water in Africa (Blignaut et al., 2009; Yazdanpanah et al., 2014), water and its resources play a vital role in sustaining the food production process. Hence, the importance of water to the agricultural sector and the natural environment cannot be overemphasized in Sub-Saharan Africa (Allan et al., 2012; Dalin & Conway, 2016; Gleick, 1998; Sissoko et al., 2011; Union, 2003). It, therefore, follows that availability of water in the right quantity and quality is needed for the smooth functioning of the natural environment. Hence, threats to water availability will impact the ecosystem and economy of individual states within the region. Water is made available within the region due to precipitation in the form of rainfall. Therefore, an adequate supply of precipitation during the monsoon seasons ensures that water is available for use. On the contrary, due to the changing climate and other pressures on the natural environment, precipitation regime is being affected and shifts are being observed regarding intensity, magnitude and frequency of precipitation across the subregion. Specifically, the threats to precipitation regime within the African continent include but are not limited to dry spells (Olusegun et al., 2022) and droughts (Masih et al., 2014). Droughts can either be meteorological, hydrological or agricultural (Orimoloye et al., 2021; Sivakumar, 1991).

Several studies on drought have been conducted in East Africa, West Africa and South Africa (Ogunjo & Olusola, 2022; Orimoloye et al., 2022; Sivakumar, 1991). In East Africa and other parts of SSA, access to freshwater is in a very critical state as a result of drought (Ntale & Gan, 2003; Orimoloye et al., 2022; Thomas et al., 2021; Verschuren et al., 2000) and other factors such as but not limited to sedimentation (Ashley et al., 2004; Reed & Cumberlidge, 2006), pollution, land degradation (Maitima et al., 2009; Stahl et al., 1993; Wynants et al., 2021), high rates of evaporation from Lake Victoria (Nicholson et al., 2021; Yin et al., 2000; Yin & Nicholson, 1998) and the anoxic situation in Lake Tanganyika (Huc et al., 1990; Nahimana et al., 2008; Rudd, 1980). In Southern Africa, most countries such as South Africa, Botswana, Namibia and Zimbabwe present a lower than global average mean annual precipitation (Shongwe et al., 2009) that impacts rainfall–runoff relationships, economic growth and hydrological cycle dynamics. In Southern Africa, renewable water resources amount to around 2300 km^3 annually (https://www.giz.de/en/worldwide/14931.html). However, as observed in other regions, there is a considerable variation in its distribution and accessibility. Approximately 70% of this water comes from transboundary rivers and the remainder from lakes and groundwater (https://www.giz.de/en/worldwide/14931.html). The situation in West Africa is not entirely different. Even though the region experiences a high amount of rainfall during the monsoon seasons, changing rainfall regimes and late-onset and cessation of rains due to prolonged dry spells frustrate the water supply across the region. Southern Africa experiences significant precipitation, although not as high as West Africa. Precipitation distribution across the regions is highly seasonal; even within each region, considerable variations exist across landscapes.

Drought indices can be estimated using meteorological, hydrological, remote sensing or composite variables. Drought indices based on meteorological variables include the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Standardized Anomaly Index (SAI) and Palmer Drought Severity Index (PDSI). Depending on the indices' values, drought properties such as duration, severity and intensity can be estimated. The sum of the integral area below zero of each drought event is referred to as the drought severity, while the number of months in each drought event is the duration. Drought duration and severity give information about the impact of a drought event in a region. A high value of drought severity with a long duration implies severe water scarcity that persists for several months. This has more economic implications than a drought of low severity and duration. Globally, drought duration, severity and frequency increased significantly between 1951 and 2010 (Spinoni et al., 2014). Drought duration and severity have been evaluated for regions of Africa including East Africa (Ayugi et al., 2020; Kalisa et al., 2020), West Africa (Gebrechorkos et al., 2022) and Central Africa (Gizaw & Gan, 2017). One of the common approaches to understanding the relationship between drought duration and severity is the use of copulas (Khan et al., 2021; Shiau, 2006). Spatial analysis of drought severity and duration over South Africa revealed more severe droughts in the southern and western regions compared to the eastern and northern regions (Botai et al., 2017). El Niño events have been associated with the intensity and spatial extent of drought in Southern Africa (Rouault & Richard, 2005). It has also been reported that drought severity and duration in the Sub-Saharan region is driven by both the North Atlantic Oscillations and Southern Oscillation Index (Henchiri et al., 2021).

Estimating drought indices requires meteorological variables such as precipitation. Unfortunately, there is a lack of historical observational meteorological data in Africa. This is due to several factors, such as large land mass, funding, insecurity and adequate manpower. This impact is not limited to our understanding of past weather but also our ability to project future weather events. To this end, scientists complement limited observational data with satellite and reanalysis climate data. Some of the gridded observational data available over the African region include the Global Precipitation Climatology Centre (GPCC), the University of Delaware (UDEL), Climate Prediction Center Africa Rainfall Climatology (CPC-ARC) and Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS). Most of these products have been found to have good performance over different regions of Africa (Agutu et al., 2017; Ogunjo et al., 2022). Meteorological data can also be obtained from global climate models (GCMs), a complex mathematical representation of the major climate system components and processes. However, these are usually at a low resolution over the entire world. GCMs can be downscaled with regional climate models (RCMs), which offer higher resolutions on a regional scale. RCMs have been used to evaluate drought over different regions of the world, such as Brazil (de Medeiros et al., 2022). The variation in performance of the simulations within the region and across different regions is a function of how well the GCMs physics are integrated to those of the RCMs and more importantly how these are being infused in the high-resolution setting of the downscaling experiments (Dosio et al., 2021; Gnitou et al., 2021; Tamoffo et al., 2022). This statement has also been corroborated in another study by Dosio et al. (2021). Dosio et al. (2021) stated that variations in drying and wetting over different regions as observed in their study could be related to specific physical mechanisms that are better resolved by the higher models. In their study, Gnitou et al. (2021) stated that the CORDEX-CORE simulations' deficiencies are likely related to how certain processes are represented within the RCM models. The authors added that CORDEX-CORE simulations could be a valuable product for Africa's high-resolution precipitation data. The CCLM model, driven by a reanalysis model, has been found to succinctly capture the precipitation dynamics of East Asia (Zhou et al., 2016). From the foregoing, there is a high dependence on water resources across Africa (Abiodun et al., 2019).

Drought poses a clear, present and future threat to water resources in the different regions of Africa. There has been an attempt to understand the trend, variations and other statistical characteristics of drought within the region over the last few decades. However, most of these studies have been conducted at the country or regional level. Furthermore, drought characteristics (intensity, frequency, duration and severity) in different regions of Africa have not been adequately explored. Furthermore, the few studies that examined drought characteristics did not consider the statistical relationship between drought duration and severity. Therefore, it is not enough to examine historical droughts and their characteristics in the different regions of the world; there is also the need to investigate projected droughts for climate change mitigation and adaptation. There is, therefore, a need to monitor and predict future drought trajectories and drought duration–severity relationships across Africa to aid timely and efficient coordinated response to drought events. Hence, this study aims to investigate historical and projected drought, including the relationship between drought duration and severity, over different regions of Africa using a simulated daily precipitation obtained from three regional climate models participating in the Coordinated Output for Regional Evaluations within the Coordinated Regional Downscaling Experiment (CORDEX-CORE). To achieve the stated aim, the study will answer the following questions: (1) What is the distribution and variation in historical and projected drought characteristics—duration and severity?; (2) Are there any association or dependence between drought duration and severity across regions in Africa? (3) How well do regional climate models evaluate meteorological droughts within Africa?

2 | DATA AND METHODS

2.1 | Gridded observation data products

This study used three high-resolution gridded daily precipitation as reference datasets. They are (1) the Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS) is a blended gauge–satellite product that consists of gauge-calibrated, infrared precipitation estimates over land areas at a resolution of 0.25° (Funk et al., 2015b). It is freely available from the UC Santa Barbara Climate Hazard Group's website https://data.chc.ucsb.edu/products/CHIRPS-2.0 at a daily temporal resolution. (2) Climate Prediction Center Africa Rainfall Climatology Version 2.0

(CPC-ARC2) at a resolution of 0.1° (Novella & Thiaw, 2013). It combines the 3-hourly geostationary infrared data centred over Africa from the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) and the Global telecommunication Systems gauge observations reporting 24 h rainfall over Africa. The data is freely available at https://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.CPC/.FEWS/.Africa/.DAILY/.ARC2/.daily/.est_prcp/dataselection.html?Set-Language=en. (3) Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT) version 3 at a resolution of 0.0375° (Maidment et al., 2017) which is freely available at https://www.tamsat.org.uk/data. These three datasets are sourced from gauge and satellite observations with long continuous records and overall good performance over the study area (Dembélé et al., 2020). For instance, Bichet and Diedhiou (2018a, 2018b) in their study on precipitation extremes found a good performance of CHIRPS datasets in the representation of mean precipitation, intensity of precipitation, number of wet days and average length of dry spell when compared with 18 daily rainfall observing stations across the the Sahel and Guinea coast of West Africa. Also, the performance of CHIRPS over Africa (Maidment et al., 2015), and in particular the subregions of focus (i.e., Eastern Africa (Dinku et al., 2018), Western Africa (Sacré Regis et al., 2020), Southern Africa (du Plessis & Kibii, 2021) and Central Africa (Camberlin et al., 2019)) shows a good agreement with other sources of observational data as well as gauge measurement. It is, therefore, suitable for drought monitoring and analysis. The weakness of one is overcome by the strength of the other since there appears to be no single dataset capable of absolute replication of both the temporal and spatial distribution or magnitude of rainfall across the region. Hence, the choice of the three datasets is expected to account for the uncertainties arising from the lack of continuous in situ precipitation data over the entire region.

2.2 | Data from model simulations

Simulated daily precipitation at a horizontal resolution of 0.22° (about 25 km) was obtained from three regional climate models participating in the Coordinated Output for Regional Evaluations within the Coordinated Regional Downscaling Experiment CORDEX-CORE, hereafter referred to as CORE (Gutowski Jr et al., 2016; Remedio et al., 2019). COSMO-CLM5 (CCLM5; Baldauf et al., 2011; http://cosmo-model.org) is a three-dimensional nonhydrostatic regional climate model version of the operational weather forecast model Consortium for Small-scale Modeling (COSMO) of the German Weather Service. A detailed description of the CORE experiment protocols' model setup and configuration are explained in Sørland et al. (2021), Doms et al. (2011) and Panitz et al. (2014). REMO2015 (Remedio et al., 2019) developed at the Climate Service Center Germany (GERICS) is a three-dimensional, limited-area hydrostatic, atmospheric circulation model (Jacob et al., 2012). RegCM4 Giorgi et al. (2012) model employs the hydrostatic dynamical core from the mesoscale model MM5 (Grell et al., 1994) that is based on split-explicit advection, sigma-*p* vertical coordinates, an Arakawa-*b* staggered horizontal grid and different choices of physics parameterizations. Each of the three RCMs is driven by three global climate models from the Coupled Model Intercomparison Project Phase 5 (CMIP5). Table 1 shows the list of the RCMs, their driving GCMs and the parameterizations. Simulations from COSMO-CLM5 and the three driving GCMs are hereafter referred to as CCLM-HAD, CCLM-NCC and CCLM-MPI; from the REMO2015 model are hereafter referred to as REMO-HAD, REMO-NCC and REMO-MPI; and from the RegCM4 model are hereafter referred to as REG-HAD, REG-NCC and REG-MPI.

The model simulations data of daily precipitation were retrieved from the archive of the Earth System Grid Federation (https://cordex.org/data-access/esgf/) index nodes for the period 1991–2020 and 2070–2099. These periods cover the historical and projected future forced by observed natural/anthropogenic sources and Representative Concentration Pathways 8.5 (RCP8.5) (Van Vuuren et al., 2011), respectively. The selected 1991–2020 reference period agrees with the World Meteorological Organization's recently adopted climatological standard normal and would be considered for model evaluation and future projection. All model simulations of precipitation were remapped to the same grid as CHIRPS reference observation.

2.3 | Subregions of focus in Africa

The lack of homogeneous spatial and temporal precipitation regimes over Africa necessitates the analysis of drought duration and severity for smaller subregions with fairly uniform geographical characteristics. Here we divided the African continent into four subregions of focus as depicted in Figure 1. The areas within Southern Africa examined in this study are bounded by latitudes 18°–35°S and longitudes 12°–38°E. Similarly, for Western Africa areas within latitudes 4°–15°N and longitudes 10°W–10°E; Eastern Africa bounded at latitudes 15°S–20°N and longitudes 25°–40°E; Central Africa at latitudes 10°S–10°N and longitudes 10°–25°E.

TABLE 1 Parameterizations of RCMs used in the CORDEX-CORE Africa domain

Model	Driving GCMs/resolution	Parameterization	Schemes	References
RegCM4	HadGEM2-ES (Jones et al., 2011) 1.25° × 1.85°	Boundary layer processes	Holtslag	Holtslag et al. (1990) and Holtslag and Boville (1993)
	MPI-ESM-MR (Stevens et al., 2013) 1.8653° × 1.875°	Interaction surface-atmosphere	Community land model version 4.5 (CLM4.5)	Oleson et al. (2008)
	NorESM1-M (Iversen et al., 2013) 1.8947° × 2.5°	Turbulent fluxes over sea	Zeng scheme	Zeng et al. (1998)
		Cumulus convection	Tiedtke over the land and Kain-Fritsch over the sea	Tiedtke (1989) and Kain (2004)
		Radiation scheme	NCAR community climate model 3	Kiehl (1996)
		Large-scale precipitation	Subgrid explicit moisture scheme (SUBEX)	Pal et al. (2000)
REMO2015	HadGEM2-ES (Jones et al., 2011) 1.25° × 1.85°	Boundary layer	Monin–Obukhov similarity theory	Louis (1979)
	MPI-ESM-LR (Giorgetta et al., 2013) 1.8653° × 1.875°	Cumulus	Tiedtke with modifications	Tiedtke (1989)
				Nordeng (1994)
	NorESM1-M (Iversen et al., 2013) 1.8947° × 2.5°	Microphysics	Lohmann and Roeckner (1996)	Lohmann and Roeckner (1996)
COSMO-CLM5	HadGEM2-ES (Jones et al., 2011) 1.25° × 1.85°	Radiation scheme	Ritter and Geleyn	Ritter and Geleyn (1992)
	MPI-ESM-LR (Giorgetta et al., 2013) 1.8653° × 1.875°	Convection	Tiedtke scheme being modified by the German Weather Service DWD	Tiedtke (1989)
	NorESM1-M (Iversen et al., 2013) 1.8947° × 2.5°	Microphysics	Four category microphysics scheme that includes cloud water, rain water, snow and ice	Doms et al. (2013)
				Heise and Schrodin (2002)
		Land surface	Soil–vegetation–atmosphere transfer submodel TERRA-ML	Doms et al. (2011)

2.4 | Drought

The Standardized Precipitation Index (SPI) as defined by McKee et al. (1993) was considered in this study. The SPI has been used for several investigations of drought events within the African region (Dutra et al., 2013; Kalisa et al., 2020; Ogunjo, 2021; Ogunjo et al., 2019a). The SPI approach evaluates precipitation departure from the mean value during a given period using a probability distribution. The precipitation data are fitted to the Gamma distribution (Equation (1)), and parameters are estimated using the maximum likelihood method,

$$G(y) = \frac{1}{\beta^{\theta}\Gamma(\theta)} \int_0^y y^{\theta-1} e^{-y/\beta} dx, \tag{1}$$

where $y > 0$, Γ is the gamma function, θ and β are the form and scale parameter, respectively. The SPI values were evaluated at 3-month time scale.

From the computed SPI values, drought duration and severity can be defined. The severity is estimated as

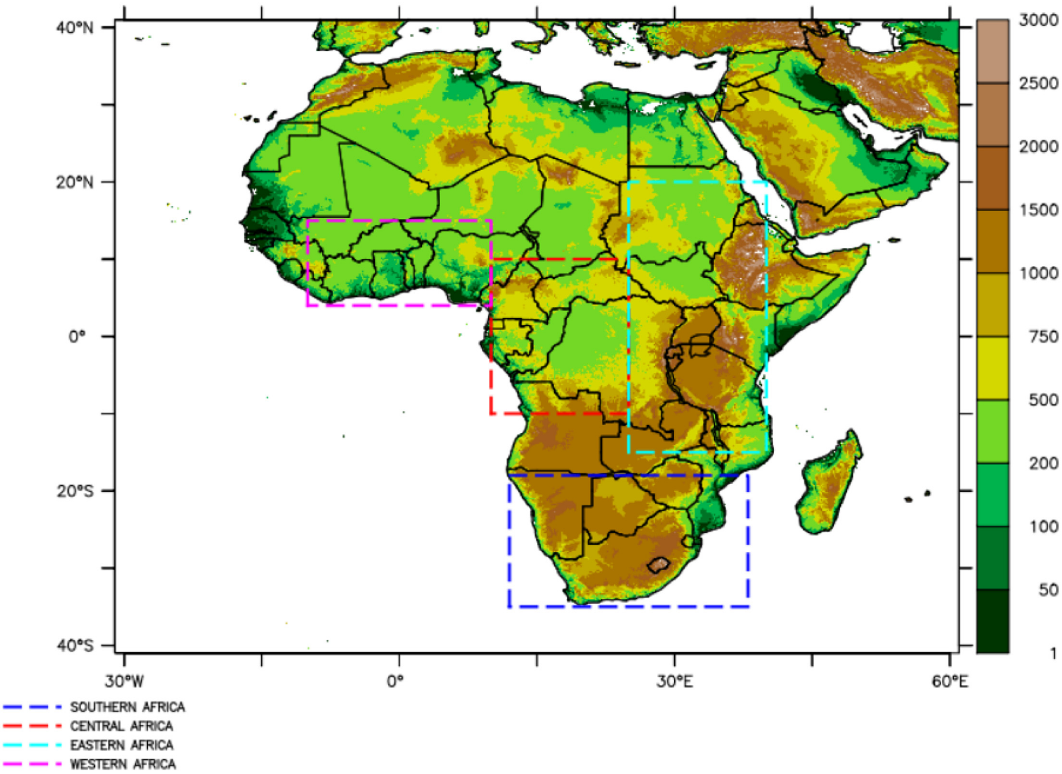

FIGURE 1 Elevation relative to sea level (m) for Africa and the subregions of focus. The GEBCO_2020 Grid, a continuous terrain model for oceans and land at 15 arc-second intervals (https://coastwatch.pfeg.noaa.gov/erddap/griddap/GEBCO_2020.html) [Colour figure can be viewed at wileyonlinelibrary.com]

$$S = -\sum_{i=1}^{d} \mathrm{SPI}_i. \tag{2}$$

The duration is defined as the longest duration, in months, of the drought event. The definition of a drought event has been considered as 0 (Almedeij, 2014; EskandariPour & Soltaninia, 2022), −0.5 (Wang et al., 2022), −0.8 (Das et al., 2020) and −1 (Jehanzaib et al., 2021). Therefore, this study considers a drought event when SPI ≤ -1.

2.5 | Copula

Copula allows for assessing dependence between two variables using probability distribution functions. Two or more probability distributions are combined in copula to create multivariate distributions. Consider two random variables, x and y, with probability distribution functions defined as $\Psi_x(x)$ and $\Psi_y(y)$, respectively. These two probability functions can be linked by a copula function C, such that

$$\Psi_{x,y}(x,y) = C\left(\Psi_x(x), \Psi_y(y)\right). \tag{3}$$

In this study (Table 2), two families of copulas were considered: Archimedean (Frank, Clayton, Gumbel) and Elliptical (Gaussian, Student's t). The performance of the copula functions was estimated using the Akaike information criteria (AIC).

3 | RESULTS AND DISCUSSION

The statistical properties of precipitation from the various models and observations in different regions of Africa were computed (Figure 2). Generally, there is a good agreement in the distribution of observed precipitation among the three observational data products over the region of study. For instance, in the Central African region (Figure 2a), there is a fairly good agreement in the observed mean daily precipitation from CPC (3.87), CHIRPS (4.21) and TAMSAT (4.38). Even though these values are close, the differences in the products have been observed in other studies (Dinku et al., 2018; Ogbu et al., 2020). There is also a possibility for pronounced variation at the local scale (Fekete et al., 2004). Various reasons have been put forward to account for these variations, including but not limited to the fact that CHIRPS

TABLE 2 Distribution function of different copula families used in the study and their parameters (Azam et al., 2018)

Copula family	Copula name	Copula expression	Parameters
Archimedean	Frank	$-\frac{1}{\theta}\left[1+\frac{(e^{\theta u}-1)(e^{\theta v}-1)}{(e^{\theta}-1)}\right]$	$[-1,\infty)$
	Clayton	$(u^{-\theta}+v^{-\theta}-1)^{\frac{1}{\theta}}$	$[-\infty,\infty)$
	Gumbel	$\exp\left(-\left[\left(\ln(u)^{\theta}+\left(-\ln(v)^{\theta}\right)\right]\right)^{\frac{1}{\theta}}$	$[1,\infty)$
Elliptic	Gaussian	$\Theta_2\left(\Theta^{-1}(u),\Theta^{-1}(v),\rho\right)$	$-1\leq\rho\leq1$
	Student's t	$\int_{\infty}^{t_{\nu}^{-1}}(u)\int_{\infty}^{t_{\nu}^{-1}}(u)\frac{1}{2\pi\sqrt{1-r^2}}\left[1+\frac{x^2-2\nu xy+y^2}{\nu(1-r^2)}\right]^{\frac{-\nu+2}{2}}dxdy$	$\nu>2, 0<r<1$

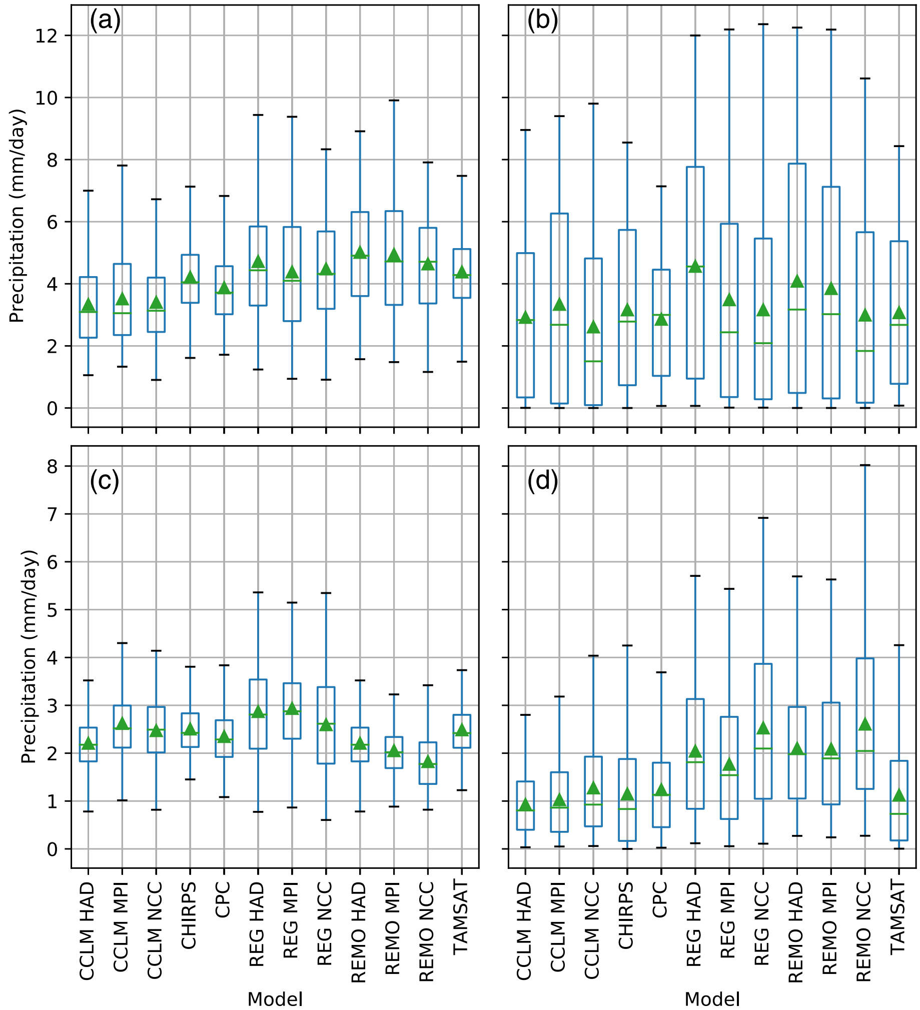

FIGURE 2 Box-plots of precipitation in 1991–2020 averaged across (a) Central Africa, (b) Western Africa, (c) Eastern Africa and (d) Southern Africa from both observations and model simulations. The box-plots upper and lower hinges represent the first and third quartile, while the central line represents the median value. The minimum and maximum are the ends of the whiskers, respectively. Outliers are not shown. Green triangles represent mean values [Colour figure can be viewed at wileyonlinelibrary.com]

relies on a fixed temperature threshold, TAMSAT is calibrated with station data and uses a local calibration to select its temperature threshold. In contrast, the CPC uses a single rain/no-rain threshold (Dinku et al., 2018). In the Central African region, the CCLM model slightly underestimates (less than 1 mm·day^{-1}) the mean precipitation values. The different boundary forcing for the RCM does not necessarily produce any drastic changes to the simulated mean values relative to the observations. The REG models also slightly overestimated (less than 1 mm·day^{-1}) the observed mean values except with REG-MPI model which replicated the observed mean value indicated in TAMSAT. However, the interquartile range was significantly larger, suggesting wider variation in the data. In addition, REMO models exhibit the highest magnitude of positive biases relative to the observations. Therefore, for the Central Africa region, precipitation simulation from CCLM models has an overall good representation of the spread in precipitation across the region when compared with observation data products.

Mean precipitation values within the West African region were lower compared to the Central African region (Figure 2b). Mean precipitation values from CPC, CHIRPS and TAMSAT were 2.86, 3.16 and 3.07 mm·day^{-1}, respectively. The CCLM-NCC underestimates the mean values of precipitation, while CCLM-MPI and CCLM-HAD exhibit a wet bias in the West Africa region. This is in line with the study from Gnitou et al. (2021), which showed that both wet and dry biases occur across West Africa in CCLM-based outputs during the June–August season with an overestimation of the annual cycle as well. However, their overall performance in representing the maximum value of precipitation has the lowest magnitude closer to the reference observation relative to other models. Hence, the precipitation spread across west West Africa is better simulated by CCLM-based models than the three observation reference datasets. On the contrary, all the REG-based and REMO-based models have a wet bias in the precipitation spread and grossly overestimate the magnitude of the maximum rainfall in the region. Mean precipitation values from East Africa's observational data lies in the range 2.35–2.51 mm·day^{-1} (Figure 2c). Mean precipitation values from observational data over the East African region were 2.35–2.51 mm·day^{-1}, with the highest and lowest values from CHIRPS and CPC, respectively. The REMO-based models underestimated the mean precipitation in East Africa, while the REG-based models overestimated it. The dry bias found in REMO models along East Africa has also been reported in Remedio et al. (2019). REG- and REMO-based models overestimated mean precipitation over Southern Africa (Figure 2d). The CCLM models provide the best estimates for mean precipitation over the region. CCLM-NCC was the best performing model in East Africa, while REG-NCC was the best performing model against both TAMSAT and CHIRPS in West Africa. In southern Africa, CCLM-MPI performed better than the other models against TAMSAT and CHIRPS, but the CCLM-NCC model performed best against the CPC observational data. However, it was outperformed by the CCLM-HAD model against CPC observational data.

In decreasing order, the mean value of precipitation was found to be in the order: Central Africa, West Africa, East Africa and South Africa. The differences in simulated daily precipitation across the RCMs for the regions suggest their strengths and weaknesses across these regions based on inherent geophysical dynamics. The observed differences across the study locations can be linked to the different simulations of the relevant physical and small-scale processes (Dosio et al., 2021; Giorgi et al., 2022; Gnitou et al., 2021). The dearth of historical observational records within different regions of Africa at both temporal and spatial scales has been a significant challenge to hydroclimatological studies over the years (Funk et al., 2015a; Zhan et al., 2016). This limits the availability of gridded precipitation data over the region. The variations in performance within each region and across regions indicates how well the GCMs physics are integrated to those of the RCMs and more importantly how these are being infused in the high-resolution setting of the downscaling experiments (Dosio et al., 2021; Gnitou et al., 2021; Tamoffo et al., 2022). This statement has also been corroborated in another study by Dosio et al. (2021). Dosio et al. (2021) stated that variations in drying and wetting over different regions as observed in their study could be related to specific physical mechanisms that the higher models better resolve. In their study, Gnitou et al. (2021) stated that the CORDEX-CORE simulations' deficiencies are likely related to how certain processes are represented within the RCM models. Considering the importance of precipitation to the socio-economic landscape of countries in Africa, there is a need for robust and reliable precipitation data. The paucity of data has hindered rigorous and reliable scientific studies, environmental and emergency planning and data-driven policy formulation. To augment the data inadequacy, data from other sources, such as remote sensing and reanalysis, are usually employed. The performance of high-resolution 3 GCMs-RCMs in simulating the drought severity and duration within the African continent was evaluated. The result will suggest the most suitable model for integrating observational data when gaps occur.

Comparison between simulated drought duration–severity across all the models and observational data were considered (Figures 3–5). There were instances of very high severity and duration exhibited by TAMSAT in some of the regions. These can be attributed to the influence of cloud cover, especially in the mountainous areas of the regions (Dinku et al., 2011). The correlation between drought duration and severity is an important quantity. A strong positive correlation indicates that long periods of droughts are associated with more intense droughts. Increasing correlation in future projections compared to historical implies that drought severity–duration will become more intense. This understanding will drive mitigation and adaptation plans. The ability of GCMs and RCMs to reconstruct the correlation between drought duration and severity will indicate their performance within a region (Figures 3–5). Historical observational data suggests higher correlation values from TAMSAT and CPC in West Africa and East Africa (Table 3). This high correlation can be attributed to the influence of large-scale oscillations driving precipitation

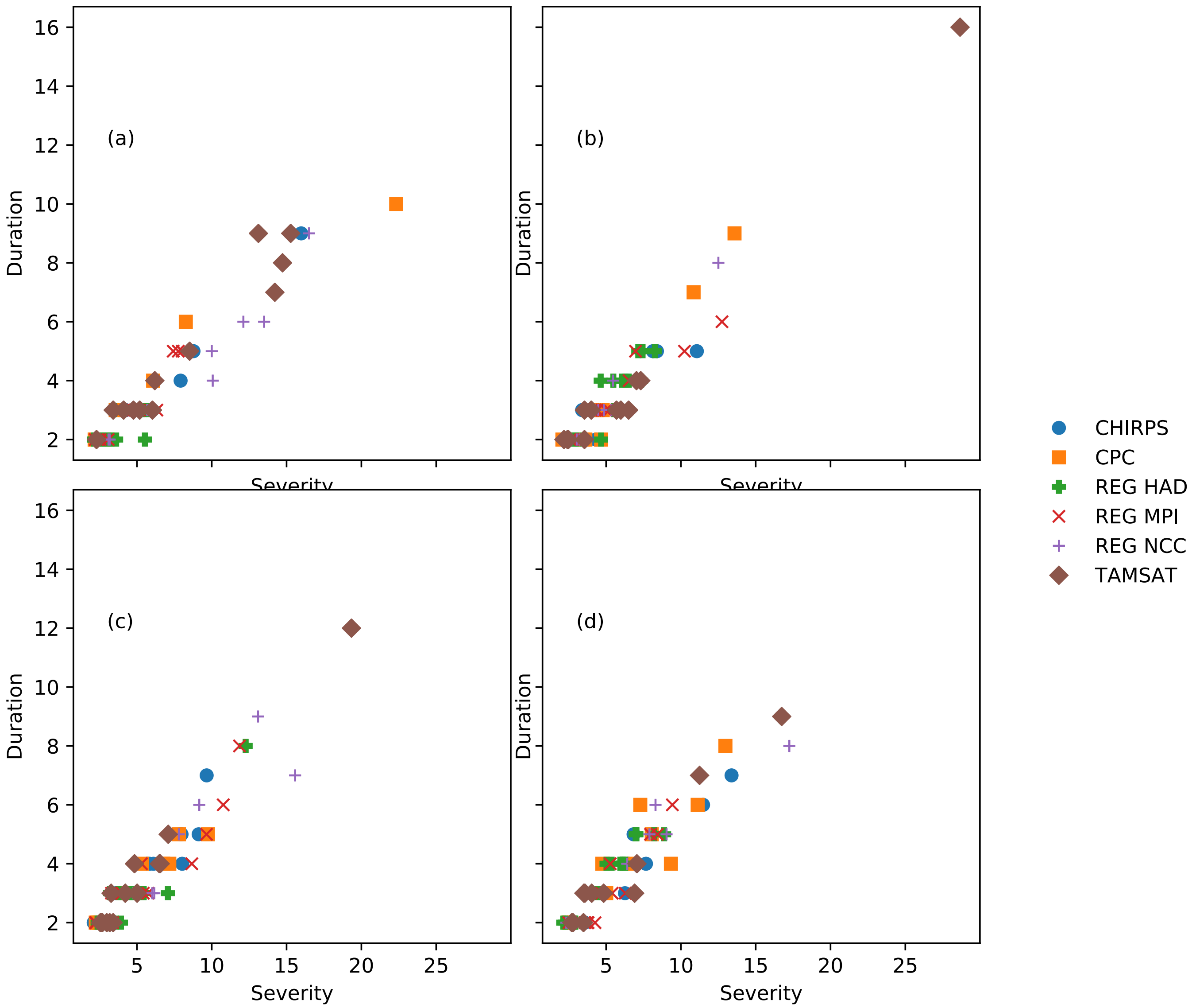

FIGURE 3 Comparison of duration–severity graphs for REG based models in (a) Central Africa, (b) Western Africa, (c) Eastern Africa and (d) Southern Africa [Colour figure can be viewed at wileyonlinelibrary.com]

in both regions (Funk, 2012; Ogunjo et al., 2019b). Across East and West Africa, rainfall is a result of strong moist convection and these generate both convective and stratiform clouds. In addition, both regions have a high mean relative humidity for their respective seasons (Dezfuli et al., 2017).

In Southern and Central Africa, CHIRPS showed a higher drought severity–duration correlation than Western and Eastern African data. The ability of the models to capture the drought severity–duration was also considered and reported (Table 3). The REMO-based models underestimated the drought severity duration correlation against all the observational data except REMO-NCC against CPC in southern Africa. The largest underestimation was found in the REMO-HAD model. The CCLM-based models performed very well in simulating the duration–severity correlation within West Africa. Underestimation was observed in East Africa by CCLM-MPI and Central Africa by both CCLM-HAD and CCLM-NCC. Generally, the HAD-based RCM grossly underestimated the correlation in Central Africa. Comparing the correlation from historical models to projection values, the REMO-based models reported higher correlation values in the period 2050–2099, except in West Africa (REMO-MPI and REMO-NCC) and Southern Africa (REMO-HAD). This suggests that the regions will most likely experience more severe droughts with longer duration. All correlation values in the projection data from CCLM-based models showed higher correlation values compared to the historical data. CCLM-MPI reported identical correlation values in Western and Southern Africa with the historical model data. Lower correlation values were

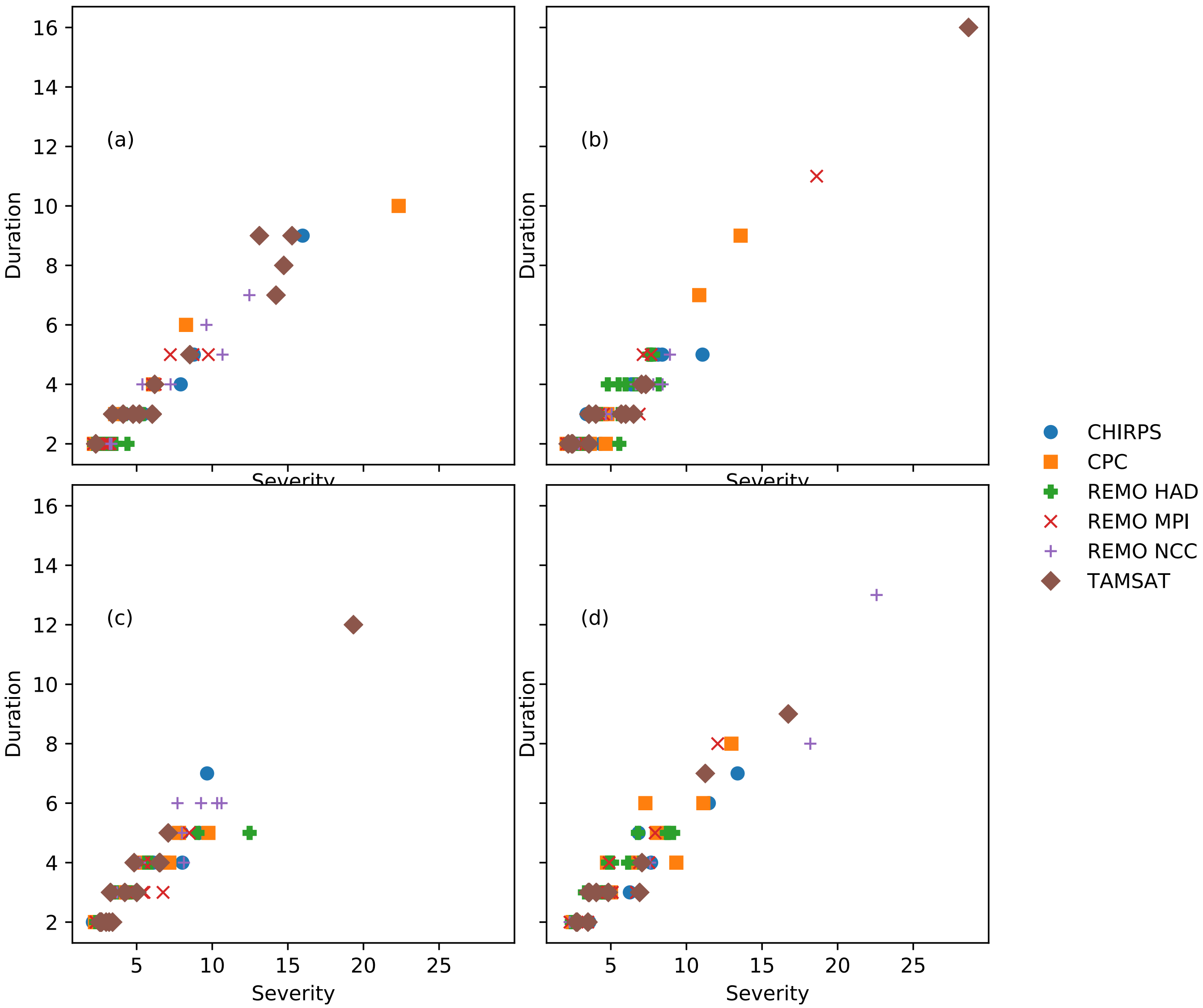

FIGURE 4 Comparison of duration–severity graphs for REMO based models in (a) Central Africa, (b) Western Africa, (c) Eastern Africa and (d) Southern Africa [Colour figure can be viewed at wileyonlinelibrary.com]

reported in the projection data in southern Africa (REG-HAD), all regions except Southern Africa (REG-MPI) and Eastern Africa (REG-NCC).

The capability of different copula models to capture the drought severity–duration within various regions of Africa was also explored in this study (Figures 3–6 and Table 4). It is not enough for models to capture the precipitation and drought statistics, the underlying distribution must also be represented. This will help in robust climate analysis and projection. Gumbel and Student's *t* distribution were the best model for CHIRPS and CPC data in the central African region. However, Gaussian and Student's *t* have identical performances in the TAMSAT data. The worst copula distribution for the observational data was Clayton, except in the TAMSAT data, where the Gumbel distribution has the worst performance. Within the central African region, REG-MPI and REG-NCC models were found to have Gaussian and Student's *t* distribution as the best, similar to the result in TAMSAT. However, REG-HAD was able to replicate the distribution found in CHIRPS. All the REMO-based models showed Gumbel as the best copula fit for drought severity–duration in the central African region. This suggests that the REMO models could capture the dynamics of CHIRPS but not CPC and TAMSAT. Clayton has the worst fit among all the copula models. The performances of the CCLM models were as observed in the REMO models. Within the West African region, Gumbel distribution is the best fit while Clayton is the worst. This was also observed in the REG-based models. The same result was replicated in REMO-based models, except REMO-HAD, which showed Student's *t* distribution as the best copula fit. Also, CCLM-HAD and CCLM-MPI showed

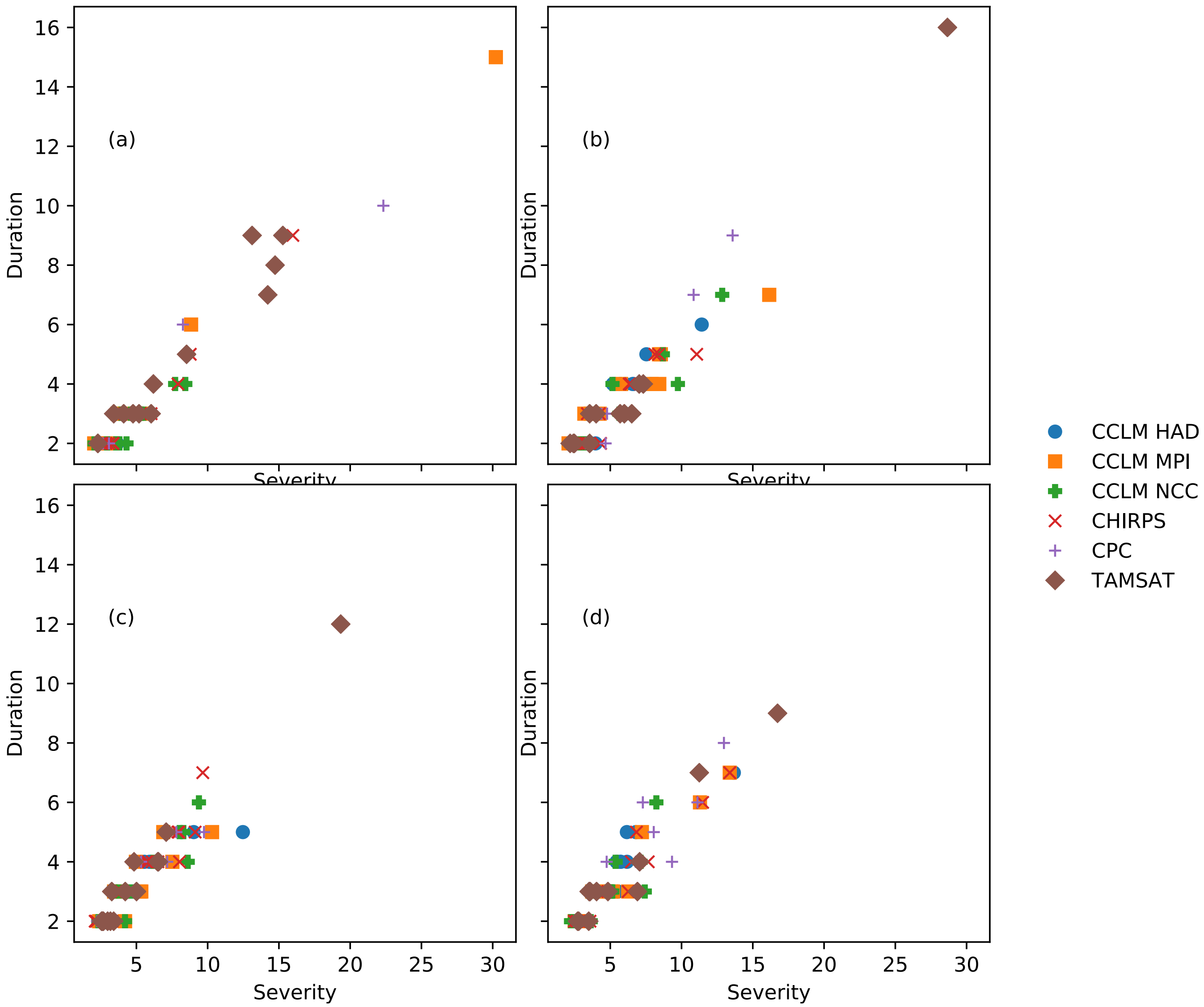

FIGURE 5 Comparison of duration–severity graphs for CCLM based models in (a) Central Africa, (b) Western Africa, (c) Eastern Africa and (d) Southern Africa [Colour figure can be viewed at wileyonlinelibrary.com]

the Gaussian copula as the best fit against Gumbel reported by the observational data. TAMSAT and CPC reported Gumbel copula as the best fit compared to Student's *t* observed in CHIRPS observational data in Eastern Africa. All the models captured the best and worst copula except the Frank copula observed in REG-NCC, Student's *t* in REMO-MPI and Gaussian in CCLM-MPI. The best copula in the observational data in Southern Africa was Gumbel for CHIRPS and TAMSAT, and Student's *t* and Gaussian for CPC. The NCC and MPI models agreed with CHIRPS and TAMSAT that Gumbel is the best copula fit. However, HAD model showed Frank copula as the best fit in both REG and REMO, and Gaussian in CCLM models. Different copula fit has been reported for different regions of the world. These include Frank and Gaussian in South Korea (Azam et al., 2018), Clayton copula in Iran (EskandariPour & Soltaninia, 2022) and Frank copula in China (Wang et al., 2022). The ability of different copula models to capture the dynamics of drought duration–severity suggests their potential in modelling and predicting the drought parameters. The drivers of precipitation vary from region to region; hence, drought parameters have different probability distributions. Therefore, the differences in suitable copula model are attributed to the different drivers of precipitation in the different regions.

Meteorological and hydrological droughts pose a significant challenge to the African continent due to the role of rain-fed agriculture in the region (Ogunjo & Olusola, 2022). Therefore, it is pertinent to investigate and understand the projected drought scenario for proactive planning and mitigation of its impact. While drought

TABLE 3 Correlation values of drought duration–severity from CORDEX-CORE models in different regions of Africa

		Historical				Projection			
Model	**Model**	**WA**	**EA**	**SA**	**CA**	**WA**	**EA**	**SA**	**CA**
OBS	CHIRPS	0.93	0.94	0.96	0.98				
	TAMSAT	0.99	0.99	0.97	0.97				
	CPC	0.99	0.97	0.92	0.98				
REMO	HAD	0.85	0.92	0.94	0.70	0.94	0.95	0.91	0.78
	MPI	0.98	0.86	0.94	0.96	0.96	0.96	0.97	0.98
	NCC	0.98	0.94	0.98	0.96	0.87	0.98	0.98	0.97
CCLM	HAD	0.91	0.92	0.94	0.78	0.95	0.96	0.96	0.95
	MPI	0.97	0.86	0.97	0.99	0.97	0.89	0.97	1.00
	NCC	0.94	0.94	0.86	0.88	0.96	0.98	0.98	0.95
REG	HAD	0.92	0.93	0.96	0.67	0.92	0.96	0.91	0.70
	MPI	0.95	0.94	0.95	0.94	0.93	0.82	0.97	0.85
	NCC	0.96	0.93	0.97	0.97	0.97	0.85	0.98	0.99

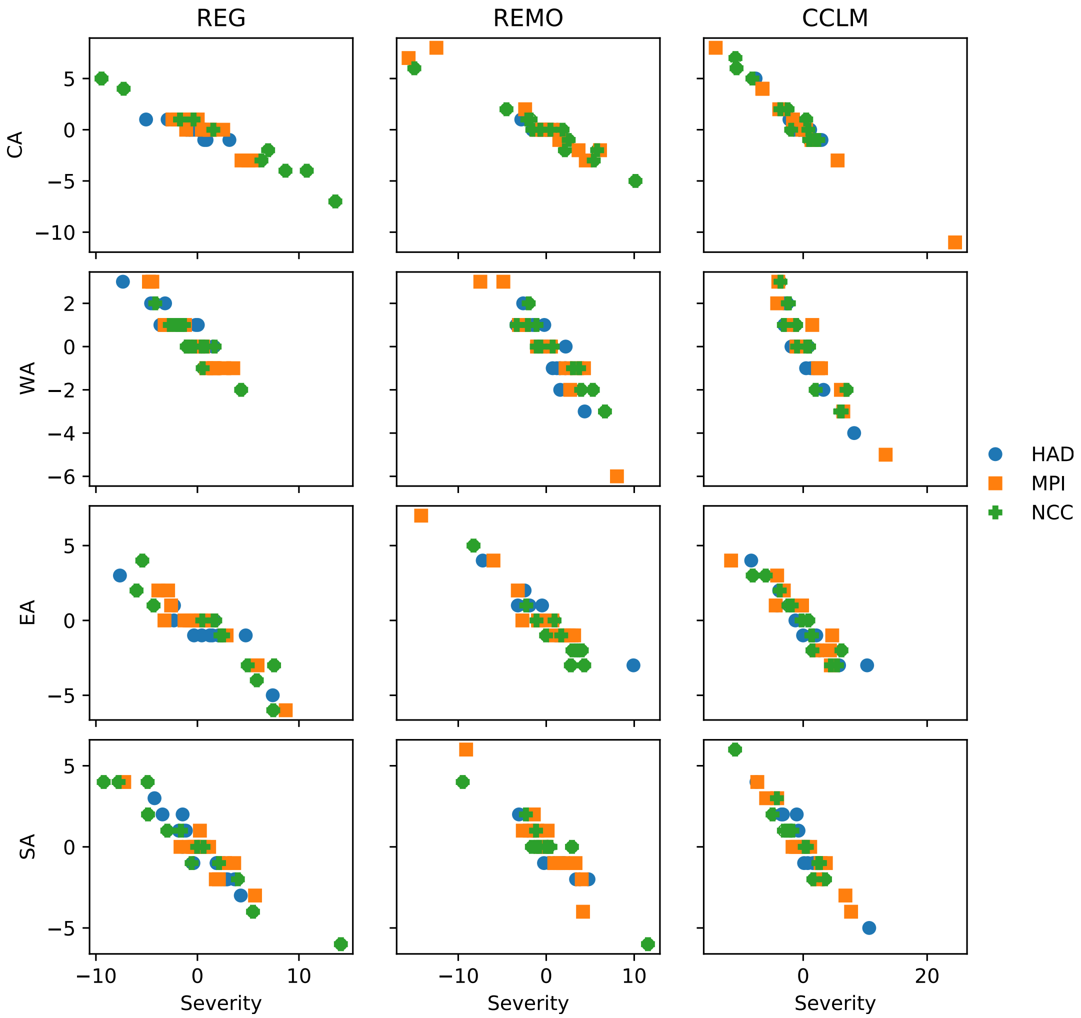

FIGURE 6 Differences between historical and projected drought duration–severity [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Performance evaluation of different copula in representation of drought duration–severity using AIC

		REG					REMO					CCLM				
Region	**Model**	**Frank**	**Clayton**	**Gaussian**	**Gumbel**	**Student's *t***	**Frank**	**Clayton**	**Gaussian**	**Gumbel**	**Student's *t***	**Frank**	**Clayton**	**Gaussian**	**Gumbel**	**Student's *t***
CA	CHIRPS	−9.21	*−8.25*	−9.24	**−9.53**	−9.25	−9.21	*−8.25*	−9.24	**−9.53**	−9.25	−9.21	*−8.25*	−9.24	**−9.53**	−9.25
	CPC	−7.95	*−6.81*	−8.02	−8.5	**−13.05**	−7.95	*−6.81*	−8.02	−8.5	**−13.05**	−7.95	*−6.81*	−8.02	−8.5	**−13.05**
	HAD	−6.55	*−4.89*	−6.76	**−6.96**	−6.76	−5.97	*−3.95*	−6.41	**−6.73**	−6.41	−4.67	*−2.62*	−5.53	**−5.9**	−5.53
	MPI	−8.71	*−8.54*	**−8.96**	−8.81	**−8.96**	−9.39	*−8.24*	−9.23	**−9.4**	−9.23	−8.63	*−8.05*	−8.81	**−8.93**	−8.81
	NCC	−9.12	*−8.78*	**−9.36**	−9.34	**−9.36**	−9.61	*−8.66*	−9.59	**−9.75**	−9.59	−8.51	*−7.78*	−8.66	**−8.77**	−8.66
	TAMSAT	−9.24	−9.08	**−9.26**	*−9.05*	**−9.26**	−9.24	−9.08	**−9.26**	*−9.05*	**−9.26**	−9.24	−9.08	**−9.26**	*−9.05*	**−9.26**
WA	CHIRPS	−8.64	*−7.73*	−8.6	**−8.76**	−8.61	−8.64	*−7.73*	−8.6	**−8.76**	−8.61	−8.64	*−7.73*	−8.6	**−8.76**	−8.61
	CPC	−7.49	*−6.63*	−7.67	**−8.03**	−7.7	−7.49	*−6.63*	−7.67	**−8.03**	−7.7	−7.49	*−6.63*	−7.67	**−8.03**	−7.7
	HAD	−9.35	*−8.47*	−9.38	**−9.42**	−9.38	−8.59	*−8.32*	−8.5	−8.46	**−8.63**	−8.69	*−8.5*	**−8.96**	−8.9	−8.95
	MPI	−9.38	*−9.04*	−9.67	**−9.76**	−9.67	−9.34	*−8.39*	−9.37	**−9.61**	−9.37	−9.04	*−8.94*	**−9.25**	−9.15	−9.25
	NCC	−9.31	*−8.22*	−9.37	**−9.68**	−9.38	−9	*−8.11*	−8.97	**−9.1**	−8.96	−8.57	*−7.78*	−8.66	**−8.74**	−8.66
	TAMSAT	−8.62	*−7.98*	−8.81	**−9**	−8.81	−8.62	*−7.98*	−8.81	**−9**	−8.81	−8.62	*−7.98*	−8.81	**−9**	−8.81
EA	CHIRPS	−9.44	*−9.09*	−9.48	−9.43	**−9.49**	−9.44	*−9.09*	−9.48	−9.43	**−9.49**	−9.44	*−9.09*	−9.48	−9.43	**−9.49**
	CPC	−9.17	*−8.17*	−9.07	**−9.2**	−9.07	−9.17	*−8.17*	−9.07	**−9.2**	−9.07	−9.17	*−8.17*	−9.07	**−9.2**	−9.07
	HAD	−8.64	*−7.97*	−8.79	**−8.81**	−8.79	−9.17	*−8.16*	−9.08	**−9.24**	−9.08	−9.17	*−8.16*	−9.08	**−9.24**	−9.08
	MPI	−9.23	*−8.5*	−9.39	**−9.6**	−9.39	*−7.7*	−8.04	−8.01	−7.93	**−14.56**	−7.44	*−7.31*	**−7.83**	−7.64	−7.82
	NCC	**−9.45**	*−8.88*	−9.33	−9.11	−9.33	−8.34	**−8.64**	−8.43	*−8.16*	−8.46	−8.99	*−8.37*	−9.11	**−9.17**	−9.11
	TAMSAT	−9.01	*−8.06*	−9.08	**−9.36**	−9.08	−9.01	*−8.06*	−9.08	**−9.36**	−9.08	−9.01	*−8.06*	−9.08	**−9.36**	−9.08
SA	CHIRPS	−9.23	*−8.69*	−9.34	**−9.41**	−9.34	−9.23	*−8.69*	−9.34	**−9.41**	−9.34	−9.23	*−8.69*	−9.34	**−9.41**	−9.34
	CPC	−8.29	*−8.19*	**−8.55**	−8.52	**−8.55**	−8.29	*−8.19*	**−8.55**	−8.52	**−8.55**	−8.29	*−8.19*	**−8.55**	−8.52	**−8.55**
	HAD	**−10.17**	*−9.69*	−10.15	−9.97	−10.15	**−9.9**	*−9.49*	−9.85	−9.63	−9.85	−9.52	*−9.29*	**−9.76**	−9.7	**−9.76**
	MPI	−9.07	*−8.14*	−9.13	**−9.34**	−9.12	−8.8	*−8.76*	−9.19	**−9.23**	−9.19	−9.22	*−8.5*	−9.35	**−9.54**	−9.35
	NCC	−8.71	*−7.62*	−8.67	**−8.91**	−8.67	−8.88	*−7.83*	−8.85	−9.22	**−13.61**	−8.97	*−8.32*	−9.01	**−9.08**	−9.01
	TAMSAT	−8.89	*−8.42*	−9.12	**−9.27**	−9.12	−8.89	*−8.42*	−9.12	**−9.27**	−9.12	−8.89	*−8.42*	−9.12	**−9.27**	−9.12

Note: Values in bold and italic represent minimum and maximum AIC values, respectively.

duration gives an insight into the length of the drought, drought severity provides information on the seriousness of the drought event. Increasing drought duration and severity suggest that longer drought will be very severe. Model projection suggests that drought duration–severity will increase in 2050–2099. The increase is due to the combined change in temperature and potential evapotranspiration (Spinoni et al., 2020). Results showed that government policies should be targeted at mitigating the impact of climate change. This can be achieved through cutting emissions and developing adaptation strategies. Climate change has been suggested to increase conflict due to dwindling resources (Mwiturubani & Van Wyk, 2010; Theisen et al., 2013). Alliances should be formed within the continent to economically harvest and utilize water resources for domestic and agricultural irrigation.

The ability to effectively predict the outcome of an event is a significant step in developing comprehensive and integrated monitoring and evaluation schemes. Various tools and products are available for monitoring extreme events, such as in situ data, space and airborne platform datasets. However, data scarcity has been an issue across most African regions, especially in situ datasets. Hence, the use of products that have been validated provides a way to monitor and assess various environmental challenges across the continent. Understanding future drought-severity is very important as this helps to design and develop proactive-innovative solutions to mitigating drought risks and their impacts (Adedeji et al., 2020; Archer et al., 2022; Orimoloye et al., 2021; Tan et al., 2020). The ability of the CORDEX-CORE to provide high-resolution information across various African regions is a strong testament to the fact the the developed CORDEX-COmmon Regional Experiment (CORE) Framework provides a basis for assessing future extreme events such as droughts for regions in Africa.

4 | CONCLUSION

The paucity of data within Africa makes long-term study and investigation of climate and climate-related issues difficult. To overcome this challenge, scientists and researchers use satellites and simulated data for analysis. The efficiency and effectiveness of these global and regional climate models need continuous evaluation to make reliable inferences and deductions from their study. It is not enough for simulations to capture precipitation but also its characteristics and features, such as dry and wet spells, drought duration and severity. The performance of several precipitation simulations from RCMs was considered against three gridded observational data over the African continent. Different regions of Africa were found to have unique RCMs with the best performance for precipitation and drought features.

Second, this study demonstrates the performance of copula modelling of drought duration and severity in the CORDEX-CORE regional climate models over Africa. The copula models considered showed high accuracy in simulating the drought duration and severity in different regions of Africa. Africa has had several severe drought events and dry spells over the last few decades. While several approaches have been considered in gaining a deeper understanding of the occurrence and relationship, this study used a probabilistic approach. The copula method models the drought duration and severity using the underlying distribution. A comparison between simulated drought duration–severity across all the models and observational data was investigated. A strong positive correlation suggests that long periods of droughts are associated with more intense droughts. Similarly, a high correlation in the future projections implies an intensified drought severity–duration. For each region, the optimal copula model has been proposed. The projected relationship between drought severity and duration suggests a more positive relationship. This implies that more intense droughts should be expected across different regions of Africa in the future. This result will help develop and implement mitigation and adaptation plans for each region. Practical approaches such as prudent allocation and utilization of water resources, design and construction of large reservoirs, and robust water conservation policies should be implemented.

Lastly, the performance of the different RCMs varies for each subregion according to their representation of the physical and small-scale processes. A comparison between simulated drought duration–severity across all the models and observational data was investigated. The correlation between drought duration and severity gives information on the intensity of a drought event. A strong positive correlation suggests that long periods of droughts are associated with more intense droughts. Similarly, a high correlation in the future projections implies an intensified drought severity–duration. It is expected that the availability of this information will enhance the successful implementation of mitigation and adaptation plans in a region with limited capacity to ameliorate climate change impacts. CCLM model, irrespective of the driving global climate models, has a generally good representation of precipitation spread across each of the subregions within Africa compared to the reference observation datasets.

AUTHOR CONTRIBUTIONS

Christiana Funmilola Olusegun: Data curation; supervision; conceptualization; writing – review and editing; validation; investigation; formal analysis; writing – original draft. **Samuel Ogunjo:** Formal analysis; conceptualization;

writing – review and editing; methodology; validation; investigation. **Adeyemi Olusola:** Writing – original draft; conceptualization; writing – review and editing; validation; investigation.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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