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Joint Modelling of Drought Severity and Duration using Copula Theory: A Case Study of Ghana

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ABSTRACT

Analysing and understanding the occurrence and development of droughts is of great significance in mitigating drought impacts. This study assessed the possible changes in the joint distribution of drought duration and severity in two major cities of Ghana, Accra and Yendi. The duration and severity of droughts, estimated using the Standardized Precipitation Index (SPI), were determined based on run theory. The best-fitted Copula models were used to combine the drought duration and severity to analyse the drought return period. The gamma, lognormal and Weibull distributions were considered to select the marginal distributions for the duration and severity, while the normal, t, Gumbel, Joe, Clayton and Frank copulas to select the best-fit Copula model. Bias corrected climate simulations of six Global Climate Models (GCMs) of the CMIP6 were used to project drought characteristics for the near and far futures. The results showed the Clayton and Frank copulas as the most suitable for fitting the joint distribution of drought duration and severity at Accra and Yendi, respectively. Lognormal and Weibull distributions were the most suitable for the marginal distributions of severity and duration, respectively. The joint return periods of droughts showed almost no change in the future compared to the historical period in Accra with a historical mean of 11.36 and a near and far future mean of 12.26 and 10.30 respectively but significantly reduced return periods in the future in Yendi with a near and far future means of 1.47 and 2.13 respectively compared to a historical mean of 17.40. The drought risks estimated for different future periods can provide useful information in planning, management, and assessing the adequacy of the water structures in the region.

1. Introduction

The effects of climate change have become apparent in every service sector. This has necessitated the formulation of policies to contain the impacts, as witnessed in various summits such as the recent Glasgow climate change conference in 2021. A notable increase in temperature and a significant change in precipitation patterns have been noticed all over the globe (Song et al., 2021). These collectively increased the drought risk in many regions (Shiru et al., 2018; Song et al., 2022). It is important to study the regional characteristics of these changes as it differs in severity and trend across the earth.

Previous drought studies mostly focused on the independent analysis of the two main drought features, severity and duration, ignoring their interdependence (Montaseri et al., 2018; Saghafian and Mehdikhani, 2014). However, univariate analysis of drought severity and duration cannot describe their dependence structure. Therefore, a joint analysis of these drought features is necessary to assess potential risks (Shiau and Modares, 2009). Copula functions have been extensively used in different research areas, including the hydrological, financial and medical sectors (Hui-Mean et al., 2019; Sung et al., 2022), to define and model the joint distribution characteristics of the various variables.

The use of GCMs is one of the most effective methods of

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investigating the effects of global climate change (Sehgal et al., 2018). However, raw GCM simulations are not suitable for the regional scale impact assessment due to coarse resolution (Hay et al., 2000). GCMs are therefore downscaled to attain finer resolutions for regional studies. Over the years, the Coupled Model Inter-comparison Project (CMIP) has made several improvements in climate modelling. The latest CMIP6 has made significant error reductions in the models compared to the previous models provided in CMIP5 as shown in some recent studies (Piani et al., 2010; Sylla et al., 2016).

According to the United Nations, countries below the Sahara, including Ghana, have experienced an increase in the intensity and frequency of climatic extremes due to climate change. Hartman et al. (2013) found that near-surface air temperatures in the Sahara have increased higher than in any other periods on record, including the Palaeolithic periods. These changes have led to the increases in droughts and flood events and a consequential food insecurity and economic instability in the sub-Saharan region has occurred.

The everyday dynamics of livelihood in Ghana are largely dependent on climate. Most farmers rely on the rainfall pattern to regulate and plan agricultural activities. Besides, the majority of Ghana's domestic water provision relies on runoff. Climate change has affected rainfall and runoff and, therefore, the lives of the people of Ghana has been threatened in terms of food and daily domestic water availability (Twisa and Manfred, 2019).

This study calculated the Standardized Precipitation Index (SPI) for Accra and Yendi cities in Ghana to derive drought duration and severity using the run theory. Marginal distribution functions were determined for both duration and severity, and a joint distribution using copula theory was built. Return periods were calculated from the joint distribution. Six GCMs were downscaled and bias-corrected, and the best performing GCMs were used to project the SPI of the two cities. Drought duration and severity were derived from the projected SPI using the run theory. Future return periods were calculated from the projected joint distribution to show the possible changes in the joint distribution of drought duration and severity in two cities.

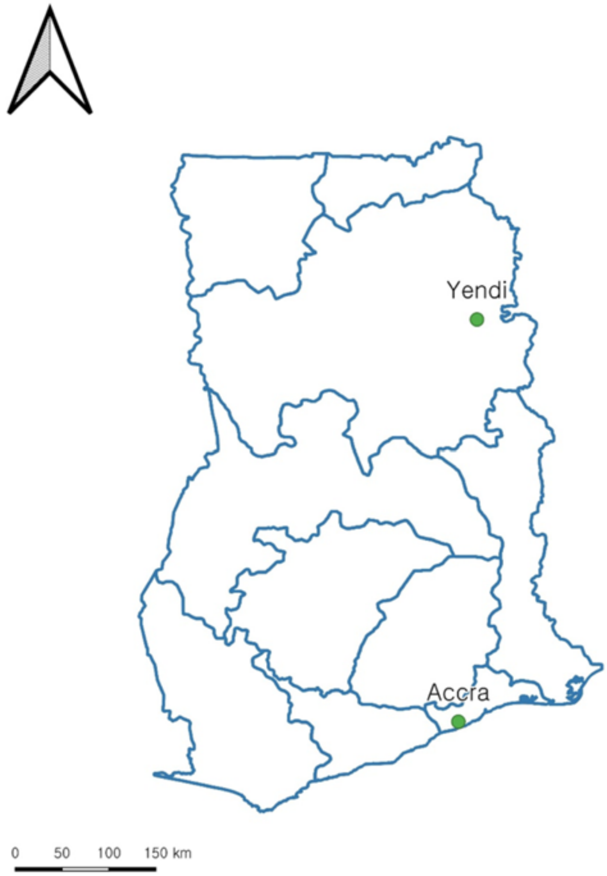


Fig. 1. Map of the Study Area (The location of the meteorological stations is shown using solid green circles.)

2. Study Area and Data

2.1 Study Area

Two major cities of Ghana, Accra and Yendi, were selected as the case study areas in this study (Fig. 1). Most regions in southern Ghana lies in the green zone with frequent rainfall. However, most of northern Ghana is semi-arid or arid. Accra, the capital of Ghana, is located in the south. It has the largest population in the region. It is also the city with the fastest population growth in the country. The average rainfall is between 78 and 216 mm per month, and the temperature ranges between 24°C and 32°C. The increase in population has had a significant effect on agriculture since most people rely on agriculture for livelihood. Roudier et al. (2014) found that population factors influence runoff such as land use, water consumption and the effect of higher carbon concentration. Their results showed that the carbon effect as well as water withdrawals can potentially have significant impacts on runoff changes in West Africa. Yendi, on the other hand, is located in the north. It has a very low population and population growth rate. It experiences an average rainfall of 3 to 203 mm and a temperature range between 19 and 36°C. Yendi suffers from occasional droughts due to rainfall variability. Acquisition of accurate data in these two cities is very hard due to the lack of recording stations. The climate data for this study was acquired from the Global Precipitation and Climate Centre (GPCC), Climate Research Unit (CRU) and the Ghana Meteorological Association (GMA). The historical drought analysis was conducted for 1961 – 2014, and the future projections for 2015 – 2100. Many researchers recommend considering study periods of at least 30 years and most climate models have projections up to the year 2100.

2.2 Global Circulation Models and Shared Socioeconomic Pathways

GCMs are the most advanced tools currently available for modelling the response of the global climate system to increasing greenhouse gas concentrations (IPCC, 2013). While simpler models have been used to provide globally- or regionally-averaged estimates of the climate response, only GCMs have the potential to provide geographically and physically consistent estimates of global climate change required for impact analysis. There have been past generations of GCMs with the CMIP6 being the latest. Shared Socioeconomic Pathways (SSPs) are used to derive greenhouse gas emissions scenarios with different climate policies up to 2100 for the CMIP6. The scenarios used in this study were SSP 2-4.5 and SSP 5-8.5. The SSP 5-8.5 describes a speedy global economic growth, free trade fuelled by carbon-intensive fuels, high technological advancement, low regard for zero carbon emissions and sustainable development goals. The SSP2-4.5 mimics a path where social, economic, and technological trends stay relatively along with the current trends. Development and income growth proceed unevenly, with some countries making relatively good progress while others fall short of expectations. Most economies are stable due to stabilized political factors.

3. Methodology

In this study, temperature and rainfall trends were first estimated using the Mann-Kendall (MK) trend test. SPI was calculated for the historical period, and the drought severity and duration were quantified from SPI using run theory. Subsequently, the goodness of fit test for the marginal distributions of the severity and duration are evaluated considering three distributions (gamma, lognormal and Weibull). The goodness of fit tests for the joint distribution of severity and duration using five different copula functions were conducted, and the return periods of severity, duration and the joint duration/severity were calculated. GCM projections for rainfall and temperature were downscaled, and the procedure was repeated to estimate the return periods of severity, duration and the joint duration/severity of droughts for future periods to show their changes in the future compared to the base period. Fig. 2 shows the flow chart for the methodology used in this study.

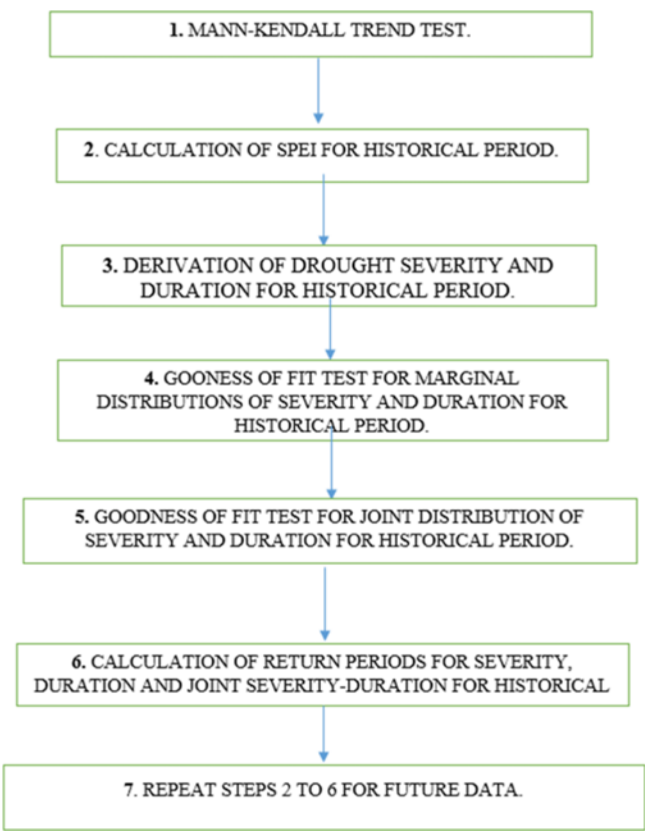


Fig. 2. Flow Chart of the Methodology Used in This Study

3.1 Mann-Kendall Trend Analysis

The MK is a non-parametric trend test applicable for any data distribution. The MK trend test analyses the difference in signs between earlier and later data points. If a trend is present, the sign values increase or decrease constantly. The MK test assumes that observations are independent and random. There is no serial correlation in observations. The MK test was conducted on the historical precipitation and temperature data of both cities. The test statistics z is given by

$$z = \begin{cases} \dfrac{s-1}{\sqrt{var(s)}} & \text{if } s > 0 \\ 0 & \text{is } s = 0 \\ \dfrac{s+1}{\sqrt{var(s)}} & \text{if } s < 0, \end{cases} \tag{1}$$

where s is given by

$$s = \sum_{h=1}^{n-1}\sum_{t=h+1}^{n} F(y_t - y_h)\,, \tag{2}$$

and F is

$$F = \begin{cases} 1 & \text{if } F(x) > 0 \\ 0 & \text{if } F(x) = 0 \\ -1 & \text{if } F(x) < 0. \end{cases} \tag{3}$$

3.2 Standardized Precipitation Index

Generally, SPI performs better for increasing time step in drought analyses (Alamgir et al., 2019). For this method, a one-month SPI typically compares to the average rainfall for that month. The three-month SPI can usually interpret the short-term moisture conditions and provides a good seasonal estimate. Six-month SPI represents medium-term moisture conditions. 9-month SPI is a fair indicator of hydrological patterns as they are often associated with impacts on agriculture and reservoir levels. 12-month and 24-month SPIs show long term hydrological conditions and long term reservoir or groundwater levels, respectively. Drought can be considered extreme when SPI values are below -2, severe when between -2 and -1.5, moderate when between -1.5 and -1, and mild when between -1 and 0. It is considered no drought when SPI values are greater than 0 (Hartman et al., 2013).

The first step of SPI estimation is to determine the probability density function (PDF), which best describes the distribution of the data (Karavitis et al., 2011). Each data set is fitted to the gamma PDF with shape parameter α and scale parameter β to define the relationship of probability. With a mean of 0 and a standard deviation of unity, the gamma cumulative distribution function (CDF) is standardized and converged to normal CDF. The calculated SPI values are compared to a scale to determine their extent and probability. A continuous random variable X follows a gamma distribution if its PDF is

$$g(x, \alpha, \beta) = \frac{1}{\beta^{\alpha} * \Gamma(\alpha)} x^{\alpha-1} * e^{-\frac{x}{\beta}}. \tag{4}$$

For $\alpha > 0$, the gamma function $\Gamma(\alpha)$ is

$$\int_0^{\infty} x^{\alpha-1} * e^{-x} dx. \tag{5}$$

For $x > 0$ and α, $\beta > 0$, α and β are defined by the following equations

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{\frac{4A}{3}}\right), \tag{6}$$

and

$$\beta = \frac{\bar{x}}{\alpha}. \tag{7}$$

Finally, for n observations, A is defined as

$$A = \ln(\bar{x}) - \frac{\sum \ln x}{n}. \tag{8}$$

3.3. Bias Correction

The bias correction methods used in this study were the parametric transformation method and the quantile mapping method. The results from both methods were compared and the best method was chosen for the Bias correction.

3.3.1 Parametric Transformation

The quantile-quantile relation can be modelled directly using parametric transformations. Here, the suitability of the following parametric transformations was explored:

$$P_o = bP_m, \tag{9}$$

$$P_o = a + bP_m, \tag{10}$$

$$P_o = bP_m^c \tag{11}$$

$$P_o = (a + bP_m)\left(1 - e^{\frac{-P_m}{\tau}}\right) \tag{12}$$

where P_o and P_m are the probability of the observed and modelled variables, respectively, and a, b, c, and τ are related parameters subject to calibration. The equation used in this study was Eq. (12).

3.3.2 Quantile Mapping

Quantile mapping (QM) equates Cumulative Distribution Functions (CDFs) of the observed and modelled data for the historical period. This leads to the following transfer function,

$$\hat{x}_{m,p}(t) = F_O^{-1}\{F_m[x_{m,p}(t)]\}, \tag{13}$$

where F_o and F_m are cdfs of the observed data and modelled data, respectively. The variables $\hat{x}_{m,p}$ and $x_{m,p}$ are bias-corrected data value at time, t with some projected and modelled data to be bias-corrected.

3.4 Run Theory

Run theory can be used to calculate drought characteristic variables such as drought duration and drought severity and reveal the basic attributes of drought. It is referred to as either a positive run or a negative run because, a run is the portion of a time series of a drought variable in which all values are either below or above the chosen truncation level (Mishra and Singh, 2010). In order to avoid the inaccuracy of identifying drought events by setting only a single truncation level, two characteristic variables, duration, and severity of drought events, were separated from the calculated SPEI sequence by using the optimized run theory. Drought duration is the period from drought occurrence to termination, and drought severity is the absolute value of the accumulated SPEI value during the drought event. Three truncation levels, X0 (SPI = 0), X1 (SPI = -0.5), and X2 (SPI = -1.0) were set. The identification process of drought events is as follows:

1. When the SPI value is less than X1, it is preliminarily determined that drought occurs in that month.
2. When the drought event lasts only one month, and the corresponding SPI value is greater than X2, it is considered that there is no drought in this month.

The severity is calculated using the run theory as follows.

$$S = \left|-\sum_1^D SPI_i\right| \tag{14}$$

where S is the severity and D is the duration of one drought event.

3.5 Marginal Distributions

The marginal distribution function of drought duration and severity was first determined, and the dependence between the two features was considered. Three distributions were fitted to the drought duration and severity, the two-parameter lognormal distribution, the gamma distribution and the Weibull distribution functions. These three distributions are known to be widely used in the West Africa area especially the gamma distribution. Their performances were estimated using the maximum likelihood method.

The PDF of the Weibull distribution is given by

$$f(x, \lambda, k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\frac{x^k}{\lambda}}, & x \geq 0 \\ 0, x < 0 \end{cases} \tag{15}$$

where k is the shape parameter and λ is the scale parameter. β is the rate parameter, and μ and σ are the mean and standard deviation of the variable's natural logarithm.

The PDF of gamma distribution is given in Eq. (4).

The PDF of the lognormal distribution is given by

$$f(x)=\frac{1}{x\sigma\sqrt{2\pi}}\exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right). \quad (16)$$

The univariate return periods of drought duration and severity are as follows:

$$R(d)=\frac{N}{n*[1-f(d)]}, \quad (17)$$

and

$$R(s)=\frac{N}{n*[1-f(s)]}. \quad (18)$$

The bivariate return period is given by

$$R(d,s)=\frac{N}{n*[1-c(d,s)]}. \quad (19)$$

3.6 Joint Distributions

Copulas are generally used to describe the dependence structure (inter-correlation) between random variables. Copulas minimize the errors at the tails of a distribution, such errors are common in most distribution functions. This study tested six copula functions to generate the joint distribution characteristics of drought duration and severity, the normal, student's t, Clayton, Gumbel, Frank and Joe copulas, as shown in Table 1. These six copulas represent some of the most widely used Archimedean copulas. The best copula was used to generate joint cdf.

3.7 Goodness of Fit Tests

The various copulas were tested to determine how they best fit the bivariate data. Using the Kolmogorov-Smirnov and the Cramer von Mises tests.

3.7.1 Kolmogorov-Smirnov Test

With the observations U_{ij} for i = 1,….., n, j = 1,…., d and **u** is a member of $[0,1]^d$ is the empirical copula given by $C_n = \frac{1}{n}\sum_{i=1}^{n}\boldsymbol{I}(U_{i1}\le u_1,\dots,U_{id}\le u_d)$. Let the rescaled observations be $V_1=C_n(U_1),\dots,V_n=C_n(U_n)$. The distribution function of V shall be K. The estimated version is given by

$$K_n(v)=\frac{1}{n}\sum_{i=1}^{n}\boldsymbol{I}(V_i\le v). \quad (20)$$

With v being a member of $[0,1]^d$. The testable H_0 is

K is a member of $K_0=\{K_\theta$: θ, *being a member of of* $\theta\}$

With v being an open subset of R^p for an integer $p>1$ (Genest and Favre, 2007). The resulting Kolmogorov-Smirnov test statistics is

$$T=\sqrt{n}\,sup_{v[0,1]}\left|K_n(v)-K_{\theta n}\right|. \quad (21)$$

3.7.2 Cramer von Mises Test

The Cramer von Mises is very similar to the Kolmogorov-Smirnov. The test statistic is given by

$$T=n\int_0^1(K_n(v)-K_{\theta n})^2 dK_{\theta n}(v). \quad (22)$$

3.7.3 Akaike Information Criteria

The Akaike information criterion (AIC) is an estimator of prediction error and, thereby, the relative quality of statistical models for a given data set. The AIC is given by

$$AIC=2k-2\ln(L). \quad (23)$$

where k is the number of estimated parameters, and L is the maximum value of the likelihood function.

4. Results

The results of this study are arranged as follows. First, the SPI results for the historical period are shown. Next, the bias correction results are provided. The estimated drought duration and severity, the marginal distribution and joint distribution results are then provided. The return periods for historical joint duration and severity is next shown. Lastly, the return periods for future joint duration and severity are presented.

The Mann-Kendall test statistics for Accra's historical rainfall

Table 1. Copula Families Used in the Study

Copula	Formula	Parameter range
Normal	$\int_{-\infty}^{\varphi^{-1}(u)}\int_{-\infty}^{\varphi^{-1}(v)}\frac{1}{2\pi\sqrt{1-\theta^2}}\exp\left(\frac{2\theta xy-x^2-y^2}{2(1-\theta^2)}\right)dxdy$	θ ∈ [-1,1]
t-copula	$\int_{-\infty}^{\theta_2(u)}\int_{-\infty}^{\theta_2(v)}\frac{\Gamma\left(\frac{\theta_2+2}{2}\right)}{\Gamma\left(\frac{\theta_2}{2}\right)\pi\theta_2\sqrt{1-\theta_1^2}}\left(1+\frac{x^2-2\theta_1 xy+y^2}{\theta_2}\right)^{(\theta_2+2)/2}dxdy$	θ1 ∈ [-1, 1] and θ2 ∈ (0, ∞)
Clayton	$\text{Max}(u^{-\theta}+v^{-\theta}-1,0)^{-1/\theta}$	θ ∈ [-1, ∞)\0
Frank	$\frac{-1}{\theta}\ln\left[1+\frac{(\exp(-\theta u)-1)(\exp(-\theta v)-1)}{\exp(-\theta)-1}\right]$	θ ∈ R\0
Gumbel	$\exp\{-[(-\ln(u))^\theta+(\ln(v))^\theta]^{1/\theta}\}$	θ ∈ [1, ∞)
Joe	$1-[(1-u)^\theta+(1-v)^\theta-(1-u)^\theta(1-v)^\theta]^{1/\theta}$	θ ∈ [1, ∞)

Table 2. Drought Characteristics at Accra and Yendi

Accra	SPI 3		SPI 6		SPI 9		SPI 12		SPI 24	
	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category
Extreme Drought	3	0.46%	0	0%	0	0%	0	0.00%	0	0%
Severe Drought	2	0.31%	3	0%	0	0%	0	0.00%	0	0%
Moderate Drought	31	4.79%	7	1%	4	1%	0	0.00%	0	0%
Mild Drought	306	47.30%	286	44%	269	42%	257	40.22%	248	40%
No drought	305	47.14%	349	56%	369	57%	382	59.78%	379	60%
Total	647	100.00%	645	100%	642	100%	639	100.00%	627	100%
Yendi	SPI 3		SPI 6		SPI 9		SPI 12		SPI 24	
	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category
Extreme Drought	4	0.62%	0	0%	0	0%	0	0.00%	0	0%
Severe Drought	4	0.62%	0	0%	0	0%	0	0.00%	0	0%
Moderate Drought	29	4.48%	9	1%	0	0%	0	0.00%	0	0%
Mild Drought	328	50.62%	293	45%	278	43%	255	39.91%	243	39%
No drought	283	43.67%	343	53%	363	57%	384	60.09%	384	61%
Total	648	100.00%	645	100%	641	100%	639	100.00%	627	100%

was -1.090 and for temperature was 5.7789. The Mann-Kendall test statistics for Yendi's historical rainfall was -1.062 and for temperature was 4.5028. The results showed a significant trend in the variation of temperature in both cities but showed no significant trend in the variations of rainfall in both cities. This is in line with the findings of researchers with respect to the fact that the behaviour of rainfall is sporadic and unpredictable due to the effects of climate change.

4.1 SPI for Historical Period

The SPI results for Accra showed extreme to moderate drought cases in the 3, 6 and 9-month time steps, with the 3-month step being the only case of the occurrence of extreme drought with the lowest SPI occurring in 2014. As time increases, drought cases continually reduce and converge around mild and no drought cases. Table 2 shows the cases of drought for Accra and Yendi based on the SPI according to the Yevjevich scale. Similarly, in the case of Yendi, extreme and severe droughts were recorded only for the 3- and 6-month time steps, with the lowest SPI occurring in 2008.

4.2 Results of Bias Correction

Data from six GCMs, CanESM5, ACCESS-ESM1-5, FGOALS, MIROC6, CESM2 and BCC-CSM2-MR for SSP 2-4.5 and SSP 5-8.5 were analysed in this study. The GCMs for 2015-2100 were bias-corrected using GPCC as the observed data. The results

Table 3. Efficiency of Bias Correction Methods

Quantile mapping				Parametric transformation			
City	GCM	MSE	RMSE	City	GCM	MSE	RMSE
Accra	CanESM5 2-4.5	8832.83	93.98	Accra	CanESM5 2-4.5	6660.4	81.61
Yendi	CanESM5 5-8.5	6382.55	79.89	Yendi	CanESM5 5-8.5	5339.6	73.07
Accra	ACCESS-ESM1-5 2-4.5	7925.33	89.02	Accra	ACCESS-ESM1-5 2-4.5	5016.82	70.83
Yendi	ACCESS-ESM1-5 5-8.5	4722.11	68.72	Yendi	ACCESS-ESM1-5 5-8.5	4598.31	67.81
Accra	FGOALS 2-4.5	9010.23	94.92	Accra	FGOALS 2-4.5	6843.12	82.72
Yendi	FGOALS 5-8.5	8522.75	92.32	Yendi	FGOALS 5-8.5	5831.65	76.37
Accra	MIROC6 2-4.5	8739.21	93.48	Accra	MIROC6 2-4.5	6733.12	82.06
Yendi	MIROC6 5-8.5	8059.53	89.77	Yendi	MIROC6 5-8.5	5112.74	71.50
Accra	CESM2 2-4.5	8734.827	93.46	Accra	CESM2 2-4.5	6614.57	81.33
Yendi	CESM2 5-8.5	5043.84	71.02	Yendi	CESM2 5-8.5	9302.6	96.45
Accra	BCC-CSM2-MR 2-4.5	8022.11	89.57	Accra	BCC-CSM2-MR 2-4.5	7031.58	83.8545169
Yendi	BCC-CSM2-MR 5-8.5	5148.93	71.76	Yendi	BCC-CSM2-MR 5-8.5	5544.92	74.4642196

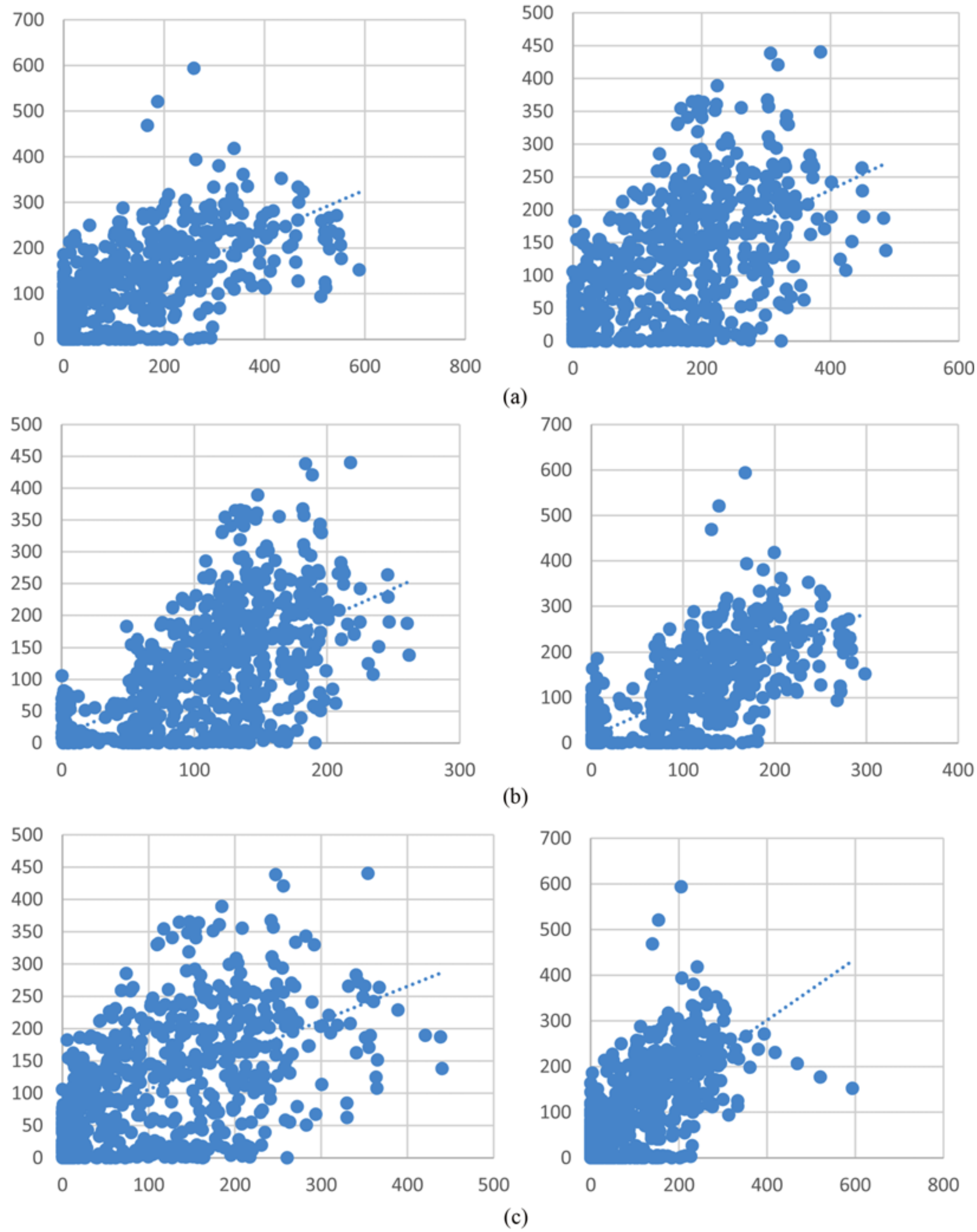


Fig. 3. Scatter Plot of Bias Correction Results at Accra and Yendi: (a) Observed and Raw GCM, (b) Observed and Parametric Transformed GCM Data, (c) Observed and Bias-Corrected GCM Data Using Quantile Mapping

showed that parametric transformation performed the best in both cities for all GCMs. ACCESS-ESM5-1 performed the best with a Root Mean Square Error (RMSE) and Mean Square Error (MSE) of 70.83 and 5016.82, respectively, for Accra, and 67.81 and 5016.82, respectively, for Yendi. The GCM ACCESS-ESM5-1 under SSP 2-4.5 was therefore used for the future projections in this study. Table 3 shows the MSE and RMSE between the GCMs and observed data for both correction methods in Accra and Yendi. Fig. 3 shows the Q-Q plot between observed and raw data (a), observed and bias-corrected data using parametric transformation (b) and observed and bias-corrected data using quantile mapping (c), for Accra and Yendi.

4.3 Duration and Severity Results

The duration was characterized as the occurrence of a drought event until its termination, where the drought event is subject to the constraints of the criteria used in the run theory. The results showed that Accra had more drought occurrences than Yendi. It also had a higher average drought duration than Yendi. The results also show that Accra generally had more severe drought

Table 4. Drought Characteristics according to Run Theory

Drought Characteristics	Accra	Yendi
Number of droughts	257	200
Longest Drought duration (months)	7	7
Average drought duration (months)	3.13	2.63
Maximum drought severity	10.73	8.5
Average drought severity	2.37	2.25

cases than Yendi. This characterization indicates that drought duration and severity are highly correlated in the two cities. Table 4 shows the drought characteristics of Accra and Yendi according to the run theory criteria.

4.4 Marginal Distribution Results

The drought severity of Accra was fitted to the various marginal distributions and their performances using the Kolmogorov-Smirnov and Cramer von Mises tests. The Kolmogorov-Smirnov and the Cramer von Mises tests measure the observed and expected data distance. Therefore, the larger the distance value, the poorer the performance of the distribution. Both AIC and BIC measure the amount of information lost by a model. Therefore, the lower the AIC and BIC, the better the representative distribution. In this study, three distributions were used to model the behaviour of drought duration and severity in Accra and Yendi.

Results showed that the lognormal was best for the drought severity with a Kolmogorov-Smirnov test statistic of 0.07, Cramer von Mises test statistics of 0.08 and an AIC and BIC of 288.60 and 293.41, respectively, for Accra. The Weibull was best for the duration with a Kolmogorov-Smirnov test statistic of 0.13, Cramer von Mises test statistics of 0.26 and an AIC and BIC of 314.53 and 319.34, respectively, for Accra. Table 5 shows the test statistics results for Accra and Yendi for both duration and severity. Fig. 4 shows the pdfs of the tested distribution for Accra for (a) severity and (b) duration.

Results showed that the lognormal was best for the drought

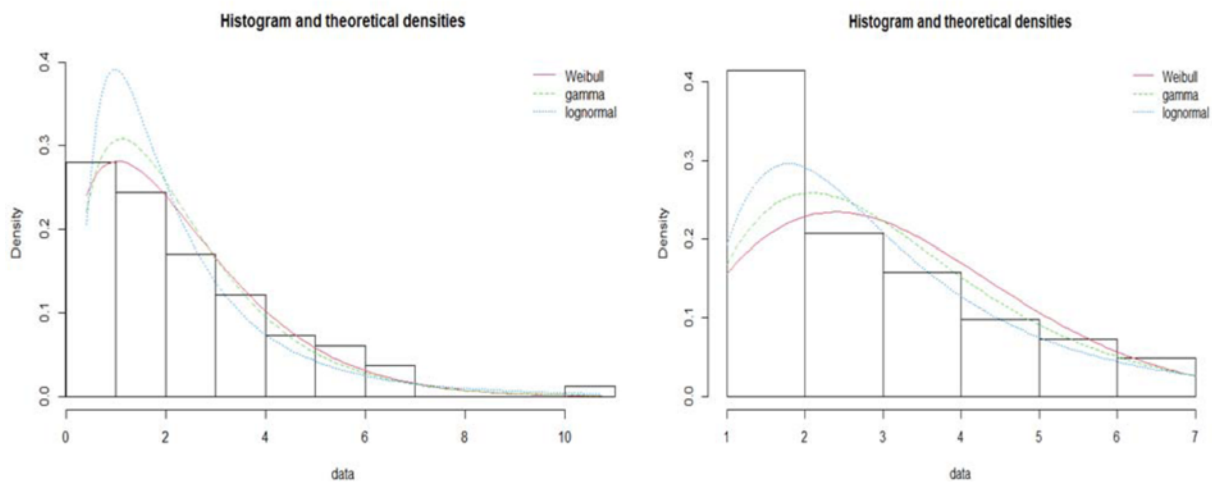


Fig. 4. Histogram of the Probability Density Functions of Three Test Distributions at Accra

Table 5. Test Statistics for Three Distributions in Accra and Yendi

Accra	Severity			Duration		
	Weibull	Gamma	Lognormal	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov	0.08	0.08	0.07	0.13	0.15	0.17
Cramer von Mises	0.10	0.10	0.08	0.26	0.29	0.38
Anderson-Darling	0.76	0.70	0.56	1.85	2.12	2.81
AIC	296.21	292.74	288.60	314.53	314.41	317.50
BIC	301.02	297.55	293.41	319.34	319.22	322.31
Yendi	Severity			Duration		
	Weibull	Gamma	Lognormal	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov	0.11	0.11	0.09	0.17	0.18	0.20
Cramer von Mises	0.14	0.15	0.15	0.43	0.45	0.55
Anderson-Darling	0.91	0.93	0.87	2.70	2.89	3.50
AIC	266.23	263.54	260.48	255.70	251.01	251.27
BIC	270.89	268.20	265.14	260.36	255.68	255.93

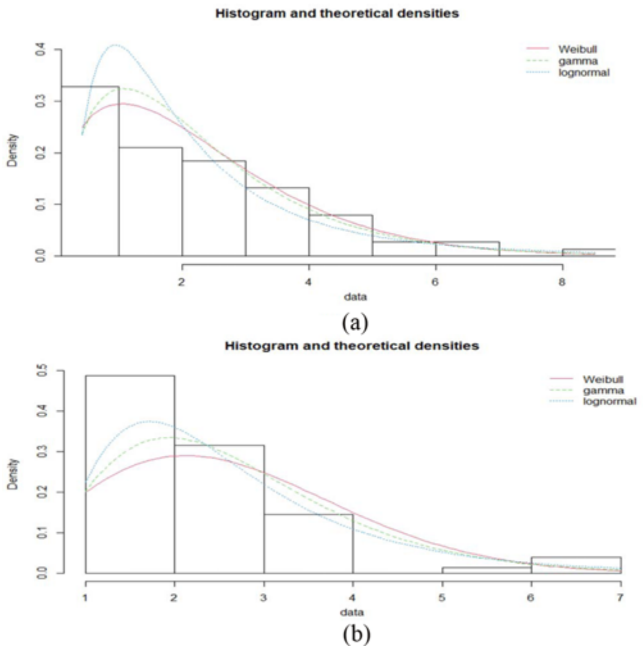


Fig. 5. Histogram of the Probability Density Functions of Three Test Distributions at Yendi

severity with a Kolmogorov-Smirnov test statistic of 0.09, Cramer von Mises test statistics of 0.15 and an AIC and BIC of 260.48 and 265.14, respectively, for Accra. The Weibull was the best for the duration with a Kolmogorov-Smirnov test statistic of 0.17, Cramer von Mises test statistics of 0.43 and an AIC and BIC of 255.70 and 260.36, respectively, for Accra. Fig. 5 shows the densities of the tested distribution for Yendi for (a) severity and (b) duration.

4.5 Joint Distribution Results

Six copulas were tested to determine which would best fit the joint distribution of duration and severity. The Kolmogorov-Smirnov and the Cramer von Mises tests were used to check the performance of the copulas. A joint cdf was then built using the best performing copula. The Spearman correlation between duration and severity for Accra was 0.85, and the Kendall correlation was 0.72. For Yendi, the Spearman correlation between duration and severity was 0.83, and the Kendall correlation was 0.69. The goodness of fit test showed that the Clayton copula performed the best for Accra while the Joe copula performed the poorest. For Yendi, the Gumbel copula performed the best, while the Joe copula performed the poorest. Table 6 shows the test results for both Accra and Yendi.

Table 6. Test Statistics for the Goodness of Fit Test of Copulas

Copula	Kolmogorov-Smirnov		Cramer von Mises	
	Accra	Yendi	Accra	Yendi
Clayton	0.689	1.062	0.165	0.293
Frank	0.870	0.747	0.212	0.158
Normal	0.831	0.739	0.143	0.144
T	1.254	0.866	0.411	0.202
Gumbel	0.899	0.711	0.199	0.150
Joe	1.328	1.141	0.504	0.392

Table 7. Drought Categories Based on Duration and Severity (Wang et al., 2020)

Drought partition	Definition
Mild drought	D = 3; S = 3
Moderate drought	D = 6; S = 6
Severe drought	D = 9; S = 9
Extreme drought	D = 12; S = 12

4.6 Return Period

According to Wang et al. (2020), greater duration and severity lead to higher losses and thus, larger duration and severity indicate more severe drought. The return period is the inverse of frequency, meaning higher drought frequency has lower return periods and are less serious. Table 7 shows the drought categories to characterize drought according to duration and severity. Drought duration and severity less than 3 are generally considered as mild. Those that fall between 3 and 6 are considered moderate and so on as shown in Table 7.

4.7 Bivariate Analysis of Return Period

The copula function was used to generate CDF for computing the joint return periods. Fig. 6(a) shows that higher drought frequency had lower return periods or were less severe. Accra, in 1970, 2001, 2007, and 2012 had a drought duration of 7 months with correspondingly return periods of 64.84, 70.35, 75.95 and 64.43 years, respectively. The 6-month drought duration with a severity of 10.73 had a return period of 145.15 in Accra in 2014. Yendi, in 1988, 2007, 2011, and 2014 had a drought duration of 7 months with correspondingly return periods of 106.84, 186.45, 173.42 and 234.5 years, respectively. Fig. 6(b) shows the graph of joint return periods of duration and severity for Yendi.

4.8 SPI for the Future Period

SPI for the future period based on ACCESS for SSP 2-4.5 was calculated for 2015-2057 (Near future) and 2058-2100 (Far future). The results showed significant extreme drought cases for the 3-month SPI for Accra in the far future. However, the 3-month droughts showed very few extreme and severe cases in the near future. It is also noteworthy that there were no moderate 9- and 12-month droughts in Accra in the near future but twenty-nine 9-month and four 12-month moderate drought cases in the far future. There were 46 and 446 mild and no drought for 24-month time steps in the near future, which increased to 513 and 3 cases, respectively, in the far future. There were no extreme, severe and moderate 6-month droughts in the near future, but 1 extreme, 12 severe, and 52 moderate droughts in the far future. Table 8 shows the future SPI values for Accra according to the Yevjevich scale.

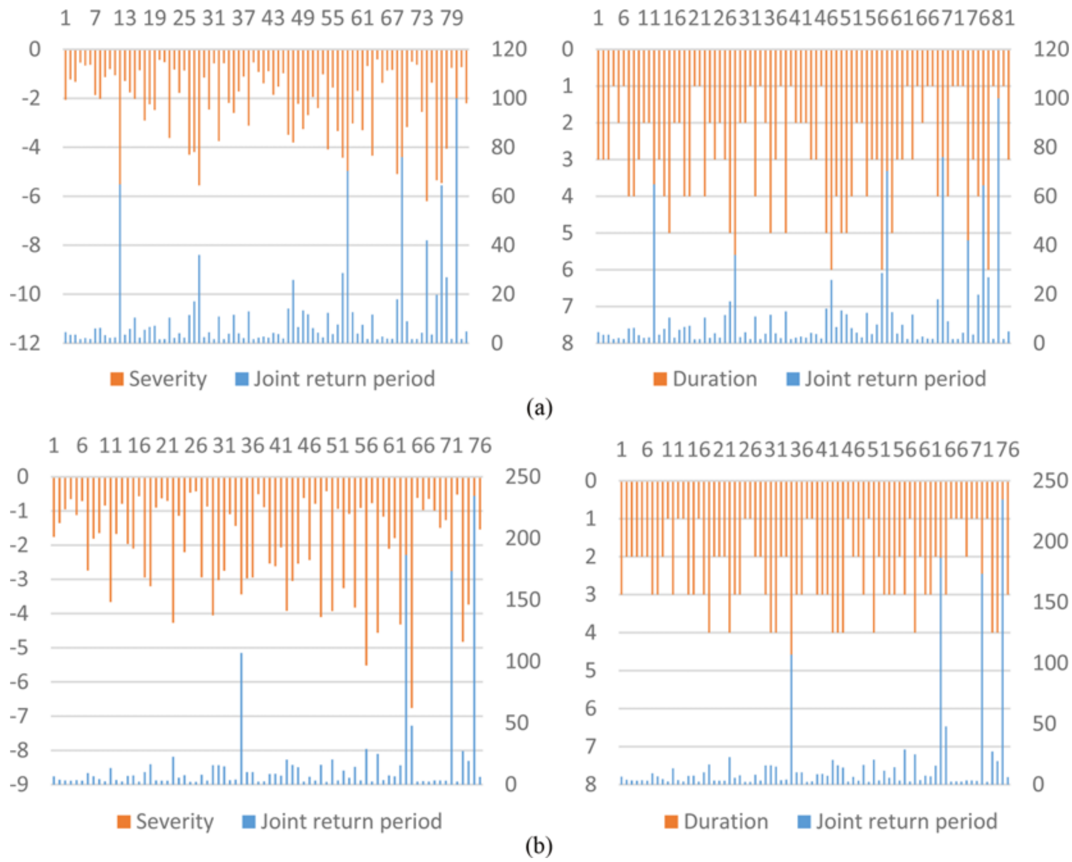


Fig. 6. Comparison of Bivariate Return Periods with Severity and Duration for: (a) Accra, (b) Yendi

Table 8. Future Drought Characteristics of Accra

Near future	SPI3		SPI 6		SPI 9		SPI 12		SPI24	
	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category
Extreme Drought	0	0.00%	0	0%	0	0%	0	0.00%	0	0%
Severe Drought	1	0.19%	0	0%	0	0%	0	0.00%	0	0%
Moderate Drought	13	2.53%	0	0%	0	0%	0	0.00%	0	0%
Mild Drought	167	32.55%	179	35%	133	26%	53	10.52%	45	9%
No drought	332	64.72%	331	65%	374	74%	451	89.48%	445	91%
Total	513	100.00%	510	100%	507	100%	504	100.00%	492	100%
Far future	SPI 3		SPI 6		SPI 9		SPI 12		SPI 24	
	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category
Extreme Drought	18	3.52%	1	0%	0	0%	0	0.00%	0	0%
Severe Drought	35	6.84%	12	2%	0	0%	0	0.00%	0	0%
Moderate Drought	71	13.87%	52	10%	19	4%	4	81.00%	0	0%
Mild Drought	145	28.32%	281	54%	389	78%	472	95.93%	513	99%
No drought	243	47.48%	170	33%	89	18%	16	3.25%	3	1%
Total	512	100.00%	516	100%	497	100%	492	100.00%	516	100%

The results for Yendi generally showed fewer extreme and severe droughts than Accra according to the Yevjevich scale. There were no extreme 3-month droughts at Yendi in the near and far futures. There were also no moderate, severe and extreme 6- to 24-month droughts in the near future, but five 6-month moderate droughts in the far future. Indeed, there are no extreme or severe 3-month droughts in the near and far futures, but 5 severe droughts in the far future. Table 9 shows the future SPIs for Yendi according to the Yevjevich scale.

Table 9. Future Drought Characteristics of Yendi

Near future	SPI3		SPI6		SPI9		SPI12		SPI24	
	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category
Extreme Drought	0	0.00%	0	0%	0	0%	0	0.00%	0	0%
Severe Drought	0	0.00%	0	0%	0	0%	0	0.00%	0	0%
Moderate Drought	4	0.78%	0	0%	0	0%	0	0.00%	0	0%
Mild Drought	248	48.30%	226	44%	189	37%	64	12.70%	12	2%
No drought	261	50.88%	284	56%	318	63%	440	87.30%	480	98%
Total	513	100.00%	510	100%	507	100%	504	100.00%	492	100%
Far future	SPI3		SPI6		SPI9		SPI12		SPI24	
	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category	Occurrence	Time in Category
Extreme Drought	0	0.00%	0	0%	0	0%	0	0.00%	0	0%
Severe Drought	5	0.97%	0	0%	0	0%	0	0.00%	0	0%
Moderate Drought	25	4.84%	5	1%	0	0%	0	0.00%	0	0%
Mild Drought	229	44.29%	256	50%	254	49%	214	41.39%	210	41%
No drought	258	49.90%	256	50%	263	51%	303	58.61%	307	59%
Total	517	100.00%	517	100%	517	100%	517	100.00%	517	100%

Table 10. Drought Characteristics for Accra and Yendi according to Run Theory

Drought Characteristics	Near future	Far future
	Accra	
Number of droughts	188	186
Longest Drought duration (months)	6	6
Average drought duration (months)	3.42	3.96
Maximum drought severity	10.34	10.28
Average drought severity	3.11	5.53
Drought Characteristics	Yendi	
Number of droughts	213	208
Longest Drought duration (months)	6	6
Average drought duration (months)	4.95	4.43
Maximum drought severity	5.35	6.26
Average drought severity	3.41	3.8

4.9 Results for Duration and Severity for the Future Period

Drought severity and duration were also characterized according to their length, average duration, average severity and maximum severity. The results showed no droughts longer than 6-months in Accra in the near future. A similar result was also noticed for the far future. However, an increase in average drought duration by 3.96 and severity by 5.53 was noticed in the far future than in the near future. Accra showed 213 droughts in the near future and 208 in the far future. Yendi had an average drought duration of 4.95 and 4.43 and an average drought severity of 3.41 and 3.80 for the near and far futures, respectively. Table 10 shows the future drought characteristics for Accra and Yendi according to the run theory.

4.10 Marginal Distribution of Duration and Severity for the Future Period

The marginal distribution at Accra showed the Weibull as the best in fitting severity and duration in the near future, with a Kolmogorov-Smirnov test statistic of 0.076 and a Cramer von Mises test statistic of 0.048 for severity and 0.20 and 0.32 for the duration, respectively. The AIC and BIC were 208.32 and 212.30 for severity and 175.38 and 179.35 for the duration, respectively. The test results for the far future also showed the Weibull as the best distribution function, with a Kolmogorov-Smirnov test and Cramer von Mises test of 0.12 and 0.11 respectively for severity and 0.24 and 0.35 for the duration, respectively. The AIC and BIC were 222.88 and 226.58 for severity and 163.99 and 167.69 for the duration. Fig. 7 shows the densities of the tested distributions for the near and far futures at Accra, while the test statistics of fitted probability distributions are given in Table 11.

As Yendi, the Weibull showed the best performance in fitting drought duration and the gamma for severity in the near future, with a Kolmogorov-Smirnov test statistic of 0.066 and a Cramer von Mises test statistic of 0.027 for severity and 0.384 and 1.390 for the duration, respectively. The AIC and BIC were 93.334 and 96.857 for severity and 74.533 and 78.056 for the duration, respectively. For the far future, the Weibull showed the best performance for both duration and severity, with a Kolmogorov-Smirnov test and Cramer von Mises test statistics of 0.172 and 0.280, respectively for severity and 0.347 and 0.929 for the duration, respectively. The AIC and BIC were 144.545 and 148.245 for severity and 141.455 and 141.155 for the duration, respectively. Fig. 8 shows the densities of the tested distributions in the near and far futures. The test statistics of fitted probability distributions are given in Table 11.

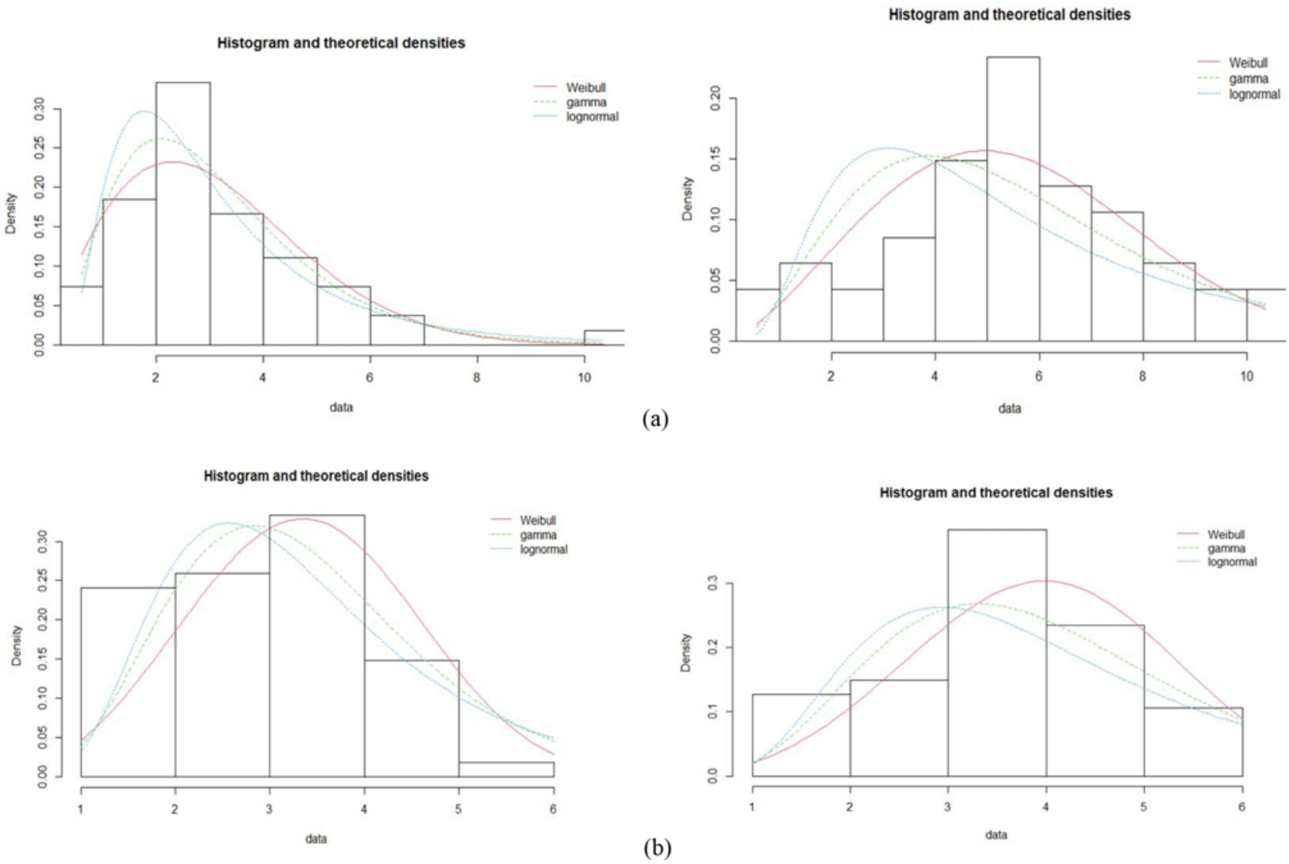


Fig. 7. Densities of Three Tested Distributions at Accra in the: (a) Near Future, (b) Far Future

Table 11. Test Statistics of Fitted Distribution Functions at Accra

Near future	Severity			Duration		
	Weibull	Gamma	Lognormal	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov	0.08	0.09	0.13	0.20	0.18	0.23
Cramer von Mises	0.05	0.05	0.13	0.32	0.41	0.49
Anderson-Darling	0.33	0.35	0.79	1.82	2.33	2.88
AIC	208.32	206.88	210.14	175.38	182.85	190.24
BIC	212.30	210.86	214.12	179.35	186.82	194.22
Far future	**Severity**			**Duration**		
	Weibull	Gamma	Lognormal	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov	0.12	0.16	0.20	0.24	0.29	0.30
Cramer von Mises	0.11	0.29	0.50	0.35	0.55	0.70
Anderson-Darling	0.83	1.70	2.90	2.10	3.17	4.08
AIC	222.88	230.98	243.96	163.99	176.38	186.84
BIC	226.58	234.68	247.66	167.69	180.08	190.54

4.11 Joint Distribution of Duration and Severity for the Future Period

Clayton performed the best at Accra for the near future with a Kolmogorov-Smirnov test statistic of 0.78 and a Cramer von Mises test statistic of 0.19. At Yendi, Frank copula performed best with a Kolmogorov-Smirnov and Cramer von Mises test statistics of 1.22 and 0.69, respectively. Gumbel performed the best at Accra for the far future with a Kolmogorov-Smirnov test statistic of 0.78 and a Cramer von Mises test statistic of 0.10. The Frank copula performed best at Yendi in the far future with a Kolmogorov-Smirnov and Cramer von Mises test statistics of 0.90 and 0.0.31, respectively. It can be noted that at Yendi, the Frank copula performed the best for both near and far future, indicating that the dynamics of the

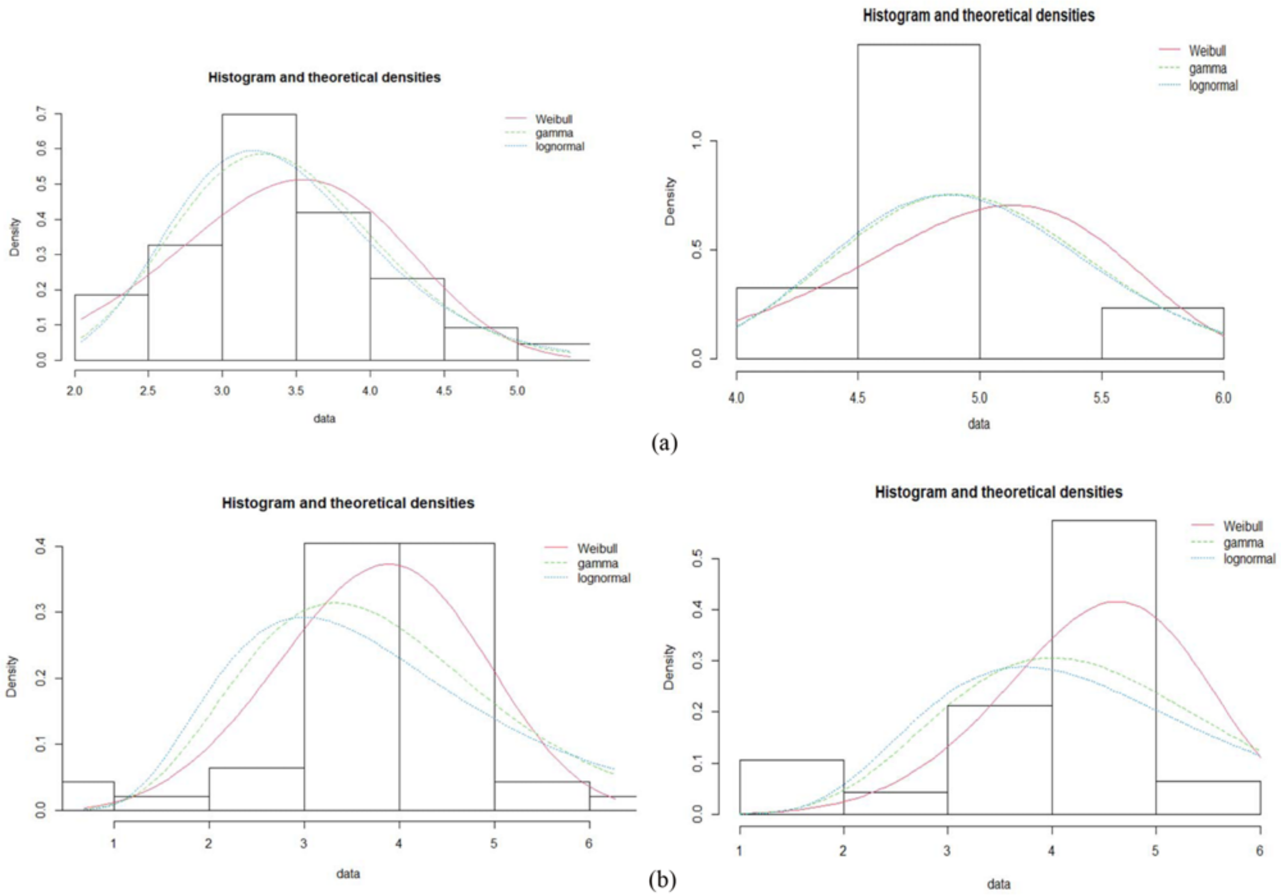


Fig. 8. Densities of Tested Distribution Functions at Yendi in the: (a) Near Future, (b) Far Future

Table 12. Test Statistics of Fitted Distribution Functions at Yendi

Near future	Severity			Duration		
	Weibull	Gamma	Lognormal	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov	0.10	0.07	0.07	0.38	0.39	0.39
Cramer von Mises	0.11	0.03	0.02	1.39	1.41	1.42
Anderson-Darling	0.66	0.19	0.19	6.51	6.71	6.78
AIC	98.61	93.33	93.43	74.53	71.43	72.02
BIC	102.13	96.86	96.96	78.06	74.95	75.55
Far future	Severity			Duration		
	Weibull	Gamma	Lognormal	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov	0.17	0.22	0.25	0.35	0.33	0.33
Cramer von Mises	0.28	0.61	0.82	0.93	1.12	1.22
Anderson-Darling	1.65	3.35	4.52	5.04	5.87	6.34
AIC	144.55	161.01	174.85	141.46	163.07	173.66
BIC	148.25	164.71	178.55	145.16	166.77	177.36

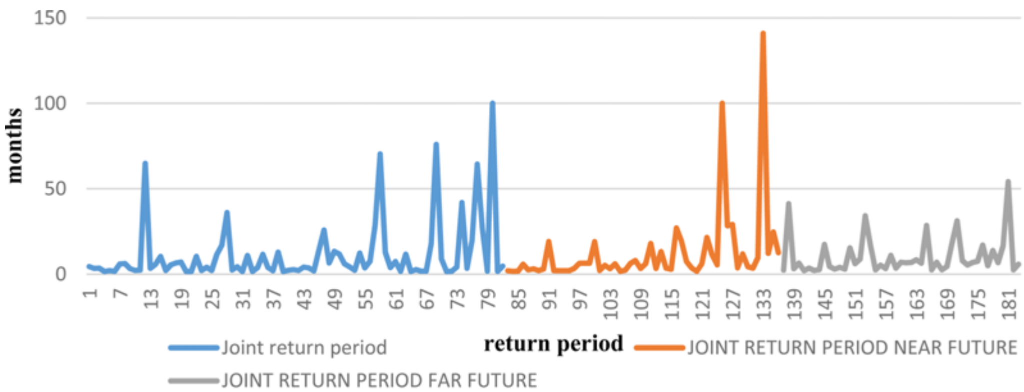
joint distribution of drought duration and severity remained relatively the same, whilst in Accra, the change from Clayton to Gumbel indicates a change in the dynamics of joint distribution of drought duration and severity for the near and far future.

4.12 Comparison of Historical and Future Return Periods

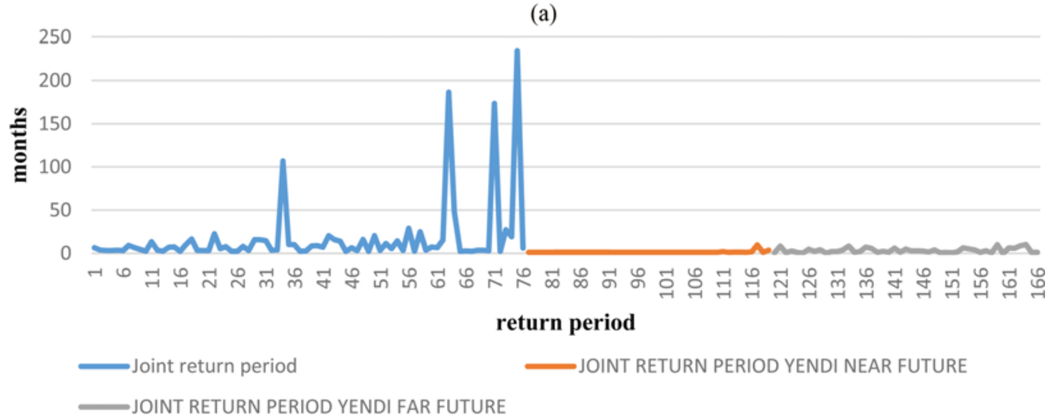
The historical return periods of both cities were compared in the near and far futures to determine the possible future changes. The results showed that the mean historical return periods of droughts at Accra (11.36) were similar to in the near and far

Table 13. Test Statistics of Copulas in Fitting Joint Distribution of Drought Duration and Severity for the Future Periods

Near Future					Far Future				
Copula	Kolmogorov-Smirnov		Cramer von Mises		Copula	Kolmogorov-Smirnov		Cramer von Mises	
	Accra	Yendi	Accra	Yendi		Accra	Yendi	Accra	Yendi
Clayton	0.783	1.395	0.192	0.719	Clayton	0.783	1.026	0.135	0.290
Frank	0.883	1.220	0.288	0.691	Frank	1.005	0.902	0.234	0.310
Normal	0.888	1.328	0.235	0.697	Normal	0.822	0.915	0.132	0.310
T	1.032	1.390	0.330	0.729	T	1.180	0.908	0.344	0.312
Gumbel	1.019	1.371	0.346	0.776	Gumbel	0.775	1.052	0.102	0.331
Joe	1.383	1.337	0.700	0.843	Joe	0.819	1.131	0.110	0.420



(a)



(b)

Fig. 9. Joint Historical and Future Return Periods for Accra and Yendi: (a) Historical Versus Future (Accra), (b) Historical Versus Future (Yendi)

futures (12.26 and 10.30, respectively). For the historical period, the maximum return period was 100 years, while the return periods in the near and far futures were 140 years and 54 years, respectively. However, the results showed significant differences at Yendi. The mean historical return period of droughts was 17.40, which was projected to reduce to 1.47 and 2.13 in the near and far futures, respectively. The maximum return period was 234 years for the historical period, while 9.65yrs and 10.20 yrs for the near and far futures, respectively. Fig. 9 shows the joint return period graph for the historical and future periods at. Accra and Yendi. Table 14 shows the statistical analysis of the return periods of droughts for the historical and future periods. This means that Accra is at a higher risk of serious drought compared to Yendi. This could be due to the fact that Accra, being the capital, has serious greenhouse gas emissions and a rapid population

Table 14. Statistics of Historical and Future Return Periods of Droughts

City	Period	Mean	Maximum	Standard deviation	Inter-quatile Range
Accra	Historical	11.36	100.00	18.39	9.37
	Near Future	12.26	140.88	23.05	9.16
	Far Future	10.30	54.19	11.06	8.99
Yendi	Historical	17.40	234.51	39.72	11.22
	Near Future	1.47	9.65	1.34	0.02
	Far Future	2.13	10.20	1.26	1.12

growth compared to Yendi. Outliers can be located using the Interquartile Range (IQR). The IQR may also show how skewed the dataset is. Industralisation and urbanization coupled with hazardous environmental practises in the capital contributes to the erratic nature of precipitation and an increase in temperature.

5. Conclusions

This study modelled drought duration and severity using copula theory. SPEI was calculated for a historical period from 1961 to 2014. The drought severity and duration were derived using run theory. The results showed that the Weibull and lognormal distributions best describe the distribution of drought severity and duration, respectively, in Accra and Yendi. The results also showed that the Clayton copula and Gumbel copula best model the marginal distributions of drought severity and duration at Accra and Yendi. The bias-corrected ACCESS-ESM1-5 showed the best performance among the six GCMs in simulating rainfall and temperature at the study locations. The future projection showed a reduced drought duration and severity in Accra, correspondingly high return periods in near and far futures. In contrast, significantly lower drought return periods in the near and far futures were projected at Yendi. The limitations of this study include the lack of data and the lack of scientific studies in the study area. Understandably, the results might be improved with more distribution and copula functions, although the ones employed are popularly used. The addition of more GCMs and different SSPs can also improve the reliability of this assessment. These results are very important for this area due to the low number of studies conducted and most importantly, the few research conducted in these areas show that, the West Africa region suffers significantly from the effects of climate change when compared to the rest of the world.

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