Observed trends in heavy rainfallover tropical catchments: case study of the Oti river basin, West Africa

ABSTRACT

Climate change has exacerbated heavy rainfall which causes severe floods in West Africa.The global warning accelerates the evapotranspiration process which further alters the rainfall regime due to the increased capacity of the atmosphere to hold moisture according to the Clausius-Clapeyron relationship. Understanding how heavy rainfall events are changing locally is a useful step in the implementation of efficient strategies for flood risk management. This study aims at analyzing heavy rainfall over the Oti river basin. Daily rainfall and temperature data were collected from national meteorological stations in Benin, Ghana and Togo. Thus, seven (07) heavy rainfall indices were calculated using observed daily data from 1921 -2018.The methodology used to estimate heavy rainfall quantiles is an index storm regional frequency analysis based on L-moments of AMAX. The Mann–Kendall and Sen's slope tests were used for the trend analysis. The results showeddecreasing trends in most of the heavy rainfall indices. In addition,the occurrence of heavy rainfall of higher return periods has slightly decreased in a large part of the study area. Also, the analysis of the annual maximum rainfall revealed that the Generalized Extreme Value is the most appropriate three-parameter frequency distribution for predicting extreme rainfall in the Oti river basin. These results are useful for efficient flood risk management and accurateestimation of design rainfalls in the study area.

Keywords: climate change;heavy rainfalls; Oti river basin; Togo, trends

INTRODUCTION

. Global mean temperature increment of about 0.7 °C since the last century has been reported by IPCC 2007b(IPCC, 20007b; Ilori&Ajayi, 2020). The global warning accelerates the evapotranspiration process which further alters the rainfall regime due to the increased capacity of the atmosphere to hold moisture according to the Clausius-Clapeyron relationship .The hydrological cycle is expected to intensify with global warming, which likely increases the intensity of extreme precipitation events and the risk of flooding(Tabari, 2020). Thus, the frequency and intensity of extreme rainfall events are expected to change under climate change in many regions of the world including West Africa (WA) and the need of information to manage the risk related to climate extremes is increasing (Klein et al., 2009)(Klassou and Komi, 2021).Rainfall in WA is controlled by the seasonal variation in the geographical position of the Intertropical Convergence Zone (ITCZ) which is the most important meteorological phenomenon in the region (Nicholson, 2009). The ITCZ appears at the ascending branch of atmospheric Hadley cells. In boreal winter, the ITCZ is situated around 5°S on the tropical Atlantic and the continent is dry. Then, it moves to the north, following the northward migration of the maximum of received solar radiation energy. The ITCZ reaches its most northern position in August between 10°N and 12°N before retreating to the South. As a consequence, areas located north of the 8th parallel north experience only one (1) rainy season while those situated south of this parallel are characterized by two (2) rainy seasons(Nicholson, 20009).During the last decades, rainfalls in West Africa had been characterized by a pronounced variability over a range of temporal scales (Nicholson 2001). In this region, heavy rainfalls are usually from deep westward propagating convective systems embedded within the West African monsoon system (Pante and Knippertz, 2019).Increase in heavyrainfalls could contribute to more floods in some regions with severe impacts on human life and socio-economic activities.For instance, many West African countrieshave experienced severe floods during the last decades.With at least 612 persons killed, the 2022 floods in Nigeria were among the deadliest in the country history.InSeptember2007, floods killed 23, 46 and 56 people in Togo, Burkina Faso and Ghana respectively (Tschakert *et al.*, 2010). Furthermore, the Oti river basin (ORB) experienced other damaging flood events in 1998, 2008, 2010 and 2018. These tolls show the high level of vulnerability of communities in this region.On the other hand, the growing frequency of floods in ORBraises theimportant question whether they were triggered by heavy rainfall or they were caused by deforestation and other changes in land use and land cover or uncontrolled urban expansion (Klassou, 2018).

Studies on climate extreme are useful to understand the changes in extreme climate events and provide the basis for efficient adaptation to climate change(Klassou and Komi, 2021). Thus, the World meteorological organization(WMO) held at Ashville in North Carolina (3 to 6 June 1997) an international workshop on indices and indicators of extreme climate in order to promote their analysis techniques (Karl *et al.*, 1999).This initiative has enhanced the emergence of several studies about climate extremes around the world. For instance,in West Africa, Barry *et al.* (2018) performed a regional analysis of climate extreme showed “non-coherent” changes of rainfall indices throughout the region except the simple daily intensity and maximum5-day precipitation indices which exhibited significant increasing trend whilst Hounkpè *et al.*2016 analysed change in heavy rainfall characteristics over the Ouémé river basin and found that 82% of the meteorological stations showed statistically significant change in daily precipitation, among which 57% exhibited a positive change and 43%negative change. Furthermore, Klassou and Komi (2021), analyzedextreme rainfall in the ORB and highlighted an increasing trend in dry spells indices. In North Africa, Hadri*et al.*(2020) examined trends in extreme climate indices in Chichaoua Mejjate region (Morocco) and found a general downward trends in the heavy rainfall threshold, in the number of days with rainfall greater than 10 or 20 mm as well as in the consecutivewet days(Klassou and Komi, 2021).In Europe,Gentilucci *et al*. (2019)analysed extreme precipitation in the Marche region (central Italy) and showed significant countertrends for extreme precipitation indices. In Asia, Tirkey *et al*. (2020) pointed out both positive and negative trends in monthly and seasonal precipitation over Satluj Basin (India) during 1901-2013. The analysis of changes in extreme rainfall at local scale is useful to provide scientific knowledge for waterresources management in order to reduce the vulnerability of the communities to the adverse effects of climate change. However, most of the previous studies focused mainly on moderate extreme rainfall and very few of them have examined changes in daily extreme rainfall over the ORB. Hence, the main objective of this study is to provide a holistic analysis of observed trends in heavy rainfalls in thestudy area. Specifically, this study aims at i) examining the spatio-temporal changes in heavy rainfall indices, ii) identifying the best probability distribution to predictheavy rainfalls and iii) analyzing trends in rainfalls of higher return periods in the study area(Klassou and Komi, 2021).

MATERIALS AND METHODS

Study area

The ORB is a sub-basin of the Volta basin in West Africa. It is a transboundary river basin shared by four (4) countries namely Togo, Ghana, Burkina Faso and Benin.The study area refers to the central ORBand covers an area of about 41, 863.56 km^2. It lies between latitudes 8.59° N – 11.35 ° N and longitudes 0.37° W – 1.70° E with minimum and maximum elevation of respectively 74 m and 833 m above mean sea level(Figure 1). The climate of the ORB is tropical and characterized by a single rainy season occurring between April and October when theITCZ is in its northern position and a dry season lasting from November to March (Figure 2)**(Klassou and Komi, 2021)**. The mean annual rainfall is comprised between 1000 and 1400 mm (1961-2018). The maximum temperature is observed in the dry season with mean values varying from 34 to 36 °C while the minimum temperature is comprised between 20 and 24 °C (Klassou, 2018).

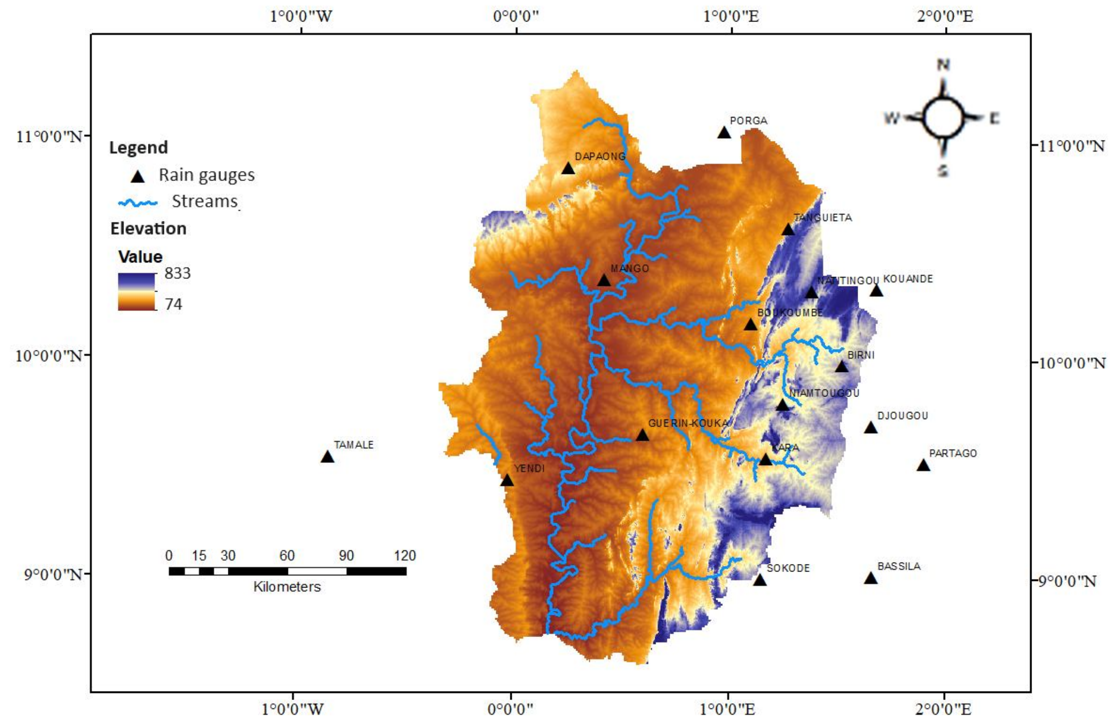

Figure1. Location of the study area showing the meteorological stations used in this study as well as the river network

Data and quality control

Daily rainfall and temperature data were collected from national meteorological stations in Benin, Ghana and Togo. A total of 17 stations were used in this study for the calculation of both the indices and the extreme quantiles of interest. The period of available observed data of good quality varied by stations depending on the countries where the stations are located (Table 1). These data were subjected to two (2) types of quality control. First, the freely available software Rclimdex 1.0 (Zhang and Yang, 2004) was used to detect errors caused by data pre-processing. Some unrealistic data such as daily rainfall greater than 500 mm were found and replaced by missing values(Klassou and Komi, 2021)**.**After this step, the time series were tested for homogeneity in order to identify artificial shift in the collected data using the R package RHtests_dlyPrcp developed for the homogenization of daily precipitation data (Wang and Feng, 2013).Some change points were detected in the daily rainfall data and the adjustment were made using the mean-adjusted algorithm (Wang *et al.*, 2010)(Klassou and Komi, 2021).Secondly, the mean annual maximum (AMAX) rainfall of 17 meteorological stations was screened for discordancyin a regional frequency analysis process using a test proposed by Hosking and Wallis (1997). The discordancy measure (Di) is a statistic test based on the difference between the L-moment ratios of a site and the mean L-moment ratios of a group of sites. The critical value ofDi depends on the number of sites (N)in a given group. For N ≥ 15, Di should be less or equal to three (3)for a site to be used in a regional frequency analysis. In this study, no discordant site from the whole group has been observed(Table 1)(Klassou and Komi, 2021)

Table 1: Characteristics of the meteorological stations used in this study

No	name	Longitude	Latitude	Altitude (m)	Data periods	Country	AMAX (mm)	Di
1	BASSILA	1.66	9.01	384	1953-2004	Benin	72.71	2.53
2	BIRNI	1.52	9.98	430	1953-2001	Benin	77.12	2.03
3	BOUKOUMBE	1.1	10.17	247	1923-2001	Benin	74.36	0.44
4	DAPAONG	0.25	10.88	230	1961-2018	Togo	80.42	0.52
5	DJOUGOU	1.66	9.7	439	1921-2007	Benin	84.25	0.59
6	GUERIN-KOUKA	0.6	9.66	267	1961-2018	Benin	66.04	0.27
7	KARA	1.17	9.55	342	1961-2018	Togo	74.99	0.14
8	KOUANDE	1.68	10.33	442	1931-2010	Benin	75.93	0.51
9	MANGO	0.42	10.37	146	1961-2018	Togo	75.84	0.1
10	NATITINGOU	1.38	10.32	461	1921-2010	Benin	71.84	0.64
11	NIAMTOUGOU	1.25	9.8	462	1961-2018	Togo	68.55	1.46
12	PARTAGO	1.9	9.53	397	1969-2007	Benin	78.05	1.72
13	PORGA	0.97	11.05	160	1964-1999	Benin	67.82	3
14	SOKODE	1.15	9	400	1961-2018	Togo	77.16	0.59
15	TAMALE	-0.85	9.55	183	1961-2010	Ghana	80.54	0.28
16	TANGUIETA	1.27	10.61	225	1937-2008	Benin	74.12	2.1
17	YENDI	-0.02	9.45	195.2	1960-2010	Ghana	80.32	0.06

Calculation of descriptive heavy rainfall indices

Seven (07) heavy rainfall indices were selected among the list of 27 climate extreme indices that have been developed by theExpert team on climate change detectionand Indices (ETCCDI).These indices are based on station level thresholds such as the 99th percentile of daily precipitation amount or the number of days with rainfall amount greater than 10 mm (Zhang and Yang, 2004). For rainfall, these thresholds are calculated from the sample of all wet days (rainfall greater than or equal to 1mm) in the reference period which is defined in this study as 1971-2000. For a completed description of these indices and the formulas to compute them, the reader is referred to the ETCCDI web site(Klassou and Komi, 2021). The following indices were calculated annually from daily rainfall data using the freely available Rclimdex software 1.0 (Zhang and Yang, 2004):

i. CWD (Consecutive wet days) = Highest number of consecutive days with precipitation ≥ 1mm (days)
ii. Rx1day (maximum 1-day precipitation)=Annual maximum 1 day precipitation
iii. Rx5day (Max 5-day precipitation amount) = Monthly maximum consecutive 5-day precipitation (mm)
iv. R10 (Number of heavy precipitation days)= Annual count when precipitation ≥ 10 mm (days)
v. R20 (Number of very heavy precipitation days) = Annual count when precipitation ≥ 20 mm (days)
vi. R95p (Very wet days) = Annual total precipitation when daily precipitation > 95th percentile (mm)
vii. R99p (Extremely wet days) =Annual total precipitation when daily precipitation > 99th percentile (mm)

Estimation of heavy rainfall quantiles

The methodology used to estimate heavy rainfall quantiles is an index storm regional frequency analysis based on L-moments of AMAX which was introducedby Hosking and Wallis (1997). This approach is suitable for short sample of data as it is the case in the present study and assumes that sites from a homogeneous region have the same probability distribution apart from the mean of site data which represents the scaling factor of this site(Klassou and Komi, 2021).Thus, this method requires testing the homogeneity of the proposed region and selecting the best frequency distribution

Homogeneity test

The aim of this homogeneity test in a regional frequency analysis is to estimate the level of homogeneity in a group of sites(Klassou and Komi, 2021). In this work, the H-statistic with the measures of L-coefficient of variation (H1), L-skewness (H2) and L-kurtosis were used. For a detailed information on the calculation of the H-statistic, the reader is referred to Hosking and Wallis (1997). The values of the homogeneity measures computed using the AMAX of the 17 meteorological stations are the following:

- H1 = 1.23
- H2 = -0.6

- H3 = -1.27

Originally, an H value of 1.0 was suggested to decide if a group is homogeneous or not. However, according to Hosking and Wallis (1997), the threshold for rejection of the hypothesis ofhomogeneity at significance level 10% is H = 1.28.. Based on the latter criterion, the study area is considered as a homogeneous region(Klassou and Komi, 2021).

Selection of the best frequency distribution

Many goodness-of-fit methods have been developed for selecting the most appropriate frequency distribution of sample data among which the quantile-quantile plots, the Kolmogrov-Smirnov,Cramer-von Mises, Anderson-Darling tests as well as those based on L-moment statistics. In the present study, The Z-statistic (Z^{Dist}) which was introduced by Hosking and Wallis (1997) was used to identify the best frequency distribution.This statistic evaluates the difference between the theoretical L-kurtosis of the fitted three parameters distribution and the regionalaverage L-kurtosis of the observed data. This testis defined in Equation 1 as follows:

$$Z^{Dist} = \left(\tau_4^{Dist} - t_4^R + B_4\right)/\sigma_4 \qquad (1)$$

Where D_{ist} refers to a particular distribution, $\tau_4^{Dist}$is the L-kurtosis of the selected distribution,t_4^R is the regional weighted average of sample L-kurtosis, B_4 and σ_4 are respectively the bias of t_4^R and the standard deviation of sample L-kurtosis. The fit of the distributionis considered satisfactory if the absolute value of Z for a candidate distribution is less or equal to 1.64 (Hosking and Wallis, 1997).After the homogeneity test, the hypothesis of fitting the Generalised Extreme Value (GEV), the Generalised Pareto (GPA) and Pearson type III distributions to AMAX rainfall of the study area was made. The values of the Z^{Dist}were -0.96 , -2.81 and -7.50 respectively for the GEV, Pearson type III and GPA distributions indicating that the GEV is the most robust three parameters probability distribution for estimating heaving rainfall quantile in the middle portion of the ORB.

Estimation of the parameters and quantiles for GEV distribution

The quantile function of the GEV distribution is given by Equations 2 and 3:

$$q_R = \varepsilon + \frac{\alpha}{k}\left\{1 - \left[-log\left(\frac{T-1}{T}\right)\right]^k\right\} \qquad \text{for } k \neq 0 \qquad (2)$$

$$q_R = \varepsilon - \alpha \left\{ log \left[-log \left(\frac{T-1}{T} \right) \right] \right\} \quad \text{for } k = 0 \tag{3}$$

Where, α, ε, k are respectively the scale, location and shape parameters of the distributions. T is the return period and $q_R$is the regional growth curve.

The estimated values of α,ε, k are respectively 0.23, 0.85 and -0.04. The rainfallassociated with 25, 50, 75 and 100 year return periods at each of the meteorological station in the homogeneous group were computed by multiplying the values of the growth factor corresponding to the same return period on the AMAX at each site(Klassou and Komi, 2021).

Statistical tests for trends analysis

In this study, the Mann-Kendall (MK) trend test based on Sen’s slope estimator was applied to assess trends in the daily rainfall data. This test, recommended by the WMO has been used in many previous studies to estimate trends in hydro-climatologic data (e,g.Aguilar *et al*. 2009; Rahmat et al. 2015; Liu and Xu 2019).Since, the existence of serial correlation in time series can increase the number of false rejections of the null hypothesis of the MK test which supposes that the data are independent and identically distributed, the MK test was applied to take into account the existence of autocorrelation in the indices series using the same approach as in previous work analyzing trends in climate extremes (Wang and Swail 2001).

The MK trend test is a non-parametric method which does not require the data to follow a specific distribution(Klassou and Komi, 2021). It has both the advantage of being robust to the presence of outliers in the time series and is less sensitive to inhomogeneous data. In order to carry out a MK test, the differences between later observed values and those from earlier time periods are computed. Hence, the test statistic, S, is estimated using the formulae given by Equations 4 and 5:

$$S = \sum_{K=1}^{n-1} \sum_{j=k+1}^{n} sgn\left(x_j - x_k\right) \tag{4}$$

With

$$sgn = \left(x_{j-}x_k \right) = \begin{cases} +1 & if \ \left(x_j - x_k \right) > 0 \\ 0 & if \ \left(x_j - x_k \right) = 0 \\ -1 & if \ \left(x_j - x_k \right) < 0 \end{cases} \tag{5}$$

x_j and x_k are data values at times *j* and *k* respectively, while *n* is the number of data points. For *n*< 10, the value of |S| is compared to the theoretical distribution of S derived by Mann and Kendall. In the cases where n > 10, the standard normal variable Z is calculated by(Klassou and Komi, 2021):

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}} if S > 0 \\ 0 \quad if S = 0 \\ \frac{S+1}{\sqrt{VAR(S)}} if S < 0 \end{cases} \quad (6)$$

Where

$$VAR\ (S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p-1)(2t_p+5)}{18} \quad (7)$$

q is the number of tied groups while tp is the number of data values in the pth group. Positive values of Z show an upward trend whereas negative values of Z indicate downward trend. At 0.05 significance level, if |Z| is greater than 1.96 the null hypothesis is rejected, indicating that the trend is significant(Klassou and Komi, 2021).

TheSen's slope estimator uses a linear model to compute the true slope of a trend.First, the slope estimates of N pairs of data are calculated as follows:

$$Q_i = \frac{x_{j-} x_k}{j-k} \text{for} \quad i = 1,......N \quad (8)$$

Then, Sen's slope estimator is the median of these N values of Qi:

$$Q_{med} = \begin{cases} Q_{\frac{N+1}{2}} & if\ N\ is\ odd \\ \frac{1}{2}\left(Q_{\frac{N}{2}} + Q_{\frac{N+2}{2}}\right) & if\ N\ is\ even \end{cases} \quad (9)$$

Uncertainty in trend magnitudes

To investigate uncertainty in trend results, the errors around zero of the estimated slopes were computed for each indices as root mean square error (RMSE) using the following expression (Helsel et al., 2020):

$$\text{RMSE} = \sqrt{\frac{\sum(m-0)^2}{n}} \quad (10)$$

where *m* is the magnitude of the trend and *n* , the number of meteorological stations

RESULTS AND DISCUSSION

Trends in descriptive extreme indices during 1921-2018

The computed heavy rainfall indices for each selected meteorological station were plotted with the trends and all the graphs are provided in the supplementary materials. Table 2 summarizes the observations by showing the number of meteorological stations with positive, negative, positive significant and negative significant as well as the mean of both weather stations trend and weather stations with a significant trend(Klassou and Komi, 2021).In order to explore the spatial patterns of the trends over the whole study area, the trends were interpolated using inverse distance weighted (IDW) method in geographic information system (GIS) software and the results are shown inFigures 2 and 3.

Table 2. Summary of the trends (1921-2018)

Indices	Positive trends	Negative trends	Significative Positive trends	Significative Negative trends	Average trends	Average significative trends	RMSE
CWD	8	9	3	1	0.02	0.06	0.05
Rx1day	7	10	1	3	-0.09	-0.19	0.29
Rx5day	6	11	2	4	-0 .09	-0.16	0.40
R10	5	12	2	6	-0 .02	-0.05	0.12
R20	6	11	1	4	-0.03	-0.06	0.08
R95p	5	12	1	2	-0.68	-1.29	1.63
R99p	8	9	0	3	-0 .24	-1.63	0.92

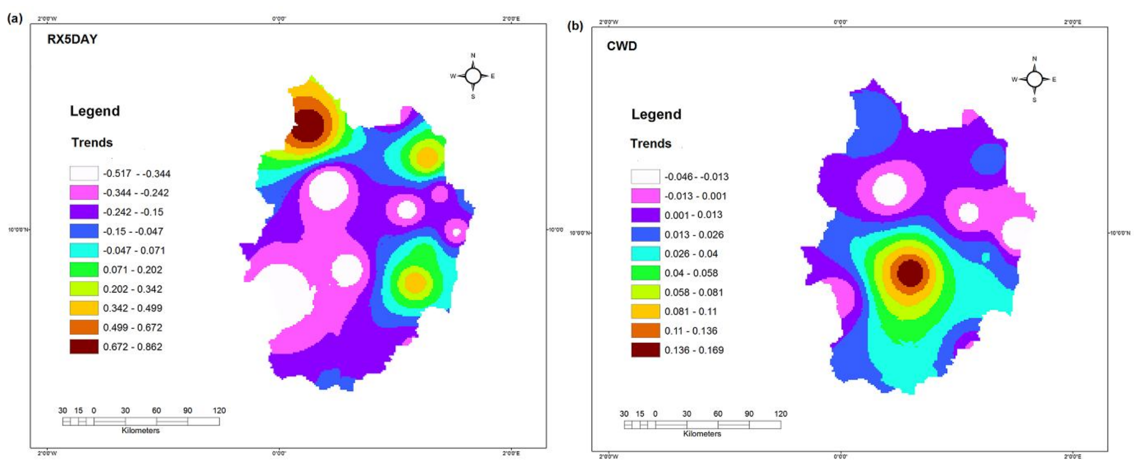

Figure 2. Spatial distribution of trends in RX5DAY (a) and CWD (b), during 1921-2018

As shown in Table 2, the consecutive wet days and the extremely wet day indices have the same percentage of positive trends and almost equalproportion between the weather stations with positive trend and those where the trend is negative although there is a slight prevalence of significant positive trend (18 %) against 6 % of significant negative trends.

Furthermore,Rx5 day and R20 showed identical rate of positive trend (37 %). As for the latter indices, the proportion of positive trends in both R10 and R95p are equal (29%)(Klassou and Komi, 2021). However, very small number (less than 18%) of these positive trends were significant at a level of 0.05 for the selected while R10 exhibited identical and highest rate of significant and negative trends (37 %).

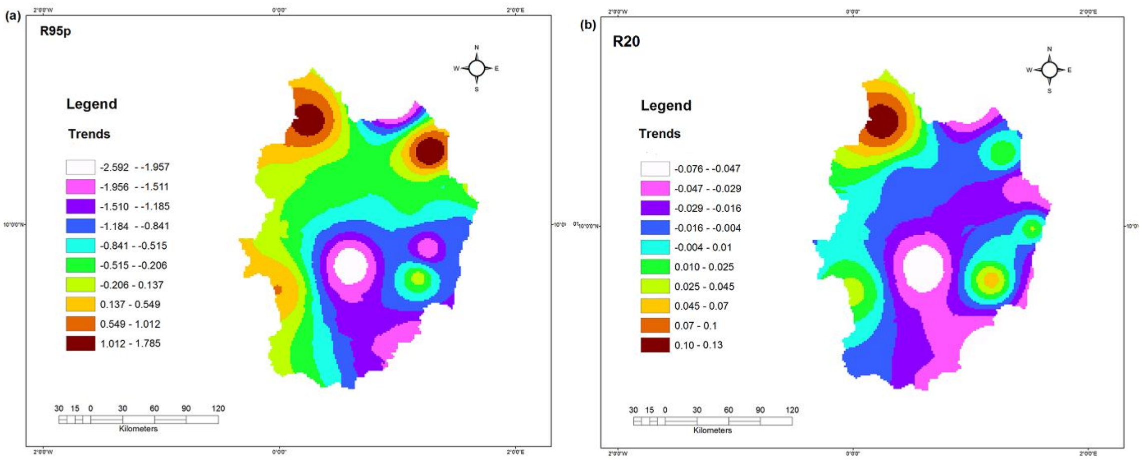

Figure 3. Spatial distribution of trends in R95p (a) and R20 (b)during 1921-2018

It should be noted that the decreasing trend in the indices (except CWD and R99p) have affected large parts of the middle ORB during 1921-2018. These trends can be explained by local scale variability in atmospheric circulation. Some positive correlations have been found in the number of heavy rainfall days over Ghana (West Africa) and the sea surface temperatures over the Atlantic Ocean (Atiah et al. 2020)

Trends in heavy rainfall of higher return periods

Table 3 and Figure 4 shows respectively the summary of the trends and their interpolated spatial variability(Klassou and Komi, 2021). While 65 % and 59% of the weather stations exhibited negative trends for respectively the 25 and 75-year heavy rainfall, the proportion of rain gauges with positive trends and those which showed negative trends are almost identical for the 50 and 100 - year heavy storm. In fact, the highest increase in 50, 75 and 100 years heavy rainfall are mainly located in the northern part of the study area. However, on average, both the observed positive and negative trends are very small (about 1 day per century)

Table 3. Summary of the trends in heavy rainfall of higher return periods.

Return	Positive	Negative	Significative	Significative	Average	Average	RMSE

periods	trends	trends	positive trends	negative trends	trends	significative trends	
25-Years	6	11	1	3	-0 .01	-0.01	0.01
50-Years	9	8	1	3	-0 .00	-0.01	0.01
75-Years	7	10	1	3	-0.00	-0.00	0.01
100-Years	8	9	1	2	-0.00	-0.00	0.00

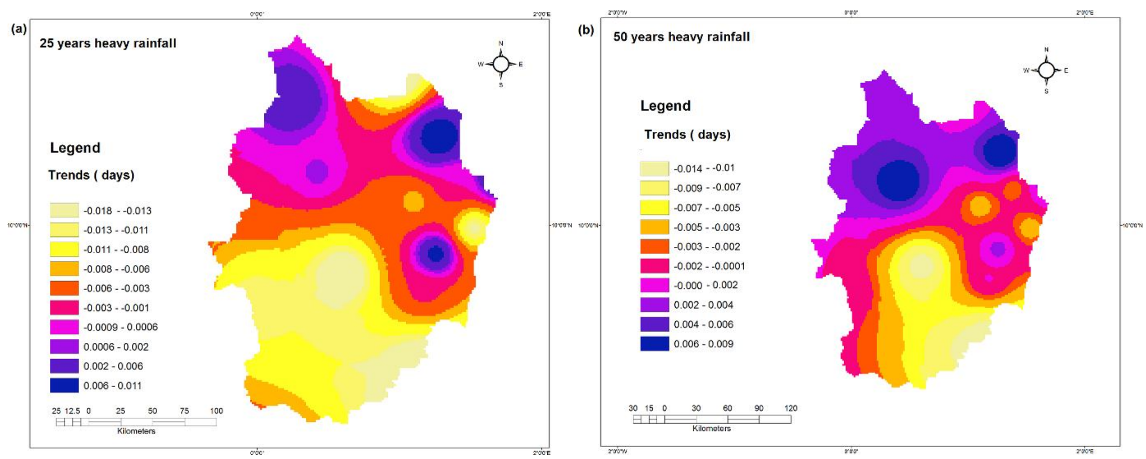

Figure 4. Spatial distribution of trends in heavy rainfalls of 25 (a) and 50 (b) years return periods

Comparison with previous studies

The development of the ETCCDI indices has enabled the comparison of trends in climate extreme indices between different regions(Klassou and Komi, 2021). An upward trend in most of the heavy precipitation indices had been observed at a global scale (Alexander et al. 2006), in Europe (Acero et al., 2011) , in South America (Pedron et al.,2016), in Asia (Li et al., 2015) and in Western part of North Africa (Donat et al. 2013).Moreover, Panthou et al. 2014 reported that the proportion of annual rainfall associatedwith extreme rainfall has increased from 17% in 1970–1990 to 19% in 1991–2000 and to 21% in 2001–2010in the Central Sahel (West Africa). On the contrary, a general reduction in heavy rainfall indices (except the dry spells) and a very slight decreasing trends in occurrence of heavy rainfall of higher return periods namely 25,50, 75 and 100 years have been found in this study(Klassou and Komi, 2021).This is in agreement with the findingsof Aguilar et al. (2009)which indicated downward trends in heavy rainfall indices in Central Africa and in Guinea Conakry. Similarly,decreasing trends of extreme rainfall were observed in North ITCZ and Central Tropics (McGree et al. 2014). Furthermore, in relation to our results regarding heavyrainfall, the study of M'Po et al. (2017) predicted a decreasing trends in heavy rainfall indices underthe worst climate change scenario (RCP8.5) of the International Panel on Climate Change over the Oueme River Basin in Benin Republic (West Africa) while Amoussou et al. (2020) pointed out a significant increase in the intensity of heavy rainfall by 2050 in Mono River Basin (Togo and Benin)(Klassou and Komi, 2021). One of the factors contributing to the reduction of heavy rainfall might be the rising deforestation in this region for many purpose such as agriculture and biomass energy which can lead to a weak monsoon as the dynamics of the West African monsoon and the associated rainfall patternare sensitive to the changes in land use pattern (Abiodun et al., 2006). This work also demonstrates the robustness of the GEV distribution in analyzing heavy rainfall in the study of Oti River Basin. This is similar to the results of Amoussou et al. (2020) and Panthou et al. (2014) who showed the suitability of GEV distribution in predicting intense rainfall over respectively the the Mono River Basin and central Sahel in West Africa.

CONCLUSIONS

This study has analysed he trends in heavy rainfall in the ORB. Using on daily rainfall time series of 17 weather stations from 1921-2018, seven (07)ETCCDIheavy rainfall indiceswere calculated and their trends were examinedafter quality control and homogeneity testing. First, the results indicates that five(05) over seven (07)of the selected heavy rainfall indices namely R10, R20, Rx1DAY, Rx5DAY an R95p have decreased in a large part of the study area during 1921-2018. In addition, theoccurrence of heavy rainfall of the 25, 50, 75 and 100 -year heavy rainfall has slightlydecreased.The second important result apart from the general negative trend of the heavy rainfall indicesis the robustness of GEV in analyzing the frequency of heavy rainfall in the ORB.Despite,this study does not take into account the impacts of climate change onfuture trends in extreme rainfall in study area, the results are useful for efficient flood risk management as well as accurate estimations of design rainfalls in the ORB.

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