Analysis of extreme rainfall in Oti River Basin (West Africa)
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ABSTRACT

Understanding how extreme rainfall is changing locally is a useful step in the implementation of efficient adaptation strategies to negative impacts of climate change. This study aims to analyze extreme rainfall over the middle Oti River Basin. Ten moderate extreme precipitation indices as well as heavy rainfall of higher return periods (25, 50, 75, and 100 years) were calculated using observed daily data from 1921 to 2018. In addition, Mann–Kendall and Sen’s slope tests were used for trend analysis. The results showed decreasing trends in most of the heavy rainfall indices while the dry spell index exhibited a rising trend in a large portion of the study area. The occurrence of heavy rainfall of higher return periods has slightly decreased in a large part of the study area. Also, 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. The novelty of this study lies in the combination of both descriptive indices and extreme value theory in the analysis of extreme rainfall in a data-scarce river basin. The results are useful for water resources management in this area.

Key words | climate change, extreme rainfall, Oti River Basin, Togo, trends

HIGHLIGHTS

- Observed trends of extreme rainfall in the Oti River Basin from 1921 to 2018.
- The occurrence of heavy rainfall of higher return periods has slightly decreased in a major part of the study.
- Consecutive dry days index has increased in a large part of the study area.
- Generalized Extreme Value is the best three parameter distribution for analyzing the frequency of extreme rainfall in the Oti River Basin.

INTRODUCTION

Anthropogenic climate change is now evident. 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. Thus, the frequency and intensity of extreme natural events are expected to change under climate change in many regions of the world including West Africa and the need of information to manage the risk related to climate extremes is increasing (Klein et al. 2009). These changes may not be uniform across the globe due to differences in local or regional atmospheric circulation patterns and the high level of spatio-temporal variation in rainfall. Rainfall in West Africa 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 experience only one rainy season while those situated south of this parallel are characterized by two rainy seasons (Nicholson 2009). During the last decades, rainfall in West Africa had been characterized by a pronounced variability over a range of temporal scales (Nicholson 2001). Increase in extreme rainfall could contribute to more floods or droughts in some regions with severe impacts on human life and socio-economic activities. For instance, many West African countries have experienced severe drought since the late 1960s, and the 1980s were the driest decade of the century in this region (Nicholson 2001). In contrast, the Oti River Basin (ORB) experienced damaging flood events in 1998, 2007, 2008, 2010, and 2018 with huge loss of human lives and infrastructure damage, particularly in 2007. These tolls show the high level of vulnerability of communities in this region. On the other hand, the growing frequency of floods in ORB raises the important question whether they were triggered by heavy rainfall or if they were caused by deforestation and other changes in land use and land cover.

The issue of insufficient studies on observed trends in climate extremes was first raised in the Second Assessment Report of the International Panel on Climate Change (Nicholls et al. 1996). These studies are useful to understand the changes in extreme climate events and provide the basis for efficient adaptation to climate change. Thus, the World Meteorological Organization (WMO) held at Asheville in North Carolina (from 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 and showed ‘non-coherent’ changes of rainfall indices throughout the region except the simple daily intensity and maximum 5-day precipitation indices which exhibited significant increasing trend. In North Africa, Hadri et al. (2020) examined trends in extreme climate indices in Chichaoua Mejate 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 consecutive wet days. In Europe, Gentiluccia et al. (2019) analyzed 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 water resources 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 Oti River Basin (ORB). Hence, the main objective of this study is to provide a holistic analysis of observed trends in extreme rainfall in the ORB. Specifically, this study aims at (i) examining the spatio-temporal changes in extreme rainfall indices, (ii) identifying the best probability distribution to predict extreme rainfall, and (iii) analyzing trend in rainfall of higher return periods in the study area.

**MATERIALS AND METHODS**

**Study area**

The Oti River Basin is a sub-basin of the Volta Basin in West Africa. It is a transboundary river basin shared by four countries, namely, Togo, Ghana, Burkina Faso, and Benin. The study area refers to the middle ORB and covers an area of about 41,863.56 km². It lies between latitudes 8.59°N–11.35°N and longitudes 0.37°W–1.70°E with minimum and maximum elevation of 74 and 835 m, respectively, 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 the ITCZ is in its northern position and a dry season lasting from November to March. The mean annual rainfall is
between 1,000 and 1,400 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 between 20 and 24 °C.

**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 types of quality control. First, the freely available software Rclimdex 1.0 (Zhang & 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. 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 & Feng 2013). Some change points were detected in the daily rainfall data and the adjustments were made using the mean-adjusted algorithm (Wang et al. 2010). Second, the mean annual maximum (AMAX) rainfall of 17 meteorological stations were screened for discordancy in a regional frequency analysis process using a test proposed by Hosking & 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 of Di depends on the number of sites (N) in a given group. For \( N \geq 15 \), \( Di \) should be less or equal to 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).

**Calculation of descriptive extreme rainfall indices**

Ten extreme precipitation indices were selected among the list of 27 climate extreme indices that have been developed
by the Expert Team on Climate Change Detection and Indi-
ces (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 & Yang 2004). For precipitation, these
thresholds are calculated from the sample of all wet days
(rainfall greater than or equal to 1 mm) 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. The following indices were calculated annually from
daily rainfall data using the freely available Rclimdex soft-
ware 1.0 (Zhang & Yang 2004):

i. CDD (consecutive dry days) = largest number of con-
secutive days with no precipitation (days)

ii. CWD (consecutive wet days) = highest number of con-
secutive days with precipitation ≥1 mm (days)

iii. PRCPTOT (annual total wet-day precipitation) = annual
total precipitation from days with precipitation ≥1 mm
(mm)

iv. Rx1day (maximum 1-day precipitation) = annual maxi-
imum 1 day precipitation

v. Rx5day (maximum 5-day precipitation amount) =
monthly maximum consecutive 5-day precipitation (mm)

vi. R10 (number of heavy precipitation days) = annual
count when precipitation ≥10 mm (days)

vii. R20 (number of very heavy precipitation days) = annual
count when precipitation ≥20 mm (days)

viii. R95p (very wet days) = annual total precipitation when
daily precipitation >95th percentile (mm)

ix. R99p (extremely wet days) = annual total precipitation
when daily precipitation >99th percentile (mm)

x. SDII (simple daily intensity index) = the ratio of annual
total precipitation to the number of wet days (mm/day).

**Estimation of extreme rainfall quantiles**

A limitation of the descriptive indices is their focus on mod-
erate extreme events which occur many times every year
rather than rare extreme events associated with high
return periods. Hence, extreme value theory is used in this
study in order to analyze the trend of rare rainfall events
such as the ones of 25-, 50-, 75-, and 100-year return periods
too. This will enable a holistic trend analysis of extreme

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

| No. | Name       | Longitude | Latitude | Altitude (m) | Data periods | Country | AMAX (mm) | SDI |
|-----|------------|-----------|----------|--------------|--------------|---------|-----------|-----|
| 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   | Kounde     | 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  | Tanguiesta | 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|
rainfall in the ORB. The methodology used to estimate extreme rainfall quantiles is an index storm regional frequency analysis based on L-moments of annual maximum rainfall, which was introduced by Hosking & Wallis (1997). This approach is suitable for short samples of data, as 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. 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. In this work, the H-statistic with the measures of L-coefficient of variation (H1), L-skewness (H2), and L-kurtosis were used. For detailed information on the calculation of the H-statistic, the reader is referred to Hosking & Wallis (1997). The values of the homogeneity measures computed using the annual maximum rainfall of the 17 meteorological stations are shown in Table 2.

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

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, are 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 ($Z_{\text{Dist}}$) which was introduced by Hosking & 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 regional average L-kurtosis of the observed data. This test is defined in Equation (1) as follows:

$$Z_{\text{Dist}} = (t_4^\text{Dist} - t_4^R + B_4)/\sigma_4$$  \hspace{1cm} (1)

where $D_{\text{Dist}}$ refers to a particular distribution, $t_4^\text{Dist}$ is the L-kurtosis of the selected distribution, $t_4^R$ is the regional weighted average of sample L-kurtosis, $B_4$ and $\sigma_4$ are, respectively, the bias of $t_4^R$ and the standard deviation of sample L-kurtosis. The fit of the distribution is considered satisfactory if the absolute value of $Z$ for a candidate distribution is less or equal to 1.64 (Hosking & Wallis 1997). After the homogeneity test, the hypothesis of fitting the generalized extreme value (GEV), the generalized Pareto (GPA), and Pearson type III distributions to AMAX rainfall of the study area was made. The values of the $Z_{\text{Dist}}$ 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 of the three parameters’ probability distribution for estimating extreme 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):

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

$$q_R = \epsilon - \frac{\alpha}{k} \left\{ -\log \left( \frac{T - 1}{T} \right) \right\} \quad \text{for } k \neq 0$$  \hspace{1cm} (3)

where, $\alpha, \epsilon, k$ 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 $\alpha, \epsilon, k$ are, respectively, 0.23, 0.85, and $-0.04$. The rainfall associated with 25-, 50-, 75- and 100-year return periods at each of the meteorological stations

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**Table 2** | Values of the homogeneity measures

| Homogeneity measures | $H_1$ | $H_2$ | $H_3$ | Homogeneity |
|----------------------|------|------|------|-------------|
| Group of 17 rain gauges | 1.23 | $-0.6$ | $-1.27$ | Homogeneous |
in the homogeneous group was computed by multiplying the values of the growth factor corresponding to the same return period on the AMAX at each site.

### Statistical tests for trends analysis

In this study, the Mann–Kendall (MK) trend test based on Sen’s slope estimator was applied to assess trend 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 & 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 indice series using the same approach as in previous work analyzing trend in climate extremes (Wang & Swail 2001).

The MK trend test is a non-parametric method which does not require the data to follow a specific distribution. 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, is estimated using the formulae given by Equations (4) and (5):

\[
S = \sum_{j=1}^{n-1} \sum_{k=j+1}^{n} \text{sgn}(x_j - x_k)
\]

(4)

with

\[
\text{sgn} = \begin{cases} 
+1 & \text{if } (x_j - x_k) > 0 \\
0 & \text{if } (x_j - x_k) = 0 \\
-1 & \text{if } (x_j - x_k) < 0 
\end{cases}
\]

(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:

\[
Z = \begin{cases} 
\frac{S - 1}{\sqrt{\text{VAR}(S)}} & \text{if } S > 0 \\
0 & \text{if } S = 0 \\
\frac{S + 1}{\sqrt{\text{VAR}(S)}} & \text{if } S < 0
\end{cases}
\]

(6)

where

\[
\text{VAR}(S) = \frac{n(n - 1)(2n + 5) - \sum_{p=1}^{q} t_p^2(t_p - 1)(2t_p + 5)}{18}
\]

(7)

\(q\) is the number of tied groups while \(t_p\) is the number of data values in the \(p\)th group. Positive values of \(Z\) show an upward trend whereas negative values of \(Z\) indicate a 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.

The Sen’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:

\[
Q_i = \frac{x_{j} - x_{k}}{j-k} \text{ for } i = 1, \ldots, N
\]

(8)

Then, Sen’s slope estimator is the median of these \(N\) values of \(Q_i\):

\[
Q_{med} = \begin{cases} 
\frac{Q_N + 1}{2} & \text{if } N \text{ is odd} \\
\frac{1}{2} \left( \frac{Q_N + Q_{N+2}}{2} \right) & \text{if } N \text{ is even}
\end{cases}
\]

(9)

### Uncertainty assessment

Uncertainty in trend results is vital to give insight into the confidence that can be attributed to the analyses. To investigate uncertainties in trend results, the root mean square error (RMSE) and the confidence intervals (CI) of the mean trend magnitude were computed using the same approaches as in Burgan & Aksoy (2020) and Helsel et al.
(2020), respectively, for the RMSE and the CI:

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (m_i - \bar{m})^2} \]

\[ (100 - \alpha)\% CI = \left[ \bar{m} + t_{(\frac{3}{2}, n-1)} \sqrt{\frac{S^2}{n}}, \bar{m} + t_{(1-\frac{3}{2}, n-1)} \sqrt{\frac{S^2}{n}} \right] \]

where \( m_i \) is the slope estimate from the subsample \( i \) and \( \bar{m} \) denotes the mean of the \( n \) values of \( m_i \). \( s \) is the standard deviation of the slopes. For a 95% confidence interval, \( \alpha = 0.05 \). The critical \( t \)-values such as \( t_{(\frac{3}{2}, n-1)} \) and \( t_{(1-\frac{3}{2}, n-1)} \) were computed using the \( qt \) function in R software.

RESULTS AND DISCUSSION

Trends in descriptive extreme indices during 1921–2018

The computed extreme rainfall indices for each selected meteorological station were plotted with the trends and some of the graphs are provided in the Supplementary materials. Table 3 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. 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 a geographic information system (GIS) software and the results are shown in Figures 2 and 3.

As shown in Table 3, only the consecutive dry day index had positive trends for more than half of the stations (88%). The consecutive wet days and the extremely wet day indices have the same percentage of positive trends and almost equal proportion between the weather stations with positive trend and those where the trend is negative, although there is a slight prevalence of significant positive trends (18%) against 6% of significant negative trends.

Furthermore, PRCPTOT, Rx5day, R20, and SDII showed identical rates of positive trend (37%). As for the latter indices, the proportion of positive trends in both R10 and R95p are equal (29%). However, a very small number (less than 18%) of these positive trends were significant at a level of 0.05 for the selected indices except the CDD which exhibited 47% of significant positive trends while both R10 and SDII exhibited identical and highest rate of significant and negative trends (37%). Moreover, it can be deduced from Figures 2 and 3 that the rising trend in CDD and decreasing one in the remaining indices (except CWD and R99p) have affected large parts of the middle ORB during 1921–2018.

In contrast to the study of Panthou et al. (2014), which indicated a tendency of wetter conditions in the Central Sahel (West Africa) due to increasing trends in extreme rainfall, the middle ORB experienced, on average, drier conditions in the period of 1921–2018. This is shown by the reduction of rainfall amount contributed by both the

| Table 3 | Summary of the trends (1921–2018) |
|---|---|---|---|---|---|---|
| Indices | Positive trends | Negative trends | Significant positive trends | Significant negative trends | Mean trends | Mean significant trends |
| CDD | 15 | 2 | 8 | 0 | 0.36 | 0.60 |
| PRCPTOT | 6 | 11 | 2 | 3 | -0.79 | 0.12 |
| CWD | 8 | 9 | 3 | 1 | 0.02 | 0.06 |
| Rx1day | 7 | 10 | 1 | 3 | -0.09 | -0.19 |
| Rx5day | 6 | 11 | 2 | 4 | -0.09 | -0.16 |
| R10 | 5 | 12 | 2 | 6 | -0.02 | -0.05 |
| R20 | 6 | 11 | 1 | 4 | -0.03 | -0.06 |
| R95p | 5 | 12 | 1 | 2 | -0.68 | -1.29 |
| R99p | 8 | 9 | 0 | 3 | -0.24 | -1.63 |
| SDII | 6 | 11 | 2 | 6 | -0.02 | -0.03 |
very wet and extremely wet days. For instance, R95p had decreased significantly with a rate of 12.9 mm/decade while the statistically significant downward trend of R99p was 16.3 mm/decade (Table 3).

**Trends in heavy rainfall of higher return periods**

Table 4 and Figure 4 show, respectively, the summary of the trends and their interpolated spatial variability. 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 trend and those which showed negative trend are almost identical for the 50- and 100-year extreme storms. In fact, the highest increases in 50-, 75-, and 100-year 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).

**Uncertainty in trend magnitudes**

Table 5 shows the RMSE, the lower confident limits (Lcl) as well as the upper confident limits (Ucl) of the mean of the trend magnitudes. The best values of RMSE are those which are close to zero. The annual rainfall index has the largest amount of uncertainty that can be attributed to
errors in observation. The sources of uncertainties in rainfall amount include change in recording methodology, poor maintenance of the recording equipment, as well as gap filling methods. Furthermore, uncertainty in trend slopes can be caused by noise in the data, difference in the trend estimation methods, and the sample size.

Table 4 | Summary of the trends in heavy rainfall of higher return periods

| Return periods | Positive trends | Negative trends | Significant positive trends | Significant negative trends | Mean trends | Mean significant trends |
|----------------|-----------------|-----------------|-----------------------------|------------------------------|------------|------------------------|
| 25 years       | 6               | 11              | 1                           | 3                            | −0.01      | −0.01                  |
| 50 years       | 9               | 8               | 1                           | 3                            | −0.00      | −0.01                  |
| 75 years       | 7               | 10              | 1                           | 3                            | −0.00      | −0.00                  |
| 100 years      | 8               | 9               | 1                           | 2                            | −0.00      | −0.00                  |
Comparison with previous studies

The development of the ETCCDI indices has enabled the comparison of trends in climate extreme indices between different regions. An upward trend in most of the extreme 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 the western part of North Africa (Donat et al. 2013). Moreover, Panthou et al. (2014) showed an increase in the proportion of annual rainfall associated with extreme rainfall from 17% in 1970–1990 to 19% in 1991–2000 and to 21% in 2001–2010 in the Central Sahel (West Africa). On the contrary, a general reduction in extreme rainfall indices (except the dry spells) and a very slight decreasing trend in occurrence of heavy rainfall of higher return periods, namely, 25, 50, 75, and 100 years have been found in this study. This is in agreement with the findings of 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 heavy rainfall, the study of M’Po et al. (2017) predicted a decreasing trend in heavy rainfall indices under the 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 to a significant increase in the intensity of heavy rainfall by 2050 in Mono River Basin (Togo and Benin). One of the factors contributing to the reduction of heavy rainfall might be the rising deforestation in this
region for many purposes, 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 pattern are sensitive to the changes in land use pattern (Abiodun et al. 2007). This work demonstrates also the robustness of the GEV distribution in analyzing heavy rainfall in the study of the ORB. 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 Mono River Basin and Central Sahel in West Africa.

CONCLUSIONS

This study has analyzed for the first time extreme rainfall in the ORB in West Africa. Based on daily rainfall time series of 17 weather stations from 1921 to 2018, ten ETCCDI extreme precipitation indices and heavy rainfall of 25-, 50-, 75-, and 100-year return periods were calculated and their trends were examined after quality control and homogeneity testing. First, the results indicate that seven of ten of the selected heavy rainfall indices, namely, PRCPTOT, R10, R20, Rx1day, Rx5day, R95p, SDII have decreased in a large part of the study area during 1921–2018 while CDD has increased in a large portion of the ORB. In addition, the occurrence of heavy rainfall of the 25-, 50-, 75-, and 100-year heavy rainfall has slightly decreased. The second important result apart from the general negative trend of the heavy rainfall indices and the rising trend of CDD is the robustness of GEV in analyzing the frequency of heavy rainfall in the ORB. In fact, analyzing the trends in extreme rainfall in this basin is necessary for both hydrological risk management and the implementation of adaptation strategies to the impacts of climate change in various socioeconomic sectors. The upward trends in CDD means that some drought and dry spells might be expected to occur in future due to global warming and could have severe consequences on water availability, agricultural yields, energy supply, and on ecosystems in the basin. For example, increasing dry spells could lead to crop failure and reduction in food consumption which could cause childhood malnutrition. In addition, meteorological droughts have negative effects on water quantity and quality resulting in health issues such as diarrhea and hydroelectric power shortage due to lack of water in dams. Meteorological droughts can also be responsible for loss of biodiversity. Therefore, there is a need to implement integrated drought management strategies in order to reduce the adverse impacts of drought on local communities. In this context, future research on how climate change will impact extreme hydrometeorological events, such as drought in the study area, is of a great importance.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.
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