Trend analysis of observed precipitation, temperature, and streamflow for Hadejia-Nguru wetlands catchment, Nigeria

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Abstract
This study investigated trends in hydro-climate data (precipitation, maximum/minimum temperatures, and streamflow) for the period 1980–2016 around a semi-arid Hadejia-Nguru wetlands (HNWs) in Northern Nigeria. Four meteorological stations (Bauchi, Kano, Hadejia, and Nguru) and three streamflow gauge stations (Hadejia, Katagum, and Gashua) were used to cover the HNWs’ catchment. The data was checked for normality using Anderson–Darling and Shapiro–Wilk tests. Pettit’s test was used to check for homogeneity in the data series, and absolute homogenization, using RHtestsV4 software, was applied to homogenize and pre-whiten the data series. Trend analysis was carried out using modified Mann–Kendall and Sen’s slope tests. Results revealed increasing positive trends at all the stations for monthly minimum, average annual minimum, average annual maximum, and annual average temperature data series, while monthly maximum temperature series of Bauchi and Kano stations indicated the presence of an increasing trend with magnitudes 0.0035 °C and 0.0019 °C; and no trend was detected for Hadejia and Nguru stations. For monthly precipitation, no trends were detected at all stations. However, an increasing trend was detected at Bauchi, Hadejia, and Nguru stations for mean annual precipitation with magnitude 7.7960 mm/year, 8.1766 mm/year, and 5.7214 mm/year, respectively. A decreasing trend was detected for monthly and annual streamflow series at Hadejia gauge station with magnitude −0.0115 m³/s/month and −3.7037 m³/s/year, respectively; and no trend was detected for monthly and annual streamflow series at Katagum and Gashua gauge stations. The trend analysis may be helpful for planning and management of water resources in the HNWs.

1 Introduction
Rapid population growth and industrial activities have resulted in the rise of average temperature of the earth leading to global warming over many regions around the globe (Ali et al. 2019). Precipitation and streamflow conditions are influenced by energy exchange between the sun, the earth, and the atmosphere (Ayeni et al. 2015; Umar et al. 2018). The Intergovernmental Panel on Climate Change (IPCC) in its fifth assessment report gave detailed description based on scientific findings of the physical driving forces of climate change and the potential threats likely to be faced in the future (IPCC 2013). The report indicated that mean annual global air temperature for the period 1880–2012 had a significant upward trend notably from 1979 to 2012 with a 0.25–0.27 °C increment per decade (IPCC 2013).

There is no doubt that climate change and global warming represent a potential effect on the hydrologic cycle (Chattopadhyay et al. 2017; Ali et al. 2019; Kocsis et al. 2020). This was observed through increasing temperature, thereby altering precipitation patterns. Precipitation is one of the essential components of hydrologic cycle (Chow et al. 1988). The altered precipitation trends have direct impacts on streamflow (Chow et al. 1988; Aich et al. 2014; Kocsis et al. 2020). Streamflows are also found to be very sensitive to changes in precipitation patterns (Ezemonye et al. 2016; Okafor and Ogbu 2018; Umar et al. 2018). The construction of hydraulic structures, such as dams, barrages, and large weirs, can also cause streamflow reduction (Umar and Ankidawa 2016; Umar et al. 2018). Changes in hydrologic cycle may in turn affect the availability and quality of water resources and the sustainability of water management, particularly in dry regions (Aich et al. 2014; Ahmad et al. 2015; Kocsis et al. 2020). Thus, it is very important to evaluate the
trends in precipitation, temperature, and streamflow for sustainable development of water resources and at the same time maintain adequate environmental flow releases downstream of any hydraulic structure (Goes 2001; Olalekan et al. 2014).

Several authors have reported that trend assessment of precipitation, temperature, and streamflow is important in making long-term water resources management plans ( Chattopadhyay and Edwards 2016; Chen et al. 2016; Chattopadhyay et al. 2017; Ali et al. 2019). In this regard, a review of the literature revealed that several studies were conducted to understand the changing characteristics of streamflow using precipitation and temperature data around the world, including Nigeria (Ezemonye et al. 2016; Okafor and Ogbu 2018; Umar et al. 2018).

There are quite a number of statistical test methods used for trend detection in hydrological and hydro-climatic time series (Yue et al. 2002; Hamed 2008). These statistical test methods are classified as parametric and non-parametric tests (Hamed 2008). Parametric tests, although more powerful, require data to be independent and normally distributed, which is rarely true for hydrological time series data (Hamed 2008; Ahmad et al. 2015; Kocsis et al. 2020). Parametric tests are more sensitive to outliers. On the other hand, non-parametric tests are not affected by the actual distribution of the data and are less sensitive to outliers (Hamed 2008; Ahmad et al. 2015; Kocsis et al. 2020). A common requirement of both parametric and non-parametric trend tests is that the data be independent (free from serial correlation). The effect of serial correlation can be dealt with either by eliminating serial correlation from the data before applying trend tests (pre-whitening) or by adjusting the original trend test to account for serial correlation (Yue et al. 2002; Hamed 2008; Kocsis et al. 2020).

One of the most common and widely used non-parametric test in studying hydrologic time series is the Mann–Kendall (MK) trend test (Hamed 2008; Ahmad et al. 2015; Kocsis et al. 2020). However, an observable weakness of the MK test is that, serial correlation as very often seen in the hydro-climate data is not accounted for (Hamed and Rao 1998; Yue et al. 2002; Yue and Wang 2004). Studies have shown that if autocorrelation is not considered, the existence of positive autocorrelation will overestimate the magnitude of both positive and negative trends; likewise, negative autocorrelation will underestimate the magnitude of both positive and negative trends (Hamed and Rao 1998; Yue et al. 2002). A modified MK test with trend-free pre-whitening and variance correction were proposed and applied in an attempt to eliminate the impact of serial correlation (Hamed and Rao 1998; Yue et al. 2002; Yue and Wang 2004).

The aim of this study is to investigate the possible trends and variations in mean precipitation, average maximum and minimum temperatures, and mean streamflow around Hadejia-Nguru wetlands (HNWs) for the period (1980–2016). This was carried out by analyzing monthly and annual time series through modified Mann–Kendall (MMK) with trend-free pre-whitening test using RStudio. The results of the analysis may serve as input or source of reference information for decision-making and planning processes to prepare against the negative impacts of climate change.

## 2 Materials and methods

### 2.1 Study area and datasets

The HNWs (Fig. 1) are located between 12° 15′~13° 00′N and 10° 00′~11° 00′E in a semi-arid region of Northern Nigeria between the towns of Hadejia and Nguru. It had an approximate surface area of about 3500km² (Okali and Bdliya 1998). The catchment’s mean precipitation and average air temperature from 1980 to 2016 range between 500 and 600 mm and 12 °C during harmattan season (cold) to about 40 °C during the hot season, respectively, with an annual average evaporation around 3000 mm (NIMET 2017). The flood-plain complex comprised of seasonally flooded lands and dry uplands. The hydrology of the area is described by a peak runoff flow occurring in August and September during which the banks overflow and the area inundated (Umar and Ankidawa 2016).

The HNWs lie between Bauchi, Kano, Hadejia, and Nguru meteorological stations and Hadejia, Katagum, and Gashua streamflow gauge stations on rivers Hadejia, Jama’are, and Yobe, respectively. Hadejia and Jama’are Rivers, located upstream of the wetlands, join at Gashua to form the Yobe River downstream.

HNWs are on the list of Ramsar wetlands of international importance due to its fundamental ecological functions, socioeconomic value, and presence of protected area. It supports at least 250 species of flowering plants, over 136 types of aquatic flora and fauna, and more than 103 species of fishes and 377 species of birds (Ayeni et al. 2019). However, some of the wildlife resources are going into extinction as a result of water reduction, climate change, bio-invasion, and inadequate monitoring and protection of the resources. It also support a population of about 1.5 million people including farmers, herders, and fishermen who primarily depend on the ecosystem for their livelihood (Olalekan et al. 2014).

Monthly precipitation and maximum and minimum temperatures of Bauchi, Kano, Hadejia, and Nguru stations (1980–2016) of the Nigerian Meteorological Agency (NIMET) were obtained from Hadejia Jama’are Komadugu Yobe Basin-Trust Fund (HJKYB-TF), Damaturu. The meteorological stations are located in and near the surroundings of the HNWs, and, therefore, monthly observed streamflows at Hadejia, Katagum, and Gashua gauge stations on rivers...
Hadejia, Jama’are and Yobe, respectively (covering HNWs), for the period of 1980–2016 were also obtained from the HJKYB-TF.

Many researchers have used varying time steps in analyzing trends for different variables (Burn and Elnur 2002; Kumar et al. 2009; Partal 2010; Ahmad et al. 2015; Kocsis et al. 2020). It was suggested, therefore, that the same length of records should be used when analyzing trends of different variables to avoid misleading conclusions (Drápela and Drápelová 2011; Chen et al. 2016; Ali et al. 2019). Therefore, precipitation, temperatures, and streamflow of the same record length of 37 years for the period 1980–2016 would be adequate for the trend analysis in this study.

### 2.2 Pre-processing of data

The 37 years monthly hydro-climatic time series were first tested for normality using R statistical software to determine whether to use parametric or non-parametric tests. The Anderson–Darling and Shapiro–Wilk normality tests were used for this study. After normality test, and in accordance with World Meteorological Organization (WMO 2011) guidelines, the data series were subsequently tested for homogeneity (to detect change points in the time series) and serial correlation.

There are various methods used in detecting inhomogeneity of a data series. For this study, a non-parametric homogeneity test, Pettitt’s test, was used. The approach was introduced by Pettitt (1979) and commonly applied to detect a single change-point in hydrological or climate series with continuous data. The test was used because it gives information about the location of the shift (probable change point). The test statistic is defined as

$$U_y = 2 \sum_{i=1}^{y} r_i - y(n + 1), y = 1, 2, \ldots, n$$

(1)

The break is detected near the year $y$ given that

$$U_y = \max_{1 \leq y \leq n} \left| U_y \right|$$

(2)

where $n$ is the data set length, $r_i$ is the rank of the years $y_i$, and $U_y$ is the test’s critical value. For homogeneity test, the null hypothesis states that at 95% confidence level, a data series is homogenous between two given times if $p$-values are greater than 0.05. If, however, inhomogeneity is

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**Fig. 1** Location of Hadejia-Nguru wetlands, Nigeria
detected, the data series are adjusted before further analysis; this adjustment is called homogenization. Several homogenization methodologies were developed that allow for the elimination or reduction of, as much as possible, these unwanted alterations. The methodologies were further classified under two broad categories: absolute (in which series are tested separately) and relative (in which discontinuities are detected by comparison to applicable reference stations). Homogenization in this study followed an absolute method using RHtestsV4 software.

Serial correlation (or autocorrelation) is when observations of the error term are uncorrelated with each other in a data series (Wang et al. 2015). Relevant studies highlighted the need to check for autocorrelation in a data series prior to trend analysis (Drápeľa and Drápelová 2011; Droogers et al. 2012; Gocic and Trajkovic 2013; Shiru et al. 2018; Umar et al. 2018; Ali et al. 2019), because the presence of autocorrelation may lead to incorrect estimation of trend or disproportionate rejection of the null hypothesis of no trend, whereas the null hypothesis is actually true (Yue et al. 2002). The hydro-climatic data passing the homogeneity test were next examined for the presence of autocorrelation, and if present, it was corrected before proceeding to trend analysis. The first-order autocorrelation coefficient, $r_1$, at 95% confidence interval using a two-tailed test was calculated from Eq. (3):

$$ r_1 = \frac{1}{n-1} \sum_{i=1}^{n-1} (x_i - \bar{x}) (x_{i+1} - \bar{x}) $$

$$ r_1 \leq \frac{-1.96 \sqrt{n-2}}{n-1} \leq r_1 \leq \frac{1.96 \sqrt{n-2}}{n-1} $$

If $-1.96 \sqrt{n-2} \leq r_1 \leq 1.96 \sqrt{n-2}$, then the data series is considered to be serially independent at 5% significant level and free from the first-order autocorrelation AR (1). Elsewhere, the data series are considered serially correlated and requires correction (pre-whitening) before further analysis.

Several remedies exists for autocorrelation; the trend-free pre-whitening (TFPW) approach introduced by Yue et al. (2002) and embedded in the modified Mann–Kendall test R-package was used for this study.

### 2.3 Trend detection and characterization

Several studies supported the use of non-parametric methods of trend detection, noting that in situ hydro-climatic data are often distinctly non-normal with positive skewness (Sonali and Kumar 2013; Gocic and Trajkovic 2013; Ahmad et al. 2015; Chattopadhyay and Edwards 2016; Kocsis et al. 2020).

The non-parametric Mann–Kendall test (Mann 1945; Kendall 1975) was adopted for this study. The Mann–Kendall test is based on a rank correlation test of the observed values and their order in time. The Mann–Kendall test statistics $S$ of a series $x$ is given by Eq. (4):

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

where $\text{sgn}$ is the signum function defined as

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

$x_j$ and $x_k$ = data points at time $j$ and $k$ respectively

$n$ = number of observations

For independent and randomly ordered data for large $n$, the $S$ statistic approximates a normal distribution with mean $E(S) = 0$ and a variance, $\text{Var}(S) = n(n-1)(2n+5)/18$ (Osuch and Wawrzyniak 2016).

The significance of the trend is tested by comparison of the standardized test statistic, $Z$, with the standard normal cumulative distribution at a selected significance level. The standard test statistic $Z$ is computed as

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

Positive value of $Z$ statistics indicates an increasing trend, while negative $Z$ value indicates a decreasing trend. The trend is statistically significant at 0.05 significance level when the absolute value of $Z$ is greater than 1.96.

If autocorrelation exist in a data series, a modified Mann–Kendall test based on Yue et al. (2002) approach is applied to avoid the above uncertainty. A pre-whitened series $x^*_i$ is created from Eq. (7):

$$ x^*_i = x_i - r_1 x_1 $$

Then, the original Mann–Kendall test is applied to the pre-whitened series to assess the trend.

The Theil-Sen’s slope estimator, a non-parametric method to quantify trends (or magnitude) in a time series was used in this study. The Sen’s slope estimator for monotonic and linear trend is expressed by the linear mode $f(t)$ as

$$ f(t) = Q + B $$

where

$$ f(t) = \text{linear model} $$
\( Q_t = \text{the slope} \)

\[ B = \text{constant} \]

The slope \( Q \) between any two values of a time series \( x \) can be derived from

\[ Q_i = \frac{x_j - x_k}{k - j}, \quad k \neq j, \quad i = 1, 2, \ldots, N \]  

\((9)\)

\( x_j \) and \( x_k \) represent data values at time \( j \) and \( k \), respectively.

If there are \( n \) values of \( x_j \) in the time series, we get as many as \( N = n(n - 1)/2 \) slope estimates of \( Q_i \). The \( N \) values of \( Q_i \) are ranked from the smallest to the largest, and the median of these \( N \) values of \( Q_i \) is the overall Sen’s slope estimator \( Q \) computed as

\[ Q = \begin{cases} Q_{(N+1)/2} & \text{if } N \text{ is odd} \\ \frac{1}{2}(Q_{N/2} + Q_{(N+2)/2}) & \text{if } N \text{ is even} \end{cases} \]  

\((10)\)

In trend test, the null (\( H_0 \)) and alternative hypotheses (\( H_a \)) are equal to the nonexistence and existence of a trend in the observational data series, respectively. Existence of a trend with positive \( p \)-values indicates increasing, while negative values indicate decreasing trends in the data series. The \( p \)-value was set at a significance level (\( \alpha \)) of 0.05, implying that any station’s statistics that produces a \( p \)-value less than the set significance level will lead to the rejection of \( H_0 \) and that a trend exists in the data series. On the other hand, where the \( p \)-value obtained was more than the level of significance (\( \alpha \)), then, the \( H_0 \) of no trend was accepted.

### 3 Results

#### 3.1 Results of normality check

The normality test conducted on the monthly precipitation, temperature (maximum and minimum), and streamflow series (1980–2016) indicates that all the data series did not exhibit Gaussian distribution when Anderson–Darling and Shapiro–Wilk normality tests were applied. Table 1 illustrates the test results.

The null hypotheses (\( H_0 \)) of the Anderson–Darling and Shapiro–Wilk tests state that a sample belongs to a normal distribution if \( p \)-values are greater than alpha (\( \alpha \)) at 0.05 significance level. From Table 1, the null hypotheses of the Anderson–Darling and Shapiro–Wilk tests were rejected, and the alternatives were accepted for all the data series. This is because \( p \)-values were less than \( \alpha \). Thus, a non-parametric test approach was therefore used to analyze these data series.

### 3.2 Results of homogeneity check

Homogeneity implies that the data in the series are similar and hence have no breaks over time. The null hypothesis states that a data series is homogenous between two given times if \( p \)-values are greater than alpha (\( \alpha \)) at significance level of 0.05. Pettit’s (non-parametric) homogeneity test was utilized for the hydro-climatic data. The result is presented in Table 2 for monthly climatic and streamflow data series.

From Table 2, occurrence of inhomogeneous series was detected for maximum and minimum temperatures of Bauchi station and minimum temperatures of all other stations. Thus, the \( p \)-values obtained were less than alpha (\( \alpha \)) at 0.05 significance level, thereby rejecting the null hypothesis of homogeneity. However, precipitation series of all the stations accepted the null hypothesis and were classified as homogeneous. Furthermore, for streamflow data series, the null hypothesis was accepted with the exception of Hadejia gauging station. Therefore, the inhomogeneous data series must be homogenized before further analysis.

The inhomogeneous hydro-climate data series were homogenized using the RHtestsV4 software. Thus, the
S. Dan’azumi, U. A. Ibrahim

Results of homogeneity test for precipitation, temperatures (maximum and minimum), and streamflow data series

| Station | Variable       | Pettit’s test | Interpretation |
|---------|----------------|---------------|----------------|
|         |                | \(U\) | \(p\)-value | |
| Bauchi  | Precipitation  | 5429          | 2.664e-01 | Accept \(H_0\) |
|         | Maximum temperature | 9339          | 5.133e-03 | Reject \(H_0\) |
|         | Minimum temperature | 13,413        | 9.100e-06 | Reject \(H_0\) |
| Kano    | Precipitation  | 4319          | 5.854e-01 | Accept \(H_0\) |
|         | Maximum temperature | 6171          | 1.479e-01 | Accept \(H_0\) |
|         | Minimum temperature | 10,851        | 6.362e-06 | Reject \(H_0\) |
| Hadejia | Precipitation  | 4884          | 3.913e-01 | Accept \(H_0\) |
|         | Maximum temperature | 6105          | 1.563e-01 | Accept \(H_0\) |
|         | Minimum temperature | 10,243        | 1.530e-03 | Reject \(H_0\) |
| Nguru   | Precipitation  | 4875          | 4.150e-01 | Accept \(H_0\) |
|         | Maximum temperature | 5357          | 2.890e-01 | Accept \(H_0\) |
|         | Minimum temperature | 10,902        | 5.897e-04 | Reject \(H_0\) |
| Hadejia | Streamflow     | 24,255        | < 2.2e-16  | Reject \(H_0\) |
| Katagum | Streamflow     | 2460          | 1.322e+00 | Accept \(H_0\) |
| Gashua  | Streamflow     | 6348          | 1.270e-01 | Accept \(H_0\) |

Results of autocorrelation test on precipitation, temperatures (maximum and minimum), and streamflow data series

| Station | Variable       | \(AR(1), \tau_1\) |
|---------|----------------|-----------------|
| Bauchi  | Precipitation  | 0.686           |
|         | Maximum temperature | 0.607          |
|         | Minimum temperature | 0.710          |
| Kano    | Precipitation  | 0.660           |
|         | Maximum temperature | 0.533          |
|         | Minimum temperature | 0.732          |
| Hadejia | Precipitation  | 0.620           |
|         | Maximum temperature | 0.535          |
|         | Minimum temperature | 0.736          |
| Nguru   | Precipitation  | 0.598           |
|         | Maximum temperature | 0.554          |
|         | Minimum temperature | 0.743          |
| Hadejia | Streamflow     | 0.773           |
| Katagum | Streamflow     | 0.589           |
| Gashua  | Streamflow     | 0.680           |

3.3 Results of autocorrelation check

3.4 Results of trend check

The modified Mann–Kendall test (TFPW approach) was applied on the 37 years (1980–2016) monthly and annual scales to detect trends in the hydro-climatic data series. More so, the magnitude of trends in the monthly and annual data series was determined using the Sen’s slope estimator.
Hadejia station showed a decreasing trend with magnitude of $-0.0115\,m^3/s/\text{month}$ and a negative tau value indicating a very weak trend.

### 3.5 Annual analysis of the data series

Modified Mann–Kendall trend test was performed on mean annual precipitation (MAP), average annual maximum temperature (AATMax), average annual minimum temperature (AATMin), and mean annual streamflow (MAS) data series for all the stations, and the test statistics obtained from the trend test at 95% confidence level are presented in Table 5. MAP and MAS were obtained by aggregating the monthly data series using the Hydrognomon software. Unlike aggregation in precipitation and streamflow series, monthly temperature series were averaged to obtain the annual series. The AAT was obtained by finding the average between the AATMax and AATMin series for each station.

The null ($H_0$) and alternative hypotheses ($H_a$) correspond to non-existence and existence of annual trend, respectively. Results of MAP indicated that the null hypothesis ($H_0$) was rejected for Bauchi, Hadejia, and Nguru stations signifying positive trend with magnitude of $7.7960\,\text{mm/year}$, $8.1766\,\text{mm/year}$, and $5.7214\,\text{mm/year}$, respectively. However, $H_0$ was accepted for Kano station which indicates no trend was present (Table 5).

A Kendall’s tau ($\tau$) value less than 0.5 indicates a weak trend; Bauchi and Nguru station’s precipitation revealed a weak trend with the exception of Hadejia station. This was further supported by low coefficient of determination ($R^2$) values depicting 31.57% and 29.51% of variability in the MAP of Bauchi and Nguru stations, respectively (Fig. 2).

More so, time series plots showing trends of MAP, AATMax, and AATMin from 1980 to 2016 for the meteorological stations are presented in Figs. 2, 3, and 4, respectively.

The result of AATMax and AATMin (Table 5) indicated an existence of positive trend in the data series for all the stations. The Sen’s slope suggested that AATMax
and AATMin at Bauchi, Kano, Hadejia, and Nguru stations are increasing annually at magnitudes of 0.0377 °C, 0.0275 °C, 0.0208 °C, and 0.0189 °C, respectively. Furthermore, AATMax series of the stations displayed Kendall’s tau (τ) values less than 0.5 indicating a weak trend except for Bauchi. This was further supported by the low $R^2$ values presented in Fig. 3. However, a strong trend was observed for all the station’s AATMin series.

More so, the result of AAT (Table 5) depicted the presence of a positive trend. The magnitudes of the increasing trend, suggested by the Sen’s slope, are 0.0487 °C, 0.0439 °C, 0.0444 °C, and 0.0453 °C per annum for Bauchi, Kano, Hadejia, and Nguru stations, respectively. This is in conformity with IPCC (2007) that “global temperature has been increasing since the 1980’s”.

The results of the MMK trend test from Table 5 revealed that streamflow has a decreasing trend at Hadejia gauging station. The trend shows a negative change of $-3.7037 \text{ m}^3/\text{s/year}$. However, no trend was detected for Katagum and Gashua gauging stations. This decrease in streamflow at Hadejia gauge station may be attributed to the combination of climate change and anthropogenic activities upstream of the gauge station. Anthropogenic activities such as Tiga and Challawa Gorge reservoirs and irrigation practices account for more of this reduction.

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**Fig. 2** Trend of mean annual precipitation (MAP) for the stations
Discussion

Decision-making in water resources management of HNWs requires researchers and policy makers to examine the variability of hydro-climatic parameters for developing suitable water management practices and measures. HNWs are a Ramsar site and important birds’ area of international recognition. The wetlands are considered as one of the most important ornithological site in West Africa. It is home to 165 species of birds, including some globally endangered species. It provides a stop-over and wintering ground for migratory birds that travel from as far as Europe and Asia to Africa in search for food and favorable weather (Birdlife International 2022; Sabo 2016). Several treaties have been put in place to safeguard migratory and resident birds, and Nigeria is a signatory. The treaties include the Ramsar Convention on Wetlands in 1971, the Convention on the Conservation of Migratory Species of Wild Animals in 1979, and the Agreement on the Conservation of African-Eurasian Migratory Waterbirds in 1999 (Ringim et al. 2017). The HNWs had experienced tremendous change in flow regime due to the construction of Tiga and Challawa Gorge dams upstream as well as climate change. These, combined with hunting, fishing, grazing, and extensive farming, have had a serious impact on the wetlands (Ringim et al. 2017). The implications of changes in hydro-meteorological parameters on the wetlands are discussed in the following paragraphs.

Mean annual precipitation (MAP) over the period of study for Bauchi, Hadejia, and Nguru stations showed a weak increasing trend of magnitudes 7.7960 mm/year,
8.1766 mm/year, and 5.7214 mm/year, respectively. This result follows the same statistical trends reported by Okonkwo et al. (2014) and Sylla et al. (2010). Findings were consistent with results from Zhu et al. (2017), Ndehedehe et al. (2016), and Ibrahim et al. (2014). The studies by Ndehedehe et al. (2016) and Ibrahim et al. (2014) have not only detected the increase in the total precipitation but also the average increase in the frequency of rainy days, resulting in partial recovery of precipitation. However, Adeyeri et al. (2017) and Odunuga et al. (2011) detected a decreasing trend in precipitation over Komadugu Yobe Basin with a shift in seasonal precipitation towards the dry season. The observed increasing trend in the mean annual precipitation could be due to the partial recovery of precipitation in the study area, resulting from warming over the northern Atlantic Ocean. The increase may also be attributed to the increased anthropogenic greenhouse gases and aerosol emission in the atmosphere (Mahmood et al. 2019). Although increase in precipitation over HNWs catchment could benefit agriculture, biodiversity, and pastoral operations, it can also cause environmental problems such as floods and invasion of alien Typha grass species. Changes in rainfall are generally attributed to anthropogenic activities, build-up of atmospheric dust, sea surface temperature changes, depletion of forest cover, climate change, and weakening global monsoon (Adeyeri et al. 2017).

The AATMax, AATMin, and AAT temperature for the study area showed increasing trends. The magnitudes of
the detected trends were consistent with results reported by Umar and Ankidawa (2016), Okonkwo et al. (2014), Odunuga et al. (2011), and Sylla et al. (2010). Similarly, Collins (2011) and Sylla et al. (2010) projected a twenty-first century temperature increase of 3–4 °C/annum and 1.6–6 °C/annum over Africa and West Africa, respectively. Strong increasing AAT trend of 0.0439 to 0.0487 °C per annum detected in this study suggests that the wetlands catchment is vulnerable to global warming. The increasing temperature in the HNWs catchment severely changes the trophic state of the wetlands leading to loss in biodiversity (decrease in migratory bird species), stress on water resources, reduction in crop productivity, reduction in fishing, and increase in vector-waterborne diseases. Consequently, this has led to loss of habitats (aquatic micro-organisms and benthic invertebrates), modification in the hydrology, and water quality and quantity reduction (Abubakar et al. 2017). Temperature rise results to increased evapotranspiration leading to a reduction in the wetlands surface area and volume of water, thus, causing socio-economic problems such as food and water insecurity, farmer-harder conflicts, human displacements, youth restiveness, and insurgency. There exist a substantial evidence that ecosystems around the globe suffers from temperature increase. IPCC (2013) reported that “the increasing concentrations of greenhouse gases in the atmosphere has been the dominant cause of observed warming since 1950, with 95% confidence.” Africa is regarded as the most affected continent by the global climate change, even though its contribution to the global warming is little, with an average greenhouse gas emissions of only 1 metric ton per capita annually (Mahmood et al. 2019).

Even though no trend in streamflow was detected at Katagum and Gashua gauge stations, the trend in streamflow at Hadejia gauge station showed a negative change of −0.0115 m³/s and −3.7037 m³/s for monthly and mean annual flows, respectively. The reduction is in line with Goes (2001) who revealed that average peak flows in the upstream parts of Hadejia River were reduced by 64% between 1964 and 1973. Likewise, Thompson and Polet (2000) reported a decrease in streamflow downstream of Hadejia River at Hadejia gauge station. Apart from climate change effects, this decrease is attributed to human activities such as the construction of Tiga and Challawa Gorge dams upstream of the basin, leading to decline in flow into the wetlands, thus, affecting the hydrology and biogeochemistry of the wetlands which have a far-reaching effect on agricultural and fishing activities in the wetlands. The pre Tiga dam flow was modified which resulted in siltation of the river and *typa* weed growth that inhibit year-round agriculture and fishing at the HNWs. Odunuga et al. (2011) noted that subsistence agriculture upstream of HNWs may enhance further deforestation and land degradation that has a long-term impact on land productivity. They further suggested for a sustainable dry season irrigation upstream and need for wetlands flooding.

### 4.1 Suggestions for restoration of HNWs

Climate change and human activities are the main drivers of desertification which leads to vegetation loss and depletion of water resources. According to the BirdLife International (2022), the surface area of HNWs shrank from 4125 to 3500 km² which affected its water resources, making some animal and plant species endangered. From the analysis carried out, it is clearly observed that climate change greatly affected flows into the HNWs. Therefore, potential water management alternatives aimed at adapting to the negative impacts of climate change on the wetlands need to be adopted. Such alternatives include adopting satisfactory operational rules for water releases from upstream Tiga and Challawa Gorge dams to meet HNWs water requirements. Similarly, there is a need for a paradigm shift in HNWs catchment management from the traditional approaches that are not environmentally friendly to a more sustainable approach. In the context of Sahel region, where HNWs is located, Jane Madgwick, CEO of the Wetlands International, stated that “Driving forward inclusive and sustainable development in the Sahel is an urgent, global priority. But this will only be achieved by shifting from the traditional development paradigms and hard infrastructure schemes which play havoc with the natural hydrology of the region. Maintaining and restoring the natural resource base is essential to increase water and food productivity and provide livelihood strategies to cope with a changing climate. In this context, wetlands such as river floodplains and lakes are disproportionately important; especially to the most marginalized and poor people of the region.” Even though, the carbon footprint of Africa is relatively small compared to the developed world, there is the urgent need for Nigeria to adopt clean technologies by switching to renewable energy sources that have less or no effect on climate.

### 5 Conclusion

This study assessed the presence of trends in monthly and annual precipitation, maximum/minimum temperatures, and streamflow around HNWs over a 37-year study period (1980–2016). The HNWs’ catchment covers Bauchi, Kano, Hadejia, and Nguru meteorological stations and Hadejia, Katagum, and Gashua streamflow gauge stations on rivers Hadejia, Jama’are, and Yobe, respectively. Trends were detected using modified Mann–Kendall and Sen’s slope estimator tests. The results of the study showed that all the stations have increasing positive trends for monthly minimum, average annual minimum, average annual maximum, and annual
average temperature data series. While monthly maximum temperature series of Bauchi and Kano stations indicated the presence of an increasing trend, no trend was detected for Hadejia and Nguru stations. Furthermore, no trends were detected for monthly precipitation series at all stations. But an increasing trend was detected at Bauchi, Hadejia, and Nguru stations for mean annual precipitation. More so, a decreasing trend was detected for monthly and annual streamflow series at Hadejia gauge station; and no trend was detected for monthly and annual streamflow series at Katagum and Gashua gauge stations.

The trends detected for precipitation and temperature series were all in the positive direction and associated with weather stations covering the HNWs, which may be related to strong changes in monthly and annual data in association with human activities, leading to climate change. Additionally, the decreased inflows at Hadejia gauge station on Hadejia River indicated evidence of anthropogenic activities upstream of the gauge station. Therefore, authorities should take proactive measures to prepare for the effect of climate change and to develop adaptation measures against them. The above findings will contribute to water resource planning and management in the semi-arid Hadejia Jarna’are Komadugu Yobe Basin of Nigeria.

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U. A. Ibrahim; a PhD graduate at Bayero University Kano under Prof. S. Dan’azumi’s supervision. He drafted the manuscript as part of his PhD Thesis.

Data availability All data are available on request.

Code availability RStudio software was used, and the codes are available.

Declarations

Ethics approval Non-open access (if available); lack of funding.

Consent to participate If found worthy.

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Conflict of interest The authors declare no competing interests.

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