

# Quantitative Analysis of the Impact of Climate Change and Human Activities on Runoff Variation in Akwa Ibom State, Nigeria

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## Abstract

The non-parametric Mann-Kendall (MK) trend test, including the Sen's slope test and Pettitt's test, was used to determine trends, magnitudes, and change points in hydro-meteorological variables from 1972 to 2021. The slope change ratio of accumulative quantity (SCRAQ) method was then used to calculate the relative contributions of climate change and human activities to runoff variation in the Uyo-Itu river basin. Annual rainfall, maximum temperature, minimum temperature, and runoff showed significant increasing trends, whereas annual relative humidity, solar radiation, and potential evapotranspiration showed significant decreasing trends. Between 1992 and 2010, there were abrupt changes in hydro-meteorological variables. However, the runoff shift occurred in 2003. The time period under consideration was divided into two parts: baseline period A and change (impacted) period B. Climate change dominates runoff variation in period B, accounting for 103.6 percent of the variation, while human activities have a negative impact (-3.6%). The results indicate that climate change is the primary driver of runoff variation and that its impact is becoming more severe. Furthermore, the Budyko hypothesis was used to validate the contributions of human activities and climatic changes based on the SCRAQ method. The results showed that the contributions of human activities and climatic changes computed using the SCRAQ method are comparable with those computed using the sensitivity-based method. From this study, it can be concluded that assessing the influence of climate changes and human activities on variations and identifying the major driving forces causing the variations are critical for more efficient water resources management for sustainable economic growth.

**Keywords:** Climate change, Human activities, Runoff variation, SCRAQ, Budyko Hypothesis

## 1. Introduction

The hydrological cycle, which is the most inseparably linked to humans, is the main cause for the sustained regeneration of water resources. Climate change and human activities have had a large impact on the water resources system and the hydrological cycle by causing the mean global surface temperature to increase during the last century [1]. Climate change and human activities are regarded as two primary factors influencing changes in the hydrological cycle, which include rainfall, evapotranspiration, infiltration, and runoff [2-3]. Studies by Jung et al. [4] and Thompson [5] have

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shown that climate variability, along with global warming, is expected to increase the intensity and frequency of extreme weather, resulting in more severe droughts, floods, and massive damages. Extreme weather and environmental catastrophes, such as severe rain, floods, and droughts, are being recorded more often [6-10].

Human activities are regarded as a key element driving changes in hydrological, ecological, and geochemical processes at many geographical scales across the world, and the impact of human activities often include both direct and indirect effects [12]. Water conservation construction and operation [12], irrigation [13], underground mining activities [14], and other human modifications are examples of direct impacts, whereas indirect influences are primarily through changes in land cover [15], such as urbanisation, industrialization, soil conservation, and water conservation [16-17]. Furthermore, human activities are intensifying, which all impact runoff processes, particularly large-scale changes in land use [19-20]. Along with rising populations and rapid economic growth in certain areas, water demand for the industrial and agricultural sectors has grown exponentially, resulting in an enormous difference in runoff. Runoff is an essential indicator of accessible water from a resource perspective, and it plays a vital role in the use of water resources for sustainable development and improved management [20]. However, numerous rivers in mangrove and semiarid areas of Nigeria and other parts of the world have undergone significant variations in runoff over the last several decades, causing major ecological issues and affecting livelihoods [21].

In recent years, assessing the effects of human activities and climate change on runoff variance has received a lot of interest in hydrologic and climatic studies [12, 22-23]. As a response, several hydrologists have set out to investigate the effects of human activities and climate change on runoff processes [24-26]. Earlier research has shown that human activities and climate change have altered the water cycle in numerous catchments across the world [27-28]. Several methodologies have been used to assess the effects of climate change and human activities on runoff changes [22, 29-32].

The hydrological modelling method and the quantitative assessment method are the primary approaches for determining the contributions of the two components at the basin scale [33]. Other approaches include the empirical statistics method, the elasticity method, the ecohydrology method [34], the paired catchments method [35], and the decomposition method [36]. The paired catchment method is an approach extensively used in forestry and hydrology to examine the influence of land change on runoff. However, the paired catchments approach is better suited for small areas since it is difficult to identify realistic catchments in medium- and large-scale regions [37]. The ecohydrology approach developed by Tomer and Schilling [34] is a model that is used to assess long-term water energy consumption in a basin. The ecohydrology method can differentiate the influence of human activities and land changes on a basin's hydrology, but it can only offer a qualitative assessment [38]. Wang and Hejazi [36] developed the decomposition approach based on the Russian scientist Budyko's hypothesis about the atmospheric water energy balance [39]. The hydrological model method is an approach for investigating hydrological processes using conceptual, physical, or numerical models.

Several studies, however, have used hydrological models to examine the responses of runoff processes to synthetic climatic variability under various catchment scenarios. Examples are Wang et al. [40], who used the variable infiltration capacity model to quantify the impacts of human activities and climate change on hydrological responses in a Yellow River sub-catchment in China. Guo-qing et al. [41] used the SIMHYD model to study the effects of human activities and climatic variability on runoff in the Fenhe River, which is located in the centre of the Yellow River basin in China. Siriwardena et al. [42] assessed the influence of climate change and human activities on surface runoff in the Comet River, Australia, using the simple conceptual daily rainfall-runoff model (SIMHYD). According to the results of this model, local deforestation increased streamflow by 40%. Zhang et al. [43] investigated the variables influencing streamflow variation in the Sang-Kan River on the Loess Plateau using the SWAT (Soil and Water Assessment Tools) model. Climate change reduced streamflow by 39.1%, whereas changes in water use and land cover increased streamflow by 2.2% to 3.9%. They also stated that in recent years, water diversion and dam building have contributed to

63.1% to 64.8% of the drought. Although the above hydrological models were important instruments for addressing these problems, the research findings were fraught with uncertainty due to parameter calibration, structural drawbacks, and the scale issue. To address these issues, Huang et al. [1] used the slope change ratio of accumulative quantity (SCRAQ) approach to quantify the relative contributions of human activities and climate change to decrease runoff in the Wei River Basin in China. Using 1960–1969 as the baseline for the period, the contributions of climate change and human activity were 26.47% and 73.53%, respectively, for the period 1970–1993 and 23.33% and 76.67%, respectively, for 1993–2005. Furthermore, when they used 1970–1993 as the baseline, the contributions of climate and human influences from 1994–2005 were 18.88% and 81.12%, respectively. Their findings suggested that human activities were the primary determinants of runoff reduction. They also applied the Budyko hypothesis to validate the contributions of human activities and climate change using the SCRAQ approach. According to their findings, the contributions of human activities and climate change based on the SCRAQ technique were consistent with the sensitivity-based method.

Time trend analysis, double mass curves, and linear regression are common empirical statistics used to examine the influence of human activities and climate change on runoff. Long-term data series are used to determine the variation and consistency of runoff and characteristics of relevance like sediment output [44–45]. Chang et al. [46] performed a double mass curve analysis of four sections of the Yellow River at Lanzhou, Toudaoguai, Huayuankou, and Lijin from 1956–2010. Their findings revealed that, since 1990, the variation in streamflow caused by human activities were 74.87%, 82.20%, 80.63%, and 88.71% in these four areas, respectively. Zhao et al. [47] used linear regression to examine the Yangtze River's streamflow and sediment discharge from 1953 to 2013. According to this study, climate change was responsible for around 72% of the drop in stream flow in the Yangtze River basin, while human activities were responsible for 71% to 102% of the decrease in sediment discharge.

The impact of climate change and human activities on runoff variation is exceedingly complex, particularly in developing countries where hydrological and meteorological data are scarce. These regions have had severe water crises, economic stagnation, and environmental degradation. Many earlier studies [48] have found that the relative impacts of human activities and climate change vary across regions. Quantifying the relative contributions of climate change and human activities to runoff variation is required for a better understanding of hydrological mechanisms in watershed planning.

## 2. Study Area and Datasets

### 2.1. Description of the Uyo-Itu River Basin

The Uyo-Itu River Basin (Figure 1) was selected as the study area for this research. The Wei River is the largest tributary of the Ikpa/Cross River, which flows to the Atlantic Ocean. It lies between 7.510°E and 8.4°E and 4.523°N and 5.15°N, and it covers a total area of 874.45 km<sup>2</sup>. The River Basin, which is located in the tropical monsoon climate zone, is distinguished by relatively heavy rainfall and low temperatures during the rainy season and scanty rainfall and extremely high temperatures during the dry season. The basin's average annual rainfall ranges from 1599.5 mm to 3855.5 mm [49]. Rainfall varies monthly and annually; the flood season (June to September) accounts for around 60% of total annual rainfall [50,69]. The yearly rainfall also fluctuates significantly due to the unpredictable characteristics of intensity, duration, and proximity to the Atlantic Ocean coastline. The height decreases topographically from the highest mountainous areas in Itu to the lowest Uyo Plain land in the basin's southern reaches.

The Uyo Plain has been identified as the state's major economic development area, promoting economic growth in the surrounding towns. As a consequence, the economic growth of the Uyo Plain will have a direct impact on the long-term development of the economy and society in this region. However, due to climate change and human activity, the basin's discharge has significantly changed in

recent decades. It suffers from floods, which cause extensive damage and impede socioeconomic growth and environmental sustainability. Furthermore, severe water pollution reduces the availability of water resources. Given the importance of water security in the basin for socioeconomic development, further research is needed to quantify the effects of climate change and human activities on runoff variation.

## **2.2. The dataset**

This study employed daily rainfall, maximum temperature, minimum temperature, relative humidity, solar radiation, and evapotranspiration data for the period 1972–2021 that were acquired from the NiMet meteorological station in the Uyo-Itu River Basin. Daily runoff data was obtained by the Cross River Basin Development Authority (CRBDA).

## **2.3. Human activities in the Uyo-Itu River Basin**

Human activities have intensified on the basin's lower plain during the last several decades. The growing population and rapid economic growth have raised demand for surface and groundwater. In Akwa Ibom State, the population of Uyo and Itu was 498.62 thousand and 127.86 thousand in 2006 and had been projected to increase to 1.2 million and 163.20 thousand in 2021, at 5.11% and 1.50% growth rates, respectively. Due to increased food consumption, population development has resulted in an increase in farmland. Rapid population growth is associated with high water demand. Furthermore, the basin's economy has grown considerably during the last 20 years. Its average economic growth rate was 5.70%. This region's urbanisation rate was just 18.80% in 2007, but it was expected to rise to 27.40% by 2021. These factors caused a large increase in water requirements.

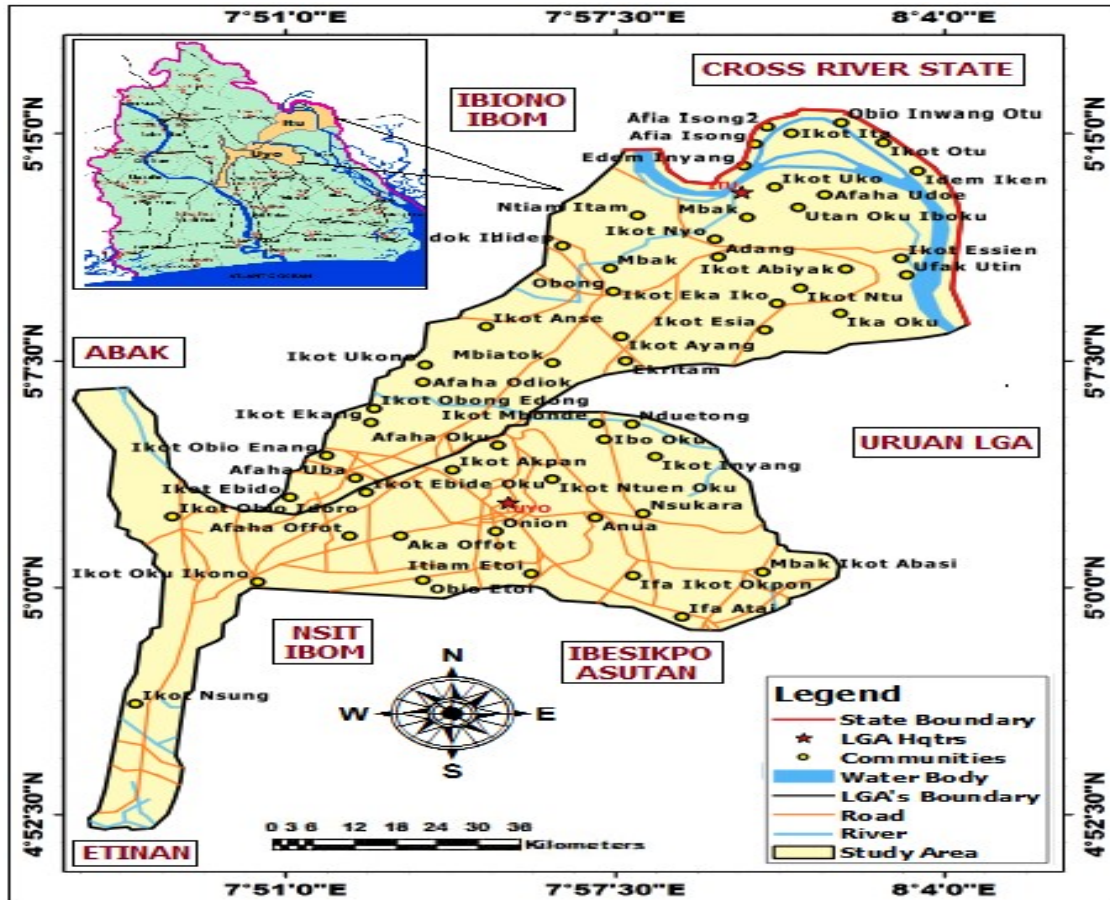


Figure 1. The study area map

### 3. Methodology

The Mann-Kendall trend test, Sen's slope estimator, Pettitt change-point test, slope change ratio of accumulative quantity (SCRAQ) and elasticity method based on the Budyko hypothesis were used in this study to further evaluate the trends, abrupt change-point, and variation of hydrological data in the Uyo-Itu River Basin.

#### 3.1. The Mann-Kendall (MK) test

The Mann-Kendall (MK) test [52], is a non-parametric approach that does not require normally distributed data and can reveal precise patterns over time. The approach is frequently used to detect monotonic trends in hydro-meteorological variables such as rainfall, temperature, runoff, and evapotranspiration [33, 52]. This test is recommended by the World Meteorological Organization for detecting trends in a set of hydrological data [53]. The Mann-Kendall trend test is known for its strong consistency, and several studies have demonstrated that it is appropriate for trend verification of time series data [54]. This approach does not require that a sample maintain a certain statistical distribution. Additionally, it is unaffected by a small number of outliers and is particularly appropriate for non-normally distributed datasets such as meteorological and hydrological data. The test is essentially a two-tailed test with the null hypothesis that the data sequence has no significant trend. If the null



hypothesis is rejected, the data sequence shows a statistically significant trend. A statistic  $S$  is defined as

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i), \quad (1)$$

$$\text{sng}(X_j - X_i) = \begin{cases} +1 & \text{if}(X_j - X_i) > 0, \\ 0, & \text{if}(X_j - X_i) = 0, \\ -1 & \text{if}(X_j - X_i) < 0, \end{cases} \quad (2)$$

where  $x_1, x_2, x_3, \dots, x_n$  are the data arranged in time, and  $n$  is the amount of data. In the case of  $n \geq 10$ , the statistic  $S$  will follow a normal distribution, which means that the variation will be as follows, and the test statistic  $Z$  of the double-tailed test may be obtained:

$$\text{Var}(S) = \frac{[n(n-1)(2n+5)]}{18}, \quad (3)$$

$$Z_S = \begin{cases} \frac{(S-1)}{\sqrt{\text{var}(S)}} & \text{if } S > 0, \\ 0 & \text{if } S = 0, \\ \frac{(S+1)}{\sqrt{\text{var}(S)}} & \text{if } S < 0, \end{cases} \quad (4)$$

In this trend test,  $Z > 0$  indicates an increasing trend, while  $Z < 0$  indicates a decreasing trend. Under the 90% confidence level, according to the critical value method, if the  $Z$  value is larger (smaller) than positive (negative) 1.65, then the null hypothesis is rejected, indicating that the data have a significant trend. Also, at a 95% confidence level, the null hypothesis of no trend is rejected if  $|Z| > 1.96$ . A positive value of  $Z$  denotes an increasing trend, and the opposite corresponds to a decreasing trend.

### 3.2. Sen's slope estimator test

One of the most commonly used models for identifying linear trends is simple linear regression. This strategy, however, needs the assumption of residual normality [55]. Many hydrological variables are skewed to the right due to the effects of natural processes and do not follow a normal distribution. Thus, the Sen [56] slope estimator is proven to be an effective tool for developing linear connections. Sen's slope has an advantage over the regression slope in that, in a huge data series, mistakes and outliers have little impact. To determine the magnitude of a trend, the MK approach is always used in conjunction with the Sen's Slope method. Sen [56] and Hirsch et al. [57] developed the Sen's Slope method, which has been widely employed in recent research to investigate the slope of the trend [58-60]. This test is also recommended by the World Meteorological Organization as part of the trend analysis of hydro-meteorological data [53]. The Sen's Slope equation for  $N$  data sample pairs is expressed as follows:

$$Q_i = \left( \frac{X_j - X_i}{j - i} \right) / dt \text{ for } i = 1, 2, 3 \dots, N, \quad (5)$$

where  $x_j$  and  $x_i$  show the data values at times  $j$  and  $k$  ( $j > i$ ), respectively.  $dt$  is the chosen time interval. If there is only one datum in each time period, then  $N = \frac{n(n-1)}{2}$  where  $n$  is the number of time periods.

Otherwise,  $N < \frac{n(n-1)}{2}$ , where  $n$  is the total number of observations. The median of the “ $n$ ” values of  $N$  values of  $Q$  is Sen’s estimator of slope. A positive value of  $Q$  shows an increasing trend, while a negative value shows a decreasing trend in the climatic time series data. The slope ( $Q$ ) of the “ $n$ ” values were sorted from smallest to the largest and the Sen’s estimator was evaluated using Equation (6):

$$\text{Sen's estimator } (Q_{\text{med}}) = Q_{\frac{n+1}{2}} \text{ if } n \text{ is odd, } \frac{1}{2} \left[ Q_{\frac{n}{2}} + Q_{\frac{n+1}{2}} \right] \text{ if } n \text{ is even} \quad (6)$$

where the sign of  $Q_{\text{med}}$  show the data trend pattern, whereas its value shows the steepness of the trend.

### 3.3. Change point detection using Pettitt test

Identifying abrupt change points is one of the most significant statistical strategies for assessing the impacts of climate variability and human activities on runoff data. The Pettitt test is a non-parametric test technique that is independent of distribution and uses rank statistics to identify the occurrence of a change-point at a given significant level. This method is frequently used to calculate the change-point of hydrological and meteorological variables. This approach considers a time series as two samples represented by  $x_1, x_2, \dots, x_t$  and  $x_{t+1}, x_{t+2}, \dots, x_N$ . The following formula can be used to compute the Pettitt indices [61]. The Pettitt test is used to identify a single change point in rainfall, temperature, relative humidity, sun radiation, PET, and runoff time series with a consistent variable. In general, if an adjacent change point exists in a series, the change point will be identified as the maximum value  $K_T$ . Its statistic  $K_T$  and the associated probabilities used in significance testing are given as follows:

$$K_T = \max |U_{t,T}|, \quad (7)$$

$$U_{t,T} = \sum_{i=1}^t \sum_{j=t+i}^T \text{sgn}(X_i - X_j) \quad (t = 1, \dots, n), \quad (8)$$

$$\text{sng}(\theta) = \begin{cases} +1 & \theta > 0, \\ 0 & \theta = 0, \\ -1 & \theta < 0, \end{cases} \quad (9)$$

If  $|U_{t,T}|$  increases with time  $t$ , this indicates that the order does not have a change point over the year in long-term datasets; conversely, if  $|U_{t,T}|$  indicates a decreasing trend compared to time  $t$ , this indicates that a change point happened in the series. The change point of the series is situated at  $K_T$ , which showed that the statistic is significant. The significance probability of  $K_T$  is approximated for  $p \cong 0.05$  with

$$p = 2 \exp \left[ \frac{-6K_T^2}{T^3 + T^2} \right], \quad (10)$$

Since evapotranspiration and rainfall can influence runoff generation, long-term changes in these two meteorological components can influence runoff data under natural conditions. To be more confident in selecting the most appropriate change points in the annual runoff time series, it was proposed that yearly rainfall and evapotranspiration data change points be assessed concurrently [31].

### 3.4. Slope Change Ratio of Accumulative Quantity (SCRAQ) method

This study developed a method based on the slope change ratio of accumulative quantity (SCRAQ) to analyse the contributions of climate change and human activities to runoff change in the Uyo-Itu River Basin. Wang et al. [21] developed the SCRAQ approach, in which year is the independent variable and annual rainfall/evapotranspiration is the dependent variable. The addition of these components greatly reduces the influence of the observed data's inter-annual changes. Therefore, the developed correlation of the relationship between years and these accumulations is quite excellent, providing a favourable environment for future quantitative investigation of the impacts of climate change and human activities on runoff changes.

For a natural watershed, the annual water balance is expressed as  $P - Q - ET = \Delta w$ , where P denotes rainfall, ET stands for actual evapotranspiration, Q represents runoff and  $\Delta w$  denotes the variation of the water storage. For a long time period (10 years or more),  $\Delta w$  can be regarded as zero, thus ET can be calculated by means of  $ET = P - Q$ . Thus, the change in P and ET directly results in the variation of runoff, and the relationship between runoff and rainfall/evaporation can be seen as linear in the long term (10 years or more). Hence, the changes in runoff are determined by the changes in rainfall, evaporation and related human activities. The contribution rate of rainfall ( $C_P$ , unit: %) is expressed as follows:

$$C_P = 100 \times \frac{\left( \left| \frac{S_{P_a}}{S_{P_b}} \right| - 1 \right)}{\left( \left| \frac{S_{R_a}}{S_{R_b}} \right| - 1 \right)}, \quad (11)$$

where  $S_{R_a}$  and  $S_{R_b}$  are the linear relationship slopes between time (i.e., year) and accumulative runoff, after and before the inflection points (mm/year);  $S_{P_a}$  and  $S_{P_b}$  are the linear relation slopes between time (i.e., year) and accumulative rainfall, after and before the inflection point (mm/year).

The evapotranspiration contribution ratio ( $C_{ET}$ , unit: %) was calculated by:

$$C_{ET} = 100 \times \frac{\left( \left| \frac{S_{ET_a}}{S_{ET_b}} \right| - 1 \right)}{\left( \left| \frac{S_{R_a}}{S_{R_b}} \right| - 1 \right)}, \quad (12)$$

where  $S_{ET_a}$  and  $S_{ET_b}$  are the linear relation slopes between time (i.e., year) and accumulative evapotranspiration, after and before the inflection point (mm/year).

The contribution rate of human activities ( $C_H$ , unit: %) on the runoff variation was computed by:

$$C_H = 100 - C_P - C_{ET}, \quad (13)$$

The contribution of evapotranspiration was given by:



$$C_{ET} = -100 \times \frac{\left(\frac{\overline{E}_a - \overline{E}_b}{\overline{E}_b}\right)}{\left(\frac{\overline{R}_a - \overline{R}_b}{\overline{R}_b}\right)}, \quad (14)$$

where,  $\overline{E}_a$  and  $\overline{E}_b$  are the mean annual evapotranspiration after and before the inflection point (mm).

The mean annual evapotranspiration in different period can be calculated based on the evapotranspiration (ET) model provided by Zhang et al. [62]. The evapotranspiration (ET) model has been used in large number of basins around the world. When the annual rainfall ranges from 2000 and 3500 mm, the evapotranspiration is the same as the Budyko method. Furthermore, the rainfall in the study basin is in the interval between 2000 and 3500 mm. Therefore, the mean annual evapotranspiration in different period was estimated as:

$$ET = \left( f \frac{1 + 2 \frac{1410}{p}}{1 + 2 \frac{1410}{p} + \frac{p}{1410}} + (1 - f) \frac{1 + 0.5 \frac{1100}{p}}{1 + 0.5 \frac{1100}{p} + \frac{p}{1100}} \right) \times p, \quad (15)$$

where,  $f$  is the mean fraction of forest cover (%) in baseline period and assessment periods;  $p$  is the mean annual rainfall (mm) in corresponding period; 1410 mm is the assumption of evapotranspiration when the forest is the main land use and plant-available water coefficient is 2.0; 1100 mm is the assumption of evapotranspiration when the herbaceous plants is the main land use and plant-available water coefficient is 0.5.

### 3.5. Budyko hypothesis

In comparison to the standard mathematical method, the Budyko hypothesis examines the influence of potential evapotranspiration on runoff change, and its physical relevance is clearer than that of the standard mathematical method, which is typically employed in the attribution identification of runoff change. Potential evaporation and rainfall are the main factors influencing how rainfall is divided between mean-annual runoff and evaporation in different catchments [63]. The long-term water balance of the basin is expressed as:

$$R = P - E - \Delta S, \quad (16)$$

where  $R$  is the average runoff depth (mm);  $P$  is the average rainfall (mm);  $E$  is the average actual evaporation (mm);  $\Delta S$  is the change of water storage (mm). In the analysis of long-time scale runoff change,  $\Delta S$  is generally assumed to be zero.

Yang et al. [64] used dimensional analysis and quantitative statistics to deduce the water-energy balance equation on an annual average scale, based on the Budyko hypothesis, and paired with the empirical formula of yearly evaporation. The following is the expression:

$$E = \frac{P \times ET_0}{(P^n + ET_0^n)^{\frac{1}{n}}}, \quad (17)$$

where  $n$  is the underlying surface parameter.

Combined with Equations (16) and (17), the water balance equation can be expressed as the following formula:

$$R = P - \frac{P \times ET_0}{(P^n + ET_0^n)^{\frac{1}{n}}}, \quad (18)$$

The following completely differential form can be used to depict the variance in yearly runoff depth R:

$$dR = \frac{\partial R}{\partial P} dP + \frac{\partial R}{\partial ET_0} dET_0 + \frac{\partial R}{\partial n} dn, \quad (19)$$

The elastic coefficients of rainfall, potential evaporation, and underlying surface characteristic parameter to runoff was calculated by formula (20a-20c) [65].

$$\varepsilon_P = \frac{\left(1 + \left(\frac{ET_0}{P}\right)^n\right)^{\frac{1}{n}+1} - \left(\frac{ET_0}{P}\right)^{n+1}}{\left(1 + \left(\frac{ET_0}{P}\right)^n\right) \left[\left(1 + \left(\frac{ET_0}{P}\right)^n\right)^{1/n} - \left(\frac{ET_0}{P}\right)\right]}, \quad (20a)$$

$$\varepsilon_{ET_0} = \frac{1}{\left(1 + \left(\frac{ET_0}{P}\right)^n\right) \left[\left(1 + \left(\frac{ET_0}{P}\right)^n\right)^{1/n}\right]}, \quad (20b)$$

$$\varepsilon_n = \frac{\ln\left(1 + \left(\frac{ET_0}{P}\right)^n\right) - \left(\frac{ET_0}{P}\right)^n \ln\left(1 + \left(\frac{ET_0}{P}\right)^{-n}\right)}{\left(1 + \left(\frac{ET_0}{P}\right)^n\right) \left[\left(1 + \left(\frac{ET_0}{P}\right)^n\right)^{1/n} - \left(\frac{ET_0}{P}\right)\right]}, \quad (20c)$$

where  $\varepsilon_P$  is the elastic coefficient of rainfall,  $\varepsilon_{ET_0}$  is the elastic coefficient of potential evaporation, and  $\varepsilon_n$  is the elastic coefficient of the underlying surface characteristic parameters.

Combined with the water balance equation, the elastic coefficient of runoff on each influencing factor can be expressed as follows:

$$\varepsilon_x = \frac{\partial R}{\partial x} \times \frac{x}{R}, \quad (21)$$

According to the analysis of mutation results, the runoff depth in the base period is recorded as  $R_1$ , the runoff depth in the mutation period is  $R_2$ , and the difference of runoff depth between the two periods is  $\Delta R$ .

$$\Delta R = R_1 - R_2, \quad (22)$$

According to the elastic coefficient of runoff on each influencing factor, the change caused by the corresponding factor on the runoff depth can be calculated, expressed as  $\Delta R_x$ ;  $x$  represents  $P$ ,  $ET_0$ , or  $n$ .

$$\Delta R_x = \varepsilon_x \frac{R}{x} \Delta x, \quad (23)$$

The calculated runoff depth variation  $\Delta R'$  is obtained by summing, which is expressed as follows:

$$\Delta R' = \Delta R_P + \Delta R_{ET_0} + \Delta R_n, \quad (24)$$

The contribution rate of each factor to the change of runoff is calculated according to the following formula:

$$\eta_P = \frac{\Delta R_P}{\Delta R'} \times 100\%, \quad (25a)$$

$$\eta_{ET_0} = \frac{\Delta R_{ET_0}}{\Delta R'} \times 100\%, \quad (25b)$$

$$\eta_n = \frac{\Delta R_n}{\Delta R'} \times 100\%, \quad (26c)$$

## 4. Results and discussion

### 4.1. Mann-Kendall trend and Sen's slope estimator of hydro-meteorological series

The Mann-Kendall test and Sen's slope estimator were used to analyse the time series from 1972 to 2021 for the seven hydro-meteorological variables: rainfall, maximum temperature, lowest temperature, relative humidity, solar radiation, potential evapotranspiration, and runoff. Table 1 and Fig. 2 show the results of using the two non-parametric tests for annual meteorological and hydrological variables. At a 5% confidence level, the MK test revealed significant increasing trends in the annual rainfall, maximum temperature, minimum temperature, and runoff date series. However, trends in annual relative humidity, sun radiation, and PET decreased significantly at the same 5% confidence level. Interestingly, trend analysis results demonstrate that rainfall, maximum, and minimum temperatures all have a significant impact on the runoff trend. Sen's slope rate of mean annual rainfall increase was 19.39 mm/y, while average maximum and minimum temperatures increased at the rates of 0.05 °C and 0.013 °C per year, respectively. The annual runoff trend had a magnitude of 0.028 m<sup>3</sup>/s per year. Conversely, the Sen's slope rates for the mean annual relative humidity, solar radiation, and PET decrease were -0.104%, -8.78 MJ/m<sup>2</sup>/day, and -1.440 mm per year, respectively.

Table 1. Trend analysis by Mann-Kendall and Sen's slope estimator for annual data series

Annual data series	First Year	Last Year	p-value	Z- test	Sen's slope		
					Q	Qmin	Qmax
Rainfall (mm)	1972	2021	0.0073	2.690	19.390	4.390	35.44
Max. Temperature (°C)	1972	2021	3.0E-09	5.930	0.050	0.040	0.06
Min. Temperature (°C)	1972	2021	5.2E-03	2.794	0.013	0	0.022
Relative humidity (%)	1972	2021	0.034	-2.066	-0.104	-0.180	-0.010
Solar radiation (MJ/m <sup>2</sup> /day)	1972	2021	1.6E-05	-4.320	-8.780	-12.75	-4.89
PET (mm)	1972	2021	0.00012	-3.848	-1.440	-2.061	-0.842
Runoff (m <sup>3</sup> /s)	1972	2021	0.013	2.484	0.028	-0.026	0.096

Analyzing changes in meteorological data is an important task for detecting climate change. Identifying hydro-meteorological trends, in addition, is critical for assessing climate change and variability at both the basin and regional levels [66,68]. There is certainly a relationship between the future impacts of climate change on water resources and climate variability trends. Understanding the changes in hydro-meteorological variables is essential to improve water resource planning, management, and sustainability. This is especially true in places undergoing fast urbanisation and those that are very sensitive to climate change, both of which are typical in developing countries.

Rainfall, temperature, relative humidity, and solar radiation are important meteorological indices for describing climate change, and their magnitude influences the availability of natural water supplies. Although climate change impact assessments should be conducted in all locations, they are especially important in urban areas since the negative effects of urbanisation and related human activities may aggravate the impacts.

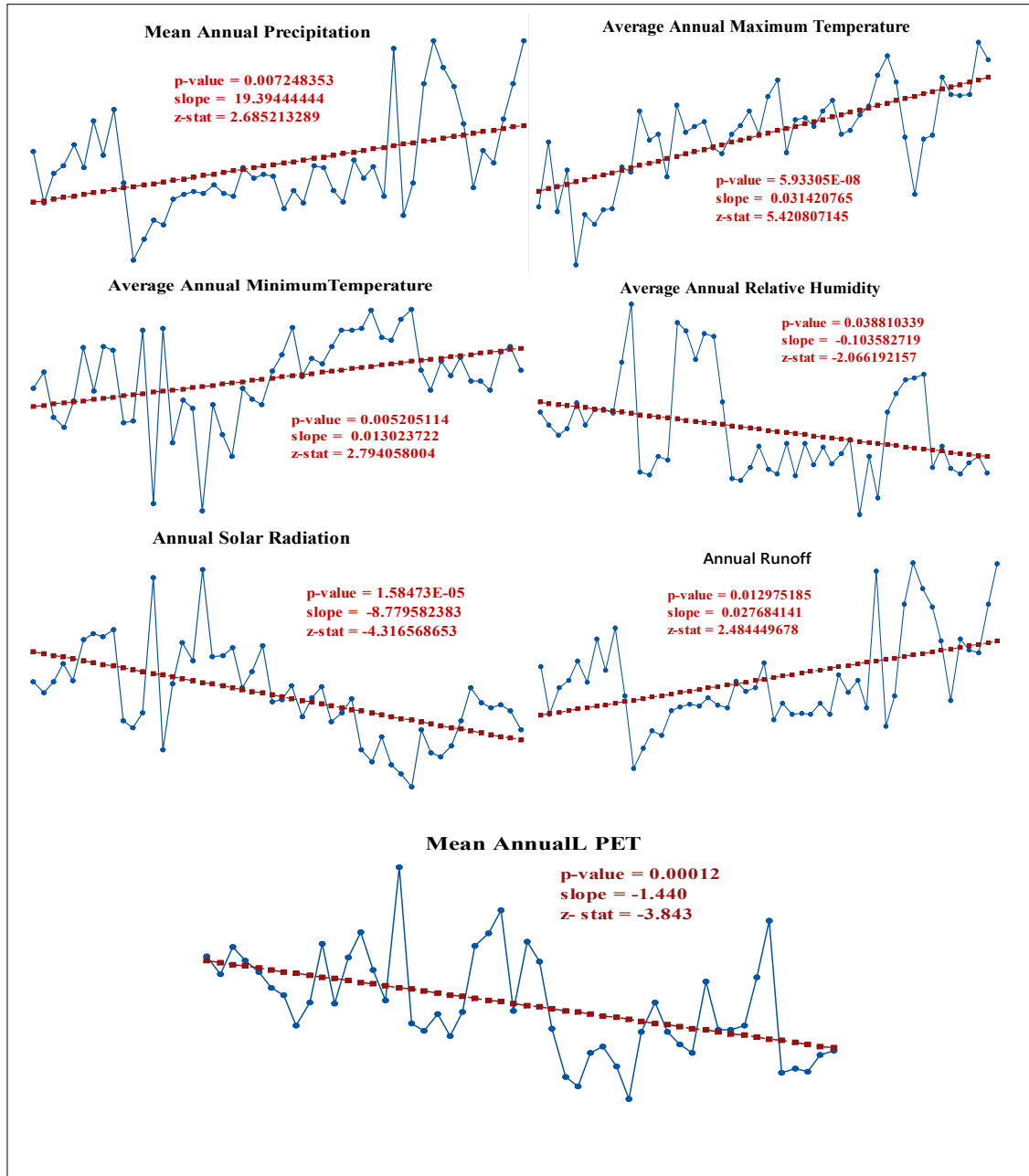


Figure 2. M-K trend and Sen's slope estimator of annual hydro-meteorological series from 1972 to 2021

#### 4.2. Change-point detection analysis using Pettitt's test

Pettitt's test was used to analyse an annual series of rainfall, maximum temperature, minimum temperature, relative humidity, solar radiation, potential evapotranspiration, and runoff for change-point detection. Table 2 and Figure 3 show the test statistics for various tests, as well as the acceptance or rejection of the null hypothesis for the parameters. The procedures provided below were used to select the change point for a particular parameter [67]:

- a. No change point or homogeneous (HG): A series may be considered homogeneous, if the test rejects the null hypothesis at a 5% significant level.
- b. Doubtful series (DF): A series may be considered inhomogeneous and critically evaluated before further analysis if the test rejects the null hypothesis at a 5% significant level.
- c. Change point or inhomogeneous (CP): A series may have a change point or be inhomogeneous in nature if the test rejects the null hypothesis at a 5% significant level.

Table 2. Pettitt's change-point analysis of annual hydro-meteorological series

Annual data series	Shift year	Pre	Post	p-value	Change point
Rainfall (mm)	2010	2450	3634	0.006	Yes
Max. Temperature (°C)	1993	30.919	31.708	<0.0001	Yes
Min. Temperature (°C)	1995	22.828	23.421	0.001	Yes
Relative humidity (%)	1992	81.838	76.247	0.003	Yes
Solar radiation (MJ/m <sup>2</sup> /day)	1998	6612	6316	<0.0001	Yes
PET (mm)	1998	1490	1440	<0.0001	Yes
Runoff (m <sup>3</sup> /s)	2003	3.268	4.555	0.003	Yes

Climate change is a major contributor to runoff variability. Erratic temperatures, evaporation, and rainfall distribution can all have an influence on the temporal and spatial characteristics of water resources. Furthermore, persistent variations in the climate and land use might impact runoff. Pettitt's change-point detection test was used to detect shifts in the mean annual series of rainfall, maximum temperature, minimum temperature, relative humidity, solar radiation, potential evapotranspiration, and runoff from 1972 to 2021. According to the annual rainfall series, there was a significant change-point in 2010. After the change-point, the mean annual rainfall increased by 1184 mm, from 2450 mm to 3634 mm. The presence of a significant change-point in the annual runoff series was identified in 2003, and the mean annual increase was from 3.268m<sup>3</sup>/s to 4.555 m<sup>3</sup>/s after the change-point, with a percentage increase rate of 28.3%. The annual maximum and minimum temperatures increased from 30.919°C to 31.708°C and 22.828°C to 23.421°C, respectively, with increments of 0.789°C and 0.593°C after the change-points. These significant temperature changes occurred in 1993 and 1995. Significant change points in these series identified from 1972 to 1990 may be linked to the influence of fast growing industrial and commercial activities in the region, particularly oil and gas exploration. However, there were abrupt changes in relative humidity, solar radiation, and PET after the change-point in 1992, 1998, and 1998, with decreased rates of 5.591%, 296 MJ/m<sup>2</sup>/day, and 3.4%, respectively. According to Dey and Mishra [31], the changing points of runoff should be within the range of rainfall and evapotranspiration. As a result, the year 2003 was chosen as the final change point for the entire 50-year period.

Since there were fewer human activities between 1972 and the 2000s, variations in runoff were greatly influenced by variations in rainfall. Since 2003, human activities have gradually increased and, to some extent, affected the variance of runoff. To estimate the contributions of climate change and human activities to annual runoff variation, the period 1972–2002 was considered the baseline period A, while the other change period 2003–2021 (B) was taken as the change (impacted) period. Table 3 shows the mean annual values of runoff, rainfall, and evapotranspiration data for the two periods based on the change points of the annual runoff time series. This study included two data sources for comparing observed evapotranspiration data to calculated evapotranspiration data. NiMet provided the

observed evapotranspiration data. The alternative option was to determine the mean annual evapotranspiration in each period using Equation (15). The proportion of forest cover ( $f$ ) is the most essential parameter in this equation. The mean proportion of forest cover for the baseline period A (1972–2002) was calculated using land use maps between 1976 and 1991 (0.56). For the change period B (2003–2021), the mean proportion of forest cover was estimated using the 2007 and 2021 land use maps (0.47), which is the mean of two forest coverage values. Table 3 shows the mean fraction of forest cover for each period as well as the calculated value of mean annual evapotranspiration for each period.

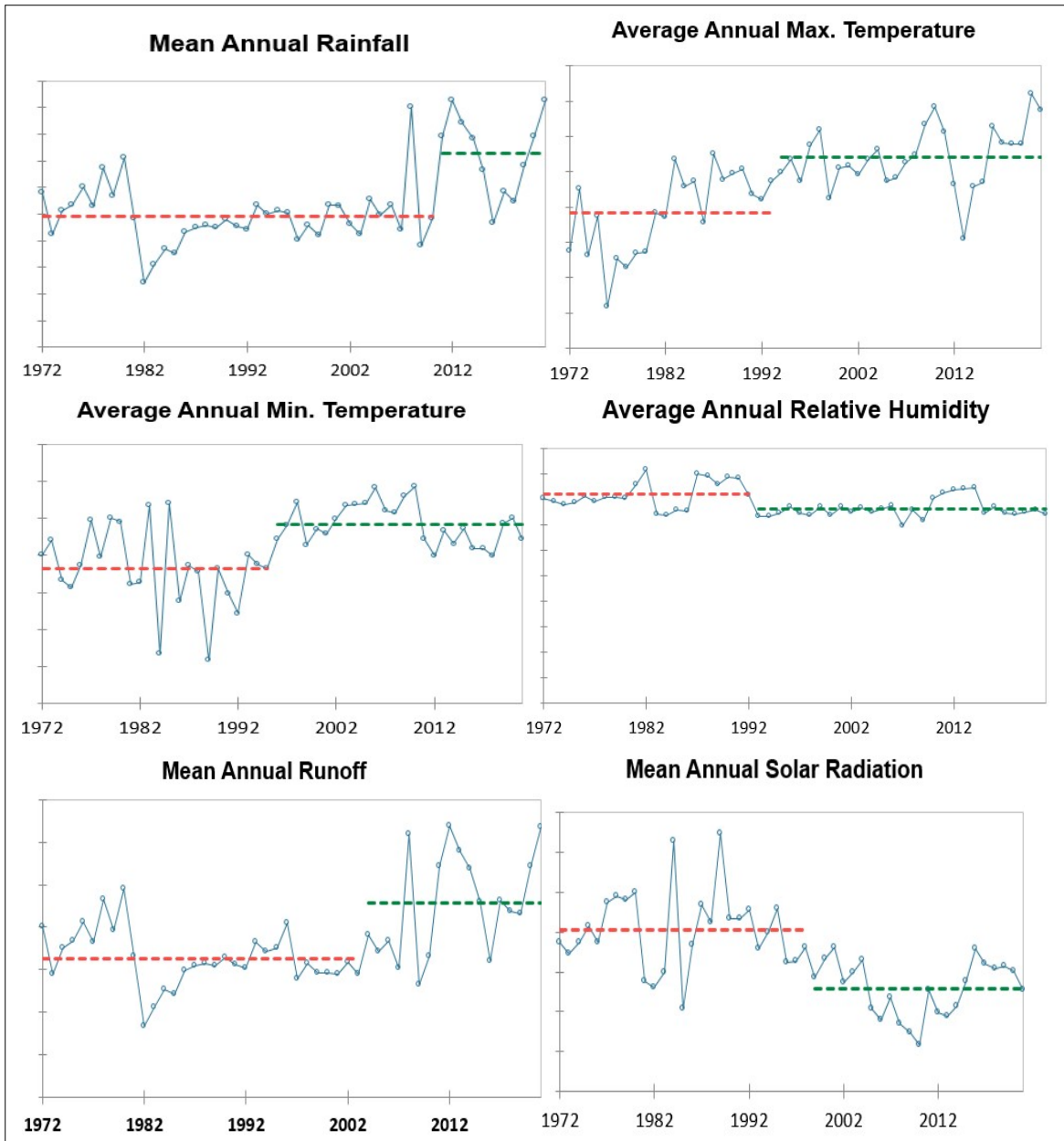


Figure 3. Pettitt's change-point test of annual hydro-meteorological series from 1972 to 2021



Table 3. Summary of the annual rainfall, runoff and PET in different periods.

Periods	Mean Annual Rainfall (mm)	Mean Annual Runoff (mm)	Mean Annual PET (mm) <sup>a</sup>	Mean Fraction of Forest Cover (f)	PET (mm) <sup>b</sup>
A	2451	103.99	1489.95	0.56	1130.50
B	3532	139.63	1442.25	0.47	1183.40

Based on NiMet evapotranspiration, the mean annual rainfall during the change period B increased by 30.6%, evapotranspiration decreased by 3.2%, and runoff increased by 25.5%. However, as compared to the baseline period A, the mean annual evapotranspiration increased by 4.5% based on the evapotranspiration calculated by Equation (15). In general, the change rate of annual rainfall and evapotranspiration in change period B was greater than the total of runoff, indicating that climate change during this time was intense and might be the most important influencing factor for the rise in runoff.

### 4.3. Slope Change Ratio of Accumulative Quantity (SCRAQ) method

#### 4.3.1. Relationships between year, accumulative runoff, rainfall and PET

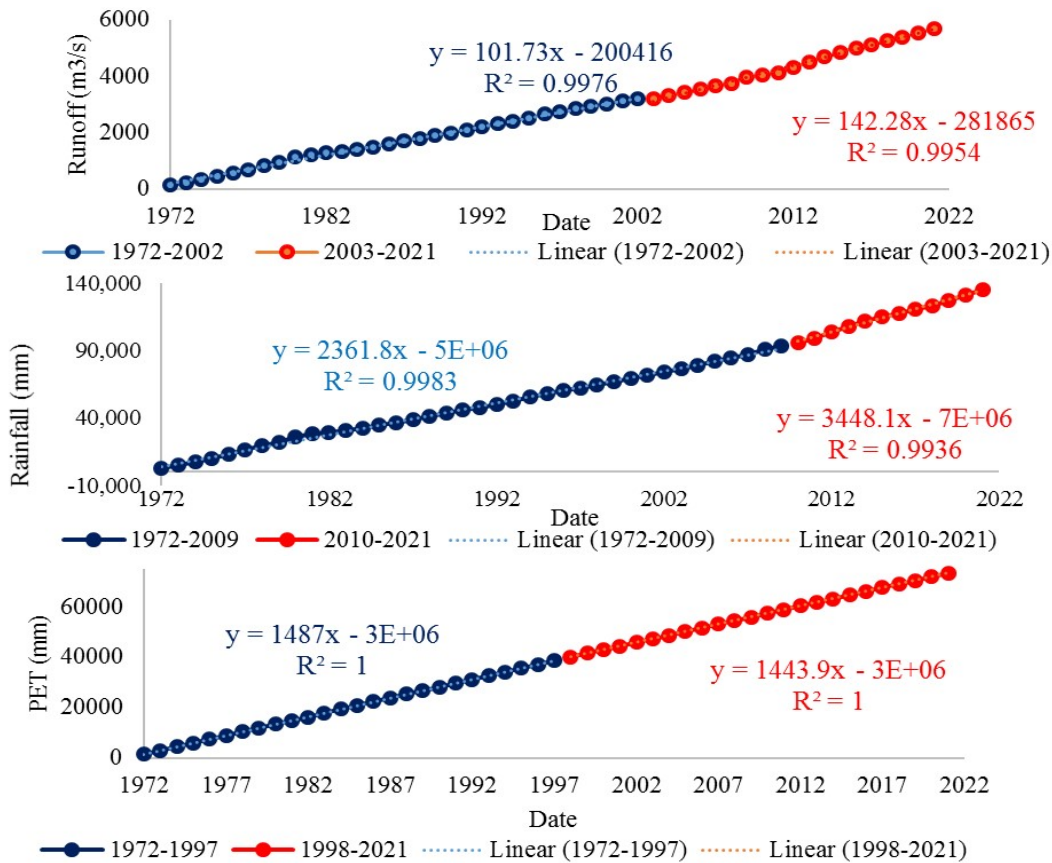


Figure 4. The relationships between year, accumulative runoff, rainfall and PET

Table 4. Slopes from the relationships between accumulative variables and year in different periods

<b>Period</b>	<b>Baseline Period A</b> (1972–2002)	<b>Change Period B</b> (2003–2021)
The slope between accumulative runoff and year ( $S_R$ : mm/year)	101.73	142.28
<b>Period</b>	<b>Baseline Period A</b> (1972–2009)	<b>Change Period B</b> (2010–2021)
The slope between accumulative rainfall and year ( $S_P$ : mm/year)	2361.8	3448.1
<b>Period</b>	<b>Baseline Period A</b> (1972–1997)	<b>Change Period B</b> (1998–2021)
The slope between accumulative evapotranspiration and year ( $S_{ET}$ : mm/year) <sup>a</sup>	1487	1443.9

Figure 4 shows the scatter distributions and fitted lines by linear regression between accumulative runoff and year, accumulative rainfall and year, and accumulative evapotranspiration and year for the various time periods. The correlation coefficients of the  $R^2$  values are all strong for the three periods, even exceeding 0.99. Simultaneously, the p-value confidence levels are less than 0.0001. Therefore, the correlation of accumulative runoff with the year is good in every period. Table 4 also shows the slope parameters obtained for every period.

#### 4.3.2. Quantification of the impacts of climate change and human interactions

Table 5 shows the results of the contribution rates of rainfall, evapotranspiration, and human activities to runoff variation based on the parameters presented in Tables 3 and 4. It is clear that the effect of rainfall on runoff variation was positive and significantly greater than that of potential evapotranspiration (Table 5).

Table 5. Contributions rates of climate change and human activities to runoff variation by Slope Change Ratio of Accumulative Quantity (SCRAQ) method.

<b>Influencing Factor</b>	<b>Contribution Rate to Runoff Change Based on A (1972–2002) (%)</b>	
	<b>B (2003-2021)</b>	
Contribution of rainfall ( $C_p$ )	115.39	
Contribution of evapotranspiration ( $CET$ ) <sup>a</sup>	7.27	
Contribution of evapotranspiration ( $CET$ ) <sup>b</sup>	-11.74	
Contribution of climate change ( $C_p+CET$ ) <sup>a</sup>	<b>122.6</b>	
Contribution of human activities ( $CH$ )	-22.66	
Contribution of climate change ( $C_p+CET$ ) <sup>b</sup>	<b>103.65</b>	
Contribution of human activities ( $CH$ )	-3.65	

When the period A (1972–2002) was treated as the reference period, the contribution of rainfall to the runoff variation for the period B (2003–2021) was 115.39%. When the potential evapotranspiration data obtained from NiMet was used, the contribution to the runoff variation for the period B was 7.27%. Hence, the contribution of climate variability (rainfall and potential evapotranspiration) to runoff changes was 122.6%. The influence of human activities was negative (-22.66%), implying that human actions were responsible for the variation of runoff in the study area. As a result, climate change was the primary driving factor during the transition period. When the potential evapotranspiration data were calculated using Equation (15), it was observed that the contribution of evapotranspiration to the runoff variation for the measurement period B was -11.74%. On the whole, the contribution of climate change (rainfall and evapotranspiration) to runoff variation was 103.6 percent. Therefore, the contribution of human activities to the variation in runoff was -3.65%. In general, in the change period B, climate change was the main driving factor, but 18.95% less than when NiMet data was used.

#### 4.4. Budyko hypothesis method

In this method, rainfall (P), potential evaporation (ET<sub>0</sub>), and the underlying surface characteristic parameters ( $\omega$ ) were used to estimate the elastic coefficient of climate and land cover to runoff change. The underlying surface characteristic parameter ( $\omega$ ) depended on soil type, topographic factors, and vegetation coverage, assuming that the soil types and topographical factors in the study area have not changed since 1972 and using vegetation change instead of land cover change. The period 1972-2021 was divided into two sub-periods based on the results of change-point analysis; the T1 period (1972-2002) and the T2 period (2003-2021). Table 6 illustrates the elastic coefficients of climatic and underlying surface parameters at the station before and after the abrupt change in runoff. The elastic coefficients of runoff to rainfall, potential evapotranspiration and the underlying surface were 1.22, 0.55, and -0.12, respectively, from the perspective of the entire study period, suggesting that runoff was negatively correlated with n, but positively correlated with P and ET<sub>0</sub>. It also demonstrated that when rainfall and potential evapotranspiration rose by 1%, the runoff increased by 1.22% and 0.55%, respectively, whereas an underlying surface parameter (n) rising by 1% decreased the runoff intensity by 0.12%.

Table 6. Statistics of hydrological and climatic factors in the study area during 1972-2021 period.

Period	P/mm	R/mm	ET <sub>0</sub> /mm	n	Elasticity Coefficients		
					$\epsilon_P$	$\epsilon_{ET_0}$	$\epsilon_n$
1972-2002	2402	103.99	1481.59	1.1	1.34	0.41	-0.08
2003-2021	3213	141.70	1443.33	1.2	1.22	0.55	-0.12

Based on Equations (20) - (21), the specific results of  $\Delta R_P$ ,  $\Delta R_{ET_0}$ ,  $\Delta R_n$ ,  $\Delta R'$ , and  $\Delta R$  are shown in Table 7. The difference between the calculated runoff change ( $\Delta R = -641.68\text{mm}$ ) and the actual runoff depth change ( $\Delta R = -37.71\text{mm}$ ). Rainfall had the greatest impact, reducing runoff by 641.68mm, accounting for 133.34%; potential evapotranspiration came in second, increasing runoff by 18.91mm, accounting for -3.11% and the underlying surface had the least impact, resulting in an increment of runoff by 14.57mm, accounting for -2.40%. Rainfall was the biggest contributor to runoff changes in the basin. According to Table 7, the runoff reduction in the study area was mainly caused by climate change. The underlying surface parameter n was mainly related to the basin's topography, soil, land-use, vegetation, and reservoir (Xu et al., 2014). It is generally believed that the terrain and soil are relatively stable and change little in a short time. Therefore, the value of n is mainly related to land-use and vegetation factors.

Table 7. Contributions of underlying surface and climatic factors to the changes in runoff during the study period

$\Delta R_P$	$\Delta R_{ET0}$	$\Delta R_{\eta}$	$\Delta R'$	$\Delta R$	$\eta P$	$\eta ET0$	$\eta \eta$
-641.68	18.91	14.57	-608.21	-37.71	<b>133.34</b>	-3.11	-2.40

#### 4.5. Comparison of the two methods

Tables 5 and 7 present the calculated contributions of climate change and human activities in the basin based on the SCRAQ and Budyko Hypothesis methods. When the results of the two methods are compared, it is evident that the contributions of climate change and human activities in the basin based on the SCRAQ method are similar to those based on the Budyko Hypothesis method, which further validates the reliability of the contributions of human activities and climate change based on the SCRAQ method. Furthermore, both techniques show that climate change is the main driving factor in runoff variations and that climate pressure is intensifying.

#### 4.6. Land use changes of the study area

Table 8 and Fig. 5 show the study area's land use and land distribution from 1976 to 2021. The study area's land-use types were predominantly forest land, accounting for 61% of the area in 1976 and decreasing linearly to 43.1% in 2021. Secondary forest land > cultivated land > primary forest land > built-up land > water bodies were the land-use types. Other land types have not changed much, with the exception of a significant increase in built-up land and a significant decrease in primary forest land. This means that some forest land had been converted into built-up land. The total land area developed increased from 96.1 km<sup>2</sup> to 230.0 km<sup>2</sup>. Since 2007, the area of built-up land has increased significantly, from 165.05 km<sup>2</sup> to 230.0 km<sup>2</sup>. This shows that human activities have increased since 2007. The built-up land near the water body (Itu-River) where the CRBDA hydrological station was located did not increase. The area was dominated by primary and secondary forest, which might explain why human activities did not contribute to the variation in runoff.

Table 8. Change in land-use area in different years in the study area

Year	Land-Use Pattern (km <sup>2</sup> ) (%)				
	Primary Forest	Secondary Forest	Built-up Area	Cultivated Land	Water Body
1976	301.2 (35.7)	210.1 (25.3)	96.1 (10.2)	188.0 (20.1)	51.05 (8.6)
1991	146.0 (15.3)	304.0 (36.3)	110.05 (14.9)	247.0 (28.3)	40.4 (5.2)
2007	112.7 (15.7)	288.8 (33.6)	165.05 (18.8)	240.5 (26.7)	40.4 (5.2)
2021	96.8 (10.6)	280.6 (32.5)	230.0 (27.4)	210.05 (25.4)	30.0 (4.2)

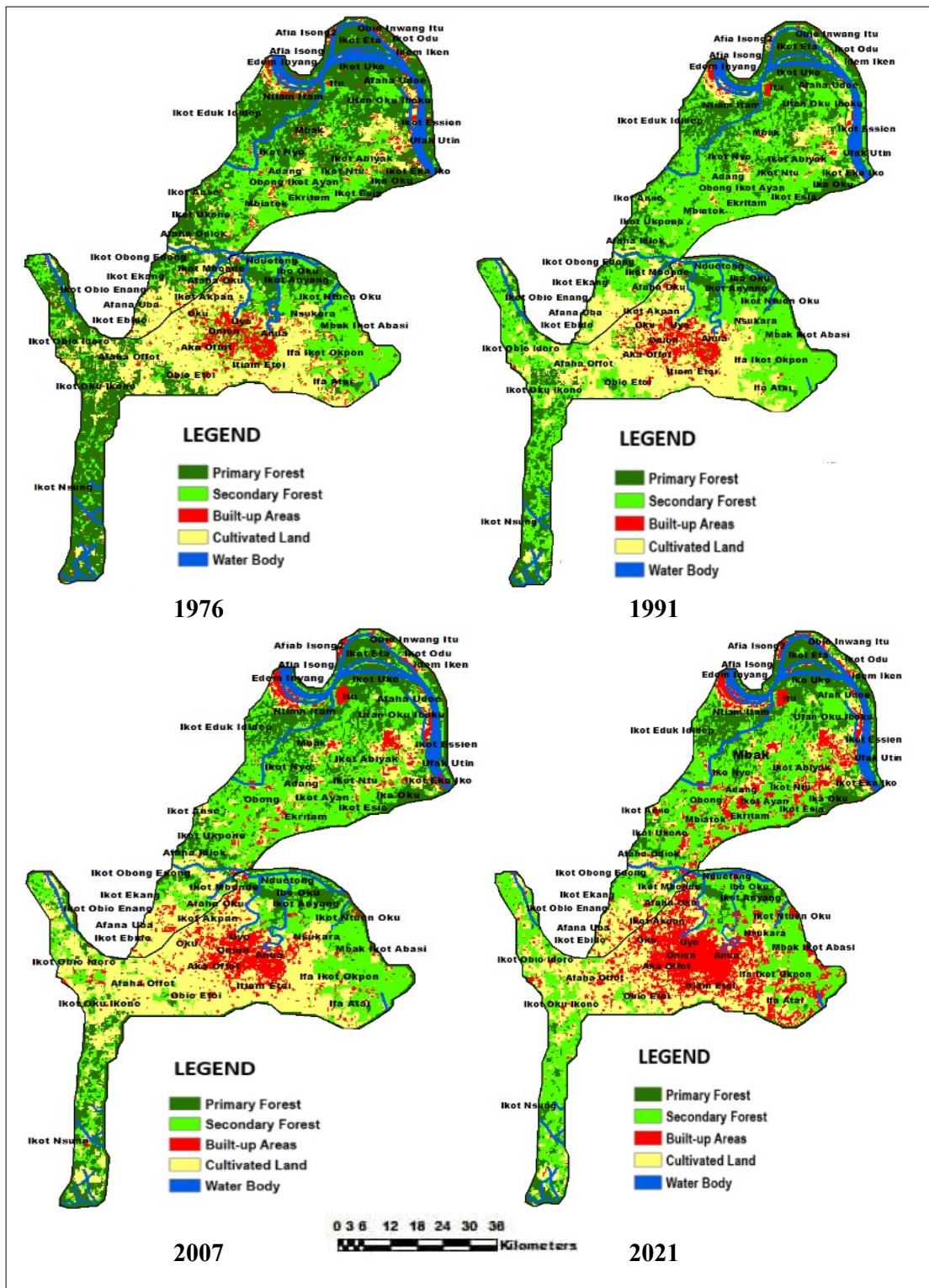


Figure 5. Land use details of Uyo-Itu River Basin, Akwa Ibom State.



## 5. Conclusion

Within the framework of global climate change, changing climate and human activities are seen as the driving causes behind several natural disasters in the global river basin. This study was conducted to quantitatively assess the contributions of climate change and human activities to runoff variation in the Uyo-Itu River Basin in Akwa Ibonm State. Using long-term data series, the Mann-Kendall tests and Sen's slope estimator were used to identify the trend and magnitude in rainfall, maximum and minimum temperatures, relative humidity, solar radiation potential evapotranspiration, and runoff. Using Pettitt's test method, the abrupt change point of the hydro-meteorological series was determined from 1972 to 2021. The SCRAQ technique was used to assess the contribution of climate change and human activities to runoff variation, while the Budyko hypothesis was applied to validate the contributions of human activities and climate change based on the SCRAQ method. The time series in the study were divided into two periods: the baseline period of 1972–2002 and the change (impacted) period of 2003–2021.

The influence of human actions in this context refers to activities such as agriculture, construction, and so on that may alter waterbody channels or reduce the surface area of vegetation. Human activities, such as exploration, mining, and industrialization, emit greenhouse gases, which increase the amount of water vapour in the atmosphere and may cause changes in rainfall patterns and intensity. Human actions continue to play an indirect role in runoff variation. Climate change impacts on runoff variations in this basin might be linked to continuously rising air temperatures, which may induce or change rainfall intensity and pattern, resulting in an increase in high and mean runoff in the catchment. Runoff is an important component of the hydrological cycle because variations in runoff can have a significant impact on human safety, environmental well-being, and water resources. Climate change is the most prominent driving factor impacting runoff variation in the river basin, and its influence is becoming more intense, posing a new challenge for policymakers to enhance water resource management in the basin. Therefore, appropriate modifications to water use and control structures are urgently required to support the basin's socioeconomic development while also preventing flooding. Finally, this study can provide suggestions to decision-makers and researchers on how to restrict human intervention while also developing relevant adaptation measures for mitigating the effects of climate change on water resources and ensuring a reasonable allocation of water resources in the River Basin.

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## Conflict of interest

The authors have no competing interests to declare that are relevant to the content of this article.

## References

- [1] Huang, S., Liu, D., Huang, Q., & Chen, Y. (2016). Contributions of climate variability and human activities to the variation of runoff in the Wei River Basin, China. *Hydrological Sciences Journal*, 61(6), 1026-1039. <https://doi.org/10.1080/02626667.2014.959955>
- [2] Milliman, J. D., Farnsworth, K. L., Jones, P. D., Xu, K. H., & Smith, L. C. (2008). Climatic and anthropogenic factors affecting river discharge to the global ocean, 1951–2000. *Global and Planetary Change*, 62(3-4), 187-194. <https://doi.org/10.1016/j.gloplacha.2008.03.001>



- [3] Azizabadi Farahani, M., & Khalili, D. (2013). Seasonality characteristics and spatio-temporal trends of 7-day low flows in a large, semi-arid watershed. *Water Resources Management*, 27, 4897-4911. <https://doi.org/10.1007/s11269-013-0445-6>
- [4] Jung, G., Wagner, S., & Kunstmann, H. (2012). Joint climate–hydrology modeling: an impact study for the data-sparse environment of the Volta Basin in West Africa. *Hydrology Research*, 43(3), 231-248. <https://doi.org/10.2166/nh.2012.044>
- [5] Thompson, J. R. (2012). Modelling the impacts of climate change on upland catchments in southwest Scotland using MIKE SHE and the UKCP09 probabilistic projections. *Hydrology Research*, 43(4), 507-530. <https://doi.org/10.2166/nh.2012.105>
- [6] Hamilton, S. K., Hussain, M. Z., Lowrie, C., Basso, B., & Robertson, G. P. (2018). Evapotranspiration is resilient in the face of land cover and climate change in a humid temperate catchment. *Hydrological Processes*, 32(5), 655-663. <https://doi.org/10.1002/hyp.11447>
- [7] Parry, M., Lowe, J., & Hanson, C. (2009). Overshoot, adapt and recover. *Nature*, 458(7242), 1102-1103. <https://doi.org/10.1038/4581102a>
- [8] Hasan, E., Tarhule, A., Kirstetter, P. E., Clark III, R., & Hong, Y. (2018). Runoff sensitivity to climate change in the Nile River Basin. *Journal of Hydrology*, 561, 312-321. <https://doi.org/10.1016/j.jhydrol.2018.04.004>
- [9] Huntington, T. G. (2006). Evidence for intensification of the global water cycle: Review and synthesis. *Journal of Hydrology*, 319(1-4), 83-95. <https://doi.org/10.1016/j.jhydrol.2005.07.003>
- [10] Zhao, Y., Yang, N., Wei, Y., Hu, B., Cao, Q., Tong, K., & Liang, Y. (2019). Eight hundred years of drought and flood disasters and precipitation sequence reconstruction in Wuzhou City, Southwest China. *Water*, 11(2), 219. <https://doi.org/10.3390/w11020219>
- [11] van Roosmalen, L., Sonnenborg, T. O., & Jensen, K. H. (2009). Impact of climate and land use change on the hydrology of a large-scale agricultural catchment. *Water Resources Research*, 45(7). <https://doi.org/10.1029/2007WR006760>
- [12] Han, Z., Long, D., Fang, Y., Hou, A., & Hong, Y. (2019). Impacts of climate change and human activities on the flow regime of the dammed Lancang River in Southwest China. *Journal of Hydrology*, 570, 96-105. <https://doi.org/10.1016/j.jhydrol.2018.12.048>
- [13] Zhao, G., Li, E., Mu, X., Wen, Z., Rayburg, S., & Tian, P. (2015). Changing trends and regime shift of streamflow in the Yellow River basin. *Stochastic Environmental Research and Risk Assessment*, 29, 1331-1343. <https://doi.org/10.1007/s00477-015-1058-9>
- [14] Galván, L., Olías, M., de Villarán, R. F., Santos, J. D., Nieto, J. M., Sarmiento, A. M., & Cánovas, C. R. (2009). Application of the SWAT model to an AMD-affected river (Meca River, SW Spain). Estimation of transported pollutant load. *Journal of Hydrology*, 377(3-4), 445-454. <https://doi.org/10.1016/j.jhydrol.2009.09.002>
- [15] Zhang, A., Zhang, C., Fu, G., Wang, B., Bao, Z., & Zheng, H. (2012). Assessments of impacts of climate change and human activities on runoff with SWAT for the Huifa River Basin, Northeast China. *Water Resources Management*, 26, 2199-2217. <https://doi.org/10.1007/s11269-012-0010-8>
- [16] Liang, K., Liu, C., Liu, X., & Song, X. (2013). Impacts of climate variability and human activity on streamflow decrease in a sediment concentrated region in the Middle Yellow River. *Stochastic Environmental Research and Risk Assessment*, 27, 1741-1749. <https://doi.org/10.1007/s00477-013-0713-2>
- [17] Wu, L., Wang, S., Bai, X., Luo, W., Tian, Y., Zeng, C., Luo, G., & He, S. (2017). Quantitative assessment of the impacts of climate change and human activities on runoff change in a typical karst watershed, SW China. *Science of the Total Environment*, 601, 1449-1465. <https://doi.org/10.1016/j.scitotenv.2017.05.288>
- [18] Jiang, S., Ren, L., Yong, B., Fu, C., & Yang, X. (2012). Analyzing the effects of climate variability and human activities on runoff from the Laohahe basin in northern China. *Hydrology Research*, 43(1-2), 3-13. <https://doi.org/10.2166/nh.2011.133>
- [19] Yang, C., Yu, Z., Hao, Z., Zhang, J., & Zhu, J. (2012). Impact of climate change on flood and drought events in Huaihe River Basin, China. *Hydrology Research*, 43(1-2), 14-22. <https://doi.org/10.2166/nh.2011.112>
- [20] Zhang, Z., Chen, X., Xu, C. Y., Yuan, L., Yong, B., & Yan, S. (2011). Evaluating the non-stationary relationship between precipitation and streamflow in nine major basins of China during the past 50 years. *Journal of Hydrology*, 409(1-2), 81-93. <https://doi.org/10.1016/j.jhydrol.2011.07.041>
- [21] Wang, S., Yan, M., Yan, Y., Shi, C., & He, L. (2012). Contributions of climate change and human activities to the changes in runoff increment in different sections of the Yellow River. *Quaternary International*, 282, 66-77. <https://doi.org/10.1016/j.quaint.2012.07.011>

- [22] Guo, Y., Li, Z., Amo-Boateng, M., Deng, P., & Huang, P. (2014). Quantitative assessment of the impact of climate variability and human activities on runoff changes for the upper reaches of Weihe River. *Stochastic Environmental Research and Risk Assessment*, 28, 333-346. <https://doi.org/10.1007/s00477-013-0752-8>
- [23] Wu, J., Miao, C., Zhang, X., Yang, T., & Duan, Q. (2017). Detecting the quantitative hydrological response to changes in climate and human activities. *Science of the Total Environment*, 586, 328-337. <https://doi.org/10.1016/j.scitotenv.2017.02.010>
- [24] Miao, C., Ni, J., Borthwick, A. G., & Yang, L. (2011). A preliminary estimate of human and natural contributions to the changes in water discharge and sediment load in the Yellow River. *Global and Planetary Change*, 76(3-4), 196-205. <https://doi.org/10.1016/j.gloplacha.2011.01.008>
- [25] Xu, J. (2011). Variation in annual runoff of the Wudinghe River as influenced by climate change and human activity. *Quaternary International*, 244(2), 230-237. <https://doi.org/10.1016/j.quaint.2010.09.014>
- [26] Ye, X., Zhang, Q., Liu, J., Li, X., & Xu, C. Y. (2013). Distinguishing the relative impacts of climate change and human activities on variation of streamflow in the Poyang Lake catchment, China. *Journal of Hydrology*, 494, 83-95. <https://doi.org/10.1016/j.jhydrol.2013.04.036>
- [27] Zhao, G., Tian, P., Mu, X., Jiao, J., Wang, F., & Gao, P. (2014). Quantifying the impact of climate variability and human activities on streamflow in the middle reaches of the Yellow River basin, China. *Journal of Hydrology*, 519, 387-398. <https://doi.org/10.1016/j.jhydrol.2014.07.014>
- [28] Mohammadi Ghaleni, M., & Ebrahimi, K. (2015). Effects of human activities and climate variability on water resources in the Saveh plain, Iran. *Environmental Monitoring and Assessment*, 187, 1-17. <https://doi.org/10.1007/s10661-014-4243-2>
- [29] Rougé, C., Ge, Y., & Cai, X. (2013). Detecting gradual and abrupt changes in hydrological records. *Advances in Water Resources*, 53, 33-44. <https://doi.org/10.1016/j.advwatres.2012.09.008>
- [30] Chen, Y., Guan, Y., Shao, G., & Zhang, D. (2016). Investigating trends in streamflow and precipitation in Huangfuchuan Basin with wavelet analysis and the Mann-Kendall test. *Water*, 8(3), 77. <https://doi.org/10.3390/w8030077>
- [31] Dey, P., & Mishra, A. (2017). Separating the impacts of climate change and human activities on streamflow: A review of methodologies and critical assumptions. *Journal of Hydrology*, 548, 278-290. <https://doi.org/10.1016/j.jhydrol.2017.03.014>
- [32] Xin, Z., Li, Y., Zhang, L., Ding, W., Ye, L., Wu, J., & Zhang, C. (2019). Quantifying the relative contribution of climate and human impacts on seasonal streamflow. *Journal of Hydrology*, 574, 936-945. <https://doi.org/10.1016/j.jhydrol.2019.04.095>
- [33] Bo, H., Dong, X., Li, Z., Hu, X., Reta, G., Wei, C., & Su, B. (2019). Impacts of climate change and human activities on runoff variation of the intensive phosphate mined Huangbaihe River basin, China. *Water*, 11(10), 2039. <https://doi.org/10.3390/w11102039>
- [34] Tomer, M. D., & Schilling, K. E. (2009). A simple approach to distinguish land-use and climate-change effects on watershed hydrology. *Journal of hydrology*, 376(1-2), 24-33. <https://doi.org/10.1016/j.jhydrol.2009.07.029>
- [35] Brown, A. E., Zhang, L., McMahon, T. A., Western, A. W., & Vertessy, R. A. (2005). A review of paired catchment studies for determining changes in water yield resulting from alterations in vegetation. *Journal of Hydrology*, 310(1-4), 28-61. <https://doi.org/10.1016/j.jhydrol.2004.12.010>
- [36] Wang, D., & Hejazi, M. (2011). Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. *Water Resources Research*, 47(10). <https://doi.org/10.1029/2010WR010283>
- [37] Li, Z., Ning, T., Li, J., & Yang, D. (2017). Spatiotemporal variation in the attribution of streamflow changes in a catchment on China's Loess Plateau. *Catena*, 158, 1-8. <https://doi.org/10.1016/j.catena.2017.06.008>
- [38] Gao, G., Fu, B., Wang, S., Liang, W., & Jiang, X. (2016). Determining the hydrological responses to climate variability and land use/cover change in the Loess Plateau with the Budyko framework. *Science of the Total Environment*, 557, 331-342. <https://doi.org/10.1016/j.scitotenv.2016.03.019>
- [39] Budyko, M. I. (1974). *Climate and Life*. Academic Press: New York, NY, USA.
- [40] Wang, G., Xia, J., & Chen, J. (2009). Quantification of effects of climate variations and human activities on runoff by a monthly water balance model: A case study of the Chaobai River basin in northern China. *Water Resources Research*, 45(7). <https://doi.org/10.1029/2007WR006768>
- [41] Guo-qing, W. A. N. G., Jian-yun, Z. H. A. N. G., & Rui-min, H. E. (2006). Impacts of environmental change on runoff in Fenhe river basin of the middle Yellow River. *Advances in Water Science*, 17(6), 853-858. ISSN 1001-6791

- [42] Siriwardena, L., Finlayson, B. L., & McMahon, T. A. (2006). The impact of land use change on catchment hydrology in large catchments: The Comet River, Central Queensland, Australia. *Journal of Hydrology*, 326(1-4), 199-214. <https://doi.org/10.1016/j.jhydrol.2005.10.030>
- [43] Zhang, L., Karthikeyan, R., Bai, Z., & Srinivasan, R. (2017). Analysis of streamflow responses to climate variability and land use change in the Loess Plateau region of China. *Catena*, 154, 1-11. <https://doi.org/10.1016/j.catena.2017.02.012>
- [44] Gao, P., Mu, X. M., Wang, F., & Li, R. (2011). Changes in streamflow and sediment discharge and the response to human activities in the middle reaches of the Yellow River. *Hydrology and Earth System Sciences*, 15(1), 1-10. <https://doi.org/10.5194/hess-15-1-201>
- [45] Wu, J., Miao, C., Zhang, X., Yang, T., & Duan, Q. (2017). Detecting the quantitative hydrological response to changes in climate and human activities. *Science of the Total Environment*, 586, 328-337. <https://doi.org/10.1016/j.scitotenv.2017.02.010>
- [46] Chang, J., Wei, J., Wang, Y., Yuan, M., & Guo, J. (2017). Precipitation and runoff variations in the Yellow River Basin of China. *Journal of Hydroinformatics*, 19(1), 138-155. <https://doi.org/10.2166/hydro.2016.047>
- [47] Zhao, Y., Zou, X., Liu, Q., Yao, Y., Li, Y., Wu, X., Wang, C., Yu, W. & Wang, T. (2017). Assessing natural and anthropogenic influences on water discharge and sediment load in the Yangtze River, China. *Science of the Total Environment*, 607, 920-932. <https://doi.org/10.1016/j.scitotenv.2017.07.002>
- [48] Yang, Y., & Tian, F. (2009). Abrupt change of runoff and its major driving factors in Haihe River Catchment, China. *Journal of Hydrology*, 374(3-4), 373-383. <https://doi.org/10.1016/j.jhydrol.2009.06.040>
- [49] Afangideh, C. B., & Udokpoh, U. U. (2021). Spatiotemporal variability assessment of rainwater quality in oil and gas exploration region of Nigeria. *Journal of Human, Earth, and Future*, 2(4), 355-370. <http://dx.doi.org/10.28991/HEF-2021-02-04-04>
- [50] Udokpoh, U. U., Ndem, A. U., Salihu, Z. A., Bashir, Y. A., & Saleh, D. (2021). Comparative Assessment of Groundwater and Surface Water Quality for Domestic Water Supply in Rural Areas Surrounding Crude Oil Exploration Facilities. *Journal of Environment Pollution and Human Health*, 9(3), 80-90. <http://doi:10.12691/jephh-9-3-2>
- [51] Kendall, M. G. (1975). Rank Correlation Methods, 4th ed.; Charles Griffin: London, UK, pp.202.
- [52] Some'e, B. S., Ezani, A., & Tabari, H. (2012). Spatiotemporal trends and change point of precipitation in Iran. *Atmospheric research*, 113, 1-12. <https://doi.org/10.1016/j.atmosres.2012.04.016>
- [53] Aditya, F., Gusmayanti, E., & Sudrajat, J. (2021, November). Rainfall trend analysis using Mann-Kendall and Sen's slope estimator test in West Kalimantan. In *IOP Conference Series: Earth and Environmental Science*, 893(1), 012006. <https://doi.10.1088/1755-1315/893/1/012006>
- [54] Lee, C. H., & Yeh, H. F. (2019). Impact of climate change and human activities on streamflow variations based on the Budyko framework. *Water*, 11(10), 2001. <https://doi.org/10.3390/w11102001>
- [55] McBean, E., & Motiee, H. (2008). Assessment of impact of climate change on water resources: a long term analysis of the Great Lakes of North America. *Hydrology and Earth System Sciences*, 12(1), 239-255. <https://doi.org/10.5194/hess-12-239-2008>
- [56] Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63(324), 1379-1389. <https://doi.org/10.2307/2285891>
- [57] Hirsch, R. M., Slack, J. R., & Smith, R. A. (1982). Techniques of trend analysis for monthly water quality data. *Water Resources Research*, 18(1), 107-121. <https://doi.org/10.1029/WR018i001p00107>
- [58] Dinpashoh, Y., Jhajharia, D., Fakheri-Fard, A., Singh, V. P., & Kahya, E. (2011). Trends in reference crop evapotranspiration over Iran. *Journal of Hydrology*, 399(3-4), 422-433. <https://doi.org/10.1016/j.jhydrol.2011.01.021>
- [59] Tabari, H., & Aghajanloo, M. B. (2013). Temporal pattern of aridity index in Iran with considering precipitation and evapotranspiration trends. *International Journal of Climatology*, 33(2), 396-409. <https://doi.org/10.1002/joc.3432>
- [60] Zhang, A., Zheng, C., Wang, S., & Yao, Y. (2015). Analysis of streamflow variations in the Heihe River Basin, northwest China: Trends, abrupt changes, driving factors and ecological influences. *Journal of Hydrology: Regional Studies*, 3, 106-124. <https://doi.org/10.1016/j.ejrh.2014.10.005>
- [61] Pettitt, A. N. (1979). A non-parametric approach to the change-point problem. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 28(2), 126-135. <https://doi.org/10.2307/2346729>
- [62] Zhang, L., Dawes, W. R., & Walker, G. R. (2001). Response of mean annual evapotranspiration to vegetation changes at catchment scale. *Water Resources Research*, 37(3), 701-708. <https://doi.org/10.1029/2000WR900325>

- [63] Wang, H., Lv, X., & Zhang, M. (2021). Sensitivity and attribution analysis based on the Budyko hypothesis for streamflow change in the Baiyangdian catchment, China. *Ecological Indicators*, 121, 107221. <https://doi.org/10.1016/j.ecolind.2020.107221>
- [64] Yang, H., Yang, D., Lei, Z., & Sun, F. (2008). New analytical derivation of the mean annual water-energy balance equation. *Water Resources Research*, 44(3). <https://doi.org/10.1029/2007WR006135>
- [65] Xu, X., Yang, D., Yang, H., & Lei, H. (2014). Attribution analysis based on the Budyko hypothesis for detecting the dominant cause of runoff decline in Haihe basin. *Journal of Hydrology*, 510, 530-540. <https://doi.org/10.1016/j.jhydrol.2013.12.052>
- [66] Banda, V. D., Dzwauro, R. B., Singh, S. K., & Kanyerere, T. (2021). Trend analysis of selected hydro-meteorological variables for the Rietspruit sub-basin, South Africa. *Journal of Water and Climate Change*, 12(7), 3099-3123. <https://doi.org/10.2166/wcc.2021.260>
- [67] Jaiswal, R. K., Lohani, A. K., & Tiwari, H. L. (2015). Statistical analysis for change detection and trend assessment in climatological parameters. *Environmental Processes*, 2, 729-749. <https://doi.org/10.1007/s40710-015-0105-3>
- [68] Garba, H., & Udokpoh, U. U. (2023). Analysis of Trend in Meteorological and Hydrological Time-series using Mann-Kendall and Sen's Slope Estimator Statistical Test in Akwa Ibom State, Nigeria. *International Journal of Environment and Climate Change*, 13(10), 1017-1035. <https://doi.org/10.9734/IJECC/2023/v13i102748>
- [69] Afangideh, C.B. & Udokpoh, U.U. (2022). Environmental impact assessment of groundwater pollution within cemetery surroundings. *Indian Journal of Engineering*, 19(51), 100-115. ISSN 2319-7757