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Investigation of Climatic Variability with Hybrid Statistical Analysis

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Abstract The study of the stationarity of hydrologic time series is a common method to detect climate change and the influence of anthropogenic activities on hydrologic variability. The power of different stationary tests is herein investigated with generated hydrologic time series. This study also combines a standard unit root test and an alternative stationary test to yield a new hybrid statistical analysis (HSA) model. The HSA model is implemented to study the effect of climate change in the Hamun Lake basin, Iran. The implementation results demonstrate that there is evidence of climatic change in the Lake Hamun basin.

Keywords Unit-root test · Stationary test · Hybrid statistical analysis (HSA) model · Stationarity · Long memory · Climate change

1 Introduction

Hydrologic time series have various components such as trends, seasonality, auto regressive persistence, long memory, outliers and others. The characteristics of hydrologic time series may vary due to climate change and human activities. Therefore, the study of the properties of hydrologic time-series is a common method of detection of climate change and of the influence of anthropogenic activities on hydrologic variability.

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The stationarity of hydrologic time series is commonly assumed for historic time series in the evaluation of water systems (i.e. Farhangi et al. 2012; Ahmadi et al. 2014; Bozorg-Haddad et al. 2013, 2014, 2015a, b; Fallah-Mehdipour et al. 2013a, b, c, Fallah-Mehdipour et al. 2014; Shokri et al. 2013; Bolouri-Yazdeli et al. 2014), yet, several studies have considered climate change and land-use change in hydrologic studies (i.e. Ahmadi et al. 2015; Ashofteh et al. 2013a, b; Ashofteh et al. 2015a, , c; Jahandideh-Tehrani et al. 2015). Several studies have evaluated the stationarity of hydrologic time series to detect climate change and the variability of hydrologic phenomena (i.e. Milly et al. 2008; Delju et al. 2013; Cheng et al. 2014; Yilmaz et al. 2014; Abdul-Aziz et al. 2013; Ashofteh et al. 2016). These studies have demonstrated that the condition of stationarity is not satisfied under a changing environment. Also, Estrada and Perron (2014) presented a literature review of application of stationary tests to detection of climate change.

Hitherto, many stationarity tests have been developed in many fields of inquiry, especially those dealing with economic data (see, Estrada and Perron 2014, for example). A standard unit root (SUR) test was presented by Dickey and Fuller (1979) that ensures that the null hypothesis of a unit root is accepted unless there is strong evidence against it. Kwiatkowski et al. (1992) developed a stationary test that carries out a test of the null hypothesis of stationarity against the alternative of a unit root and it is herein called the alternative stationary (AS) test. Although the power of these tests has been assessed primarily with economic time series (i.e., Becker et al. 2006; Sephton 2008; Khedhiri and El Montasser 2012), they differ from hydrologic time series in many respects.

This work examines the power of the standard unit root (SUR) and the alternative stationary (AS) tests in evaluating the stationarity of hydrologic time series and detection of climate variability using artificial time series. Also, a hybrid statistical analysis (HSA) model is herein developed as a combination of the SUR and AS tests. The HSA model is applied to evaluate the effects of climate change and human activities on precipitation, evaporation, and stream flow time series in the Hamun Lake basin.

2 Methodology

The main goal of a stationarity test is to ascertain whether or not the statistical characteristic of a time series changes over time. Therefore, stationary tests are suitable methods for investigating climate change. This study employs the SUR and AS tests, which are based on linear regression and require the normality assumption for statistical inference. Therefore, normalizing of time series is discussed in this section. Thereafter, the SUR and AS tests are described and subsequently, the HSA model is developed based on the SUR and AS tests. Lastly, the SUR and AS tests as well as the HSA model are implemented to detect stationarity and long memory of hydrologic time series.

2.1 Normalizing Time Series

This study employs the logarithmic transformation on original time series (OTS) of precipitation, evaporation, and streamflow. It is known that the logarithmic transformation converts an exponential trend present in data into a linear trend as follows:

$$y_t = Ln(x_t + a) \quad t = 1, 2, ..., T \tag{1}$$

in which y_t = normalized time series (NTS) at time t, x_t = OTS, t = time step, a = shift constant, and T = number of time steps in a time series. The shift constant (a) in Equation (1) assures that all data in the time series to be transformed are larger than 1 (Osborne 2010).

2.2 The Standard Unit Root (SUR) Test

The standard unit root (SUR) tests are conducted through Ordinary Least Square (OLS) estimation of regression models (Dickey and Fuller 1979; Said and Dickey 1984). Consider the AR(1) model:

$$y_t = \rho . y_{t-1} + \varepsilon_t \quad t = 1, 2, ..., T \tag{2}$$

in which ρ= an autoregressive coefficient of first order, ε_t= a real valued sequence of independent random variables with mean zero and variance σ^2, at time step t. First, $\rho$is estimated, if $|\rho| < 1$, the process y_t is stationary, otherwise it is non-stationary. Maximum Likelihood method may be used to estimateρ (Wang et al. 2005), as follows:

$$\hat{\rho} = \left(\sum_{t=2}^{T} y_{t-1}^2 \right)^{-1} \times \sum_{t=2}^{T} y_t \cdot y_{t-1} \tag{3}$$

in which $\hat{\rho}$ = the estimator ofρ. The SUR test statistic is calculated with Equation (4):

$$\hat{t} = \frac{\hat{\rho}-1}{\hat{\sigma}_{\hat{\rho}}} \tag{4}$$

in which $\hat{\sigma}_{\hat{\rho}}$ = the usual OLS standard error for the estimated coefficient, which is calculated with Equations (5) and (6):

$$\hat{\sigma}_{\hat{\rho}} = S_e \left(\sum_{t=2}^{T} y_{t-1}^2 \right)^{-\frac{1}{2}} \tag{5}$$

$$S_e = \frac{1}{T-2} \sum_{t=2}^{T} \left(y_t - \hat{\rho}\, y_{t-1} \right)^2 \tag{6}$$

Dickey and Fuller (1979) derived the limiting distribution of the statistic t under the null hypothesis of non-stationary. The null hypothesis is accepted if $t$is greater than a critical value of t with significance level α. Otherwise, the null hypothesis is rejected. The basic autoregressive unit root test has been generalized to accommodate the general AR (p, q) models (Said and Dickey 1984). Said and Dickey (1984) showed that the Dickey-Fuller procedure, which was originally developed for autoregressive representations of known order, remains valid asymptotically for a general ARIMA (p, 1, q) process in which p and q are of unknown orders. The critical values of t at significance levels α=1, 5, and 10 % are −3.44, −2.836, and −2.57, respectively (Fuller 1976).

2.3 The Alternative Stationary (AS) Test

The alternative stationary (AS) test was introduced by Kwiatkowski et al. (1992), and can be applied to test stationarity about a fixed level (AS-L) or a deterministic trend (AS-T). Let y_t, $t = 1, 2, \ldots, T$, be the time series in interest whose stationarity of y_t is evaluated. Assume that y_t

can be decomposed into the sum of a deterministic trend, a random walk, and a stationary error with the following linear regression model:

$$y_t = r_t + \beta t + e_t \tag{7}$$

in which $r_{t.}$ = a random walk, i.e., $r_{t.} = r_{t\text{-}1} + u_t$, u_t = independent and identically distributed (iid) normal process with zero mean and varianceσ_u^2, respectively, or $(N(0, \sigma_u^2))$,βt = a deterministic trend with slope β, and e_t = a stationary error at time step t. The null hypothesis is β = 0 when the series is stationary about a fixed value. Trend stationarity is another type of stationarity in which the series is stationary about a deterministic trend. In this case the null hypothesis is σ_u^2 = 0, against the alternative of a positiveσ_u^2. In this case the intercept is a fixed value. In the case of level stationarity, the residuals e_t are from a regression of y on the intercept only, that is $e_t = y_t - \overline{y}$ (y= mean of normalized time series). The mean is usually a fixed level in the AS-L test. In the case of trend stationary (the AS-T test) the residuals e_t are from the regression of y on an intercept and time trend, thus, $e_t = \varepsilon_t$. Let the partial sum S_t of e_t be defined by Equation (8):

$$S_t = \sum_{j=1}^{t} e_j \tag{8}$$

Let σ^2 be the long-run variance of e_t, which is defined as $\sigma^2 = \lim_{t\to\infty} t^{-1} E\left[S_t^2\right]$. A consistent estimator of σ^2 is calculated from the residuals e_t by Equation (9) provided by Newey and West (1987):

$$\hat{\sigma}^2(l) = \frac{1}{T}\sum_{t=1}^{T} e_t^2 + \frac{2}{T}\sum_{j=1}^{l} w_j(l)\cdot\sum_{t=j+1}^{T} e_t \cdot e_{t-j} \tag{9}$$

in which $\sigma^2(l)$ = estimated long-run variance, l = truncation lag, and $w_j(l)$ = an optional weighting function in time step of j, that corresponds to the choice of a special window, in this study Bartlett (1950) window used: $w_j(l) = 1 - \frac{j}{l+1}$. The AS test statistic is given by Equation (10):

$$\eta = \frac{1}{T^2}\sum_{t=1}^{T} \frac{S_t^2}{\hat{\sigma}^2(l)} \tag{10}$$

in which η = the AS test statistics. The null hypothesis of the AS test is $H_0 : \eta < 1$, which represents stationarity. Critical values of the AS test were tabulated by Kwiatkowski et al. (1992). Critical values of the AS test statistics for the AS-L test for 1, 5, and 10 % significant levels are 0.739, 0.463, and 0.347, respectively. The critical values for the AS-T test for significance levels 1, 5 and 10 % are 0.216, 0.146, and 0.119, respectively.

An important practical issue for implementation of the SUR and AS tests is the specification of the truncation lag values of l. Kwiatkowski et al. (1992) state that the AS test statistics are fairly sensitive to the choice of l, and for every series the value of the test statistics decreases as l increases. If l is too small then the remaining serial correlation in the error biases the test towards rejecting the null hypothesis. If l is too large then the power of the test will suffer. The larger the l, the less likely the null hypothesis will be rejected. The lag length is chosen according to Equation (11) (Schwert 1989):

$$1 = \mathrm{int}\left[c\cdot\left(\frac{T}{100}\right)^{\frac{1}{4}}\right] \tag{11}$$

in which int[] = the nearest integer of the calculated expression and c = a constant. Schwert (1989), Kwiatkowski et al. (1992), and Wang et al. (2005) considered the value of c to be 4 or 12. The stationarity test is herein performed for lags ranging from 1 through 24 in addition to those calculated with Equation (11). The range of 1 to 24 was chosen because the lag calculated with Equation (11) places it within this range. This allows an evaluation of the capacity of this well-known equation to choose a proper lag. Moreover, the lag range 1 to 24 permits conducting a sensitivity analysis of the stationarity tests in hydrologic time series.

2.4 The Hybrid Statistical Analysis (HSA) Model

The HSA model combines features of the SUR and AS tests. Figure 1 shows the pseudo code of the HSA model.

The AS-L and AS-T tests can be used with the HSA model. The HSA-L and HSA-T refer to HSA models about a fixed level and about a deterministic trend, respectively. To satisfy the SUR and AS assumptions the OTSs are transformed to NTSs using Equation (1). The HSA model is unable to ascertain stationarity in the presence of seasonality due to the weakness of the SUR and AS tests, as reported by Becker et al. (2006) and Khedhiri and El Montasser (2012). The seasonality of hydrologic time series is removed by monthly standardization or using Fourier analysis. Subsequently, the NTSs are standardized using monthly means and variances to remove the annual seasonality and achieve standardized time series (STS). Trend detection and slope estimation of NTSs and STSs were carried out in the HSA model with the Mann-Kendall test and Sen slope estimator, respectively. The Mann-Kendall test and Sen slope estimator were implemented in MATLAB (MATLAB 1998) in this work.

```
Begin
Normalize time series
Remove the trend and seasonality
Conduct the SUR test
Conduct the AS test
If the null hypothesis of the SUR test is rejected
    If the null hypothesis of the AS test is rejected
        Time series has long memory
    Else
        Time series is stationary
    End if
Else
    If the null hypothesis of the AS test is rejected
        Time series has unit root
    Else
        There is not conclusive result
    End if
End if
End
```

Fig. 1 Pseudo code of the HSA model

2.5 Analysis of the Power of the SUR and AS Tests

This work relied on 1000 artificial time series (ATS) each with length of 500 values for the analysis of the power of the SUR and AS test. The artificial time series were generated randomly with a standard normal distribution (zero mean and unit variance). Subsequently, the three cases including monotonic trend of mean; monotonic trend of variance; and outliers were added to the ATSs.

A random number in the interval of 0.001 to 0.01 was generated to represent the trend slope in assessing the power of the SUR and AS test in the presence of a monotonic trend in the mean. A plus sign (increasing trend) or a minus sign (decreasing trend) was assigned to the trend slope randomly. This signed number is a trend slope, and by multiplying this signed number times the time steps (1 through 500) the trend component was produced. By adding the trend component to the ATS an artificial time series with monotonic trend in the mean (ATSM) is calculated. The trends of ATSMs were analyzed with the Mann-Kendall test. The Mann-Kendall test established that 888, 66, and 46 series have a significant trend at significance levels equal to 10, 5 and 1 %, respectively.

Another 1000 ATSs were generated to analyze the power of the SUR and AS tests in the presence of a monotonic trend in the variance. A uniform random numbers in the range 0.0021 to 0.0039 for each ATS was generated. Artificial time series with a monotonic trend in the variance (ATSV) for each time steps (1 through 500) were calculated by multiplying the generated series of uniform random numbers times the ATSs and times the time steps. The Mann-Kendall test was employed to evaluate whether or not the trends of all the 1000 ATSVs were significant. The Mann-Kendall results show that 952 ATSVs were trend free and 48 ATSVs had a significant trend at the 5 % significance level. These 48 ATSVs were de-trended by using the Sen slope estimator. This assured that all the ATSV have zero mean and pronounced non-stationary variance. In other words, ATSVs have first order stationarity and second order non-stationarity.

An additional set of 1000 ATSs was generated and employed to analyze the power of the stationarity test in the presence of outliers. In the STSs of precipitation, evaporation, and streamflow it was calculated that the occurrence probability of outliers is about 0.0056 (the probability of a value larger than 3 times the variance of a time series with 336 time steps is 0.0023 according to the normal distribution). Also, the magnitude of outliers in the STSs is about 3 to 4.5 times the variance. The occurrence of outliers, as it can be seen in the analyzed time series, is considered to be random. Based on this observation, outliers 3 to 4.5 times the variance, that is, with a probability of 0.0056 (uniform distribution) and random occurrence, were added to ATSs and 1000 artificial time series with outliers (ATSO) with length of 500 each were generated.

2.6 Study Area and Data

The HSA model was implemented to detect stationarity and long memory (persistence) of hydrologic time series, which include standardized precipitation, evaporation, and streamflow time series of the Lake Hamun basin. Hamun Lake lies in southeastern Iran. Monthly time series of precipitation, evaporation, and streamflow for the period 1982–2009 were analyzed in this study. Table 1 lists the geographic locations and data for the hydrometric and synoptic stations within the Lake Hamun basin.

Table 1 Data about Hamun Lake basin's stations

Station name	Station type	Longitude	Latitude	Altitude (m)
Zabol	Synoptic	61° 29′	31° 20′	489
Sistan river	Hydrometric	61° 44′	30° 51′	490

3 Results

3.1 Results of Analyzing the Power of the SUR and AS Tests with Artificial Time Series

The power of a statistical test in classic statistics is defined as the probability of rejecting the null hypothesis of the test when the null hypothesis is true. The null hypothesis of SUR test is that the time series is non-stationary whereas the null hypothesis of AS test is that the time series is stationary.

Results of the stationarity test for the artificial time series are shown in Fig. 2. Figure 2(a) shows that the power of the SUR test increases as the lag increases. The AS test, on the other hand, is effective in testing stationarity in the presence of monotonic trend in mean. This is so because the stationarity of the ATSMs are firmly rejected with the AS-L test, and the AS-T test accepted the stationarity of the majority of the ATSM series about a deterministic trend. Thus, if a monotonic trend in the mean exists in a time series it is suggested that the longest significant lag be selected for the SUR test, or, that proper de-trending method be applied on a time series prior to applying the SUR test. Another feature which can be inferred from Fig. 2(a) is the long memory of the ATSMs. It is seen in the HSA flowchart of Fig. 1 that if the null hypotheses of the SUR and AS test are rejected then the time series has a long memory. Figure 2(a) shows the null hypothesis rejection of most ATSMs by the SUR and AS-L tests for small lag. This indicates long memory of the ATSMs. A long memory occurs when there is a trend in the mean of the ATSMs. This is why the long memory vanishes as the lag increases.

Figure 2(b) depicts the low power of the stationarity tests in assessing the ATSVs' non-stationarity of variance, given that the majority of the ATSVs reported stationarity when they were, in fact, non-stationary. Results achieved by analysis of the power of the SUR and AS tests under the presence of monotonic trend in variance show that they are ineffective in testing such non-stationarity.

Figure 2(c) portrays the percent of ATSOs reported as stationary at a significance level equal to 5 %. It is seen in Fig. 2(c) that the SUR test rightly reported all of the 1′000 ATSO stationary. Therefore, the SUR test is powerful in testing stationarity in the presence of outliers. The AS test, on the other hand, reported some ATSO as non-stationary. Specifically, the AS-T test is less powerful than the AS-L test in testing the stationarity of time series with outliers because the latter test reported, correctly, more stationary series than the former. The same phenomenon was observed in daily stream flow time series by Wang et al. (2006). Otero and Smith (2005) showed that the AS test power is sensitive to outliers' values and locations. Similar results were obtained in this section. The trend component of the AS-T test is adversely affected when outliers are present at the beginning and end of a time series, which may lead to considerable errors. This makes the AS-T test a questionable choice to test time series when outliers are present. So it is recommended the AS test not be used for stationarity testing when outliers are present.

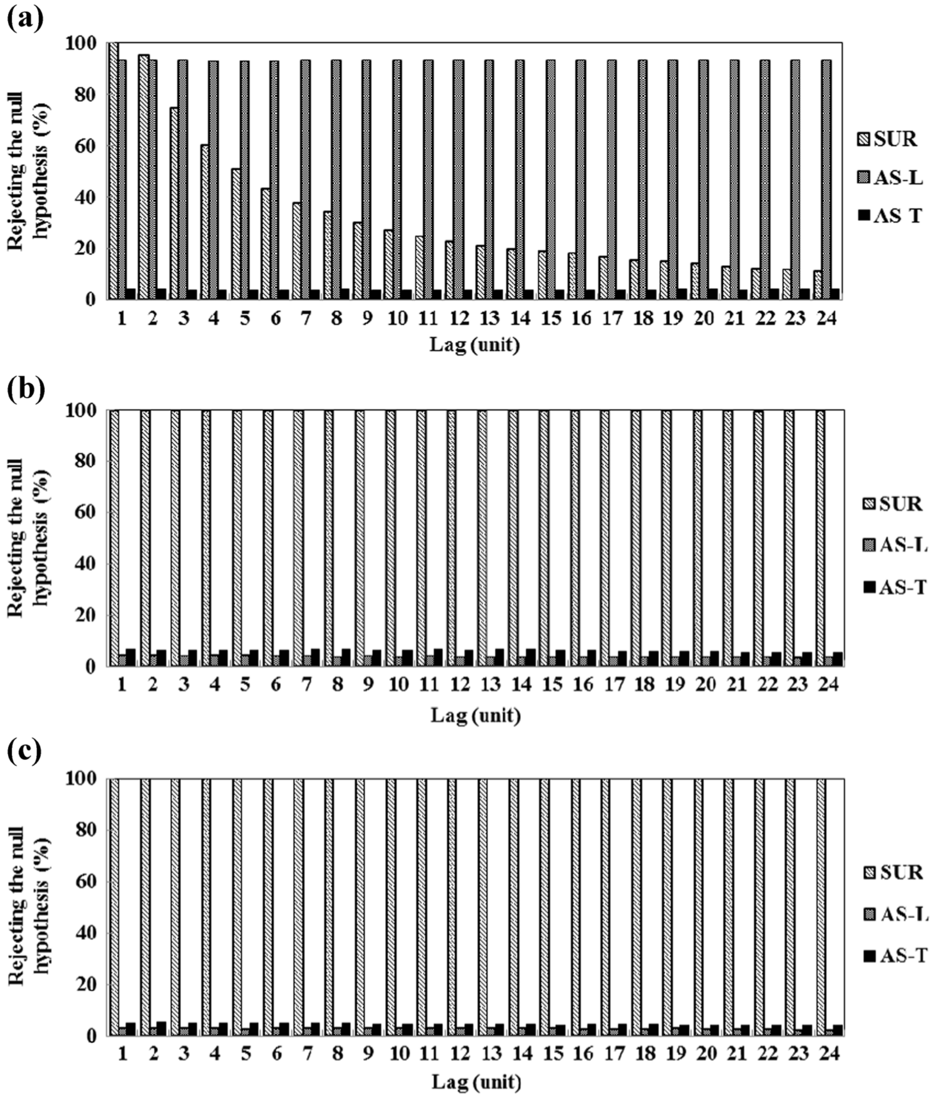

Fig. 2 Results of the SUR and AS tests power analysis in (**a**) presence of monotonic trend in the mean; (**b**) monotonic trend in the variance; and (**c**) outliers

3.2 Results of Testing Stationarity of Hydrological Time Series of Hamun Lake Basin Using the HSA Model

First, the time series are normalized to generate NTSs. The NTSs may have trends, seasonality, and outliers, but it was mentioned that the HSA model is unable to ascertain stationarity in the presence of seasonality due to the weakness of the SUR and AS tests. So the NTSs were standardized with the monthly mean and standard of deviation and the STSs were calculated. The ACF of NTSs and STSs are plotted in Fig. 3 that reveals that unlike NTSs, seasonality is deleted from STSs.

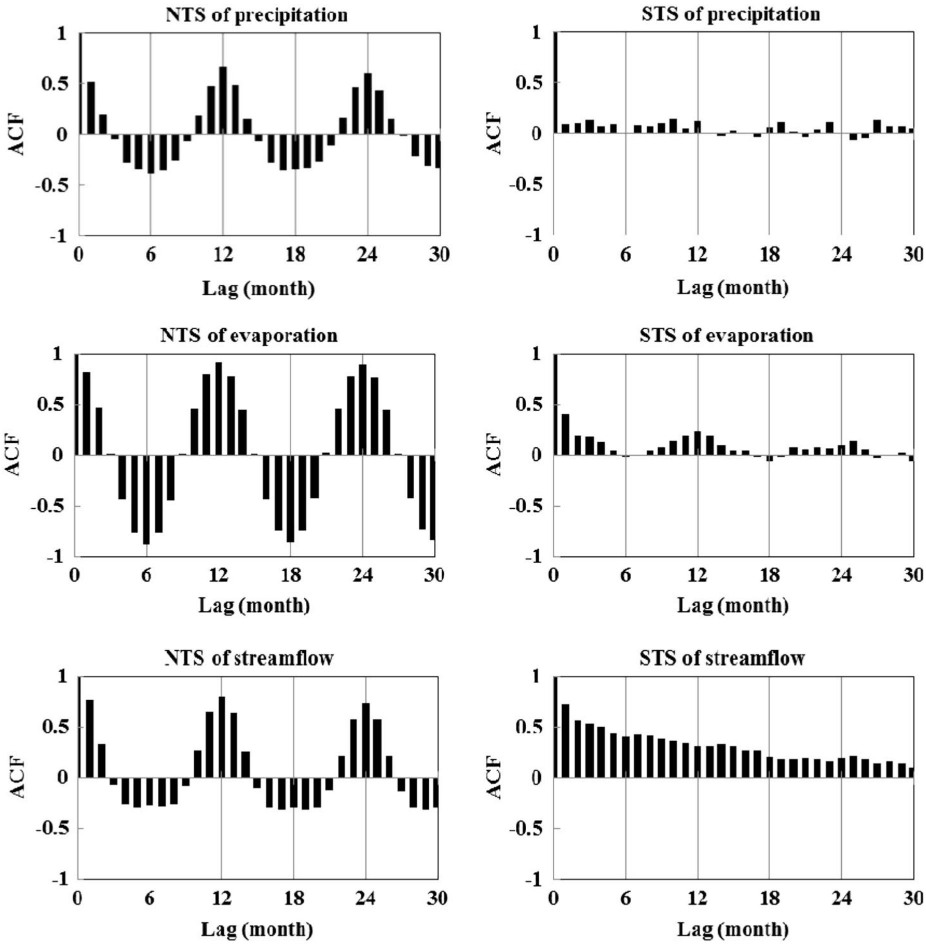

Fig. 3 ACF plots related to NTSs and STSs of Hamun Lake basin

The trends of the STSs were investigated using the Mann-Kendall test and the results are listed in Table 2. Rejection of the null hypothesis of the Mann-Kendall test means that the trend is significant. Mann-Kendall statistic in Table 2 is the calculated statistic of the Mann-Kendall test. The null hypothesis is rejected at a 5 % significance level if the Mann-Kendall statistic is smaller than −1.96 or larger than +1.96.

Table 2 Mann-Kendall test results of Hamun Lake basin's STSs with 5 % significance level

	Time series		
Parameter	Precipitation	Evaporation	Streamflow
Null hypothesis	Rejected	Rejected	Rejected
Mann-Kendall statistic	-2.7	3.3	-5.21
Sen slope	-1.8×10^{-3}	1.8×10^{-3}	-3.8×10^{-3}

Sen slope denotes the Sen slope estimator in Table 2, whose positive values indicate an increasing trend and negative values indicate decreasing trends.

The HSA model was employed to test the STS of precipitation, evaporation, and streamflow of the Hamun Lake basin and the results are reported in Table 3.

3.2.1 Results of Testing Stationarity of Precipitation STSs of Hamun Lake Basin Using the HSA Model

The Mann-Kendall test results of precipitation STS at a 5 % significance level are listed in Table 2. It is worth mentioning that the observed trend in STS of precipitation is a combination of the trends in the mean and in the variance. Also results of the precipitation STS stationarity HSA-L test at 5 % significance level are reported in Table 3.

It is evident in Table 3 the long memory of precipitation STSs. The main reason for this long memory is the significant trend reported by the Mann-Kendall test in Table 2. In general, all the precipitation time exhibit a significant decreasing trend.

Table 3 Results of the HSA model for Hamun Lake basin's STSs with 5 % significance level

	Precipitation		Evaporation		Streamflow	
Lag	HSA-L	HSA-T	HSA-L	HSA-T	HSA-L	HSA-T
1	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
2	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
3	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
4	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
5	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
6	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
7	Long memory	Long memory	Long memory	Long memory	Long memory	Long memory
8	Long memory	Long memory	Long memory	Stationary	Long memory	Long memory
9	Long memory	Stationary	Long memory	Stationary	Long memory	Long memory
10	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
11	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
12	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
13	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
14	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
15	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
16	Long memory	Stationary	Long memory	Stationary	Long memory	Stationary
17	Stationary	Stationary	Long memory	Stationary	Long memory	Stationary
18	Stationary	Stationary	Long memory	Stationary	Stationary	Stationary
19	Stationary	Stationary	Long memory	Stationary	Stationary	Stationary
20	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary
21	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary
22	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary
23	Stationary	Stationary	Stationary	Stationary	Inconclusive	Inconclusive
24	Stationary	Stationary	Stationary	Stationary	Inconclusive	Inconclusive

3.2.2 Results of Testing the Stationarity of Evaporation STSs of Hamun Lake Basin Using the HSA Model

The trends of evaporation STS were investigated using the Mann-Kendall test and the results are listed in Table 2 that shows that there is a significant increasing trend. The results of HSA-L model for STS of Evaporation are listed in Table 3. It is worth mentioning that the trend of the STS of evaporation is significant by the Mann-Kendall test, and the HSA-L model also reports long memory.

The HSA-T model was employed with the evaporation STS, in order to investigate the effect of trends on long memory. Our results indicate that the main source of long memory of the evaporation STS was the presence of a trend. For example, the long memory of the evaporation STS was reduced from lag 19 to 7.

3.2.3 Results of Testing Stationarity of Streamflow STSs of Hamun Lake Basin Using the HSA Model

The results of the Mann-Kendall at the 5 % significance level are reported in Table 2. A pronounced decreasing trend is evident in all streamflow STSs. The HSA-L model results for the streamflow STS are listed in Table 3. Long memory arises in these series because of the trend. In order to investigate the impacts of trend on long memory, the HSA-T model was also applied to stream flow STS, with results tabulated in Table 3 which shows that the long memory of the streamflow STS decreases dramatically.

3.3 Climate Change and Long Memory in the Hamun Lake Basin

This study applied the developed HSA model for testing the non-stationarity of precipitation, evaporation, and streamflow time series searching for evidence of climatic change effects in the Hamun Lake basin. It is concluded that the precipitation time series are non-stationary. Also, the evaporation time series were found to be non-stationary, due to significant trend, but the trends do not follow similar patterns. On the other hand, severe non-stationarity of stream flow time series was observed, which does not correspond with precipitation and evaporation non-stationarity. The main reasons of observed trends in stream flow time series are: crop- pattern changes, increase in the cultivated area, and increase in urbanization in the Hamun Lake basin, which have encouraged water withdrawal from rivers and increase the dependence on surface water bodies. Some non-stationarity was reported in the precipitation and evaporation time series, provide a strong evidence of significant change towards drier conditions. Therefore, it is concluded that climate change has affected the hydrology of the Hamun Lake basin.

One key advantage of the HSA model is its ability to detect long memory. Our results show that by removing of trend and seasonality the long memory of hydrologic time series falls dramatically. Also, it was observed that the long memory in stream flow STS is stronger than in precipitation and evaporation STS. The main reason for this difference is the complex underlying mechanism in streamflow production in basins. Storage is mainly responsible for the long memory in streamflow STS. Storage in streamflow processes may arise from springs, snow cover, and groundwater recharge.

4 Concluding Remarks

This study investigated the power of the standard unit root (SUR) and alternative stationary (AS) tests in assessing the stationarity of hydrologic time series and detecting climate variability using artificial time series. The hybrid statistical analysis (HSA) model was developed as a combination of the SUR and AS tests and it was employed to investigate the effects of climate change and human activities on precipitation, evaporation, and streamflow flow time series in Hamun Lake basin. The results showed that the power of the SUR test to study climate change which cause monotonic trend in mean of hydrologic time series depends on the lag length while the power of the AS test is sensitive to outliers' values and locations. The AS test, on the other hand, is effective for testing stationarity in the presence of monotonic trend in mean. It is also concluded that although these tests are effective in testing first- order stationarity of hydrologic time series, they do not provide any information about climate change which causes second-order non- stationarity. In addition, one advantage of the HSA model is its ability to detect long memory. Lastly, it was concluded that Lake Hamun basin is affected by climate change and streamflow time series also exhibit non-stationarity caused by human activities including crop-pattern changes, increase in the cultivated area, and urban growth.

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