Homogeneity analysis of streamflow records in arid and semi-arid regions of northwestern Iran Postprint

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Abstract

Homogeneity analysis of the streamflow time series is essential to hydrological modeling, water resources management and climate change studies. In this study, five absolute homogeneity tests and one clustering approach were used to determine the homogeneity status of the streamflow time series (over the period 1960–2010) in 14 hydrometric stations of three important basins (i.e., Aras River Basin, Urmia Lake Basin and Sefid-Roud Basin) in northwestern Iran. Results of the Buishand range test, von Neumann ratio test, cumulative deviation test, standard normal homogeneity test and Pettitt test for monthly streamflow time series detected that about 42.26%, 38.09%, 33.33%, 39.28% and 68.45% of the streamflow time series were inhomogeneous at the 0.01 significance level, respectively. Streamflow time series of the stations located in the eastern parts of the study area or within the Urmia Lake Basin were mostly homogeneous. In contrast, streamflow time series in the stations of the Aras River Basin and Sefied-Roud Basin showed inhomogeneity at annual scales. Based on the overall classification for the monthly and annual streamflow series, we determined that about 45.60%, 11.53% and 42.85% of the time series were categorized into the 'useful', 'doubtful' and 'suspect' classes according to the five absolute homogeneity tests. We also found the homogeneity patterns of the streamflow time series by using the clustering approach. The results suggested the effectiveness of the clustering approach for homogeneity analysis of the streamflow time series in addition to the absolute homogeneity tests. Moreover, results of the absolute homogeneity tests and clustering approach indicated obvious decreasing change points of the streamflow time series in the 1990s over the three basins, which were mostly related to the hydrological droughts.

Full Text

Preamble

Homogeneity analysis of streamflow records in arid and semi-arid regions of northwestern Iran

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Abstract: Homogeneity analysis of streamflow time series is essential for hydrological modeling, water resources management, and climate change studies. In this study, five absolute homogeneity tests and one clustering approach were used to determine the homogeneity status of streamflow time series (over the period 1960–2010) at 14 hydrometric stations across three important basins (i.e., Aras River Basin, Urmia Lake Basin, and Sefid-Roud Basin) in northwestern Iran. Results from the Buishand range test, von Neumann ratio test, cumulative deviation test, standard normal homogeneity test, and Pettitt test for monthly streamflow time series detected that approximately 42.26%, 38.09%, 33.33%, 39.28%, and 68.45% of the streamflow time series were inhomogeneous at the 0.01 significance level, respectively. Streamflow time series at stations located in the eastern parts of the study area or within the Urmia Lake Basin were mostly homogeneous. In contrast, streamflow time series at stations in the Aras River Basin and Sefid-Roud Basin showed inhomogeneity at annual scales. Based on the overall classification for monthly and annual streamflow series, we determined that approximately 45.60%, 11.53%, and 42.85% of the time series were categorized into the 'useful', 'doubtful', and 'suspect' classes according to the five absolute homogeneity tests. We also identified homogeneity patterns in the streamflow time series using the clustering approach. The results suggested the effectiveness of the clustering approach for homogeneity analysis of streamflow time series in addition to the absolute homogeneity tests. Moreover, results from the absolute homogeneity tests and clustering approach indicated obvious decreasing change points in the streamflow time series in the 1990s across the three basins, which were mostly related to hydrological droughts.

Keywords: streamflow time series; homogeneity test; clustering analysis; inhomogeneity; Urmia Lake; northwestern Iran

1 Introduction

Hydrological time series increasingly exhibit non-stationary behavior, and their variables such as streamflow and precipitation series do not show a consistent mean or median over long periods, primarily due to natural and anthropogenic changes (Rougé et al., 2013). Homogeneity analysis in hydrological time series used for water resources management and project planning is important for detecting data accuracy and validity. Meanwhile, homogeneity analysis of streamflow time series is essential for hydrological modeling and climate change studies.

Hydrologic time series sequences result from particular natural conditions and might show irregular fluctuations when natural conditions of the river basin are relatively steady. However, hydrologic time series sequences can exhibit evident trends or jumps if natural conditions change noticeably (Wong et al., 2006). In this regard, two important methods can be used to analyze the homogeneity of streamflow time series, including statistical homogeneity tests and clustering approaches. Statistical homogeneity tests have been used in hydrological analysis for detecting non-homogeneity, as suggested by Hirsch et al. (1982), Hirsch and Slack (1984), Hirsch (1988), and McCuen (2002). Generally, homogeneities of streamflow time series can be determined by two different statistical approaches, including relative and absolute homogeneity tests (Peterson et al., 1998). Relative homogeneity tests are rarely recommended for use, considering that neighboring stations are hypothetically homogeneous. However, absolute homogeneity tests are recommended when the two time series of neighboring stations are not adequately correlated (Wijngaard et al., 2003).

Several studies have applied statistical homogeneity tests and clustering approaches for hydro-climatic time series (e.g., Conrad and Pollak, 1950; Wijngaard et al., 2003; Kahya et al., 2008; Sahin and Cigizoglu, 2010; Dikbas et al., 2013; Hosseinzadeh Talaee et al., 2014; Seyam and Othman, 2015; Omar et al., 2017). For example, Wijngaard et al. (2003) used statistical homogeneity tests to analyze climatic variables across the European continent and reported that approximately 25% of precipitation series and 94% of temperature series were labeled 'suspect' or 'doubtful' over the period 1901–1999. Sahin and Cigizoglu (2010) applied four homogeneity tests (i.e., standard normal homogeneity test, Pettitt test, Von Neumann ratio test, and bivariate test) to meteorological time series in Turkey and revealed that the four homogeneity tests showed similar results for the time series in most cases. Dikbas et al. (2013) utilized the K-means clustering method to classify maximum annual flows and identify hydrologically homogeneous groups in Turkey, suggesting that homogeneous regions defined by the K-means clustering method can be used for regional flood frequency analysis. Seyam and Othman (2015) analyzed long-term variation of annual streamflow regime in the Selangor River over a 50-year period (from 1961 to 2010) using normality and homogeneity tests (including Shapiro-Wilk test and Pettitt test), finding that maximum annual streamflow totally increased whereas minimum annual streamflow significantly decreased with respect to time.

Understanding the characteristics and sensitivities of alternative tests is very important for analyzing the homogeneity of streamflow time series, mainly due to the large array of available statistical homogeneity tests. Applying a statistical test that is insensitive to a specific type of homogeneity can result in failure to determine homogeneity (McCuen, 2002). In this study, we analyzed the homogeneity of streamflow time series (over the period 1960–2010) at 14 hydrometric stations in three important basins in northwestern Iran using five absolute homogeneity tests that are commonly used in hydro-climatic data analysis and clustering analysis.

2 Study Area and Data Collection

The study area is located in northwestern Iran and consists of three important basins: Aras River Basin (ARB), Urmia Lake Basin (ULB), and Sefid-Roud Basin (SRB). The ARB covers an area of 41.0$×10^{3}$ km^{2}. The second basin, ULB, covers an area of 51.8$×10^{3}$ km^{2} and includes three important rivers: Aji Chai River, Zarrineh-Roud River, and Simineh-Roud River. The SRB, with an area of 60.5$×10^{3}$ km^{2}, is located between the Zagros Mountain Ranges and Alborz Mountain Ranges. The study area exhibits different soil and vegetation types. In this study, 14 available hydrometric stations with valid and adequate data over 1960–2010 were selected. The spatial distribution of these 14 stations is shown in Figure 1 [Figure 1: see original paper], and characteristics of the hydrometric stations are presented in Table 1 .

3.1 Cumulative Deviations

The adjusted partial sums or cumulative deviations (S_k^*) from the mean can be used for testing the homogeneity of the data series (Eq. 1).

$$S_k^* = \sum_{i=1}^{k}(Y_i - \bar{Y}), \quad k = 1, 2, \ldots, n$$

where Y_i is the observed value of the climate parameter i; $\bar{Y}$ is the sample mean; and n is the number of records in the data series. The rescaled adjusted partial sums (S_k^{**}) can be obtained using Equation 2:

$$S_k^{**} = \frac{S_k^*}{D_x}, \quad k = 1, 2, \ldots, n$$

where D_x is the sample standard deviation, which can be calculated as follows:

$$D_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

In this study, we used the Q statistic to measure sensitivity to departures from homogeneity:

$$Q = \max_{1 \le k \le n} |S_k^{**}|$$

Higher values of the Q statistic indicate non-homogeneity in the time series. The critical values of Q for some specified values of n are given by Buishand (1982), which were based on 19,999 synthetic sequences of Gaussian random numbers. The critical values of the Q statistic in the cumulative deviation test are shown in Table 2 .

3.2.1 Buishand Range Test

R is another statistic that can be used for homogeneity analysis (Eq. 5):

$$R = \max_{1 \le k \le n} S_k^{**} - \min_{1 \le k \le n} S_k^{**}$$

The critical values of the R statistic in the Buishand range test are shown in Table 2.

3.2.2 Von Neumann Ratio Test

The ratio of the mean square successive difference to the variance is defined as the von Neumann ratio (N), which is described by Buishand (1982) and can be calculated as follows:

$$N = \frac{\sum_{i=1}^{n-1} (Y_i - Y_{i+1})^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}$$

The value of the N statistic tends to be lower than the expected value when the sample contains a break, and the values of the N statistic are \$ \$2 if the sample has rapid variations in the mean (Bingham and Nelson, 1981). However, this test cannot identify the year of the break. The critical values of the N statistic in the von Neumann ratio test are given in Table 3 .

3.2.3 Standard Normal Homogeneity Test

The standard normal homogeneity test typically shows higher sensitivity to breaks near the beginning and end parts of the time series. Alexandersson (1986) defined the $T(k)$ statistic for the standard normal homogeneity test:

$$z_1 = \frac{1}{k} \sum_{i=1}^{k} Y_i, \quad z_2 = \frac{1}{n-k} \sum_{i=k+1}^{n} Y_i$$

$$T(k) = \frac{k(n-k)}{n} \cdot \frac{(z_1 - z_2)^2}{s^2}, \quad k = 1, 2, \dots, n$$

where z_1 and z_2 are parameters of the $T(k)$ statistic; k is the years of record; $\bar{Y}$ is the mean of the time series; Y_i is the annual series to be tested; and s is the standard deviation. Based on calculation of the mean of the first k years and the last $n-k$ years of the time series, we assumed that the $T(k)$ statistic reaches its maximum value when a break occurs at year k. The T_0 statistic in the standard normal homogeneity test is described as follows (Eq. 9):

$$T_0 = \max_{1 \le k \le n-1} T(k)$$

The critical values of the T_0 statistic are given in Table 4 . According to the standard normal homogeneity test, the null hypothesis will be rejected if the T_0 statistic exceeds the critical values.

3.2.4 Pettitt Test

The Pettitt test, as a non-parametric approach, is suitable for detecting breaks that occur near the middle of the time series. This approach is based on the Wilcoxon test developed by Pettitt (1979). The ranks $r_1, r_2, \ldots, r_k$ of the $Y_1, Y_2, \ldots, Y_k$ were used to calculate the X_k statistic in the Pettitt test:

$$X_k = \sum_{i=1}^{k} r_i - \frac{k(n+1)}{2}, \quad k = 1, 2, \ldots, n$$

Based on the Pettitt test, the absolute value of the X_k statistic will reach its maximum value if a break occurs in a given year (Eq. 11):

$$X = \max_{1 \le k \le n} |X_k|$$

The critical values of the X_k statistic in the Pettitt test suggested by Pettitt (1979) are presented in Table 5 .

3.2.5 Clustering Approach of the Streamflow Time Series

The clustering approach can classify several time series into different clusters. Many researchers have applied different kinds of classification methods (Lagacherie et al., 1997; Ramachandra Rao and Srinivas, 2006; Kahya et al., 2008; Hsu and Li, 2010; Zahraie and Roozbahani, 2011; Dikbas et al., 2013; Kousari et al., 2013). The clustering approach was applied to facilitate homogeneity analysis in addition to the absolute homogeneity tests in this study. Time series typically show relatively different averages and variances, so it is essential to normalize the initial time series before clustering (Kousari et al., 2013). In this study, hierarchical clustering was considered, and Ward' s algorithm with squared Euclidean distance was preferred. The hierarchical clustering approach aims to group a set of cases such that cases in the same group or cluster are more similar to each other, which leads to minimized variance within a group or cluster (Everitt, 1993; Kahya et al., 2008). We classified the normalized streamflow time series based on dendrograms. We also used the overall classification and qualitative interpolation of the five absolute homogeneity tests. The classification is based on the number of homogeneity tests that reject the null hypothesis (Wijngaard et al., 2003).

3.3 Data Analysis

Microsoft Office, XLSTAT, and ArcGIS were used for data analysis and figure mapping.

4 Results and Discussion

The descriptive statistics of the annual streamflow series shown in Table 6 can better reflect streamflow regime patterns in the study area. The results indicated that in the SRB, Estoor station with an average annual discharge of 79.43 m^3/s had the highest annual water yield, while Lighvan station with an average annual discharge of 0.78 m^3/s showed the lowest annual water yield. Moreover, Ghermizi Gol station with a coefficient of variation (CV) of 98.80% exhibited the highest temporal variability, while Lighvan station with a CV value of 28.86% had the lowest temporal variability.

In this study, five absolute homogeneity tests were used, and their results for the cumulative deviation test and Buishand range test are shown in Tables 7 and 8, respectively. The observation data for each station were analyzed at a significance level of 0.01, and inhomogeneities were detected. For monthly streamflow series, the results of the $Q/\sqrt{n}$ statistic in the cumulative deviation test showed that 42.26% of the streamflow time series at the stations were inhomogeneous. The monthly streamflow series at Lighvan station were found to be homogeneous in all 12 months, while the monthly streamflow series at Mashiran station exhibited high inhomogeneity in 9 out of 12 months. Additionally, the results of the Buishand range test indicated that approximately 38.09% of the streamflow time series were inhomogeneous at the 0.01 significance level. Furthermore, in most streamflow time series, the cumulative deviation test detected the change year in the 1990s at the 0.01 significance level. According to Hawkins (1997), the cumulative deviation test is more sensitive when a break occurs in the middle part of a data series.

The outputs of three absolute homogeneity tests—namely, the von Neumann ratio test, standard normal homogeneity test, and Pettitt test—are presented in Tables 9, 10, and 11, respectively. The von Neumann ratio test, standard normal homogeneity test, and Pettitt test identified that approximately 33.33%, 39.28%, and 68.45% of the streamflow time series were inhomogeneous at monthly scales at the 0.01 significance level, respectively. The results of the von Neumann ratio test showed that the total number of inhomogeneities in streamflow time series during cold seasons (autumn and winter) was greater than during warm seasons (spring and summer). The highest number of inhomogeneities in monthly streamflow series was found in February based on the von Neumann ratio test. Homogeneity analysis of precipitation series in Iran indicated that the total number of inhomogeneities was greater in cold season months or winter months than in warm season months (Hosseinzadeh Talaee et al., 2014). It was previously reported that in semi-arid regions, the variability of streamflow time series was usually larger in warm season months than in cold season months, mainly due to natural and anthropogenic changes (e.g., Hereford and Webb, 1992; Barlow et al., 2001; Das et al., 2011). In this study, the standard normal homogeneity test and Pettitt test did not show any specific particular pattern for monthly streamflow series over the period 1960–2010. The monthly streamflow series at Mashiran, Estoor, Pol Dokhtar, and Motor Khaneh stations exhibited inhomogeneous patterns.

Results of the five absolute homogeneity tests for annual streamflow series are shown in Figure 2 [Figure 2: see original paper]. The cumulative deviation test and Buishand range test determined that streamflow time series at 5 and 6 stations (out of 14 stations) were homogeneous, respectively. Meanwhile, the results of the standard normal homogeneity test were the same as those of the cumulative deviation test. Furthermore, the von Neumann ratio test and Pettitt test identified streamflow time series at 5 and 3 stations (out of 14 stations) as homogeneous, respectively. Based on these results, we inferred that the Pettitt test is more sensitive than the other absolute homogeneity tests in determining homogeneity of streamflow time series. As a consequence, the results of the five homogeneity tests determined that streamflow time series at stations located in the east of the study area or within the ULB were mostly found to be homogeneous. In contrast, the annual streamflow series at all stations located in the ARB and SRB were inhomogeneous. The streamflow time series at three stations in the ULB—namely Ghermizi Gol, Lighvan, and Sari Ghamish stations —were identified as homogeneous by all homogeneity tests. Generally, since absolute homogeneity tests have different sensitivities to variability and changes in the streamflow time series at a given station, the outputs of the tests sometimes show discrepancies. These discrepancies were also noted by Wijngaard et al. (2003), Feng et al. (2004), Sahin and Cigizoglu (2010), and Hosseinzadeh Talaee et al. (2014).

The overall classification determined that approximately 45.60% of the streamflow time series were labeled as 'useful' , suggesting no obvious evidence of inhomogeneity in the streamflow time series. According to Wijngaard et al. (2003), the 'useful' class is adequately homogeneous for variability and trend analyses. Approximately 11.53% of the streamflow time series were labeled as 'doubtful' . In other words, 11.53% of the monthly and annual streamflow series at the stations were critical in terms of possible inhomogeneities. The third class, known as 'suspect' , refers to situations where the null hypothesis is rejected by three or four tests at the 0.01 significance level. Finally, 42.85% of the streamflow time series were labeled in this class. It is obvious that streamflow time series labeled as 'suspect' have insufficient credibility and should not be applied in issues related to time series studies.

Figure 3 [Figure 3: see original paper] indicates the different clusters of the normalized annual streamflow series with some clear fluctuations in the clusters. Moreover, downtrend alterations or change points in the streamflow time series occurred after 1990 for all stations, and the results from the five absolute homogeneity tests were almost the same. Meanwhile, fluctuation of the third cluster (Fig. 3c) was more dramatic than those of the first (Fig. 3a) and second (Fig. 3b) clusters. It was evident that the first cluster (Fig. 3a) contained most of the streamflow time series compared with the other two clusters (Figs. 3b and c). Since these curves did not show a spatial distribution in the study area, the distributions of various clusters of specific streamflow time series were mapped in Figure 4 [Figure 4: see original paper]. The results showed that most streamflow time series were in the first cluster. For monthly streamflow series, we found that only Estoor station was in the third cluster in January, April, May, November, and December. As mentioned earlier, the number of inhomogeneities in streamflow time series was greater in the third cluster than in the first and second clusters. The results indicated that clustering time series could identify the homogeneity of streamflow time series at most stations. Homogeneity tests determined that most streamflow time series at Estoor station were inhomogeneous. Meanwhile, most streamflow time series at this station were classified in the third cluster, which showed high fluctuations and inhomogeneity. All streamflow time series except for February at Estoor and Pol Dokhtar stations were classified in the second and third clusters. Furthermore, inhomogeneity was also detected in most streamflow time series at the stations by the five absolute homogeneity tests.

Generally, hydrometric stations located in the SRB were classified in the second and third clusters for most streamflow time series, while stations in the ULB were categorized in the first cluster, which exhibited low inhomogeneity of streamflow time series. Therefore, the results of this study clearly proved the effectiveness of the clustering approach for homogeneity analysis of streamflow time series in addition to the homogeneity tests. Kahya et al. (2008) applied clustering analysis to classify streamflow time series into regions with relatively similar streamflow patterns in Turkey and indicated that regions with the same streamflow patterns would not be covered adequately by climatic zones. Kousari et al. (2013) suggested that the clustering approach is suitable for analyzing trends in climatic variables across Iran.

Results of the absolute homogeneity tests and clustering approach indicated that stations located in the three basins (SRB, ARB, and ULB) have similar fluctuations and alterations in streamflow time series during most of the study period. Moreover, obvious decreasing change points were observed in the 1990s across the three basins. It is clear that inhomogeneity of streamflow time series cannot be completely explained by local changes at hydrometric stations or watershed conditions, such as changes in station locations or land use changes. From the results, we concluded that alterations in streamflow time series in the study area are mostly related to hydrological droughts. The droughts that occurred in the 1990s were more devastating to water resources and agriculture, resulting in accelerated urbanization (Agrawala et al., 2001; Yazdani and Haghsheno, 2008). According to Raziei et al. (2009), over half of Iran' s population was affected by prolonged droughts in the 1990s. Nikbakht et al. (2013) and Tabari et al. (2013) analyzed streamflow droughts in northwestern Iran and found the most severe streamflow scarcities in the 1990s. The decreasing trend of streamflow time series in the study area can be considered an important cause of inhomogeneities at most stations.

5 Conclusions

The current research employed five absolute homogeneity tests and a clustering approach to determine the homogeneity of streamflow time series (over the period 1960–2010) in three important basins (SRB, ARB, and ULB) located in northwestern Iran. The results of the cumulative deviation test, Buishand range test, von Neumann ratio test, standard normal homogeneity test, and Pettitt test for monthly streamflow series showed that approximately 42.26%, 38.09%, 33.33%, 39.28%, and 68.45% of the time series were inhomogeneous at the 0.01 significance level, respectively. Among the five absolute homogeneity tests, the Pettitt test was found to be much more sensitive than the other four homogeneity tests in determining homogeneity of streamflow time series.

Results of the five absolute homogeneity tests determined that streamflow time series at stations located in the east of the study area or within the ULB were mostly homogeneous. In contrast, streamflow time series at all stations in the ARB and SRB were inhomogeneous at annual scales. Since absolute homogeneity tests have various sensitivities to variability and changes in streamflow time series at a station, the outputs of these tests may show discrepancies in some cases. The overall classification and qualitative interpolation of monthly and annual streamflow series based on the five absolute homogeneity tests showed that approximately 45.60%, 11.53%, and 42.85% of the series were categorized into 'useful' , 'doubtful' , and 'suspect' classes, respectively. Furthermore, the effectiveness of the clustering approach for analyzing homogeneity of streamflow time series was demonstrated in addition to the absolute homogeneity tests. Both the results of absolute homogeneity tests and clustering approach indicated relatively similar fluctuations and alterations in streamflow time series at the stations. Moreover, obvious decreasing change points in streamflow time series were detected in the 1990s across the three basins. It can be inferred that inhomogeneity and alterations in streamflow time series across the three basins are related to the natural and anthropogenic conditions of the basins.

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Note: Figure translations are in progress. See original paper for figures.