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Evaluation of Wavelet Transform Application for Detecting Trends in River Flow Discharge (Case Study: Halilrood River in Iran)

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ABSTRACT

Background and Objectives: River flow, one of the most influential factors affecting water resources and hydrological phenomena, interacts with climatic factors. Consequently, detecting changes in river discharge over time can reveal the presence or absence of climate change in a specific region. Previous studies have shown that river discharge varies owing to changes in hydrological patterns, human intervention, changes in vegetation, or annual climate fluctuations. The innovation of the current research lies in evaluating the discharge trend of the Halilrood River in the Hamon-e Jaz-Murian basin in Iran using wavelet transform, assessing its performance, and comparing it with the Mann-Kendall method.

Materials and Methods: In this study, a wavelet transform was used to detect possible trends in the discharge flow of the Halilrood River, one of the most important rivers in south-eastern Iran. For this purpose, discharge data from the Hossein-Abad station from 1963 to 2010 and the Kohank-Sheibani station from 1982 to 2012 were analyzed on the Halilrood River. Moreover, the model's results were compared with the Mann-Kendall trend test.

Results: The monthly, seasonal, and annual trends at both stations showed consistent downward trends, indicating a decrease in the river discharge. Moreover, the trend detection results obtained using the wavelet transform, indicated a negative trend at all scales in the Hossein-Abad station, with a significance level of 0.001. The same result was observed at Kohank-Sheibani station. Both the Mann-Kendall and wavelet transform methods recognize the downward or upward trend well. For the annual trend analysis, both modes of the wavelet transform method outperformed the Mann-Kendall method, exhibiting higher values and greater significance across various significance levels. In the seasonal mode, the Mann-Kendall method outperformed the wavelet transform at the second level, but showed weaker performance at the first level. In the monthly analysis at the Kohank-Sheibani station, a basin outlet, the Mann-Kendall method's trend values show greater significance.

Conclusion: The wavelet transforms and the Mann-Kendall trend test was used to detect the possible trends in the discharge flow of the Halilrood River at the Hossein-Abad and the Kohank-Sheibani stations. In general, the results showed a decrease in discharge at this station on all timescales. Wavelet transform analysis revealed a significant downward trend in discharge at the Kohank-Sheibani station across monthly, seasonal, and annual scales, all at the 0.001 significance level. Overall, the results indicate a decrease in discharge at the stations across all scales throughout the periods.

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ارزیابی کاربرد تبدیل موجک برای تشخیص روند دبی جریان رودخانه (منطقه مورد مطالعه: رودخانه هلیل‌رود ایران)

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چکیده

سابقه و هدف: جریان رودخانه‌ها به‌عنوان یکی از تأثیرگذارترین عوامل در منابع آبی و پدیده‌های هیدرولوژیکی، در تعامل با عناصر اقلیمی است. درنتیجه، تشخیص تغییرات دبی رودخانه در یک دوره زمانی می‌تواند وجود یا عدم وجود تغییرات آب‌وهوای یک منطقه خاص را اثبات کند. مطالعات قبلی نشان داده‌اند که دبی رودخانه به‌دلیل تغییرات در الگوهای هیدرولوژیکی، مداخلات انسانی، تغییرات در پوشش گیاهی یا نوسانات آب و هوایی سالانه متفاوت است. نوآوری پژوهش حاضر در ارزیابی روند دبی رودخانه هلیل‌رود در حوضه جازموریان در ایران با استفاده از تبدیل موجک، ارزیابی عملکرد آن و مقایسه با روش من-کندال است.

مواد و روش‌ها: در این پژوهش از تبدیل موجک برای تشخیص روند احتمالی دبی رودخانه هلیل‌رود که یکی از رودخانه‌های مهم جنوب شرق ایران است، استفاده شد. بدین‌منظور داده‌های دبی ایستگاه‌های حسین‌آباد و کهنک شیبانی واقع در رودخانه هلیل‌رود به ترتیب در بازه زمانی ۱۳۴۲ تا ۱۳۸۹ و ۱۳۶۱ تا ۱۳۹۱ مورد تجزیه‌وتحلیل قرار گرفت. هم‌چنین نتایج مدل با آزمون من-کندال مقایسه شد.

یافته‌ها: نتایج روند ماهانه، فصلی و سالانه در هر دو ایستگاه روند نزولی ثابتی را نشان دادند که بیانگر کاهش دبی رودخانه است. هم‌چنین نتایج روند به‌دست‌آمده توسط تبدیل موجک بیانگر

روند منفی در تمامی مقیاس‌ها در ایستگاه حسین‌آباد با سطح معنی‌داری ۰/۰۰۱ است. نتایج بیان‌شده در ایستگاه کهنک شیبانی نیز مشاهده شد. هر دو روش من-کندال و تبدیل موجک نوع روند نزولی یا صعودی را به‌خوبی تشخیص دادند. برای تحلیل روند سالانه، هر دو حالت روش تبدیل موجک از روش من-کندال بهتر عمل کردند و مقادیر بالاتر و اهمیت بیش‌تری را در سطوح مختلف معنی‌داری نشان دادند. در حالت فصلی، روش من-کندال از روش تبدیل موجک در سطح دوم بهتر عمل کرد اما عملکرد ضعیف‌تری را در سطح اول نشان می‌دهد. در تحلیل ماهانه در ایستگاه کهنک-شیبانی، خروجی حوضه، مقادیر روند روش من-کندال اهمیت بیش‌تری نشان می‌دهد.

نتیجه‌گیری: برای تشخیص روند احتمالی دبی رودخانه هلیل‌رود در ایستگاه‌های حسین‌آباد و کهنک شیبانی از تبدیل موجک و آزمون روند من-کندال استفاده شد. به‌طورکلی نتایج نشان‌دهنده کاهش دبی جریان در این ایستگاه در تمامی مقیاس‌های زمانی بود. تجزیه‌وتحلیل تبدیل موجک روند نزولی قابل‌توجهی را در دبی مربوط به ایستگاه کهنک شیبانی در مقیاس ماهانه، فصلی و سالانه نشان داد که همگی در سطح ۰/۰۰۱ معنی‌دار بودند. به‌طورکلی، نتایج بیانگر کاهش دبی در ایستگاه‌ها در تمامی مقیاس‌ها در طول دوره‌ها بود.

استناد: دوراندیش، شیما، مقبلی، عاطفه، مهدوی-میمند، امین، ذونعمت کرمانی، محمد (۱۴۰۳). ارزیابی کاربرد تبدیل موجک برای تشخیص روند دبی جریان رودخانه (منطقه مورد مطالعه: رودخانه هلیل‌رود ایران). *پژوهش‌های حفاظت آب و خاک*، ۳۱ (۴)، ۱۳۶-۱۱۳.

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Introduction

The scientific management of surface water resources requires accurate forecasting and estimation of future river flow. River flow is an important parameter in hydrology and water resource management and relates to climatic elements. Changes in climatic elements have led to altered frequencies of floods and droughts, which are some of the consequences of climate change. Therefore, understanding the behavior of hydrological variables, particularly river flow, is an issue that has garnered the attention of designers and managers of water resources [1-3]. Previous studies have shown that river discharge varies owing to changes in hydrological patterns [4], human interventions [5], changes in vegetation [6], or annual climate fluctuations [7, 8]. Therefore, evaluating the changes in river flow and understanding the main factors affecting them are crucial for accurate prediction.

Mathematical and physical methods are considered for short-term predictions and have a favorable simulation capability. However, these methods for long-term predictions have high errors, owing to the complexity of the simulation. Therefore, data-based forecasting methods are becoming increasingly common owing to their time-saving nature, minimal information requirements, and ease of implementation. Due to the non-linear nature and temporal and spatial variable characteristics in predicting river flow, statistical methods are insufficient for analysing multi-scale trends. One of the mathematical theories recently recognized as highly useful for trend analysis in time series observations is the wavelet transform, a method suitable for analysing unstable time series records. Moreover, the results obtained from the wavelet analysis were compared with other river flow forecasting methods such as the non-parametric Mann-Kendall test [9]. The Mann-Kendall test is a suitable method for revealing the trend of a time series flow with skewness and outliers [10].

Zhang et al. (2006) investigated the trend of annual maximum river flow and water level in the Yangtze River basin in China during the last 130 years using the Mann-Kendall method and the wavelet transform. The results of their study showed that there is a significant upward trend at the middle path of the Yangtze River. A consistent increase in water levels was observed from the upstream to the downstream sections of the river. Moreover, the period of water level changes over time is decreasing [11].

Adamowski and Sun (2010) stated that the wavelet transform is very flexible and accurate for detecting and estimating complex signals [12]. Kisi and Cimen (2011) used the coupled wavelet model and support vector machine (SVM) to predict the monthly discharge of the Goksudere River in eastern Turkey. The comparison analysis of their results showed that the developed hybrid model enhances the prediction accuracy of the regular SVM in monthly flow forecasting [13]. Abghari et al. (2013) studied the trend of river flow in western Iran over the last 40 years concerning the influence of rainfall. Correlation analysis showed strong relationships between river flow and rainfall on an annual scale [14].

Nassaji Zavareh et al. (2014) presented an evaluation of the discharge trend of the Kesilian River using three methods: Theil-Sen, plotting a diagram in the coordinate system, and Man-Kendall. The results showed that although the Theil-Sen is a suitable method for determining the amount of the river flow trend, the Mann-Kendall method is suitable for determining the significance and time of the trend. Moreover, the method of drawing a graph in the coordinate system can be used as a simple and suitable method to determine the trend of the lower, middle, and upper values of the time series [15].

Wang et al. (2012) investigated the climate trends in the lower reaches of the Xiang River basin in northwest China using wavelet transform and Mann-Kendall test. To determine the optimal composition, they applied the Mann-Kendall test to the series obtained from the discrete wavelet transform [16]. Rashida et al. (2015) used a combination of a continuous wavelet transform (CWT) with a Mann–Kendall test to examine the trends in patchy rainfall for 13 stations in southern Australia. According to the obtained results, they stated that this method is desirable for basins that have high spatial and temporal variability [17].

Solgi et al. (2017) used the gene expression programming (GEP) model to model the flow on daily and monthly scales in the Gamasiab River. For this purpose, they used the data of rainfall, temperature, evaporation, and flow of the Gamasiab River at Varaineh station with a statistical period of 43 years (1348-1390). In addition, to increase the performance of the model, they used two methods of data preprocessing: wavelet transformation and decomposition into principal components (PCA). A comparison of the combined gene expression-wavelet programming model with the gene expression programming model showed that the performance of the combined model was better than that of the simple model in both daily and monthly periods [18].

Seyedian et al. (2019) first determined the base discharge using the two-parameter Eckhardt method and then calculated the base discharge index in six stations (Tamar, Lazoureh, Nodeh, Arazkuse, Sedgorgan and Taghiabad). They investigated the relationship between temperature and rainfall with the base flow index at six stations located in the Gorgan River watershed over 33 years (1981-2013) using continuous wavelet transfer and wavelet coherence methods. The correlation analysis of annual temperature and precipitation data shows the effect of two parameters of temperature and precipitation on the basic discharge index. Examining the intensity of correlation between rainfall and the base discharge index in the studied stations showed that there is the highest correlation in the periods of 1 to 4 years, and this correlation is indirect in the middle years of Gorgan and Taghiabad dam stations and direct in other stations and the beginning and end years of Taghiabad station [19].

Ruwangika et al. (2020) used the Mann-Kendall, sequential Mann-Kendall, innovative trend analysis, and wavelet methods to analyse rainfall trends in the Badula Oya catchment in Sri Lanka. After examining the advantages and disadvantages of methods, it was stated that the Mann-Kendall test is powerful for producing statistically significant rainfall trends qualitatively and quantitatively. Discrete wavelet transform is also effective in identifying rainfall patterns [20]. Zamrane et al. (2021) investigated the influence of climatic indicators on the hydrological conditions of Morocco using continuous wavelet analysis [21]. Guo et al. (2023) used wavelet analysis to investigate the correlation between the summer discharge of the Mekong River and two South Asian summer monsoon subsystems SAMI1 and SAMI2 [22]. Using wavelet coherence analysis, Yin et al., (2023) stated that there is a strong coherence between the operation of the Three Gorges Dam and the discharge of the Yangtze River. They also observed a slight seasonal correlation between the dam operation and rainfall [23]. Addou et al. (2023) used the wavelet analysis method to extract the temporal variability of rainfall modes in the Moulouy basin in northeastern Morocco. The main goal of this stage was to identify the periodic or quasi-periodic patterns in the rainfall series and evaluate how these fluctuation modes change in the studied area. The analysis suggests that it is possible to divide the studied basin into two homogeneous clusters that differ only in variability and rainfall regime [24]. Sharma et al. (2024) used the hydrologic engineering center-hydrologic modeling system (HEC-HMS) to simulate the rainfall runoff in a basin. They also used continuous wavelet transform to examine patterns and seasonal interconnections within rainfall data. The results confirmed the efficiency of this hybrid methodology in simulating rainfall-runoff [25]. Song et al. (2024) used MIKE21 to simulate the tide-river and then employed cross-wavelet transform to analyse the relation between the simulated and measured values. They reported that the simulation results were compelling [26].

In this study, wavelet transformation was used as a new tool to investigate river discharge trends, as wavelets can analyse phenomena with fast and slow changes in time series. The main advantage of wavelets in forecasting is their ability to express future challenges using overlapping scales, which makes it easier to extract periodic information. Moreover, the wavelet transform can display different aspects of diverse data, breakpoints, and discontinuities that may not be shown by other analysis methods. The innovation of the current research lies in evaluating the discharge trend of the Halilrood River in the Hamon-e Jaz-Murian basin in Iran using wavelet transform, assessing its performance, and comparing it with the Mann-Kendall method. The sediments and solutes carried by this river are important for the agricultural activities of the downstream areas. Therefore, the present study provides valuable insights into future management decisions.

Materials and Methods

Study Area and Data Collection

The Halilrood River is located in the southeast of Iran and is one of the main sub-basins of the Jaz Murian watershed (West Jaz-Murian). The Halilrood River has an average annual discharge of 8 cubic meters per second. Fig. 1 shows the Halilrood River watershed and the location of this watershed in Iran. The Halilrood basin with an average rainfall of 250 mm and an average altitude of 1774 m can be divided into two parts in terms of climate. The mountainous part upstream of the basin has a semi-arid climate and cold winters, and the plain downstream has a dry climate. In this study, the statistics from Hossein-Abad and Kohank-Sheibani stations were used; their locations in the Halilrood watershed are shown in Fig. 1. Moreover, the geographical coordinates and more details of the database of these stations are presented in Tables 1 and 2. A decreasing trend in the time series of data related to station Kohank-Shibani is shown in Fig. 2.

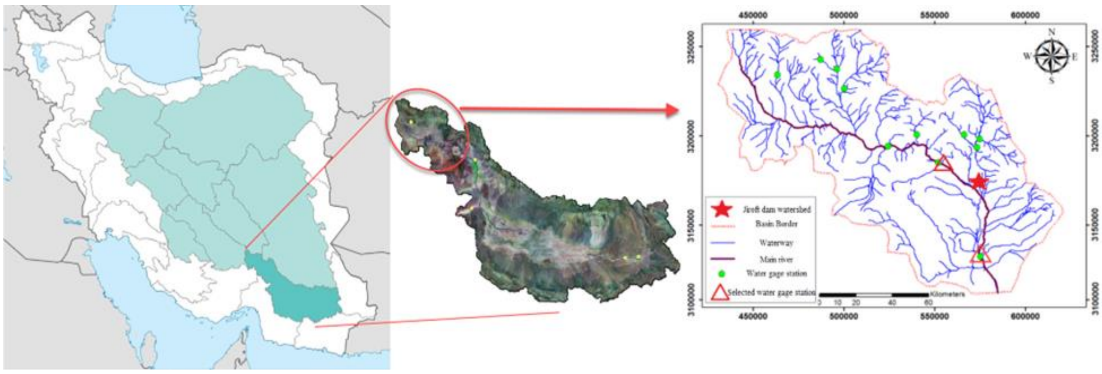

Figure 1. The location of the Halilrood watershed in Iran.

Table 1. Geographical coordinates of the stations used in this research.

Station name	Geographic coordinates (degrees, minutes, seconds)		Height (meters)	Station code	Statistical period length
	Length	Width			
Hossein-Abad	57-33-00	28-47-00	920	44-007	1963-2010
Kohank-Sheibani	57-46-00	28-18-00	520	44-011	1982-2012

Table 2. Statistical characteristics of the used stations.

Station name	Monthly discharge parameter (cubic meters per second)			standard deviation	Coefficient of variation
	Average	Maximum	Minimum		
Hossein-Abad	10.65	167.6	0.198	19.39	1.82
Kohank-Sheibani	7.52	175.78	0.01	15.43	2.05

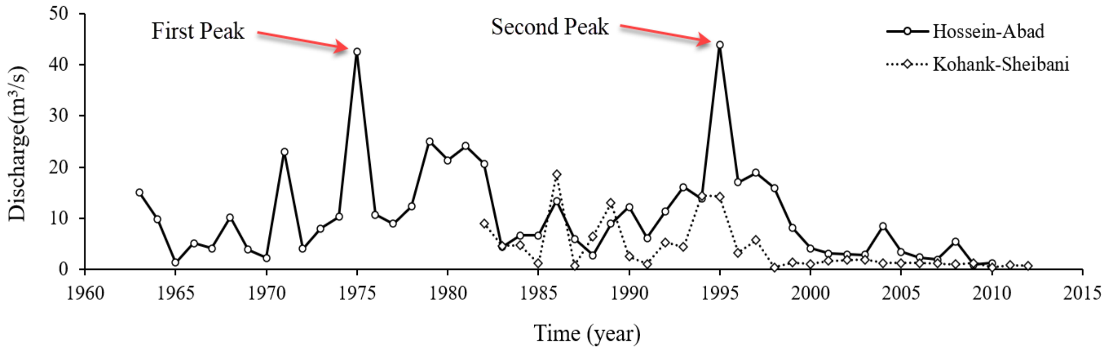

Figure 2. Annual time series graph of flow discharge at Hossein-Abad and Kohank-Shibani hydrometric stations in periods 1963-2010 and 1982-2012, respectively.

Wavelet Transform

Many reports and articles have been published on wavelet functions, providing resources to learn about these advanced mathematical concepts. The wavelet function has two important characteristics: volatility and short-term. Is a wavelet function if its Fourier transform satisfies the following condition [27]:

$$C_g = \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega < \infty \qquad (1)$$

This condition is known as the acceptance condition for wavelet. The above relationship can be considered equivalent to equation (2). In other words, for the wavelet to have the above condition, the following equation must be confirmed:

$$\int_{-\infty}^{+\infty} \Psi(x) dx = 0 \qquad (2)$$

This feature of the function with zero mean is not overly restrictive, allowing various functions to be considered as wavelets. Is the mother wavelet function, in which the functions used in the analysis change the size and location of the analyzed signal with the two mathematical operations of translation and dilation. Finally, the wavelet coefficients at any point of the signal (b) and for any value of the scale (a) can be calculated with the following relationship:

$$\Psi_{a,b}(x) = \frac{1}{\sqrt{a}} \Psi\left(\frac{x-b}{a}\right) \qquad (3)$$

$$\begin{aligned} CWT(a,b) &= wf(a,b) \\ &= \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(x) \Psi\left(\frac{x-b}{a}\right) dx \\ &= \int_{-\infty}^{+\infty} f(x) \Psi_{a,b}(x) dx \end{aligned} \qquad (4)$$

To convert the scale to frequency, the following relationship can be used [25]:

$$F_a = \frac{F_c}{\alpha.\Delta} \qquad (5)$$

F_a is frequency corresponds to the scale of a, F_c is the main frequency of each wavelet function, and Δ is the sampling period. In wavelet transform, when using a function, the property of its moments vanishing is very important. The kth moment of wavelet is equal to:

$$\int_{-\infty}^{+\infty} x^k \Psi(x) = 0 \tag{6}$$

Therefore, a wavelet has m vanishing moments (VM) if the following relationship applies to it:

$$\int_{-\infty}^{+\infty} x^k \Psi(x) dx = 0 \tag{7}$$

$k = 0,1,2, \dots, m-1$

From this relationship, it can be concluded that each wavelet function has at least one vanishing moment. Another form of wavelet transform (WT), called discrete wavelet transform (DWT), is also used in signal analysis. The transmission and scale parameters are chosen discontinuously in the DWT such that:

$$a = 2^{-j} \quad b = 2^{-j}k \tag{8}$$

where j and k are integers. As a result, by replacing a and b, the following relationship is obtained:

$$\Psi_{j,k}(x) = 2^{j/2}\Psi(2^j x - k)dx \tag{9}$$

According to the definition of a wavelet function, many functions have these characteristics. In recent years, a large number of wavelet functions have been developed, demonstrating various capabilities in numerous applications, each being widely used in their respective fields.

After selecting the mother wavelet function, the wavelet coefficients can be calculated for any value (integer and positive decimal) of a (scale). For various purposes, calculating the wavelet coefficients for certain values of a is sufficient. With computers, complex calculations can be easily performed, enabling the calculation of the wavelet coefficients for a wide range of a and choosing a range of a that fulfils a specific purpose [27].

Mann-Kendall Test

The Mann-Kendall test is considered one of the most common non-parametric methods of trend analysis of hydrological and meteorological series. Various studies employing the desired test highlighted its significance and great applicability in analyzing trends in time series data [28]. This method is used to test the randomness assumption of the data sequence against the existence of a trend [29]. According to the literature, its application is recommended for two reasons [10]: 1) It can be used for all types of non-normal, incomplete, and seasonal data. 2) It has the greatest inherent ability in data analysis. For example, Tarar et al. (2018) applied the Mann-Kendall test to identify trend changes in the hydrological series of the Indus River in Pakistan based on low-frequency components. They claimed that this test is widely used in the identification of trend changes in hydro-meteorological data series [30]. Also, in another study the Mann-Kendall (MK) test was employed to identify trends. The time scale that influenced the trends detected in each homogenous region was then determined by combining the DWT with the MK test and doing a sequential MK analysis [31].

Moreover, the strength of the Mann-Kendall method is its suitability for time series that do not follow a specific distribution. Another advantage of this method is its resilience to the effects of outlier values that are observed in some time series [32]. While parametric tests are more effective than non-parametric ones in determining trends, they are very susceptible to outliers and require normal distribution data. As a result, flow time series with skewness and outliers can be effectively trended using the Mann-Kendall test [15]. In this test, the null hypothesis is that the set of sample observations is independent of each other and randomly distributed, and as a result, there is no trend in the data. While the alternative hypothesis indicates the existence of a trend in the data [33].

Parametric and nonparametric trend tests require independent data. A positive rank correlation among observational data increases the probability of a significant trend in the absence of a trend. For this purpose, it is necessary to remove rank correlation before using the test [15]. For data such as monthly flow discharge and smaller time scales in which there is periodicity, Kendall's seasonal method can be used [34, 35].

Yue et al. (2002) showed that if the data exhibit rank correlation, the Mann-Kendall trend test significantly overestimates the trend. The trend-free pre-whitening (PFTW) method is used to remove this correlation [33].

In the first step, the trend slope of the time series is estimated using equation (10). In the second step, the calculation process is removed from the main time series based on equation (11).

$$\beta = Median\left[\frac{x_j - x_i}{j - i}\right] \qquad (10)$$

$$for\ all\ \ i < j, x_i, x_j$$

$$Y_t = X_t - \beta \times t \qquad (11)$$

where X_t is the original time series and t is time. In the third stage, the Lag 1-Autocorrelation (ACF) is calculated. If the autocorrelation is not significant, the Mann-Kendall test is applied directly to the original time series. Otherwise, the autocorrelation of the first stage is removed from the time series by equation (12).

$$Y_t{}' = Y_t - ACF \times Y_{t-1} \qquad (12)$$

Finally, the trend removed in the first step is returned to the time series using equation (13):

$$Y_t{}'' = Y_t{}' + \beta \times t \qquad (13)$$

Represents the time series with the main trend reintegrated but without autocorrelation. To determine the significance of autocorrelation, the significance test of autocorrelation coefficient is conducted using equation (14):

$$r_k = \frac{\frac{1}{n-1}\sum_{t=1}^{n-k}[x_t - E(x_t)][x_{t-k} - E(x_t)]}{\frac{1}{n}\sum_{t=1}^{n}[x_t - E(x_t)]^2} \qquad (14)$$

$$E(x_t) = \frac{1}{n}\sum_{t=1}^{n} x_t \qquad (15)$$

where, is the rank correlation coefficient with delay k for data and is the average of the data. The significance of the rank correlation with a time delay step was obtained at the significance level of 10% for the two-sided test using equation (16):

$$\frac{-1 - 1.645\sqrt{n-2}}{n-1} \le r_1 \le \frac{-1 + 1.645\sqrt{n-2}}{n-1} \qquad (16)$$

If the rank correlation coefficient calculated by equation (14) is within the confidence interval of equation (16), the data are independent and the Mann-Kendall test is directly applied to the time series. Otherwise, the data has a significant rank correlation, and after removing the autocorrelation, the Mann-Kendall trend test is used.

The Mann-Kendall trend test is based on the correlation of time series ranks and their order as follows:

$$\tau = {}^{2S}\!/_{[N(N-1)]} \qquad (17)$$

In this equation, S is defined as follows:

$$S = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} sgn(x_j - x_i) \qquad (18)$$

where and are consecutive data, and N is the number of statistical observation data:

$$sgn(q) = \begin{cases} +1 & q > 0 \\ 0 & q = 0 \\ -1 & q < 0 \end{cases} \quad (19)$$

$$\theta = (x_j - x_i) \quad (20)$$

The mean of S statistic is zero (E(s)=0) and the standard deviation of S() is calculated as follows:

$$S_s = \sqrt{\frac{1}{18}(N(N-1)(2N+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5))} \quad (21)$$

$If\ n > 10$

$$S_s = \sqrt{\frac{N(N-1)(2N+5)}{18}} \quad (22)$$

$If\ n < 10$

where is the number of identical data in the i-th category, in which the data is duplicated, and m is the number of consecutive rank groups. If the number of samples is greater than 10, the value of the normal and standard variable Z is obtained from the following equation [35]:

$$Z = \begin{cases} (S-1/\sigma_s) & if \quad S > 0 \\ 0 & if \quad S = 0 \\ (S+1/\sigma_s) & if \quad S < 0 \end{cases} \quad (23)$$

According to the two-sided chi-square statistical test:

$$X^2 = \sum_{j=1}^{P} ({Z_j}^2 - P\bar{Z}^2) \quad (24)$$

At the certain significance level α, the null hypothesis is accepted and there is no trend. The p-value for the monthly series is 1 to 12. Positive values of S indicate an upward trend and negative values indicate a downward trend. The trend component is obtained using the turning point test from the following relations:

$$E(p) = \frac{2(N-2)}{3} \quad (25)$$

$$Var(p) = \frac{16N-29}{90} \quad (26)$$

$$E(p) = \frac{P - E(p)}{(Var(p))^{0.5}} \quad (27)$$

In the above equations, p is the number of rotation points and Var(p) is the variance of p. A turning point is a state in which each number is greater than both the number before and after it or when each number is smaller than both the number before it and the number after it. The value of Z is tested at a significance level of 5% and if it is between -1.96 and +1.96, the data has no trend. Moreover, if the value of Z is tested at a significance level of one percent and it falls between -2.58 and +2.58, the data does not have a trend.

Table 3 shows the discharge trends for different months for the Hussain-Abad station at different significance levels. According to this Table, the discharge trend was positive in July, September, October, and November, and this positive trend was significant at a significance level of 0.05. In May, June, and December, the discharge trend was negative, but this trend was not significant at any significant level. In April, the discharge trend was negative with a value of -2.37, significant at a significance level of 0.05. In August and March, the discharge trend was negative, which was significant at the significance levels of 0.05 and 0.01. Only in February, with a z value equal to -4.01, was the negative trend significant at the significance levels of 0.5, 0.01, and 0.001.

Table 4 shows the discharge trend in different seasons for Hussain-Abad station at different significance levels. As shown in Table 4, a negative trend was observed in discharge in the spring season, which was not significant. In the summer and autumn seasons, a positive trend in discharge at the Hossein-Abad station has been observed, but this trend was not statistically significant. However, in the winter season, with a z value of -4.22, there was a negative trend in discharge at the station, and this trend was significant at the significance levels of 0.05, 0.01, and 0.001. In Table 5, a summary of the analysis of discharge trends in different years for the Hussain Abad station is presented at different levels of significance. It is clear that the trend of flow was negative with a value of -1.75 and this negative trend was not significant. The values obtained from the examination of each year with Mann-Kendall and Sens coefficient methods for the last 5 years are presented in Table 6, which confirms the above results.

Table 3. The results of the Mann-Kendall method and Sens coefficient for the monthly period at the Hossein-Abad station.

Month	Test z	Signific.	Q	B	Sen's estimate
April	-2.37	*	-0.3447	24.176	16.08
May	-1.59		-0.1433	11.826	8.46
June	-0.01		-0.0026	4.079	4.02
July	1.10		-0.0329	2.177	2.95
August	-2.71	**	-0.0623	1.456	2.92
September	2.53	*	0.0571	1.112	2.45
October	2.10	*	0.0504	1.080	2.26
November	2.53	*	0.0511	0.8762	2.08
December	0.88		0.0236	2.5211	3.08
January	-1.16		-0.0422	5.740	4.75
February	-4.01	***	-0.3585	18.624	10.20
March	-4.01	**	-0.5286	25.347	12.92

Table 4. The results of the Mann-Kendall method and Sens coefficient for different seasons at the Hossein-Abad station.

Season	Test z	Signific.	Q	B	Sen's estimate
Spring	-1.70	+	-0.1657	14.634	10.74
Summer	1.57		0.0400	2.519	3.46
Autumn	1.89	+	0.0420	1.426	2.41
Winter	-4.22	***	-0.467	22.893	11.92

Table 5. Summary of results for the annual period at the Hossein-Abad station.

Data Type		Q	-1.34E-01	B	1.08E+1
Years	1963-2010	Qmin99	-2.95E-01	Bmin99	1.50E+01
n	48	Qmax99	6.43E-02	Bmax99	6.56E+00
Test S		Qmin99	-2.48E-01	Bmin95	1.31E+01
Test Z	-1.75	Qmax99	1.69E-02	Bmax95	7.82E+00
Signific	+	Equation of the lines:		F(year)=Q*(year-firstDataYear) + B	

Table 6. The values of the Mann-Kendall test and Sens coefficient at the Hossein-Abad station.

Year	Data	Sen's estimate	99 % conf. min	99 % conf. max	95 % conf. min	95 % conf. max	Residual
2006	2.3286	5.0432	2.3185	9.3197	2.4805	8.5492	-2.7146
2007	1.9462	4.9090	2.0239	9.3840	2.2324	8.5661	-2.9628
2008	5.4828	4.7748	1.7293	9.4483	1.9842	8.5830	0.7079
2009	0.9327	4.6406	1.4347	9.5126	1.7361	8.6000	-3.7079
2010	1.2472	4.5065	1.1401	9.5768	1.4880	8.6169	-3.2592

Results and Discussion

The results of trend analysis for Kohanek-shibani station

Table 7 shows the discharge trend in different months at the Kohank-Sheibani station at different significance levels. According to this table, the discharge had a downward and negative trend at this station for all months. This negative trend was not significant in July, September, and November. Moreover, the negative trend in discharge in June and October has been significant at a significance level of 0.05. In May, December, February, and March, the negative trend was significant at significance levels of 0.05 and 0.01. The trend of discharge in April, August, and December was significant at the significance levels of 0.05, 0.01, and 0.001. In general, discharge has been decreasing at this station in all months.

Table 8 shows the discharge trend in different seasons at the Kohank-Sheibani station at different significance levels. There has been a downward and negative trend in all seasons of discharge at this station. This trend was significant in the summer season at the significance level of 0.05 and 0.01 and in the rest of the seasons, it was significant at the significance level of 0.05, 0.01, and 0.001.

In Table 9 a summary of the analysis of the discharge trend in different years at the Hossein-Abad station is presented at different levels of significance. According to Table 9, the flow rate is negative with a value of -3.60 and this negative trend is significant at significance levels of 0.05, 0.01, and 0.001. In general, discharge has been decreasing at this station in all years. The values obtained from the examination of each year with Mann-Kendall and the Sens coefficient methods for the last 5 years are presented in Table 10, which confirms the above results.

Table 7. The results of the Mann-Kendall method and the Sens coefficient for the monthly period at the Kohnek-Shibai station.

Month	Test z	Signific.	Q	B	Sen's estimate
April	-3.77	***	-0.6623	17.749	9.86
May	-2.62	**	-0.1510	4.788	2.45
June	-2.07	*	-0.056	2.078	1.24
July	-1.43		-0.0236	1.0964	0.74
August	-3.35	***	-0.2179	6.641	3.37
September	-1.26		-0.0384	2.884	2.31
October	-2.23	*	-0.0647	3.589	2.62
November	-0.82		-0.0549	2.52	1.70
December	-4.22	***	-0.2556	7.214	3.38
January	-2.86	**	-0.3042	10.108	5.55
February	-3.23	**	-0.5107	16.051	8.39
March	-2.96	**	-0.5392	16.938	8.85

Table 8. The results of the Mann-Kendall method and Sens coefficient for different seasons at the Kohnek-Shibai station.

Season	Test z	Signific.	Q	B	Sen's estimate
Spring	-3.37	***	-0.3744	11.4476	5.83
Summer	-2.70	**	-0.0849	3.421	2.15
Autumn	-3.60	***	-0.1584	5.106	2.73
Winter	-3.47	***	-0.5745	18.308	4.69

Table 9. Summary of results for the annual period at the Kohnek-Shibai station.

Data Type		Q	-1.58E-01	B	5.11E+1
Years	1982-2012	Qmin99	-3.07E-01	Bmin99	8.34E+01
n	31	Qmax99	-3.90E-02	Bmax99	2.43E+00
Test S		Qmin99	-2.76E-01	Bmin95	7.74E+01
Test Z	-3.60	Qmax99	-7.51E-02	Bmax95	3.12E+00
Signific	***	Equation of the lines:		F(year)=Q*(year-firstDataYear) + B	

Table 10. The values of Mann-Kendall test and Sens coefficient at the Kohnek-Shibai station.

Year	Data	Sen's estimate	99 % conf. min	99 % conf. max	95 % conf. min	95 % conf. max	Residual
2008	0.986667	0.986667	0.36082696	1.41395295	0.56422325	1.16459291	-5.6E-16
2009	1.220567	0.828241	0.05410261	1.37499384	0.28819679	1.08954251	0.392326
2010	0.391444	0.669815	-0.2526217	1.33603474	0.01217033	1.01449212	-0.27837
2011	0.791133	0.511389	-0.5593461	1.29707564	-0.2638561	0.93944172	0.279744
2012	0.766667	0.352963	-0.8660704	1.25811654	-0.5398826	0.86439133	0.413704

The trends of annual discharge using the Mann-Kendall test and Sens coefficient at the Hossein-Abad and Kohnek-Shibai stations are shown in Fig. 3. The results in terms of p-values from the Mann-Kendall trend test are shown in Fig. 3, with a significance level of α = 0.05.

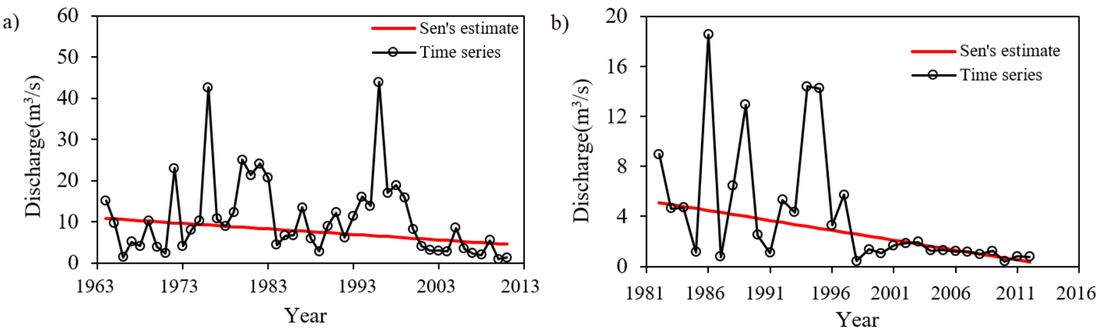

Figure 3. Investigating the trend of annual discharge using the Mann-Kendall test and Sens coefficient, a) Hossein-Abad station and b) Kohnek-Shibai station.

Results related to the wavelet transform

To perform the time series analysis process, the number of analysis steps, the method of dealing with the boundary conditions of the signal, and the most suitable type of Daubechies mother wavelet (db) should be optimally selected. For proper execution and accurate analysis of the process as well as to identify the frequency structure affecting the flow rate at different time steps, the Mann-Kendall test was performed. This test was applied to components resulting from the analysis, including both detailed and approximation components.

Fig. 4 shows the monthly discharge at the Hossein-Abad station, analysed at level 6 with db2 wavelet function. In Fig. 4, S is the signal or the main component of the monthly discharge, A is the approximation component at the 6th analysis level, and D is the detail component at the 1st to 6th analysis levels.

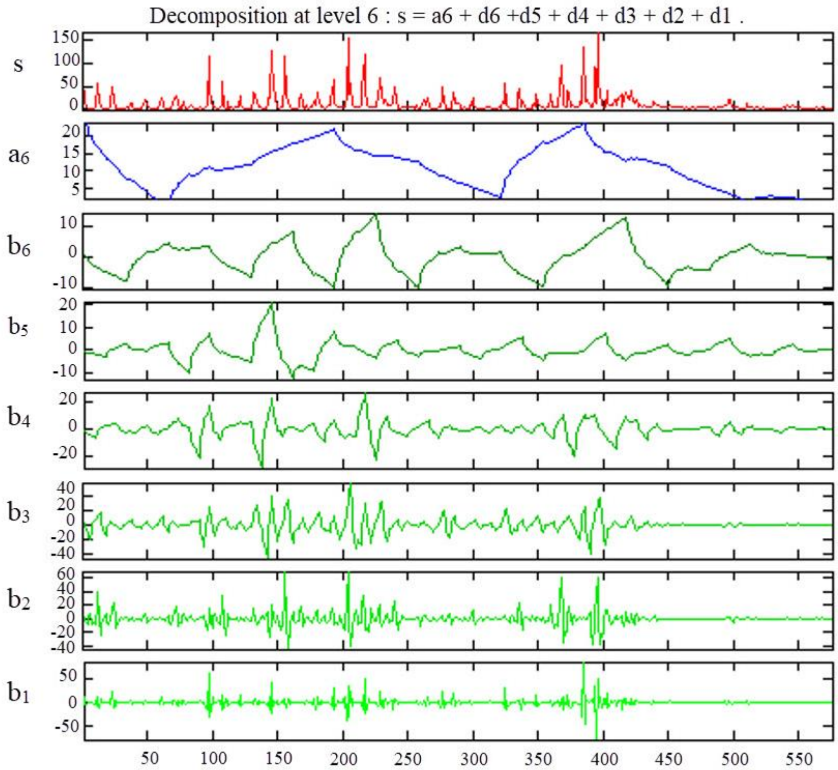

Figure 4. Components obtained from the monthly flow time series analysis at the Hossein-Abad station using wavelet transform.

The results of the trend investigation for the Halilrood River basin are presented in Table 11 and Table 12. According to Table 11, at the Hossein-Abad station, a significant negative trend was observed in the annual series and the winter season series in the main and approximation components. However, it was not observed in the rest of the seasonal series. According to Table 12 at the Kohnek-Shibai station, a significant negative trend was observed for all scales in the main data and the approximation component.

Table 11. The Mann-Kendall test values for the components resulting from the analysis of the time series of average discharge at different time scales at the Hossein-Abad station.

Data	Monthly	Seasonal	Yearly	Winter	Autumn	Summer	Spring
Main	-4.93***	-3.51***	-1.75+	-4.22***	1.82+	1.21	-2.28*
A	-3.27***	-2.54*	-2.50*	-9.77***	1.84+	-1.98*	-0.88
D1	-2.19*	-0.31	1.08	1.15	1.67+	-3.43***	-4.70***
D2	-2.11*	0.51	0.48	0.99	2.11*	1.38	1.57
D3	0.22	0.65	-0.02	-0.76	2.30*	0.86	1.55
D4	0.26	0.68	0.12	0.42	1.07	1.32	0.69
D5	0.36	---	---	---	1.03	---	1.49
D6	-0.22	---	---	---	---	---	---
D1+A	-5.07***	-6.36***	-4.05***	-5.75***	2.36*	-2.20*	-4.73***
D2+A	-4.14***	-6.19***	-3.62***	-7.19***	1.37	0.88	-2.86**
D3+A	-1.49	-1.97*	-3.95***	-6.92***	1.41	1.59	-2.77**
D4+A	-1.21	-2.02*	-3.65***	-4.46***	1.02	1.52	-2.52*
D5+A	-1.67	---	---	---	1.03	---	-2.26*
D6+A	-1.95	---	---	---	---	---	---
D1+D2+A	-3.27***	2.56*	-3.64***	-5.26***	2.19*	-1.73+	-3.50***
D1+D3+A	-2.18*	-1.84+	-4.06***	-5.37***	0.77	1.11	-1.49
D1+D4+A	-1.74+	-1.38	-3.34***	-4.36***	1.05	0.92	-1.48
D1+D5+A	-1.85+	---	---	---	0.83	---	-1.63
D1+D6+A	-2.19*	---	---	---	---	---	---
D2+D3+A	-1.29+	-1.73+	-3.53***	-6.18***	1.89+	1.68+	-3.73***
D2+D4+A	-1.17	-1.51+	-2.53*	-4.13***	1.02	1.10	-1.79+
D2+D5+A	-1.29	---	---	---	1.25	---	-2.09*
D2+D6+A	-2.15*	---	---	---	---	---	---
D3+D4+A	-0.63	-1.30+	-3.48***	-4.65***	2.31*	1.68+	-4.17***
D3+D5+A	-1.24	---	---	---	1.78+	---	-2.44*
D3+D6+A	-1.25	---	---	---	---	---	---
D4+D5+A	-0.90	---	---	---	2.45*	---	-3.20**
D4+D6+A	-1.03	---	---	---	---	---	---
D5+D6+A	-0.99	---	---	---	---	---	---

Table 12. The Mann-Kendall test values for the components resulting from the analysis of the time series of average flow at different time scales at the Kohank-Sheibani station.

Data	Monthly	Seasonal	Yearly	Winter	Autumn	Summer	Spring
Main	-4.07***	-1.83+	-3.60***	-3.47***	-3.60***	-2.70**	-3.37***
A	-10.76***	-4.28***	-7.85***	-7.85***	-7.85***	-7.85***	-7.89***
D1	2.27*	2.10*	-2.45*	-0.82	-2.45*	1.53	-7.21***
D2	-1.19	-0.30	0.48	0.95	0.48	1.09	1.50
D3	-0.42	-0.35	0.51	0.88	0.51	0.85	0.78
D4	0.22	0.32	0.71	0.51	0.71	-0.51	0.71
D5	-0.48	---	---	---	-0.88	---	1.33
D6	-0.05	---	---	---	---	---	---
D1+A	-4.15***	-4.30***	-4.32***	-4.39***	-4.39***	-4.01***	-5.71***
D2+A	-3.99***	-3.79***	-5.47***	-4.56***	-5.03***	-4.52***	-5.98***
D3+A	-1.57	-2.92**	-4.69***	-4.73***	-3.91***	-4.25***	-4.32***
D4+A	-0.32	-2.13	-7.34***	-5.98***	-6.97***	-3.64***	-7.48***
D5+A	-7.3	---	---	---	-7.85***	---	-7.82***
D6+A	-1.16	---	---	---	---	---	---
D1+D2+A	-10.81***	-2.79**	-3.84***	-3.64***	-3.33***	-3.43***	-5.44***
D1+D3+A	-7.91***	-2.83**	-3.81***	-4.15***	-2.52*	-4.01***	-3.94***
D1+D4+A	-1.66+	-1.70+	-4.25***	-4.08***	-3.94***	-2.96**	-5.51***
D1+D5+A	-1.14	---	---	---	-4.32***	---	-5.40***
D1+D6+A	0.04	---	---	---	---	---	---
D2+D3+A	-3.04**	-2.73**	-4.01***	-4.42***	-3.26**	-3.91***	-4.59***
D2+D4+A	-2.61**	-1.91+	-5.23***	-4.73***	-4.93***	-2.92**	-5.68***
D2+D5+A	-2.61**	---	---	---	-5.47***	---	-5.68***
D2+D6+A	-2.23*	---	---	---	---	---	---
D3+D4+A	-2.23*	-1.73+	-5.06***	-4.45***	-4.01***	-3.26**	-5.23***
D3+D5+A	-2.21*	---	---	---	-4.69***	---	-4.11***
D3+D6+A	-1.92+	---	---	---	---	---	---
D4+D5+A	-0.70	---	---	---	-7.34***	---	-7.31***
D4+D6+A	-0.44	---	---	---	---	---	---
D5+D6+A	-0.85	---	---	---	---	---	---

Since the long-term change trends are usually reflected in the approximation component (A), combining this component with one and two detail components was investigated at the Halilrood basin stations. Fig. 5 to 7 show the analyzed components of monthly, seasonal, and annual discharge at the Hossein-Abad station at analysis level 2. The calculated trend values, derived from combining the approximation component with the two partial components, show the combined effect of different frequency factors on the fluctuating flow structure. At a monthly scale, two groups of combinations of frequencies are considered the dominant oscillatory patterns, which are high frequencies and low frequencies. These results indicate that the discharge fluctuating behaviour is concurrently affected by both high and low frequencies, reflecting a multifaceted interaction. High frequencies are related to the effect of short-term phenomena on the discharge fluctuating behaviour, while low and long-term frequencies are indicative of the occurrence of relatively stabilized or more static phenomena. This situation is also shown in the analysis of seasonal and annual time series results, where the combined component of high and low frequencies is known as the dominant frequency in seasonal data. Considering the long-term time base of annual data compared to seasonal and monthly data, the dominant frequency is more towards a combination of low and long-term frequencies (24 and 48), which seems logical and reasonable. Fig. 8 to 10 show the decomposed components of monthly, seasonal, and annual discharge at the Kohank-Sheibani station at decomposition level 2.

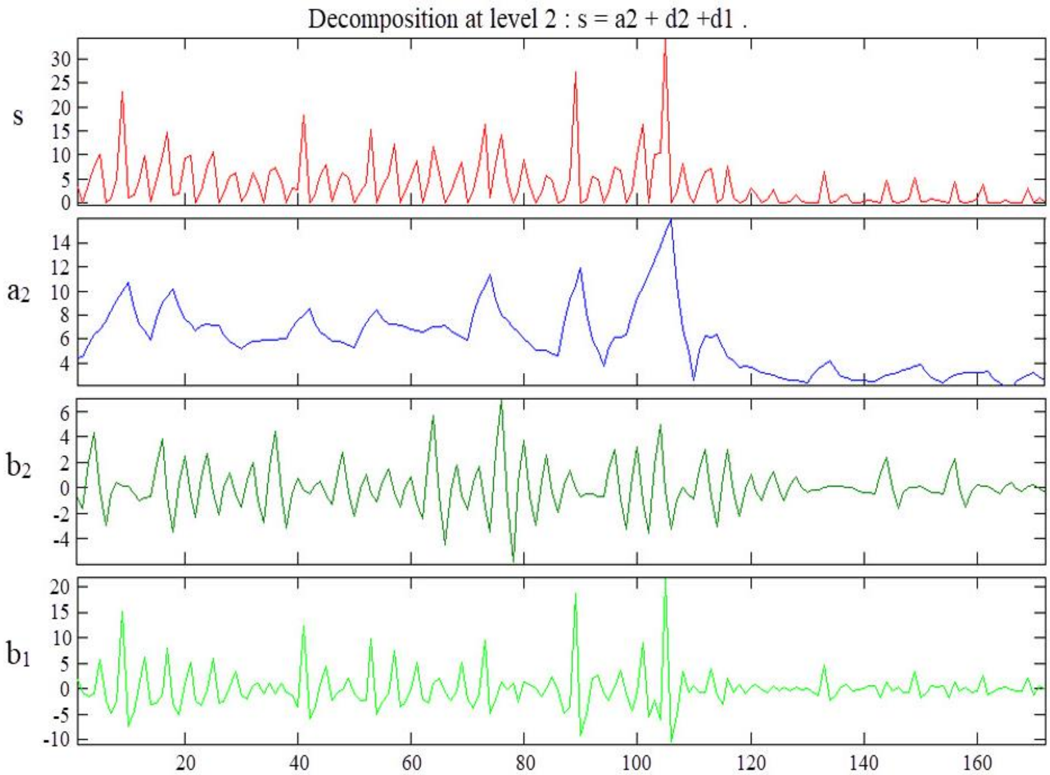

Figure 5. Decomposed monthly discharge components of Hossein-Abad station with wavelet transformation.

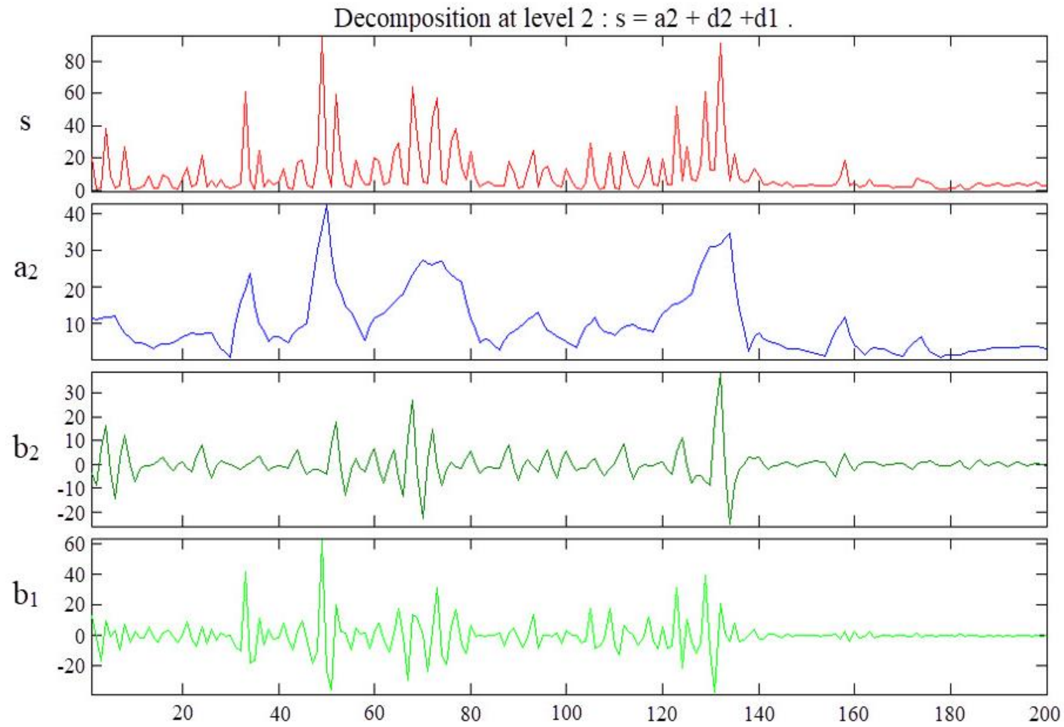

Figure 6. Decomposed components of seasonal discharge for Hossein-Abad station with wavelet transform.

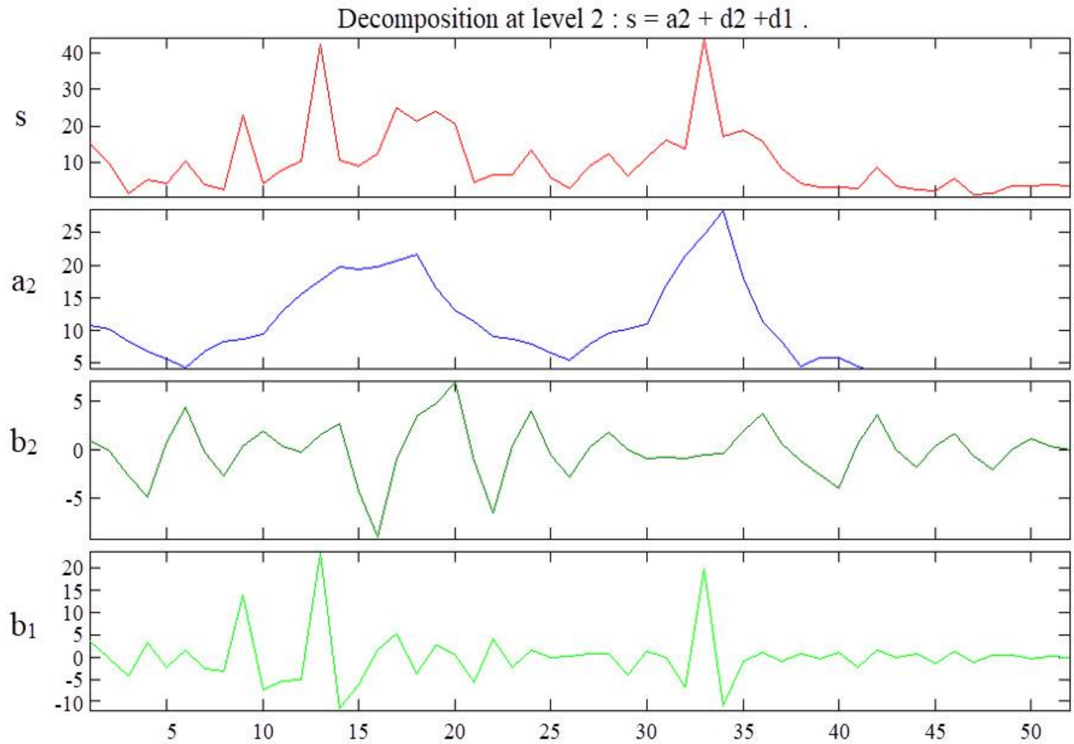

Figure 7. Decomposed annual discharge components for Hossein-Abad station with wavelet transform.

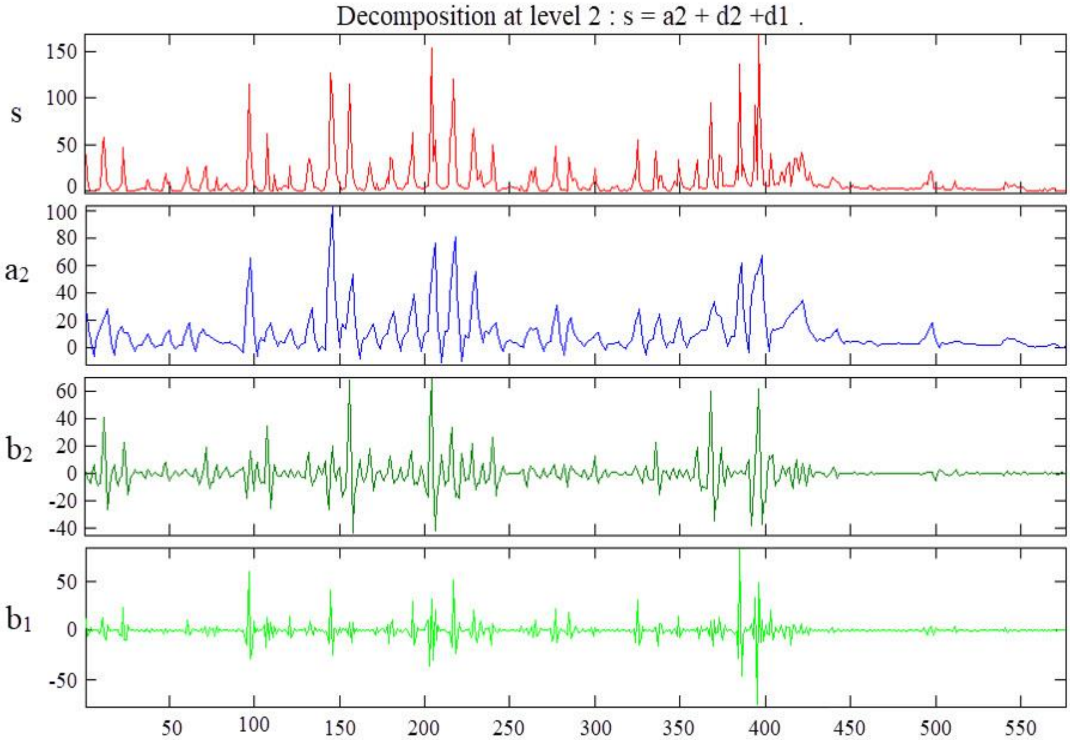

Figure 8. Decomposed components of monthly discharge for Kohank-Sheibani station with wavelet transform.

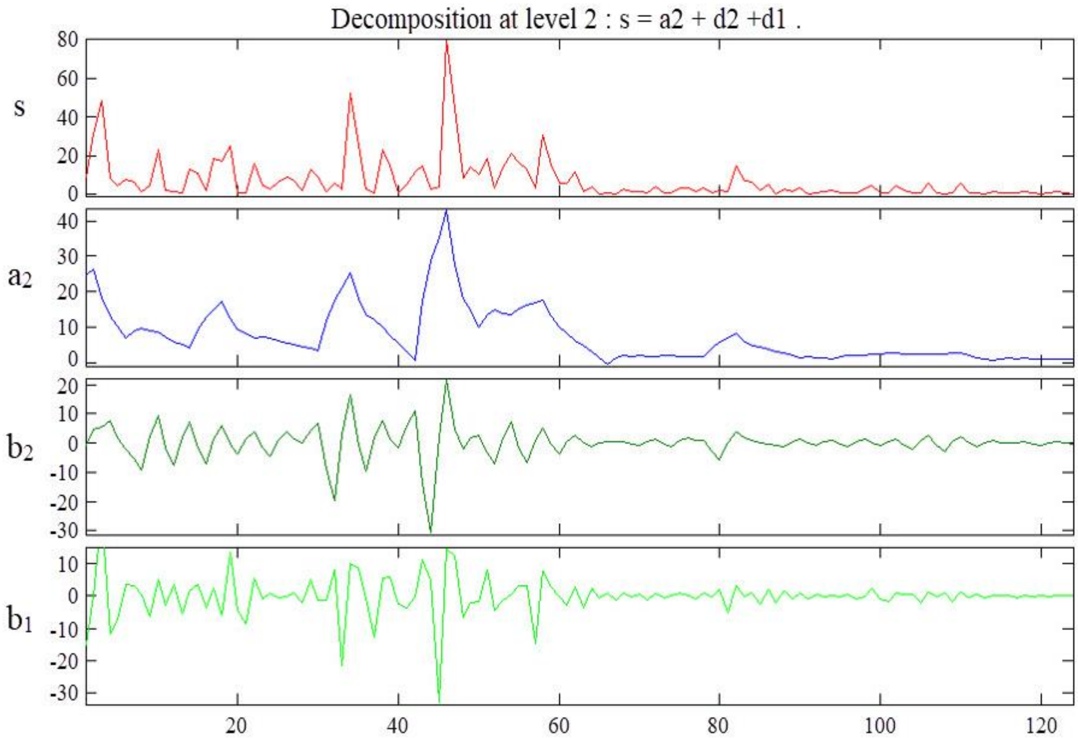

Figure 9. Decomposed seasonal discharge components for Kohank-Sheibani station with wavelet transform.

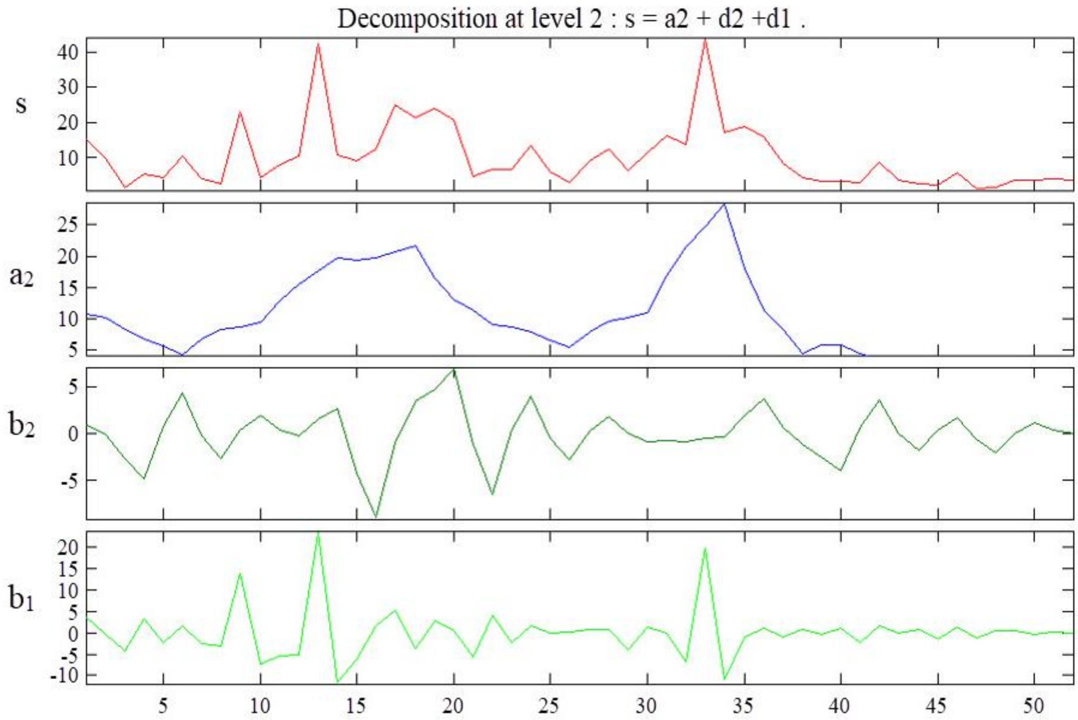

Figure 10. Decomposed annual discharge components for Kohank-Sheibani station with wavelet transform.

Regarding the effectiveness of the methods, according to the existence of outlier data, outlier data have different effects on Mann-Kendall and wavelet methods. The Mann-Kendall method is less affected by outliers due to its non-parametric statistical nature [36] This method is more resistant to outlier data by using data ranking and without the need for distributional hypotheses. In contrast, the wavelet method, which is used to analyze time series and extract periodic information, is more sensitive to outliers. Outlier data can affect the results of wavelet analysis and cause changes in the extracted patterns [37, 38].

Comparison of different methods

The results of trend analysis of different methods are presented in Table 13. According to Table 13, both Mann-Kendall and wavelet transform methods have recognized the type of downward or upward trend well. For the annual trend analysis, both modes of the wavelet transform method outperformed the Mann-Kendall method, exhibiting higher values and greater significance across various significance levels. In seasonal mode, the Mann-Kendall method outperforms the wavelet transform at the second level but shows weaker performance at the first level. In the monthly analysis at the Kohank-Sheibani station, a basin outlet, the Mann-Kendall method's trend values show greater significance. The observed trends can be attributed to the joining of several branches before reaching these stations in different months of the year and the upward trend observed in some months at this station.

Table 13. Comparison of the results of different methods in different time scales at the studied stations.

Station	Type	Monthly	Seasonal	Yearly
Hossein-Abad	Mann-Kendall	-4.93***	-3.51***	-1.75+
	Wavelet Transform (at the first level)	-5.07***	-6.36***	-4.05***
	Wavelet Transform (at the second level)	-4.14***	-6.19***	-3.62***
Kohank-Sheibani	Mann-Kendall	-4.07***	-1.83+	-3.60***
	Wavelet Transform (at the first level)	-4.15***	-4.30***	-4.32***
	Wavelet Transform (at the second level)	-3.99***	-3.79***	-5.47***

Conclusion

In this study, the wavelet transform method was used to investigate the discharge trend of the Halilrood River in the Hamon-e Jaz Murian catchment in Iran. The results of this method were compared with the Mann-Kendall method. The results indicated a significant downward trend at the Hossein-Abad station on a monthly scale, with a significance level of 0.001. The mentioned station exhibited a significant downward trend during the seasonal period at the 0.001 level, while the annual period also showed a downward trend, though it was not significant. The wavelet transform analysis revealed a significant downward trend at the Hossein-Abad station across monthly, seasonal, and annual scales, all at the 0.001 significance level. In general, the results showed a decrease in discharge at this station in all time scales. The monthly discharge data for the Kohank-Sheibani station reveal a significant downward trend at the 0.001 level. During the seasonal period, a downward trend was observed at the station, though it did not reach the 0.001 significance level. In contrast, the annual scale showed a significant downward trend. The wavelet transform analysis revealed a significant downward trend in discharge at the Kohank-Sheibani station across monthly, seasonal, and annual scales, all at the 0.001 significance level. In general, the results showed a decrease in discharge at this station in all time scales.

Data availability

The data of this research is related to the Master's thesis of the first author, which can be accessed by correspondence with the corresponding author.

Declaration of competing interest

The authors declare that they have no competing or conflict of interests that could have appeared to influence the work reported in this paper.

Author contributions

All authors contributed critically to the writing process and approved the final version of the manuscript.

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Ethics

The authors have considered the ethical principles in carrying out and publishing this research and this issue is approved by all of them.

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