Using wavelet transform to analyze the dynamics of climatic variables; to assess the status of available water resources in Iran (1961–2020)

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Abstract

In recent years, the effects and consequences of climate change have shown themselves by creating irregularities and trends in the essential climatic variables. In most cases, the trend of climatic variables is associated with periodicity. In this study, the trends and periodicity of these data (precipitation, temperature, evapotranspiration, and net available water (NWA)) have been investigated in a period of 60 years in Iran. The Mann–Kendall trend test and Sen's slope estimator are applied for analyzing the trend and its magnitude. Wavelet transform is used to detect the periodicity of time series and to determine the correlation between NWA and temperature, precipitation, and evapotranspiration in common periodicity. The results show that the stations located in eastern and western Iran have more significant increasing/decreasing trends. Evapotranspiration shows the highest increasing trend in most stations, followed by temperature, while NWA and precipitation have trends at lower significance levels and decreasing direction. The examination of periodicity in time series showed that, among all the studied stations, evapotranspiration has the most extended periodicity with an average length of 8.3 years, followed by NWA, temperature, and precipitation with 7.3 years, 5.8 years, and 5.5 years. The results of the correlations investigation showed that in about 80% of the stations, there is a high correlation between precipitation and NWA in the short-term periodicity and at the end of the studied period. The evapotranspiration variable in most stations has a high correlation in different periodicities with the amount of NWA.

Keywords Wavelet transform · Mann–Kendall Test · Periodicity · Water Availability · Trend

Communicated by: Hassan Babaie

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Introduction

Emissions of greenhouse gases from human activities have risen dramatically since 1980, likely contributing to global warming in recent decades (IPCC 2013). Any changes in the balance of the climate system, including the atmosphere, land surface, and oceans, has a significant impact on health, livelihoods, food security, water supply, human security, and economic growth (Katipoğlu 2023; Verbruggen et al. 2011; Koycegiz and Buyukyildiz 2023a). There are compelling shreds of evidence of climate change around the globe, such as increases in average temperature and heavy precipitations, floods, and droughts (Westra et al. 2013; Hosseinzadeh Talaee et al. 2014; Kwiecien et al. 2022; Tabari 2020; Tabari and Willems 2018; Meza et al. 2020). Any changes in the global climate system have a significant impact on a smaller regional scale, therefore analyzing the detail of long-term time series of hydro-climatic variables is crucial. Upon reviewing some of the relevant studies conducted globally, it became clear that most of them have reached

similar findings regarding the trends of critical climate variables such as precipitation, temperature, and evapotranspiration. It is, however, worth noting that the magnitude and direction of changes observed in each region are primarily linked to the climate type and the latitude and longitude of the study area (Topçu et al. 2022). It cannot be confidently stated that climate change is the sole cause of a significant trend in precipitation, temperature, and evapotranspiration measurements; however, it can increase its likelihood. Precipitation, temperature, and evapotranspiration are the main parameters for defining the climate and water balance of a region. In Iran, similar to many other countries across the globe, the most significant impact of climate change has been observed in the form of the above-mentioned variables. Iran has a predominantly dry and semi-arid climate, and the agricultural sector in this country consumes more than 85% of freshwater resources. As a result, Iran is particularly susceptible to the long-term changes in these variables induced by climate change. This irregularity in the water circulation system can cause significant challenges in managing water resources and related sectors (Tabari et al. 2019). Planning and implementation of sustainable water resources management programs depend on the availability and potential of water resources in the region (Koycegiz and Buyukyildiz 2023b). Therefore, analyzing trends in precipitation and evapotranspiration variables simultaneously can provide a more accurate and comprehensive picture of water resources for planners and decision-makers in this field (Dabanlı et al. 2016). Katipoğlu (2023) conducted a study in order to investigate the variable trend of potential evapotranspiration in several watersheds of Türkiye, study's results indicate a general trend towards increased potential evapotranspiration (PET) values over time, particularly at the Erzincan and Bayburt meteorological stations in Turkey. analysis identified increasing trends in PET data across various ranges. Additionally, the sequential Mann–Kendall (SQMK) test highlighted the initiation of these trends around key years such as 1995, 2005, and 2010. These findings underscore the urgent need for effective water resource management and agricultural adaptation strategies to counteract the negative effects of rising PET values on crop yields and overall agricultural productivity.

The atmosphere is a dynamic and highly complex system, which is the result of multiple factors influencing climatic variables and the significant interaction between these variables (Suni et al. 2015). As noted by Franzke (2010), these factors are often periodic in nature, indicating that this characteristic may also be present in climatic variable data. Therefore, it is crucial to study and analyze dominant periods in time series in addition to examining any underlying trend (Barry and Chorley 2009; Tarbuck and Lutgens 2013). Research by Topçu (2022) examines meteorological drought characteristics, focusing on intensity and patterns of change

in Turkey from 1925 to 2016. Using the Mann–Kendall test, this study identifies a significant upward trend in the occurrence of severe drought in central Turkey, especially evident in 20-year cycles.

A comprehensive literature study on climatic variables suggests that precipitation levels have decreased while temperature and evapotranspiration have increased. However, recent extreme events have deviated from this trend. This feature highlights the need for a more detailed analysis of the periodicity of these trends (Malaekeh et al. 2022; Koycegiz 2024a). The variables in question have a significant impact on the ecosystem, environment, and human societies. The slightest disturbance or changes in these variables, even in the short term, can lead to significant damage in relevant sectors, e.g., agriculture, forestry, and natural disasters (Adhikari et al. 2020; Ojara et al. 2020). Precipitation, temperature, and evapotranspiration data are continuous, random, and non-linear, which makes them not follow a specific statistical distribution. They typically follow a very skewed distribution. Due to the many difficulties and practical restrictions of measuring these variables, there are often many missing values in these data sets. Non-parametric methods, such as the Mann–Kendall method, are helpful in detecting trends in such time series (Wang et al. 2020). This method has been effectively used in numerous studies, including Makokha and Shisanya (2010), Marofi et al. (2012), De Lima et al. (2013), Martínez-Austria et al. (2016), Sonali and Kumar (2013), Araghi et al. (2015), Hamed and Rao (1998),Topçu (2022),Yilmaz and Tosunoglu (2019). Koycegiz (2024a) in his study, investigates the relationship between seasonality and the trends and long-term persistence of precipitation and temperature time series within the Konya Endorheic Basin, a semi-arid region located in central Anatolia, Turkey. Utilizing the Mann–Kendall (MK) test, the research identifies a significant increase in temperature across the basin, indicating a positive trend in temperature patterns. This finding highlights the significant consequences of climate change in this particular semi-arid area of central Anatolia, Turkey. Analyzing trends in hydrological time series is crucial to understanding data instability (Akçay et al. 2022). Climatic variables have nonlinear characteristics and significant uncertainty and often with multiple trends observed on different time scales, making it difficult to detect trends using statistical methods alone in these data (Vogel et al. 2024). However, by using mathematical methods (such as wavelet transform) along with statistical methods, trends in different time scales can be detected (Volvach et al. 2024). This approach has been used in various hydrological and climatic studies (Adamowski et al. (2012); Adamowski and Chan (2011); Adamowski et al. (2013); Belayneh et al. (2014); Campisi-Pinto et al. (2012); Karran et al. (2014); Nalley et al. (2012); Nourani et al. 2013, 2014; Prokoph et al. 2012; Tiwari and Adamowski 2013, Araghi et al. 2018). Large-scale weather events exert a significant

impact on hydrological systems. Many studies have been done on the correlation between significant changes in climate variables, specifically storms and droughts, and large-scale weather patterns. Cross-wavelet transform is a helpful method for analyzing data in the time–frequency domain and detecting correlations between two time series at different scales. Researchers have widely used this method to analyze the relationship between climate fluctuations and large-scale atmospheric factors, which has yielded useful results such as Liu et al. (2020), Wu and Wang (2022), Ojara et al. (2020), Padakandla et al. (2021), de Oliveira-Júnior et al. (2022) and Yin et al. (2009), used wavelet coherence (WTC), cross-wavelet transform (XWT) methods to study the relationship between floods and droughts and Southern El- Niño oscillations from 1857 to 2003. A review of existing literature reveals a focus on one or two variables for investigations, often conducted at basin or regional scales. These studies typically analyze the magnitude and slope of change in these variables. While these investigations in core climatic variables offer valuable insights, they are insufficient to understand exactly how the changes occur. The underlying processes driving these trends are equally important and warrant exploration. Furthermore, a regional focus limits spatial comparisons of results across a climate-diverse country like Iran. This research addresses this gap by constructing a comprehensive and practical perspective on the magnitude and nature of changes in key climatic variables (precipitation, temperature, and evapotranspiration) across Iran. Additionally, it presents a novel contribution by evaluating changes in potentially available water resources over a significant timeframe (60 years), an aspect previously unexplored in Iranian climate research.

This study examines time series data for precipitation, temperature, and potential evapotranspiration. Additionally, it analyzes the net water available (NWA) time series, which is determined by the difference between precipitation and evapotranspiration values. This time series, which is recently used in water resources and climatology studies, shows the general state of the water balance (Das et al. 2022). In this study, we evaluated trends and their magnitude in precipitation, evapotranspiration, NWA, and temperature using the discrete wavelet transform method and the Mann–Kendall test (initial, modified, and sequential). Additionally, we used the WTC and XWT methods to analyze the correlation between these variables and NWA data at different time scales and frequencies.

Materials and methods

Study area and dataset

Iran is situated in the Middle East, encompassing an extensive area of 1.648 million km^2. Its geographical coordinates range approximately from 44.03° to 63.32° E in longitude and from 25.06° to 39.77° N in latitude. The country features 30 major basins and displays diverse hydro-climatic, geomorphological, and land cover characteristics. About 45.9% of Iran experiences a warm-arid climate, 21.5% a cold-arid climate, 19.3% a moderate-arid climate, 7.6% a cold-humid climate, 3.2% a moderate-humid climate, and 2.5% a warm-humid climate. The average annual precipitation is roughly 200 mm, with significant spatial variability, ranging from as low as 15 mm/year in the central deserts to as high as 2000 mm/year in the northern regions (Khosravi et al. 2020). As shown in Fig. 1, which is related to the Koppen Geiger climate classification, Iran is known as a country with high climate diversity, among which the share of arid and semi-arid climates is much higher than other types of climates. In arid and semi-arid climates, available and stored water resources are mainly provided through precipitation, because in these areas, the amount of surface and underground flows and the amount of water resources stored for the future are either absent or very low. The variables of precipitation, temperature, and evapotranspiration are among the most critical climatic variables affecting the hydrological cycle and water balance, which have been investigated in this study.

The abbreviation and description of the Koppen Geiger climate classification are shown in Table 1.

In the Table 2, the geographical features, climate classification and the average variables of precipitation, temperature and transpiration are given.

In this study, we used precipitation, temperature (average, maximum, and minimum), relative humidity, sunshine, and wind speed data from 36 synoptic stations in Iran from 1960 to 2020 (Fig. 1).

Evapotranspiration values were calculated using the FAO Penman–Monteith standard method, as outlined by Allen et al. (1998).

In the next step, the necessary pre-processing was done on the data, in this step, outliers and missing data were first identified. For this purpose, the outlier data was detected using Grubbs' test (Grubbs 1969; Stefansky 1972) and after checking these data with nearby stations (the stations that had the highest correlation with the desired station), if necessary, it was decided to remove and estimate these data.

Estimation of missing or omitted data was done by the methods of comparisons and ratios and regression. In the next step, the homogeneity of the data was checked by 3 common methods (Pettitt, Buishand, and Standard Normal Homogeneity Test (SNHT)) in this field. In this context, Rahmdel (2021) conducted a comprehensive study to investigate the homogeneity and change points in climate data such as precipitation, temperature, wind speed, relative humidity, etc. 1960 to 2020, he announced that the presence of heterogeneity in station data (synoptic) can be influenced by human factors such as changing the
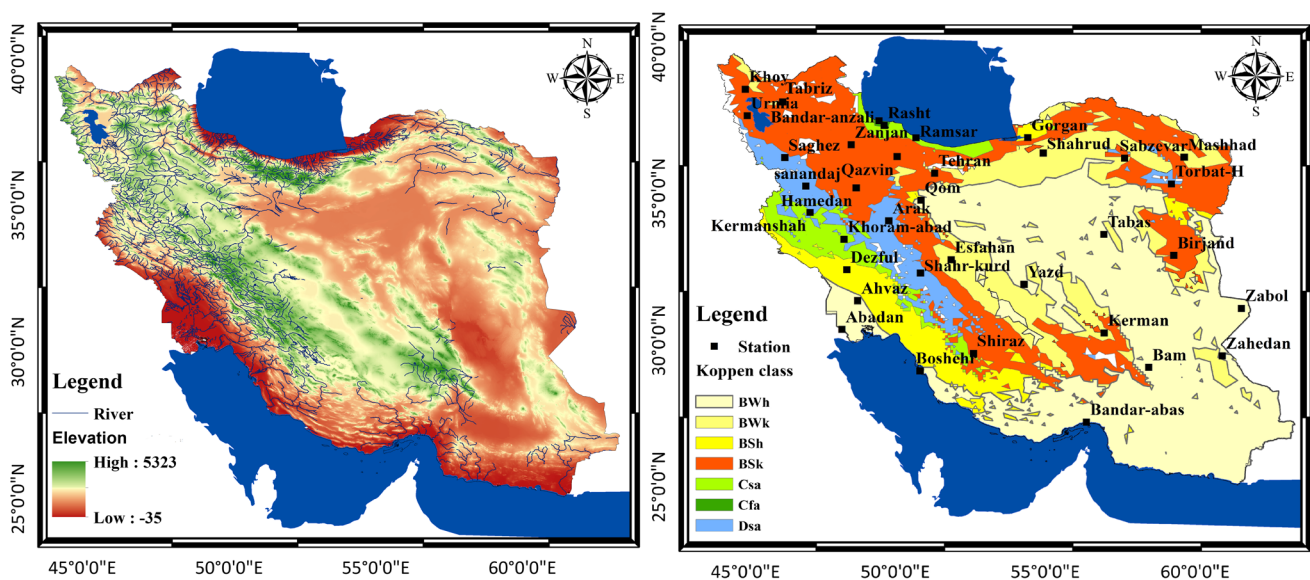
Fig. 1 Right: Study area and location of synoptic stations (indicated by black squares), Colors indicate climate type based on Koppen Geiger climate classification (Kottek et al. 2006). Left: Information about the Digital Elevation Model (DEM) and flow network in the study area

Table 1 Abbreviation of Koppen Geiger climate classification

Abbreviation	Description
BWh	Arid, desert, hot
BWk	Arid, desert, cold
BSh	Arid, steppe, hot
BSk	Arid, steppe, cold
Csa	Temperate, dry summer, hot summer
Cfa	Temperate, no dry season, hot summer
Dsa	Cold, dry summer, hot summer

measuring instrument of the variables, moving the location of the station, construction around the station over time or natural factors such as climate change. In this study, after checking the homogeneity of the data, the results of this section were compared with the results of the Rahmdel (2021) study, and in case of heterogeneity due to human factors, the data were homogenized with other nearby stations.

In a specific time frame and geographic location, the amount of fresh and accessible water needed to meet the needs of agriculture, drinking, industry, recharge aquifers, etc., can be determined by analyzing the difference between the precipitation and evapotranspiration of the region. By creating a time series of this difference and examining it, we can gain a comprehensive understanding of the water balance in the area (Das et al. 2022; Tadese et al. 2020). For this purpose, in this study, the Net Water Available (NWA) index is also considered to evaluate and show more precisely the potential of water resources in different parts of Iran.

Calculation ETo

The FAO Penman–Monteith method, established by the Food and Agriculture Organization, offers a widely adopted standard for calculating reference evapotranspiration (ETo) (Allen et al. 1998). ETo signifies the potential rate of evapotranspiration from a hypothetical, well-watered reference surface (Zotarelli et al. 2010). This method leverages a physically-based approach, incorporating key meteorological variables like radiation, temperature, wind speed, and humidity. Due to its robust foundation, the FAO Penman–Monteith method finds application in diverse climatic regions, facilitating standardized comparisons of ETo across locations. However, the method necessitates the acquisition of multiple climatic data points (Córdova et al. 2015).

Trend

The Mann–Kendall (MK) trend tests are used to identify the presence, direction, and significance of trends in time series data sets. These methods can be divided into two categories: parametric and non-parametric. The choice of method depends on the type of data being analyzed (Köyceğiz and Büyükyıldız 2023). Studies in hydrology and climatology have found that non-parametric methods, such as the Mann–Kendall method, are more reliable. These methods are less sensitive to extreme or missing values and do not require the data to conform to a stationary distribution (Zhai and Feng 2009). Additionally, non-parametric methods are more flexible in dealing with non-linear data (Hirsch et al. 1982; Wang et al. 2005; Yue et al. 2002). The Mann–Kendall

Table 2 The information of the investigated synoptic stations in Iran

Station Name	Latitude	Longitude	Elevation	Precipitation		Temperature		Evapotranspiration		C_Class
				Mean	CV	Mean	CV	Mean	CV	
Abadan	30.38	48.21	6.6	151.9	40.7	25.7	4.4	2293.2	8.1	**BWh**
Ahvaz	31.34	48.74	22.5	330.7	28.8	13.9	7.2	1309.5	6.2	**BWh**
Bam	29.08	58.45	940	58.1	47.0	23.5	4.0	1943.7	10.9	**BWh**
Bandar-abas	27.21	56.37	9.8	170.7	64.6	27.1	2.8	1835.0	6.8	**BWh**
Bushehr	28.96	50.82	9	238.8	43.8	24.9	3.1	1794.8	6.0	**BWh**
Qom	34.77	50.86	879.1	148.8	32.5	18.6	5.7	1678.3	7.8	**BWh**
Tabas	33.60	56.95	711	83.8	40.3	22.7	3.6	1788.8	15.1	**BWh**
Yazd	31.90	54.29	1230.2	55.6	45.5	19.8	5.4	1832.0	7.9	**BWh**
Zabol	31.09	61.54	489.2	54.2	54.2	22.7	5.1	3050.2	16.5	**BWh**
Zahedan	29.47	60.90	1370	80.0	49.4	18.8	4.7	1953.8	6.8	**BWh**
Esfahan	32.74	51.86	1551.9	123.4	36.9	16.6	4.6	1493.4	7.2	**BWk**
Kerman	30.26	56.96	1754	136.0	33.9	17.1	6.4	1795.6	7.9	**BWk**
Mashhad	36.24	59.63	999.2	251.2	27.1	14.5	8.7	1380.2	13.4	**BWk**
Sabzevar	36.21	57.65	962	187.3	32.5	17.8	5.1	1874.2	11.8	**BWk**
Shahroud	36.38	54.93	1325.2	157.8	33.7	14.8	5.3	1412.5	10.6	**BWk**
Dezful	32.40	48.38	143	387.5	32.9	24.4	4.6	1849.3	8.3	**BSh**
Gorgan	36.91	54.41	0	564.6	21.8	17.7	4.8	1183.2	15.5	**BSh**
Shiraz	29.56	52.60	1488	315.3	33.6	18.2	5.0	1634.7	6.2	**BSh**
Birjand	32.89	59.28	1491	159.6	31.4	16.8	4.8	1767.0	10.3	**BSk**
Hamedan	35.20	48.69	1679.7	315.4	25.8	11.3	8.4	1397.1	6.6	**BSk**
Khoy	38.56	45.00	1103.4	292.4	26.8	12.7	9.0	1052.1	9.4	**BSk**
Urmia	37.66	45.06	1328	332.7	29.3	11.2	8.7	1135.6	9.8	**BSk**
Qazvin	36.26	50.06	1279.1	318.0	26.5	14.3	8.7	1282.4	5.3	**BSk**
Tabriz	38.12	46.24	1361	283.9	27.9	12.5	7.9	1463.2	8.0	**BSk**
Tehran	35.69	51.31	1191	234.8	31.2	17.6	5.4	1634.4	6.1	**BSk**
Zanjan	36.66	48.52	1659.4	305.7	25.1	11.6	10.4	1272.1	8.8	**BSk**
Kermanshah	34.35	47.15	1318.5	443.3	26.9	15.0	6.7	1504.7	7.8	**Csa**
Khorramabad	33.44	48.28	1147.8	501.5	25.2	17.3	7.5	1450.2	11.9	**Csa**
Ramsar	36.90	50.68	-20	1237.6	23.4	16.2	5.2	832.2	7.9	**Csa**
Bandar-anzali	37.48	49.46	-23.6	1766.6	19.5	16.4	4.6	866.9	6.7	**Cfa**
Rasht	37.32	49.62	-8.6	1334.6	19.4	16.3	4.6	964.4	7.8	**Cfa**
Arak	34.07	49.78	1702.8	223.8	37.5	26.3	3.0	2064.6	8.9	**Dsa**
Sanandaj	35.25	47.01	1373.4	438.2	27.3	14.3	6.4	1351.2	8.1	**Dsa**
Saqqez	36.22	46.31	1522.8	480.2	25.8	12.1	10.8	1234.6	9.5	**Dsa**
Shahrekord	32.29	50.84	2048.9	324.5	27.8	12.3	9.2	1274.7	10.0	**Dsa**
Torbat-H	35.33	59.21	1451	255.9	31.0	14.1	7.4	1568.4	10.8	**Dsa**

non-parametric method is commonly used to detect trends in meteorological and climatological data. It was first introduced by Mann (1945) and later developed by Kendall (1975).

Mann–Kendall test which determines the intensity of the trend in the data according to the volume of data, at different significance levels. The Z statistic of the Mann–Kendall test is a measure without units, and this issue provides the possibility of examining and comparing trends in variables with different fluctuation ranges and units. In this study, taking into account that three different variables of precipitation,

temperature and evapotranspiration as well as the NWA index were considered for a long period of 60 years, Mann–Kendall method was chosen due to the simplicity of calculations, high accuracy and the possibility of comparing the results of these variables.

Hydrological data often exhibit autocorrelation, which can affect the variance and increase the likelihood of detecting false trends (Akçay et al. 2022). To address this, researchers have proposed methods that check for autocorrelation and, if present, remove its effects from the data (prewhitening) (Partal and Kahya 2006; WMO 2017). In this

study, the Durbin and Watson statistic (Durbin and Watson 1992), was used to determine the presence of autocorrelation. According to Hamed and Rao (1998), autocorrelation in data can lead to errors in variance calculation. Their method addresses this issue by taking into account the effect of autocorrelation in the data and calculating a corrected variance. (Koycegiz and Buyukyildiz 2022).

A linear trend in a time series can be detected using a nonparametric method developed by Theil (1950) and modified by Sen (1968). In this study, this practical and accurate method is used to calculate the linear slope of changes.

The sequential MK test is a progressive form of the MK test that has been recommended by the World Meteorological Organization (WMO) as an inappropriate method for analyzing progressive trends (Sneyers 1990). The sequential MK test considers the relative values of all terms in the time series. The test involves comparing the original time series to its reverse version to identify potential trends. The traditional MK test is widely used due to its simplicity and effectiveness in detecting monotonic trends (Bisai et al. 2014). However, the sequential MK test is suitable for datasets where understanding the progression of trends over time is essential. This could include long-term climate studies or monitoring environmental pollutants over extended periods (Zeybekoğlu 2023). In this study, the sequential MK test was used to show and compare the progress of trends over time in the original time series and the composites obtained from the wavelet transform analysis.

Wavelet transform

The wavelet transforms, first introduced by Grossmann and Morlet (1984), is a method for transferring data from argument space to frequency space. It has been widely used in various domains, particularly for analyzing hydrological and climate data. Researchers have found this method helpful in analyzing data with characteristics such as trends, different periodicities, noise, and missing data. Unlike the Fourier transforms method, which decomposes signals into smooth, unlimited oscillations, wavelet transform allows for the analysis of signals as waves with limited duration and varying frequencies and zero means. The method is done by changing the scale and functional parameters of the mother wavelet, which act as high-pass and low-pass filters that separate fast and small fluctuations in high frequencies from slow, large-scale fluctuations in low frequencies.

The continuous wavelet transform (CWT) method is divided into two categories, discrete and continuous. CWT decomposes the signal at all levels and produces a large amount of information that can reduce the accuracy of surveys. On the other hand, the discrete wavelet transform (DWT) method decomposes the signal into specific scales, which makes it more useful in various sciences, including

hydrological studies. Researchers such as Araghi et al. (2015) and Adamowski et al. (2012) have used DWT in their research.

The details of the mother wavelet function are given below.

$$\Psi_{(a,b)} \left\{ \frac{t - \gamma}{s} \right\} = \frac{1}{(s_0)^{\frac{a}{2}}} \psi \left\{ \frac{t - b\gamma_0 s_0^a}{s_0^a} \right\} \tag{1}$$

In this equation, ψ represents the mother wavelet, t is an independent value, γ is the translation factor,

and S is the dilation factor. a and b represent the dilation and translation of the wavelet, respectively,

and they are integers. The dilation step, denoted as s0, is a constant value greater than 1. The location.

variable, denoted as γ0, has a value greater than zero.

In the mathematical realm, the equation $W\psi$ (a, b) serves as a cornerstone of signal processing, offering a unique perspective on the transformation of signals. $W\psi$ (a, b) is a wavelet transform that hinges on two crucial parameters: a, which controls the scaling, and b, responsible for the translation. This equation, as represented in Eq. (2), is at the heart of various applications, uncovering hidden insights within signals by manipulating these key parameters (Partal and Kahya 2006).

$$W_\psi(a, b) = \frac{1}{(2)^{\frac{a}{2}}} \sum_{t=0}^{N-1} x_t \psi \left[\frac{t}{2^a} - b \right] \tag{2}$$

In order to use the wavelet transform method for data analysis, one must first choose the exact type of the mother wavelet function and the number of required levels of analysis. Among the four common types of functions in discrete wavelet transform (Haar, Meyer, Morlet, and Daubechies), the Daubechies type is the most used in this field, which is used in this study. Considering that the DB family itself has ten different types, for the selection of the proper function of the Db and the most optimal number of decomposition levels, used from the error measurement indicators, mean relative error MRE and relative error e_r.

The details of these indicators are:

$$MRE = \frac{1}{n} \sum_{j=1}^{n} \frac{\left| a_j - X_j \right|}{\left| x_j \right|} \tag{3}$$

Where n is the number of data, x_j is the original time series, and a_j is the approximation value of x_j.

$$e_r = \frac{\left| z_a - z_0 \right|}{z_0} \tag{4}$$

Where z_a is the MK Z-value of the last approximation for the decomposition level used, and z_0 is the MK Z-value of the original time series.

According to the results obtained from the above relationships, 6, 5, and 4 levels of analysis were selected for

monthly, seasonal, and annual time series, respectively. In Table 3, it is mentioned that each of these levels represents the periodicity in the data.

There is a clear correlation between hydrological and climatic events. However, traditional correlation analysis methods are unsuitable for studying this relationship as they can only analyze the time series with linear characteristics and do not account for changes over time and at different scales. Wavelet transform correlation (WTC and XWT) methods, on the other hand, can effectively show the correlation between two, time series at different frequencies without restrictions. In this study, we used the WTC method to examine the relationship between precipitation, temperature, evapotranspiration, and NWA. More information on wavelet cross-correlation (WCC) can be found in references such as Labat (2008), Torrence and Compo (1998), and Grinsted et al. (2004).

Climate variable data often include periods of different scales, ranging from short to long-term, each of which can be associated with a trend (Adamowski et al. 2013). In this study, the highest frequency was identified among all compounds. These compositions include an approximate component and one or two detailed components. To detect the dominant periodicity composition, two criteria were used: the difference between the trend of the main time series and each combination, and the correlation between the sequential Mann–Kendall values of the main time series and each combination. These criteria were evaluated using MAE, RMSE, and R^2 indices.

Results

Autocorrelation

Autocorrelation in the data can affect trend detection, as positive autocorrelation increases the likelihood of rejecting the null hypothesis (absence of trend), and negative correlation reduces it. In this study, the autocorrelation of the data was checked first, and then trends in each time series were investigated using the Mann–Kendall or modified Mann–Kendall methods (Koycegiz 2024b). The results showed that the autocorrelation rate for the precipitation variable in all stations was about 0.45, likely due to the inherent characteristics of this variable, such as the absence of specific order and pattern in temporal and spatial distribution. For the temperature and evapotranspiration variables, the investigations showed that in all stations, the autocorrelation rate was significant in degrees 1, 6, and 12 and had values between 0.84 and 0.97. For the NWA variable, the results showed that the autocorrelation in this variable in stations with humid climates is similar to the precipitation variable and it is at the maximum rate of 0.53. On the contrary, in stations with dry climates, the autocorrelation of NWA is more than 0.8. Since the NWA variable is the result of the difference between precipitation and evapotranspiration, the statistical characteristics of the NWA series in these regions are mostly similar to the evapotranspiration variable.

In order to better analyze the results of the autocorrelation analysis in the data, researchers have explained relationships in which a threshold is determined to detect the significance of the autocorrelation value obtained in the data. In this study, after determining the autocorrelation value in the data, its significance has also been checked, and if it is significant, the modified Mann–Kendall method has been used. In the modified Mann–Kendall method, the effect of autocorrelation in the data is removed, which is called data pre-whitening. Various methods have been introduced by researchers for pre-whitening the data, and in this study, the most widely used method, Hamed and Rao's method, is used.

Dominant periodic components

The exact details of how to detect the dominant periodicity during the sample for Motaghar Barash and Mashhad station are given in Table 4. From the examination of Table 4 and the tables of other stations, it seems that there is no clear relationship between the periodicity in different time scales (monthly, seasonally, and annually). This is because when surveys are conducted on an annual scale, fluctuations with a larger amplitude and intensity are considered, and seasonal fluctuations are not considered due to their smaller amplitude. It should be noted that in some cases, it has been observed that periodicity on the annual scale has also been recognized in the long-term periodicity of the seasonal scale. Another point from these tables is that when

Table 3 The abbreviations for periodicities in monthly, seasonal and annual time scales (Araghi et al. 2015)

	Monthly	Seasonal	Annual
D1	2 months	2 seasons and 6 months	2 years, 8 seasons, and 24 months
D2	4 months	1 year, 4 seasons, and 12 months	4 years, 16 seasons, and 48 months
D3	8 months	2 years, 8 seasons, and 24 months	8 years, 32 seasons, and 96 months
D4	16 months	4 years, 16 seasons, and 48 months	16 years, 64 seasons, and 192 months
D5	32 months	8 years, 32 seasons, and 96 months	
D6	64 months		

Table 4 The R^2, RMSE, and MAE error metrics between the sequential Mann–Kendall results for the main time series and each of the periodicities, as well as the Z value of the Mann–Kendall test in different time scales, for the precipitation variable in Mashhad station

	Monthly				Seasonal				Annual			
	Z	R^2	RMSE	MAE	Z	R^2	RMSE	MAE	Z	R^2	RMSE	MAE
Orginal TS	3.53				3.07				6.73			
A6	21.1	0.9	13.31	12.08	14	0.91	8.22	7.39	7.71	0.97	2.61	1.97
D1	-0.09	0.43	1.5	1.1	0.14	-0.38	1.41	1.11	0.16	0.52	3.22	2.38
D2	-0.28	0.67	1.66	1.3	-0.15	0.35	1.53	1.12	0.08	0.08	3.45	2.6
D3	-0.06	0.17	1.45	1.02	-0.09	0.23	1.93	1.6	0.67	-0.1	3.37	2.75
D4	0.05	0.21	1.81	1.41	2.14	-0.1	1.9	1.66	0.79	0.43	3.66	3.03
D5	1.18	0.02	1.69	1.38	0.76	-0.28	3.43	2.91				
D6	5.55	0	4.84	3.91								
A6+D1	14.75	0.95	6.91	5.47	3.08	0.94	0.31	0.26	7.52	0.99	0.64	0.56
A6+D2	12.36	0.95	4.66	3.51	3.07	0.93	0.5	0.42	7.89	0.98	0.86	0.74
A6+D3	2.72	0.9	0.26	0.18	13.1	0.92	5.7	4.53	7.21	0.97	0.96	0.63
A6+D4	12.29	0.95	5.02	3.95	14.8	0.9	7.26	5.79	7.97	0.95	1.79	1.67
A6+D5	22.18	0.92	11.58	9.27	14.3	0.9	7.38	6.61				
A6+D6	24.86	0.91	12.84	10.52								
A6+D1+D2	11.99	0.95	3.91	2.95	2.71	0.94	0.25	0.19	7.37	0.99	0.63	0.45
A6+D1+D3	2.7	0.92	0.26	0.21	2.95	0.91	0.28	0.24	*7.1*	*0.99*	*0.45*	*0.32*
A6+D1+D4	12	0.95	4.2	3.26	3.19	0.98	0.46	0.43	7.02	0.99	0.58	0.5
A6+D1+D5	14.72	0.95	6.67	5.18	*3.03*	*0.99*	*0.19*	*0.15*				
A6+D1+D6	21.52	0.95	7.1	5.37								
A6+D2+D3	2.55	0.93	0.29	0.25	2.94	0.94	0.41	0.29	7.46	0.98	0.58	0.47
A6+D2+D4	9.86	0.95	3.28	2.5	3.27	0.94	0.37	0.3	7.74	0.98	0.97	0.89
A6+D2+D5	12.66	0.95	4.59	3.44	3.18	0.96	0.52	0.42				
A6+D2+D6	13.94	0.95	4.84	3.42								
A6+D3+D4	3.32	0.95	0.27	0.23	13.1	0.71	5.79	4.45	7.12	0.97	1.62	1.12
A6+D3+D5	2.78	0.96	0.19	0.14	13.2	0.81	5.45	4.33				
A6+D3+D6	*3.04*	*0.99*	*0.18*	*0.14*								
A6+D4+D5	12.51	0.94	4.95	3.85	15.0	0.97	6.63	5.2				
A6+D4+D6	13.8	0.95	5.21	3.88								
A6+D5+D6	24.01	0.93	11.5	8.82								

examining periodicity on a seasonal scale, the natural annual periodicity and hot and cold seasons (spring and summer are hot seasons and autumn and winter are cold seasons) can be distinguished.

As mentioned in the previous articles, a combination of periods (short-term and long-term) can have the best description of how a climate variable changes, such as precipitation, temperature, and transpiration. that in no variable and station, individual periodicities were not recognized as the most dominant periodicity. (Tables related to other stations are available in the supplementary material).

The results of the detection of the most dominant periodicity in the data (Table 4) related to the 36 investigated stations are given in Table 5.

Figure 2 shows the average of the dominant periodicities in each station ("Mean" column in Table 5). According to Table 5 and Fig. 2, the average periodicity of each station is between 4 and 10 years. With further investigation, it was found that these periods can be divided into three periods,

4 to 6 years, 6 to 8 years, and 8 to 10 years, which represent short-term, medium-term, and long-term periods, respectively. The number of stations in these three types of periodicities is: short-term 12 stations, medium-term 15 stations, and long-term 9 stations.

After examining the periodicities in a stationary manner, the results of this section were also examined for the variable. Table 6 shows the mean of the dominant periodicity duration of each variable among all the investigated stations. According to Table 6, it can be seen that, in general the evapotranspiration variable has the longest periodicity, followed by NWA, temperature, and precipitation respectively.

In order to better examine the relationship between the dominant periodicity between the variables and the stations, calculations have also been made at the same time, the results of which are shown in Fig. 3. Figure 3 shows the cumulative values of the series of important periodicities (short-term and long-term) in the stations. In this figure, eight graphs are drawn in such a way that the first graph

Table 5 Annual periodicity periods (separated between long-term (L–T) and short-term (S-T)) along with average and cumulative values of them, in each time series and desired stations

Station	Precipitation		Temperature		Evapotranspiration		NWA		Sum	Mean
	S-T	L–T	S-T	L–T	S-T	L–T	S-T	L–T		
	Seri1	Seri2	Seri3	Seri4	Seri5	Seri6	Seri7	Seri8		
Abadan	4	16	2	4	2	8	2	8	46	5.75
Arak	2	8	2	4	2	16	2	16	52	6.5
Ahvaz	4	8	4	16	2	4	2	4	44	5.5
Bam	2	4	2	8	8	16	8	16	64	8
Bandar-abas	2	8	2	4	2	16	2	16	52	6.5
Bandar-anzali	2	8	2	4	8	16	2	16	58	7.25
Birjand	2	4	2	16	2	16	4	8	54	6.75
Bushehr	2	16	2	8	2	8	8	16	62	7.75
Dezful	4	16	2	8	2	8	2	8	50	6.25
Esfahan	2	8	2	8	2	8	2	16	48	6
Gorgan	2	4	2	4	2	8	2	8	32	4
Hamedan	2	8	2	4	8	16	4	8	52	6.5
Kerman	2	4	4	16	8	16	2	16	68	8.5
Kermanshah	2	4	4	16	8	16	2	16	68	8.5
Khoram-abad	2	4	4	16	4	8	2	16	56	7
Khoy	4	8	4	8	4	16	4	16	64	8
Mashhad	2	8	2	8	2	4	2	16	40	5
Urmia	2	16	2	4	4	16	2	16	62	7.75
Qazvin	2	8	4	8	2	16	2	16	58	7.25
Qom	4	8	2	16	8	16	8	16	78	9.75
Ramsar	2	4	2	8	8	16	2	4	46	5.75
Rasht	4	8	2	4	4	16	2	4	44	5.5
Sabzevar	2	16	2	4	4	8	2	4	42	5.25
Sanandaj	8	1	4	8	8	16	2	8	55	6.875
Saqez	2	4	4	16	2	8	2	8	46	5.75
Shahre kord	2	4	2	16	4	8	4	16	56	7
Shahroud	2	16	2	4	8	16	2	4	54	6.75
Shiraz	2	16	4	8	2	16	2	16	66	8.25
Tabas	2	8	2	16	4	8	8	16	64	8
Tabriz	2	16	2	4	2	8	2	8	44	5.5
Tehran	2	8	2	4	2	16	2	4	40	5
Torbat-heydarieh	2	8	2	16	4	16	4	16	68	8.5
Yazd	2	4	2	8	2	8	2	4	32	4
Zabol	2	16	4	16	4	16	4	16	78	9.75
Zahedan	2	8	2	4	4	8	2	8	38	4.75
Zanjan	2	8	4	8	4	16	4	8	54	6.75

(light blue graph) only includes short-term periodicity in the precipitation variable in each of the stations, and in the same way, the highest of them, which is displayed in brown color, is the values of column 10 "Sum", in Table 5, which is the cumulative value of all important periods in each of the stations.

By examining Fig. 3, it can be concluded that there is a relatively good correlation in the length of the periodicity between different time series (precipitation, temperature, evapotranspiration, and NWA in one station. In this way, if the duration of the periodicity in the temperature variable in station A is longer than in station B, it will most likely be the same in the case of the evapotranspiration variable. This point can indicate that the effect of a hypothetical factor such as climate change on creating periodicity in the time series of important variables such as precipitation, temperature, and evapotranspiration was approximately the same.

Fig. 2 Average periodicity periods (resulting from 4 desired time series) in each station on the annual scale
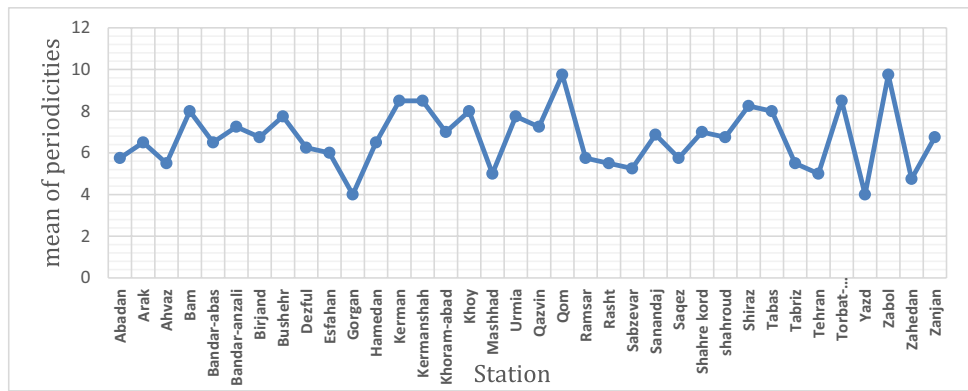

Table 6 Average periods of periodicity related to each of the time series in all stations on an annual scale

	Precipitation	Temperature	Evapotranspi-ration	NWA
Average periodicity length (years)	5.5	5.8	8.3	7.3

Trend

In the previous section, the dominant periodicities in the desired time series were investigated, which indicated the manner and details of the changes in the time series. In this section, the Mann–Kendall test (original and modified) and Theil-Sen slope test were used to check the amount of time changes (intensity and slope) of the data.

Precipitation trend

As it is clear in Fig. 4, there is a significant decreasing trend in the stations in the west and east of the country, although the number of these stations is more in the west of the country and the trend is more severe. The noteworthy point is

that the stations of Ramsar, Qazvin, Tehran, Esfahan, Shiraz, Bushehr, etc., which are located in latitudes 50 to 51, have an increasing trend or a weak decreasing trend in this variable. The highest increasing trend is seen in the Esfahan, Tehran, and Ramsar stations, while the highest decreasing trend is found in the Gorgan, Sanandaj, and Kermanshah stations. A study by Malaekeh et al. (2022) found that the majority of the stations with decreasing trends in precipitation were concentrated in the northwestern, western regions of the country between 1986 and 2015, which does align with the results presented in Fig. 4. Additionally, it appears that the long-term trend (60 years) of precipitation significantly differs from the shorter-term trend (30 years). Even though various studies have noted that precipitation lacks a specific pattern compared to temperature and other variables due to its higher spatial and seasonal variations, an almost specific, particular pattern of the amount and direction of changes was identified in the examination of this variable for 60 years in Iran.

A study by Some'e et al. (2012) found that the northwestern and southeastern regions of Iran had the most extreme trends in the precipitation variable, determined by examining the annual data time series from 1967 to 2006. These results align with the present study, except that the southeastern

Fig. 3 In the figure above, there are eight graphs in different colors according to Table 5, which respectively consist of a blue line (seri 1), red line (sum of series 1 and 2), green line (sum of series 1, 2, and 3), the dark blue line (sum of series 1,2,3, and 4), the light blue line (sum of series 1,2,3,4, and 5), orange line (sum of series 1,2,3,4,5, and 6), yellow line (sum of series 1,2,3,4,5,6, and 7), brown line (sum of series 1,2,3,4,5,6,7, and 8)
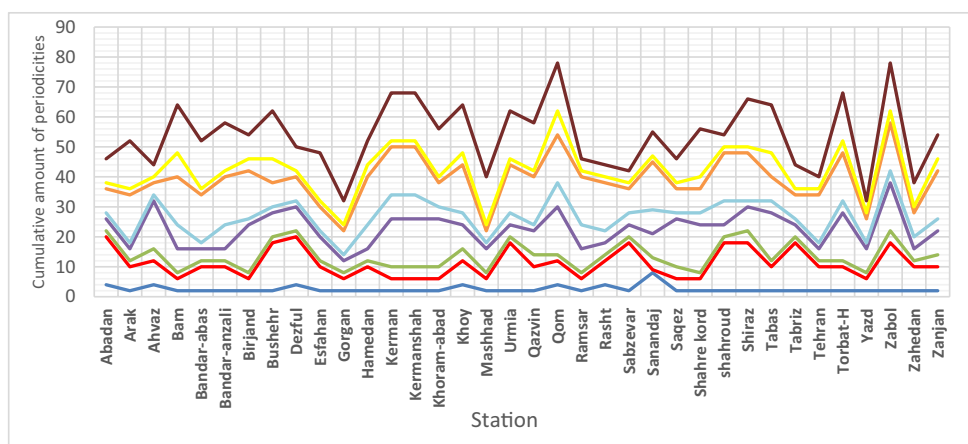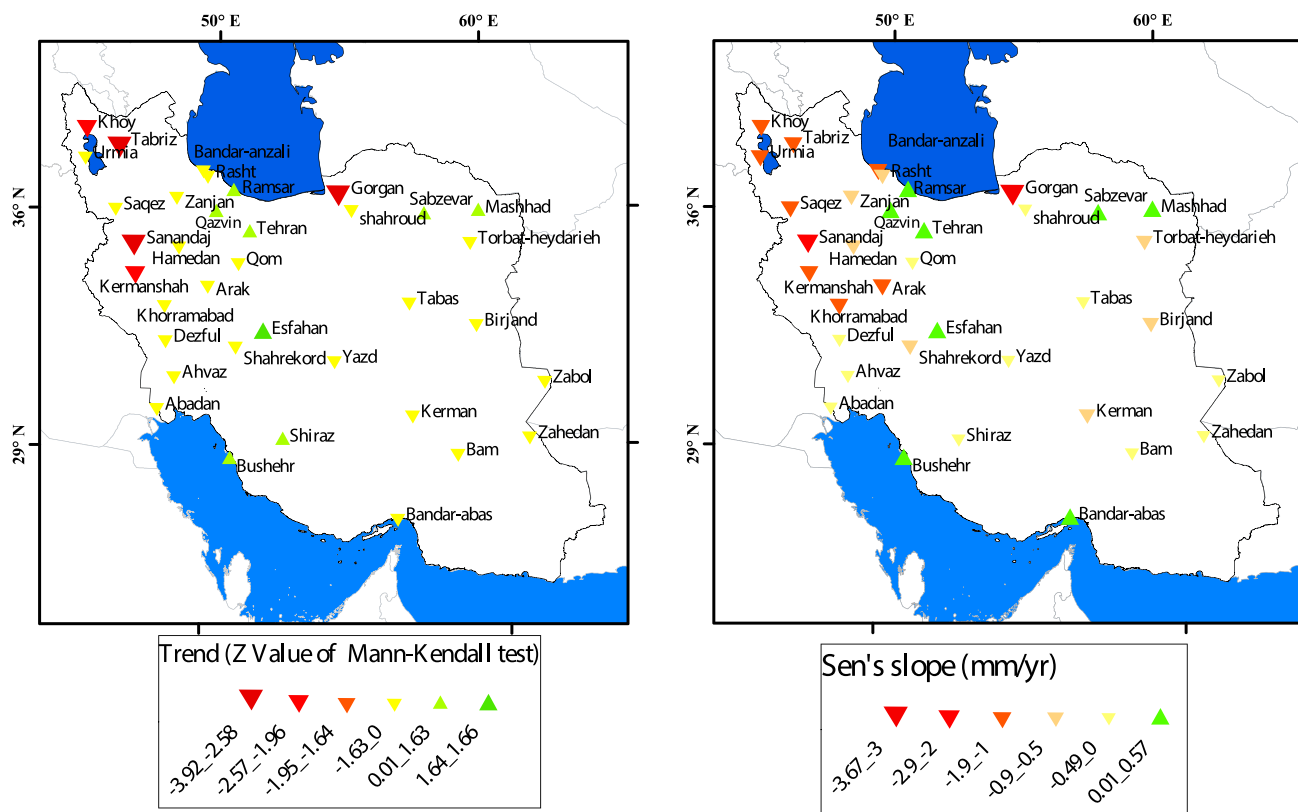
Fig. 4 Left: The value of the trend in the 36 investigated stations related to the time series of precipitation, which is the value of the Mann–Kendall test (significance levels of 90, 95, and 99% are included in the classification of domains). Right: the numerical value of the trend calculated by the Sen's slope test (unit: mm/year)

regions now have a non-significant and weak trend, which may be attributed to changes in the recent years' trend (2006 to 2020).

Temperature trend

According to Fig. 5, which illustrates the trend of temperature variations in Iran, it can be observed that the stations located on the central strip, from north to south, have a significant increasing trend. This includes stations Rasht, Ramsar, Tehran, Esfahan, Yazd, Tabas, Shiraz, and Bushehr. Notably, thesestations had a very low increasing or decreasing trend in investigating the precipitation variable. However, stations such as Tabriz, Khoy, Urmia, Zahedan, and Kermanshah have a trend of increasing temperature and decreasing precipitation, which can have detrimental effects on the climate of these regions.

In a study by Malaekeh et al. (2021) on the trend of hydroclimatic variables throughout Iran for 30 years from 1986 to 2015. They found that the intensity of the trend in the temperature variable has an inverse relationship with the mean temperature in most stations. However, in this current study, it was found that there is no relationship between the intensity of the trend and the average temperature in the 36 stations in question in the period from 1961 to 2020. A study by Ghasemi (2015) also concluded that regions with hot climates in Iran are warming faster than the cold regions, which is consistent with the results of this current study in Fig. 5. In general, the results of this study suggest that the trend of increasing temperature and decreasing precipitation has occurred more and is dominant in Iran. This result is supported by various previous studies (Alizadeh-Choobari and Najafi 2018; Tabari and Talaee 2011a, b). However, it should be noted that the length of the studied period can have a significant effect on the results of the investigation of the trend. A 60-year period seems to result in a more reliable trend analysis. Studies in this field have stated that the major changes and unprecedented slope in the trend of hydroclimatic data started from the 1980s onwards and have since increased significantly (Capstick et al. 2015). According to the reports of the International Committee on Climate Change, the reason for this issue is global warming caused by human activities (IPCC 2013).
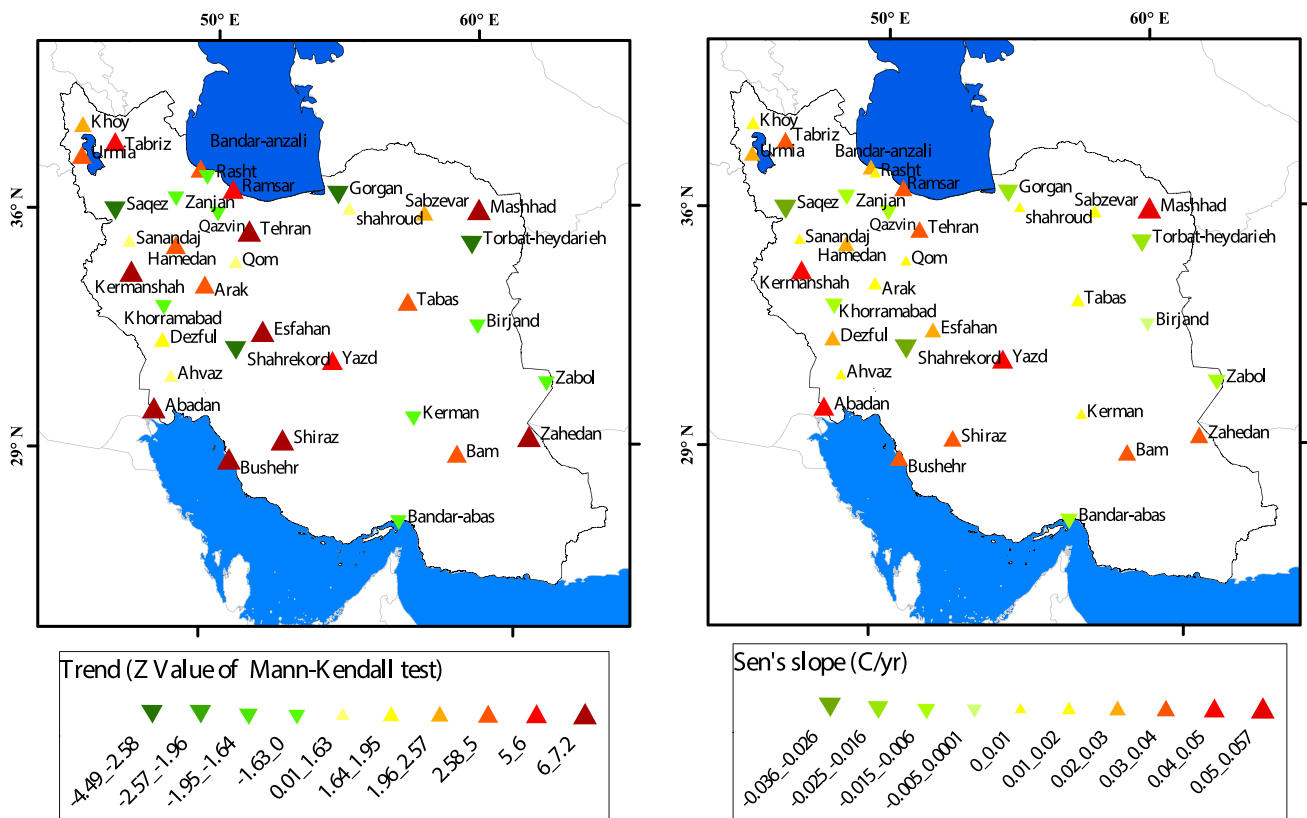
Fig. 5 Left: the value of the trend in the 36 investigated stations related to the time series of temperature, which is the value of the Mann–Kendall test (significance levels of 90, 95 and 99% are included in the classification of domains). Right: the numerical value of the trend calculated by the Sen's slope test (unit: °C/year)

Evapotranspiration trend

The results of investigating the trend in the evapotranspiration time series are given in Fig. 6. There is a significant trend in the time series of evapotranspiration in most western and eastern stations of the country like precipitation, but with the difference the evapotranspiration data series has an increasing trend. With further investigation, it was found that except for Dezful and Ahvaz stations in the west and Torbat Heydarieh in the east, the rest of the stations in these parts have a significant increasing trend. In the studies of Malaekeh et al. (2022) and Dinpashoh et al. (2011) a significant increasing trend has been detected in the northwest and eastern border areas.

Kousari and Ahani (2012) announced that the investigation of the variable trend of evapotranspiration during the 30 years from 1975 to 2005 shows that there is a significant increasing trend in the northwestern and eastern border areas of Iran, which is consistent with the results obtained in this study. They also examined the sensitivity of the evapotranspiration variable to other parameters affecting it and declared that the trend in the wind speed data in different regions has the greatest impact and correlation

with the trend created in the evapotranspiration data series. Nasrollahi et al. (2021) in a study investigated the variable trend of evapotranspiration during the 30 years from 1988 to 2017. They also recognized a significant increasing trend in the northwestern parts. According to Fig. 5 and Fig. 6, it can be seen that all the stations that had a significant trend in the temperature variable do not have a significant increasing trend in the evapotranspiration variable. In contrast, the relationship between these two variables is expected to be direct. But according to the obtained results, it seems that this hypothesis is not entirely correct. This discrepancy can be attributed to the complexity of the atmospheric dynamic system and the interactions between various climatic variables. As mentioned in the first content of this chapter, the evapotranspiration values were calculated using the standard FAO Penman–Monteith method. Unlike other methods that largely depend only on the average temperature, this method estimates the amount of evapotranspiration with eight parameters in hand, the most important of which are temperature, wind speed, relative air humidity, and the number of sunny hours. Therefore, while an increase in temperature would typically result in an increase in evapotranspiration, other factors such as wind speed, relative
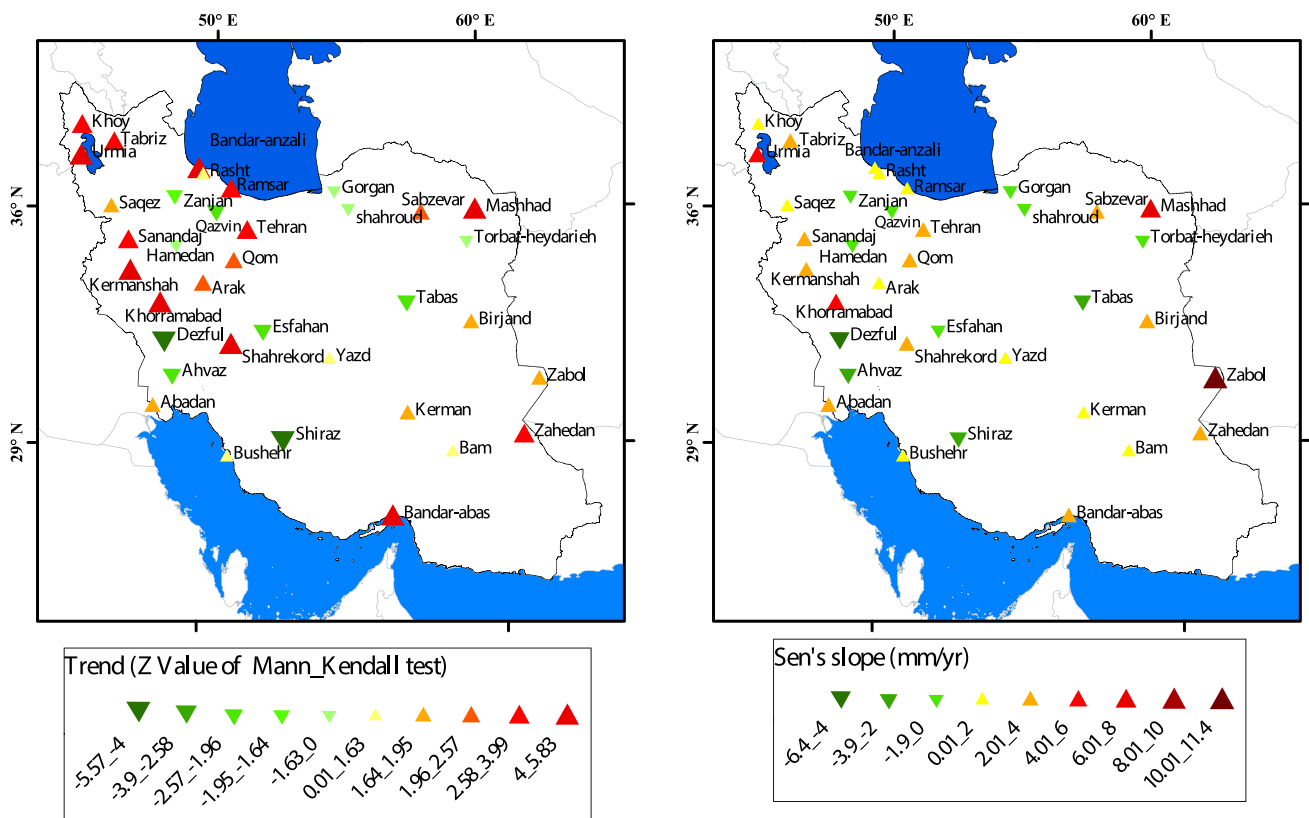
Fig. 6 Left: the value of the trend in the 36 investigated stations related to the time series of evapotranspiration, which is the value of the Mann–Kendall test (significance levels of 90, 95 and 99% are included in the classification of domains). Right: the numerical value of the trend calculated by the Sen's slope test (unit: mm/year)

humidity, and sunshine hours can also play a significant role. Table 7 examines this issue in more detail by analyzing the trend of temperature, wind speed, relative humidity, and sunshine hours in 14 stations that do not follow the initial

assumption of a direct relationship between temperature and evapotranspiration.

According to the Z values presented in Table 7, the probability of accepting the hypothesis that other effective

Table 7 The value of Mann Kendall's z statistic related to the variables of evapotranspiration, temperature, wind speed, relative humidity, and sunshine hours

	Evapotran-spiration	Temperature	Wind Speed	Relative Humidity	Sunshine Hours
Ahvaz	-2.22	0.17	-4.2	-0.56	1.9
Bandar-abas	4.41	-1.29	1.35	-0.86	1.26
Birjand	1.7	-0.93	3.6	-2.6	3.4
Dezful	-5.57	1.8	-3.9	2.67	-1.37
Esfahan	-2.16	6.12	-5.61	-3.17	-0.27
Hamedan	-0.6	4.82	-3.86	0.58	-0.61
Kerman	1.8	-0.1	-4.51	-0.57	2.69
Khorramababd	4.04	-1.35	4.12	-0.99	0.26
Saqqez	1.96	-3.97	5.38	1.52	1.6
Shahrekord	4.32	-4.49	4.87	-1.28	0.53
Shiraz	-5.02	6.94	-6.43	-2.54	0.32
Tabas	-2.01	3.59	4.64	-1.11	0.15
Torbat-heydarieh	-0.65	-3.57	1.97	-0.28	0.39
Zabol	1.93	-1.52	6.14	-1.43	0.34

parameters can neutralize the effect of temperature on the rate of evapotranspiration increases significantly. This means that in cases such as the Dezful station, where there is a significant trend of decreasing temperature, the trend of evapotranspiration data may also be decreasing due to a significant decreasing trend in wind speed and sunshine hours at this station. However, further and more detailed investigations are needed to fully accept or reject this hypothesis, which is beyond the scope of this research. A study by Shadmani et al. (2012) investigated the trends in evapotranspiration data in the country from 1965 to 2005. By comparing the results of this study with the current study, it is found that among the common stations between the two studies, most stations in the past had significant decreasing trends or insignificant increasing trends. However, in the current surveys, it can be seen that the increasing trends have intensified and are now significant, while the decreasing trends are very subtle or have changed to increasing trends. There are also stations such as Shiraz that have been associated with a significant decreasing trend in both studies, and the Ahvaz station, which had an increasing trend in the past, but now has a significantly decreasing trend.

NWA trend

Figure 7 shows the trend in the NWA time series in the country. According to the results of this section, it can be concluded that, in general, the amount of available water or the potential of water resources in the whole country has decreased, which can be caused by an increase in transpiration or a decrease in precipitation. However, it is essential to note that this situation may not be entirely clear in reality, as there are other factors involved. For example, while there may be an increase in the capacity and amount of water storage, there may also be a significant increase in water consumption and harvesting, which can lead to water scarcity. Factors such as population growth, expansion of cultivated land, and changes in consumption patterns in both domestic and industrial sectors can contribute to this increase in consumption.

The general result of trends analysis

Table 8 shows the frequency of stations at significant levels for variables such as precipitation, tem- perature, evapotranspiration, and NWA. The table shows that evapotranspiration
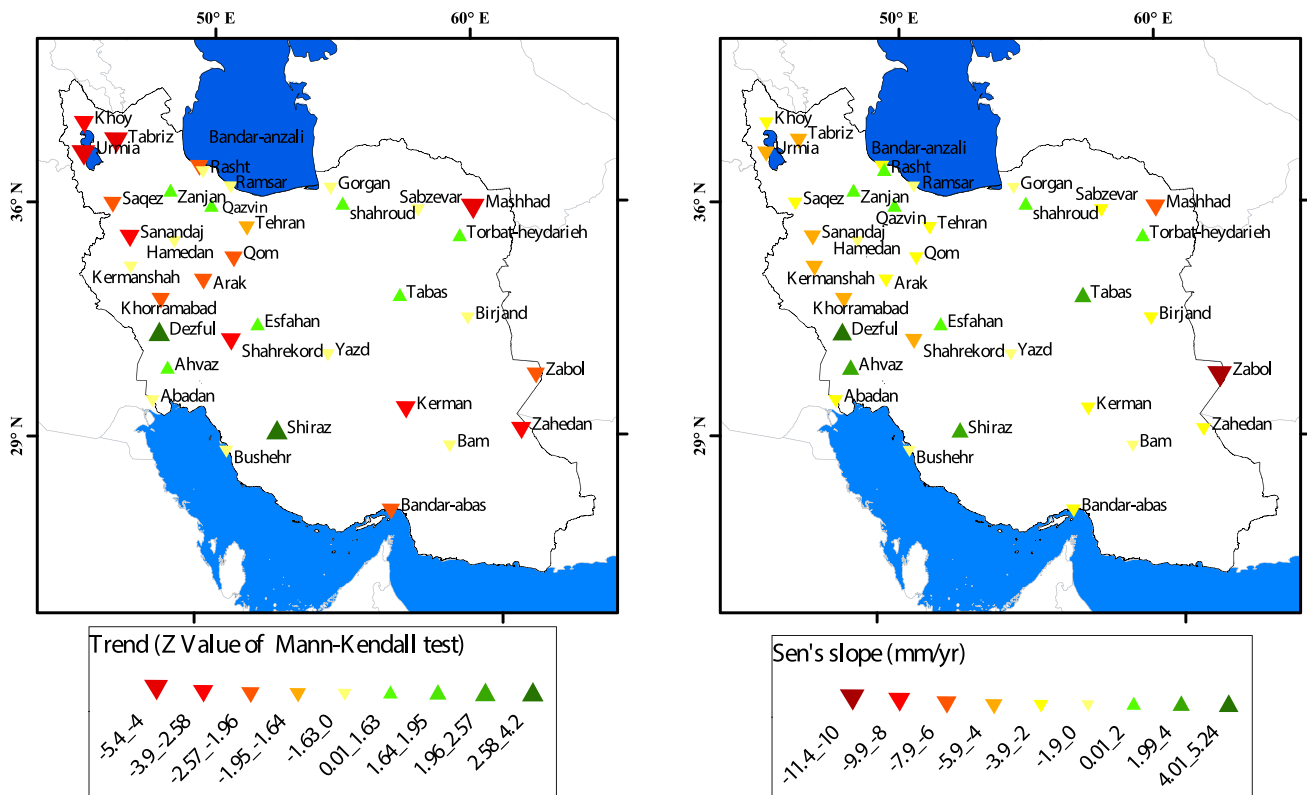

Fig. 7 left: the value of the trend in the 36 investigated stations related to the time series of NWA, which is the value of the Mann–Kendall test (significance levels of 90, 95, and 99% are included in the classification of domains). Right: the numerical value of the trend calculated by the Sen's slope test (unit: mm/year)

is the most frequent, followed by temperature with 24 stations, NWA with 18 stations, and precipitation with six stations. According to Table 8, it is clear that only six stations in the country have a significant trend in the precipitation variable, of which five stations have a decreasing trend. These results are supported by the studies of Araghi et al. (2015) and Malaekeh et al. (2022). Considering the high sensitivity and dependence on this variable in Iran, a decreasing trend at the level of several stations can also cause disruption and deficiency in the hydrological cycle and water resources.

In order to further analyze the results obtained from data trending, investigations were carried out on the relationship and correlation between trend values and climate type and elevation, which is shown in Fig. 8.

Figure 8 (right) illustrates the trend of each variable of precipitation, temperature, evapotranspiration, and the NWA index across different climate classes as defined by the Köppen-Geiger climate classification. The data reveal that temperature and evapotranspiration exhibit a pronounced increasing trend in nearly all climates, except the Bsh climate, which does not follow this trend for the evapotranspiration variable. Precipitation generally shows a decreasing trend, although this trend is often statistically insignificant across the various climates. The NWA index, which is a measure of net water availability, also demonstrates a decreasing trend in all climates except for the Bsh climate. A noteworthy detail regarding the Bsh climate class is that it is represented by only 3 out of the 36 stations investigated. These stations display a very strong decreasing trend in potential evapotranspiration. This is significant because, despite the weak decreasing trend in precipitation observed at these stations, the NWA index still shows an increasing trend, with a mean Mann Kendall's Z value of 2. The Dsa climate classification, shown by the purple line on the radar

Table 8 Frequency of stations with trends (increasing and decreasing) at significance levels of 90, 95 and 99% in the annual time scale

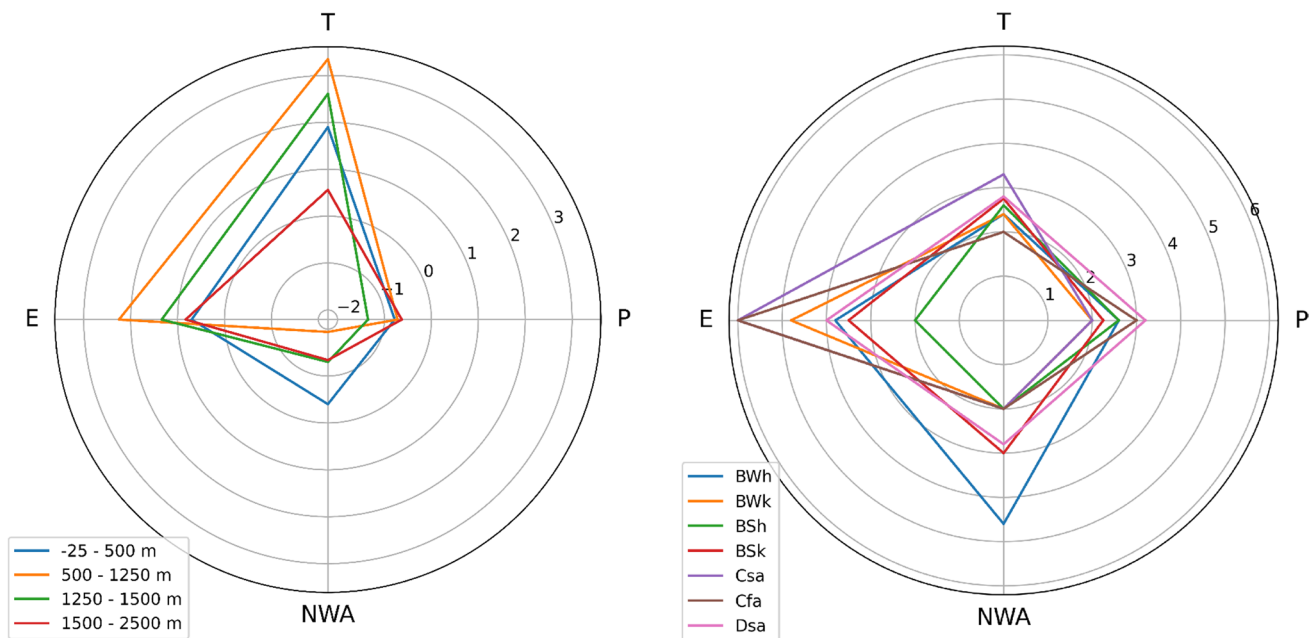|	Precipitation		Temperature		Evapotranspiration		NWA	
	Increase	decrease	Increase	decrease	Increase	decrease	Increase	decrease
Significance level								
90% (Z > 1.64)	1	0	1	0	5	1	0	1
95% (Z > 1.96)	0	2	2	0	3	4	0	7
99% (Z > 2.58)	0	3	17	4	13	2	2	8
Sum	1	5	20	4	21	7	2	16
Total sum	6		24		28		18	

Fig. 8 right: Radar chart of long-term trend of variables P: Precipitation, T: Temperature, E: Evapotranspiration, and NWA index in each climate classification. Left: Radar chart of the long-term trend of variables P: precipitation, T: temperature, E: evapotranspiration, and NWA index for different elevation ranges

chart, shows a complex trend characterized by a significant decrease in temperature over time. At the same time, there is a moderate decrease in precipitation and an increase in evapotranspiration. In general, these changes cause a sharp downward trend in the NWA index. This issue emphasizes that temperature changes are not a good measure of the amount of water resources available in a region, and a detailed investigation should be done on the basic parameters of the water balance of the region.

In general, the radar chart provided below highlights that the trends of these fundamental variables precipitation, temperature, evapotranspiration, and the NWA index are largely similar across the different climate classes.

The radar chart in Fig. 8 (left) showcases the relationship between elevation and the long-term trends of precipitation, temperature, evapotranspiration, and net water available (NWA) index in Iran. According to the figure, it can be seen that the height range of 1250 to 1500 has more significant and intense trends than other ranges and after that the range of 1250 to 1500. The noteworthy point is that low elevations (-25 to 500 m) and high elevations (1500 to 2500 m) have fewer trends than the two middle elevation ranges. The reason for this can be the proximity of low elevation points to the coasts and the pressure drop and temperature drop at high elevation.

In this section, the results of precise trend calculations for each time series are presented. To thoroughly analyze these findings, various perspectives were considered, including the desired variable, climatic classification, altitude range, trend significance, and the direction of the trend (increasing or decreasing). It is noteworthy that this study marks the

first comprehensive analysis of trending results for critical climatic variables in Iran over a 60-year period, highlighting the significance of the findings.

Furthermore, to consolidate and visually present the trend results for each variable and station across different significance levels, diagrams were created and are displayed in Figs. 9 and 10. These figures facilitate the simultaneous comparison of time series trends and stations.

Correlation between NWA and variables

After analyzing the results of wavelet-based correlation analysis among the studied stations, it was observed that precipitation and NWA exhibit a high correlation in shorter periodicities, ranging from 70 to 80 percent of the stations. This correlation tends to be significant, primarily observed in the later years of the studied period. These findings indicate the emergence of transient fluctuations with short-term return periods in the precipitation variable across the country. Regarding the evapotran- spiration variable, it holds greater importance and serves as a determining factor in NWA and aridity. In most stations, a strong correlation is observed between evapotranspiration and NWA across various periodicities. This suggests the significant influence of evapotranspiration on NWA values.

Examining the results regarding the temperature variable showed that there is no specific and significant pattern or relationship between this variable and the NWA series. This lack of correlation can be attributed to the relatively complex interactions between temperature, precipitation, and evapotranspiration, which are the primary parameters in
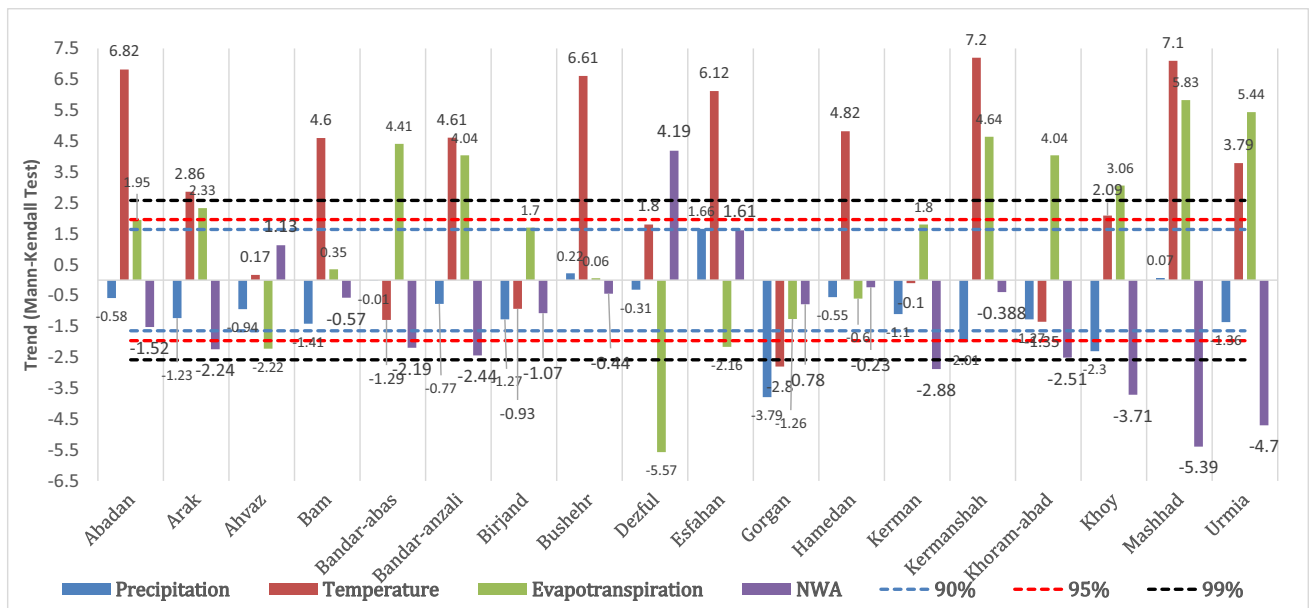

Fig. 9 Trends of precipitation, temperature and evapotranspiration variables, and NWA in the annual scale—the first 18 stations
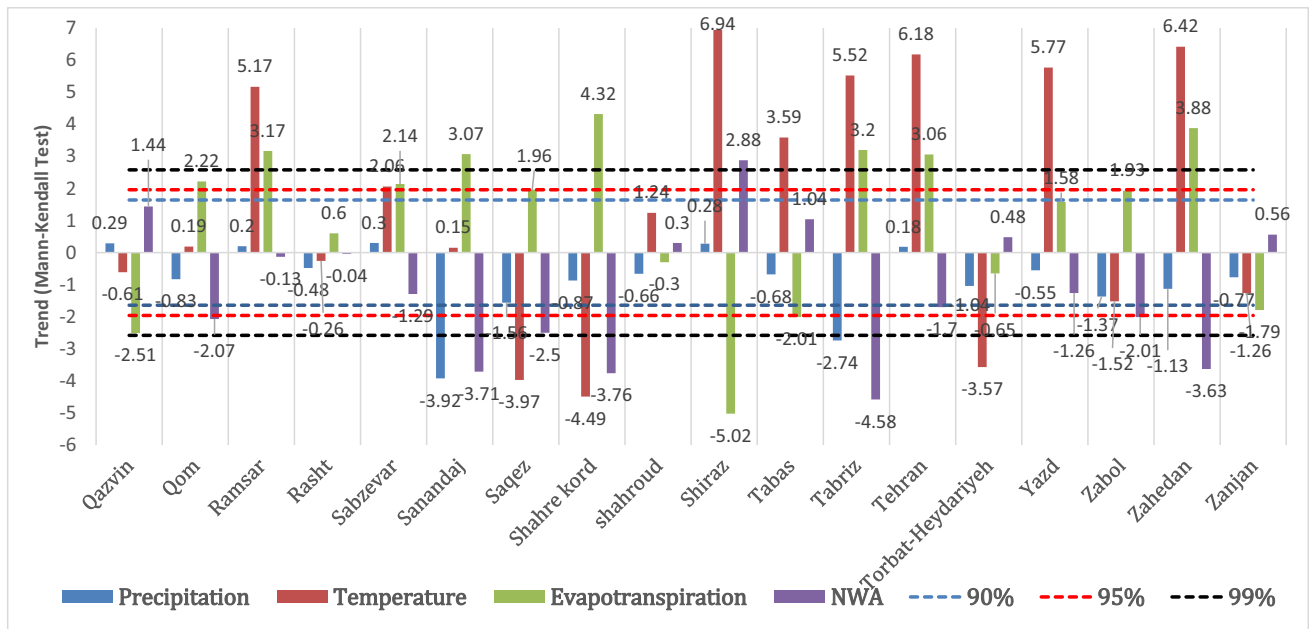
Fig. 10 Trends of precipitation, temperature and evapotranspiration variables, and NWA in the annual scale—the second 18 stations

determining NWA values. Overall, the utilization of wavelet function-based methods to investigate correlations between these variables has effectively shed light on the manner and extent of the influence exerted by important climatic variables, namely precipitation, temperature, and evapotranspiration, on the availability of water resources. The results of this analysis demonstrate that these correlations are not constant over time and vary across different periodicities. Such findings are consistent and logical considering the magnitude and direction of long-term changes in climatic variables in other regions and over time.

In the figures below, the color guide on the right indicates the degree of correlation (between 0 and 1) and the direction of the arrows shows the type of relationship between the two time series, which respectively include: a direct relationship (right direction), a relationship Inversely (downward direction), there is an inverse relationship with time delay (upward direction) and a direct relationship with time delay (downward direction).

In the following, the results of investigating this type of correlation between variables in Tehran (Fig. 11) and Esfahan (Fig. 12) stations are given as examples and analyzed.

In the results related to the Tehran station given in Fig. 11, it can be seen that in general, the precipitation variable has a high correlation (coefficient 0.7 to 0.9) with the NWA index from 2005 onwards in all periodicities. The correlation of the temperature variable with the NWA index is low in most years and all periodicities, however, in the last years of the period (the last 10 years), a relatively high correlation of about 0.7 to 0.8 is observed in the periodicities of 4 to 8 years. The

evapotranspiration variable has a high correlation with the NWA index in periodicities of 1 to 8 years, although this correlation has decreased from 2000 to 2020 and is more present in short-term periodicities of 1 to 4 years.

The results of this survey for Esfahan station are shown in Fig. 12. The noteworthy point in the results of this station is the existence of an area with a correlation higher than 0.9 in the last 10 to 20 years of the studied period in all three variables of precipitation, temperature, and evapotranspiration, this pattern was also observed in most of the studied stations. It is noteworthy that this area exists especially in the precipitation variable and then in the evapotranspiration variable in many stations. A study has been conducted in the northwestern neighborhood of Iran, in Turkey. Topçu (2022) analyzed the characteristics of meteorological drought, including the severity and the manner of changes in Turkey from 1925 to 2016, and the results of the Mann–Kendall test in this study show that there is no significant increase in the trend of droughts, but the periodicity of droughts has become shorter, which is also observed in the stations located in the northwest of Iran, in such a way that the beginning of short-term periodicity in the decreasing trends of precipitation in three stations Tabriz, Urmia and Khoy can be recognized in the results in recent years.

Discussion

This study was conducted with the aim of comprehensive (temporal and spatial) and accurate analysis of precipitation, temperature and evapotranspiration time series in Iran.
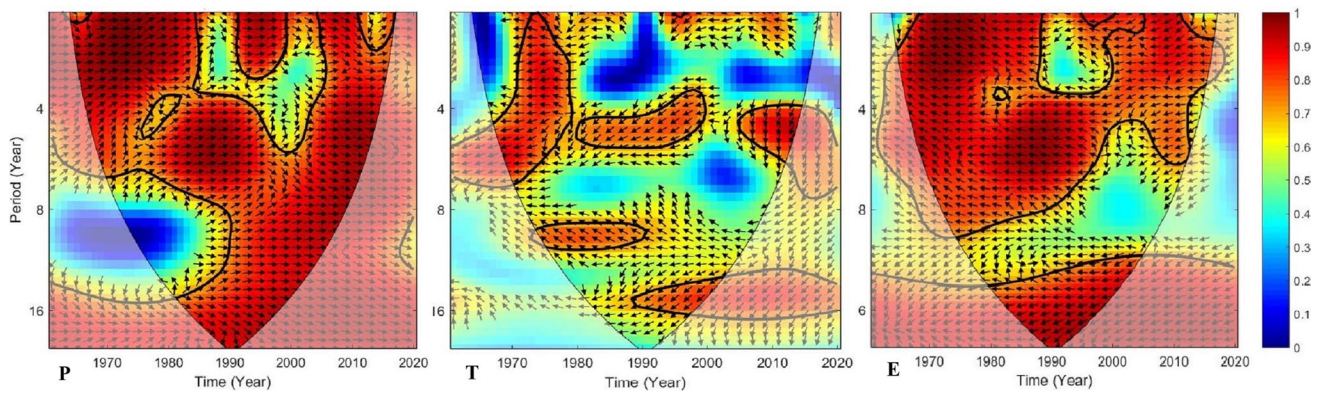
Fig. 11 Wavelet cross correlation between NWA index and variables of precipitation (P) and temperature (T) and evapotranspiration (E). (Tehran Station)
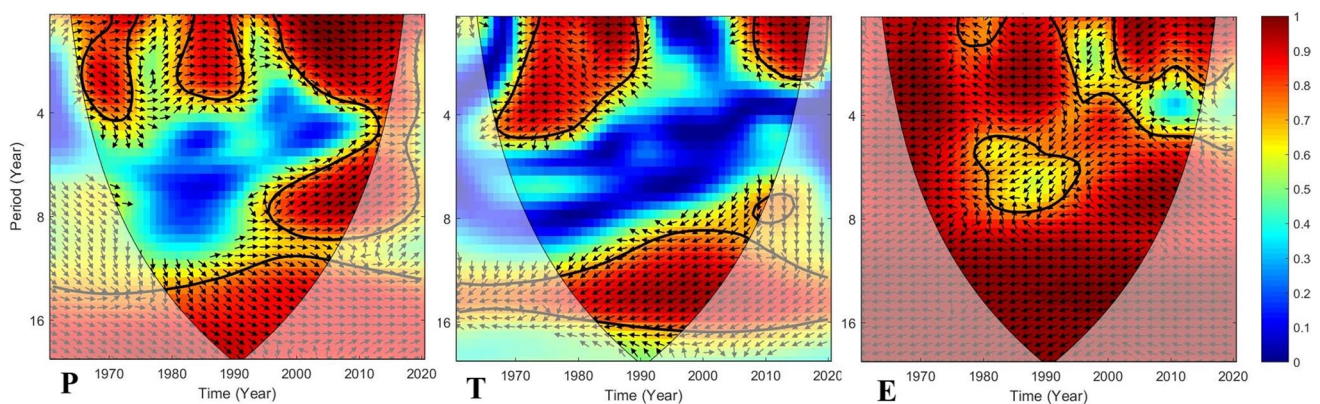

Fig. 12 Wavelet cross correlation between NWA index and variables of precipitation (P) and temperature (T) and evapotranspiration (E) (Esfahan Station)

These evaluations have included an unprecedented unveiling of the various aspects of the behavior of these variables during a long period of 60 years. The improvement of mathematical and statistical methods was able to obtain very precise and practical and new results from the various dimensions of these variables, which have not been observed in the study until now. These results generally show how much these variables have changed in a long period of time and under what pattern and fluctuation these changes happened. In the meantime, the turning point of the beginning of these changes was determined in the homogeneity of the data, which made all aspects of a significant change to be examined. The results of these investigations were able to give a very complete and documented answer to the questions of this study. However, this study pursues a higher goal, which was to relate these results to the general situation of water resources in Iran. By calculating and creating the NWA index and conducting investigations on this index along with other variables, a very valuable view of the climate situation based on the potential of available water

resources was formed. This part of the study is done for the first time in the geographical area of Iran.

In the end, it can be said that, in general, these surveys showed that the potential of available water resources in different regions of the country has changed and to what extent? And which climatic variables have played a more important role in these changes? This study has tried to include complete and accurate details of these results.

Conclusions and suggestions

This research investigated the water balance in Iran from 1960 to 2020 by analyzing time series data of key climatic variables precipitation, temperature, evapotranspiration, and the amount of available water (NWA) across monthly, seasonal, and annual time scales from 36 stations. The study aimed to uncover trends and periodicity using a combined method of wavelet transforms and the Mann–Kendall test (both original and modified). The analysis revealed several

critical findings. Potential evapotranspiration exhibited the most extended periodicity of 8.3 years and the highest number of stations with significant trends (28 stations at significance levels above 90%). In contrast, precipitation showed the lowest number of stations with significant trends (6 stations) and the shortest cycle period (5.5 years). These results suggest that previous studies, which primarily linked water scarcity to decreased precipitation over periods of less than 40 years, might have overlooked other crucial factors such as increased water output (evapotranspiration), population growth, changes in consumption patterns, and the expansion of agricultural areas. Temperature trends were observed in 24 stations with an average periodicity of 5.8 years. Additionally, trends in NWA were noted in 18 stations, with an average periodicity of 7.3 years. Cross-wavelet transform (XWT) and wavelet transform coherence (WTC) functions were utilized to assess the correlation between the different time series values over time and across various periodicities. This analysis enabled the determination of the influence of precipitation and evapotranspiration on the available water in different years.

Overall, the application of wavelet transforms and Mann–Kendall methods proved effective for time series analysis of climatic variables, providing a comprehensive understanding of water availability changes across 36 points in Iran with varying climates.

It is suggested that in a study with data on the consumption of water resources in different sectors (agriculture, industry, drinking, etc.), the allocated amount of available water resources in each sector should be considered, because in general, the amount of water resources available in most parts of the country is decreasing, the results of these surveys can be used in the best possible way to optimize the distribution of water resources between different sectors. The results of this research showed that there is no significant long-term trend in the investigated stations, considering that this trend analysis was done on the total amounts of precipitation, it is suggested to conduct a study on the spatial changes of intensity and number of precipitation, to achieve a more accurate understanding of the complex behavior and dynamics of precipitation.

Authors' contributions Ali Rezaee: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Visual- ization; Writing – Original draft; Writing – Review and editing. Abolfazl Mosaedi: Supervision, Conceptualization, Formal analysis; Methodology, Visualization; Review and editing. Aliasghar Beheshti: Supervision; Review and editing. Azar Zarrin: Supervision; Visualization; Writing – Review and editing.

Declarations

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