

Research

doi: 10.22034/jcema.2022.339827.1085

Evaluation and Analysis of Drought on the Quantity and Quality Water Resources in Lorestan Province (Case study of Khorram River)

Reza Hassanzadeh ^{*1}, Mehdi Komasi ²

¹ Department of civil engineering, Ayatollah Ozma Borujerdi University, Borujerd, Iran.

² Assistant Professor, Hydraulic Structure, Department of Civil Engineering, Faculty of Engineering, University of Ayatollah ozma Borujerdi, Borujerd, Iran.

*Correspondence should be addressed to Reza Hassanzadeh, Department of civil engineering, Ayatollah Ozma Borujerdi University, Borujerd, Iran. Tel: +989195902380; Email: reza.hassanzadeh@abru.ac.ir

ABSTRACT

In recent decades following a lot of droughts, many changes have been made in the quantity and quality of the country's water resources. This factor has caused many uncertainties in the management of the country's water resources. The purpose of this study is to improve the understanding of drought effects on the quantity and quality of water resources in Lorestan province from the years 2008 to 2018 by coherence and cross wavelet method. To achieve this goal, first, drought assessment according to precipitation data has been examined using (SPI) index, and then the effect of drought on Khorram river runoff is analyzed. Then, the global index of water and the drought impact on this index in the Khorram River were evaluated. Also, the global index of water quality (WQI) and the impact of drought on this index in the Khorram River are evaluated. The results of coherence and cross wavelet indicated the relative effect of precipitation with a wavelet coherence coefficient of 0.6 on changes in water runoff in the Khorram River is of degree first importance. Also, the relative impact of drought with a wavelet coherence coefficient of 0.4 changes in water quality of Khorram River has been more than other factors. Therefore, climatic factors in reducing the water runoff of the Khorram River from factors other are more important. Also, the results showed human factors as the most important ones in water quality changes in the Khorramabad River.

Keywords: Index SPI, Drought, Khorram River, WQI Index, Coherence Wavelet

Copyright © 2022 Reza Hassanzadeh. This is an open access paper distributed under the [Creative Commons Attribution License](#). *Journal of Civil Engineering and Materials Application* is published by [Pendar Pub](#); Journal p-ISSN 2676-332X; Journal e-ISSN 2588-2880.

1. INTRODUCTION

Rivers are a small part of the world's running water and carry about 32 to 37 cubic kilometers of water to the ocean each year. Rivers are one of the main sources of water supply for various purposes such as agriculture, drinking, and industry. Iran is located on the world's drought belt by being in the position of 25 to 40-degree north latitude and for a long time and now is facing the problem of drought. This subject, besides the

occurrence of severe and prolonged droughts, created conditions for the country, which has faced serious challenges. Numerous studies have been conducted to identify the effects of drought on the quantity and quality of water resources. For example, Researchers studied the statistical analysis relating variations in groundwater levels to droughts on Jeju Island, Korea. This study indicated that PCA could be a powerful tool for

summarizing large datasets to select index wells that are vulnerable to droughts, which would significantly reduce the expense of monitoring programs (Jung et al. 2021) [11]. In this regard, Komasi et al. (2016) examined the routing and classification of factors affecting the reduction of groundwater levels by using coherence and cross wavelets in the Silakhor plain. The result of this study showed that the runoff time series, which represents human effects, has a greater effect on reducing the aquifer level of Silakhor plain than the precipitation and temperature time series, which represents climate change [2]. Also, Soleimani Motlagh et al. (2015), in a study on the aquifer resources of Lorestan province, showed that drought has a significant effect on water quality variables such as Ci , Na , TDS , and EC . One of the important results of this research is that the water quality based on Schuler and Wilcox diagrams has changed due to drought, and the quality of drinking water has decreased [3]. Wolff et al. (2021) studied the impact of the 2018 drought on pharmaceutical concentrations and the general water quality of the Rhine and Meuse rivers. The results showed that low flow combined with high temperatures resulted in a general deterioration of surface water quality of both the Meuse and Rhine rivers during the 2018 drought. Also, the trend of declining groundwater levels continues to decline, and the continuation of this trend will further reduce the runoff of wells, canals, and springs [4]. Han et al. (2020) studied the effects of vegetation restoration on groundwater drought in the Loess Plateau, China. Results indicated that the normalized difference Vegetation Index (NDVI) during 2003 – 2015 in the LP was growing rapidly; meanwhile, groundwater storage significantly decreased ($p < 0.01$), and groundwater drought intensified in terms of its area and intensity [5]. Piravi et al. (2015) a study evaluated and analyzed the effects of drought on the water quality of rural wells in the Kashfar area of Mashhad plain. The results showed that the groundwater level decreased quantitatively and qualitatively from 2007 to 2011, and a significant relationship exists between changes in water level and water hardness [6]. The results of a study examining the groundwater drought index in the United States have shown that the SPI drought index with a delay of 12 and 24 months has the highest correlation with the SWI index (Tatiana 2019) [7]. Zhao et al. (2021) investigated quantitative analysis of nonlinear climate change impact on drought based on the standardized precipitation and evapotranspiration index. The results indicated that drought on the SNP has been mitigated marginally during 1961–2016, mainly during spring, winter, the growing season, and on the annual timescale [8]. In another study, neural network and regression models were used to predict drought in the Polish-Ethiopian river basin. The results showed that the linear regression model is better than the artificial neural network (Mishra et al. 2012) [9]. Kim et al. (2019) investigated the quantitative vulnerability assessment of water quality to

extreme drought in a changing climate. The results of this study showed that due to severe droughts, the water quality of the Nakdong River has decreased [10]. Ghaffari et al. (2021) studied the Spatial and temporal variation of groundwater quality around a volcanic mountain in northwest Iran. The results indicated that groundwater quality in the studied area is deteriorating [11]. On the other hand, Nourani et al. (2015) investigated the changes in hydrological processes using the entropy wavelet criterion in Lake Urmia. Using this criterion, they introduced the reduction of water flow time series fluctuations in the Urmia Lake basin as the most important factor in reducing the water level of this lake [12]. To investigate the complexity of the entropy method, he used several scales for rainfall and runoff time series and observed that the results obtained at higher time scales were different from the results obtained at lower time scales (Chou 2014) [13]. Feng et al. (2022) investigated climate change impacts on concurrences of hydrological droughts and high-temperature extremes in a semi-arid river basin of China. Results showed that the frequency of CHDHEs increased by 160% from 1961 to 1988 to the recent period 1989–2016 [14]. Evan & Timothy. (2021) studied the effects of climate and land use changes on the water quantity and quality of coastal watersheds of Narragansett Bay. Results showed significant effects of climate change and land-use change on the watershed, with demonstrated impacts on sediment loading, organic N, organic P, and nitrates. Climate impacts were much more significant than land-use effects, but land-use impacts displayed greater regional variation [15]. Mohd & Abhishek. (2020), the investigated groundwater quality assessment in the Lower Ganga Basin using entropy information theory and GIS. The results obtained in this paper are useful for identifying suitable sites for tube wells and bore-wells for drinking and agricultural purposes and also for developing an effective strategy to avoid further contamination of groundwater aquifers in the region [16]. Kubicz et al. (2021) studied the effects of drought on environmental health risks posed by groundwater contamination. This study found that in some cases, the occurrence of drought did not cause an increase in the non-carcinogenic threat expressed by the hazard index [17]. Hassanzadeh et al. (2021) investigated the effect of climate change on the decline of Khorramabad groundwater level using an entropy wavelet. The results showed that climatic factors (precipitation) had a greater effect on reducing the groundwater level [18]. According to the research background, the analysis of data and time series by wavelet transform with high speed and accuracy was performed, and unlike other methods of signal analysis, the trend of sudden changes, breakpoints, and discontinuities can be identified. Due to the comprehensiveness and suitability of the SPI index for drought monitoring, therefore, from SPI standard precipitation index to drought monitoring and also, in order to analyze and evaluate the quantity and

quality of Khorram river water with different factors have been used, cross and coherence wavelet and the global

quality index WQI.

2. MATERIALS AND METHODS

2.1. CASE STUDY

Khorram River is in Khorramabad city in Iran, which is located between the lengths of 47 °55' to 48 °50' east and latitudes 40 °32' to 34 °20' north and at an altitude of 1147 meters above sea level. Also, the length of this river is about 110km, of which about 5km passes through the city of Khorramabad. This river joins the Kashkan River in the place of two waters and after a long route and joining rivers such as Cholhol and Madian River in the place of Gaumishan Bridge; it is connected to Seymareh River. The

city has a temperate and semi-moderate Mediterranean climate, with favorable precipitation, especially in spring. The water of the Khorram River enters through four stations Bahramjo, Chamanjir, Doabvisian, and Karganeh. The highest and lowest runoff of the Khorramabad River in the years 2008 to 2019 was in 2018 and 2012, respectively. [Table 1](#) shows the statistical characteristics of the study area.

Table 1. Statistical information of the study area from 2008 to 2018

Parameter	Minimum	Maximum	Average	Standard deviation	Skewness
Precipitation (mm)	0	125.5	38.1	46.5	1.5
Temperature (degree Celsius)	-1	40.3	19.2	8.5	0.8
Evaporation (mm in month)	0	360.5	152.2	140.3	0.2
Runoff (Cubic meters per second)	146.5	452.1	238.2	144.7	2.2

2.2. STANDARD PRECIPITATION INDEX (SPI)

The SPI index is a powerful tool to process the precipitation data, and its purpose is to assign a numerical value to precipitation through which areas with different climates can be compared together. One of the advantages of SPI is that the calculation of SPI is based on rainfall data and does not depend on soil moisture conditions; another advantage is that this index is not affected by topography

(Komasi et al. 2013) [\[19\]](#). In general, this index is defined to express drought as follows: when the SPI is permanently negative and reaches a value -1 or less and when the value is positive. Therefore, positive values indicate above-average rainfall, and negative values indicate less rainfall than average rainfall, which is shown in [Table \(2\)](#) (Komasi et al. 2013) [\[19\]](#).

Table 2. Drought classification based on SPI index (Hassanzadeh et al. 2012) [\[20\]](#)

Drought intensity	Index values
extreme wet	2 and more
very wet	1.5 to 1.99
Moderate wet	1 to 1.49
Near to normal	-0.99 to 0.99
Moderate drought	-1.49 to -1
very drought	-1.99 to -1.5
extreme drought	-2 and lees

The main data of the SPI index are rainfall data of rain gauge stations. After ensuring the homogeneity and randomness of the monthly data, the time series is formed in the intervals of 6 and 12 months, and its time series is

fitted with the gamma distribution, the probability or plenty function of which is given in Equation 1 (Mckee et al. 1993) [\[21\]](#).

$$f(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} X^{\alpha-1} e^{-x/\beta} \tag{1}$$

In this relation $x \geq 0$ is the amount of precipitation, $\alpha > 0$ is the shape parameter, $\beta > 0$ is the scale parameter and Γ

(α) is the gamma function represented by Equation 2.

$$(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \tag{2}$$

In equation (2), the parameters α and β related to the gamma density function are estimated for each station and for each time scale, and for each month of the year. Mckee et al.

estimated α and β coefficients using the optimal maximum proofing base on equations (3) to (5). (Mckee et al. 1993) [21].

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{a}} \right) \tag{3}$$

$$A = \ln(\bar{X}) - \frac{\sum \ln(X)}{n} \tag{4}$$

$$\beta = \frac{\bar{x}}{a} \tag{5}$$

In the above equation, n is the number of precipitation observations, and x is the average precipitation for several months. The calculated parameters to find the cumulative probability of precipitation used for a specific time in each

station; this probability can be converted to an incomplete gamma function according to equation 6 with the assumption $t = x/\beta$.

$$G(X) \int_0^X g(X) dX = \frac{1}{\Gamma(\alpha)} \int_0^X t^{(\alpha-1)} e^{-t} dt \tag{6}$$

Since the gamma function is not defined for $x=0$, the rainfall distribution has a value of zero the cumulative

probability is calculated as equation 7.

$$H(X) = q + (1 - q)G(X) \tag{7}$$

Q is the probability of rainfall zero, and m is the number of zeros in the rainfall time series, which estimates (q) as

the product of m divided by the total number of data (n), then by having $H(X)$ and relations 8 to 11, SPI is obtained.

$$SPI = - \left[t - \frac{C_0 + C_1 t + C_2 t}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right] \quad 0 \leq H(X) \leq 0.5 \tag{8}$$

$$SPI = + \left[t - \frac{C_0 + C_1 t + C_2 t}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right] \quad 0.5 \leq H(X) \leq 1 \tag{9}$$

$$t = + \sqrt{\ln \left(\frac{1}{H(X)^2} \right)} \quad 0 \leq H(X) \leq 0.5 \tag{10}$$

$$t = + \sqrt{\ln \left(\frac{1}{(1-H(X))^2} \right)} \quad 0.5 \leq H(X) \leq 1 \tag{11}$$

In these relation, the coefficients are constant $C_0, C_1, C_2, d_1, d_2, d_3$ which should be placed from table 3

in relationships 8 to 11 (Mckee et al. 1993) [21].

Table 3. Coefficients values of SPI calculation formulas (Mckee et al. 1993) [21]

Coefficient	d ₁	d ₂	d ₃	C ₀	C ₁	C ₂
Value	1.43	0.18	0.01	2.51	0.80	0.10

2.3. CROSS WAVELET TRANSFORMATION

The main purpose of a cross wavelet is to obtain a complete time-frequency representation of a local and temporary event that varies on time scales. Cross wavelet transformation diagrams are examined to identify periods that offer regions with high wavelet spectra. Cross wavelet

diagrams identify periods that provide areas with high examined wavelet spectra examined. According to equation 12 with any desired mother wavelet, like Morlet's mother wavelet, equation 13 can estimate the wavelet

transform for the time series of each hydrological data $x(t)$ (Labat. 2010) [22].

$$C_{\psi}^{*x}(a, b) = \int x(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (12)$$

$$\psi_0(\eta) = \Pi^{-1/4} e^{i\omega_0 \eta} e^{-\eta^2/2} \quad (13)$$

Ψ_0 is a function of the mother wavelet, e exponential function and ω frequency without dimension η time are dimensionless, and also mark "*" refers to a mixed mating of the mother wavelet. The parameter "a" is expressed as a scale factor if it is $a > 1$, the time series expands along the time axis, and if $a < 1$ the time series contracts along the time axis. Parameter "b" is used as a position factor and

allows you to study the time series $x(t)$ around time b . the concept of wavelet transform can be used to investigate the relationship between two different time series related to two separate hydrological processes. For this purpose, the wavelet spectrum $W_x(a,b)$ of the time series $x(t)$ is similar to Fourier analysis and is defined by the absolute value of the wavelet coefficient.

$$W_x(a,b) = C_{\psi}^x(a, b) C_{\psi}^{*x}(a, b) = |C_x(a,b)|^2 \quad (14)$$

This wavelet spectrum can be averaged in time, which is generally defined as the average wavelet power spectrum and allows to specify the scale specification (Torrence & Compo 1998) [23]. The vacillation alternation period specification is determined using the overall wavelet

spectrum. Similar to the Fourier coherence spectrum and wavelet coherence spectrum $W_{xy}(a,b)$ is defined between two different hydrological time series $x(t)$ and $y(t)$, as follows.

$$W_{xy}(a,b) = C_{\psi}^x(a, b) C_{\psi}^{*y}(a, b) \quad (15)$$

Which $C_{\psi}^x(a, b)$ and $C_{\psi}^{*x}(a, b)$ are the continuous-time series wavelet coefficients $x(t)$ and mixed, the wavelet

coefficient is $y(t)$. The wavelet spectrum averaging technique is used to express the mutual covariance of time series $x(t)$ and $y(t)$ and their distribution at different scales.

2.4. COHERENCE WAVELET TRANSFORMATION

The coherence wavelet spectrum was inappropriate to express the interrelationship between the two processes, and hence the use of coherence wavelet transforms in time series processing which is more appropriate to find a criterion of correlation between two-time series at different frequencies and time (Nourani et al. 2015) [24].

In this regard (Torrence & Webster 1999) [25] suggested that the wavelet communication be determined using smooth wavelet spectrum estimation. Smooth wavelet spectrum $SW_{xx}(a,b)$ and wavelet coherence spectrum $SW_{xy}(a,b)$ are defined as below:

$$SW_{xx}(\alpha, b) = \int_{t-\delta/2}^{t+\delta/2} W_{xx}^*(a,b) W_{xx}(a,b) da db \quad (16)$$

$$SW_{xy}(\alpha, b) = \int_{t-\delta/2}^{t+\delta/2} W_{xy}^*(a,b) W_{xy}(a,b) \quad (17)$$

In this regard, δ represent the size of the two-dimensional filter (Luterbacher et al. 2002) [26]. Finally, the criterion

of coherence wavelet transform relation can also be defined similarly to Fourier coherence as follows:

$$WC(\alpha, b) = \frac{|SW_{xy}(a,b)|}{\sqrt{|SW_{xx}(a,b)| \cdot |SW_{yy}(a,b)|}} \quad (18)$$

2.5. WATER QUALITY INDEX (WQI)

The water quality index WQI is one of the techniques used to evaluate water quality. This method was first proposed by Horton in the year 1970. This factor is usually obtained with the number of general parameters of water, including dissolved oxygen, acidity, hardness, water-soluble solids, temperature, turbidity, and the electrical conductivity of

water, nitrite, nitrate, chlorine, and some of the main ions. Some studies use this statistical technique to evaluate the water quality index by using the weight score of each parameter analyzed (Toledo et al. 2002) (table 4) [27]. In this classification, waters with WQI less than 50 are in the very good category, 50 to 100 are in a good category, 100

to 200 are in the poor category, 200 to 300 are in the very poor category, and more than 300, are in the class of unsuitable drinking water. In this study, the parameters PH, TDS, Ca, Mg, Na, K, HCO₃, Cl, SO₄, TH, and EC were used for the WQI index. In WQI index calculation,

the first step is weighting for each parameter. According to its relative importance, specific weight is assigned (table 4). The second step is the calculation of relative weight based on equation (19):

$$W = \frac{w_i}{\sum_{i=1}^n w_i} \tag{19}$$

Where, w_i weight of each parameter n number of parameters.

Table 4. Weight ratio of chemical parameters (WHO Standard)

Chemical parameters	Unit	WHO Standard	Weight	Weight ratio
PH	-	6.5-8.5	4	0.129
TH	Mg/l	200	2	0.064
EC	μ mhos/cm	250	3	0.096
Ca	Mg/l	75	2	0.064
Mg	Mg/l	50	1	0.032
K	Mg/l	12	2	0.064
Na	Mg/l	200	2	0.064
HCO ₃	Mg/l	120	3	0.096
Cl	Mg/l	250	3	0.096
SO ₄	Mg/l	250	4	0.129
TDS	Mg/l	600	5	0.161
Total	-	-	31	-

The third step is to calculate the quality rate scale. This scale (q_i) is calculated by dividing the concentration of

each parameter in each water sample by the standard value of that parameter according to equation (20).

$$q_i = \frac{c_i}{s_i} \times 100 \tag{20}$$

Which in C_i concentration and S_i chemical standard each parameter in the water sample is in Mg/l. then to estimate

WQI, S_i for each chemical parameter is determined by equations (21) and (22):

$$SI_i = W \times q_i \tag{21}$$

$$WQI = \sum_{i=1}^n SI_i \tag{22}$$

Table 5. Water quality classification based on WQI index (Ramakrishanaiah et al. 2009) [28]

Quality class	Value of the index obtained
Unsuitable	300
Very weak	200-300
Weak	100-200
good	50-100
Excellent	<50

3. RESULT AND DISCUSSION

3.1. DROUGHT INDEX RESULT

To calculate the drought index, from precipitation data obtained, the meteorological organization of Lorestan province has been used. The result of the SPI drought index with an annual scale is shown in [figure \(1\)](#). According to the results of the SPI drought index, it can be

said that the Khorram River in the year 2012 was in moderate drought; in the years 2016 and 2018, respectively was wet and very wet. In other years, it has a steady and near to normal trend. This indicates that the Khorram River has always been exposed to drought.

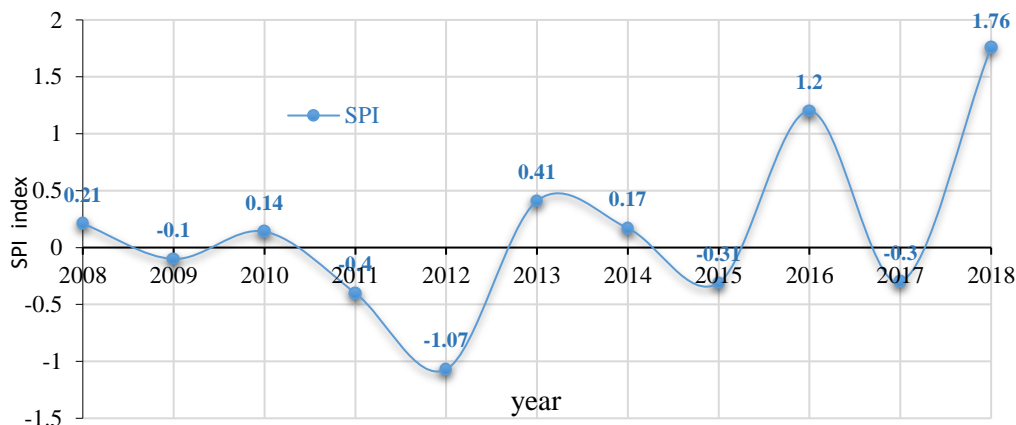


Figure 1. Result of drought in the years 2008 to 2018 in the study area

3.2. WATER QUALITY INDEX RESULTS

To calculate the WQI water quality index used from water quality data obtained from the Lorestan province regional water company. The results of the water quality index with an annual scale are shown in [table \(6\)](#). According to the results, it can be said that the water quality of the Khorram River has been in favorable condition according to the

WQI index in the period of 2008 to 2018. This means that the water of the Khorram River was suitable for drinking, agriculture, and industrial uses. Table 7 shows the results of correlation coefficients of quantitative and qualitative parameters of Khorram River with influencing factors.

Table 6. Values and description of WQI water quality index during the years 2008 to 2018

Year	WQI Index	Descriptive equivalent
2008	82.23	good
2009	75.38	good
2010	71.13	good
2011	74.75	good
2012	74.46	good
2013	71.76	good
2014	80.13	good
2015	75.27	good
2016	73.59	good
2017	70.60	good
2018	72.12	good

Table 7. Results of correlation coefficients of quantitative and qualitative parameters of Khorram River with influential factors

Index	SPI	Precipitation	TH	PH	Cl	Ca	Mg	SO ₄	HCO ₃	TDS	Na
WQI Quality	0.002	0.006	0.286	0.056	0.355	0.267	0.295	0.076	0.170	0.672	0.151
Runoff	0.36	0.209	0.089	0.070	0.14	0.103	0.006	0.022	0.070	0.001	0.015

The result presented in [table \(7\)](#) shows that the highest and lowest correlation in quantitative parameters, respectively, is runoff-drought and runoff-total dissolved solids in water (TDS). Also, the highest and lowest correlation in quality parameters, respectively, is quality-total dissolved solids

in water (TDS) and quality precipitation. The results of the correlation table do not show the communication of the quantities well, so used the quantities communication solution is based on coherence and cross wavelet.

3.3. RESULTS OF IDENTIFYING THE RELATIONSHIP OF TIME SERIES BY COHERENCE AND CROSS WAVELET

In this study, in order to determine the effect of climatic and human factors on changes in the quantity and quality of water in the Khorram river, we used four parameters precipitation, runoff, drought(SPI), and quality(WQI). Precipitation and drought are representative of climatic factors, and the runoff parameter due to increased human harvest from surface water resources to meet the needs of drinking, agriculture, and industry reduce the water flow is considered a representative human factor. Coherence and cross wavelet transformation have been used to evaluate the effect of the mentioned parameters on the quantity and quality of Khorram river water. Coherence and cross wavelet estimate the rate of interplay and phase delay of two-time series relative to each other. This transformation indicates in what period and with what phase delay the time series are related. For this purpose, the time series, quality (WQI) – precipitation, quality (WQI)-drought (SPI), runoff-precipitation, and runoff-drought (SPI) in

pair enter the coherence and cross wavelet algorithm that is programmed in Matlab software, and are measured the rate of impact and interactions between these time series. In the results of coherence and cross wavelet, the areas marked with bold lines and dense arrows are the areas where the coherence and cross wavelet have shown local behavior. This concept means that there is a significant correlation between the corresponding fluctuations of the two time series in the periodicity (coherence band). The arrows to the right indicate that the two-time series are in the same phase, and the arrows to the left indicate that they are not in a phase. The up or down arrows indicate that a time series with a 90-degree angle leads to another. Figure 3 shows the process of determining the impact of time series on the quantity and quality of Khorram river water by coherence and cross wavelet. The results of coherence and cross wavelet transformation for the time series are mentioned in [figures 3, 4, and 5](#) are shown.

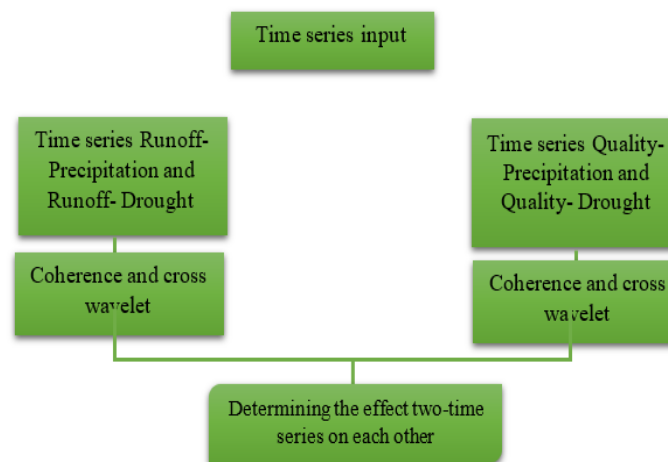


Figure 2. The process of determining the impact of time series on the quantity and quality of Khorram river water by coherence and cross wavelet.

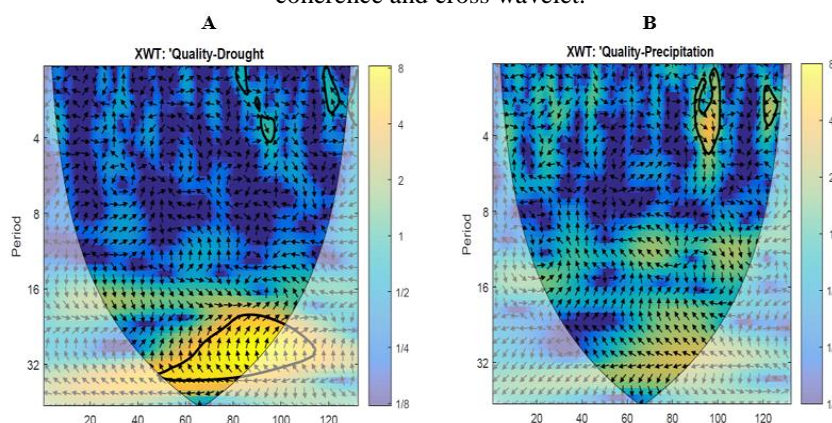


Figure 3. Results cross wavelet transformation for time series comparison, A: quality-drought and B: quality-precipitation.

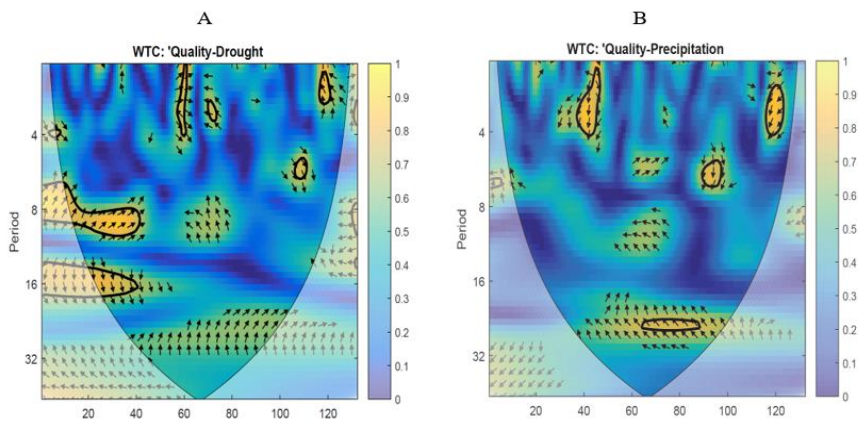


Figure 4. Results coherence wavelet transformation for time series, A: quality-drought and B: quality-precipitation.

Figure 4 shows the cross wavelet transformation of two quality-drought time series with a communication band range of approximately 16 to 32 months. On the other hand, according to figure 5, the wavelet coherence coefficient average obtained from this conversion is estimated to be 0.4. While the reciprocal wavelet transformation of two quality-precipitation time series with coherence wavelet band range from 16 to 32 months, the coherence wavelet coefficient is 0.2. The phase difference between the two quality-drought time series is

90 degrees according to the direction of the arrows, which are generally downward. Also, the phase difference of two-time series quality-precipitation according to the direction of the arrows, which are generally to the left, shows that the two-time series have opposed phases. Based on this interpretation, it can be said the relative effect of drought time series compared with precipitation time series on changes in water quality of Khorram River has been more from 2008 to 2018.

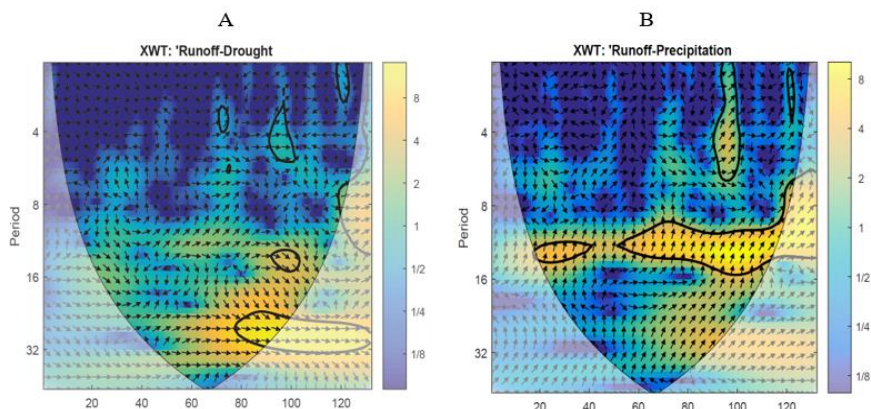


Figure 5. Results of cross wavelet transformation for time series comparison, A: Runoff-drought and B: Runoff-precipitation.

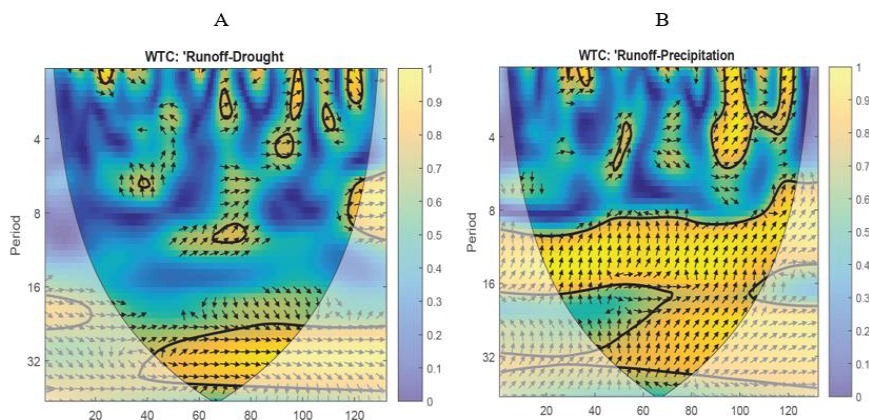


Figure 6. Results of coherence wavelet transformation for time series, A: runoff-drought and B: runoff-precipitation

Figure 5 shows the runoff-precipitation coherence wavelet transform with the communication band range of the two series for about 6 to 15 months. Another hand, the coherence wavelet average coefficient obtained from this transformation is estimated to be 0.6. In contrast, the coherence wavelet transformation of the two-time series runoff-drought with a band range of 16 to 32 months has a coherence wavelet coefficient of 0.1. Also, the phase difference between the two-time series runoff-

precipitation and runoff-drought according to the direction of the arrow, which is generally to the right, shows that the two-time series are in the same phase. Based on this interpretation, it can be said the relative impact of precipitation time series compared with drought time series on changes in Khorram river runoff has been more from the years 2008 to 2018. Table (8) shows the results coherence wavelet average coefficient for hydrological time series.

Table 8. Wavelet coherence coefficient average between Khorram river hydrological time series

Time series	Runoff-Drought	Runoff-Precipitation	Quality-Drought	Quality-Precipitation
Wavelet coherence coefficient average	0.1	0.6	0.4	0.2

According to the results of table (8), it can be concluded that the low coherence wavelet coefficient between runoff-drought shows the effect of farmers' uncontrolled withdrawals from Khorram river water and the effect of human factors in reducing the water runoff in Khorram River. On the other hand, the high coherence wavelet coefficient between runoff-precipitation shows the effect of climatic factors on the changes in water runoff in the Khorram River. Also, the high coherence wavelet coefficient of the quality-drought wave indicates that due to farmers' uncontrolled withdrawals from Khorram river water, the concentration of Khorram river water has also increased as a result. In a study, Yousefzadeh et al. (2013) studied the water quality of Khorram River using the water quality index (NSFWQI) and its zoning with GIS. Their results showed that the water quality of the Khorram River

had the necessary standard for different uses [29]. It is worth mentioning that the most important parameter that is effective for accurately recognizing time series fluctuations by these two criteria (coherence and cross wavelet) is data continuity. Data continuity means that in the process of changing the time series of hydrological data, there is no discontinuity, so in order to maintain continuity during the time series of unrecorded data, there are no hydrological data during the time series fluctuations. On the other hand, coherence and cross wavelet criterion only deal with time series, so physical parameters such as soil permeability coefficients, type of vegetation in the area, etc., will not have any effect on the results of these two criteria. Figure 7 shows the coherence wavelet coefficient diagram and the correlation coefficient between time series.

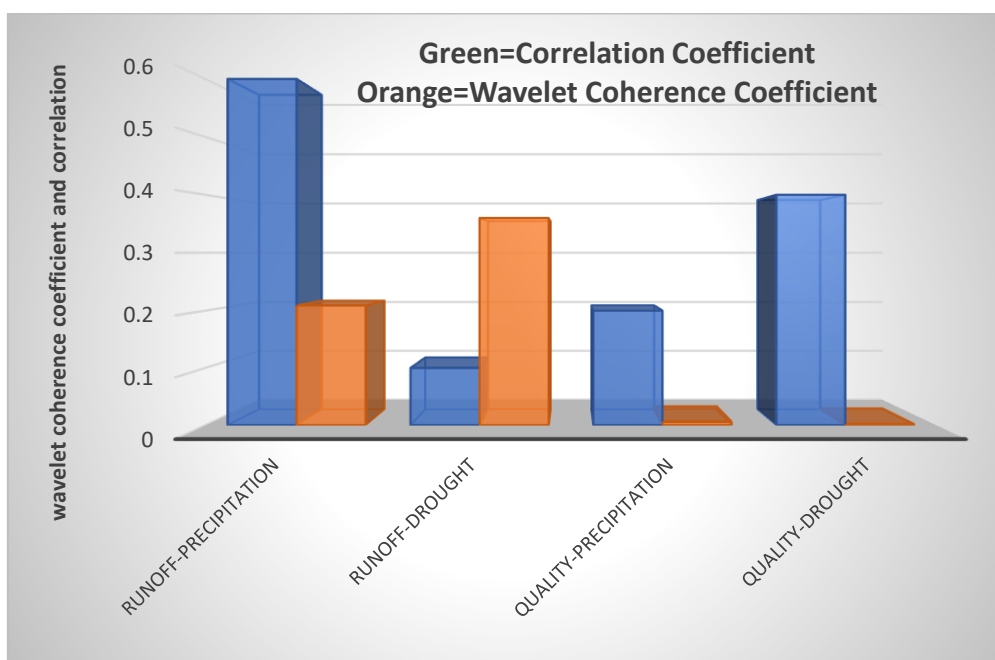


Figure 7. Diagram wavelet coherence coefficient average and correlation coefficient between time series

4. CONCLUSION

Identifying the most important factors in lowering the quantity and quality of water resources is very important for future planning. In this research, first, drought analysis according to the SPI drought index based on precipitation data from the Lorestan province meteorological organization has been done. The finding showed that in the year 2012, the situation of the Khorram river was moderately drought in 2016 and 2018, the situation of the Khorram river respectively was moderately wet and very wet, and in other years it was near normal. Then the water runoff of the Khorram River and the effects of drought on it were studied. Study findings showed that the water runoff of the Khorram River has always been upward and downward and has not been stable in any year. It should be noted that this issue is one of the significant points and needs attention. The correlation between drought and runoff Khorram River with correlation coefficient is the scale of 0.36. in the next step, the water quality of the Khorram river was analyzed according to the global index (WQI), which the research findings showed the waters entering the Khorram river according to the standard of the world health organization (WHO) is in good, desirable conditions and suitable for various uses such as agriculture, drinking, industry and etc. using different methods and criteria to determine and classify the factors affecting the reduction of runoff and quality of aquifers is an effective step towards managing surface waters resources. In this regard, this research has tried to determine the relationship between different parameters

for reducing or increasing the runoff rate and quality of the Khorram river water by using coherence and cross wavelets. For this purpose, the degree of impact and interrelationship between the time series of quality-drought and quality-precipitation as well as runoff-drought and runoff-precipitation was determined by coherence and cross wavelet. According to the obtained results, the relative effect of precipitation with a wavelet coherence coefficient of 0.6 on changes in Khorram river water runoff has been more than other factors. Also, the relative impact of drought with a wavelet coherence coefficient of 0.4 on changes in water quality of Khorram River has been more than other factors. According to the results of the wavelet coherence coefficients of time series, it can be said that farmers' uncontrolled perceptions of Khorram river water, which show the impact of human factors, have been more effective in the changes in Khorram river runoff. Also, this factor caused an increase in the concentration of water in the Khorram River. And as a result, the quality of water in the Khorram River has changed. In completing the present study, it is suggested that the proposed method be applied to daily and annual data to compare the results with the results obtained from monthly data. The use of other criteria and methods of analysis of time series trends, such as the Entropy wavelet criterion, can be a suitable suggestion to investigate the effects of climate change on the quantity and quality of water resources for future research.

FUNDING/SUPPORT

Not mentioned any Funding/Support by authors.

ACKNOWLEDGMENT

Not mentioned by authors.

AUTHORS CONTRIBUTION

This work was carried out in collaboration among all authors.

CONFLICT OF INTEREST

The author (s) declared no potential conflicts of interests with respect to the authorship and/or publication of this paper.

5. REFERENCES

- [1] Jung H, Ha K, Koh DC, Kim Y, Lee J. Statistical analysis relating variations in groundwater level to droughts on Jeju Island, Korea. *Journal of Hydrology: Regional Studies*. 2021 Aug 1;36:100879. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).
- [2] Hassanzadeh R, Komasi M, Ahmadi M. Evaluation and analysis of climate change on the quantity and quality water resources in Lorestan province (Case study of Khorram river). 2016 ,Year 7. Number 28. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).
- [3] Soleimani Motlagh M, Talebi A, Zareei M. The study of drought on the quality of surface water resources in Kashkan watershed. *Journal of Watershed Management Research*. 2016 Jan 10;6(12):154-65. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).
- [4] Wolff E, van Vliet MT. Impact of the 2018 drought on pharmaceutical concentrations and general water quality of the Rhine and Meuse rivers. *Science of the Total Environment*. 2021 Jul 15;778:146182. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).
- [5] Han Z, Huang S, Huang Q, Bai Q, Leng G, Wang H, Zhao J, Wei X, Zheng X. Effects of vegetation restoration on groundwater drought in the Loess Plateau, China. *Journal of Hydrology*. 2020 Dec 1;591:125566. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).
- [6] Peiravi R, Alidadi H, Javid AB, Najafpoor AA, Esmaeili H, Joulaei F. Modeling of drought effect on the Total Hardness and Total Dissolved Solids inground water of Mashhad plain. *Journal of*

Research in Environmental Health. 2015 Aug 23;1(2):85-94. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[7] Gámez TE, Benton L, Manning SR. Observations of two reservoirs during a drought in central Texas, USA: Strategies for detecting harmful algal blooms. *Ecological Indicators*. 2019 Sep 1;104:588-93. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[8] Zhao R, Wang H, Chen J, Fu G, Zhan C, Yang H. Quantitative analysis of nonlinear climate change impact on drought based on the standardized precipitation and evapotranspiration index. *Ecological Indicators*. 2021 Feb 1;121:107107. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[9] Mishra AK, Singh VP. Drought modeling—A review. *Journal of Hydrology*. 2011 Jun 6;403(1-2):157-75. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[10] Kim JS, Jain S, Lee JH, Chen H, Park SY. Quantitative vulnerability assessment of water quality to extreme drought in a changing climate. *Ecological Indicators*. 2019 Aug 1;103:688-97. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[11] Ghaffari M, Chavoshbashi AA, Eslami A, Hatami H, Pourakbar M, Hashemi M. Spatial and temporal variation of groundwater quality around a volcanic mountain in northwest of Iran. *Groundwater for Sustainable Development*. 2021 Aug 1;14:100627. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[12] Nourani V, Ranjbar S, Tootoonchi F. Change detection of hydrological processes using wavelet-entropy complexity measure case study: Urmia Lake. *Journal of Civil and Environmental Engineering*. 2015 Nov 22;45(80):75-86. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[13] Chou CM. Complexity analysis of rainfall and runoff time series based on sample entropy in different temporal scales. *Stochastic Environmental Research and Risk Assessment*. 2014 Aug;28(6):1401-8. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[14] Feng S, Hao Z, Zhang X, Wu L, Zhang Y, Hao F. Climate change impacts on concurrences of hydrological droughts and high temperature extremes in a semi-arid river basin of China. *Journal of Arid Environments*. 2022 Jul 1;202:104768. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[15] Ross ER, Randhir TO. Effects of climate and land use changes on water quantity and quality of coastal watersheds of Narragansett Bay. *Science of the total environment*. 2022 Feb 10;807:151082. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[16] Hasan MS, Rai AK. Groundwater quality assessment in the Lower Ganga Basin using entropy information theory and GIS. *Journal of Cleaner Production*. 2020 Nov 20;274:123077. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[17] Kubicz J, Lochyński P, Pawełczyk A, Karczewski M. Effects of drought on environmental health risk posed by groundwater contamination. *Chemosphere*. 2021 Jan 1;263:128145. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[18] Hassanzadeh R, Komasi M, Derikvand A. Assessing climate change effects on declining groundwater levels using wavelet entropy (case study of Khorramabad city). *Water Supply*. 2022 Mar;22(3):2452-64. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[19] Komasi M, Alami M, Nourani V. Drought forecasting by SPI index and ANFIS model using fuzzy C-mean clustering. *Journal of Water and Wastewater; Ab va Fazilab (in persian)*. 2013 Aug 1;24(4):90-102. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[20] Hassanzadeh Y, Lotfollahi-Yaghin MA, Shahverdi S, Farzin S, Farzin N. De-noising and prediction of time series based on the wavelet algorithm and chaos theory (Case study: SPI drought monitoring index of Tabriz city). *Iran-Water Resources Research*. 2013 Jan 20;8(3):1-3. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[21] McKee TB, Doesken NJ, Kleist J. The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology 1993* Jan 17 (Vol. 17, No. 22, pp. 179-183). [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[22] Labat D. Cross wavelet analyses of annual continental freshwater discharge and selected climate indices. *Journal of Hydrology*. 2010 May 7;385(1-4):269-78. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[23] Torrence C, Compo GP. A practical guide to wavelet analysis. *Bulletin of the American Meteorological society*. 1998 Jan;79(1):61-78. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[24] Nourani V, Nezamdoost N, Samadi M, Daneshvar V, Vossoughi F. Wavelet-based trend analysis of hydrological processes at different timescales. *Journal of Water and Climate Change*. 2015 Sep;6(3):414-35. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[25] Torrence C, Webster PJ. Interdecadal changes in the ENSO–monsoon system. *Journal of climate*. 1999 Aug;12(8):2679-90. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[26] Luterbacher J, Xoplaki E, Dietrich D, Rickli R, Jacobeit J, Beck C, Gyalistras D, Schmutz C, Wanner H. Reconstruction of sea level pressure fields over the Eastern North Atlantic and Europe back to 1500. *Climate Dynamics*. 2002 Mar;18(7):545-61. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[27] Toledo LG, Nicoella G. Water quality index for agricultural and urban watershed use. *Scientia Agricola*. 2002;59:181-6. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[28] Sharma RC, Rawat JS. Monitoring of aquatic macroinvertebrates as bioindicator for assessing the health of wetlands: A case study in the Central Himalayas, India. *Ecological indicators*. 2009 Jan 1;9(1):118-28. [\[View at Google Scholar\]](#); [\[View at Publisher\]](#).

[29] Yosefzadeh, A. Shams Gh. Godini, H. Investigation of water quality in Khorra river with water quality index (NSFWQI) and its zoning with GIS. *Journal of Scientific Research [Iran]*. 2013, Pp 92-82.