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Hydrological Drought and Time Series Analysis: A Case Study of the Zarrinehrood Basin

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Abstract

Drought is a significant aspect of Iran's climate, affecting both dry and wet regions. This study examines the river flow data from four hydrometric stations in the Zarrinehrood Basin (Dareh-Panbedan (DP), Pol-Anian (PA), Sonateh and Nezamabad) to analyze and forecast hydrological drought in the present and future periods, considering the impact of climate change. Additionally, the study aims to account for and mitigate the dam's effect on one of the studied stations. The analysis of river flow changes at the studied stations indicated a decreasing trend over the study period. To predict the hydrological drought index for the study area, the SDI index was utilized for reference periods of 3, 6, 9, and 12 months, along with climate change predictors derived from the CanESM2 climate model as outlined in the fifth IPCC report. The CARMA model and climate predictors were employed to simulate and forecast river flow for future periods. The results of the CARMA model investigation for simulating river flow in the test phase indicate that the error value at DP station is 4.07, at PA station is 6.46, at Sonateh station is 4.07, and at Nezamabad station is 70.14 cubic meters per second. These findings suggest that the hydrological drought in the studied basin is expected to worsen in the coming years.

Keywords: Bukan Dam, Forecasting, Hydrological Drought, Multivariate Modeling, SDI index

1. Introduction

Investigating the hydrological drought is very important in the discussion of water resources, urban water supply, river flow, agriculture, industry, planning the use of dam reservoirs, etc. Since the issue of hydrological drought is investigated only using river discharge data and has simple calculations, it is of interest to researchers and especially engineers. Stream flow drought index (SDI) is one of the most important indicators in this regard. Using this index, a good estimate of hydrological drought can be obtained. In addition to simplicity in calculations, this index shows the state of hydrological drought well, which has been investigated in different climates and by different researchers.

Tigkas et al. (2012) by investigating the hydrological drought and using the SDI index showed that the highest frequency of drought occurred in the northwest of Iran during 1997-2008. Kooshki et al. (2017) investigated the meteorological and hydrological drought in Karkheh River. The results of their research showed that hydrological drought occurs with a very short time delay after meteorological drought. Nazeri Tahroudi et al. (2020) proposed a new method for modeling meteorological and hydrological droughts (SDI) based on conditional density of copula functions. They analyzed the joint frequency of duration-duration and severity-severity characteristics of meteorological and hydrological droughts. The results of their research showed that knowing the conditional density, one can easily estimate the characteristics of hydrological drought.

Nazeri Tahroudi et al. (2022) studied the hydrological drought of SDI and analyzed the frequency of its occurrence in Zarinehrood sub-basin, North-West of Iran in the period of 1995-2016. They determined the duration of hydrological drought with certain return periods for the duration of specific meteorological drought in the studied station.

Ozkaya et al. (2023) investigated the relationship between hydrological and meteorological droughts with spatial and temporal variability of meteorological drought on the upper part of the Tigris river catchment. The results of their research were based on the SDI index. Kamali and Asghari (2023) investigated the effect of drought and its impact on groundwater storage and future drought events under climate change conditions in Najafabad, central Iran. They investigated the impact of meteorological drought on groundwater changes. Deger et al. (2023) used the SDI drought index to obtain the intensity and duration of the drought using the mean monthly river flow of 36 stations in the Euphrates basin, considering the scales of 3 and 6 months. Analysis of marginal distributions in their research showed that lognormal and Weibull distributions are the best distributions for drought duration and intensity in SDI-3, while lognormal and gamma are the best distributions for duration and intensity in SDI-6. Yuce et al. (2023) studied the SDI hydrological drought index for scales 1, 3, 6, 9 and 12 against the data of 24 stations in Yeşilrmak basin. They reported that the most common type of drought throughout the basin is mild drought, with the highest percentage of occurrence. They also mentioned that since 2000, the region has endured some of the longest and most severe droughts in history.

Regarding the simulation and modeling of drought indicators, various studies have been conducted in different regions. In this regard, there have been various models, of which time series models are the most important (Khalili et al., 2014). Due to its stochastic nature, these models model extreme events such as floods and droughts well (Khalili and Nazeri Tahroudi, 2016). Also Camacho et al. (1985) showed that multivariate models show the statistical characteristics of time series in the best way, for this reason, it works better for predicting extreme values such as drought.

Considering the dependence of meteorological and hydrological values on each other and other parameters, the use of multivariable models increases the certainty of simulations due to the involvement of effective parameters. Contemporaneous autoregressive moving average (CARMA) models, as a special subset of ARMA models, are suitable models for modeling hydrological parameters in multivariate and combined mode (Salas et al., 1980, Camacho et al. al., 1985). Furthermore, multiple research studies have demonstrated the superior accuracy and performance of these models compared to univariate models (Camacho et al., 1985; Shahidi et al., 2020).

By predicting the river flow in the coming years, it is possible to indirectly predict the hydrological drought. Komorník et al., (2006) compared and predicted the efficiency of time series hydrological models in the Czech Republic. They stated that the effectiveness of the mentioned models in predicting hydrological processes is acceptable. Borji et al., (2016) investigated the support vector regression model and artificial neural network to predict SDI drought index in different time scales. The results showed the poor performance of the proposed models in forecasting using the SDI index for time scales (3, 6, 9, 12), while the results were good for the 24-month period.

Yap and Musa (2023) predicted the river flow of Temerloh and Lubok Paku stations of Pahang River using ARIMA, ARMA and SARIMA models. They claimed that the SARIMA model has improved the accuracy of river flow forecasting compared to the ARIMA model by addressing seasonality.

This study has presented a new approach regarding the simulation and prediction of river flow on a monthly scale with regard to climate change predictors. In this study, with the aim of investigating the performance of multivariate time series models in modeling and predicting hydrological drought in the Zarinehrood basin, the data related to monthly river flow with a period of 25 years (1990-2014) for the base period and 2014-2030 for the future period were used. In fact, the innovation of this research is the prediction of river flow under the condition of climate change in the studied area. The main difference between this research and other researchers is the consideration of climate change in simulation and forecasting the river flow.

2. Materials and Methods

2.1. Case study

Zarinehrood River is located in the southeast of West Azarbaijan province, south of Lake Urmia and northwest of Iran. With an area of 11,729 square kilometers and a length of 230 kilometers, this river is the longest river in West Azarbaijan province, which runs the length of Shahindej and Miandoab cities and finally flows into Lake Urmia. In this study, the monthly river flow (m^3/s) of the 25-year period (1990-2014) of four hydrometric stations, Dareh-Panbedan (P.A), Pol-Anian (P.A), Sonateh and Nezamabad were used. The Nezamabad hydrometric station is located next to the Bukan dam, which makes the river flow of this hydrometric station regulated. For this reason, the effect of Bukan dam has been removed and the river flow data of this hydrometric station has been modified. In figure 1 and table 1 the location and studied hydrometric stations are given. In order to monitor hydrological drought, the streamflow drought index (SDI) has been used for all stations in two historical (1990-2014) and future (2014-2030) periods. Each of the observed stations is situated on a sub-branch of the Zarinehrood. Therefore, the Dareh-Panbedan hydrometric station is located on the Saqez Cham sub-branch, the Pol-Anian hydrometric station is on the Jaghto sub-branch, and the Sonateh hydrometric station is situated on the Cham-Khorkhore sub-branch, each with its own specific discharge. Additionally, the Nezamabad hydrometric station is the final station before the Lake Urmia. The spatial distribution of the stations can reveal the characteristics of drought in different branches of the river.

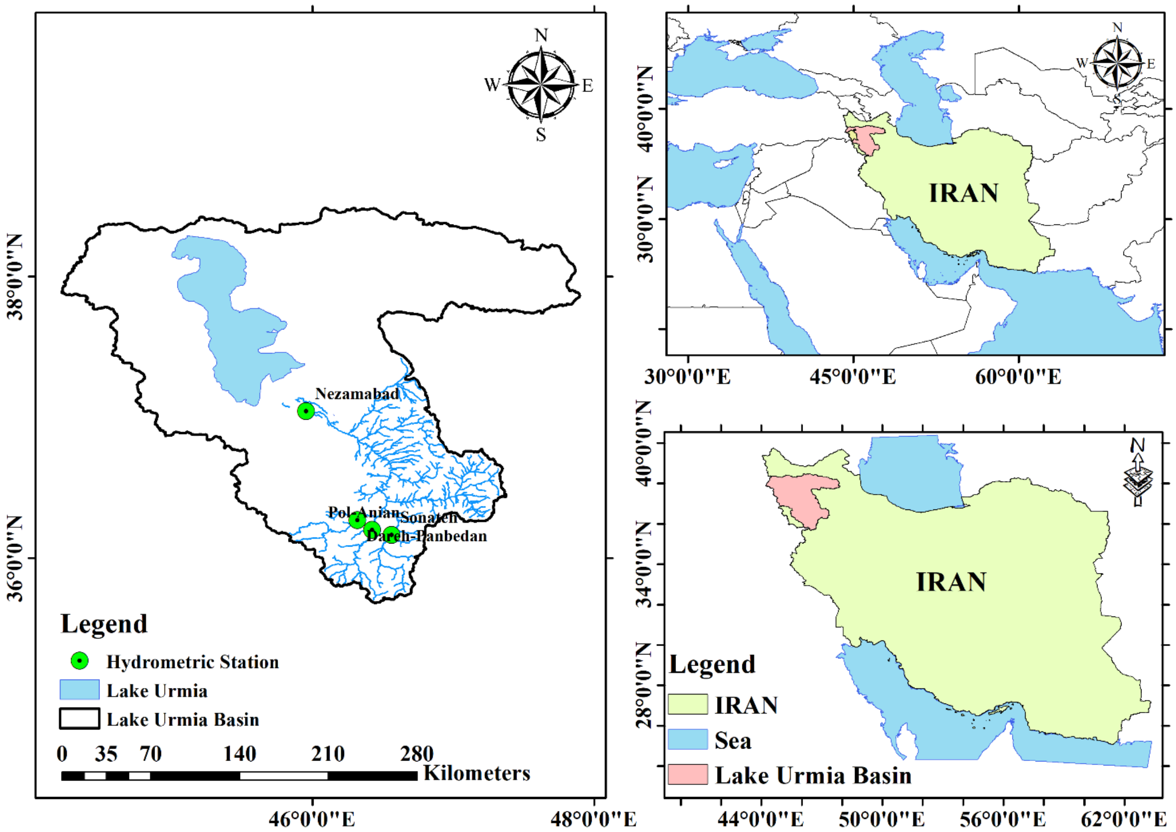

Fig. 1. Location of Zarinehrood basin, and studied stations in Lake Urmia Basin

Table 1. The location of the studied hydrometric stations

Station	Nezamabad	Sonateh	Pol-Anian (PA)	Dareh-Panbedan (DP)
latitude	$37^o\ 3'$ N	$36^o\ 10'$ N	$36^o\ 12'$ N	$36^o\ 17'$ N
Longitude	$45^o\ 56'$ E	$46^o\ 33'$ E	$46^o\ 26'$ E	$46^o\ 22'$ E
Elevation above mean sea level (m)	1283	1370	1460	1470

2.2. Streamflow drought index (SDI)

In this study, the SDI index in order to determine the state of hydrological drought, which is based on the cumulative volume of the river flow, has been used for reference periods of 3, 6, 9 and 12 months. Correcting and completing the data, as well as addressing the lack of a significant trend in data preprocessing, have been taken into consideration.

In SDI index: if assumed that monthly time series of river flow volume ($q_{i,j}$) are available, then i refers to the hydrological year and j refers to the month in a hydrological year. Based on these series, the cumulative volume of the river flow will be as follows:

$$Q_{i,j} = \sum_{j=1}^{3k} q_{i.j} \quad i \; and \; j = 1,2,... \quad ,k = 1,2,3,4 \tag{1}$$

Where $Q_{i,j}$ is the cumulative volume of the river flow for the i-th hydrological year and the k-th reference period, k=1 for September-November, k=2 for September -February, k=3 for September -May and k=4 for September-August. Based on the cumulative flow volume $Q_{i,j}$, SDI index for each reference period k and i-th hydrological year is defined as follows:

$$SDI = \frac{Q_{i,k} - \overline{Q_k}}{S_k} \quad i = 1,2,... \quad ,k = 1,2,3,4 \tag{2}$$

Where $\overline{Q_k}$ and S_k are the mean and standard deviation of the cumulative volume of the river flow of the reference period k, respectively, which are estimated in the long-term period. The river flow drought index is actually equivalent to the standardized river volume. In table 2, the hydrological drought classification is determined using the SDI index, which is divided into 5 conditions.

Table 2. Determination of hydrological drought conditions using SDI index

SDI Range	Probability of occurrence (%)	Classification
SDI ≥ 0	50	No drought
-1 ≤ SDI < 0	34.1	Mild drought
-1.5 ≤ SDI < -1	9.2	Moderate drought
-2 ≤ SDI < -1.5	4.4	Severe drought
SDI < -2	2.3	Very severe drought

2.3. CanESM2 climate model

In this research, we have investigated the effectiveness of the Canadian Earth System Model, second generation (CanESM2) atmospheric general circulation model in the simulation of river flow in studied stations. The daily observational data are called predictors and the river flow time series are predict based on these predictors. The large-scale predictor data includes 26 variables, which are available in two periods from 1961 to 2005 and the future period from 2006 to 2100. The CanESM2 model is the second generation of the Canadian Earth Model, released by the Canadian Center for Climate Modeling and Analysis (CCCma). CanESM2 data are standardized long-term daily series that can be extracted based on the longitude and latitude of each station (Mirakbari et al., 2018). In this model, the whole earth is gridded as a cell and has a grid with dimensions of 1*1 degree longitude and latitude. The data of this model are presented under three scenarios: RCP2.6, RCP4.5, and RCP8.5, which are used to predict the near future (2006-2036), the middle future (2037-2078), and the far future (2079-2100). The purpose of these scenarios is to provide a set of information from the results of which the main factors of climate change can be tracked and used in modeling and conducting studies. The RCP scenarios are shown in Table 3:

Table 3. Overview of RCP scenarios

Scenario	Description
RCP 2.6	Optimistically
RCP 4.5	Tend to be optimistic
RCP 8.5	Pessimistically

2.4. Contemporaneous Autoregressive Moving Average Model (CARMA)

Modeling of multivariable hydrological processes based on the full multivariable ARMA model, usually there are problems in estimating its parameters. The CARMA model was recommended as a simpler alternative to the full multivariate ARMA model (Salas et al., 1980). In the CARMA(p,q) model, the parameters matrix of both the autoregressive model and the moving average model are assumed to be diagonal. The CARMA(p,q) model for *n* stations is shown as follows:

$$Y_t = \sum_{i=1}^{p} \varphi_j Y_{t-j} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (3)$$

where Y_t is an n*1 column matrix of observation series with normal distribution and zero mean representing different stations, $\varphi_1, \varphi_2, \ldots, \varphi_p$ is n*n diagonal matrix of autoregressive model parameters and $\theta_1, \theta_2, \ldots, \theta_q$ is n*n diagonal matrix of the moving average model parameters. ε_t is an n*1 matrix of normal random data with zero mean and variance-covariance g.

$$\begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \cdot \\ \cdot \\ \cdot \\ Y_t^{(n)} \end{bmatrix} = \begin{bmatrix} \varphi^{11} & \varphi^{12} & \cdot & \cdot & \cdot & \varphi^{1n} \\ \varphi^{21} & \varphi^{22} & \cdot & \cdot & \cdot & \varphi^{2n} \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \varphi^{n1} & \varphi^{n2} & \cdot & \cdot & \cdot & \varphi^{nn} \end{bmatrix} . \begin{bmatrix} Y_{t-1}^{(1)} \\ Y_{t-1}^{(2)} \\ \cdot \\ \cdot \\ \cdot \\ Y_{t-1}^{(n)} \end{bmatrix} + \begin{bmatrix} \theta^{11} & \theta^{12} & \cdot & \cdot & \cdot & \theta^{1n} \\ \theta^{21} & \theta^{22} & \cdot & \cdot & \cdot & \theta^{2n} \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \theta^{n1} & \theta^{n2} & \cdot & \cdot & \cdot & \theta^{nn} \end{bmatrix} . \begin{bmatrix} \varepsilon_t^{(1)} \\ \varepsilon_t^{(2)} \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_t^{(n)} \end{bmatrix} \qquad (4)$$

The CARMA model is able to maintain the zero delay of mutual correlation in the space between different stations, also the dependence of the time structure for each station is defined by parameters p and q (Salas et al., 1980).

2.5. Estimation of CARMA model parameters

Considering *n* years of data in the desired stations *i* with observational data $Y_t^{(i)}$ and i=1,2,3,...,n, the matrix of the general model Y_t is displayed as follows:

$$Y_t = \mu + \sigma Z_t \qquad (5)$$

where, μ and σ are the mean and variance of Y_t, respectively, and the standardization of the variables will be calculated using the Eq. 6:

$$Z_t^{(i)} = \frac{(y_t^{(i)} - \mu_t^{(i)})}{\sigma^{(i)}} \qquad (6)$$

The parameters of the CARMA(p,q) model are defined like the parameters of the ARMA model. The residual series has a time-independent model, but it is dependent among itself, which is modeled using the following equations:

$$\begin{aligned} \varepsilon_t^{'(i)} &= \frac{\varepsilon_t^{(i)}}{\sigma_t^{(i)}} \\ \varepsilon_t^{'} &= B\xi_t \\ \widehat{B}\widehat{B}^T &= \widehat{M}_o \end{aligned} \qquad (7)$$

where, $\widehat{M}_o$ is the matrix of the autocorrelation function with zero delay, which is calculated from the following matrix:

$$\widehat{M}_k = \begin{vmatrix} r_k^{11} & r_k^{12} & \ldots & r_k^{1n} \\ r_k^{21} & r_k^{22} & \ldots & r_k^{2n} \\ \vdots & \vdots & & \vdots \\ r_k^{n1} & r_k^{n2} & \ldots & r_k^{nn} \end{vmatrix}$$

$$r_k^{ij} = \frac{\sum_{t=1}^{N-K} (\varepsilon_t^{(i)} - \varepsilon_t^{-(i)})(\varepsilon_{t+k}^{(j)} - \varepsilon_{t+k}^{-(j)})}{\sqrt{\left[\sum_{t=1}^{N-k} (\varepsilon_t^{(i)} - \varepsilon_t^{-(i)})^2 . \sum_{t=1}^{N-k} (\varepsilon_{t+k}^{(j)} - \varepsilon_{t+k}^{-(j)})^2\right]}} \qquad (8)$$

where, $\varepsilon_t^{-(i)}$ is the average of N-k data related to station *i* and $\varepsilon_{t+k}^{-(i)}$ is the average of N-k data is related to station *j*. Then the matrix of parameters of CARMA(p,q) model is obtained using the Eq.9 (Matalas, 1967):

$$\widehat{A} = \widehat{M_1}\widehat{M_0^{-1}} \qquad (9)$$

2.6. Model evaluation criteria

In this research, to evaluate the used models, two common statistical indicators, root mean square error (RMSE) and Nash Sutcliffe efficiency (NSE) have been used as Eqs. 10 and 11.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_o - Q_s)^2}{N}} \qquad (10)$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Q_s - Q_o)^2}{\sum_{i=1}^{n}(Q_o - \bar{Q}_o)^2}\right] \qquad (11)$$

According to the above equations, Q_s is the simulated river flow, Q_o is the observed river flow, and $\bar{Q}_o$ is the average observed river flow.

3. Results and Discussion

In this study, with the aim of investigating the performance of multivariate time series models in modeling and forecasting hydrological drought based on climate change in the Zarinehrood Basin, northwest Iran. As mentioned, in this study is based on the monthly river flow time series in the 25-year period of 1990-2014 for the base period and the period of 2014-2030 for the future period.

3.1. The results of the SDI index in the basic period

Using the monthly river flow data of the studied stations, their average and standard deviation and finally, the SDI values were calculated. According to the results obtained from the SDI index, Zarinehrood basin has experienced hydrological drought with different intensities. At first, SDI values were investigated and extracted in the basic period in the studied stations, and the results can be seen in Figure 2. Based on Figure 2, it is evident that the most frequent occurrence of hydrological drought in the Santeh, PA, and DP stations during the basic period (1990-2014) is in the September-June period of 1998. In Nezamabad station, the highest frequency occurred in the period of September-June in 2008. In general, according to the obtained results, the years 1991 to 2006 can be introduced as wet period and 2006 to 2014 as drought period.

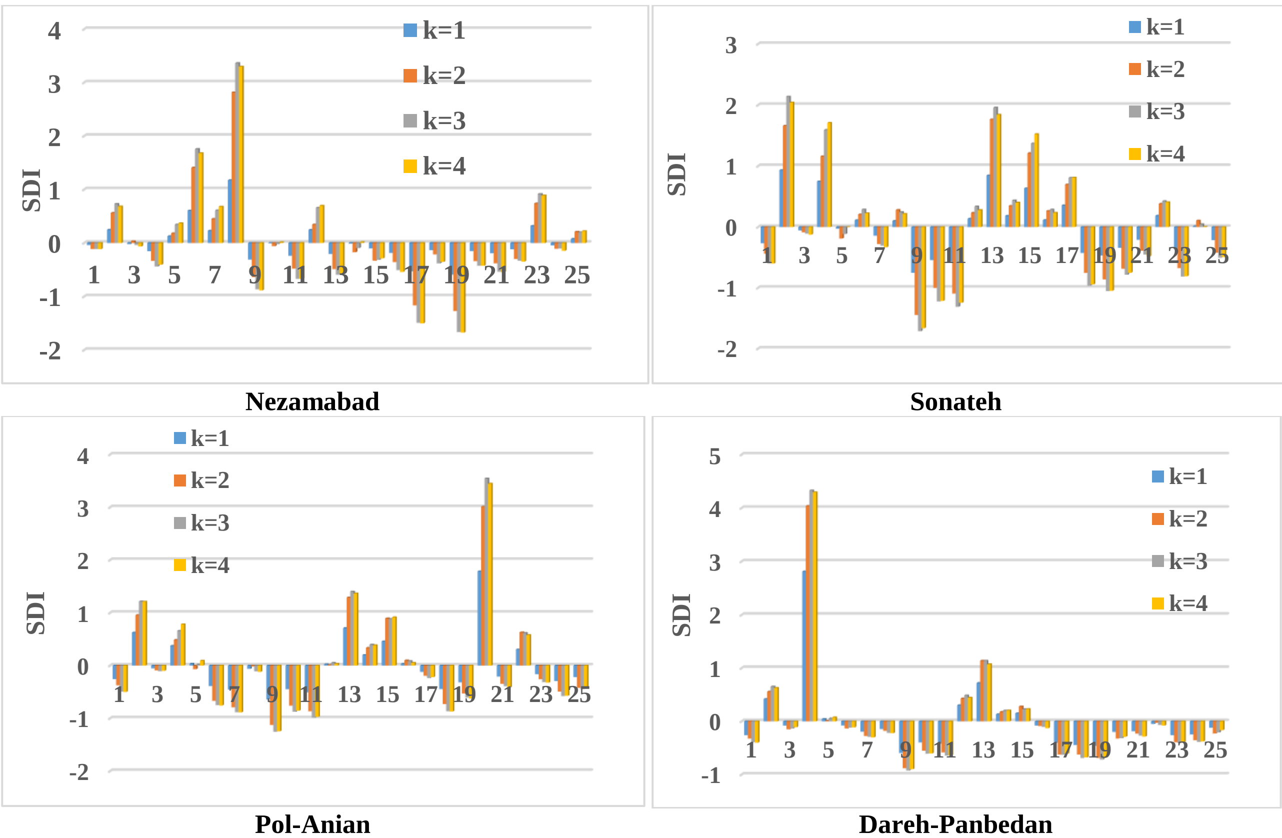

Fig. 2. Comparison of hydrological drought in 3, 6, 9 and 12 months periods in the studied hydrometric stations

3.2. Simulation and prediction of river flow values affected by climate change

In this study, climate change predictors extracted from the CanEsm2 climate model were used to simulate and predict river flow values. Considering the multivariable nature of the CARMA model, first the correlation of river flow values with climate predictors was checked and according to the parameters with high correlation (more than 0.3), simulation of river flow values was done in multivariable mode. The chosen predictors, with a correlation coefficient of over 0.3 at each station, are detailed in Appendix A.

The training and testing of the CARMA model was investigated using river flow data and climate predictors in the basic period, and finally, according to the climate predictors in the future period, the river flow values were predicted to 2030. To evaluate the CARMA multivariate model in the basic period, simulation was performed in two phases of training and testing, where 80% of the data was considered as the training phase and 20% as the testing phase.

The results of investigation the error values and efficiency coefficient of the model were evaluated using RMSE and NSE statistics, respectively. The results of investigation the error values and efficiency coefficient of the CARMA model in simulating and predicting the river flow values affected by climate change were presented in Table 4 for both training and testing phases. According to Table 4, it can be seen that the coefficient of efficiency of the model (NSE) in the simulation of river flow values in the training phase in Nezamabad, Sonateh, Pol-Anian and Dareh-Panbedan stations is equal to 0.99, 0.93, 0.95 and 0.91 respectively, and in the testing phase these values are equal to 0.98, 0.92, 0.94 and 0.88 respectively. The lowest error value in the simulation of the river flow values in the test phase is related to the Sonateh and Dareh-Panbedan stations with the RMSE of 4.07 cubic meters per second. Since the test phase is the most important phase in the simulation and prediction of the river flow values, the results of the simulation of the river flow values in the test phase were presented in Figure 3.

According to the results presented in Figure 3, we can see a correlation of more than 90% between the observed and simulated values of river flow in the test phase. The lowest correlation value among the studied stations is related to DP station with a correlation of 0.80 (Fig. 3-a) and the highest correlation is related to Nezamabad station with a correlation of 0.98 (Fig. 3-c). Finally, the simulated values of river flow in the future period were presented as Figure 4.

3.3.Derivation of SDI values for the future period

After checking the error rate and efficiency coefficient of the CARMA model in predicting and simulating the river flow values according to the climate predictors, the SDI index was extracted for the predicted river flow values. The results of extracting SDI index values in the period of 2014-2030 were presented in Figure 5. The results of SDI values in the future period showed that the highest hydrological drought in DP, PA, Sonateh and Nezamabad stations will be in 2030, 2028, 2030 and 2025, respectively. According to Figure 5, it is possible to see the increase of hydrological drought in the second half of the upcoming period (2014-2030) in DP and PA stations. According to Figure 5, the changes of hydrological drought in Sonateh and Nezamabad stations in the second half of the studied period (2014-2030) have a different behavior with DP and PA stations.

In general, according to the results obtained from the four studied stations, it can be concluded that hydrological drought prevails in the Zarinehrood basin, and the upward trend of drought is obvious, and the results of this drought have many negative effects on the Lake Urmia Urmia. According to the results of extracting the SDI values in the study area, the highest frequency of drought can be seen in Pol Anian station with a value of -1.882, which is among severe droughts. The studies of Tabari et al. (2013) also showed that in recent decades, most of the studied stations have experienced a drop in river flow and Lake Urmia has suffered a hydrological drought. Similarly, similar results have been observed in other stations in Lake Urmia Basin. The decrease in river flow in hydrometric stations may be influenced by factors such as annual rainfall reduction, water harvesting for uses such as agricultural and industrial expansion (Tabari et al., 2013; Nazeri Tahroudi et al., 2019).

Table 4. The results of model evaluation criteria in simulation the river flow using CARMA model and climate change predictors

Evaluation Criteria		Nezamabad	Sonateh	Pol-Anian	Dareh-Panbedan
RMSE (m^3/s)	Train	13.58	3.78	5.94	3.70
	Test	14.70	4.07	4.46	4.07
NSE	Train	0.99	0.93	0.95	0.910
	Test	0.98	0.92	0.94	0.88

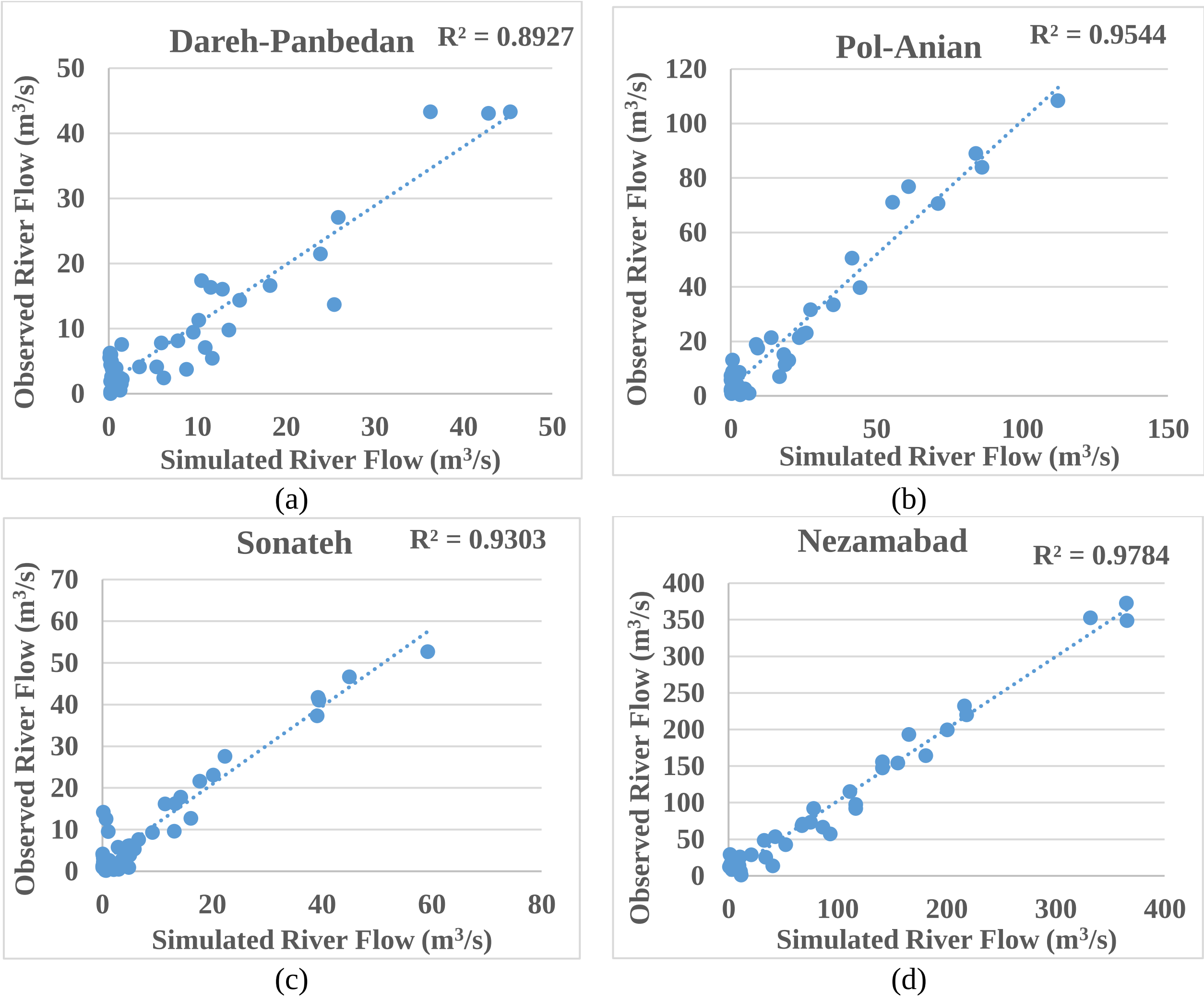

Fig. 3. Validation results of the CARMA model in forecasting the monthly river flow in the studied stations (a: DP, b: PA, c: Sonateh and d: Nezamabad)

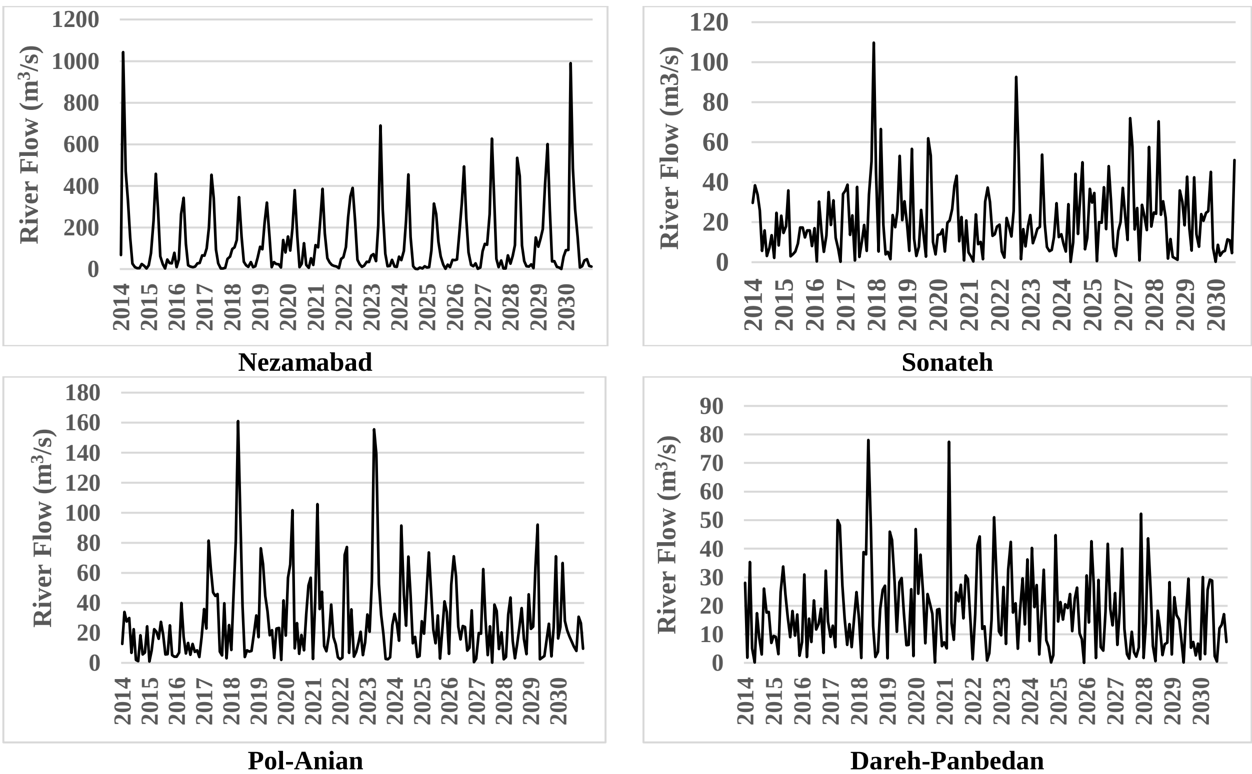

Fig. 4. The simulated values of flow rate in the future period based on CARMA model

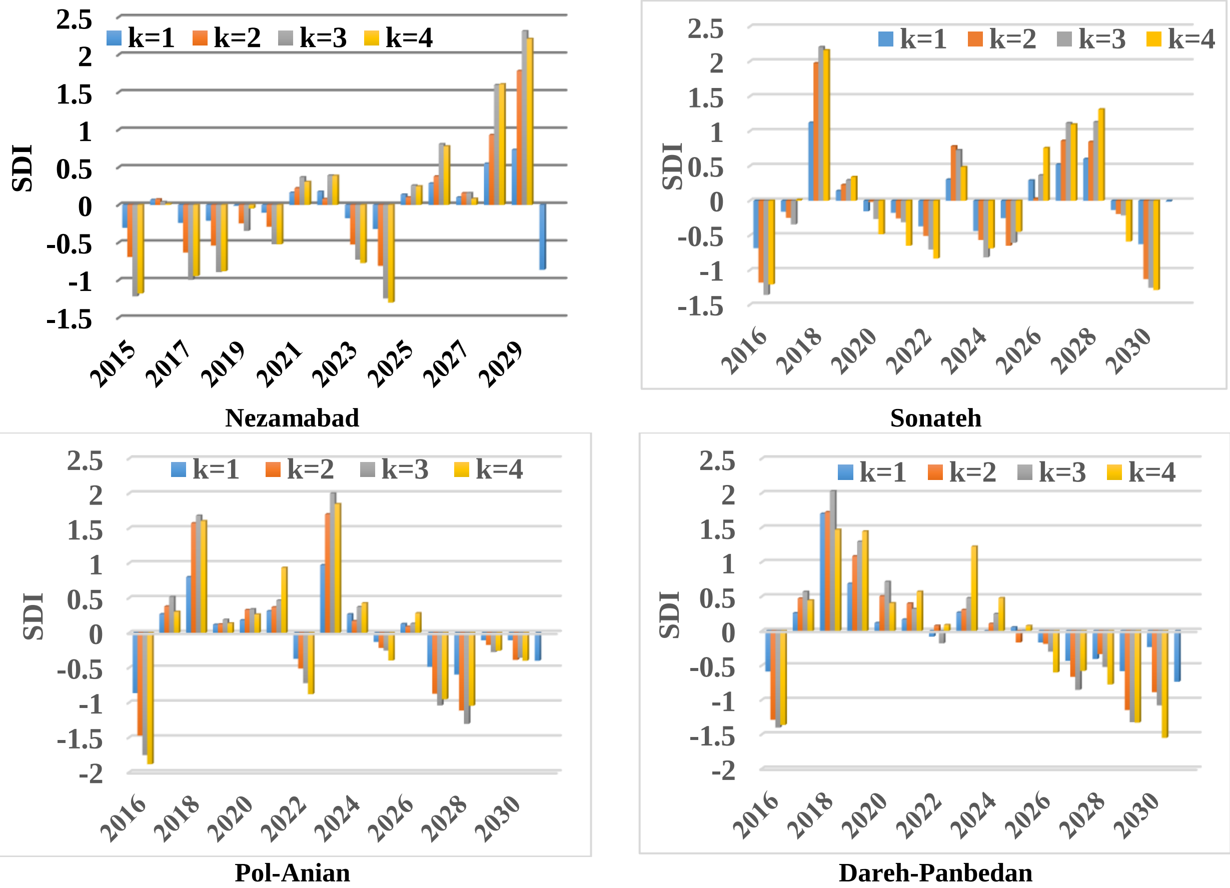

Fig. 5. Comparison of SDI values in scales of 3, 6, 9 and 12 months in the studied hydrometric stations for the future period

According to the results of this research, the monthly discharge data have the ability to detect drought to a large extent. As the results show, there is a good match between SDI in 9 months (October-June) and 12 months (October-September). Also, due to the fact that there is much less rainfall in the last 3 months of the hydrological year, for this reason, the total rainfall in 9 months and 12 months are close to each other. In general, according to the obtained results, the years 2015 to 2019 can be introduced as wet period and 2020 to 2030 as drought period.

According to the graphs of the SDI index, in all four studied hydrometric stations, the hydrological drought is far more intense in the last years of the studied period. The minimum values of SDI as the highest frequency of hydrological drought in the study area according to the upcoming period (2014-2030) were presented in Table 5. According to table 5, it can be seen that in the future period (2014-2030), the minimum values of SDI in DP, PA, Sonateh and Nezamabad stations are equal to -1.55 (in 12-month scale), -1.88 (in 12-month scale), -1.36 (in 9-month scale) and -1.3 (in 12-month scale) respectively.

Table 5. The greatest values of SID hydrological drought in the scales of 3, 6, 9 and 12 months for the period of 2014-2030

Station	12-Month	9-Month	6-Month	3-Month
DP	-1.55	-1.4	-1.29	-0.74
PA	-1.88	-1.75	-1.47	-0.86
Sonateh	-1.29	-1.36	-1.18	-0.68
Nezamabad	-1.3	-1.24	-0.81	-0.86

The use of data from several hydrometric stations in this study made it possible to perform spatial analysis which is consistent with the studies of Salarijazi et al. (2023) and Modabber-Azizi et al. (2023). Also in this study, nonstationary behavior was investigated and corrected only at Nezamabad station, and the effect of the dam was considered in the time series. Considering nonstationary behavior in various studies due to climate changes can provide more accurate results to users (Kousali et al., 2023)

4. Conclusion

In this study, in the first step to calculate the hydrological drought, the SDI index was used in the time scale of 3, 6, 9 and 12 months. The results of the hydrological drought assessment in the studied area showed that this drought prevails in the Zarinehrood basin and the increasing trend of drought is evident in the basic period (1990-2014). In the second step, Climate change predictors were used to investigate the hydrological drought in the future period in the study area and also to evaluate the CARMA model in predicting the river flow. In each station, a number of predictors were selected according to the correlation between predictor parameters and river flow. For CARMA multivariate modeling, 15 years of monthly river flow data (1990-2014) were used for each hydrometric station, 80% of the data were selected for model training and 20% of the data were selected for validation and testing phase. By using the fifth scenario of IPCC and the climate predictors extracted from it, the correlation of data with monthly discharge was calculated and the CARMA model was fitted on the data. The results of the simulation of river flow values under the condition of occurrence of climate change predictors were checked and confirmed using two statistics, RMSE and NSE. The highest amount of drought occurs in the summer season due to lack of rain and high evaporation. In the upcoming period (2014-2030), the results of the SDI index showed that the greatest hydrological drought will occur in the DP station in 2030, where the SDI index is equal to -1.55 cubic meters per second. In PA station, the greatest hydrological drought will occur in 2015 with SDI=-1.88 cubic meters per second. In Sonteh station as well as PA station, the highest amount of drought was in 2015, and the SDI index is equal to -1.35 cubic meters per second. In Nezamabad station, based on the predicted SDI values, the lowest SDI amount is -1.29 cubic meters per second for 2023. According to the studies of other researchers and the statistics and information obtained in this study, we have come to the conclusion that in the last ten years, all the hydrometric stations located in the Zarinehrood River have experienced a severe drop in river flow and the four investigated stations in this study have similar results.

5. Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix A

The selected predictors, with a correlation coefficient of over 0.3 at each station

Station	Selected Pridictor									
Dareh-Panbedan	Vgl	zgl	zhgl	5-zgl	5-zhgl	8-vgl	500gl	cpgl		
Pol-Anian	Vgl	zgl	zhgl	5-zgl	5-zhgl	8-vgl	500gl	cpgl		
Nezamabad	Ugl	Vgl	zgl	thgl	zhgl	5-zgl	8-ugl	8-vgl	8-thgl	500gl	cpgl
Sonateh	Vgl	zgl	zhgl	5-zgl	850gl	cpgl				

Vgl	1000hPa Meridional wind component	8-vgl	850hPa Meridional wind component
zgl	1000hPa Relative vorticity of wind	500gl	500hPa Geopotential
zhgl	1000hPa Divergence of true wind	cpgl	Total precipitation
5-zgl	500hPa Relative vorticity of wind	Ugl	1000hPa Zonal wind component
5-zhgl	500hPa Divergence of true wind	thgl	1000hPaWind direction
8-ugl	850hPa Zonal wind component	8-thgl	850hPa Wind direction
850gl	850hPa Geopotential		