

Original Research Paper

Application of Time Series Modeling to Study River Water Quality

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Abstract: Water deficit problem originates from two factors: population increase and water pollution. However, studying and forecasting the quality of water are necessary to avoid serious problems in future through managerial works. In present study, using time series modeling, the quality of Madian Rood River is studied at Baraftab station using time series analysis. Nine parameters of water quality are studied such as: TDS, EC, HCO_3^- , Cl^- , SO_4^{2-} , Ca^{2+} , Mg^{2+} , Na^+ and SAR. Investigation of observed time series shows that there is a common increasing trend for all parameters unless Na^+ and SAR. The order of models for each parameter was determined using Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) of time series. The ARIMA model was used to generate and forecast the quality of stream flows. Akaike Information Criterion (AIC), Determination Coefficient (R^2), Root Mean Square Error (RMSE) and (Volume Error in Percent (VE %)) criteria were referred to evaluate the generation and validation results. The Results show that time series modeling is quite capable of water quality forecasting. For the majority of forecasts, the value of R^2 was greater than 0.6 between predicted and observed values.

Keywords: ARIMA, Time Series, Trend Elimination, Water Quality

Introduction

Water quality is a main subject of life due to its direct impact on human health. Water quality could be affected by geologic structure, salinity, overdraw of groundwater, urban and domestic wastewater entrance into surface streams as well as agricultural drainage and a wide range of chemical compounds (Tsakiris and Alexakis, 2012).

Different methods and approaches are used to investigate and forecast the quality of water. Also the majority of water software such as SWAT, QUAL2K and MIKE-11 benefit from especial tools to assess the quality of streams. Time series analysis is one of the useful methods which are applied in water quality modeling and forecasting.

Time series analyses is useful in understanding and analyzing the process of different phenomena. It is also helpful in generating past observations forecasting the future values based on the past memory.

Time series is composed of a string of data over time with an equal interval between all data. The interval can be defined as daily, weekly, monthly as well as yearly time steps. Time series analyzing is used in decision making in many hydrological processes and operation systems. Time series analysis in hydrology has two main goals:

1. Understand and model the stochastic mechanism of a hydrologic process and
2. Forecast the future values for the process

Applied Time-Series Analysis

Main statistical characteristics of a hydrologic time series could be reproduced using ARIMA (autoregressive, integrated, moving average) models. ARIMA models have been used to examine runoff and river discharge (Kurunç *et al.*, 2005;), water levels of lakes (Sheng and Chen 2011, Ghashghaie and Nozari, 2018), sediment yield

(Hanh *et al.*, 2010) and water quality (Ahmad *et al.*, 2001, Lehmann and Rode, 2001; Faruk, 2010; Hanh *et al.*, 2010; Durdu, 2010; Khalil Arya and Zhang, 2015).

Auto correlated models were used in some studies on stream analyzing (Thomas and Fiering, 1962). McKerchar and Delleur (1974) established the main step to apply time series in hydrology using Autoregressive Integrated Moving Average. They used seasonal modeling as well to analyze seasonal characteristics of stream parameters. Time series modeling is efficient in identifying and forecasting monthly stream pattern and integrated water resources management (Jalal Kamali, 2002). It has been widely used to forecast hydrologic variables such as rainfall and discharge as well as flood (Komornik *et al.*, 2006; Damle and Yalcin, 2007).

Many studies have focused on water quality parameters, a Brief reviews of which are mentioned as follow.

Applied Time Series Analysis on Surface Water Quality

Hirsch *et al.* (1982) used new methods to analyze monthly water quality data for monotonic trends. Also temporal changes in water quality parameters such as pH, Alkalinity, total Phosphorous and Nitrate concentrations have been studied using data series of Niagara (El-Shaarawi *et al.*, 1983). Yu *et al.* (1993) analyzed surface water quality data of the Arkansas, Verdigris and Neosho as well as Walnut river basin to study trends in 17 major constituents using 4 different nonparametric methods.

The trend of upland stream and water quality data from Plynlimon, mid wales were examined (Robson and Neal, 1996) applying the seasonal Kendall test. studied the time series of water quality parameters and the discharge of Strymon River in Greece from 1980 to 1997. Gangyan *et al.* (2002) investigated the temporal sediment load characteristics of the Yangtze River using the turning point test, Kendall's rank correlation test. Jassby *et al.* (2003) developed a time series model for Secchi depth in Lake Tahoe, USA. Panda *et al.* (2011) studied the trends in sediment load of a tropical river basin in India.

Applied Time Series Analysis on Groundwater Quality

Time series analysis has been applied on the groundwater quality modeling in different regions. Chang (1988) developed a modeling technique including the homogeneity test of data and the best model selection to fit the water loss series using a stochastic process.

Wilson *et al.* (1992) determined groundwater quality changes as a result of anthropogenic activities using a time series analysis of well water quality data from 1964 to 1965. Loftis (1996) reviewed national assessments of agricultural and urban, point source and hazardous waste

studies on regional and localized groundwater quality all over the world including a few snapshots. Lee and Lee (2003) evaluated and quantified the potential of natural reduction of groundwater in an industrial area of Seoul, Korea. Different studies have focused on water temperature time series () Kim *et al.* (2005) applied time series analysis in a study through which the effect of tide on groundwater quality in a coastal area of Korea was investigated. Also temporal variability of turbidity, dissolved oxygen, conductivity, temperature and fluorescence in the lower Mekong River as investigated using time series analysis (Irvine *et al.*, 2011). Water quality modeling plays an important role in water quality management and conservation (Singh *et al.*, 2004; Chenini and Khemiri 2009; Fang *et al.*, 2010; Su *et al.*, 2011;; Prasad *et al.*, 2014; Seth *et al.*, 2013; Parmar and Bhardwaj, 2014).

Application of time series analyzing in water resources demonstrates the efficiency and capability of this approach since it considers stochastic nature of hydrological processes. This study aims to use this methodology in water quality analyzing.

In present study, water quality parameters of Madian Rood are investigated at Baraftab station. The methodology and the study area are presented at the following section.

Materials and Methods

The Study Area

The study area is located in the west of Iran in Kuhdasht region. Figure 1 shows the study area in Iran. This station of the river is located at 47°48'E and 33°18'N. The area of basin is about 1108 Km² which is located at Kashkan basin of Karkheh watershed.

Time series of 9 water quality parameters such as TDS, EC, HCO₃⁻, Cl⁻, SO₄²⁻, Ca²⁺, Mg²⁺, Na⁺ and SAR of Baraftab station at Madian Rood River were studied in this research.

Methodology

The theory and application of the ARIMA modeling have been conducted in different studies (Pankratz, 1983; Vandaele, 1983; Box and Jenkins, 1976). The background of this methodology is presented briefly. Autoregressive (AR) models estimate the values for the dependent variable, Z_t , as regression function of previous values, $Z_{t-1}, Z_{t-2} \dots Z_{t-n}$. An AR model of order 1 (i.e. an AR (1) model) is defined as Equation 1:

$$Z_t = \Phi_1 Z_{t-1} + \alpha_t \quad (1)$$

where, Z_t and Z_{t-1} show deviations from the mean, Φ_1 is the first-order AR coefficient and describes the effect of a unit change in Z_{t-1} on Z_t and α_t is the white noise.

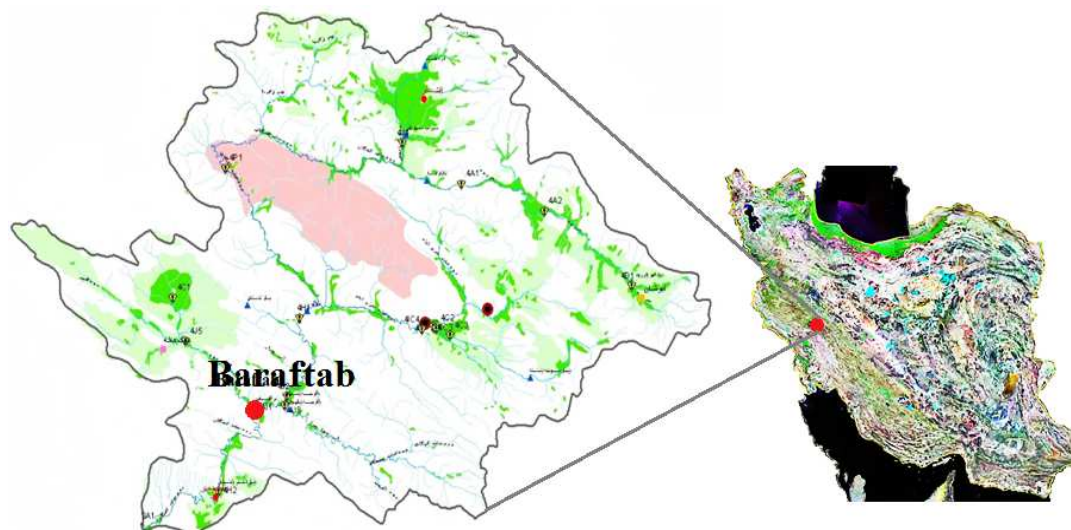


Fig. 1: The location of the study area

The α_t values are assumed normally distributed and independent with the mean value of 0 and a constant value of variance. The value of variance for a stationarity model of Z_t is positive and finite (Vandaele, 1983) and $|\Phi_1|$ must be less than 1 to meet these conditions. The Higher order of AR models are possible, similar to a multiple regression; for this case, the absolute value of each AR coefficient should be less than 1.

Moving Average (MA) models incorporate the past random fluctuations to show the time series. An MA model of order 1 (i.e., an MA (1) model) can be expressed as Equation 2:

$$Z_t = \alpha_t - \theta_1 \alpha_{t-1} \quad (2)$$

where, θ_1 is the MA coefficient and the random shocks (white noise) (α_t) are assumed normally distributed and independent with the mean value of 0 and a constant value of variance. The value of $|\theta_1|$ must be less than 1. The Values greater than 1 show that the observations further in the past have a greater effect on Z_t than more recent observations which is not plausible in a hydrologic time series. Higher order of the MA models is possible. Similar to the AR model coefficients, the absolute value of each MA coefficient should be less than 1. Since the parsimony is important in a time series modeling it sometimes could be met using a mixed (ARMA) model instead of a pure AR or MA model. Also representing a time series with an ARMA (1,1) model is more parsimonious in comparison with an AR (3) model because the model requires fewer parameter estimation. Mixing models is possible because they could be theoretically denoted as pure AR or MA models of infinite order (Vandaele, 1983). A mixed

model can supply more flexibility to describe the results of interaction between the processes (Salas *et al.*, 1980).

The main goal of a time series analysis is to understand seasonal patterns and/or trends over time. Most of the time hydrologic time series show a regular seasonal pattern which can be removed by standardizing the data for the seasonal mean and standard.

Also understanding and modeling the correlational structure in the time series is another goal of time series analysis. The basic stages in the ARIMA modeling are composed of: (1) Identifying the model, (2) estimating the orders of the model and (3) verifying the model using the standard tests. The results are presented in the following section.

Results and Discussion

In this study, nine water quality parameters were studied. Using one lag the data were transformed to make a yearly stationary time series. At the second stage MINITAB 14 was used in this study to analyze these 9 time series. The ACF and PACF of time series were plotted at the second stage.

After identifying the ACF and PACF of each time series the order of model was determined at first. Then 4 criteria were used to compare the results of series generation through the suggested models and 35 data-time series were generated. Based on 4 criteria, the best model was selected for each time series of 35 data and these models were used to forecast 5 values of time series. These 4 criteria were R^2 , AIC, RMSE and VE % (Karamouz and Araghinejad, 2005). The value of AIC is estimated through Equation 3:

$$AIC = (n \times \ln(\sigma^2) + 2 \times (p + q)) \quad (3)$$

where, σ is the standard error of residuals; n is the sample size; p and p show the order of AR and MA respectively. Also the value of VE % is calculated using (Equation 4):

$$VE \% = \frac{\sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|}{n} \quad (4)$$

where, y_i and \hat{y}_i show the observed and estimated values respectively and n is the sample size.

At the next stage forecasting the water quality parameters was accomplished. Results are shown in the following figs. Previously mentioned criteria (AIC, RMSE and VE %) were used at this stage for demonstrating the capability of each model to forecast the value of data.

Figure 2 shows the standardized time series of water quality data for TDS parameter and the forecasted values of 5 successive years.

Standard series of TDS show that this parameter has a positive trend, which was removed and modeled as it is demonstrated in Table 1.

The Results show that the model is capable of modeling the time series well. However, there is an increasing trend for the observed values of 5 successive years which is not the same for forecasted one.

For the second parameters, as it is clear from Fig. 3, EC time series follows an increasing trend which was removed at the second stage. Then using the best model, it was forecasted for 5 years.

Also Table 2 shows the results for modeling and choosing the best fit.

Figure 4 shows HCO_3^- time series and forecasted series for 5 years. The forecasted values for 5 successive years are shown in this Figure as well.

Similar to the previous parameters HCO_3^- follows an increasing slope and, the modeling was accomplished after trend elimination. Table 3 shows the results of modeling for this parameter.

Standardized time series of Cl^- is presented in Fig. 5. Also the forecasted values of this parameter are shown in this Figure.

The results show that the selected model, shown in Table 4, is capable of modeling the series well.

Figure 6 demonstrates the standard series of SO_4^{2-} . Modeling the SO_4^{2-} series was done on the original series without trend elimination. The forecasted values for 5 years are shown in this Figure too.

The results of generation and the best fit are shown in Table 5.

Also the standard series of Ca^{2+} is presented in Fig. 7 and the forecasted values of this parameter are shown in this Figure.

The results presented in Table 6 show that the selected model, shown in Table 6, is capable of modeling the series well.

Fig. 8 demonstrates the standard series of Mg^{2+} . The Fig.8 shows that the series follow an increasing trend. Modeling the Mg^{2+} series was done after trend elimination which is presented in this Figure as well.

Table 7 shows that the selected model is capable of modeling the series well.

Table 1: The results of TDS generation, order (1,3)

MODEL	R	R ²	AIC	RMSE	VE %
(1,1,2)	0.81	0.66	-93.05	0.04	1.13
(1,1,3)	0.86	0.74	-98.83	0.03	1.02
(2,1,3)	0.86	0.74	-96.95	0.03	1.00

Table 2: The results of EC generation, order (1,1)

MODEL	R	R ²	AIC	RMSE	VE %
(1,1,1)	0.73	0.54	-76.97	0.05	1.36
(1,1,2)	0.81	0.66	-89.01	0.04	1.29
(2,1,1)	0.83	0.68	-90.36	0.04	1.25
(2,1,2)	0.83	0.69	-89.82	0.04	1.27
(1,1,3)	0.85	0.73	-94.32	0.04	1.21
(2,1,3)	0.86	0.73	-92.51	0.04	1.18

Table 3: The results of HCO_3^- generation, order (1,2)

MODEL	R	R ²	AIC	RMSE	VE %
(1,1,2)	0.79	0.62	-43.72	0.11	2.66
(2,1,2)	0.77	0.59	-39.39	0.12	3.74
(1,1,3)	0.80	0.64	-48.27	0.11	2.39
(2,1,3)	0.76	0.58	-39.17	0.12	4.68

Table 4: The results of Cl^- generation, order (1,2)

MODEL	R	R ²	AIC	RMSE	VE %
(1,1,1)	0.84	0.70	-81.94	0.04	0.80
(1,1,2)	0.84	0.70	-77.96	0.04	0.80
(2,1,2)	0.84	0.70	-76.12	0.04	0.79
(1,1,3)	0.84	0.70	-75.97	0.04	0.80
(2,1,1)	0.82	0.67	-74.52	0.05	0.90

Table 5: The results of SO_4^{2-} generation, order (1,1)

MODEL	R	R ²	AIC	RMSE	VE %
(1,0,1)	0.51	0.26	-27.71	0.11	1.18
(1,1,1)	0.46	0.21	-23.09	0.11	1.42
(1,1,2)	0.49	0.24	-21.10	0.11	1.42
(2,1,1)	0.56	0.31	-20.58	0.11	1.70
(2,1,2)	0.60	0.36	-21.25	0.11	1.67
(1,1,3)	0.55	0.30	-22.47	0.11	1.64

Table 6: The results of Ca^{2+} generation, order (1,1)

MODEL	R	R ²	AIC	RMSE	VE %
(1,0,1)	0.77	0.59	-61.39	0.06	1.32
(1,0,2)	0.82	0.67	-66.36	0.06	1.33
(2,0,1)	...				
(2,0,2)	...				
(1,1,1)	0.78	0.60	-61.90	0.06	1.15
(1,1,2)	0.84	0.70	-69.94	0.05	1.16
(2,1,1)	0.87	0.76	-76.41	0.05	1.23
(2,1,2)	0.87	0.76	-74.52	0.05	1.22

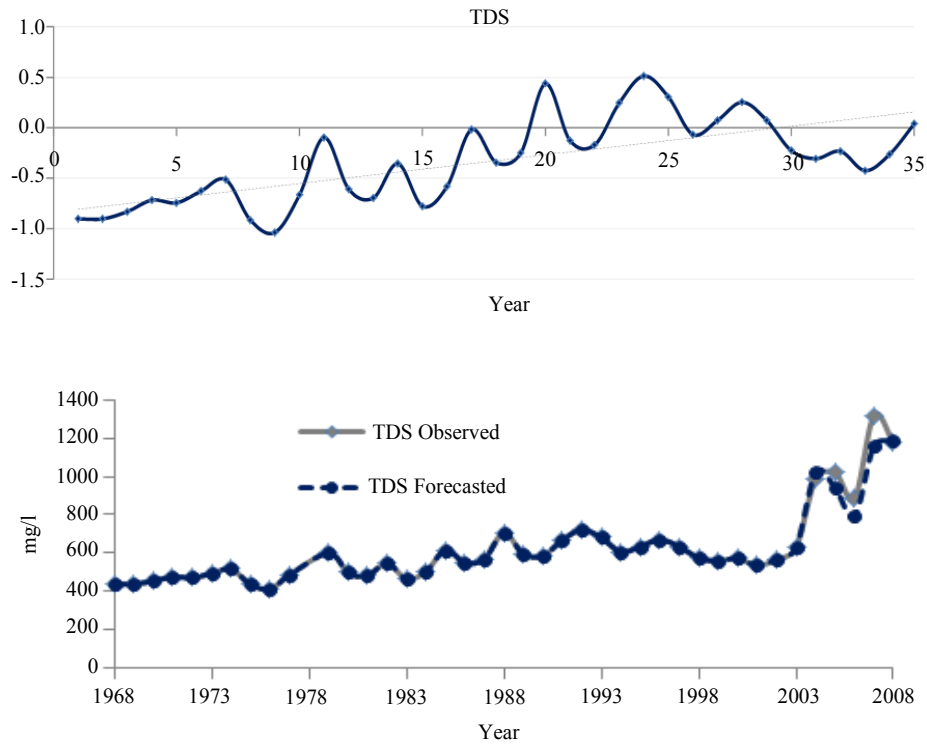


Fig. 2: Standardized time series of TDS and the forecasted values for 5 years

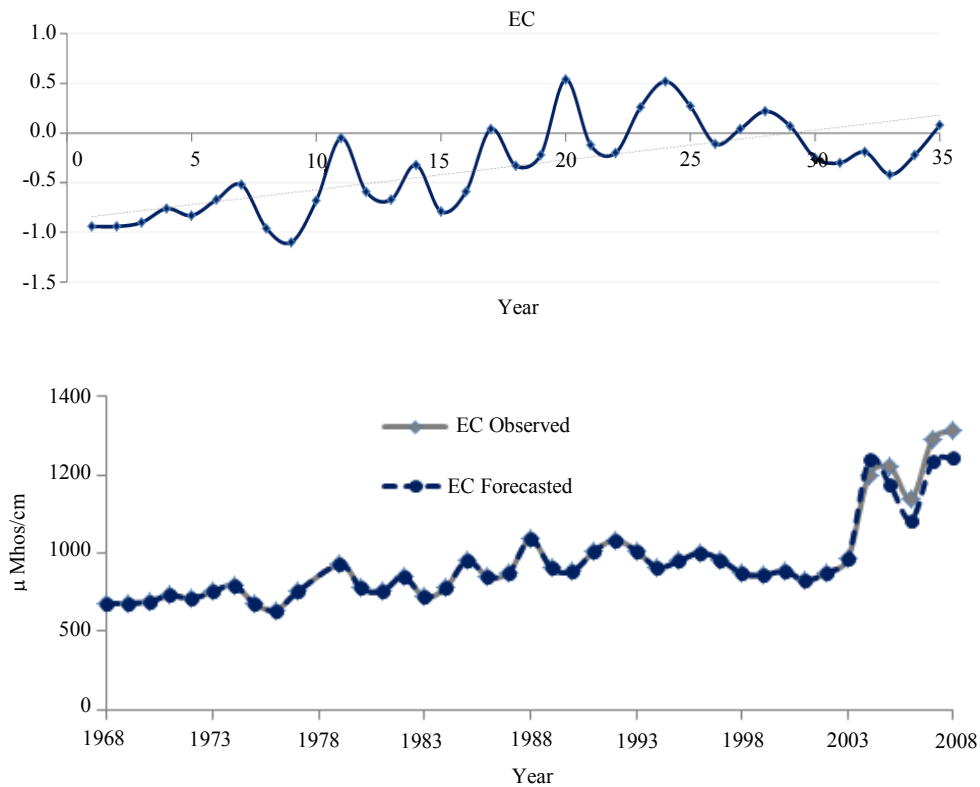


Fig. 3: Standardized time series of EC and the forecasted values for 5 years

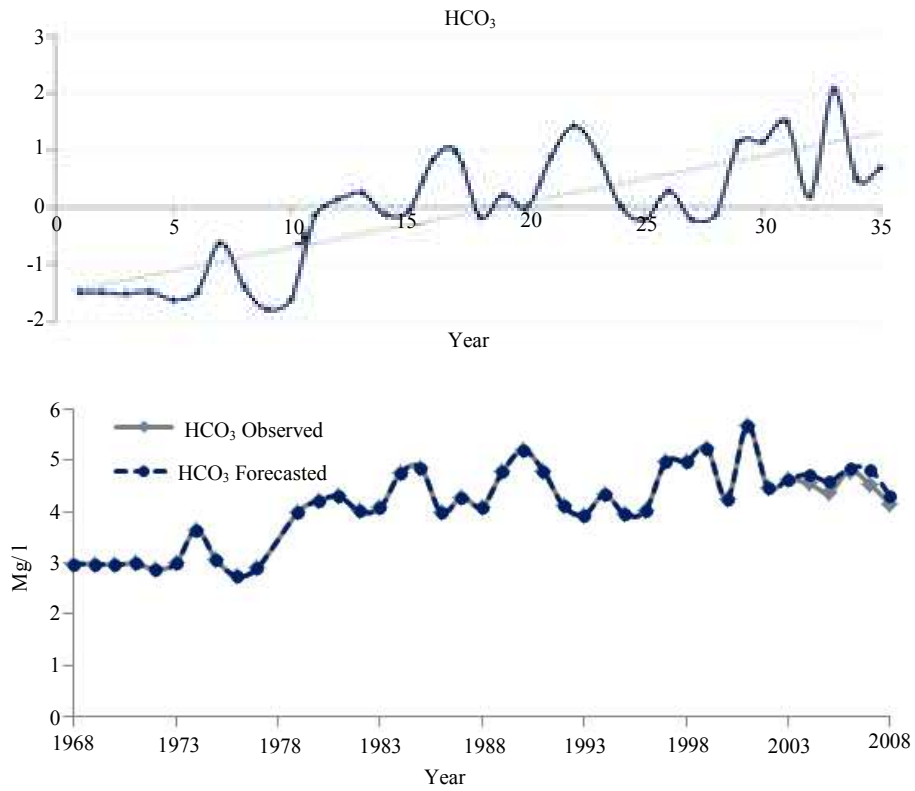


Fig. 4: Standardized time series of HCO_3^- and the forecasted values for 5 years

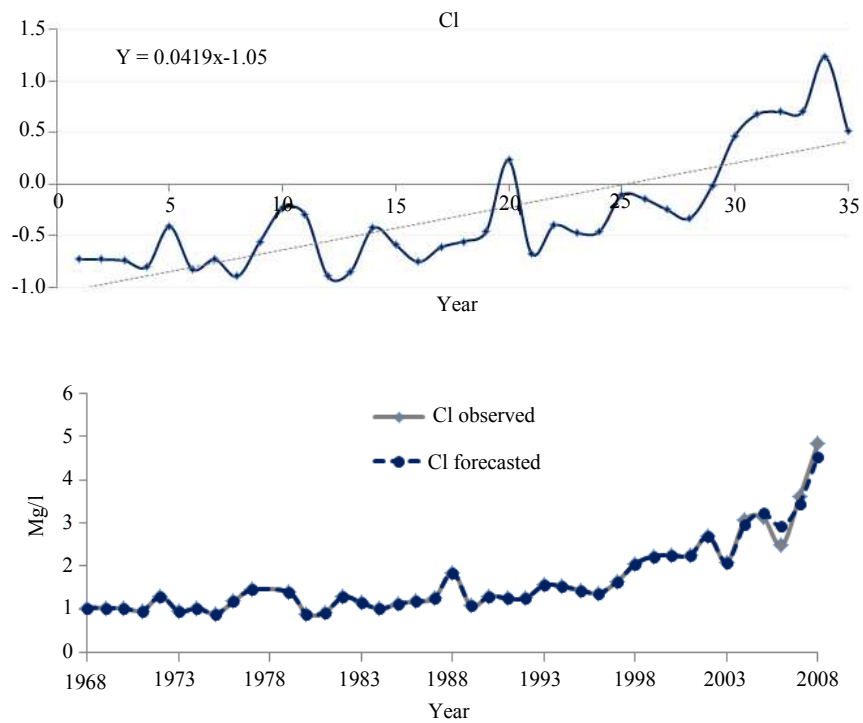


Fig. 5: Standardized time series of Cl^- and the forecasted values for 5 years

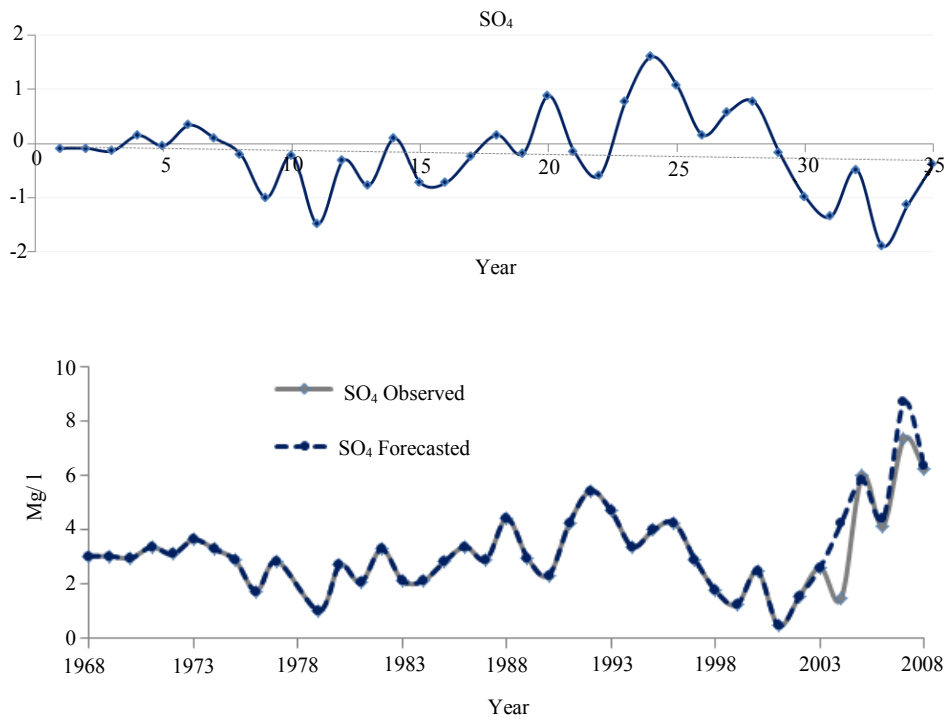


Fig. 6: Standardized time series of SO₄²⁻ and the forecasted values for 5 years

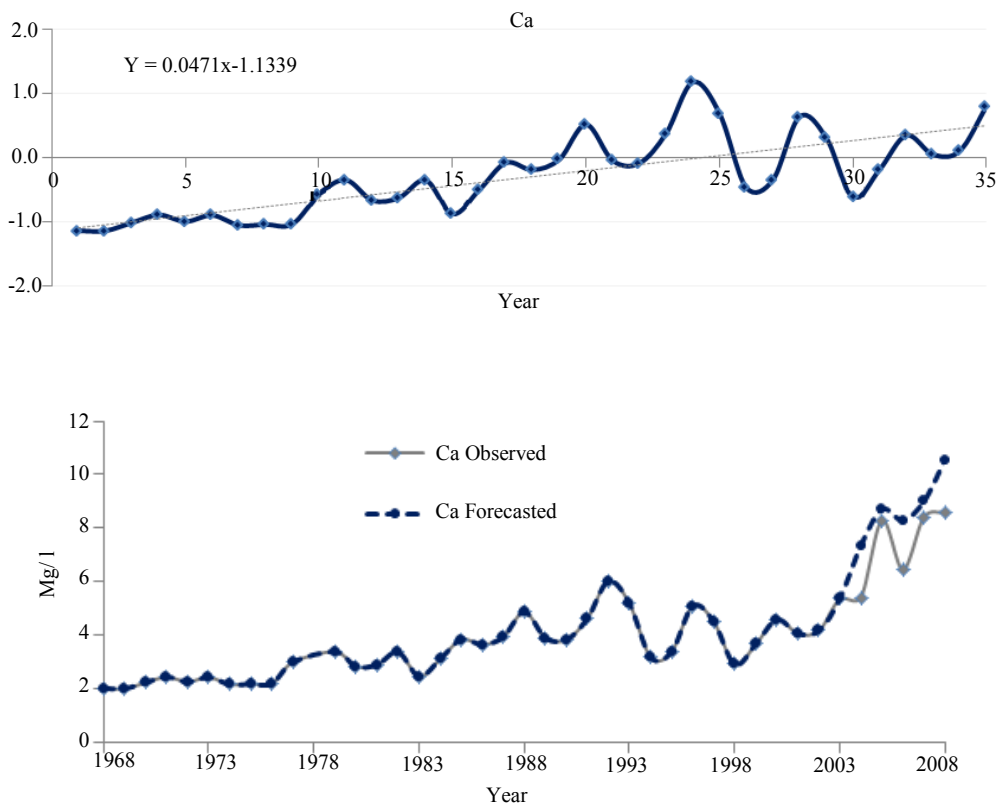


Fig. 7: Standardized time series of Ca²⁺ and the forecasted values for 5 years

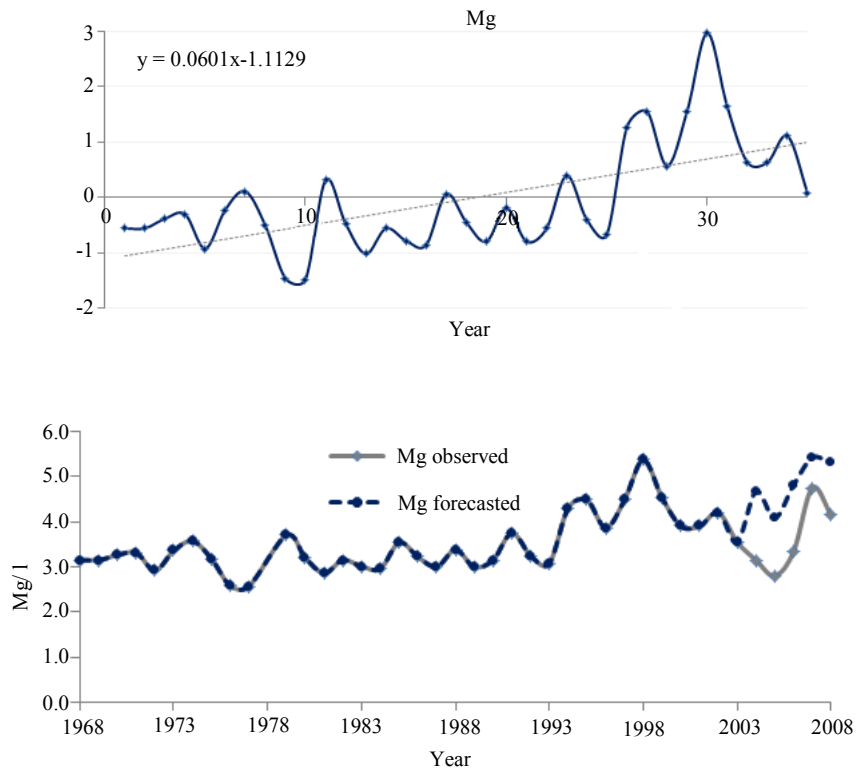


Fig. 8: Standardized time series of Mg^{2+} and the forecasted values for 5 years

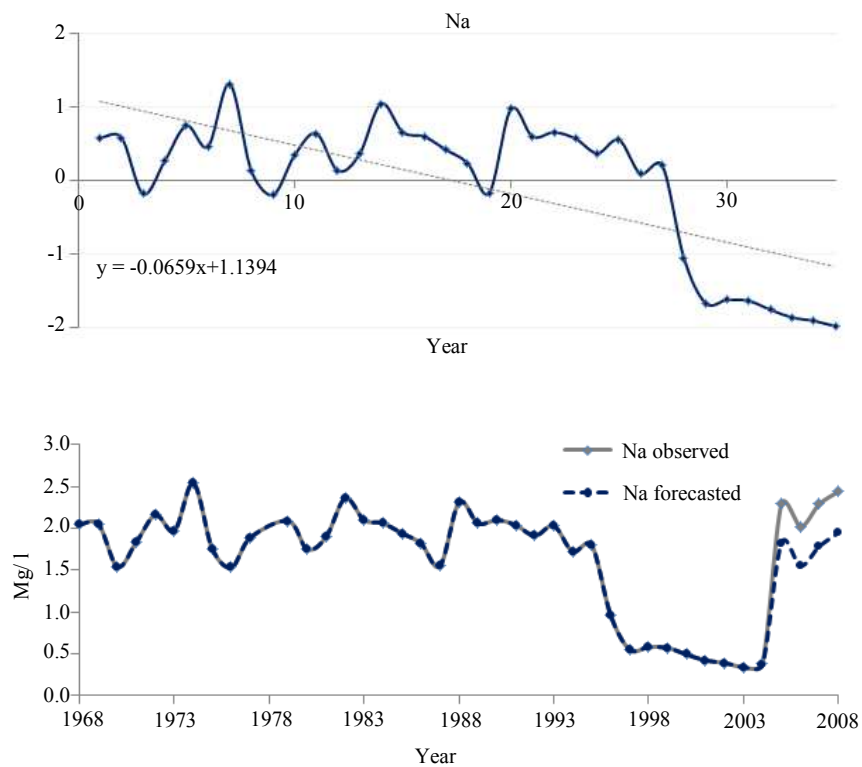


Fig. 9: Standardized time series of Na^{+} and the forecasted values for 5 years

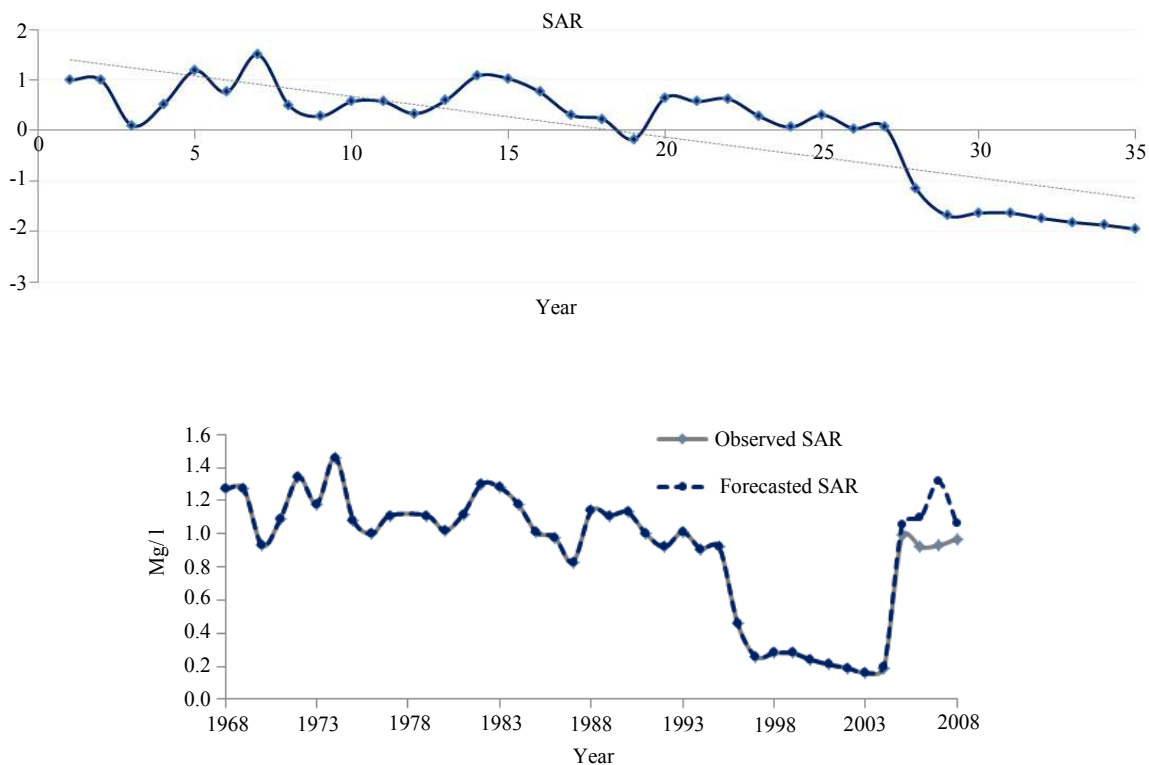


Fig. 10: Standardized time series of SAR and the forecasted values for 5 years

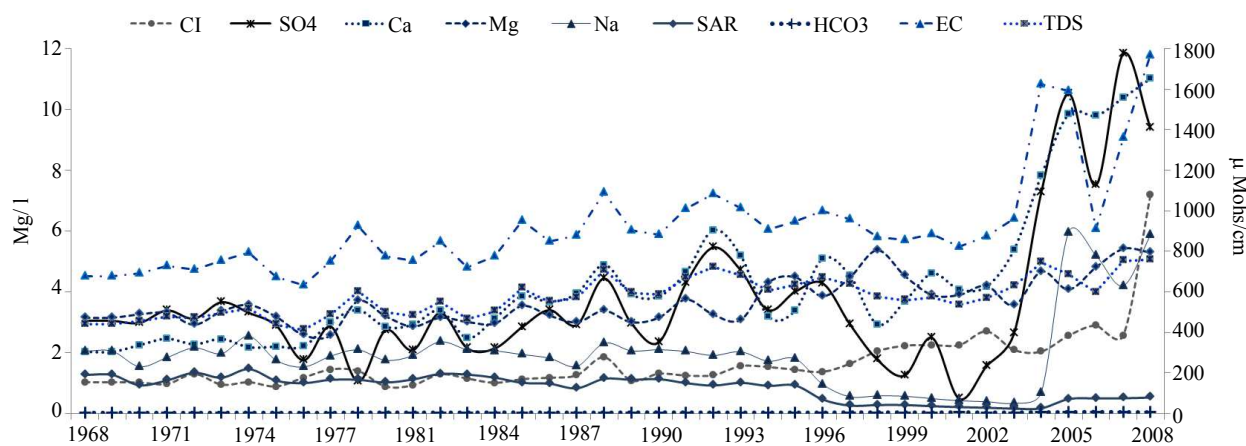


Fig. 11: Time series of forecasted values for the last 5 years of water quality parameters

Figure 9 shows standard series of Na^+ . The Figure shows that series follow a decreasing trend. Modeling was done for Na^+ series after trend elimination which is presented in this Figure as well.

The results show that the selected model, shown in Table 8, is capable of modeling the series well.

Finally, Fig. 10 demonstrates standard series of SAR. Modeling the SAR series was done after trend elimination which is presented in this Figure as well.

Table 9 shows that the selected model is capable of modeling the series well.

The Results of Forecasting

Table 10 shows the results of forecasting for 9 parameters. Also time series of HCO_3^- , Cl^- , SO_4^{2-} , Ca^+ , Mg^{2+} , Na^+ , SAR, TDS and EC are shown in Fig. 11. The last 5 years of time series demonstrate the forecasted values for parameters.

Table 7: The results of Mg²⁺ generation, order (1,1)

MODEL	R	R ²	AIC	RMSE	VE %
(1,0,1)	0.72	0.51	-19.21	0.11	1.02
(1,1,1)	0.69	0.48	-19.63	0.11	1.03
(1,0,2)	0.73	0.53	-22.28	0.10	1.05
(2,0,1)	0.67	0.45	-16.90	0.12	1.12
(2,0,2)	0.80	0.64	-29.81	0.09	0.84
(1,1,2)	0.79	0.62	-27.97	0.10	0.84
(2,1,1)	0.80	0.65	-29.72	0.09	0.94
(2,1,2)	0.80	0.65	-27.76	0.10	0.95

Table 8: The results of Na⁺ generation, order (1, 2)

MODEL	R	R ²	AIC	RMSE	VE %
(1,0,1)	0.87	0.75	-47.43	0.08	1.06
(1,1,1)	0.87	0.75	-46.73	0.08	0.93
(1,0,2)	0.87	0.75	-45.56	0.08	1.07
(2,0,1)	...				
(2,0,2)	0.89	0.80	-50.54	0.07	0.95
(1,1,2)	0.89	0.78	-49.33	0.07	0.91
(2,1,1)	0.87	0.76	-45.04	0.08	0.94
(2,1,2)	0.89	0.78	-47.42	0.07	0.91

Table 9: The results of SAR generation, order (1,2)

MODEL	R	R ²	AIC	RMSE	VE %
(1,0,1)	...				
(1,1,1)	0.91	0.83	-56.16	0.07	0.83
(1,0,2)	0.90	0.82	-52.50	0.07	1.03
(2,0,1)	...				
(2,0,2)	...				
(1,1,2)	0.91	0.83	-54.13	0.07	0.81

Table 10: Results of forecasting the 5 years of parameters

Parameter	RMSE	VE %	R ²
TDS	40.91	0.07	0.79
EC	60.33	0.08	0.65
HCO ₃ ⁻	0.09	0.04	0.86
Cl ⁻	0.12	0.07	0.95
SO ₄ ²⁻	0.62	0.44	0.73
Ca ²⁺	0.68	0.20	0.70
Mg ²⁺	0.56	0.26	0.88
Na ⁺	0.19	0.18	1.00
SAR	0.09	0.16	0.91

Conclusion

In this study, nine water quality parameters of Madian Rood River were studied at Baraftab station. The ARIMA modeling process was found suitable in generating and forecasting the parameters. SO₄²⁻, Na⁺ and SAR show a decreasing trend in spite of other elements of water quality, which show an increasing trend. However, using one lag to eliminate the trend stationary time series were prepared to work on.

Also investigation of observed time series shows that there is a common increasing trend for all parameters except for SO₄²⁻, Na⁺ and SAR. EC, Cl⁻, Ca²⁺, Mg²⁺ and HCO₃⁻ show an increasing trend which is a sign for deterioration of water quality in the region.

Based on the field studies (JCE, 2005), the high growth and relative density of population, increasing the consumption of artificial stocks, leaving urban wastewaters and majority of rural sewage in traditional method through rivers, inconvenient methods of burying litters, dispersion of rubbishes and litters in surface waters and streams which finally inflow through rivers are considered as the major reasons of water quality deterioration. Agricultural wastewaters and livestock are other reasons which make surface waters polluted. Also the danger of water quality aggravation is increasing as a result of high population growth in the region and efficient actions are necessary in the region to prevent more environmental destruction.

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Author's Contributions

Maryam Ghashghaie, KavehOstad-Ali-Askari, Vijay P. Singh and Saeid Eslamian designed the study, collected data, wrote the manuscript and revised it.

Ethics

This study approved by Water Resources Engineering Department, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, 6517833131, Iran.

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