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Forecasting the annual flow rate of the Tigris river using stochastic modelling

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ABSTRACT

The monthly and annual time series of the flow of the Tigris River at Al-Amara barrage was analyzed in order to forecast the annual and monthly future values of discharge of that river. The monthly series from 1980-2010 was used as data for this analysis. Non-homogeneity was detected in the series with significant positive jump's observed in the periods 1987-1988 and 1992-1997. The non-homogeneity was removed using the method suggested by Referance [1]. A Box and Cox [2] transformation was then used to normalize the homogeneous series. The dependent stochastic component was obtained from the series after removing the periodic component, which was observed using harmonic analysis after fitting the normalized series. A first-order auto-regressive model (Markovian chain) was then used to model the last obtained component. The data in the period 1980-2000 was used to conduct that analysis. For generation of a future series, the model was verified using the remaining 9-years, 2001-2010. Some statistical properties were obtained for both the forecasted and the observed series and then used to compare the two series. The comparison indicates that the model is capable of forecasting acceptable future data.

Keywords: Non-homogeneous, Periodic component and Dependent stochastic

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1. Introduction

Al-Amara Barrage is located on the Tigris River. Four regulators branch off upstream, namely: Al-Biterah, Al-Musharah, Al-Areedh, and Al-Kahlaa. Al-Amara Barrage is located about 450 m upstream of the Al-Kahlaa branch. The barrage has a navigation lock and a fish passage. In addition, it provides an adequate quantity of water to irrigate the land located on both sides of the Tigris River. Many marshes in the south of Iraq are fed predominately by the Tigris and its distributaries such as the Al- Huwaizah and Al-Hammar marshes. These marshes collect overflow water from the main channel of the Tigris during the wet season. Thus, it is important to predict the future values of the discharge of the Tigris River in order to sustain all the projects mentioned above. In addition, predicting a river flow is an important task for some events such as flood, managing of water resources, operation of reservoirs and planning, as well as designing new projects, etc. Therefore, a mathematical model was built using a time-series technique to estimate the statistical parameters. In this study, the data of the monthly discharge of the Tigris River at Al-Amara barrage was used to build a stochastic model in order to predict the future flowrate of this river.
In reference [4], the data of Total suspended solid TSS in the Euphrates River were used to build the mathematical model using the first-order auto-regressive model (Markovian chain) to predict future concentration. The result of the observed model indicates that it is capable of producing acceptable future data. In Reference [11], the researchers implemented a forecasting system for the Danube, Rhine and Elbe rivers in Germany using two approaches: the hydrological model with the statistical approach using empirical relationship and meteorological data with streamflows. They found that; for some stations; the meteorological forcing has more effect on seasonal forecast than the initial hydrological conditions. In Reference [13], a simple, low-cost method was innovated using combinations of well-known techniques (the Monte Carlo method, regression analysis and cumulative probability distribution function) to forecast the annual and

monthly streamflows of a hydrological year. The new method showed accurate results, in which, it's improved as the observed months increases. The peak river flow statistics were estimated using a hydrological model (Niger-HYPE) [12]. The authors tested the estimated peak flow with the observation values. The results show that the model capable in simulating the peak discharge (on average + 20%). The model was then used with a meteorological data to test the forecasting capacity. The results show good forecasting capacity with 17% deviation. In Reference [15] three models hydrologic sensitivity, multi-regression and hydrologic model simulations were used to assist the impact of human activities and climate change on the Lower Zab River basin (LZRB). The long-term runoff series from 1979 to 2013 was used for this analysis. The researcher was find that the climate variability was the main causes of reduction (66–97%) in streamflow, while human activities caused reductions of 4–34%. Two methods, namely, Chi-Square Automatic Interaction Detector (CHAID) and Optimally Pruned Extreme Learning Machine (OPELM) were used to model the deterministic parts of monthly streamflow equations, while for the stochastic parts, Autoregressive Conditional Heteroskedasticity (ARCH) was used in modeling monthly streamflow equations [16]. All the mentioned models were integrated to enhance the accuracy of these models. The results remarkably reveal that modified models show more accurate results comparing with the other models. In reference [9], a Hidden Markov Model was used to forecast meteorological droughts in Nile river basin. The results obtained from the Hidden Markov Model agree with the observed values regarding the SPI time series. Several models namely: Seasonal AutoRegressive Integrated Moving Average (SARIMA) model, Periodic AutoRegressive Moving Average (PARMA) model, Deseasonalized AutoRegressive Moving Average (DARMA) model, and; and the nonlinear Artificial Neural Network (ANN) model were used for modeling monthly streamflow at Eldiem station [7]. It was concluded that the nonlinear model (ANN) was more accurate than the other models in forecasting the monthly streamsflow. The monthly and annual flow rate of the Jarrahi river were forecasted using the stochastic model [6]. The authors used an auto-regressive moving average for modeling annual data and a multivariate auto-regressive moving average for modeling monthly data. In reference [5], the authors developed short-term flow forecasting models for the Bow River in Canada. The daily discharges collected from three-gauge stations were used to evaluate the accuracy of several regression models and the base difference (newly proposed). They suggested that the Banff and Calgary stations could be considered for forecasting the flow in Calgary because it require a few number of gauge stations. Two commonly used hydrologic models; the Deseasonalized Auto-Regressive Moving Average (DARMA) models and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) models were selected for modeling monthly streamflow in the White Nile; Blue Nile; Atbara River and the Nile river [14]. It was concluded that the DARMA model performs better than the SARIMA model for monthly streamflow in rivers. In reference [3], three different models, namely multiple regression, second-order auto-regressive, and classic Box–Jenkins [2] models were used for simulating and predicting daily stream water temperatures on the Moisie River. The results indicated that the second-order auto-regressive model provided the best results.

In general, the time series of any hydrological model may consist of two components according to the variable as well as the average time interval. For instance, in a seasonal river flowrate series (Qt), two components may exist, namely the deterministic and stochastic components (εQ) and the flowrate is detected from those components. The deterministic part may consist of three components, namely the jump (JQ), trend (TQ), and periodic or cyclic components (PQ). These components may be formulated by:

$$Q_t = J_Q + T_Q + P_Q + \varepsilon_Q \tag{1}$$

The deterministic part (1) is represented by the first three components, while the fourth component represents the non-deterministic part. By using a suitable formulation, the deterministic part (represented by the three mentioned components) should be detected and separated from the stochastic component.

2. Methodology and results

The following process was employed to perform the analysis:

Test the homogeneity of the data series by some statistical tests, if non-homogeneity exists, it will be removed by a suitable method. This was achieved using the spilt-sample method of dividing the sample into two sub-samples. The difference between the mean and standard deviation of these two sub-samples at the 95 percent probability level of significance were tested using the t-test method. The non-homogeneity was detected for the series and found to be non-homogeneous for the periods of 1987-1988 and 1992-1997, as shown in Figure. (1).

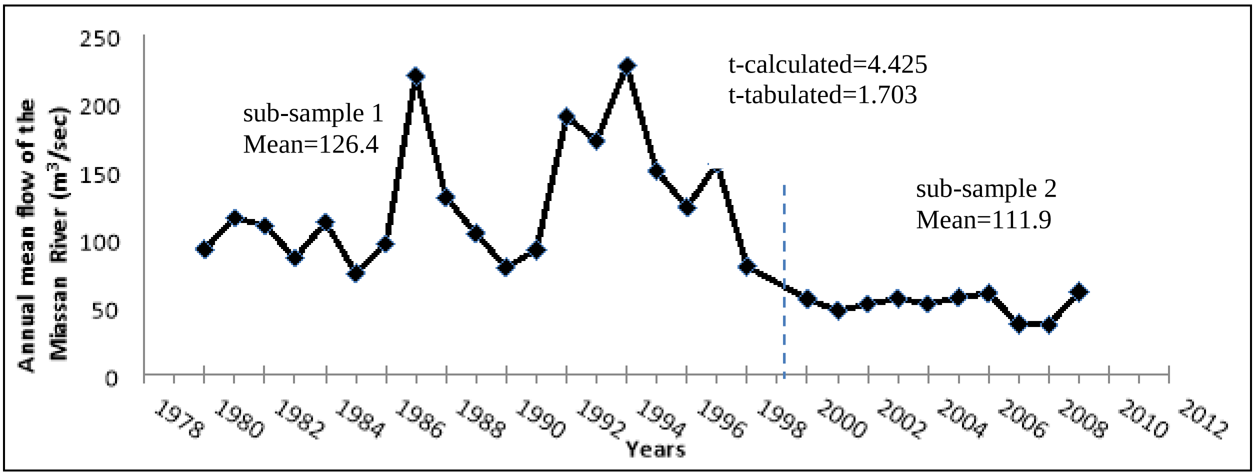

Figure 1. The original historical data divided into two sample tests

Using (2), the calculated t-value was found to be greater than the tabulated t-value. In order to remove the non-homogeneity from the series, the method suggested by Reference [1] was used. This was done using a linear regression equation for the annual mean, as well as for the annual standard deviation. The regression coefficient of the first sub-sample was calculated and the results summarized in Table 1.

$$\boldsymbol{t} = \frac{\overline{\boldsymbol{X}}_1 - \overline{\boldsymbol{X}}_2}{\boldsymbol{S} \times \sqrt{\frac{\boldsymbol{n}_1 - \boldsymbol{n}_2}{\boldsymbol{n}_1 \times \boldsymbol{n}_2}}} \tag{2}$$

And,

$$S = \sqrt{\frac{\sum_{i=1}^{n_1} (X_i - \overline{X_1})^2 + \sum_{j=1}^{n_2} (X_j - \overline{X_2})^2}{n_1 + n_2 - 2}} \tag{3}$$

where,
X1 = mean of first sub-sample
X2 = mean of second sub-sample
n1, n2 = number of years in the first and second sub-samples, respectively
Xi, Xj = annual value of the first and second sub-samples, respectively

Table 1. The regression coefficient of the first sub-sample.

Parameter	The regression coefficient of mean		The regression coefficient of sd	
Data	97.864	2.8491	45.918	0.4542

The first sub-sample was then transformed using the following equation:

$$Y_{j,t} = \frac{X_{j,t} - \overline{X}_j}{S_j} sd_2 + Av_2 \tag{4}$$

where,
Y = homogeneous series (transformed)
X = non-homogeneous series (historical)
j, t = the position of the annual and seasonal original data, respectively
Xj, Sj = equations of linear regression for annual mean and standard deviation versus Years
Av2, Sd2 = the average and standard deviation for the second subsample, respectively

Two sub-samples were established; the period 1980-2000 represents the first sub-sample, while the second sub-sample is represented by the period 2001-2010. The first sub-sample was transformed according to (4). The homogeneity was checked again for the two sub-samples using a t-test.

Fig. (2) and Table 2 show the results of applying (4). The calculated t-values are less than the tabulated t-values. Thus, the transformed series is homogeneous.

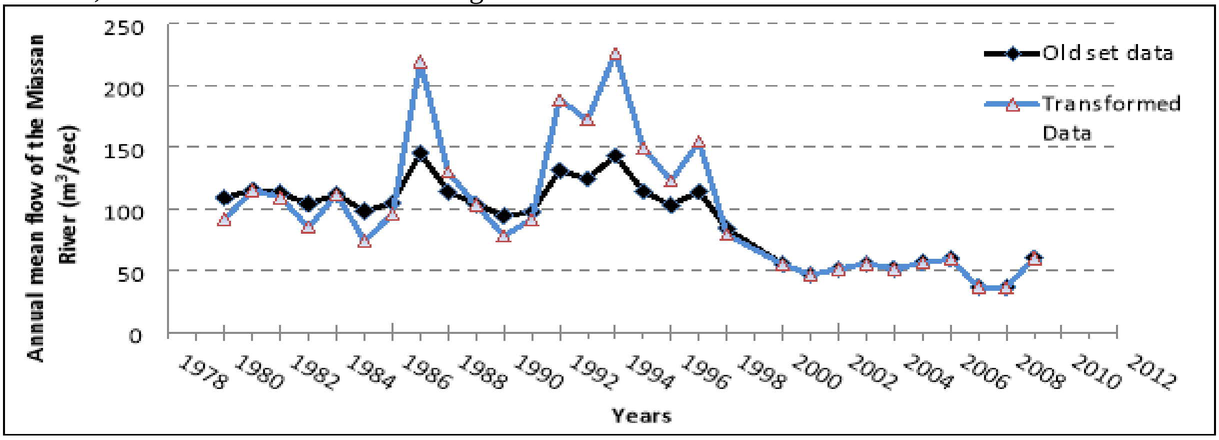

Figure 2. The original series and the series after removing the non-homogeneity

Table 2. Mean and standard deviation of both sub-samples before and after removing the non-homogeneity.

	Before removal		After removal	
	Mean	Standard deviation	Mean	Standard deviation
Sub-sample 1	126.4	41.38	111.9	14.28
Sub-sample 2	111.9	14.28	111.9	14.28

The homogenous data was transformed to a normal distribution using Box and Cox transformation [2]. This is done by removing the skewness in the data, in other words, make it equal to zero. In order to perform the above transformation, the transformation coefficient value (λ) was estimated. This coefficient is strongly associated with the skewness coefficient (Cs) and has a value between (λ = -2) and (λ = 2). By using different values of λ, the values of Cs were computed for each transformed series, the results are shown in Table 3. These values were found to be best fitted by a second polynomial equation, as shown in Fig. (3).

$$\lambda = 0.1957C_s^2 + 1.4911C_s + 1.0807 \qquad (5)$$

Table 3. Different values of the Skewness coefficient versus Box and Cox transformation coefficient.

λ	-0.8	-0.6	-0.4	-0.2	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6
Cs	-1.606	-1.376	-1.167	-0.977	-0.640	-0.487	-0.341	-0.200	-0.061	0.075	0.209	0.342

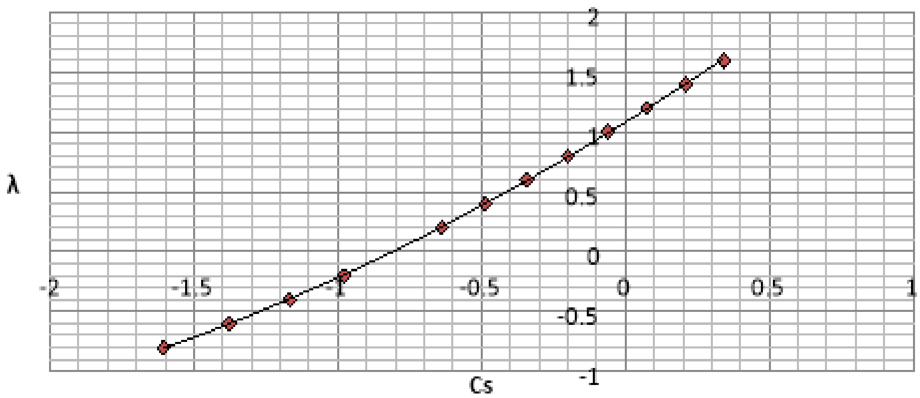

Figure 3. Best fit of a second polynomial equation between the Skewness coefficient (Cs) and Box and Cox transformation coefficient (λ)

For normalizing the data, the skewness coefficient Cs (5) is replaced by zero. Thus, the value of the transformation coefficient (λ) becomes equal to 1.0807. Using (6) for the Box and Cox transformation, the (λ) value was used obtain a new series.

$$y = \frac{(x-1)^{\lambda}}{\lambda} \qquad (6)$$

where,
y: Series after transformation
x: Historical series

The monthly mean and standard deviation for the historical series and the series after transformation are shown in Table 4.

Table 4. Mean and standard deviation for the observed and normalized series for the period 1980 - 2010

	original series		normalized series	
	AV.monthly	S.d monthly	AV.monthly	S.d monthly
Oct.	83.414	32.865	110.152	46.624
Nov.	88.489	36.227	117.527	51.749
Dec.	92.127	33.546	122.609	48.032
Jan	96.248	38.81	128.776	55.7
Feb	96.437	37.602	128.973	54.092
Mar.	94.581	37.281	126.278	53.629
Apr.	105.311	31.912	141.56	46.146
May	101.198	36.43	135.805	52.375
Jun.	94.8	34.911	126.504	50.106
Jul.	85.824	30.076	113.442	42.889
Aug.	81.505	28.577	107.233	40.619
Sep.	81.266	29.235	106.928	41.474

To detect the existence of a periodic component, a correlogram was found using the serial correlation coefficient calculated using (7):

$$r_k = \frac{\sum_{t=1}^{N-k}(y_t-\bar{y})(y_{t+k}-\bar{y})}{\sum_{t=1}^{N}(y_t-\bar{y})^2} \qquad (7)$$

where,
Y: the normalized series using to the transformation of Box and Cox
rk: Lag-k serial correlation coefficient (r1=Lag1, r2=Lag2, … etc)
$\bar{y}$: Mean of all the observations
t: Position of the value in the series

A Matlab program was written and a correlogram was drawn, as shown in Fig. (4), which indicates the periodicity. This figure, which is a plot of the serial correlation coefficient against the Lag, exhibits an oscillation at the same frequency.

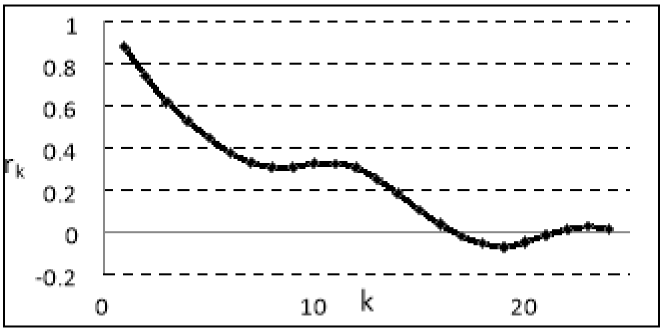

Figure 4. Correlogram of the normalized Series

The periodic component removal can be done by applying a non-parametric method for the normalized series by using the equation below.

$$\varepsilon_{i,j} = \frac{y_{i,j} - \bar{y}_j}{\sigma_j} \quad (8)$$

where,
$\varepsilon_{i,j}$ = Dependent stochastic part
$\bar{y}_j$ = Mean value of the data, i represents the position (month)
σ_j = Standard deviation value, j represents the position (month)
The result of (8) represents the dependent stochastic parts ($\varepsilon_{i,j}$). Fig. (5) shows the correlogram of the dependent stochastic component. From this figure, it should be noted that there are no seasonal fluctuations or any other oscillations.

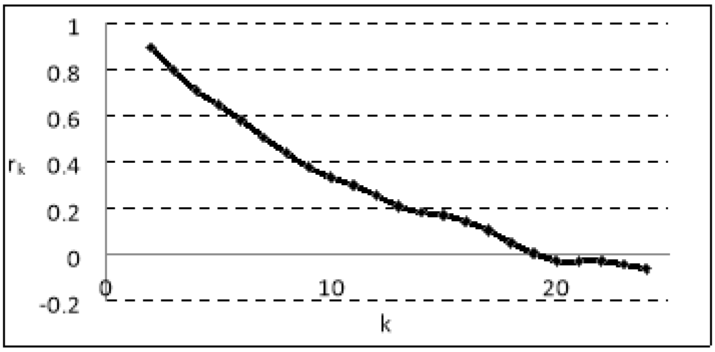

Figure 5. Correlogram of the stochastic component ($\varepsilon_{p,t}$).

To obtain the independent stochastic component ($\xi_{i,j}$), the most common model, namely the auto-regressive model, was used. The value of $\varepsilon_{i,j}$ was fitted by this model in which its parameters were found depending on the correlation represented by the lag rk serial correlation coefficient model (rk), as shown in Fig. (6). The first degree of the auto-regressive model (Markov model) was selected and its capability to eliminate the series of the dependent part ($\varepsilon_{i,j}$) was examined. The value of the lag-one (r1) serial correlation coefficient was found to be r1=0.8957. This was then used in the Markov model, which expresses the relationship between $\varepsilon_{i,j}$ and $\xi_{i,j}$ as follows:

$$\varepsilon_{i,j} = r_1 \varepsilon_{i,j-1} + \sqrt{1 - r_1^2} \quad (9)$$

Using the value of r1=0.8957 in (9), the independent stochastic series $\xi_{i,j}$, could be found as follow:

$$\xi_{i,j} = (\varepsilon_{i,j} - 0.8957\, \varepsilon_{i,j-1})/0.4446 \quad (10)$$

The adequacy of the first degree of the auto-regressive model was tested. This was done by finding the correlogram of the independent stochastic component (ξi,j). From Fig. (6), all the coefficient values of serial correlation are almost near a zero value. Thus meaning that the first degree of the auto-regressive model (Markov model) is suitable since the dependents of the value (εi,j) were removed, as shown in Fig. (6).

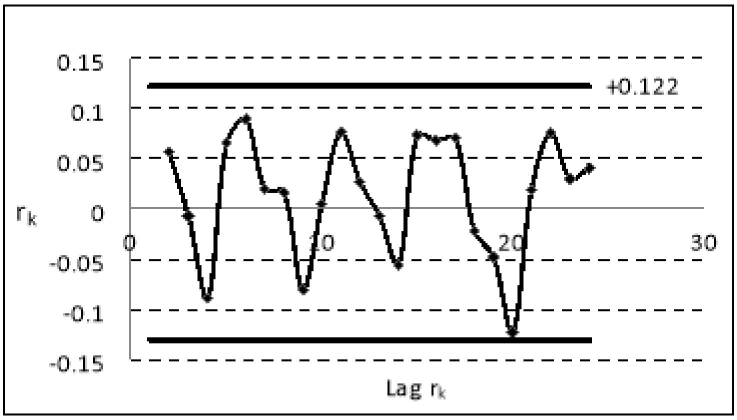

Figure **6.** Correlogram of the Independent Stochastic Component ($\xi_{i,j}$) according to first-order auto-regressive model.

After finding the parameters of the model, this model was verified using the remaining data that was not previously included in the process of estimating the parameters of the model. This data was in the period 2001-2010. The Matlab program was used for generation of future series of the flowrate. The forecasted series was then compared with the observed one in order to test the performance of the new model. Nine series were generated as shown in Table 6, Table 7 and Table 8 for three runs (run1, run2, and run3). Fig. (7) illustrate the values of the monthly mean streamflow obtained using the generated series run1, run2, and run3, as well as the observed flowrate. It can be noticed that the model performs well for most of the months, when compared with the observed data.
The mean values, standard deviation and coefficient of skewness of the forecasted series as well as the observed values are shown in table 9.

Table 6. The monthly forecasted series (run1)($\xi_{i,j}$) for 9 years

	Oct.	Nov.	Dec.	Jan	Feb	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.
2001-2002	27.96	31.86	31.45	43.68	47.88	48.00	49.22	42.74	53.44	50.38	51.11	48.22
2002-2003	45.20	47.92	52.70	53.09	50.53	51.79	61.94	65.91	62.22	50.13	55.05	52.57
2003-2004	53.52	48.94	58.42	64.25	63.91	70.01	78.68	77.70	73.58	64.02	54.69	57.72
2004-2005	55.72	50.55	43.86	38.58	48.00	56.98	48.79	46.51	40.75	37.04	46.66	49.05
2005-2006	50.10	42.36	43.36	41.23	43.85	43.55	44.75	43.18	52.02	48.05	52.36	55.78
2006-2007	55.75	73.16	69.94	67.71	60.31	46.46	53.57	62.48	59.86	52.37	50.27	52.40
2007-2008	52.76	61.22	51.10	56.04	51.03	51.57	51.85	49.04	50.77	45.77	42.56	42.09
2008-2009	42.53	46.04	52.62	63.16	61.37	52.22	58.11	52.37	45.62	38.07	34.17	34.42
2009-2010	42.93	39.73	41.43	39.26	40.24	50.00	47.32	50.76	53.92	47.56	48.97	52.49
mean	47.39	49.09	49.43	51.89	51.90	52.29	54.91	54.52	54.69	48.15	48.43	49.42

Table 7. The monthly forecasted series (run2) ($\xi_{i,j}$) for 9 years

	Oct.	Nov.	Dec.	Jan	Feb	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.
2001-2002	35.92	30.53	32.56	37.65	30.85	24.66	32.97	35.79	43.66	36.64	39.47	43.30
2002-2003	36.58	41.03	52.25	48.21	49.46	57.04	57.28	51.06	55.36	54.09	52.85	47.75
2003-2004	47.72	51.77	48.79	40.68	47.47	58.27	61.28	48.98	47.68	43.23	40.77	38.06
2004-2005	41.34	41.15	55.04	62.02	67.04	53.77	60.78	56.59	59.54	52.96	43.23	49.23

2005-2006	51.35	51.09	49.20	41.00	52.25	57.18	53.22	61.31	54.21	54.87	46.93	40.24
2006-2007	51.22	47.85	50.46	39.90	51.46	49.52	47.13	46.21	48.76	46.11	46.81	49.21
2007-2008	51.74	44.69	54.42	57.01	61.98	58.16	57.68	65.15	72.52	70.30	67.28	68.86
2008-2009	67.58	70.25	73.83	87.00	75.18	67.62	65.01	76.48	60.25	66.82	55.82	47.80
2009-2010	52.71	60.13	56.19	66.59	65.61	71.50	76.96	64.36	57.09	50.80	48.71	48.48
mean	48.46	48.72	52.53	53.34	55.70	55.30	56.92	56.21	55.45	52.87	49.10	48.10

Table 8. The monthly forecasted series (run3) ($\xi_{i,j}$) for 9 years.

	Oct.	Nov.	Dec.	Jan	Feb	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.
2001-2002	31.75	29.47	30.30	25.77	31.69	38.97	52.23	53.12	59.23	56.10	55.78	51.94
2002-2003	51.51	56.95	61.04	65.22	55.96	55.61	51.93	48.60	36.04	41.08	42.85	44.17
2003-2004	51.08	56.68	55.73	52.82	50.18	52.63	56.65	51.69	48.70	43.53	35.63	39.62
2004-2005	46.47	44.42	46.87	48.44	55.40	51.80	46.52	41.64	45.81	49.40	40.40	42.40
2005-2006	38.31	42.02	43.97	51.48	45.31	45.33	51.74	55.83	53.69	50.81	53.94	54.32
2006-2007	53.59	50.89	55.66	58.22	57.12	61.50	62.44	65.25	61.78	48.31	49.58	50.55
2007-2008	50.83	58.30	66.99	78.35	70.10	60.72	55.44	52.49	48.11	42.50	42.83	48.45
2008-2009	49.67	51.43	57.17	57.44	51.55	47.13	52.42	58.46	66.16	57.60	60.59	48.03
2009-2010	50.83	57.74	58.06	64.02	57.71	63.10	69.98	64.28	58.29	55.13	59.74	58.45
mean	47.12	49.77	52.87	55.75	52.78	52.98	55.48	54.60	53.09	49.38	49.04	48.66

Table 9. The properties of the forecasted series and the observed series

	Mean	Standard deviation	Skewness coefficient
Run1	46.22	11.00	0.40
Run2	52.73	11.39	0.28
Run3	51.79	9.05	-0.30
Observed data	50.71	13.77	0.56

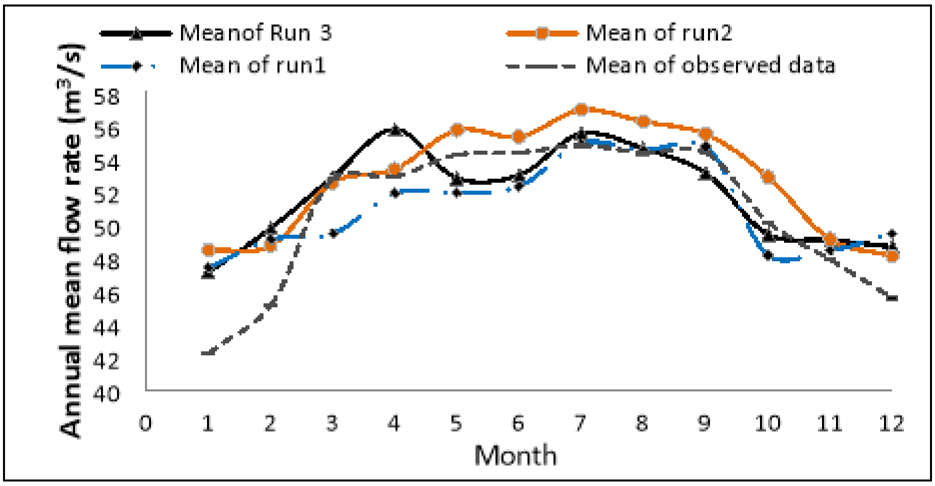

Figure 7. Comparison between the forecasted and observed series

3. Conclusions

1. Non-homogeneity was detected for the series of the flowrate from the Al-Amara Barrage on the Tigris River.
2. A seasonal pattern was detected for the data series. This pattern may be because of the annual cyclic pattern of the hydrological inputs to the barrage.
3. The power of the Box and Cox transformation equation (λ) was found to be equal to 1.0807.

4. The first order auto-regressive model was found to be capable of estimating the independent stochastic component.
5. The forecasted series was found to have the same properties as the observed series, i.e. mean, standard deviation and skewness coefficient. Thus, the obtained model can predict future flowrate values.

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