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Trend analysis and forecasting of the Gökırmak River streamflow (Turkey)

by

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Abstract

The objective of this paper is to determine the trend and to estimate the streamflow of the Gökırmak River. The possible trend of the streamflow was forecasted using an autoregressive integrated moving average (ARIMA) model. Time series and trend analyses were performed using monthly streamflow data for the period between 1999 and 2014. Pettitt's change point analysis was employed to detect the time of change for historical streamflow time series. Kendall's tau and Spearman's rho tests were also conducted. The results of the change point analysis determined the change point as 2008. The time series analysis showed that the streamflow of the river had a decreasing trend from the past to the present. Results of the trend analysis forecasted a decreasing trend for the streamflow in the future. The decreasing trend in the streamflow may be related to climate change. This paper provides preliminary knowledge of the streamflow trend for the Gökırmak River.

Key words: climate change, flow monitoring, forecast, river, water resources, seasonal, ARIMA

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Introduction

Water resources are key natural resources for sustainable development. Water resources are also crucial for socio-economic development and healthy ecosystems (Yıldız 2017). Therefore, water resource management is a significant issue for the future of water resources. Changes in the hydrologic environment resulting from climate change and other anthropogenic activities have caused problems in the amount and quality of water resources (Lee & Yeh 2019). A better understanding of the hydrologic environment is necessary for the assessment of water availability. Therefore, the assessment of hydrologic responses to the effects of climate change and anthropogenic activities is of vital importance to water resource managers and policymakers.

Issues related to the impact of climate change on river flows have attracted considerable attention in recent years. Durdu (2010) investigated the effects of climate change on water resources in the Büyük Menderes River Basin and pointed out that climate change has caused a decrease in the streamflow of the river. Bahadir (2011) analyzed changes in the Kızılırmak River streamflow and indicated that a decrease in the streamflow was closely related to climate change. Bozkurt and Sen (2013) examined the effects of climate change on the Dicle and Fırat river basins and stated that climate change has led to a significant decrease in the streamflow of the rivers. Kale et al. (2016a) examined climate change effects on the streamflow of the Karamenderes River and noted that climate change reduced the streamflow. Kale et al. (2016b) studied the impact of climate change on the Bakırçay River streamflow and documented that the streamflow was reduced due to climatic changes. Ejder et al. (2016a) investigated the effects of climate change on the streamflow of the Kocabaş Stream and reported that climate change resulted in a decrease in the streamflow. Ejder et al. (2016b) studied the effects of climate change on the streamflow of the Sarıçay Stream and indicated that a downward trend in the streamflow was due to climate change. Kale et al. (2018) pointed out that those decreasing trends in the runoffs of the Büyük Menderes, Gediz, and Tuzla rivers were observed due to climate change. Sönmez and Kale (2020) investigated climate change effects on the annual streamflow of the Filyos River and concluded that climate change caused a reduction in the streamflow. On the other hand, a comparison matrix related to the key criteria (climate, water, soil, land use and land cover, topography and geomorphology, socio-economy, management) of desertification determined for Turkey was constructed by TÜBİTAK-BİLGEM-YTE (2015) and the weights of the criteria were estimated. Climate was identified as the criterion with the greatest weight – 35.6%. In addition, the Kızılırmak River Basin was identified as a basin with a high level of moderate risk of desertification (Türkeş et al. 2020).

Researchers have used several methods to understand the impact of climate and anthropogenic factors on rivers. Published papers revealed that anthropogenic and climatic factors play different roles in different river basins. In some river basins, climatic factors have greater impact than the anthropogenic ones, while in others anthropogenic factors were more effective than climatic factors. Some authors reported that the contribution of human factors was greater than that of climatic factors (Jiang et al. 2011; Hu et al. 2012; Zhan et al. 2014; Kanani et al. 2020; Fu et al. 2020). Understanding the factors that trigger changes in water resources and determining the role of each of them in reducing the surface runoff or water resources is important when addressing water resource management issues (Kanani et al. 2020).

Rivers and streams are systems that prevent flooding and other damage caused by climate change and anthropogenic activities. Therefore, accurate assessment of the availability and streamflow of rivers is an important issue for water resource managers. Hydroclimatic changes and anthropogenic activities may cause an important change in streamflow time series (Sönmez & Kale 2019). Past and present trends of water resources should be investigated for their effective management. Villarini et al. (2011) recommended that change point analysis must be employed for a time series of the hydrologic process prior to the trend assessment. Determining the trends in streamflow time series is an important tool to detect changes in hydrologic systems (Chang 2007). Historical monitoring data will significantly contribute to the assessment of future trends (Blöschl & Montanari 2010). Different methods are used to determine trends in water parameters (Sen 1968; Hirsch et al. 1982; Helsel & Hirsch 2002; Şen 2012; Şen et al. 2019). Trend analysis has been used to determine trends in hydrologic and climatic variables (Cigizoglu et al. 2005; Saplıoğlu et al. 2014; Ay & Kişi 2017; Tosunoğlu 2017; Tosunoglu & Kisi 2017; Kale 2017a,b; Ali et al. 2019). Many scientists have investigated trends in water resources by using trend analysis (Kahya & Kalayci 2004; Cigizoglu et al. 2005; Bahadir 2011; Kale et al. 2016a,b; Ejder et al. 2016a,b; Kale et al. 2018; Ay & Kişi 2017; Ercan & Yüce 2017; Ay et al. 2018; Kale & Sönmez 2018a,b; Myronidis et al. 2018; Kale & Sönmez 2019a,b,c; Kişi et al. 2018; Yildiz et al. 2019; Sönmez & Kale 2020).

Although numerous studies have been carried out on the streamflow of other rivers, there are no studies on streamflow trends for the Gökırmak River. Therefore, this study aimed to determine trends in the streamflow of the Gökırmak River.

Materials and methods

Study area and streamflow data

The Gökırmak River, one of the largest tributaries of the Kızılırmak River, has its source in Ilgaz Mountain in the Kastamonu province, flows through Kastamonu, Taşköprü, Hanönü, Boyabat, Durağan and reaches the Kızılırmak River (the longest river that is completely within the borders of Turkey). The Gökırmak River is 221 km long and the basin is about 7000 km^2 (Yildirim et al. 2013). The region has a semiarid climate and is used for intensive agriculture, mainly rice cultivation (Dengiz et al. 2015). The Gökırmak River and its tributaries are frequently bordered by fluvial strath terraces that are covered by 3 to 5 m thick gravel deposits, which contain mostly well-rounded pebbles (Yildirim et al. 2013). Furthermore, Dengiz et al. (2015) reported that the soil texture class of the Gökırmak River varies from sandy loam to clay. Precipitation is observed in all seasons, while the mean annual temperature is 13.7°C and maximum evaporation is generally observed in July (Tanatmış 2004). In addition, floods caused by extreme rainfall and sudden snowmelt often occur in the river basin (Baduna Koçyiğit et al. 2017).

The streamflow data analyzed in the present study were collected from a streamflow gauging station at the Purtulu Station (E15A045) in the Kastamonu province (Fig 1). The General Directorate of State Hydraulic Works (DSİ) has been observing the streamflow at this station since 1 October 1998. In this study, the streamflow data for the period between 1999 and 2014 were processed on the basis of annual, seasonal, and monthly analyses. There is one more station recording flow data for the river. However, that station has been operating since 2013. The present study covers the period between 1999 and 2014. Therefore, data derived from the recently operated station were not included in the study. Due to some lack of monthly data in 2012 and 2013, observed available data were excluded from the streamflow data during the calculation of descriptive percentages.

Our initial assumption was that the data were normally distributed. Skewness, kurtosis, Kolmogorov–Smirnov and Shapiro–Wilk tests were used to evaluate the normality of the data. If the distribution of data is non-normal, transformations of data are applied to make the distribution of data as normal as possible. As stated by Feng et al. (2014), the log transformation is the most popular transformation used to transform data into data that follow a nearly normal distribution. In our study, the log transformation was used to make the data to conform to normality.

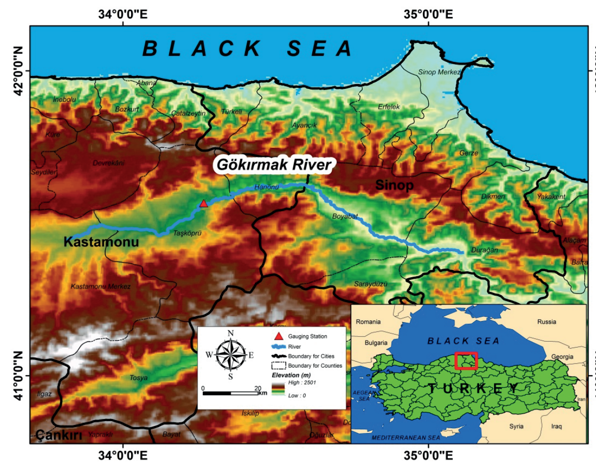

Figure 1

The Gökırmak River and the location of the streamflow gauging station

Change point analysis

Change point analysis is a non-parametric test and it was first developed by Pettitt (1979) to detect significant changes in mean values of a time series. In our work, the change point analysis was performed using the R statistical software (R Core Team 2019).

The null hypothesis of this analysis was that variables follow distributions that have a similar position parameter and that there is no change point, contrary to the alternative hypothesis that a change point exists. The following equations were used:

$$K_T = max\left|U_{t,T}\right|$$

and for

$$t = 2,......,T$$

$$U_{t,T} = \sum_{i=1}^{t}\sum_{j=t+1}^{T} sgn\left(x_i - x_j\right)$$

The null hypothesis is calculated with K_T and $U_{t,T}$ confirms whether two examples ($x_1,\ldots, x_t$ and $x_t+1,\ldots, x_T$) are in the same population or not. The associated probability (p) is used to compute the significance level.

Trend analysis

Trend analysis is a commonly used technique to determine a trend in a hydrologic time series. Box and Jenkins (1976) proposed a technique to find the best fit of a time-series model to historical values of a time series. In the present study, the trend analysis (Box & Jenkins 1976) was used to determine streamflow trends. It is based on linear, discontinuous, and stochastic processes. For stationary processes, autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models are performed. On the other hand, the autoregressive integrated moving average (ARIMA) model is efficient for non-stationary processes. The purpose of these models is to find the best fitted model to a time series with the least number of parameters. The AR model requires that the sum of squared errors is minimized using the smallest number of terms, which ensures a good fit to data. The MA model is useful to provide a good fit for various datasets, and changes in multiple exponential smoothing including models can switch periodic components and trends in data. The ARMA model can be developed by merging AR and MA models and can be applied to model a time series with a smaller number of terms that are more extensive than both AR and MA models. ARMA models are rich in terms and above all suitable for stationary and ergodic processes. Mixed models, which can be applied in a wider range of situations, can be created by merging AR and MA models. These well-known mixed models are the ARMA and ARIMA models. In ARMA models, the AR and MA models are merged together as a model of order (p, q), where p is the AR term and q is the MA term. The ARMA model is described below:

$$X_t = \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + e_t + \ldots + \theta_l e_{t-1} + \ldots + \theta_q e_{t-q}$$

In this equation, Φ is an autoregressive parameter to be predicted, θ is a moving average parameter to be predicted, X is the original series, and e is a series of unknown random errors that are expected to follow the normal distribution of the probability. In ARMA models, the null hypothesis assumes that the series is non-stationary as opposed to the alternative hypothesis rejecting the null hypothesis and defining the series as stationary.

On the other hand, while the ARMA model assumes that a time series is stationary, trends and periodicity actually occur in such datasets. Therefore, there is a requirement to reduce these effects before models can be run. Elimination is usually accomplished by adding a primary difference period to the model, which shows that there is no obvious trend or periodicity until the series reaches the lowest level about stationery. The differencing process is defined in the order of differentiation, which is similar to the AR and MA processes. These three components produce multiple forms (p, d, q), which explains the applied model form. At this point, the model is described as an ARIMA model. In ARIMA models, p refers to the number of AR terms, q refers to the number of MA terms and d refers to the order of differencing. The models are ordinarily listed as ARMA (p, q) models if no differencing is performed ($d = 0$). The letter "*I*" in ARIMA is the initial letter of the term "integrated" and indicates that a dataset was predominantly differentiated. The dataset must then be combined for final approximations and forecasts when modelling is concluded. The objective of these models is to detect the best model fitting to a time series and to take account of minimum parameters (Box and Jenkins, 1976). The ARIMA model employs a linear combination to forecast a time series. ARIMA supports the selection of the right model to fit a time series. The ARIMA model used in the study is as follows:

$$X_t = c + \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + \theta_1 e_{t-1} + \theta_q e_{t-q} + e_t$$

where X_t is the variable that will be defined in t time, e_t is the error in t time, θ is the coefficient of parameter q, Φ is the coefficient of parameter p, and c is the constant.

Many scientists have frequently applied trend analysis to determine trends in the streamflow of rivers (Ejder et al. 2016a,b; Kale et al. 2016a,b; Myronidis et al. 2018; Kale et al. 2018; Kale & Sönmez 2018a; Khairuddin et al. 2019; Sönmez & Kale 2020). Therefore, this model was implemented to determine the trend in the streamflow data. Trend analyses were performed in SPSS and Minitab statistical software. The identification of ARIMA models is based on calculations of autocorrelation. In addition, autocorrelation analyses were performed to calculate the consistency of trend analysis results.

ARIMA modelling can be divided into three stages. Initially, the order of differencing and degrees of AR and MA was determined using the autocorrelation function (ACF) and the partial autocorrelation function (PACF). It was then predicted that the parameters confirm that the residuals are white noise. Finally, the best-fit model was obtained in the third stage as a result of the analysis of residuals. The Ljung–Box test statistic was used to check the randomness. The normalized Bayesian Information Criterion (BIC), R-squared and p values were compared. The ARIMA models with the minimum normalized BIC, p and R-squared values were selected as the best fit models and used for forecasting. The accuracy of the models was assessed by means of commonly used performance measures, which are the mean absolute deviation (MAD), the mean squared deviation (MSD) and the mean absolute percentage error (MAPE).

Mann–Kendall and Spearman's rho test

The Mann–Kendall test was initially presented by Mann (1945) and then developed by Kendall (1955). The Mann–Kendall test is a comprehensive test to examine a trend in a time series. One of the advantages of this non-parametric test is that data do not have to follow any specific distribution. The following equation was employed:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} sgn(x_k - x_i)$$

In this equation, the time series x_i is derived from i = 1, 2, …, n – 1, and x_k from k =i + 1, …, n.

$$sgn(\theta) = \begin{cases} +1, & \theta > 0 \\ 0, & \theta = 0 \\ -1, & \theta = 0 \end{cases}$$

The normalized test statistic is calculated using the following equation:

$$Z_c = \begin{cases} \frac{S-1}{\sqrt{var(S)}}, & S > 0 \\ & S = 0 \\ \frac{S+1}{\sqrt{var(S)}}, & S < 0 \end{cases}$$

In this equation, the test statistic is Z_c and when $|Z_c| > Z_{1-\alpha/2}$, where $Z_{1-\alpha/2}$ is the standard normal variable and α is the significance level for the test, H_0 will be rejected. The size of the trend is calculated using the following equation:

$$\beta = Median\left(\frac{x_i - x_j}{i-j}\right), \forall_j < i$$

where $1 < j < i < n$.

A positive value of β indicates an increasing trend, while a negative value of β indicates a decreasing trend.

Spearman's rho test, a non-parametric test, is used to measure the strength of a monotonic relationship between two variables (Lehmann 1975; Sneyers 1990). It was performed to determine the relationship between two variables before the model was produced. Non-parametric Spearman's rho and Mann–Kendall tests yield more reliable results than parametric tests (Kale & Sönmez 2018a).

Results

The first assumption is that the data are normally distributed. Descriptive statistics of the streamflow data were calculated and are presented in Table 1. The descriptive statistics include: the mean, standard deviation (SD), coefficient of variation (CV), coefficient of skewness (CS), skewness, kurtosis, maximum value, minimum value, and range. CV is the most selective feature among these statistics. If the coefficient of variation is greater than 0.9, the parameter shows high variability, whereas it shows low variability when the CV value is less than 0.1 (Durdu 2010). The calculated value of CV for the annual and seasonal streamflow is less than 0.9 and greater than 0.1. However, the CV value for summer is close to 0.9 (CV = 0.73). These findings show that the statistic can be considered as an indicator to understand the variability in the streamflow. The skewness measures the asymmetry (should be around zero) of a distribution. The kurtosis is a measure of "peakedness" of a given distribution. Skewness and kurtosis values between –2 and +2 are acceptable (George & Mallery 2010), although both values are equal to zero in the normal distribution. Similarly, Kim (2013) remarked that the null hypothesis (assuming that data show a normal distribution) should be rejected when absolute Z scores for either skewness or kurtosis are not between –1.96 and 1.96 for small samples (n < 50). Z scores can be obtained by dividing the skew values or excess kurtosis by their standard errors (Kim 2013). Therefore, skewness and kurtosis were also used to evaluate the normality of data in addition to Shapiro–Wilk and Kolmogorov–Smirnov tests. Table 2 shows the obtained values of skewness, kurtosis, Shapiro–Wilk and Kolmogorov–Smirnov tests. Values are within the acceptable ranges.

Table 1

Descriptive statistics of the streamflow data

Streamflow	Mean	SD	CV	CS	Maximum value	Minimum value	Range
Annual	28.48	3.43	0.45	202.46	49.90	10.46	39.44
Spring	64.89	8.16	0.47	415.31	111.77	25.37	86.40
Summer	21.27	4.17	0.73	78.39	50.71	3.64	47.06
Autumn	8.70	0.89	0.38	69.84	13.90	1.38	12.52
Winter	19.07	2.53	0.50	105.58	34.73	5.00	29.73

Table 2

Results of skewness, kurtosis and normality tests

Streamflow	Skewness	$SE_{skewness}$	$Z_{skewness}$	Kurtosis	$SE_{kurtosis}$	$Z_{kurtosis}$	Kolmogorov–Smirnov*		Shapiro–Wilk	
							Statistics	*p*-value	Statistics	*p*-value
Annual	0.04	0.597	0.067	−1.35	1.154	−0.001	0.175	0.200*	0.935	0.200*
Spring	0.18	0.597	0.302	−1.53	1.154	−0.001	0.139	0.200*	0.921	0.200*
Summer	0.42	0.597	0.704	−1.01	1.154	−0.001	0.182	0.200*	0.924	0.200*
Autumn	−0.58	0.597	−0.972	0.55	1.154	0.000	0.129	0.200*	0.853	0.042
Winter	0.21	0.597	0.352	−1.12	1.154	−0.001	0.137	0.200*	0.956	0.200*

Note: *indicates the lower limit of the true significance.

[a] indicates the Lilliefors Significance Correction

Box and Jenkins (1976) recommended that the autocorrelation function (ACF) and the partial autocorrelation function (PACF) as the major analyses to determine the ARIMA model sequence. The ACF and PACF results obtained using the natural logarithm for the annual and mean seasonal streamflow data are presented in Figure 2. Moreover, the ACF results using the natural logarithm for the mean monthly streamflow data are shown in Figure 3, whereas the PACF results using the natural logarithm for the mean monthly streamflow data are presented in Figure 4. The best fitted model is the model at a certain significance level. Thus, the significance levels of the ARIMA models were compared with each other and the Ljung–Box test statistic was used to check the randomness. The R-squared values were considered when selecting the best fitted model. R-squared values that are closer to zero and lower values of the normalized Bayesian Information Criterion (BIC) indicate a good fit. Therefore, the ARIMA (0,1,1) model was selected to forecast the future trends in the streamflow (Table 3). The accuracy of the models was assessed by employing the commonly used performance measures, which are the mean absolute deviation (MAD), the mean squared deviation (MSD) and the mean absolute percentage error (MAPE).

The results of the change point analysis indicate that the change point for the mean annual streamflow was 2008. Trend analysis results showed a decreasing trend for the mean annual streamflow (Fig. 5).

The change point analysis was carried out to understand seasonal trends in the streamflow. The analysis identified 2005, 2008, 2006, and 2005 as change points for spring, summer, autumn, and winter, respectively. The results of the trend analysis showed that the streamflow tends to increase in summer and decrease in other seasons (Fig. 6).

For monthly trends in the streamflow, the change point analysis determined 2004, 2004, 2010, 2005, 2005, 2009, 2008, 2005, 2005, 2001, 2006, and 2006 as change points for the monthly streamflow data from January to December, respectively. The results of the trend analysis showed that the mean monthly streamflow tends to increase in May, June, and July. On the other hand, the streamflow showed a decreasing trend for January, March, April, August, September, October, and November (Fig. 7). There is no upward or downward trend in February and December.

Although increasing and decreasing trends were determined for the streamflow of the Gökırmak River by monthly, seasonal and annual analyses, the determined trends were found to be statistically insignificant according to the results of Spearman's rank correlation test and the Mann–Kendall trend test. Test statistics for both tests are presented in Table 4.

Table 3

Parameters of ARIMA models for annual streamflow data

Parameters	Models			
	ARIMA (1, 1, 0)	ARIMA (0, 1, 1)	ARIMA (1, 1, 1)	
	AR	MA	AR	MA
Coefficient	−0.637	0.890	−0.126	0.894
SE	0.255	0.314	0.377	344
p-value	0.029	0.016	0.746	0.027
Normalized BIC	15.616	15.409	15.863	
R^2	−0.565	−0.272	−0.479	
Ljung–Box Statistics	25.31	19.11	18.12	
Ljung–Box *p*-value	0.005	0.039	0.034	

Note: ARIMA means autoregressive integrated moving average; AR – autoregressive; MA – moving average; SE – standard error; BIC – Bayesian Information Criterion.

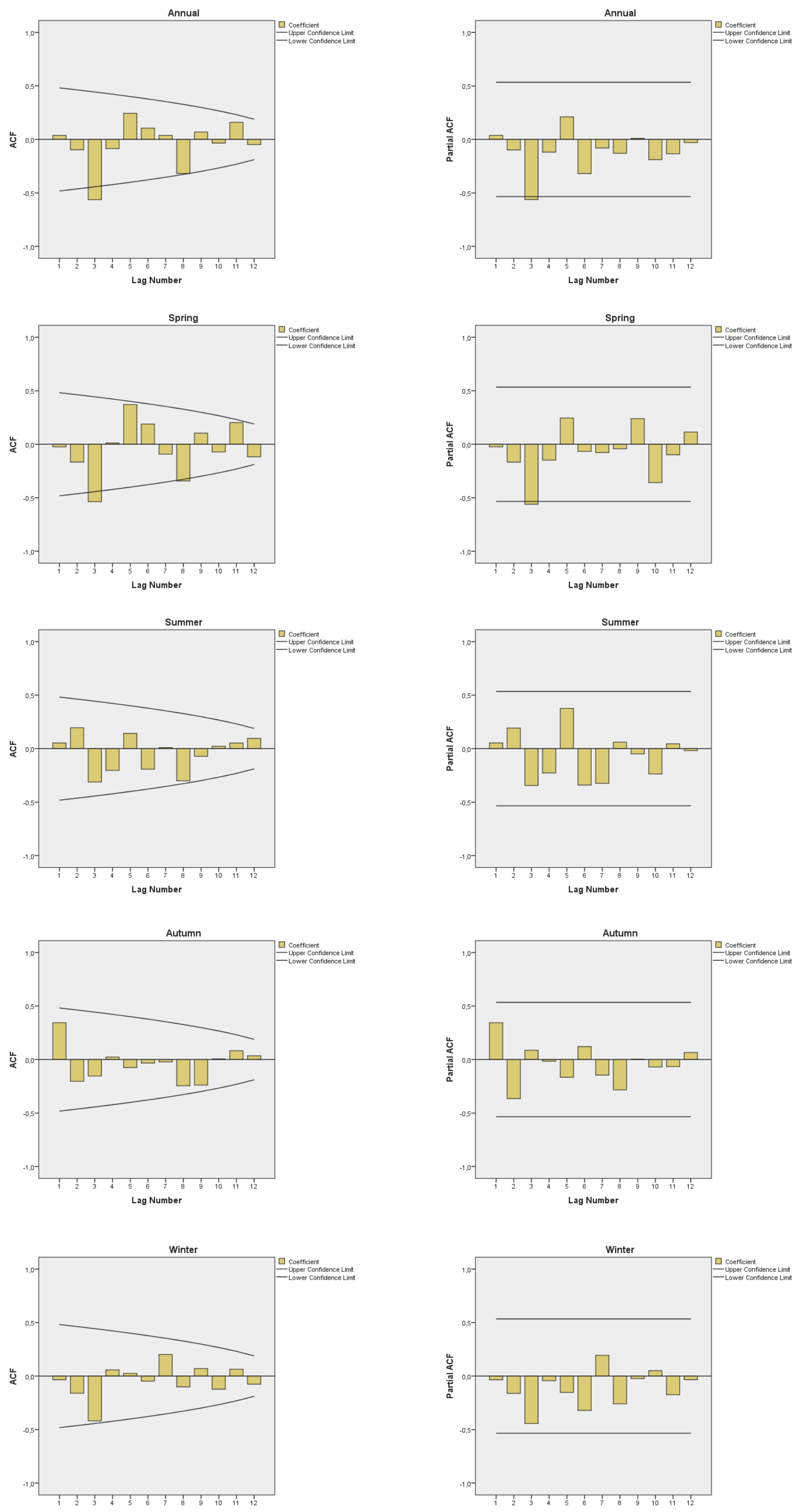

Figure 2

The autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the natural logarithm of annual and mean seasonal streamflow data. The lines represent the 95% confidence interval.

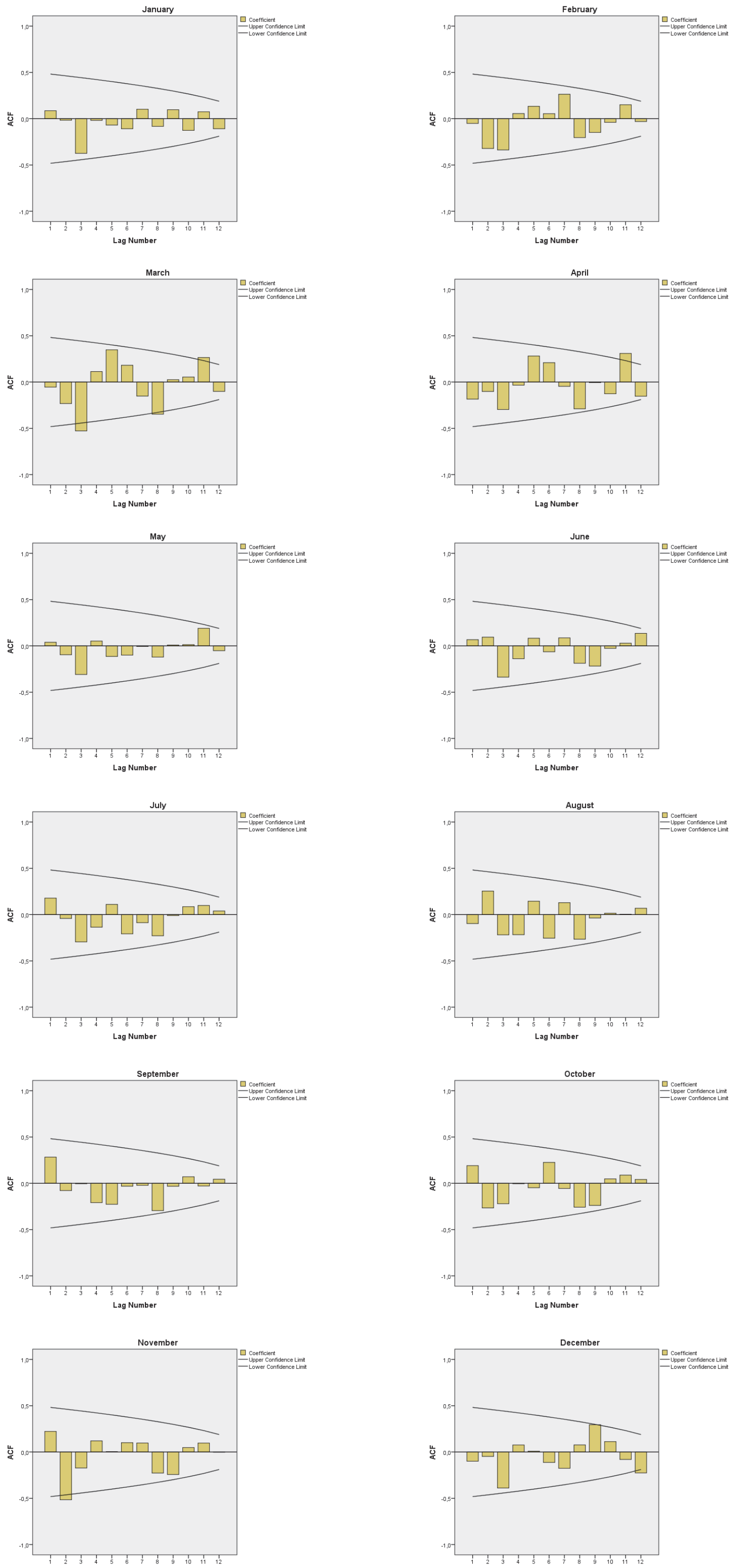

Figure 3

The autocorrelation functions (ACF) of the natural logarithm of mean monthly streamflow data. The lines represent the 95% confidence interval.

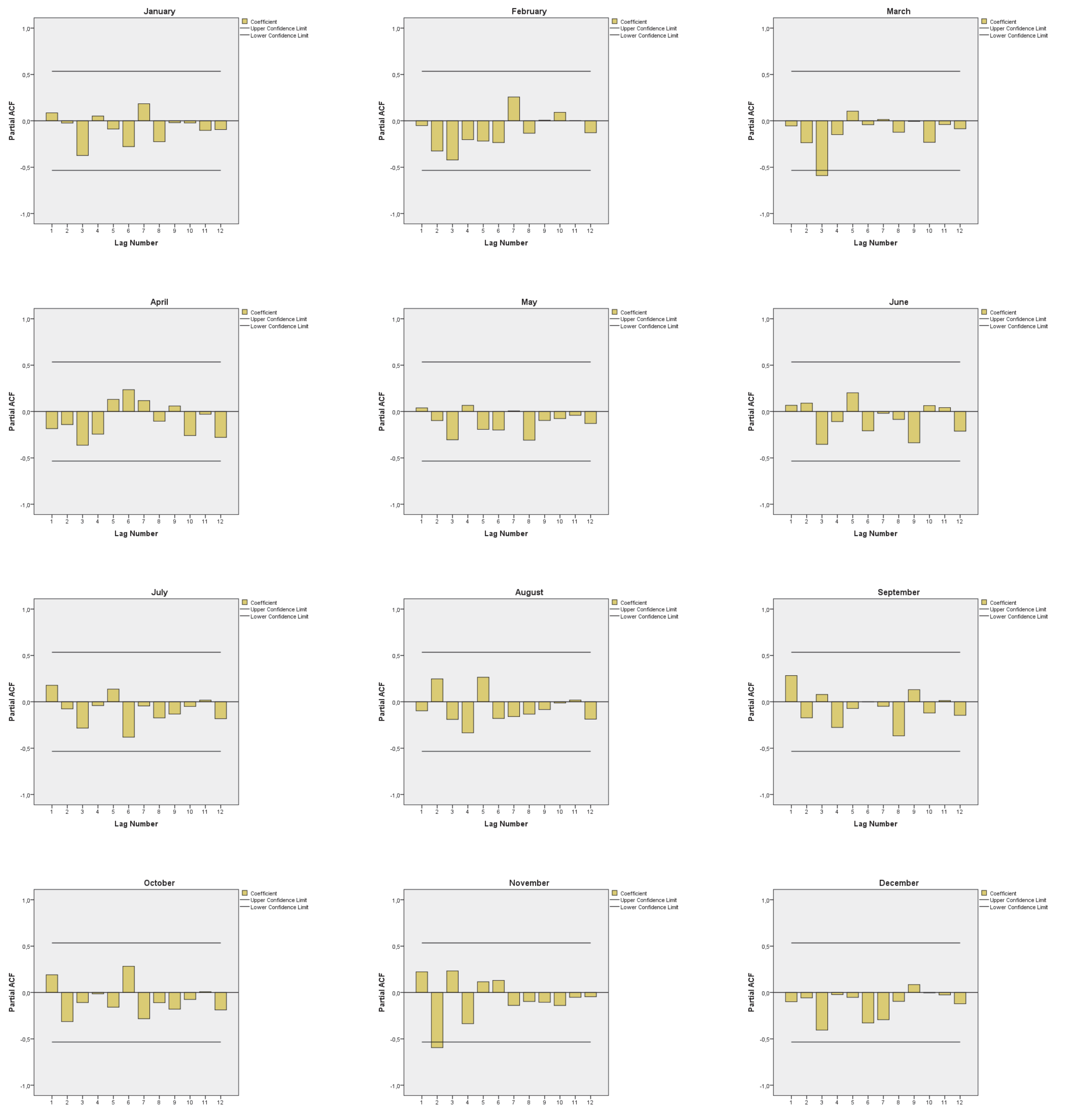

Figure 4

The partial autocorrelation functions (PACF) of the natural logarithm of the mean monthly streamflow data. The lines represent the 95% confidence interval.

Discussion

Due to climate change and global warming, some countries will face severe water shortages or scarcities of the limited water resources (Hisar et al. 2015). The monitoring of changes in climatic factors is important for predicting possible climate change in the future. It is important to consider the assumptions of different climate change scenarios and to better understand the impact of climate change on river streamflow (Kale et al. 2016a). In this context, research on the past and present trends in water resources provides a valuable

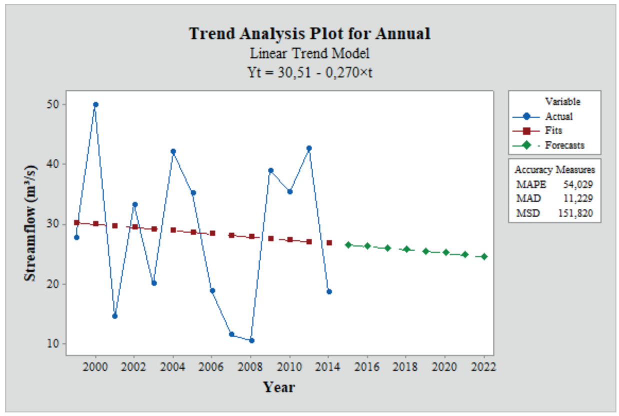

Figure 5

Trend analysis results for mean annual streamflow. In variable box; actual is the observed value; forecasts are the predicted values; fits are calculated values that best fitting to forecast. The accuracy of models was assessed by using commonly used performance measures which are mean absolute deviation (MAD), mean squared deviation (MSD), mean absolute percentage error (MAPE).

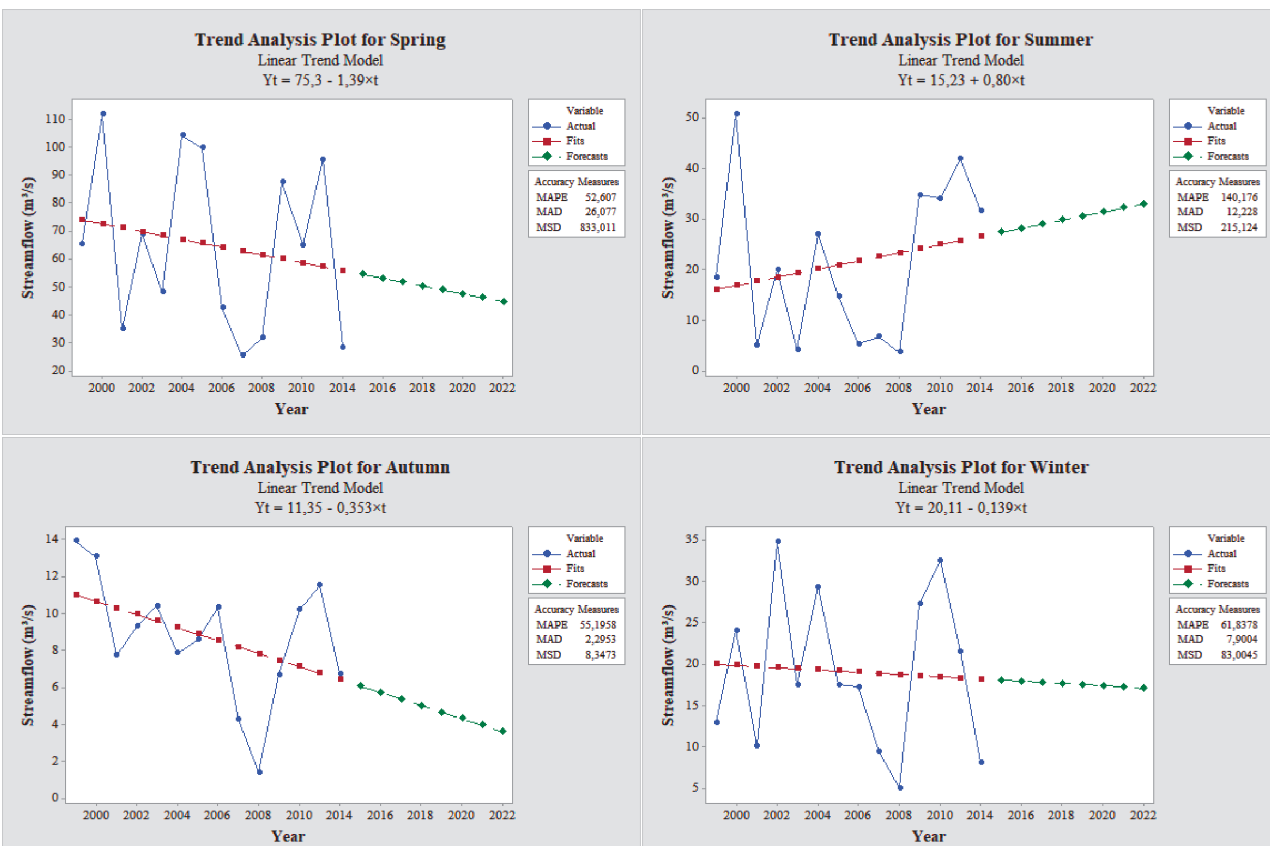

Figure 6

Trend analysis results for mean seasonal streamflow. In variable box; actual is the observed value; forecasts are the predicted values; fits are calculated values that best fitting to forecast. The accuracy of models was assessed by using commonly used performance measures which are mean absolute deviation (MAD), mean squared deviation (MSD), mean absolute percentage error (MAPE).

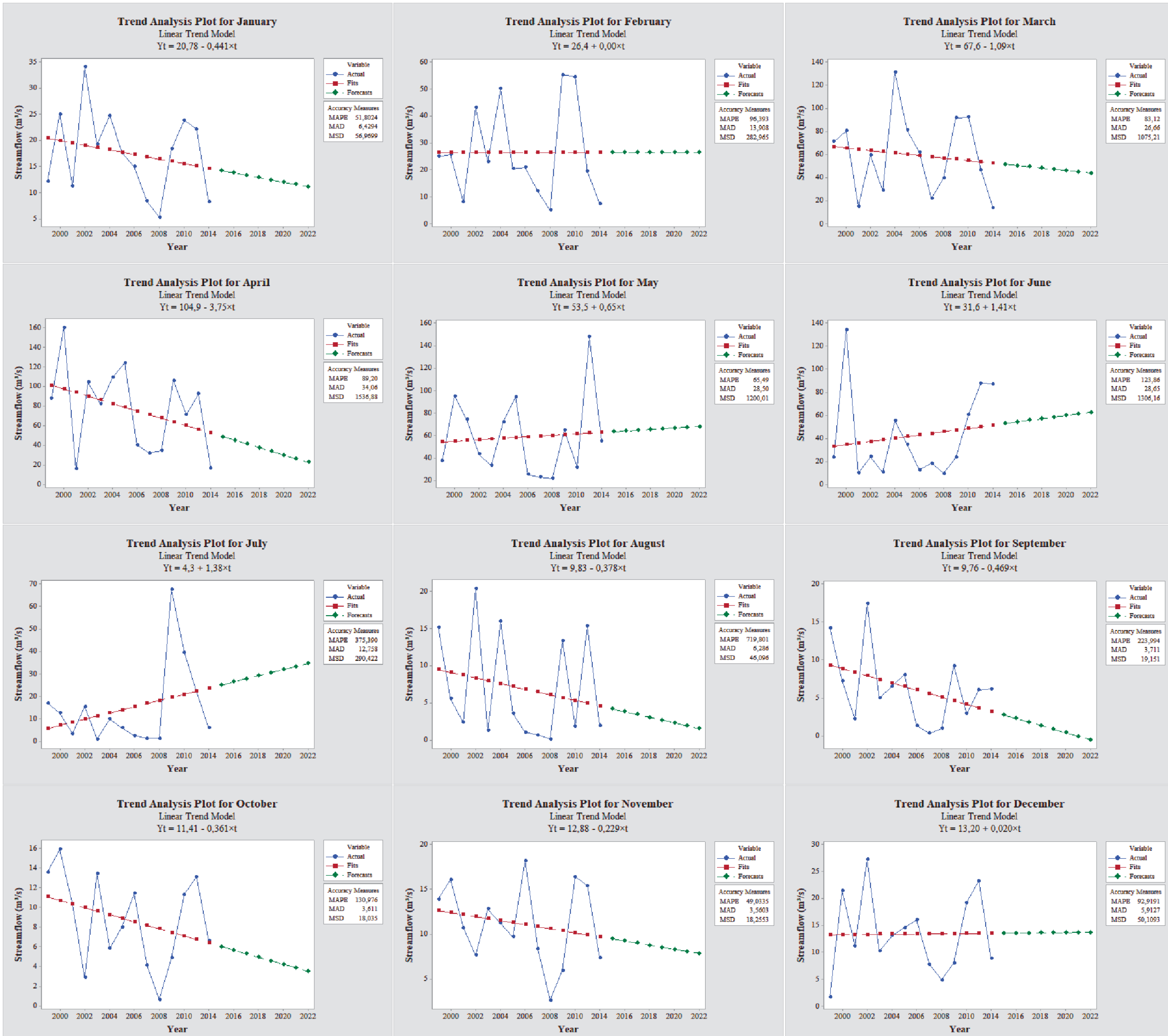

Figure 7

Trend analysis results for mean monthly streamflow. In variable box; actual is the observed value; forecasts are the predicted values; fits are calculated values that best fitting to forecast. The accuracy of models was assessed by using commonly used performance measures which are mean absolute deviation (MAD), mean squared deviation (MSD), mean absolute percentage error (MAPE).

contribution to the current knowledge used in water resource management and decision-making processes to mitigate and adapt to possible effects of climate change. Thus, many researchers studied possible effects of climate change on water resources and they reported that climate change can have a serious impact on the availability of water resources (Durdu 2010; Kale et al. 2016a,b; Ejder et al. 2016a,b; Kale et al. 2018; Kale & Sönmez 2018a,b; Kale & Sönmez 2019a,b,c; Sönmez & Kale 2020). Consequently, research on changes in the river streamflow is of major importance.

Annual, seasonal and monthly streamflow data were analyzed in this study using the trend analysis. The analysis showed a decreasing trend in the annual streamflow of the Gökırmak River. Furthermore, decreasing trends were also determined for all seasons except summer. Similarly, many researchers reported decreasing trends in the river streamflow (Kahya & Kalayci 2004; Alcamo et al. 2007; Ozkul 2009; Durdu 2010; Türkeş & Acar Deniz 2011; Saplıoğlu et

Table 4

Values of non-parametric tests and trend status

Period	Streamflow	Kendall's tau	*p*	Trend	Spearman's rho	p	Trend
Annual	Annual	−0.055	0.784	▼	−0.055	0.852	▼
Seasonal	Spring	−0.209	0.298	▼	−0.297	0.303	▼
	Summer	0.143	0.477	▲	0.240	0.409	▲
	Autumn	−0.297	0.169	▼	−0.437	0.118	▼
	Winter	−0.099	0.622	▼	−0.108	0.714	▼
Monthly	January	−0.209	0.298	▼	−0.262	0.366	▼
	February	−0.165	0.412	▼	−0.204	0.483	▼
	March	−0.055	0.784	▼	−0.099	0.737	▼
	April	−0.209	0.298	▼	−0.288	0.318	▼
	May	−0.143	0.477	▼	−0.143	0.626	▼
	June	0.209	0.298	▲	0.244	0.401	▲
	July	0.011	0.956	▲	0.156	0.594	▲
	August	−0.231	0.250	▼	−0.288	0.318	▼
	September	−0.209	0.298	▼	−0.341	0.233	▼
	October	−0.231	0.250	▼	−0.349	0.221	▼
	November	−0.209	0.298	▼	−0.226	0.436	▼
	December	0.033	0.870	▲	−0.011	0.970	▼

Note: ▼ indicates decreasing trends; ▲ indicates increasing trends

al. 2014; Herawati et al. 2015; Zhou et al. 2015; Li et al. 2016; Pumo et al. 2016). Bahadır (2011) reported a decreasing trend of the Kızılırmak River streamflow. Ejder et al. (2016a) identified a decreasing trend for the Sarıçay Stream. Ejder et al. (2016b) reported a decreasing trend for the Kocabaş streamflow. Kale et al. (2016a) identified a decreasing trend in the Karamenderes River streamflow. Kale et al. (2016b) described a declining trend in the Bakırçay River streamflow. In addition, Ay & Kişi (2017) and Ercan et al. (2017) reported a decreasing trend in the Kızılırmak River streamflow. Kale and Sönmez (2018a) reported decreasing trends for the annual, seasonal and monthly streamflow of the Daday Stream. Kale and Sönmez (2018b) defined a decreasing trend for the Akkaya streamflow. Kişi et al. (2018) found increasing and decreasing trends for the monthly streamflow in three different basins in Turkey. Yildiz et al. (2019) determined a decreasing trend in the long-term streamflow of the Euphrates River. Kale & Sönmez (2019a) indicated a declining trend in the Ilgaz streamflow. Kale & Sönmez (2019b) documented a declining trend in the Araç streamflow. Kale & Sönmez (2019c) reported that the annual and seasonal streamflow of the Devrekani Stream tends to decrease. Sönmez & Kale (2020) stated that increasing temperature and decreasing precipitation due to climate change caused a reduction in the streamflow of the Filyos River. The Gökırmak River is located near the Filyos, Ilgaz, Akkaya, Daday, Araç, Devrekani and Kızılırmak rivers in Turkey. Therefore, the downward trends in the streamflow of rivers may continue in the future.

Both decreasing and increasing trends were observed in the monthly streamflow, whereas no trend was found for February and December. Although some researchers reported decreasing trends in the streamflow of rivers, increasing trends were also reported in the literature. Topaloğlu (2006) reported both decreasing and increasing trends for 26 basins in Turkey. Ali et al. (2019) documented that there were both increasing and decreasing trends in the streamflow of the Yangtze River. Lee & Yeh (2019) determined an increase in the streamflow of the Lanyang River, while the streamflow of the Keelung River showed a downward trend. Rani & Sreekesh (2019) described a reduction in the streamflow of the Western Indian Himalaya Watershed due to reduced snow cover resulting from the increasing temperature. Wang et al. (2019) reported that the streamflow in data-scarce mountain basins of Northwest China increased with a warm and wet climate. In this study, the streamflow in the summer season showed great variability. Therefore, this fluctuation in the streamflow in summer could be the main reason for the increasing trend.

In general, variations in the streamflow of rivers could be related to climate change, human impact, population, precipitation patterns, land use and land cover. In this study, both increasing and decreasing trends were determined for the streamflow of the Gökırmak River during the monitoring period. These fluctuations in the Gökırmak River streamflow can be attributed to climatic changes, changes in evaporation and precipitation patterns, snow melting seasons and the amount, volume and time of glacier flow, as well as human impact. Similarly, many scientists have reported that climate change could reduce the streamflow of rivers (Kahya & Kalayci 2004; Bozkurt & Sen 2013; Ligaray et al. 2015; Li & Jin 2017; Naz et al. 2018; Dinpashoh et al. 2019; Hirpa et al. 2019; Lee and Yeh 2019; Yan et al. 2019). Anil & Ramesh (2017) reported an increase in the annual and monthly streamflow of the Harangi Stream due to a reduction in the forest area. Kale et al. (2018) stated that variations in precipitation patterns can have a direct impact on the river streamflow. In addition, Kale and Sönmez (2018b) indicated that the rate of streamflow and water resources may be related to a rise in temperature and evaporation patterns, reduction in rainfall and snowmelt, and additional factors associated with climate change. Furthermore, it was documented that the water surface area (Kale & Acarli 2019a) and shoreline (Kale & Acarli 2019b) of the Atikhisar Reservoir showed spatial and temporal variations due to climate change. On the other hand, Bates et al. (2008) concluded that trends in the streamflow were not always related to changes in precipitation. Furthermore, a number of scientists stated that other factors may affect the streamflow in addition to the effects of climate change, such as agricultural (Durdu 2010; Dügel & Kazanci 2004; Yercan et al. 2004; Chen et al. 2019) and non-agricultural human activities (Li et al. 2007; Gao et al. 2011; Jackson et al. 2011; Jiang et al. 2011; Hu et al. 2012; Wang et al. 2012; Chang et al. 2014; Zhan et al. 2014; Zhou et al. 2015; Guo et al. 2016; Qian et al. 2016; Huang et al. 2018; Saidi et al. 2018; Shahid et al. 2018; Lee and Yeh 2019; Lv et al. 2019; Fu et al. 2020; Kanani et al. 2020).

Conclusions

This is the first study on the streamflow trends for the Gökırmak River. Monthly, seasonal and annual trends in the Gökırmak River streamflow were investigated. Most of the streamflow trends identified during the monitoring period were downward trends. Therefore, trends in the streamflow should be continuously monitored to develop better management strategies for sustainable use of water resources in the future. This paper presents the results of the research on the past and present trends in the streamflow, thus contributing with new knowledge for decision makers and water resource managers.

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References

Alcamo, J., Moreno, J.M., Nováky, B., Bindi, M., Corobov, R. et al. (2007). Europe. In M.L. Parry, O.F. Canziani, J. Palutikof, P. van der Linden & C. Hanson (Eds.), *Climate change 2007: Impacts, adaptation and vulnerability* (pp. 541–580). Cambridge, New York: Cambridge University Press.

Ali, R., Kuriqi, A., Abubaker, S. & Kisi, O. (2019). Long-term trends and seasonality detection of the observed flow in Yangtze River using Mann-Kendall and Sen's innovative trend method. *Water* 11(9): 1855. DOI: 10.3390/w11091855.

Anil, A.P. & Ramesh, H. (2017). Analysis of climate trend and effect of land use land cover change on Harangi streamflow, South India: a case study. *Sustainable Water Resources Management* 3(3): 257–267. DOI: 10.1007/s40899-017-0088-5.

Ay, M. & Kişi, Ö. (2017). Trend analysis of streamflows at some gauging stations over the Kizilirmak River. İMO *Teknik Dergi* 28(2): 7779–7794. DOI: 10.18400/tekderg.304034.

Ay, M., Karaca, Ö.F. & Yıldız, A.K. (2018). Comparison of Mann-Kendall and Sen's innovative trend tests on measured monthly flows series of some streams in Euphrates-Tigris Basin. *Erciyes University Journal of Institute of Science and Technology* 34(1): 78–86.

Baduna Koçyiğit, M., Akay, H. & Yanmaz, A.M. (2017). Effect of watershed partitioning on hydrologic parameters and estimation of hydrograph of an ungauged basin: a case study in Gokirmak and Kocanaz, Turkey. *Arabian Journal of Geosciences* 10(15): 331. DOI: 10.1007/s12517-017-3132-8.

Bahadir, M. (2011). A statistical analysis of the flow changes of Kızılırmak River. *Turkish Studies-International Periodical for the Languages, Literature and History of Turkish or Turkic* 6: 1339–1356.

Bates, B.C., Kundzewicz, Z.W., Wu, S. & Palutikof, J.P. (2008). *Climate change and water*. Geneva: IPCC Secretariat.

Blöschl, G. & Montanari, A. (2010). Climate change impacts – throwing the dice? *Hydrological Processes* 24(3): 374–381. DOI: 10.1002/hyp.7574.

Box, G.E.P. & Jenkins, G. (1976). *Time series analysis: Forecasting and control*. Holden Day, San Francisco.

Bozkurt, D. & Sen, O. L. (2013). Climate change impacts in the Euphrates–Tigris Basin based on different model and scenario simulations. *Journal of Hydrology* 480: 149–161. DOI: 10.1016/j.jhydrol.2012.12.021.

Chang, H. (2007). Comparative streamflow characteristics in urbanizing basins in the Portland Metropolitan Area, Oregon, USA. *Hydrological Processes* 21(2): 211–222. DOI: 10.1002/hyp.6233.

Chang, J., Wang, Y., Istanbulluoglu, E., Bai, T., Huang, Q. et al. (2014). Impact of climate change and human activities on runoff in the Weihe River Basin, China. *Quaternary International* 380–381: 169–179. DOI: 10.1016/j.quaint.2014.03.048.

Chen, C., Tian, Y., Zhang, Y-K., He, X., Yang, X. et al. (2019). Effects of agricultural activities on the temporal variations of streamflow: trends and long memory. *Stochastic Environmental Research and Risk Assessment* 33(8–9): 1553–1564. DOI: 10.1007/s00477-019-01714-x.

Cigizoglu, H.K., Bayazit, M. & Onoz, B. (2005). Trends in the maximum, mean and low flows of Turkish rivers. *Journal of Hydrometeorology* 6(3): 280–290. DOI: 10.1175/JHM412.1.

Dengiz, O., Özyazici, M.A. & Sağlam, M. (2015). Multi-criteria assessment and geostatistical approach for determination of rice growing suitability sites in Gokirmak catchment. *Paddy and Water Environment* 13(1): 1–10. DOI: 10.1007/s10333-013-0400-4.

Dinpashoh, Y., Singh, V.P., Biazar, S.M. & Kavehkar, S. (2019). Impact of climate change on streamflow timing (case study: Guilan Province). *Theoretical and Applied Climatology*, 138(1–2): 65–76. DOI: 10.1007/s00704-019-02810-2.

Dügel, M. & Kazanci, N. (2004). Assessment of water quality of the Büyük Menderes River (Turkey) by using ordination and classification of macroinvertebrates and environmental variables. *Journal of Freshwater Ecology* 19(4): 605–612. DOI: 10.1080/02705060.2004.9664741.

Durdu, Ö.F. (2010). Effects of climate change on water resources of the Büyük Menderes river basin, western Turkey. *Turkish Journal of Agriculture and Forestry* 34(4): 319–332. DOI: 10.3906/tar-0909-402.

Ejder, T., Kale, S., Acar, S., Hisar, O. & Mutlu, F. (2016a). Effects of climate change on annual streamflow of Kocabaş Stream (Çanakkale, Turkey). *Journal of Scientific Research and Reports* 11(4): 1–11. DOI: 10.9734/JSRR/2016/28052.

Ejder, T., Kale, S., Acar, S., Hisar, O. & Mutlu, F. (2016b). Restricted effects of climate change on annual streamflow of Sarıçay stream (Çanakkale, Turkey). *Marine Science and Technology Bulletin* 5(1): 7–11.

Ercan, B., Yüce, Ş. & Yüce, M.İ. (2017). Analysis of streamflow trends in the Kızılırmak River Basin. *Proceedings of IV. International Multidisciplinary Congress of Eurasia* 2: 405–414.

Feng, C., Wang, H., Lu, N., Chen, T., He, H. et al. (2014). Log-transformation and its implications for data analysis. *Shanghai Archives of Psychiatry* 26(2): 105–109. DOI: 10.3969/j.issn.1002-0829.2014.02.009.

Fu, X., Shen, B., Dong, Z. & Zhang, X. (2020). Assessing the impacts of changing climate and human activities on streamflow in the Hotan River, China. *Journal of Water and Climate Change* 11(1): 166–177. DOI: 10.2166/wcc.2018.281.

Gao, P., Mu, X.M., Wang, F., Li, R. (2011). Changes in streamflow and sediment discharge and the response to human activities in the middle reaches of the Yellow River. *Hydrology and Earth System Sciences* 15(1): 1–10. DOI: 10.5194/hess-15-1-2011.

George, D. & Mallery, M. (2010). SPSS for Windows Step by Step: A Simple Guide and Reference, 17.0 update (10th ed.) Boston: Pearson.

Guo, Q., Yang, Y. & Xiong, X. (2016). Using hydrologic simulation to identify contributions of climate change and human activity to runoff changes in the Kuye River Basin, China. *Environmental Earth Sciences* 75(5): 417. DOI: 10.1007/s12665-016-5280-7.

Helsel, D.R. & Hirsch, R.M. (2002). *Statistical Methods in Water Resources Techniques of Water Resources Investigations*. U.S. Geological Survey: https://pubs.usgs.gov/twri/twri4a3/pdf/twri4a3-new.pdf. Accessed 22 October 2019.

Herawati, H., Suripin & Suharyanto. (2015). Impact of climate change on streamflow in the tropical lowland of Kapuas River, West Borneo, Indonesia. *Procedia Engineering* 125: 185–192. DOI: 10.1016/j.proeng.2015.11.027.

Hirpa, F.A., Alfieri, L., Lees, T., Peng, J., Dyer, E. et al. (2019). Streamflow response to climate change in the Greater Horn of Africa. *Climatic Change* 156(3): 341–363. DOI: 10.1007/s10584-019-02547-x.

Hirsch, R.M., Slack, J.R. & Smith, R.A. (1982). Techniques of trend analysis for monthly water quality analysis. *Water Resources Research* 18(1): 107–121.

Hisar, O., Kale, S. & Özen, Ö. (2015). Sustainability of effective use of water sources in Turkey. In W. Leal Filho & V. Sümer (Eds.), *Sustainable Water Use and Management: Examples of New Approaches and Perspectives* (pp. 205–227). Switzerland: Springer International Publishing.

Hu, S., Zheng, H., Wang, Z. & Yu, J. (2012). Assessing the impacts of climate variability and human activities on streamflow in the water source area of Baiyangdian Lake. *Journal of Geographical Sciences* 22(5): 895–905. DOI: 10.1007/s11442-012-0971-9.

Huang, X-R., Gao, L-Y., Yang, P-P. & Xi, Y-Y. (2018). Cumulative impact of dam constructions on streamflow and sediment regime in lower reaches of the Jinsha River, China. *Journal of Mountain Science* 15(12): 2752–2765. DOI: 10.1007/s11629-018-4924-3.

Jackson, C.R., Meister, R. & Prudhomme, C. (2011). Modelling the effects of climate change and its uncertainty on UK Chalk groundwater resources from an ensemble of global climate model projections. *Journal of Hydrology* 399(1–2): 12–28. DOI: 10.1016/j.jhydrol.2010.12.028.

Jiang, S., Ren, L., Yong, B., Singh, V.P., Yang, X. et al. (2011). Quantifying the effects of climate variability and human activities on runoff from the Laohahe basin in northern China using three different methods. *Hydrological Processes* 25(16): 2492–2505. DOI: 10.1002/hyp.8002.

Kahya, E. & Kalaycı, S. (2004). Trend analysis of streamflow in Turkey. *Journal of Hydrology* 289(1–4): 128–144. DOI:

10.1016/j.jhydrol.2003.11.006.

Kale, S. & Acarlı, D. (2019a). Spatial and temporal change monitoring in water surface area of Atikhisar Reservoir (Çanakkale, Turkey) by using remote sensing and geographic information system techniques. *Alinteri Journal of Agriculture Sciences* 34(1): 47–56. DOI: 10.28955/alinterizbd.574361.

Kale, S. & Acarli, D. (2019b). Shoreline change monitoring in Atikhisar Reservoir by using remote sensing and geographic information system (GIS). *Fresenius Environmental Bulletin* 28: 4329–4339.

Kale, S. & Sönmez, A.Y. (2018a). Trend analysis of mean monthly, seasonally and annual streamflow of Daday Stream in Kastamonu, Turkey. *Marine Science and Technology Bulletin* 7(2): 60–67. DOI: 10.33714/masteb.418234.

Kale, S. & Sönmez, A.Y. (2018b). Trend analysis of streamflow of Akkaya Stream (Turkey). In F. Dadaşoğlu, E. Tozlu, F. Çığ & E. Yıldırım (Eds.), *Proceedings of the 1st International Conference on Food, Agriculture and Animal Sciences* (pp. 33–45). Antalya, Turkey.

Kale, S. & Sönmez, A.Y. (2019a). Trend analysis for annual streamflow of Ilgaz Stream (Turkey). In *Proceeding Book of the 2nd International Congress on Engineering and Life Science* (pp. 631–639).

Kale, S. & Sönmez, A.Y. (2019b). Trend analysis for annual streamflow of Araç Stream (Turkey). In *Proceeding Book of the 2nd International Congress on Engineering and Life Science* (pp. 706–713).

Kale, S. & Sönmez, A.Y. (2019c). Trend Analysis for Streamflow of Devrekani Stream (Turkey). *Review of Hydrobiology* 12(1–2): 23–37.

Kale, S. (2017a). Climatic trends in the temperature of Çanakkale city, Turkey. *Natural and Engineering Sciences* 2(3): 14–27. DOI: 10.28978/nesciences.348449.

Kale, S. (2017b). Analysis of climatic trends in evaporation for Çanakkale (Turkey). *Middle East Journal of Science* 3(2): 69–82. DOI: 10.23884/mejs.2017.3.2.01.

Kale, S., Ejder, T., Hisar, O. & Mutlu, F. (2016a). Climate change impacts on streamflow of Karamenderes River (Çanakkale, Turkey). *Marine Science and Technology Bulletin* 5(2): 1–6.

Kale, S., Ejder, T., Hisar, O. & Mutlu, F. (2016b). Effect of climate change on annual streamflow of Bakırçay River. *Adıyaman University Journal of Science* 6(2): 156–176.

Kale, S., Hisar, O., Sönmez, A.Y., Mutlu, F. & Filho, W.L. (2018). An assessment of the effects of climate change on annual streamflow in rivers in western Turkey. *International Journal of Global Warming* 15(2): 190–211. DOI: 10.1504/IJGW.2018.092901.

Kanani, R., Fakheri Fard, A., Ghorbani, M.A. & Dinpashoh, Y. (2020). Analysis of the role of climatic and human factors in runoff variations (case study: Lighvan River in Urmia Lake Basin, Iran). *Journal of Water and Climate Change* 11(1): 291–302. DOI: 10.2166/wcc.2019.186.

Khairuddin, N., Aris, A.Z., Elshafie, A., Sheikhy Narany, T., Ishak, M.Y. et al. (2019). Efficient forecasting model technique for river stream flow in tropical environment. *Urban Water Journal* 16(3): 183–192. DOI: 10.1080/1573062X.2019.1637906.

Kendall, M.G. (1955). *Rank correlation methods*. 2nd ed. New York: Hafner Publishing Co.

Kişi, Ö., Guimarães Santos, C.A., Marques da Silva, R. & Zounemat-Kermani, M. (2018). Trend analysis of monthly streamflows using Şen's innovative trend method. *Geofizika*, 35(1): 53–68.

Lee, C-H. & Yeh, H-F. (2019). Impact of climate change and human activities on streamflow variations based on the Budyko framework. *Water* 11(10): 2001. DOI: 10.3390/w11102001.

Lehmann, E.L. (1975). *Nonparametrics: Statistical Methods Based on Ranks*. San Francisco: Holden-Day.

Li, F., Zhang, G. & Xu, Y. J. (2016). Assessing climate change impacts on water resources in the Songhua River Basin. *Water* 8(10): 1–17. DOI: 10.3390/w8100420.

Li, L.J., Zhang, L., Wang, H., Yang, J.W., Jiang, D.J. et al. (2007). Assessing the impact of climate variability and human activities on streamfow from the Wuding River Basin in China. *Hydrological Processes* 21(25): 3485–3491. DOI: 10.1002/hyp.6485.

Li, Z. & Jin, J. (2017). Evaluating climate change impacts on streamflow variability based on a multisite multivariate GCM downscaling method in the Jing River of China. *Hydrology and Earth System Sciences* 21(11): 5531–5546. DOI: 10.5194/hess-21-5531-2017.

Ligaray, M., Kim, H., Sthiannopkao, S., Lee, S., Cho, K.H. et al. (2015). Assessment on hydrologic response by climate change in the Chao Phraya River Basin, Thailand. *Water* 7(12): 6892–6909. DOI: 10.3390/w7126665.

Mann, H.B. (1945) Nonparametric tests against trend. *Econometrica* 13: 245–259.

Myronidis, D., Ioannou, K., Fotakis, D. & Dörflinger, G. (2018). Streamflow and hydrological drought trend analysis and forecasting in Cyprus. *Water Resources Management* 32(5): 1759–1776. DOI: 10.1007/s11269-018-1902-z.

Naz, B.S., Kao, S-C., Ashfaq, M., Gao, H., Rastogi, D. et al. (2018). Effects of climate change on streamflow extremes and implications for reservoir inflow in the United States. *Journal of Hydrology* 556: 359–370. DOI: 10.1016/j.jhydrol.2017.11.027.

Ozkul, S. (2009). Assessment of climate change effects in Aegean river basins: the case of Gediz and Buyuk Menderes Basins. *Climatic Change* 97(1–2): 253–283. DOI: 10.1007/s10584-009-9589-z.

Pettitt, A.N. (1979). A non-parametric approach to the change-point problem. *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 28: 126–135.

Pumo, D., Caracciolo, D., Viola, F. & Noto, L.V. (2016). Climate change effects on the hydrological regime of small non-perennial river basins. *Science of The Total Environment*

542(Part A): 76–92. DOI: 10.1016/j.scitotenv.2015.10.109.

Qian, B., Zhange, D., Wang, J., Huang, F. & Wu, Y. (2016). Impacts of reservoirs on the streamflow and sediment load of the Hanjiang River, China. *Environmental Monitoring and Assessment* 188(11): 646. DOI: 10.1007/s10661-016-5652-1.

R Core Team. (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria URL https://www.R-project.org/.

Rani, S. & Sreekesh, S. (2019). Evaluating the responses of streamflow under future climate change scenarios in a Western Indian Himalaya Watershed. *Environmental Processes* 6(1): 155–174. DOI: 10.1007/s40710-019-00361-2.

Saidi, H., Dresti, C., Manca, D. & Ciampittiello, M. (2018). Quantifying impacts of climate variability and human activities on the streamflow of an Alpine river. *Environmental Earth Sciences* 77(19): 690. DOI: 10.1007/s12665-018-7870-z.

Saplıoğlu, K., Kilit, M. & Yavuz, B.K. (2014). Trend analysis of streams in the western Mediterranean Basin of Turkey. *Fresenius Environmental Bulletin* 23(1): 1–12.

Sen, P.K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association* 63(324): 1379–1389.

Şen, Z. (2012). Innovative trend analysis methodology. *Journal of Hydrologic Engineering,* 17(9): 1042–1046. DOI: 10.1061/(ASCE)HE.1943-5584.0000556.

Şen, Z., Şişman, E. & Dabanli, I. (2019). Innovative polygon trend analysis (IPTA) and applications. *Journal of Hydrology* 575: 202–210. DOI: 10.1016/j.jhydrol.2019.05.028.

Shahid, M., Cong, Z. & Zhange, D. (2018). Understanding the impacts of climate change and human activities on streamflow: a case study of the Soan River basin, Pakistan. *Theoretical and Applied Climatology* 134(1–2): 205–219. DOI: 10.1007/s00704-017-2269-4.

Sneyers, R. (1990). *On the statistical analysis of series of observations*. World Meteorological Organization, Technical Note no. 143, WMO no. 415.

Sönmez, A.Y. & Kale, S. (2020). Climate change effects on annual streamflow of Filyos River (Turkey). *Journal of Water and Climate Change* 11(2): 420–433. DOI: 10.2166/wcc.2018.060.

Stellwagen, E. & Tashman, L. (2019). ARIMA: The Models of Box and Jenkins. *Foresight: The International Journal of Applied Forecasting* 30: 28–33.

Tanatmış, M. (2004). The Ephemeroptera (Insecta) fauna of the Gökırmak river basin (Kastamonu) and of the seashore lying between Cide (Kastamonu)-Ayancık (Sinop). *Türk Entomoloji Dergisi* 28(1): 45–56.

Topaloğlu, F. (2006). Trend detection of streamflow variables in Turkey. *Fresenius Environmental Bulletin* 15(7): 644–653.

Tosunoglu, F. & Kisi, O. (2017). Trend analysis of maximum hydrologic drought variables using Mann–Kendall and Şen's innovative trend method. *River Research and Applications,* 33(4): 597–610. DOI: 10.1002/rra.3106.

Tosunoğlu, F. (2017). Trend analysis of daily maximum rainfall series in Çoruh Basin, Turkey. *Iğdır University Journal of the Institute of Science and Technology* 7(1): 195–205. DOI: 10.21597/jist.2017127432.

TÜBİTAK-BİLGEM-YTE. (2015). Havza İzleme ve Değerlendirme Sistemi (HİDS, Basin Monitoring and Assessment System). TÜBİTAK Informatics and Information Security Research Center (BİLGEM) Software Technologies Research Institute (YTE). Ankara, Turkey.

Türkeş, M. & Acar Deniz, Z. (2011). Climatology of South Marmara Division (North West Anatolia) and observed variations and trends. *International Journal of Human Sciences* 8(1): 1579–1600.

Türkeş, M., Öztaş, T., Tercan, E., Erpul, G., Karagöz, A. et al. (2020). Desertification vulnerability and risk assessment for Turkey via an analytical hierarchy process model. *Land Degradation & Development* 31(2): 205–214. DOI: 10.1002/ldr.3441.

Villarini, G., Smith, J.A., Serinaldi, F. & Ntelekos, A.A. (2011). Analyses of seasonal and annual maximum daily discharge records for Central Europe. *Journal of Hydrology* 399(3–4): 299–312. DOI: 10.1016/j.jhydrol.2011.01.007.

Wang, C., Xu, J., Chen, Y. & Li, W. (2019). An approach to simulate the climate-driven streamflow in the data-scarce mountain basins of Northwest China. *Journal of Earth System Science* 128(4): 95. DOI: 10.1007/s12040-019-1117-6.

Wang, S., Yan, M., Yan, Y., Shi, C. & He, L. (2012). Contributions of climate change and human activities to the changes in runoff increment in different sections of the Yellow River. *Quaternary International* 282: 66–77. DOI: 10.1016/j.quaint.2012.07.011.

Yan, T., Bai, J., Arsenio, T., Liu, J. & Shen, Z. (2019). Future climate change impacts on streamflow and nitrogen exports based on CMIP5 projection in the Miyun Reservoir Basin, China. *Ecohydrology & Hydrobiology* 19(2): 266–278. DOI: 10.1016/j.ecohyd.2018.09.001.

Yercan, M., Dorsan, F. & Ul, M. (2004). Comparative analysis of performance criteria in irrigation schemes: A case study of Gediz river basin in Turkey. *Agricultural Water Management* 66: 259–266.

Yildirim, C., Schildgen, T.F., Echtler, H., Melnick, D., Bookhagen, B. et al. (2013). Tectonic implications of fluvial incision and pediment deformation at the northern margin of the Central Anatolian Plateau based on multiple cosmogenic nuclides. *Tectonics* 32(5): 1107–1120. DOI: 10.1002/tect.20066.

Yıldız, D. (2017). The importance of water in development. *World Water Diplomacy & Science News* 10006(1–4): 1–7.

Yildiz, D., Yildiz, D. & Güneş, M.Ş. (2019). Analysis of long-term natural streamflow trends in Upper Euphrates River Basin.

European Journal of Science and Technology 15: 118–131. DOI: 10.31590/ejosat.500548.

Zhan, C.S., Jiang, S.S., Sun, F.B., Jia, Y.W., Niu, C.W. et al. (2014). Quantitative contribution of climate change and human activities to runoff changes in the Wei River basin, China. *Hydrology and Earth System Sciences* 18(8): 3069–3077. DOI: 10.5194/hess-18-3069-2014.

Zhou, Y., Shi, C., Fan, X. & Shao, W. (2015). The influence of climate change and anthropogenic activities on annual runoff of Huangfuchuan basin in northwest China. *Theoretical and Applied Climatology* 120(1–2): 137–146. DOI: 10.1007/s00704-014-1160-9.