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Determining the lengths of dry periods in annual and monthly stream flows using runs analysis at Karasu River, in Turkey

Okan Mert Katipoğlu and İbrahim Can

ABSTRACT

Drought analysis is a vital component of water resources planning and management for dam and hydroelectric power plant (HPP) construction, reservoir operation and flood control. In this study, stochastic models were developed to estimate the monthly and annual flows of the Karasu River in the upper section of the Euphrates River valley. A time series model of flows was established based on the Box–Jenkins methodology. An autoregressive (AR) model was selected as the most suitable model. One hundred synthetic series, having the same length as the historical series (40 years), were produced using the AR model. It was also possible to control whether or not the generated time series maintained the statistical characteristics (mean and standard deviation) of the historical time series. After applying specified threshold levels ($q = 0.5$; $q = 0.3$; $q = 0.1$), the historic and synthetic flow series were subjected to runs analysis. Dry period lengths (run sum and run length) of historic and synthetic flow series were determined. Future droughts are estimated using maximum dry period lengths.

Key words | Akaike information criterion, autoregressive model, drought, runs analysis

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INTRODUCTION

A knowledge of the statistical properties of drought periods in various regions of Turkey is a key input into the planning of reservoirs which can meet water requirements during drought periods, determination of the amount of water received from other water sources and for forecasting of the effects of droughts on the economy and society. The Runs Analysis method can be used to objectively identify drought periods in a series of flows. The lengths of droughts, their return periods and the required storage volume of a reservoir to maintain water supply in these periods can be calculated by virtue of this analysis (Sen 1976; Khedun *et al.* 2013; Wu *et al.* 2015).

Runs theory widely uses probabilistic methodology in drought characterization, which allows the estimation of return periods of extreme events. This was initially proposed by Yevjevich (1967), and it models the recurrence of extreme periods based on one selected magnitude (e.g., cumulative deficit, duration, or mean intensity (see Sen 1976; Dracup *et al.* 1980).

A run analysis of drought is based on the theory of runs for discrete variables, although the theory is also applicable to continuous variables. Run theory quantitatively describes how a hydrological process crosses above and below some critical threshold value called the truncation level (Dracup *et al.* 1980).

Time series modeling is a process that can be simple or complex, depending on the characteristics of the available sample series, on the type of model to use, and on the selected techniques of modeling. Researchers in hydrology have used more refined methodologies suggested by Box and Jenkins and others, especially for improving the estimates of the parameters of the model, for verifying the

doi: 10.2166/ws.2017.203

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conditions to be met by those parameters, for verifying or checking the assumptions of the model and for selecting among competing models (Salas 1980).

A stochastic approach is presented for modeling a time series by an autoregressive moving average (ARMA) model. This enforces stationarity on the autoregressive parameters and in inevitability on the moving average parameter, thus taking into account the uncertainty about the correct model by averaging the parameter estimates. Several stochastic models have been proposed for modeling hydrological time series and generating synthetic stream flows. These include ARMA models, disaggregation models, and models based on the concept of pattern recognition. Most of the time-series modeling procedures fall within the framework of multivariate ARMA models (Otache *et al.* 2008). Generally, autoregressive (AR) and autoregressive integrated moving average (ARIMA) models have an important place in the stochastic modeling of hydrologic data. Such models are of value in handling what might be described as the short-run problem: that of modeling the seasonal variability in a stochastic flow series (Musa 2013).

The determination of drought conditions is the basis for solving a wide range of water management problems. Drought can occur in almost all climate regions. However, its characteristics can change considerably from one region to another. There are many drought classifications from different viewpoints (Dracup *et al.* 1980). Hydrological drought is considered to be the period when stream flows are below a threshold level over a given period of time in a given climatic region. The severity of drought can be objectively defined using the runs theory. The threshold level specifies the statistical significance of the drought variable and is used to divide the time series into periods of deficit and surplus. (Smakhtin & Hughes 2004; Abebe & Foerch 2008).

Drought forecasting is a critical component of drought hydrology that plays a key role in risk management, risk assessment, preparedness and mitigation of droughts. Significant studies have been undertaken to model various aspects of droughts including the identification and prediction of drought characteristics. However, the main challenge faced in research is developing appropriate techniques to estimate drought characteristics. One of the shortcomings of mitigating the effects of a drought is the degree of accuracy when predicting drought conditions months or years before (Mirabbasi *et al.* 2012).

Researchers have used this modelling approach for many scientific and technical applications. Can & Yerdelen (2005) constructed an ARMA model for mean monthly stream flows of the M. Kemal Pasa River located in the Susurluk Basin in Turkey. Şengül & Can (2011) produced an AR model of mean monthly flows in the Karasu River in Turkey.

Saldarriaga & Yevjevich (2007) noted run-lengths, as statistical properties of time series, represent attractive parameters for studying droughts and surpluses. The distributions and parameters of run lengths (duration of a run) and run sums (total water deficit with respect to the threshold level along a run) have been analysed by the theory of runs (Sen 1976; Dracup *et al.* 1980).

In this study, drought durations and severities have been determined by subjecting the historical series of threshold levels to a Runs Analysis ($q = 0.5$; $q = 0.3$; $q = 0.1$). A further aim was to determine if more severe droughts were likely to be seen in the historical series. To this end, a mathematical model of historical runs was created. More severe droughts that are likely to occur have been calculated by producing synthetic series compatible with historical series, using this model. In this way, it has become possible to predict the charcteristics of droughts likely to take place in the future (Katipoğlu 2015).

STUDY AREA AND DATA

The Karasu River, or Western Euphrates River, is a long river that flows through eastern Turkey. It is one of the two sources of the Euphrates River. It has a length of about 450 km, a drainage basin area of 28.86 km^2 and elevation of 1,675 m above sea level. The location of the Karasu River is shown in Figure 1.

For this study, streamflow data recorded at gauging station No. 2154 for the period 1969 to 2009 was obtained from the General Directorate of Electrical Power Resources Survey and Development Administration (shortened as EIE). This contains 480 monthly observations covering 40 years. The streamflow data were available in water years,

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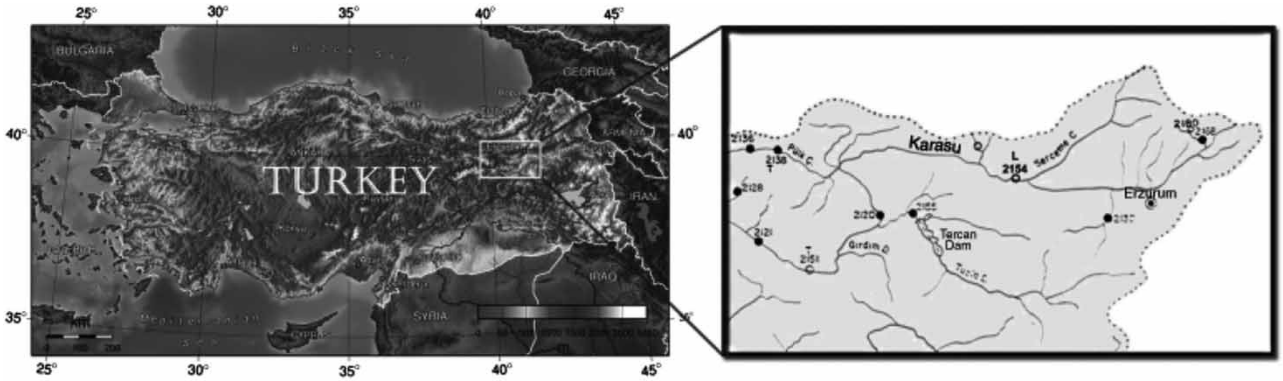


Figure 1 | Location of the Karasu River in the upper Euphrates River Basin.

referring to the period between 1 October of one year and 30 September of the next year.

METHODS

Run theory

Run theory is a method used to analyse droughts (Yevjevich 1967). The drought characteristics – namely duration, magnitude and severity of drought – are defined by this theory. This theory determines the start and end of a drought, based on the upper limit and lower limit of a critical threshold flow (Masud *et al.* 2015).

D_j is defined as the sum of the jth drought, while X_0 is defined as the sum of the severity under the threshold level.

$$D_j = \sum_{i=1}^{m} X_0 - X_j \quad (1)$$

The drought intensity (I_j) is calculated from the ratio of the negative run length of the sum of deficiencies as follows:

$$I_j = \frac{D_j}{N_j^-} \quad (2)$$

Yevjevich (1967) proposed the runs theory to determine the drought parameters and to examine their statistical properties (duration, severity, and intensity). The most basic element for deriving these parameters is the truncation or the threshold level, which may be a constant or function of time. A run is defined as a portion of time series of the drought variable X_j, in which all values are either below or above the selected threshold value X_0. Accordingly, it is called either a negative run or a positive run. Figure 2 represents a plot of a drought variable denoted by X_j that is intersected at many places by the truncation level X_0, which can be a deterministic variable, a stochastic variable, or a combination thereof. Various statistical parameters concerning drought duration, magnitude and intensity at different truncation levels are very useful for drought characterization (Kwak *et al.* 2012; Hayes *et al.* 2004).

Selecting the threshold flow

The threshold flow can be selected in a variety of ways, and the choice can also be a function of the water deficit to be examined (Dracup *et al.* 1980). In some applications, the threshold is a well-defined flow rate, e.g. the specific yield of a reservoir. It is also possible to apply low flow indices,

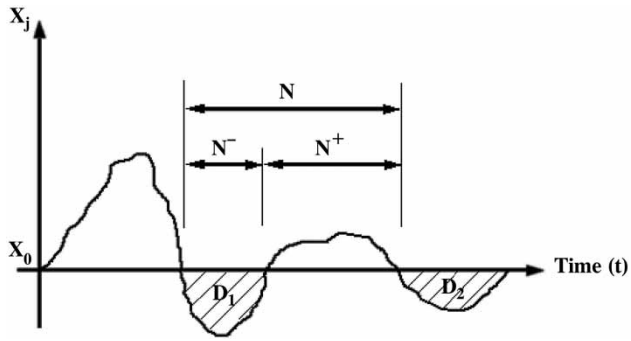


Figure 2 | Definition of run characteristics.

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e.g. a percentage of the mean flow or a percentile from a flow duration curve. A flow duration curve represents the relationship between the magnitude and frequency of daily, monthly or some other time interval of streamflow. It can be calculated in various ways (Vogel & Fennessey 1994). If daily data are analysed, the flow duration curve shows the relationship between each daily flow (usually expressed as a percentage of the period-of-record mean flow) and the corresponding flow exceedance. Flow exceedance is a dimensionless index that expresses the proportion of time that a specified daily flow is equalled or exceeded during the period of record. Expressing flows as exceedance values allows flow conditions in different rivers to be compared. The flow exceedance is often given in terms of percentiles. For instance, the 90th percentile flow, or Q_{90}, is the flow which is equalled or exceeded for 90% of the period of record (Salas *et al.* 2005).

ANALYSIS OF HISTORICAL FLOWS

Runs analysis of historical annual average flows

Threshold levels of annual average flows in historical series were determined by plotting the flow duration curve (Figure 3). The drought, which will be used to find the recurrence intervals, has been determined by subjecting to historical series runs analysis for the determined threshold levels.

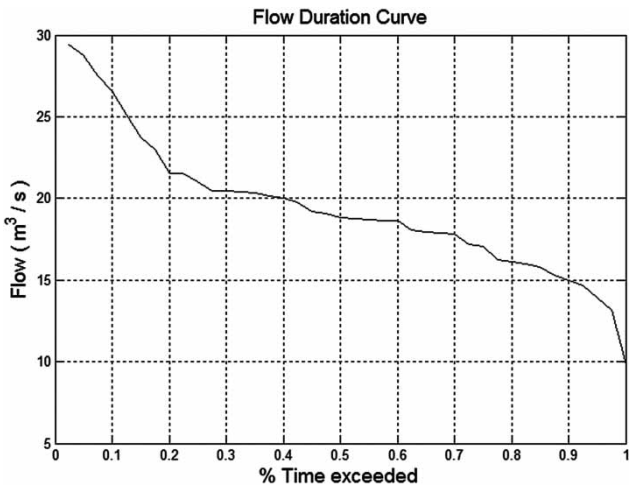


Figure 3 | The flow duration curve of the Chronological series average annual flows.

The flow rates corresponding to the threshold levels can be determined from the flow duration curve. Q_{90} corresponds to the flow that is exceeded 90% of the time, and the threshold level is defined as $q = 0.1$. Likewise $Q_{70:}$ corresponds to the flow that is exceeded 70% of the time, and the threshold level is defined as $q = 0.3$. Q_{50} corresponds to a threshold level defined as $q = 0.5$. An example which compares these thresholds to annual average flows is given in Figure 4.

Threshold levels obtained from the flow duration curve are shown below (Table 1).

Drought duration and severity of historical series annual average flows have been determined for $q = 0.5$ by runs analysis (Table 2).

The maximum duration of drought for $q = 0.5$ of historical series annual flows was observed between 1999 and 2003, and its period was 5 years while its severity was 11.61 (m^3/s)(refer to Table 2).

The maximum duration of drought for the historical series average annual flow of $q = 0.3$ is 3 years, which was observed between 1973 and 1975, while maximum severity is 7.68 (m^3/s), which occurred in 1983 (see Table 3).

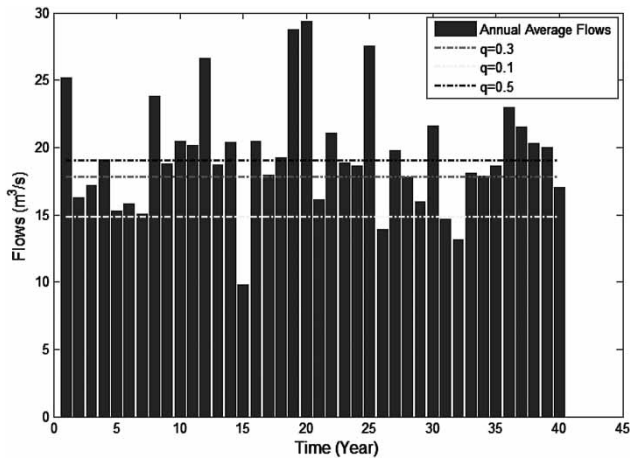


Figure 4 | Historical series of annual average flows.

Table 1 | Threshold levels for historical annual average flows

Historical series annual average flows			
Threshold level (m^3/s)	$q = 0.5$	$q = 0.3$	$q = 0.1$
Flow (m^3/s)	18.8	17.5	14.8

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Table 2 | Runs analysis results of historical annual average flows for q = 0.5

q = 0.5 Threshold flow		
Date	**Time (years)**	**Severity (m^3/s)**
1970–1971	2	4.18
1973–1975	3	10.31
1977	1	0.05
1981	1	0.10
1983	1	8.99
1985	1	0.86
1989	1	2.68
1992	1	0.14
1994	1	4.91
1996–1997	2	3.82
1999–2003	**5[a]**	**11.61[a]**
2008	1	1.77

[a]Maximum droughts.

Table 3 | Runs analysis results of historical annual average flows for q = 0.3

q = 0.3 Threshold flow		
Date	**Time (years)**	**Severity (m^3/s)**
1970–1971	2	1.57
1973–1975	3[a]	6.39
1983	1	7.68[a]
1989	1	1.37
1994	1	3.61
1997	1	1.52
1999–2000	2	7.18
2008	1	0.46

[a]Maximum droughts.

The maximum duration of drought for the historical series average annual flow of q = 0.3 is 2 years, and has been observed between 1999 and 2000, while the maximum severity is 5.02 (m^3/s) which was observed in 1983 (see Table 4).

Runs analysis of historical monthly average flows

The droughts to be used for the recurrence intervals for the threshold levels have been determined by analyzing the monthly historical series. Threshold levels of historical monthly average flows were obtained by using the 'quantile' command of Matlab R2014a software (Table 5).

Table 4 | Runs analysis results of historical annual average flows for q = 0.1

q = 0.1 Threshold flow		
Date	**Time (years)**	**Severity (m^3/s)**
1983	1	5.02[a]
1994	1	0.95
1999–2000	2[a]	1.86

[a]Maximum droughts.

Table 5 | Threshold level of historical monthly average flows

Threshold flows			
Month	**q = 0.5**	**q = 0.3**	**q = 0.1**
October	6.21	5.60	4.61
November	7.99	6.97	5.89
December	7.62	6.83	5.66
January	6.64	6.19	5.36
February	7.33	6.54	5.83
March	15.16	12.4	9.34
April	56.64	46.73	35.4
May	69.30	56.06	37.15
June	25.15	13.26	10.96
July	7.09	5.79	3.61
August	4.48	3.69	2.66
September	4.34	3.74	2.86

The drought duration and severity of the historical monthly average flows obtained by undertaking a runs analysis for q = 0.5 are presented in Table 6.

The maximum duration of drought seen for the historical series monthly flows for q = 0.5 is 18 months and is seen between October 1975 and March 1976 (refer to Table 6).

The drought duration and the severity obtained by undertaking a runs analysis of the historical monthly average flows for q = 0.3 are shown in Table 7.

The maximum duration of drought for q = 0.3 of historical monthly average flows is 7 months and is observed between November and May of 1983 (refer Table 7).

The maximum severity for q = 0.3 of historical series monthly flows is 55.83 (m^3/s) and is observed between November and May 1983 (see Table 7).

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Table 6 | Runs analysis of historical monthly average flows for q = 0.5

q = 0.5 Threshold flow

Date	Month	Time (months)	Severity (m^3/s)
1969	December–February	3	4.40
.			
.			
.			
1975	October–March	**18**[a]	48.76
.			
.			
.			
1982	August–October	15	**102.72**[a]
.			
.			
.			
2008	April–September	4	65.48

[a]Maximum droughts.

Table 7 | Runs analysis of historical monthly average flows for q = 0.3

q = 0.3 Threshold flow

Date	Month	Time (months)	Severity (m^3 / s)
1969	January–February	2	2.39
.			
.			
.			
1983	November–May	**7**[a]	**55.83**[a]
.			
.			
.			
2008	April–June	3	29.75

[a]Maximum droughts.

The drought duration and the severity obtained by undertaking a runs analysis of the historical monthly average flows for q = 0.1 are shown in Table 8.

The maximum duration of drought for q = 0.1 of historical monthly average flows is 5 months and is observed between June and October of 1989 (refer to Table 8).

The maximum severity for q = 0.1 of historical series monthly flows is 20.45 (m^3/s) and was observed between April and May 1983 (see Table 8).

Table 8 | Runs analysis of historical monthly average flows for q = 0.1

q = 0.1 Threshold flow

Date	Month	Time (months)	Severity (m^3/s)
1969	February	1	1.56
.			
.			
.			
1983	April–May	2	**20.45**[a]
.			
.			
.			
1989	June–October	**5**[a]	13.15
.			
.			
.			
2008	May	1	4.95

[a]Maximum droughts.

NUMERICAL MODELLING

Univariate modelling of monthly flows

For most hydrologic time series, for example for flow series, the underlying physics involves many phenomena and their interactions, such as rainfall, interception, detention, infiltration, snowmelt, groundwater flow, evapotranspiration, etc. Most of these phenomena have variations in time and space, and as a result the physics of the phenomena to be represented by stochastic processes is too complex to be expressed in simple lumped models, or is not well understood. Some physical explanations have been given to some models. For example, the MA process may be considered as a model to relate mean annual runoff to mean annual rainfall, and a rainfall-runoff transformation has been suggested for the simulation of annual flows by an ARMA(l, 1) model (Salas 1980).

Autoregressive (AR) models have been extensively used in hydrology and water resources since the early 1960s, for modeling annual and periodic hydrologic time series. The application of these models has been attractive in hydrology mainly because the autoregressive form has an intuitive type of time dependence (the value of a variable at the present

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time depends on the values at previous times), and they are the simplest models to use. Autoregressive models may have constant parameters, parameters varying with time, or a combination of both (Salas 1980).

While the droughts determined from the runs analysis of the historical series are of interest, of equal interest are possible droughts of even greater duration. In order to estimate possible greater droughts, a mathematical model having similar statistical features to the historical series was needed. The aim was to predict more severe drought scenarios that were likely to occur by producing 100 synthetic series similar to the historical series.

Conversion and normalisation of the data series

Most of the probability theories and statistical techniques referenced in hydrology are based on the assumption that the variables are normally distributed. However, hydrological variables usually have asymmetric distribution.

The excessive deviation of the historical monthly flows from a normal distribution was an indication that the data were not normally distributed. Therefore, logarithms of the flows were taken to eliminate the distortion, i.e. $y_{v,\tau} = \log_e(x_{v,\tau})$ where $(x_{v,\tau})$ represents the historical series. It was also understood that the monthly flows were not normally distributed according to figures and previous studies (Şengül & Can 2011).

The converted $y_{v,\tau}$ series was also normalised as follows, $z_{v,\tau} = (y_{v,\tau} - \mu_\tau)/\sigma_\tau$.

The monthly flows were internally dependent because they had exceeded Anderson 95% probability limits (Şengül & Can 2011).

Parameter estimation and confidence interval

Lower and upper limits of the 95% confidence interval of the predicted AR model parameter:

$$\phi_1 \mp 1.96^{*}0.0018 = \begin{cases} 0.5547 \\ 0.5617 \end{cases}$$

Because the AR model parameter (ϕ_1) does not include zero at the 95% confidence interval, it is statistically significant and indicates that the model is available (Anderson 1977).

Goodness-of-fit tests of selected models

A common rule for choosing between models is the principle of parsimony, which requires a model with the smallest number of parameters. One criterion for selecting among competing ARMA(p,q) models is the information criterion proposed by Akaike (1974).

The Akaike test was used to make a selection between competing models (the recommended potential models) and the model providing the minimum value of Akaike information criterion (AIC) as selected (Akaike 1974).

$$\mathrm{AIC}(p, q) = \mathrm{IN}(\mathrm{MLE\ of\ residual\ variance}) + 2(p + q) \quad (3)$$

where N is the sample size. The preferred ARMA (p, q) model is the one that yields the minimum value of AIC of the equation, where MLE refers to maximum likelihood estimation (Salas 1980).

Akaike's final prediction error (FPE) supports the results for the estimated model in compliance with the Akaike test.

As can be seen in Table 9, when the FPE of the probable models and the AIC were compared, the model with the smallest values (0.6769, −0.3902) was the AR (1) model, and this was selected as the most suitable model. The AIC(p,q) = IN (MLE of residual variance) + 2(p + q) equation was calculated by the 'present' and 'aic' commands of the Matlab software. The AR (1) model was selected by evaluating the results.

Table 9 | Comparison of FPE and AIC values of all models

Model	FPE	AIC
AR (1)	**0.6769**	**− 0.3902**
ARMA(1,1)	0.681	− 0.3841
AR(2)	0.6811	− 0.3840
ARMA(2,1)	0.6838	− 0.3801
ARMA(2,2)	0.6857	− 0.3772
AR(3)	0.6831	− 0.3810
ARMA(3,1)	0.6866	− 0.3758
ARMA(3,2)	0.6894	− 0.3717
ARMA(3,3)	0.6859	− 0.3768

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Generation of synthetic series

Data generation is an important subject in stochastic hydrology, and has received considerable attention in the hydrologic literature. The major uses and applications of modelling hydrological time series are the generation of synthetic samples (as potential future inputs of water resource systems) (Lane & Frevert 1990; Karabörk & Kahya 1999).

Checking the reliability of the model

The statistical characteristics, such as periodic averages and periodic standard deviations of historical series monthly flows and synthetic series, were found and 95% confidence intervals of historical series monthly flows were determined. As can be understood from Figures 5 and 6, the historical series and the synthetic series produced were compatible. It is seen that the historical series values were within the confidence limits (Cigizoglu & Bayazit 1998).

Control of annual flows

Annual average flows were obtained by virtue of the synthetic series produced by establishing the AR model of historical series monthly flows.

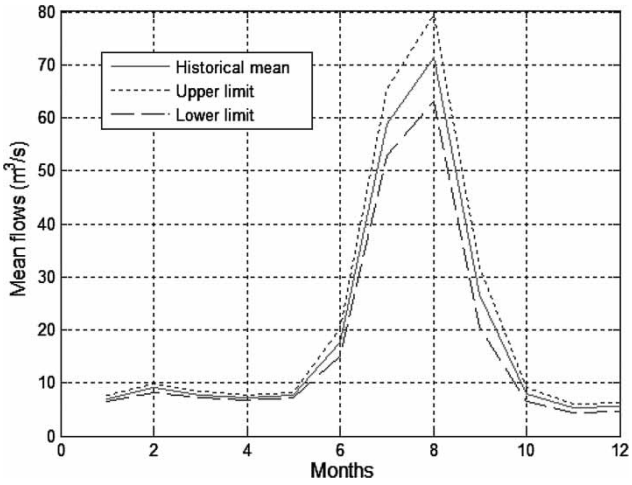


Figure 5 | 95% confidence interval of the derived synthetic series and mean of the historical monthly average flows.

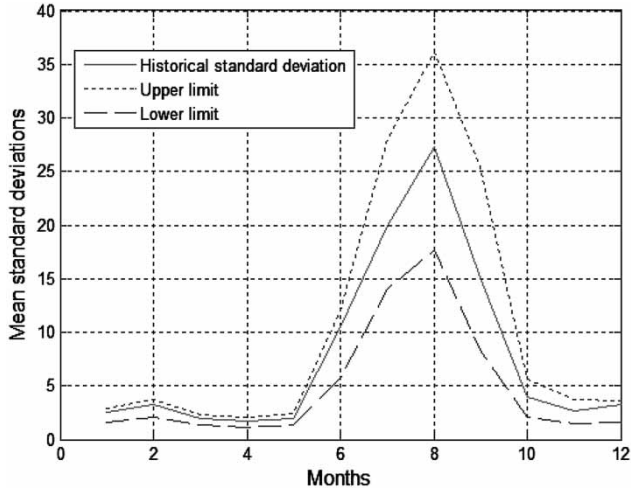


Figure 6 | 95% confidence interval of the derived synthetic series and standard deviations of the historical monthly average flows.

Control of the averages

Average flows were obtained for each year based on the monthly synthetic series produced with similar features to the historical series. The standard deviations of these average flows were also found, and the upper and lower limits of the historical series were calculated. The 95% confidence interval of the obtained synthetic series and historical averages are shown in Figure 7. It is shown that historical averages were within confidence limits in all months (Figure 7).

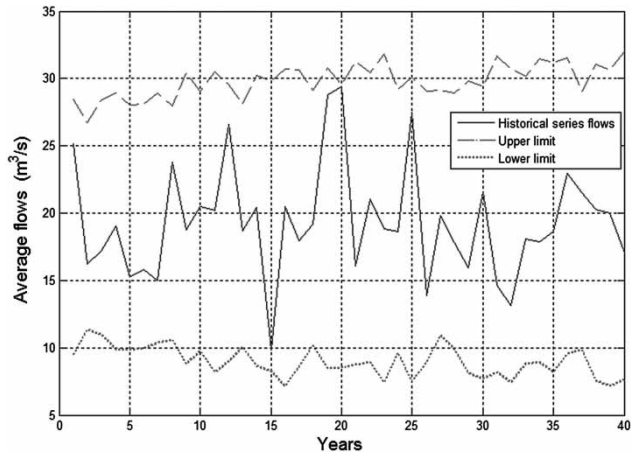


Figure 7 | 95% confidence interval of the derived synthetic series and mean of the historical average annual flows.

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Control of standard deviations

Average standard deviations were obtained for each year based on the monthly synthetic series produced with similar features to the historical series. The standard deviations of these average flows were also found. The 95% confidence interval of the obtained synthetic series and historical averages are shown in Figure 8. It is shown that historical averages were within confidence limits in all years except year 19 (refer to Figure 8).

The distribution of drought characteristics

The box plots used for showing the frequency distribution of a variable are useful, because they show the centre of the distribution (median), and the level of distribution of the variables.

The form and extreme values of the box diagrams of the data distribution of deficit values corresponding to the same drought length were visualised by the drought duration and severity, obtained by subjecting the average annual synthetic series to runs analysis for $q = 0.5$, $q = 0.3$, $q = 0.1$ threshold levels in the appendix (available with the online version of this paper).

The maximum drought duration and severity of the produced synthetic series for $q = 0.5$ are 10 years and 41.4171 (m^3/s) (Table 10).

The maximum drought duration and severity of the produced synthetic series for $q = 0.3$ are 10 years and 28.3431 (m^3/s) (Table 11).

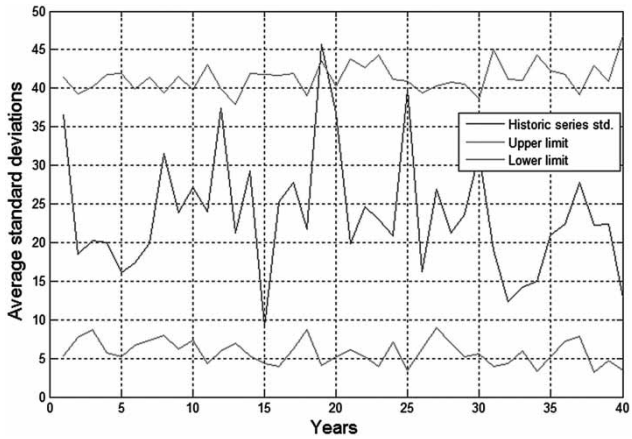


Figure 8 | 95% confidence interval of the derived synthetic series and standard deviations of the historical average annual flow.

Table 10 | Other droughts seen by analysing the synthetic series for $q = 0.5$ threshold flow

Duration	Severity
8	15.06
8	17.88
8	26.86
8	27.83
8	28.55
8	32.25
8	37.48
9	28.26
9	29.46
10*	41.42[a]

[a]Maximum droughts.

Table 11 | Other droughts seen by analysing the synthetic series $q = 0.3$ threshold flow

Duration	Severity
7	17.79
7	18.12
7	27.40
8	16.40
10[a]	28.34[a]

[a]Maximum droughts.

CONCLUSIONS

(1) The results of this study show that the AR(1) model was selected as the best model for the Karasu River.
(2) The maximum duration and severity of drought for $q = 0.5$ of annual averages of the synthetic series are 10 (years) and 41.4171 (m^3/s), respectively. The maximum duration and severity of drought for $q = 0.3$ of annual averages of the synthetic series are 10 (years) and 28.3431 (m^3/s), respectively. The maximum duration and severity of drought for $q = 0.1$ of annual averages of the synthetic series are 6 (years) and 5.3247 (m^3/s), respectively.
(3) Dry period lengths obtained by runs analysis give support to size and plan reservoirs, to determine the water supply risk for irrigation systems, to determine the risk of deterioration of the capacity of hydroelectric systems, and to plan studies on future reservoir operations.

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ACKNOWLEDGEMENTS

The authors would like to thank the anonymous referees for their detailed reviews of the first submission, which have led to a significantly improved paper. In this research, MATLAB 2014 was used for data analysis, downloaded from the official webpage of Ataturk University. This article has been extracted from the postgraduate thesis advocated on 28 August 2015.

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First received 8 May 2017; accepted in revised form 25 September 2017. Available online 10 October 2017

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