MATHEMATICAL MODEL OF LAMAS RIVER DAILY FLOWS

A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of
Dokuz Eylul University
In Partial Fulfillment of the Requirements for
The Degree of Master of Science in Civil Engineering,
Hydraulics & Hydrology & Water Resources Program

by
Cem Polat ÇETİNKAYA

July, 2001
İZMİR

Ms.Sc. THESIS EXAMINATION RESULT FORM

We certify that we have read the thesis, entitled **"Mathematical Model of Lamas River Daily Flows"** completed by Cem Polat ÇETİNKAYA under supervision of Prof. Dr. Ertuğrul BENZEDEN and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Prof. Dr. Ertuğrul BENZEDEN
Supervisor

Committee Member
Prof. Dr. Nilgün HARMANCIOĞLU

Committee Member
Prof. Dr. Yüksel K. BİRSOY

Approved by the
Graduate School of Natural and Applied Sciences

Prof.Dr.Cahit Helvacı
Director

ACKNOWLEDGMENTS

The author deeply thanks to the instructor of this Master of Science Thesis, Prof. Dr. Ertuğrul BENZEDEN, for his precious helps, for the valuable information he provided and his endless patience during the preparation of this study.

The author also thanks to Ms. Gülay Onuşluel and the other persons for their efforts.

ABSTRACT

Lamas River has been used for years for the urban water supply and irrigation purposes. Since 1980's, certain planning and feasibility studies to exploit the hydroelectric potential of Lamas River are carried out.

This study consists of modeling Kızılgeçit daily river flows, which can be used in planning, design and operation purposes of proposed water resource systems in the basin. In this respect, the alternative stationary and nonstationary mathematical models of daily flows at Kızılgeçit covering the period 1962-1994 have been investigated.

Regarding the results of the study, due to the presence of a downward trend, none of the stationary models have been found satisfactory in representing the characteristics of the historical flows. Among the various nonstationary models applied, the ARIMA (3,1,0) model has been found satisfactory considering the correlogram and normalized spectrum of the residuals series.

ÖZET

Lamas Nehri, içme ve sulama suyu amaçlarıyla yıllardır kullanılmaktadır. 1980'li yıllardan başlayarak, Lamas Nehri hidroelektrik potansiyelini değerlendirmek üzere bazı planlama ve fizibilite çalışmaları yapılmıştır.

Bu çalışma, havzada önerilen su kaynakları sistemlerinin planlanması, tasarımı ve işletilmesi amaçlarıyla kullanılabilecek Kızılgeçit günlük akışlarının modellenmesini kapsamaktadır. Bu çerçevede 1962-1994 dönemini kapsayan Kızılgeçit günlük akışlarının, durağan ve durağan olmayan matematik modelleri incelenmiştir.

Çalışmadan elde edilen sonuçlara göre, akışlardaki azalma eğilimi nedeniyle, durağan modellerin hiçbirinin tarihsel akışların karakteristiklerini temsil etmekte yeterli olmadığı görülmüştür. Durağan olmayan değişik modeller arasından, kalıntılar serisinin korelogram ve normalize kümülatif spectrumları dikkate alındığında, ARIMA (3,1,0) modelinin tatminkar olduğu sonucuna varılmıştır.

CONTENTS

Page

Chapter Four

HISTORICAL DATA AVAILABLE

Chapter Five

ALTERNATIVE MODELS OF KIZILGEÇİT DAILY FLOWS

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

CHAPTHER ONE
INTRODUCTION

1.1. PURPOSE OF THE STUDY

In the planning of a water resource project, the prediction of characteristics of future water supply has a vital importance. Therefore, a detailed study of the complex processes influencing the river runoff must be achieved. This study may be accomplished either with the proper description of all variables and their interactions in the process, or the process may be regarded as the random output of a lumped system in a black-box approach, with a limited knowledge of the system. This black-box approach is commonly denoted as stochastic hydrology (Quimpo, 1967; Vargas-Semprun, 1977).

In stochastic hydrology, model building and testing are accomplished regarding structural analysis of time series. The structural models built may be used either to generate synthetic streamflows for planning and design purposes or to forecast the immediate future of the process.

The common approach in stochastic hydrology is to assume that hydrologic time series consists of deterministic and stochastic components. The deterministic component may contain both a transient and a periodic part, while the stochastic component contains dependent and independent parts over time. Thereafter, structural analysis of hydrologic time series are made in several ways; i) investigation of whether various parameters of time series are periodic or nonperiodic; ii) determination of significant harmonics in the periodic parameters;

iii) analysis of whether stochastic components are dependent or independent; iv) fitting adequate mathematical dependence models and the computation of independent stochastic variables from dependent stochastic components; v) fitting probability distribution functions to independent stochastic components and selecting the function of best fit (Yevjevich 1972a).

With the increasing demand for water, allocation of available water with traditional methods among challenging purposes are no longer sufficient, hence models of daily flows have essential importance in solving water management problems.

In Lamas River Basin, four diversion hydroelectric power plants are planned and hydrology of Lamas River has been studied in detail (DEU, 1985,1986,1996,1999). Though the diversion power plants are designed and operated on a daily basis, no attempt has been made in the past to model Lamas River daily flows.

In this regard, this study aimed to estimate mathematical models of Lamas River daily flows, which can be used to generate synthetic data for risk based planning and design and to forecast immediate future flows for operation of planned diversion power plants. It is hoped that design and feasibility studies and multiple purpose water use problems in the basin, as well as the real time operation of the proposed schemes, can be treated more efficiently by the use of synthetic daily flow sequences and forecasts.

1.2. SCOPE OF THE STUDY

To fulfill the objectives given above, statistical properties of daily flows at Kızılgeçit stream gauging station, which is very close to the weir sites, are investigated. Because of the high skewness coefficients of daily flows, natural logarithmic transformation of original data has been decided. With the considerable reduction in skewness coefficients, the log-transformation has allowed obtaining a "close to normal" series. Although it is known that a presence of a downward trend in last decade of available data, daily flow records at Kızılgeçit have initially assumed homogenous and periodicities in the mean and standard deviations of log-transformed daily flows are examined. It has been decided that both parameters have 6 significant harmonics and log-transformed series are standardized with parametric approach. Several stationary stochastic models have been fitted to explain the stochastic component of the given time series, but unfortunately none of the models were satisfactory in representing the process.

The homogeneity of the available data has been investigated and a downward trend after the year 1983 has been detected through double mass curve analysis with other stream gauging stations in adjacent basins. The presence of a downward trend has been proved but the actual reason of that trend could be either the drought observed in last two decades overall in Turkey or the excess use of the available water in basin for urban water supply and irrigation. Regarding that, application of linear nonstationary models has been decided and ARIMA (3,1,0) model has been found adequate to represent the process during the correlogram and normalized integrated spectrum of its residuals series.

CHAPTER TWO
RELEVANT LITERATURE ON THE MODELING DAILY FLOWS

2.1. LITERATURE REVIEW ON MODELING DAILY FLOWS

The historical streamflow data are commonly available as time series of averages over time intervals such day, month or year. In this chapter, the contributions in the literature for modelling the daily streamflows will be discussed.

The structure of daily streamflows is analysed first by Quimpo in 1967. Regarding the virginity of their flows, 17 streamflow gauging stations in USA are selected and seasonal components in means and standard deviation are detected through spectral analysis. At the end of harmonic analysis, it has been observed that in all but one of the stations, the first six harmonics accounted for more than 80 percent of explained variances due to the annual cycle and its subharmonics. The author used the parametric approach for removing the periodicity:

$$Y_t = \frac{X_t - \hat{\mu}_t}{\hat{\sigma}_t} \qquad (2.1)$$

After the removal of periodicity, Y_τ series did not have a mean equal to zero and a variance equal to one, so another standardization was necessary:

$$Z_t = \frac{Y_t - \overline{Y}_t}{S_y} \qquad (2.2)$$

Correlogram analysis performed to Z_τ series has shown the existence of a linear association between successive values. The multi-lag Markov models of first, second and third order were investigated. After the removal of autoregressive dependence, the correlogram of obtained ξ_τ series was tested for significant departures from zero, but because of the size of the sample, the confidence band found too narrow for practical use. The author then resorted to a test of equality of variances. The author's conclusions are; i) in general, in daily streamflow series, the periodicity is caused by annual astronomic cycle, ii) after the deterministic periodic component has been removed, the standardized Z_t series can be represented by a lag-two autoregressive scheme.

Hall et al. (1972) used the same approach that Quimpo (1967) had used and analysed the mean daily river flows of Swincombe in West Devon (U.K.) recorded between 1934-1968. The authors searched for a trend in data. Data were divided in two sub-sets of equal size and variances and means of both sub-sets were examined by F-test and small-sample t-test respectively, but neither of the tests proved to be significant at the 5 percent confidence level, indicating the absence of any significant trend component. The presence of a trend component was also searched by cumulative double-mass curve by using the precipitation as reference variable and Swincombe data appeared both consistent and homogeneous. Because of the high variances of daily flows, natural logarithms of them were taken and six pairs of harmonics provided an adequate description of the annual cycle of the daily averages within the series. After the standardization which are above with equations 2.1 and 2.2 mentioned, it was seen that first order Markov model was sufficient to represent the data. Through the use of GAUSS and RANDU subroutines of I.B.M. to obtain random normal deviates with zero mean and unit variance, and with the help of the built model, flow sequences in equal length to historical record were generated. As a result, the first and second order moments, the daily averages and their standard deviations were found to be remarkably similar of those of the historical data, and their performance were accepted for operational purposes.

Green (1973) proposed a scheme that was based on a linear interpolation of the logarithms of 5-day average flows for modelling the daily flow series. The 5-day series were generated by the model, which had been developed by Kottegoda in 1970 (quoted in Green, 1973). The model was intending to preserve the long-term average properties of daily data, while the short-term characteristics are imposed by interpolation scheme. The author also superimposed a random noise to interpolated value in order to avoid the deterministic character of the interpolation. On the other hand, Vargas-Semprun (1977) mentions, "This technique does not introduce persistence among interpolated values and therefore it fails to reproduce extremes, as it is recognized by the author. Furthermore, the generated sequences are forced to follow the historic series so closely that sampling variations tend to be perpetuated".

Keloglu (1974) analysed in his M. Sc. Thesis the mathematical models of Manavgat River's (Turkey) daily flows at three successive stream gauging stations through the use of autocorrelation and spectral analysis techniques. The author first determined the deterministic periodic components of daily flows with the help of Fourier series, and represented the periodic components with a complex periodic function with 4-6 harmonics. Then, the stochastic residuals are obtained by subtracting the periodical components from daily flows;

$$\eta_\tau = X_\tau - P_\tau \qquad (2.3)$$

where η_τ represents the stochastic residuals, and

$$P_\tau = \mu_x + \sum_{j=1}^{m}\left(A_j \cos\frac{2\pi j}{w} + B_j \sin\frac{2\pi j}{w}\right). \qquad (2.4)$$

The author has found that the stochastic residuals could be expressed as a linearly dependent second order Markov process. Thus the mathematical model of Manavgat River's daily flows was determined. It was also concluded that two of the gauging stations were affected by the karstic spring flows that are present in Manavgat basin. Through the analysis of daily precipitation, it was observed that the precipitation in the neighbour basins contribute to Manavgat River's daily flows after a lag time around 20-30 days because of the routing in karstic groundwater system.

Vargas-Semprun (1977) studied the potential of the approaches, based either on linear or non-linear dependence models, to perform the structural analysis of daily streamflow series. First the effect of inferring a number of significant harmonics in periodic parameters on the performance of daily streamflow models was investigated. Some models for describing the dependence structure of standardized daily runoff series by the removal of periodicity in parameters were also studied and their power for describing the process was tested. The various alternatives to how structural analysis of daily streamflows is actually performed were explored with the emphasis on checking the robustness of existing estimation techniques. The author concluded; **i)** underestimation or overestimation of the number of significant harmonics in periodic parameters completely distorts further stages of estimation, **ii)** the selection of the number of significant harmonics should be based on the experience, because the Fisher's test nearly always overestimates the number of significant harmonics, **iii)** the daily runoff processes studied in the research are sensitive to the skewness, while "the estimation procedures used in the hydrologic structural analysis of daily streamflow series are only appropriate for gaussian processes", **iv)** the structural analysis of original daily streamflows can be improved by transforming them into a "close-to-normal" process, "however, the limited data and the difficulties in obtaining normal marginal distributions render residuals non-normally distributed", **v)** in the majority of the studied cases, the estimation procedures of applied ARMA models' parameters yielded the values, which were outside the region of stationarity, so those estimation procedures should be subjected to a thorough review, **vi)** the inconsistent behaviour of Box-Pierce $Q(\lambda)$-statistic was found. The author thinks that may have resulted either from the not removed non-stationarities in the residuals, or from the non-normality of their distribution, to which this statistic is very sensitive.

Yakowitz (1979) applied a non-parametric N'th order Markov model to the daily flows of Cheyenne River (South-western USA) that has a significant fluctuation in flows between wet and dry seasons. The author compared the applied Markov model with the parametric ARMA modelling, where the non-parametric Markov model were "at least moderately successfull" for representing the daily flows of Cheyenne

River. It was concluded that proposed Markov model was easier to calculate than an ARMA model that is in upper order than 3rd.

Kelman (1980) proposed a new approach for the modelling of daily streamflows, in which the basic assumption was that the rising and falling limbs of hydrographs are to be modelled separately due to the fact that they translate different physical processes; i.e. rising limb is mostly due to the external factors, while the falling one is governed by the emptying water from the watershed. The author assumed two linear reservoirs, which are the conceptual representation of the watershed. Any sequence of recession discharge was then a stochastic output from these two reservoirs. The groundwater was represented by reservoir 1, while the surface detention, bank and channel storages were represented by reservoir 2. It was considered that the runoff at the outlet of a watershed is the sum of three components; $q_1(t)$, and $q_2(t)$ the outflow from reservoirs 1 and 2 respectively and $q_3(t)$, the direct runoff, which is governed by the precipitation directly. The model applied to the Powel River (Tennessee, USA) and the data were divided into 26 seasons each 14 days long, adding up to 364 days. The model was tested through the generation of 40 years long samples and by the Smirnov two sample test, and the results were almost "satisfactory". On the other hand a critic can be added here that the Kelman's proposed model is not so sufficient for the months, in which in Powell River the low flows occur. By the way the observed and theoretical discharges in the days of low flows are far different than each other.

Periodic gamma autoregressive processes for operational hydrology were studied by Fernandez and Salas (1986) for the application to weekly flow data. The authors proposed a new class of univariate models, which incorporate skewed and correlation properties within the model structure without the necessity of transformations that are generally used for nonnormal hydrologic series. The models assume a gamma marginal distribution and a constant or periodic autoregressive structure. The gamma models were tested and compared in relation to transformed normal AR models by simulations based on five weekly streamflow series. The authors concluded that the gamma models are better in reproducing the overall mean, standard deviation and skewness coefficient, as well as the overall variation of seasonal mean, standard deviation, skewness coefficient and lag-one autocorrelation coefficient than the corresponding gaussian normal models.

Clossimo et al. (1988) studied the daily flows of Crati River (Southern Italy). Crati River's daily flows between 1926 and 1951 were chosen, in order to avoid the non-homogeneity in the flows, which appeared after the construction of a dam after the last mentioned year. The authors used the parametric Fourier series approach for determining the periodicity and significant harmonics (a number of two) in mean and standard deviation and removed the deterministic periodic component by standardization, which had been previously used by Quimpo (1967). The stochastic dependence structure of the series after removal of periodicity, has shown also periodicity in autoregressive parameter, and hence PAR (1) model was also examined. However, since the amplitude of the periodic component in $\rho_{1,\tau}$ is very small, an autoregressive model with constant coefficient was decided. The correlogram and variance density spectrum of the residuals were calculated and it was possible to assert that the residuals are independent and random, thus a probability distribution could be fitted and the complete mathematical model for the representation of the daily flows of Crati River were possible.

Rasmussen et al. (1996) studied the periodic autoregressive moving average models (PARMA) for streamflow simulation. The authors represented the periodicity in the autocovariance structure by PARMA models, i.e., autoregressive moving average models that vary with seasons. The statistical properties of low-order models such as the PARMA (2,2) model were examined and the periodic moment equations were derived, which could be used to estimate the periodic covariance structure of a given model. The application of the contemporaneous PARMA models were carried out on the weekly flow data for two catchments in the Ottawa River basin. The authors concluded that the care must be exercised when fitting high-order models to series of small time scales, such as weekly flows, because parameter estimates may be unstable and lead poor reproduction of some of the most important statistics, for example, the periodic variance.

Lu and Berliner (1999) proposed a model that involves switching among various regimes. Model was a mixture of three autoregressive models, which accommodate rising, falling and normal states in the daily runoff process. The model for switching among regimes was given by a three-state Markov chain model, whose transition probabilities were modelled on the basis both past runoff values and of a time series of rainfall data.

Mitosek (2000) analysed daily flows of five stations with records over 50 years. The analysis resulted, i) days with high mean have also high variance; ii) the coefficient of variation cannot be considered to be constant even approximately; iii) the lag-one autocorrelation functions $\rho_i(1)$, i = 1,2,......, 365, estimated "over realizations" have at least half of their coefficients significantly different from other coefficients; iv) autocorrelation functions estimated "over time" are greater than the absolute value for data, which have not been standardized but were initially treated with the logarithmic transformation only; v) autocorrelation functions estimated "over realizations" are preferred to autocorrelation functions estimated "over time" because the daily river process is not ergodic. It was suggested that the description of daily flows as ergodic stochastic processes should be abandoned and the autocorrelation functions should be estimated "over realizations". The "over time" estimated autocorrelation functions may only be treated as a very rough approximation of the "over realizations" autocorrelation functions.

2.2. PREVIOUS HYDROLOGIC STUDIES IN LAMAS RIVER BASIN

Dokuz Eylul University (DEU) first examined the hydrology of Lamas basin in 1985 and in 1986 with hydrologic data covering the period 1961-1983. Hydrologic analyses of the basin in the content of Lamas III and Lamas IV hydroelectric power plants was revised by DEU using additional hydrologic data collected in the period 1984-1994 (DEU, 1996). In 1999 the last report was considerably based on the revised hydrologic report prepared by DEU in 1996 and had the purpose of determining water potential available for hydroelectric power generation at Lamas I and II hydroelectric schemes. In this respect; i) correlation and regression analyses has been carried out between the flows at the Kızılgeçit and nearby stream-gauging stations. The streamflow records of Kızılgeçit was extended for the period 1961-66 by regression on Sarıaydın, in order to complete the monthly data covering the period of 1961-94, and daily data of 1962-1994; ii) the analyses with regard to the contribution of karst spring discharges yielded mean karst spring effluents of 2.8 m^3/s at Sarıaydın, 4.3 m^3/s at Kızılgeçit, 1.5 m^3/s in the intermediate basin; resulting in surface runoff values of 1.2, 1.8 and 0.6 m^3/s respectively; iii) the analysis of rainfall-runoff relations led to the conclusion that almost 10 % of annual rainfall feeds the surface runoff, while 20 % the karst springs upstream of Kızılgeçit.

CHAPTER THREE
BACKGROUND MATERIAL AND METHODS

3.1 DESCRIPTION OF COMPONENTS OF HYDROLOGIC TIME SERIES

Hydrologic time series can be divided into two basic groups (Salas et. al., 1985); i) single time series at a specified point (univariate); ii) multiple series at several points or multiple series of different kinds at one point (multivariate). Regarding the objectives of this study, the analyses on univariate hydrologic time series will be discussed in this chapter.

Univariate series are generally described by estimating their statistical characteristics such as the mean, standard deviation and time dependence (Salas et. al., 1985).

A hydrologic continuous univariate time series may also be composed of deterministic components, in the form of trends, jumps and periodicity, and of a stochastic component. The basic hypothesis of model building is that time series can be separated into these components (Yevjevich, 1972a).

Almost all hydrologic time series of daily, weekly and monthly values have deterministic components occurring due to astronomic cycle and therefore they are periodic-stochastic series in nature; on the other hand none of the hydrologic time series are purely deterministic or periodic.

The deterministic components in time series can be mainly classified as;

a) Transient components (trends and jumps)

b) Periodic components

3.2 INCONSISTENCY AND NONHOMOGENITY (TRENDS & JUMPS)

Systematic errors (inconsistency) and changes in nature by man-made or by natural processes (nonhomogenity) are mainly responsible for the trends and sudden changes, namely jumps. In order to determine properly the time series characteristics, inconsistency and nonhomogenity must be identified and removed, by the way of regional analyses such environmental changes in river basin, and the study on operation of gauging station at and around the basin should always support the statistically detected trends and jumps, which must be statistically tested. Their significance must be proved before considering them as population characteristics of the time series (Yevjevich 1972a, Salas et. al., 1985).

A systematic and continuous change of any parameter of a time series along time is often called a trend. The usual assumption is that trends are mainly found only in the mean. Trends as deterministic components often occur in hydrologic series due to natural or man-made activities in a river basin, and cause nonstationarity.

Trends should be conceived as a transient component in a given realization or sample series of a stationary process, and they are not expected to repeat themselves with the same properties, or appear at all in other sample of hydrologic sequences (Yevjevich, 1972a). Trends may be linear or nonlinear and can be identified by the least squares method of smoothing by moving average schemes.

Various water resources problems require identification, description, and removal of trends from past observations in order to reduce the observed series to homogenous samples. Trends are identified by both statistical techniques and by physical (or historic) analyses of various changes in the hydrologic environment.

Another approach in trend analysis is to investigate its effects on the various sample properties of a homogenous series. This second approach is carried out for deciding whether the order of magnitude of these effects is sufficient to warrant detailed identification, description and removal of trends from a given series. If these effects are not of sufficient order sensitivity, they cannot be detected and usually neglected. A combination of statistical and physical methods, if possible, is often gives the most reliable results, especially when the reliable quantitative information is available about the historical physical changes and man-made activities.

It has been proven that a trend introduces a very high positive serial correlation into a homogenous time series (Yevjevich & Jeng, 1967).

3.3. AUTOCORRELATION ANALYSIS

The autocorrelation function (acf) or autocorrelation coefficients, ρ_k, for an infinite ($N \rightarrow \infty$) discrete time series with Δt sampling intervals is defined as the correlation between items of the series that are $\tau = k\,.\,\Delta t$ lag apart from each others:

$$\rho_k = \frac{\operatorname{cov}(X_i, X_{i+k})}{\operatorname{var}(X_i)} = \frac{\frac{1}{N-k}\sum_{i=1}^{N-k}(X_i - \mu)(X_{i+k} - \mu)}{\frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2} \qquad (3\text{-}1)$$

where X_i and X_{i+k} are realizations of the series at time $t = i\,.\,\Delta t$ and $t+\tau=(i+k)\Delta t$, and $\mu = E_{N\to\infty}\{X_i\}$ is the expected value or the population mean of X_t.

The sample estimates of acf, r_k , from a discrete series of length N, usually computed by an open series approach given by;

$$r_k = \frac{\operatorname{cov}(X_i, X_{i+k})}{\{\operatorname{var}(X_i)\operatorname{var}(X_{i+k})\}^{1/2}} \qquad (3\text{-}2)$$

where;

$$\mathrm{cov}(X_i, X_{i+k}) = C_{xx}(k) = \frac{1}{N\quad k}\sum_{i=1}^{N\quad k} X_i X_{i+k} \quad \bar{X}_1\,\bar{X}_2 \tag{3-3}$$

$$\mathrm{var}(X_i) = C_{xx}^{(1)}(0) = \frac{1}{N\quad k}\sum_{i=1}^{N\quad k} X_i^2 \quad \bar{X}_1^2 \tag{3-4}$$

$$\mathrm{var}(X_{i+k}) = C_{xx}^{(2)}(0) = \frac{1}{N\quad k}\sum_{i=1}^{N\quad k} X_{i+k}^2 \quad \bar{X}_2^2 \tag{3-5}$$

in which $\bar{X}_1$ and $\bar{X}_2$ are defined as

$$\bar{X}_1 = \frac{1}{N-k}\sum_{i=1}^{N-k} X_i \qquad \text{and} \qquad \bar{X}_2 = \frac{1}{N-k}\sum_{i=1}^{N-k} X_{i+k} \tag{3-6}$$

Thus, the open-series approach uses the first and the last N-k long parts of the series in estimating the product-moment correlation coefficients between the members of that series that are k lags (or k Δt intervals) apart.

Another alternative procedure to estimate the sample acf of a finite series is to use the circular-series approach, in which the first k number of items of the series is supposed to occur as the last k items of the truncated series; i.e $X_{N+1}=X_1, X_{N+2}=X_2, \ldots\ldots\ldots\ldots, X_{N+k}=X_k$.

This assumption made in the circular-series approach states that the mean and the variance of the observed series are considered as constants, $\bar{X}$ and S_x^2, and does not depend on the lag k. Then, the sample autocorrelation coefficients are computed through;

$$r_k = \frac{\left\{\dfrac{1}{N}\displaystyle\sum_{i=1}^{N} X_i X_{i+k} - \bar{X}^2\right\}}{S_x^2} \tag{3-7}$$

where $\bar{X}$ and S_x^2 are the sample mean and the sample variance.

For both continuous and discrete series in hydrology it is not advisable to use the circular approach because the first and the last part of the series may be independent while its corresponding adjacent parts (with N-k items) may be highly dependent.

The 100(1-α)% tolerance limits of r_1 estimated by circular series approach, according to Anderson, are (Yevjevich, 1972a, Salas et.al., 1985) if N is sufficiently large

$$TL(r_1) = \frac{-1 \mp Z_{\alpha/2}\sqrt{N-2}}{N-1} \qquad (3\text{-}8)$$

which implies that the sampling distribution of r_1 is normal with $\rho_1 = E(r_1) \cong 0$ and in Eq. (3-8) $Z_{\alpha/2}$ is the critical standard normal deviate with probability (1-α/2).

The Anderson's 100(1-α) % approximate tolerance limits for r_k in open series approach is,

$$TL(r_k) = -\frac{1}{N-k} \mp t_{\alpha/2}\frac{\sqrt{N-k-1}}{N-k} \text{ and } \nu = N-k-1 \qquad (3\text{-}9)$$

which produces a gradually increasing tolerance band as k increases (Yevjevich, 1972a).In Eq. (3-9) $t_{\alpha/2}$ is the critical student-t variate with probability (1-α/2) and υ = N- k-1 degrees of freedom.

3.4. PERIODICITY

Seasonal patterns in runoff data are usually apparent in the form of periodic behavior of the original series ($X_{p,\tau}$), having a year as the fundamental period (ω). When this is the case, one approach is to regard the entire time series as an ensemble of N realizations of the hypothesized stochastic process, with N the number of years.

Values at the same time interval (τ) within the year are then treated as random drawings from the same distribution (Jenkins & Watts, 1968).

Most hydrologic time series are periodic-stochastic processes in which the stochastic component is mixed with periodic parameters. Denoting the time series by $X_{p,\tau}$ with time interval a fraction of the year, the stochastic component is defined here by

$$Z_{p,\tau} = \frac{X_{p,\tau} - \mu_\tau}{\sigma_\tau} \quad p = 1,2,\ldots..,N \text{ and } \tau = 1,2,\ldots...,\omega \qquad (3\text{-}10)$$

where p is the sequence of years in a sample size of N, τ is the sequence of time intervals (or seasons) within the year, μ_τ and σ_τ are the periodic functions of the population mean, and standard deviation. The parameters of stochastic dependence and marginal probability distributions of the $Z_{p,\tau}$ series may or may not be periodic. In principle, all parameters may be periodic, and a general treatment of hydrologic time series requires techniques for proper inference of their significant harmonics, which will be discussed in the next sections. The estimation of periodic functions of Eq. 3-10 is a prerequisite for a correct modeling of the stochastic component (Yevjevich & Obeysekera, 1985).

In order to obtain the stationary stochastic components of a time series properly, periodicity in the basic parameters, such as the mean and standard deviation, must be detected and removed from the original hydrologic time series.

3.4.1 Non-parametric Approach

The non-parametric approach is to use the sample estimates of $\bar{X}_\tau$ and S_τ at seasons τ = 1,2,.....,ω as the population values of the parameters, μ_τ and σ_τ . Hence, Eq. 3-10 takes the form,

$$Z_{p,\tau} = \frac{X_{p,\tau} - \bar{X}_\tau}{S_\tau} \qquad (3\text{-}11)$$

This approach uses 2ω number of parameters, which is considerably large for ω ≥12. The reduced series, $Z_{p,\tau}$,has the mean zero and $S_{z,\tau}$=1 at each season τ, therefore the series $Z_{p,\tau}$ is fully standardized.

3.4.2. Parametric Approach (Fourier Series Approximation)

Non-parametric approach may be adequate when the modeling is performed with a relatively small number of time intervals, such as 12 in the case of monthly flows. When the number of intervals is large, such as the case of daily series, the parametric method is preferred because: i) it gives an opportunity of the parsimony in the number of parameters to be estimated, and ii) it smoothes out the sampling variability in daily means and standard deviations (Box & Jenkins, 1976).

Regarding the application of the parametric method, sample means $\bar{X}_\tau$ and sample standard deviations S_τ are estimated from data, and then they are represented by a set of harmonic functions of τ in the Fourier series analysis, with a selected *number of harmonics* (m_o for the mean and m_s for the standard deviation) much smaller than ω/2. Harmonic function fitted for the $\overline{X}_\tau$ series is in the form of

$$\hat{\mu}_\tau = \overline{X} + \sum_{j=1}^{m_o}\left(A_{jo}\cos\frac{2\pi j\tau}{\omega} + B_{jo}\sin\frac{2\pi j\tau}{\omega}\right) \qquad (3\text{-}12)$$

where $\overline{X}$ is the average of ω of $\overline{X}_\tau$, A_{jo} and B_{jo} are the Fourier coefficients estimated from ω values of $\overline{X}_\tau$, and m_o is the number of significant harmonics selected. A similar representation of S_τ is in the form of

$$\hat{\sigma}_\tau = \overline{S} + \sum_{j=1}^{m_s}\left(A_{js}\cos\frac{2\pi j\tau}{\omega} + B_{js}\sin\frac{2\pi j\tau}{\omega}\right) \tag{3-13}$$

where $\overline{S}$ is the mean of the S_τ series.

The parametric model is assumed to represent better the seasonal variation of μ_τ and σ_τ. By using the estimated periodic functions, periodicity in hydrologic time series is treated in the same way as using models for stochastic dependence and probability distribution functions for the resulting independent stochastic components (Yevjevich & Obeysekera, 1985).

The standardization (removing periodic mean and standard deviations from sample series) can be carried out through a similar procedure as in the non-parametric approach, considering that μ_τ and σ_τ are replaced by fitted $\hat{\mu}_\tau$ and $\hat{\sigma}_\tau$ respectively. Hence Eq. 3-10 now takes the form

$$Z_{p,\tau} = \frac{X_{p,\tau} - \hat{\mu}_\tau}{\hat{\sigma}_\tau} \tag{3-14}$$

$Z_{p,\tau}$ series is not fully standardized, since the error terms $\overline{X}_\tau - \hat{\mu}_\tau$ and $S_\tau - \hat{\sigma}_\tau$ exist unless $m_o = m_s = \omega/2$, if ω is even, and $m_o = m_s = (\omega-1)/2$ if ω is odd, although the mean and standard deviation of $Z_{p,\tau}$ is close to zero and unity.

An important point raised at this stage has to do with the numbers of significant harmonics, i.e., m_o and m_s to be included in the Fourier representation of $\hat{\mu}_\tau$ and $\hat{\sigma}_\tau$ in Eqs. 3-10 and 3-11. The identification and choice of the dependence structure are crucially influenced from the estimation of the standardized $Z_{p,\tau}$.

Two procedures are currently used in hydrological modeling to infer periodicity in hydrologic time series, classical Fisher's test and an empirical approach.

Fisher's test was developed for a process composed of the sum of harmonics and a normal independent process, a situation rarely encountered in streamflow series. This test has been applied to hydrologic series by violating its underlying assumptions, taking for granted a sort of robustness never claimed by Fisher.

Yevjevich (1972a) discussed the previous method and realized the incompatibilities of its application to hydrologic series. As a result of experience with real data, he developed an approximate empirical procedure based on the cumulative percentage of variance explained by the first harmonics up to sixth, found by Quimpo (1967) as the number of significant harmonics most likely to explain more than 80 % of the variance of estimates of a periodic parameter (Vargas-Semprun, 1977).

Suppose that q_τ , τ = 1,2,.....,ω denotes any periodic parameter (or statistics) of a time series $X_{p,\tau}$, with a mean $\bar{q}$ and variance var q_τ around its mean.

$$\bar{q} = \frac{1}{\omega}\sum_{\tau=1}^{\omega} q_\tau$$

$$\operatorname{var} q_\tau = \frac{1}{\omega}\sum_{\tau=1}^{\omega}(q_\tau - \bar{q})^2 = \sum_{j=1}^{M}\left(C_{jq}^2 / \nu_j\right) \tag{3-15}$$

where M is $\omega/2$ if ω is even and $(\omega-1)/2$ if ω is odd, and $\upsilon_j=2$ for all j except for the M th harmonic when ω is even ($\upsilon_M=1$). The periodic components of q_τ defined by the first m number of harmonics may be expressed mathematically as

$$\hat{q}_\tau = \bar{q} + \sum_{j=1}^{m}\left\{A_{jq}\cos\left(\frac{2\pi j\tau}{\omega}\right) + B_{jq}\sin\left(\frac{2\pi j\tau}{\omega}\right)\right\} \tag{3-16}$$

where A_{jq} and B_{jq} are estimated through (if ω is odd)

$$A_{jq} = \frac{2}{\omega}\sum_{j=1}^{\omega} q_{\tau} \cos\left(\frac{2\pi j \tau}{\omega}\right)$$

$$j = 1,2,\ldots\ldots M \qquad (3\text{-}17)$$

$$B_{jq} = \frac{2}{\omega}\sum_{j=1}^{\omega} q_{\tau} \sin\left(\frac{2\pi j \tau}{\omega}\right)$$

Since the number of harmonics considered in defining $\hat{q}_{\tau}$ is less than M an error term, ε_{τ}, will essentially remain, that is

$$q_{\tau} = \hat{q}_{\tau} + \varepsilon_{\tau} \qquad (3\text{-}18)$$

Hence the variance of q_{τ} will be divided into two parts, the variance explained by the first m number of harmonics, $\operatorname{var}\hat{q}_{\tau}$, and the error variance, var ε_{τ}. The variance explained by the j th harmonic is

$$H_j = \frac{\left(A_{jq}^2 + B_{jq}^2\right)}{v_j} = C_{jq}^2 / v_j \qquad (3\text{-}19)$$

where C_{jq} is the amplitude of the j th harmonic

$$C_{jq} = \sqrt{A_{jq}^2 + B_{jq}^2} \quad ; \quad \theta_{jq} = \operatorname{arctg}\left\{ -B_{jq} / A_{jq} \right\} \qquad (3\text{-}20)$$

and θ_{jq} defined above is the angular phase of the j th harmonic.

The cumulative variance explained by the first m number of harmonics is defined by

$$V_m = \operatorname{var}\hat{q}_{\tau} = \sum_{j=1}^{m} H_j = \sum_{j=1}^{m} C_{jq}^2 / v_j \qquad (3\text{-}21)$$

Dividing H_j by var q_τ the relative (or percentage) explained variance of the j th harmonic is (normalized line spectrum ordinates at frequency j / M)

$$\Delta P_j = {H_j}\Big/{\mathrm{var}\, q_\tau} = \frac{\left(C_{jq}^2 / \nu_\tau\right)}{\mathrm{var}\, q_\tau} \tag{3-22}$$

and dividing H_m by var q_τ relative (or percentage) explained cumulative variance of the first m number of harmonics are (normalized cumulative periodogram ordinates at frequency m / M)

$$P_m = \sum_{j=1}^{m} \Delta P_j = \sum_{j=1}^{m} \frac{\left(C_{jq}^2 / \nu_\tau\right)}{\mathrm{var}\, q_\tau} \tag{3-23}$$

Plots of P_m versus m is called "relative (or normalized) cumulative periodogram" (Fig. 3-1) and is used as an aid in selecting the total number of significant harmonics.

The critical value of m which before it sharp rises occur, is selected to be the total number of significant harmonics that should be considered for the definition of the periodic components in q_τ.

If the variation of q_τ is due to random changes, that is, q_τ fluctuates around its mean randomly, its cumulative periodogram follow nearly a straight line connecting points (0,0) and (M,1), because of the equal variance contributions, $H_1=H_2=\ldots\ldots=H_M = \sigma_\varepsilon^2 / M$ (Box & Jenkins, 1976).

The experience in using Fourier analysis for estimating periodic parameters of hydrologic time series has shown that for small interval series, such as daily and weekly series, only the first 4 to 6 number of harmonics explain almost 95% to 99% of the total variation. For instance, when dealing with daily series there are a total of 182 harmonics. However, out of this number rarely more than 6 harmonics are needed for obtaining a Fourier series estimate $\hat{q}_\tau$ which will closely fit the q_τ.

Generally the number of harmonics decided for the mean is used also for the standard deviation.

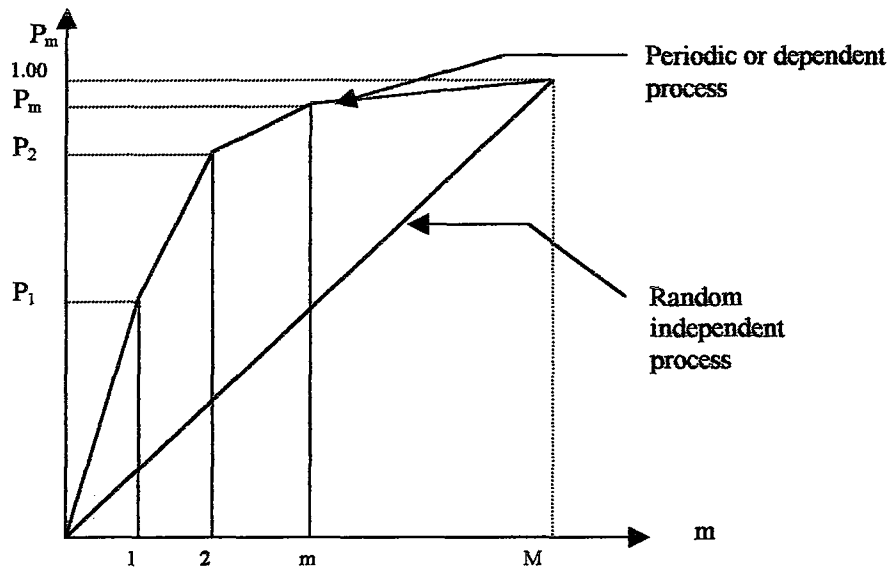

Fig.3-1: Normalized cumulative periodogram

The overestimation or the underestimation of harmonics in the mean and standard deviation have crucial effects on the stochastic dependence structure of the $Z_{p,\tau}$ series. This problem has been discussed by Yevjevich & Obeysekera (1985).

3.5 SPECTRAL ANALYSIS

The Fourier transform pair of a time series X_t in the range $-T/2 \leq t \leq T/2$ is defined as (Jenkins & Watts, 1968)

$$\mathbf{F}(\lambda_j) = \frac{1}{T}\int_{-T/2}^{T/2} X_t e^{-i\lambda_j t} dt$$

$$X_t = \int_{j=-\infty}^{\infty} F(\lambda_j) e^{-i\lambda_j t} \qquad (3\text{-}24)$$

where X_t is considered to have a mean zero and $\lambda_j = 2\,\pi\, f_j$ is the angular frequency. The variance of the process is then

$$\sigma_x^2 = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} X_t^2 dt = \lim_{T\to\infty} \left\{ \frac{1}{T} \sum_{j=-\infty}^{\infty} \left[T \left| F(\lambda_j) \right|^2 \right] \right\} = \int_{-\infty}^{\infty} \Gamma_{xx}(f) df \qquad (3\text{-}25)$$

where $\Gamma_{xx}(f) = \lim_{T\to\infty} \left[T \left| F(\lambda_j \right|^2 \right]$ and is called Fourier power spectrum of the X_t process.

The function derived by dividing $\Gamma_{xx}(f)$ by the variance σ_x^2 is called the spectral density or the variance density spectrum and defined as

$$\nu(f) = \Gamma_{xx}(f) \Big/ \sigma_x^2 = \int_{-\infty}^{\infty} \rho_{xx}(\tau)\, e^{-2\pi i f \tau} d\tau = 2 \int_{0}^{\infty} \rho_{xx}(\tau)\, e^{-2\pi i f \tau} d\tau \qquad (3\text{-}26)$$

Hence the spectral density function is the Fourier transform of the autocorrelation function of X_t and it is symmetric. Properties of the spectral density function are analogous to an ordinary probability distribution function. Since υ is a symmetric function of f, that is, $\upsilon(f) = \upsilon(-f)$, we can represent the total variance density at frequencies $0 \le |f| \le \infty$ by

$$\gamma(f) = 2\nu(f) = 4 \int_{0}^{\infty} \rho(\tau) \cos(2\pi f \tau) d\tau \qquad (3\text{-}27)$$

In practice Eq. (3-27) is generally used in spectral analyses and it is called as the variance density spectrum (Yevjevich, 1972b).

Integration of $\Gamma_{xx}(f)$ over a given frequency interval ($-f_a \le f \le f_a$) gives the integrated spectrum

$$I_{xx}(f_a) = \int_{-f_a}^{f_a} \Gamma_{xx}(f) df \qquad (3\text{-}28)$$

When the integrated spectrum is divided by σ_x^2, a function is then defined as

$$I_n(f) = I_{xx}(f)/\sigma_x^2 \tag{3-29}$$

which is very similar to the cumulative probability distribution and is so called the normalized integrated variance density spectrum.

For the time series discretized by Δ time intervals, the variance density spectrum can be shown as

$$\gamma(f) = 2\Delta\left\{1 + 2\sum_{k=1}^{\infty}\rho_k \cos(2\pi fk\Delta)\right\},\ 0 \le f \le \frac{1}{2\Delta} \tag{3-30}$$

If the series has only N number of discrete samples, then the raw sample estimates of variance density spectrum are

$$g(f) = 2\Delta\left\{1 + 2\sum_{k=1}^{M-1} r_k \cos(2\pi fk\Delta)\right\}, 0 \le f \le \frac{1}{2\Delta} \tag{3-31}$$

where M is the maximum lag or "the truncation point" of the sample correlogram, and it is assumed that $E(r_k)=0$ for $k \ge M$. Spectral densities estimated by Eq. (3-31) are biased raw estimates of $\gamma(f)$, and depends on factors such as Δ, M, N and f (Box & Jenkins, 1976).

Spectral windows are kernels or functions of lag (k) or frequency (f), and multiplied by the sample autocovariances or autocorrelations during the estimation procedure. The sampling interval Δ=1 (day, week, month, year…) is generally used, and hence the frequency interval for spectral estimates is $0 \le f \le 1/2$. Using a lag window (filtering or weighting function), W (k), the spectral densities in their smoothed form is defined as

$$\hat{g}(f) = 2\left\{1 + 2\sum_{k=1}^{M-1} W(k) r_k \cos(2\pi f k)\right\}, \quad 0 \le f \le 1/2 \qquad (3\text{-}32)$$

The variance of the smoothed spectral estimates depends on the truncation point M, and spectral window (or smoothing function) used for estimation. The variance of $\hat{g}_\tau$ can be reduced by selecting smaller M; however, reducing M increases the bias and cause much more distortion than the wider windows do. Therefore, the exact choice of M is a vital matter (Jenkins & Watts, 1968).

In practice, an alternative of Eq. (3-32) is used

$$\hat{g}(f_i) \cong 2\left\{1 + 2\sum_{k=1}^{M-1} W(k) r_k \cos\left(\frac{\pi i k}{F}\right)\right\}, \; i = 1,2,\ldots F \qquad (3\text{-}33)$$

where F is selected as $F \ge (2\sim3)M$, and $f_i = i / 2F$.

Some widely used spectral windows and their properties are given in Table 3-1 (Jenkins & Watts, 1968).

Table 3-1. Spectral windows

Spectral Window	Standardized bandwidth (b_1)	Degrees of freedom $\upsilon = 2Nb_1 / M$
Rectangular $W(k) = \begin{cases} 1, & \lvert k\rvert \le M \\ 0, & \lvert k\rvert > M \end{cases}$	0.5	N/M
Bartlett $W(k) = \begin{cases} 1 - \lvert k\rvert/M, & \lvert k\rvert \le M \\ 0, & \lvert k\rvert > M \end{cases}$	1.5	3N/M
Tukey $W(k) = \begin{cases} 1/2\left(1 + \cos\frac{\pi k}{M}\right), & \lvert k\rvert \le M \\ 0, & \lvert k\rvert > M \end{cases}$	4/3	8N/3M

3.5.1. The Spectrum of an Ideal White Noise and Its Tolerance Limits

The spectral density function of an ideal white noise is

$$\gamma_n(f) = 2, \qquad 0 < f < 0.5 \tag{3-34}$$

where f is the ordinary frequency. Integration of this function yields, the integrated normalized spectrum of an ideal white noise process

$$I_n(f) = \int_0^f \gamma_n(f)df = 2f, \quad 0 < f < 0.5 \tag{3-35}$$

In hydrologic practice, spectral analysis is used as a tool of verification or adequacy of the model postulated for a given sample series. The residuals series obtained after transformation and removal of periodic and dependent components from the original series is expected to be random, independent and normally distributed. One of the alternative ways of testing whether the residuals series is close to an ideal white noise is to construct tolerance limits of an ideal white noise as

$$\Pr\left\{\frac{\gamma_n(f)\chi^2_{v,\alpha/2}}{v} < E[g(f)] < \frac{\gamma_n(f)\chi^2_{v,1-\alpha/2}}{v}\right\} = 1-\alpha \tag{3-36}$$

where γ_n (f) = 2 for an ideal white noise, α is selected significance level (probability of having a Type I error), $\chi^2_{v,\alpha/2}$ and $\chi^2_{v,1\ \alpha/2}$ are chi-square statistics for the probability of exceedance α/2 and 1-α/2 with υ degrees of freedom. Critical values of chi-square distribution can be approximated by the Wilson-Hilferty transformation given by

$$\chi^2_{v,.} \cong v\left[1-\frac{2}{9v} \mp |Z_{\alpha/2}|\sqrt{\frac{2}{9v}}\right]^3 \tag{3-37}$$

if υ is sufficiently large (υ>10).

The sample normalized integrated spectrum, I_ε (f), of the residuals series is calculated simply by numerical integration of $\hat{g}(f_i)$ with Δf =1/2F sampling intervals.

Confidence (or tolerance) limits of the integrated spectrum of an ideal white noise is given by Kolmogorov and Smirnov as (Box & Jenkins, 1976)

$$\begin{aligned} UCL[I_n(f)] &= 2f + d \\ LCL[I_n(f)] &= 2f - d \end{aligned} \qquad (3\text{-}38)$$

where

$$d = \frac{\lambda}{\sqrt{\frac{N}{2} - 1}} \qquad (3\text{-}39)$$

in which λ =1.22 for 1-α =0.90, and λ = 1.36 for 1-α =0.95.

The residuals series is an independent process if I_ε (f) is within the confidence limits. The relative cumulative periodogram of a series is quite similar to the normalized integrated spectrum.

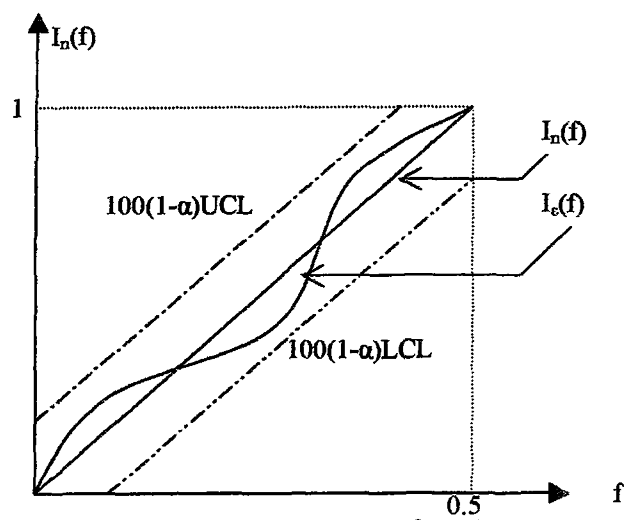

Fig.3-2: Normalized integrated spectrum of a white noise and its confidence limits

3.6. STATIONARY AND NONSTATIONARY LINEAR STOCHASTIC MODELS

Several stationary hydrologic models have been developed for modelling hydrologic time series. These models, which have been used for modelling streamflow time series, in particular are i) autoregressive models (AR), ii) fractional Gaussian noise models (FGN), iii) autoregressive moving average models (ARMA), iv) broken line models (BL), v) shot-noise models (SN), vi) Markov mixture models (MM), vii) ARMA-Markov models; and viii) general mixture models (Salas et. al., 1981). These stationary models can be utilized for generating synthetic samples and for forecasting purposes.

The nonstationary linear stochastic models , such as integrated moving average (IMA), autoregressive integrated moving average (ARIMA), and multiplicative ARIMA models are especially used in practice used in practice for modelling econometric time series which does not have a fixed mean but their successive differences constitute a stationary time series. These models may be able to remove trends and periodic components in the historical time series by differencing operation but can only be used for forecasting purposes (Box&Jenkins, 1976; Salas et. al., 1985).

3.6.1. Stationary Autoregressive-Moving Average (ARMA) Models

Autoregressive (AR), moving average (MA) and their mixtures of ARMA models are statistically based on the assumption that a random normally distributed input (ε_t) is transformed into a dependent stationary output (Z_t) by a linear system (Fig. 3-3). Denoting the random input (random shocks or white noise) with zero mean and variance σ_ε^2 by ε_t and output (linear stochastic process) with zero mean and variance $\sigma_z^2 = \sigma_x^2$ by $\widetilde{Z}_t$ we can write:

$$\tilde{Z}_t = X_t - \mu_t = \varepsilon_t + \Psi_1\varepsilon_{t-1} + \Psi_2\varepsilon_{t-2} + \ldots\ldots \qquad (3\text{-}40)$$

or, introducing the backward shift operator, $B^m\varepsilon_t = \varepsilon_{t-m}$,

$$\tilde{Z}_t = \Psi(B)\varepsilon_t \qquad (3\text{-}41)$$

where X_t is the time series generated at time t and μ_x is the level (or mean), and

$$\Psi(B) = 1 + \Psi_1 B + \Psi B^2 + \ldots\ldots \qquad (3\text{-}42)$$

is the linear operator (or transfer function of the filter) that transforms ε_t into $\tilde{Z}_t$ (Box&Jenkins, 1976).

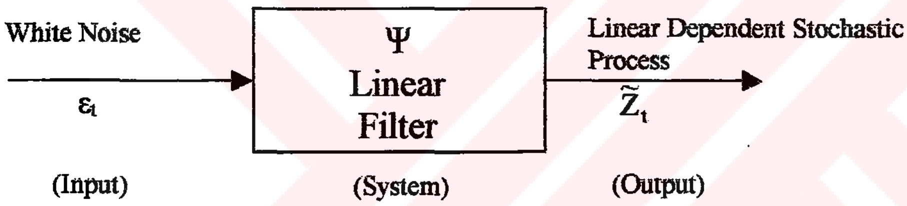

Fig. 3-3 Transformation process

Under suitable conditions $\tilde{Z}_t$ can be defined as a weighted sum of its own past values (that is, ε_t can be defined in terms of $\tilde{Z}_t$'s)

$$\varepsilon_t = \tilde{Z}_t - \Pi_1\tilde{Z}_{t-1} - \Pi_2\tilde{Z}_{t-2} - \ldots\ldots \qquad (3\text{-}43)$$

or

$$\varepsilon_t = \Pi(B)\tilde{Z}_t \qquad (3\text{-}44)$$

where $\Pi(B)$ is the inverse of the transfer function $\Psi(B)$,

$$\Pi(B) = \Psi^{-1}(B) = 1 - \Pi_1 B - \Pi_2 B - \dots\dots\dots \qquad (3\text{-}45)$$

To ensure that stochastic process generated by the Ψ weights is stationary (that is $\tilde{Z}_t$ has a finite variance and covariances) the infinite series $\Psi(B)$ given by Eq. (3-45) must converge for $|B| \leq 1$. On the other hand, the process is invertible (Eq. 3-43) only and only if the $\Pi(B)=\Psi^{-1}(B)$ series is convergent for all $|B| \leq 1$ (Box&Jenkins, 1976).

The above given formulation of linear stationary stochastic processes is more general and the model given Eq. (3-43) is an infinite order moving average process while Eq. (3-45) is an infinite order autoregressive process. These models proposed first by Yule in 1927 are commonly applied in time series modeling with finite number of Ψ of Π weights.

A mixture of finite number of moving average Ψ and autoregressive Π weights of linear stationary stochastic processes is so called "autoregressive-moving average" (ARMA) processes. Denoting Π_j weights by α_j and Ψ_j weights by $-\theta_j$ an ARMA (p,q) process with finite number of autoregressive (p) and moving average (q) parameters can be written in its implicit form as,

$$\Pi(B)\tilde{Z}_t = \Psi(B)\varepsilon_t \qquad (3\text{-}46)$$

or, in its explicit form as,

$$\tilde{Z}_t - \alpha_1 \tilde{Z}_{t-1} - \alpha_2 \tilde{Z}_{t-2} - \dots - \alpha_p \tilde{Z}_{t-p} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \qquad (3\text{-}47)$$

where the weighting functions (or transfer functions) of linear system are

$$\Pi(B) = \alpha(B) = 1 - \alpha_1 B - \alpha_2 B^2 - \dots\dots\dots - \alpha_p B^p \qquad (3\text{-}48)$$

and

$$\Psi(B) = \theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots\dots\dots - \theta_q B^q \qquad (3\text{-}49)$$

The mathematical expression of an ARMA (p,q) process in its conventional form is

$$\tilde{Z}_t = \sum_{j=1}^{p} \alpha_j \tilde{Z}_{t-j} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (3\text{-}50)$$

and has p + q + 2 number of parameters (p number of autoregressive parameters, q number of moving average parameters, the level or the mean of the series μ_x , and noise variance σ_ε^2).

The p th order AR (p) process or the q th order MA (q) process both are special cases of an ARMA (p,q) process, that is an AR (p) process is equivalent to an ARMA (p,0), and an MA (q) process to an ARMA (0,q) process.

In hydrologic practice p and q are seldom greater than 2, and in most cases an ARMA (1,1) model is found satisfactory. The stationary ARMA models have a physical justification in hydrology. The low flows in a river mainly result from groundwater and the flow at a particular time is a fraction of previous flows during the recession period, which may be represented by an autoregressive dependence structure. The high flows during the wet season are formed mainly by heavy rainfall or snowmelts or both, and therefore may be represented by moving average scheme (Salas et. al., 1985).

Because of its simplicity and of its importance in hydrology, basic properties of an ARMA (1,1) process are given below. The ARMA (1,1) process is in the form of

$$\tilde{Z}_t = \alpha_1 \tilde{Z}_{t-1} + \varepsilon_t - \theta_t \varepsilon_{t-1} \qquad (3\text{-}51)$$

The variance of $\tilde{Z}_t$ is

$$\sigma_z^2 = \left(1+\theta_1^2 - 2\alpha_1\theta_1\right)\sigma_\varepsilon^2 / \left(1-\alpha_1^2\right) \tag{3-52}$$

and the lag one (k=1) covariance is

$$\operatorname{cov}\left(\tilde{Z}_t \tilde{Z}_{t-1}\right) = \left(1-\alpha_1\theta_1\right)\left(\alpha_1 - \theta_1\right)\sigma_\varepsilon^2 / \left(1-\alpha_1^2\right) \tag{3-53}$$

For lags (k) greater than 1 the autocovariance function of an ARMA (1,1) process behaves like an AR (1) process, since $\operatorname{cov}\left(\tilde{Z}_t \varepsilon_{t-k}\right) = 0$ for $k > 1$:

$$\operatorname{cov}\left(\tilde{Z}_t \tilde{Z}_{t-k}\right) = \alpha_1 \operatorname{cov}\left(\tilde{Z}_t \tilde{Z}_{t-k-1}\right) \tag{3-54}$$

Dividing both sides of Eq. (3-53) and Eq. (3-54) by σ_z^2 yields autocorrelation function of an ARMA (1,1) process as in the following:

$$\rho_1 = \frac{\operatorname{cov}\left(\tilde{Z}_t \tilde{Z}_{t-1}\right)}{\sigma_z^2} = \frac{\left(1-\alpha_1\theta_1\right)\left(\alpha_1 - \theta_1\right)}{1+\theta_1^2 - 2\alpha_1\theta_1} \tag{3-55}$$

$$\rho_k = \frac{\operatorname{cov}\left(\tilde{Z}_t \tilde{Z}_{t-k}\right)}{\sigma_z^2} = \alpha_1 \rho_{k-1}\, , k > 1 \tag{3-56}$$

Therefore the dependence structure of an ARMA (1,1) process after k>1 dumps exponentially and/or decays exponentially by oscillating in sign when α_1 is negative.

Since the partial autocorrelation function of an AR (1) process has a cut-off at lags k>1, while the partial autocorrelation function of MA (1) process behaves similar to the autocorrelation function of the AR (1), the partial autocorrelation function of an ARMA (1,1) process starts with an initial value $\Phi_{11}=\alpha_1$ at lag k=1, and then behaves like a MA (1) which is dominated by a damped exponential (Box&Jenkins, 1976).

$$\Phi_{11} = \alpha_1 \tag{3-57}$$

$$\Phi_{kk} = -\theta_1^k \left(1-\theta_1^2\right)/\left(1-\theta_1^{2(k+1)}\right) \tag{3-58}$$

Preliminary or moment estimates of α_1 and θ_1 from a given sample series can be obtained from Eq. (3-56) and Eq. 3-(55). Using the sample first and second serial correlation coefficients r_1 and r_2 in Eq. (3-56) α_1 is first calculated

$$\hat{\alpha}_1 = r_2 / r_1 \tag{3-59}$$

Inserting $\hat{\alpha}_1 = r_2 / r_1$ in Eq. (3-53) and rearranging gives the following quadratic equation

$$\hat{\theta}_1^2 - (1/r_1)\hat{\theta}_1 + 1 = 0 \tag{3-60}$$

which has the roots

$$\hat{\theta}_1 = (-1/2r_1) \mp \left(1/4r_1^2 - 1\right)^{1/2} \tag{3-61}$$

An ARMA (1,1) model to be stationary and invertible both conditions in the following should be met:

$$\begin{aligned} -1 < \alpha_1 < 1 \\ -1 < \theta_1 < 1 \end{aligned} \tag{3-62}$$

In the special case when $\alpha_1 = \theta_1$ the process is a white noise (random independent process) and cannot be used for modelling the dependence structure of a time series (Box&Jenkins, 1976).

For an AR (p) process the autoregressive parameters, α_j , can be estimated in terms of autocorrelations of sample series. The autocorrelation function (acf) of an AR (p) process satisfies the following recursive equation (Yevjevich, 1972a; Box&Jenkins, 1976; Salas et.al, 1985):

$$\rho_k = \alpha_1\rho_{k-1} + \alpha_2\rho_{k-2} + \dots\dots\dots\dots\alpha_k\rho_{k-p} \text{ , } k > 0 \qquad (3\text{-}63)$$

Substituting sample autocorrelations for k = 1, 2,……, p in Eq. (3-63) a set of linear equations which can be solved for α_1, α_2,……., α_p are derived:

$$\begin{aligned}
\rho_1 &= \alpha_1 1 + \alpha_2\rho_2 + \dots\dots\dots\dots\dots\alpha_p\rho_{p-1} \\
\rho_2 &= \alpha_1\rho_1 + \alpha_2 1 + \dots\dots\dots\dots\dots\alpha_p\rho_{p-2} \\
. \quad & \quad . \quad\quad . \quad\quad\quad\quad . \\
. \quad & \quad . \quad\quad . \quad\quad\quad\quad . \\
\rho_p &= \alpha_1\rho_{p-1} + \alpha_2\rho_{p-2} + \dots\dots\dots\dots\alpha_p 1
\end{aligned} \qquad (3\text{-}64)$$

This set of equations usually called as YULE-WALKER equations. The set of equations (3-64) can also be defined in matrix notation.

If we call autocorrelation matrix as R_p the solution for α parameters is;

$$\alpha = \mathbf{R}_\mathbf{p}^{-1}.\mathbf{r}_\mathbf{p} \qquad (3\text{-}65)$$

where $\mathbf{r}_\mathbf{p}$ are column vector of estimates r_k.

The Yule-Walker estimates of an AR (p+1) process may be obtained when the estimates for an AR (p) process, fitted to the same time series, are known by recursive formulae given by Durbin (Salas et.al.,1985);

$$\hat{\Phi}_{p+1,j} = \hat{\Phi}_{p,j} - \hat{\Phi}_{p+1}\hat{\Phi}_{p-j+1}$$

$$\hat{\Phi}_{p+1,p+1} = \frac{r_{p+1} - \sum_{j=1}^{p} \hat{\Phi}_{pj} r_{p+1-j}}{1 - \sum_{j=1}^{p} \hat{\Phi}_{pj} r_j} \tag{3-66}$$

where for example for AR (2) process $\hat{\Phi}_{21} = \alpha_1$ and $\hat{\Phi}_{22} = \alpha_2$.

Since the p number of sample autocovariances C_1, C_2, ..., C_p and sample autocorrelations r_1, r_2, ...r_p are estimated from sample series of reduced sizes N-1, N-2,......, N-p, the moment (or Yule-Walker) estimates of the α_j's are only initial (or approximate) values. The least squares estimates of the autoregressive parameters can be found through multiple linear regressions between $\tilde{Z}_t$, $\tilde{Z}_{t+1}$, $\tilde{Z}_{t+2}$, ...,$\tilde{Z}_{t+p}$ series each of size N-p. Means and variances of the truncated series are not equal in this estimation procedure, and the autocovariances are different from C_1, C_2, ..., C_p. Therefore all the series should be standardized with respect to their means and standard deviations before applying multiple linear regressions. Having the parameter estimates $\{\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_p\}$ the unbiased estimate of the noise variance is then calculated from (Box & Jenkins, 1976)

$$\hat{S}_e^2 = \frac{1}{(N-p)}\left(D_{11} - \sum_{j=1}^{p} \hat{\alpha}_j D_{1,j+1}\right) \tag{3-67}$$

where

$$D_{1,j} = \hat{\alpha}_1 D_{j,2} + \hat{\alpha}_2 D_{j,3} + ...\hat{\alpha}_p D_{j,p+1} \qquad j = 2, 3, ..., p+1 \tag{3-68}$$

and (Box&Jenkins, 1976)

$$D_{ij} = D_{ji} = \frac{N}{(N+2-i-j)} \sum_{\ell=0}^{N+\ell-i-j} Z_{i+\ell} Z_{j+\ell} \tag{3-69}$$

As an example, the least squares estimate of the parameter α_1 of an AR(1) process is calculated from

$$\hat{\alpha}_1 = \left(\frac{N}{N\ 1}\right) \sum_{\ell=0}^{N-2} Z_{\ell+1} Z_{\ell+2} \bigg/ \left(\frac{N}{N-2}\right) \sum_{\ell=0}^{N-2} Z_{\ell+2}^2 = D_{12}/D_{22} \tag{3-70}$$

while the initial or moment estimate of α_1 is $\hat{\alpha}_1 = r_1$.

The approximate maximum likelihood estimates of the autoregressive parameters have been derived by Box&Jenkins (1976). This method uses the same equations given by Eqs. (3-68) and (3-69), and differ from the least squares method if the user has information (that is, if the user may predict) about the first p number of residuals, (ε_1, ε_2, ..., ε_p) and uses them in estimation. For example, the maximum likelihood estimate of α_1 in AR (1) process is

$$\hat{\alpha}_1 = \sum_{\ell=0}^{N-1} Z_\ell Z_{\ell+1} \bigg/ \sum_{\ell=0}^{N-1} Z_{\ell+1}^2 \tag{3-71}$$

Note that if $\varepsilon_1 = Z_1 - \hat{\alpha}_1 Z_o$ is not predicted the summations of Eq. (3-71) could not include the initial value of Z_o of the given sample series in which case the approximate maximum likelihood estimate of Eq. (3-71) would not differ from the least squares estimate of Eq. (3-70).

Initial parameter estimations for a MA (q) process may be achieved using the first q sample autocorrelations in Eq. (3-72)

$$r_k = \frac{-\theta_k + \theta_1\theta_{k+1} + \theta_2\theta_{k+2} + \ldots\ldots\ldots\ldots + \theta_{q-k}\theta_k}{1 + \theta_1^2 + \theta_2^2 + \ldots\ldots\ldots + \theta_q^2}, \quad k = 1, 2, \ldots\ldots, q \tag{3-72}$$

And the relationship

$$S_e^2 = S_z^2 \Big/ \left(1 + \sum_{j=1}^{q} \theta_j^2\right) \tag{3-73}$$

where S_z^2 is the sample variance of the time series.

Preliminary estimates of the θ's and σ_ε^2 can be obtained by solving these q+1 numbers of nonlinear equations using an iterative numerical procedure, and then the preliminary estimate of σ_ε^2 (the noise variance) may be obtained from

For example, the initial estimates of the parameters of a MA (2) process require solving simultaneously the three nonlinear equations

$$\begin{aligned} \sigma_\varepsilon^2 &= \sigma_z^2/\left(1+\theta_1^2+\theta_2^2\right) \\ \theta_1 &= \theta_1\theta_2 \quad \rho_1\left(1+\theta_1^2+\theta_2^2\right) \\ \theta_2 &= \quad \rho_2\left(1+\theta_1^2+\theta_2^2\right) \end{aligned} \tag{3-74}$$

Introducing the sample variance $C_o = S_z^2$ of the Z_t series, and the first two sample autocovariances C_1 and C_2, the set of q+1 = 2+1 =3 nonlinear equations to be solved can be written as

$$\begin{aligned} S_e^2 &= S_z^2/(1+\hat{\theta}_1^2+\hat{\theta}_2^2) \\ \hat{\theta}_1 &= \left(C_1/S_e^2+\hat{\theta}_1\hat{\theta}_2\right) \\ \hat{\theta}_2 &= C_2/S_e^2 \end{aligned} \tag{3-75}$$

Initial estimates of σ_ε^2, θ_1, θ_2 can be obtained by setting the parameters θ_1, and θ_2 equal to zero to start the iterative procedure. The values of $\hat{\theta}_1$, $\hat{\theta}_2$, S_e^2 to be used in any subsequent calculation, are the most up to date values available.

3.6.2. Periodic Autoregressive-Moving Average (PARMA) Models

By applying the method of moments the periodic autoregression coefficients are found to be functions of the periodic correlation coefficients. It can be seen that periodic correlation coefficients can be either the sample estimates or, as in the case of periodic mean and periodic standard deviation, the Fourier series can be fitted to the sample estimates (Salas et.al., 1985).

After standardization of the series with periodic means and standard deviations, the periodic correlation coefficients $\hat{r}_{k,\tau}$ must be computed. Through the use of sample autocorrelations of $Z_{p,\tau}$, the estimates of the periodic autoregressive parameters of the model may be obtained.

$$\rho_{k,\tau} = \sum_{j=1}^{p} \alpha_{j,\tau} \rho_{|k-j|\,,\,\tau-\ell_j} \qquad k > 0 \tag{3-76}$$

where $\ell_j = \min(k, j)$ and $\rho_{0,\tau} = 1$. This equation can be used for estimating the parameters $\alpha_{j,\tau}$ of the model as well as determining the correlogram $\rho_k(\tau)$ for a given set of parameters. In general, if it is to determine the correlogram $\rho_k(\tau)$ for a periodic AR (p) model, Eq. (3-76) must be solved recursively. However, this will not be pursued further since it has seldom been used in practice.

Approximate (or initial) estimates of $\alpha_{j,\tau}$ and $\theta_{k,\tau}$ may be obtained from generalizations of the Yule-Walker equations, for example, for ARMA (1,0), ARMA (2,0), and ARMA (1,1) processes,

PARMA (1,0) $\qquad \alpha_{1,\tau} = r_{1,\tau}$

PARMA (2,0) $\qquad \alpha_{1,\tau} = \dfrac{r_{1,\tau} - r_{1,\tau-1} r_{2,\tau}}{1 - r_{1,\tau-1}^2}$

$$\alpha_{2,\tau} = \frac{r_{2,\tau} - r_{1,\tau} r_{1,\tau-1}}{1 - r_{1,\tau-1}^2} \tag{3-77}$$

PARMA (1,1) $\qquad \alpha_{1,\tau} = \dfrac{r_{2,\tau}}{r_{1,\tau}} \qquad \theta_{1,\tau} = \dfrac{-1}{2r_{1,\tau}} \mp \left(\dfrac{1}{4r_{1,\tau}^2} - 1 \right)^{1/2}$

The periodic autocorrelation coefficients $r_{k,\tau}$ may be replaced by their fitted (or smoothed) estimates $\hat{r}_{k,\tau}$, which are obtained by Fourier series approximation.

3.6.3. Autoregressive Integrated Moving Average (ARIMA) Models

Many empirical time series (for example, stock prices) behave as though they had no fixed mean. Even so, they exhibit homogeneity in the sense that, apart from local level, or perhaps local level and trend, one part of the series behaves much like any other part. Models, which describe such homogeneous nonstationary behaviour, can be obtained by supposing some suitable *difference* of the process to be stationary. Consider the properties of the important class of models for which the d th difference is a stationary mixed autoregressive-moving average process will be given in the following. These models are called autoregressive integrated moving average (ARIMA) processes.

If the series does not have a fixed mean but its successive changes or differences are stationary, then it is possible to extend the ARMA models to nonstationary series by working with their differences. It is possible to take the first, second, or in general, the d-th difference, which leads to simple nonperiodic ARIMA (p,d,q) models. It is also possible to take periodic or seasonal differences at lag ω such as the 12th difference of monthly series, which leads to periodic ARIMA $(P,D,Q)_{\omega}$ models (Salas et.al., 1985).

Differencing of the time series may be used to remove its nonstationarity. The first order differencing is defined by

$$u_t = X_t - X_{t-1} \tag{3-78}$$

Taking the first difference of a series may remove the trend in series. Another second consecutive differencing may also be carried out if the series is nonstationary both in level and slope.

$$w_t = u_t - u_{t-1} = X_t - 2X_{t-1} - X_{t-2} \qquad (3\text{-}79)$$

In general, the differencing operation may be done several times but in practice only one or two differencing operations are required.

If the series exhibits periodicity then seasonal differencing may be used.

$$u_t = X_t - X_{t-\omega} \qquad (3\text{-}80)$$

where ω is the period. Typically ω is equal to 365 for daily series.

Differencing alone may not be sufficient to achieve the stationarity, therefore the logarithmic transformation of the data may also be useful. Other transformations may also be used (Salas et.al., 1985).

The behaviour of the differenced series u_t or w_t may be represented by a stationary ARMA (p,q) process.

3.7. TESTING THE GOODNESS OF FIT (OR PERFORMANCE) OF THE SELECTED MODEL

Determination of most parsimonious and adequate model for a time series is a vital matter. Many applied models can represent the process but for the sake of parsimony and adequacy in representing, the proper model should be decided.

A mathematical formulation, which considers the principle of parsimony, is Akaike Information Criterion (AIC) proposed by Akaike in 1974 (Salas et.al.,1985). In order to compare among competing ARMA models, he used

$$AIC(p,q) = N\ln(\hat{\sigma}_{\varepsilon}^{2}) + 2(p+q) \qquad (3\text{-}81)$$

where N is the sample size and $\hat{\sigma}_{\varepsilon}^{2}$ is the maximum likelihood estimate of the residual variance. The model, which gives the minimum AIC is the one to be selected.

Another method to compare the competing AR (p) models is the partial f-test. We may desire to test the null hypothesis that the effect of the deleted terms on the variation (or, in the definition of the $\tilde{Z}_t$ process) of $\tilde{Z}_t$ is not significant at a chosen level of significance α, using the f-test statistic.

After the removal of stochastic components, the residuals ε_τ are to be tested, whether they are independent and normal (white noise).

The Port Manteau Lack of Fit Test is used for testing the independence of ε_τ series. Consider that a time series X_t of size N is represented by an ARIMA (p,d,q) model and assume further that in such model ε_τ is the residual series. In order to check the independency of ε_τ series, this test uses the statistic

$$Q = (N - d)\sum_{k=1}^{L} r_k^2(\varepsilon) \tag{3-82}$$

where r_k (ε) is the correlogram of the residuals ε_t and L is the maximum lag considered. The static Q is approximately chi-square distributed with L-p-q degrees of freedom. The adequacy of the ARIMA model for Z_t may be checked by comparing the statistic Q with the critical chi-square value χ^2 (L-p-q) of a given significance level. If Q < χ^2 (L-p-q), ε_t is an independent series and the model is adequate, otherwise the model is inadequate.

When the ε_t series is obtained from a PARMA model, the modified statistic Q_1 may be used as

$$Q_1 = N\sum_{k=1}^{L}\sum_{\tau=1}^{\omega} r_{k,\tau}^2(\varepsilon) \qquad (3\text{-}83)$$

where ω is the number of time intervals (Salas et.al.,1985)

The independence of the residuals series can also be tested by correlogram analysis together with Anderson's tolerance limits.

Another alternative way of testing the independence of residuals series is to test whether the spectral density (or normalized integrated spectrum) of the residuals series in between tolerance limits of an ideal white noise given by Eq. (3-36) and Eq.(3-38).

CHAPTER FOUR
HISTORICAL DATA AVAILABLE

4.1. HYDROLOGIC DATA AVAILABLE

Lamas River is situated in Southern Turkey and it spills to Mediterranean Sea very close to Erdemli. The basin has karstic formations and the contribution of karstic springs to the flows is very significant.

Lamas River has three main tributaries; Susama, Aksıfat and Evdilek Creeks (Fig. 4-1). Two stream gauging stations (SGS) have been operated on the river; namely Sarıaydın (17-12) and Kızılgeçit (1717). Sarıaydın SGS was closed after September 1971, therefore it covers observations only from 1961 to 1971. Kızılgeçit SGS has been started to operate in October 1967 and it is being operated yet.

Beside Kızılgeçit and Sarıaydın SGS, streamflows recorded at four SGSs at the adjacent basins are used in testing homogeneity of the observed Kızılgeçit flows. Various characteristics and their operation periods of the stations are given in Table 4-1.

The annual precipitations recorded at Güzeloluk raingauges are also used in this study in order to identify nonhomogeneities in the form of a trend in irrigation seasons.

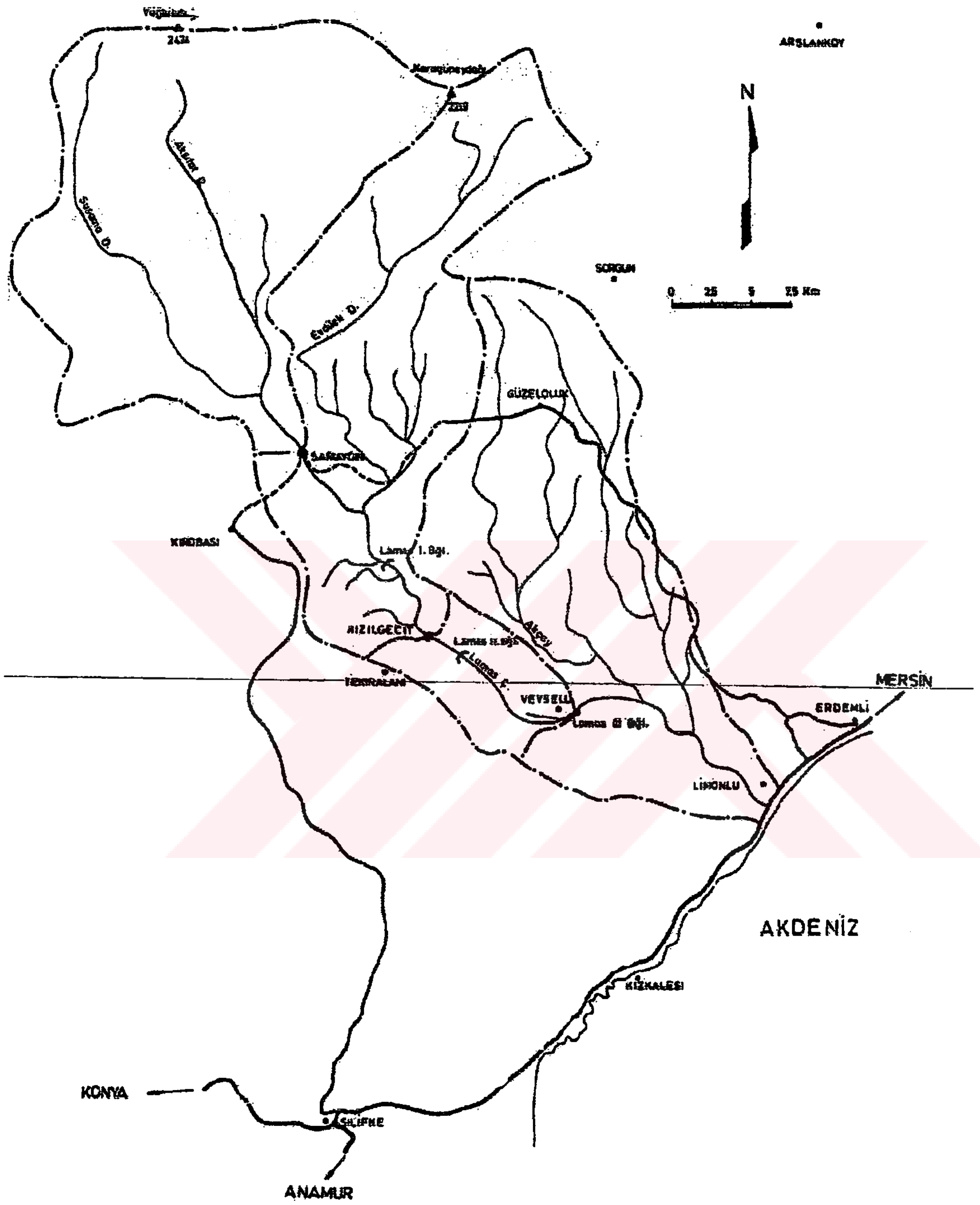

Fig. 4-1: Lamas River Basin

Table 4-1: SGSs on Lamas and adjacent basins

Station No	Station Name	River	Operating Institution	Drainage Area (Km^2)	Height (m)	Monitoring period	Annual Meanflow m^3/sn)
17-12	Sarıaydın	Lamas	DSİ	504	1297	1961-71	5.26
1717	Kızılgeçit	Lamas	EİE	995	970	1967-94	6.01
1612	Denircik	Ibrala S.	EİE	268	1052	1957-92	2.45
1708	Muhat Köprü	Tarsus	EİE	1416	50	1954-92	38.74
1712	Bucakkışla	Göksu	EİE	2689	397	1962-92	29.81
1704/ 1720	Selamlı/ Hamam	Göksu	EİE	4304	127	1947-92	45.22

4.2. EXTENDING KIZILGEÇİT FLOWS

As mentioned above, Sarıaydın SGS was closed in 1971. In order to extend Kızılgeçit flows for the period 1962-1966 Sarıaydın records has been used (DEU, 1999). For this purpose correlation and regression analyses was carried out. Results of the linear, logarithmic, and exponential regression analyses and correlation coefficients taken from DEU's (1999) study presented in Table 4-2.

The simple linear regression of Kızılgeçit on Sarıaydın given by Eq. 4-1 was decided to use and the equation for the extension of daily flows was (DEU, 1999),

$$Q_{KG} = 1.65 + 1.15\ Q_{SA} \qquad (4\text{-}1)$$

Since Sarıaydın SGS was not operated in May 1961, Kızılgeçit flows for that year were not extended for the sake of homogeneity. That extension enabled a complete set of daily flows from 1962 to 1994 at Kızılgeçit SGS is then available, which is mainly examined in this study.

Table 4-2: Regressions between Kızılgeçit and Sarıaydın daily flows

Regression Model	N	Correlation Coeff R	Regression Parameters		
			A	B	C
$Q_{KG}=A+BQ_{SA}$	1826	0.966	1.65	1.15	---
$Q_{KG}=AQ_{SA}^{B}$	1826	0.956	2.13	0.79	---
$Q_{KG}=A+BQ_{SA}+CQ_{SA}^{2}$	1826	0.966	2.31	0.97	0.007

Since Sarıaydın SGS was not operated in May 1961, Kızılgeçit flows for that year were not extended for the sake of the homogeneity. That extension enabled a complete set of daily flows from 1962 to 1994 at Kızılgeçit SGS is then available, which is mainly examined in this study.

CHAPTER FIVE

ALTERNATIVE MODELS OF KIZILGEÇİT DAILY FLOWS

5.1. WATER RESOURCES STUDIES IN LAMAS RIVER BASIN

Lamas River flows has been used for years for the irrigation and urban water supply purposes. During the last two decades an increase in water consumption for irrigation and urban water supply has evidently been observed due to increase in population and agricultural land use. Furthermore, beginning from 1980's the State Hydraulic Works (DSI) and its contractors, such as TGT, have started planning and feasibility studies to exploit the hydroelectric power potential of Lamas River by a cascade of four diversion type power plants. In various stages of Lamas Project the Department of Civil Engineering of Dokuz Eylül University has carried out detailed hydrologic studies on Kızılgeçit flows (DEU, 1986,1996).

The latest revision of the Lamas Basin hydrology has been realized by DEU (1999) in order to clarify that the exploitable waterpower potential of Lamas River is somewhat decreased because of the excess rural and agricultural water uses in the basin. In the scope of the latest hydrologic revision project various parametric and nonparametric tests, and comparisons of Lamas flows with precipitations and flows recorded at the adjacent similar basins have been performed. However, the actual situation has never been clarified since there were no systematic records on water use time series in the basin and a severe drought covering Turkey entirely during the last decade was agreed.

Modeling of Kızılgeçit daily river flows is the major objective of this study, and it is hoped that design and feasibility studies and multiple purpose water use problems in the basin, as well as the real time operation of the proposed schemes, can be treated more efficiently by the use of synthetic daily flow sequences and forecasts.

5.2. STATISTICAL PROPERTIES OF KIZILGEÇİT DAILY FLOWS

Kızılgeçit daily flows extended for the period 1962-1994 are put in a matrix of N=33 columns $\times$ ω = 365 days by excluding the observed February 29 flows in the years of 366 days. Despite the fact that daily flows upstream to Kızılgeçit SGS may involve transient components in the form of trends and small jumps, seasonal variation of certain sample statistics of daily flows are treated as it were homogenous and stationary.

Basic sample statistics of Kızılgeçit daily flows, such as the mean $(\overline{X}_\tau)$, the standard deviation (S_τ), coefficient of variation $(C_{V\tau})$, and coefficient of skewness $(C_{S\tau})$, are calculated and given in Table 5-1. Annual hydrographs of mean daily flows and standard deviations are shown in Fig.5-1 and Fig. 5-2, while coefficient of variation in Fig. 5-3, and coefficient of skewness in Fig. 5-4.

Lag-one $(r_{1\tau})$ and lag-two $(r_{2\tau})$ seasonal autocorrelations for each day have also given in Table 5-1, and their seasonal variation are shown in Fig.5-5 and Fig. 5-6.

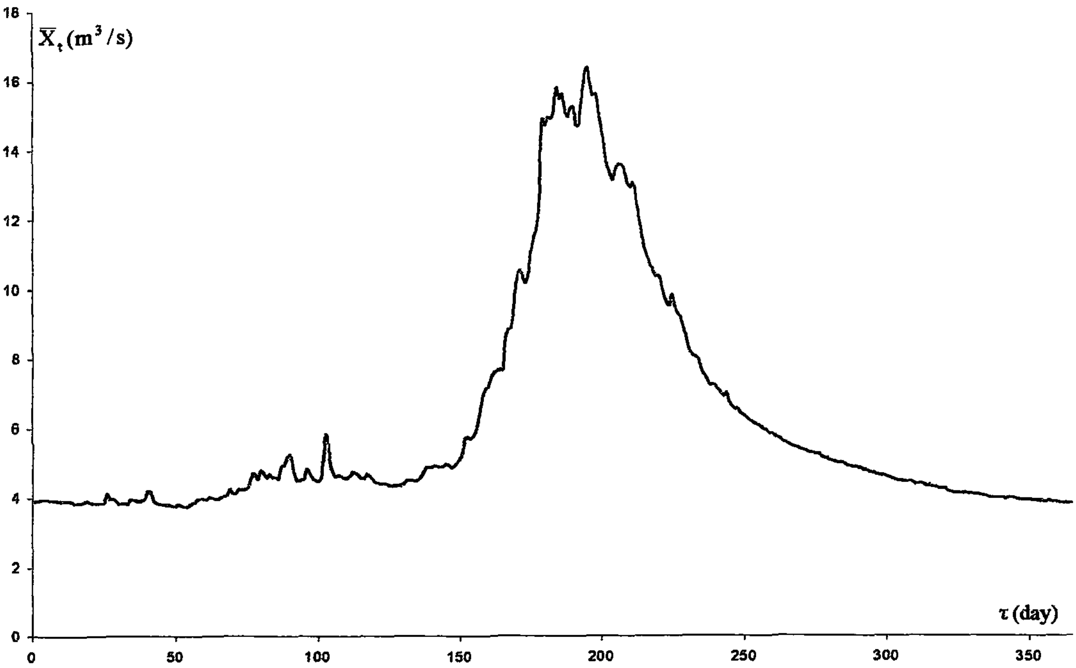

Fig. 5-1: Observed daily mean flows at Kızılgeçit

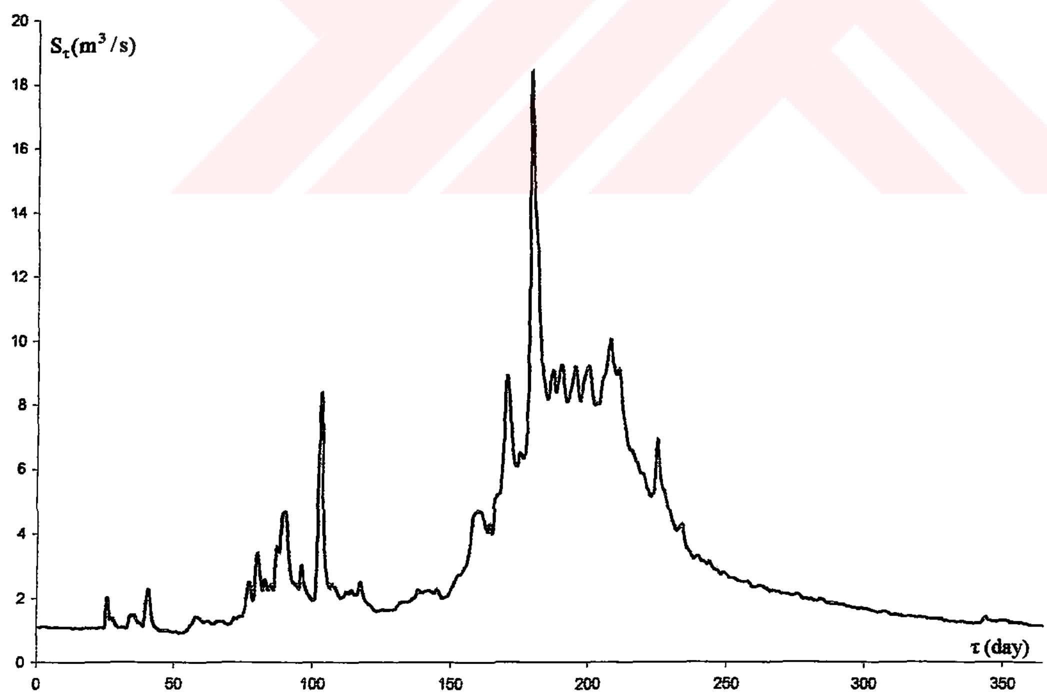

Fig. 5-2: Standard deviations of Kızılgeçit daily flows

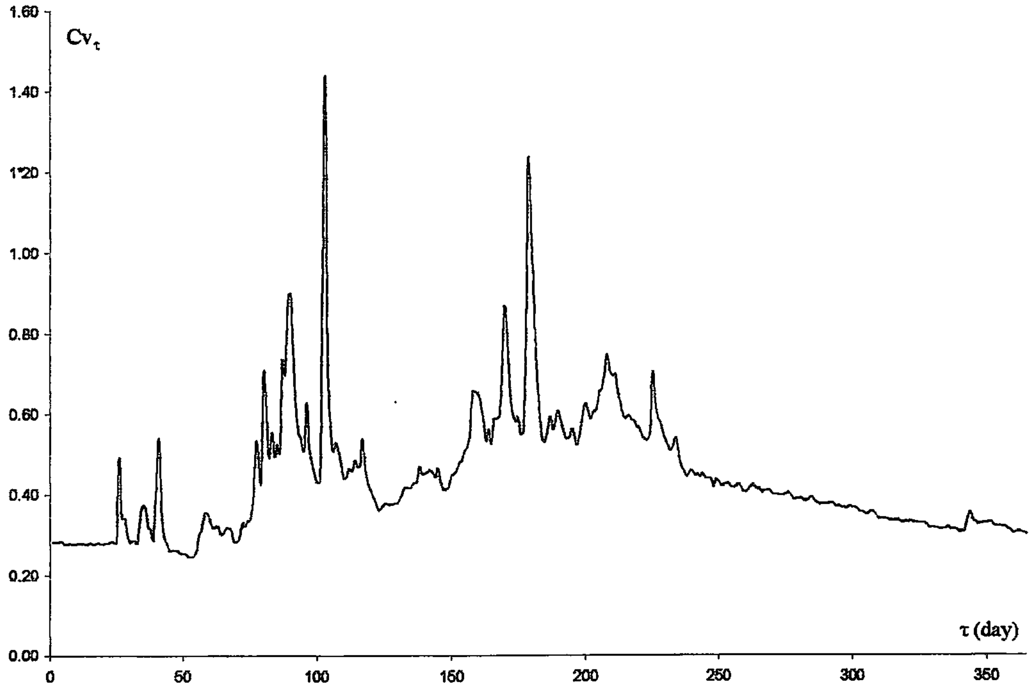

Fig. 5-3: Coefficient of variation of Kızılgeçit daily flows

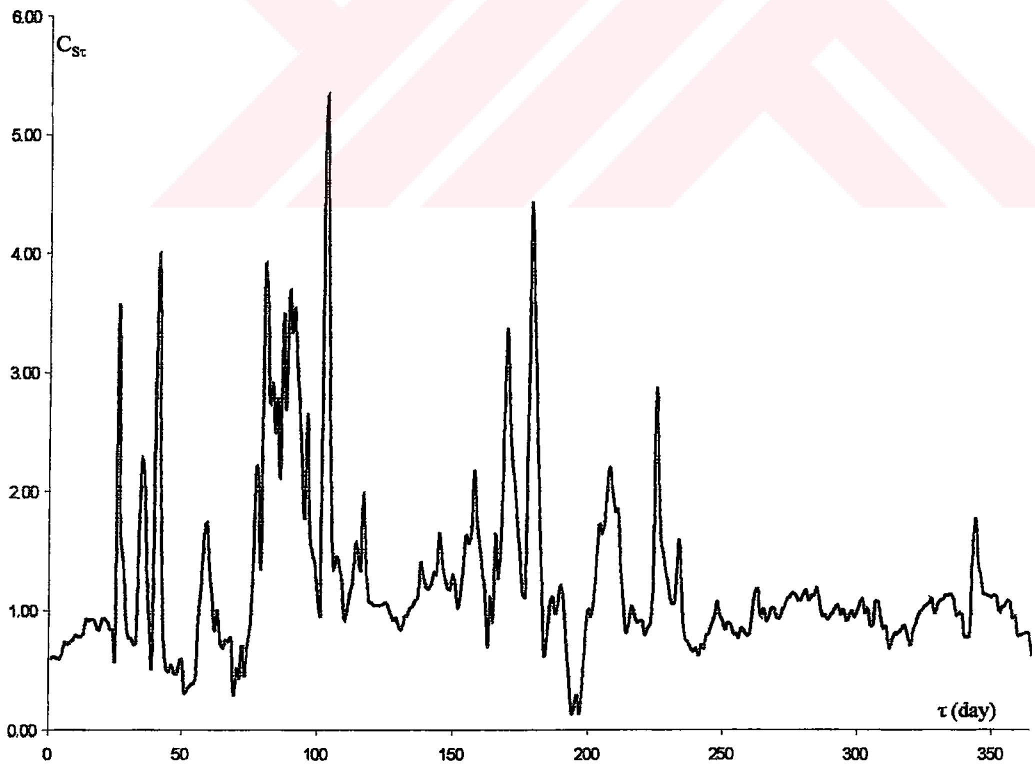

Fig. 5-4: Coefficient of skewnesses of Kızılgeçit daily flows

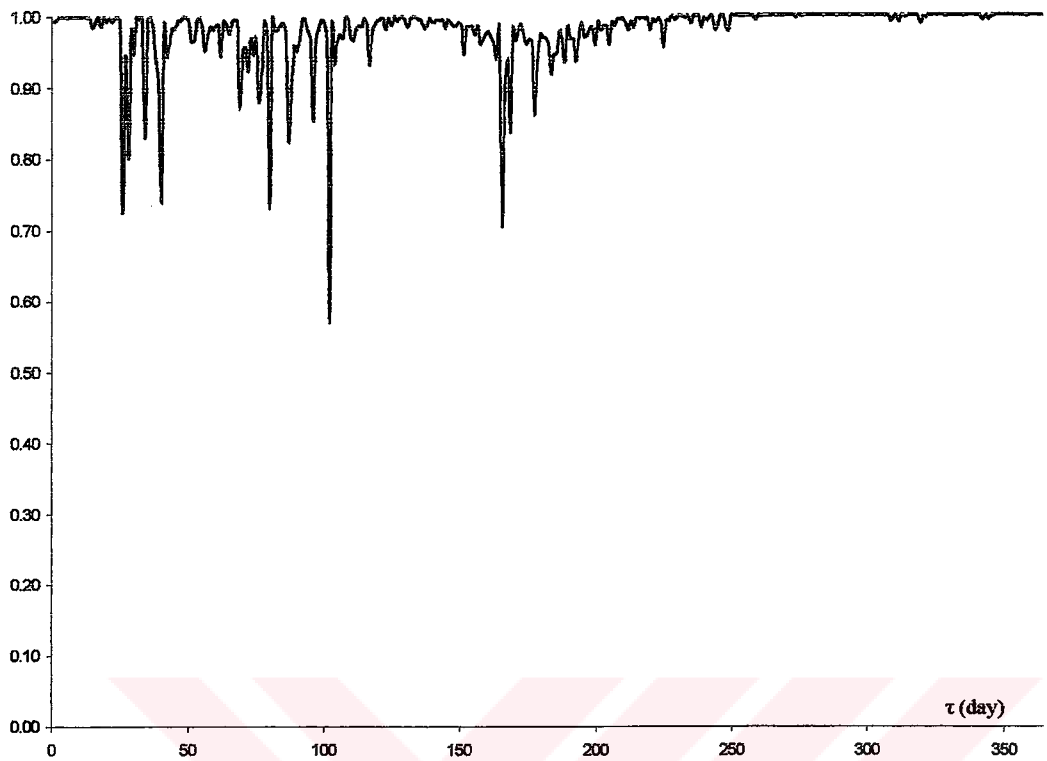

Fig. 5-5: Lag-one autocorrelation coefficients $(r_{1\tau})$ of Kızılgeçit daily flows

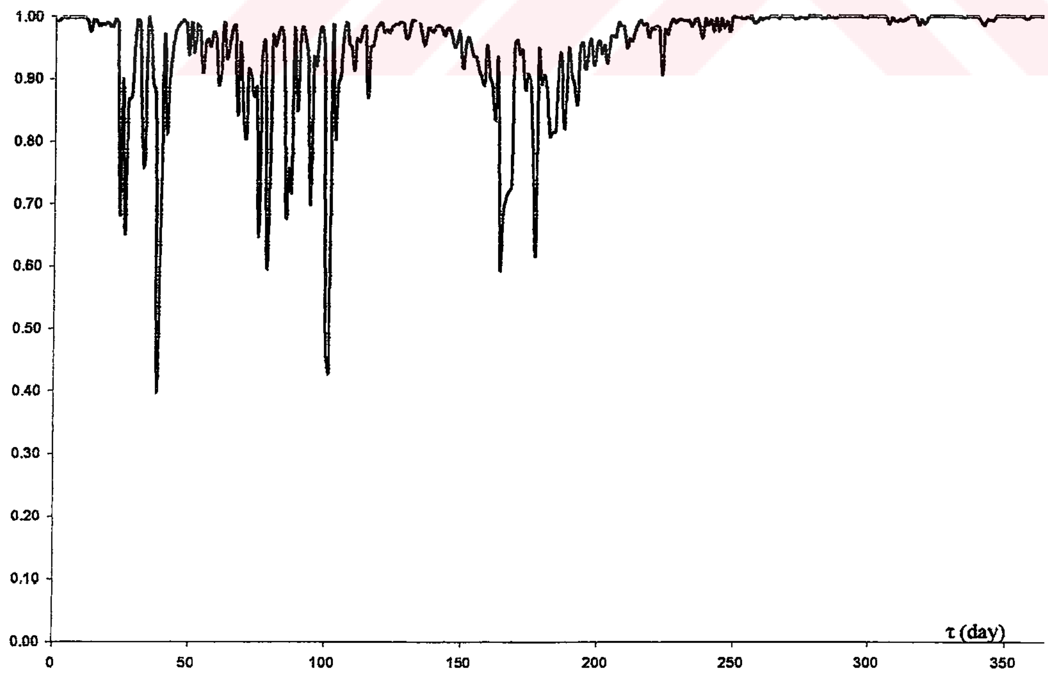

Fig. 5-6: Lag-two autocorrelation coefficients $(r_{2\tau})$ of Kızılgeçit daily flows

Table 5.1: Basic sample statististics of Kızılgeçit daily flows

τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$	τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$	τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$
1	3.92	1.11	0.28	0.60	0.994	0.994	**28**	3.98	1.35	0.34	1.37	0.801	0.870	**55**	3.80	0.99	0.26	0.43	0.985	0.953
2	3.92	1.11	0.28	0.61	0.996	0.996	**29**	3.90	1.19	0.31	0.92	0.980	0.939	**56**	3.85	1.15	0.30	0.94	0.952	0.965
3	3.94	1.11	0.28	0.60	0.999	0.998	**30**	3.83	1.09	0.28	0.77	0.947	0.995	**57**	3.88	1.22	0.31	1.19	0.969	0.952
4	3.94	1.12	0.28	0.60	0.998	0.997	**31**	3.83	1.09	0.28	0.77	0.998	0.993	**58**	3.95	1.40	0.35	1.61	0.986	0.976
5	3.95	1.11	0.28	0.65	0.999	0.998	**32**	3.84	1.10	0.29	0.71	0.997	0.822	**59**	3.96	1.40	0.35	1.73	0.981	0.965
6	3.93	1.09	0.28	0.73	0.998	0.999	**33**	3.82	1.07	0.28	0.73	0.998	0.765	**60**	3.96	1.33	0.34	1.38	0.986	0.890
7	3.93	1.09	0.28	0.71	1.000	0.999	**34**	3.95	1.39	0.35	1.77	0.829	0.996	**61**	3.95	1.26	0.32	1.10	0.989	0.910
8	3.92	1.09	0.28	0.73	0.999	0.998	**35**	3.94	1.48	0.37	2.26	0.994	0.977	**62**	4.02	1.28	0.32	0.83	0.943	0.991
9	3.92	1.09	0.28	0.75	0.999	0.999	**36**	3.93	1.44	0.37	2.09	0.999	0.894	**63**	4.00	1.29	0.32	1.00	0.994	0.933
10	3.90	1.09	0.28	0.79	0.999	0.999	**37**	3.89	1.25	0.32	1.26	0.984	0.871	**64**	3.97	1.20	0.30	0.72	0.987	0.956
11	3.90	1.09	0.28	0.78	1.000	0.998	**38**	3.92	1.22	0.31	0.85	0.939	0.404	**65**	3.98	1.21	0.30	0.68	0.976	0.980
12	3.90	1.09	0.28	0.78	0.999	0.993	**39**	3.95	1.14	0.29	0.54	0.909	0.634	**66**	4.02	1.28	0.32	0.75	0.992	0.986
13	3.90	1.09	0.28	0.80	0.999	0.976	**40**	4.18	1.89	0.45	3.08	0.740	0.969	**67**	4.05	1.29	0.32	0.73	0.995	0.842
14	3.88	1.07	0.28	0.92	0.997	0.995	**41**	4.20	2.26	0.54	3.98	0.988	0.812	**68**	4.07	1.26	0.31	0.77	0.994	0.958
15	3.84	1.08	0.28	0.91	0.984	0.995	**42**	3.95	1.42	0.36	1.95	0.943	0.900	**69**	4.23	1.20	0.28	0.30	0.874	0.853
16	3.85	1.07	0.28	0.92	0.994	0.985	**43**	3.87	1.15	0.30	0.81	0.959	0.941	**70**	4.13	1.17	0.28	0.51	0.951	0.805
17	3.85	1.07	0.28	0.92	0.999	0.989	**44**	3.83	1.07	0.28	0.53	0.983	0.972	**71**	4.12	1.22	0.30	0.43	0.957	0.915
18	3.88	1.09	0.28	0.86	0.986	0.987	**45**	3.82	0.99	0.26	0.49	0.983	0.985	**72**	4.22	1.38	0.33	0.70	0.922	0.903
19	3.89	1.08	0.28	0.84	0.997	0.992	**46**	3.80	0.99	0.26	0.54	0.993	0.991	**73**	4.23	1.36	0.32	0.45	0.969	0.871
20	3.86	1.07	0.28	0.92	0.993	0.986	**47**	3.79	0.99	0.26	0.47	0.994	0.995	**74**	4.22	1.41	0.33	0.70	0.946	0.886
21	3.84	1.07	0.28	0.93	0.998	0.983	**48**	3.78	0.98	0.26	0.47	0.998	0.989	**75**	4.25	1.43	0.34	0.86	0.968	0.646
22	3.84	1.07	0.28	0.90	0.992	0.997	**49**	3.77	0.96	0.25	0.55	0.997	0.938	**76**	4.37	1.67	0.38	1.25	0.879	0.928
23	3.84	1.09	0.28	0.84	0.997	0.991	**50**	3.77	0.95	0.25	0.58	0.995	0.992	**77**	4.69	2.48	0.53	2.19	0.923	0.959
24	3.84	1.08	0.28	0.83	0.998	0.681	**51**	3.80	0.96	0.25	0.31	0.964	0.941	**78**	4.65	2.27	0.49	2.10	0.993	0.602
25	3.86	1.08	0.28	0.60	0.995	0.901	**52**	3.78	0.93	0.25	0.34	0.966	0.987	**79**	4.53	1.95	0.43	1.41	0.971	0.748
26	4.11	2.03	0.49	3.57	0.724	0.651	**53**	3.76	0.92	0.25	0.37	0.994	0.978	**80**	4.79	3.36	0.70	3.89	0.730	0.969
27	3.94	1.36	0.34	1.68	0.946	0.864	**54**	3.75	0.93	0.25	0.39	0.998	0.909	**81**	4.67	2.86	0.61	3.65	0.997	0.952

Table 5.1 (continued)

τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$	τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$	τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$
82	4.58	2.26	0.49	2.75	0.979	0.971	**109**	4.57	2.18	0.48	1.25	0.996	0.949	**136**	4.57	1.95	0.43	1.08	0.994	0.955
83	4.69	2.59	0.55	2.91	0.982	0.982	**110**	4.56	2.01	0.44	0.94	0.970	0.914	**137**	4.72	2.04	0.43	1.12	0.983	0.981
84	4.59	2.26	0.49	2.49	0.988	0.948	**111**	4.64	2.06	0.44	0.99	0.965	0.963	**138**	4.88	2.29	0.47	1.40	0.984	0.980
85	4.60	2.41	0.52	2.76	0.990	0.683	**112**	4.76	2.21	0.47	1.13	0.981	0.959	**139**	4.88	2.20	0.45	1.30	0.996	0.975
86	4.55	2.29	0.50	2.13	0.973	0.756	**113**	4.70	2.16	0.46	1.27	0.986	0.980	**140**	4.88	2.20	0.45	1.20	0.992	0.983
87	4.90	3.59	0.73	3.49	0.825	0.718	**114**	4.66	2.26	0.48	1.56	0.984	0.984	**141**	4.91	2.23	0.45	1.18	0.992	0.985
88	4.94	3.44	0.70	2.69	0.883	0.979	**115**	4.57	2.14	0.47	1.47	0.997	0.869	**142**	4.90	2.25	0.46	1.22	0.994	0.982
89	5.14	4.53	0.88	3.67	0.957	0.848	**116**	4.55	2.14	0.47	1.36	0.988	0.950	**143**	4.89	2.22	0.45	1.32	0.994	0.969
90	5.21	4.68	0.90	3.34	0.951	0.957	**117**	4.67	2.52	0.54	1.98	0.931	0.952	**144**	4.90	2.17	0.44	1.31	0.994	0.980
91	4.88	3.68	0.75	3.53	0.966	0.983	**118**	4.63	2.18	0.47	1.40	0.977	0.977	**145**	4.96	2.30	0.46	1.65	0.983	0.981
92	4.59	2.83	0.62	3.10	0.995	0.962	**119**	4.54	1.93	0.43	1.08	0.989	0.987	**146**	4.93	2.14	0.43	1.44	0.994	0.966
93	4.50	2.48	0.55	2.74	0.996	0.935	**120**	4.44	1.82	0.41	1.07	0.995	0.990	**147**	4.86	2.00	0.41	1.30	0.991	0.951
94	4.52	2.44	0.54	2.27	0.980	0.699	**121**	4.43	1.75	0.39	1.05	0.996	0.974	**148**	4.91	2.03	0.41	1.20	0.986	0.961
95	4.56	2.32	0.51	1.77	0.966	0.933	**122**	4.39	1.67	0.38	1.04	0.997	0.979	**149**	5.01	2.09	0.42	1.18	0.986	0.972
96	4.82	3.03	0.63	2.64	0.852	0.921	**123**	4.41	1.60	0.36	1.04	0.981	0.974	**150**	5.14	2.28	0.44	1.30	0.991	0.916
97	4.71	2.44	0.52	1.66	0.965	0.967	**124**	4.38	1.60	0.37	1.05	0.996	0.984	**151**	5.36	2.42	0.45	1.18	0.985	0.951
98	4.55	2.18	0.48	1.49	0.981	0.983	**125**	4.36	1.64	0.38	1.07	0.987	0.987	**152**	5.66	2.61	0.46	1.03	0.946	0.966
99	4.50	2.05	0.45	1.40	0.994	0.955	**126**	4.34	1.64	0.38	1.04	0.998	0.987	**153**	5.75	2.75	0.48	1.16	0.985	0.954
100	4.48	1.93	0.43	1.16	0.993	0.470	**127**	4.34	1.63	0.37	0.96	0.994	0.991	**154**	5.70	2.76	0.48	1.37	0.984	0.936
101	4.58	1.98	0.43	0.97	0.965	0.433	**128**	4.36	1.64	0.38	0.93	0.997	0.989	**155**	5.80	2.93	0.51	1.63	0.984	0.935
102	5.31	5.07	0.95	4.58	0.570	0.976	**129**	4.36	1.65	0.38	0.94	0.997	0.964	**156**	6.00	3.11	0.52	1.57	0.974	0.912
103	5.83	8.37	1.44	5.31	0.987	0.804	**130**	4.40	1.67	0.38	0.87	0.995	0.969	**157**	6.37	3.57	0.56	1.68	0.985	0.903
104	4.98	3.67	0.74	3.41	0.934	0.886	**131**	4.49	1.77	0.39	0.84	0.984	0.994	**158**	6.87	4.49	0.65	2.17	0.960	0.891
105	4.75	2.73	0.58	1.99	0.962	0.903	**132**	4.51	1.85	0.41	0.95	0.996	0.993	**159**	7.14	4.67	0.65	1.76	0.966	0.953
106	4.61	2.34	0.51	1.36	0.974	0.960	**133**	4.50	1.88	0.42	0.96	0.998	0.990	**160**	7.19	4.68	0.65	1.56	0.973	0.904
107	4.64	2.45	0.53	1.45	0.970	0.991	**134**	4.49	1.87	0.42	1.01	0.997	0.989	**161**	7.44	4.68	0.63	1.36	0.977	0.889
108	4.62	2.33	0.51	1.40	0.998	0.958	**135**	4.51	1.88	0.42	1.03	0.995	0.966	**162**	7.60	4.40	0.58	1.10	0.968	0.834

Table 5.1 (continued)

τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$	τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$	τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$
163	7.65	4.07	0.53	0.69	0.959	0.929	**190**	15.24	9.24	0.61	1.20	0.984	0.907	**217**	10.73	6.28	0.59	0.97	0.996	0.989
164	7.70	4.31	0.56	1.10	0.941	0.601	**191**	14.73	8.54	0.58	1.10	0.967	0.891	**218**	10.58	6.13	0.58	0.90	0.995	0.965
165	7.68	4.03	0.52	0.92	0.983	0.683	**192**	14.71	8.09	0.55	0.68	0.966	0.859	**219**	10.38	5.87	0.57	0.91	0.996	0.981
166	8.50	4.99	0.59	1.63	0.705	0.706	**193**	15.40	8.26	0.54	0.39	0.935	0.948	**220**	10.40	5.85	0.56	0.91	0.979	0.979
167	8.83	5.18	0.59	1.27	0.880	0.719	**194**	16.22	8.77	0.54	0.14	0.967	0.957	**221**	10.20	5.54	0.54	0.79	0.994	0.984
168	8.90	5.30	0.60	1.64	0.937	0.728	**195**	16.36	9.17	0.56	0.20	0.989	0.915	**222**	9.88	5.30	0.54	0.84	0.991	0.981
169	9.49	6.71	0.71	2.63	0.836	0.947	**196**	15.87	8.59	0.54	0.29	0.970	0.939	**223**	9.63	5.14	0.53	0.90	0.996	0.905
170	10.25	8.86	0.86	3.36	0.981	0.962	**197**	15.58	8.12	0.52	0.14	0.971	0.964	**224**	9.52	5.33	0.56	1.23	0.987	0.978
171	10.54	8.44	0.80	2.76	0.964	0.939	**198**	15.61	8.73	0.56	0.46	0.982	0.921	**225**	9.83	6.91	0.70	2.84	0.955	0.971
172	10.36	6.89	0.67	2.27	0.977	0.945	**199**	15.15	9.07	0.60	0.80	0.981	0.947	**226**	9.50	5.97	0.63	2.15	0.992	0.986
173	10.19	6.17	0.61	2.09	0.988	0.883	**200**	14.70	9.18	0.62	1.00	0.958	0.961	**227**	9.31	5.47	0.59	1.61	0.992	0.995
174	10.45	6.06	0.58	1.71	0.969	0.907	**201**	14.27	8.64	0.61	0.94	0.991	0.940	**228**	9.17	5.27	0.57	1.46	0.998	0.989
175	11.03	6.50	0.59	1.43	0.960	0.890	**202**	13.64	8.00	0.59	1.06	0.978	0.953	**229**	8.81	4.82	0.55	1.29	0.994	0.995
176	11.50	6.32	0.55	1.13	0.967	0.745	**203**	13.33	8.03	0.60	1.34	0.984	0.924	**230**	8.55	4.54	0.53	1.15	0.997	0.995
177	11.77	6.51	0.55	1.11	0.965	0.621	**204**	13.13	8.02	0.61	1.71	0.984	0.966	**231**	8.26	4.26	0.52	1.06	0.999	0.993
178	12.59	9.07	0.72	2.50	0.863	0.944	**205**	13.41	8.75	0.65	1.64	0.959	0.969	**232**	8.10	4.11	0.51	1.06	0.998	0.992
179	14.87	18.22	1.23	4.39	0.929	0.892	**206**	13.57	8.96	0.66	1.73	0.990	0.967	**233**	8.04	4.20	0.52	1.32	0.997	0.993
180	14.71	15.05	1.02	3.46	0.974	0.906	**207**	13.57	9.51	0.70	2.01	0.985	0.990	**234**	7.97	4.29	0.54	1.58	0.998	0.983
181	14.93	13.12	0.88	2.70	0.969	0.874	**208**	13.45	10.03	0.75	2.19	0.994	0.985	**235**	7.71	3.76	0.49	0.94	0.989	0.994
182	14.90	10.67	0.72	1.94	0.968	0.808	**209**	13.08	9.26	0.71	2.00	0.995	0.984	**236**	7.54	3.52	0.47	0.77	0.998	0.996
183	15.06	9.21	0.61	1.27	0.959	0.814	**210**	12.94	8.94	0.69	1.83	0.995	0.949	**237**	7.42	3.38	0.46	0.74	0.997	0.979
184	15.77	8.55	0.54	0.62	0.918	0.815	**211**	13.03	9.07	0.70	1.84	0.988	0.964	**238**	7.25	3.21	0.44	0.68	0.998	0.966
185	15.48	8.17	0.53	0.76	0.945	0.892	**212**	12.64	8.20	0.65	1.34	0.980	0.960	**239**	7.25	3.29	0.45	0.66	0.983	0.996
186	15.60	8.79	0.56	1.05	0.948	0.939	**213**	12.12	7.56	0.62	1.07	0.991	0.976	**240**	7.24	3.32	0.46	0.68	0.996	0.985
187	15.24	9.02	0.59	1.11	0.977	0.823	**214**	11.73	6.96	0.59	0.82	0.984	0.986	**241**	7.12	3.17	0.45	0.62	0.993	0.994
188	14.98	8.38	0.56	0.98	0.964	0.870	**215**	11.28	6.63	0.59	0.88	0.996	0.993	**242**	6.99	3.13	0.45	0.70	0.998	0.975
189	15.17	8.87	0.58	1.07	0.934	0.947	**216**	10.98	6.53	0.59	1.03	0.995	0.985	**243**	6.92	3.06	0.44	0.68	0.998	0.997

Table 5.1 (continued)

τ	**$X_τ$**	**$S_τ$**	**$Cv_τ$**	**$Cs_τ$**	**$R_{1τ}$**	**$R_{2τ}$**	**τ**	**$X_τ$**	**$S_τ$**	**$Cv_τ$**	**$Cs_τ$**	**$R_{1τ}$**	**$R_{2τ}$**	**τ**	**$X_τ$**	**$S_τ$**	**$Cv_τ$**	**$Cs_τ$**	**$R_{1τ}$**	**$R_{2τ}$**
244	7.00	3.15	0.45	0.78	0.980	0.975	**271**	5.34	2.13	0.40	0.94	1.000	0.998	**298**	4.61	1.68	0.36	0.99	0.999	0.998
245	6.75	2.97	0.44	0.80	0.984	0.996	**272**	5.31	2.11	0.40	1.00	0.999	0.995	**299**	4.62	1.71	0.37	0.94	0.998	0.998
246	6.61	2.89	0.44	0.88	0.998	0.981	**273**	5.28	2.10	0.40	1.03	0.999	0.996	**300**	4.59	1.68	0.37	0.99	0.999	0.998
247	6.53	2.86	0.44	0.96	0.999	0.992	**274**	5.26	2.09	0.40	1.10	0.996	0.997	**301**	4.57	1.67	0.37	1.04	0.999	0.999
248	6.54	2.73	0.42	1.07	0.983	0.974	**275**	5.25	2.10	0.40	1.11	1.000	0.998	**302**	4.54	1.64	0.36	1.10	0.999	0.998
249	6.43	2.80	0.44	0.96	0.977	0.998	**276**	5.24	2.12	0.40	1.15	0.998	0.996	**303**	4.50	1.60	0.36	0.98	0.999	0.999
250	6.36	2.73	0.43	0.91	0.999	0.998	**277**	5.17	2.04	0.40	1.12	0.999	0.998	**304**	4.47	1.59	0.36	1.02	0.999	0.999
251	6.30	2.64	0.42	0.84	0.999	0.997	**278**	5.12	1.97	0.39	1.08	0.999	0.999	**305**	4.45	1.56	0.35	0.88	0.999	0.998
252	6.22	2.62	0.42	0.90	0.999	0.998	**279**	5.11	1.98	0.39	1.09	1.000	0.998	**306**	4.45	1.56	0.35	0.88	1.000	0.997
253	6.17	2.63	0.43	0.88	0.998	0.995	**280**	5.06	1.96	0.39	1.14	0.999	0.999	**307**	4.44	1.58	0.36	1.07	0.998	0.987
254	6.11	2.57	0.42	0.81	0.998	0.998	**281**	5.04	1.96	0.39	1.17	0.999	0.999	**308**	4.44	1.58	0.36	1.06	0.999	0.997
255	6.08	2.53	0.42	0.80	0.998	0.997	**282**	5.02	1.92	0.38	1.09	1.000	0.997	**309**	4.43	1.53	0.35	0.91	0.991	0.992
256	6.03	2.51	0.42	0.77	0.998	0.999	**283**	5.00	1.92	0.38	1.12	0.999	0.996	**310**	4.37	1.48	0.34	0.85	0.995	0.991
257	5.97	2.51	0.42	0.85	0.999	0.990	**284**	5.01	1.95	0.39	1.13	0.998	0.999	**311**	4.37	1.49	0.34	0.86	1.000	0.995
258	5.94	2.50	0.42	0.83	0.999	0.990	**285**	4.97	1.95	0.39	1.18	0.999	0.997	**312**	4.38	1.48	0.34	0.68	0.990	0.992
259	5.85	2.38	0.41	0.79	0.992	0.997	**286**	4.92	1.88	0.38	1.08	0.999	0.997	**313**	4.35	1.47	0.34	0.73	0.998	0.995
260	5.83	2.35	0.40	0.81	0.999	0.995	**287**	4.89	1.84	0.38	0.95	0.999	0.997	**314**	4.32	1.45	0.34	0.81	0.997	0.997
261	5.77	2.37	0.41	1.00	0.998	0.997	**288**	4.88	1.82	0.37	0.96	0.999	0.998	**315**	4.33	1.44	0.33	0.80	0.998	0.999
262	5.71	2.39	0.42	1.15	0.999	0.997	**289**	4.88	1.82	0.37	0.93	0.999	0.998	**316**	4.30	1.44	0.33	0.82	0.999	0.999
263	5.67	2.39	0.42	1.18	0.998	0.998	**290**	4.85	1.82	0.37	0.96	0.999	0.999	**317**	4.29	1.43	0.33	0.85	1.000	0.998
264	5.59	2.31	0.41	0.96	0.998	0.999	**291**	4.83	1.81	0.37	0.98	0.999	0.999	**318**	4.27	1.42	0.33	0.87	0.999	0.986
265	5.56	2.29	0.41	1.01	0.999	0.998	**292**	4.78	1.80	0.38	1.03	0.999	0.998	**319**	4.24	1.40	0.33	0.80	0.998	0.994
266	5.51	2.22	0.40	0.91	0.999	0.997	**293**	4.77	1.79	0.38	1.04	0.999	0.999	**320**	4.26	1.42	0.33	0.71	0.987	0.987
267	5.47	2.23	0.41	0.95	0.998	0.998	**294**	4.73	1.75	0.37	0.97	0.999	0.998	**321**	4.21	1.39	0.33	0.82	0.997	0.995
268	5.43	2.21	0.41	1.01	0.999	0.998	**295**	4.71	1.74	0.37	1.01	0.999	0.999	**322**	4.16	1.39	0.33	0.89	0.996	0.999
269	5.41	2.22	0.41	1.02	0.999	0.998	**296**	4.67	1.71	0.37	0.91	0.999	0.998	**323**	4.15	1.37	0.33	0.96	0.999	0.999
270	5.36	2.14	0.40	0.94	0.999	0.999	**297**	4.65	1.70	0.37	0.95	0.999	0.997	**324**	4.14	1.36	0.33	0.99	1.000	0.999

Table 5.1 (continued)

τ	X_τ	S_τ	Cv_τ	Cs_τ	$R_{1\tau}$	$R_{2\tau}$
325	4.14	1.36	0.33	1.02	1.000	0.999
326	4.13	1.35	0.33	1.05	0.999	0.999
327	4.12	1.35	0.33	1.07	1.000	0.998
328	4.13	1.34	0.32	1.10	0.999	0.999
329	4.11	1.30	0.32	0.98	0.999	0.998
330	4.08	1.30	0.32	1.04	0.998	0.999
331	4.07	1.29	0.32	1.08	0.999	0.998
332	4.07	1.28	0.32	1.10	0.999	0.998
333	4.06	1.27	0.31	1.13	0.999	0.998
334	4.04	1.27	0.31	1.13	0.999	0.998
335	4.04	1.27	0.31	1.14	0.999	0.998
336	4.01	1.28	0.32	1.10	0.998	0.999
337	3.99	1.25	0.31	0.96	0.999	0.999
338	3.99	1.25	0.31	0.98	1.000	0.998
339	3.99	1.25	0.31	0.96	1.000	0.998
340	3.99	1.22	0.31	0.78	0.999	0.997
341	3.99	1.22	0.31	0.78	0.999	0.990
342	3.96	1.22	0.31	0.78	0.998	0.985
343	3.98	1.33	0.33	1.44	0.993	0.994
344	3.98	1.41	0.35	1.77	0.998	0.994
345	3.97	1.34	0.34	1.41	0.993	0.993
346	3.95	1.30	0.33	1.29	0.997	0.998
347	3.93	1.28	0.33	1.14	0.998	0.999
348	3.92	1.28	0.33	1.14	1.000	0.999
349	3.93	1.29	0.33	1.12	0.999	0.999
350	3.93	1.29	0.33	1.11	1.000	0.998
351	3.91	1.29	0.33	1.13	0.999	0.998
352	3.92	1.29	0.33	1.12	1.000	0.998
353	3.89	1.25	0.32	0.99	0.999	0.999
354	3.88	1.24	0.32	1.03	0.999	0.999
355	3.88	1.24	0.32	1.04	1.000	0.999
356	3.87	1.24	0.32	1.08	0.999	0.999
357	3.88	1.24	0.32	1.06	1.000	0.995
358	3.87	1.21	0.31	0.94	0.999	0.996
359	3.86	1.20	0.31	0.94	0.997	0.999
360	3.85	1.17	0.30	0.79	0.999	0.999
361	3.84	1.17	0.30	0.80	1.000	0.999
362	3.84	1.17	0.31	0.80	1.000	0.999
363	3.83	1.16	0.30	0.81	0.999	0.999
364	3.83	1.16	0.30	0.80	0.999	0.999
365	3.82	1.14	0.30	0.62	0.999	0.998

5.3. STATISTICAL PROPERTIES OF LOG-TRANSFORMED DAILY FLOWS

As it was seen in Table 5-1 and shown on Fig. 5-4 that Kızılgeçit daily flows are highly skewed. The alternative models commonly used in time series modeling are based on the normality assumption. Hence, natural base log-transformation ($Y_{p,\tau}$ = ln $X_{p,\tau}$) is applied on the Kızılgeçit daily flows in order to reduce skewness of the flows especially at the wet seasons.

Computed basic sample statistics of the log-transformed Kızılgeçit daily flows, such as the mean $(\overline{Y}_{\tau})$, the standard deviation $(S_{y\tau})$, coefficient of skewness $(C_{Sy\tau})$, lag-one $(r_{1\tau})$ and lag-two $(r_{2\tau})$ serial correlations are given in Table 5-2, and their seasonal variations are shown on Fig. 5-7 through 5-11. As it can be seen from Table 5-2 and Fig. 5-9 that the log-transformation reduces the sample skewnesses effectively, and the skewnesses of the log-transformed data are changing in the range $-0.5 < (C_{Sy\tau}) < 0.5$ in general.

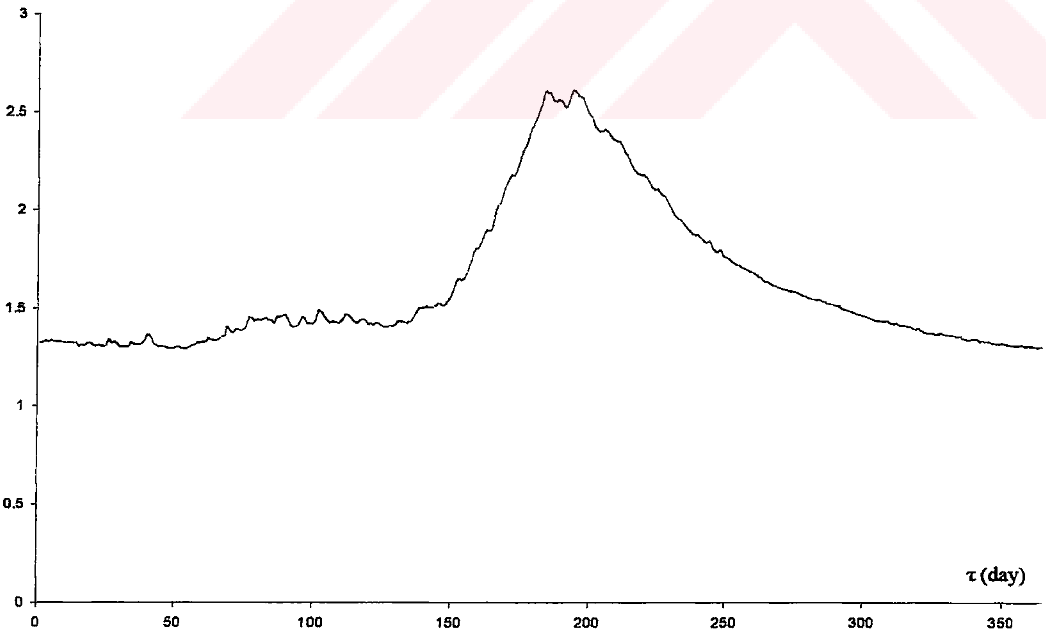

Fig. 5-7: Logarithmic mean $(\overline{Y}_{\tau})$ of Kızılgeçit daily flows

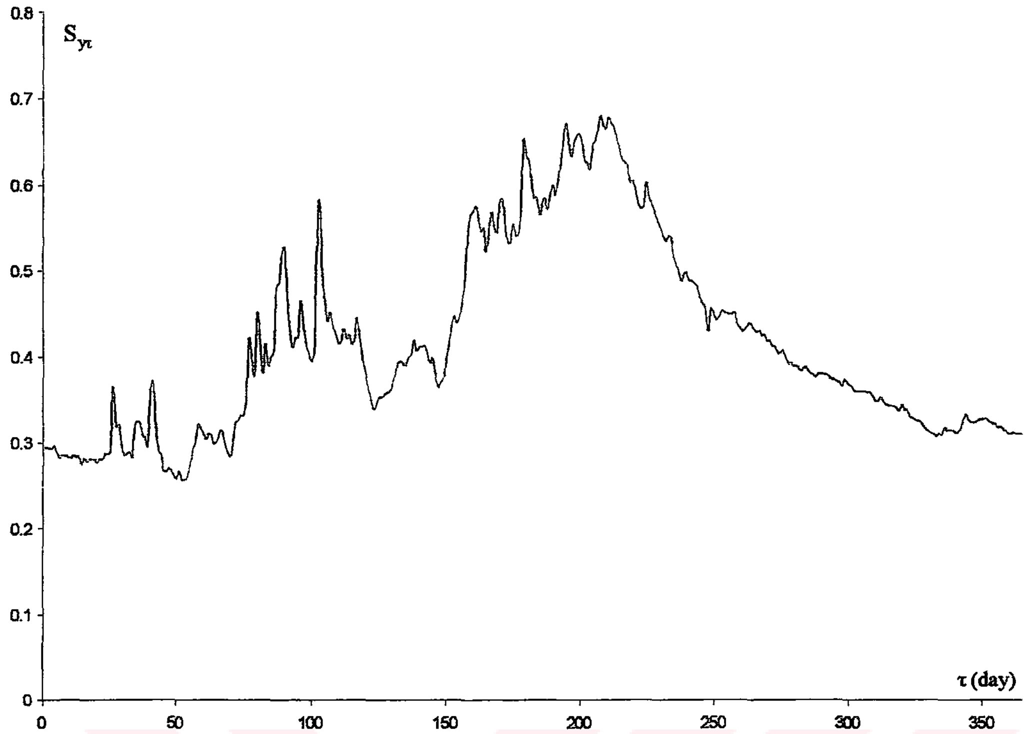

Fig. 5-8: Standard deviations of log-transformed Kızılgeçit daily flows

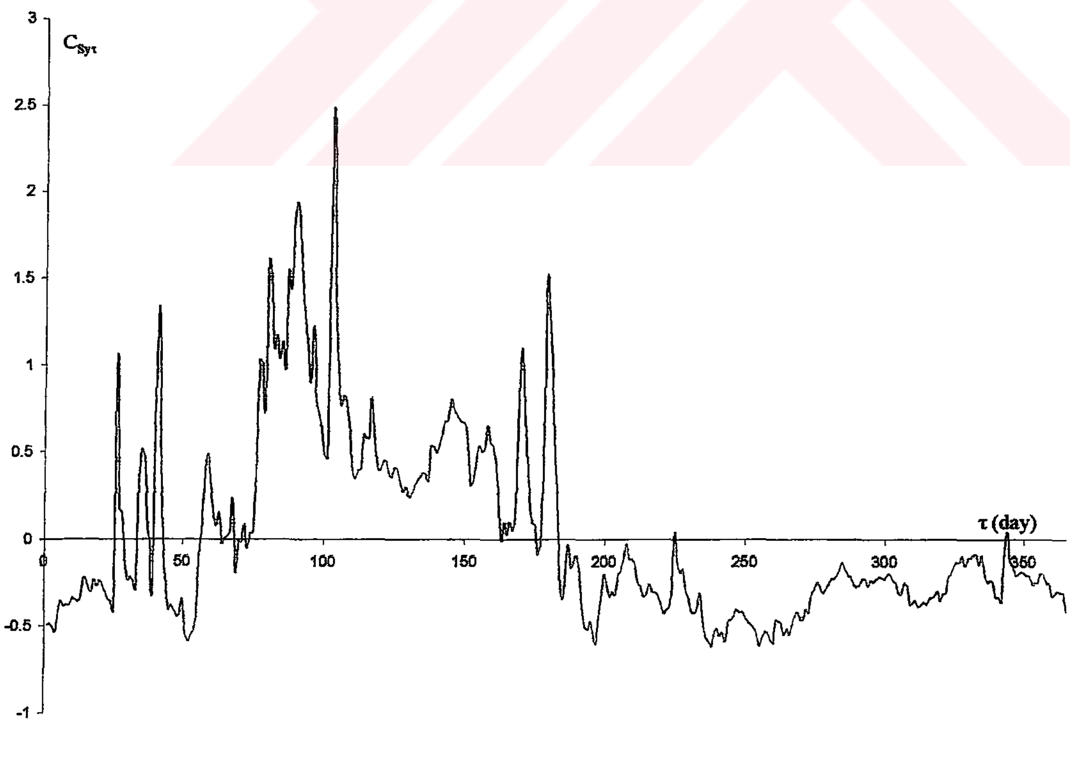

Fig. 5-9: Coefficient of skewness of log-transformed Kızılgeçit daily flows

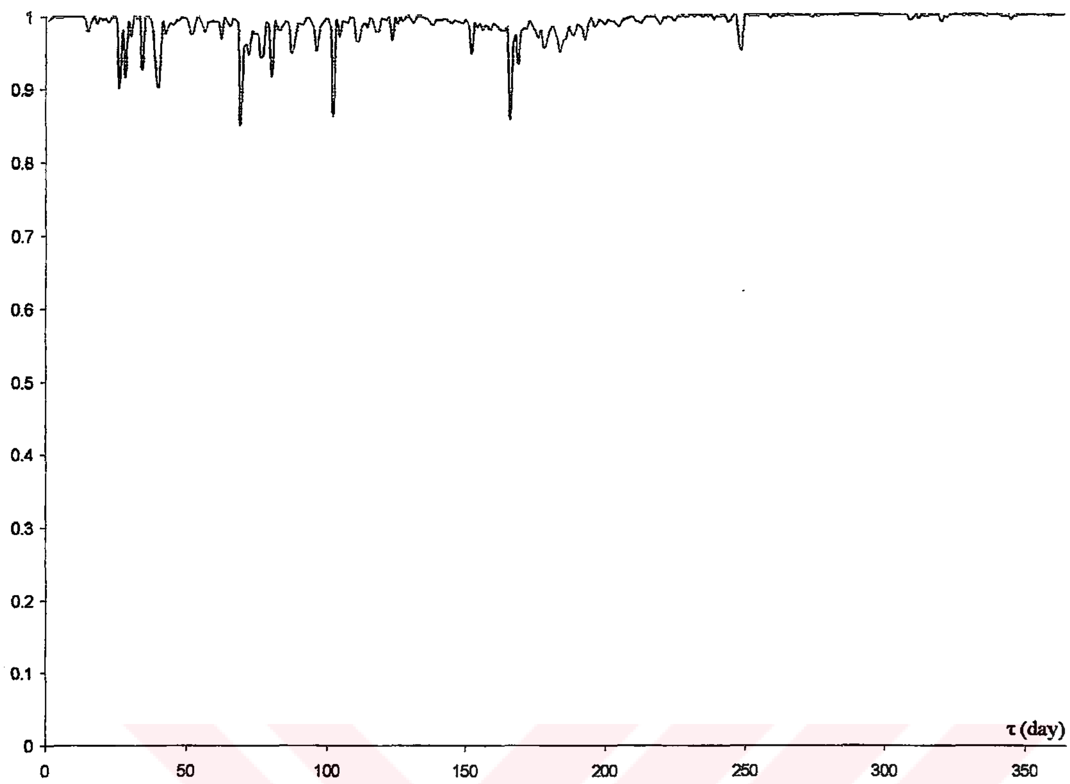

Fig. 5-10: Lag-one Autocorrelation Coefficients ($r_{1\tau}$) of log-transformed Kızılgeçit daily flows

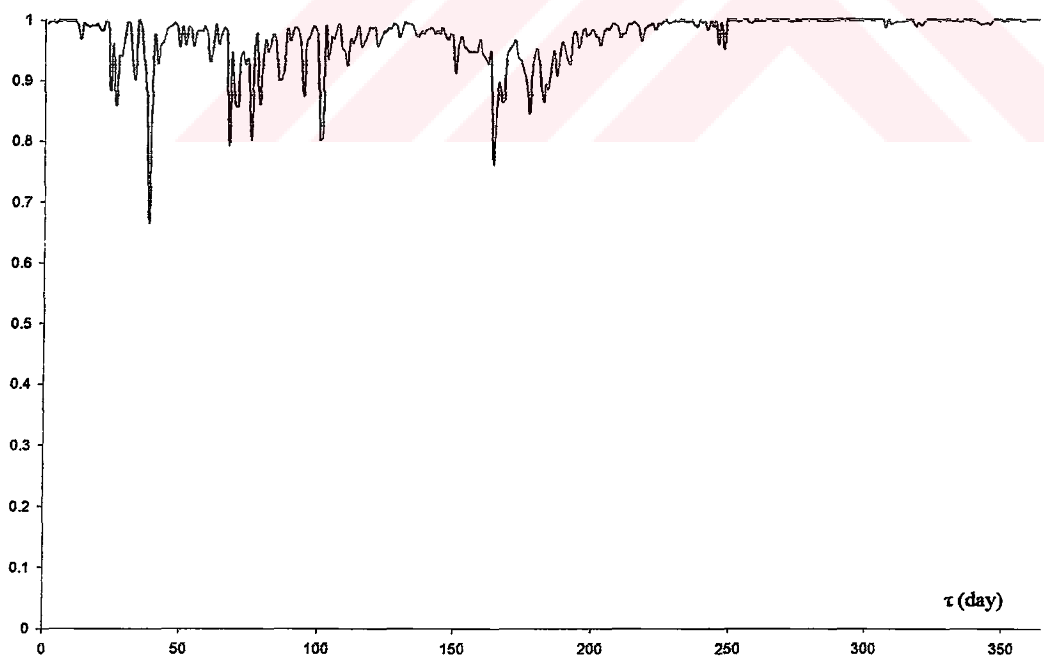

Fig. 5-11: Lag-two Autocorrelation Coefficients ($r_{2\tau}$) of log-transformed Kızılgeçit daily flows

Table 5-2: Basic sample statististics of Kızılgeçit log-transformed daily flows

τ	Y_τ	$S_{Y\tau}$	Cv_τ	$Cs_{Y\tau}$	$r_{1Y\tau}$	$r_{2Y\tau}$	τ	Y_τ	$S_{Y\tau}$	Cv_τ	$Cs_{Y\tau}$	$r_{1Y\tau}$	$r_{2Y\tau}$	τ	Y_τ	$S_{Y\tau}$	Cv_τ	$Cs_{Y\tau}$	$r_{1Y\tau}$	$r_{2Y\tau}$
1	1.32	0.29	0.22	-0.49	0.994	0.995	**28**	1.33	0.32	0.24	0.16	0.916	0.940	**55**	1.30	0.27	0.21	-0.43	0.990	0.978
2	1.33	0.29	0.22	-0.48	0.997	0.997	**29**	1.32	0.30	0.23	-0.07	0.991	0.969	**56**	1.31	0.29	0.22	-0.07	0.979	0.982
3	1.33	0.29	0.22	-0.50	0.999	0.998	**30**	1.30	0.29	0.22	-0.23	0.973	0.995	**57**	1.31	0.30	0.23	0.08	0.989	0.980
4	1.33	0.30	0.22	-0.53	0.998	0.995	**31**	1.30	0.29	0.22	-0.21	0.998	0.994	**58**	1.32	0.32	0.24	0.44	0.992	0.989
5	1.33	0.29	0.22	-0.42	0.998	0.999	**32**	1.30	0.29	0.22	-0.24	0.997	0.923	**59**	1.32	0.32	0.24	0.49	0.994	0.974
6	1.33	0.28	0.21	-0.35	0.999	0.998	**33**	1.30	0.28	0.22	-0.29	0.998	0.903	**60**	1.33	0.31	0.24	0.31	0.992	0.931
7	1.33	0.29	0.21	-0.38	0.999	0.999	**34**	1.32	0.32	0.24	0.33	0.927	0.997	**61**	1.33	0.30	0.23	0.16	0.991	0.955
8	1.33	0.28	0.21	-0.38	0.999	0.999	**35**	1.32	0.33	0.25	0.52	0.997	0.991	**62**	1.34	0.31	0.23	0.08	0.969	0.993
9	1.33	0.28	0.21	-0.38	1.000	0.999	**36**	1.31	0.32	0.25	0.46	0.999	0.945	**63**	1.34	0.31	0.23	0.15	0.996	0.961
10	1.32	0.28	0.21	-0.34	0.999	0.999	**37**	1.31	0.31	0.23	0.09	0.994	0.887	**64**	1.34	0.30	0.22	-0.02	0.993	0.975
11	1.32	0.28	0.22	-0.34	1.000	0.999	**38**	1.32	0.31	0.23	-0.03	0.965	0.664	**65**	1.34	0.30	0.23	0.00	0.986	0.987
12	1.32	0.28	0.21	-0.36	0.999	0.993	**39**	1.33	0.30	0.22	-0.30	0.916	0.854	**66**	1.34	0.31	0.23	0.02	0.995	0.980
13	1.32	0.28	0.21	-0.34	0.999	0.969	**40**	1.36	0.36	0.26	0.83	0.904	0.975	**67**	1.35	0.31	0.23	0.05	0.995	0.793
14	1.32	0.28	0.21	-0.22	0.995	0.994	**41**	1.35	0.37	0.27	1.33	0.991	0.928	**68**	1.36	0.30	0.22	0.23	0.990	0.945
15	1.31	0.28	0.22	-0.23	0.980	0.992	**42**	1.32	0.32	0.24	0.42	0.975	0.958	**69**	1.40	0.29	0.21	-0.18	0.851	0.861
16	1.31	0.28	0.21	-0.29	0.991	0.988	**43**	1.31	0.29	0.22	-0.03	0.986	0.963	**70**	1.38	0.28	0.21	-0.01	0.957	0.856
17	1.31	0.28	0.21	-0.30	0.999	0.991	**44**	1.30	0.29	0.22	-0.25	0.990	0.982	**71**	1.37	0.30	0.22	-0.02	0.961	0.936
18	1.32	0.28	0.21	-0.23	0.990	0.990	**45**	1.31	0.27	0.21	-0.40	0.988	0.987	**72**	1.39	0.32	0.23	0.08	0.948	0.946
19	1.32	0.28	0.21	-0.27	0.997	0.993	**46**	1.30	0.27	0.20	-0.38	0.994	0.990	**73**	1.39	0.33	0.23	-0.05	0.977	0.926
20	1.31	0.28	0.21	-0.24	0.995	0.984	**47**	1.30	0.27	0.21	-0.42	0.994	0.995	**74**	1.39	0.33	0.24	0.03	0.976	0.935
21	1.31	0.28	0.22	-0.27	0.997	0.982	**48**	1.30	0.27	0.21	-0.45	0.998	0.989	**75**	1.39	0.33	0.24	0.04	0.974	0.801
22	1.31	0.28	0.22	-0.30	0.992	0.997	**49**	1.29	0.26	0.20	-0.42	0.998	0.955	**76**	1.41	0.35	0.25	0.38	0.944	0.934
23	1.31	0.29	0.22	-0.34	0.997	0.994	**50**	1.30	0.26	0.20	-0.34	0.995	0.988	**77**	1.45	0.42	0.29	1.03	0.946	0.976
24	1.31	0.29	0.22	-0.36	0.998	0.883	**51**	1.30	0.27	0.20	-0.53	0.975	0.958	**78**	1.45	0.40	0.27	1.01	0.991	0.862
25	1.31	0.29	0.22	-0.41	0.997	0.961	**52**	1.30	0.26	0.20	-0.59	0.978	0.988	**79**	1.43	0.38	0.26	0.74	0.987	0.916
26	1.34	0.36	0.27	1.06	0.902	0.858	**53**	1.29	0.26	0.20	-0.55	0.994	0.986	**80**	1.44	0.45	0.31	1.60	0.917	0.966
27	1.32	0.32	0.24	0.18	0.980	0.940	**54**	1.29	0.26	0.20	-0.52	0.998	0.956	**81**	1.44	0.42	0.29	1.50	0.992	0.947

Table 5-2 (continued)

T	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$	τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$	τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$
82	1.44	0.38	0.27	1.10	0.982	0.959	**109**	1.43	0.42	0.30	0.65	0.996	0.946	**136**	1.44	0.40	0.28	0.37	0.995	0.972
83	1.45	0.41	0.29	1.17	0.980	0.976	**110**	1.43	0.42	0.29	0.39	0.967	0.923	**137**	1.47	0.40	0.27	0.34	0.988	0.980
84	1.44	0.39	0.27	1.04	0.986	0.965	**111**	1.45	0.42	0.29	0.35	0.966	0.968	**138**	1.49	0.42	0.28	0.54	0.987	0.977
85	1.44	0.40	0.28	1.14	0.992	0.899	**112**	1.47	0.43	0.29	0.40	0.984	0.962	**139**	1.50	0.41	0.27	0.53	0.993	0.983
86	1.42	0.41	0.29	0.99	0.985	0.900	**113**	1.46	0.42	0.29	0.41	0.989	0.977	**140**	1.50	0.41	0.27	0.50	0.993	0.985
87	1.45	0.48	0.33	1.54	0.950	0.920	**114**	1.45	0.43	0.29	0.60	0.984	0.988	**141**	1.51	0.41	0.27	0.55	0.994	0.987
88	1.45	0.49	0.33	1.44	0.960	0.984	**115**	1.43	0.41	0.29	0.58	0.997	0.955	**142**	1.50	0.41	0.27	0.61	0.995	0.977
89	1.46	0.52	0.36	1.84	0.989	0.967	**116**	1.42	0.42	0.30	0.58	0.993	0.962	**143**	1.50	0.40	0.27	0.68	0.994	0.981
90	1.46	0.53	0.36	1.94	0.988	0.981	**117**	1.44	0.44	0.31	0.81	0.980	0.971	**144**	1.51	0.39	0.26	0.68	0.991	0.977
91	1.44	0.47	0.33	1.73	0.988	0.988	**118**	1.44	0.42	0.29	0.56	0.979	0.986	**145**	1.52	0.40	0.26	0.80	0.990	0.987
92	1.41	0.43	0.31	1.47	0.995	0.979	**119**	1.43	0.40	0.28	0.41	0.994	0.985	**146**	1.52	0.38	0.25	0.75	0.993	0.975
93	1.41	0.41	0.29	1.26	0.997	0.958	**120**	1.42	0.38	0.27	0.40	0.996	0.987	**147**	1.51	0.37	0.24	0.72	0.992	0.967
94	1.41	0.42	0.30	1.10	0.990	0.874	**121**	1.42	0.37	0.26	0.44	0.994	0.957	**148**	1.52	0.37	0.24	0.69	0.990	0.976
95	1.42	0.42	0.30	0.90	0.975	0.963	**122**	1.42	0.35	0.25	0.45	0.996	0.966	**149**	1.54	0.38	0.24	0.67	0.989	0.973
96	1.45	0.46	0.32	1.22	0.952	0.971	**123**	1.43	0.34	0.24	0.38	0.967	0.978	**150**	1.56	0.40	0.25	0.66	0.994	0.912
97	1.45	0.44	0.30	0.80	0.983	0.984	**124**	1.42	0.34	0.24	0.36	0.996	0.978	**151**	1.59	0.41	0.26	0.52	0.985	0.952
98	1.42	0.42	0.29	0.73	0.990	0.988	**125**	1.41	0.35	0.25	0.41	0.989	0.986	**152**	1.64	0.43	0.27	0.31	0.949	0.971
99	1.42	0.40	0.28	0.65	0.995	0.971	**126**	1.41	0.35	0.25	0.40	0.996	0.985	**153**	1.65	0.45	0.27	0.34	0.988	0.955
100	1.42	0.39	0.28	0.49	0.995	0.802	**127**	1.41	0.35	0.25	0.34	0.993	0.993	**154**	1.64	0.44	0.27	0.45	0.983	0.953
101	1.44	0.40	0.28	0.46	0.978	0.805	**128**	1.41	0.36	0.25	0.28	0.997	0.990	**155**	1.65	0.45	0.27	0.53	0.989	0.946
102	1.49	0.52	0.35	1.84	0.863	0.986	**129**	1.41	0.36	0.26	0.30	0.998	0.970	**156**	1.68	0.46	0.27	0.50	0.981	0.946
103	1.48	0.58	0.39	2.48	0.992	0.934	**130**	1.42	0.36	0.26	0.25	0.995	0.981	**157**	1.73	0.49	0.28	0.53	0.986	0.947
104	1.46	0.50	0.34	1.35	0.972	0.970	**131**	1.43	0.38	0.26	0.25	0.989	0.995	**158**	1.77	0.54	0.30	0.65	0.983	0.948
105	1.44	0.46	0.32	0.95	0.991	0.969	**132**	1.43	0.39	0.27	0.29	0.998	0.993	**159**	1.80	0.56	0.31	0.55	0.981	0.967
106	1.42	0.44	0.31	0.77	0.992	0.986	**133**	1.43	0.39	0.28	0.33	0.998	0.993	**160**	1.81	0.57	0.31	0.53	0.988	0.945
107	1.43	0.45	0.32	0.83	0.990	0.993	**134**	1.43	0.39	0.27	0.36	0.997	0.990	**161**	1.84	0.57	0.31	0.39	0.985	0.937
108	1.43	0.44	0.31	0.78	0.998	0.955	**135**	1.43	0.39	0.27	0.38	0.996	0.975	**162**	1.88	0.56	0.30	0.19	0.981	0.928

Table 5-2 (continued)

T	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$	τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$	τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$
163	1.89	0.55	0.29	-0.01	0.979	0.946	**190**	2.56	0.60	0.23	-0.09	0.986	0.948	**217**	2.20	0.63	0.28	-0.30	0.998	0.985
164	1.90	0.55	0.29	0.09	0.978	0.764	**191**	2.53	0.59	0.23	-0.17	0.984	0.932	**218**	2.19	0.62	0.28	-0.30	0.998	0.965
165	1.91	0.52	0.27	0.03	0.982	0.837	**192**	2.53	0.60	0.24	-0.37	0.980	0.927	**219**	2.18	0.60	0.28	-0.31	0.991	0.985
166	1.99	0.55	0.28	0.10	0.857	0.895	**193**	2.57	0.62	0.24	-0.50	0.966	0.976	**220**	2.18	0.60	0.28	-0.36	0.988	0.989
167	2.02	0.57	0.28	0.05	0.956	0.863	**194**	2.61	0.65	0.25	-0.51	0.984	0.979	**221**	2.17	0.60	0.27	-0.42	0.996	0.991
168	2.04	0.55	0.27	0.16	0.973	0.869	**195**	2.60	0.67	0.26	-0.47	0.996	0.953	**222**	2.14	0.58	0.27	-0.40	0.996	0.994
169	2.09	0.55	0.26	0.73	0.933	0.941	**196**	2.59	0.65	0.25	-0.54	0.985	0.975	**223**	2.12	0.57	0.27	-0.39	0.998	0.983
170	2.13	0.58	0.27	1.10	0.978	0.951	**197**	2.58	0.63	0.25	-0.60	0.986	0.985	**224**	2.10	0.58	0.27	-0.29	0.996	0.994
171	2.16	0.58	0.27	0.85	0.981	0.959	**198**	2.57	0.65	0.25	-0.45	0.994	0.973	**225**	2.11	0.60	0.29	0.04	0.991	0.993
172	2.18	0.55	0.25	0.45	0.982	0.966	**199**	2.53	0.66	0.26	-0.30	0.992	0.977	**226**	2.09	0.59	0.28	-0.12	0.998	0.996
173	2.18	0.53	0.24	0.22	0.992	0.940	**200**	2.49	0.66	0.26	-0.20	0.988	0.983	**227**	2.07	0.58	0.28	-0.19	0.998	0.998
174	2.21	0.53	0.24	0.09	0.984	0.932	**201**	2.47	0.65	0.26	-0.27	0.994	0.973	**228**	2.06	0.57	0.28	-0.17	0.999	0.994
175	2.25	0.55	0.25	0.08	0.979	0.918	**202**	2.44	0.63	0.26	-0.33	0.992	0.970	**229**	2.03	0.56	0.27	-0.29	0.997	0.996
176	2.30	0.54	0.23	-0.09	0.970	0.896	**203**	2.41	0.62	0.26	-0.30	0.991	0.958	**230**	2.01	0.55	0.27	-0.34	0.998	0.997
177	2.33	0.54	0.23	-0.03	0.979	0.844	**204**	2.40	0.62	0.26	-0.32	0.987	0.978	**231**	1.98	0.54	0.27	-0.41	0.999	0.997
178	2.36	0.57	0.24	0.58	0.956	0.909	**205**	2.40	0.65	0.27	-0.21	0.984	0.985	**232**	1.96	0.53	0.27	-0.42	0.998	0.998
179	2.41	0.65	0.27	1.50	0.959	0.941	**206**	2.41	0.65	0.27	-0.18	0.992	0.982	**233**	1.95	0.54	0.28	-0.39	0.999	0.998
180	2.44	0.63	0.26	1.28	0.976	0.951	**207**	2.40	0.66	0.28	-0.11	0.993	0.992	**234**	1.94	0.54	0.28	-0.31	0.999	0.996
181	2.48	0.62	0.25	0.98	0.984	0.910	**208**	2.38	0.68	0.29	-0.03	0.995	0.992	**235**	1.92	0.52	0.27	-0.46	0.997	0.996
182	2.51	0.60	0.24	0.53	0.978	0.865	**209**	2.36	0.67	0.28	-0.11	0.997	0.988	**236**	1.91	0.51	0.27	-0.55	0.999	0.998
183	2.55	0.58	0.23	0.15	0.966	0.893	**210**	2.35	0.66	0.28	-0.11	0.997	0.969	**237**	1.89	0.50	0.26	-0.58	0.998	0.992
184	2.60	0.58	0.22	-0.26	0.950	0.886	**211**	2.35	0.68	0.29	-0.15	0.991	0.975	**238**	1.88	0.49	0.26	-0.61	0.999	0.988
185	2.60	0.56	0.22	-0.34	0.966	0.925	**212**	2.33	0.67	0.29	-0.25	0.991	0.978	**239**	1.87	0.50	0.26	-0.54	0.994	0.998
186	2.59	0.58	0.22	-0.21	0.968	0.948	**213**	2.30	0.67	0.29	-0.27	0.989	0.992	**240**	1.87	0.50	0.27	-0.51	0.998	0.995
187	2.56	0.58	0.23	-0.03	0.982	0.907	**214**	2.27	0.65	0.29	-0.32	0.995	0.993	**241**	1.86	0.49	0.26	-0.55	0.998	0.996
188	2.56	0.57	0.22	-0.16	0.974	0.935	**215**	2.24	0.64	0.29	-0.32	0.998	0.996	**242**	1.84	0.49	0.27	-0.54	0.999	0.983
189	2.56	0.59	0.23	-0.13	0.973	0.962	**216**	2.22	0.63	0.28	-0.26	0.998	0.993	**243**	1.83	0.48	0.26	-0.58	0.998	0.997

Table 5-2 (continued)

τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$	τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$	τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$
244	1.84	0.48	0.26	-0.47	0.989	0.988	**271**	1.60	0.42	0.26	-0.46	1.000	0.998	**298**	1.47	0.37	0.25	-0.22	0.999	0.998
245	1.81	0.47	0.26	-0.46	0.993	0.997	**272**	1.59	0.41	0.26	-0.40	0.999	0.996	**299**	1.47	0.37	0.25	-0.22	0.998	0.999
246	1.79	0.46	0.26	-0.44	0.999	0.959	**273**	1.59	0.41	0.26	-0.42	0.999	0.996	**300**	1.46	0.37	0.25	-0.23	1.000	0.999
247	1.78	0.46	0.26	-0.40	0.999	0.995	**274**	1.58	0.40	0.26	-0.32	0.997	0.998	**301**	1.46	0.37	0.25	-0.20	0.999	0.999
248	1.79	0.43	0.24	-0.42	0.960	0.950	**275**	1.58	0.40	0.26	-0.29	0.999	0.998	**302**	1.45	0.36	0.25	-0.20	0.999	0.998
249	1.77	0.45	0.26	-0.41	0.952	0.998	**276**	1.58	0.41	0.26	-0.25	0.999	0.998	**303**	1.44	0.36	0.25	-0.24	0.999	0.999
250	1.76	0.45	0.26	-0.44	0.999	0.998	**277**	1.57	0.40	0.25	-0.27	0.999	0.999	**304**	1.44	0.36	0.25	-0.26	0.999	0.999
251	1.75	0.44	0.25	-0.47	0.999	0.997	**278**	1.56	0.39	0.25	-0.31	0.999	0.999	**305**	1.43	0.36	0.25	-0.31	0.999	0.999
252	1.74	0.44	0.26	-0.49	0.999	0.998	**279**	1.56	0.39	0.25	-0.29	0.999	0.998	**306**	1.43	0.36	0.25	-0.31	1.000	0.998
253	1.73	0.45	0.26	-0.50	0.998	0.996	**280**	1.55	0.39	0.25	-0.26	0.999	0.999	**307**	1.43	0.36	0.25	-0.25	0.999	0.986
254	1.72	0.45	0.26	-0.54	0.998	0.998	**281**	1.55	0.39	0.25	-0.23	0.999	0.999	**308**	1.43	0.36	0.25	-0.27	0.999	0.998
255	1.71	0.45	0.26	-0.61	0.998	0.998	**282**	1.54	0.38	0.25	-0.23	1.000	0.997	**309**	1.43	0.35	0.25	-0.37	0.992	0.993
256	1.71	0.45	0.26	-0.57	0.999	0.999	**283**	1.54	0.38	0.25	-0.21	0.999	0.998	**310**	1.42	0.35	0.25	-0.36	0.996	0.994
257	1.70	0.45	0.26	-0.54	0.999	0.994	**284**	1.54	0.39	0.25	-0.18	0.999	0.999	**311**	1.42	0.35	0.25	-0.35	1.000	0.996
258	1.69	0.45	0.27	-0.53	0.999	0.994	**285**	1.53	0.39	0.25	-0.13	0.999	0.998	**312**	1.42	0.35	0.25	-0.38	0.994	0.995
259	1.68	0.44	0.26	-0.58	0.995	0.998	**286**	1.53	0.38	0.25	-0.17	0.999	0.998	**313**	1.41	0.35	0.25	-0.38	0.999	0.996
260	1.68	0.43	0.26	-0.59	0.999	0.998	**287**	1.52	0.38	0.25	-0.21	0.999	0.998	**314**	1.41	0.34	0.24	-0.36	0.998	0.998
261	1.67	0.43	0.26	-0.46	0.998	0.997	**288**	1.52	0.38	0.25	-0.21	0.999	0.998	**315**	1.41	0.34	0.24	-0.37	0.998	0.999
262	1.66	0.43	0.26	-0.47	0.999	0.997	**289**	1.52	0.38	0.25	-0.26	0.999	0.998	**316**	1.40	0.34	0.24	-0.34	0.999	0.999
263	1.65	0.44	0.26	-0.48	0.998	0.999	**290**	1.51	0.38	0.25	-0.27	0.999	0.999	**317**	1.40	0.34	0.24	-0.34	1.000	0.998
264	1.63	0.44	0.27	-0.55	0.999	0.999	**291**	1.51	0.38	0.25	-0.26	0.999	0.999	**318**	1.40	0.34	0.24	-0.32	0.999	0.988
265	1.63	0.43	0.27	-0.52	0.999	0.999	**292**	1.50	0.38	0.25	-0.23	0.999	0.998	**319**	1.39	0.34	0.24	-0.30	0.998	0.995
266	1.62	0.43	0.26	-0.55	1.000	0.997	**293**	1.49	0.38	0.25	-0.22	0.999	0.999	**320**	1.39	0.34	0.25	-0.35	0.990	0.990
267	1.62	0.43	0.27	-0.48	0.999	0.998	**294**	1.49	0.37	0.25	-0.27	0.999	0.998	**321**	1.38	0.34	0.24	-0.31	0.998	0.996
268	1.61	0.42	0.26	-0.44	0.999	0.999	**295**	1.48	0.37	0.25	-0.24	0.999	0.999	**322**	1.37	0.34	0.25	-0.31	0.996	0.999
269	1.60	0.43	0.27	-0.42	0.999	0.999	**296**	1.48	0.37	0.25	-0.25	0.999	0.998	**323**	1.37	0.33	0.24	-0.22	0.999	0.999
270	1.60	0.42	0.26	-0.46	0.999	0.999	**297**	1.47	0.37	0.25	-0.23	0.999	0.998	**324**	1.37	0.33	0.24	-0.20	1.000	0.999

Table 5-2 (continued)

τ	Y_τ	$S_{y\tau}$	Cv_τ	$Cs_{y\tau}$	$r_{1y\tau}$	$r_{2y\tau}$
325	1.37	0.33	0.24	-0.15	0.999	0.999
326	1.37	0.33	0.24	-0.13	1.000	0.998
327	1.37	0.32	0.24	-0.13	1.000	0.998
328	1.37	0.32	0.23	-0.10	0.998	0.999
329	1.37	0.32	0.23	-0.15	0.999	0.998
330	1.36	0.31	0.23	-0.11	0.999	0.999
331	1.36	0.31	0.23	-0.10	1.000	0.997
332	1.36	0.31	0.23	-0.09	0.999	0.997
333	1.36	0.31	0.23	-0.09	0.999	0.999
334	1.35	0.31	0.23	-0.14	0.999	0.996
335	1.35	0.31	0.23	-0.09	0.999	0.997
336	1.34	0.32	0.24	-0.20	0.997	0.999
337	1.34	0.31	0.23	-0.25	1.000	0.999
338	1.34	0.31	0.23	-0.23	1.000	0.998
339	1.34	0.31	0.23	-0.25	1.000	0.998
340	1.34	0.31	0.23	-0.33	0.999	0.997
341	1.34	0.31	0.23	-0.33	0.999	0.993
342	1.33	0.31	0.24	-0.36	0.997	0.992
343	1.33	0.32	0.24	-0.07	0.997	0.993
344	1.33	0.33	0.25	0.04	0.998	0.994
345	1.33	0.33	0.25	-0.12	0.992	0.991
346	1.32	0.32	0.25	-0.15	0.997	0.997
347	1.32	0.32	0.25	-0.20	0.998	0.999
348	1.32	0.32	0.25	-0.20	1.000	0.999
349	1.32	0.33	0.25	-0.18	0.999	0.999
350	1.32	0.33	0.25	-0.19	1.000	0.997
351	1.31	0.33	0.25	-0.21	0.999	0.998
352	1.31	0.33	0.25	-0.21	0.999	0.999
353	1.31	0.32	0.25	-0.25	0.999	0.999
354	1.31	0.32	0.25	-0.25	0.999	0.999
355	1.31	0.32	0.25	-0.24	1.000	0.999
356	1.31	0.32	0.24	-0.20	0.999	0.999
357	1.31	0.32	0.24	-0.21	1.000	0.997
358	1.31	0.31	0.24	-0.25	0.999	0.997
359	1.30	0.31	0.24	-0.25	0.998	0.999
360	1.30	0.31	0.24	-0.32	0.999	0.999
361	1.30	0.31	0.24	-0.31	1.000	0.999
362	1.30	0.31	0.24	-0.29	1.000	0.999
363	1.30	0.31	0.24	-0.30	1.000	0.999
364	1.30	0.31	0.24	-0.31	1.000	0.999
365	1.30	0.31	0.24	-0.41	0.999	0.998

5.4. PERIODIC COMPONENTS OF KIZILGEÇİT DAILY FLOWS

Daily flows have periodic components at least in their mean and standard deviations due to astronomic cycle. The common procedure, so called the harmonic analysis has been applied to determine the significant harmonics in various sample statistics of Kızılgeçit daily flows. The periodic components in the logarithmic mean ($\hat{\mu}_{y\tau}$) and logarithmic standard deviations ($\hat{\sigma}_{y\tau}$) are estimated by use of a computer program developed by Benzeden (1982).

Harmonic coefficients (A_j, B_j), amplitudes (C_j), angular phases (θ_j) explained variances (ΔP_j), harmonic intensities ($h_j = \omega C_j^2 / \nu$), and cumulative explained variances (P_m) of the first 10 number of harmonics for the logarithmic means are given in Table 5-3, while the results of harmonic analyses of the logarithmic standard deviations are in Table 5-4, lag-one and lag-two sample autocorrelations are in Table 5-5 and Table 5-6. Relative cumulative periodograms of the seasonal sample statistics $\overline{Y}_\tau$, $S_{y\tau}$, $r_{1\tau}$, and $r_{2\tau}$ are shown in Fig. 5-12 thru 5-15.

Table 5-3: Harmonic coefficients of logarithmic mean

j	Aj	Bj	Cj	θj	ΔPj	hj	Pm
1	-0.414	-0.156	0.442	2.78	0.7026	35.73	0.70264
2	0.171	0.137	0.219	5.61	0.172	8.74	0.8746
3	-0.114	-0.096	0.149	2.439	0.0795	4.04	0.9541
4	0.081	0.053	0.097	5.706	0.0337	1.71	0.98776
5	-0.04	-0.013	0.042	2.837	0.0063	0.32	0.99401
6	0.019	0.014	0.024	5.667	0.002	0.1	0.996
7	-0.019	-0.006	0.02	2.839	0.0014	0.07	0.99737
8	0.009	0.002	0.009	6.089	0.0003	0.02	0.99768
9	-0.003	-0.003	0.005	2.318	0.0001	0	0.99776
10	0.009	0.005	0.01	5.756	0.0004	0.02	0.99811

Table 5-4: Harmonic coefficients of logarithmic standard deviation

j	Aj	Bj	Cj	θj	ΔPj	hj	Pm
1	-0.135	-0.034	0.139	2.897	0.7731	3.54	0.77315
2	0.023	0.028	0.036	5.409	0.0517	0.24	0.82485
3	-0.014	-0.041	0.044	1.897	0.0757	0.35	0.90057
4	0.024	0.017	0.029	5.657	0.0338	0.16	0.9344
5	-0.004	0.011	0.011	4.347	0.005	0.02	0.93945
6	-0.016	-0.01	0.019	2.571	0.0137	0.06	0.95316
7	0.008	-0.004	0.009	0.483	0.0029	0.01	0.95609
8	-0.001	-0.01	0.01	1.691	0.0037	0.02	0.95979
9	0.003	0	0.003	6.115	0.0003	0	0.96009
10	-0.002	-0.003	0.004	2.217	0.0006	0	0.96067

Table 5-5: Harmonic coefficients of lag-one autocorrelation coefficients

j	Aj	Bj	Cj	θj	ΔPj	hj	Pm
1	0.004	-0.01	0.011	1.22	0.1541	0.02	0.15409
2	-0.001	-0.003	0.003	1.863	0.0139	0	0.16799
3	0.006	-0.001	0.006	0.176	0.049	0.01	0.217
4	-0.003	0.002	0.004	3.792	0.0178	0	0.23478
5	0.003	-0.004	0.005	0.938	0.0341	0	0.26888
6	0.001	0.001	0.001	5.529	0.0014	0	0.2703
7	0.002	0	0.002	0.133	0.0066	0	0.27686
8	0.003	0.002	0.004	5.509	0.0165	0	0.29338
9	-0.001	0.003	0.003	4.402	0.0096	0	0.30295
10	-0.002	0.002	0.003	3.823	0.0128	0	0.31579

Table 5-6: Harmonic coefficients of lag-two autocorrelation coefficients

j	Aj	Bj	Cj	θj	ΔPj	hj	Pm
1	0.013	-0.026	0.029	1.118	0.231	0.15	0.231
2	-0.005	-0.006	0.008	2.246	0.018	0.01	0.249
3	0.018	-0.003	0.018	0.154	0.090	0.06	0.339
4	-0.009	0.005	0.01	3.674	0.031	0.02	0.370
5	0.009	-0.009	0.013	0.818	0.047	0.03	0.417
6	0.002	0.004	0.004	5.154	0.005	0	0.422
7	0.006	-0.001	0.006	0.115	0.010	0.01	0.431
8	0.003	0.007	0.008	5.128	0.018	0.01	0.450
9	-0.002	0.006	0.006	4.344	0.010	0.01	0.460
10	-0.007	0.003	0.008	3.559	0.016	0.01	0.476

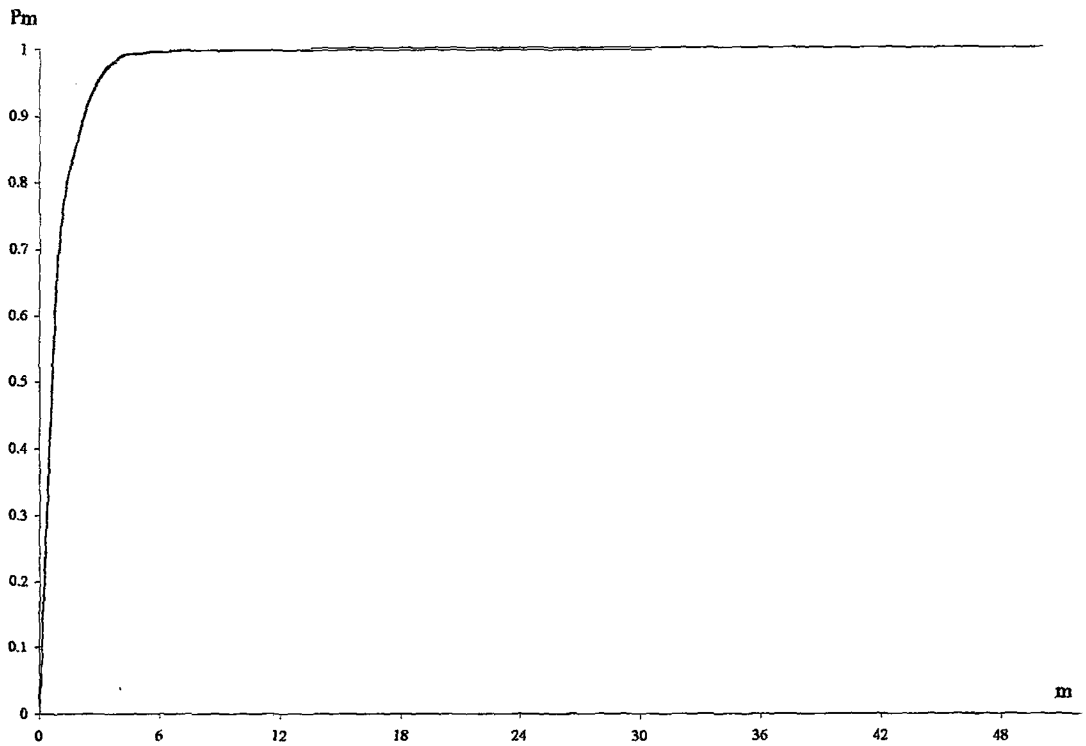

Fig. 5-12: Periodogram of logarithmic means (m_o=6)

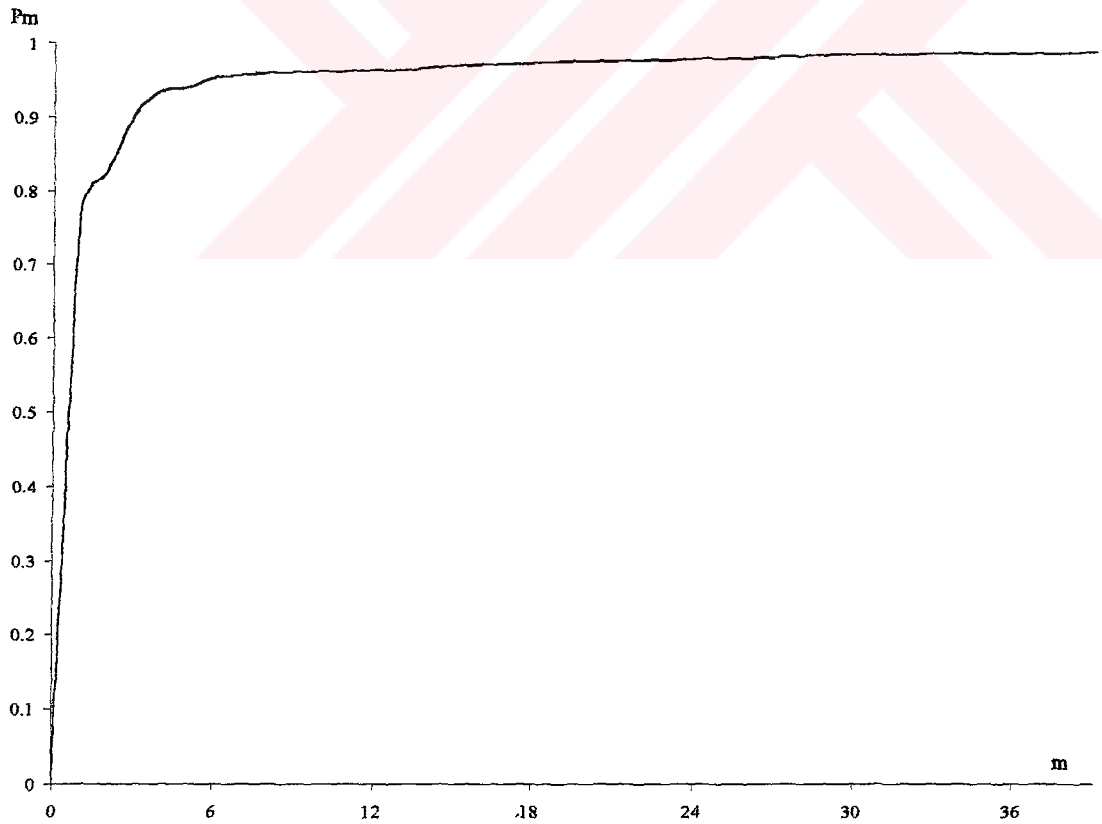

Fig. 5-13: Periodogram of logarithmic standard deviations (m_s=6)

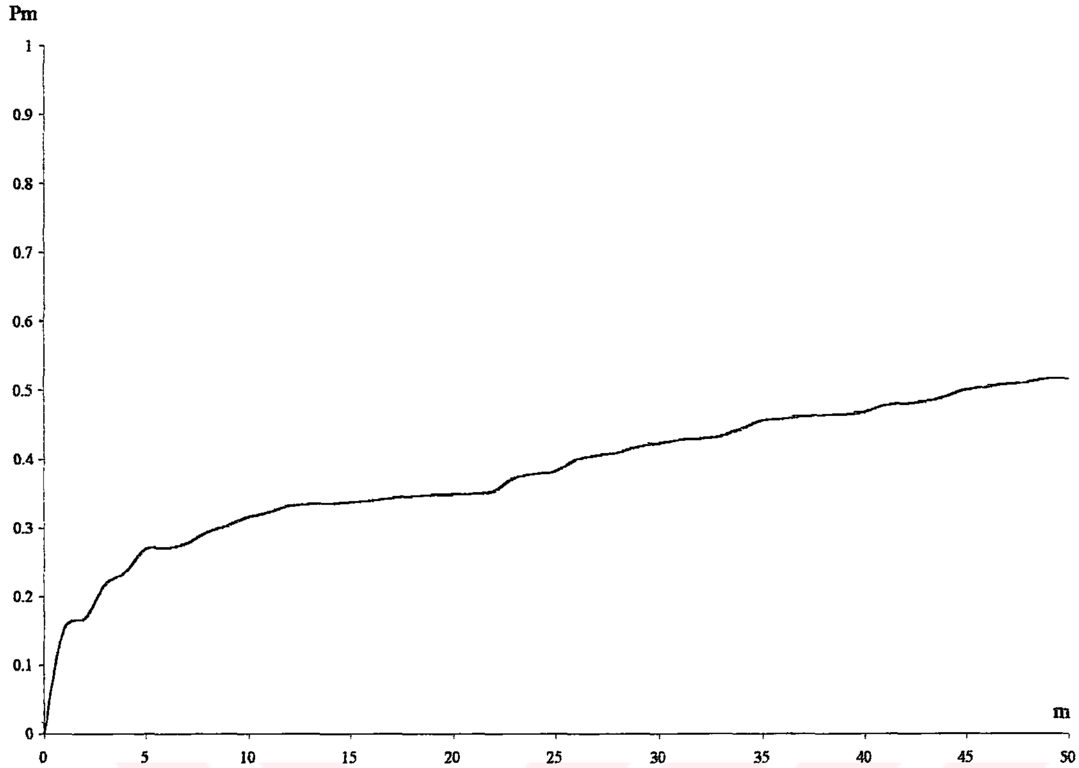

Fig. 5-14: Periodogram of lag-one autocorrelation coefficients (m=5)

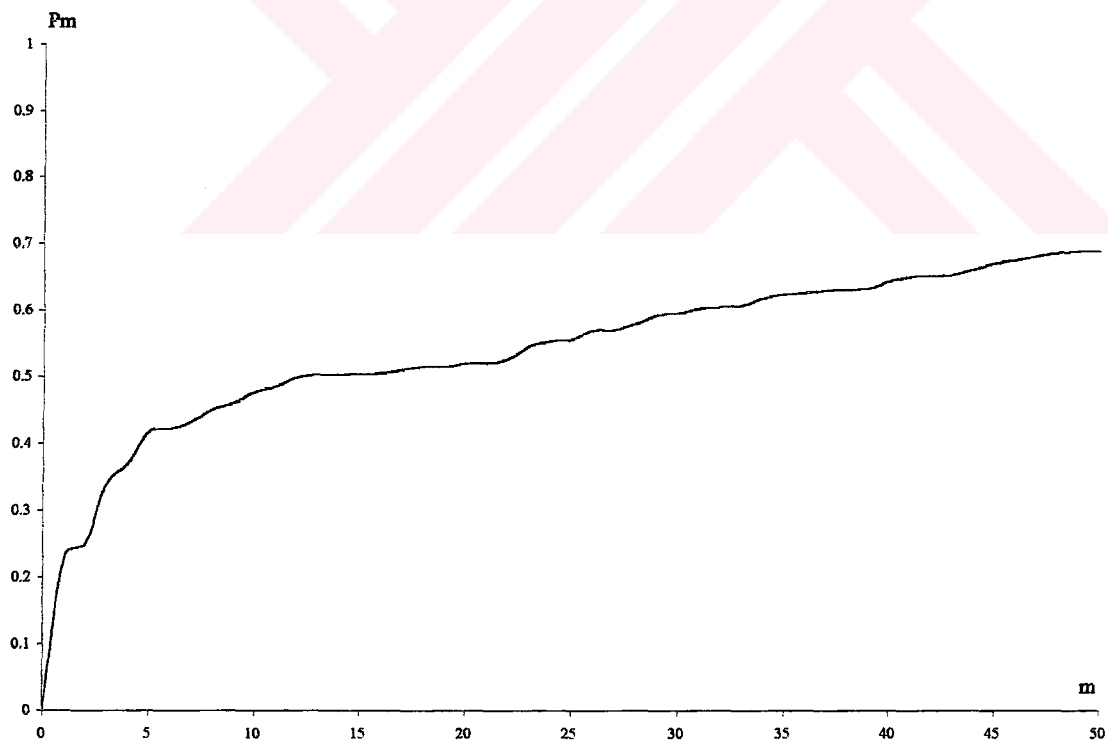

Fig. 5-15: Periodogram of lag-two autocorrelation coefficients (m=5)

Regarding the significant harmonics in the mean (m_o) and in the standard deviations (m_s), to be used in Fourier series representation of $\overline{Y}_\tau$ and $S_{y\tau}$, the empirical method of selecting number of significant harmonics, proposed by Yevjevich (1972a) is used. The number of significant harmonics in both parameters is chosen as 6.

Using the first 6 harmonics for the logarithmic means and for the logarithmic standard deviations, periodic components in these two parameters have been estimated and shown in Fig. 5-16 and 5-17.

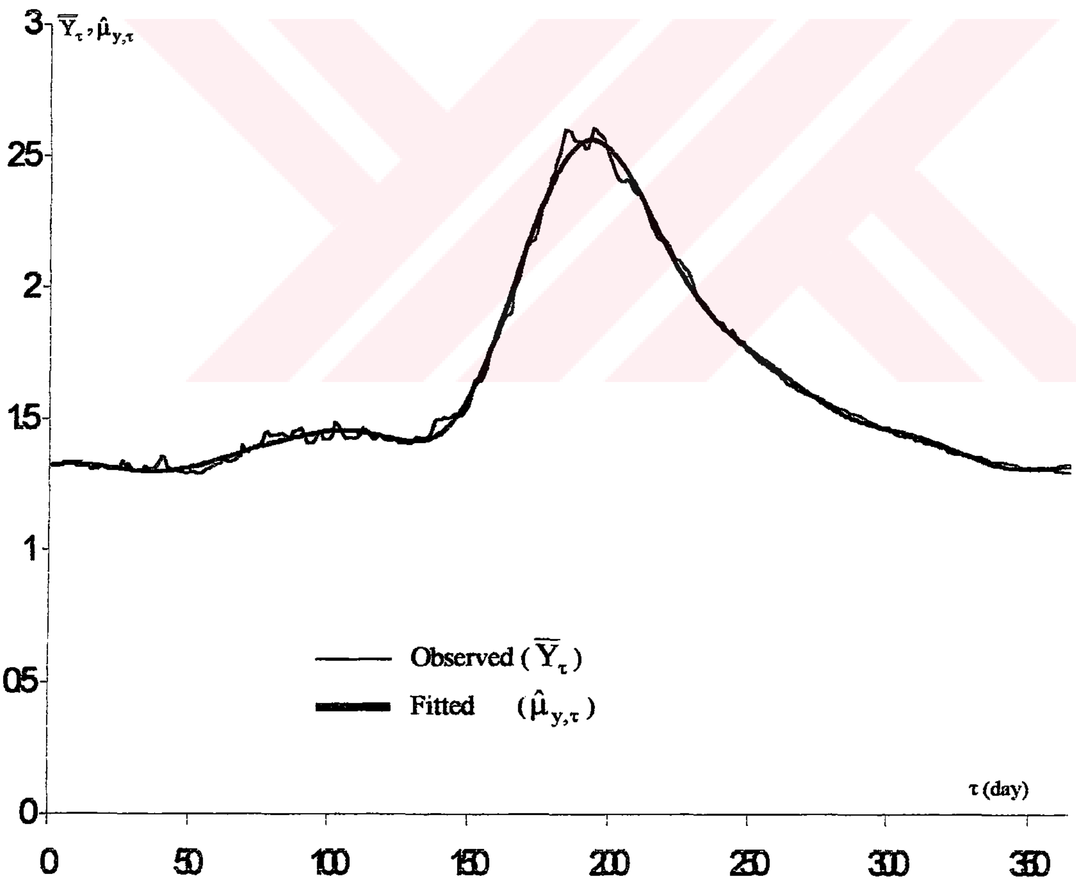

Fig. 5-16: Observed and fitted periodic components of logarithmic means (m=6)

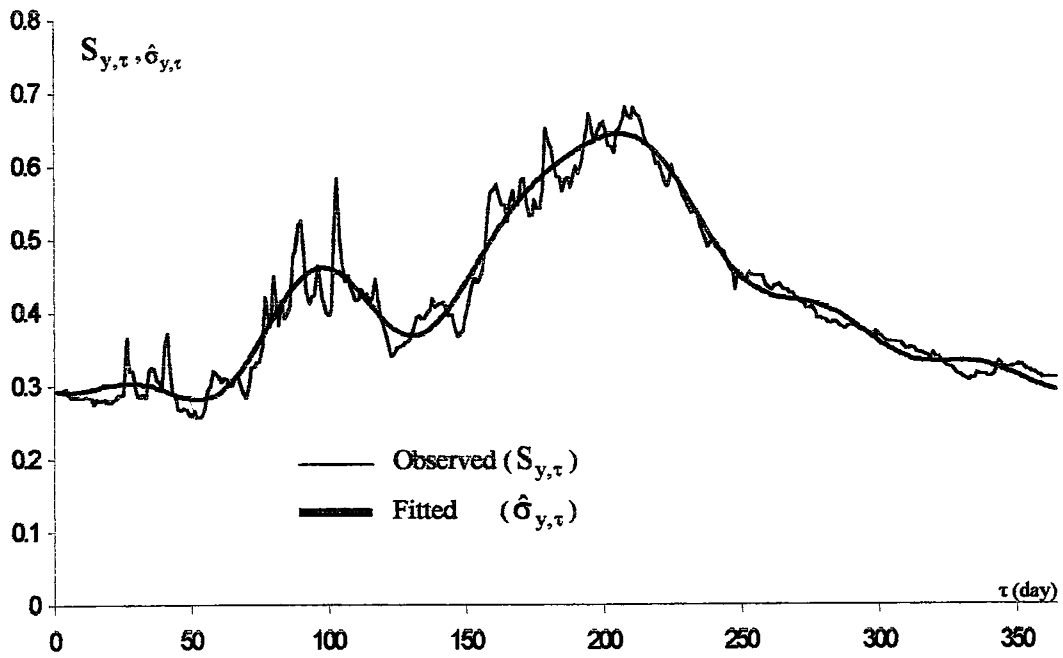

Fig. 5-17: Fitted periodic components of logarithmic standard deviations (m=6)

5.5. LINEAR STATIONARY STOCHASTIC MODELS OF KIZILGEÇİT DAILY FLOWS

The first attempt in modeling Kızılgeçit daily flows is performed under the assumption that nonstationary (or periodic movement) in the transformed daily flows is mainly created by the periodic mean and standard deviation. Therefore, the second order weak stationary stochastic components $(Z_{p,\tau})$ are calculated then by nonparametric standadization (Eq. 3-14). The autocorrelation coefficients up to lag 600 are calculated. As it can be seen from the first four auocorrelations in Table 5-7 the sample correlogram of the $(Z_{p,\tau})$ series indicates a long memory dependence structure in stochastic components.

Linear autoregressive models of order 2, 3, and 4 are investigated using their initial parameter estimators. The estimated parameters for each model are given in Table 5-7. The partial f-test is applied to determine the appropriate order of autoregressiveness (p). Regarding the results of partial f-tests, the AR (3) model is found significantly better than AR (2), and at a 5% significance level AR (4) model is not significantly better than AR (3). Hence, AR (3) model is assumed to represent the dependence structure of the process.

The parameters estimated from Yule-Walker equations are used as a first approximation for the removal of stochastic dependence (Eq. 3-62) in the $(Z_{p,\tau})$ series. The sample correlogram of the residuals series (ε_τ) of AR (3) model is shown in Fig. 5-18. Spectral analysis is also carried out in order to check whether the residuals series is a white noise. The normalized integrated spectrum of the ε_τ series (Fig. 5-19) is partly out of the 95% tolerance limits at low frequencies. A second approach for the dependence structure of the stochastic components is made by the least squares estimators (Table 5-7) of stationary AR (3) model. The integrated spectrum of the residuals series after removal of AR (3) dependence with least squares estimators were still out of the tolerance limits of an ideal white noise (Fig. 5-20).

Another attempt is done by application of ARMA (2,1) model. The initial parameters estimated by method of moments are given in Table 5-7. The sample correlogram (Fig. 5-21) and integrated spectrum of residuals series of ARMA (2,1) model (Fig. 5-22) are still out of the tolerance limits.

Table 5-7: Parameters of the alternative stationary ARMA (p,q) models

Parameters	Alternative Models					
	r (k)	AR (2)	AR (3)	AR (4)	AR (3)*	ARMA (2,1)
α_1	0.98731	1.23321	1.27128	1.26663	1.27125	0.6575
α_2	0.96850	- 0.24906	- 0.43758	- 0.42425	- 0.43800	0.31935
α_3	0.95208	—	0.15287	0.11416	0.15333	—
α_4	0.93820	—	—	0.03045	—	—
θ_1		—	—	—	—	- 0.6382
S_e^2		0.02309	0.02255	0.02252	0.02312	0.02220
Partial f			≈285	≈0	—	—
(*) Model parameters of AR (3) are estimated by method of least-squares (**) The critical f-value is 1.645 for α=0.05						

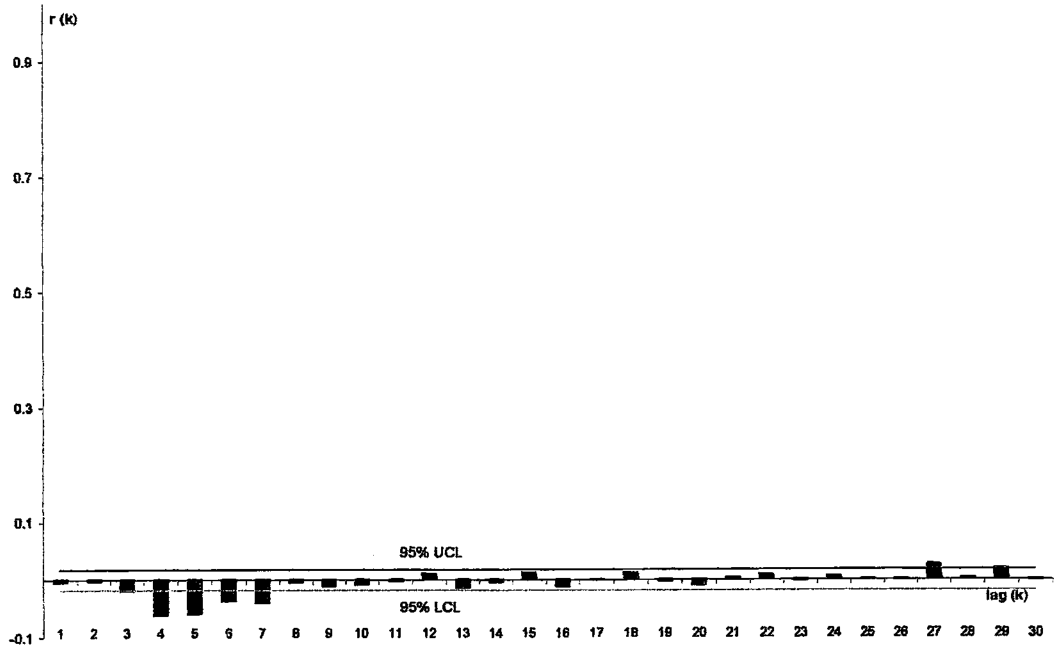

Fig. 5-18: Correlogram of AR (3) residuals series.

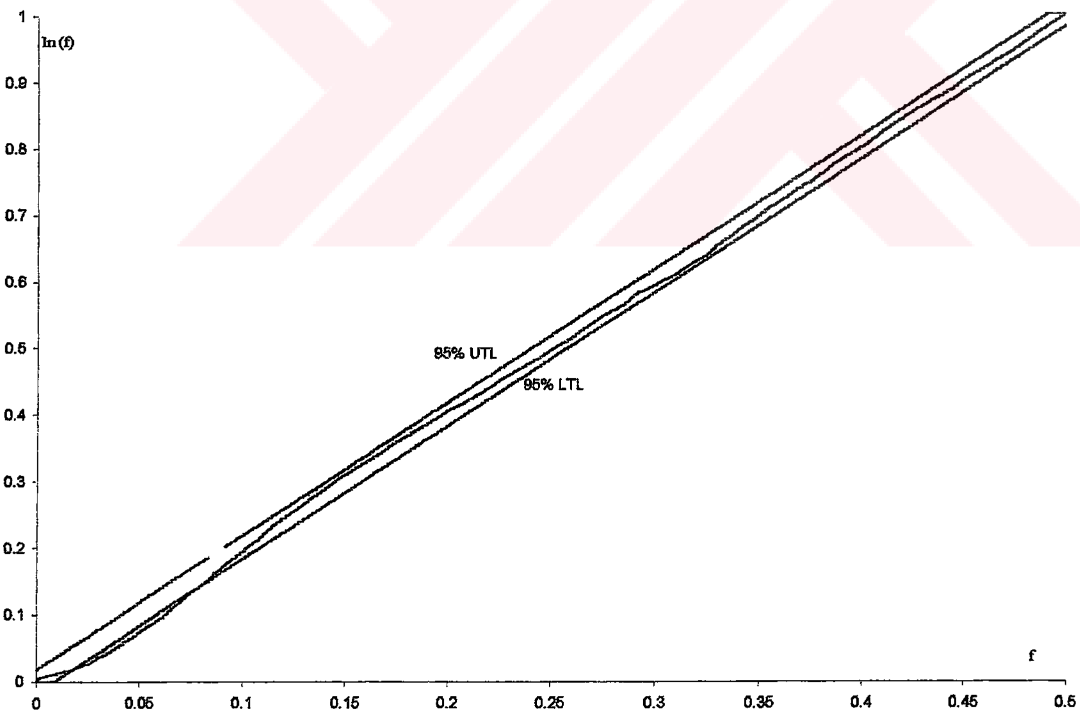

Fig. 5-19: Integrated spectrum of residuals series of AR (3)

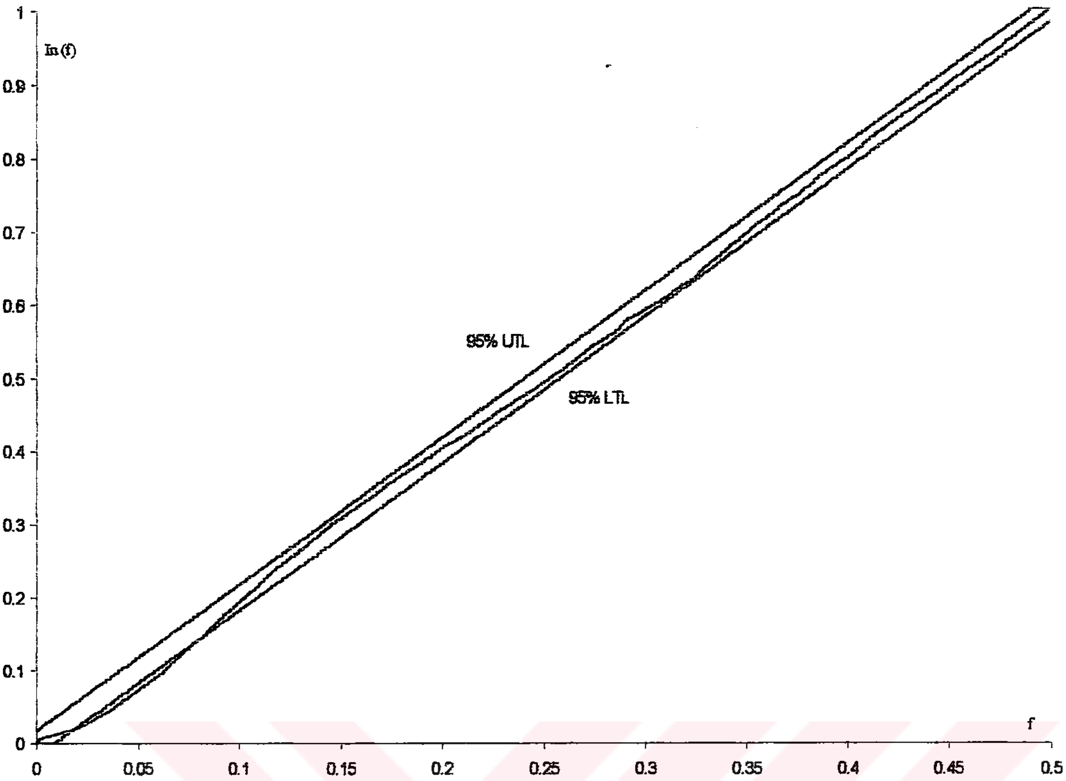

Fig. 5-20: Integrated spectrum of residuals series of AR (3) (least-squares)

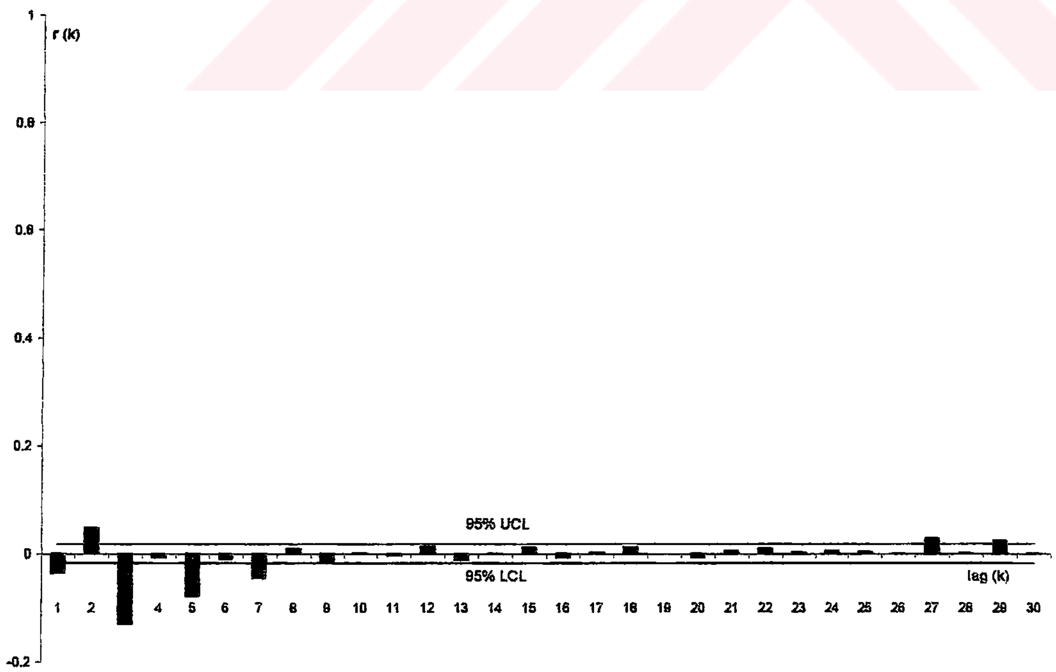

Fig. 5-21: Correlogram of ARMA (2,1) residuals series.

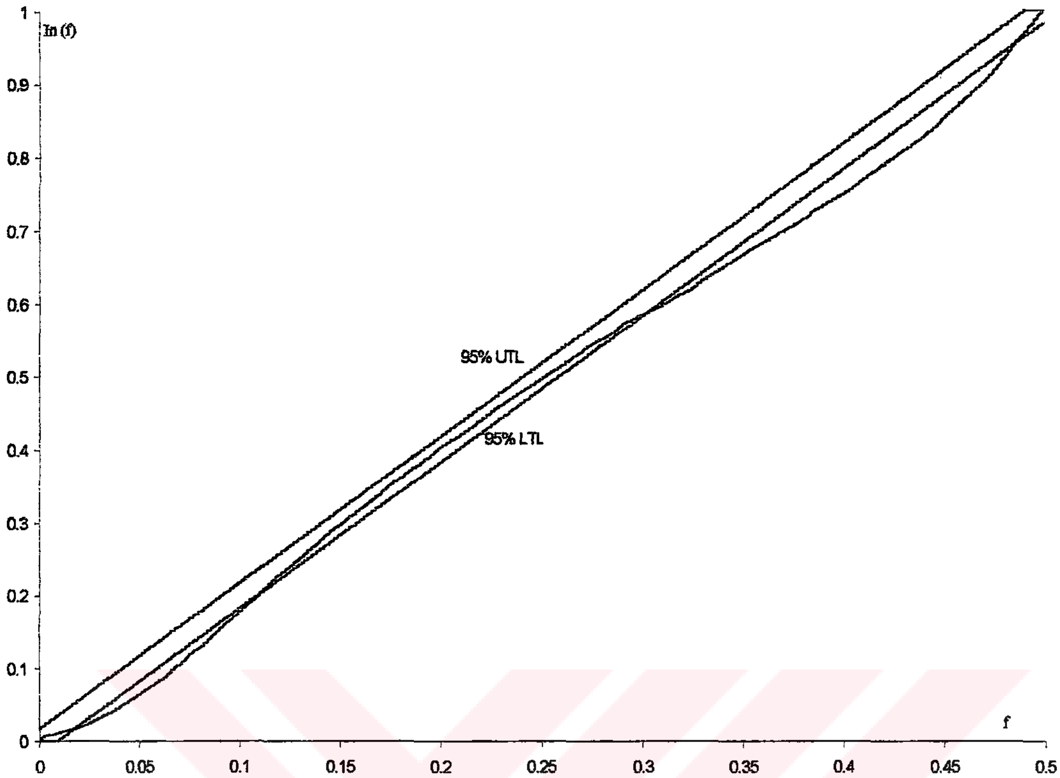

Fig. 5-22: Integrated spectrum of residuals series of ARMA (2,1)

5.6. APPLICATION OF AUTOREGRESSIVE MODELS WITH PERIODIC PARAMETERS

The sample estimates of the seasonal lag-one and lag-two autocorrelations of the log-transformed and standardized $Z_{p,\tau}$ series are shown in Fig. 5-23 and 5-24. In order to check if the log-transformed Kızılgeçit daily flows is nonstationary in the lag-one and/or in the lag-two autocovariances, harmonic analyses of $r_{1\tau}$ and $r_{2\tau}$ of parametrically standardized series $Z_{p,\tau}$ are carried out.

The cumulative periodograms of $r_{1\tau}$ and $r_{2\tau}$ are shown in Fig. 5-25 and 5-26. Both of correlation coefficients are decided that they have 5 significant harmonics. The sample and fitted autocorrelations of both lags are shown in Fig. 5-27 and 5-28.

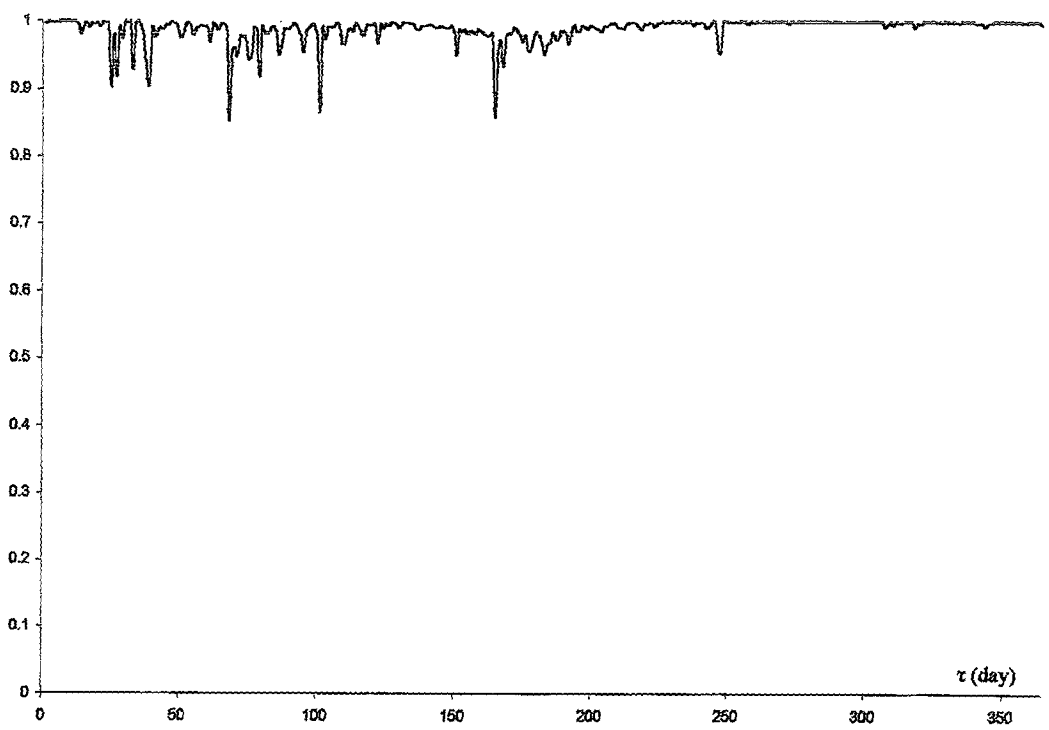

Fig. 5-23 Sample lag-one autocorrelation coefficients

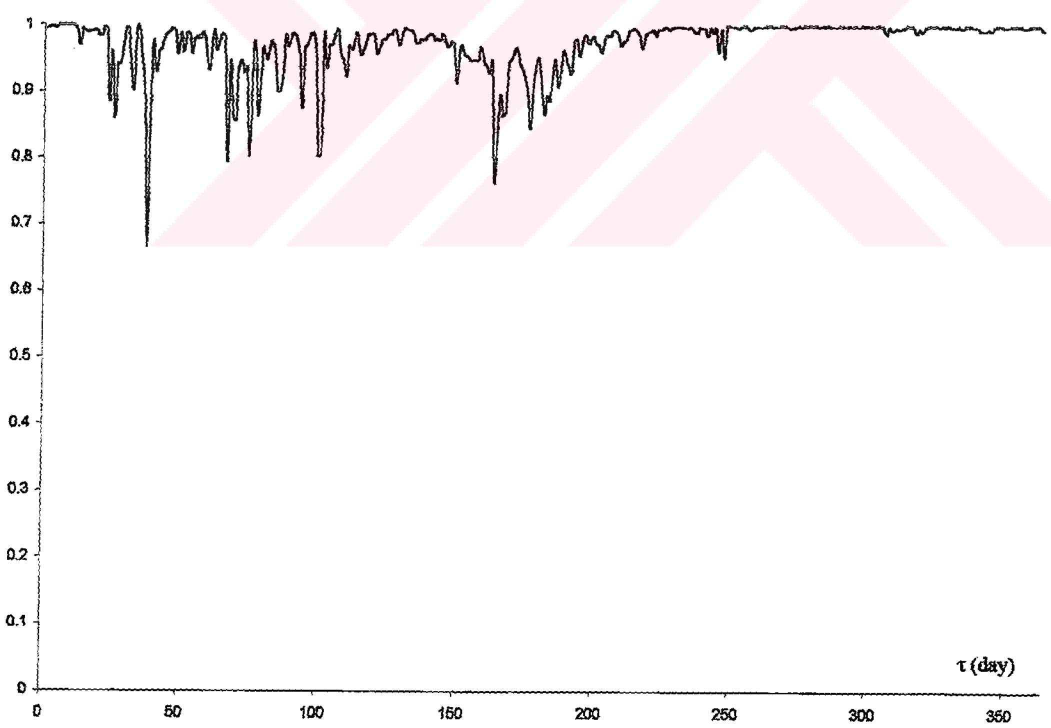

Fig. 5-24 Sample lag-two autocorrelation coefficients

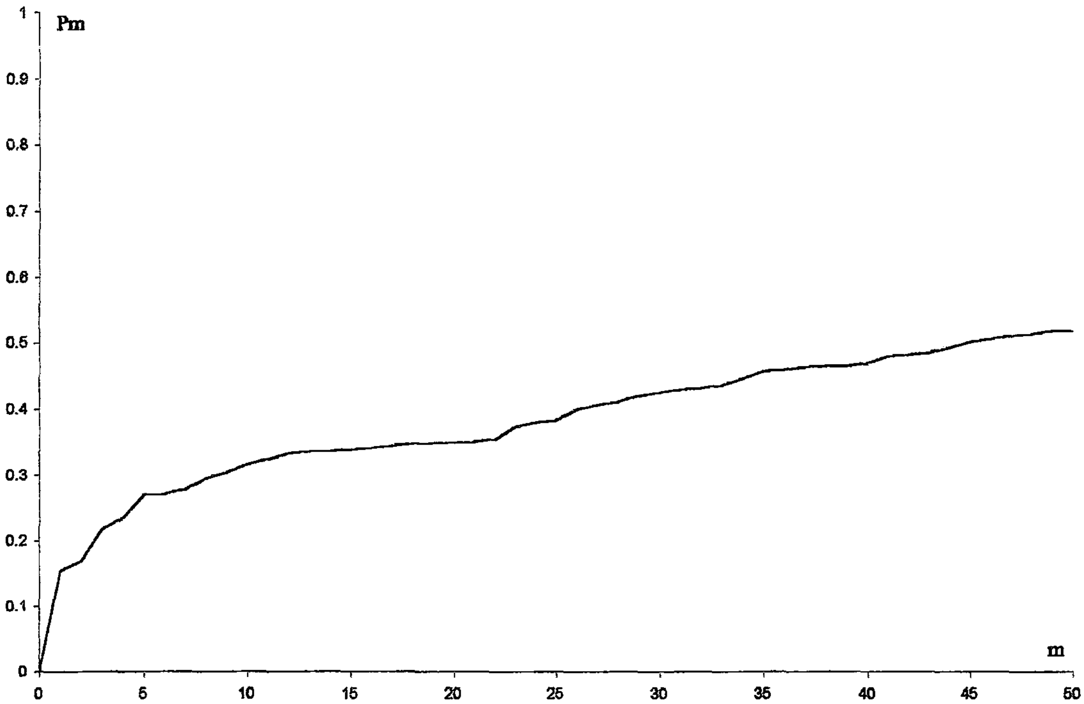

Fig. 5-25 Periodogram of Lag-one Autocorrelation Coefficients

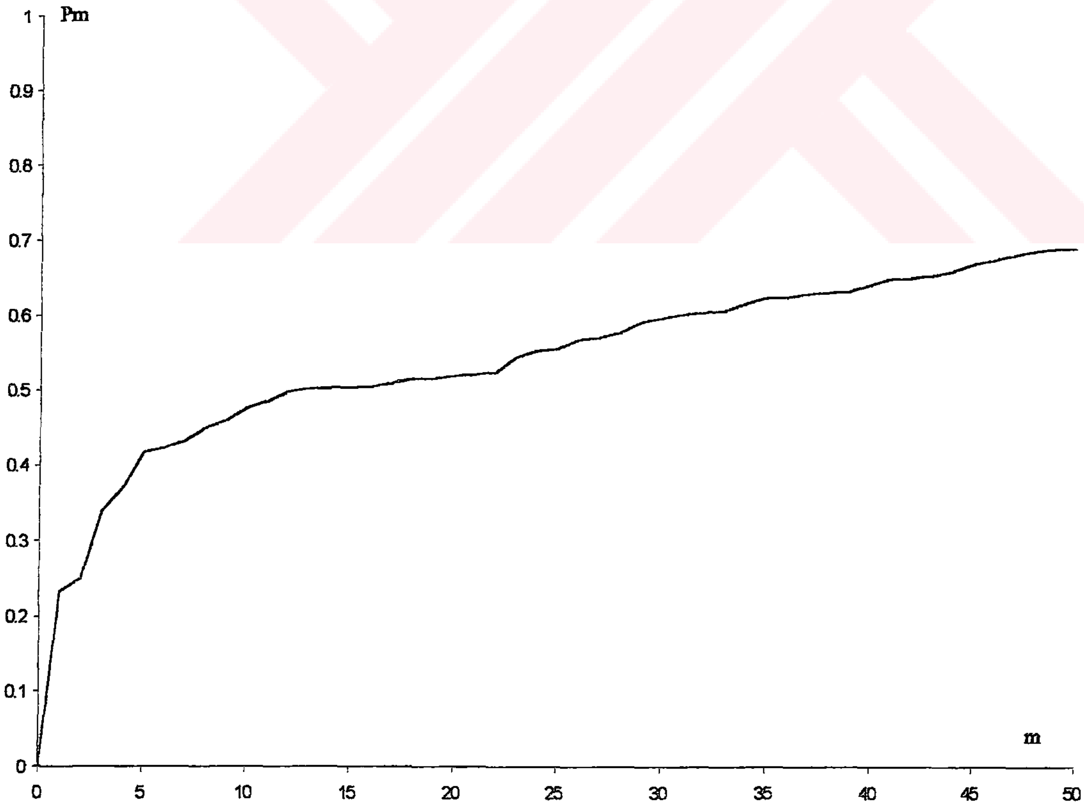

Fig. 5-26: Periodogram of Lag-two Autocorrelation Coefficients

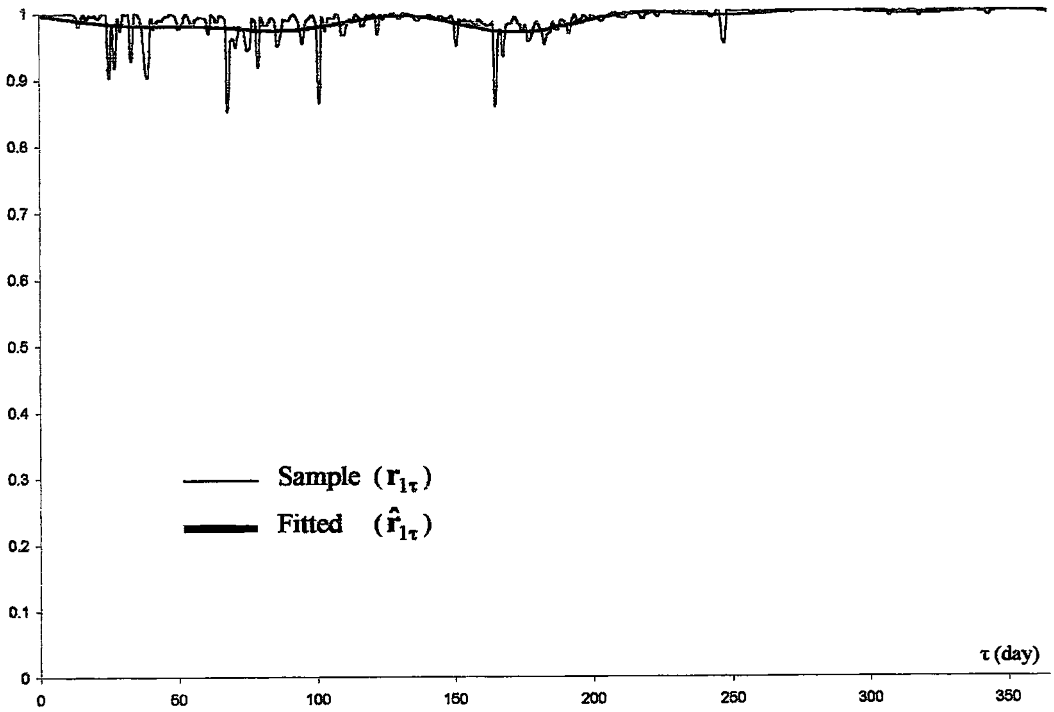

Fig. 5-27 Sample and fitted lag-one autocorrelation coefficients

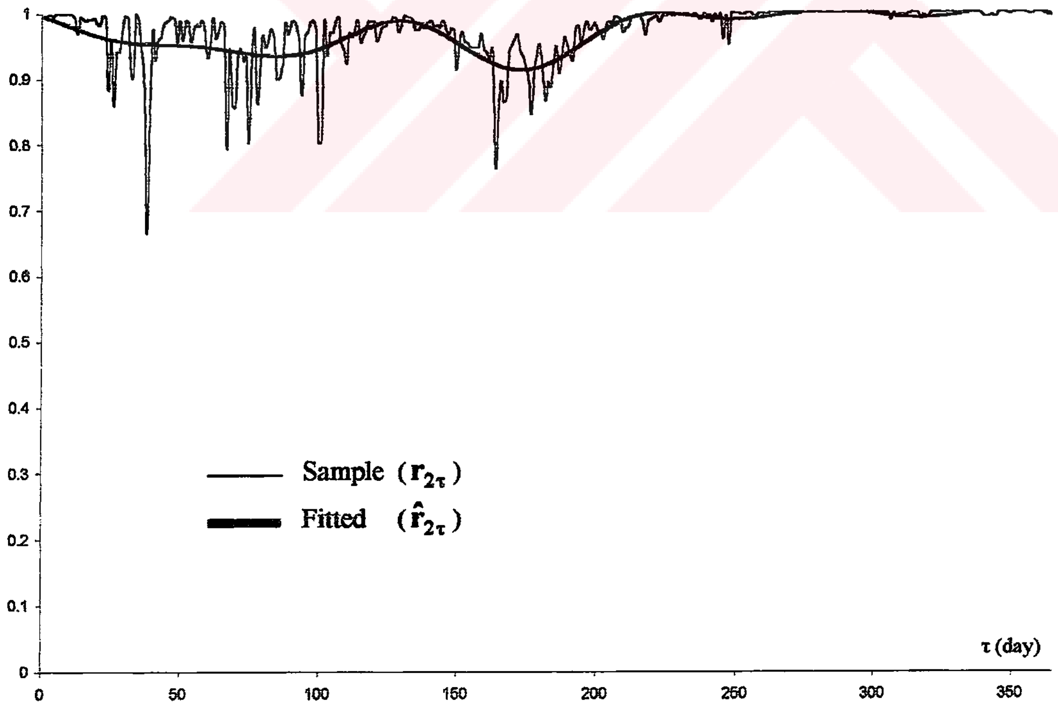

Fig. 5-28 Sample and fitted lag-two autocorrelation coefficients

Initially, the PAR (1) model is applied to $Z_{p,\tau}$ series, and correlogram and integrated spectrum of estimated residuals series are shown in Fig. 5-29 and 5-30 respectively. Both of them are out of the tolerance limits, hence PAR (2) process is examined. Periodic parameters for each 365 days are calculated but some of the days are not satisfied the stationary condition. Because of the inadequacy of PAR (1), and nonstationarity of PAR (2), both models are abandoned.

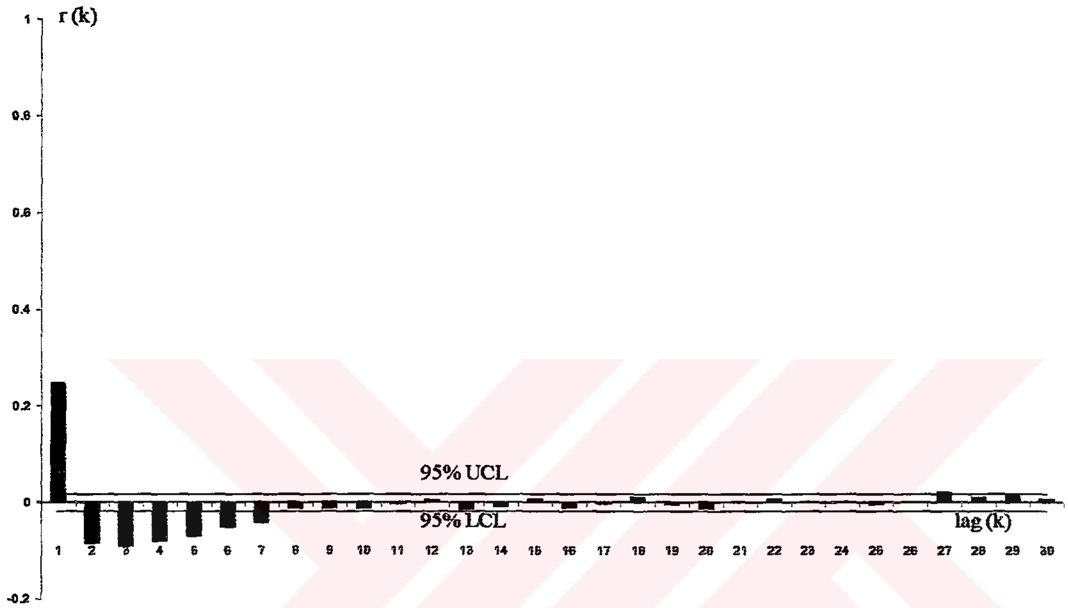

Fig. 5-29: Correlogram of PAR (1) residuals series

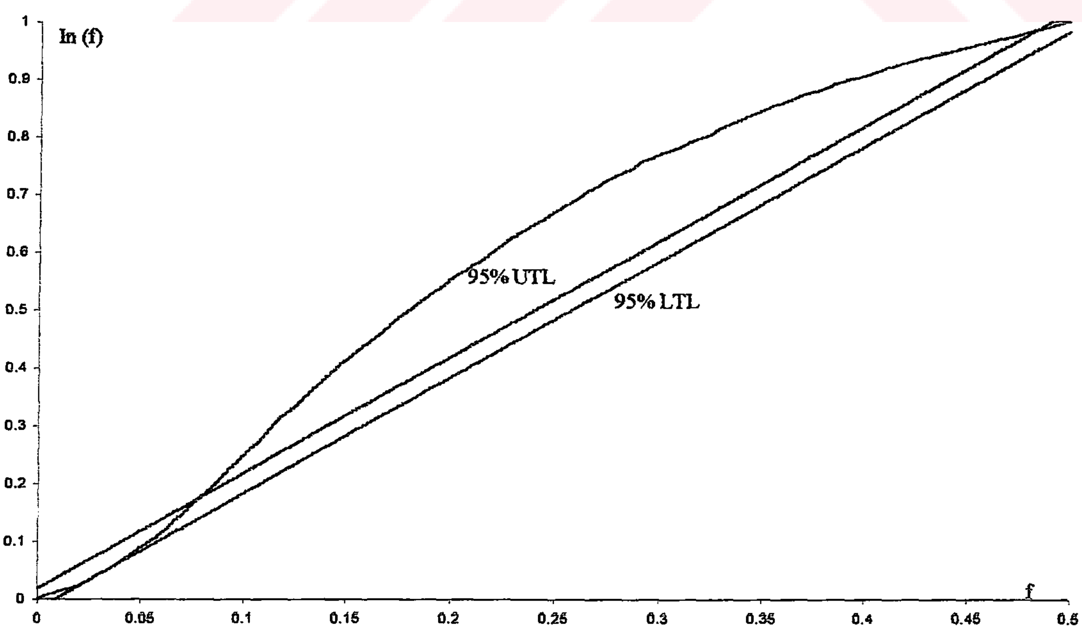

Fig. 5-30: Normalized integrated spectrum of PAR (1) residuals series.

5.7. LINEAR NONSTATIONARY STOCHASTIC MODELS OF KIZILGEÇİT DAILY FLOWS

It is mentioned that Lamas River water potential has somewhat decreased due to allocated and distributed water to urban water supply and irrigation. On the other hand, a drought covering Turkey in the last two decades is also evidently present in the basin, but the actual reason of this decrease is never clarified because of the lack of systematic records of the mentioned water uses (DEU, 1999).

The inadequacy of previously applied linear stationary and periodic stochastic models namely ARMA (p,q) and PARMA (p,q) to Kızılgeçit daily flows leads us to search an evident trend in available data and to the application of linear nonstationary ARIMA (p,d,q) models.

Initially, averages of the monthly flows of five months (from May to September) covering the period 1967-1994 in irrigation season are examined. In Fig. 5-31, the plotted average flows of five months and the fitted trend line are shown. The estimated trend is not significant if the observations in the period 1983-1994 which is a rather dry period are not taken into account.

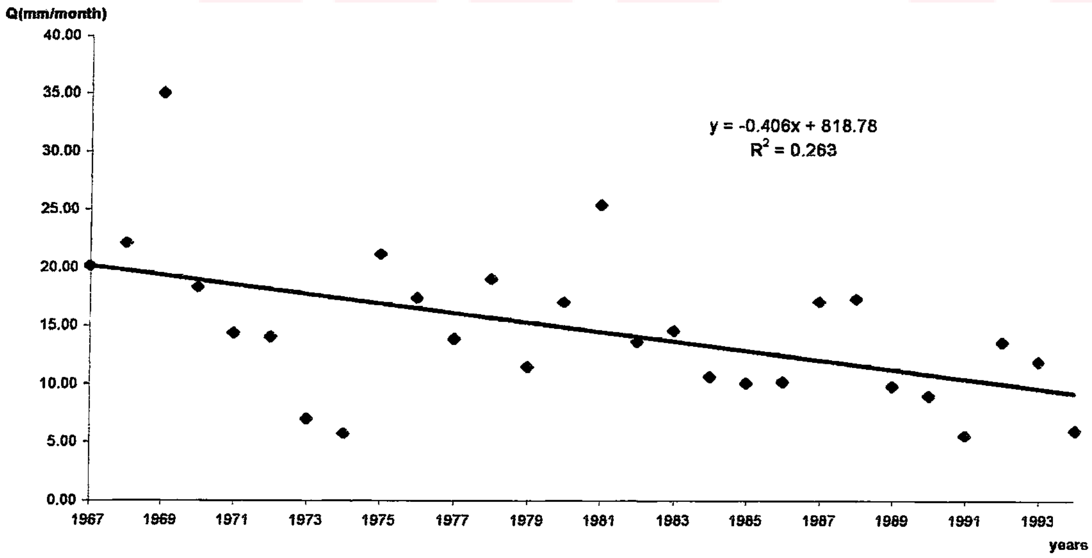

Fig. 5-31: Five monthly average flows of Kızılgeçit SGS (May-September) in between years 1967-1994

The presence of a trend in Kızılgeçit flows is analyzed with double-mass curve, in which cumulative annual runoff totals are plotted against cumulative annual average flows of four SGS's (Denircik-1612, Muhat Köprü-1708, Bucakkışla-1712, Selamlı-1720) in adjacent basins for the common period from 1962 to 1992 (Fig. 5-32). A trend after the year 1982 is detected. The estimated (homogenous) and recorded Kızılgeçit annual flows and their differences are given in Table 5-8.

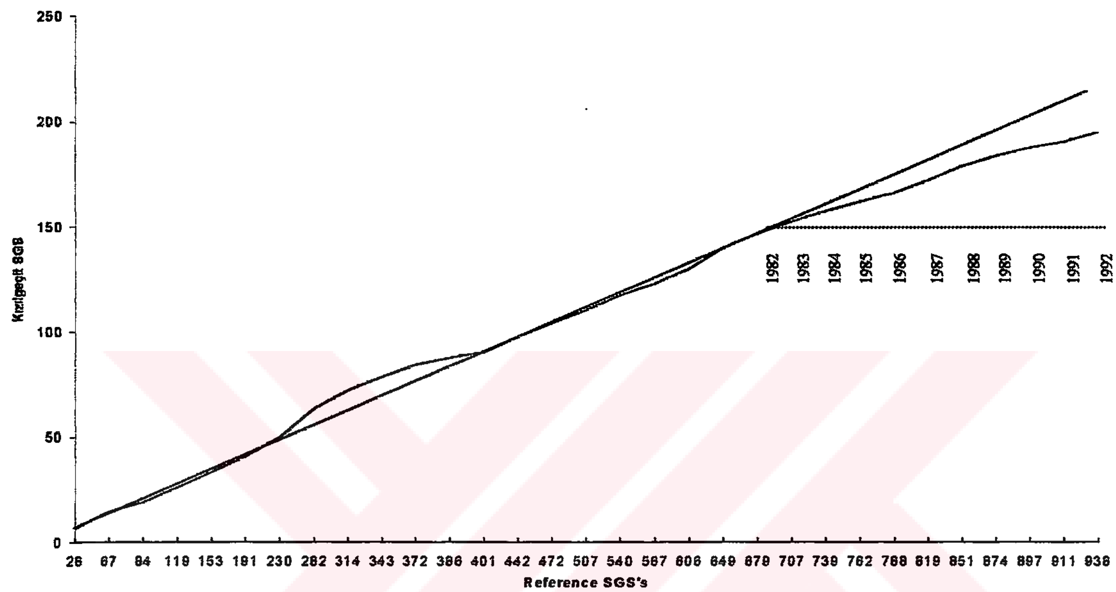

Fig. 5-32: Cumulative double-mass curve of Kızılgeçit and Reference SGSs

Table 5-8: Estimated and recorded yearly average flows and their differences calculated by double-mass curve analysis

Years	Q_{ref} (Cum.)	Q_{KG} (Cum.)	Q_{KG} (recorded)	Q_{ref} (average)	Slope (tg α)	Estimated Q_{KG}	Difference
83	707.4	152.1	5.85	28.2	0.215	6.05	0.20
84	738.9	156.9	4.89	31.5	0.215	6.77	1.88
85	762.4	161.5	4.51	23.5	0.215	5.04	0.53
86	788.5	165.9	4.45	26.1	0.215	5.61	1.16
87	818.9	171.6	5.69	30.5	0.215	6.55	0.86
88	850.9	178.2	6.57	32	0.215	6.89	0.32
89	874.1	183.1	4.89	23.2	0.215	4.98	0.09
90	896.7	187.1	4.04	22.6	0.215	4.85	0.81
91	911	189.8	2.72	14.4	0.215	3.08	0.36
92	938.4	194.4	4.62	27.4	0.215	5.9	1.28

The presence of a trend especially after the year 1982 is obvious, but water consumption for rural and irrigation purposes is not solely responsible of that nonhomogeneity. On the other hand, if it were assumed that present trend were due to diverted water from the river, it would also be hard to remove it from the recorded Kızılgeçit flows because of the lack of the systematic records of water uses.

Regarding that, the ARIMA (p,d,q) models has the capability in removing deterministic components, so this type of models has also been examined. The differencing operation (Sec. 3.6.3) is applied for lag-one (d=1) to the log-transformed Kızılgeçit daily flows and the correlogram of the obtained u_t series is shown in Fig. 5-33. ARIMA (0,1,2), ARIMA (2,1,1) and ARIMA (3,1,0) models are fitted to the u_t series and their parameters estimated by maximum likelihood method are given in Table 5-9. The correlograms and integrated spectrums of the residuals series of applied ARIMA (p,d,q) models are shown in Fig. 5-34 thru 5-39.

Table 5-9: Alternative ARIMA (p,d,q) models

Parameters	**Alternative Models**		
	ARIMA (0,1,2)	**ARIMA (2,1,1)**	**ARIMA (3,1,0)**
α_1	---	0.82976	0.34984
α_2	---	-0.2783	-0.1393
α_3	---	---	-0.0159
θ_1	–0.3525	0.49313	---
θ_2	0.0035	---	---

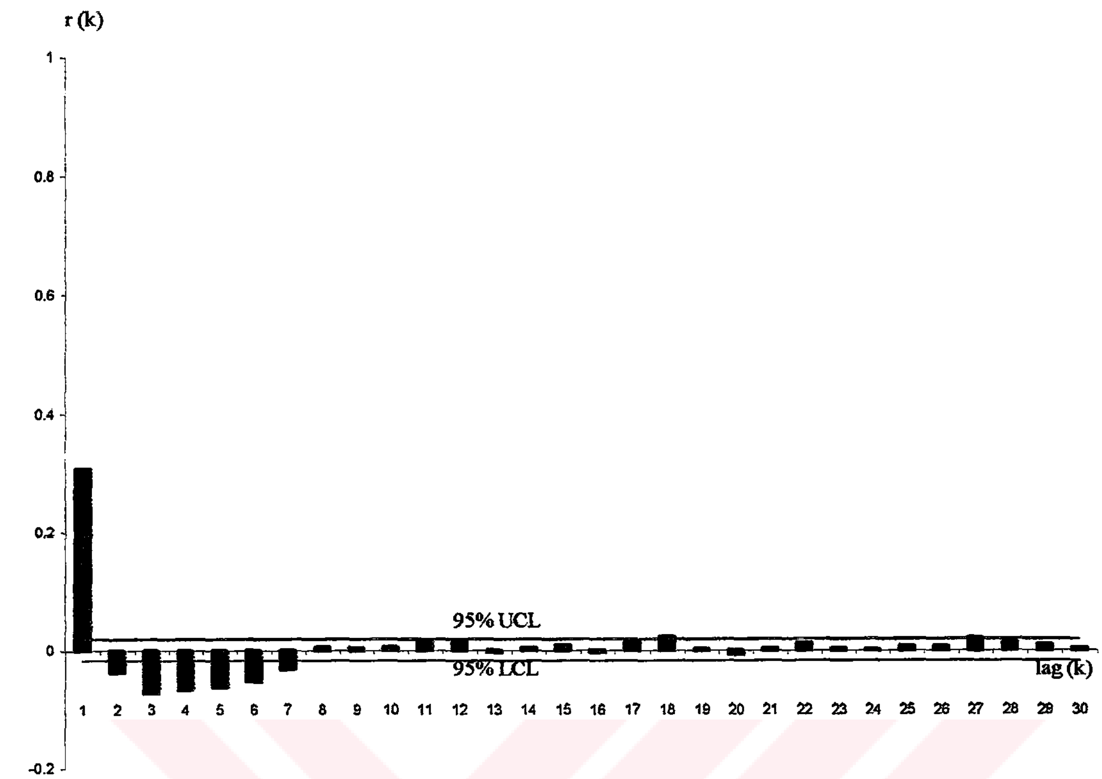

Fig. 5-33: Correlogram of u_t series

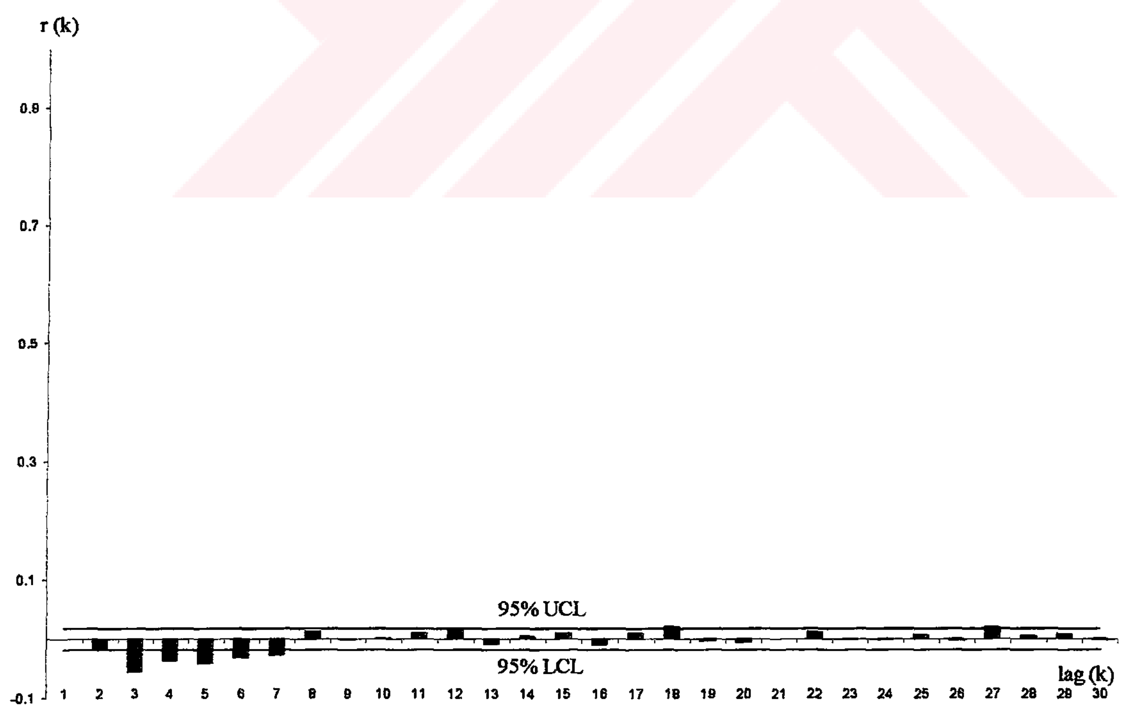

Fig. 5-34: Correlogram of ARIMA (0,1,2) residuals series

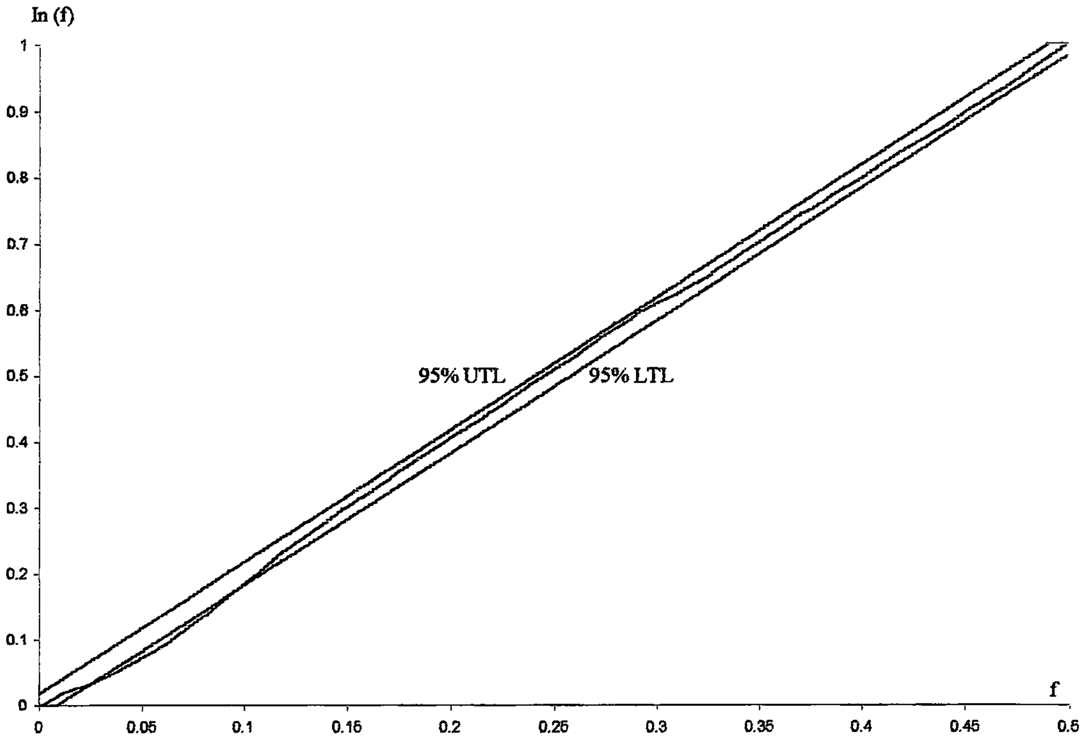

Fig. 5-35: Normalized integrated spectrum of ARIMA (0,1,2) residuals series.

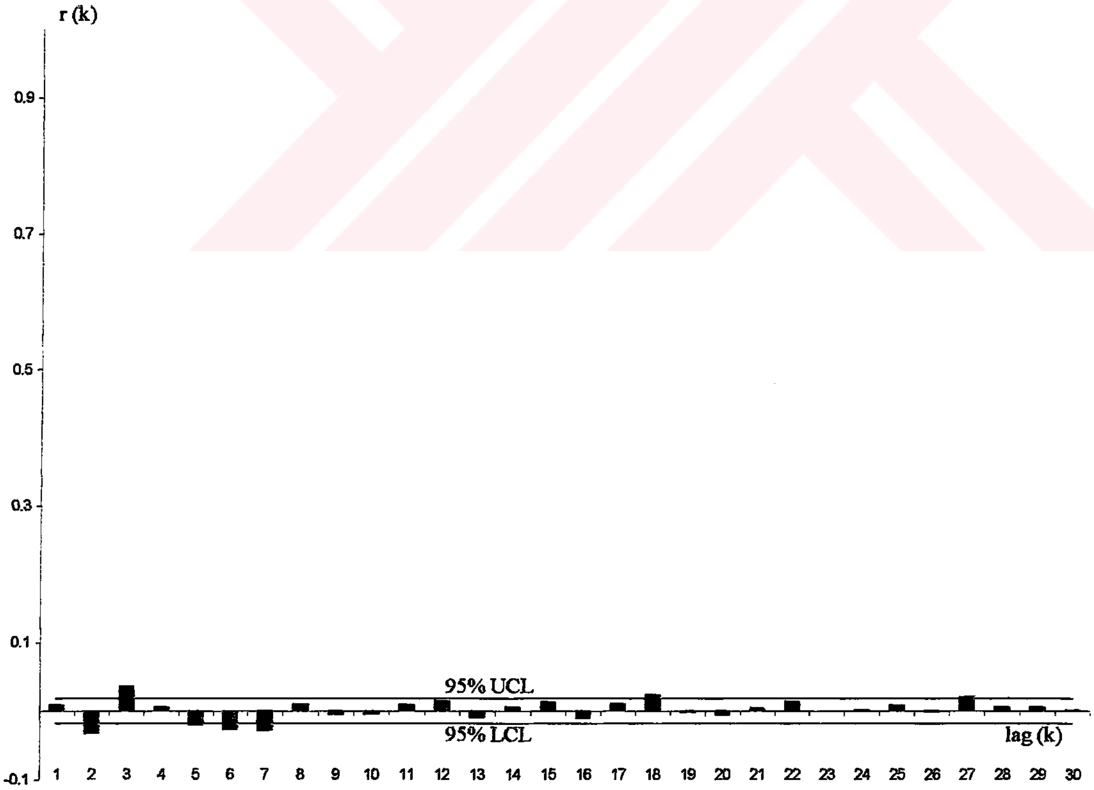

Fig. 5-36: Correlogram of ARIMA (2,1,1) residuals series

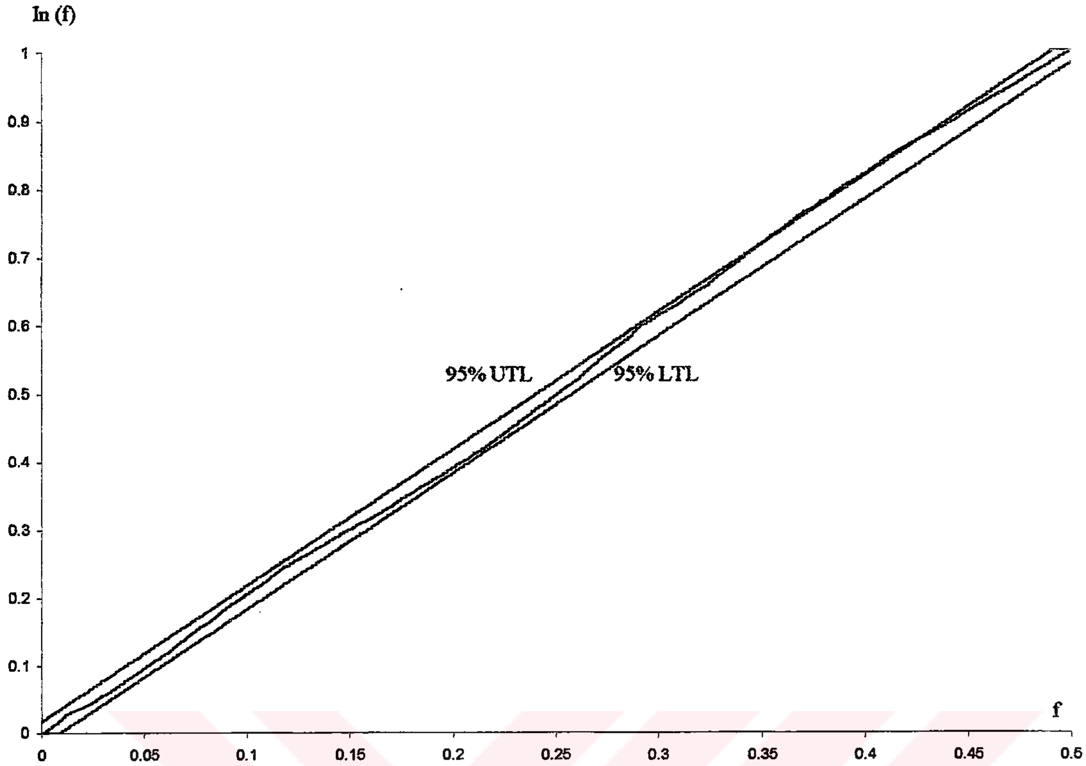

Fig. 5-37: Normalized integrated spectrum of ARIMA (2,1,1) residuals series.

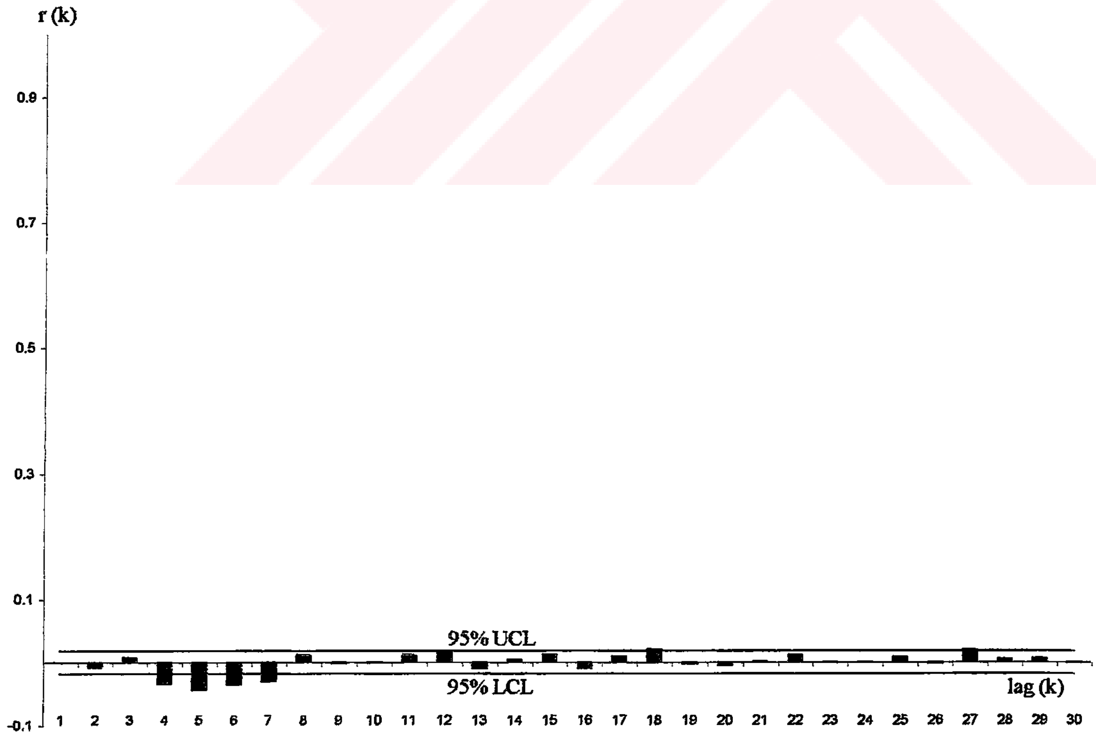

Fig. 5-38: Correlogram of ARIMA (3,1,0) residuals series

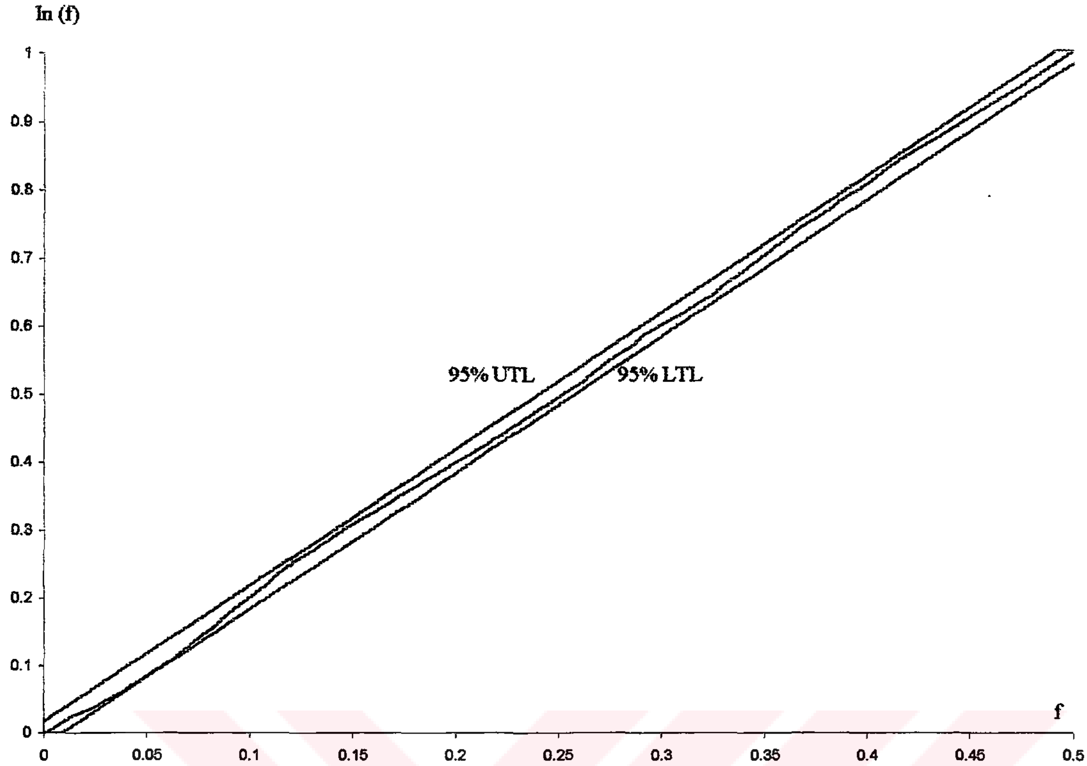

Fig. 5-39: Normalized integrated spectrum of ARIMA (3,1,0) residuals series.

The integrated spectrum of residuals series of ARIMA (0,1,2) model is out of the tolerance limits in lower frequencies, while the spectrum of the residuals series of ARIMA (2,1,1) is out of the tolerance limits in higher frequencies. The integrated spectrum of residuals series of ARIMA (3,1,0) model is totally within th 95% tolerance limits. Hence, ARIMA (3,1,0) model can adequately represent the Kızılgeçit daily flows and it can be used for forecasting purposes during the operation of planned diversion power plants. Unfortunately it is impossible to use these kinds of models in synthetic data generation.

CONCLUSION

In this study linear stationary and nonstationary stochastic models of Lamas River daily flows at Kızılgeçit are investigated. The adequacy of the applied models is tested with correlograms and normalized integrated spectrums of residuals series at 95% confidence limits.

In order to build mathematical model of daily flows at Kızılgeçit following steps has been followed.

1) The daily flows are generally highly skewed. In order to reduce the skewness of observed data, a natural logarithmic transformation has been applied. The skewness coefficients have been reduced and a close to normal series has been obtained.

2) It has been found that the mean flows and standard deviations of Kızılgeçit daily flows can sufficiently be explained with 6 harmonics for each.

3) It has been revealed that the stochastic components obtained by parametric standardization, cannot be adequately represented by linear stationary models such as AR(2), AR (3), AR (4) and ARMA (2,1). It is probable that the reason of inadequacy of this kind of models might be the downward trend in Lamas River daily flows.

4) Through the analysis of five monthly average flows in irrigation season, it has been decided that in 1983 and following years a downward

trend exists due to excess water use and the drought during last ten years. The cumulative double-mass curve analysis with four stream gauging stations in the adjacent basins has indicated the presence of a decrease in Kızılgeçit daily flows. The differences between estimated (homogenous) and observed flows are varying order of magnitude from one year to another.

5) In order to take the existing trend into account, linear nonstationary models such as ARIMA (0,1,2), ARIMA (2,1,1), and ARIMA (3,1,0) have been applied to the log-transformed daily flows at Kızılgeçit. Among these models, the ARIMA (3,1,0) model has been decided as the most satisfactory one in representing the characteristics of Kızılgeçit daily flows.

6) Unfortunately, because of the downward trend none of the alternative linear stationary stochastic models is applicable, and therefore synthetic data generation is impossible. The proposed ARIMA (3,1,0) model can be successfully used for forecasting purpose during the operation of proposed water resource projects in the basin.

7) This study has reminded us of that observing the flows of a river is not solely sufficient; the allocated and diverted water from the basin for varying purposes such as urban water supply and irrigation must be also monitored. This monitoring activity may allow estimating the existing nonhomogeneities and inconsistencies in observed flows.

REFERENCES

Box, G. E. P., Jenkins, G. M. (1976). Time Series Analysis, Forecasting and Control. San Francisco: Holden Day.

Clossimo, C., Copertino, V.A., D'Ippolito, G. (1988). Computer Methods and Water Resources-Computational Hydrology: Computational Mechanics Publications, Springer-Verlag, Stochastic Modeling of the Daily Flows in the River Crati, Southern Italy

DEU (1985). Mersin – Limonlu havzası Lamas hidroelektrik santralları (IIIA, B;IV) yapılabilirlik etüdü hidroloji raporları, Cilt I: Genel Su Poatansiyeli. İzmir, DEÜ Mühendislik Fakültesi İnşaat Mühendisliği Bölümü

DEU (1986). Mersin – Limonlu havzası Lamas hidroelektrik santralları (I ve II) yapılabilirlik etüdü hidroloji raporu. İzmir, DEÜ Mühendislik Fakültesi İnşaat Mühendisliği Bölümü

DEU (1996). Mersin – Limonlu havzası Lamas hidroelektrik santralları (III ve IV) yapılabilirlik etüdü revize hidroloji raporları, Cilt I: Genel Su Poatansiyeli. İzmir, DEÜ Mühendislik Fakültesi İnşaat Mühendisliği Bölümü

DEU (1999). Mersin – Limonlu havzası Lamas hidroelektrik santralları (I ve II) yapılabilirlik etüdü revize hidroloji raporu. İzmir, DEÜ Mühendislik Fakültesi İnşaat Mühendisliği Bölümü

Fernandez, B., Salas, J. D. (1986). Periodic Gamma Autoregressive Processes for Operational Hydrology. Water Resources Research, 22, 10, 1385-1396

Green, N.M.D. (1973). A Synthetic Model for Daily Streamflow. Journal of Hydrology, 20, 351-364

Hall, M. J., O'Connell, P.E. (1972). Time Series Analysis of Mean Daily River Flows. Water and Water Engineering, April, 125-133

Jenkins, G. M., Watts, D. G. (1968). Spectral Analysis and its Applications. San Francisco: Holden-Day Series in Time Series Analysis

Kelman, J. (1980). A Stochastic Model for Daily Streamflow. Journal of Hydrology, 47, 235-249

Keloğlu, N (1974). Manavgat Irmağı Günlük Akımlarının Modelleri. Yüksek Lisans Tezi. Yön. Doç. Dr. Ünal Öziş. İzmir: Ege Üniversitesi Mühendislik Bilimleri Fakültesi İnşaat Mühendisliği Bölümü

Lu, Z.Q., Berliner, L.M. (1999). Markov switching time series models with application to a daily runoff series. Water Resources Research, 35, 2, 523-534

Mitosek, H. T. (2000). On stochastic properties of daily river flow processes. Journal of Hydrology, 288, 188-205

Quimpo, R. G. (1967). Stochastic Model of Daily River Flow Sequences. Hydrology Papers Colorado State University, 18

Rasmussen, P. F., Salas, J. D., Fagherazzi, L., Rassam, J. C., Bobée, B. (1996). Estimation and validation of contemporaneous PARMA models for streamflow simulation. Water Resources Research, 32, 10, 3151-3160

Salas, J. D., Delleur, J. W., Yevjevich, V., Lane, W. L. (1985). Applied Modeling of Hydrologic Time Series (2nd Edition). Littleton, Colorado: Water Resources Publications

Salas, J. D., Obeysekera, J. T. B., Smith, R. A. (1981). Identification of streamflow stochastic models. ASCE Journal of Hydraulics Division, 107, HY7, 853-868

Vargas-Semprun, D. (1977). On the Stochastic Modeling of Daily Streamflows. Ph. D. Thesis, Fort Collins, Colorado: Colorado State University

Yakowitz, S.J. (1979). A Nonparametric Markov Model for Daily River Flow. Water Resources Research, 15, 5, 1035-1043

Yevjevich, V. (1972a). Structural Analysis of Hydrologic Time Series. Hydrology Papers Colorado State University, 56

Yevjevich, V. (1972b). Stochastic Processes in Hydrology. Fort Collins, Colorado: Water Resources Publications

Yevjevich, V., Jeng, R. I. (1967). Effects Of Inconsistency and Non-Homogeneity on Hydrologic Time Series. International Hydrology Symposium Fort Collins, Colorado, Proceedings Vol I, 451-458

Yevjevich, V., Obeysekera, J. T. B. (1985). Effects of Incorrectly Removed Periodicity in Parameters on Stochastic Dependence. Water Resources Research, 21, 5, 685-690