TIME SERIES MODELING AND DROUGHT FREQUENCY ANALYSIS FOR THE ANNUAL RAINFALL OF NORTH CYPRUS

A THESIS SUBMITTED TO
THE BOARD OF GRADUATE PROGRAMS
OF
MIDDLE EAST TECHNICAL UNIVERSITY, NORTHERN CYPRUS CAMPUS

BY

NAZLICAN YÜCEL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN SUSTAINABLE ENVIRONMENT AND ENERGY SYSTEMS PROGRAM

SEPTEMBER 2021

Approval of the Board of Graduate Programs

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ABSTRACT

TIME SERIES MODELING AND DROUGHT FREQUENCY ANALYSIS FOR THE ANNUAL RAINFALL OF NORTH CYPRUS

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September 2021, 177 pages

Cyprus which is the third biggest island in the Mediterranean Sea is located in the south of Turkey. The island has a semi-arid climate The rainfall is the main source of the island, therefore, the analysis of existing rainfall data across the island has vital importance for a better sustainable water resource management. In this study, annual rainfall data of 33 meteorological stations across North Cyprus were used. The main objectives of the study are modeling the annual observed rainfall of North Cyprus by using ARIMA models and finding the return period of the most critical historical drought events by using ARIMA models. As a result, low order ARIMA models were generally found suitable for North Cyprus annual rainfall data. Also, for average annual North Cyprus rainfall, the return period of the most severe drought event with severity of 406.3 mm, was found as 63 years. For the four sub-regions of North Cyprus namely, the West part of North Cyprus, North Coast and Mesaria Plain, Central Mesaria Plain, and West Coast and Karpas Peninsula, the return periods of the most severe droughts with the severity of 572.4 mm, 319.5 mm, 319.8 mm, and 555.1 mm, were obtained as 137 years, 26 years, 40 years, and 116 years, respectively. These results will be very beneficial for the sustainable water resource management of North Cyprus. Important precautions can be taken to minimize the devastating effects of climate change by the related government authorities.

Keywords: ARIMA, Rainfall, North Cyprus, Sustainable Water Resource Management, Drought Frequency Analysis

ÖZ

KUZEY KIBRIS YILLIK YAĞIŞLARININ ZAMAN SERİSİ MODELLEMESİ VE KURAKLIK FREKANS ANALİZİ

Yücel, Nazlıcan
Yüksek Lisans, Sürdürülebilir Çevre ve Enerji Sistemleri
Tez Yöneticisi: Dr. Öğrt. Üyesi Bertuğ Akıntuğ

Eylül 2021, 177 Sayfa

Kıbrıs Türkiye'nin güneyinde bulunan, Akdeniz'in üçüncü en büyük adasıdır ve yarı kurak iklime sahiptir. Adanın ana su kaynağı yağmur olduğu için, adada hali hazırda bulunan ve Türkiye'den gelen su kaynaklarının sürdürülebilir bir şekilde kullanılması büyük önem arz etmektedir. Bu çalışmada, Kuzey Kıbrıs genelinde 33 meteoroloji istasyonunda gözlemlenen yıllık yağış verileri kullanılmıştır. Bu çalışmanın temel amaçları, ARIMA modelleri kullanarak Kuzey Kıbrıs'ta gözlemlenen yıllık yağışların modellemesi ve bu modelleri kullanarak en kritik tarihsel kuraklığın geri dönüş periyodunun bulunmasıdır. Sonuç olarak, genellikle düşük değerli ARIMA modellerin bu veriye uygun olduğu bulunmuştur. Ayrıca, Kuzey Kıbrıs genelinde şiddeti 406.3 mm olarak hesaplanan en şiddetli kuraklığın geri dönüş periyodu 63 yıl olarak hesaplanmıştır. Kuzey Kıbrıs'ın Batı kesimi, Kuzey kıyısı ve Mesarya Ovası, Orta Mesarya ve Karpaz Yarımadası için en şiddetli kuraklıkların geri dönüş süreleri sırasıyla 572.4 mm ile 137 yıl, 319.5 mm ile 26 yıl, 319.8 mm ile 40 yıl ve 555.1 mm ile 116 yıl olarak bulunmuştur. Tüm bu sonuçlar, Kuzey Kıbrıs'ın sürdürülebilir su kaynakları yönetimi için çok faydalı olacak ve iklim değişikliğinin yıkıcı etkilerini en aza indirmek için devlet yetkilileri tarafından önemli önlemler alınabilmesine yardımcı olacaktır.

Anahtar Kelimeler: ARIMA, Yağmur, Kuzey Kıbrıs, Sürdürülebilir su kaynakları yönetimi, Kuraklık frekans analizi

To My Family

This thesis is dedicated to my beloved grandparents, Turkan Algan, and Irfan Algan, who raised me. Although they did not have formal education, they always inspired me and shared their wisdom and encouragement to study.

ACKNOWLEDGMENTS

From the bottom of my heart, I would like to thank the following people whose assistance was a milestone in the completion of this master thesis. This success is attributed to many people because my completion of this thesis could not have been accomplished without their understanding, encouragement, and support.

Foremost, I would like to pay my special regards to my supervisor, Asst. Prof. Dr. Bertuğ Akıntuğ, for his dedicated support and enthusiasm during the running of this thesis. He continuously encouraged and helped me not only regarding my thesis but also in other academic topics with his extensive knowledge and precious experiences. I do not know how to thank him enough for allowing me to work on this topic and complete my master's degree successfully.

Secondly, I would like to thank my all instructors in the Sustainable Environment and Energy System program who helped me to improve my skills and knowledge in different ways by teaching interdisciplinary courses. Also, I would further thank the Meteorological Office of Northern Cyprus for sharing data with me.

Thirdly, I am extremely grateful to my lovely family for their continued patient, support, and motivating approach during my master's journey. My parents Nejla Yücel and Ergün Yücel, my one and only sister Berfin Yücel always gave me the strength to be successful in this work. Also, I wish to express my deepest gratitude to my grandparents Türkan Algan and Irfan Algan for their prayers, valuable support, and unique love.

In addition, I would like to present my appreciation to the Economics department of METU NCC which gave me an opportunity to work as a teaching assistant as a part of the scholarship to afford my tuition fee.

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LIST OF ABBREVIATIONS

ABBREVATIONS	
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller Test
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
DHF	Dickey-Hasza-Fuller
ETS	Exponential Smoothing State Space
FGN	Fractional Gaussian Noise
HSM	Hidden State Markov
KNN	K-nearest neighbor
KNNR	K-nearest neighbor-based time resampling
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LMC	Leybourne-McCabe
MA	Moving Average
MJRS	Mejia-Rouselle
MUDRAIN	Multivariate Disaggregation Rainfall
NC	Northern Cyprus

PACF	Partial Auto Correlation Function
PAR	Periodic Autoregressive
PARMA	Periodic Autoregressive Moving Average
SARIMA	Seasonal Autoregressive Integrated Moving Average
SBC	
SPI	Schwartz-Bayesian Criterion
	Standard Precipitation Index
SPIGOT	Synthetic Streamflow Generation Software Package
SWRM	Sustainable Water Resource Management
TRNC	Turkish Republic of Northern Cyprus
VLSH	Valencia-Schaake
WRF	Weather Research and Forecasting
WRM	Water Resource Management

CHAPTER 1

INTRODUCTION

Sustainability plays a significant role on the Earth for a long time. However, it became a necessity for the welfare of all living creatures for today and in the future, since it aims to meet the demands of all creatures today without making the future generations worse off (Loucks, 2000). The sustainability concept includes three main pillars that are environment, economy, and society (Duran et al., 2015), and all of them are connected. Especially water resources sustainability as a part of environmental sustainability became one of the critical issues in the last decades. Water resources started to be depleted because of the climate change impacts and increasing demand for water caused by population increase. Besides, climate change, having insufficient information, and making wrong decisions about water resources may affect water demand and supply negatively (Uba & Bakari, 2015). So, nowadays, managing water resources in a sustainable manner gains more significance especially for the countries where the main source of water is only rainfall like North Cyprus. For a better water resources management (WRM), analysis of rainfall is essential, especially in arid areas (Dastorani et al., 2016) because it is known that rainfall is one of the significant components of the hydrologic cycle and it plays a vital role for all living creatures all around the world (Papalaskaris et al., 2016).

Although the times series are generally used in finance and statistics (Maina et al., 2019), time series modeling also became one of the most important and effective techniques for decision making of hydrological elements, simulation, data generation, and forecasting (Dastorani et al., 2016). A time series is an observed data sequence that is represented in time order and it has two components which are deterministic (physical) and stochastic (statistical) (Dabral et al., 2016). Salas et al. (1988) mentioned that while the deterministic approach follows the representation of the hydrologic system with physical relationships, the stochastic approach aims to assume a model which represents the most related statistical properties of the historical time series. Once the historical hydrologic time series data are available, some future scenarios can be predicted using time series models. Although the time series variables are assumed to be independent and identically distributed, they might not be indeed, and they might include some pattern in the long period. So, applying time series modeling for predictions gives values to the actual ones. (Adhikari K. & R.K., 2013). That is why the results of many studies in the literature indicate that the stochastic time series models are useful and appropriate to represent and forecast the precipitation data. There are several types of these models such as Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Markov Switching models, and transfer function noise modeling. (Dastorani et al., 2016). One of the most common and popular stochastic time series models is the ARIMA model, which includes AR, MA, and integration (I) processes. According to Adhikari & Agrawal (2013), this is the most preferable model among several stochastic time series models because it represents the time series in a simple form, builds the most appropriate model by using Box-Jenkins methodology and its implementation is understandable. So, one of the important objectives of this study is modeling the annual rainfall of North Cyprus by using ARIMA models.

In hydrology, in most cases, regional and sub-regional hydrologic analyses are required. In order to find which rainfall station will be the member of a region or sub-region, clustering methodologies are used. In this study, clustering methodologies that consider the characteristic of time series are employed.

In practice, after finding the orders of the ARIMA model for a given time series, the parameters of the model are estimated and very long synthetic series that have the same statistical properties as the original data can be generated (Mirakbari et al., 2010, as cited in Ganji et al.,2001). Generated series provides a large number of scenarios, so detecting possible extreme events and calculating their exceedance probabilities and return periods can be possible.

In addition to ARIMA modeling, the disaggregation approach is a commonly used stochastic approach in hydrologic time-series analyses. The main importance of the disaggregation models is preserving the historical statistics at more than one level (Salas, 1988). For instance, if the monthly data are modeled directly, annual statistics may not be preserved. However, after modeling annual data, it can be disaggregated into the monthly time series by using the disaggregation approach and this monthly data preserves the statistical properties at both seasonal and annual levels.

In statistical and stochastic hydrology, drought frequency analysis is one of the most common applications and this application is very important in water resource management practices for all countries. When historical hydrologic time series are used together with stochastic time series models, the frequency of historical drought parameters such as duration, severity, and magnitude can be obtained (Tallaksen, 2000). Without knowing the frequency or in other words the return period of extreme drought events, the sustainable management of water resources is not possible under changing climate.

1.1 Motivation

Water is a very fundamental natural resource for all living organisms on this planet. Especially, freshwater is one of the most challenging issues all around the world. Water demand has been increasing gradually in the regions which have semi-arid and arid climates especially. In those regions, such as North Cyprus, water supply is not sufficient to fulfill water demand because existing water resources and annual rainfall amounts are restricted. In the last two decades, these regions suffer from extreme events such as droughts, floods, heatwaves, etc. because of climate change and these events have a direct role in water resources management (WRM). Rainfall is one of the most important climate factors for human-being and the hydrological cycle. It is also very valuable for the countries where the main source of water is rainfall like North Cyprus. Therefore, sustainable water resource management (SWRM) is required for North Cyprus. If extreme events cannot be under control, their consequences may be destructive for environments, societies, and economies. For example, agricultural production levels, freshwater quality, and living organisms in the biodiversity may be affected in a negative way seriously. The main motivations of this study are to find the best fitted time series model to annual rainfall patterns of North Cyprus and to detect the return period of the most extreme drought event by means of generated synthetic scenarios. The results of this study will be helpful in steps of SWRM decisions because these decisions are taken according to the rainfall predictions and forecasts in both the short and long run, rainfall characteristics, and return periods of extreme events.

1.2 Objectives of the Study

This study aims to find out the historical drought parameters and return periods of critical droughts in Northern Cyprus by modeling annual time series rainfall data using Box and Jenkins methodology. First of all, annual rainfall data are transformed to normal as an assumption of the ARIMA models. Then, by applying clustering analysis the study area is divided into regions. where they have different rainfall and geographical characteristics. So useful information can be inferred from the regional evaluations. In the next step, the most appropriate models are identified based on the ARIMA modeling procedure. Then, synthetic data from annual aggregated rainfall data are generated according to the suitable models. In the one framework, frequency analysis will be performed to average annual observed rainfall data of North Cyprus, and drought severity and magnitude and their return periods are estimated. In another framework, generated annual data are disaggregated spatially into regions by preserving statistical properties at both the general North Cyprus level and regional level. Lastly, frequency analysis is applied for each region, and drought properties and return periods of the most critical drought for every region are obtained.

1.3 Structure of the Paper

In this section, the organization of the thesis is given as the following. Chapter 2 aims to provide previous studies related to clustering, ARIMA modeling applications, disaggregation approach, and drought frequency analysis and their general conclusions for rainfall time series. The study area and the data are represented in Chapter 3. Chapter 4 explains the methods that are used. Chapter 5 incorporates the results of the analyses and interpretations of them. Lastly, the thesis is concluded in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

This chapter points out the previous studies and approaches in the literature about the most used modeling procedures and necessary analysis and tests before application of them.

2.1 Stationarity Check

The Box and Jenkins methodology aims to create the best-fitted model of a time series by using historic values for the purpose of forecasting, synthetic data generation, etc. There are four stages of this methodology which are model identification, parameter estimation, and diagnostic checking. The data should be checked whether it is stationary or not in the first stage because stationarity is an important condition for ARIMA modeling (Babazadeh and Shamsnia, 2014). There are several methods and tests to control stationarity such as visual check (Hyndman& Athanasopoulos, 2018), Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots (Nielsen, 2019), unit root tests such as Augmented Dickey-Fuller (ADF) and Dickey-Hasza-Fuller (DHF) tests, and stationarity tests such as KPSS (Kwiatkowski–Phillips–Schmidt–Shin) and LMC (Leybourne-McCabe). These methods were used in many studies in the literature before making statistical analyses.

For example, Yusof & Kane (2012) aimed to model the rainfall data of two stations in Malaysia from 1968 to 2003 by using SARIMA and Exponential Smoothing State Space (ETS) models. After the authors plotted the data of two locations visually, they noticed the seasonal components and eliminated them by means of differencing to make the data stationary. After differencing, visuals showed zero means, i.e. time series is stationary.

Also, Pazvakawambwa and Ogunmokun (2013) conducted a study that aims to model Windhoek monthly rainfall data between 1891 and 2011. They checked the stationarity in the time series data by using visualization of the values in the data. It is found that the time series is stationary because the mean and variance do not vary with time.

Babazadeh and Shamsnia (2014) examined the monthly precipitation and the mean temperature data of Shiraz Synoptic Station in Iran from 1983 to 2004. Authors have aimed to model and simulate the time series data with stochastic techniques to make forecasting. In this study, trend and seasonality are found by using ACF and PACF plots. To remove them, the differencing operation was used and achieved stationarity in the time series.

Etuk & Mohamed (2014) performed a time series analysis for monthly data of Gadaref rainfall gauge in Sudan for the years 1971-2010. They have used the ADF unit root test in order to check stationarity and it was concluded that the time series is stationary. However, the ACF plot showed that the data is non-stationary because the seasonality was detected in the data. After seasonal differencing application, both the ADF test and ACF plot confirmed that the time series is stationary.

In another study, Papalaskaris et al. (2016) performed the different models of the ADF Unit Root Test on total monthly precipitation data in order to check whether the time series satisfy the stationarity condition or not. The authors have aimed to reveal potential precipitation trends in Kavala city by analyzing the rainfall data between the years 2006 and 2014 with the help of statistical analysis methods. The results of three different ADF tests represent that time series data is stationary because there are no unit-roots.

Also, there is another study about time series modeling of monthly rainfall data from 1971 to 2010 in Nyala Station in Sudan. The stationarity condition was checked by using the ADF test and ACF plot and illustrations and results showed that the time series is not stationary. Differencing was applied in order to make rainfall data stationary. After it, seasonally differenced data satisfied the stationarity condition and this conclusion was confirmed by ADF test results (Mohamed & Ibrahim, 2016).

Kamath & Kamat (2018) have carried out a time series analysis of precipitation data of the Idukki district in Kerala. Monthly rainfall data from 2006 to 2016 has been used. In this study, stationarity is checked by means of the ADF test and correlation plots (ACF and PACF). Both of these methods conclude that the time series is stationary.

Sidiq (2018) has studied rainfall forecasting by applying time series modeling for the monthly precipitation data of Bandung city in Indonesia between January 2011 and

December 2013. In this study, Sidiq (2018) tested the stationarity of data by plotting the historical rainfall values and autocorrelation coefficients. It was found that the time series is not stationary and the data was differenced in the attempt in achieving stationarity. After differencing, visual checking supported that the time series became stationary.

There is another study that has focused on time series modeling of rainfall characteristics of Nakuru county in Kenya. Maina et al. (2019) has aimed to find the best-fitted model for Nakuru by using monthly rainfall data from 1997 to 2016. The authors have checked the time series plot of the precipitation data and they saw that the mean was stationary because there is no trend in the mean. However, they realized that a kind of transformation is required because the variance was not constant over time as the oscillations showed. After stationary variance was obtained using the square root transformation, they plotted the time series again and they saw that there was a strong seasonality. In order to remove it, they have performed one degree seasonal differencing and achieved stationary data. Although everything seems proper visually, they applied the ADF test in order to confirm the stationarity formally and results ($p\text{-value} = 0.01 < 0.05$) represented that transformed data was stationary (Maina et al., 2019).

Ampaw et al. (2020) have conducted a study that aims to develop a time series model which represents the precipitation patterns in New Juaben Municipality in Ghana well over the 18 years between 1993 and 2011. The data were checked for stationarity and they saw that it is non-stationary but they have performed a formal test as a confirmation. According to KPSS test results, the time series was not stationary and a transformation should be performed. After differencing operation, it was tested again with the help of the KPSS test and it was concluded that the differenced time series data satisfy the stationarity condition.

For instance, Papalaskaris (2020) had a study based on forecasting the total monthly precipitation of Karyes village in Greece by using the ARIMA method for the period from 1982 to 2018. The author aimed to obtain short-term estimations by using historical rainfall values and forecasting future patterns. As a prerequisite for time series analysis, the stationarity condition was tested by means of three different versions of ADF unit root tests. All cases concluded that the time series is stationary. However, data was seasonally differenced by order one because the ACF plot showed that seasonality.

2.2 Normality Check

Since the many statistical analyses assume that the variables are normally distributed, the normalization process is necessary to transform the hydrological variables before making a statistical analysis. In the literature, several common transformation techniques were used in order to make hydrological time series normally distributed such as 2 parameter log-normal, 3 parameter log-normal, and Box-Cox transformation (Sangal & Biswas (1970), Thyer et al., 2002)

2.3 ARIMA Modeling

In the past, different stochastic models are proposed to model hydrologic time series data such as autoregressive models (AR), fractional Gaussian noise models (FGN), ARMA models, disaggregation models, ARMA-Markov models, and shot-noise models. Some of these models were successful in application but they were not preferred because of their critical restrictions (Salas et al.,1988). Especially, Box and Jenkins, ARMA, SARIMA, Periodic Autoregressive (PAR), Markov processes, etc. were found useful and appropriate to represent and forecast the precipitation data (Dastorani et al., 2016). One of the most common and popular stochastic time series models is the ARIMA model, which includes AR, MA, and integration processes. According to Adhikari & Agrawal (2013), this is the most preferable model among several stochastic time series models because it represents the time series in a simple form, builds the most appropriate model by using Box-Jenkins methodology and its implementation is understandable. These models also include some limitations but they generally generate satisfying results in hydrologic data analysis (Salas et al.,1988). In the literature, ARMA, ARIMA, and SARIMA are the most preferred models for modeling hydrologic and climatic time series.

For example, in 2009, a study was conducted to find the best-fitted time series model for the rainfall data of Iran and categorizing them with the help of clustering analysis. The monthly rainfall time series data was used for 28 major stations of Iran between 1970 and 2000. Soltani et al., (2009) used the ARIMA model and results showed that pure seasonal models ($ARIMA(P, D, Q)_{12}$) and multiplicative models with low and high order parameters ((ARIMA(p,d,q) x (P, D, Q)$_{12}$) were appropriate for the monthly rainfall time series.

Momani (2009) has studied modeling rainfall time series analysis for Amman station in Jordan between 1922 and 1999. Box and Jenkin's methodology was used in this study in order to model the data and ARIMA (1,0,0) (0,1,1)$_{12}$ was found the most adequate model for the water resources analysis and strategies in Jordan.

Then, Attah and Bankkole (2011) have analyzed the rainfall data of Kaduna, Nigeria to create a model which describes the rainfall structures of the region well. In this application, the annual rainfall time series was used from 1960 to 2006 (47 years). The authors have used Box-Jenkins Methodology and found that ARMA (1,1) is the most suitable model for this dataset and it can be used to forecast the future characteristics.

Yusof & Kane (2012) have carried out a monthly time series modeling for rainfall data of two selected stations of Malaysia (Kuantan and Malacca) between 1968 and 2003. The ETS state models and SARIMA models were used in the study. According to the results, both of these models were satisfactory for forecasting.

Also, Pazvakawambwa and Ogunmokun (2013) have examined the monthly rainfall data of Windhoek from 1891 to 2011. They have aimed to find the best model which represents the data and forecast Windhoek rainfall patterns up to 2050. In this study, Box and Jenkin's modeling techniques were used and found that SARIMA (1,0,1) (1,0,2)$_{12}$ model was proper for the data and used to forecast the monthly rainfall based on this seasonal ARIMA model.

For instance, Babazadeh and Shamsnia (2014) had a study that focused on finding the most suitable model which represents the climatic parameters of Shiraz station in Iran for the period from 1983 to 2004 for consistent forecasting. The authors have used Box and Jenkin's methodology in modeling procedures and decided that ARIMA (0,0,0) $(2,1,0)_{12}$ can be used to estimate future precipitation values for the Shiraz station.

In another study, monthly rainfall data for the Gadaref station between 1970 and 2010 was used to build an appropriate model for the rainfall characteristics of the selected station. Multiplicative SARIMA models were applied and proposed three different models but SARIMA(0, 0, 0)$(0, 0, 1)_{12}$ was found the best-fitted one for the reliable forecasting and management of the rainfall in this place (Etuk & Mohamed, 2014).

Chonge et al. (2015) have used the univariate Box-Jenkins approach to obtain the best fitted ARIMA model for the monthly rainfall data of Uasin Gishu County, Kenya during the 1977-2014 period. It is concluded that SARIMA (0, 0, 0) $(0, 1, 2)_{12}$ represents better the data than other candidate models.

Balibey and Türkyilmaz (2015) aimed to confirm the suitability of sinusoidal models by using the monthly precipitation values of 270 stations over Turkey between 1999 and 2010. They have compared the results of sinusoidal and ARIMA models and validated that the sinusoidal model is more appropriate than another model for this data set.

Uba and Bakari (2015) have carried out a time series analysis by modeling monthly rainfall historical data for Maiduguri station in Nigeria. In this study, the recorded data for a period of 30 years (1981-2011) were used. Box-Jenkins modeling procedure was applied and ARIMA (1,1,0) model was found the best model for this monthly rainfall values.

Papalaskaris et al. (2016) aimed to model historical rainfall quantities of Kavala city in Greece for the years of 2006-2014 in order to use for forecasting short-term future values. This research has applied Box and Jenkin's methodology and concluded that SARIMA (0, 0, 0) $(0, 1, 1)_{12}$ is the best-fitted model for the monthly rainfall data of this region.

Mohamed and Ibrahim (2016) have conducted a time series analysis of rainfall data of Nyala station in Sudan between 1971 and 2010. In this study, SARIMA (0, 0, 0) $(0, 1, 1)_{12}$ model was found the most representative model by using the ARIMA method for rainfall data of this station.

There is another study that focused on time series analysis and forecasting of rainfall data for India. Kamath and Kamat (2018) have aimed to compare three different time series analysis techniques and their forecasting performances by using the monthly rainfall data of Idukki for the period from 2006 to 2016. Results have shown that the ARIMA model has more accurate forecasting power (with less error) than Artificial Neural Network (ANN) and Exponential Smoothing State Space (ETS). So, according to the results, the ARIMA model can be used to forecast monthly rainfall data in the future.

Additionally, a study has been done to forecast the rainfall data by using a time series model. Monthly rainfall data of the Bandung city was used well over two years between 2011 and 2013. Sidiq (2018) has used Box and Jenkin's procedures and concluded that the ARIMA model is the most successful and useful model for rainfall predictions for the upcoming years (Sidiq, 2018).

Maina et al. (2019) have carried out a time series analysis modeling of rainfall values in Nakuru Kenya. The monthly rainfall data between the years 1997 and 2016 were obtained and processed to find the best-fitted model for it. As a methodology, univariate Box and Jenkin's models were used and found that SARIMA (0, 0, 1) $(0, 1, 1)_{12}$ model is the most proper one because of the seasonal patterns in the rainfall data of Nakuru County.

A study by Ampaw et al. (2020) used monthly rainfall data of the New Juaben Municipality in Ghana between 1993 and 2011 to develop an ARIMA model that helps to predict rainfall distributions and variabilities. By using Box-Jenkins methodology, it was decided that the SARIMA model that best describes the New Juaben Municipality rainfall is SARIMA (0, 0, 0) $(2, 1, 1)_{12}$ model.

Papalaskaris (2020) studied forecasting monthly rainfall data of Karyes in Greece from 1982 to 2018 by using the ARIMA method. SARIMA (0, 0, 0) $(0, 1, 1)_{12}$ model was finally selected as the best representation among several candidate models for the short-term rainfall forecasting and long-term rainfall predictions by modeling historical values of the region.

2.4 Model Selection Criteria

In the literature, there are several criteria for model selection by comparing models such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Schwartz-Bayesian Criterion (SBC). The most fitted model for the time series data can be selected by means of comparing these statistics. The model which has the lowest AIC, BIC, or SBC value is the optimal model for the data (Babazadeh and Shamsnia, 2014). Various publications in the literature show that AIC and BIC are the most used model selection methods. For example, only AIC (Pazvakawambwa & Ogunmokun (2013), Etuk & Mohamed (2014), Mohamed & Ibrahim (2013), Sidiq (2018)) or BIC (Ampaw et al.(2020), Papalaskaris (2020)) were used in many studies to choose the optimal model. However, both AIC and BIC were used at the same time in some studies (Babazadeh & Shamsnia (2014), Papalaskaris et al. (2016), Maina et al. (2019)).

2.5 Clustering Analysis

Clustering analysis is a multivariate method that aims to classify samples based on their similar characteristics and find subgroups of the variables that are highly correlated to allow them to describe subgroups by conserving important information (Yudistira et al., n.d.). Cluster analysis helps to obtain beneficial information and results from complicated data. A data set can be divided into many subsets. If the objects belong to the same group, it means that they have a high-level similarity comparing with the objects in other subsets. There are several clustering methods such as hierarchical, partitioning, grid-based, model-based, feature-based, fuzzy, and density-based clustering. Hierarchical clustering is the most common method and it includes different distance measures which are single, complete centroid, average, median linkages, and Ward's minimum variance (Bu et al., 2020). In several studies related to hydrology in the literature, clustering analysis was applied commonly for multivariate analysis.

For example, Kajewska-Szkudlarek (2020) has studied time series prediction for rainfall data of Wroclaw-Swojec station in Poland between the years 2000 and 2018. In this study, hierarchical Ward and divisive k-means methods were used and several cluster numbers were tried from two to 20. As a result, subdividing into eight were found suitable.

Also, Teodoro et al. (2016) have conducted a cluster analysis for the monthly rainfall data of 32 stations of Mato Grosso do Sul in Brazil from 1954 to 2013. The authors have used Ward's agglomerative hierarchical clustering method and Euclidean dissimilarity metric to classify the data. They created five groups for the purpose of climate forecasts and meteorological researches.

There is another study that focused on reconsidering the climate regions by using the clustering approach in Turkey. The period of the time series of temperatures and total precipitation ranges from 1951 to 1998. Five different clustering methods were tried that are single and complete linkage, average distance within and between clusters, and Ward's technique. As a dissimilarity measure, Euclidean distance was used. As a result, it is found that the most appropriate clustering method is Ward's method because it created consistent clusters and reasonable results. In short, they have preferred to subdivide the data into seven main groups by using the selected procedures (Unal et al., 2003).

Additionally, Hussain and Lee (2009) have carried out a clustering analysis for the rainfall data of Pakistan (32 stations) between 1980 and 2006 to classify the rainfall regions. They have applied one of the hierarchical clustering techniques which is Ward's method and rainfall stations in Pakistan were clustered as 6 identical groups.

For instance, Yashwant & Sananse (2015) have compared different clustering techniques for the monthly rainfall data of 36 stations of the Marathwada region in India from 1975 to 2014. In this study, correlation coefficient distance was used in order to divide the study area into clusters by using seven hierarchical clustering methods such as Ward, complete, average, single, median, centroid, and McQuitty linkages. They have aimed to classify data into six clusters and found that single and centroid linkages are the most suitable techniques for clustering analysis for this region.

Another cluster analysis has been done by Ahmad et al. (2013) for the annual rainfall data of 59 stations of Peninsular Malaysia between the years 1975 and 2010. For this investigation, seven linkages and 11 similarity measures were used to test 77 combinations to find the best combination for the classification. As a result, it is finally found that the most appropriate combination is the complete linkage-correlation similarity measure for this rainfall data of this area.

Lastly, a cluster analysis has been performed for the rainfall data of Jember Regency to model the time series by using spatial correlations. Data for 77 stations spread over the region from 2005 to 2015 has been used in this study. The authors have applied one of the nonhierarchical methods – K-means and Euclidean distance for clustering. Based on the analysis, dividing into 4 and 6 groups were tried and clustering by 6 subsets is found the fittest for the forecasting analysis (Yudistira et al., n.d.).

2.6 Disaggregation Approach

Disaggregation is a method that can help to disaggregate the higher-level time series (key series) into lower levels (monthly, quarterly, weekly, daily, or hourly) by preserving the historical statistics such as standard deviation, mean, correlation coefficients, etc. at higher-level and lower levels. There are two main types of disaggregation which are temporal and spatial.

While spatial (in space) disaggregation aims to disaggregate the data into subzones spatially, temporal (in time) disaggregation aims to disaggregate the data with low frequency into high-frequency data (Salas et al., 1988).

There is a case study for time series rainfall modeling in Saudi Arabia. The monthly rainfall data of Surat Obeida station was used for the period of 1981 to 2010. The author has applied the seasonal ARMA and temporal disaggregation models to find the best representative model for the data. It was finally found that the disaggregation model had more reasonable results than the PARMA model because PARMA models do not capture the annual structure of the data (Saada, 2014).

Hanaish (2016) has conducted a multivariate rainfall disaggregation analysis by using hourly rainfall data of seven stations in Malaysia from 1973 to 2008. In this study, a multivariate disaggregation rainfall model (MUDRAIN) was used and it was found that this model does not work on reproducing statistics well for this study area.

Park & Chung (2020) have studied on disaggregation of daily rainfall to hourly data by using a proposed K-nearest neighbor-based time resampling method (KNNR). Hourly rainfall data of four stations in Korea was used for the period of 1961 and 2017. As a result, the modified disaggregation method gave more successful outcomes with 3-day rainfall trends because statistical features and boundary continuity are protected better than without considering 3-day patterns. Therefore, the authors have concluded that disaggregated hourly data can be used for further hydrologic analyses.

Srikanthan et al. (2004) have a study about monthly rainfall data generation by using rainfall values of 10 stations in Australia. In this article, a nonparametric model and method of fragments were used to generate rainfall monthly rainfall scenarios by using historical records and disaggregate the annual to monthly rainfall data, respectively. Results indicate that the statistical properties at annual and monthly levels were preserved for both models at the same time. However, the nonparametric model is superior to the method of fragments which is one of the temporal disaggregation methods.

Poschlod et al. (2018) have carried out a study to compare the Method of Fragments (MoF) and Weather Research and Forecasting (WRF) Model on the daily rainfall data of 10 stations in Oslo, Norway for the period from 2000 to 2017. It is concluded that although the WRF model has also some advantages, the performance of MoF is more suitable.

A study by Güntner et al. (2001) aimed to disaggregate daily rainfall data into hourly time series values. In this study, the performance and parameters of the temporal disaggregation method were compared by using rainfall data of three stations in Brazil and three stations in the United Kingdom for different periods. As a result, it was found that the model has regenerated highly accurate rainfall values for both countries which have different climates. However, the temporal disaggregation model has performed better in Brazil which has a semi-arid tropical climate.

Wey (2006) has completed a study that focuses on converting daily precipitation data to hourly data by using a temporal disaggregation approach. In this study, historical precipitation records from 15 daily and 28 hourly stations in Ontario, Canada for the period from 1961 to 1990 were chosen to use. The method of fragments was applied to produce hourly data by disaggregating the daily precipitation data. As a result, the method of fragments was determined as a suitable approach for the precipitation time series data at a daily timescale.

In another research, precipitation and evaporation data of two weather observation stations in Australia were used. The period of monthly and annual data used was covered the period from 1950 to 2009. In this study, there were two approaches for downscaling models. Firstly, a single model was used to downscale annual total values of precipitation and evaporation. Then, the annual products were disaggregated into monthly values by using four different method of fragments approaches. However, secondly, for precipitation and evaporation, a model was created for each month separately. The aim of this study was to achieve a result that supports that the first approach provides better monthly statistics than the second approach. It was concluded results and hypothesis of this paper are consistent (Sachindra & Perera, 2018).

Ismail et al. (2004) have done a synthetic simulation by using several different disaggregation models. The streamflow and rainfall time series data of Sungai Muar River in Malaysia for 26 years and 59 years were used, respectively. In this study, four possible disaggregation models such as Valencia-Schaake (VLSH) model, Mejia-Rouselle Model (MJRS), Lane model, and Synthetic Streamflow Generation Software Package (SPIGOT) were applied and their performances were compared. It was found that all models are successful in preserving the historical statistical properties of both series except the coefficient of skewness. According to the findings of the study, the VLSH model is the most suitable and successful disaggregation approach because its statistics are very close to the historical ones of both streamflow and rainfall data.

Additionally, a study by Al-Zakar et al. (2017) focused on disaggregating annual streamflow data into monthly time scales. The streamflow data of Salur (duration: 1964-1996), Cadirhoyuk (duration: 1981-2000), and Yahsihan (duration: 1939-

2000) stations along the Kızılırmak river, Turkey were used. The authors applied the K-nearest neighbor (KNN) model that is one of the nonparametric disaggregation techniques. To make a comparison, it was performed in both spatial and temporal disaggregation methods. Results have indicated that KNN is an efficient model and spatial approach is superior to temporal and it can be used in further hydrological analyses for better results.

2.7 Drought Frequency Analysis

Drought frequency analysis is one of the common and important applications in hydrology. Evaluating the frequency and probability of extreme events is very crucial for water resource management because policies, guidelines, and risk acceptance capacities can be designed by means of those evaluations. Homogeneity and independence (no serial correlation) of the hydrological data are necessary for frequency analysis (Tallaksen, 2000). Many studies on drought frequency analyses of different hydrological variables (precipitation, streamflow, etc.) are available in the literature.

For example, Mirakbari et al. (2010) have proposed a regional bivariate frequency analysis for meteorological droughts. Monthly precipitation data of 43 stations in Khuzestan, Iran were used for the period from 1960 to 2007. In this study, six homogeneous groups were created by analyzing the drought severity and durations using L-moments. The authors have concluded that drought risks and optimization of the water resource use can be evaluated thanks to the bivariate modeling of the characteristics of the drought events.

Also, Rasmussen & Akintuğ (2004) have used 57 years of annual runoff data of Saskatchewan River in Manitoba in order to compare the suitability of the AR(1), ARMA (1,1), and Hidden State Markov (HSM) models for hydrologic drought frequency analysis. As a result, the superiority of any model was not certain but HSM models generate more low flow drought events than the other models and more realistic synthetic flows.

Additionally, a hydrological drought frequency analysis was conducted for the average daily streamflow data of the Yom River in Thailand from 1998 to 2012. In this study, eight gauging stations along the river were selected and severities of streamflow droughts were found by using drought frequency analysis. A threshold value was determined and the amount of flow that is below this threshold level was characterized as a drought event. Results have indicated that more severe droughts were seen toward the downstream parts of the Yom River (Sawatpru & Konyai, 2016).

Another study conducted by Karimi et al. (2019) aimed to extract the dry periods of seven meteorological stations in the Karkheh River basin in Iran by using the Standard Precipitation Index (SPI). In this study, monthly precipitation data were used between 1987 and 2014. In order to forecast SPI time series, ARIMA models were applied. According to the results, the years that had the most severe drought were 1996 and 1998 in Dehno station.

Also, a drought frequency analysis was completed by Moon et al. (2010) in order to find the return period of the drought event by using the Palmer Drought Severity Index. The precipitation and temperature data of the 4 stations of Korea were used. As a result, the authors have concluded that extreme droughts may repeat in the 5 - 10 years range on the average in Korea.

CHAPTER 3

STUDY AREA AND DATA

Cyprus which is the third biggest island in the Mediterranean Sea is located in the south of Turkey. The area of Cyprus Island is 9.251 km^2 but North Cyprus has a surface area of 3.355 km^2. The country has a semi-arid climate and 136 m altitude. In North Cyprus, stations extend to Güzelyurt (in the west) starting from the Karpaz (in the northeast). Summers are very hot and winters are mild and rainy intensively because of the Mediterranean subtropical climate. Most of the rainfall has been recorded in the winter season (December, January, and February) while July and August are months that have the lowest amount (almost zero) of rainfall in a year. This study covers 33 observation stations in North Cyprus. Locations of 33 stations can be seen in Figure 3.1. Annual and monthly precipitation data sets spanning from 1975 to 2014 were obtained from the Meteorological Office of the Turkish Republic of Northern Cyprus (TRNC). Precipitation includes snowfall, rainfall, sleet, and hail. However, almost no snowfall is observed because there are not many areas that have high elevation and high mountains in North Cyprus. The geographical characteristics (elevation, latitude, and longitude) of each station are available in Table 3.1.

Table 3.1 Geographical characteristics of 33 selected rainfall stations throughout Northern Cyprus

Station Number	Station Name	Elevation(m)	Latitude(°)	Longitude (°)
1	Akdeniz	89	35.29972	32.96500
2	Camlibel	277	35.31611	33.07056
3	Lapta	168	35.33575	33.16336
4	Girne	10	35.34194	33.33139
5	Beylerbeyi	225	35.29729	33.35404
6	Bogaz	300	35.28825	33.28484
7	Tatlisu	168	35.22470	33.45060
8	Kantara	480	35.40056	33.91361
9	Esentepe	183	35.33273	33.57852
10	Guzelyurt	52	35.18889	32.98194
11	Gaziveren	19	35.17306	32.92194
12	Lefke	129	35.09664	32.84091
13	Yesilirmak	20	35.16639	32.73694
14	Ercan	119	35.15917	33.50194
15	Serdarli	111	35.25183	33.61024
16	Degirmenlik	168	35.25276	33.47218
17	Gecitkale	45	35.23333	33.72861
18	Gonendere	75	35.26983	33.65660
19	Vadili	54	35.13869	33.65161
20	Beyarmudu	87	35.04716	33.69582
21	Cayirova	67	35.34949	34.03129
22	Iskele	39	35.28611	33.88444
23	Mehmetcik	99	35.42222	34.07833
24	Gazimagusa	10	35.13639	33.93556
25	Salamis	6	35.18080	33.89734
26	Alevkaya	623	35.28583	33.53472
27	Zumrutkoy	129	35.17444	33.04917
28	Alaykoy	166	35.18472	33.25667
29	Lefkosa	134	35.19639	33.35194
30	Ziyamet	82	35.4535	34.12451
31	Dipkarpaz	136	35.59889	34.37917
32	Yenierenkoy	123	35.53556	34.18944
33	Dortyol	54	35.17889	33.75861

CHAPTER 4

METHODOLOGY

The study aims to model rainfall characteristics of North Cyprus using ARIMA models and find the return period of the most critical drought by generating longer synthetic data. This chapter represents methods of precondition checks for ARIMA modeling procedure, clustering methods, Box and Jenkin's methodology, types of ARIMA models, disaggregation method, and drought frequency analysis methods.

4.1 Transformation for Normalization

In statistics, many analysis techniques assume that the distributions of variables are normal. However, hydrological time series are generally not normally distributed. According to Salas et al. (1988), there are main approaches to cope with skewed hydrological data.

1. Transforming these non-normal series into normal before modeling and analyzing the time series;
2. To cope with skewness by means of the probability distribution of residuals that are uncorrelated after modeling non-normal time series

3. Finding the link between the first two moments of the observed data and normalized data to preserve the characteristics of the observed data moments.

In comparison to the second and third approaches, transforming the skewed data into normal is simpler but using this may create biases in the statistical parameters of the generated series. Salas et al. (1988) mentioned that if biases are small, the first approach can be used. In this paper, the first approach was preferred. There are some frequently-used methods to transform the skewed data into normal and they were explained under three subtitles below.

4.1.1 2-parameter Lognormal transformation

The 2-parameter lognormal transformation is one of the most common transformations for many statistical analyses. This type of transformation is applied by replacing each variable in the data with $\log(x_t)$. Log transformation decreases the importance of outliers and provides a normal distribution for a strong analysis (Metcalf & Casey, 2016).

$$y_t = \log(x_t) \tag{4.1}$$

where n: the length of observed data, t = 1, 2, …, n, x_t : observed values, y_t: transformed values.

4.1.2 3-parameter Lognormal Transformation

The 3-parameter lognormal distribution is often used for hydrological data. Sangal and Biswas (1970) mentioned that a logarithmic transformation of the reduced flow $(x_t - \alpha)$at time step *t*, i.e.

$$y_t = \log(x_t - \alpha) \tag{4.2}$$

then normally distributed observation y_t is produced. The variable x_t represents observed values in the data, α is a parameter, and $(x_t - \alpha)$ is the reduced variable. The equation of the parameter α in terms of the statistical measures of x_t is,

$$\alpha = M_x - \frac{\sigma_x^2}{2(\mu_x - M_x)} \tag{4.3}$$

where M_x is the median of x_t, σ_x is the standard deviation of the variable x_t and μ_x is the mean of x_t.

The authors also stated that there is a dimensionless form of the equation of α because the value of α cannot be a real number. In this case, the dimensionless form can be used to determine the parameter α in regional studies. Equation of it is,

$$\alpha = \beta - \frac{\gamma^2}{2(1 - \beta)} \tag{4.4}$$

where $\beta = M_x/\mu_x$ and $\gamma = \sigma_x/\mu_x$. Parameter α can be negative, zero, and positive (Sangal & Biswas, 1970).

4.1.3 Box-Cox Transformation

Box-Cox transformation is a frequently-used method to normalize skewed data. It is applied such that

$$y_t = \begin{cases} \log(x_t) & \lambda = 0 \\ \dfrac{x_t^{\lambda} - 1}{\lambda} & \lambda \neq 0 \end{cases}, \qquad t = 1,2,\dots ,n \tag{4.5}$$

where λ represents the transformation parameter which is decided to make sure that the data (y_t) are approximately normally distributed (Thyer et al., 2002) and it is estimated by using the maximum likelihood model (Xu et al., 2019).

4.1.4 Transformation Type Selection

In order to select the most appropriate transformation method, the Filliben probability plot correlation coefficient test is conducted. This test gives the near-linear normal probability plots by measuring the correlation between the transformed (ordered) observations (y_i) and their medians M_i (Filliben, 1975). Filliben probability plot correlation coefficient can be calculated as

$$\hat{r} = \frac{\sum(x_i - \bar{x})\,(M_i - \bar{M})}{\sqrt{\sum(x_i - \bar{x})^2\,\sum(M_i - \bar{M})^2}} \tag{4.6}$$

The transformation method with the highest r value which is close to 1 should be selected among the candidate methods.

4.2 Stationarity

Stationarity is one of the most fundamental assumptions for many statistical analyses of hydrological data in water resources. Stationarity means that statistical parameters such as mean, variance, and covariance do not fluctuate with the change in time. In other words, although different statistical properties are calculated from different time series, they will be distributed around the same mean. It implies that there cannot be any trend or seasonality, or combination of the two in a stationary time series (Machiwal & Jha, 2006).

Stationarity is an important assumption in time series analyses because constancy in the mean, variance, and covariance is necessary in order to estimate parameters and create the best model which represents the data precisely (Metes, 2005).

Metes (2005) also stated that stationarity can be detected by several methods such as visual tests, correlogram tests, unit root tests, and stationarity tests. After checking whether there is a trend in the data or not visually, verifying stationarity or non-stationarity by using unit root tests is a guaranteed application. If data is non-stationary, it needs to be rendered stationary data for a strong time series analysis.

There are some methods to transform non-stationary data into stationary. The most common methods are differencing and logarithmic transformation (Cromwell et al., 2011).

4.2.1 Visual check

In this method, the annual rainfall totals can be plotted and screened roughly to check whether the data have any trend or interruption in mean, autocorrelation, variance, and seasonality. If the plot has a certain upward slope, vertical changes in series, or fluctuations in autocorrelation, it can be concluded that the time series is non-stationary. Additionally, non-stationarity can be detected by means of autocorrelation and partial autocorrelation plots. In the non-stationary series, ACF dies out very slowly while it declines and decays fast to zero in stationary series (Metes, 2005).

4.2.2 Augmented Dickey-Fuller (ADF) Test

ADF test procedure checks whether the variable has a unit root or not. If there is a unit root, it indicates that the time series is non-stationary. The ADF test uses the equation below:

$$y_t = d + \emptyset * y_{t-1} + \delta t + \zeta_1 \Delta_{t-1} + \zeta_2 \Delta_{t-2} + \cdots + \zeta_k \Delta_{t-k} + \varepsilon_t \tag{4.7}$$

where k, d, δ, $\emptyset$, ε_t represent the number of lags, intercept constant called a drift, coefficient on a time trend, the coefficient that represents process root, residual term respectively (Rutkowska & Ptak, 2012).

The null and alternative hypotheses of the ADF test are formulated as:

$$\mathrm{H_0}: \emptyset = 0 \ (\text{non} - \text{stationary}) \tag{4.8}$$

$$\mathrm{H_A}: \emptyset < 0 \ (\text{stationary}) \tag{4.9}$$

If the p-value for y_t is lower than 0.05 (95 % confidence level is the default for the ADF test in MATLAB (Mathworks Inc., 2021a), the null hypothesis can be rejected and it can be concluded that the variable is stationary. Otherwise (p-value > 0.05), the null cannot be rejected and the variable is non-stationary, i.e. it has a unit root (Mathworks Inc., 2021a).

According to Rutkowska & Ptak (2012), choosing the most appropriate lag length (k) for the ADF test is also an important process. A large number of lags leads to a decrease in the performance of the ADF test. If the number of lags is small, error correlations influence the test. There are some suggested formulas and methods to decide the maximum lags by Schwert (1989) but they gave a high number of lags as a result, so finding the optimal number of lags by increasing it one by one was decided as a more reliable method than formulas. Once the lag number that leads to starting to ruin stationarity of the time series can be detected by means of this method, it can be stopped there and the last lag that satisfies the stationarity condition can be selected as the maximum lag number for the ADF test.

4.2.3 Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test

KPSS test is a stationarity test and it uses long-term variance in order to assess whether the time series has stationarity around mean or variance or it is non-stationary because of a unit root (Kwiatkowski et al., 1992). The structural model of the test is,

$$y_t = \delta t + r_t + \varepsilon_t \tag{4.10}$$

$$r_t = r_{t-1} + u_t \text{ , } u_t \sim N\,(0, \sigma^2_\varepsilon) \tag{4.11}$$

The null and alternative hypotheses of the KPSS test are,

$$H_0: \sigma_\varepsilon^2 = 0 \text{ (stationary)} \tag{4.12}$$

$$H_A: \sigma_\varepsilon^2 > 0 \text{ (non} - \text{stationary)} \tag{4.13}$$

where δ is the coefficient on a time trend, r_t is a random walk, ε_t is a stationary error and σ^2_ε is variance term.

Also, determining the optimal number of lags is important for the KPSS test. According to Kwiatkowski et al. (1992), there are two methods for it such as assessing the performance of results by starting with the small values and then increasing the number of lags and using $(T)^{1/2}$ formula in which T is the size of the sample. In this study, the optimal lag number was decided by increasing the lag number one by one starting with the small values.

As a result, if the t-statistics are in the non-rejection region, the series is stationary. The rejection region was bounded by the critical values for 95 % confidence intervals that are automatically calculated by the software (95 % is the default in MATLAB for the KPSS test (Mathworks Inc., 2021a).

4.3 Clustering

Clustering analysis is an important method to create homogenous groups from the observations based on their similarity. Among several clustering algorithms, the hierarchical clustering technique -one of the most common techniques in the literature- was used in this study. There are 2 types of hierarchical clustering which are agglomerative and divisive depending on their strategies. Agglomerative clustering starts with accepting each observation as a cluster, then collect them in the larger parent clusters by finding the closest pair of clusters (Liu et al., 2013). There are seven different hierarchical clustering methods (see Table C.1) and 11 similarity measures (see Table C.2). Both of these tables were directly taken from the User's Guide of the Statistics and Machine Learning Toolbox MATLAB (Mathworks Inc, 2021b). The most used combinations were selected from the papers in the literature and checked their suitability for the data.

In this study, complete-correlation combination was used. Complete linkage was applied because it can prevent the chaining problem which occurs in other techniques and the distribution of the stations for clusters is more equal in this linkage (Unal et al., 2003). As a distance metric, the correlation was used because the statistical method that was used in this study, ARIMA, aims to decide the most suitable model for the time series by modeling correlations in the data (Yusheng, 2009). Also, several validity indexes can be performed to decide the optimal number of the cluster such as Calinski-Harabsz, C Index, Krzanowski-Lai Index, and Hartigan Index (Ahmad et al., 2013). However, this study did not use an index because the number of stations is not very large, so the most optimal cluster number can be decided visually. The different number of clusters can be checked for all candidate combinations and the optimal number can be obtained approximately.

4.3.1 Complete Linkage

This hierarchical method uses the distance between the furthest members of two clusters as the distance between these two clusters (Bu et al., 2020).

The longest distance between cluster K and cluster L can be calculated as:

$$D(K,L) = \max\{d_{ij} \middle| i \in K, j \in L \} \tag{4.14}$$

where d_{ij} is the distance between x_i (i-th member of cluster K) and x_j (j-th member of cluster L).

After a new cluster, M was created from K and L, the distance between M and another cluster (N) is calculated by means of the same technique,

$$D(M,N) = \max\{d_{ij} | i \in M, j \in N \} \tag{4.15}$$

$$= \max\{\max\{d_{ij} | i \in K, j \in M, \max\{d_{ij} | i \in L, j \in M\}\} \tag{4.16}$$

$$= max\{D(K,M), D(L,M)\} \tag{4.17}$$

As a similarity measure, the correlation distance metric was used.

Let be X is a (m x n) matrix and includes row vectors (x_1, x_2, …, x_m). The several distances between the vector x_s and x_t , i.e. d_{st} can be calculated as:

$$d_{st} = 1 - \frac{(x_s - \overline{x_s})(x_t - \overline{x_t})'}{\sqrt{(x_s - \overline{x_s})(x_s - \overline{x_s})'}\sqrt{(x_t - \overline{x_t})(x_t - \overline{x_t})'}} \tag{4.18}$$

4.4 The modeling procedures

Box and Jenkins developed a systematic method for time series modeling of primarily financial time series but their methodology and models are the most widely used procedures in hydrological applications (Soltani et al., 2009). This approach includes three main stages which are model identification and selection, model estimation, and diagnostic checking. In this study, these procedures were used to find the best-fitted model for the data.

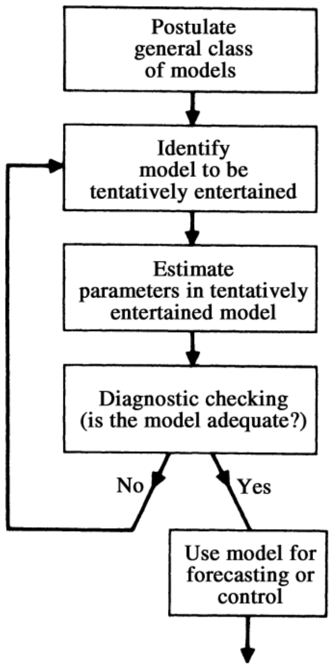

Figure 4.1 Flow chart of Box and Jenkins methodology (Box, G. E. P., Jenkins, G. M., & Reinsel, 2005)

4.4.1 Model identification and selection

After confirming normality, stationarity, and homogeneity preconditions, in this step, orders of the ARIMA model can be determined by evaluating autocorrelation (ACF) and partial autocorrelation function (PACF) plots in order to specify some potential models for the data. Then, model selection can be implemented among candidate models by means of AIC and BIC. Formulas of them can be seen below;

$$AIC_{p,q} = \frac{-2\ln\ (\sigma_a^2) + 2r}{n} \quad (4.19)$$

$$BIC_{p,q} = \ln\ (\sigma_a^2) + r\frac{\ln(n)}{n} \quad (4.20)$$

where r, $\ln(\sigma_a^2)$ and n represents the number of estimated parameters, the maximum likelihood estimate, and sample size, respectively. The model which has the minimum AIC or BIC value for the information criterion is selected as the most appropriate model among potential models (Box, G. E. P., Jenkins, G. M., & Reinsel, 2016).

4.4.2 Model Estimation

In this stage, the parameters of the best-fitted model are estimated with the help of some methods like the method of moments, maximum likelihood, and least-squares (Box, G. E. P., Jenkins, G. M., & Reinsel, 2016).

4.4.3 Diagnostic Checking

After the model selection and estimation, validation is necessary. Diagnostic checking can be applied by looking at the residuals. They need to have a normal distribution (~ N (mean = 0, constant standard deviation), minimum variance, and noncorrelation to be valid for the data. These necessities can be checked by using

ACF and PACF plots. If the residuals are independent and identically distributed with zero mean (i.e. follow Gaussian white noise) and if there is no autocorrelation between any of the groups in the time series, it can be concluded that the model fits the data well. After diagnostic checking confirms the adequacy of the model, it can be used for forecasting and synthetic data generation. (Maina et al., 2019).

4.4.4 Autoregressive (AR) Modeling

Autoregressive models are the models that are frequently used in water resources and hydrology. The first reason for applying these models is that there is a dependence between the present time values and previous time values. The second reason is that applying these models is easy. Autoregressive models assume that the data is normally distributed. If the data is non-normal, they need to be transformed. After an appropriate transformation, the transformed data y_t can be used for modeling (Salas et al.,1988). The AR model of order p can be generally written as

$$y_t = \mu_y + \emptyset_1 * (y_{t-1} - \mu_y) + \emptyset_2 * (y_{t-2} - \mu_y) + \ ... + \emptyset_p * \ (y_{t-p} - \mu_y) + \ \varepsilon_t \qquad (4.21)$$

where μ_y, σ^2_y , σ^2_ε and $\emptyset_p$ represents the mean, variance of y_t, variance of ε_t, and autoregression correlation coefficient, respectively.

$$E[y_t] = \mu_y \qquad (4.22)$$

$$E[\varepsilon_t] = 0 \tag{4.23}$$

$$Var[y_t] = \sigma_y^2 \tag{4.24}$$

$$Var[\varepsilon_t] = \sigma_\varepsilon^2 \tag{4.25}$$

$$\mu_y = \bar{y} = \frac{1}{T}\sum_{t=1}^{T} y_t \tag{4.26}$$

$$\sigma_y^2 = \frac{1}{T-1}\sum_{t=1}^{T}(y_t - \bar{y})^2 \tag{4.27}$$

$$\sigma_\varepsilon^2 = \sigma_y^2\,(1 - \sum_{j=1}^{p} \emptyset_j\,\rho_j) \tag{4.28}$$

The ρ_k represents the lag-k autocorrelation coefficient of y_t, so the autocorrelation function for AR(*p*) can be written as

$$\rho_0 = 1 \tag{4.29}$$

$$\rho_k = \emptyset_1\rho_{k-1} + \ldots + \emptyset_p\rho_{k-p}\,, \qquad k \geq 1 \tag{4.30}$$

$$\rho_k = \emptyset_1^k, \qquad k \geq 0 \tag{4.31}$$

The autoregression coefficients $\emptyset_1, \emptyset_2, \ldots \emptyset_p$ can be estimated by using equation 4.32 where the correlation coefficients of population (ρ_j) and autoregression correlation coefficients ($\emptyset_j$) are replaced by autocorrelation coefficients of the sample (r_j) and estimates $\widehat{\emptyset}_j$, respectively. So,

$$r_k = \widehat{\emptyset}_1 r_{k-1} + \widehat{\emptyset}_2 r_{k-2} \ldots + \widehat{\emptyset}_p r_{k-p}, \qquad k \geq 0 \tag{4.32}$$

4.4.5 Annual ARMA Models

These models are a combination of autoregressive and moving average models.

The ARMA model of order *p*, *q*:

$$y_t = \mu_y + \phi_1 * (y_{t-1} - \mu_y) + \ldots + \phi_p * (y_{t-p} - \mu_y) + \varepsilon_t + \theta_1 * \varepsilon_{t-1} + \ldots + \theta_q * \varepsilon_{t-q} \tag{4.33}$$

with *p* autoregressive parameters $\phi_1, \ldots, \phi_p$, and *q* moving average parameters $\theta_1, \ldots, \theta_q$.

The $\hat{\sigma}_y^2$ represents the variance and ρ_1 represents the autocorrelation at lag-1 for ARMA (1, 1) and they can be calculated as

$$\hat{\sigma}_y^2 = \frac{1 - 2\phi_1\theta_1 + {\theta_1}^2}{1 - {\phi_1}^2}\sigma_\varepsilon^2 \tag{4.34}$$

$$\rho_1 = \frac{(1 - \phi_1\theta_1)(\phi_1 - \theta_1)}{1 - 2\phi_1\theta_1 + {\theta_1}^2} \tag{4.35}$$

Also, the autocorrelation function is given as

$$\rho_k = \emptyset_1\rho_{k-1} = \rho_1{\emptyset_1}^{k-1} \quad k > 1 \tag{4.36}$$

Estimators of the moments for ARMA (1, 1)

$$\mu_y = \bar{y} \tag{4.37}$$

$$\widehat{\sigma_\varepsilon^2} = \frac{\sigma_y^2\,(1 - \widehat{\phi_1}^2)}{1 - 2\widehat{\phi_1}\widehat{\theta_1} + \widehat{\theta_1}^2} \tag{4.38}$$

$$\widehat{\phi_1} = \frac{r_2}{r_1} \tag{4.39}$$

$$\widehat{\theta_1} = \frac{-b \mp \sqrt{(b)^2 - 4(r_1 - \widehat{\phi_1})^2}}{2(r_1 - \widehat{\phi_1})} \quad (4.40)$$

$$b = 1 - 2\widehat{\phi_1} r_1 + \widehat{\phi_1}^2 \quad (4.41)$$

where μ_y : sample mean, σ_ε^2 : variance, $\widehat{\sigma_\varepsilon^2}$: estimator of the variance of ε_t , $\widehat{\phi_1}$: the estimator of the autoregression correlation coefficient, $\widehat{\phi_1}$: the estimator of moving average correlation coefficient, r_1: autocorrelation coefficient at lag 1, r_2 : autocorrelation coefficient at lag 2.

4.4.6 The ARIMA Models

In hydrology, ARMA models are usually fitted to stationary hydrologic series, such as annual series. For non-stationary series such as monthly and weekly series, the non-stationarity was removed by the periodic standardization. However, the required number of parameters is usually large. An alternative way to transform data into a stationary series with fewer parameters is possible by taking the differences of the data. It is possible to take the first, second, or in general, the d^{th} difference, which leads to non-periodic, stationary ARIMA (p,d,q) models.

4.4.7 Synthetic Data Generation

Results of the long time series analysis are more reliable than the short ones but many historical records for hydrologic variables (rainfall, streamflow, etc.) are generally not too long. Naturally, short records include a similar and limited number of realizations but records with long periods may provide different and various scenarios. Historical records can be extended using synthetic data generation techniques (Mirakbari et al., 2010). In this study, the "simulate" function of MATLAB (Mathworks Inc., 2021a) was used for this purpose. After parameters of the most fitted ARIMA model were estimated by means of the "estimate" package of MATLAB (Mathworks Inc., 2021a), the desired length of artificial data can be generated with the statistical properties that are close to the historical data. Then, this generated series can be used for further analyses.

4.5 Parameter Uncertainty

Since the stochastic model parameters are not known, they are generally estimated from the historical data. It is assumed that the parameters of the population are equal to the parameters of the sample. Sample parameters can be estimated by using the method of moments or the maximum likelihood method but hydrologic data are not generally too long, so parameter uncertainty needs to be taken into consideration to obtain more reliable and confident results (Akintuğ, 2006). In hydrology, parameter uncertainty has great importance because it may affect the predictions and decisions negatively (Van et al., 2008; Sudheer and Lakshmi, 2011). The distribution of each parameter is found and a different random value of the parameter that comes from the distribution is used for each scenario in the synthetic data generation. Using random parameters instead of fixed parameters may help to overcome the parameter uncertainty problem. However, in this study, parameter uncertainty was not considered.

4.6 Disaggregation Approach

Disaggregation models are very popular techniques in hydrological modeling. There are two main types of disaggregation in the literature which are temporal and spatial.

In this study, Valencia-Schaake (VLSH) model was used to disaggregate the synthetic data spatially. For example, in order to disaggregate the annual aggregated rainfall data (higher-level) into N annual regional rainfalls (lower-level), this approach can be used.

The basic form of the single site temporal disaggregation model has been formulated by Valencia & Schakke (1973) as:

$$Y = AX + B\underline{\varepsilon} \qquad (4.42)$$

This model was the first widely accepted model. In Equation 4.42, X is annual aggregated rainfall with zero mean, Y is zero mean annual regional rainfalls, A and B are the parameters and $\underline{\varepsilon}$ is the random variable with zero mean and constant variance (Valencia & Schaake, 1973). A and B are the matrices of parameters that can be estimated by means of the method of moments after transforming the marginal distributions of all historical aggregated annual rainfalls and annual rainfalls of each region into normal.

$$\hat{A} = S_{YX}\, S_{XX}^{-1} \tag{4.43}$$

$$\hat{B}\hat{B}' = S_{YY} - A\, S_{YY} \tag{4.44}$$

where

$$X = [x_1 \ldots x_T], \quad Y = \begin{bmatrix} y_1^{(1)} & \cdots & y_T^{(1)} \\ \vdots & \ddots & \vdots \\ y_1^{(N)} & \cdots & y_T^{(N)} \end{bmatrix} \tag{4.45}$$

S_{UV} is the sample covariance of the vectors U and V. Since their mean is zero, the sample covariance matrices can be calculated as

$$S_{XX} = \left(\frac{1}{T}\right) XX' \tag{4.46}$$

$$S_{YX} = \left(\frac{1}{T}\right) YX' \tag{4.47}$$

$$S_{YY} = \left(\frac{1}{T}\right) YY' \tag{4.48}$$

$$S_{XY} = S'_{YX} \tag{4.49}$$

The VLSH spatial disaggregation model preserves not only the correlation coefficients at lower levels but also correlations between lower levels and higher levels (Akintuğ, 2006). Most importantly, this model also has an additivity condition that means generated higher-level rainfalls can be obtained by adding generated lower-level rainfalls (Mujumdar & Kumar, 2012). In order to disaggregate the annual data into monthly series (temporal disaggregation), this method can also be used but it may create some disadvantages. For example, the correlation coefficient between the last month of any year and the first month of the next year cannot be preserved (Akintuğ, 2006). In order to solve this problem, another model was developed by Meija and Rouselle. Also, in Lane's condensed model, in order to reduce the number of parameters for temporal disaggregation, unimportant correlations are ignored but this is not desirable for spatial disaggregation because correlation coefficients between the regions are important. In addition, it was found that the VLSH model was successful in preserving the historical annual statistics (Ismail et al., 2004). So, Valencia- Schaake spatial disaggregation method was preferred for this study.

4.7 Drought Frequency Analysis

Before starting a drought frequency analysis, a drought definition is required. In the literature, there is no universally accepted drought definition but there are different drought concepts such as agricultural, hydrological, meteorological, energy, etc. In this study, meteorological drought was used because rainfall data were in progress. Meteorological drought can be defined as scarcity of rainfall compared to a selected threshold level. A drought event has three main descriptors such as duration, severity, and magnitude. Drought duration (D_L) represents the elapsed time between the start point and the endpoint of the drought. Drought severity (S_L) can be defined as the total deviations of the variable (e.g. rainfall) during the drought event. The drought magnitude (M_L) represents the average deficit from the threshold level (Akintuğ, 2006). For a frequency analysis, these components need to be calculated according to some indexes or a threshold value. In this study, the runs methodology was applied because it is a suitable method for sequential stochastic time series of hydrological and meteorological variables. In this methodology, a threshold (truncation) value is selected to divide the time series into two sections as above threshold and below the threshold. The above and below parts represent the surpluses and deficits (droughts), respectively. Truncation level can be selected arbitrarily as a constant, a function, or a deterministic variable but it is generally selected as the mean especially in annual time series. In this study, the mean of the observed data was selected as a threshold. Duration, severity, and magnitude are named as run length, run sum, and run intensity in the theory of runs methodology, respectively and their relationship can be expressed in equation 4.50 (Dracup et al., 1980).

$$S_L = M_L * D_L \tag{4.50}$$

Also, all components can be seen in Figure 4.2 (Dracup et al., 1980) visually below (X_0 represents the truncation value.)

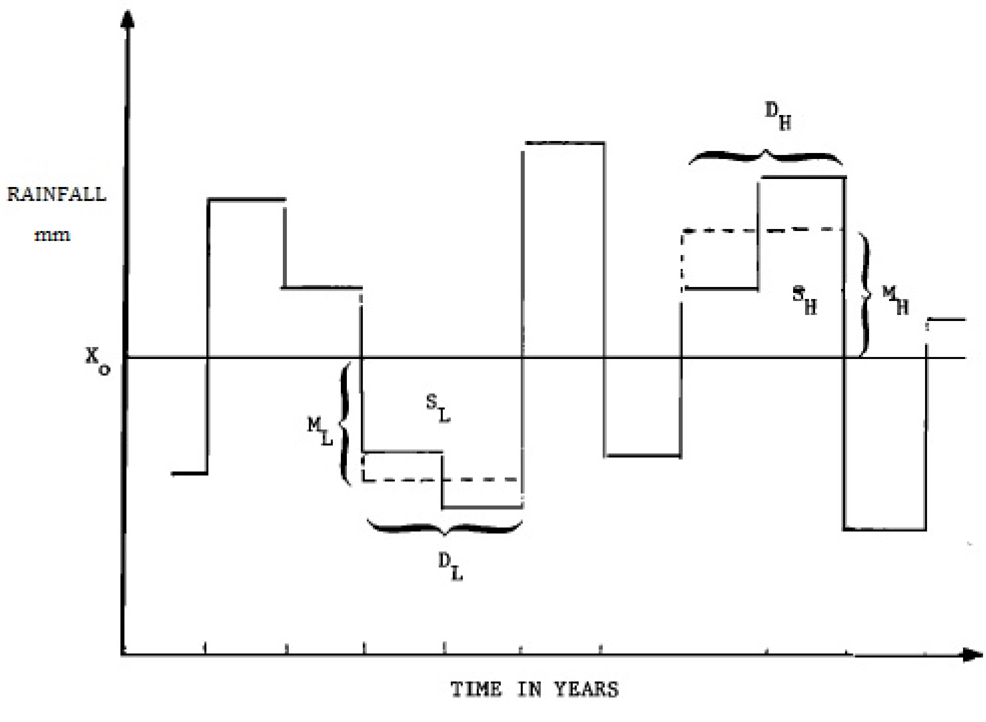

Figure 4.2 Main component of the runs of an annual series. Note. Reprinted from "On the Definition of Droughts", by Dracup et al.,1980, Water Resources Research, 16(2), p.299.

In the drought frequency analysis, the return period is a commonly used element. There are several definitions of it but it was defined as a metric that measures the average expected recurrence time of the hydrological events. If there are consecutive droughts for several years, the return period of a specified drought can be calculated as follows (DeWit, 1995; Sadeghipour & Dracup, 1985).

$$T = \frac{\tau}{P_{exc}} \tag{4.51}$$

where τ and P_{exc} represent the average cycle length of droughts and exceedance probability, respectively. τ and exceedance probability can be computed by using the following equations 4.46 and 4.47,

$$\tau = \frac{\text{total number of rainfall years}}{\text{total number of drought events}} \tag{4.52}$$

$$P_{exc} = \frac{m}{n+1} \tag{4.53}$$

In Equation 4.47, m is the order number of the drought event and n is the total number of the drought events. Also, the Weibull plotting position is used for the exceedance probability.

CHAPTER 5

RESULTS

In Chapter 4, implemented methods were presented. Some informal controls and formal tests to check pre-conditions of the selected methodology and some applications for model selection and drought frequency analysis were completed. In this chapter, the results of these informal checks, formal tests, and model selection applications, and drought frequency analysis were presented.

5.1 Homogeneity, Quality Control, and Missing Value Detection

The observed data which was obtained from the Meteorological Office of TRNC includes the rainfall values for 37 stations exactly. Zaifoğlu et al. (2017) examined this data in terms of quality, homogeneity, and missing values. According to the results of this examination, 33 stations were found suitable for further statistical analyses. During the missing value detection and quality control process, it was found that 14 stations include missing data, and they were filled by using appropriate estimation methods. Margo Station was directly removed from the data because of having a high level of missing data. According to homogeneity analysis findings, the Cayonu station was excluded from the data because it is not homogeneous (Zaifoğlu et al., 2017). Also, Kozankoy and Taskent stations were eliminated from the data because their records are not as long as others. These results were taken as a reference for further analyses in this study.

5.2 Normalization

As one of the most important preconditions of time series analysis, hydrologic variables which are used for the analysis need to follow the normal distribution. If the variables are not normally distributed, some transformations will be necessary in order to make them normal (Salas et al., 1988). The Filliben probability plot correlation coefficient was used to decide whether variables in the original data need any transformation or necessary transformation method. The highest value represents the most appropriate transformation type for normalization.

Among several transformation techniques, logarithmic, 3-parameter log-normal, and Box-Cox transformation were selected to transform non-normal stations into normal. Probability plot correlation coefficient values for the non-transformed and transformed data by using TH different transformation methods were given in Table A.1 in Appendix A. According to these results, the appropriate transformation which has the closest value to 1 was applied for necessary stations for the next steps. Except for the Güzelyurt (3-parameter log-normal), Akdeniz (2-parameter log-normal), Yenierenköy (no transformation), Lefke (3-parameter log-normal), Tatlisu (no transformation), and Alevkaya (no transformation), Box-Cox transformation was found proper for other stations.

If transformation is not necessary, it can be seen as “no transformation” in Table 5.1. If it is necessary, the name of the most suitable transformation method for each station can be seen in the same table.

Table 5.1 Transformation types for 33 selected stations

Station Name	**Transformation type**	**Probability Plot Correlation Coefficient(r)**
Akdeniz	2-parameter log-normal	0.9943
Camlibel	Box-Cox	0.9927
Lapta	Box-Cox	0.9924
Girne	Box-Cox	0.9897
Beylerbeyi	Box-Cox	0.9907
Bogaz	Box-Cox	0.9931
Tatlisu	No transformation	0.9982
Kantara	Box-Cox	0.9903
Esentepe	Box-Cox	0.9949
Guzelyurt	3-Parameter Lognormal	0.9905
Gaziveren	Box-Cox	0.9927
Lefke	3-Parameter Lognormal	0.9896
Yesilirmak	Box-Cox	0.9873
Ercan	Box-Cox	0.9872
Serdarli	Box-Cox	0.9938
Degirmenlik	Box-Cox	0.9875
Gecitkale	Box-Cox	0.9954
Gonendere	Box-Cox	0.9911
Vadili	Box-Cox	0.9950
Beyarmudu	Box-Cox	0.9944
Cayirova	Box-Cox	0.9926
Iskele	Box-Cox	0.9928
Mehmetcik	Box-Cox	0.9906
Gazimagusa	Box-Cox	0.9906
Salamis	Box-Cox	0.9906
Alevkaya	No transformation	0.9794
Zumrutkoy	Box-Cox	0.9914
Alaykoy	Box-Cox	0.9906

Lefkosa	Box-Cox	0.9790
Ziyamet	Box-Cox	0.9916
Dipkarpaz	Box-Cox	0.9890
Yenierenkoy	No Transformation	0.9959
Dortyol	Box-Cox	0.9938

5.3 Stationarity

As another precondition of time series analysis, the stationarity of the normalized data needs to be satisfied. Stationarity represents the stability in the mean and variance of the data over time (Salas et al., 1988)

The transformed time series were checked visually with the help of the plot of observed average annual rainfall data in Figure 5.1. According to the time plot, the data satisfies the stationarity condition because there is no noticeable trend and seasonality in the figure.

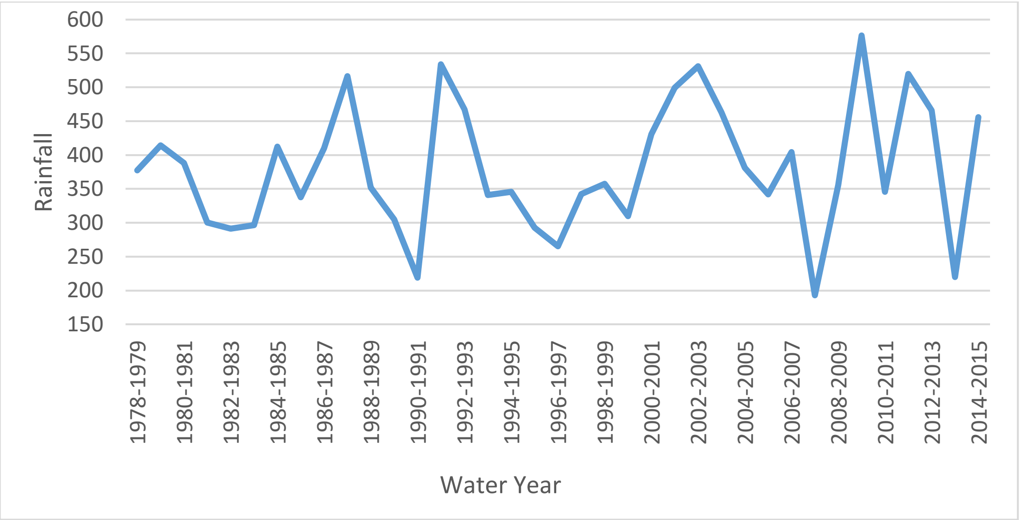

Figure 5.1 Plot of the observed annual time series for rainfall data in North Cyprus from 1978 to 2014

Also, autocorrelation values were calculated by means of the “autocorr” function in MATLAB (Mathworks Inc, 2021a) and these values have a fast decrease for all stations when the maximum lag is three. This is one of the important indications of stationarity. However, for the number of lags higher than three, t-statistic values started to be outside critical values and ruin stationarity for some stations. ACF values until lag-4 for both transformed and observed data are available in Table B.1 in Appendix B (values given in parentheses represent ACF values of observed data). Also, ACF values for four observed and transformed clusters were indicated in Table D.42 in Appendix D. It can be seen that there is no significant positive or negative change in the ACF values after the transformation. It indicates that using transformed data will not cause a huge margin of error in the results after applying back transformation.

Also, correlograms for transformed data indicated that as the lag number increases (especially after three), the stationarity of some stations cannot be satisfied. So, the suitable number of lags was determined as three for stationarity analysis.

Also, the optimal lag number was controlled by calculating the AIC and BIC values of some candidate ARIMA models for different stations which have different rainfall characteristics by using lag 0, 1, 2, and 3. As it is known, AIC and BIC values need to be minimized for the most appropriate model. In this study, there is no need to use a higher number of lags than three because AIC and BIC values start to be higher as more lags are added. As a result, it was decided that the maximum optimal lag number is three for this dataset and the time series is stationary.

Additionally, the Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were applied after the visual check of the data in order to confirm the stationarity of the time series formally. The ADF test was conducted through the “adftest” function in MATLAB (Mathworks Inc., 2021a). ADF test results indicated that time series is stationary because all p-values are smaller than 0.05 and the null hypothesis should be rejected for all stations. P-value and ADF test statistics are available in Table B.2 and Table B.3 in Appendix B.

In addition, the “kpsstest” function in MATLAB (Mathworks Inc., 2021a) was used to conduct the KPSS test and its results confirmed the ADF test results. All t-statistics are inside of the confidence intervals and it means that these values are not in the rejection regions. The null hypothesis of the KPSS test ($\sigma^2 = 0$) cannot be rejected, so it can be concluded that the stationarity condition is satisfied. Table of the p-value (Table B.4) and test statistics (Table B.5) of the KPSS test can be seen in Appendix B.

All of these results show that differencing or any type of transformation for stationarity is not necessary for the dataset.

5.4 Clustering

Among 11 distance methods and seven distance metrics, the most used combinations in the literature were applied such as Ward-Correlation, Complete-Correlation, Weighted-Correlation, Average-Correlation, and Ward-Spearman. All of these combinations were applied by using the “cluster” function in MATLAB (Mathworks

Inc., 2021b) and results were checked for 3, 4, and 5 clusters visually by means of the map of the stations. In this process, transformed data was used because this clustered data will be required for ARIMA modeling in the next step. The reason for using the correlation coefficient similarity measure is that ARIMA models use dependent relationships so, controlling correlation coefficients is very important. As a result, dividing the study area into 4 clusters by using the Complete-Correlation combination was found the smoothest one. The optimal number of clusters and the best linkage-similarity combination were decided visually since the sample size is not too long and the topographical characteristics of the study area were known well. The stations that have similar cross-correlation values were collected in the same clusters. Region 1, Region 2, Region 3, and Region 4 include two, 12, 10, and nine stations, respectively. Clusters and stations in each cluster can be seen in Figure 5.2 and Table 5.2. Region 1, 2, 3, and 4 represent the West part of Northern Cyprus, North Coast -Mesaria Plain, Central Mesaria Plain, and Karpas Peninsula, respectively. However, there is an exceptional case for the Beyarmudu station. Indeed, according to formal results of complete-correlation combination, this station needs to be included in region 4 but placing it with the Region 3 stations was more reasonable because the correlation coefficients between Beyarmudu station and Region 3 stations are higher than the stations in Region 4. Also, Beyarmudu is closer to the stations in Region 3 than Region 4 geographically. So, the Beyarmudu station was included in the third cluster instead of four. All other possible cluster maps for applied different combinations and the different number of clusters were given in the figures from C.1 to C.14 in Appendix C.

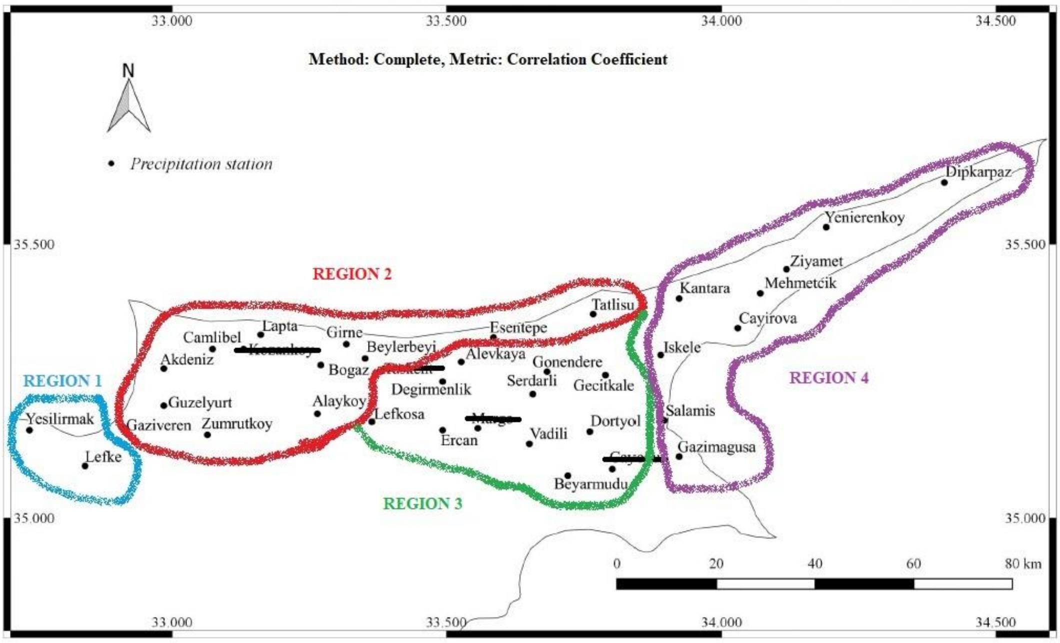

Figure 5.2 The smoothest cluster map by using complete method and correlation coefficient similarity metric

Table 5.2 Four rainfall regions produced by cluster analysis

Region 1	**Region 2**	**Region 3**	**Region 4**
Yesilirmak Lefke	Akdeniz Camlibel Lapta Girne Beylerbeyi Bogaz Tatlısu Esentepe Guzelyurt Gaziveren Zumrutkoy Alaykoy	Ercan Serdarlı Değirmenlik Gecitkale Gönendere Vadili Beyarmudu Alevkaya Dortyol Lefkosa	Cayirova Iskele Mehmetcik Magusa Salamis Kantara Ziyamet Dipkarpaz Yeni Erenkoy

Also, stations are numbered in order to prevent complexity, so the number of each station was given in Table C.3 in Appendix C. All cross-correlation values of the stations for observed and transformed data are available in Table C.4 and Table C.5 respectively in Appendix C. It can be seen that cross-correlation values are very similar for observed data and transformed data. It means that transformation for normalization did not change the structure of the raw data negatively, even it made many correlation coefficients between stations higher.

Additionally, after dividing the study area into the optimal number of clusters, cross-correlation coefficients were calculated for observed and transformed regions. First of all, observed annual rainfall records of the stations in each region were added to each other and imported to MATLAB as a 37x4 matrix. By using these aggregated annual records of regions, cross-correlation values between observed regions in Table 5.4 were calculated by using the "corrcoef" function in MATLAB software (Mathworks Inc., 2021b). Then, an appropriate transformation type was decided to transform (if necessary) the observed annual aggregated records of each cluster into normal before the ARIMA modeling step. Filliben probability plot correlation coefficient was used for this application and Box-Cox transformation was found the most appropriate transformation type for all 4 clusters. As the next step, the aggregated annual records of each region were transformed by using this type of transformation and cross-correlation coefficients between transformed regions were calculated as they can be seen in Table 5.5.

As can be seen in Tables 5.4 and 5.5, while there was an increase in correlation coefficients between region 1, region 2, and region 3 after transformation, coefficients between region 4 and other stations declined. This may be one of the disadvantages of ARIMA models. Modeling the data by using ARIMA may not be a correct decision since it altered the structure of some parts of the time series and led to a decrease in the correlation coefficients between some regions.

Also, correlation coefficients between each region and its stations and cross-correlations between the stations in the same region for both observed and the transformed data are available from Table C.6 to Table C.13 in Appendix C.

Table 5.3 Correlation coefficient of 4 clusters (Observed groups)

Groups	**OG1**	**OG2**	**OG3**	**OG4**
OG1	1.00	0.71	0.58	0.58
OG2	0.71	1.00	0.90	0.86
OG3	0.58	0.90	1.00	0.84
OG4	0.58	0.86	0.84	1.00

Table 5.4 Correlation coefficient of 4 clusters (Transformed groups)

Groups	**TG1**	**TG2**	**TG3**	**TG4**
TG1	1.00	0.84	0.87	0.56
TG2	0.84	1.00	0.91	0.58
TG3	0.87	0.91	1.00	0.67
TG4	0.56	0.58	0.67	1.00

5.5 Model Selection

After normalization and stationarity control processes, AIC and BIC values were checked in order to select the most suitable model for each rainfall station. Firstly, these criterion values of all 64 combinations with lag-3 for one representative station from different regions (Akdeniz, Lefkosa, and Dipkarpaz) were calculated and given in Table D.1, Table D.2, and Table D.3, respectively. These values were calculated by means of the "estimate" function in MATLAB (Mathworks Inc., 2021a). According to these criterion results, it was found that ARIMA models with lag-0, lag-1, and lag-2 have lower AIC and BIC values than models with lag-3. As the lag number increases, especially differentiation order, criterion values tend to be higher. So, it was decided that using lag-3 is not necessary and AIC and BIC values for 27 combinations were checked to select the best-fitted model. According to a formal rule, the model which has the lowest AIC or BIC values is the best model. This rule was taken into consideration but also lag-1 autocorrelation values were evaluated for the best model selection. Although ARIMA (0, 0, 0) was given the most appropriate model for many rainfall stations, non-ignorable autocorrelation values at lag-1 were observed in these stations such as Camlibel, Bogaz, Serdarli, Gecitkale, etc. For these stations, models that preserve the autocorrelation at the first lag were selected such as ARIMA (1, 0, 0) and ARIMA (0, 0, 1). Oppositely, for example, for Cayirova and Zumrutkoy, autocorrelations at the first lag are very small and they can be ignored. So, these stations can be modeled by using ARIMA (0, 0, 0). However, AIC and BIC values of ARIMA (0, 0, 0) and ARIMA (1, 0, 0) for these stations are very close to each other, so ARIMA (1, 0, 0), that is, AR (1) model was preferred for them without ignoring even small autocorrelations at lag 1.

The most suitable model for all 33 stations with AIC and BIC values can be seen in Table 5.5. Also, the AIC and BIC values of all stations for 27 ARIMA model combinations are available from Table D.4 to Table D.36 in Appendix D.

In addition, the most suitable models and their AIC and BIC values for each region and the annual average of North Cyprus are available in Table 5.6. All AIC and BIC values for 27 ARIMA model combinations were given in Table D.37, Table D.38, Table D.39, Table D.40, and Table D.41 in Appendix D.

According to these tables, ARIMA (1, 0, 0) was found the most suitable ARIMA model for Region 1, 2, 3, and 4. ARIMA (1, 0, 0) model does not include integration and moving average parts, so it is directly called AR (1) model. During the model selection of regions, ACF values of transformed clusters were also controlled. They can be seen in Table D.42 in Appendix D. Also, ACF values that were obtained from the observed data can be seen under the transformed values in the parentheses in the same table.

Table 5.5 The most suitable model, AIC and BIC values for 33 stations

Station Name	Suitable Model	AIC	BIC
Akdeniz	ARIMA(1,0,1)	-42.1623	-35.7186
Camlibel	ARIMA(1,0,0)	195.784	200.617
Lapta	ARIMA(0,0,2)	167.102	173.545
Girne	ARIMA(1,0,1)	137.952	144.395
Beylerbeyi	ARIMA(0,0,2)	316.361	322.805
Bogaz	ARIMA(1,0,0)	52.5766	57.4093
Tatlısu	ARIMA(1,0,1)	483.14	489.584
Kantara	ARIMA(0,0,2)	367.094	373.538
Esentepe	ARIMA(0,0,1)	355.973	360.806
Guzelyurt	ARIMA(1,0,1)	14.7803	21.224
Gaziveren	ARIMA(1,0,1)	337.942	344.385
Lefke	ARIMA(0,1,1)	15.9025	20.7353
Yesilırmak	ARIMA(1,0,0)	-141.633	-136.8
Ercan	ARIMA(0,0,1)	480.168	485
Serdarlı	ARIMA(0,0,1)	72.0329	76.8656
Değirmenlik	ARIMA(0,0,2)	456.439	462.882
Gecitkale	ARIMA(0,0,1)	567.391	572.224
Gönendere	ARIMA(0,0,1)	509.401	514.234
Vadili	ARIMA(2,0,1)	269.263	277.318
Beyarmudu	ARIMA(0,1,1)	18.8371	23.6698
Cayirova	ARIMA(1,0,0)	209.705	214.538
Iskele	ARIMA(1,0,2)	293.906	301.961
Mehmetcik	ARIMA(1,0,1)	167.881	174.325
Magusa	ARIMA(1,0,2)	31.4379	39.4925
Salamis	ARIMA(0,0,1)	186.775	191.608
Alevkaya	ARIMA(1,0,0)	468.502	473.335
Zumrutkoy	ARIMA(1,0,0)	49.0229	53.8557
Alaykoy	ARIMA(0,0,1)	345.215	350.048
Lefkosa	ARIMA(0,0,1)	407.93	412.763
Ziyamet	ARIMA(1,0,1)	106.714	113.158
Dipkarpaz	ARIMA(0,0,2)	297.875	304.319
Yeni Erenkoy	ARIMA(1,0,2)	463.077	471.132
Dortyol	ARIMA(2,0,1)	248.66	256.715

Table 5.6 The most suitable model, AIC and BIC values for four regions and the annual average of North Cyprus

Region	Suitable Model	AIC	BIC
Region 1	ARIMA(1,0,0)	-75.3313	-70.4985
Region 2	ARIMA(1,0,0)	427.663	432.496
Region 3	ARIMA(1,0,0)	777.406	782.238
Region 4	ARIMA(1,0,0)	354.637	359.47
Annual Average of North Cyprus	ARIMA(1,0,0)	485.372	490.205

5.6 Drought Frequency Analysis

Drought frequency analysis was performed for both the observed average annual rainfall data of all North Cyprus and four different regions of the country. Drought events were identified by using the theory of runs and severities, durations, and magnitudes of them were calculated. By means of these calculations, the return periods of the most severe drought event and the drought event which has the highest magnitude were found.

5.6.1 Observed Drought Events

Observed annual aggregated data of North Cyprus include the sum of the historical records of all 33 stations for one year. So, at the beginning, aggregated historical rainfall data were divided by 33 in order to obtain the average rainfall data for each water year and make the results more meaningful. Then, the mean for 37 years data was calculated and it was abstracted from average rainfall values to reach the normally distributed rainfall data. Negative values mean that the normalized rainfall of the related year is below the overall mean and a drought event occurred in that related year. Negative values represent the droughts. Drought characteristics of 37 years of normalized average observed rainfall data between 1978 and 2015 can be seen in Figure 5.3.

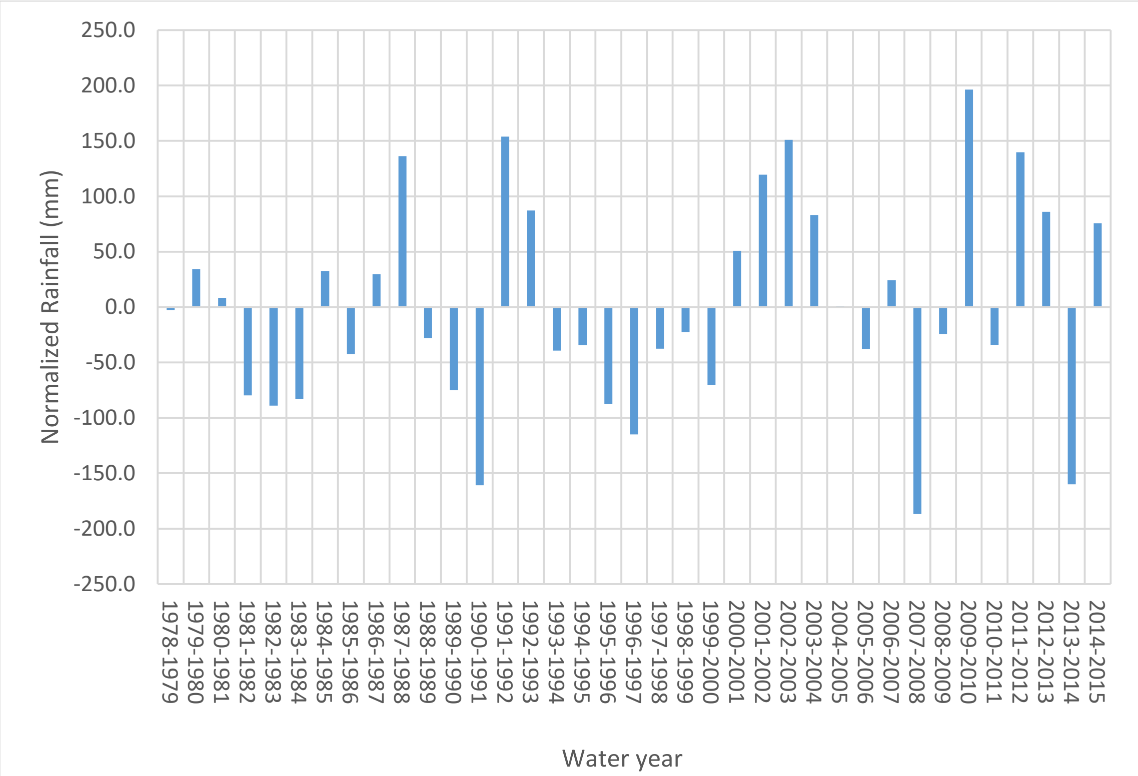

Figure 5.3 Normalized average observed annual rainfall data of North Cyprus

Also, drought years and values of the drought components (severity, duration, and magnitude) are available in Table 5.7. In this observed data, 9 drought events were identified with different durations, severities, and magnitudes. Severities were calculated by aggregating the consecutive droughts. For example, as seen from Figure 5.3, three years of consecutive droughts occurred from 1981 to 1984.

Consecutive droughts were accepted as one drought, so normalized rainfall values of each year were added to each other and a severity value was obtained for these three years. Also, magnitudes were calculated by dividing severities by durations as given in equation 4.44. The most critical drought occurred between 1993 and 2000 with 406.3 mm severity and 7-year duration.

Table 5.7 Drought parameters of the observed average annual rainfall data of North Cyprus

Drought years	Duration(year)	Severity(mm)	Magnitude(mm/year)
1978-1979	1	2.6	2.6
1981-1984	3	251.7	83.9
1985-1986	1	42.6	42.6
1988-1991	3	264.1	88.0
1993-2000	7	406.3	58.0
2005-2006	1	37.9	37.9
2007-2009	2	211.1	105.5
2010-2011	1	34.1	34.1
2013-2014	1	159.9	159.9

5.6.2 Drought Analysis of the Observed Data of Four Regions

In addition to the annual observed total of all North Cyprus, drought analysis was also conducted on the observed values of each cluster. Drought characteristics were obtained and drought parameters were calculated by using the same procedure as section 5.6.1. Drought characteristics for the Region 1, 2, 3, and 4 can be seen in Figures 5.4, 5.5, 5.6, and 5.7 respectively.

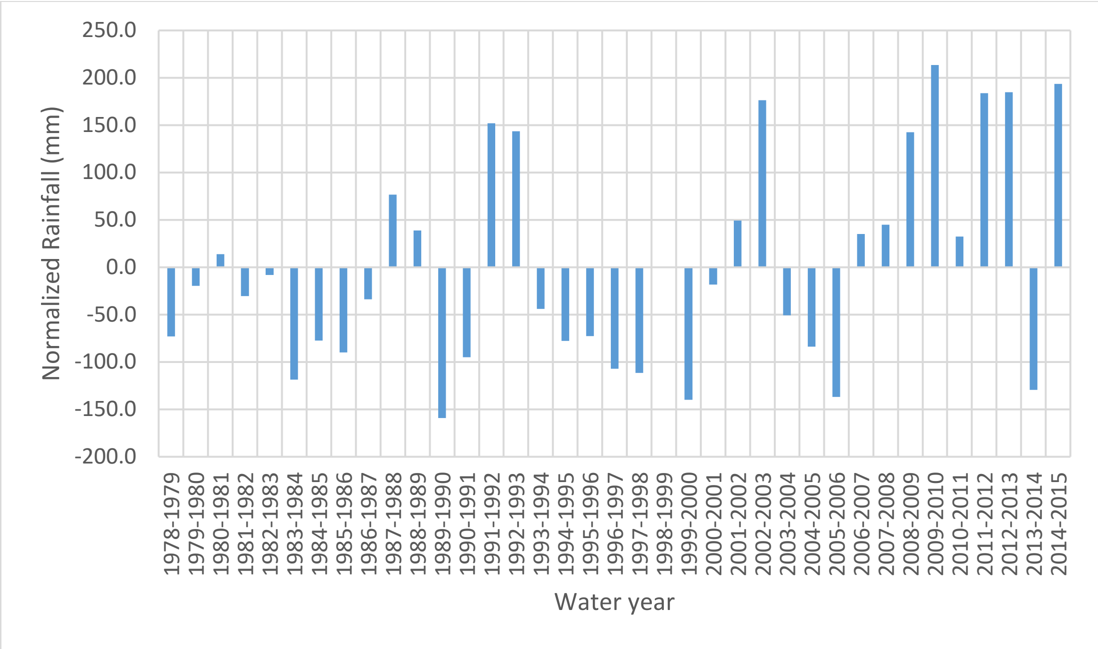

Figure 5.4 Normalized average observed annual rainfall data of Region 1

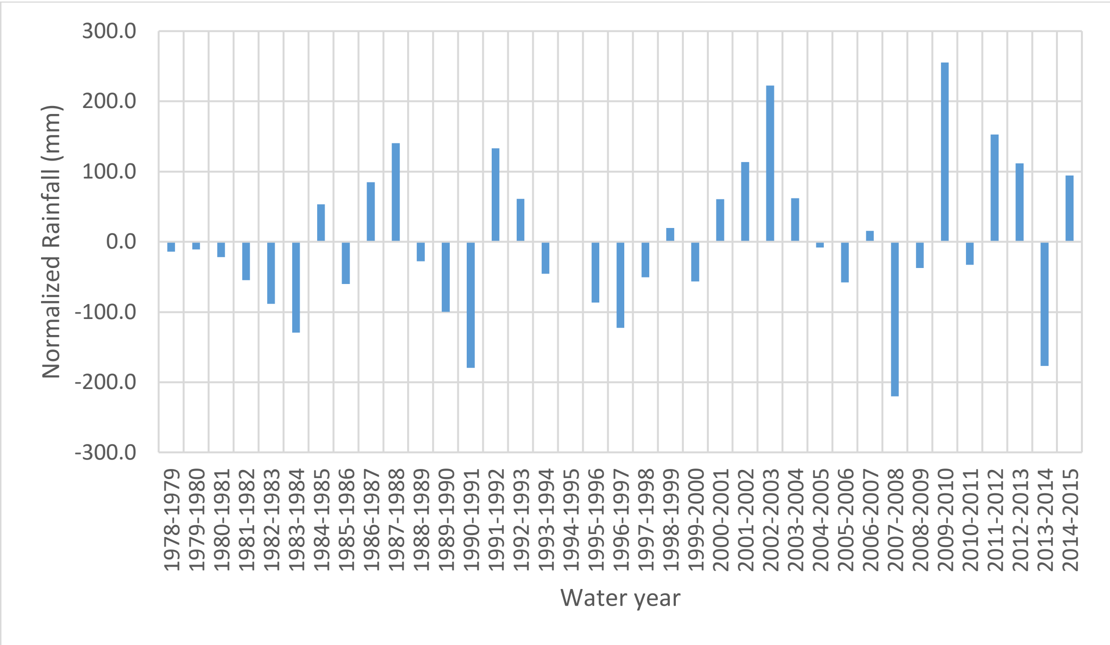

Figure 5.5 Normalized average observed annual rainfall data of Region 2

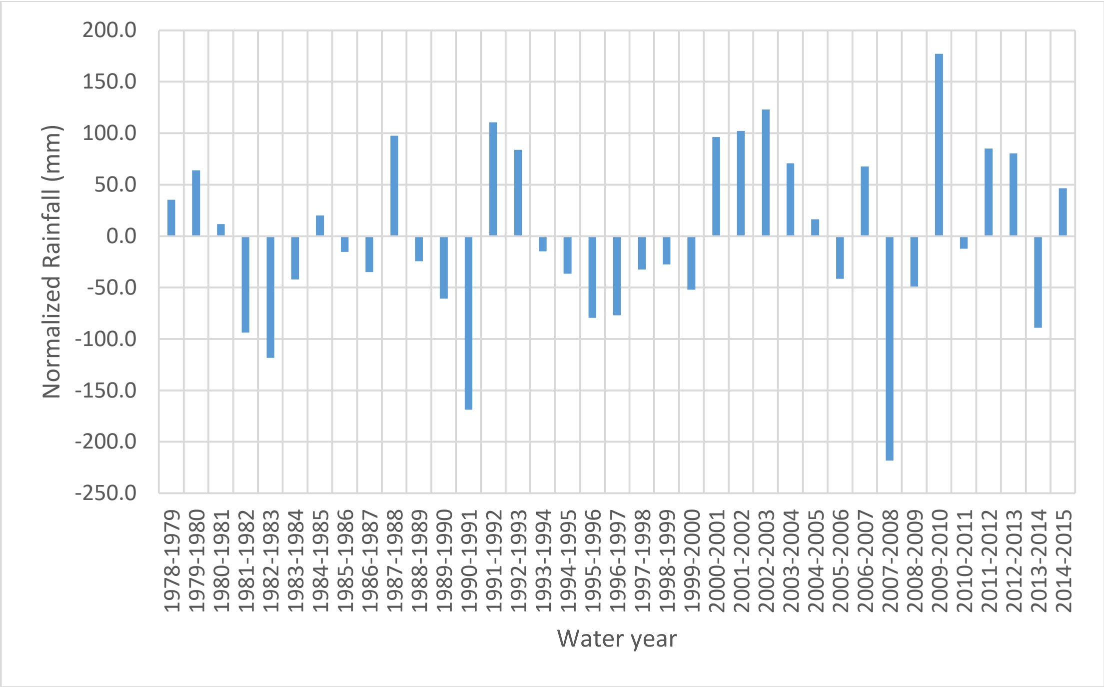

Figure 5.6 Normalized average observed annual rainfall data of Region 3

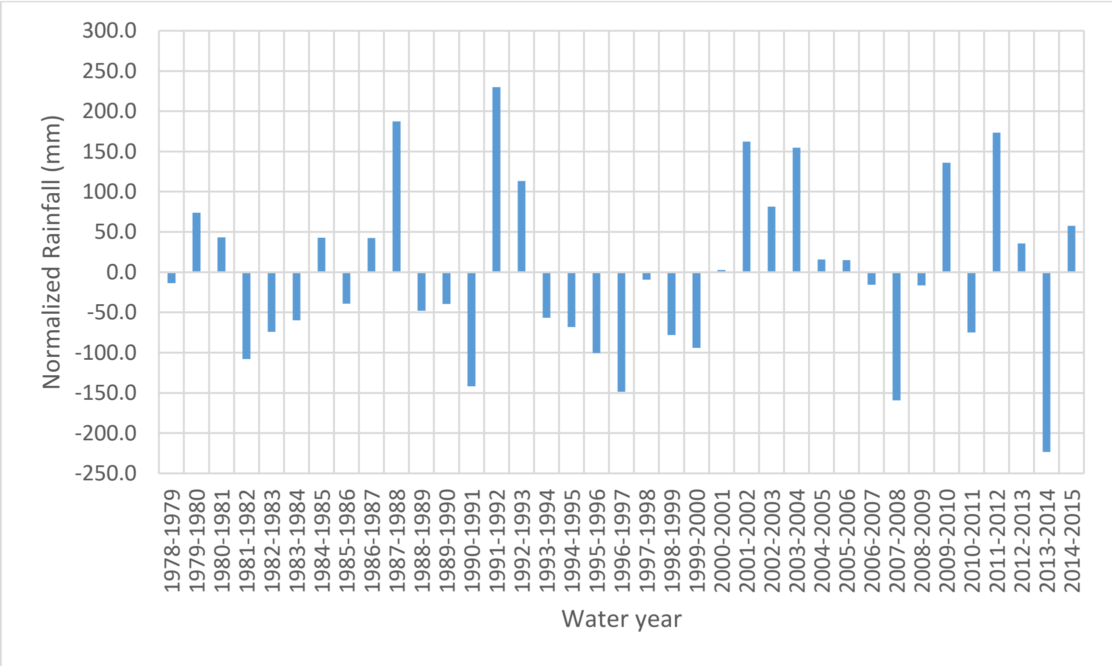

Figure 5.7 Normalized average observed annual rainfall data of Region 4

Also, drought descriptors were calculated for four different regions. They are available in Table 5.8, 5.9, 5.10, and 5.11 for Region 1, 2, 3, and 4, respectively. As it can be seen from the tables, Durations of the most critical droughts for the region 1, 2, 3, and 4 were found as 8, 6, 7, and 7 years, respectively. For example, the most severe drought of Region 1 occurred between 1993 and 2001, and its severity and magnitude were calculated as 572.4 mm and 71.5 mm/year.

Table 5.8 Drought parameters of the observed average annual rainfall data of Region 1

Drought years	Duration(year)	Severity(mm)	Magnitude(mm/year)
1978-1980	2	92.8	46.4
1981-1987	6	358.5	59.7
1989-1991	2	254.4	127.2
1993-2001	8	572.4	71.6
2003-2006	3	272	90.7
2013-2014	1	129.5	129.5

Table 5.9 Drought parameters of the observed average annual rainfall data of Region 2

Drought years	Duration(year)	Severity(mm)	Magnitude(mm/year)
1978-1984	6	319.5	53.3
1985-1986	1	59.9	59.9
1988-1991	3	307.1	102.4
1993-1994	1	45.5	45.5
1995-1998	3	260.2	86.7
1999-2000	1	56.3	56.3
2004-2006	2	65.9	33.0
2007-2009	2	257.4	128.7
2010-2011	1	32.8	32.8
2013-2014	1	176.7	176.7

Table 5.10 Drought parameters of the observed average annual rainfall data of Region 3

Drought years	Duration(year)	Severity(mm)	Magnitude(mm/year)
1981-1984	3	254.3	84.8
1985-1987	2	50.3	25.2
1988-1991	3	254.1	84.7
1993-2000	7	319.8	45.7
2005-2006	1	41.7	41.7
2007-2009	2	267.1	133.6
2010-2011	1	12.2	12.2
2013-2014	1	89.1	89.1

Table 5.11 Drought parameters of the observed average annual rainfall data of Region 4

Drought years	Duration(year)	Severity(mm)	Magnitude(mm/year)
1978-1979	1	13.6	13.6
1981-1984	3	241.8	80.6
1985-1986	1	39.2	39.2
1988-1991	3	228.8	76.3
1993-2000	7	555.1	79.3
2006-2009	3	191.0	63.7
2010-2011	1	74.8	74.8
2013-2014	1	223.2	223.2

5.6.3 Drought Frequency Analysis of Annual Total

After transforming the annual total synthetic data back, drought frequency analysis was performed and drought components were found. Synthetic data generation was performed until similar drought components with the observed data were obtained. Then, the return period of the maximum severity was calculated.

5.6.3.1 General Drought Frequency of North Cyprus

After the most suitable ARIMA model was selected for all North Cyprus, each region, and each rainfall station, the historical annual rainfall data was extended by using the "simulate" function in MATLAB (Mathworks In., 2021a). However, before the synthetic data generation, descriptive statistical properties (mean, standard deviation,and correlation coefficient) of the annual observed average data for general North Cyprus and 4 different regions were calculated and given in Table 5.12. Then, the observed data were transformed by using the Box-Cox transformation technique and lambda values for Box-Cox transformation can be seen in Table 5.12.

Table 5.12 Descriptive Statistics of observed annual rainfall data of North Cyprus and its regions

	Mean	**Std. Dev.**	**Corr. Coeff.**	**Trans. type**	**lambda**
North Cyprus	379.9	94.4	0.009	Box-Cox	0.684
Region 1	337.8	109.6	0.266	Box-Cox	-0.207
Region 2	399.8	108.3	0.076	Box-Cox	0.622
Region 3	332.1	85.5	0.116	Box-Cox	1.282
Region 4	416.1	106	0.064	Box-Cox	0.567

Next, parameters of the transformed annual average data were estimated based on ARIMA(1,0,0) model (the best-fitted model). Then, the desired length of data and the number of scenarios were generated from the transformed data. At the beginning, the sequence was selected as 1 and the length was selected as 100 years in order to make a comparison easily. Statistical properties of the synthetic scenarios were found and compared to properties of the transformed data. It was seen that they were close to each other. As the length of the synthetic data increased to 1000, 10000, etc., the statistical values have approached the transformed ones and each other. In this study, a total of 1 sequence of 3,000,000 years of synthetic rainfalls were generated. The length of the synthetic data was not selected arbitrarily. It increased gradually until the return period of the most severe drought event started to become stable. When 3,000,000 years of data were generated, it was seen that return periods are approached each other (Table 5.13). In Table 5.13, T_S represents the return period of the most severe drought event and T_M represents the return period of the drought event that has the highest magnitude. When the length is 1,000,000 or 2,000,000, the range for the return period of the most severe droughts is similar to the range in 3,000,000. However, in order to be sure that the range will not change as the length of the synthetic data increases, it was decided as 3,000,000 years.

Table 5.13 Return periods and tau values of different length of the synthetic annual data for 10 trials

Trial	Length (years)	T_S (years)	T_M (years)	Tau(τ)
10	100	$30.61 \leq T_S \leq 94.55$	$41.33 \leq T_M \leq 87.31$	$3.57 \leq \tau \leq 4.76$
10	1000	$49.37 \leq T_S \leq 87.78$	$91.19 \leq T_M \leq 248.1$	$4.13 \leq \tau \leq 4.46$
10	10.000	$58.39 \leq T_S \leq 75.83$	$122.64 \leq T_M \leq 167.07$	$4.3 \leq \tau \leq 4.18$
10	100.000	$62.54 \leq T_S \leq 65.63$	$127.83 \leq T_M \leq 143.97$	$4.21 \leq \tau \leq 4.26$
10	1.000.000	$62.83 \leq T_S \leq 64.28$	$136.8 \leq T_M \leq 142.22$	$4.24 \leq \tau \leq 4.25$
10	2.000.000	$62.98 \leq T_S \leq 63.58$	$136.41 \leq T_M \leq 140.86$	$\tau = 4.25$
10	3.000.000	$62.7 \leq T_S \leq 64.02$	$137.48 \leq T_M \leq 140.26$	$\tau = 4.25$

Then, the back transformation was applied to the generated data to obtain similar records to the observed values, and statistics were calculated from back-transformed data. It was realized that the mean, standard deviation, and correlation coefficients of the back-transformed data were very similar to the observed ones. All of these results indicate that transforming the observed data into normal was not a disadvantageous application and it did not create a high margin of error. It can be concluded that model validation was done and it showed that the model works correctly, so generated scenarios that were obtained from the model can be used for further analyses such as forecasting, drought frequency, etc. The drought frequency analysis was applied using the generated annual rainfall data of North Cyprus and drought parameters (durations, severities, and magnitudes) were calculated from one sequence. Then, the severities were sorted from the drought event that is the most severe to the lowest one. The exceedance probabilities were also calculated by means of the Weibull plotting position formula which was given in Equation 4.53 and these values are available in Table 5.14. Also, the exceedance probability-severity graph can be seen in Figure 5.8.

Table 5.14 Severities and exceedance probabilities based on the annual synthetic data of North Cyprus

Severity (S) (mm)	**Exceedance Probability (P_{exc})**
684.18	0.01
448.31	0.05
348.19	0.1
246.72	0.2
188.49	0.3
147.81	0.4
116.40	0.5
90.09	0.6
66.70	0.7
44.64	0.8
22.70	0.9
2.33	0.99

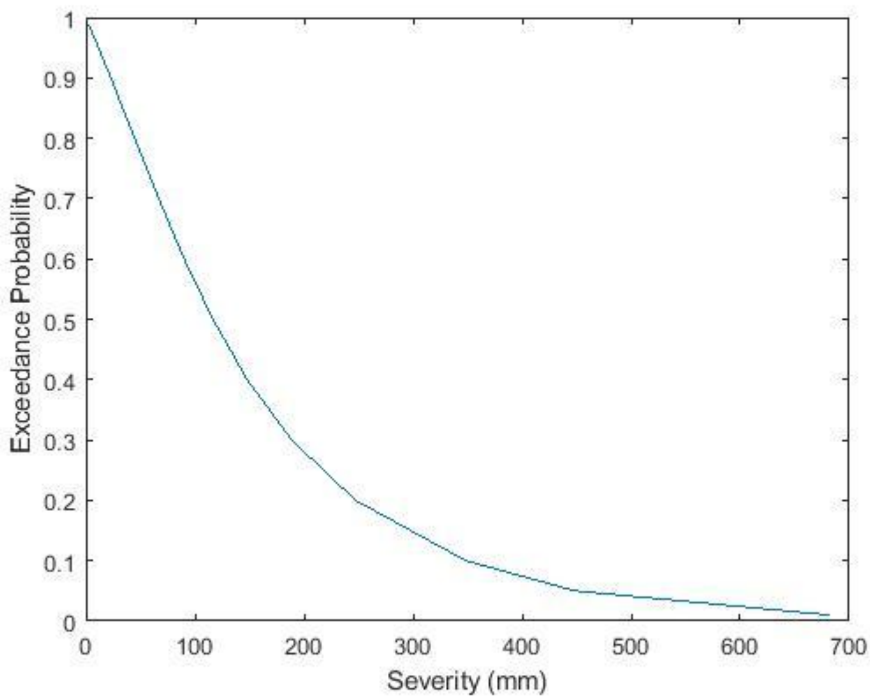

Figure 5.8 Severity-exceedance probability curve based on the annual synthetic data of North Cyprus

In order to calculate the return periods of the desired severities, first of all, a tau (τ) value in Equation 4.52 was calculated for each synthetic data. Then, return periods were found for 5, 10, 20, 50, 100, 200, 500, and 1000-years, respectively, and given in Table 5.15. Also, all return periods for different severities were presented in the severity-return period graph in Figure 5.9. For example, the return period of a drought event with a severity of 300 mm is 30 years or with a severity of 700 mm is approximately 500 years.

Table 5.15 Severities and return periods based on the annual synthetic data of NC

Severity (S) (mm)	**Return Period (T) (years)**
35.93	5
141.01	10
272.23	25
373.54	50
473.49	100
575.25	200
708.37	500
810.45	1000

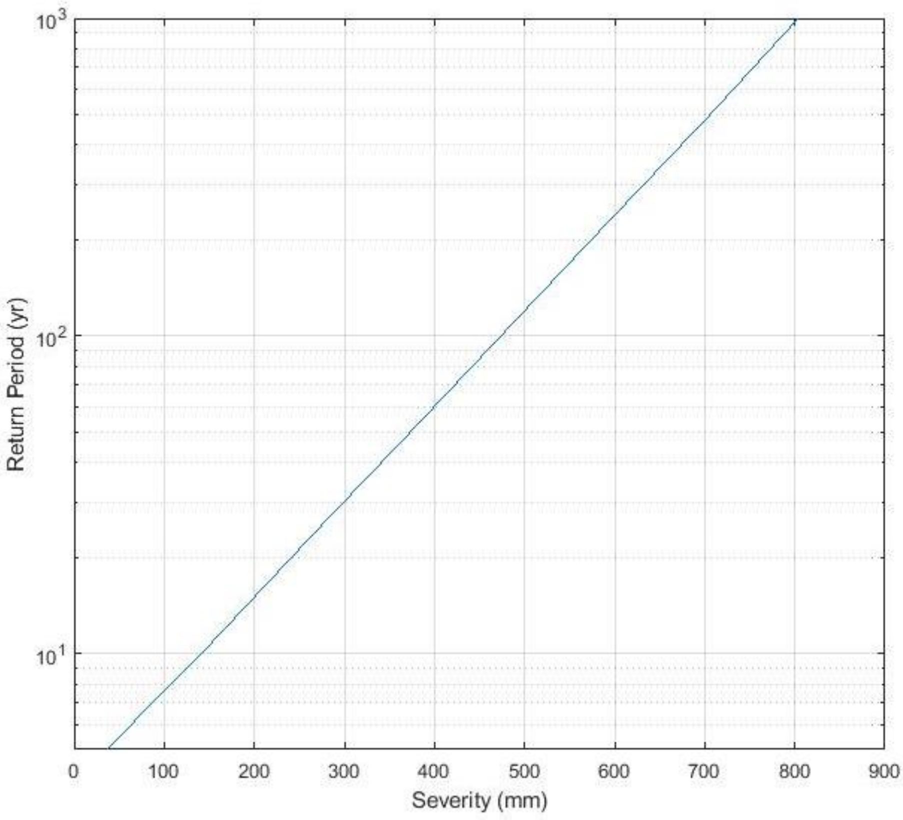

Figure 5.9 Drought Frequency line based on the annual synthetic data of North Cyprus

5.6.3.2 Regional Drought Frequency of North Cyprus

In this part, the synthetic data were disaggregated into four regions and a drought frequency analysis was performed for each region one by one to find the return period of the most severe drought of each region. In this regional frequency analysis, it was seen that generating 1 sequence of 200,000 years of synthetic data was enough to obtain stable return periods in all regions. So, the length of the synthetic data was decided as 200,000 years. The drought frequency analysis results of each region were given in the subsections separately.

5.6.3.2.1 Region 1: The West of North Cyprus

Region 1 represents the west part of North Cyprus and includes 2 stations. 200,000 years of synthetic data were generated based on the classic AR (1) model because it was found that ARIMA (1, 0, 0) model is the most suitable ARIMA model for this region. In Section 5.6.1, drought components of each region from the observed data were calculated. The most critical drought occurred between 1993 and 2001 (duration is 8 years) and its severity and magnitude were measured as 572.4 mm and 71.6 mm/year. In the next step, return periods of the maximum severity and magnitude that are obtained from 200,000 years of synthetic data were given in Table 5.16.

Table 5.16 Return periods of the maximum severity and magnitude and tau value for Region 1

Length (years)	T_S (years)	T_M (years)	Tau(τ)
200,000	137	57	4.19

Also, the severities that were obtained from the synthetic data were sorted from the drought event that is the most severe to the lowest one. The exceedance probabilities were also calculated by means of the Weibull plotting position formula which was given in Equation 4.53 and these values are available in Table 5.17. Also, the exceedance probability-severity graph can be seen in Figure 5.10.

Table 5.17 Severities and exceedance probabilities based on the annual synthetic data of Region 1

Severity (S) (mm)	**Exceedance Probability (P_{exc})**
755.33	0.01
498.13	0.05
390.50	0.1
281.28	0.2
216.42	0.3
169.94	0.4
136.73	0.5
109.35	0.6
84.29	0.7
59.13	0.8
31.40	0.9
3.39	0.99

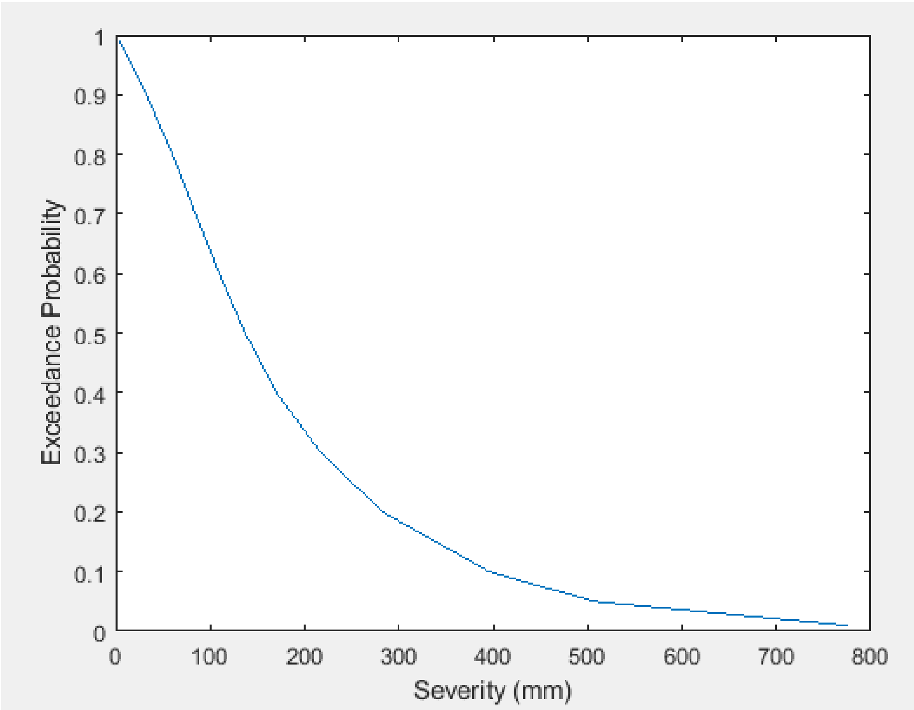

Figure 5.10 Severity-exceedance probability curve based on the annual synthetic data of region 1

In order to calculate the return periods of the desired severities, first of all, an average tau (τ) value in Equation 4.52 was calculated for each synthetic data of Region 1. Then, return periods were found for 5, 10, 20, 50, 100, 200, 500, and 1000-years, respectively, and given in Table 5.18. Also, all return periods for different severities were presented in the severity-return period graph in Figure 5.11. For example, the return period of a drought event with a severity of 400 mm is 45 years or with a severity of 700 mm is approximately 300 years.

Table 5.18 Severities and return periods based on the annual synthetic data of Region 1

Severity (S) (mm)	Return Period (T) (years)
48.50	5
162.70	10
308.99	25
417.61	50
527.29	100
640.1	200
782.15	500
900.73	1000

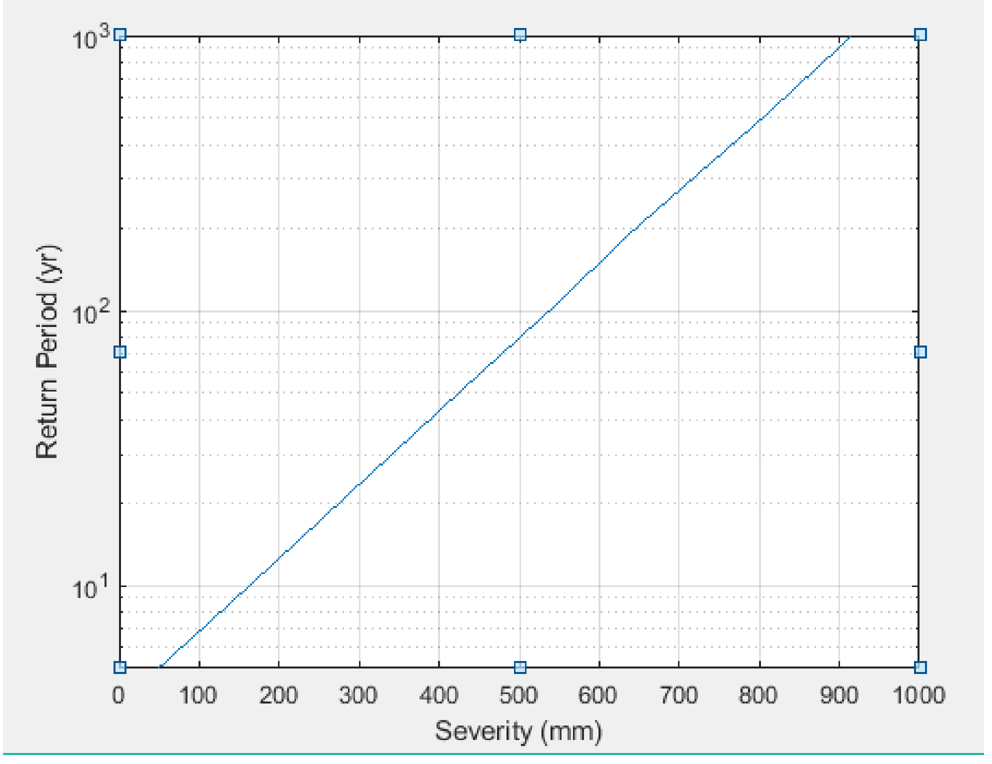

Figure 5.11 Drought Frequency line based on the annual synthetic data of Region 1

5.6.3.2.2 Region 2: North Coast-Mesaria Plain

Region 2 represents North Coast-Mesaria Plain and includes 12 stations. 200,000 years of synthetic data were generated based on the classic AR (1) model because it was found that ARIMA (1, 0, 0) model is the most suitable ARIMA model for region 2. In Section 5.6.1, drought components of each region from the observed data were calculated. The most critical drought occurred between 1978 and 1984 (duration is six years) and its severity and magnitude were measured as 319.5 mm and 53.3 mm/year. In the next step, return periods of the maximum severity and magnitude that are obtained from 200,000 years of synthetic data were given in Table 5.19.

Table 5.19 Return periods of the maximum severity and magnitude and tau value for Region 2

Length (years)	T_S (years)	T_M (years)	Tau(τ)
200,000	26	120	4.26

Also, the severities that were extracted from synthetic data were sorted from the drought event that is the most severe to the lowest one. The exceedance probabilities were also calculated by means of the Weibull plotting position formula which was given in Equation 4.53 and these values are available in Table 5.20. Also, the exceedance probability-severity graph can be seen in Figure 5.12.

Table 5.20 Severities and exceedance probabilities based on the annual synthetic data of Region 2

Severity (S) (mm)	**Exceedance Probability (P_{exc})**
804.23	0.01
524.27	0.05
406.41	0.1
287.79	0.2
218.63	0.3
171.51	0.4
135.14	0.5
104.53	0.6
77.36	0.7
51.78	0.8
26.04	0.9
2.91	0.99

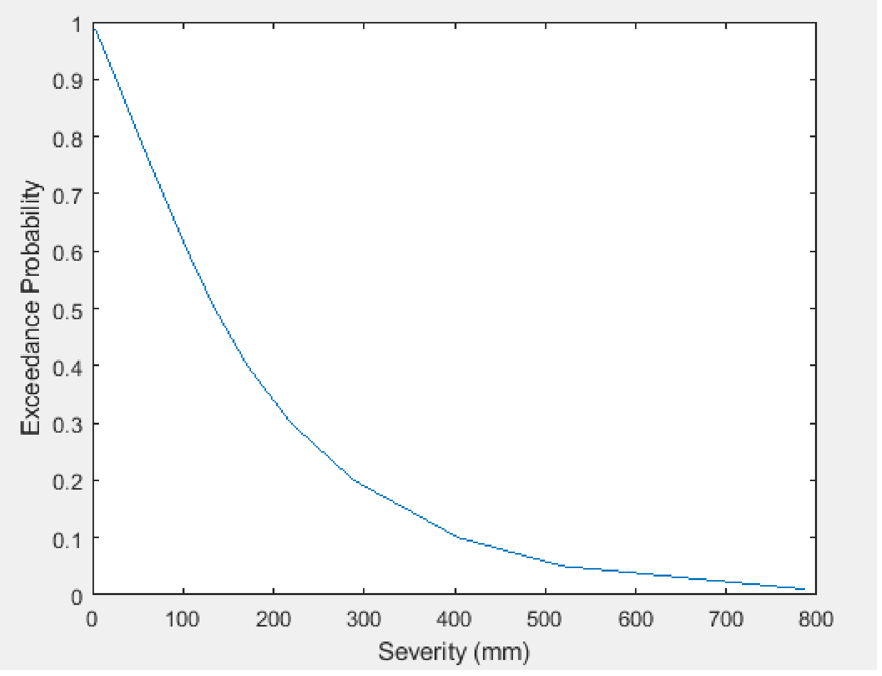

Figure 5.12 Severity-exceedance probability curve based on the annual synthetic data of Region 2

In order to calculate the return periods of the desired severities, first of all, an average tau (τ) value in Equation 4.52 was calculated for each synthetic data of Region 2. Then, return periods were found for 5, 10, 20, 50, 100, 200, 500, and 1000-years, respectively, and given in Table 5.21. Also, all return periods for different severities were presented in the severity-return period graph in Figure 5.13. For example, the return period of a drought event with a severity of 400 mm is 40 years or with a severity of 800 mm is approximately 400 years.

Table 5.21 Severities and return periods based on the annual synthetic data of Region 2

Severity (S) (mm)	**Return Period (T) (years)**
41.68	5
163.55	10
317.62	25
436.47	50
556.05	100
675.16	200
834.42	500
950.45	1000

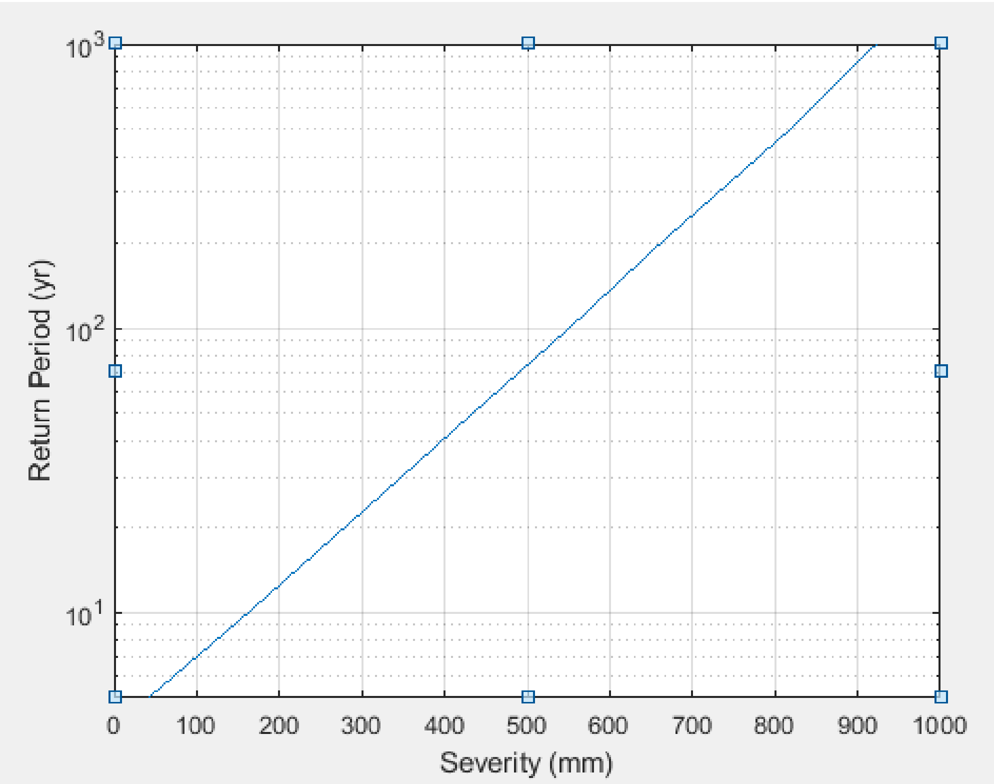

Figure 5.13 Drought Frequency line based on the annual synthetic data of Region 2

5.6.3.2.3 Region 3: Central Mesaria

Region 3 represents Central Mesaria and includes 10 stations. 200,000 years of synthetic data were generated based on the classic AR (1) model because it was found that ARIMA (1, 0, 0) model is the most suitable ARIMA model for Region 3. In Section 5.6.1, drought components of each region from the observed data were calculated. The most critical drought occurred between 1993 and 2000 (duration is seven years) and its severity and magnitude were measured as 319.8 mm and 45.7 mm/year. In the next step, return periods of the maximum severity and magnitude that are obtained from 200,000 years of synthetic data were given in Table 5.22.

Table 5.22 Return periods of the maximum severity and magnitude and tau value for Region 3

Length (years)	T_S (years)	T_M (years)	Tau(τ)
200,000	40	55	4.31

The severities that were extracted from synthetic data were sorted again from the drought event that is the most severe to the lowest one. The exceedance probabilities were also calculated by means of the Weibull plotting position formula and these values are available in Table 5.23. Also, the exceedance probability-severity graph can be seen in Figure 5.14.

Table 5.23 Severities and exceedance probabilities based on the annual synthetic data of Region 3

Severity (S) (mm)	**Exceedance Probability (P_{exc})**
660.49	0.01
427.32	0.05
330.13	0.1
230.46	0.2
173.47	0.3
133.76	0.4
102.92	0.5
78.16	0.6
56.91	0.7
37.33	0.8
18.59	0.9
1.87	0.99

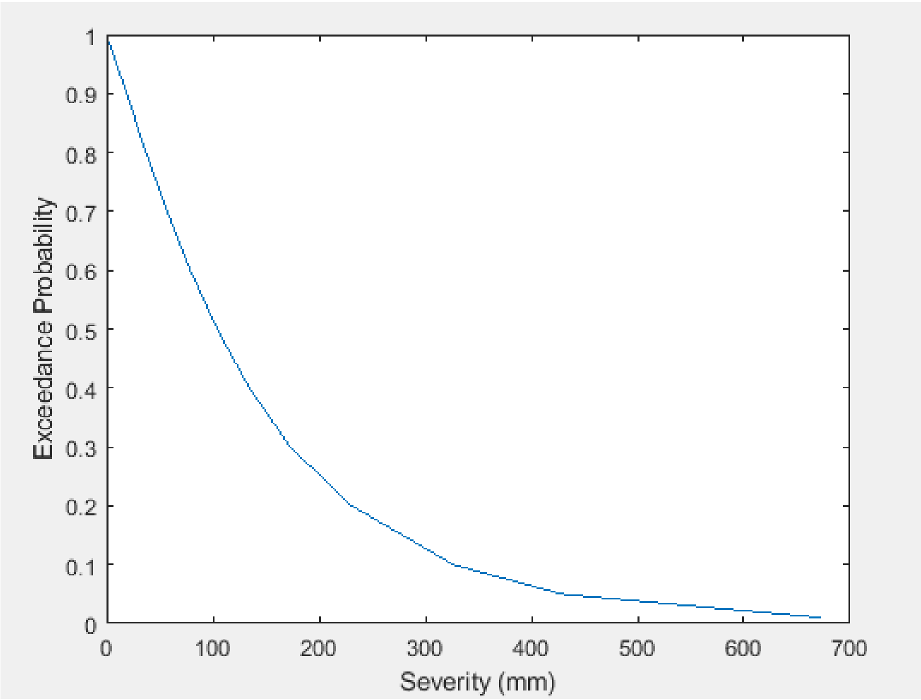

Figure 5.14 Severity-exceedance probability curve based on the annual synthetic data of Region 3

In order to calculate the return periods of the desired severities, first of all, an average tau (τ) value in Equation 4.52 was calculated for each synthetic data of Region 3. Then, return periods were found for 5, 10, 20, 50, 100, 200, 500, and 1000-years, respectively, and given in Table 5.24. Also, all return periods for different severities were presented in the severity-return period graph in Figure 5.15. For example, the return period of a drought event with a severity of 300 mm is 35 years or with a severity of 600 mm is approximately 300 years.

Table 5.24 Severities and return periods based on the annual synthetic data of Region 3

Severity (S) (mm)	Return Period (T) (years)
29.57	5
126.77	10
255.11	25
354.46	50
452.11	100
546.61	200
681.77	500
776.89	1000

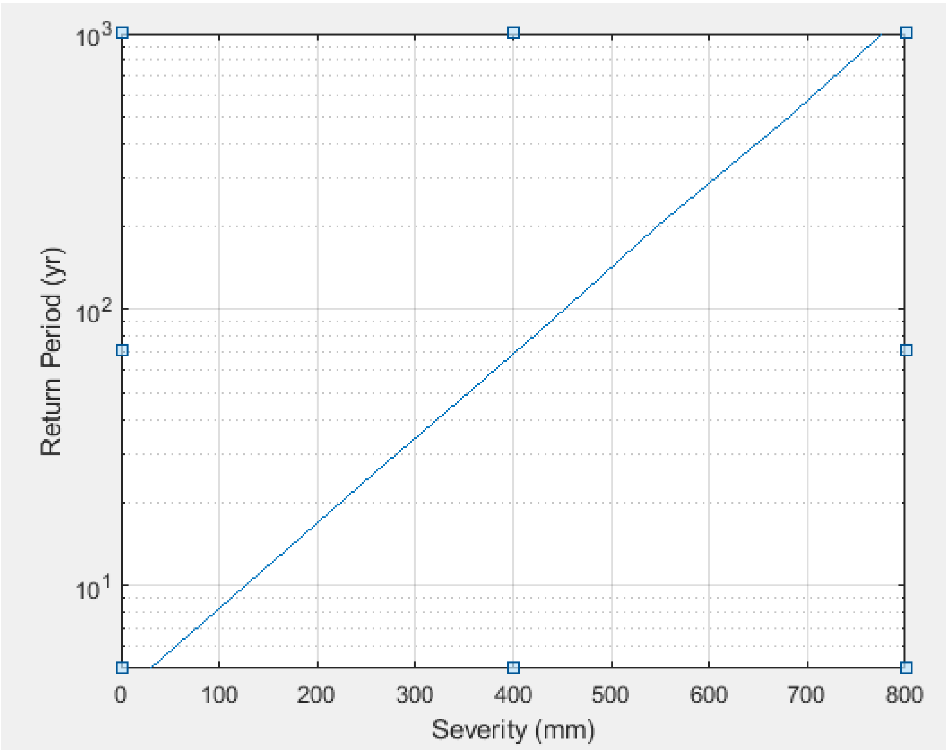

Figure 5.15 Drought Frequency line based on the annual synthetic data of Region 3

5.6.3.2.4 Region 4: Karpaz Peninsula

Region 3 represents Central Mesaria and includes 9 stations. 200,000 years of synthetic data were generated based on the classic AR (1) model because it was found that ARIMA (1, 0, 0) model is the most suitable ARIMA model for Region 4. In Section 5.6.1, drought components of each region from the observed data were calculated. The most critical drought occurred between 1993 and 2000 (duration is 7 years) and its severity and magnitude were measured as 555.1 mm and 79.3 mm/year. In the next step, return periods of the maximum severity and magnitude that are obtained from 200,000 years of synthetic data were given in Table 5.25.

Table 5.25 Return periods of the maximum severity and magnitude and tau value for Region 4

Length (years)	T_S (years)	T_M (years)	Tau(τ)
200,000	116	720	4.22

The severities that were extracted from synthetic data were sorted again from the drought event that is the most severe to the lowest one. The exceedance probabilities were also calculated by means of the Weibull plotting position formula and these values are available in Table 5.26. Also, the exceedance probability-severity graph can be seen in Figure 5.16.

Table 5.26 Severities and exceedance probabilities based on the annual synthetic data of Region 4

Severity (S) (mm)	**Exceedance Probability (P_{exc})**
772.04	0.01
500.68	0.05
392.35	0.1
277.89	0.2
212.42	0.3
167.06	0.4
132.12	0.5
102.59	0.6
76.21	0.7
51.07	0.8
26.34	0.9
2.72	0.99

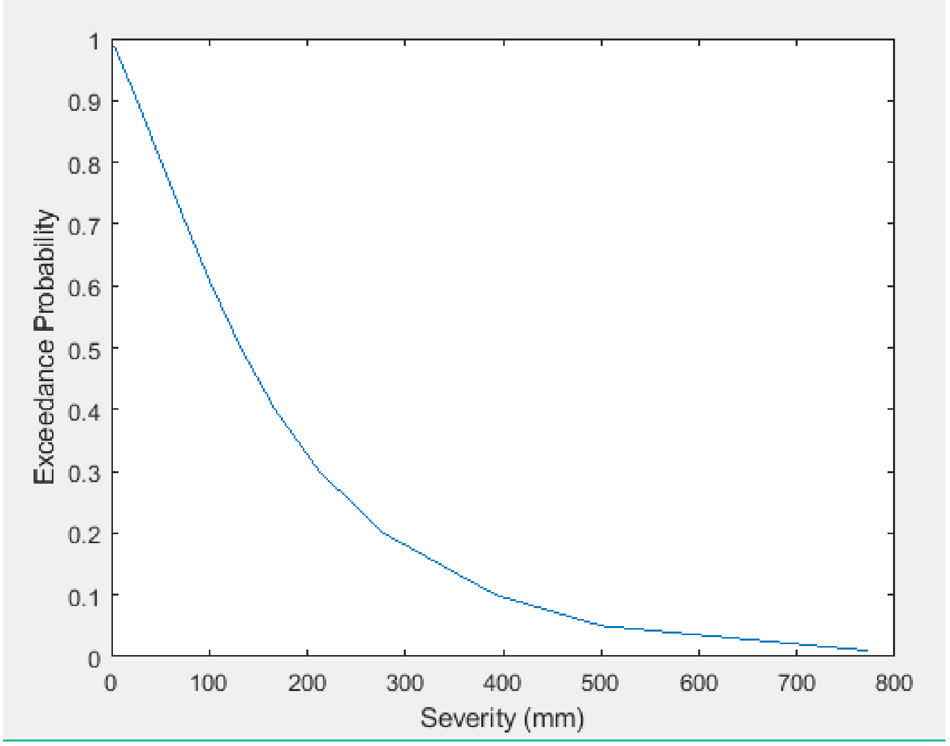

Figure 5.16 Severity-exceedance probability curve based on the annual synthetic data of Region 4

In order to calculate the return periods of the desired severities, first of all, an average tau (τ) value in Equation 4.52 was calculated for each synthetic data of Region 4. Then, return periods were found for 5, 10, 20, 50, 100, 200, 500, and 1000-years, respectively, and given in Table 5.27. Also, all return periods for different severities were presented in the severity-return period graph in Figure 5.17. For example, the return period of a drought event with a severity of 300 mm is 25 years or with a severity of 800 mm is approximately 500 years.

Table 5.27 Severities and return periods based on the annual synthetic data of Region 4

Severity (S) (mm)	**Return Period (T) (years)**
41.41	5
159.91	10
306.02	25
419.72	50
528.51	100
646.26	200
800.03	500
923.30	1000

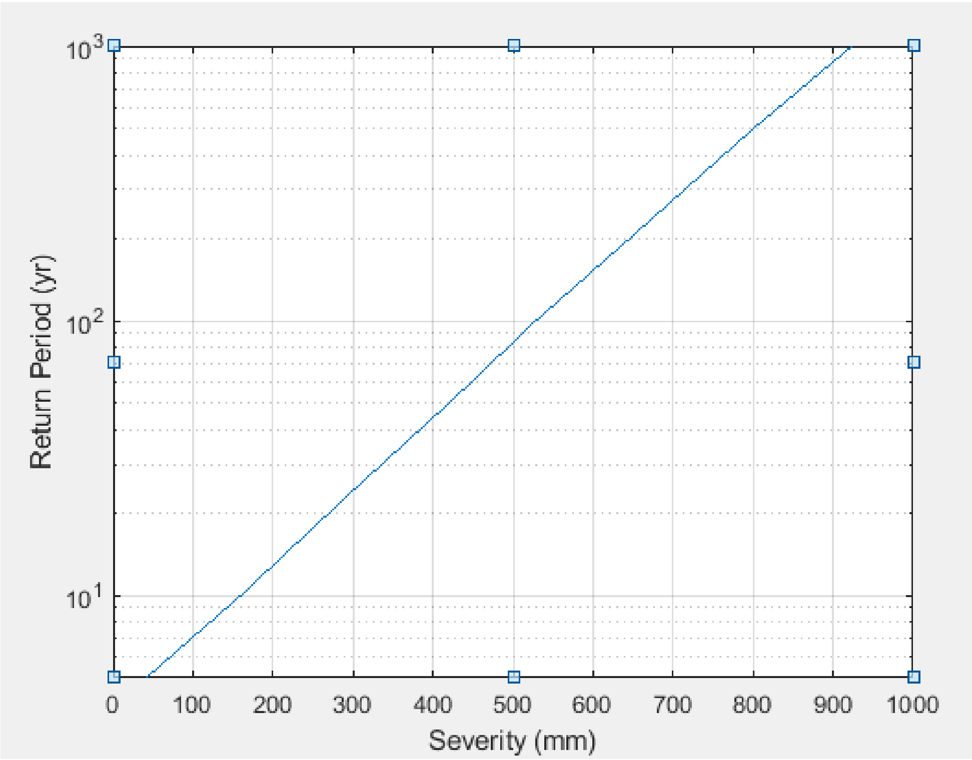

Figure 5.17 Drought Frequency line based on the annual synthetic data of Region 4

CHAPTER 6

CONCLUSIONS AND FUTURE WORKS

The main objectives of this study were to model the annual rainfall data of North Cyprus by using ARIMA models and performing drought frequency analysis to find the return period of the most severe drought event.

Clustering analysis was conducted for different clustering combinations. In the end, the study area was divided into 4 clusters as Region 1, Region 2, Region 3, and Region 4.

Then, Box-Jenkin's modeling procedure was applied to select the most suitable ARIMA model for 33 rainfall stations and four regions. The results revealed that the best ARIMA models that describe this data were low-order ARIMA combinations with lag-0 and lag-1. Eight stations were modeled by ARIMA (0, 0, 1), that is, MA (1), seven stations by ARIMA (1, 0, 1), that is, ARMA (1, 1), five stations by ARIMA (0, 0, 2), six stations by ARIMA (1, 0, 0), that is AR (1), three stations by ARIMA (1, 0, 2), two stations by ARIMA (2, 0, 1), and two stations by ARIMA (0, 1, 1). Also, the same applications were performed for clusters and overall annual data and it was decided both all of the clusters and overall data can be modeled by ARIMA (1, 0, 0), that is, AR (1) model.

For the main purpose of the study, a drought frequency analysis was performed for the annual average rainfall data of Northern Cyprus and its four regions. After synthetic data generation based on the most suitable ARIMA models, drought components (duration, severity, and magnitude) were obtained. For the annual average of North Cyprus, the return period of the most severe (406.3 mm) drought was found as 63 years and it can be concluded that it is a frequent event, and the probability of experiencing this kind of event is quite high. Also, the study area was divided into 4 regions by means of the spatial disaggregation method and regional drought frequency analysis was performed. For Region 1 and Region 4, return periods of the most severe drought events were found as 137 years (with a severity of 572.4 mm) and 116 years (with severity of 555.1 mm). This means that these drought events are relatively rare events and the probability of facing them in these regions is low since their return periods are higher than 100 years (a threshold level in drought frequency analysis). However, in Region 2 and 3, return periods were calculated as 26 and 40 years with severities of 319.5 mm and 319.8 mm. It can be concluded that these kinds of drought events can be seen frequently in the future because their return periods are way smaller than 100 years.

Despite the sample size of this study is enough for a time series analysis and longer synthetic data were generated, using longer historical data always provides better and more reliable results. As a result, it is recommended to repeat this study once more recent rainfall data are obtained.

As another suggestion, model uncertainty may occur because of some restrictions and assumptions of the models, so it should be considered for future analyses. In this study, ARIMA models were used to model the rainfall data but there are some preconditions of ARIMA models, so transformation may be required. The transformation process may ruin the data and affect the results. Also, ARIMA models are not able to model some characteristics like cyclical patterns or periodicity. Choosing a model with a restriction that is not appropriate for the observed data may cause model uncertainty. For future studies, this data can be modeled by using different time series modeling methods in order to compare with the results of this study.

In addition, frequency analysis can be applied for each rainfall station by disaggregating each region into its proper stations to obtain more detailed drought information. Also, in this study, severities were independently obtained from the durations. In another study, severities can be calculated by fixing the durations and return periods can be calculated accordingly.

Also, only mean as a threshold value may not give proper information about the drought levels. It can be suggested that different threshold levels can be used such as mean ± 1 standard deviation in order to classify more severe drought events. Additionally, any indices can be used instead of mean as a threshold level such as standardized precipitation index, rainfall anomaly index, and drought severity index.

This thesis will be very helpful and beneficial for further studies as it estimates the drought characteristics and return periods of the critical droughts of North Cyprus. As a suggestion, future rainfall characteristics of the country can be forecasted from the generated data directly for better meteorological predictions. Most importantly, better strategies can be developed in sustainable water resource management to protect the water resources of North Cyprus and important precautions can be taken to minimize the devastating effects of climate change.

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APPENDICES

A. Normalization

A.1 Introduction

In this appendix, probability plot correlation coefficients for no transformation and 3 different transformation types were shared. The best transformation type for each station was indicated in bold in Table A.1.

Table A. 1 Probability Plot Correlation Coefficients without transformation and with 3 different transformation types for 33 stations

Station Name	**Probability Plot Correlation Coefficient(r)**			
	Without transformation (original data)	**Logarithmic**	**3 parameter Log-normal**	**Box-Cox**
Akdeniz	0.9942	0.9775	0.9774	**0.9943**
Camlibel	0.9847	0.9877	0.9876	**0.9927**
Lapta	0.9830	0.9904	0.9904	**0.9924**
Girne	0.9785	0.9881	0.9880	**0.9897**
Beylerbeyi	0.9891	0.9738	0.9736	**0.9907**
Bogaz	0.9742	0.9930	0.9930	**0.9931**
Tatlisu	**0.9882**	0.9737	0.9736	0.9879
Kantara	0.9902	0.9781	0.9780	**0.9903**
Esentepe	0.9931	0.9729	0.9728	**0.9949**
Guzelyurt	0.9872	0.9827	0.9826	**0.9905**
Gaziveren	0.9924	0.9839	0.9838	**0.9927**
Lefke	0.9811	0.9895	**0.9896**	0.9895
Yesilirmak	0.9459	0.9818	0.9818	**0.9873**
Ercan	0.9865	0.9344	0.9340	**0.9872**
Serdarli	0.9780	0.9043	0.9038	**0.9938**
Degirmenlik	0.9874	0.9414	0.9410	**0.9875**
Gecitkale	0.9923	0.9538	0.9536	**0.9954**
Gonendere	0.9903	0.9574	0.9572	**0.9911**

Vadili	0.9924	0.9867	0.9866	**0.9950**
Beyarmudu	0.9790	0.9943	0.9944	**0.9944**
Cayirova	0.9876	0.9881	0.9880	**0.9926**
Iskele	0.9913	0.9853	0.9852	**0.9928**
Mehmetcik	0.9824	0.9866	0.9865	**0.9906**
Gazimagusa	0.9709	0.9906	0.9906	**0.9906**
Salamis	0.9824	0.9866	0.9865	**0.9906**
Alevkaya	**0.9794**	0.9407	0.9404	0.9790
Zumrutkoy	0.9733	0.9913	0.9912	**0.9914**
Alaykoy	0.9896	0.9727	0.9725	**0.9906**
Lefkosa	0.9789	0.9393	0.9390	**0.9790**
Ziyamet	0.9772	0.9906	0.9906	**0.9916**
Dipkarpaz	0.9849	0.9786	0.9785	**0.9890**
Yenierenkoy	**0.9959**	0.9753	0.9752	0.9959
Dortyol	0.9907	0.9873	0.9872	**0.9938**

B. Stationary Results

B.1 Introduction

In Chapter 5, stationarity of the time series was checked by using autocorrelation values at lag-0, lag-1, lag-2, and lag-3, Augmented Dickey-Fuller (ADF), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Tests. The tables in this appendix represent the p-values and t-statistics of the tests and ACF values for each station.

Table B. 1 Autocorrelation Coefficient Function (ACF) Values for transformed and observed annual data of 33 stations at Lag 0, Lag 1, Lag 2, and Lag 3

Station /ACF value	Lag 0	Lag 1	Lag 2	Lag 3
Akdeniz	1.0 (1.0)	-0.08 (-0.02)	-0.25 (-0.28)	0.02 (0.02)
Camlibel	1.0 (1.0)	-0.001 (0.03)	-0.004 (0.008)	0.23 (0.28)
Lapta	1.0 (1.0)	0.07 (0.08)	-0.17 (-0.14)	0.05 (0.03)
Girne	1.0 (1.0)	-0.007 (-0.01)	-0.08 (-0.07)	-0.13 (-0.13)
Beylerbeyi	1.0 (1.0)	-0.0003 (-0.007)	-0.16 (-0.15)	-0.05 (-0.05)
Bogaz	1.0 (1.0)	0.16 (0.19)	0.06 (0.08)	-0.04 (0.03)
Tatlısu	1.0 (1.0)	0.26 (0.26)	0.12 (0.12)	0.12 (0.12)
Kantara	1.0 (1.0)	0.06 (0.08)	-0.21 (-0.21)	-0.1 (-0.1)
Esentepe	1.0 (1.0)	0.17 (0.17)	-0.09 (-0.07)	0.01 (0.01)
Guzelyurt	1.0 (1.0)	-0.03 (-0.01)	-0.18 (-0.13)	-0.05 (-0.07)
Gaziveren	1.0 (1.0)	-0.07 (-0.06)	-0.12 (-0.11)	0.02 (0.01)
Lefke	1.0 (1.0)	0.10 (0.15)	-0.14 (-0.13)	-0.06 (-0.06)

Yesilırmak	1.0 (1.0)	0.31 (0.33)	0.06 (0.18)	-0.07 (0.1)
Ercan	1.0 (1.0)	0.22 (0.21)	-0.15 (-0.15)	-0.08 (-0.08)
Serdarlı	1.0 (1.0)	0.08 (0.08)	-0.12 (-0.15)	0.07 (0.002)
Değirmenlik	1.0 (1.0)	0.18 (0.18)	-0.2 (-0.2)	-0.02 (-0.02)
Gecitkale	1.0 (1.0)	0.14 (0.13)	-0.06 (-0.06)	-0.009 (-0.02)
Gönendere	1.0 (1.0)	0.21 (0.2)	-0.04 (-0.05)	-0.07 (-0.07)
Vadili	1.0 (1.0)	0.18 (0.18)	-0.19 (-0.17)	-0.1 (-0.12)
Beyarmudu	1.0 (1.0)	0.009 (0.01)	-0.07 (-0.02)	0.25 (0.35)
Cayirova	1.0 (1.0)	-0.01 (0.005)	-0.05 (-0.04)	0.09 (0.1)
Iskele	1.0 (1.0)	0.04 (0.05)	-0.11 (-0.1)	-0.05 (-0.06)
Mehmetcik	1.0 (1.0)	0.09 (0.1)	-0.06 (-0.04)	0.02 (0.04)
Magusa	1.0 (1.0)	0.24 (0.23)	-0.1 (-0.12)	0.001 (-0.008)
Salamis	1.0 (1.0)	0.07 (0.06)	-0.02 (-0.009)	-0.01 (-0.07)
Alevkaya	1.0 (1.0)	0.05 (0.05)	-0.11 (-0.11)	0.085 (0.08)
Zumrutkoy	1.0 (1.0)	0.009 (0.015)	-0.12 (-0.06)	0.07 (0.12)
Alaykoy	1.0 (1.0)	0.07 (0.09)	0.01 (0.005)	-0.02 (-0.03)
Lefkosa	1.0 (1.0)	0.25 (0.26)	0.18 (0.18)	-0.02 (-0.02)
Ziyamet	1.0 (1.0)	-0.10 (-0.09)	-0.02 (-0.006)	-0.08 (-0.08)
Dipkarpaz	1.0 (1.0)	0.01 (0.003)	-0.1 (-0.09)	-0.09 (-0.12)
Yeni Erenkoy	1.0 (1.0)	0.07 (0.07)	-0.14 (-0.14)	0.07 (0.07)
Dortyol	1.0 (1.0)	0.18 (0.19)	-0.2 (-0.2)	-0.15 (-0.16)

Table B. 2 p-values of Augmented Dickey-Fuller Test

Station Name/ Test Name	ADF Test			
	P-value (lag 0)	P-value (lag 1)	P-value (lag 2)	P-value (lag 3)
Akdeniz	0.001	0.001	0.03	0.003
Camlibel	0.001	0.002	0.07	0.01
Lapta	0.001	0.003	0.09	0.003
Girne	0.001	0.009	0.02	0.045
Beylerbeyi	0.001	0.003	0.03	0.01
Bogaz	0.002	0.042	0.09	0.01
Tatlısu	0.003	0.054	0.24	0.02
Kantara	0.001	0.002	0.02	0.03
Esentepe	0.002	0.011	0.13	0.02
Guzelyurt	0.001	0.002	0.02	0.004
Gaziveren	0.001	0.003	0.04	0.02
Lefke	0.001	0.002	0.014	0.08
Yesilırmak	0.015	0.04	0.09	0.16
Ercan	0.003	0.004	0.03	0.06
Serdarlı	0.001	0.003	0.05	0.03
Değirmenlik	0.001	0.001	0.01	0.03
Gecitkale	0.001	0.018	0.09	0.15
Gönendere	0.003	0.0136	0.05	0.016
Vadili	0.003	0.004	0.04	0.05
Beyarmudu	0.001	0.001	0.1	0.04
Cayirova	0.001	0.008	0.12	0.01
Iskele	0.001	0.007	0.04	0.01
Mehmetcik	0.001	0.006	0.05	0.01
Magusa	0.006	0.01	0.16	0.014
Salamis	0.001	0.019	0.1	0.1
Alevkaya	0.001	0.001	0.03	0.014
Zumrutkoy	0.001	0.002	0.04	0.022
Alaykoy	0.001	0.03	0.12	0.07
Lefkosa	0.006	0.11	0.13	0.14
Ziyamet	0.001	0.01	0.04	0.13
Dipkarpaz	0.001	0.008	0.03	0.016
Yeni Erenkoy	0.001	0.006	0.15	0.09
Dortyol	0.003	0.004	0.04	0.02

Table B. 3 t-statistics of Augmented Dickey-Fuller Test

Station Name/ Test Name	ADF Test			
	t-statistic (lag 0)	t-statistic (lag 1)	t-statistic (lag 2)	t-statistic (lag 3)
Akdeniz	-6.22	-5.37	-3.72	-4.71
Camlibel	-6.46	-4.97	-3.34	-4.24
Lapta	-5.36	-4.75	-3.22	-4.85
Girne	-5.80	-4.27	-3.78	-3.59
Beylerbeyi	-5.76	-4.78	-3.73	-4.25
Bogaz	-4.85	-3.62	-3.20	-4.00
Tatlısu	-4.69	-3.50	-2.71	-3.83
Kantara	-5.38	-4.88	-3.94	-3.69
Esentepe	-4.87	-4.20	-3.05	-3.79
Guzelyurt	-5.93	-4.90	-3.83	-4.60
Gaziveren	-6.20	-4.83	-3.60	-3.94
Lefke	-5.43	-4.95	-4.12	-3.30
Yesilırmak	-4.06	-3.64	-3.25	-2.92
Ercan	-4.75	-4.66	-3.69	-3.42
Serdarlı	-5.46	-4.73	-3.50	-3.68
Değirmenlik	-5.12	-5.58	-3.96	-3.69
Gecitkale	-5.00	-3.99	-3.24	-2.96
Gönendere	-4.79	-4.12	-3.52	-4.06
Vadili	-4.78	-4.61	-3.56	-3.53
Beyarmudu	-6.19	-5.05	-3.16	-3.65
Cayirova	-5.93	-4.32	-3.10	-4.21
Iskele	-5.46	-4.41	-3.55	-3.98
Mehmetcik	-5.27	-4.45	-3.46	-4.25
Magusa	-4.45	-4.22	-2.93	-4.09
Salamis	-5.44	-3.97	-3.19	-3.19
Alevkaya	-5.77	-5.35	-3.75	-4.11
Zumrutkoy	-5.99	-4.98	-3.58	-3.91
Alaykoy	-5.21	-3.75	-3.07	-3.34
Lefkosa	-4.42	-3.11	-3.06	-3.00
Ziyamet	-6.52	-4.23	-3.57	-3.06
Dipkarpaz	-5.63	-4.31	-3.67	-4.05
Yeni Erenkoy	-5.39	-4.42	-2.97	-3.25
Dortyol	-4.82	-4.59	-3.6	-3.85

Table B. 4 p-values of Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test

Station Name/Test Name	KPSS Test			
	P-value (lag 0)	P-value (lag 1)	P-value (lag 2)	P-value (lag 3)
Akdeniz	0.1	0.1	0.1	0.1
Camlibel	0.1	0.1	0.1	0.1
Lapta	0.1	0.1	0.1	0.1
Girne	0.1	0.1	0.1	0.1
Beylerbeyi	0.1	0.1	0.1	0.1
Bogaz	0.1	0.1	0.1	0.1
Tatlısu	0.1	0.1	0.1	0.1
Kantara	0.1	0.1	0.1	0.1
Esentepe	0.1	0.1	0.1	0.1
Guzelyurt	0.1	0.1	0.1	0.1
Gaziveren	0.1	0.1	0.1	0.1
Lefke	0.1	0.1	0.1	0.1
Yesilırmak	0.0612	0.1	0.1	0.1
Ercan	0.1	0.1	0.1	0.1
Serdarlı	0.1	0.1	0.1	0.1
Değirmenlik	0.1	0.1	0.1	0.1
Gecitkale	0.1	0.1	0.1	0.1
Gönendere	0.1	0.1	0.1	0.1
Vadili	0.1	0.1	0.1	0.1
Beyarmudu	0.1	0.1	0.1	0.1
Cayirova	0.1	0.1	0.1	0.1
Iskele	0.1	0.1	0.1	0.1
Mehmetcik	0.1	0.1	0.1	0.1
Magusa	0.1	0.1	0.1	0.1
Salamis	0.1	0.1	0.1	0.1
Alevkaya	0.1	0.1	0.1	0.1
Zumrutkoy	0.1	0.1	0.1	0.1
Alaykoy	0.1	0.1	0.1	0.1
Lefkosa	0.1	0.1	0.1	0.1
Ziyamet	0.1	0.1	0.1	0.1
Dipkarpaz	0.1	0.1	0.1	0.1
Yeni Erenkoy	0.1	0.1	0.1	0.1
Dortyol	0.1	0.1	0.1	0.1

Table B. 5 t-statistics of Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test

Station Name/ Test Name	KPSS Test			
	t-statistic (lag 0)	t-statistic (lag 1)	t-statistic (lag 2)	t-statistic (lag 3)
Akdeniz	0.0327	0.0356	0.0451	0.0514
Camlibel	0.0475	0.0531	0.0629	0.0634
Lapta	0.0422	0.0397	0.0443	0.0460
Girne	0.0342	0.0345	0.0366	0.0408
Beylerbeyi	0.0283	0.0285	0.0324	0.0363
Bogaz	0.0825	0.0727	0.0690	0.0698
Tatlısu	0.0882	0.0731	0.0686	0.0655
Kantara	0.0417	0.0392	0.0448	0.0518
Esentepe	0.0562	0.0487	0.0503	0.0516
Guzelyurt	0.0339	0.0351	0.0412	0.0471
Gaziveren	0.0279	0.0305	0.0356	0.0388
Lefke	0.0536	0.0509	0.0588	0.0704
Yesilırmak	0.1399	0.1084	0.1008	0.1024
Ercan	0.0503	0.0419	0.0443	0.0484
Serdarlı	0.0603	0.0568	0.0621	0.0639
Değirmenlik	0.0747	0.0650	0.0728	0.0806
Gecitkale	0.0770	0.0676	0.0676	0.0681
Gönendere	0.0441	0.0371	0.0370	0.0389
Vadili	0.0446	0.0376	0.0400	0.0442
Beyarmudu	0.0568	0.0617	0.0745	0.0735
Cayirova	0.0436	0.0451	0.0487	0.0489
Iskele	0.0453	0.0432	0.0457	0.0485
Mehmetcik	0.0649	0.0606	0.0640	0.0668
Magusa	0.0577	0.0465	0.0465	0.0468
Salamis	0.0469	0.0446	0.0448	0.0454
Alevkaya	0.0683	0.0665	0.0739	0.0759
Zumrutkoy	0.0350	0.0365	0.0433	0.0473
Alaykoy	0.0725	0.0680	0.0663	0.0663
Lefkosa	0.0901	0.0723	0.0628	0.0598
Ziyamet	0.0396	0.0453	0.0485	0.0530
Dipkarpaz	0.0378	0.0376	0.0401	0.0437
Yeni Erenkoy	0.0482	0.0455	0.0489	0.0489
Dortyol	0.0421	0.0356	0.0380	0.0425

C. Clustering

C.1 Introduction

In this appendix, all linkages and distance metrics were shared. Table C.1 and Table C.2 were directly taken from the User's Guide of the Statistics and Machine Learning Toolbox of MATLAB. There are 7 distance methods and 11 distance metrics to create an optimal number of clusters by using the appropriate linkage and similarity measures. In all figures between Figure C.1 and C.14, Group 1, Group 2, Group 3, and Group 4 represent the West part of NC (Region 1), North Coast and West Mesaria Plain (Region 2), Central Mesaria Plain (Region3), and Karpaz Peninsula (East-Coast) (Region 4).

Table C. 1 Linkages

Distance Methods
Average
Centroid
Complete
Median
Single
Ward
Weighted

Table C. 2 Distance Metrics

Distance Metrics
Euclidean
Squared Euclidean
Mahalanobis
Cityblock
Minkowski
Chebychev
Cosine

Correlation
Hamming
Jaccard
Spearman

Table C. 3 Number of each station

Station Number	Station Name
1	Akdeniz
2	Camlibel
3	Lapta
4	Girne
5	Beylerbeyi
6	Bogaz
7	Tatlısu
8	Kantara
9	Esentepe
10	Guzelyurt
11	Gaziveren
12	Lefke
13	Yesilırmak
14	Ercan
15	Serdarlı
16	Değirmenlik
17	Gecitkale
18	Gönendere
19	Vadili
20	Beyarmudu
21	Cayirova
22	Iskele
23	Mehmetcik
24	Magusa
25	Salamis
26	Alevkaya
27	Zumrutkoy
28	Alaykoy
29	Lefkosa
30	Ziyamet
31	Dipkarpaz
32	Yeni Erenkoy
33	Dortyol

CLUSTER MAPS FOR 3 CLUSTERS

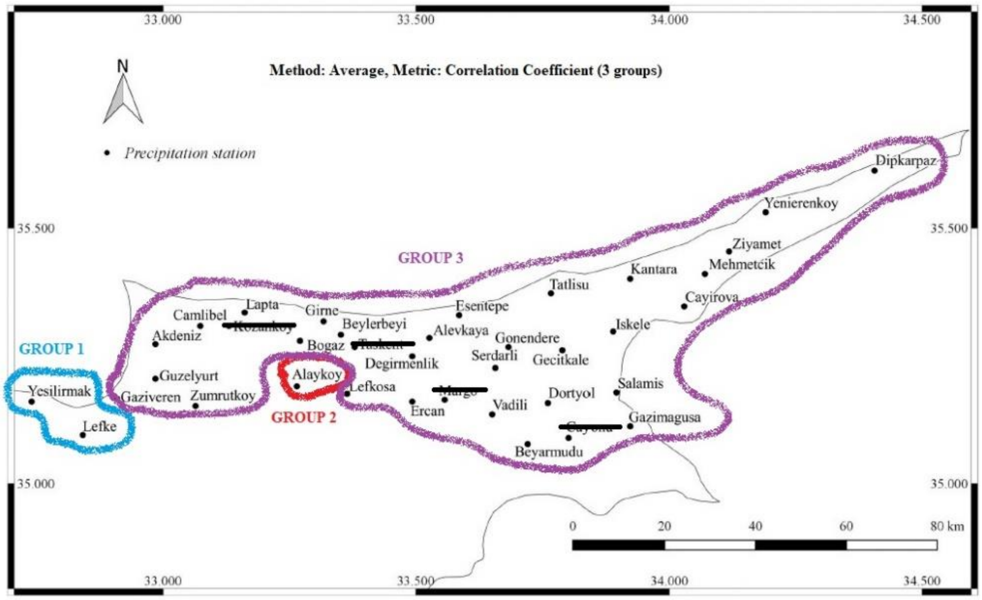

Figure C. 1 Average-Correlation combination with 3 clusters

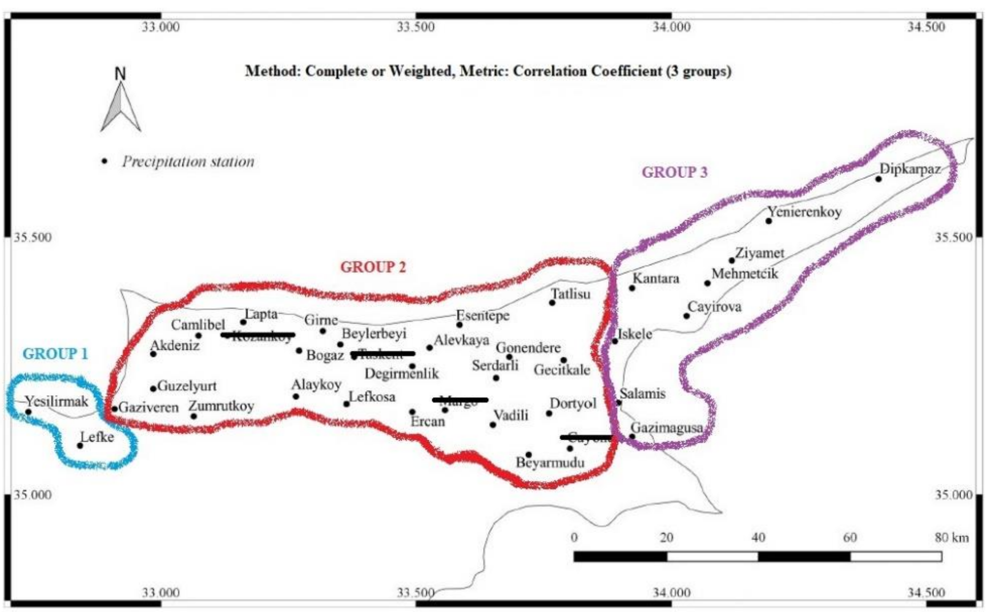

Figure C. 2 Complete or Weighted-Correlation combination with 3 clusters

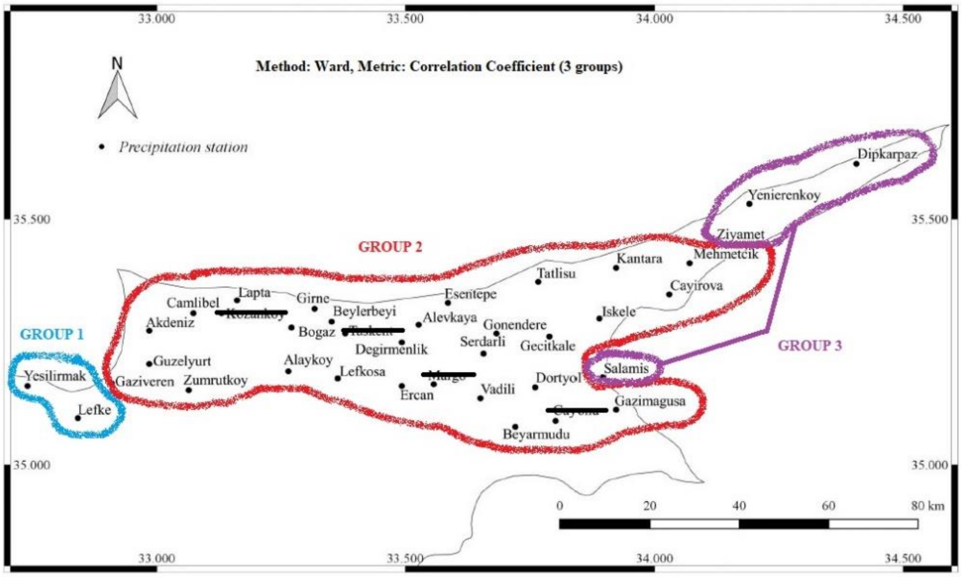

Figure C. 3 Ward-Correlation combination with 3 clusters

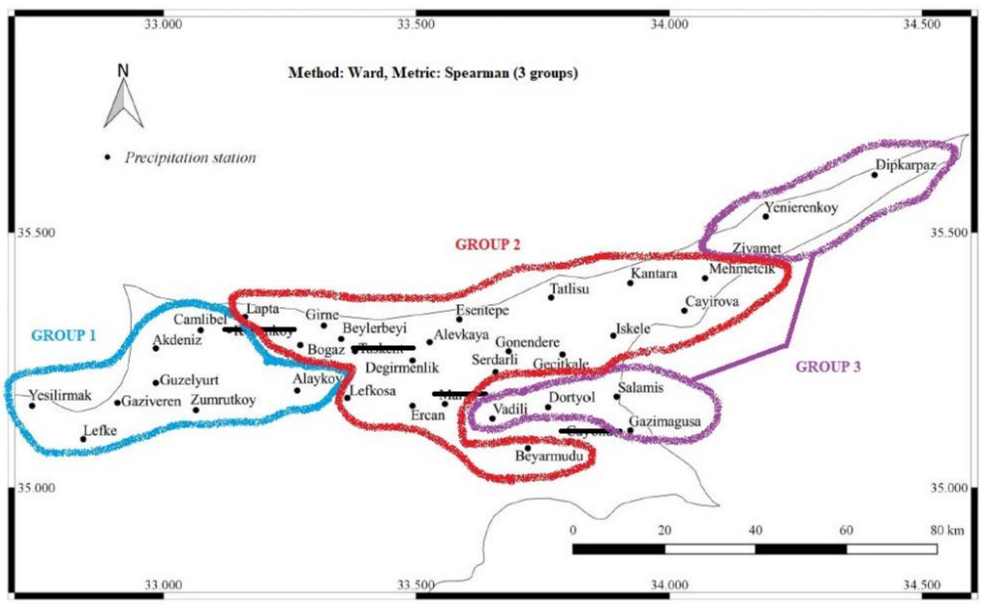

Figure C. 4 Ward-Spearman combination with 3 clusters

CLUSTER MAPS FOR 4 CLUSTERS

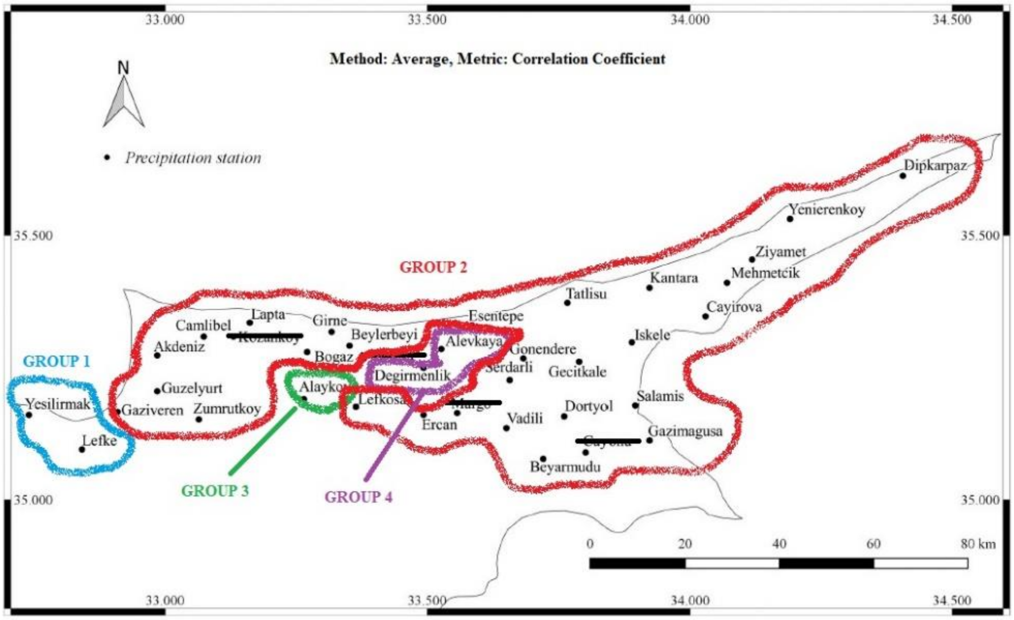

Figure C. 5 Average-Correlation combination with 4 clusters

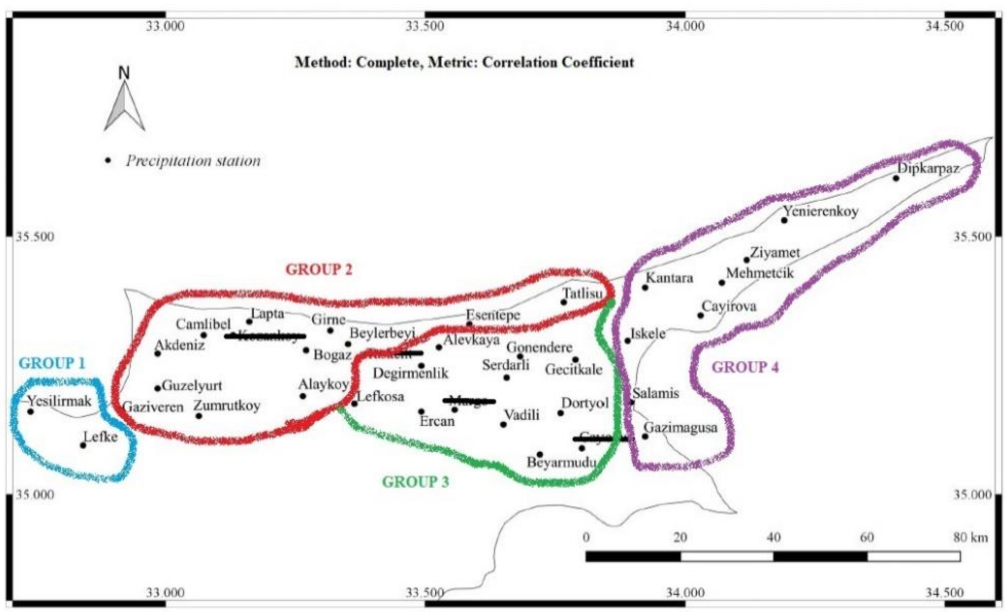

Figure C. 6 Complete-Correlation combinations with 4 clusters

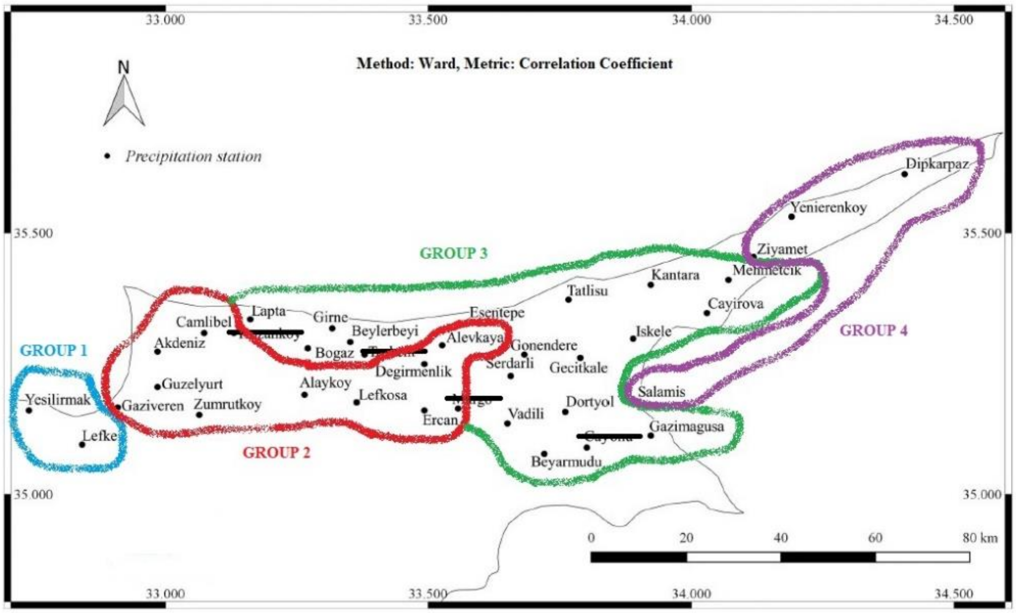

Figure C. 7 Ward-Correlation combination with 4 clusters

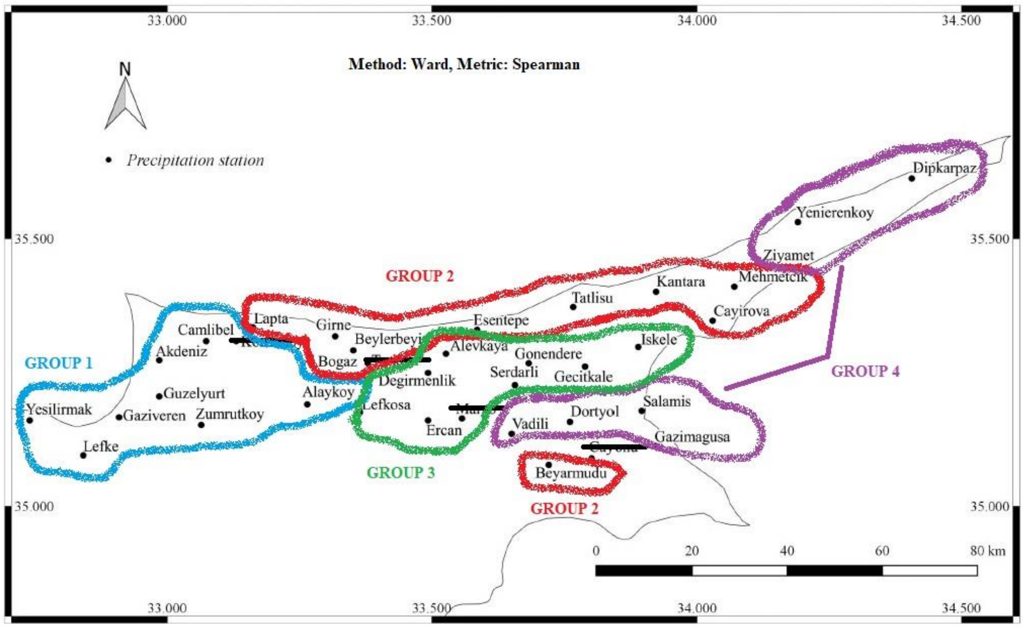

Figure C. 8 Ward-Spearman combination with 4 clusters

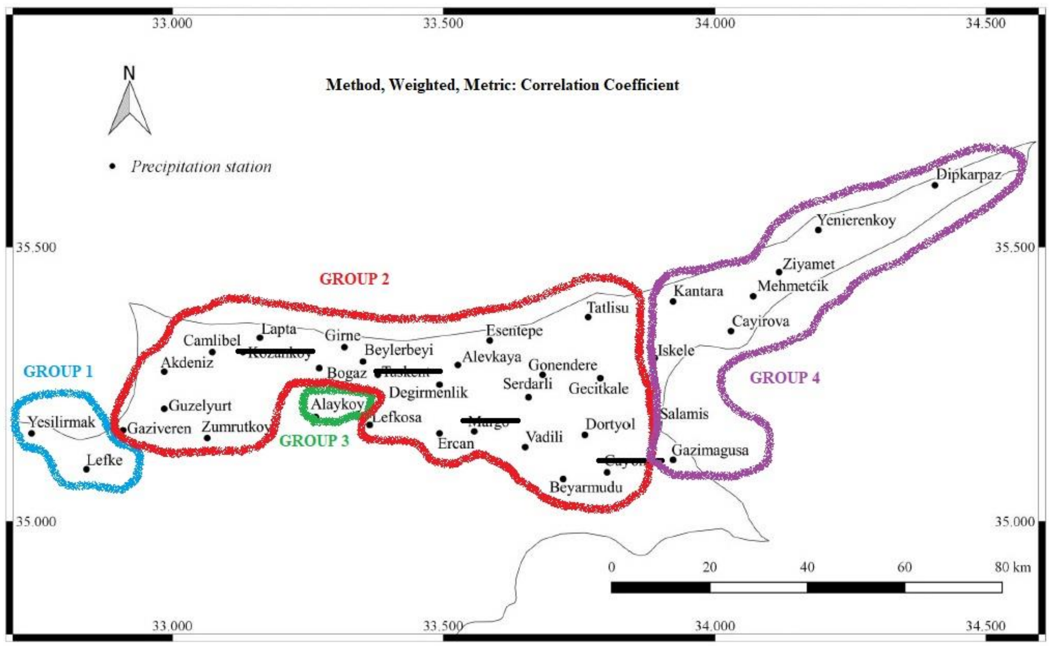

Figure C. 9 Weighted-Correlation combination with 4 clusters

CLUSTER MAPS FOR 5 CLUSTERS

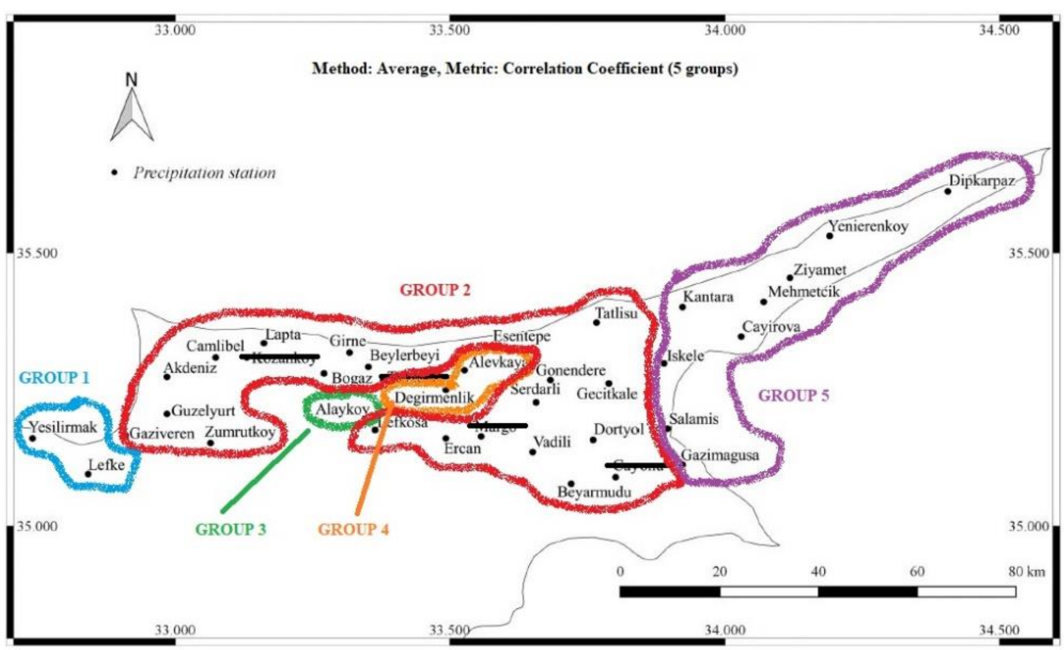

Figure C. 10 Average-Correlation combination with 5 clusters

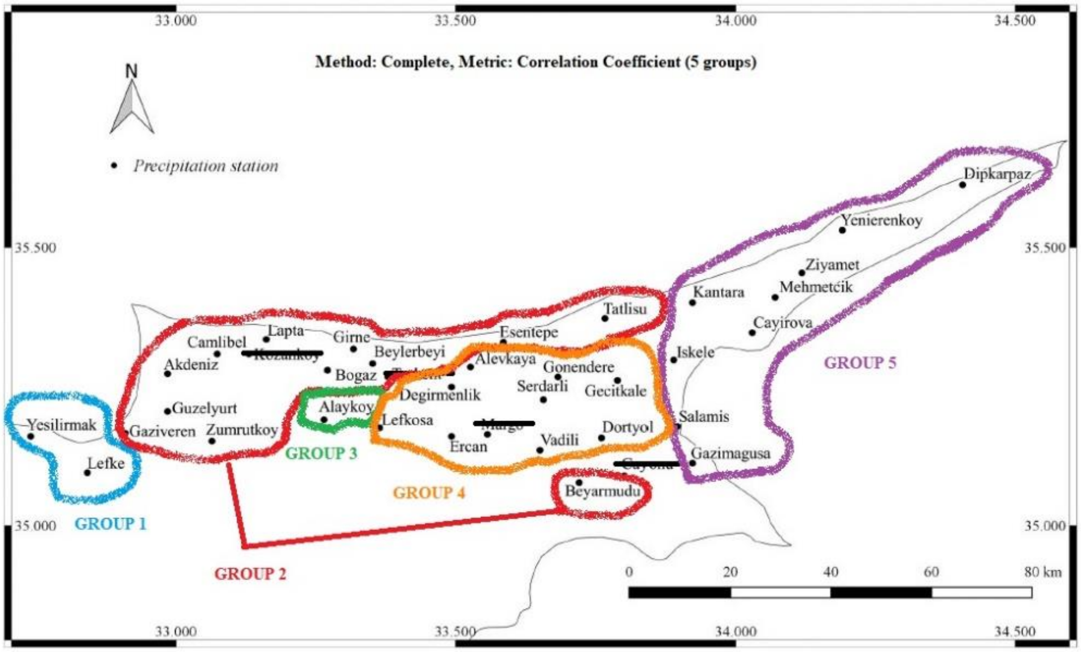

Figure C. 11 Complete-Correlation Combination with 5 clusters

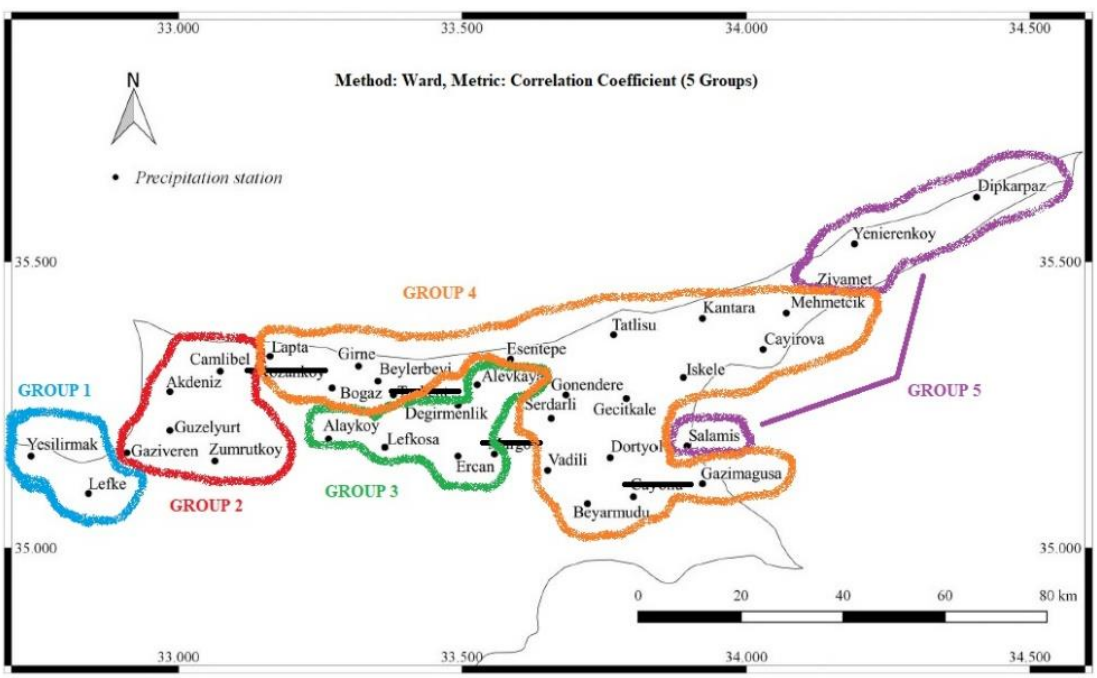

Figure C. 12 Ward-Correlation combination with 5 clusters

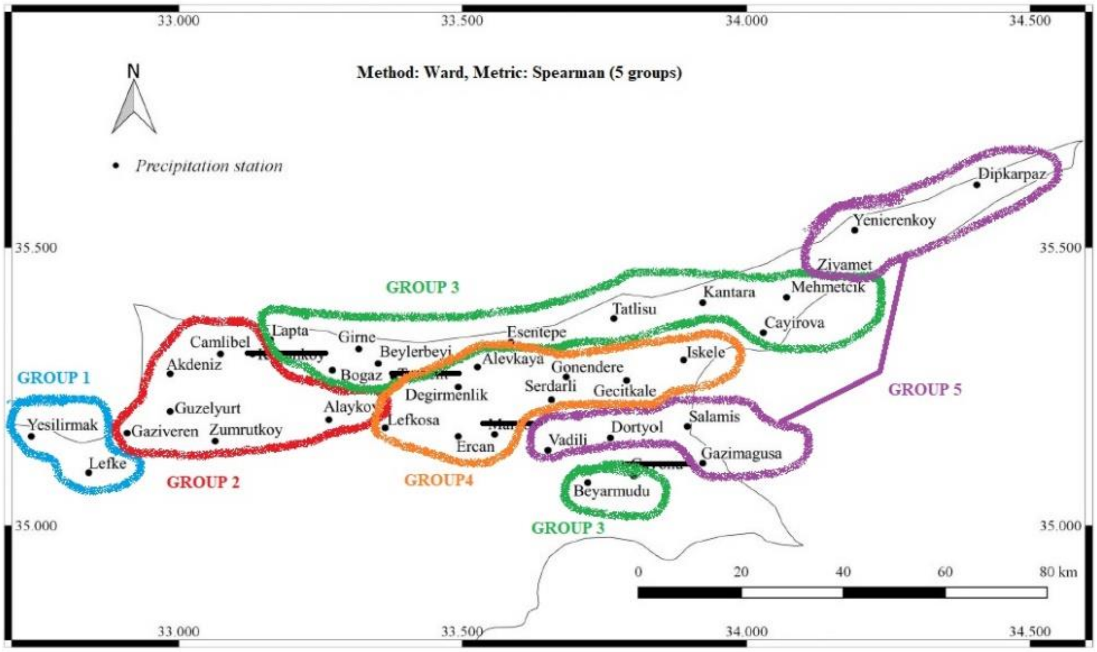

Figure C. 13 Ward-Spearman combination with 5 clusters

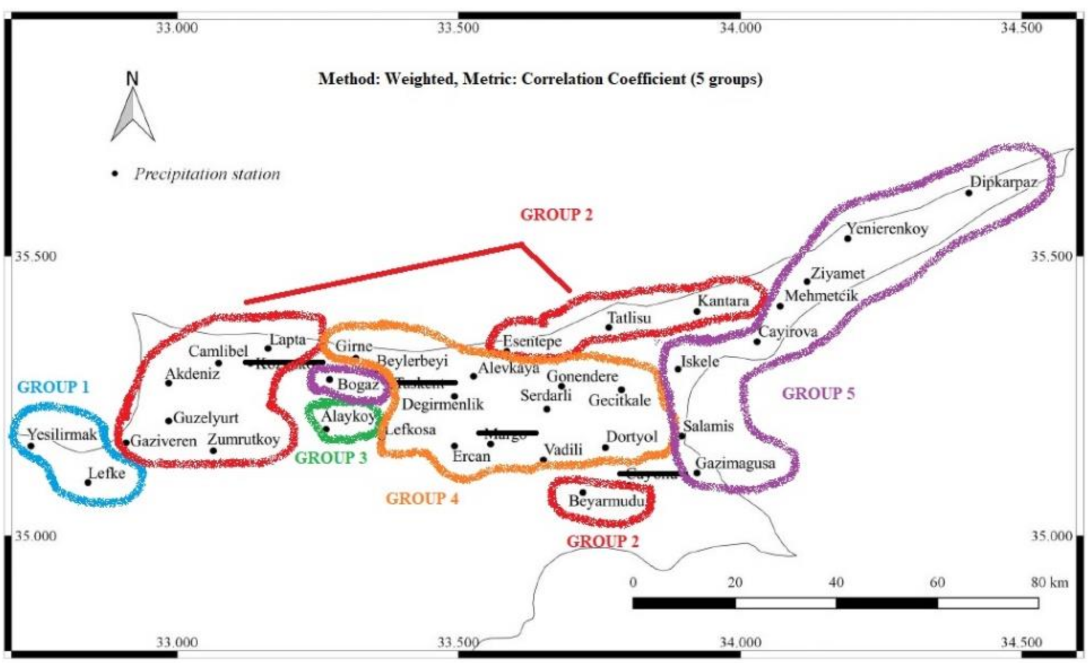

Figure C. 14 Weighted-Correlation with 5 clusters

Table C. 4 Correlation Coefficient Matrix of observed annual data of 33 stations

Station #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	1.00	0.83	0.81	0.64	0.69	0.62	0.70	0.72	0.71	0.89	0.79	0.49	0.57	0.63	0.58	0.56	0.57	0.62	0.71	0.71	0.68	0.66	0.69	0.68	0.61	0.61	0.82	0.66	0.57	0.68	0.61	0.68	0.67
2	0.83	1.00	0.80	0.60	0.68	0.64	0.73	0.68	0.73	0.78	0.70	0.61	0.67	0.63	0.63	0.59	0.60	0.65	0.61	0.73	0.70	0.62	0.72	0.60	0.48	0.73	0.83	0.66	0.63	0.55	0.60	0.58	0.53
3	0.81	0.80	1.00	0.71	0.81	0.80	0.68	0.71	0.63	0.81	0.75	0.58	0.65	0.74	0.61	0.53	0.59	0.71	0.74	0.74	0.74	0.69	0.76	0.75	0.61	0.66	0.74	0.64	0.66	0.61	0.69	0.70	0.68
4	0.64	0.60	0.71	1.00	0.92	0.70	0.75	0.69	0.68	0.73	0.68	0.56	0.51	0.77	0.70	0.60	0.75	0.82	0.83	0.70	0.65	0.73	0.62	0.71	0.64	0.67	0.72	0.62	0.71	0.60	0.56	0.67	0.75
5	0.69	0.68	0.81	0.92	1.00	0.78	0.80	0.77	0.70	0.74	0.69	0.52	0.57	0.79	0.74	0.72	0.72	0.82	0.81	0.74	0.71	0.79	0.73	0.75	0.64	0.76	0.75	0.64	0.73	0.63	0.59	0.69	0.75
6	0.62	0.64	0.80	0.70	0.78	1.00	0.67	0.62	0.64	0.67	0.65	0.57	0.71	0.61	0.61	0.50	0.68	0.71	0.69	0.74	0.76	0.72	0.72	0.75	0.51	0.70	0.74	0.54	0.54	0.47	0.54	0.49	0.69
7	0.70	0.73	0.68	0.75	0.80	0.67	1.00	0.73	0.84	0.67	0.64	0.50	0.44	0.65	0.70	0.61	0.71	0.76	0.78	0.72	0.77	0.74	0.74	0.77	0.62	0.63	0.74	0.55	0.65	0.65	0.65	0.66	0.74
8	0.72	0.68	0.71	0.69	0.77	0.62	0.73	1.00	0.70	0.67	0.62	0.56	0.51	0.65	0.66	0.60	0.65	0.67	0.69	0.68	0.77	0.83	0.83	0.78	0.72	0.71	0.73	0.58	0.59	0.69	0.70	0.79	0.72
9	0.71	0.73	0.63	0.68	0.70	0.64	0.84	0.70	1.00	0.69	0.60	0.41	0.39	0.63	0.72	0.59	0.73	0.70	0.68	0.64	0.71	0.68	0.65	0.64	0.52	0.63	0.78	0.68	0.67	0.62	0.54	0.56	0.73
10	0.89	0.78	0.81	0.73	0.74	0.67	0.67	0.67	0.69	1.00	0.91	0.56	0.61	0.71	0.64	0.58	0.64	0.71	0.76	0.72	0.63	0.65	0.65	0.63	0.58	0.60	0.90	0.73	0.69	0.58	0.47	0.60	0.66
11	0.79	0.70	0.75	0.68	0.69	0.65	0.64	0.62	0.60	0.91	1.00	0.57	0.60	0.70	0.66	0.50	0.63	0.76	0.70	0.72	0.65	0.65	0.64	0.63	0.56	0.57	0.83	0.71	0.68	0.48	0.41	0.55	0.66
12	0.49	0.61	0.58	0.56	0.52	0.57	0.50	0.56	0.41	0.56	0.57	1.00	0.63	0.44	0.35	0.24	0.47	0.45	0.54	0.64	0.53	0.54	0.52	0.55	0.44	0.41	0.60	0.42	0.36	0.34	0.54	0.50	0.50
13	0.57	0.67	0.65	0.51	0.57	0.71	0.44	0.51	0.39	0.61	0.60	0.63	1.00	0.46	0.33	0.32	0.40	0.49	0.52	0.70	0.52	0.38	0.60	0.54	0.38	0.57	0.69	0.46	0.32	0.31	0.42	0.40	0.47
14	0.63	0.63	0.74	0.77	0.79	0.61	0.65	0.65	0.63	0.71	0.70	0.44	0.46	1.00	0.83	0.71	0.72	0.82	0.81	0.69	0.59	0.65	0.66	0.67	0.62	0.75	0.67	0.64	0.85	0.52	0.50	0.65	0.74
15	0.58	0.63	0.61	0.70	0.74	0.61	0.70	0.66	0.72	0.64	0.66	0.35	0.33	0.83	1.00	0.77	0.83	0.85	0.77	0.65	0.70	0.79	0.66	0.68	0.66	0.79	0.69	0.57	0.75	0.51	0.45	0.61	0.78
16	0.56	0.59	0.53	0.60	0.72	0.50	0.61	0.60	0.59	0.58	0.50	0.24	0.32	0.71	0.77	1.00	0.68	0.66	0.59	0.51	0.56	0.67	0.59	0.48	0.55	0.78	0.64	0.53	0.71	0.52	0.41	0.55	0.58
17	0.57	0.60	0.59	0.75	0.72	0.68	0.71	0.65	0.73	0.64	0.63	0.47	0.40	0.72	0.83	0.68	1.00	0.81	0.79	0.72	0.80	0.83	0.71	0.71	0.70	0.67	0.70	0.68	0.71	0.70	0.60	0.61	0.80
18	0.62	0.65	0.71	0.82	0.82	0.71	0.76	0.67	0.70	0.71	0.76	0.45	0.49	0.82	0.85	0.66	0.81	1.00	0.83	0.70	0.72	0.79	0.69	0.73	0.63	0.74	0.72	0.59	0.77	0.53	0.53	0.63	0.82
19	0.71	0.61	0.74	0.83	0.81	0.69	0.78	0.69	0.68	0.76	0.70	0.54	0.52	0.81	0.77	0.59	0.79	0.83	1.00	0.76	0.70	0.77	0.66	0.82	0.79	0.66	0.72	0.55	0.66	0.68	0.65	0.72	0.86
20	0.71	0.73	0.74	0.70	0.74	0.74	0.72	0.68	0.64	0.72	0.72	0.64	0.70	0.69	0.65	0.51	0.72	0.70	0.76	1.00	0.84	0.69	0.76	0.81	0.69	0.68	0.74	0.51	0.53	0.56	0.58	0.61	0.71
21	0.68	0.70	0.74	0.65	0.71	0.76	0.77	0.77	0.71	0.63	0.65	0.53	0.52	0.59	0.70	0.56	0.80	0.72	0.70	0.84	1.00	0.84	0.87	0.87	0.77	0.67	0.69	0.56	0.56	0.70	0.73	0.68	0.76
22	0.66	0.62	0.69	0.73	0.79	0.72	0.74	0.83	0.68	0.65	0.65	0.54	0.38	0.65	0.79	0.67	0.83	0.79	0.77	0.69	0.84	1.00	0.82	0.83	0.80	0.74	0.70	0.62	0.67	0.73	0.68	0.75	0.82
23	0.69	0.72	0.76	0.62	0.73	0.72	0.74	0.83	0.65	0.65	0.64	0.52	0.60	0.66	0.66	0.59	0.71	0.69	0.66	0.76	0.87	0.82	1.00	0.83	0.72	0.69	0.70	0.61	0.62	0.69	0.70	0.74	0.70
24	0.68	0.60	0.75	0.71	0.75	0.75	0.77	0.78	0.64	0.63	0.63	0.55	0.54	0.67	0.68	0.48	0.71	0.73	0.82	0.81	0.87	0.83	0.83	1.00	0.85	0.65	0.63	0.45	0.48	0.69	0.69	0.78	0.84
25	0.61	0.48	0.61	0.64	0.64	0.51	0.62	0.72	0.52	0.58	0.56	0.44	0.38	0.62	0.66	0.55	0.70	0.63	0.79	0.69	0.77	0.80	0.72	0.85	1.00	0.61	0.53	0.49	0.50	0.77	0.69	0.81	0.82
26	0.61	0.73	0.66	0.67	0.76	0.70	0.63	0.71	0.63	0.60	0.57	0.41	0.57	0.75	0.79	0.78	0.67	0.74	0.66	0.68	0.67	0.74	0.69	0.65	0.61	1.00	0.75	0.58	0.65	0.46	0.52	0.58	0.65
27	0.82	0.83	0.74	0.72	0.75	0.74	0.74	0.73	0.78	0.90	0.83	0.60	0.69	0.67	0.69	0.64	0.70	0.72	0.72	0.74	0.69	0.70	0.70	0.63	0.53	0.75	1.00	0.73	0.68	0.54	0.47	0.54	0.66
28	0.66	0.66	0.64	0.62	0.64	0.54	0.55	0.58	0.68	0.73	0.71	0.42	0.46	0.64	0.57	0.53	0.68	0.59	0.55	0.51	0.56	0.62	0.61	0.45	0.49	0.58	0.73	1.00	0.78	0.60	0.46	0.48	0.58
29	0.57	0.63	0.66	0.71	0.73	0.54	0.65	0.59	0.67	0.69	0.68	0.36	0.32	0.85	0.75	0.71	0.71	0.77	0.66	0.53	0.56	0.67	0.62	0.48	0.50	0.65	0.68	0.78	1.00	0.53	0.43	0.52	0.61
30	0.68	0.55	0.61	0.60	0.63	0.47	0.65	0.69	0.62	0.58	0.48	0.34	0.31	0.52	0.51	0.52	0.70	0.53	0.68	0.56	0.70	0.73	0.69	0.69	0.77	0.46	0.54	0.60	0.53	1.00	0.75	0.76	0.70
31	0.61	0.60	0.69	0.56	0.59	0.54	0.65	0.70	0.54	0.47	0.41	0.54	0.42	0.50	0.45	0.41	0.60	0.53	0.65	0.58	0.73	0.68	0.70	0.69	0.69	0.52	0.47	0.46	0.43	0.75	1.00	0.74	0.68
32	0.68	0.58	0.70	0.67	0.69	0.49	0.66	0.79	0.56	0.60	0.55	0.50	0.40	0.65	0.61	0.55	0.61	0.63	0.72	0.61	0.68	0.75	0.74	0.78	0.81	0.58	0.54	0.48	0.52	0.76	0.74	1.00	0.74
33	0.67	0.53	0.68	0.75	0.75	0.69	0.74	0.72	0.73	0.66	0.66	0.50	0.47	0.74	0.78	0.58	0.80	0.82	0.86	0.71	0.76	0.82	0.70	0.84	0.82	0.65	0.66	0.58	0.61	0.70	0.68	0.74	1.00

Table C. 5 Correlation Coefficient Matrix of transformed annual data of 33 stations

Station #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	1.00	0.83	0.82	0.67	0.71	0.68	0.70	0.75	0.71	0.92	0.80	0.50	0.55	0.62	0.59	0.59	0.59	0.63	0.70	0.72	0.72	0.68	0.74	0.72	0.63	0.62	0.84	0.66	0.56	0.68	0.62	0.69	0.67
2	0.83	1.00	0.80	0.61	0.67	0.65	0.72	0.70	0.71	0.77	0.70	0.63	0.60	0.62	0.65	0.59	0.61	0.65	0.61	0.70	0.72	0.65	0.75	0.64	0.51	0.71	0.80	0.65	0.61	0.61	0.64	0.60	0.54
3	0.82	0.80	1.00	0.75	0.81	0.82	0.69	0.71	0.63	0.81	0.75	0.56	0.64	0.74	0.62	0.56	0.62	0.73	0.75	0.76	0.77	0.70	0.77	0.78	0.65	0.67	0.76	0.64	0.66	0.64	0.70	0.72	0.68
4	0.67	0.61	0.75	1.00	0.92	0.79	0.75	0.69	0.70	0.74	0.71	0.56	0.52	0.79	0.73	0.64	0.78	0.84	0.82	0.74	0.70	0.76	0.67	0.75	0.67	0.69	0.74	0.66	0.74	0.61	0.56	0.66	0.77
5	0.71	0.67	0.81	0.92	1.00	0.82	0.80	0.77	0.71	0.75	0.71	0.52	0.51	0.80	0.74	0.73	0.73	0.83	0.81	0.75	0.73	0.80	0.76	0.78	0.66	0.76	0.76	0.66	0.75	0.64	0.58	0.69	0.76
6	0.68	0.65	0.82	0.79	0.82	1.00	0.69	0.63	0.68	0.73	0.68	0.55	0.66	0.67	0.65	0.57	0.72	0.75	0.73	0.74	0.74	0.73	0.72	0.74	0.53	0.73	0.79	0.60	0.62	0.52	0.54	0.51	0.72
7	0.70	0.72	0.69	0.75	0.80	0.69	1.00	0.72	0.83	0.66	0.64	0.51	0.38	0.65	0.71	0.61	0.71	0.76	0.78	0.71	0.78	0.75	0.74	0.80	0.63	0.63	0.74	0.55	0.65	0.66	0.65	0.66	0.74
8	0.75	0.70	0.71	0.69	0.77	0.63	0.72	1.00	0.71	0.71	0.63	0.58	0.46	0.65	0.66	0.61	0.65	0.67	0.68	0.69	0.79	0.83	0.84	0.79	0.73	0.71	0.77	0.59	0.59	0.71	0.69	0.79	0.72
9	0.71	0.71	0.63	0.70	0.71	0.68	0.83	0.71	1.00	0.70	0.60	0.41	0.34	0.64	0.72	0.60	0.73	0.70	0.68	0.63	0.71	0.70	0.67	0.68	0.54	0.63	0.79	0.68	0.68	0.63	0.53	0.56	0.75
10	0.92	0.77	0.81	0.74	0.75	0.73	0.66	0.71	0.70	1.00	0.91	0.56	0.61	0.70	0.66	0.61	0.66	0.71	0.75	0.75	0.69	0.68	0.70	0.69	0.63	0.62	0.91	0.72	0.66	0.59	0.50	0.62	0.69
11	0.80	0.70	0.75	0.71	0.71	0.68	0.64	0.63	0.60	0.91	1.00	0.60	0.63	0.70	0.66	0.51	0.64	0.76	0.71	0.76	0.67	0.66	0.66	0.68	0.59	0.57	0.85	0.71	0.67	0.50	0.43	0.56	0.68
12	0.50	0.63	0.56	0.56	0.52	0.55	0.51	0.58	0.41	0.56	0.60	1.00	0.69	0.45	0.43	0.27	0.51	0.47	0.50	0.62	0.53	0.55	0.54	0.51	0.44	0.42	0.58	0.46	0.37	0.37	0.56	0.52	0.49
13	0.55	0.60	0.64	0.52	0.51	0.66	0.38	0.46	0.34	0.61	0.63	0.69	1.00	0.46	0.34	0.26	0.39	0.49	0.51	0.67	0.50	0.35	0.55	0.52	0.41	0.51	0.62	0.44	0.29	0.28	0.42	0.39	0.48
14	0.62	0.62	0.74	0.79	0.80	0.67	0.65	0.65	0.64	0.70	0.70	0.45	0.46	1.00	0.82	0.71	0.71	0.82	0.81	0.73	0.61	0.66	0.68	0.71	0.63	0.75	0.69	0.65	0.85	0.54	0.49	0.65	0.75
15	0.59	0.65	0.62	0.73	0.74	0.65	0.71	0.66	0.72	0.66	0.66	0.43	0.34	0.82	1.00	0.76	0.83	0.83	0.78	0.68	0.72	0.80	0.69	0.74	0.68	0.79	0.72	0.57	0.74	0.53	0.48	0.61	0.79
16	0.59	0.59	0.56	0.64	0.73	0.57	0.61	0.61	0.60	0.61	0.51	0.27	0.26	0.71	0.76	1.00	0.67	0.66	0.60	0.55	0.60	0.68	0.63	0.54	0.57	0.78	0.67	0.55	0.71	0.55	0.42	0.55	0.58
17	0.59	0.61	0.62	0.78	0.73	0.72	0.71	0.65	0.73	0.66	0.64	0.51	0.39	0.71	0.83	0.67	1.00	0.80	0.80	0.74	0.81	0.83	0.73	0.75	0.71	0.66	0.73	0.68	0.70	0.71	0.61	0.60	0.81
18	0.63	0.65	0.73	0.84	0.83	0.75	0.76	0.67	0.70	0.71	0.76	0.47	0.49	0.82	0.83	0.66	0.80	1.00	0.83	0.74	0.73	0.80	0.70	0.76	0.65	0.73	0.73	0.60	0.77	0.56	0.53	0.63	0.83
19	0.70	0.61	0.75	0.82	0.81	0.73	0.78	0.68	0.68	0.75	0.71	0.50	0.51	0.81	0.78	0.60	0.80	0.83	1.00	0.79	0.72	0.77	0.67	0.85	0.80	0.66	0.74	0.56	0.67	0.68	0.64	0.72	0.86
20	0.72	0.70	0.76	0.74	0.75	0.74	0.71	0.69	0.63	0.75	0.76	0.62	0.67	0.73	0.68	0.55	0.74	0.74	0.79	1.00	0.83	0.69	0.75	0.82	0.72	0.68	0.74	0.55	0.58	0.58	0.57	0.64	0.73
21	0.72	0.72	0.77	0.70	0.73	0.74	0.78	0.79	0.71	0.69	0.67	0.53	0.50	0.61	0.72	0.60	0.81	0.73	0.72	0.83	1.00	0.84	0.86	0.88	0.79	0.68	0.74	0.59	0.58	0.73	0.74	0.70	0.75
22	0.68	0.65	0.70	0.76	0.80	0.73	0.75	0.83	0.70	0.68	0.66	0.55	0.35	0.66	0.80	0.68	0.83	0.80	0.77	0.69	0.84	1.00	0.82	0.83	0.80	0.75	0.73	0.64	0.68	0.75	0.69	0.76	0.83
23	0.74	0.75	0.77	0.67	0.76	0.72	0.74	0.84	0.67	0.70	0.66	0.54	0.55	0.68	0.69	0.63	0.73	0.70	0.67	0.75	0.86	0.82	1.00	0.83	0.71	0.70	0.74	0.65	0.64	0.74	0.70	0.74	0.70
24	0.72	0.64	0.78	0.75	0.78	0.74	0.80	0.79	0.68	0.69	0.68	0.51	0.52	0.71	0.74	0.54	0.75	0.76	0.85	0.82	0.88	0.83	0.83	1.00	0.86	0.67	0.69	0.50	0.54	0.69	0.68	0.80	0.83
25	0.63	0.51	0.65	0.67	0.66	0.53	0.63	0.73	0.54	0.63	0.59	0.44	0.41	0.63	0.68	0.57	0.71	0.65	0.80	0.72	0.79	0.80	0.71	0.86	1.00	0.62	0.57	0.52	0.53	0.74	0.68	0.83	0.81
26	0.62	0.71	0.67	0.69	0.76	0.73	0.63	0.71	0.63	0.62	0.57	0.42	0.51	0.75	0.79	0.78	0.66	0.73	0.66	0.68	0.68	0.75	0.70	0.67	0.62	1.00	0.76	0.59	0.65	0.48	0.52	0.58	0.66
27	0.84	0.80	0.76	0.74	0.76	0.79	0.74	0.77	0.79	0.91	0.85	0.58	0.62	0.69	0.72	0.67	0.73	0.73	0.74	0.74	0.74	0.73	0.74	0.69	0.57	0.76	1.00	0.73	0.69	0.57	0.49	0.57	0.69
28	0.66	0.65	0.64	0.66	0.66	0.60	0.55	0.59	0.68	0.72	0.71	0.46	0.44	0.65	0.57	0.55	0.68	0.60	0.56	0.55	0.59	0.64	0.65	0.50	0.52	0.59	0.73	1.00	0.79	0.62	0.47	0.49	0.60
29	0.56	0.61	0.66	0.74	0.75	0.62	0.65	0.59	0.68	0.66	0.67	0.37	0.29	0.85	0.74	0.71	0.70	0.77	0.67	0.58	0.58	0.68	0.64	0.54	0.53	0.65	0.69	0.79	1.00	0.56	0.43	0.52	0.62
30	0.68	0.61	0.64	0.61	0.64	0.52	0.66	0.71	0.63	0.59	0.50	0.37	0.28	0.54	0.53	0.55	0.71	0.56	0.68	0.58	0.73	0.75	0.74	0.69	0.74	0.48	0.57	0.62	0.56	1.00	0.78	0.79	0.68
31	0.62	0.64	0.70	0.56	0.58	0.54	0.65	0.69	0.53	0.50	0.43	0.56	0.42	0.49	0.48	0.42	0.61	0.53	0.64	0.57	0.74	0.69	0.70	0.68	0.68	0.52	0.49	0.47	0.43	0.78	1.00	0.75	0.65
32	0.69	0.60	0.72	0.66	0.69	0.51	0.66	0.79	0.56	0.62	0.56	0.52	0.39	0.65	0.61	0.55	0.60	0.63	0.72	0.64	0.70	0.76	0.74	0.80	0.83	0.58	0.57	0.49	0.52	0.79	0.75	1.00	0.73
33	0.67	0.54	0.68	0.77	0.76	0.72	0.74	0.72	0.75	0.69	0.68	0.49	0.48	0.75	0.79	0.58	0.81	0.83	0.86	0.73	0.75	0.83	0.70	0.83	0.81	0.66	0.69	0.60	0.62	0.68	0.65	0.73	1.00

Table C. 6 Correlation Coefficients between the stations in REGION 1, and annual total REGION 1 (sub O represents the observed values)

Groups/ Stations	**GROUP 1**		
	G1$_{O}$	**Lefke$_{O}$**	**Yesilirmak$_{O}$**
G1$_{O}$	1.00	0.84	0.95
Lefke$_{O}$	0.84	1.00	0.63
Yesilirmak$_{O}$	0.95	0.63	1.00

Table C. 7 Correlation Coefficients between the stations in REGION 2, and annual total REGION 2 (sub O represents the observed values)

Groups/ Stations	**GROUP 2**												
	G2$_{O}$	**Akdeniz$_{O}$**	**Camlibel$_{O}$**	**Lapta$_{O}$**	**Girne$_{O}$**	**Beylerbeyi$_{O}$**	**Bogaz$_{O}$**	**Tatlısu$_{O}$**	**Esentepe$_{O}$**	**Guzelyurt$_{O}$**	**Gaziveren$_{O}$**	**Zumrutkoy$_{O}$**	**Alaykoy$_{O}$**
G2$_{O}$	1.00	0.72	0.75	0.77	0.84	0.88	0.75	0.80	0.77	0.78	0.75	0.81	0.69
Akdeniz$_{O}$	0.72	1.00	0.83	0.81	0.64	0.69	0.62	0.70	0.71	0.89	0.79	0.82	0.66
Camlibel$_{O}$	0.75	0.83	1.00	0.80	0.60	0.68	0.64	0.73	0.73	0.78	0.70	0.83	0.66
Lapta$_{O}$	0.77	0.81	0.80	1.00	0.71	0.81	0.80	0.68	0.63	0.81	0.75	0.74	0.64
Girne$_{O}$	0.84	0.64	0.60	0.71	1.00	0.92	0.70	0.75	0.68	0.73	0.68	0.72	0.62
Beylerbeyi$_{O}$	0.88	0.69	0.68	0.81	0.92	1.00	0.78	0.80	0.70	0.74	0.69	0.75	0.64
Bogaz$_{O}$	0.75	0.62	0.64	0.80	0.70	0.78	1.00	0.67	0.64	0.67	0.65	0.74	0.54
Tatlısu$_{O}$	0.80	0.70	0.73	0.68	0.75	0.80	0.67	1.00	0.84	0.67	0.64	0.74	0.55
Esentepe$_{O}$	0.77	0.71	0.73	0.63	0.68	0.70	0.64	0.84	1.00	0.69	0.60	0.78	0.68
Guzelyurt$_{O}$	0.78	0.89	0.78	0.81	0.73	0.74	0.67	0.67	0.69	1.00	0.91	0.90	0.73
Gaziveren$_{O}$	0.75	0.79	0.70	0.75	0.68	0.69	0.65	0.64	0.60	0.91	1.00	0.83	0.71
Zumrutkoy$_{O}$	0.81	0.82	0.83	0.74	0.72	0.75	0.74	0.74	0.78	0.90	0.83	1.00	0.73
Alaykoy$_{O}$	0.69	0.66	0.66	0.64	0.62	0.64	0.54	0.55	0.68	0.73	0.71	0.73	1.00

Table C. 8 Correlation Coefficients between the stations in REGION 3, and annual total REGION 3 (sub O represents the observed values)

Groups/ Stations	GROUP 3										
	G3$_O$	**Ercan$_O$**	**Serdarlı$_O$**	**Değirmenlik$_O$**	**Gecitkale$_O$**	**Gönendere$_O$**	**Vadili$_O$**	**Beyarmudu$_O$**	**Alevkaya$_O$**	**Dortyol$_O$**	**Lefkosa$_O$**
G3$_O$	1.00	0.91	0.92	0.81	0.89	0.92	0.88	0.81	0.86	0.86	0.82
Ercan$_O$	0.91	1.00	0.83	0.71	0.72	0.82	0.81	0.69	0.75	0.74	0.85
Serdarlı$_O$	0.92	0.83	1.00	0.77	0.83	0.85	0.77	0.65	0.79	0.78	0.75
Değirmenlik$_O$	0.81	0.71	0.77	1.00	0.68	0.66	0.59	0.51	0.78	0.58	0.71
Gecitkale$_O$	0.89	0.72	0.83	0.68	1.00	0.81	0.79	0.72	0.67	0.80	0.71
Gönendere$_O$	0.92	0.82	0.85	0.66	0.81	1.00	0.83	0.70	0.74	0.82	0.77
Vadili$_O$	0.88	0.81	0.77	0.59	0.79	0.83	1.00	0.76	0.66	0.86	0.66
Beyarmudu$_O$	0.81	0.69	0.65	0.51	0.72	0.70	0.76	1.00	0.68	0.71	0.53
Alevkaya$_O$	0.86	0.75	0.79	0.78	0.67	0.74	0.66	0.68	1.00	0.65	0.65
Dortyol$_O$	0.86	0.74	0.78	0.58	0.80	0.82	0.86	0.71	0.65	1.00	0.61
Lefkosa$_O$	0.82	0.85	0.75	0.71	0.71	0.77	0.66	0.53	0.65	0.61	1.00

Table C. 9 Correlation Coefficients between the stations in REGION 4, and annual total REGION 4 (sub O represents the observed values)

Groups/ Stations	GROUP 4									
	G4$_O$	**Cayirova$_O$**	**Iskele$_O$**	**Mehmetcik$_O$**	**Magusa$_O$**	**Salamis$_O$**	**Kantara$_O$**	**Ziyamet$_O$**	**Dipkarpaz$_O$**	**Yeni Erenkoy$_O$**
G4$_O$	1.00	0.9	0.91	0.9	0.91	0.88	0.9	0.85	0.85	0.89
Cayirova$_O$	0.9	1.00	0.84	0.87	0.87	0.77	0.77	0.70	0.73	0.68
Iskele$_O$	0.91	0.84	1.00	0.82	0.83	0.80	0.83	0.73	0.68	0.75
Mehmetcik$_O$	0.9	0.87	0.82	1.00	0.83	0.72	0.83	0.69	0.70	0.74
Magusa$_O$	0.91	0.87	0.83	0.83	1.00	0.85	0.78	0.69	0.69	0.78
Salamis$_O$	0.88	0.77	0.80	0.72	0.85	1.00	0.72	0.77	0.69	0.81
Kantara$_O$	0.9	0.77	0.83	0.83	0.78	0.72	1.00	0.69	0.70	0.79
Ziyamet$_O$	0.85	0.70	0.73	0.69	0.69	0.77	0.69	1.00	0.75	0.76
Dipkarpaz$_O$	0.85	0.73	0.68	0.70	0.69	0.69	0.70	0.75	1.00	0.74
Yeni Erenkoy$_O$	0.89	0.68	0.75	0.74	0.78	0.81	0.79	0.76	0.74	1.00

Table C. 10 Correlation Coefficients between the stations in REGION 1, and annual total REGION 1 (sub T represents the transformed values)

Groups/ Stations	GROUP 1		
	$G1_T$	$Lefke_T$	$Yesilirmak_T$
$G1_T$	1.00	0.58	0.49
$Lefke_T$	0.58	1.00	0.69
$Yesilirmak_T$	0.49	0.69	1.00

Table C. 11 Correlation Coefficients between the stations in REGION 2 and annual total REGION 2 (sub T represents the transformed values)

Groups/ Stations	GROUP 2												
	$G2_T$	$Akdeniz_T$	$Camlibel_T$	$Lapta_T$	$Girne_T$	$Beylerbeyi_T$	$Bogaz_T$	$Tatlısu_T$	$Esentepe_T$	$Guzelyurt_T$	$Gaziveren_T$	$Zumrutkoy_T$	$Alaykoy_T$
$G2_T$	1.00	0.72	0.74	0.78	0.86	0.88	0.79	0.80	0.78	0.78	0.76	0.83	0.7
$Akdeniz_T$	0.72	1.00	0.83	0.82	0.67	0.71	0.68	0.70	0.71	0.92	0.80	0.84	0.66
$Camlibel_T$	0.74	0.83	1.00	0.80	0.61	0.67	0.65	0.72	0.71	0.77	0.70	0.80	0.65
$Lapta_T$	0.78	0.82	0.80	1.00	0.75	0.81	0.82	0.69	0.63	0.81	0.75	0.76	0.64
$Girne_T$	0.86	0.67	0.61	0.75	1.00	0.92	0.79	0.75	0.70	0.74	0.71	0.74	0.66
$Beylerbeyi_T$	0.88	0.71	0.67	0.81	0.92	1.00	0.82	0.80	0.71	0.75	0.71	0.76	0.66
$Bogaz_T$	0.79	0.68	0.65	0.82	0.79	0.82	1.00	0.69	0.68	0.73	0.68	0.79	0.60
$Tatlısu_T$	0.80	0.70	0.72	0.69	0.75	0.80	0.69	1.00	0.83	0.66	0.64	0.74	0.55
$Esentepe_T$	0.78	0.71	0.71	0.63	0.70	0.71	0.68	0.83	1.00	0.70	0.60	0.79	0.68
$Guzelyurt_T$	0.78	0.92	0.77	0.81	0.74	0.75	0.73	0.66	0.70	1.00	0.91	0.91	0.72
$Gaziveren_T$	0.76	0.80	0.70	0.75	0.71	0.71	0.68	0.64	0.60	0.91	1.00	0.85	0.71
$Zumrutkoy_T$	0.83	0.84	0.80	0.76	0.74	0.76	0.79	0.74	0.79	0.91	0.85	1.00	0.73
$Alaykoy_T$	0.7	0.66	0.65	0.64	0.66	0.66	0.60	0.55	0.68	0.72	0.71	0.73	1.00

Table C. 12 Correlation Coefficients between the stations in REGION 3 and annual total REGION 3 (sub T represents the transformed values)

Groups/ Stations	GROUP 3										
	G3$_T$	**Ercan$_T$**	**Serdarlı$_T$**	**Değirmenlik$_T$**	**Gecitkale$_T$**	**Gönendere$_T$**	**Vadili$_T$**	**Beyarmudu$_T$**	**Alevkaya$_T$**	**Dortyol$_T$**	**Lefkosa$_T$**
G3$_T$	1.00	0.79	0.77	0.69	0.78	0.84	0.83	0.82	0.78	0.80	0.77
Ercan$_T$	0.79	1.00	0.82	0.71	0.71	0.82	0.81	0.73	0.75	0.75	0.85
Serdarlı$_T$	0.77	0.82	1.00	0.76	0.83	0.83	0.78	0.68	0.79	0.79	0.74
Değirmenlik$_T$	0.69	0.71	0.76	1.00	0.67	0.66	0.60	0.55	0.78	0.58	0.71
Gecitkale$_T$	0.78	0.71	0.83	0.67	1.00	0.80	0.80	0.74	0.66	0.81	0.70
Gönendere$_T$	0.84	0.82	0.83	0.66	0.80	1.00	0.83	0.74	0.73	0.83	0.77
Vadili$_T$	0.83	0.81	0.78	0.60	0.80	0.83	1.00	0.79	0.66	0.86	0.67
Beyarmudu$_T$	0.82	0.73	0.68	0.55	0.74	0.74	0.79	1.00	0.68	0.73	0.58
Alevkaya$_T$	0.78	0.75	0.79	0.78	0.66	0.73	0.66	0.68	1.00	0.66	0.65
Dortyol$_T$	0.80	0.75	0.79	0.58	0.81	0.83	0.86	0.73	0.66	1.00	0.62
Lefkosa$_T$	0.77	0.85	0.74	0.71	0.70	0.77	0.67	0.58	0.65	0.62	1.00

Table C. 13 Correlation Coefficients between the stations in REGION 4 and annual total REGION 4 (sub T represents the transformed values)

Groups/ Stations	**GROUP 4**									
	G4$_T$	**Cayirova$_T$**	**Iskele$_T$**	**Mehmetcik$_T$**	**Magusa$_T$**	**Salamis$_T$**	**Kantara$_T$**	**Ziyamet$_T$**	**Dipkarpaz$_T$**	**Yeni Erenkoy$_T$**
G4$_T$	1.00	0.55	0.46	0.59	0.55	0.44	0.55	0.34	0.51	0.47
Cayirova$_T$	0.55	1.00	0.84	0.86	0.88	0.79	0.79	0.73	0.74	0.70
Iskele$_T$	0.46	0.84	1.00	0.82	0.83	0.80	0.83	0.75	0.69	0.76
Mehmetcik$_T$	0.59	0.86	0.82	1.00	0.83	0.71	0.84	0.74	0.70	0.74
Magusa$_T$	0.55	0.88	0.83	0.83	1.00	0.86	0.79	0.69	0.68	0.80
Salamis$_T$	0.44	0.79	0.80	0.71	0.86	1.00	0.73	0.74	0.68	0.83
Kantara$_T$	0.55	0.79	0.83	0.84	0.79	0.73	1.00	0.71	0.69	0.79
Ziyamet$_T$	0.34	0.73	0.75	0.74	0.69	0.74	0.71	1.00	0.78	0.79
Dipkarpaz$_T$	0.51	0.74	0.69	0.70	0.68	0.68	0.69	0.78	1.00	0.75
Yeni Erenkoy$_T$	0.47	0.70	0.76	0.74	0.80	0.83	0.79	0.79	0.75	1.00

D. ARIMA Model Selection

D.1 Introduction

In this Appendix, AIC and BIC values of 64 ARIMA combinations (including lag 3 combinations) for 3 representative stations from different regions and AIC anD BIC values of 27 ARIMA combinations (excluding lag 3 combinations) for 33 stations were given. Also, the most suitable ARIMA model for each station was highlighted in the tables.

Table D. 1 AIC, BIC values of all 64 ARIMA combinations for Akdeniz station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,0)	-37.1803	-33.9584
ARIMA(0,1,1)	-33.7223	-28.8895
ARIMA(0,2,2)	-7.26443	-0.820755
ARIMA(0,3,3)	21.4951	29.5497
ARIMA(0,0,1)	-35.6916	-30.8588
ARIMA(0,0,2)	-41.9155	-35.4719
ARIMA(0,0,3)	-39.9173	-31.8627
ARIMA(0,1,0)	-8.92044	-5.6986
ARIMA(0,2,0)	27.1285	30.3503
ARIMA(0,3,0)	64.2588	67.4806
ARIMA(0,1,2)	-31.7947	-25.351
ARIMA(0,1,3)	-36.7426	-28.688
ARIMA(0,2,1)	-2.23489	2.59786
ARIMA(0,3,1)	30.7779	35.6106
ARIMA(0,2,3)	-6.06962	1.98497
ARIMA(0,3,2)	20.3008	26.7445
ARIMA(1,0,0)	-35.4314	-30.5987
ARIMA(1,1,1)	-32.4966	-26.0529
ARIMA(1,2,2)	-8.38818	-0.333587
ARIMA(1,3,3)	12.5204	22.1859
ARIMA(1,1,0)	-14.4467	-9.61398
ARIMA(1,1,2)	-32.274	-24.2194
ARIMA(1,1,3)	ERROR	ERROR
ARIMA(1,0,1)	-42.1623	-35.7186
ARIMA(1,2,1)	-9.34231	-2.89864
ARIMA(1,3,1)	19.9466	26.3903
ARIMA(1,0,2)	-39.9197	-31.8652
ARIMA(1,0,3)	-38.3001	-28.6346
ARIMA(1,2,0)	16.1136	20.9463
ARIMA(1,3,0)	50.7861	55.6188
ARIMA(1,2,3)	-17.1907	-7.52521
ARIMA(1,3,2)	15.7421	23.7967
ARIMA(2,0,0)	-36.5563	-30.1126
ARIMA(2,1,1)	-32.7605	-24.7059
ARIMA(2,2,2)	-18.1592	-8.49369
ARIMA(2,3,3)	ERROR	ERROR
ARIMA(2,0,1)	-35.5025	-27.4479
ARIMA(2,0,2)	-38.8455	-29.18
ARIMA(2,0,3)	ERROR	ERROR
ARIMA(2,1,0)	-22.3843	-15.9407
ARIMA(2,2,0)	-2.78952	3.65415
ARIMA(2,3,0)	24.8324	31.2761
ARIMA(2,1,2)	-33.5603	-23.8948
ARIMA(2,1,3)	ERROR	ERROR
ARIMA(2,2,1)	-20.1296	-12.075
ARIMA(2,3,1)	1.36576	9.42035
ARIMA(2,2,3)	ERROR	ERROR
ARIMA(2,3,2)	3.20829	12.8738
ARIMA(3,0,0)	-34.5605	-26.5059
ARIMA(3,1,1)	-30.7609	-21.0954
ARIMA(3,2,2)	-16.3506	-5.0742
ARIMA(3,3,3)	-6.85022	6.03713
ARIMA(3,0,1)	-40.2609	-30.5954
ARIMA(3,0,2)	-36.969	-25.6926
ARIMA(3,0,3)	-40.4329	-27.5456
ARIMA(3,1,0)	-20.4147	-12.3601
ARIMA(3,2,0)	-2.73703	5.31756
ARIMA(3,3,0)	18.7097	26.7643
ARIMA(3,1,2)	-31.7468	-20.4704
ARIMA(3,1,3)	-32.59	-19.7026
ARIMA(3,2,1)	-18.1727	-8.50723
ARIMA(3,3,1)	2.23731	11.9028
ARIMA(3,2,3)	-26.792	-13.9047
ARIMA(3,3,2)	3.2239	14.5003

Table D. 2 AIC, BIC values of all 64 ARIMA combinations for Lefkosa station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,0)	407.918	411.14
ARIMA(0,1,1)	411.202	416.035
ARIMA(0,2,2)	420.226	426.669
ARIMA(0,3,3)	433.407	441.462
ARIMA(0,0,1)	407.93	412.763
ARIMA(0,0,2)	408.475	414.919
ARIMA(0,0,3)	410.202	418.256
ARIMA(0,1,0)	421.849	425.071
ARIMA(0,2,0)	460.671	463.893
ARIMA(0,3,0)	505.06	508.282
ARIMA(0,1,2)	410.865	417.309
ARIMA(0,1,3)	411.164	419.219
ARIMA(0,2,1)	424.851	429.684
ARIMA(0,3,1)	462.642	467.474
ARIMA(0,2,3)	422.023	430.077
ARIMA(0,3,2)	433.122	439.566
ARIMA(1,0,0)	407.336	412.169
ARIMA(1,1,1)	409.656	416.1
ARIMA(1,2,2)	421.365	429.42
ARIMA(1,3,3)	435.295	444.96
ARIMA(1,1,0)	415.74	420.572
ARIMA(1,1,2)	411.309	419.364
ARIMA(1,1,3)	412.571	422.237
ARIMA(1,0,1)	409.241	415.684
ARIMA(1,2,1)	419.552	425.996
ARIMA(1,3,1)	445.403	451.847
ARIMA(1,0,2)	410.321	418.376
ARIMA(1,0,3)	412.194	421.86
ARIMA(1,2,0)	439.969	444.801
ARIMA(1,3,0)	474.367	479.2
ARIMA(1,2,3)	422.767	432.432
ARIMA(1,3,2)	434.498	442.553
ARIMA(2,0,0)	408.704	415.148
ARIMA(2,1,1)	411.109	419.164
ARIMA(2,2,2)	421.267	430.932
ARIMA(2,3,3)	ERROR	ERROR
ARIMA(2,0,1)	410.607	418.662
ARIMA(2,0,2)	406.251	415.917
ARIMA(2,0,3)	411.74	423.017
ARIMA(2,1,0)	416.895	423.339
ARIMA(2,2,0)	432.82	439.263
ARIMA(2,3,0)	459.91	466.353
ARIMA(2,1,2)	413.097	422.762
ARIMA(2,1,3)	411.836	423.113
ARIMA(2,2,1)	419.234	427.289
ARIMA(2,3,1)	436.576	444.63
ARIMA(2,2,3)	422.84	434.116
ARIMA(2,3,2)	434.563	444.228
ARIMA(3,0,0)	410.345	418.4
ARIMA(3,1,1)	412.124	421.79
ARIMA(3,2,2)	422.649	433.926
ARIMA(3,3,3)	434.852	447.74
ARIMA(3,0,1)	409.083	418.748
ARIMA(3,0,2)	409.318	420.595
ARIMA(3,0,3)	410.789	423.676
ARIMA(3,1,0)	418.745	426.8
ARIMA(3,2,0)	431.06	439.115
ARIMA(3,3,0)	450.789	458.844
ARIMA(3,1,2)	408.326	419.602
ARIMA(3,1,3)	414.509	427.397
ARIMA(3,2,1)	420.711	430.377
ARIMA(3,3,1)	434.294	443.959
ARIMA(3,2,3)	424.645	437.532
ARIMA(3,3,2)	436.292	447.568

Table D. 3 AIC, BIC values of all 64 ARIMA combinations for Dipkarpaz station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,0)	300.656	303.878
ARIMA(0,1,1)	302.585	307.417
ARIMA(0,2,2)	324.306	330.749
ARIMA(0,3,3)	344.845	352.899
ARIMA(0,0,1)	302.651	307.484
ARIMA(0,0,2)	297.875	304.319
ARIMA(0,0,3)	297.778	305.832
ARIMA(0,1,0)	325.525	328.747
ARIMA(0,2,0)	361.687	364.909
ARIMA(0,3,0)	401.537	404.759
ARIMA(0,1,2)	304.582	311.026
ARIMA(0,1,3)	ERROR	ERROR
ARIMA(0,2,1)	329.814	334.646
ARIMA(0,3,1)	363.55	368.383
ARIMA(0,2,3)	325.982	334.037
ARIMA(0,3,2)	344.529	350.973
ARIMA(1,0,0)	302.652	307.485
ARIMA(1,1,1)	304.585	311.028
ARIMA(1,2,2)	325.257	333.312
ARIMA(1,3,3)	346.684	356.35
ARIMA(1,1,0)	319.302	324.135
ARIMA(1,1,2)	306.563	314.617
ARIMA(1,1,3)	ERROR	ERROR
ARIMA(1,0,1)	304.618	311.061
ARIMA(1,2,1)	324.004	330.447
ARIMA(1,3,1)	350.574	357.018
ARIMA(1,0,2)	302.186	310.24
ARIMA(1,0,3)	299.068	308.734
ARIMA(1,2,0)	346.872	351.705
ARIMA(1,3,0)	379.321	384.153
ARIMA(1,2,3)	321.046	330.712
ARIMA(1,3,2)	345.782	353.837
ARIMA(2,0,0)	304.163	310.607
ARIMA(2,1,1)	306.129	314.184
ARIMA(2,2,2)	310.601	320.266
ARIMA(2,3,3)	344.567	355.843
ARIMA(2,0,1)	299.988	308.043
ARIMA(2,0,2)	299.264	308.93
ARIMA(2,0,3)	301.148	312.425
ARIMA(2,1,0)	317.252	323.695
ARIMA(2,2,0)	335.833	342.276
ARIMA(2,3,0)	360.679	367.123
ARIMA(2,1,2)	308.112	317.778
ARIMA(2,1,3)	ERROR	ERROR
ARIMA(2,2,1)	319.639	327.693
ARIMA(2,3,1)	341.212	349.266
ARIMA(2,2,3)	327.181	338.457
ARIMA(2,3,2)	343.073	352.738
ARIMA(3,0,0)	305.747	313.801
ARIMA(3,1,1)	307.883	317.549
ARIMA(3,2,2)	337.685	348.961
ARIMA(3,3,3)	340.527	353.415
ARIMA(3,0,1)	297.227	306.892
ARIMA(3,0,2)	300.573	311.85
ARIMA(3,0,3)	ERROR	ERROR
ARIMA(3,1,0)	319.013	327.067
ARIMA(3,2,0)	336.345	344.4
ARIMA(3,3,0)	357.479	365.533
ARIMA(3,1,2)	301	312.277
ARIMA(3,1,3)	307.354	320.241
ARIMA(3,2,1)	321.044	330.71
ARIMA(3,3,1)	341.381	351.047
ARIMA(3,2,3)	328.515	341.402
ARIMA(3,3,2)	359.217	370.493

Table D. 4 AIC and BIC values of all 27 ARIMA combinations for Akdeniz station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	-35.6916	-30.8588
ARIMA(0,0,2)	-41.9155	-35.4719
ARIMA(0,1,0)	-8.92044	-5.6986
ARIMA(0,2,0)	27.1285	30.3503
ARIMA(1,0,0)	-35.4314	-30.5987
ARIMA(2,0,0)	-36.5563	-30.1126
ARIMA(1,0,1)	-42.1623	-35.7186
ARIMA(1,0,2)	-39.9197	-31.8652
ARIMA(1,1,0)	-14.4467	-9.61398
ARIMA(1,2,0)	16.1136	20.9463
ARIMA(2,1,0)	-22.3843	-15.9407
ARIMA(0,1,1)	-33.7223	-28.8895
ARIMA(0,1,2)	-31.7947	-25.351
ARIMA(2,0,1)	-35.5025	-27.4479
ARIMA(0,2,1)	-2.23489	2.59786
ARIMA(2,0,2)	-38.8455	-29.18
ARIMA(2,2,0)	-2.78952	3.65415
ARIMA(0,2,2)	-7.26443	-0.820755
ARIMA(1,1,2)	-32.274	-24.2194
ARIMA(1,2,1)	-9.34231	-2.89864
ARIMA(2,1,1)	-32.7605	-24.7059
ARIMA(2,2,1)	-20.1296	-12.075
ARIMA(2,1,2)	-33.5603	-23.8948
ARIMA(1,2,2)	-8.38818	-0.333587
ARIMA(0,0,0)	-37.1803	-33.9584
ARIMA(1,1,1)	-32.4966	-26.0529
ARIMA(2,2,2)	-18.1592	-8.49369

Table D. 5 AIC and BIC values of all 27 ARIMA combinations for Camlibel station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	195.784	200.617
ARIMA(0,0,2)	197.781	204.224
ARIMA(0,1,0)	218.776	221.998
ARIMA(0,2,0)	255.679	258.901
ARIMA(1,0,0)	195.784	200.617
ARIMA(2,0,0)	197.783	204.227
ARIMA(1,0,1)	197.784	204.228
ARIMA(1,0,2)	198.68	206.735
ARIMA(1,1,0)	210.211	215.044
ARIMA(1,2,0)	242.203	247.036
ARIMA(2,1,0)	200.26	206.703
ARIMA(0,1,1)	198.805	203.638
ARIMA(0,1,2)	200.744	207.188
ARIMA(2,0,1)	199.667	207.722
ARIMA(0,2,1)	221.853	226.685
ARIMA(2,0,2)	197.918	207.583
ARIMA(2,2,0)	215.778	222.222
ARIMA(0,2,2)	224.192	230.636
ARIMA(1,1,2)	197.005	205.06
ARIMA(1,2,1)	214.017	220.46
ARIMA(2,1,1)	200.909	208.964
ARIMA(2,2,1)	206.412	214.466
ARIMA(2,1,2)	197.502	207.167
ARIMA(1,2,2)	212.616	220.671
ARIMA(0,0,0)	193.784	197.006
ARIMA(1,1,1)	200.484	206.927
ARIMA(2,2,2)	205.223	214.889

Table D. 6 AIC and BIC values of all 27 ARIMA combinations for Lapta station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	173.396	178.229
ARIMA(0,0,2)	167.102	173.545
ARIMA(0,1,0)	193.358	196.58
ARIMA(0,2,0)	227.699	230.921
ARIMA(1,0,0)	173.536	178.369
ARIMA(2,0,0)	174.117	180.56
ARIMA(1,0,1)	172.588	179.031
ARIMA(1,0,2)	166.391	174.446
ARIMA(1,1,0)	190.77	195.603
ARIMA(1,2,0)	219.443	224.276
ARIMA(2,1,0)	183.492	189.935
ARIMA(0,1,1)	179.573	184.406
ARIMA(0,1,2)	179.049	185.492
ARIMA(2,0,1)	168.949	177.004
ARIMA(0,2,1)	196.986	201.819
ARIMA(2,0,2)	167.37	177.035
ARIMA(2,2,0)	197.552	203.996
ARIMA(0,2,2)	194.571	201.015
ARIMA(1,1,2)	173.269	181.323
ARIMA(1,2,1)	195.486	201.93
ARIMA(2,1,1)	180.389	188.443
ARIMA(2,2,1)	186.845	194.899
ARIMA(2,1,2)	173.545	183.21
ARIMA(1,2,2)	196.519	204.574
ARIMA(0,0,0)	171.752	174.974
ARIMA(1,1,1)	181.315	187.758
ARIMA(2,2,2)	183.574	193.239

Table D. 7 AIC and BIC values of all 27 ARIMA combinations for Girne station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	144.279	149.112
ARIMA(0,0,2)	141.412	147.856
ARIMA(0,1,0)	167.983	171.205
ARIMA(0,2,0)	207.111	210.332
ARIMA(1,0,0)	144.279	149.112
ARIMA(2,0,0)	146.025	152.469
ARIMA(1,0,1)	137.952	144.395
ARIMA(1,0,2)	138.853	146.907
ARIMA(1,1,0)	161.018	165.851
ARIMA(1,2,0)	188.638	193.471
ARIMA(2,1,0)	159.999	166.443
ARIMA(0,1,1)	146.355	151.187
ARIMA(0,1,2)	148.264	154.708
ARIMA(2,0,1)	137.777	145.831
ARIMA(0,2,1)	171.271	176.104
ARIMA(2,0,2)	140.116	149.781
ARIMA(2,2,0)	181.08	187.523
ARIMA(0,2,2)	165.271	171.715
ARIMA(1,1,2)	146.444	154.499
ARIMA(1,2,1)	164.979	171.422
ARIMA(2,1,1)	150.282	158.337
ARIMA(2,2,1)	164.39	172.445
ARIMA(2,1,2)	148.436	158.102
ARIMA(1,2,2)	166.074	174.129
ARIMA(0,0,0)	142.281	145.503
ARIMA(1,1,1)	148.326	154.769
ARIMA(2,2,2)	166.379	176.045

Table D. 8 AIC and BIC values of all 27 ARIMA combinations for Beylerbeyi station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	319.129	323.962
ARIMA(0,0,2)	316.361	322.805
ARIMA(0,1,0)	342.18	345.402
ARIMA(0,2,0)	378.848	382.07
ARIMA(1,0,0)	319.129	323.962
ARIMA(2,0,0)	320.015	326.459
ARIMA(1,0,1)	321.129	327.573
ARIMA(1,0,2)	316.334	324.388
ARIMA(1,1,0)	337.464	342.297
ARIMA(1,2,0)	365.98	370.812
ARIMA(2,1,0)	333.618	340.062
ARIMA(0,1,1)	322.57	327.402
ARIMA(0,1,2)	324.228	330.672
ARIMA(2,0,1)	317.048	325.103
ARIMA(0,2,1)	344.657	349.49
ARIMA(2,0,2)	317.556	327.221
ARIMA(2,2,0)	353.096	359.54
ARIMA(0,2,2)	337.889	344.333
ARIMA(1,1,2)	322.649	330.703
ARIMA(1,2,1)	341.125	347.569
ARIMA(2,1,1)	325.504	333.559
ARIMA(2,2,1)	338.461	346.516
ARIMA(2,1,2)	324.724	334.39
ARIMA(1,2,2)	339.462	347.517
ARIMA(0,0,0)	317.129	320.351
ARIMA(1,1,1)	324.559	331.002
ARIMA(2,2,2)	340.282	349.948

Table D. 9 AIC and BIC values of all 27 ARIMA combinations for Bogaz station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	52.6807	57.5135
ARIMA(0,0,2)	54.3135	60.7572
ARIMA(0,1,0)	69.0414	72.2632
ARIMA(0,2,0)	105.963	109.185
ARIMA(1,0,0)	52.5766	57.4093
ARIMA(2,0,0)	54.5272	60.9709
ARIMA(1,0,1)	54.7709	61.2146
ARIMA(1,0,2)	56.5336	64.5882
ARIMA(1,1,0)	63.9262	68.7589
ARIMA(1,2,0)	89.6106	94.4433
ARIMA(2,1,0)	63.8408	70.2845
ARIMA(0,1,1)	53.7413	58.574
ARIMA(0,1,2)	54.679	61.1227
ARIMA(2,0,1)	56.5188	64.5734
ARIMA(0,2,1)	70.9245	75.7573
ARIMA(2,0,2)	56.9887	66.6542
ARIMA(2,2,0)	79.886	86.3297
ARIMA(0,2,2)	ERROR	ERROR
ARIMA(1,1,2)	56.7224	64.777
ARIMA(1,2,1)	65.7734	72.2171
ARIMA(2,1,1)	56.5409	64.5955
ARIMA(2,2,1)	65.6259	73.6804
ARIMA(2,1,2)	58.725	68.3905
ARIMA(1,2,2)	55.6943	63.7489
ARIMA(0,0,0)	51.6597	54.8816
ARIMA(1,1,1)	54.5612	61.0049
ARIMA(2,2,2)	57.2883	66.9538

Table D. 10 AIC and BIC values of all 27 ARIMA combinations for Tatlisu station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	487.537	492.369
ARIMA(0,0,2)	489.238	495.682
ARIMA(0,1,0)	500.97	504.192
ARIMA(0,2,0)	537.205	540.426
ARIMA(1,0,0)	487.155	491.987
ARIMA(2,0,0)	489.041	495.485
ARIMA(1,0,1)	483.14	489.584
ARIMA(1,0,2)	490.1	498.155
ARIMA(1,1,0)	496.732	501.565
ARIMA(1,2,0)	524.114	528.947
ARIMA(2,1,0)	494.551	500.994
ARIMA(0,1,1)	490.3	495.132
ARIMA(0,1,2)	488.425	494.869
ARIMA(2,0,1)	487.729	495.784
ARIMA(0,2,1)	504.941	509.774
ARIMA(2,0,2)	488.288	497.953
ARIMA(2,2,0)	506.784	513.227
ARIMA(0,2,2)	501.634	508.078
ARIMA(1,1,2)	490.812	498.867
ARIMA(1,2,1)	499.917	506.36
ARIMA(2,1,1)	492.943	500.997
ARIMA(2,2,1)	496.302	504.357
ARIMA(2,1,2)	492.552	502.217
ARIMA(1,2,2)	501.268	509.323
ARIMA(0,0,0)	488.204	491.426
ARIMA(1,1,1)	490.038	496.482
ARIMA(2,2,2)	498.847	508.513

Table D. 11 AIC and BIC values of all 27 ARIMA combinations for Kantara station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	367.962	372.794
ARIMA(0,0,2)	367.094	373.538
ARIMA(0,1,0)	389.219	392.44
ARIMA(0,2,0)	424.47	427.692
ARIMA(1,0,0)	368.094	372.927
ARIMA(2,0,0)	367.825	374.269
ARIMA(1,0,1)	369.558	376.002
ARIMA(1,0,2)	365.871	373.926
ARIMA(1,1,0)	386.212	391.045
ARIMA(1,2,0)	413.978	418.811
ARIMA(2,1,0)	382.026	388.47
ARIMA(0,1,1)	368.137	372.969
ARIMA(0,1,2)	369.831	376.275
ARIMA(2,0,1)	365.745	373.8
ARIMA(0,2,1)	393.639	398.472
ARIMA(2,0,2)	367.966	377.631
ARIMA(2,2,0)	403.892	410.335
ARIMA(0,2,2)	390.35	396.794
ARIMA(1,1,2)	370.454	378.509
ARIMA(1,2,1)	391.175	397.618
ARIMA(2,1,1)	369.264	377.319
ARIMA(2,2,1)	384.09	392.145
ARIMA(2,1,2)	371.102	380.768
ARIMA(1,2,2)	392.248	400.302
ARIMA(0,0,0)	366.286	369.508
ARIMA(1,1,1)	370.042	376.485
ARIMA(2,2,2)	394.616	404.281

Table D. 12 AIC and BIC values of all 27 ARIMA combinations for Esentepe station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	355.973	360.806
ARIMA(0,0,2)	356.799	363.243
ARIMA(0,1,0)	373.705	376.927
ARIMA(0,2,0)	410.051	413.272
ARIMA(1,0,0)	356.402	361.234
ARIMA(2,0,0)	357.727	364.171
ARIMA(1,0,1)	356.971	363.414
ARIMA(1,0,2)	358.736	366.79
ARIMA(1,1,0)	370.806	375.639
ARIMA(1,2,0)	398.114	402.946
ARIMA(2,1,0)	366.882	373.325
ARIMA(0,1,1)	357.123	361.956
ARIMA(0,1,2)	357.657	364.101
ARIMA(2,0,1)	358.761	366.816
ARIMA(0,2,1)	378.806	383.638
ARIMA(2,0,2)	354.23	363.895
ARIMA(2,2,0)	382.223	388.667
ARIMA(0,2,2)	377.026	383.469
ARIMA(1,1,2)	358.569	366.624
ARIMA(1,2,1)	372.976	379.419
ARIMA(2,1,1)	368.601	376.655
ARIMA(2,2,1)	369.157	377.212
ARIMA(2,1,2)	365.934	375.6
ARIMA(1,2,2)	373.795	381.85
ARIMA(0,0,0)	355.64	358.862
ARIMA(1,1,1)	357.838	364.281
ARIMA(2,2,2)	370.763	380.429

Table D. 13 AIC and BIC values of all 27 ARIMA combinations for Guzelyurt station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	19.2944	24.1271
ARIMA(0,0,2)	17.4357	23.8793
ARIMA(0,1,0)	43.778	46.9999
ARIMA(0,2,0)	80.1323	83.3542
ARIMA(1,0,0)	19.3157	24.1484
ARIMA(2,0,0)	19.7498	26.1935
ARIMA(1,0,1)	14.7803	21.224
ARIMA(1,0,2)	16.4454	24.5
ARIMA(1,1,0)	38.4226	43.2553
ARIMA(1,2,0)	67.4475	72.2802
ARIMA(2,1,0)	34.0234	40.4671
ARIMA(0,1,1)	20.3683	25.201
ARIMA(0,1,2)	22.3669	28.8105
ARIMA(2,0,1)	15.9705	24.0251
ARIMA(0,2,1)	50.9698	55.8025
ARIMA(2,0,2)	17.6464	27.3119
ARIMA(2,2,0)	53.6921	60.1358
ARIMA(0,2,2)	47.5979	54.0416
ARIMA(1,1,2)	22.9039	30.9585
ARIMA(1,2,1)	45.2727	51.7164
ARIMA(2,1,1)	22.4971	30.5517
ARIMA(2,2,1)	39.4213	47.4759
ARIMA(2,1,2)	23.4222	33.0877
ARIMA(1,2,2)	46.9699	55.0245
ARIMA(0,0,0)	17.352	20.5738
ARIMA(1,1,1)	22.0184	28.462
ARIMA(2,2,2)	40.9919	50.6574

Table D. 14 AIC and BIC values of all 27 ARIMA combinations for Gaziveren station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	341.482	346.315
ARIMA(0,0,2)	341.841	348.285
ARIMA(0,1,0)	367.166	370.388
ARIMA(0,2,0)	405.058	408.28
ARIMA(1,0,0)	341.543	346.376
ARIMA(2,0,0)	342.882	349.326
ARIMA(1,0,1)	337.942	344.385
ARIMA(1,0,2)	339.928	347.983
ARIMA(1,1,0)	360.153	364.986
ARIMA(1,2,0)	390.414	395.246
ARIMA(2,1,0)	354.918	361.362
ARIMA(0,1,1)	341.476	346.309
ARIMA(0,1,2)	343.259	349.703
ARIMA(2,0,1)	344.755	352.809
ARIMA(0,2,1)	373.512	378.345
ARIMA(2,0,2)	339.83	349.495
ARIMA(2,2,0)	375.615	382.059
ARIMA(0,2,2)	368.263	374.707
ARIMA(1,1,2)	338.664	346.719
ARIMA(1,2,1)	366.499	372.943
ARIMA(2,1,1)	343.812	351.867
ARIMA(2,2,1)	358.033	366.087
ARIMA(2,1,2)	345.487	355.152
ARIMA(1,2,2)	367.715	375.77
ARIMA(0,0,0)	339.735	342.957
ARIMA(1,1,1)	342.882	349.325
ARIMA(2,2,2)	358.956	368.622

Table D. 15 AIC and BIC values of all 27 ARIMA combinations for Lefke station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	17.3923	22.2251
ARIMA(0,0,2)	18.6474	25.0911
ARIMA(0,1,0)	36.8792	40.1011
ARIMA(0,2,0)	71.3588	74.5806
ARIMA(1,0,0)	17.5577	22.3904
ARIMA(2,0,0)	18.4257	24.8694
ARIMA(1,0,1)	18.7958	25.2395
ARIMA(1,0,2)	20.639	28.6936
ARIMA(1,1,0)	34.0413	38.874
ARIMA(1,2,0)	61.2456	66.0783
ARIMA(2,1,0)	30.523	36.9667
ARIMA(0,1,1)	15.9025	20.7353
ARIMA(0,1,2)	17.5824	24.026
ARIMA(2,0,1)	20.3959	28.4505
ARIMA(0,2,1)	41.4104	46.2431
ARIMA(2,0,2)	17.7815	27.447
ARIMA(2,2,0)	54.9665	61.4102
ARIMA(0,2,2)	37.3406	43.7843
ARIMA(1,1,2)	18.6717	26.7263
ARIMA(1,2,1)	39.0441	45.4878
ARIMA(2,1,1)	16.612	24.6666
ARIMA(2,2,1)	34.8106	42.8652
ARIMA(2,1,2)	18.5973	28.2628
ARIMA(1,2,2)	39.3387	47.3933
ARIMA(0,0,0)	15.9899	19.2118
ARIMA(1,1,1)	17.8828	24.3265
ARIMA(2,2,2)	34.9678	44.6333

Table D. 16 AIC and BIC values of all 27 ARIMA combinations for Yesilirmak station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	-141.554	-136.721
ARIMA(0,0,2)	-139.767	-133.323
ARIMA(0,1,0)	-130.229	-127.007
ARIMA(0,2,0)	-98.7287	-95.5069
ARIMA(1,0,0)	-141.633	-136.8
ARIMA(2,0,0)	-139.836	-133.392
ARIMA(1,0,1)	-139.756	-133.313
ARIMA(1,0,2)	-137.767	-129.713
ARIMA(1,1,0)	-130.739	-125.906
ARIMA(1,2,0)	-107.569	-102.736
ARIMA(2,1,0)	-131.119	-124.675
ARIMA(0,1,1)	-139.753	-134.92
ARIMA(0,1,2)	-141.518	-135.074
ARIMA(2,0,1)	-140.965	-132.91
ARIMA(0,2,1)	-126.618	-121.785
ARIMA(2,0,2)	-138.853	-129.187
ARIMA(2,2,0)	-111.881	-105.438
ARIMA(0,2,2)	-126.989	-120.545
ARIMA(1,1,2)	-139.637	-131.583
ARIMA(1,2,1)	-126.297	-119.853
ARIMA(2,1,1)	-139.888	-131.834
ARIMA(2,2,1)	-127.802	-119.747
ARIMA(2,1,2)	-138.533	-128.867
ARIMA(1,2,2)	-127.85	-119.795
ARIMA(0,0,0)	-139.24	-136.019
ARIMA(1,1,1)	-141.356	-134.912
ARIMA(2,2,2)	-137.961	-128.295

Table D. 17 AIC and BIC values of all 27 ARIMA combinations for Ercan station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	480.168	485
ARIMA(0,0,2)	481.594	488.038
ARIMA(0,1,0)	496.326	499.548
ARIMA(0,2,0)	529.633	532.854
ARIMA(1,0,0)	481.149	485.982
ARIMA(2,0,0)	481.373	487.817
ARIMA(1,0,1)	481.714	488.157
ARIMA(1,0,2)	482.311	490.365
ARIMA(1,1,0)	496.076	500.908
ARIMA(1,2,0)	521.837	526.669
ARIMA(2,1,0)	492.521	498.965
ARIMA(0,1,1)	489.708	494.541
ARIMA(0,1,2)	487.416	493.86
ARIMA(2,0,1)	482.16	490.215
ARIMA(0,2,1)	498.957	503.79
ARIMA(2,0,2)	484.099	493.765
ARIMA(2,2,0)	512.06	518.504
ARIMA(0,2,2)	497.469	503.912
ARIMA(1,1,2)	488.871	496.925
ARIMA(1,2,1)	499.243	505.687
ARIMA(2,1,1)	490.239	498.293
ARIMA(2,2,1)	499.052	507.106
ARIMA(2,1,2)	490.86	500.525
ARIMA(1,2,2)	498.934	506.988
ARIMA(0,0,0)	481.196	484.417
ARIMA(1,1,1)	489.176	495.62
ARIMA(2,2,2)	500.606	510.271

Table D. 18 AIC and BIC values of all 27 ARIMA combinations for Serdarli station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	72.0329	76.8656
ARIMA(0,0,2)	72.5486	78.9923
ARIMA(0,1,0)	92.5048	95.7266
ARIMA(0,2,0)	129.911	133.133
ARIMA(1,0,0)	72.1331	76.9659
ARIMA(2,0,0)	73.4222	79.8658
ARIMA(1,0,1)	72.6994	79.1431
ARIMA(1,0,2)	74.2822	82.3368
ARIMA(1,1,0)	88.2554	93.0882
ARIMA(1,2,0)	118.012	122.845
ARIMA(2,1,0)	82.28	88.7237
ARIMA(0,1,1)	77.3912	82.2239
ARIMA(0,1,2)	78.341	84.7847
ARIMA(2,0,1)	74.0628	82.1174
ARIMA(0,2,1)	94.5657	99.3984
ARIMA(2,0,2)	76.0836	85.7491
ARIMA(2,2,0)	99.467	105.911
ARIMA(0,2,2)	81.044	87.4877
ARIMA(1,1,2)	79.4623	87.5168
ARIMA(1,2,1)	90.2429	96.6866
ARIMA(2,1,1)	80.2014	88.256
ARIMA(2,2,1)	87.3946	95.4492
ARIMA(2,1,2)	81.1032	90.7687
ARIMA(1,2,2)	82.7087	90.7633
ARIMA(0,0,0)	70.4086	73.6305
ARIMA(1,1,1)	78.5254	84.9691
ARIMA(2,2,2)	89.1154	98.7809

Table D. 19 AIC and BIC values of all 27 ARIMA combinations for Degirmenlik station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	456.544	461.377
ARIMA(0,0,2)	456.439	462.882
ARIMA(0,1,0)	474.117	477.339
ARIMA(0,2,0)	508.652	511.874
ARIMA(1,0,0)	457.506	462.339
ARIMA(2,0,0)	457.092	463.536
ARIMA(1,0,1)	457.411	463.855
ARIMA(1,0,2)	458.428	466.483
ARIMA(1,1,0)	473.085	477.918
ARIMA(1,2,0)	500.294	505.127
ARIMA(2,1,0)	466.91	473.353
ARIMA(0,1,1)	465.49	470.323
ARIMA(0,1,2)	465.13	471.574
ARIMA(2,0,1)	457.999	466.053
ARIMA(0,2,1)	476.219	481.052
ARIMA(2,0,2)	460.171	469.837
ARIMA(2,2,0)	487.176	493.62
ARIMA(0,2,2)	468.453	474.897
ARIMA(1,1,2)	466.091	474.146
ARIMA(1,2,1)	475.294	481.738
ARIMA(2,1,1)	464.35	472.405
ARIMA(2,2,1)	473.384	481.438
ARIMA(2,1,2)	466.319	475.985
ARIMA(1,2,2)	469.946	478.001
ARIMA(0,0,0)	456.86	460.082
ARIMA(1,1,1)	466.221	472.665
ARIMA(2,2,2)	466.414	476.079

Table D. 20 AIC and BIC values of all 27 ARIMA combinations for Gecitkale station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	567.391	572.224
ARIMA(0,0,2)	569.175	575.618
ARIMA(0,1,0)	586.288	589.51
ARIMA(0,2,0)	623.721	626.942
ARIMA(1,0,0)	567.57	572.403
ARIMA(2,0,0)	569.338	575.782
ARIMA(1,0,1)	569.292	575.735
ARIMA(1,0,2)	567.302	575.356
ARIMA(1,1,0)	581.86	586.693
ARIMA(1,2,0)	609.88	614.713
ARIMA(2,1,0)	579.134	585.577
ARIMA(0,1,1)	569.149	573.982
ARIMA(0,1,2)	570.053	576.497
ARIMA(2,0,1)	571.17	579.225
ARIMA(0,2,1)	589.433	594.266
ARIMA(2,0,2)	568.49	578.155
ARIMA(2,2,0)	598.73	605.174
ARIMA(0,2,2)	584.463	590.907
ARIMA(1,1,2)	573.196	581.25
ARIMA(1,2,1)	604.335	610.779
ARIMA(2,1,1)	571.722	579.776
ARIMA(2,2,1)	581.129	589.183
ARIMA(2,1,2)	575.113	584.778
ARIMA(1,2,2)	585.837	593.892
ARIMA(0,0,0)	566.273	569.495
ARIMA(1,1,1)	581.61	588.054
ARIMA(2,2,2)	590.166	599.832

Table D. 21 AIC and BIC values of all 27 ARIMA combinations for Gonendere station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	509.401	514.234
ARIMA(0,0,2)	511.259	517.703
ARIMA(0,1,0)	526.169	529.391
ARIMA(0,2,0)	562.217	565.439
ARIMA(1,0,0)	509.712	514.545
ARIMA(2,0,0)	511.403	517.847
ARIMA(1,0,1)	511.255	517.698
ARIMA(1,0,2)	511.593	519.648
ARIMA(1,1,0)	523.613	528.446
ARIMA(1,2,0)	549.747	554.579
ARIMA(2,1,0)	522.484	528.928
ARIMA(0,1,1)	515.328	520.161
ARIMA(0,1,2)	513.984	520.428
ARIMA(2,0,1)	510.603	518.658
ARIMA(0,2,1)	528.093	532.926
ARIMA(2,0,2)	507.912	517.578
ARIMA(2,2,0)	538.435	544.878
ARIMA(0,2,2)	540.11	546.553
ARIMA(1,1,2)	515.927	523.981
ARIMA(1,2,1)	525.73	532.173
ARIMA(2,1,1)	516.158	524.213
ARIMA(2,2,1)	525.525	533.58
ARIMA(2,1,2)	518.674	528.339
ARIMA(1,2,2)	ERROR	ERROR
ARIMA(0,0,0)	509.375	512.597
ARIMA(1,1,1)	514.274	520.717
ARIMA(2,2,2)	524.172	533.838

Table D. 22 AIC and BIC values of all 27 ARIMA combinations for Vadili station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	276.07	280.903
ARIMA(0,0,2)	276.899	283.343
ARIMA(0,1,0)	293.79	297.011
ARIMA(0,2,0)	326.381	329.602
ARIMA(1,0,0)	276.913	281.746
ARIMA(2,0,0)	276.3	282.743
ARIMA(1,0,1)	277.474	283.918
ARIMA(1,0,2)	270.973	279.028
ARIMA(1,1,0)	293.357	298.19
ARIMA(1,2,0)	319.3	324.133
ARIMA(2,1,0)	289.166	295.61
ARIMA(0,1,1)	281.345	286.178
ARIMA(0,1,2)	279.521	285.965
ARIMA(2,0,1)	269.263	277.318
ARIMA(0,2,1)	305.26	310.092
ARIMA(2,0,2)	271.258	280.924
ARIMA(2,2,0)	309.79	316.234
ARIMA(0,2,2)	306.856	313.3
ARIMA(1,1,2)	276.924	284.979
ARIMA(1,2,1)	304.181	310.624
ARIMA(2,1,1)	285.079	293.134
ARIMA(2,2,1)	292.645	300.699
ARIMA(2,1,2)	281.06	290.725
ARIMA(1,2,2)	298.73	306.785
ARIMA(0,0,0)	276.303	279.525
ARIMA(1,1,1)	283.326	289.77
ARIMA(2,2,2)	294.643	304.309

Table D. 23 AIC and BIC values of all 27 ARIMA combinations for Beyarmudu station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	22.4104	27.2431
ARIMA(0,0,2)	23.6193	30.063
ARIMA(0,1,0)	44.9113	48.1331
ARIMA(0,2,0)	83.0592	86.281
ARIMA(1,0,0)	22.411	27.2438
ARIMA(2,0,0)	24.1854	30.629
ARIMA(1,0,1)	23.143	29.5867
ARIMA(1,0,2)	24.4063	32.4609
ARIMA(1,1,0)	38.7289	43.5617
ARIMA(1,2,0)	71.1439	75.9766
ARIMA(2,1,0)	27.7778	34.2214
ARIMA(0,1,1)	18.8371	23.6698
ARIMA(0,1,2)	20.5135	26.9571
ARIMA(2,0,1)	23.8917	31.9463
ARIMA(0,2,1)	47.5681	52.4009
ARIMA(2,0,2)	25.7564	35.4219
ARIMA(2,2,0)	46.6287	53.0724
ARIMA(0,2,2)	33.0905	39.5342
ARIMA(1,1,2)	22.5876	30.6422
ARIMA(1,2,1)	42.0568	48.5005
ARIMA(2,1,1)	29.7172	37.7718
ARIMA(2,2,1)	29.7714	37.826
ARIMA(2,1,2)	23.0325	32.698
ARIMA(1,2,2)	34.7046	42.7591
ARIMA(0,0,0)	20.4147	23.6365
ARIMA(1,1,1)	20.7201	27.1638
ARIMA(2,2,2)	21.3567	31.0222

Table D. 24 AIC and BIC values of all 27 ARIMA combinations for Cayirova station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	209.705	214.537
ARIMA(0,0,2)	211.22	217.663
ARIMA(0,1,0)	233.661	236.883
ARIMA(0,2,0)	272.291	275.513
ARIMA(1,0,0)	209.705	214.538
ARIMA(2,0,0)	211.588	218.031
ARIMA(1,0,1)	208.797	215.241
ARIMA(1,0,2)	212.948	221.002
ARIMA(1,1,0)	225.792	230.625
ARIMA(1,2,0)	256.492	261.325
ARIMA(2,1,0)	220.477	226.92
ARIMA(0,1,1)	209.412	214.245
ARIMA(0,1,2)	211.396	217.84
ARIMA(2,0,1)	213.5	221.554
ARIMA(0,2,1)	235.751	240.583
ARIMA(2,0,2)	212.022	221.687
ARIMA(2,2,0)	233.138	239.581
ARIMA(0,2,2)	218.855	225.299
ARIMA(1,1,2)	212.253	220.308
ARIMA(1,2,1)	227.858	234.302
ARIMA(2,1,1)	221.628	229.683
ARIMA(2,2,1)	223.334	231.389
ARIMA(2,1,2)	214.418	224.084
ARIMA(1,2,2)	220.758	228.813
ARIMA(0,0,0)	207.711	210.933
ARIMA(1,1,1)	211.407	217.851
ARIMA(2,2,2)	224.363	234.028

Table D. 25 AIC and BIC values of all 27 ARIMA combinations for Iskele station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	297.72	302.553
ARIMA(0,0,2)	298.043	304.486
ARIMA(0,1,0)	319.567	322.789
ARIMA(0,2,0)	356.159	359.381
ARIMA(1,0,0)	297.744	302.577
ARIMA(2,0,0)	299.117	305.561
ARIMA(1,0,1)	299.582	306.026
ARIMA(1,0,2)	293.906	301.961
ARIMA(1,1,0)	313.99	318.823
ARIMA(1,2,0)	342.178	347.011
ARIMA(2,1,0)	311.16	317.604
ARIMA(0,1,1)	297.828	302.661
ARIMA(0,1,2)	299.722	306.166
ARIMA(2,0,1)	294.277	302.331
ARIMA(0,2,1)	328.613	333.446
ARIMA(2,0,2)	294.704	304.37
ARIMA(2,2,0)	328.052	334.496
ARIMA(0,2,2)	326.638	333.082
ARIMA(1,1,2)	300.857	308.912
ARIMA(1,2,1)	321.438	327.882
ARIMA(2,1,1)	301.301	309.355
ARIMA(2,2,1)	313.338	321.392
ARIMA(2,1,2)	302.355	312.02
ARIMA(1,2,2)	322.036	330.091
ARIMA(0,0,0)	295.828	299.049
ARIMA(1,1,1)	299.749	306.193
ARIMA(2,2,2)	314.857	324.522

Table D. 26 AIC and BIC values of all 27 ARIMA combinations for Mehmetcik station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	172.026	176.859
ARIMA(0,0,2)	171.267	177.71
ARIMA(0,1,0)	191.635	194.856
ARIMA(0,2,0)	226.227	229.449
ARIMA(1,0,0)	172.1	176.933
ARIMA(2,0,0)	173.778	180.221
ARIMA(1,0,1)	167.881	174.325
ARIMA(1,0,2)	169.768	177.823
ARIMA(1,1,0)	187.307	192.139
ARIMA(1,2,0)	215.415	220.248
ARIMA(2,1,0)	183.217	189.661
ARIMA(0,1,1)	171.872	176.705
ARIMA(0,1,2)	173.526	179.97
ARIMA(2,0,1)	169.866	177.92
ARIMA(0,2,1)	198.357	203.19
ARIMA(2,0,2)	171.259	180.925
ARIMA(2,2,0)	198.478	204.922
ARIMA(0,2,2)	195.836	202.28
ARIMA(1,1,2)	172.191	180.245
ARIMA(1,2,1)	193.128	199.572
ARIMA(2,1,1)	174.41	182.465
ARIMA(2,2,1)	185.17	193.225
ARIMA(2,1,2)	174.225	183.89
ARIMA(1,2,2)	195.016	203.07
ARIMA(0,0,0)	170.429	173.651
ARIMA(1,1,1)	173.295	179.738
ARIMA(2,2,2)	183.502	193.168

Table D. 27 AIC and BIC values of all 27 ARIMA combinations for Magusa station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	35.1744	40.0071
ARIMA(0,0,2)	34.3836	40.8273
ARIMA(0,1,0)	52.969	56.1908
ARIMA(0,2,0)	84.8101	88.0319
ARIMA(1,0,0)	37.8324	42.6652
ARIMA(2,0,0)	38.3159	44.7596
ARIMA(1,0,1)	34.6364	41.0801
ARIMA(1,0,2)	31.4379	39.4925
ARIMA(1,1,0)	52.5966	57.4293
ARIMA(1,2,0)	79.139	83.9717
ARIMA(2,1,0)	46.9655	53.4092
ARIMA(0,1,1)	39.7857	44.6184
ARIMA(0,1,2)	36.8613	43.3049
ARIMA(2,0,1)	36.3341	44.3887
ARIMA(0,2,1)	55.0737	59.9064
ARIMA(2,0,2)	33.0312	42.6967
ARIMA(2,2,0)	60.4593	66.9029
ARIMA(0,2,2)	47.8688	54.3124
ARIMA(1,1,2)	36.2568	44.3114
ARIMA(1,2,1)	54.664	61.1077
ARIMA(2,1,1)	46.3698	54.4243
ARIMA(2,2,1)	50.7244	58.779
ARIMA(2,1,2)	37.9157	47.5812
ARIMA(1,2,2)	48.8465	56.9011
ARIMA(0,0,0)	38.184	41.4058
ARIMA(1,1,1)	39.5461	45.9898
ARIMA(2,2,2)	49.0678	58.7333

Table D. 28 AIC and BIC values of all 27 ARIMA combinations for Salamis station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	186.775	191.608
ARIMA(0,0,2)	188.733	195.177
ARIMA(0,1,0)	207.598	210.82
ARIMA(0,2,0)	245.64	248.862
ARIMA(1,0,0)	186.79	191.623
ARIMA(2,0,0)	188.74	195.184
ARIMA(1,0,1)	188.738	195.182
ARIMA(1,0,2)	187.621	195.676
ARIMA(1,1,0)	200.842	205.674
ARIMA(1,2,0)	229.239	234.072
ARIMA(2,1,0)	198.597	205.041
ARIMA(0,1,1)	186.735	191.567
ARIMA(0,1,2)	188.533	194.977
ARIMA(2,0,1)	188.542	196.596
ARIMA(0,2,1)	215.743	220.575
ARIMA(2,0,2)	188.306	197.971
ARIMA(2,2,0)	217.418	223.861
ARIMA(0,2,2)	212.656	219.099
ARIMA(1,1,2)	189.916	197.97
ARIMA(1,2,1)	208.581	215.025
ARIMA(2,1,1)	190.729	198.783
ARIMA(2,2,1)	200.994	209.049
ARIMA(2,1,2)	191.895	201.561
ARIMA(1,2,2)	207.226	215.281
ARIMA(0,0,0)	185.024	188.246
ARIMA(1,1,1)	188.734	195.178
ARIMA(2,2,2)	202.916	212.581

Table D. 29 AIC and BIC values of all 27 ARIMA combinations for Alevkaya station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	468.47	473.303
ARIMA(0,0,2)	468.709	475.152
ARIMA(0,1,0)	488.147	491.369
ARIMA(0,2,0)	525.573	528.795
ARIMA(1,0,0)	468.502	473.335
ARIMA(2,0,0)	469.867	476.31
ARIMA(1,0,1)	470.003	476.447
ARIMA(1,0,2)	469.755	477.809
ARIMA(1,1,0)	483.591	488.423
ARIMA(1,2,0)	513.321	518.153
ARIMA(2,1,0)	476.443	482.887
ARIMA(0,1,1)	476.17	481.003
ARIMA(0,1,2)	477.954	484.397
ARIMA(2,0,1)	468.954	477.009
ARIMA(0,2,1)	505.157	509.99
ARIMA(2,0,2)	471.034	480.7
ARIMA(2,2,0)	492.492	498.936
ARIMA(0,2,2)	475.621	482.065
ARIMA(1,1,2)	477.718	485.772
ARIMA(1,2,1)	486.378	492.822
ARIMA(2,1,1)	477.894	485.948
ARIMA(2,2,1)	484.138	492.193
ARIMA(2,1,2)	477.922	487.587
ARIMA(1,2,2)	504.213	512.268
ARIMA(0,0,0)	466.671	469.893
ARIMA(1,1,1)	478.093	484.537
ARIMA(2,2,2)	485.694	495.359

Table D. 30 AIC and BIC values of all 27 ARIMA combinations for Zumrutkoy station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	49.022	53.8548
ARIMA(0,0,2)	50.1084	56.5521
ARIMA(0,1,0)	71.8621	75.0839
ARIMA(0,2,0)	109.33	112.552
ARIMA(1,0,0)	49.0229	53.8557
ARIMA(2,0,0)	50.3794	56.8231
ARIMA(1,0,1)	50.2988	56.7425
ARIMA(1,0,2)	51.2725	59.3271
ARIMA(1,1,0)	66.4215	71.2543
ARIMA(1,2,0)	96.3659	101.199
ARIMA(2,1,0)	59.8092	66.2529
ARIMA(0,1,1)	48.0445	52.8773
ARIMA(0,1,2)	50.0432	56.4868
ARIMA(2,0,1)	51.189	59.2436
ARIMA(0,2,1)	80.8514	85.6841
ARIMA(2,0,2)	53.2823	62.9478
ARIMA(2,2,0)	80.625	87.0687
ARIMA(0,2,2)	77.9538	84.3975
ARIMA(1,1,2)	50.8164	58.871
ARIMA(1,2,1)	75.1756	81.6193
ARIMA(2,1,1)	49.635	57.6896
ARIMA(2,2,1)	65.5224	73.5769
ARIMA(2,1,2)	50.7277	60.3932
ARIMA(1,2,2)	76.8825	84.937
ARIMA(0,0,0)	47.0261	50.248
ARIMA(1,1,1)	49.4466	55.8903
ARIMA(2,2,2)	67.2962	76.9617

Table D. 31 AIC and BIC values of all 27 ARIMA combinations for Alaykoy station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	345.215	350.048
ARIMA(0,0,2)	347.213	353.656
ARIMA(0,1,0)	365.38	368.602
ARIMA(0,2,0)	402.754	405.976
ARIMA(1,0,0)	345.212	350.045
ARIMA(2,0,0)	347.212	353.656
ARIMA(1,0,1)	347.21	353.654
ARIMA(1,0,2)	344.308	352.362
ARIMA(1,1,0)	358.799	363.631
ARIMA(1,2,0)	386.363	391.195
ARIMA(2,1,0)	357.377	363.821
ARIMA(0,1,1)	345.509	350.342
ARIMA(0,1,2)	347.325	353.769
ARIMA(2,0,1)	344.154	352.209
ARIMA(0,2,1)	367.893	372.726
ARIMA(2,0,2)	349.964	359.63
ARIMA(2,2,0)	375.426	381.87
ARIMA(0,2,2)	358.881	365.325
ARIMA(1,1,2)	349.225	357.279
ARIMA(1,2,1)	361.06	367.503
ARIMA(2,1,1)	349.28	357.334
ARIMA(2,2,1)	359.393	367.448
ARIMA(2,1,2)	350.738	360.404
ARIMA(1,2,2)	359.686	367.74
ARIMA(0,0,0)	343.422	346.644
ARIMA(1,1,1)	347.281	353.725
ARIMA(2,2,2)	360.8	370.465

Table D. 32 AIC and BIC values of all 27 ARIMA combinations for Lefkosa station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	407.93	412.763
ARIMA(0,0,2)	408.475	414.919
ARIMA(0,1,0)	421.849	425.071
ARIMA(0,2,0)	460.671	463.893
ARIMA(1,0,0)	407.336	412.169
ARIMA(2,0,0)	408.704	415.148
ARIMA(1,0,1)	409.241	415.684
ARIMA(1,0,2)	410.321	418.376
ARIMA(1,1,0)	415.74	420.572
ARIMA(1,2,0)	439.969	444.801
ARIMA(2,1,0)	416.895	423.339
ARIMA(0,1,1)	411.202	416.035
ARIMA(0,1,2)	410.865	417.309
ARIMA(2,0,1)	410.607	418.662
ARIMA(0,2,1)	424.851	429.684
ARIMA(2,0,2)	406.251	415.917
ARIMA(2,2,0)	432.82	439.263
ARIMA(0,2,2)	420.226	426.669
ARIMA(1,1,2)	411.309	419.364
ARIMA(1,2,1)	419.552	425.996
ARIMA(2,1,1)	411.109	419.164
ARIMA(2,2,1)	419.234	427.289
ARIMA(2,1,2)	413.097	422.762
ARIMA(1,2,2)	421.365	429.42
ARIMA(0,0,0)	407.918	411.14
ARIMA(1,1,1)	409.656	416.1
ARIMA(2,2,2)	421.267	430.932

Table D. 33 AIC and BIC values of all 27 ARIMA combinations for Ziyamet station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	108.189	113.022
ARIMA(0,0,2)	110.089	116.533
ARIMA(0,1,0)	136.04	139.262
ARIMA(0,2,0)	176.25	179.472
ARIMA(1,0,0)	108.222	113.055
ARIMA(2,0,0)	110.183	116.627
ARIMA(1,0,1)	106.714	113.158
ARIMA(1,0,2)	108.407	116.461
ARIMA(1,1,0)	124.339	129.172
ARIMA(1,2,0)	153.862	158.695
ARIMA(2,1,0)	122.318	128.762
ARIMA(0,1,1)	109.552	114.385
ARIMA(0,1,2)	111.305	117.749
ARIMA(2,0,1)	108.713	116.768
ARIMA(0,2,1)	140.985	145.817
ARIMA(2,0,2)	107.115	116.781
ARIMA(2,2,0)	144.912	151.356
ARIMA(0,2,2)	131.531	137.975
ARIMA(1,1,2)	111.69	119.744
ARIMA(1,2,1)	131.479	137.923
ARIMA(2,1,1)	112.375	120.429
ARIMA(2,2,1)	125.636	133.69
ARIMA(2,1,2)	111.142	120.808
ARIMA(1,2,2)	132.188	140.242
ARIMA(0,0,0)	106.658	109.88
ARIMA(1,1,1)	110.507	116.951
ARIMA(2,2,2)	117.385	127.05

Table D. 34 AIC and BIC values of all 27 ARIMA combinations for Dipkarpaz station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	302.651	307.484
ARIMA(0,0,2)	297.875	304.319
ARIMA(0,1,0)	325.525	328.747
ARIMA(0,2,0)	361.687	364.909
ARIMA(1,0,0)	302.652	307.485
ARIMA(2,0,0)	304.163	310.607
ARIMA(1,0,1)	304.618	311.061
ARIMA(1,0,2)	302.186	310.24
ARIMA(1,1,0)	319.302	324.135
ARIMA(1,2,0)	346.872	351.705
ARIMA(2,1,0)	317.252	323.695
ARIMA(0,1,1)	302.585	307.417
ARIMA(0,1,2)	304.582	311.026
ARIMA(2,0,1)	299.988	308.043
ARIMA(0,2,1)	329.814	334.646
ARIMA(2,0,2)	299.264	308.93
ARIMA(2,2,0)	335.833	342.276
ARIMA(0,2,2)	324.306	330.749
ARIMA(1,1,2)	306.563	314.617
ARIMA(1,2,1)	324.004	330.447
ARIMA(2,1,1)	306.129	314.184
ARIMA(2,2,1)	319.639	327.693
ARIMA(2,1,2)	308.112	317.778
ARIMA(1,2,2)	325.257	333.312
ARIMA(0,0,0)	300.656	303.878
ARIMA(1,1,1)	304.585	311.028
ARIMA(2,2,2)	310.601	320.266

Table D. 35 AIC and BIC values of all 27 ARIMA combinations for Yeni Erenkoy station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	466.62	471.453
ARIMA(0,0,2)	466.691	473.135
ARIMA(0,1,0)	487.649	490.871
ARIMA(0,2,0)	523.894	527.115
ARIMA(1,0,0)	466.77	471.603
ARIMA(2,0,0)	467.813	474.257
ARIMA(1,0,1)	468.17	474.614
ARIMA(1,0,2)	463.077	471.132
ARIMA(1,1,0)	483.284	488.116
ARIMA(1,2,0)	513.178	518.011
ARIMA(2,1,0)	476.492	482.936
ARIMA(0,1,1)	466.398	471.231
ARIMA(0,1,2)	468.2	474.644
ARIMA(2,0,1)	468.588	476.642
ARIMA(0,2,1)	490.842	495.675
ARIMA(2,0,2)	464.674	474.34
ARIMA(2,2,0)	495.372	501.816
ARIMA(0,2,2)	483.866	490.31
ARIMA(1,1,2)	469.065	477.119
ARIMA(1,2,1)	486.094	492.538
ARIMA(2,1,1)	469.348	477.403
ARIMA(2,2,1)	479.203	487.257
ARIMA(2,1,2)	470.276	479.941
ARIMA(1,2,2)	484.387	492.441
ARIMA(0,0,0)	464.937	468.159
ARIMA(1,1,1)	468.275	474.719
ARIMA(2,2,2)	483.877	493.542

Table D. 36 AIC and BIC values of all 27 ARIMA combinations for Dortyol station

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	256.892	261.725
ARIMA(0,0,2)	253.608	260.051
ARIMA(0,1,0)	274.913	278.135
ARIMA(0,2,0)	307.958	311.179
ARIMA(1,0,0)	257.763	262.596
ARIMA(2,0,0)	257.089	263.532
ARIMA(1,0,1)	258.247	264.69
ARIMA(1,0,2)	252.512	260.566
ARIMA(1,1,0)	274.363	279.195
ARIMA(1,2,0)	300.24	305.072
ARIMA(2,1,0)	270.852	277.296
ARIMA(0,1,1)	263.343	268.176
ARIMA(0,1,2)	261.171	267.615
ARIMA(2,0,1)	248.66	256.715
ARIMA(0,2,1)	282.433	287.266
ARIMA(2,0,2)	250.314	259.98
ARIMA(2,2,0)	290.604	297.048
ARIMA(0,2,2)	283.046	289.489
ARIMA(1,1,2)	260.896	268.951
ARIMA(1,2,1)	281.78	288.224
ARIMA(2,1,1)	265.61	273.664
ARIMA(2,2,1)	274.691	282.746
ARIMA(2,1,2)	260.06	269.725
ARIMA(1,2,2)	278.156	286.211
ARIMA(0,0,0)	257.059	260.281
ARIMA(1,1,1)	264.577	271.02
ARIMA(2,2,2)	276.689	286.354

Table D. 37 AIC and BIC values of all 27 ARIMA combinations for REGION 1 (up to 2 lags)

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	-75.5525	-70.7197
ARIMA(0,0,2)	-73.5754	-67.1317
ARIMA(0,1,0)	-60.4619	-57.2401
ARIMA(0,2,0)	-28.0902	-24.8684
ARIMA(1,0,0)	-75.3313	-70.4985
ARIMA(2,0,0)	-73.7096	-67.266
ARIMA(1,0,1)	-73.5734	-67.1297
ARIMA(1,0,2)	-75.0633	-67.0087
ARIMA(1,1,0)	-62.0566	-57.2238
ARIMA(1,2,0)	-36.8552	-32.0225
ARIMA(2,1,0)	-64.1452	-57.7015
ARIMA(0,1,1)	-77.543	-72.7103
ARIMA(0,1,2)	-76.7456	-70.3019
ARIMA(2,0,1)	-74.8953	-66.8407
ARIMA(0,2,1)	-56.2188	-51.386
ARIMA(2,0,2)	-76.0039	-66.3384
ARIMA(2,2,0)	-42.0033	-35.5596
ARIMA(0,2,2)	-57.9157	-51.472
ARIMA(1,1,2)	-74.822	-66.7674
ARIMA(1,2,1)	-56.922	-50.4783
ARIMA(2,1,1)	-75.9286	-67.874
ARIMA(2,2,1)	-60.194	-52.1394
ARIMA(2,1,2)	-74.1481	-64.4826
ARIMA(1,2,2)	-56.6499	-48.5954
ARIMA(0,0,0)	-75.4895	-72.2677
ARIMA(1,1,1)	-76.3361	-69.8924
ARIMA(2,2,2)	-65.666	-56.0005

Table D. 38 AIC and BIC values of all 27 ARIMA combinations for REGION 2 (up to 2 lags)

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	427.556	432.389
ARIMA(0,0,2)	426.444	432.888
ARIMA(0,1,0)	448.683	451.905
ARIMA(0,2,0)	484.752	487.974
ARIMA(1,0,0)	427.663	432.496
ARIMA(2,0,0)	428.901	435.344
ARIMA(1,0,1)	429.23	435.674
ARIMA(1,0,2)	428.1	436.154
ARIMA(1,1,0)	444.408	449.241
ARIMA(1,2,0)	473.357	478.19
ARIMA(2,1,0)	439.473	445.916
ARIMA(0,1,1)	427.046	431.879
ARIMA(0,1,2)	428.926	435.369
ARIMA(2,0,1)	428.923	436.978
ARIMA(0,2,1)	450.75	455.583
ARIMA(2,0,2)	427.791	437.457
ARIMA(2,2,0)	455.341	461.785
ARIMA(0,2,2)	435.569	442.013
ARIMA(1,1,2)	428.218	436.273
ARIMA(1,2,1)	446.436	452.88
ARIMA(2,1,1)	440.346	448.4
ARIMA(2,2,1)	441.614	449.669
ARIMA(2,1,2)	426.872	436.538
ARIMA(1,2,2)	437.272	445.326
ARIMA(0,0,0)	425.761	428.983
ARIMA(1,1,1)	428.943	435.387
ARIMA(2,2,2)	442.416	452.082

Table D. 39 AIC and BIC values of all 27 ARIMA combinations for REGION 3 (up to 2 lags)

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	777.148	781.981
ARIMA(0,0,2)	777.809	784.253
ARIMA(0,1,0)	796.583	799.804
ARIMA(0,2,0)	832.968	836.19
ARIMA(1,0,0)	777.406	782.238
ARIMA(2,0,0)	778.697	785.141
ARIMA(1,0,1)	784.282	790.725
ARIMA(1,0,2)	779.32	787.375
ARIMA(1,1,0)	793.422	798.255
ARIMA(1,2,0)	821.824	826.657
ARIMA(2,1,0)	789.338	795.782
ARIMA(0,1,1)	783.09	787.923
ARIMA(0,1,2)	786.235	792.679
ARIMA(2,0,1)	779.969	788.023
ARIMA(0,2,1)	813.728	818.56
ARIMA(2,0,2)	779.798	789.463
ARIMA(2,2,0)	806.985	813.428
ARIMA(0,2,2)	813.015	819.459
ARIMA(1,1,2)	788.289	796.344
ARIMA(1,2,1)	820.495	826.938
ARIMA(2,1,1)	783.29	791.344
ARIMA(2,2,1)	796.749	804.804
ARIMA(2,1,2)	787.085	796.75
ARIMA(1,2,2)	814.766	822.82
ARIMA(0,0,0)	775.929	779.151
ARIMA(1,1,1)	797.867	804.31
ARIMA(2,2,2)	788.622	798.287

Table D. 40 AIC and BIC values of all 27 ARIMA combinations for REGION 4 (up to 2 lags)

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	354.589	359.422
ARIMA(0,0,2)	351.717	358.16
ARIMA(0,1,0)	376.159	379.38
ARIMA(0,2,0)	411.652	414.874
ARIMA(1,0,0)	354.637	359.47
ARIMA(2,0,0)	355.55	361.994
ARIMA(1,0,1)	356.31	362.754
ARIMA(1,0,2)	349.867	357.921
ARIMA(1,1,0)	371.735	376.568
ARIMA(1,2,0)	400.402	405.235
ARIMA(2,1,0)	367.069	373.513
ARIMA(0,1,1)	354.769	359.602
ARIMA(0,1,2)	356.604	363.048
ARIMA(2,0,1)	357.372	365.426
ARIMA(0,2,1)	381.432	386.264
ARIMA(2,0,2)	ERROR	ERROR
ARIMA(2,2,0)	384.701	391.145
ARIMA(0,2,2)	377.786	384.23
ARIMA(1,1,2)	358.045	366.1
ARIMA(1,2,1)	376.803	383.247
ARIMA(2,1,1)	357.646	365.701
ARIMA(2,2,1)	369.085	377.139
ARIMA(2,1,2)	359.342	369.007
ARIMA(1,2,2)	378.263	386.318
ARIMA(0,0,0)	352.758	355.98
ARIMA(1,1,1)	356.701	363.145
ARIMA(2,2,2)	369.192	378.858

Table D. 41 AIC and BIC values of all 27 ARIMA combinations for North Cyprus annual average

ARIMA MODEL	AIC	BIC
ARIMA(0,0,1)	485.173	490.006
ARIMA(0,0,2)	482.899	489.342
ARIMA(0,1,0)	505.448	508.67
ARIMA(0,2,0)	540.712	543.934
ARIMA(1,0,0)	485.372	490.205
ARIMA(2,0,0)	486.317	492.761
ARIMA(1,0,1)	486.49	492.933
ARIMA(1,0,2)	484.077	492.131
ARIMA(1,1,0)	502.129	506.962
ARIMA(1,2,0)	530.685	535.518
ARIMA(2,1,0)	497.147	503.591
ARIMA(0,1,1)	485.485	490.317
ARIMA(0,1,2)	487.047	493.491
ARIMA(2,0,1)	484.047	492.102
ARIMA(0,2,1)	508.389	513.222
ARIMA(2,0,2)	482.244	491.909
ARIMA(2,2,0)	512.814	519.258
ARIMA(0,2,2)	502.405	508.849
ARIMA(1,1,2)	492.574	500.628
ARIMA(1,2,1)	504.777	511.22
ARIMA(2,1,1)	497.351	505.406
ARIMA(2,2,1)	499.167	507.221
ARIMA(2,1,2)	494.541	504.206
ARIMA(1,2,2)	503.729	511.783
ARIMA(0,0,0)	483.626	486.848
ARIMA(1,1,1)	487.051	493.495
ARIMA(2,2,2)	499.499	509.164

Table D. 42 Autocorrelation Coefficient Function (ACF) Values for transformed and observed annual data of 4 clusters at Lag 0, Lag 1, Lag 2 and Lag 3

Group/ACF value	**Lag 0**	**Lag 1**	**Lag 2**	**Lag 3**
Group 1	1.0 (1.0)	0.21 (0.25)	-0.02 (0.04)	-0.06 (0.04)
Group 2	1.0 (1.0)	0.06 (0.07)	-0.12 (-0.09)	0.016 (0.02)
Group 3	1.0 (1.0)	0.12 (0.11)	-0.11 (-0.12)	-0.007 (-0.02)
Group 4	1.0 (1.0)	0.05 (0.06)	-0.14 (-0.13)	-0.01 (-0.03)