ISTANBUL TECHNICAL UNIVERSITY ★ INFORMATICS INSTITUTE

ESTIMATING CLIMATE EXTREMES
FOR TURKEY AND ITS REGION

M.Sc. THESIS

Yeliz YILMAZ

Computational Science and Engineering Department

Computational Science and Engineering Programme

AUGUST 2012

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ BİLİŞİM ENSTİTÜSÜ

TÜRKİYE VE BÖLGESİ İÇİN
İKLİM UÇ DEĞER İSTATİSTİKLERİNİN KESTİRİMİ

YÜKSEK LİSANS TEZİ

Yeliz YILMAZ
(702091019)

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Yeliz YILMAZ, a M.Sc. student of ITU Informatics Institute 702091019 successfully defended the thesis entitled **"ESTIMATING CLIMATE EXTREMES FOR TURKEY AND ITS REGION"**, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. H. Nüzhet DALFES** Istanbul Technical University	....
Jury Members :	**Prof. Dr. Ömer Lütfi ŞEN** Istanbul Technical University	....
	Yrd. Doç. Dr. Adem TEKİN Istanbul Technical University	....

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To my family,

FOREWORD

I wish to thank my adviser H. Nüzhet Dalfes. He has directed this thesis with endless patience and guided my research. And i have had a colleague within the climate research group whom i wish to thank: Yasemin Ergüner Baytok. She has helped and supported me in several steps of my research. Most of all, I wish to thank my family and Barış because of their support during the all periods of my research.

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Yeliz YILMAZ
Master Student

TABLE OF CONTENTS

Page

ABBREVIATIONS

CDO	: Climate Data Operators
EVA	: Extreme Value Analysis
EVT	: Extreme Value Theory
GCM	: Global Climate Model
GEV	: Generalized Extreme Value
GP	: Generalized Pareto
IPCC	: Intergovernmental Panel on Climate Change
MLE	: Maximum Likelihood Estimation
netCDF	: Network Common Data Form
NCL	: NCAR Command Language
NCO	: NetCDF Operators
NNRP	: NCEP/NCAR Reanalysis Project
POT	: Peaks Over Threshold
PWM	: Probability Weighted Moments
RCM	: Regional Climate Model
Tmax	: Maximum Temperature
Tmin	: Minimum Temperature
TSMS	: Turkish State Meteorological Service
WMO	: World Meteorological Organization

LIST OF TABLES

LIST OF FIGURES

Page

LIST OF SYMBOLS

μ	:	Location parameter of distribution
σ	:	Scale parameter of distribution
ξ	:	Shape parameter of distribution

ESTIMATING CLIMATE EXTREMES
FOR TURKEY AND ITS REGION

SUMMARY

Extreme climate events have high socio-economic impacts all around the world, in recent years. Especially in last decade (2001-2010), studies on extreme climate events have been increasing. According to report of Turkish State Meteorological Service (TSMS), 555 extreme climate events had recorded since 1940 in 2010 for Turkey.

In this study is aimed to extract such information about estimating the distribution of extreme events by using station data and dynamically downscaled climate projections for Turkey and its region. Another point is to find answers for questions such as how important these extreme climate events for Turkey.

Analyses are mainly focused on extremes in temperature and precipitation. For this purpose, Extreme Value Analysis (EVA) was used to estimate extreme value statistics. EVA has been used in many disciplines such as hydrology, earth sciences, finance, insurance, metallurgy, environmental research and meteorology etc.

In this thesis, Generalized Extreme Value (GEV) distribution models was used for analyses. GEV model was fitted to daily maximum temperature, daily minimum temperature and daily total precipitation for Turkey and its region. Moreover, GEV method allows to analyzing return values, return level, at different time scales such as monthly, seasonal, annual, etc. Return level means that it is exceeded by the maximum value in any particular time scale with probability.

In the study of Bozkurt et al., results of global climate models (GCMs) such as ECHAM5, CCSM and HadCM3 are downscaled to force at the boundaries a regional climate model (RCM), RegCM3, to obtain dynamically downscaled climate fields at a resolution of 27 km for the historical (1961-1990) reference period and the 21st Century (2000-2099). EVA is applied to these model outputs and compared with results of NCEP/NCAR Reanalyses data for reference period.

All of these analyses were done under the stationary assumption. But it is known that climate data are nonstationary. In extreme value analysis, assumption of time-dependent models is more realistic. The nonstationary extreme value analysis is a developing research area. In this study, probability weighted moments method was used to estimate the parameters (location, shape and scale) of GEV distributions under the assumption of stationary.

Uncertainties for GEV parameters were estimated through resampling methods to measure the accuracy of parameters. Resampling methods such as jackknife was applied to reference and projected climate data.

TÜRKİYE VE BÖLGESİ İÇİN
İKLİM UÇ DEĞER İSTATİSTİKLERİNİN KESTİRİMİ

ÖZET

Uç değer iklim olaylarına aşırı yağışlar, aşırı sıcaklıklar, fırtınalar, seller, kuraklıklar, sıcak veya soğuk hava dalgaları örnek olarak verilebilir. Nadir görülmelerine karşın etkileri çok yüksek olmaktadır.

Son yıllarda, dünyanın her yerinde uç iklim olaylarının büyük sosyo-ekonomik etkileri görülmektedir. Özellikle son 10 yılda (2001-2010), uç iklim olayları üzerindeki çalışmalar artmıştır. Meteoroloji Genel Müdürlüğü'nün raporuna göre, 2010 yılında, 1940 yılından itibaren Türkiye'de 555 uç iklim olayı kaydedilmiştir.

Uç değer olaylar geriye dönük bir şekilde kestirilebilirler. Fakat ortalamalar dışındaki farklı istatistiki kurallara uydukları için uç değerler ile çalışmak zordur.

Bu tez çalışmasıda, istasyon ve dinamik olarak küçülmüş iklim projeksiyon verileri kullanılarak, Türkiye ve bölgesi için uç iklim olaylarının dağılımının kestirimi amaçlanmaktadır. Ayrıca bu uç iklim olaylarının Türkiye için önemi konusundaki sorulara cevaplar aranmaktadır.

Analizler çoğunlukla uç sıcaklıklar ve uç yağışlar üzerine odaklanmaktadır. Bu amaçla, uç değer istatistiklerinin hesaplaması için Uç Değer Analizi (UDA) yöntemi kullanılmıştır. UDA hidroloji, yer bilimleri, finans, sigortacılık, vb. gibi birçok disiplinde kullanılmaktadır.

Uç değer analizi yöntemi, diğer istatistiki yaklaşımların aksine, dağılımın kuyruk kısmı ile ilgilenir. Çünkü uç değerler dağılımın kuyruklarında yer almaktadır. Bu sebeple ne kadar büyük veri setleri ile çalışılırsa çalışılsın, veri her zaman azdır.

İklim araştırmalarında UDA yönteminin kullanılması aslında yakın zamanlarda başlamıştır. Ama uç değer iklim olaylarının sayılarının ve etkilerinin artmasıyla beraber, bu alandaki çalışmalar hızlanarak artmaktadır.

Bu tezde, analizler için, Genelleştirilmiş Uç Değer (GUD) dağılım modeli kullanılmaktadır. Türkiye ve bölgesinde, günlük en yüksek sıcaklık, günlük en düşük sıcaklık ve günlük toplam yağış verileri için GUD modeli uydurulmuştur.

Genelleştirilmiş Uç Değer dağılımının parametrelerinin kestirimi için birçok yöntem mevcuttur. Bu çalışmada en çok olabilirlik (EÇO) ve olasılıkla ağırlıklandırılmış momentler (OAM) yöntemleri parametre kestirimleri için kullanılmıştır.

EÇO yöntemi özellikle büyük veri setleri için güçlü ve kesin bir yöntem olmasına rağmen küçük veri setlerinde sonuç vermemektedir. Bu durumun yağış verisine UDA uygulama konusunda sorunlar çıkardığı tespit edilmiştir. Bunun ardından OAM yönteminin parametre kestirimlerinde kullanılmıştır. EÇO yöntemi bir optimizasyon yöntemi olup, dağılımının parametrelerinin zamana bağlı bir şekilde hesaplanmasını sağlar.

Uç değerlerin kestirimi ve yorumları dönüş seviyeleri üzerinden yapılmaktadır. GUD yöntemi aylık, mevsimsel, yıllık, vb. gibi farklı zaman ölçeklerinde dönüş seviyeleri, dönüş seviyesi analizlerinin yapılmasına olanak tanımaktadır. Dönüş seviyesi, bu değerin belli bir zaman ölçeğinde bir olasılıkla en büyük değer tarafından aşılacağı anlamına gelmektedir. Bu modelin çıktıları olan dağılım parametreleri kullanılarak da dönüş seviyeleri hesaplanmıştır. Çünkü iklim uç değerleri, dönüş seviyesi ile ifade edilmekte ve bu değerler yorumlanarak uç değer analizi yapılmaktadır.

Bozkurt ve diğerlerinin çalışmasında, tarihi referans aralığı (1961-1990) ve 21. yüzyıl (2000-2099) için, ECHAM5, CCSM ve HadCM3 gibi küresel iklim modellerinin (KİM) çıktıları sınırlarda bölgesel iklim modeli (BİM), RegCM3, kullanılarak 27 kilometrelik bir alanda, dinamik olarak ölçek küçülmüştür.

ECHAM5 model çıktıları ve NCEP/NCAR Reanalysis (NNRP) verilerinin sonuçlarına UDA uygulanarak, tarihi referans aralığı için karşılaştırma yapılmıştır. 20. yüzyıl için yapılan model karşılaştırmalarının yanısıra, 21. yüzyıl için de otuzar yıllık periyodlarda UDA sonuçları karşılaştırılmıştır.

Bu analizlerin hemen hemen hepsi durağanlık kabulü altında yapılmıştır. Ama iklim verilerinin durağan olmadığı bilinir. Uç değer analizinde, zamana bağlı modellerin kabulü daha gerçekçidir. Durağan olmayan uç değer analizi gelişmekte olan bir alandır ama henüz bu konuda genel bir teori yoktur. Durağan olmayan uç değer analizi için parametreler EÇO yöntemi ile kestirilebilmektedirler. Bu çalışmada yapılan uygulamalarda durağan olmayan modellerin genel olarak daha iyi sonuç verdiği görülmüştür.

Bu çalışmada, durağanlık kabulü altında, GUD dağılımının parametrelerinin (konum, ölçek, şekil) kestirimi için olasılıkla ağırlıklandırılmış momentler (OAM) yöntemi kullanılmıştır.

Model çıktıları ile yapılan analizlerin yanısıra istasyon verileri ile de analizler yapılıp ardından sonuçları model çıktılarınınki ile kıyaslanmıştır. Sonuçların yakın olduğu görülmüştür.

Dönüş seviyesi analizleri 30 yıllık bir dönüş periyodu kullanılarak hesaplanmıştır. Bir diğer hesaplama da artan dönüş periyodları için dönüş seviyesinin nasıl değiştiğini analiz etmek amacıyla yapılmıştır.

Yapılan tüm analizlerin belirsizliğinin tespiti için yaygın olarak kullanılan bazı yöntemler vardır. Bunlara örnek olarak hiyerarşik modelleme, Markov zinciri Monte Carlo yöntemi, yeniden örnekleme yöntemleri (bootstrap, jackknife, çapraz doğrulama, ...) verilebilir. Analizin amacı doğrultusunda yeniden örnekleme yöntemleri belirsizlik analizi için tercih edilmiştir.

Bu çalışmada, GUD parametrelerinin belirsizliği için de test yapılmıştır. Belirsizlik yeniden örnekleme yöntemleri ile kestirilmeye çalışılarak, kesinliği test edilmiştir. Jackknife yöntemi kullanılarak tarihi referans ve projeksiyon verilerine UDA uygulanmıştır.

Sonuç olarak, uç değerler persfektifinden bakıldığnda maksimum ve minimum sıcaklıkların uç değerlerlerinin yükseldiği, yağışların uç değerlerinin de zamanla azaldığı görülmüştür. Ama azalmalara rağmen kuzeydoğu Karadeniz bölgesindeki yağışların miktarı bir hayli fazla olarak görülmektedir. Sıcaklıklarda ise güney ve batı kıyılarındaki ve güneydoğu Anadolu bölgesindeki sıcaklık artışı göze çarpmaktadır.

Durağan olmayan uç değer analizi için ise, bir gelecek çalışması olarak doğrusal değişimler dışında farklı modellerle hesap yapılması amaçlanmaktadır.

1. INTRODUCTION

Climate extremes are highly unusual events which have extreme impacts all around the world. In recent years, studies on extreme climate events have been increasing.

1.1 Importance of Extremes for Climate Impact Analyses

Extreme climate events such as droughts, storms, floods, heat waves and cold waves with small probably rarely happen but have tremendous impacts on society, economy and biophysical systems. On the other hand, according to World Meteorological Organization (WMO) number of recorded devastating extreme climate events has been increased in recent years. WMO published a brochure which provides a sample of extreme events for the past decade (2001-2010) [1].

Also, Taleb defines a “Black Swan” event as rare, have extreme impact and predictable retrospectively, not prospectively in his book [2].

Climate extreme events have been hard to study and even harder to predict because they are, by definition, rare and obey different statistical laws than averages. But studies on extreme events have been gradually increasing in many disciplines in recent years [3]. The report of Intergovernmental Panel on Climate Change (IPCC) which published in 2012 focuses on the relationship between climate change and extreme weather and climate events [4].

According to TSMS, 555 harmful extreme climate events have recorded for Turkey since 1940 in 2010. For example, one of the extreme rainfall event caused to death of 13 people in Rize in 2010 [5].

1.2 Examples of Extreme Value Theory Applications in Climate Research

Extreme Value Theory (EVT) has been applied to a variety problems in many disciplines such as hydrology, earth sciences, finance, insurance etc. Applications in climate researches have been popular recently [3].

In the study of Kharin and Zwiers, they had used EVT to analyze the extremes of near-surface climate and their changes under projected anthropogenic forcing as simulated by Canadian Global Coupled Model (CGCM1) in an ensemble of three transient integrations [6]. This study can be accepted as one of the important first application of EVT in climatology.

It is mentioned that application of EVT in climate studies has been fairly recent, in the paper of Naveau et al. They had applied principles of EVT to three different case studies: lichenometry, volcanic forcing and the simulated atmospheric impact of an ocean circulation change. As a result of these case studies, they states that appropriate answers for questions about climate extremes can be provided by EVT. Especially, GEV is the proper fit to maxima than any continuous distribution [3].

There are five beneficial case studies as applications of EVT to problems of variety disciplines, in the last chapter of the book of Reiss and Thomas. Case studies are about as, respectively: ground level ozone data from Mexico city, nonstationary pollution series, increasing the low temperatures with the global warming, windstorm losses in Central Europe, Vrancea earthquakes [7].

Extreme temperatures is one of the popular topic in climatic extremes which increasing frequencies. For future extreme temperatures in Europe, Frias et al. have a study. According to their paper, extremes are expressed in terms of return values using a time-dependent GEV model [8]. Also, cold temperature extremes under the influence of North Atlantic Atmospheric Blocking had been studied by Sillmann et al. for Europe [9].

Katz et al. are mentioned about the importance of EVA for water resources design and management. There exist applications of hydrological extremes such as maximum precipitation, streamflow, flood damage, maximum sea level in their paper [10].

Rust et al. are studied on seasonality in extreme precipitation for the United Kingdom in their paper [11].

1.3 Essential Climate Variables and Data Sources

Extreme Value Analysis was applied to two data sets for Turkey and its region. Model output data and station data were used to analyze climate extremes. It was aimed that comparing results of the analyses for both data sets and measuring the performance of EVA.

Station data are provided by Turkish State Meteorological Service (TSMS). These data are monthly mean temperature and daily total precipitation from 247 meteorological stations which has distribution in figure2.1 in Turkey [12].

Also, NCEP/NCAR Reanalysis Project (NNRP) and ECHAM5 model output data were used to apply EVA for Turkey and its region. Temperature and precipitation data are provided from research of Bozkurt et al. for 20^{th} and 21^{st} centuries.

Table 1.1: Information about data sets which are used for extreme value analysis for Turkey and its region.

Data Name	**Description**	**Period**
Station	From 247 meteorological stations	1930-2006
NNRP	Taken from NCEP/NCAR Reanalysis	1961-1990
ECHAM5	Outputs of ECHAM5 GCM	1961-1990
A2 ECHAM5	Outputs of A2 scenario of ECHAM5 GCM	2011-2099

2. MATERIAL AND METHODS

First, data which were used in this research will be described and then theoretical framework of Extreme Value Analysis will be mentioned in this chapter.

2.1 Data

Data format which has *.nc* extension is netCDF (Network Common Data Form). CDO (Climate Data Operators) and NCO (netCDF Operators) tools were used for management and filtering of climate variables before the analyses. To calculate the parameters of GEV distribution and return values, the *fExtremes* library of R which is an open source programming language is used. R, also called GNU S, not only is an open source statistical software product, but also supports the *parallelism* very recently [13]. Finally, NCL (NCAR Command Language) tool was used for visualization of the maps.

2.1.1 Station data

A regional data set including the TSMS climate observations which had been used in study of Bozkurt et al. in Figure 2.1 have been used in the analyses to compare with results of parameter estimates and return levels for model outputs in several points in Turkey and its region.

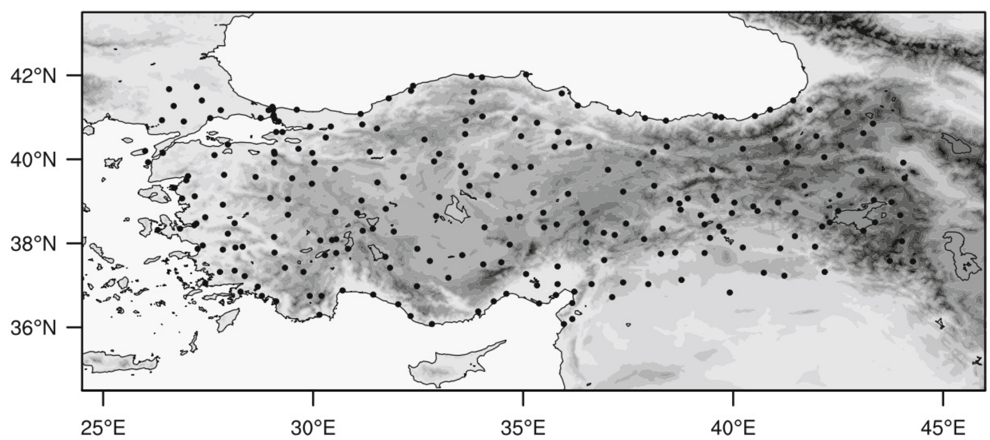

Figure 2.1: Distribution of the stations.

Daily total precipitation data from stations were used to compare with results of model output data of 20^{th} century NNRP and ECHAM5 for 1961-1990 reference period.

2.1.2 Dynamically downscaled model output

In the study of Bozkurt et al., outputs of ECHAM5 global climate model (GCM) were downscaled to force at the boundaries a regional climate model (RCM), RegCM3, for the historical (1961-1990) reference period for the eastern Mediterranean-Black Sea region. To display the performance of the RCM, NNRP data were also downscaled for same region [14].

In this thesis, these dynamically downscaled ECHAM5 and NNRP model output data were used to estimate distribution parameters for Turkey and its region at a resolution of 27 km for 1961-1990 reference period. For 21^{st} Century (2011-2099), A2 scenario of ECHAM5 data were used for same region.

Two dataset groups (20^{th} and 21^{st} centuries) consist of daily maximum temperature (Tmax), minimum temperature (Tmin) and total precipitation. From these data, seasonal minimum and maximum temperatures were chosen. Winter minimum temperatures and summer maximum temperatures were used in the analyses. All daily precipitation values were grouped in a data set.

2.2 Theoretical Framework for Extreme Value Analyses

Extreme value theory (i.e. Extreme value analysis) is the branch of probability and statistics dedicated to characterizing the behavior of the any probability distribution without any knowledge of the form. In statistical studies, focus is typically on central tendencies but EVT is interested only to describing the tail behavior. When studying extremes, even with large data sets, data are always poor [15], [16].

Two approaches exist to fit the tail of a distribution function.

- Valid for maxima over very large blocks
- Excess over a very high threshold

First item is the Generalized Extreme Value (GEV) family (block maxima) and the second one is the Generalized Pareto (GP) family (excesses over a high threshold).

2.2.1 The generalized extreme value distribution

Let $X_1, ..., X_n$, is a sequence of independent and identically distributed (i.i.d.) random variables having a common distribution function F.

$$M_n = max\{X_1, \ldots X_n\} \tag{2.1}$$

If n is the number of observations in a year, then M_n corresponds to the annual maximum. In theory the distribution of M_n can be derived exactly for all values of n:

$$\begin{aligned} Pr\{M_n \leq z\} &= Pr\{X_1 \leq z, ..., X_n \leq z\} \\ &= Pr\{X_1 \leq z\} x ... x Pr\{X_n \leq z\} \\ &= \{F(z)\}^n \end{aligned} \tag{2.2}$$

The possible limit distributions for M_n^* is given by Theorem 1, the extremal types theorem.

Theorem 1: If there exist sequences of constants $\{a_n > 0\}$ and $\{b_n\}$ such that

$$Pr\{(M_n - b_n)/a_n \leq z\} \to G(z) \qquad \text{as } n \to \infty\,,$$

G is a non-degenerate distribution function and one of the following families:

$$\begin{aligned} I : G(z) &= exp\left\{-exp\left[-\left(\frac{z-b}{a}\right)\right]\right\}, -\infty < z < \infty \\ II : G(z) &= \begin{cases} 0, & z \leq b, \\ exp\left\{-\left(\frac{z-b}{a}\right)^{-\alpha}\right\}, & z > b, \end{cases} \\ III : G(z) &= \begin{cases} exp\left\{-\left[-\left(\frac{z-b}{a}\right)^{\alpha}\right]\right\}, & z < b, \\ 1, & z \geq b, \end{cases} \end{aligned} \tag{2.3}$$

for parameters $a > 0$, b and, in the case of families II and III, $\alpha > 0$.

These are extreme value distributions and generally known as the Gumbel, Frechet and Weibull families, respectively. Each family has a location and scale parameter, b and

a respectively; additionally, the Frechet and Weibull families have a shape parameter α [17].

The Gumbel, Frechet and Weibull families can be combined into a single distribution family functions of the form.

Theorem 2: If there exist sequences of constants $\{a_n > 0\}$ and $\{b_n\}$ such that

$$Pr\{(M_n - b_n)/a_n \leq z\} \rightarrow G(z) \qquad \text{as } n \rightarrow \infty\,,$$

for a non-degenerate distribution function G is a member of the GEV family

$$G(z) = exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, \tag{2.4}$$

define on $\left\{z : 1+\xi\dfrac{(z-\mu)}{\sigma} > 0\right\}$, where $-\infty < \mu < \infty$, $\sigma > 0$ and $-\infty < \xi < \infty$. The GEV distribution family has three parameters: a location parameter, μ a scale parameter, σ and a shape parameter, ξ [17].

The shape parameter determines the tail behavior. If $\xi < 0$, $\xi = 0$ and $\xi > 0$, families are defined as Weibull, Gumbel, Frechet, respectively. In words, If ξ is negative, the upper tail is bounded i.e. light tail; If ξ is positive, the upper tail is unbounded i.e. heavy tail [3].

Extremes are generally described in terms of return levels which are transformations of parameters of GEV distribution.

$$z_p = \begin{cases} \mu - \dfrac{\sigma}{\xi}\left[1-\{-log(1-p)\}^{-\xi}\right], & for\ \xi \neq 0, \\ \mu - \sigma log\{-log(1-p)\}, & for\ \xi = 0, \end{cases} \tag{2.5}$$

where $G(z_p) = 1-p$. z_p is the return level associated with the return period $1/p$, the level z_p is expected to be exceeded on average once every $1/p$ years [17].

2.3 Approaches to the Estimation of Distribution Parameters

In this thesis, only parameters of GEV distribution and return values were estimated. Estimation of parameters of GP distribution may be a part of future works. To estimate the distribution parameters such as location, scale, and shape, there exist various approaches: Method of moments type, maximum likelihood, exhaustive tail-index approaches, least squares...

Probability weighted moments method was chosen in this research to estimation of parameters of GEV distribution. And then by using these parameters, return values were calculated.

2.3.1 Maximum likelihood estimation

Maximum likelihood estimation (MLE) method provides to estimating the unknown parameters of a statistical model. This approach dedicated to maximize the sample likelihood. Especially for large samples, it is powerful and precise. But it has two important drawbacks. For small numbers, MLE can be heavily biased and failure. The other drawback, cost of computation can be high to solve complex nonlinear equations [18].

Let $f_x(x;\theta)$ be the probability density function of a random variable X with parameters $\theta = \{\theta_1, ..., \theta_p\}$. Suppose that $x = \{x_i, i = 1, ..., n\}$ be n independent realizations of the random variable X. The log-likelihood function for θ based on data x is given by

$$l_{x_1 \dots x_n}(\theta) = \sum_{i=1}^{n} ln f_x(x_i;\theta). \tag{2.6}$$

The maximum likelihood estimator $\widehat{\theta}$ is the value of θ that maximizes $l_{x_1 \dots x_n}(\theta)$ [19].

Let $Z_1, ..., Z_m$ are independent variables and have the GEV distribution. For $\xi \neq 0$ case, the log-likelihood for the GEV parameters is

$$l(\mu,\sigma,\xi) = -m log\sigma - (1+1/\xi)\sum_{i=1}^{m} log\left[1+\xi\left(\frac{z_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{m}\left[1+\xi\left(\frac{z_i-\mu}{\sigma}\right)\right]^{-1/\xi} \tag{2.7}$$

provided that

$$1+\xi\left(\frac{z_i-\mu}{\sigma}\right) > 0, \qquad \text{for } i = 1, ..., m.$$

For $\xi = 0$ case, by using Gumbel limit, the log-likelihood is

$$l(\mu,\sigma) = -mlog\sigma - \sum_{i=1}^{m}\left(\frac{z_i-\mu}{\sigma}\right) - \sum_{i=1}^{m} exp\left\{-\left(\frac{z_i-\mu}{\sigma}\right)\right\}. \quad \textbf{(2.8)}$$

Maximization of these two equations (2.7) and (2.8) gives parameter vector (μ,σ,ξ) of GEV distribution [17].

2.3.2 Probability weighted moments

Probability weighted method (PWM) is an alternative approach to estimate the parameters of any distribution. PWM sometimes can be used when no result taken with MLE method.

Let F be the cumulative distribution function of random X variables.

$$M_{i,j,k} = E\left[X^iF^j(1-F)^k\right] = \int_0^1 [x(F)]^iF^j(1-F)^k dF \quad \textbf{(2.9)}$$

where i, j and k are real numbers.

Let the distribution F equals to the GEV, a subclass of PWM $(i = 1, j = 0,1,2,...$ and $k = 0)$ can be explicitly obtained

$$M_{1,j,0} = \frac{1}{j+1}\left(\mu - \frac{\sigma}{\xi}\left[1-(j+1)^{\xi}\Gamma(1-\xi)\right]\right), \quad \textbf{(2.10)}$$

for $\xi < 1$ and $\xi \neq 0$. This provides a system of three equations which gives parameter vector (μ,σ,ξ) of GEV distribution [20].

$$\begin{cases} M_{1,0,0} = \mu - \dfrac{\sigma}{\xi}(1-\Gamma(1-\xi)) \\ 2M_{1,1,0} - M_{1,0,0} = \dfrac{\sigma}{\xi}\Gamma(1-\xi)(2^{\xi}-1) \\ \dfrac{3M_{1,2,0}-M_{1,0,0}}{2M_{1,1,0}-M_{1,0,0}} = \dfrac{3^{\xi}-1}{2^{\xi}-1} \end{cases} \quad \textbf{(2.11)}$$

2.4 Dealing with Nonstationarity

The nonstationary extreme value analysis is a developing research area [21]. Assumption of stationary accepts that there is no change through the time. Anthropogenic change of Earth's climate is altering the means and climate extremes [22]. So, nonstationary climatic phenomena should be taken into account by using covariate information when estimate the distribution parameters. There exist several applications of nonstationary extreme value analysis with block maxima and POT methods [23], [24], [8], [25].

Let F_i be an annually constant distribution of X_i variables. Annual maxima M_j of year t are modeled by independent variables with a GEV distribution:

$$G(x) = \begin{cases} exp\left\{-1+\xi\left(\frac{x-\mu(t)}{\sigma(t)}\right)^{-1/\xi}\right\}, & if\xi \neq 0, \\ exp\left\{-exp\left(-\frac{x-\mu(t)}{\sigma(t)}\right)\right\}, & if\xi = 0, \end{cases}$$

The parameters of a nonstationary GEV model is $(\mu(t), \sigma(t), \xi), \quad t = 1, ..., n$. Generally, it shall suppose that ξ doesn't depend on time.

2.5 Dealing with Uncertainties for Estimation Parameters

Uncertainty is present in every step of climate change researches. To measure how accurate are parameter estimates or return levels, there are several statistical methods such as hierarchical modeling and Markov chain Monte Carlo simulation techniques [26]. In this thesis, resampling methods were used to deal with uncertainties for estimating parameters.

2.5.1 Resampling methods

Resampling is a statistical technique used to create a new version of sample when measuring the accuracy of the statistics. There exist two main approaches such as creating subsets with proper data and creating random sets with original data.

There are four types of resampling methods for i.i.d. data.

- Randomization exact test
- Cross validation
- Jackknife
- Bootstrap

The principles of cross validation, Jackknife and bootstrap are very similar. These four techniques were developed by different people at different periods of time [27].

Jackknife is an adequate method for this research to understand the impacts of extremes. Therefore, this method was chosen to illustrate uncertainty.

2.5.1.1 Jackknife

This method is also known as Quenouille-Tukey Jacknife method and created by Maurice Quenouille in 1949 and developed by John W. Tukey in 1958. The Jackknife name is given by Tukey because of that it is a multipurpose statistical tool.

In Jackknife method, new data sets are created by one of the data are extracted from the original data set at every turn. This technique is useful if extreme values are present in the data set.

For example, the Jackknife subdatasets are for a $X = \{x_1, x_2, x_3, x_4\}$ data set as below:

$$\begin{aligned} X^{*1} &= (x_2, x_3, x_4) \\ X^{*2} &= (x_1, x_3, x_4) \\ X^{*3} &= (x_1, x_2, x_4) \\ X^{*4} &= (x_1, x_2, x_3) \end{aligned} \qquad (\mathbf{2.12})$$

One sample data point was deleted and then the parameters were estimated in each step. As a result of these procedure, an histogram was created for each parameter. In this research, four different histograms were generated in a specific grid box for each parameters of distribution and return levels.

3. RESULTS

Extreme Value Theory had applied to estimate the parameters distribution of daily maximum, minimum temperature and daily total precipitation extremes. Estimation results were compared for different models and time scales. Analyses results of research is as below:

3.1 Estimates Under the Stationary Assumption

Probability weighted moments method was chosen in this research to estimation of parameters of GEV distribution. Because, sample size of especially precipitation is too small for MLE approach. Return level results of MLE and PWM were compared by using temperature data. But MLE approach gave no results for precipitation data.

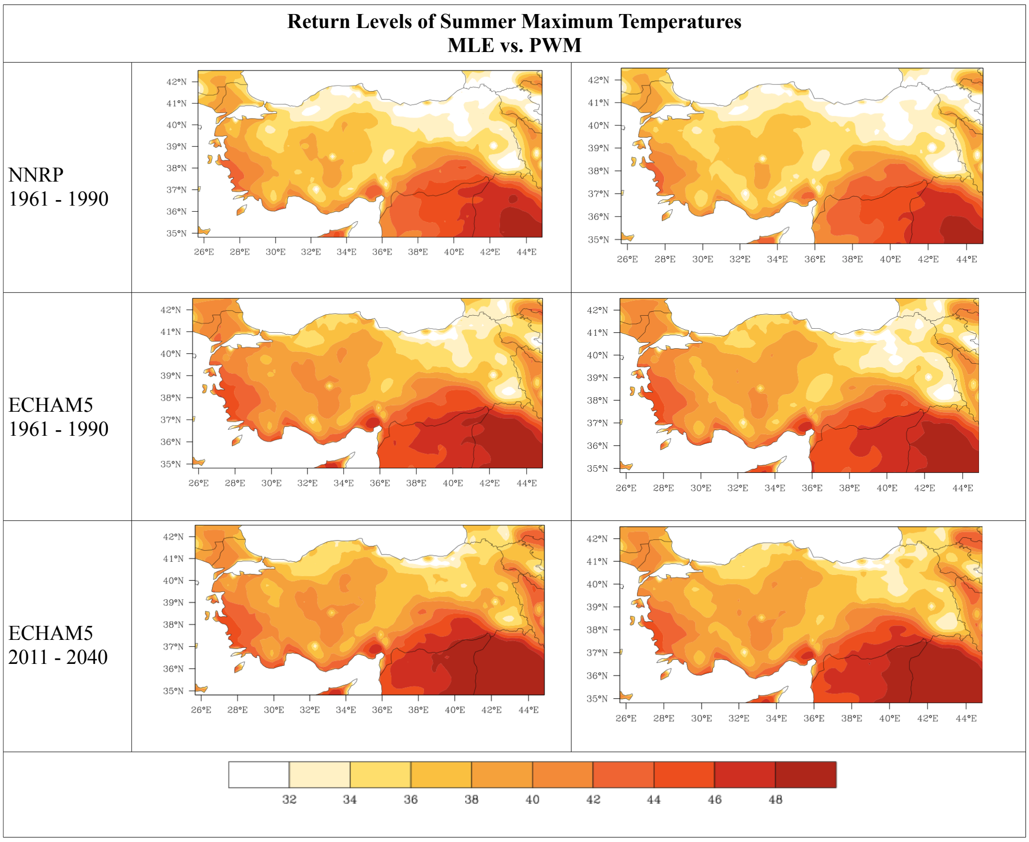

Figure 3.1: Comparison of return level results of MLE and PWM.

It can be seen from the Figure 3.1, results of return level for NNRP and ECHAM5 are approximately same for both estimation approaches all around the Turkey. Because of this reason, PWM method was chosen to estimation process except nonstationary case.

3.1.1 Comparison between estimation results of different climate models

Parameters for GEV distribution ad return levels were estimated by PWM method for seasonal maximum and minimum temperatures for Turkey and its region. Then, results of analyses for NNRP and ECHAM5 outputs were compared for reference period (1961-1990) in Figure A.1 and Figure A.2.

In Figure A.1, it has seen that spatial variability is less and smooth for ECHAM5 model for all parameters (μ, σ, ξ) and return levels. Eastern Black Sea region is more homogeneous for scale (σ) parameter.

Likewise, results for two data sets have similar behaviors for minimum temperature in Figure A.2. It means that observation and model data are consistent. Same procedure had applied to precipitation data. It has seen that precipitation amount is very high in the north eastern Black Sea region.

3.1.2 Comparison of estimation results between models and station data

To compare difference between estimation results of model and station data, some specific areas were chosen. Below, there are four comparison of estimation results of different areas.

Table 3.1: Comparison of parameter estimates for total precipitation of Bartın for reference period (1961-1990).

Data	Location (μ)	Scale (σ)	Shape (ξ)	Return Level
Station	0.25	0.79	0.73	11.87
NNRP	0.27	0.74	0.67	9.83
ECHAM5	0.28	0.79	0.70	11.20

Table 3.2: Comparison of parameter estimates for total precipitation of Sinop for reference period (1961-1990).

Data	Location (μ)	Scale (σ)	Shape (ξ)	Return Level
Station	0.14	0.45	0.76	7.32
NNRP	0.16	0.43	0.69	6.00
ECHAM5	0.15	0.42	0.69	5.80

Table 3.3: Comparison of parameter estimates for total precipitation of Rize for reference period (1961-1990).

Data	Location (μ)	Scale (σ)	Shape (ξ)	Return Level
Station	0.72	2.06	0.67	27.08
NNRP	1.24	2.71	0.56	28.47
ECHAM5	0.84	2.13	0.63	25.97

Table 3.4: Comparison of parameter estimates for total precipitation of Şanlıurfa for reference period (1961-1990).

Data	Location (μ)	Scale (σ)	Shape (ξ)	Return Level
Station	0.05	0.20	0.85	4.07
NNRP	0.08	0.27	0.78	4.64
ECHAM5	0.05	0.19	0.82	3.55

3.1.3 Comparison of return levels in different time scales

Another calculation was done for return levels with 96.7% confidence interval for 30 years return period of maximum temperatures, minimum temperatures and total precipitation at a different time scales. It's clear that degrees temperatures are increasing and total precipitation amount is decreasing from the perspective of extremes.

For different three cities of Turkey, return levels were calculated for 1961-1990 (green) and 2011-2020 (blue) ECHAM5 data. For Hatay, one of the hottest city of Turkey, it can be seen that return levels for maximum temperature are nearly same for increasing return periods. Return levels of minimum temperature in 2011-2020 are colder than past (1961-1990) for Van which is the one of coldest city in winter. In Rize, return levels of total precipitation is decreasing in 2011-2020.

3.2 Estimates Considering Nonstationary

As mentioned in Chapter 2.4, climate data were accepted as nonstationary. In this section, comparisons were done between results of stationary and nonstationary analyses.

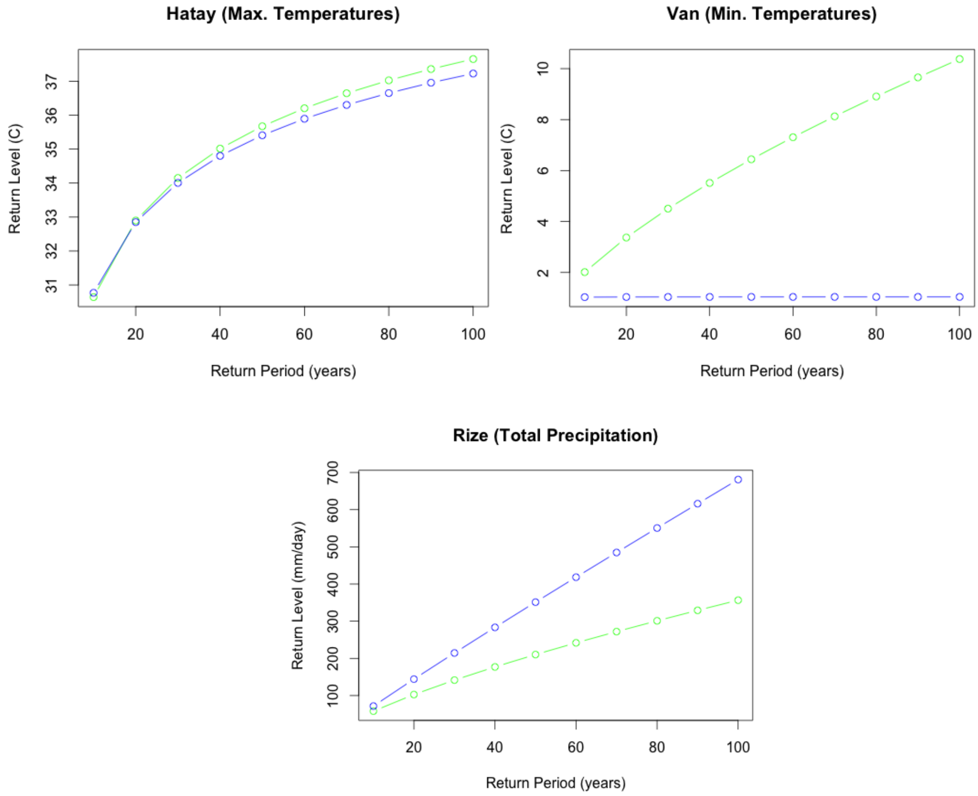

Figure 3.2: Return values of three different gridboxes in different time scales.

Model 0 is GEV parameters under the stationary assumption. There are linear trend in only location (μ) parameter for Model 1 and linear trend in location (μ) and logarithmic trend scale (σ) parameters in Model 2.

To choose best model for climate extremes, some comparisons were done for GEV parameters of Tmax and Tmin for Turkey and its region, below.

Table 3.5: Comparison of parameter estimates for maximum temperature (K) of Diyarbakır in midcentury (2041-2050).

Model	**nllh**	μ_0	μ_1	σ_0	σ_1	ξ
0	2578.16	310.52		4.40		-0.41
1	2572.89	309.96	0.0013	4.39		-0.43
2	2599.63	311.76	-0.0014	1.41	0.0002	-0.45

According to negative log-likelihood values, Model 2 is best model for two different gridboxes (Diyarbakır (Lat: 38.00172, Lon: 40.13868) and Kars (Lat: 40.50070, Lon: 43.03646)).

Table 3.6: Comparison of parameter estimates for minimum temperature (K) of Kars in midcentury (2041-2050).

Model	nllh	μ_0	μ_1	σ_0	σ_1	ξ
0	2701.02	264.24		5.53		-0.50
1	2700.94	264.35	-0.0002	5.54		-0.51
2	2939.53	268.59	-0.0080	1.96	0.0007	-1.04

3.3 Jackknife Results

By using Jackknife resampling method, how accurate the estimation results was tested. Below, there are histograms to compare the results of different model data for İzmir.

Differences in scales are arising from the difference of models. Unimodal histograms of return levels can be interpreted as uncertainty may not be predominant for this analysis.

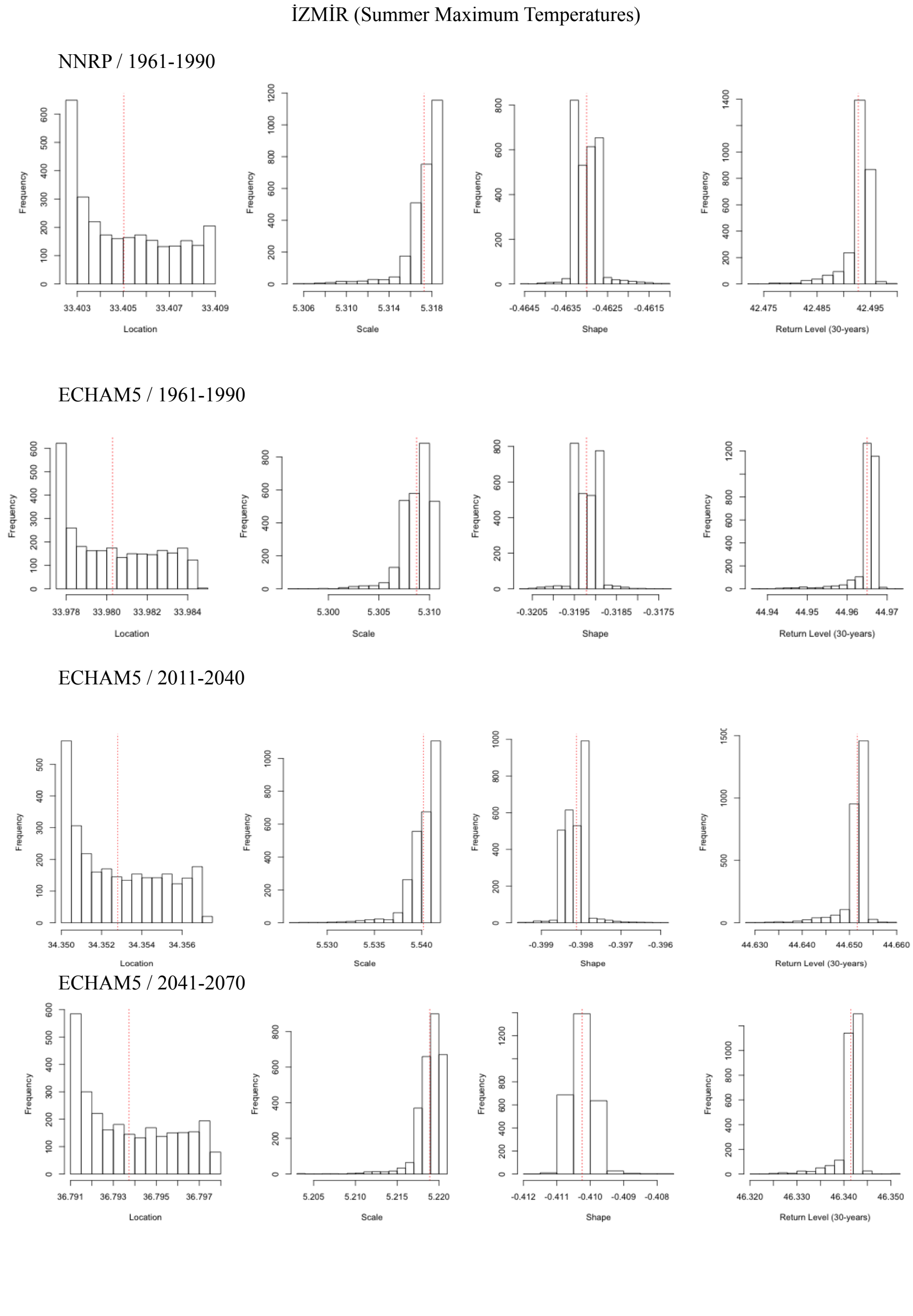

Figure 3.3: Jackknife results for summer maximum temperature data of İzmir.

4. CONCLUSIONS AND FUTURE DIRECTIONS

Extreme Value Theory had applied to estimate the parameters distribution of daily maximum, minimum temperature and daily total precipitation extremes for Turkey and its region in this research.

In this thesis, there are not only comparison for estimation results of different model data, but also comparison for different time scales.

First of all, it was shown that PWM approach to estimate the distribution parameters gives nearly same results with MLE approach. For small data size, MLE method gave no result. Therefore, PWM method was chosen to estimate the parameters of GEV distribution.

About climate extremes, estimation of parameters of GEV distribution was done under stationary assumption in Section 3.1. Nonstationary GEV was applied two different gridboxes to see the importance of nonstationarity. According to results in Section 3.2, it was seen that complex models give better results. Importance of nonstationarity should not be ignored in climate research. For a future work, more nonstationary models can be developed for Turkey and its region.

Then, station data also were used to estimate the distribution parameters. Then, station and model results were compared. Analyzing of regional climate model output gives similar results with analyses of station data.

Finally, to calculate uncertainty of parameters, resampling methods were chosen. These methods have highly computation costs. By using Jackknife resampling method, it was tested that how accurate the estimation results.

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APPENDICES

APPENDIX A : Comparisons for different models and different time scales
APPENDIX B : R Codes for calculation of parameters of GEV distribution.
APPENDIX C : NCL codes for plotting the maps of results.

APPENDIX A

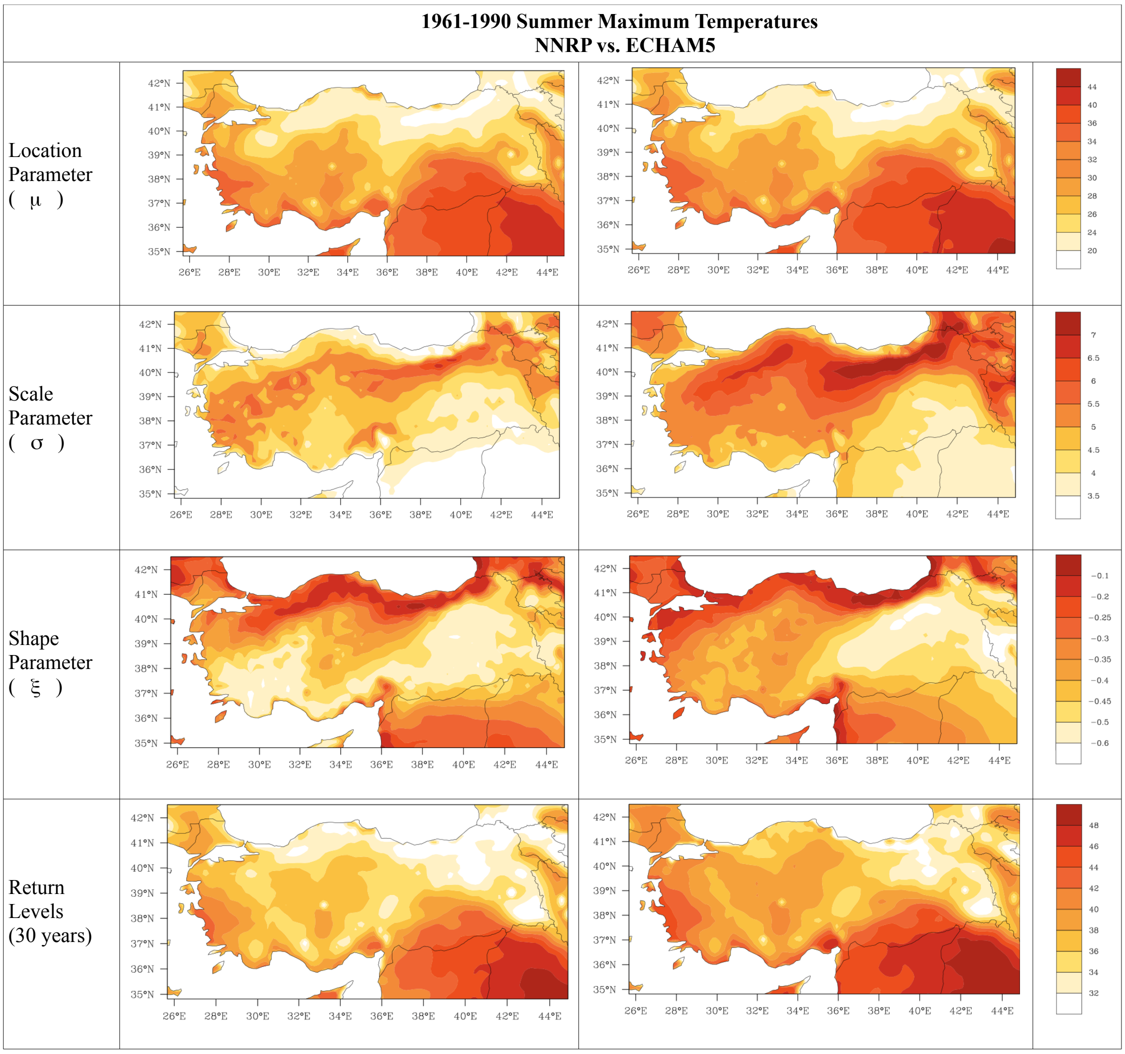

Figure A.1: Comparison between NNRP and ECHAM5 results of distribution parameters and return levels of summer maximum temperatures for reference period (1961-1990).

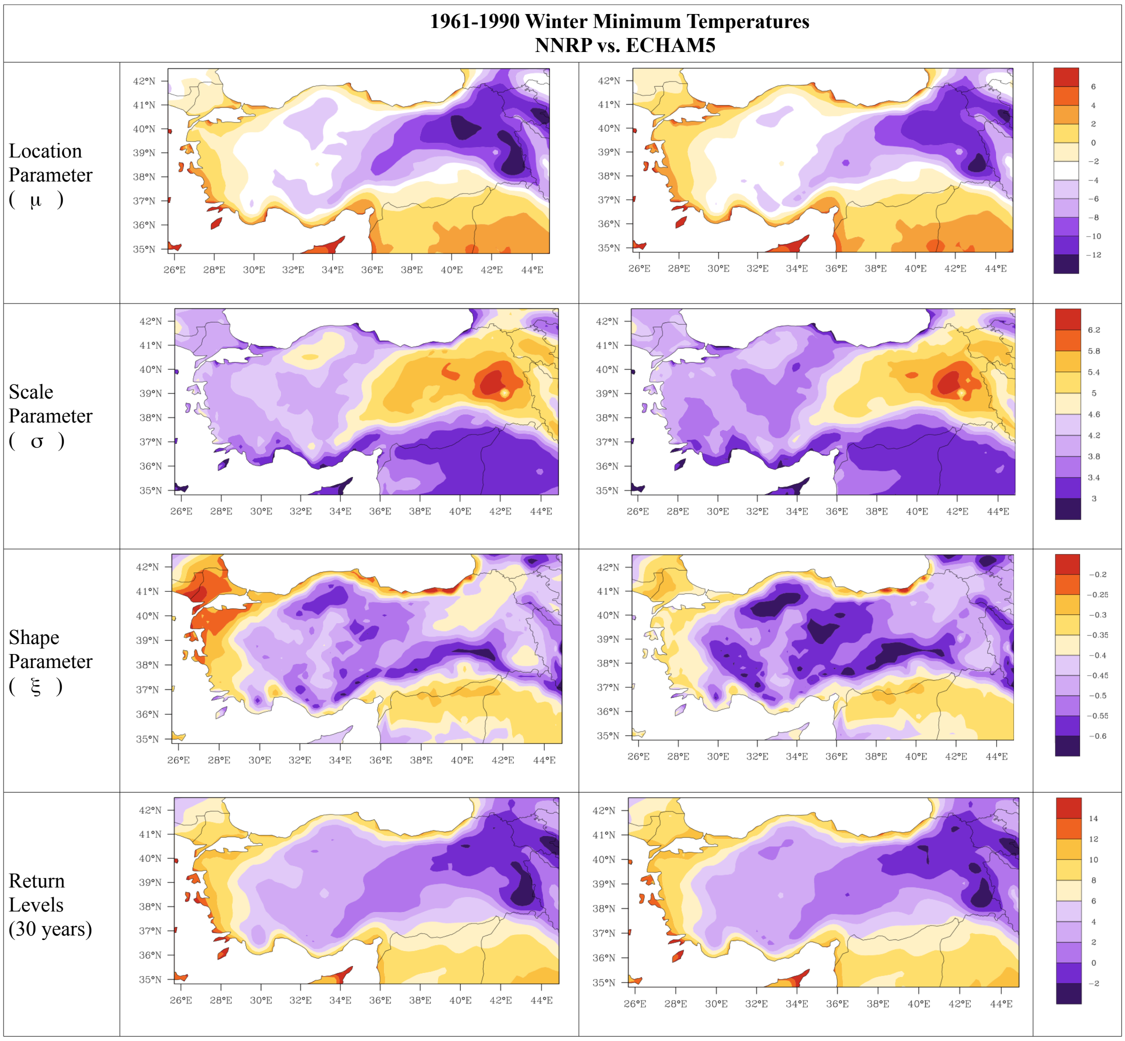

Figure A.2: Comparison between NNRP and ECHAM5 results of distribution parameters and return levels of winter minimum temperatures for reference period (1961-1990).

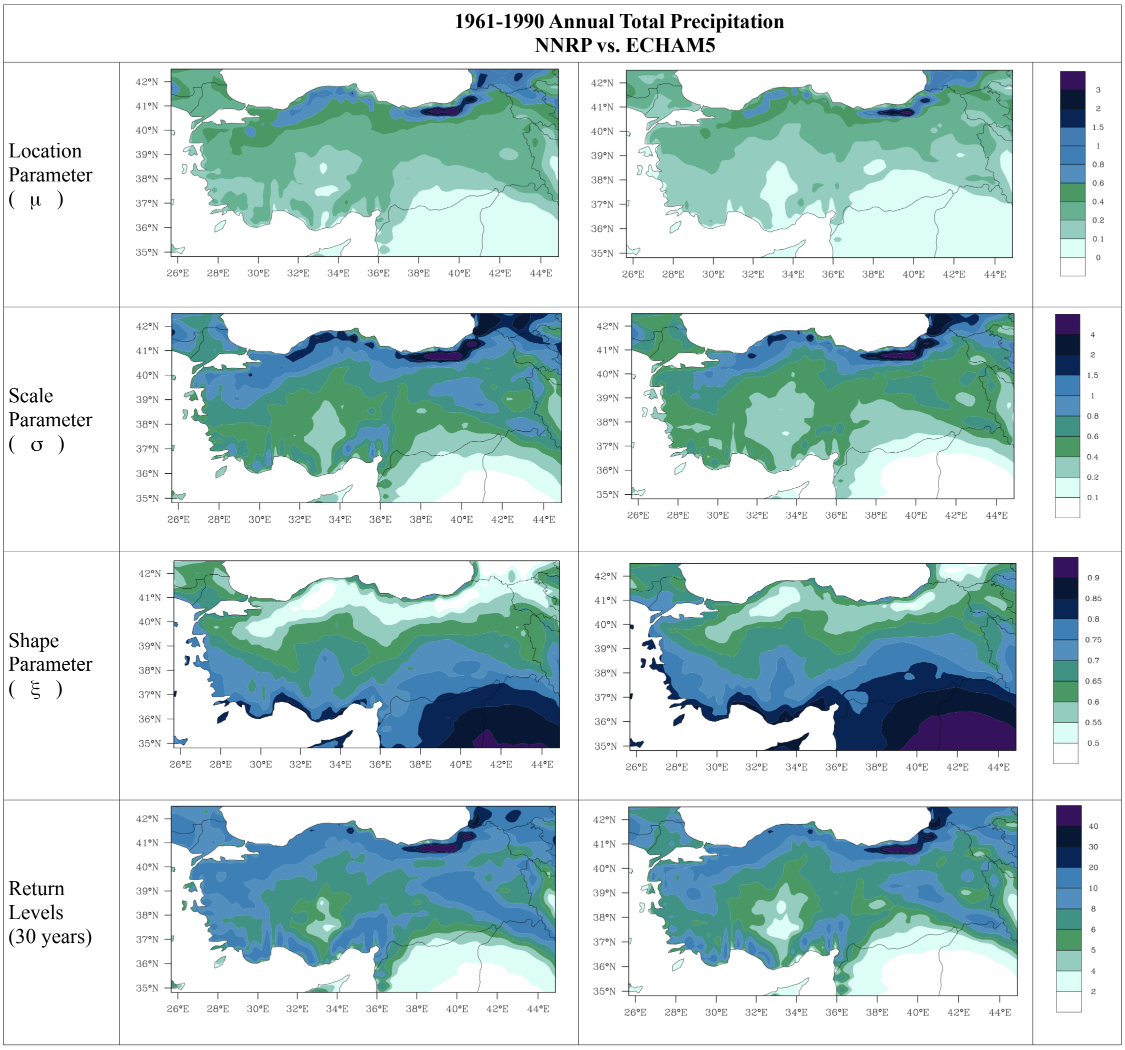

Figure A.3: Comparison between NNRP and ECHAM5 results of distribution parameters and return levels of annual total precipitation for reference period (1961-1990).

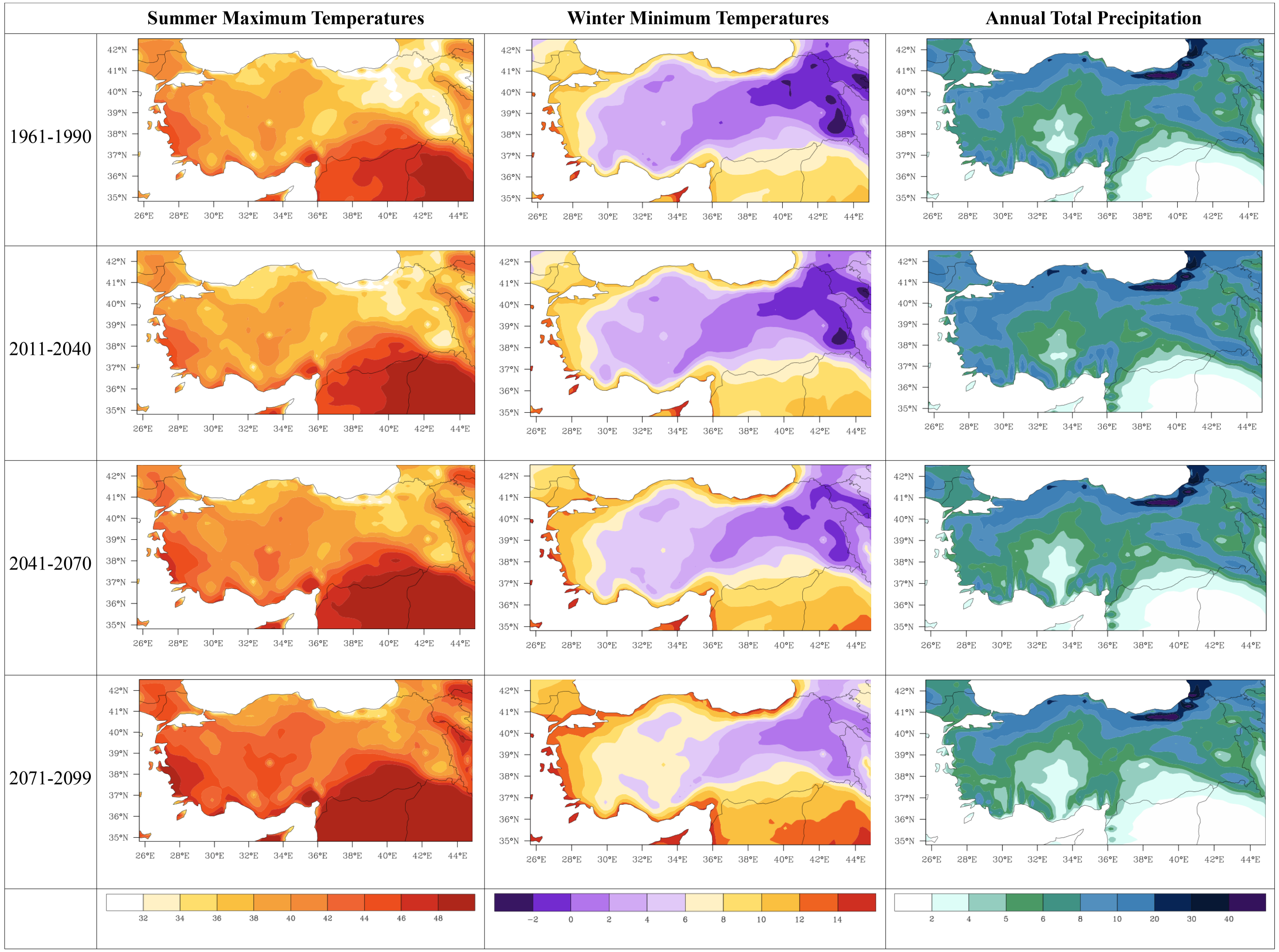

Figure A.4: ECHAM5 results of return levels of maximum temperatures, minimum temperatures and total precipitation for 20^{th} and 21^{st} centuries.

APPENDIX B

```
# Clear ex-variables
rm(list=ls())

# Libraries which are needed for some functions
library("ncdf")
library("ismev")

# Definitions
data_dir <- "..."    # Data directory
source_file <- "... .nc"    # Source file name
loc_out <- "loc.nc"     # output file of location results
sca_out <- "sca.nc"    # output file of scale results
sha_out <- "sha.nc"    # output file of shape results
rv_out <- "rv.nc"         # output file of return values
data_var_name <- ".."   # name of variable which will be analyzed
period <- 30    # return period

# Reading Data
ta.nc <- open.ncdf(paste(data_dir, source_file, sep=""))

lon <- get.var.ncdf(ta.nc, "lon")
lat <- get.var.ncdf(ta.nc, "lat")
time <- get.var.ncdf(ta.nc, "time")
TA <- get.var.ncdf(ta.nc, data_var_name)

# Allocation
nLon <- dim(lon)
nLat <- dim(lat)
n <- nLon*nLat

l <- array(NA, dim=c(nLon,nLat))
sc <- array(NA, dim=c(nLon,nLat))
sh <- array(NA, dim=c(nLon,nLat))
rv <- array(NA, dim=c(nLon,nLat))

# Stationary GEV
for (i in 1:nLon){
  for (j in 1:nLat){
    TA_gev <- gevFit(TA[i,j,], type="pwm")
    zgev=slot(TA_gev, "fit")
    l[i,j] <- zgev$par.ests[2]
```

```
    sc[i,j] <- zgev$par.ests[3]
    sh[i,j] <- zgev$par.ests[2]
    rv[i,j] <- l[i,j]+(sc[i,j]/sh[i,j])*((-log(1-1/period))^(-sh[i,j])-1)
  }
}

# Writing Results
lonDim <- dim.def.ncdf("lon", "degrees_east", lon)
latDim <- dim.def.ncdf("lat", "degrees_north",  lat)

varl <- var.def.ncdf("l", "l", list(lonDim, latDim), -1e30,
longname="Location parameter", prec="double")
varsc <- var.def.ncdf("sc", "sc", list(lonDim, latDim), -1e30,
longname="Scale parameter", prec="double")
varsh <- var.def.ncdf("sh", "sh", list(lonDim, latDim), -1e30,
longname="Shape parameter", prec="double")
varrv <- var.def.ncdf("rv", "rv", list(lonDim, latDim), -1e30,
longname="Return Values", prec="double")

l.nc <- create.ncdf(paste(data_dir,loc_out,sep=""), varl)
put.var.ncdf(l.nc, varl, l)
close.ncdf(l.nc)

sc.nc <- create.ncdf(paste(data_dir,sca_out,sep=""), varsc)
put.var.ncdf(sc.nc, varsc, sc)
close.ncdf(sc.nc)

sh.nc <- create.ncdf(paste(data_dir,sha_out,sep=""), varsh)
put.var.ncdf(sh.nc, varsh, sh)
close.ncdf(sh.nc)

rv.nc <- create.ncdf(paste(data_dir,rv_out,sep=""), varrv)
put.var.ncdf(rv.nc, varrv, rv)
close.ncdf(rv.nc)
```

APPENDIX C

```
load "$NCARG_ROOT/lib/ncarg/nclscripts/csm/gsn_code.ncl"
load "$NCARG_ROOT/lib/ncarg/nclscripts/csm/gsn_csm.ncl"

begin
in=addfile("/Users/yeliz/rv.nc","r")
ta=in->rv

dimvar = dimsizes(ta)
jlat = dimvar(0)
ilon = dimvar(1)

;***Latitude and longitude information***
topo_data = addfile("HEAD_OUT.nc","r")
lat2d  = topo_data->XLAT(time|0,lat|:,lon|:)    ; (time,lat,lon)
lon2d  = topo_data->XLON(time|0,lat|:,lon|:)    ; (time,lat,lon)

wks  = gsn_open_wks("png","ta.png")
gsn_define_colormap(wks,"sunshine_diff_12lev")

res  = True
res@cnFillOn               = True
res@cnLinesOn             = False
res@cnLineLabelsOn         = False
res@cnInfoLabelOn          = False
res@lbLabelBarOn         = False
res@mpFillOn = False
res@gsnSpreadColors = True


;***Lambert Conformal Projection Information***
res@mpLimitMode       = "Corners"
res@mpLeftCornerLatF  = lat2d(0,0)
res@mpLeftCornerLonF  = lon2d(0,0)
res@mpRightCornerLatF = lat2d(jlat-1,ilon-1)
res@mpRightCornerLonF = lon2d(jlat-1,ilon-1)
res@mpProjection        = "LambertConformal"
res@mpLambertParallel1F = 30.
res@mpLambertParallel2F = 60.
res@mpLambertMeridianF  =32
;***


res@cnLevelSelectionMode = "ExplicitLevels"
```

```
res@cnLevels             = (/-2,0,2,4,6,8,10,12,14,16,18/)
res@tmXBLabelFontHeightF  = 0.01
res@tmYLLabelFontHeightF  = 0.01
res@gsnCenterStringFontHeightF = 0.018
res@gsnMaximize = True
res@tmXTOn = False
res@tmYROn = False
res@tiMainString           = ""
res@tiMainFontHeightF      = 0.018
res@gsnDraw              = False
res@gsnFrame             = False
res@gsnAddCyclic           = False
res@tfDoNDCOverlay = True
res@mpPerimOn = True
res@pmTickMarkDisplayMode  = "Always"
res@gsnLeftString   = ""
res@gsnCenterString = "Title"
res@gsnRightString  = ""
res@cnSmoothingOn          = True

res@mpOutlineOn = True
res@mpOutlineBoundarySets       = "Geophysical"
res@mpOutlineSpecifiers       = "Turkey"
res@mpGeophysicalLineThicknessF = 1.0
res@mpNationalLineThicknessF    = 1.0
res@mpFillOn                    = True
res@mpOutlineBoundarySets = "AllBoundaries"
res@mpFillAreaSpecifiers  = (/"Water","Land"/)
res@mpSpecifiedFillColors = (/"white","white"/)
res@mpAreaMaskingOn       = True
res@mpMaskAreaSpecifiers  = "Eurasia"
res@mpGridAndLimbOn             = False
res@mpGridMaskMode      = "MaskMaskArea"
res@mpFillDrawOrder       = "PostDraw"
res@cnLineDrawOrder       = "Draw"
res@cnLabelDrawOrder      = "Draw"
res@mpOutlineDrawOrder    = "PostDraw"
res@tfDoNDCOverlay = True

res@mpDataBaseVersion = "MediumRes"

plot = gsn_csm_contour_map(wks,ta,res)

resP = True
resP@gsnPanelLabelBar = True
resP@gsnFrame = False
resP@gsnMaximize = True
resP@lbOrientation = "Horizontal"
resP@lbLabelAutoStride = True
```

```
resP@pmLabelBarWidthF = 0.6
resP@pmLabelBarHeightF = 0.05
resP@lbTitleOn        =  True
resP@lbTitleString    = ""
resP@lbTitlePosition  = "Right"
resP@lbTitleFontHeightF= .018
resP@lbTitleDirection = "Across"
resP@lbLabelStride        = 1
;resP@lbLabelFontHeightF  = 0.018
resP@pmLabelBarOrthogonalPosF = -0.015
resP@txString   = ""
gsn_panel(wks,plot,(/1,1/),resP)
frame(wks)

end
```

CURRICULUM VITAE

Name Surname: Yeliz Yılmaz

Place and Date of Birth: Niğde 08.10.1986

Adress: İstanbul Teknik Üniversitesi Ayazağa Kampüsü, Maslak, İstanbul, Turkey

E-Mail: yelizyilmaz@itu.edu.tr

B.Sc.: Pamukkale University, Science and Letters Faculty, Mathematics

M.Sc.: Istanbul Technical University, Informatics Institute, CSE

PUBLICATIONS/PRESENTATIONS ON THE THESIS

- **Yılmaz Y.**, Dalfes H.N., 2012: Extreme Value Statistics of Downscaled Climate Projections for Turkey and Its Region *European Geosciences Union General Assembly 2012 - Climate: Past, Present, Future*, April 22-27, 2012 Vienna, Austria.