

DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**ANALYSIS OF CLIMATE CHANGE EFFECTS
ON URBAN DRAINAGE IN İZMİR**

by

Khaled ALRAMLAWI

September, 2021

İZMİR

ANALYSIS OF CLIMATE CHANGE EFFECTS ON URBAN DRAINAGE IN İZMİR

**A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Doctor of
Philosophy in Civil Engineering, Hydraulics, Hydrology, and Water Resources
Program**

**by
Khaled ALRAMLAWI**

September, 2021

İZMİR

Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled “**ANALYSIS OF CLIMATE CHANGE EFFECTS ON URBAN DRAINAGE IN IZMİR**” completed by **KHALED ALRAMLAWI** under supervision of **PROF. DR. OKAN FISTIKOĞLU** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

Prof. Dr.

Okan FISTIKOĞLU

Supervisor

Assoc. Prof. Dr.

Ali GÜL

Thesis Committee Member

Prof. Dr.

Hülya BOYACIOĞLU

Thesis Committee Member

Prof. Dr.

Mustafa Tamer AYVAZ

Examining Committee Member

Assoc. Prof. Dr.

Ebru ERIŞ

Examining Committee Member

Prof. Dr. Özgür ÖZÇELİK

Director

Graduate School of Natural and Applied Sciences

ACKNOWLEDGMENTS

Foremost, I thank ALLAH for providing me the ability and strength to complete this Thesis. I would like to thanks turkey and Dokuz Eylul university for giving me the opportunity to study here, despite all challenges I faced.

I'd like to express my gratitude to my supervisor, Assoc. Prof. Dr. Okan FISTIKOĞLU, for being an exemplary advisor. His guidance and enthusiasm empowered me to make it this far. I am also thankful to Assoc. Prof. Dr. Ali Gül, Prof. Dr. Hülya BOYACIOĞLU, and Prof. Dr. Alper ELÇİ for their priceless guidance during the progress reporting periods over three years. I am particularly thankful for their flexibility in coordinating Ph.D. monitoring exams organized during the COVID-19 pandemic.

I would like to extend my appreciation for the Water Resources Management Research and Application Centre (DEÜ-SUMER) for providing me with an advanced-tech place, and the necessary resources, which greatly help me pursuing my Ph.D. research effectively.

I would like to thank my friend Dr. Mohamed NAJAR for sharing my Ph.D. journey, providing GIS technical supports, and for his appreciated help in spatial programming and producing related maps.

Finally, I am grateful to my parents for their love and sacrifices for educating me. I am extremely thankful to my wife and my children for their patience, sacrifices, and continuing support. Also, I am thankful to my brothers and sisters for their love and all supports.

Khaled ALRAMLAWI

ANALYSIS OF CLIMATE CHANGE EFFECTS ON URBAN DRAINAGE IN IZMIR

ABSTRACT

The frequency and intensity of extreme rainfall increased in the past century in several areas due to climate change. These increases threaten stormwater infrastructure systems. Intensity-Duration-Frequency (IDF) Curves are commonly used for the design and management of urban infrastructure. The currently employed IDF curves are designed mainly based on the stationary assumption, which assumes the extreme rainfall characteristics (statistically) are invariant over time. Climate change is anticipated to alter the local climate conditions. Meaning that the statistical properties of rainfall cannot be considered as a stationary assumption. Consequently, it is crucial to update the IDF curves by considering possible changes in climate. IDF curves can be updated based on Global Climate Models (GCMs). Despite the progress in GCMs, the resolutions of GCMs outputs are too coarse to directly evaluate future changes at a local scale. Therefore, downscaling of GCMs outputs to the desired resolutions are required.

This study aims to develop a new methodology that combined statistical downscaling, bias correction, and disaggregation of rainfall to update IDF curves based on GCMs under future projections.

The study demonstrated that GCMs results are not identical. The IDF curve in both GCMs (HadGEM2-CC and IPSL-CM5A-LR) tends to increase under future scenarios. In contrast, there are no significant changes in IDF curves in the remaining GCMs (MIROC-ESM-CHEM and CanESM2) under future scenarios.

The findings proved that climate change impacts the urban drainage system. Therefore, the study recommends updating the current IDF curves based on GCMs.

Keywords: Intensity-duration-frequency curve, global climate change, general circulation models, statistical downscaling, artificial neural networks, bias correction, rainfall disaggregation



İZMİR'DE İKLİM DEĞİŞİKLİĞİNİN KENTSEL DRENaj ÜZERİNDEKİ ETKİLERİNİN ANALİZİ

ÖZ

İklim değışikliğı nedeniyle aşırı yağışların sıklığı ve yoğunluğu geçtiğimiz yüzyılda birçok bölgede artmıştır. Bu aşırı yağış yağmursuyu altyapı sistemlerindeki baskıyı artırmaktadır. Şiddet-süre-tekerrür (IDF) eğrileri, kentsel altyapının tasarımı ve yönetimi için yaygın olarak kullanılmaktadır. Halihazırda kullanılan IDF eğrileri, esas olarak aşırı yağış özelliklerinin (istatistiksel olarak) zamanla değışmez olduğunu varsayan durağanlık teorisine dayalı olarak tasarlanmıştır. küresel değışikliğinin yerel iklim koşullarını değıştirmesi beklenmektedir. Yani yağışın istatistiksel özellikleri durağan bir varsayım olarak kabul edilemez. Sonuç olarak, iklimdeki olası değışiklikleri dikkate alarak IDF eğrilerini güncellemek çok önemlidir. IDF eğrileri, Küresel İklim Modellerine (GCM'ler) dayalı olarak güncellenebilir. GCM modellerindeki ilerlemeye rağmen, GCM çıktılarının çözünürlükleri, yerel ölçekte gelecekteki değışiklikleri doğrudan değerlendirmek için çok kaba kalmaktadır. Bu nedenle, GCM çıktılarının istenen çözünürlüklere indirgenmesi gerekmektedir.

Bu çalışma, gelecekteki iklim projeksiyonları altında GCM sonuçlarına dayalı IDF eğrilerini güncellemek için istatistiksel olarak ölçek indirgemeyi, taraflılık düzeltmesini ve yağışın zaman dağılımını dikkate alan yeni bir metodoloji geliştirmeyi amaçlamaktadır.

Çalışma, GCM sonuçlarının çalışma bölgesi için aynı olmadığını göstermiştir. HadGEM2-CC ve IPSL-CM5A-LR modellerinden elde edilen IDF eğrileri, gelecek senaryolarda artma eğilimindedir. Buna karşılık, MIROC-ESM-CHEM ve CanESM2 modellerinden elde edilen IDF eğrilerinde önemli bir değışiklik yoktur.

Bulgular, iklim değışikliğinin kentsel drenaj sistemini olumsuz yönde etkilediğini kanıtlamıştır. Bu nedenle, çalışma GCM'lere dayalı olarak mevcut IDF eğrilerinin güncellenmesini önermektedir.

Anahtar kelimeler: Şiddet-süre-tekerrür eğrisi, küresel iklim değışiklięi, genel dolařım modelleri, istatistiksel ölçek indirgeme, yapay sinir aęları, taraflılık düzeltmesi, yaęışın zaman dağılımı



CONTENTS

	Page
Ph.D. THESIS EXAMINATION RESULT FORM	ii
ACKNOWLEDGEMENTS	iii
ABSTRACT	iv
ÖZ	vi
LIST OF FIGURES	xii
LIST OF TABLES	xvii
CHAPTER 1 - INTRODUCTION	1
1.1 State of Art	1
1.2 Motivation of The Thesis	4
1.3 Objective of the Thesis.....	4
1.4 Organization of the Thesis	5
CHAPTER 2 - LITERATURE REVIEW.....	6
2.1 Climate Change	6
2.1.1 The Causes of Climate Change.....	7
2.1.2 Global Climate Models (GCMs)	8
2.1.3 Representative Concentration Pathways (RCPs).....	8
2.1.4 Uncertainty in GCMs.....	9
2.1.5 Global Changing of Surface Temperature and the Water Cycle	10
2.2 Downscaling Approaches.....	12
2.2.1 Background.....	12
2.2.2 Statistical Downscaling (SD) Techniques	15

2.2.3 Assumptions and Limitations of Statistical Downscaling	15
2.2.4 Categories of Statistical Downscaling	17
2.2.5 Artificial Neural Network (ANN)	18
2.2.5.1 Background	18
2.2.5.2 Structure of Artificial Neural Networks	18
2.2.5.3 ANN Applications in Hydrology	20
2.2.5.4 ANN in Statistical Downscaling	20
2.3 Bias Correction of the GCM Outputs	21
2.3.1 Bias Correction Methods	22
2.3.2 Quantile Mapping Method for Bias Correction	23
2.3.3 Equidistant CDF Matching Method (EDCDFm)	25
2.4 Intensity-Duration-Frequency Curves	27
2.4.1 Estimation of Future IDF Curves	28
CHAPTER 3 - STUDY AREA AND DATA SETS	30
3.1 Study Area	30
3.2 Data Sets	34
3.2.1 Rainfall Observations Data (Predictands)	34
3.2.2 Large-scale Reanalysis Variables (Predictors)	37
3.2.2.1 Selected Predictors	39
3.2.3 Global Climate Models (Future Predictors)	43
CHAPTER 4 - METHODOLOGY	52
4.1 The Framework of the Methodology	52
4.2 Downscaling Technique	55
4.2.1 Downscaling Using ANN:	56
4.2.2 Building Artificial Neural Networks	57
4.2.3 Predictors and Predictant	58

4.3 Bias Correction for the Current and Future Climate	60
4.4 Estimation of the Annual Maximum 24-hour Rainfall	63
4.5 Disaggregation of P_{24} to Shorter Standard Duration Rainfall.....	63
4.6 Estimation IDF Curves.....	65
 CHAPTER 5 - APPLICATION AND RESULTS	 68
5.1 Step 1: Building the Downscaling Model	69
5.2 Step 2: Bias Correction of Annual Maximum Daily Rainfall	72
5.3 Step 3: Disaggregation of AM 24-hr rainfall to Short Durations.	76
5.3.1 Estimation of the annual maximum 24-hour rainfall.....	76
5.3.2 Disaggregation of AM 24-hr Rainfall to Standard Duration	77
5.4 Step 4: Deriving IDF Curve for Observed and Estimated Rainfall.....	83
5.5 Step 5: Correction of Biases in GCMs Atmospheric Variables	85
5.5.1 Bias Correction of GCMs Historical Data.....	85
5.5.1.1 Air Temperature Correction of GCMs Historical Data	87
5.5.1.2 Precipitation Rate Correction of GCMs Historical Data	88
5.5.1.3 Sea Level Pressure Correction of GCMs Historical Data.....	89
5.5.1.4 V-Wind Correction of GCMs Historical Data	90
5.5.2 Bias Correction of GCMs Future Projections.....	91
5.5.2.1 Air temperature correction of GCMs future projections.....	93
5.5.2.2 Precipitation rate correction of the future projections:	94
5.5.2.3 Sea level pressure correction of the future projections:.....	95
5.5.2.4 V-wind Correction of the Future Projections:	96
5.6 Step 6: Deriving IDF Curve from Historical Data of GCMs and the Associated Future Scenarios (RCP4.5, RCP8.5)	97
5.6.1 Step 6.1: Applying ANN ₂ Using GCMs Data	97
5.6.2 Step 6.2: Correction of Bias in the Annual Maximum Daily Rainfall	97
5.6.2.1 AM daily rainfall based on HadGEM2-CC model.....	98
5.6.2.2 AM Daily Rainfall Based on IPSL-CM5A-LR Model	99

5.6.2.3 AM Daily Rainfall Based on MIROC-ESM-CHEM Model.....	100
5.6.2.4 AM Daily Rainfall Based on CanESM2 Model.....	101
5.6.3 Step 6.3: Disaggregation of AM Daily Rainfall to Standard Durations	102
5.6.4 Step 6.4: Generating GCM-based IDF Curves.....	102
5.6.4.1 IDF Curve Based on HadGEM2-CC Model.....	103
5.6.4.2 IDF Curve Based on IPSL-CM5A-LR Model.....	105
5.6.4.3 IDF Curve Based on MIROC-ESM-CHEM Model.....	107
5.6.4.4 IDF Curve Based on CanESM2 Model	109
5.7 Optimal Model for Representing Izmir Region to Estimate AM Daily Rainfall	
.....	111
CHAPTER 6 - CONCLUSIONS.....	114
6.1 Challenges and Recommendations.....	118

LIST OF FIGURES

	Page
Figure 2.1 The changing of the average global surface temperature over time.....	6
Figure 2.2 GHG emissions in baseline and projection scenarios for different pathways	9
Figure 2.3 Annual changing in a)the surface temperature b)the precipitation percent for RCP2.6 and RCP8.5 scenarios in 2081–2100	11
Figure 2.4 Artificial neural network structure.....	19
Figure 2.5 Exemplary procedure of QM method	24
Figure 2.6 Exemplary procedures of equidistant cumulative distribution function matching (EDCDFm) method graphically	26
Figure 3.1 Geographical locations of the study region and selected stations	30
Figure 3.2 Average temperature for Izmir region in the period between 1939-2019	31
Figure 3.3 Average monthly rainfall for Izmir region in the period between 1939-2019	31
Figure 3.4 The trend of AM rainfall for various durations (1 hr, 6 hr, 12 hr, and 24 hr)	33
Figure 3.5 The correlation between the daily rainfall from the training station (Izmir station) and the other test stations a) Adnan Menderes, b) Selcuk, c) Seferihisar, d) Cesme, and e) Odemis stations.....	35
Figure 3.6 The variation of daily rainfall for a) Izmir, b) Adnan Menderes, c) Seferihisar, d) Cesme, e) Selcuk, and f) Odemis stations	36
Figure 3.7 The variation of the atmospheric variables from NCEP/NCAR for: a) air temperature (tas), b) precipitation (pr), c) sea level pressure (slp) and, d) v-wind (vas).....	41
Figure 3.8 Box plot representation descriptive statistic of HadGEM2-CC model for the selected a) a)Air temperature b)Precipitation c) Sea level pressured) v-wind variables	45
Figure 3.9 Box plot representation descriptive statistic of IPSL-CM5A-LR model for the selected a) Air temperature b) Precipitation c)Sea level pressure, and d) V-wind variables.....	46

Figure 3.10 Box plot representation descriptive statistic of MIROC-ESM-CHEM model for the selected a) Air temperature b) Precipitation c) Sea level pressure, and d) v-wind variables.....	47
Figure 3.11 Box plot representation descriptive statistic of CanESM2 model for the selected a) Air temperature b) Precipitation c) Sea level pressure, and d) V-wind variables	48
Figure 3.12 The variation of selected atmospheric parameters from HadGEM2-CC model. a) Air temperature (tas), b) Precipitation (pr), c) Sea level pressure (slp) and, d) V-wind (vas)	49
Figure 4.1 The flow chart of the methodology for historical climate conditions	53
Figure 4.2 The methodology for future climate projections	54
Figure 4.3 Artificial neural network (ANN) architecture	57
Figure 4.4 Exemplary procedures of QM method graphically	61
Figure 4.5 Exemplary procedures of (EDCDFm) method graphically	62
Figure 4.6 The shape of AM rainfall distribution using the IMD formula for Izmir station	64
Figure 4.7 The shape of rainfall distribution using empirical ratio by Huff and Angel (1992)	65
Figure 4.8 IDF curve	66
Figure 5.1 Summarized the methodology	68
Figure 5.2 The structure of the downscaling model.....	70
Figure 5.3 The tested ANN-based downscaling models.....	70
Figure 5.4 Comparing the observed and downscaled daily rainfall series resulted from three models of the Izmir station data for the period (1948-2018)	71
Figure 5.5 The empirical and Gamma CDF of AM daily rainfall for observed and estimated.....	74
Figure 5.6 Variations of AM daily rainfall of a) the observed and the estimated (uncorrected) and (b) the observed and the estimated after bias-corrected..	75
Figure 5.7 The box plot of the AM daily rainfall of the observed, estimated (pre-corrected), and corrected in the Izmir station.....	76
Figure 5.8 The differences between annual maximum daily rainfall and the maximum 24-hour rainfall over time	77

Figure 5.9 The relation between annual maximum daily rainfall and the maximum 24-hour rainfall	77
Figure 5.10 Box plots of AM rainfall of observed (obs) and the results of disaggregated methods: IMD formula, observation ratio (TDR), and Huff and Angel's empirical ratio	81
Figure 5.11 Comparison of the observed rainfall and the rainfall disaggregation methods: IMD formula, observed ratio (TDR), and Huff and Angel's empirical ratio	82
Figure 5.12 The IDF curve based on a) observation data, b) NCEP/NCAR reanalysis datasets	84
Figure 5.13 Exemplary procedure of the QM method for HadGEM2-CC model for a) air temperature (tas), b) precipitation rate (pr), c) sea level pressure (slp), and d) V-wind (vas).....	86
Figure 5.14 The box plots of air temperature (tas) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data	87
Figure 5.15 The box plots of precipitation rate (Pr) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data	88
Figure 5.16 The box plots of sea level pressure (slp) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data.	89
Figure 5.17 The box plots of v-wind (vas) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CCcorrected data	90
Figure 5.18 Exemplary procedure of the EDCDFm method for HadGEM2-CC model for a) air temperature, b)precipitation rate, c)sea level pressure, and d)V-wind.....	92
Figure 5.19 The box plots of the air temperature (tas) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases)	93
Figure 5.20 The box plots of the precipitation (pr) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases)	94

Figure 5.21 The box plots of the sea level pressure (slp) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases).....	95
Figure 5.22 The box plots of the sea level pressure (slp) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases).....	96
Figure 5.23 AM daily rainfall obtained from HadGEM2-CC model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)	98
Figure 5.24 Box plots of annual maximum daily rainfall for HadGEM2-CC model for historical and future projections (left for RCP4.5, right for RCP 8.5)....	98
Figure 5.25 AM daily rainfall obtained from IPSL-CM5A-LR model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)	99
Figure 5.26 Box plots of AM daily rainfall for IPSL-CM5A-LR model for historical and future projections (left for RCP4.5, right for RCP 8.5).....	99
Figure 5.27 AM daily rainfall obtained from MIROC-ESM-CHEM model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)	100
Figure 5.28 Box plots of AM daily rainfall for MIROC-ESM-CHEM model for historical and future projections (left for RCP4.5, right for RCP 8.5)..	100
Figure 5.29 AM daily rainfall obtained from CanESM2 model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)	101
Figure 5.30 Box plots of annual maximum daily rainfall for CanESM2 model for historical and future projections (left for RCP4.5, right for RCP 8.5)..	101
Figure 5.31 The IDF curves obtained from the HadGEM2-CC model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario	104
Figure 5.32 The IDF curves obtained from the IPSL-CM5A-LR model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario	106
Figure 5.33 The IDF curves obtained from the MIROC-ESM-CHEM model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario	108

Figure 5.34 The IDF curves obtained from the CanESM2 model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario	110
Figure 5.35 Box plot of AM daily rainfall from observed data and results from selected GCMs	112
Figure 5.36 Q-Q Plot of AM daily rainfall between observed and estimated from the GCMs (1970-2005) a) HadGEM2-CC, b) IPSL-CM5A-LR, c) MIROC-ESM-CHEM, and d) CanESM2	113
Figure 6.1 The relation between rainfall intensity and return period for the current IDF curve and the future IDF curves under RCP4.5 and RCP8.5 according to the HadGEM2-CC model.....	118



LIST OF TABLES

	Page
Table 2.1 Projected change in air temperature to the end of 21st century with respect to the reference period 1986–2005	10
Table 2.2 Tabulate the advantages and disadvantages of the features of the dynamical and statistical downscaling methods	14
Table 2.3 Predictor selection in various studies.....	16
Table 3.1 Average temperature and precipitation from 1939-2019 for Izmir region	31
Table 3.2 The statistical characteristics of AM rainfall in standard durations at Izmir station for the period between 1938-2015	32
Table 3.3 Mann-Kendall trend test of AM rainfall in standard durations (1938-2015)	33
Table 3.4 Available meteorological stations.....	34
Table 3.5 Statistical characteristics of daily rainfall of all stations.....	36
Table 3.6 The selected predictors from NCEP/NCAR at Atmospheric surface level	40
Table 3.7 The statistical characteristics of large-scale variables of NCEP/NCAR (1948 - 2018)	40
Table 3.8 Mann-Kendall test of selected atmospheric variables from NCEP/NCAR	40
Table 3.9 Selected GCMs	43
Table 3.10 The statistical characteristics of selected atmospheric variables of GCMs (1970 – 2005)	44
Table 3.11 The statistical characteristics of large-scale variables from HadGEM2-CC model of historical and future data under scenarios RCP 4.5 and RCP 8.5 a)Air temperature b)Precipitation rate c)Sea level pressure d)v-wind	45
Table 3.12 The statistical characteristics of large-scale variables from IPSL-CM5A-LR model of historical and future data under scenarios RCP 4.5 and RCP 8.5 a)Air temperature b)Precipitation c)Sea level pressure d) V-wind	46
Table 3.13 The statistical characteristics of large-scale variables in MIROC-ESM-CHEM model of historical and future data under scenarios RCP 4.5 and	

RCP 8.5 a)Air temperature b)Precipitation c)Sea level pressure d) V-wind	47
Table 3.14 The statistical characteristics of large-scale variables from CanESM2 model of historical and future data under scenarios RCP 4.5 and RCP 8.5 a)Air temperature b)Precipitation c)Sea level pressure d) V-wind	48
Table 3.15 Mann-Kendall trend test P-value for all variables selected in both historical and future data sets	51
Table 4.1 The predictors and predictant of the three ANN models	59
Table 5.1 Summary of the three model results for the selected stations in the training and testing periods	71
Table 5.2 Statistical description of AM daily rainfall of the observed and the estimated (pre and post-bias-corrected) (1948-2018)	75
Table 5.3 Temporal Distribution of Rainfall (TDR) ratio for Izmir station.....	78
Table 5.4 The empirical ratio which was proposed by Huff and Angel	79
Table 5.5 The statistical characteristics of the annual maximum rainfall of standard durations from observation data, the IMF formula, observation ratio (TDR), and the empirical ratio (huff and angel)	80
Table 5.6 Mann-Whitney U test for observed and disaggregated rainfall using IMD formula	83
Table 5.7 The statistical characteristic of air temperature (tas) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data ..	87
Table 5.8 The statistical characteristic of precipitation (pr) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data.....	88
Table 5.9 The statistical characteristic of sea level pressure (slp) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CCcorrected data ..	89
Table 5.10 The statistical characteristic of v-wind (vas) of NCEP/NCAR reanalysis data, HadGEM2-CCraw data, HadGEM2-CC corrected data.....	90
Table 5.11 The statistical characteristics of the air temperature (tas) for the HadGEM2- CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process).....	93

Table 5.12 The statistical characteristics of the precipitation (pr) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process).....	94
Table 5.13 The statistical characteristics of sea level pressure (slp) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process).....	95
Table 5.14 The statistical characteristics of V-wind (vas) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process)	96
Table 5.15 Statistical characteristics of AM daily rainfall of the observed data, and the HadGEM2-CC model results before and after applying the bias correction process	98
Table 5.16 Statistical characteristics of AM daily rainfall of the observed data, and the IPSL-CM5A-LR model results before and after applying the bias correction process	99
Table 5.17 Statistical characteristics of AM daily rainfall of the observed data, and the MIROC-ESM-CHEM model results before and after applying the bias correction process	100
Table 5.18 Statistical characteristics of AM daily rainfall of the observed data, and the CanESM2 model results before and after applying the bias correction process	101
Table 5.19 Intensity-duration-frequency values obtained from HadGEM2-CC model based on a) historical data, b) RCP 4.5 scenario, and c)RCP 8.5 scenario	103
Table 5.20 Intensity-duration-frequency values obtained from IPSL-CM5A-LR model based on a) historical data, b) RCP 4.5 scenario, and c)RCP 8.5 scenario	105
Table 5.21 Intensity-duration-frequency values obtained from MIROC-ESM-CHEM model based on a) historical data, b) RCP 4.5 scenario, and c)RCP 8.5 scenario	107

Table 5.22 Intensity-duration-frequency values obtained from the CanESM2 model based on a) historical data, b) RCP 4.5 scenario, and c)RCP 8.5 scenario	109
Table 5.23 The statistical characteristics of annual maximum daily rainfall (1970- 2005) based on observed data, HadGEM2-CC, IPSL-CM5A-LR, MIROC- ESM-CHEM, CanESM2 models.....	111
Table 5.24 Mann-Whitney test statistics and PBIAS ratios of Annual maximum daily rainfall (1970-2005).....	113



CHAPTER 1

INTRODUCTION

1.1 State of Art

Global warming is defined as the phenomenon of increasing average surface temperatures of Earth. It has been witnessed that the global temperature increased over the past century due to human activities and associated anthropogenic Greenhouse Gas (GHG) emissions (Cheng & Aghakouchak, 2014; Stocker, 2014; Yan et al., 2021). Global GHG emissions have grown with an increase of 70% between 1970 and 2004 (IPCC, 2007). The raise of GHG has increased the global average surface temperature due to anthropogenic forces by the range of 0.5 to 1.3 °C in 1951 to 2010, and natural forces have contributed to variate the temperature by a range of -0.1°C to 0.1°C for the same period (Stocker, 2014). Studies also show that the Turkey region experiences a similar increase in temperature; for example, the statistical analyses of the temperature series in Turkey over the period of 1950–2006 showed that the annual mean temperature in Turkey has increased after the first half of the 1990s (Dogan et al., 2015).

Despite the fact that global warming and climate change definitions are often used interchangeably, global warming is only one facet of climate change. Climate changes describe the changes in climate aspects such as precipitation temperature, wind patterns, etc. The climate scientific community thinks global climate changes lead to changes in the hydrological water cycle (e.g, precipitation, evaporation, water availability) (Kusangaya et al., 2014). Climate changes can affect almost all aspects of humans; thus, it will be necessary to understand these changes in the future. Therefore, scientists over the last decades developed General Circulation Models (GCMs) to help understanding, quantifying, and simulated these impacts.

GCMs are numerical models that use mathematical equations to describe atmospheric processes (Liu et al., 2016). They simulate changes based on a set of

scenarios of anthropogenic forcings. The scientific community has defined a set of four new scenarios, denoted Representative Concentration Pathways (RCPs).

The global surface temperature change is likely to exceed 1.5°C at the end of the 21st century, comparing it with the period of 1850 to 1900 for almost all RCP scenarios (Stocker, 2014). The increase of global surface temperature is expected to raise the saturation level of vapor pressure in air, governed by the Clausius–Clapeyron theorem (Herath et al., 2018), which can lead to more intense precipitation events, particularly for short-durations (Cheng & Aghakouchak, 2014; Westra et al., 2014; Yan et al., 2021). As mentioned in the 5th Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), Extreme rainfall events are likely to rise in most regions at the end of the 21st century (Stocker, 2014).

According to the Turkish State Meteorological Service records in Turkey, the frequency and intensity of extreme rainfalls were increased in Izmir city in the last decades years. This severity of increase is rising over time; for example, the extreme rainfall, which was recorded on February 2nd, 2021, is 109.6 mm of 4-hr accumulated rainfall observed at the Izmir station; this extreme rainfall event with a similar intensity did not record since 1938.

Extreme rainfalls causes numerous hazards that can lead to individual human losses and economic damages. Increases in the intensity of rainfall is a major threat to infrastructure systems, especially stormwater infrastructure systems, e.g., flooding and landslides (Cook et al., 2020). Infrastructures are designed to carry and/or store discharges based on specific rainfall intensity, its probability of occurrence (return period), and its duration; this relationship is controlled by a so-called Intensity-Duration-Frequency (IDF) curve. IDF curves are the graphical representations of the interaction between the rainfall intensity i , the duration d , and the return period. IDF is commonly used by civil engineers in stormwater infrastructure design to reflect extreme rainfall characteristics (Agilan & Umamahesh, 2016; Anilan et al., 2022).

The current IDF curves are designed based on the stationary assumption, which assumes the extreme precipitation characteristics (statistically) are consistent with time; thus, the statistical characteristics of the historical and future extreme events are anticipated to be identical (Cheng & Aghakouchak, 2014). However, climate changes are predicted to alter the characteristics of the local climate, which means the local extreme precipitation events could change (increase or decrease) in the future. The scientific community stresses the crucial to update IDF curves to account for the possible increase in extreme precipitation (Yan et al., 2021). To cope with this challenge, several studies recommended employing the nonstationary concept by using GCMs' outputs (Srivastav et al., 2014).

Despite the technological advances used to develop GCMs, the temporal and spatial resolutions of GCM outputs are too coarse to directly used future changes on a regional scale. This demonstrates that GCMs consider very skilled in the continental scales. Yet, they are not able to describe local characteristics because of coarse spatial resolution grids for resolving local processes (Xu, 1999). Therefore, downscaling the outputs of the GCMs to the desired spatial and temporal resolutions for assessing changes in short-duration extreme precipitation are necessary.

In this context, researchers have studied and developed several approaches to estimate future precipitation and temperature of the local regions regarding the coarse global atmospheric variables. These methods are categorized into two major groups: i) dynamical statistical downscaling method, ii) statistical downscaling methods (Fistikoglu & Okkan, 2011).

Dynamical downscaling models are physically based on Regional Climate Models (RCMs) and characterize with high spatial and temporal resolutions. Here, the GCM results constitute the model domain's boundary conditions. They are computationally intensive, complex, and require substantial computational resources (Murphy, 1999; Trzaska & Schnarr, 2014). On the other hand, Statistical Downscaling Methods (SDMs) utilize statistical relationships to predict local climate variables from large-scale variables. SDMs establish quantitative relationships between large-scale

atmospheric variables and local climate variables. Statistical downscaling is relatively easy to understand, and it requires less computational effort than dynamical downscaling methods (Fistikoglu & Okkan, 2011; Goly et al., 2014; Sennikovs & Bethers, 2009).

1.2 Motivation of The Thesis

Several studies that focus on estimating sub-daily rainfall changes regarding global warming generally utilize RCMs (Mailhot et al., 2007). Due to that RCMs require, for estimating sub-daily rainfall, a long processing time, a substantial amount of input, and complex calibration procedures (Trzaska & Schnarr, 2014). Besides, they are not available in many regions. It is preferable to use GCM outputs for the aforementioned task using a statistical spatially-downscaling approach instead of RCMs. The statistical downscaling of hourly rainfall is rarely conducted because GCMs have rough temporal resolutions. So, it is also necessary to apply disaggregation techniques to estimate sub-daily rainfall.

1.3 Objective of the Thesis

The objective of the thesis is to develop a new comprehensive methodology that combines the process of statistical downscaling, bias correction, and sub-daily disaggregation of rainfall in order to derive future IDF curves based on available GCMs. This aim can be achieved through the following procedures:

- 1- Establishing ANN-based downscaling model to estimate the daily rainfall series observed in the Izmir region from the large-scale reanalysis dataset.
- 2- Correcting the bias of the estimated annual maximum daily rainfall values sampled from the daily rainfall series downscaled.
- 3- Disaggregating the estimated annual maximum daily rainfall to the sub-daily rainfall for deriving the IDF curve using the disaggregation technique.
- 4- Deriving the IDF curve from the proposed methodology, then evaluate the results with the observed IDF curve.

- 5- Using Atmospheric variables of four GCMs as inputs in the proposed methodology in order to derive future IDF curves under Representative Concentration Pathways (RCPs) scenarios (RCP 4.5 and RCP 8.5). Since the GCMs have uncertain/biased outputs in their historical and future projections, the GCM's raw data should be handled cautiously by applying the necessary correction procedures.
- 6- Comparing the observed IDF curve and the IDF curve based on the GCMs for both the historical and future (RCP 4.5 and RCP 8.5) periods.

1.4 Organization of the Thesis

The organization of this thesis is as follows; Chapter 1 introduces the state of art, motivation, and objective of the thesis. The second chapter provides an extensive literature review about the climate changes and IDF curves, then explains the theoretical behind approaches used in this study. Namely, these approaches are downscaling approach (ANN), bias correction technique, and disaggregation rainfall method. The third chapter gives information about the study area and related data statistics as well as the sources of the used data sets. Chapter 4 describes the methodology and the main approaches. Chapter 5 illustrates the applications and study results, and the final chapter is the conclusion and recommendation.

CHAPTER 2

LITERATURE REVIEW

2.1 Climate Change

Climate change is the name given to describe the change in the earth's climate over time that can be determined by the change in statistical characteristics of climate (mean, variability). This change may be a result of natural causes or human activity. Scientists were able to collect a large amount of data about the climate of the earth by using satellites and other technologies. The data collected over a long period of time reveals that the climate is changing (IPCC, 2007). Scientists have observed that there is an increase in the average global surface temperature since the 19th century; Figure 2.1 shows the change in global surface temperature relative to 1951-1980 average temperatures (NASA, 2021).

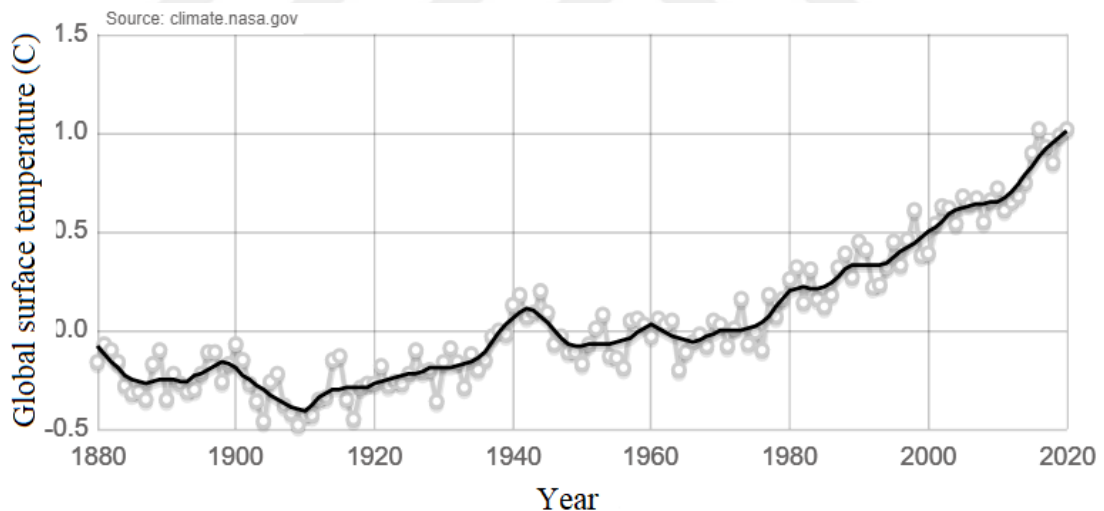


Figure 2.1 The changing of the average global surface temperature over time (NASA, 2021)

Many indicators emphasize climate change, e.g., changes of statistical characteristics of surface temperature, water vapor, precipitation, severe events, and sea level. There is numerous scientific evidence that the climate system is warming (Stocker, 2014).

Although the Earth's climate has changed throughout history, the current changing rate higher than at any point in the past (USGCRP, 2017), the current warming is occurring at an unprecedented rate across decades to millennia (USGCRP, 2018); over the last three decades, the earth's surface has been warmer than the preceding decades (Flato et al., 2013). The current warming is significant since most of it is almost certainly the consequence of human activities. The scientific community believes that the current global climate will continue to rise over the upcoming decades (IPCC, 2014).

Global climate change may result in hydrological changes that affect almost all aspects of humans, e.g., regional water availability, agricultural productivity, and floods (Kusangaya et al., 2014). Climate change threatens sustainable development (IPCC, 2014). The main strategies for reducing climate change hazards are adaptation and mitigation. If these strategies are applied over the next few decades, this can help to protect against climate risks in the 21st century and beyond. Ignoring mitigation actions would pose a very high danger and widespread impact on human life and the earth's ecosystem (IPCC, 2014).

2.1.1 The Causes of Climate Change

In the 1850s, scientists discovered that carbon dioxide and other natural greenhouse gases (GHG) in the atmosphere prevent part of the heat emanating from the Earth's surface from escaping to space (USGCRP, 2018). The planet's surface is warmed by this natural greenhouse effect, creating a favorable habitat for life. However, since the late 1800s, humans have released a growing amount of greenhouse gases into the atmosphere as a result of the combustion of fossil fuels, deforestation, and land-use change. This rise in greenhouse gases has resulted in global warming, which led to climate change (USGCRP, 2018).

Human activities have likely played a major role in the observed warming. Anthropogenic activities increases produced more than half of the reported increase in global average surface temperature from 1951 to 2010 (Stocker, 2014). Even though

natural forces such as the sun's energy influence global climate, natural elements alone would have a minor impact on global climate if human activities were not there (IPCC, 2007). Global greenhouse gases (GHG) emissions due to human activities have grown with an increase of 70% between 1970 and 2004. (IPCC, 2007). The GHG has increased the global average surface temperature due to anthropogenic forces by the range of 0.5 °C to 1.3°C in the years 1951 to 2010, and the contribution due to natural forces is ranged from -0.1°C to 0.1°C in the same period. (Stocker, 2014).

2.1.2 Global Climate Models (GCMs)

One of the best ways to address changes in the future climate conditions is using global climate models (GCMs) (Srivastav et al., 2016). GCMs are used highly advanced computer programs for simulating the intricate interactions between the atmosphere, ocean, land surface, and the global ecosystem (Flato et al., 2013). GCMs are numerical coupled atmosphere-ocean models that use mathematical equations to describe the atmospheric processes (Liu et al., 2016). GCMs require supercomputers to resolve finer spatial details (Flato et al., 2013). Researchers have made significant progress in researching the prediction of spatial and temporal changes in hydrological processes as global climate models have improved (Druyan, 2012). Today's climate models are superior to those of the past. Despite these improvements, there is still significant uncertainty about the details of many processes (Flato et al., 2013).

As mentioned in the fifth assessment report of IPCC, 42 GCMs have been developed by various research institutions (Srivastav et al., 2016). In some cases, individual models have outperformed others with respect to specific climate variables, but overall no model has been singled out as the best (Stocker, 2014).

2.1.3 Representative Concentration Pathways (RCPs)

GCMs simulate changes in response to a set of anthropogenic forcing scenarios. A new set of scenarios were updated to be compatible with contemporary climate challenges. The so-called Representative Concentration Pathways (RCPs) schema was

approved within the Coupled Model Intercomparison Project Phase 5 (CMIP5) framework of the World Climate Research Programme (IPCC, 2014).

The climate experts have defined a set of four scenarios for the severity level of (RCPs). RCPs pathways depending on GHG emissions. To this end, RCPs can be categorized into a severe mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and a very high GHG emissions scenario (RCP8.5). The number associated with RCPs represents the total amount of radiative forcing in the end 2100 relative to 1750. For example, 2.6 W.m^{-2} for RCP 2.6, 4.5 W m^{-2} for RCP 4.5, 6.0 W m^{-2} for RCP 6.0, and 8.5 W m^{-2} for RCP 8.5 (IPCC, 2014). The following Figure 2.2 shows scenarios for the future climate changes and the amount of GHG emissions for each concentration pathway (IPCC, 2014).

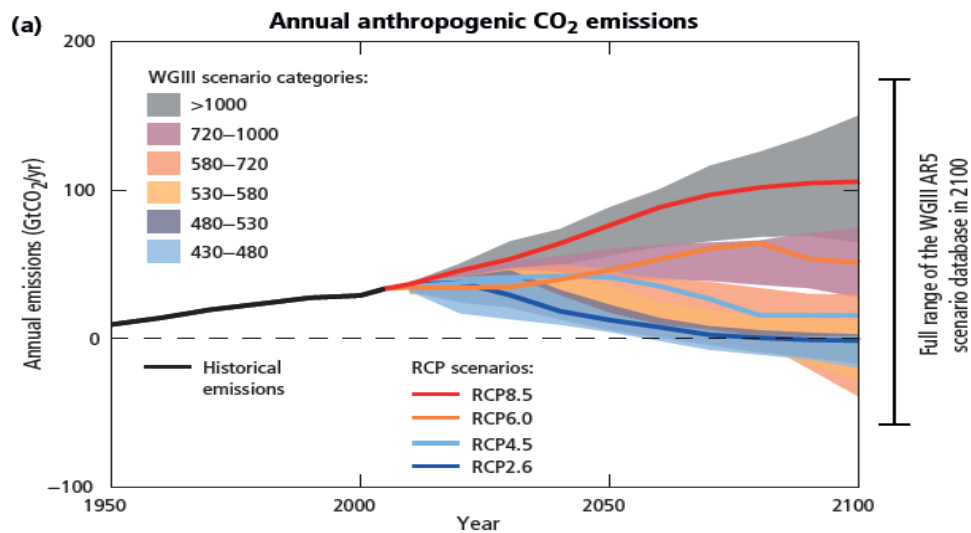


Figure 2.2 GHG emissions in baseline and projection scenarios for different pathways (IPCC, 2014)

2.1.4 Uncertainty in GCMs

Multiple model comparisons show that increased GHG emissions will result in worldwide averaged near-surface temperature warming over the next two decades. The degree of this rise, however, differs from one model to other. Furthermore, different models project opposite changes in rainfall amount in some specific regions,

highlighting the uncertainty of the estimation of future climate change, even when advanced state-of-the-art GCM methods are applied (Trzaska & Schnarr, 2014).

According to Trzaska and Schnarr (2014), there are several causes of uncertainty in GCMs outputs: i) Uncertainty regarding future human-caused emissions and natural forces as volcanic eruptions, ii) Uncertainty of the current data, which is the start point to climate project, and iii) difficulty in capturing long-term projected interannual and decadal variations.

Despite the uncertainties associated with the climate model, yet they depend on fundamental physical principles (conservation of energy, mass, and momentum). GCMs provide scientifically predictable long-term results. GCMs are very helpful for engineers and climate specialists in terms of developing, managing, applying adaptation and mitigation strategies (Flato et al., 2013).

2.1.5 Global Changing of Surface Temperature and the Water Cycle

The near-surface temperature variation is globally expected to increase by 1.5°C by the end of the 21st century comparing with the period between 1850 and 1900. This expectation is valid for all RCPs scenarios but RCP2.6. In detail, for RCP6.0 and RCP8.5, it is more likely to pass 2°C. However, RCP4.5 increases in temperature to be less than 2°C. See Table 2.1.

Table 2.1 Projected change in air temperature to the end of 21st century with respect to the reference period 1986–2005 (Stocker, 2014)

		2046–2065		2081–2100	
	Scenario	Mean	Likely range ^c	Mean	Likely range ^c
Global Mean Surface Temperature Change (°C) ^a	RCP2.6	1.0	0.4 to 1.6	1.0	0.3 to 1.7
	RCP4.5	1.4	0.9 to 2.0	1.8	1.1 to 2.6
	RCP6.0	1.3	0.8 to 1.8	2.2	1.4 to 3.1
	RCP8.5	2.0	1.4 to 2.6	3.7	2.6 to 4.8

The climate scientific community is thinking that the frequency of the hot events would increase, which subsequently would significantly influence the hydrological water cycle and earth ecosystem as well. According to IPCC 2013, the changes in the global water cycle in response to the temperature are not uniform. In general, the variation of precipitation in wet and dry regions and in wet and dry seasons will increase; however, there may be regional exceptions.

Figure 2.3 shows the differences between RCP 2.6 and 8.5 based on the mean values of the CMIP5 multi-model outputs for the period of 2081–2100 for two climate variables; temperature and precipitation.

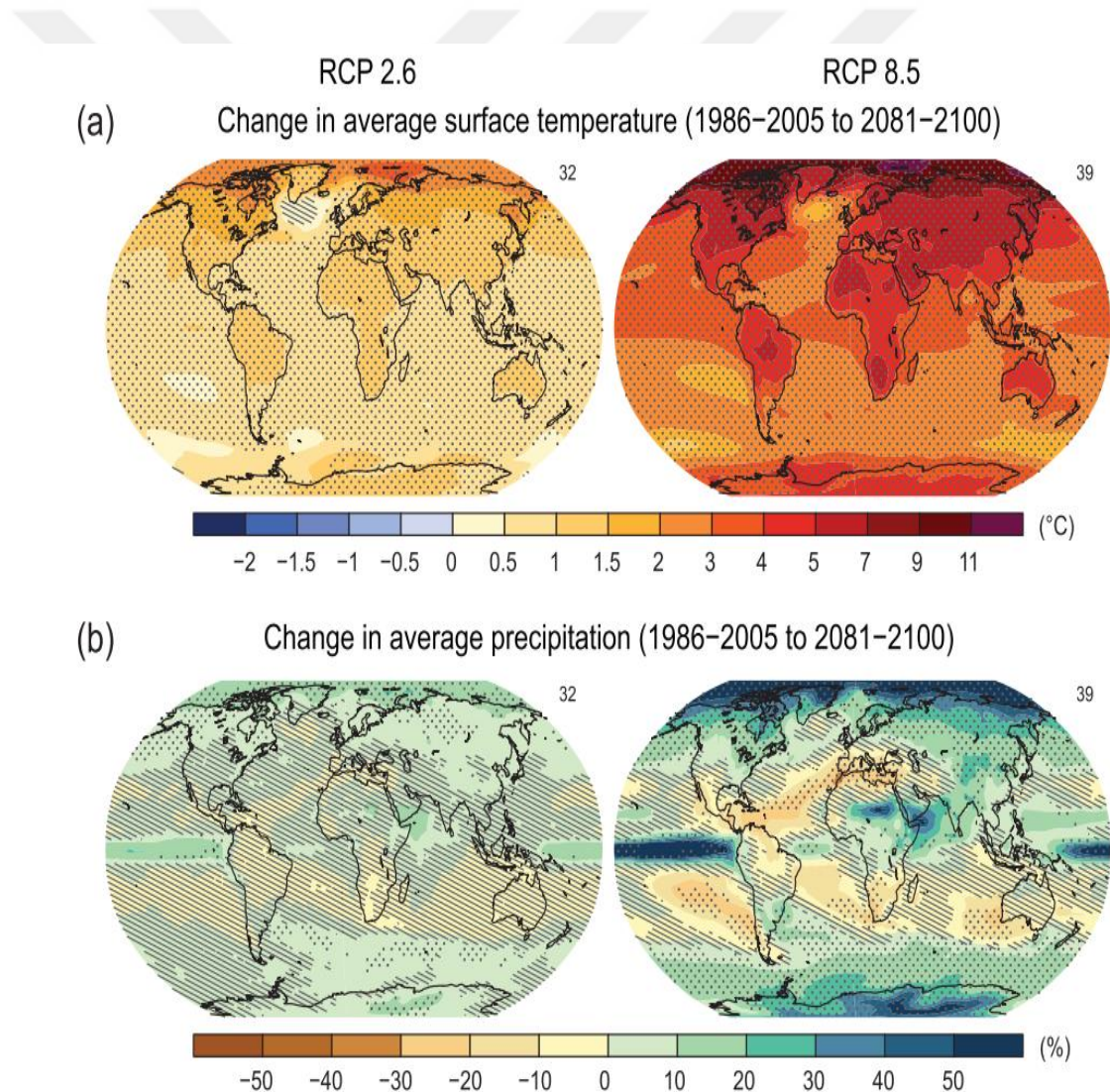


Figure 2.3 Annual changing in a)the surface temperature b)the precipitation percent for RCP2.6 and RCP8.5 scenarios in 2081–2100 (According to CMIP5 multi-model outputs) (Stocker, 2014)

2.2 Downscaling Approaches

2.2.1 Background

GCMs are very skilled in the continental scales. However, they are not able to describe local characteristics because spatial resolution grids are too coarse for resolving local processes (Trzaska & Schnarr, 2014; Xu, 1999). Downscaling techniques consider one of the best solutions to overcome this issue by downscaling the GCMs outputs to a finer resolution for both location and time aspects (Hanssen-Bauer et al., 2005).

The downscaling is based on the assumption that the local climate is conditioned by interactions between large-scale atmospheric variables and local climate variables. The core idea of downscaling techniques is transferring large-scale atmospheric variables to local weather (Trzaska & Schnarr, 2014). Downscaling methodologies are classified into two main groups, namely dynamical downscaling and statistical downscaling. Both approaches have advantages and disadvantages (Fistikoglu & Okkan, 2011).

Dynamical downscaling is typically done with a regional climate model (RCM), and RCMs are similar to GCMs in their theoretical principles, but the resolution of RCMs is greater. RCMs use large-scale data from GCMs and combine it with topography and details of physical processes to produce realistic climate data with a spatial resolution of 20–50 kilometers. The main advantage of RCMs is their ability to represent atmospheric processes at a local scale, but they are required a long time for processing and a large amount of input, besides complex calibration procedures (Trzaska & Schnarr, 2014)

Statistical downscaling is used to establish quantitative relationships between large-scale atmospheric variables and local variables. (Sennikovs & Bethers, 2009), (Goly et al., 2014). Once a relationship has been established, the future variables from GCMs are used to predict future local climate variables.

One of the main advantages of statistical downscaling is the ability to generate climate projections for a particular region besides its required very limited computational efforts when compared to dynamical downscaling. Therefore, this technique may be preferable by the institutes that have hamble logistical capacities and/or limited expertise. However, this approach still has some drawbacks associated with the initial stationary assumption that the nature of the relationship between the large-scale and local variables remains adequate under various conditions of possible future climate scenarios (Singh & Kumar, 2020). Table 2.2 illustrates the difference between the statistical downscaling and dynamical downscaling approaches.



Table 2.2 Tabulate the advantages and disadvantages of the features of the dynamical and statistical downscaling methods (Trzaska & Schnarr, 2014)

	Dynamical downscaling	Statistical downscaling
Provides	• 20 – 25 Km grid cell. • Monthly and daily time series	• Any scale, down to the level of a station. • Monthly and some method daily time series.
Requires	• High computational resources and expertise • A large amount of data inputs.	• Low or medium computer resources. • Low or Medium of data inputs.
Advantages	• Based on physical mechanisms. • The availability of historical records are not mandatory. • Addresses sub-GCM-scale atmospheric and surface processes.	• Based on statistical foundations. • Methods are flexible to adaptable to specific aims. • Methods range in complexity from simple to intricate. • The same technique can be applied in several regions based on observed data. • It can give point-scale meteorological variables for GCM output. • Tools are available and easy to apply.
Disadvantages	• Methods are complex and require supercomputers. • Due to computational difficulties, RCMs are often driven by one or two GMC. • There are just a few RCMs available, and there are no model results for many parts of the earth. • RCM outputs may require downscaling and bias adjustment. • Different RCMs produce different outcomes due to their assumptions. • Affected by bias GCM biases.	• Required observed data with high quality that may are not available for many areas. • Assumes that the linkages between large-scale and small-scale processes will continue to exist in the future in the same way. • Some methods may provide projections at a monthly resolution, rarely provide daily resolution.

2.2.2 Statistical Downscaling (SD) Techniques

Statistical downscaling techniques were aimed to establish quantitative relationships among large-scale atmospheric variables (predictors) and local variables (predictands) (Fistikoglu & Okkan, 2011). The SD model can be expressed as $Y = f(X)$ in a very simplistic form. Where: X: large-scale variables (predictors) such as air temperature and sea level pressure, etc. Y: local weather variables (predictand) such as temperature and precipitation. The functional relationship is developed using time series observed local weather variables and large-scale atmospheric variables from atmospheric reanalyzes.

The first step in statistical downscaling involves selecting the appropriate predictors. Downscaling can be done with any predictor as long as it has an acceptable correlation with the predictands (Giorgi et al., 2001; R. L. Wilby et al., 1998). However, using many predictors may not result in a better relationship relative to using a parsimonious predictor set. Stepwise regression and correlation analysis can be used to select the main explanatory predictors (Chen et al., 2010; Karl et al., 1990; Kidson & Thompson, 1998; R. L. Wilby et al., 1999).

In literature, there is not a general agreement on the selection of the most appropriate predictor variables. Generally, the selection procedure depends on the region's unique characteristics, such as its large-scale atmospheric circulation, seasonality, topography, and the predictand to be downscaled (Anandhi et al., 2009). Table 2.3 summarizes several studies on selecting various predictors for downscaling precipitation in different regions across the world.

2.2.3 Assumptions and Limitations of Statistical Downscaling

Statistical downscaling contains some assumptions i) The stationarity assumption: means the relationship among the predictor and predictand remains constant over time. ii) The predictor carries the signs of climate change. iii) The predictor has a strong relationship with predictand, and v) GCMs provide an accurate simulation of the predictor (Trzaska & Schnarr, 2014).

Table 2.3 Predictor selection in various studies

Levels	Predictor variables	This study							
		Turkey	Turkey	Sweden	France	Bangkok	China	Turkey	Canada
200 hPa	Air temperature		X						
	Geopotential height	X	X	X				X	
	Meridional and zonal winds							X	
500 hPa	Air temperature	X	X				X		X
	Geopotential height	X	X	X		X		X	X
	Relative humidity	X	X			X			X
	Specific humidity			X		X	X		
	Meridional and zonal winds			X			X		X
	Vertical pressure velocities							X	
850 hPa	Air temperature	X	X						X
	Geopotential height	X	X	X		X		X	X
	Relative humidity	X	X			X			X
	Specific humidity			X	X	X			
	Module of moisture flux			X	X				
	Meridional and zonal winds			X			X		X
Surface	Air temperature	X	X		X	X	X		
	Pressure		X						
	Precipitation	X	X	X	X				
	Relative humidity	X	X			X			
	Specific humidity					X			X
	Sea-level pressure	X	X	X	X	X	X	X	X
	Mean daily v-wind	X			X				

2.2.4 Categories of Statistical Downscaling

Statistical downscaling consists of a varied group of approaches that are often almost simple to implement but require an adequate amount of quality observed data (Trzaska & Schnarr, 2014). Statistical downscaling can be divided into three main categories:

Weather classification methods: These approaches use synoptic patterns to classify weather patterns based on their synoptic similarity. After that, they establish quantitative relationships to assign Predictants (Bardossy et al., 2005; Fistikoglu & Okkan, 2011). Although these methods are appropriate for downscaling non-normal distributions, they require a large amount of observed data (more than 30 years) to evaluate all probable weather conditions. These approaches are more computationally intensive than linear approaches (Trzaska & Schnarr, 2014).

Weather generators: These methods are replicators of local weather statistical features under the large-scale variables conditions (Kilsby et al., 2007), (Fistikoglu & Okkan, 2011). These methods are widely used in temporal downscaling.

Transfer functions: These methods build the relationship between large-scale small-scale variables. These methods are considered the most common methods in statistical downscaling. Transfer functions use various applications, including linear and non-linear regression, artificial neural networks, and redundancy analysis (R. Wilby et al., 2004) (Benestad et al., 2007), (Fistikoglu & Okkan, 2011).

It is difficult to identify the optimal downscaling approach because each study's objectives and resources are not identical. The optimal method is determined by the user's requirements and may vary depending on the geographic and temporal resolution of the needed data and the climate variables having the greatest impact on the sector under consideration (Trzaska & Schnarr, 2014).

2.2.5 Artificial Neural Network (ANN)

2.2.5.1 Background

ANN is a term that refers to computing systems whose fundamental theme is inspired by biological neural networks analogy. ANNs represent a simplified mathematical model that works like biological neural networks. ANN has the ability to learn and generalize in order to come up with meaningful solutions to problems even when the input data is incorrect or inadequate (Seyam & Mogheir, 2011).

In the last decades, Artificial Neural Networks (ANNs) were developed on a large scale in different domains, like arts, natural sciences, social sciences, industry, agriculture, sports, and entertainment. ANNs application in engineering modeling has gained increasing attention (Mohammed Seyam et al., 2020). ANN has been successfully used in various hydrological applications (Tombul & Oğul, 2006). The development was due to the features that make the ANNs very effective. The ANN is an interpolation-approximation model. An important feature is that in an ANN, the information is distributed along with the artificial neural network, being stored in the synaptic weights between the neurons. This property gives the possibility of the ANN to be tolerant to input data with distortions. One of the main features of ANN is that its ability to simulate non-linearity in a system (Moldovan, 2020).

On the downside, some articles showed that ANNs have some limitations, such as some unrealistic results, overfitting training, and human intervention in the training stage. However, ANNs can quickly capture a hydrogeological system's behavior and provide suitable and accurate predictions. (Seyam et al., 2020).

2.2.5.2 Structure of Artificial Neural Networks

The ANN structure is made up of three layers. The first is an input layer with n neurons for each variable. The second layers (one or more) represent the hidden layer which contain several neurons, and all hidden neurons transform the inputs nonlinearly

into another dimension through weight and a bias term. The last layer is the output layer (Minns & Hall, 1996; Sudheer et al., 2002). For example, Figure 2.4 shows an artificial neural network containing three layers with four neurons in the input layer, seven neurons in the hidden layer, and one neuron in the output layer.

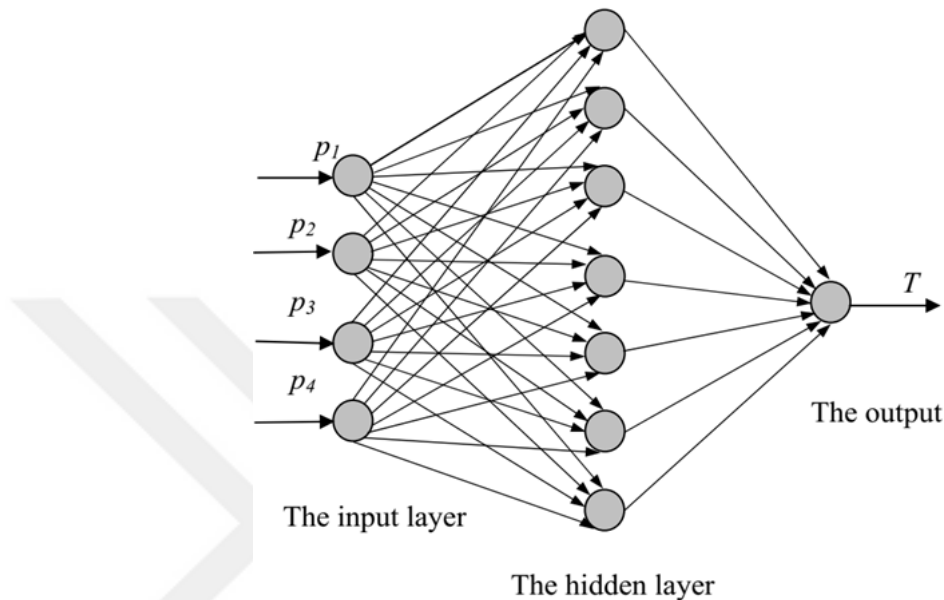


Figure 2.4 Artificial neural network structure

The process of searching the optimal weights and biases for the ANN is called the training phase, which is carried out with a known inputs and outputs. Each training phase involves a number of inputs passed forward through the network to generate a outputs trial then comparing it with observed outputs. The error is propagated backward through the network when the residual (difference between trial and observed outputs) exceeds the desired value. Once the comparison error has been reduced to an acceptable level for the entire training set, the training phase is complete. After training, the network is evaluated using a set of cases withheld from it during the training phase. After the model was completed, it was ready to be applied to any other situation. The training algorithm adjusts the connection weights based on the error. This process is referred to as back-propagation.

One of the significant points in ANN training is to choose input variables that are deeply connected with the studied problem. Understanding the problem gives an initial

idea of which input variables are possible to be influential (H. Jiang & Cotton, 2004). To construct any artificial neural network, it must determine the network and node properties, system dynamics, and the topology of a neural network.

2.2.5.3 ANN Applications in Hydrology

ANN's flexible structure is able to found a relationship with any input-output. ANN has been widely utilized as a predicting tool in many disciplines (Moldovan, 2020). The majority of hydrologic processes exhibit a high degree of temporal and geographical variability and are further complicated by concerns of physical process non-linearity and parameter estimation uncertainty. An engaging feature of ANNs is their ability to derive the relationship between the inputs and outputs even if the data have some errors. (Govindaraju & Ramachandra, 2013), (Seyam et al., 2020).

The ANN seems to be valuable for modeling most water resource issues. In the hydrology sector, ANN has produced many promising results in recent years. ANN was implemented in many hydrologic applications such as precipitation forecasting (Hung et al., 2009), rainfall-runoff relationship (Aichouri et al., 2015; Cigizoglu & Alp, 2004; Minns & Hall, 1996), water quality (Seyam et al., 2020; Seyam & Mogheir, 2011), and river flow (Aichouri et al., 2015; Moldovan, 2020).

2.2.5.4 ANN in Statistical Downscaling

Recently, numerous successful studies in statistical downscaling using ANN-based transfer functions have been conducted.

Fistikoglu & Okkan, (2011) investigated the predictor variables selected from the NCEP/NCAR data for downscaling monthly rainfall in the Tahtali area in Izmir city. It was found that ANN was able to decrease the number of predictors to downscale monthly rainfall in the area study.

In the (Goyal & Ojha, 2012) study, downscaling models were created using a Linear Multiple Regression (LMR) and ANNs for generating projections of maximum and minimum temperatures in Rajasthan State in India. The results show that ANN-based models perform better than LMR-based models. Then the ANN model was utilized to generate future climate projections for the predictands.

Salimi et al. (2019) downscaled a satellite precipitation estimation product by ANNs, and impose a correction method for five separate daily extreme precipitation events localized in Austria. Three forms of the algorithm were employed to help increase the performance of ANN: The results suggest that the performance of the imperialist competitive algorithm (ICA) was somewhat better than the results of other algorithms.

Nourani et al. (2019) downscaled three GCM outputs statistically to evaluate future changes in precipitation and temperature in Tabriz in Iran. It was observed that Different results according to different GCMs and scenarios were obtained for precipitation projection.

Laddimath & Patil (2019) examined the transfer function as a strategy for statistical downscaling for monthly mean precipitation over the Bhima basin using an ANN model. They found that ANN is a well-established and straightforward methodology for downscaling. The results of the downscaling can be employed in watershed management.

Moldovan (2020) studied ANN and used a radial basis function (RBF) architecture to estimate the flow of the Mures river in Romania. The findings indicated that the ANN performed exceptionally well in the range of the values of the series.

2.3 Bias Correction of the GCM Outputs

Climate models are important tools for exploring the future impacts of climate change. However, they often include some biases in the model output. Correcting these

biases increases its usability (McGinnis et al., 2015). Bias correction approaches are employed to help treat the various problems with biased model outputs. The core concept in the bias correction technique is to identify probable biases between observed and simulated data. Bias correction procedures utilize a transformation algorithm in order to adjust model outputs. (Teutschbein & Seibert, 2012). GCMs have uncertainty outputs of future climate change projections; For this reason, the raw data should be handled with caution and applying the necessary correction procedures (Christensen et al., 2008).

It is critical to realize that statistical downscaling models are unlikely to provide highly accurate results. Downscaling increases the uncertainty in GCMs outputs due to assumptions are added in the downscaling process. For that reason, the estimated variables from downscaling models are rarely used directly. Therefore, using the bias correction technique to treat the uncertainties in downscaling model results is necessary (Trzaska & Schnarr, 2014).

2.3.1 Bias Correction Methods

Several bias correction methods, ranging from simple to complex, have recently been developed. In climatic studies, the most common bias correction approaches are linear scaling, local intensity scaling, power transformation, and quantile mapping (Teutschbein & Seibert, 2012).

The linear scaling approach operates based on the differences between observed and estimated values. The simulated value is corrected with a factor based on the ratio of long-term mean observed and simulated values. (Teutschbein & Seibert, 2012). Although the linear scaling method treats the bias in the mean, it is unable to adjust the biases in wet-day frequency and intensity. So, Schmidli et al. (2006) suggested the "Local Intensity Scaling method" to adjust the mean values of wet and dry-days separately, then use the linear scaling factor to correct the biases. The previously mentioned methods (linear scaling and local intensity scaling) are unable to correct the biases in variance. For this reason, an exponential non-linear correction may be utilized

to treat the variance statistics utilizing the translation of power function (Leander and Buishand, 2007; Leander et al., 2008). The power transformation is an useful approach to correct both the mean and the variance, but it has some drawbacks when dealing with daily rainfall due to using the power function. Recently, the quantile mapping method has become one of the most popular methods because of its ability to overcome the problems mentioned above.

2.3.2 Quantile Mapping Method for Bias Correction

Quantile mapping (QM), and also called Distribution mapping, is a commonly used method for correcting the error in hydrological model and climate change model (Ines & Hansen, 2006; Johnson & Sharma, 2011; McGinnis et al., 2015; Michelangeli et al., 2009; Piani et al., 2010; Pierce et al., 2015; R. . Wilby et al., 2009). Teutschbein & Seibert (2012) reviewed and evaluated the different methods of bias correction. They found that the distribution mapping method is the best correction method combined with other methods because of its ability to correct the basic statistical characteristics such as mean values and standard deviation.

The main idea of QM is to correct the distribution function of simulated variables to agree with the distribution function of observed variables by creating a transfer function to reshape or shift (using a statistical approach) the distribution of simulated variables to match the distribution of the observed data (McGinnis et al., 2015). As shown in Figure 2.5, the QM method is working in two steps, i) transfer function, which aims to transfer the model from data values to probability form, this can be done by using the Cumulative distribution function (CDF) of the model, and then ii) transform back the probabilities by using the inverse CDF of the distributions derive from observations. This procedure can be expressed mathematically as Eq. (2.1).

$$X_{corrected} = CDF_{obs}^{-1}(CDF_{model}(X_{uncorrected})) \quad (2.1)$$

Where CDF, CDF^{-1} cumulative distribution function, and its inverse, obs: observation data, mod: model data.

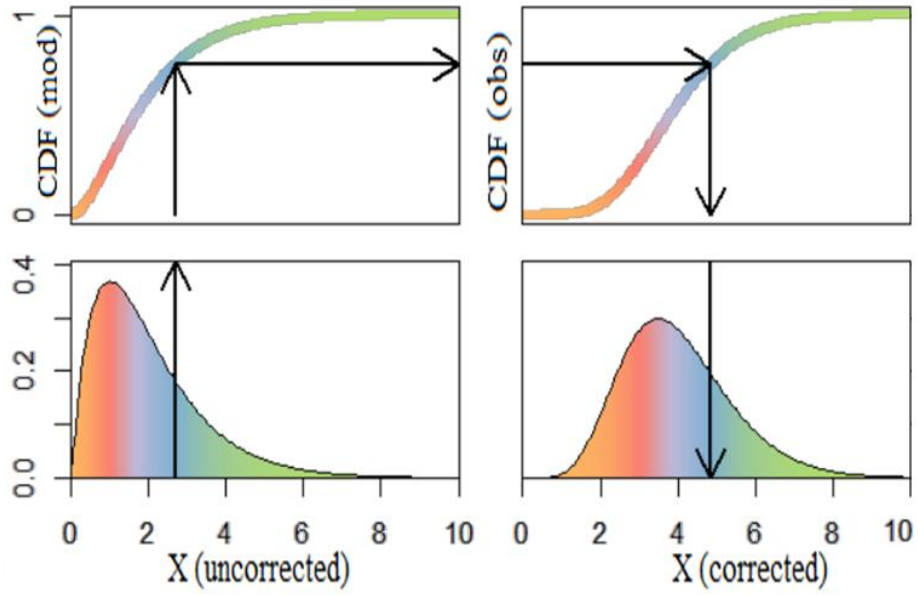


Figure 2.5 Exemplary procedure of QM method

Gamma distribution is commonly used in QM method for correcting rainfall events. Gamma distribution has been effective in analyzing precipitation and is often suitable for distributions of precipitation events (Ines & Hansen, 2006; Katz, 1999; Piani et al., 2010; Watterson & Dix, 2003). Gamma probability distribution function is expressed as Eq. (2.2):

$$f_{\gamma}(x|\alpha, \beta) = x^{\alpha-1} \cdot \frac{1}{\beta^{\alpha} \cdot \Gamma(\alpha)} \cdot e^{\frac{-x}{\beta}} \quad ; x \geq 0; \alpha, \beta > 0 \quad (2.2)$$

Where: alpha (α): shape parameter, Beta (β): scale parameter, (Γ) denotes the gamma function.

The QM procedure can be expressed mathematically using gamma distribution as below Eq. (2.3):

$$X_{\text{corrected}} = F_{\gamma}^{-1}(F_{\gamma}(X_{\text{uncorrected}}|\alpha_{\text{mod}}, \beta_{\text{mod}})|\alpha_{\text{obs}}, \beta_{\text{obs}}) \quad (2.3)$$

Where: X: variable, mod: model. Obs: observed, F_{γ} : gamma function, α , β : coefficient of Gamma function.

The major advantage of this method, clearly shown through it is the ability to adjust all data points in the distributions while maintaining the rank correlation between models and observations (Li et al., 2010). The method, however, follows the stationary concept, meaning that the climate distribution does not change over time (Meehl et al., 2007; Srivastav et al., 2014). For these reasons, this method can be used for historical data, but it cannot be considered for future model projections (Maurer & Pierce, 2014), (Pierce et al., 2015).

2.3.3 Equidistant CDF Matching Method (EDCDFm)

Li et al. (2010) suggested a new approach, the Equidistant Cumulative Distribution Function Matching (EDCDFm), to improve the traditional method (QM). EDCDFm takes into consideration the changes in the future. Guo et al. (2018) founded that the EDCDFm method is more sensitive to reducing variability and biases compared with the QM method. Recently, the EDCDFm method has been widely cited. Also, several other studies have used EDCDFm to correct bias in precipitation and/or temperature (Guo et al., 2018; Lafon et al., 2013; Pierce et al., 2015).

The EDCDFm approach is built on the hypothesis that the difference between the model and observed values over the historical period remains valid for the future projection. However, the difference between projected and historical CDFs is considered (Guo et al., 2018; Li et al., 2010). Mathematically The method can be written as Eq.(2.4).

$$X_{G_f_adjust} = X_{G_f} + F_{obs_h}^{-1}(F_{G_f}(X_{G_f})) - F_{G_h}^{-1}(F_{G_f}(X_{G_f})) \quad (2.4)$$

For gamma distribution, it can be written as the bellow Eq. (2.5):

$$\begin{aligned} X_{G_f_adjust} = & X_{G_f} + F_Y^{-1}(F_Y(X_{G_f}|\alpha_{G_f}, \beta_{G_f})|\alpha_{obs_h}, \beta_{obs_h}) \\ & - F_Y^{-1}(F_Y(P_{G_f}|\alpha_{G_f}, \beta_{G_f})|\alpha_{G_h}, \beta_{G_h}) \end{aligned} \quad (2.5)$$

Where:

- F, F^{-1} : Cumulative distribution function (CDF) and inverse CDF
- X: Variables.
- G_h : Model outputs of the historical period.
- obs_h: Historical observed records.
- G_f : Model outputs of the future period.
- G_{f_adjust} : adjusted model outputs of the future period

This method can be illustrated graphically (Figure 2.6) with the following procedures: Firstly, CDFs for historical observation, the historically modeled, and the future modeled outputs should be constructed. Secondly, by following the selected distribution (e.g, Gamma distribution), the delta (Δ) can be calculated based on the differences CDF of both observed and model data for every point. Figure 2.6 illustrates (an example with numbers) the procedures of the EDCDFm method as follow: $X_{G_f} = 295$, thus $F_{G_f}(295) = 0.5$. So $F_{obs_h}^{-1}(0.5) = 289$, and $F_{G_h}^{-1}(0.5) = 293$ can be determined. The difference between $F_{obs_h}^{-1}(0.5)$ and $F_{G_h}^{-1}(0.5)$ also can be defined as $\Delta = -4$. Finally, the correct value as adjusted $X_{G_f_adjust} = X_{G_f} + \Delta = 295 - 4 = 291$ can be calculated. The same procedure is repeated for every point for the future projection time series.

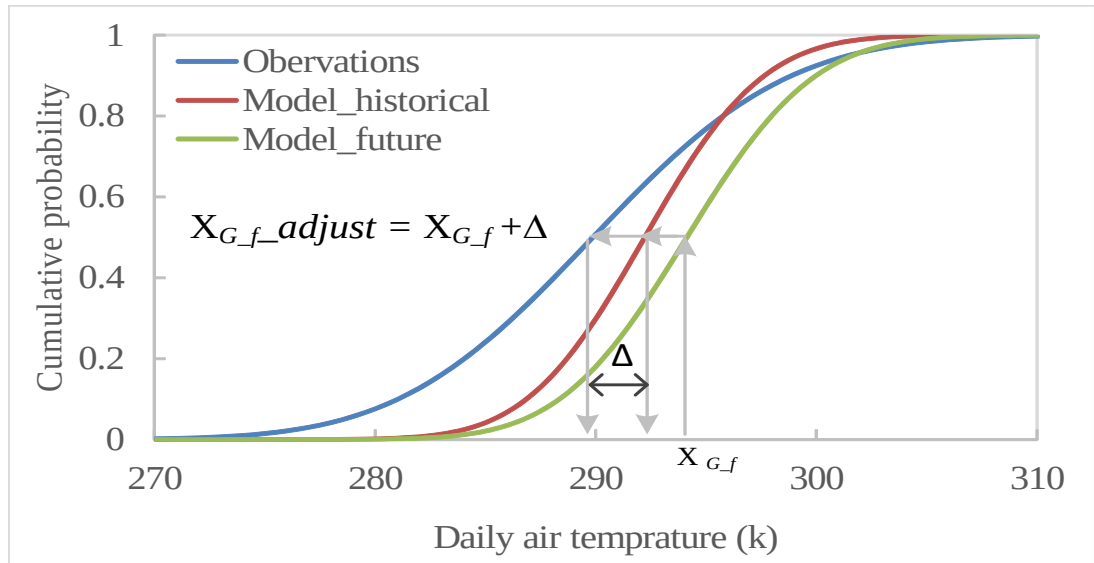


Figure 2.6 Exemplary procedures of equidistant cumulative distribution function matching (EDCDFm) method graphically

Although there are differences between the EDCDFm method and the QM method, in case the future climate CDF is very similar to the historical CDF, then both methods would provide identical outputs (Li et al., 2010). In comparison to other approaches, the EDCDFm has appealing features because it takes into account future climate distribution changes. Furthermore, this method is very straightforward, simple and easy to implement (Li et al., 2010).

2.4 Intensity-Duration-Frequency Curves

The Intensity-Duration-Frequency (IDF) curves represent the relation between rainfall intensity (i), its duration (D), and return period (T). IDF curve implementation requires obtaining detailed information about the annual maximum rainfall depths from historical rainfall records for every year over specific durations (e.g., 5, 10, 15, 30 per minute, and 1, 2, 3, 4, 5, 6, 8, 12, 18, 24 per hour). The IDF curves allow estimating rainfall intensity of a given return period (i.e., 2, 5, 10, 15, 25, 50, 100, 200 years) for different durations.

Infrastructures are designed to carry and/or store a specific intensity of rainfall, its probability of occurrence (return period), and its duration. Civil engineers and hydrologists commonly use IDF curves in stormwater infrastructure design and water resources management to represent extreme rainfall characteristics. Infrastructures are designed to carry and/or store discharges based on specific rainfall intensity, its probability of occurrence (return period), and its duration. IDF is commonly used by civil engineers in stormwater infrastructure design to reflect extreme rainfall characteristics (Agilan & Umamahesh, 2016; Anilan et al., 2022).

When local rainfall data are available, IDF curve can be generated through frequency analysis of extreme events. According to several studies (Koutsoyiannis et al., 1998; Nhat et al., 2006; Y. Sun et al., 2019), the steps for deriving the IDF curve is generally follow:

- 1- Extract annual maximum series of precipitation depth for a specific duration from metrological station records.
- 2- Determine which the best distribution function fits the extreme rainfall intensity time series for each duration. The common distributions Gumbel, lognormal, Pearson III, and Generalised Extreme Value (GEV).
- 3- Based on the selected distribution function, calculate the rainfall intensity for each specific duration and return period.
- 4- Present the information as a graph or an empirical equation, e.g., Sherman, Kimijima, and Talbot.

IDF curves can be expressed as an equation called intensity-duration-frequency equation to avoid having to read the design rainfall intensity from a graph (Chow et al., 1988). Four equations (Sherman, Kimijima, Talbot, and Bernard) are the most common formulas to derive a relationship. In this study, the Bernard formula is used; see Eq. (2.6).

$$I_T(mm/h) = \frac{K T^c}{t^b} \quad (2.6)$$

Where: I_T : intensity(mm/hr) , T : return period, t : duration (min), k,c,b : constant parameters.

2.4.1 Estimation of Future IDF Curves

The current IDF curves are designed based on the stationary assumption, which assumes the extreme precipitation characteristics (statistically) are unchanged with time. Consequently, the probability distribution in the historical and future periods is anticipated to be identical. (Cheng & Aghakouchak, 2014). However, climate changes are anticipated to alter the characteristics of the local climate, which means the local extreme precipitation events could change (increase or decrease) in the future (Yan et al., 2021). Several studies stress that the crucial to update IDF curves frequently to account for the possible increase in extreme precipitation (Yan et al., 2021)

The main concern here is how these changes will affect infrastructures that have been designed using a stationary assumption. Several studies proposed the non-stationary assumption in urban infrastructure design and stormwater management to cope with this challenge.

In literature, Nguyen et al. (2007) suggested a downscaling methodology to estimate future IDF curves using GCMs. Mailhot et al. (2007) utilized RCMs to evaluate the changes in the extreme rainfall events and generate the future IDF curve. They have found that the RCM grid findings are consistent with the observed data and recommended further study of multi-model ensembles. Solaiman et al. (2011) utilized downscaling (weather generator method) and disaggregation approach to estimate the future IDF curves. Mirhosseini et al. (2013) used downscaled approaches (temporally) using RCM data to update IDF curves. Agilan & Umamahesh (2016) created the IDF curves using 24 GCMs for two future periods based downscaling method.

According to the above studies, it is preferable to update the current IDF curve using GCMs or RCMs to cover future conditions after applying the downscaling approach, which required to enhance the temporal and spatial resolution of climate models.

Despite considerable progress in updating IDF, some methods have some drawbacks like computational intensity, using daily GCMs data directly to apply sub-daily data, and using complex disaggregation procedures (Srivastav et al., 2014). Lima et al. (2016) claim that there is no well-accepted methodology to update IDF curves.

CHAPTER 3

STUDY AREA AND DATA SETS

3.1 Study Area

The study region is Izmir city, located on the Aegean coast of Turkey (Figure 3.1). İzmir is the third-largest city in Turkey, and it covers an area of 11891 km². The city is characterized as an area of important natural, historical and ecological heritage for the Aegean Region. In 2019, İzmir city had a population of 2,97 million (Statistical Institute Turkish, 2019).

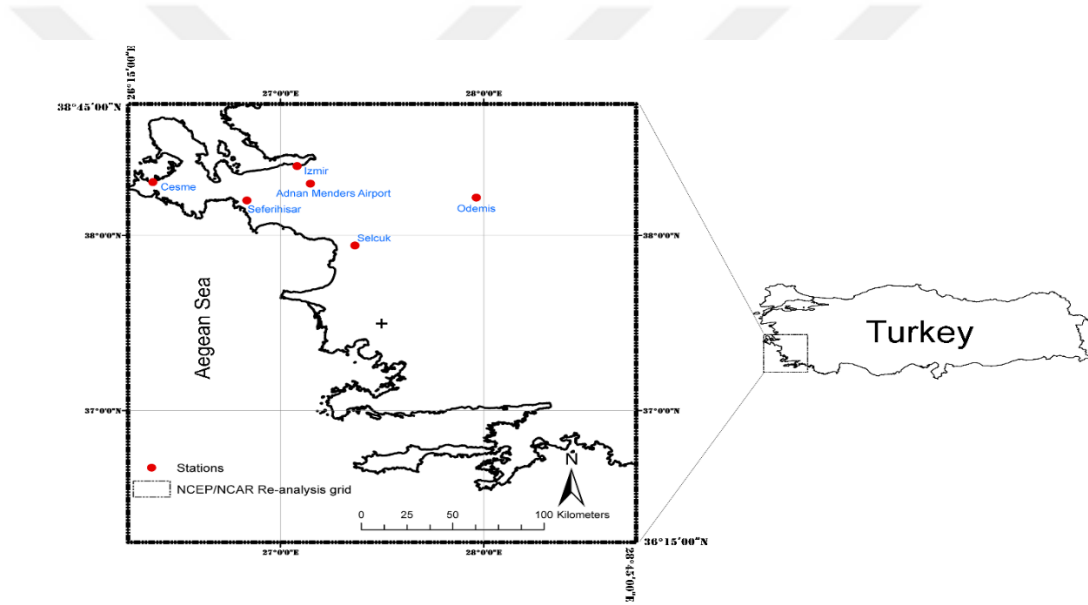


Figure 3.1 Geographical locations of the study region and selected stations

Izmir city and its environs reflect typical Mediterranean climate characteristics. The weather in winter is relatively mild and quite rainy, and rarely snows. In spring, it is very mild and less rainfall. In summer, it is dry, sunny, and not very high humidity. However, there are some periods of intense heat, which the temperature might reach up to 40 °C. Autumn starts with pleasantly warm and sunny weather, which later becomes more rainy. Figure 3.2, Figure 3.3 and Table 3.1-3 illustrate the information about temperature and rainfall in Izmir city (Turkish State Meteorological Service Official, 2021).

Table 3.1 Average temperature and precipitation from 1939-2019 for Izmir region (Turkish State Meteorological Service Official, 2021)

	Jan.	Feb.	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Average temperature (°C)	8.7	9.5	12	16	21	25	28	28	24	19	14	10.4	17.8
Average Max temperature (°C)	12.3	13.5	16	21	26	31	33	33	29	24	19	14	22.6
Average Min temperature (°C)	5.7	6.1	7.6	11	15	20	22	22	19	15	11	7.4	13.5
Rainy days	12.7	10.8	9.2	7.9	5.3	2.2	0.5	0.5	2	5.4	8.8	12.8	78.1
Average total precipitation (mm)	136	102	76	46	31	12	4.1	5.7	16	45	94	144	711.1

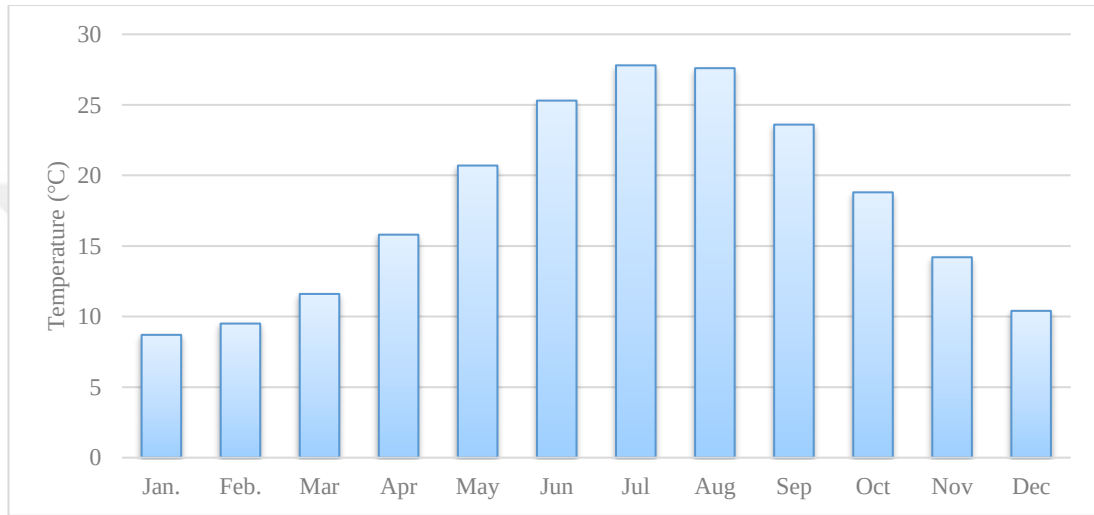


Figure 3.2 Average temperature for Izmir region in the period between 1939-2019

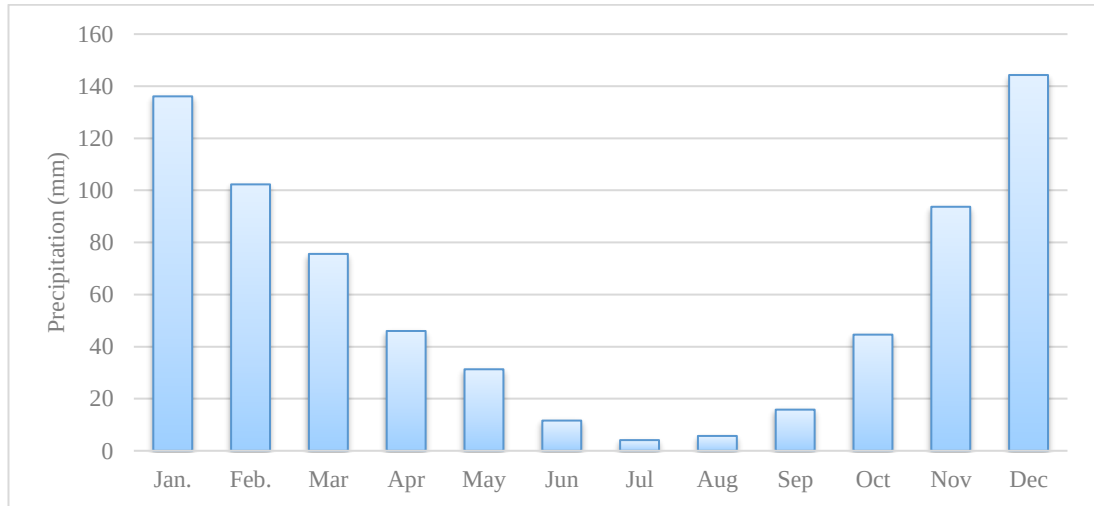


Figure 3.3 Average monthly rainfall for Izmir region in the period between 1939-2019

Izmir is a region with scarce water resources as the annual usable water value per capita average is found 383 m³, and according to the water sufficiency scale recognized worldwide, the annual water amount per capita should be a minimum of 2,000 m³, and

areas those that have less than 1,000 m are defined as water-poor. A significant amount of Izmir water is used for agricultural and industrial activities. Therefore, developing the management of water is critical in İzmir for decision-makers (IZKA, 2015).

According to Turkish State Meteorological Service (2019), the annual precipitation amount is approximately 710 mm/year, and the most rainy season in winter (up to 75% of the total annual precipitation falls between November to March), while it rains very rarely in summer. Table 3.2 shows the statistical characteristics of Annual Maximum (AM) rainfall in short durations of Izmir station from 1938 to 2015. The observation proved that the extreme rainfall in Izmir city has been increasing in Izmir city for the last years, especially in short duration (sub-daily). Figure 3.4 shows the pattern of AM rainfall in various durations (1 hr, 6 hr, 12 hr, and 24 hr) in the period (1935-2018).

Table 3.2 The statistical characteristics of AM rainfall in standard durations at Izmir station for the period between 1938-2015

	5 min	10 min	15 min	30 min	1-hr	2-hr	3-hr	4-hr	5-hr	6-hr	8-hr	12-hr	18-hr	24-hr
Mean	7.5	10.7	13.0	17.7	23.5	29.1	33.6	36.6	39.7	42.1	45.2	49.9	54.6	65.7
Median	7.1	9.6	12.5	15.9	20.9	26.0	30.8	34.3	37.6	39.1	44.1	48.9	53.9	61.7
Max	19.6	29.7	37.4	52.3	60.8	76.5	83.5	92.6	115.7	132.9	144.9	145.1	145.3	145.3
Min	1.5	2.5	2.8	4.0	6.0	6.8	7.0	7.1	9.9	10.6	11.7	11.8	11.8	31.1
Std Dev	3.09	4.49	5.58	7.87	10.96	13.37	15.22	15.74	17.57	18.79	19.92	21.91	23.43	22.89
Skewness	1.47	1.46	1.43	1.62	1.43	1.41	1.49	1.40	1.82	2.12	2.12	1.66	1.31	1.46

In order to inspect the changes of AM rainfall in Izmir station for all standard durations, the Mann-Kendall trend analysis was realized (Ghenim & Megnounif, 2016). Table 3.3 and Figure 3.4 reveal that the trend of extreme rainfall tends to increase. This observation is maintained valid for all the investigated standard durations but the durations less 30 than minutes.

Table 3.3 Mann-Kendall trend test of AM rainfall in standard durations (1938-2015)

	Z	S	vars	tau	P-value	not
5 min	0.37	89	5.36E+04	2.98E-02	0.704	no trend
10 min	1.51	350	5.37E+04	1.17E-01	0.1309	no trend
15 min	2.14	498	5.37E+04	2.44E-01	0.031	no trend
30 min	3.15	733	5.37E+04	2.96E-01	0.0051	a trend
1hr	3.82	888	5.37E+04	3.27E-01	0.00012	a trend
2 hr	4.22	981	5.37E+04	3.46E-01	2.35E-05	a trend
3 hr	4.48	1039	5.37E+04	3.56E-01	7.51E-06	a trend
4 hr	4.61	1070	5.37E+04	3.63E-01	3.97E-06	a trend
5 hr	4.69	1089	5.37E+04	3.60E-01	2.67E-06	a trend
6 hr	4.66	1083	5.37E+04	3.36E-01	3.03E-06	a trend
8 hr	4.35	1010	5.37E+04	3.12E-01	1.34E-01	a trend
12 hr	4.04	938	5.37E+04	2.75E-01	5.28E-05	a trend
18 hr	3.56	826	5.37E+04	2.14E-01	3.70E-04	a trend
24 hr	2.76	642	5.37E+04	2.14E-01	5.60E-03	a trend

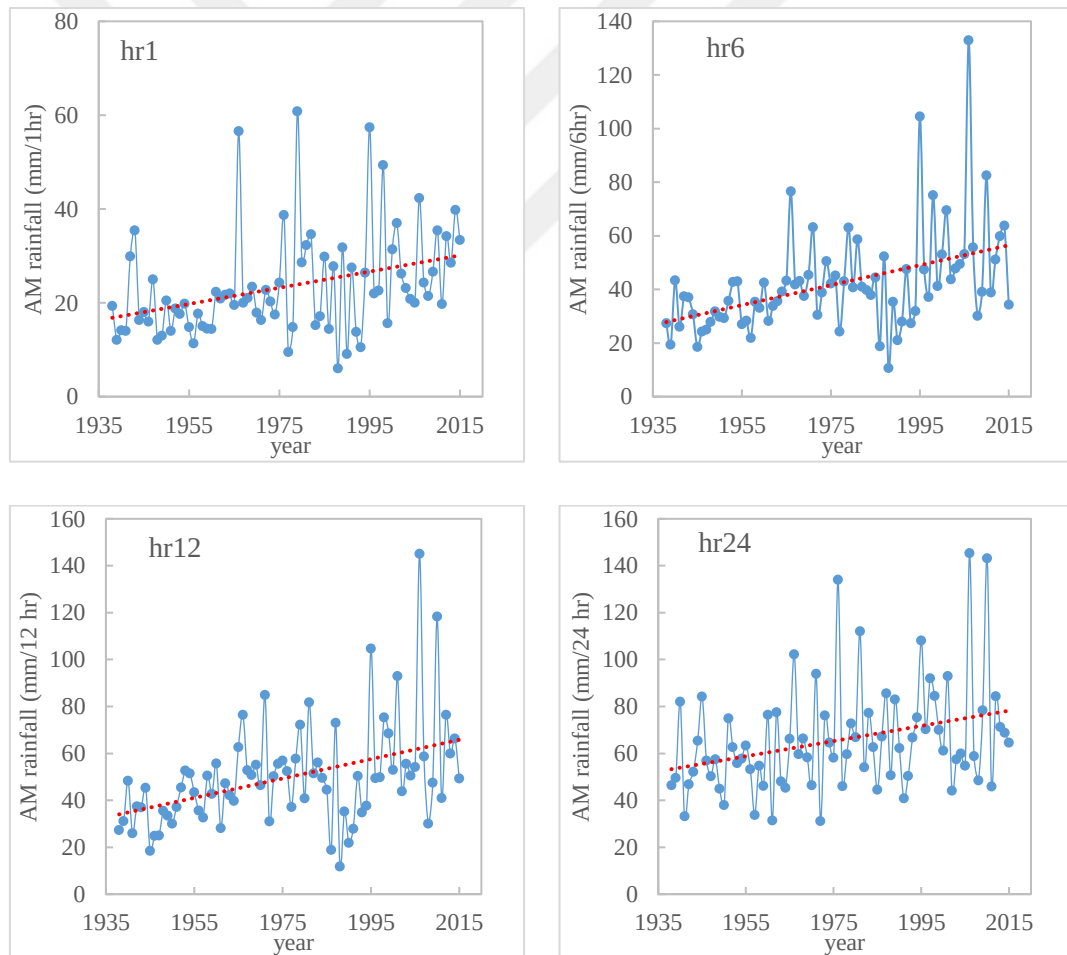


Figure 3.4 The trend of AM rainfall for various durations (1 hr, 6 hr, 12 hr, and 24 hr)

3.2 Data Sets

In this study, three types of datasets are used to apply the methodology; these datasets are i) observation station records (predictant) to develop and then validate the statistical downscaling model. ii) large-scale reanalysis data (predictors) to construct the downscaling model and to select the appropriate predictors, and iii) GCMs data (future predictors) to anticipate the climate changes in the future.

3.2.1 Rainfall Observations Data (Predictands)

Several meteorological stations are available within the İzmir region. The six stations were selected in this study area for validation and calibration of the downscaling model. The available data and location of the stations are listed in Table 3.4. The required data were obtained from the Turkish state Meteorological Service in Turkey.

Table 3.4 Available meteorological stations

Station number	Stations name	Latitude (°) N	longitude (°) E	Altitude (m)	Available data
17220	Izmir	38.3949	27.0819	29	1948 - 2018
17219	Adnan Menderes	38.295	27.1479	119	2009 - 2018
17820	Seferihisar	38.199	26.835	22	1980 - 2011
17221	Cesme	38.3036	26.3724	5	1965 - 2018
17822	Odemis	38.2157	27.9642	111	1960 - 2011
17854	Selcuk	37.9423	27.3669	18	1965 - 2011

Daily rainfall records from meteorological stations in Izmir city were used as predictands for constructing the statistical downscaling model. The ANN downscaling model was calibrated using the daily rainfall over the period 1948 to 1990 for the Izmir station (training period), while the period 1991-2018 was used for validation for the same station (testing period). In addition to that, downscaled results were compared with the five neighbor stations' observations for spatial validation of the downscaling model. Figure 3.1 illustrates the Izmir station and its five neighbor stations. Table 3.4 shows the available data associated with each station.

The observed correlations of daily rainfall between Izmir and neighboring stations ranged between 0.82–0.61. As expected, the nearer stations show higher correlations while the far stations are less correlated with the Izmir stations. Figure 3.5 shows the correlation between daily rainfall in Izmir station (main station) and its neighbor stations. It is noted that Adnan Menderes and Seferihisar stations have the highest correlation coefficient with Izmir station, $R = 0.82$ and 0.81 , respectively. While Selcuk, Cesme, and Odemis stations have medium and weak correlation $R = 0.72$, 0.63 , and 0.61 , respectively.

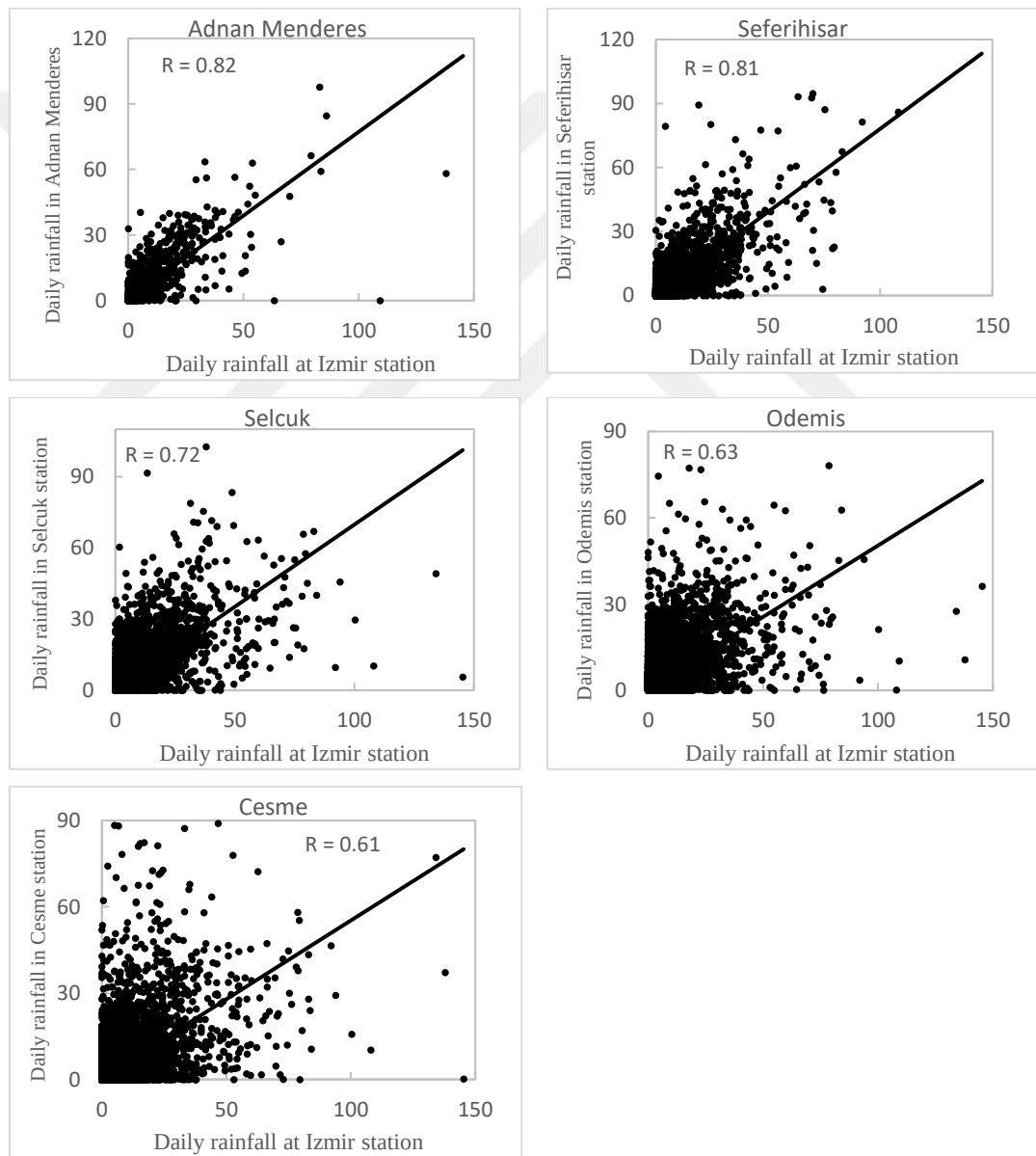


Figure 3.5 The correlation between the daily rainfall from the training station (Izmir station) and the other test stations a) Adnan Menderes, b) Selcuk, c) Seferihisar, d) Cesme, and e) Odemis stations

Figure 3.6 shows the variation of daily rainfall for all stations, and Table 3.5 tabulates the main statistical properties (mean, standard deviation, skewness, and maximum) of daily rainfall for all stations in the study region.

Table 3.5 Statistical characteristics of daily rainfall of all stations

	Izmir 1948-2018	Adnan Menderes 2009-2018	Cesme 1965-2018	Seferihisar 1980-2011	Odemis 1960-2011	Selcuk 1965-2011
Mean	1.881	2.119	1.571	1.672	1.637	1.881
Max	145.3	97.8	166.4	187	78.1	174.1
Std Dev	6.818	6.958	6.314	6.782	5.455	6.710
Skewness	6.400	5.018	7.814	8.838	5.237	6.474

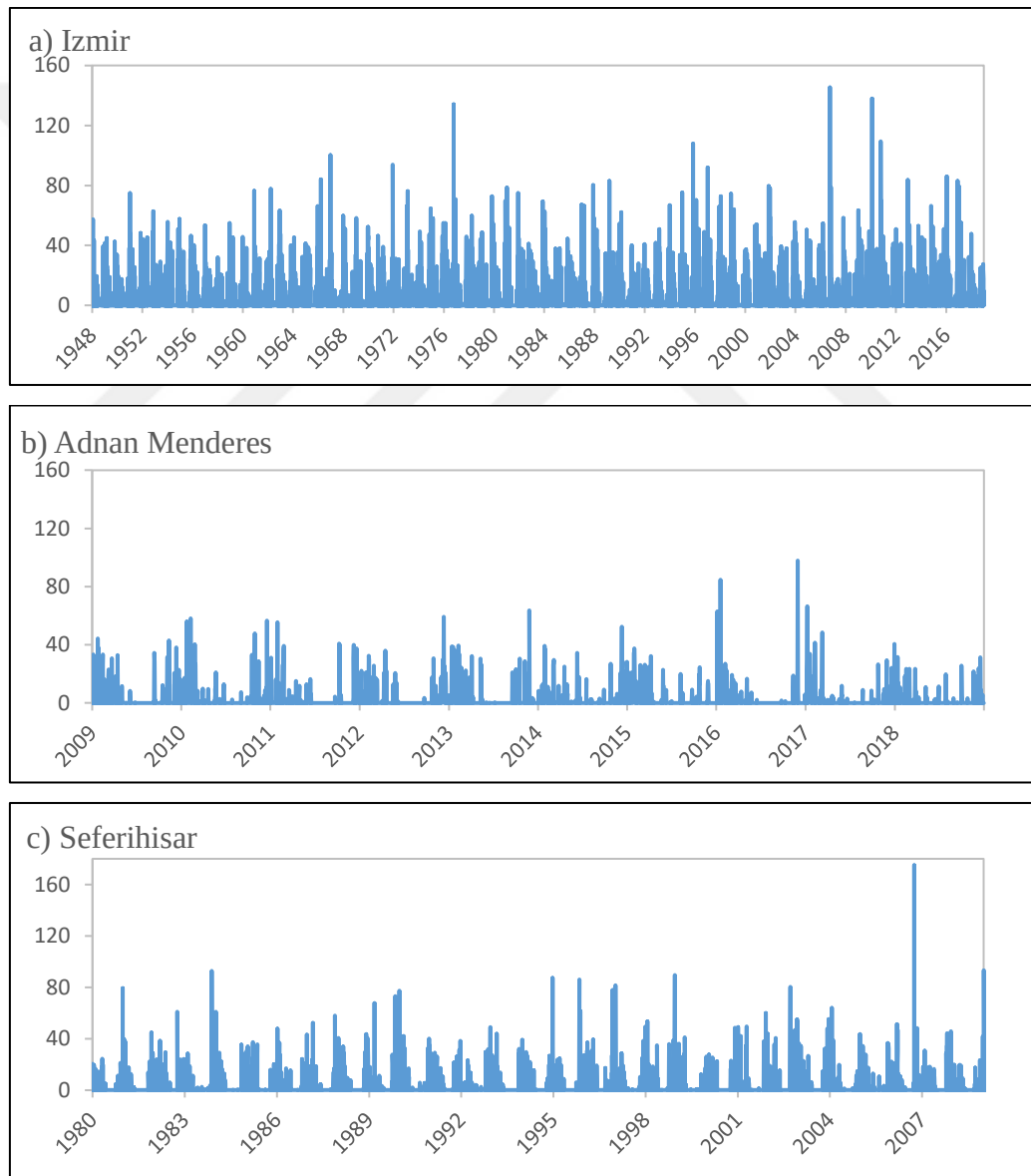


Figure 3.6 The variation of daily rainfall for a) Izmir, b) Adnan Menderes, c) Seferihisar, d) Cesme, e) Selcuk, and f) Odemis stations

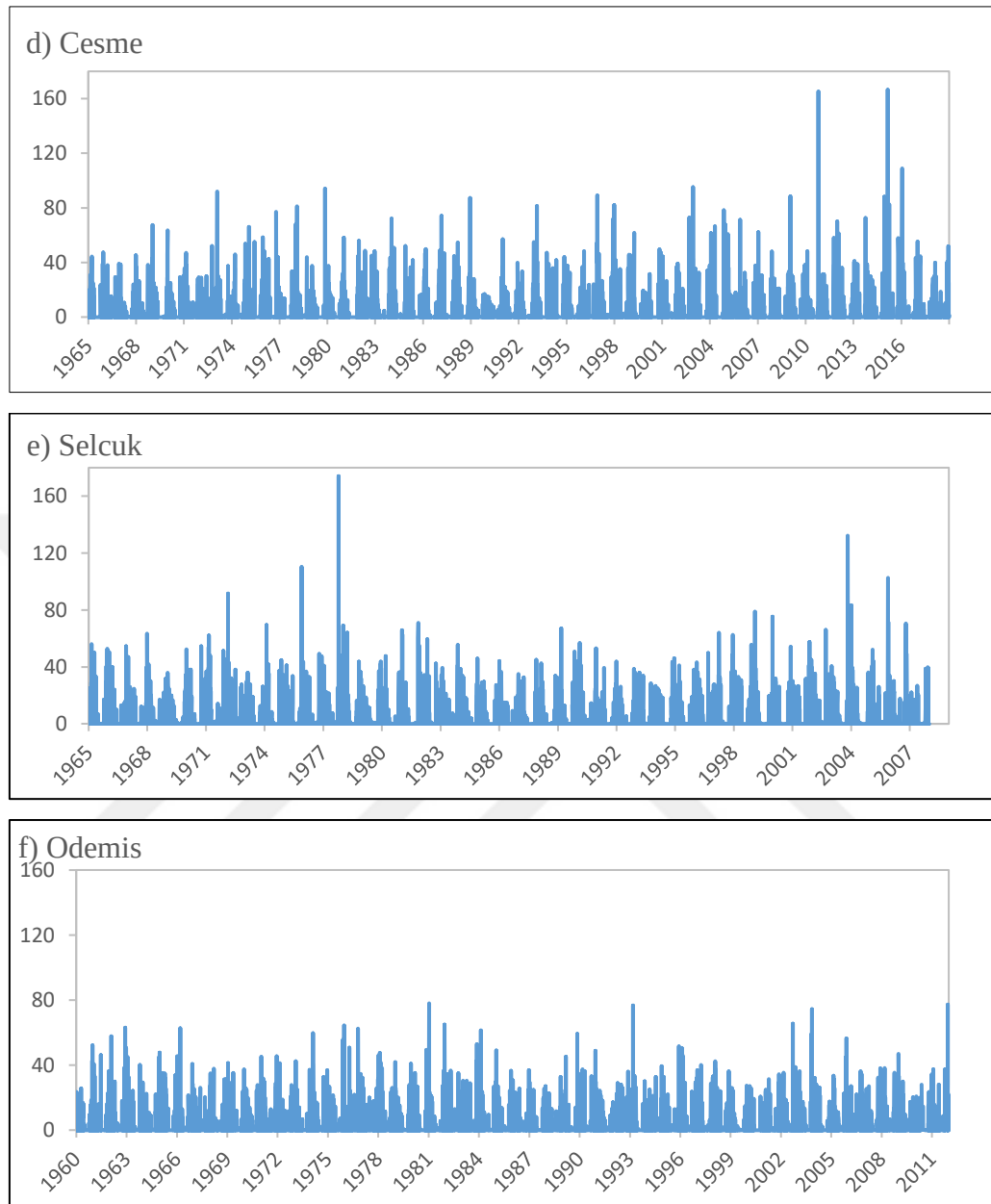


Figure 3.6 continues

3.2.2 Large-scale Reanalysis Variables (Predictors)

Local weather conditions of a region highly depend on the synoptic patterns evolving in three-dimensional large-scale atmospheric coverage over the region. The existing global large-scale atmospheric datasets assimilated to better understand climate change constructs a worldwide historical base for this large-scale coverage. The National Center for Environmental Prediction and National Center for

Atmospheric Research (NCEP/NCAR) distribute reanalysis data of the global atmosphere from 1948 to the present day at $2.5^{\circ} \times 2.5^{\circ}$ resolution (Kalnay et al., 1996a), while the European Centre for Medium-Range Weather Forecasts (ECMWF) produce ERA-Interim Reanalysis dataset from 1979 to today at $1.5^{\circ} \times 1.5^{\circ}$ resolution (Dee et al., 2011). Both datasets have been used as observed data for explanatory data analyses in historical and/or future climate studies. Both datasets were also compared in the context of representation of regional climatic variables, such as precipitation and temperature from Asia (Wang & Zeng, 2012) to Australia (Fu et al., 2016) and from Europe (Mooney et al., 2011) to Africa (L. Druyan & Fulakeza, 2013). The studies concluded that, in general, although each dataset performed almost similar results, the ERA-Interim dataset often reproduced slightly better observed climate relative to the NCEP/NCAR datasets due to the difference in their distinctive spatial resolutions that coarser-resolution smoothens the inter-variability of the observed climatological variables. Also, in terms of the temporal coverage, a longer period is generally preferred in most statistical analyses, and NCEP/NCAR contains 30 years more data, makes itself the preferred dataset. In this study, NCEP/NCAR Reanalysis data was used as observational data for explanatory data analyses in current and future climate studies. (Kalnay et al., 1996b).

Studies using reanalysis data such as NCEP/NCAR are mainly categorized into two different groups. One group regards the dataset as a benchmark relative to the estimations of the historical climate patterns of the Global Circulation Models (GCMs) (Fu et al., 2013; D. Jiang et al., 2016; Plummer et al., 2006; Tolika et al., 2006), while the other group regards the dataset as independent atmospheric variables explaining the dependent local weather variables such as precipitation or temperature via quantitative estimation approaches such as linear or non-linear regression models (Brands et al., 2012; Fistikoglu & Okkan, 2011; Sachindra & Perera, 2016; R. L. Wilby et al., 1999). The reanalysis datasets can also be used to estimate the response of a hydrological system to changing climates (Chen et al., 2012; Okkan & Fistikoglu, 2014).

3.2.2.1 Selected Predictors

There are over 80 climate variables of NCEP/NCAR reanalysis data set in different coordinate systems. There is little agreement on the selection of the most appropriate predictors for downscaling rainfall. Selection the predictors depends on the region, topography, seasonality, atmospheric variables, and the predictand to be downscaled (Anandhi et al., 2009). The first stage in the statistical downscaling is the choice of suitable predictors. Generally, predictors are chosen by a combination of experts' judgments and some statistical measures such as correlation and partial correlation (Anandhi et al., 2009; R. L. Wilby & Wigley, 2000). According to the previous studies (Chen et al., 2010; R. L. Wilby et al., 1999), the predictors can be selected using stepwise regression and analyzing correlation.

In the presented study, the predictors were selected based on three criteria: i) the acceptable correlation with the predictand (daily precipitation), ii) the preference in the previous downscaling studies in the region, and iii) the availability within GCMs. Several ANN models were constructed between the selected predictors and the daily rainfall series to determine which predictors are better suited for downscaling networks. As a result, four atmospheric variables from the NCEP/NCAR Reanalysis dataset, listed in Table 3.6, were selected as predictors. Table 3.7 shows the statistical characteristics of large-scale variables of NCEP/NCAR reanalysis data.

The selected atmospheric variables were extracted from NCEP/NCAR region that covers the coordination ranged from 36.25 °N to 38.75 °N, and 26.25°E to 28.75 °E. Figure 3.1 shows the selected NCEP/NCAR boundaries. The NCEP/NCAR data set represented the Aegean region's atmospheric conditions considerably well (Fistikoglu & Okkan, 2011). The NCEP/NCAR data was downloaded from the website: <http://www.esrl.noaa.gov/psd/data/grided/data.ncep.reanalysis.html>.

Table 3.6 The selected predictors from NCEP/NCAR at Atmospheric surface level

#	Selected variables	Unit	Abbreviation
1	Mean daily air temperature	K	Tas
2	Mean daily sea-level pressure	Pascals	Slp
3	Mean daily v-wind at 10 m	m/s	Vas
4	Mean daily precipitation rate	kg/m ²	Pr

Table 3.7 The statistical characteristics of large-scale variables of NCEP/NCAR (1948 - 2018)

	Tas (K)	Pr (kg/m ²)	Slp (Pascals)	Vas (m/s)
Mean	289.94	1.67	101352	-1.32
Median	289.37	0.01	101305	-1.72
Min	269.2	0.0	98448	-13.5
Max	307.8	43.9	103465	11.8
Std Dev	6.94	3.91	551.47	3.44
Skew	0.04	3.30	0.34	0.46

Figure 3.7 gives the variation of selected atmospheric variables from NCEP/NCAR for air temperature (tas), precipitation rate (pr), sea level pressure (slp) and, v-wind (vas). According to the Mann-Kendall trend test, there is a trend in all selected atmospheric parameters in NCEP/NCAR reanalysis data, as explained in Table 3.8.

Table 3.8 Mann-Kendall test of selected atmospheric variables from NCEP/NCAR

Variable	Z	S	vars	tau	P-value	decision
Tas	7.1	9.88E+06	1.94E+12	2.74E-02	1.22E-12	a + trend
Pr	-31.79	-3.97E+07	1.56E+12	1.45E-01	2.20E-16	a - trend
Slp	10.4	1.44E+07	1.93E+12	4.31E-02	2.20E-16	a + trend
Vas	5.94	8.27E+06	1.93E+12	2.46E-02	2.80E-09	a + trend

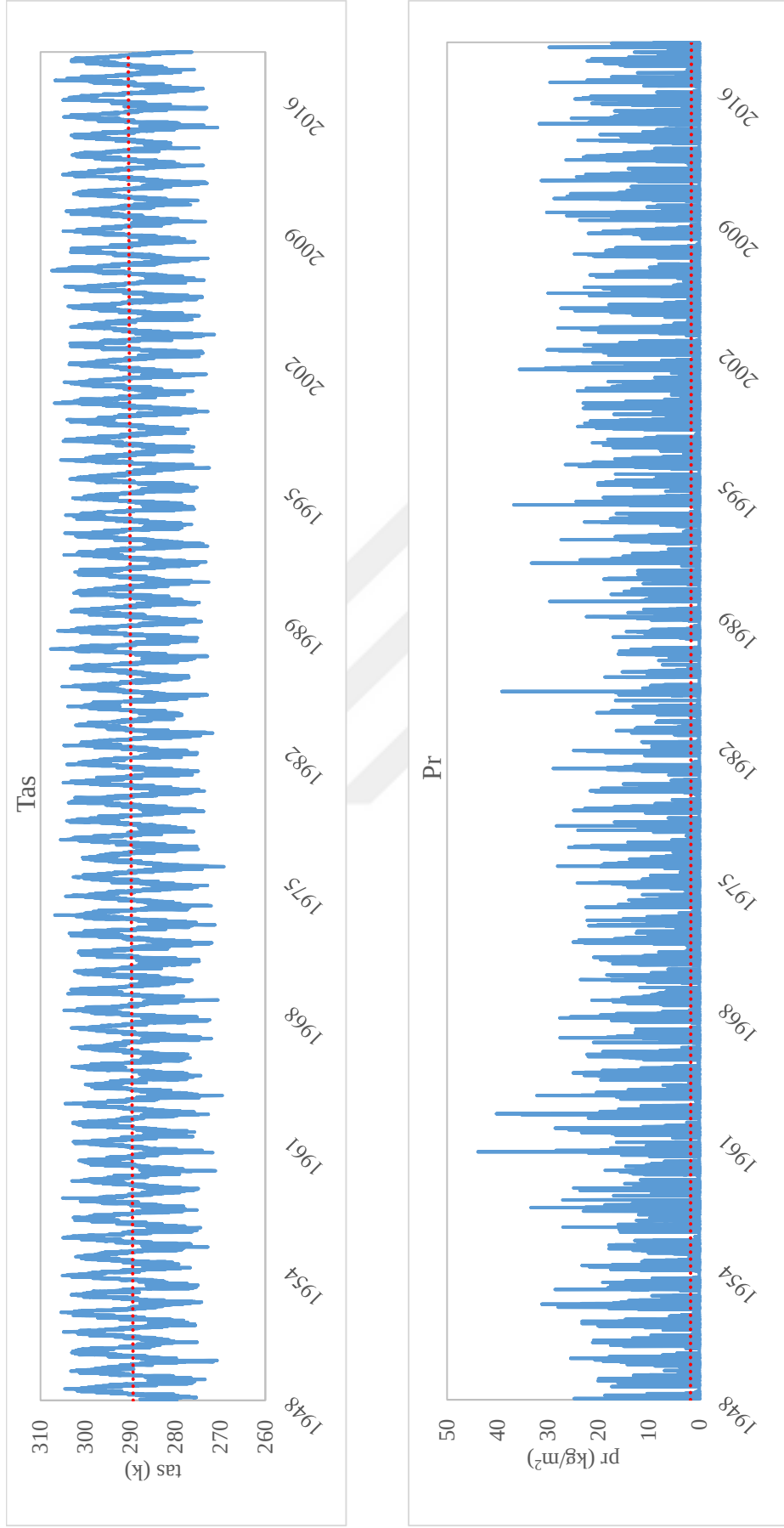


Figure 3.7 The variation of the atmospheric variables from NCEP/NCAR for: a) air temperature (tas), b) precipitation (pr), c) sea level pressure (slp) and, d) v-wind (vas)

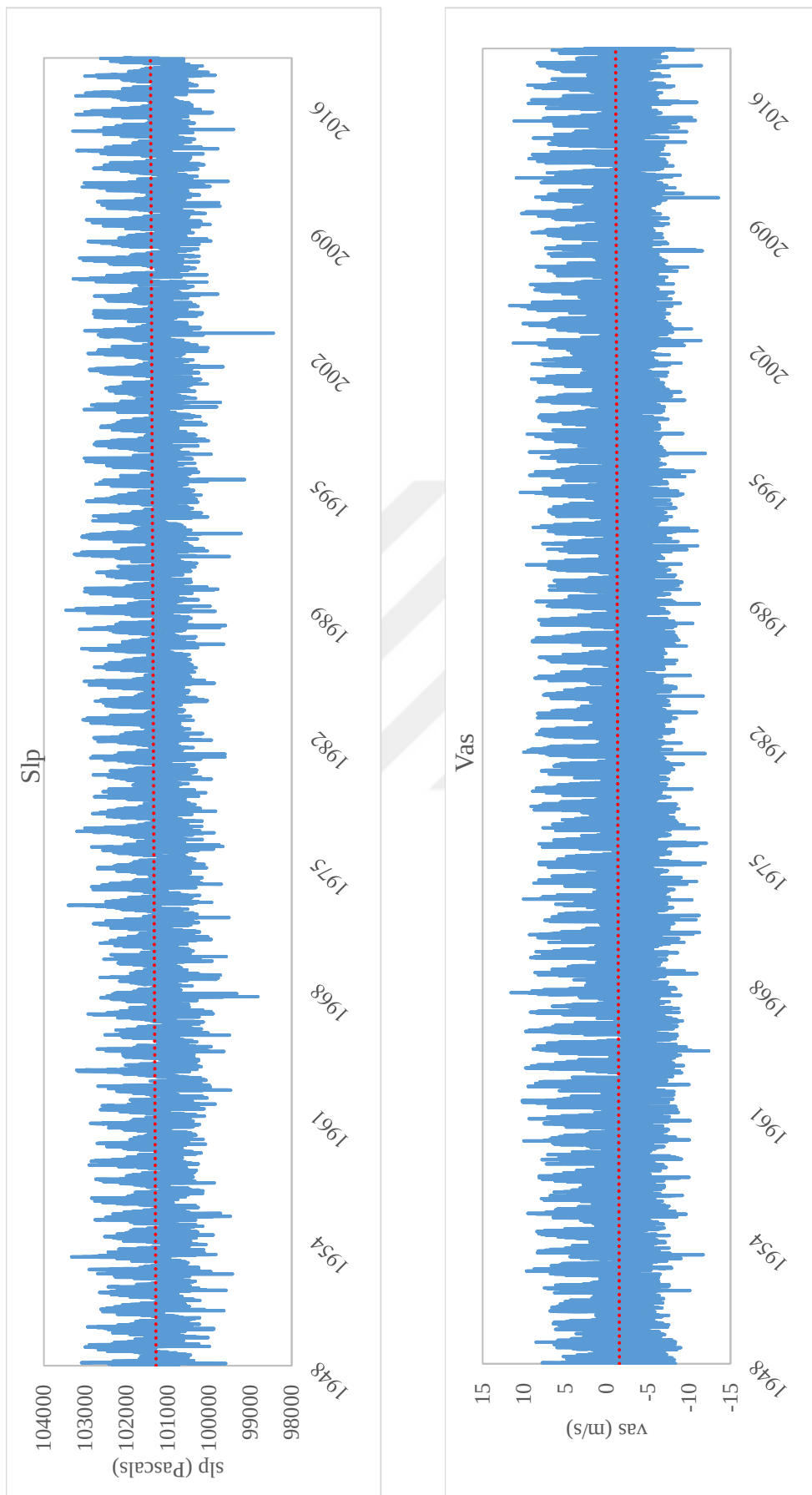


Figure 3.7 continues

3.2.3 Global Climate Models (Future Predictors)

Global Climate Models (GCMs) are commonly used for estimating climate impacts in the future on hydrology climate variables. As mentioned in the fifth assessment report of IPCC, there are 42 GCMs developed by various research centers (Srivastav et al., 2016). It is difficult to state that the performance of the particular climate model is the best representative of a region of interest, although a certain model may provide better results than other models in the case of studying selected climate variables set (Flato et al., 2013).

The scientific community has defined a set of four new scenarios (More information about RCPs scenarios see chapter 2). The CMIP5 set of experiments shares RCP simulations of various GCMs through several gateway websites operated by the Earth System Grid Federation (ESGF). In this study, the historical climate and future simulations subject to RCPs were extracted from [<https://esgf-node.llnl.gov/search/esgf-llnl/>.] website.

In the presented study, the large-scale outputs from four GCMs (listed in Table 3.9) are selected to downscale daily rainfall for the study area. They include historical climate outputs and future climate simulations under the RCP4.5 (intermediate scenario) and RCP8.5 (high GHG emissions scenario). Table 3.10 shows the statistical characteristics of the daily large-scale atmospheric variables for the selected GCMs covering the historical period (1970 – 2005).

Table 3.9 Selected GCMs

	Model	Institution	Country	Resolution (°)
1	HadGEM2-CC	Met Office Hadley Centre, UK	UK	1.25 X 1.875
2	IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	France	1.89X3.75
3	CanESM2	Canadian Center for Climate Modeling and Analysis.	Canada	2.790 X 2.812
4	MIROC-ESM-CHEM	University of Tokyo, National Institute for Environmental Studies (NIES), and Japan Agency for Marine-Earth Science and Technology (JASTEC)	Japan	2.790X2.8125

Table 3.10 The statistical characteristics of selected atmospheric variables of GCMs (1970 – 2005)

a) Tas (k)					
	NCEP/NCAR	CanESM2	HadGEM2- CC	IPSL-CM5A-LR	MIROC-ESM-CHEM
Mean	289.92	292.12	293.20	288.15	290.92
Median	289.41	291.13	294.26	287.35	289.75
Std Dev	6.97	5.14	7.98	6.96	7.05
Min.	271.33	272.66	271.01	267.91	271.73
Max.	307.75	310.9	309.61	303.05	310.93

b) Pr (kg/m²)					
	NCEP/NCAR	CanESM2	HadGEM2-CC	IPSL-CM5A-LR	MIROC-ESM-CHEM
Mean	1.45	0.96	1.83	1.54	1.41
Median	0.01	0.007	0.07	0.00	0.03
Std Dev	3.66	2.66	4.55	3.65	3.24
Min.	0.00	00	0.00	0.00	0.00
Max.	39.12	31.25	65.09	53.89	32.67

c) Slp (pa)					
	NCEP/NCAR	CanESM2	HadGEM2- CC	IPSL-CM5A-LR	MIROC-ESM-CHEM
Mean	101416.73	101617	101161	101662	101724
Median	101360.00	101598	101104	101615	101674
Std Dev	548.86	753	635	748	784
Min.	98448.00	99429	99579	98620	98823
Max.	103465.00	104262	102999	104358	104262

d) Vas (m/s)					
	NCEP/NCAR	CanESM2	HadGEM2-CC	IPSL-CM5A-LR	MIROC-ESM-CHEM
Mean	-1.31	-1.39	-0.79	-0.41	0.06
Median	-1.69	-1.68	-0.87	-0.60	-0.07
Std Dev	3.41	4.52	1.51	3.84	3.48
Min.	-11.94	-19.79	-7.35	-14.07	-13.20
Max.	11.75	16.01	7.34	13.95	12.03

Table 3.11 to 3.14 show the statistical characteristics of the selected large-scale atmospheric variables (tas, pr, slp, vas) covering both historical and future scenarios for RCP 4.5 and RCP 8.5 for HadGEM2-CC, IPSL-CM5A-LR, MIROC-ESM-CHEM, and CanESM2 models, respectively. In the same manner,

Figure 3.8 to 3.11 show the statistics through box plot presentation for the same set of models. For presentation purposes, an example of the HadGEM2-CC model is presented in Figure 3.12 to show the variation of selected a) air temperature (tas), b) Precipitation (pr), c) Sea level pressure (slp), and d) v-wind (vas) atmospheric variables of historical data and projections scenarios (RCP 4.5 and RCP 8).

Table 3.15 clearly shows, a trend was observed in most atmospheric variables (e.g., tas, pr, slp, and vas) in daily dataset series for both the historical and projections data for all GCMs.



Table 3.11 The statistical characteristics of large-scale variables from HadGEM2-CC model of historical and future data under scenarios RCP 4.5 and RCP 8.5

a)Air temperature b)Precipitation c)Sea level pressure d) v-wind

HadGEM2-CC

	Air temperature tas (K)		Precipitation pr (kg/m2/day)		Sea Level Pressure psl (pa)		V-wind vas (m/s)	
	His. 1970-2000	RCP4.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100
Mean	293.20	295.28	1.83	1.83	101161	101105	101067	-0.78
Median	294.26	296.43	0.07	0.06	101104	101068	101038	-0.85
Std Dev	7.98	8.27	4.55	4.63	635	641	650	1.45
Min.	271.01	274.00	0.00	0.00	99579	99572	99371	-5.73
Max.	309.61	313.14	65.09	118.15	102999	103073	102952	6.53

Table 3.12 The statistical characteristics of large-scale variables from IPSL-CM5A-LR model of historical and future data under scenarios RCP 4.5 and RCP 8.5 a) Air temperature b) Precipitation c) Sea level pressure d) V-wind

IPSL-CM5A-LR									
	Air temperature tas (K)			Precipitation pr (kg/m ²)			Sea Level Pressure psl (pa)		
	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100
Mean	288.15	290.34	291.78	1.54	1.37	1.19	101662	101665	101677.17
Median	287.35	289.45	290.94	0.00	0.00	0.00	101615	101597	101597.53
Std Dev	6.96	7.17	7.49	3.65	3.51	3.26	748	785	800.85
Min.	267.91	266.08	267.31	0.00	0.00	0.00	98620	98022	98248.15
Max.	303.05	306.43	310.99	53.89	59.47	65.64	104358	104943	104625.58

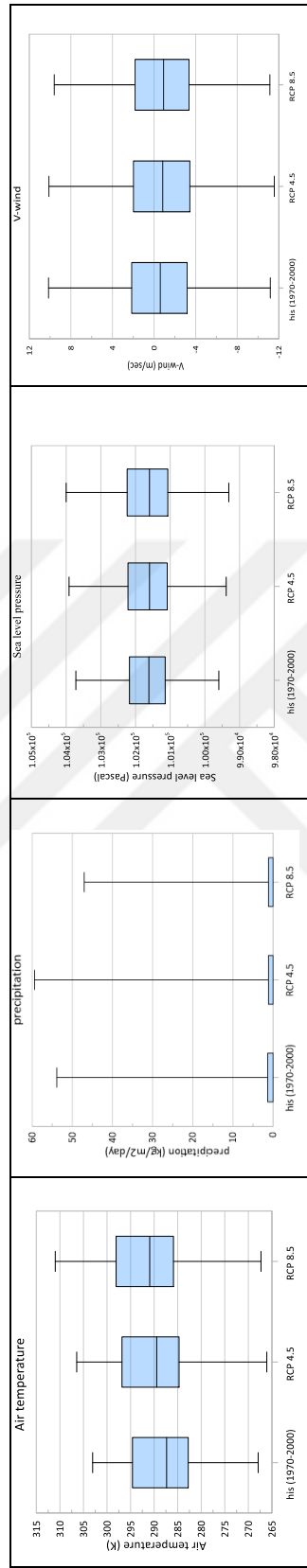


Figure 3.9 Box plot representation descriptive statistic of IPSL-CM5A-LR model for the selected a) Air temperature b) Precipitation c) Sea level pressure, and d) V-wind variables

Table 3.13 The statistical characteristics of large-scale variables in MIROC-ESM-CHEM model of historical and future data under scenarios RCP 4.5 and RCP 8.5 a) Air temperature b) Precipitation c) Sea level pressure d) V-wind

MIROC-ESM-CHEM									
	Air temperature tas (K)		Precipitation pr (kg/m ²)		Sea Level Pressure psl (pa)		V-wind vas (m/s)		
	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100
Mean	290.92	293.92	295.18	1.41	1.11	1.06	0.06	-0.30	-0.35
Median	289.75	292.39	293.65	0.03	0.02	0.01	-0.07	-0.45	-0.48
Std Dev	7.05	7.95	8.55	3.24	2.92	2.91	3.48	3.54	3.43
Min.	271.73	272.47	274.33	0.00	0.00	0.00	-13.20	-14.46	-13.73
Max.	310.93	316.86	318.97	32.67	43.95	38.39	12.03	14.93	13.45

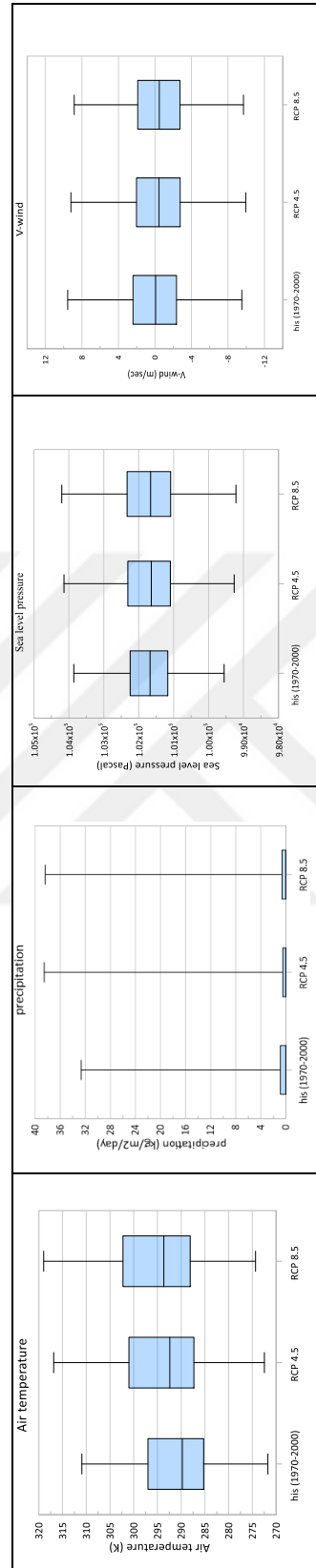


Figure 3.10 Box plot representation descriptive statistic of MIROC-ESM-CHEM model for the selected a) Air temperature b) Precipitation c) Sea level pressure, and d) v-wind variables

Table 3.14 The statistical characteristics of large-scale variables from CanESM2 model of historical and future data under scenarios RCP 4.5 and RCP 8.5 a) Air temperature b) Precipitation c) Sea level pressure d) V-wind

CanESM2

	Air temperature tas (K)			Precipitation pr (kg/m ²)			Sea Level Pressure psl (pa)			V-wind vas (m/s)		
	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100	His. 1970-2000	RCP4.5 2005-2100	RCP 8.5 2005-2100
Mean	292.12	294.13	295.43	0.96	1.014	0.9	101617	101661	101679	-1.39	-0.73	-0.87
Median	291.13	292.62	293.72	0.007	0.009	0.006	101598	101602	101617	-1.68	-0.86	-0.98
Std Dev	5.14	7.22	7.83	2.66	2.82	2.63	753	817	836	4.52	3.92	3.85
Min.	272.66	274.94	274.35	0.00	0.00	0.00	99429	98841	99082	-19.79	-17.83	-19.2
Max.	310.9	316.86	318.97	31.25	46.14	31.41	104262	104493	104947	16.01	15.01	15.93

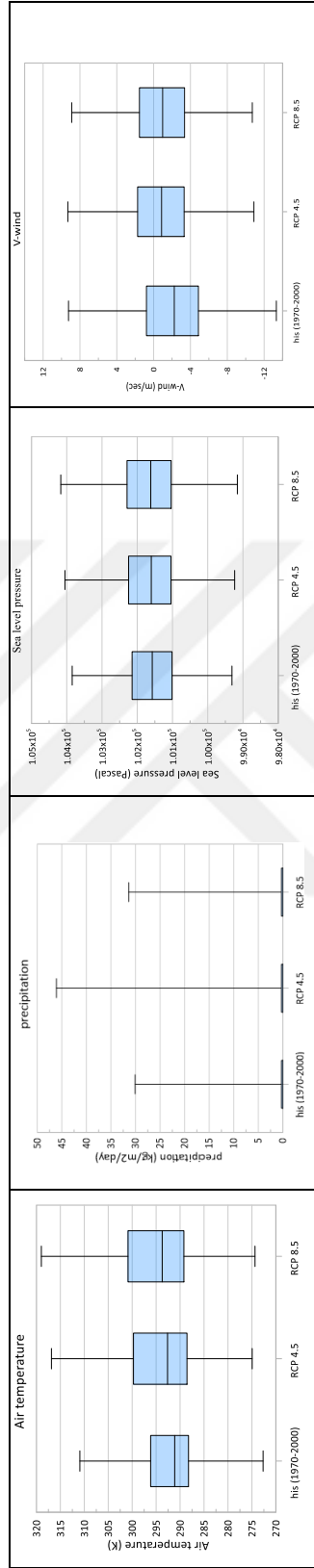


Figure 3.11 Box plot representation descriptive statistic of CanESM2 model for the selected a) Air temperature b) Precipitation c) Sea level pressure, and d) V-wind variables

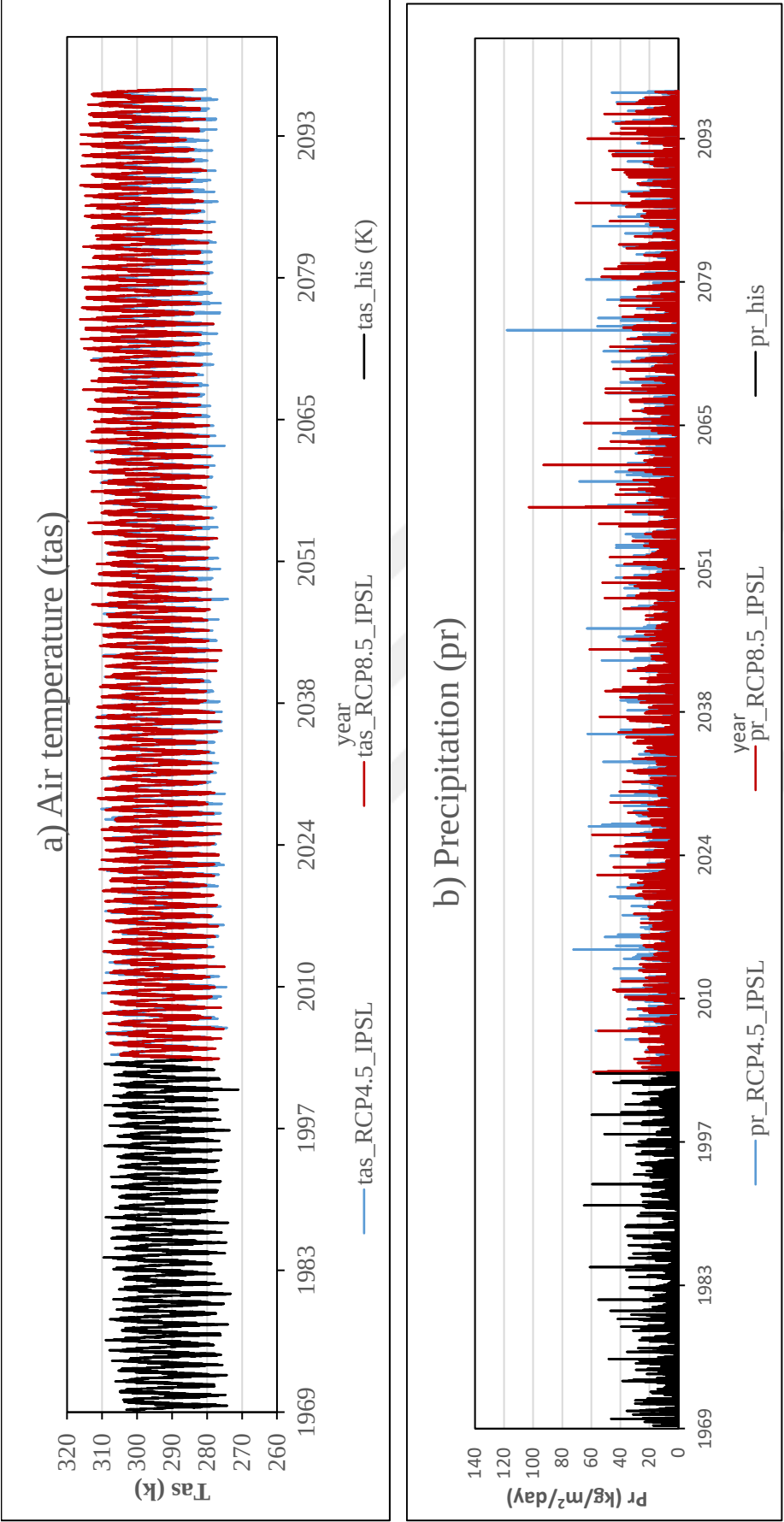


Figure 3.12 The variation of selected atmospheric parameters from HadGEM2-CC model. a) Air temperature (tas), b) Precipitation (pr), c) Sea level pressure (slp) and, d) V-wind (vas)

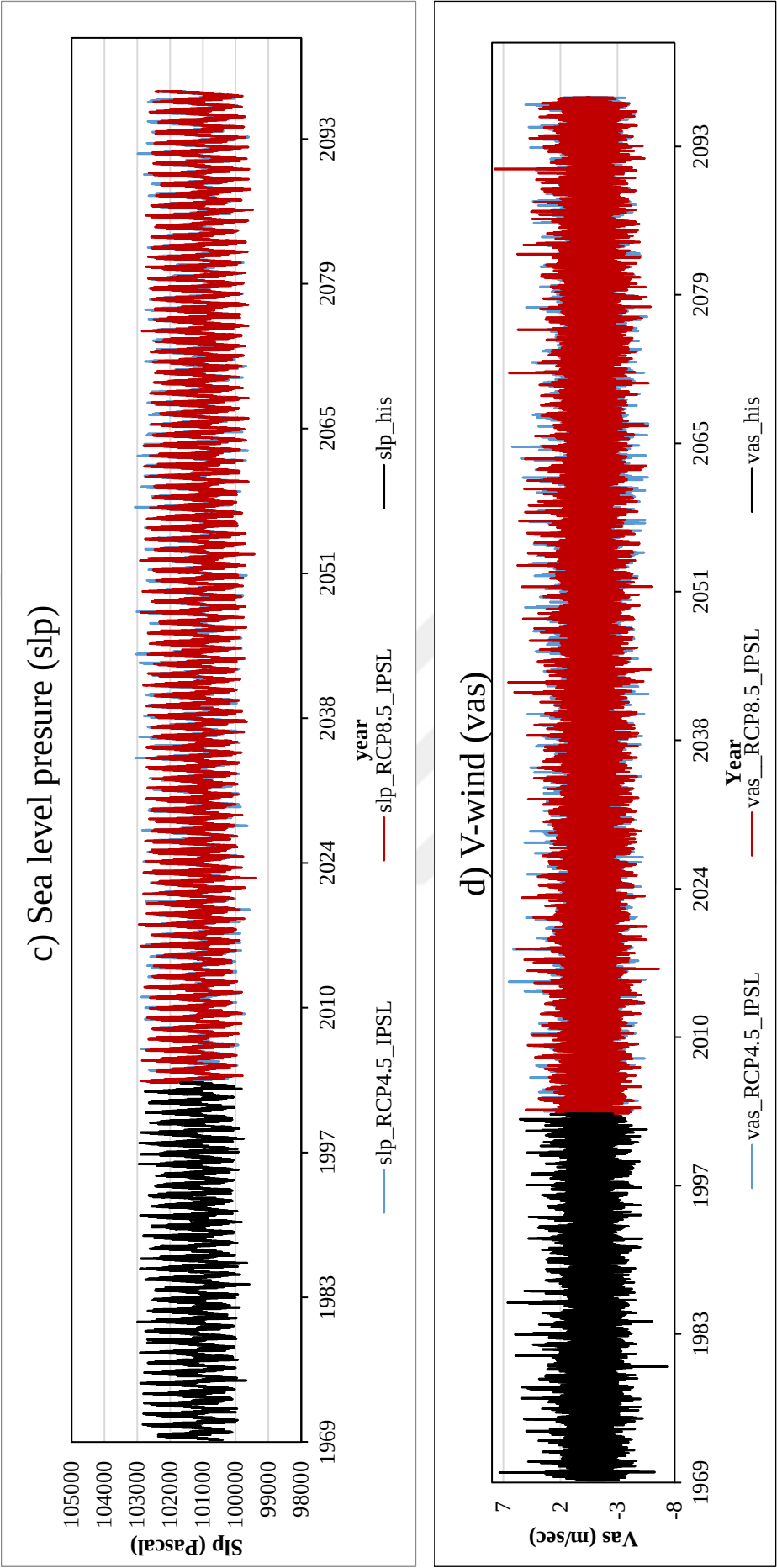


Table 3.15 Mann-Kendall trend test P-value for all variables selected in both historical and future data sets

	tas (K)		pr (kg/m ² /day)		slp (pa)		vas(m/s)		
	his.	RCP4.5	RCP 8.5	his.	RCP4.5	RCP 8.5	his.	RCP4.5	RCP 8.5
canESM2	2.2E-16	2.2E-16	2.2E-16	0.861	5.3E-06	2.2E-16	0.007	3.62E-07	2.20E-16
HadGEM2-CC	8.5E-7	2.2E-16	2.2E-16	0.037	7.7E-13	2.2E-16	1.2E-04	0.000557	2.20E-16
MIROC-ESM-CHEM	3.3E-7	2.2E-16	2.2E-16	0.705	2.2E-16	2.2E-16	0.322	0.5581	0.000204
IPSL-CM5A-LR	2.2E-4	2.2E-16	2.2E-16	1.1E-4	2.2E-16	2.2E-16	6.6E-02	0.000302	4.91E-05
								7.8E-05	0.264
							0.714	7.8E-05	0.264
							2.1E-02	0.725	0.097
							0.661	5.5E-08	2.2E-16
							1.3E-02	9.9E-06	2.2E-16

*If the p-value is less than the significance threshold (0.05), the decision is the reject the null hypothesis. Ho: that there is no trend in the series. Underline variables mean no trend.

CHAPTER 4

METHODOLOGY

4.1 The Framework of the Methodology

The framework of the methodology consists of six steps, four of which are related to constructing a model to derive the IDF curve from the current climate using NCEP/NCAR dataset, and the remaining two steps are related to deriving the IDF curve for future climate conditions using GCMs outputs. Figure 4.1 and 4.2 summarize the relationship between the steps of the methodology.

The first step involves constructing three downscaling ANN models to downscale the large-scale NCEP/NCAR Reanalysis data into station-based daily rainfall series within the study area. The best ANN structure is then determined based on the performance yield from statistical performances (e.g., R^2 , RMSE). The second step focuses on correcting the bias of the estimated annual maximum (AM) daily rainfall values sampled from the downscaled daily rainfall series by the best ANN model. This step is followed by the estimation of the annual maximum (AM) 24-hour rainfall values from the AM daily values using the observed proportions between them. Then disaggregation the AM 24-hour rainfall into the standard-duration rainfall depths using disaggregation techniques. The next step estimates the IDF curves of the study area using the probability distributions fitted to the standard-duration rainfall heights. See Figure 4.1.

The fifth and sixth steps are used for the estimation of IDF curves for future climate conditions, the fifth step is applied to correct the bias in GCM variables, and the sixth step where the repetition of the previously explained steps (from step one to four) take place to derive the future IDF curve under RCP 4.5 & 8.5 climate conditions. See Figure 4.2.

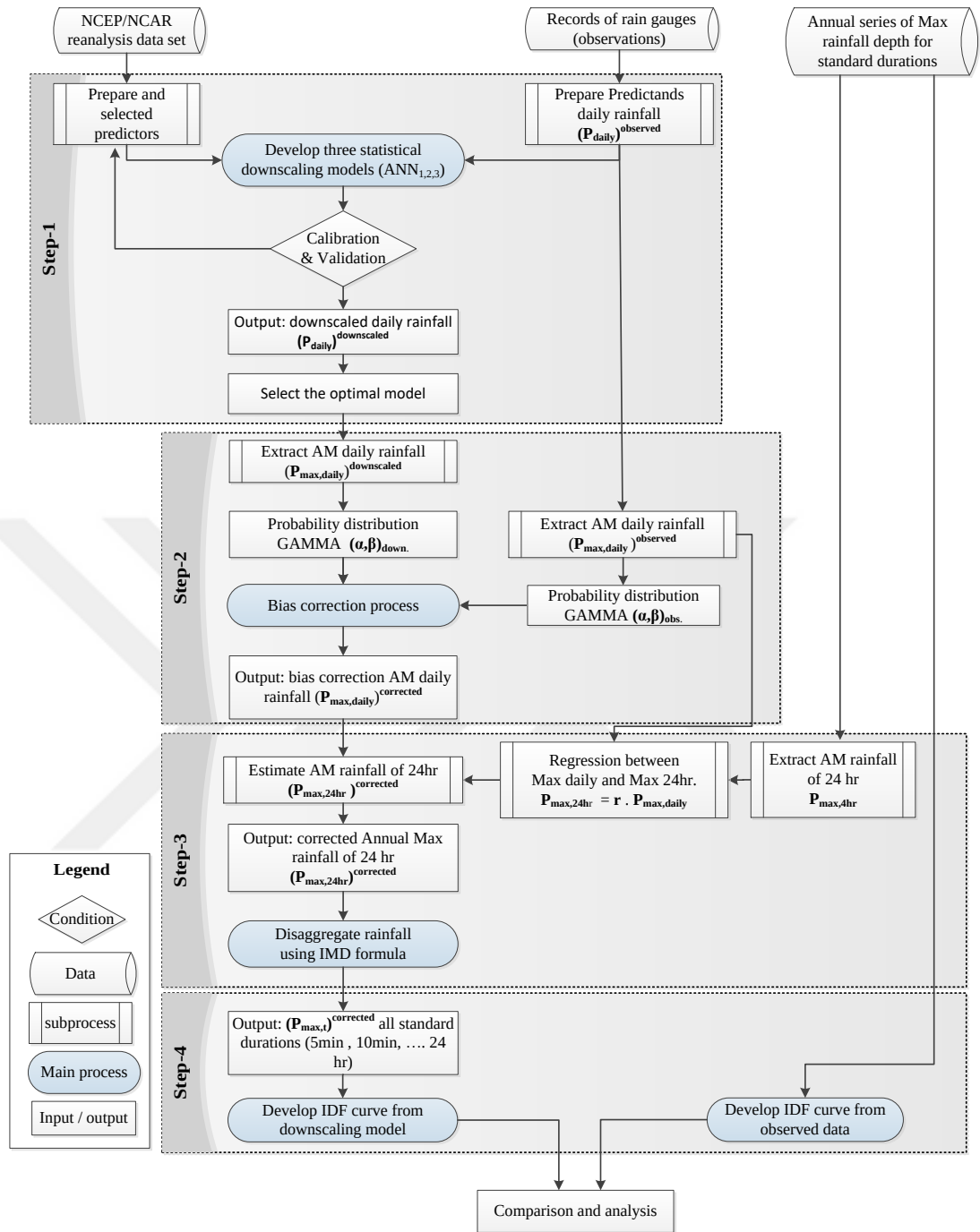


Figure 4.1 The flow chart of the methodology for historical climate conditions

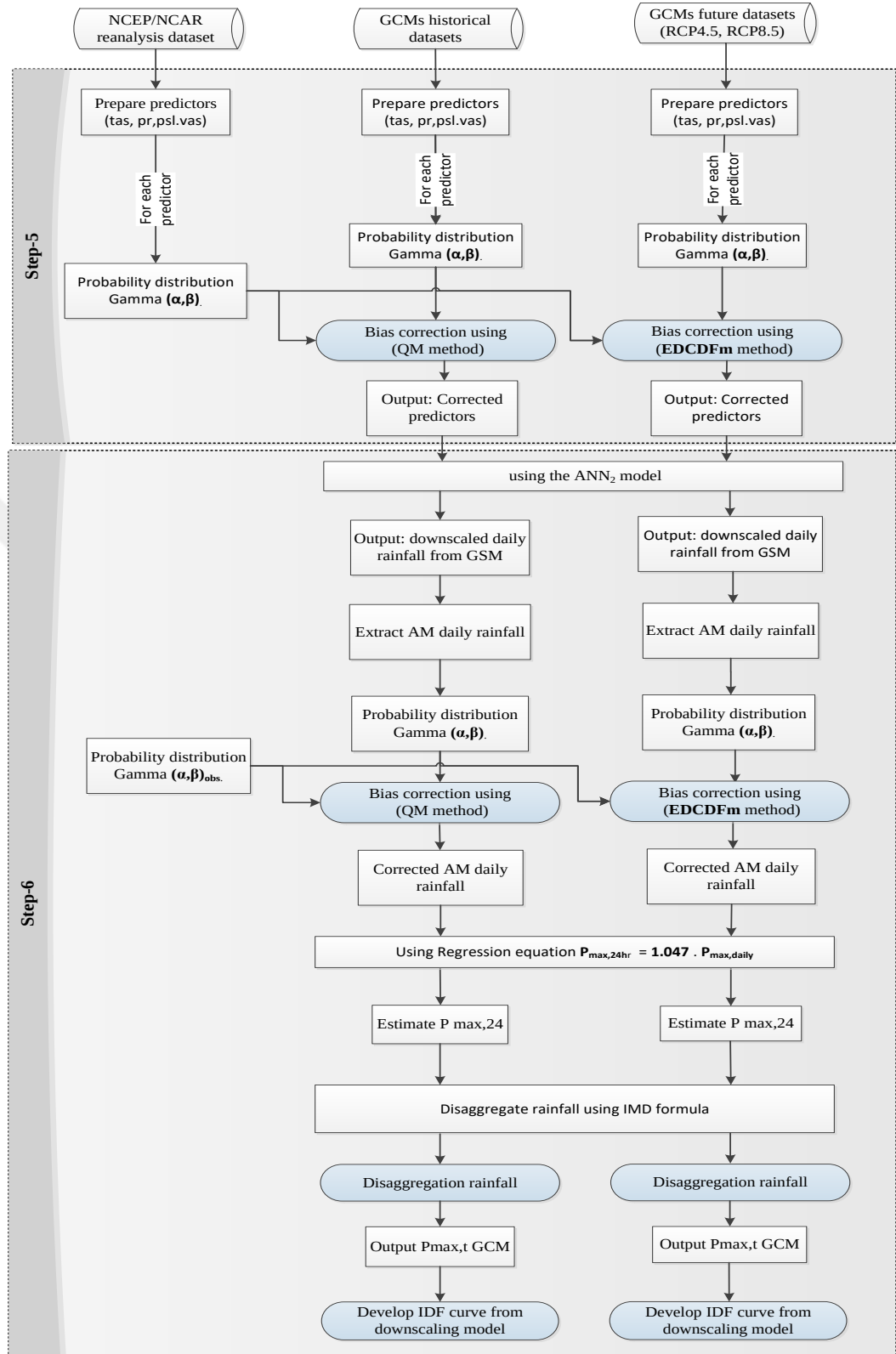


Figure 4.2 The methodology for future climate projections

As shown in the Figure 4.1 and Figure 4.2, three main approaches were used in this study to achieve the aims i) statistical downscaling approach for spatial downscaling, ii) bias correction technique for correct the downscaling outputs and GCMs variables, and iii) Rainfall disaggregation approach (temporal downscaling) to disaggregate the daily rainfall to sub-daily.

4.2 Downscaling Technique

The hydrological variables from large-scale atmospheric data (Reanalysis data or GCMs) are often unreliable for the regional and local range. Therefore one of the common solutions to overcome this obstacle is using downscaling techniques. The estimation of local weather variables (i.e., precipitation and temperature) from large-scale atmospheric data is termed downscaling. The main idea of downscaling is to transfer large-scale atmospheric variables (predictors) into local weather parameters (predictands) (Fistikoglu & Okkan, 2011; Liu et al., 2016).

Several downscaling approaches were developed, such as dynamical downscaling and statistical downscaling. The dynamical downscaling is associated with the physically-based Regional Climate Models (RCMs), where the GCM results constitute the model domain's boundary conditions. It is computationally intensive, complex, and requires substantial computational resources (Murphy, 1999; Trzaska & Schnarr, 2014). Statistical downscaling (SD) utilizes statistical relationships to predict local climate variables from large-scale variables. SD aims to create quantitative relationships between large-scale atmospheric variables and local variables (Fistikoglu & Okkan, 2011). Although the statistical downscaling methodologies have many obvious drawbacks, like the uncertain assumption of applicability in a future climate (Liu et al., 2016), it is still a computationally reasonable and statistically sound complement compared to dynamical downscaling. (Trzaska & Schnarr, 2014).

Transfer functions, weather classification methods, and weather generators are the main categories of statistical downscaling approaches (Khan et al., 2006; Trzaska & Schnarr, 2014), with transfer functions being the most commonly used category

(Schoof et al., 2007). Some examples of transfer functions include linear and non-linear regression, principal component analysis (PCA), canonical correlation, redundancy analysis, and Artificial Neural Networks (ANN) (Benestad et al., 2007; Fistikoglu & Okkan, 2011).

Numerous intercomparison studies have been conducted among different approaches in order to assess their results with respect to local weather and regional climate. These studies reveal that each approach shows a varying degree of accuracy, and there is no agreement on which is the best approach (L. Sun & Lan, 2020). Recently, several studies have proven that ANN-based transfer functions are successful at downscaling climatic variables statistically.

4.2.1 Downscaling Using ANN:

ANN was used as a well-known machine learning technique to estimate the observed daily rainfall from the large-scale atmospheric reanalysis parameters (R. L. Wilby et al., 1998). The ANN was utilized as a practical black-box tool for developing a non-linear regression between the large-scale atmospheric dataset (predictors) and observed daily rainfall (predictands) (Harpham & Wilby, 2005; Khan et al., 2006).

As some earlier studies (Harpham & Wilby, 2005; R. L. Wilby et al., 1998) concluded that ANN is not the best statistical approach due to its exclusion of the antecedent days' atmospheric parameters as inputs and the lack of bias correction of the downscaled estimations. In the presented study, in order to get over the previously mentioned weaknesses and to increase the performance of ANN model, two points are considered i) the antecedent atmospheric variables are taken into consideration as an input, and ii) a post bias correction process is applied to the produced results of the ANN model.

Details of the ANN-based downscaling method were reported by Fistikoglu and Okkan (2011), and its application in hydrological science was reviewed in the ASCE

report (ASCE, 2000). ANNs were used effectively for the daily rainfall and monthly rainfall estimations (Nourani et al., 2019; Okkan & Fistikoglu, 2014; Vu et al., 2016).

4.2.2 Building Artificial Neural Networks

The ANN structure designed consists of three types of layers; The first is an input layer with n neurons for each variable; here, the input layer is the one where the predictors (large-scale atmospheric variables) were defined. The second layer represents the hidden layer which contain several neurons, and all hidden neurons transform the inputs nonlinearly into another dimension through weight and a bias term shown in Eq. (4.1). In this study, the assumption that the number of neurons is double the number of predictors was accepted (by applying the trial and error technique). The last layer is the output layer (predictand) which in this study contains daily precipitation variables from station records. See

Figure 4.3.

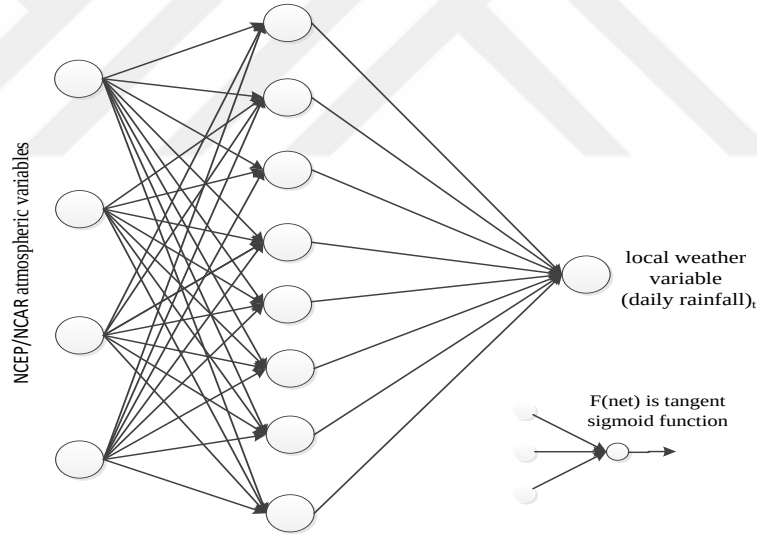


Figure 4.3 Artificial neural network (ANN) architecture

$$y_k = f_2 \left(\sum_{j=1}^k \left[f_1 \left(\sum_{i=1}^n x_i w_{ij} + w_j \right) \right] w_{jk} + w_k \right) \quad (4.1)$$

Where : y_k : output ($j=1,2, \dots, k$), x_i : input ($i=1,2,\dots,n$), w : bias value, $f_{1,2}$ are activation function at the hidden and output layer.

Three popular transfer functions are tried out in ANN construction trials: tangent sigmoid, linear, and log-sigmoid. In this study, the tangent sigmoid function was found suitable. See Eq. (4.2).

$$f(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}} \quad (4.2)$$

The search for the best value of weights and biases is referred to as ANN training phase, which is carried out with a known input and output set. Each training phase involves a set of inputs passed forward through the network to generate trial outputs then compared it to observed outputs. When the residual (difference between trial and observed outputs) exceeds the desired value, the error is passed back to the network. Once the comparison error has been reduced to an acceptable level for the entire training set, the training phase is complete. After training, the network is evaluated using a set of cases withheld from it during the training session. After the model was completed, it was ready to be applied to any other situation.

The training algorithm adjusts the connection weights based on the error. This process is referred to as back-propagation. The network is trained using the Levenberg-Marquardt feed forward-back-propagation algorithm, as shown in Eq. (4.3). The Levenberg-Marquardt feed forward-back-propagation algorithm is a second-order non-linear optimization technique which is typically faster and more reliable than any other back-propagation methodology (Fistikoglu & Okkan, 2011).

$$\Delta w = - [J^T(w)J(w) + \mu I]^{-1} J^T(w)e(w) \quad (4.3)$$

J = Jacobian matrix, w is parameter vector, μ is Marquardt parameter.

4.2.3 Predictors and Predictant

As a simple form, the statistical downscaling models can be defined as $Y = f(X)$, where: Y is predictand and X is predictors. In this study, the predictand (output data)

is the small-scale variable representing daily rainfall from meteorological stations in Izmir city. The predictors (input data) are the large-scale atmospheric variables.

The selected atmospheric variables are air temperature (tas), precipitation rate (pr), sea level pressure (slp), and v-wind (v-wind) at surface level (for more information about these variables, see chapter 2).

The ANN downscaling model was built using large-scale variables NCEP/NACR reanalysis datasets as predictors and the observation records of daily rainfall for Izmir station as predictand in the period between 1948 to 1990 (training period), while the period of 1991-2018 was used for validation for the same station (testing period). In addition to that, downscaled results were compared with the five neighbor stations' observations for spatial validation purposes of the downscaling model. After validating the model, the large-scale variables from GCMs are used as future predictors to estimate the future daily rainfall for Izmir station.

As the past and present large-scale atmospheric conditions on a daily basis influence on the present local weather conditions. Therefore the present and the antecedent large-scale atmospheric variables take in considered as input in the daily downscaling networks in this study. (Coulily et al., 2005). Therefore, in this study, three statistical downscaling models were tested using the past and present atmospheric conditions, as illustrated in Table 4.1.

Table 4.1 The predictors and predictant of the three ANN models

Predictors (Input)	ANN-based statistical downscaling model	Predictant (Output)
Daily large-scale atmospheric variables on day t. (tas, pr, slp, vas)_t	1 st Model (ANN ₁)	Daily precipitation
Daily large-scale atmospheric variables on days t and t-1. (tas, pr, slp, vas)_t, (tas, pr, slp, vas)_{t-1}	2 nd Model (ANN ₂)	Daily precipitation
Daily large-scale atmospheric variables on days t, t-1, and t-2. (tas, pr, slp, vas)_t, (tas, pr, slp, vas)_{t-1}, (tas, pr, slp, vas)_{t-2}	3 rd Model (ANN ₃)	Daily precipitation

Table 4.1 tabulates the three different models related to different input variable sets to downscale the daily precipitation. In the first model (ANN₁), the daily atmospheric variables on the current day (t) of the study are used as input (predictors). In the second model (ANN₂), the atmospheric variables of the previous day (t-1) and the current day (t) are used as predictors. In the third model (ANN₃), like the second model's input variables, two previous days were employed, meaning that the atmospheric variables of the two-day previous (t-2) and one day previous (t-1) as long the current day (t) are used as predictors.

To evaluate the performance of the three downscaling models, R² and RMSE were utilized as shown in Eq.(4.4) and Eq.(4.5) for choosing the optimal model that is taken into consideration in the estimation of daily rainfall.

$$R^2 = 1 - \frac{\sum_{i=1}^n (\text{observed } (i) - \text{predicted } (i))^2}{\sum_{i=1}^n (\text{observed } (i) - \text{mean})^2} \quad (4.4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\text{predicted } (i) - \text{observed } (i))^2}{N}} \quad (4.5)$$

4.3 Bias Correction for the Current and Future Climate

Climate modeling is an important tool for examining future climate change, but the model outputs often have some bias (McGinnis et al., 2015). Besides, the uncertainties associated with climate change impact assessment are relatively high. For these reasons, the raw data should be handled with caution and applying the necessary correction procedures (Christensen et al., 2008).

Also, it is critical to realize that statistical downscaling models are unlikely to provide highly accurate results. Where downscaling increases the uncertainty in GCMs outputs due to added assumptions that included during the downscaling process (Trzaska & Schnarr, 2014). For that reason, the estimated variables from downscaling models are rarely used directly. Thus, bias correction is a necessary application to treat

the uncertainties in downscaling model results. Bias correction methods are applied to help remedy the various problems with biased model outputs. Bias correction procedures employ a transformation algorithm for adjusting model outputs.

In recent decades, Several bias-correction approaches were developed. Teutschbein & Seibert (2012) reviewed and evaluated the different bias correction methods. They found that the quantile mapping (QM) method corrects most of the statistical characteristics of the downscaled outputs and the QM method is the best correction method compared to other methods. The core concept of QM method involves correcting the downscaled outputs based on the observed distribution function, which can be realized by shifting the downscaled model's outputs to the observed records with the same probability of non-exceedance. This method can be explained in Eq.(4.6). The procedure of the QM also can be illustrated graphically in Figure 4.4 below.

$$X_{mod_corrected} = F_{obs}^{-1}(F_{mod}(X_{mod})) \quad (4.6)$$

Where : X variables, F :Cumulative distribution function (CDF), F^{-1} The inverse of CDF, *obs*: observed, *mod*: model data.

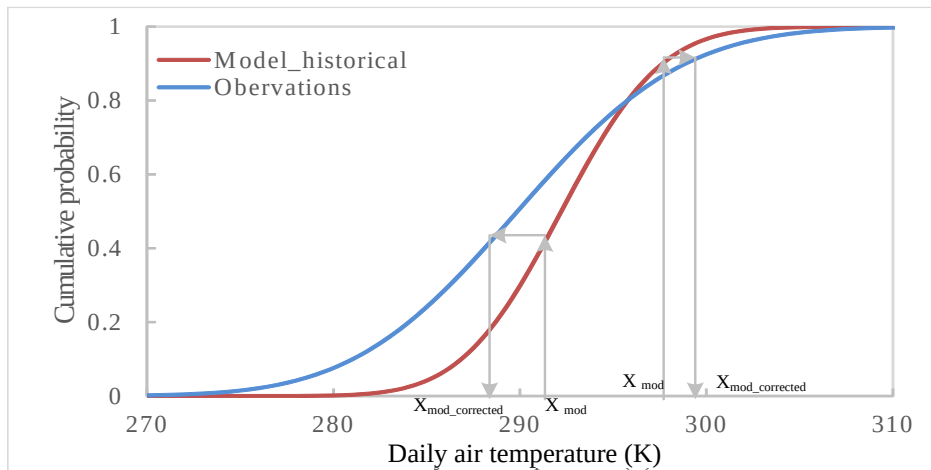


Figure 4.4 Exemplary procedures of QM method graphically

However, one of the main disadvantages in QM method is that this method assumes the distribution of variables remains constant throughout time. Meaning, it does not

take into consideration the distribution of the future modeled variables. For these reasons, this method can be used only in historical and current data, but this method cannot be applied in future model projections.

For future climate projections, Li et al. (2010) suggested the equidistant cumulative distribution function matching (EDCDFm) method to improve the traditional method (QM). EDCDFm takes into consideration the change of the distribution of the parameters in the future. Guo et al. (2018) concluded that the EDCDFm method is more sensitive for reducing variability and bias in comparison with the quantile mapping method. Recently several studies have used EDCDFm to bias-correct precipitation, e.g., (Guo et al., 2018; Lafon et al., 2013; Pierce et al., 2015; Requena et al., 2021). This method can be expressed as Eq. (4.7). Also, the procedure of the EDCDFm method can be graphically illustrated in Figure 4.5.

$$X_{mod-f_corrected} = X_{mod-f} + \left[F_{obs-h}^{-1} \left(F_{mod-f} (X_{mod-f}) \right) - F_{mod-h}^{-1} \left(F_{mod-f} (X_{mod-f}) \right) \right] \quad (4.7)$$

Where, X : variables, F : Cumulative distribution function (CDF), F^{-1} The inverse of CDF, obs : observed, mod : model data, f : future data, h : historical data.

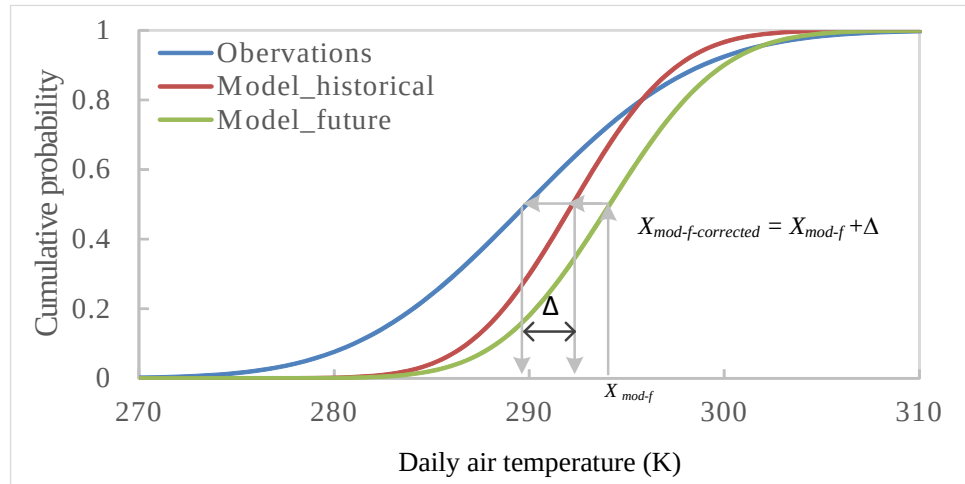


Figure 4.5 Exemplary procedures of (EDCDFm) method graphically

In this study, bias correction was applied in two steps; the first step aims to correct the raw GCMs variables such as air temperature and precipitation. Here, the presented

study, in accordance with some previous literature to correct large-scale bias (e.g., (Sachindra & Perera, 2016)), NCEP/NCAR reanalysis time series was employed as a reference to correct biases in GCMs outputs at the daily level. Despite both GCM and reanalysis outputs contain biases. Yet, GCM outputs are more bias than reanalysis outputs. This is because the quality of NCEP/NCAR reanalysis dataset is controlled and corrected against observations. While the second step is to correct results produced from the downscaling process. To this end, the quantile mapping (QM) method is used for the historical data, and the EDCDFm method is employed for future projections.

4.4 Estimation of the Annual Maximum 24-hour Rainfall

The annual maximum (AM) daily rainfall ($P_{\max, \text{daily}}$) is different from the AM 24-hour rainfall ($P_{\max, 24}$). The ($P_{\max, \text{daily}}$) is the rainfall height observed in a calendar day while the ($P_{\max, 24}$) is the rainfall height observed in 24 hours durations that might not overlap with the calendar day duration. Although they are different rainfall events, most heavy rainfall heights assigned as 24-hour rainfall may occur on a calendar day. The relation between $P_{\max, 24}$ and $P_{\max, \text{daily}}$ is given as in Eq.(4.8).

$$r = P_{\max, 24} / P_{\max, \text{daily}} \quad r \geq 1.0 \quad (4.8)$$

The empirical ratio (r) is reported as 1.13 for the US by NWS analysts (Bureau, 1953). According to Huff & Angel (1992), this ratio is between 1.01 to 1.13. In the presented study, this empirical relationship is applied to convert $P_{\max, \text{daily}}$ to $P_{\max, 24}$, it worth mentioning that both $P_{\max, \text{daily}}$ and $P_{\max, 24}$ are the outputs of the downscaling model.

4.5 Disaggregation of P_{24} to Shorter Standard Duration Rainfall

The establishment of IDF curves requires the rainfall heights to have a shorter duration than 24 hours. Shorter duration rainfalls, called standard duration rainfall, are the annual maximum rainfall height observed during storm durations, such as 5 mins, 10 mins, 15 mins, 30 mins, 1 hour., 24 hours. The common approach to determine

maximum rainfall heights at standard duration (d) requires calculating the maximum slope ($\Delta P/d$) on each year's pluviograph records. If the pluviograph records do not exist, empirical formulas between rainfall heights at standard durations and 24-hour can be used to estimate the standard durations' maximum rainfall heights. This study examines three approaches for disaggregation AM daily rainfall; these methods are explained as follow:

The Indian Meteorological Department (IMD) utilizes an empirical formula Eq. (4.9) to estimate the short-duration rainfall heights from 24-hour rainfall (Al Mamun et al., 2018). This formula has been used in several studies (Chowdhury et al., 2007; Jahnavi et al., 2014). As an example, Figure 4.6 illustrates rainfall distribution for Izmir station using the IMD formula.

$$P_d = P_{24hr} \left(\frac{d}{24} \right)^{(1/3)} \quad (4.9)$$

Where P_d : the rainfall depth (mm) at duration d (hr), P_{24hr} : rainfall depth in 24 hours (mm).

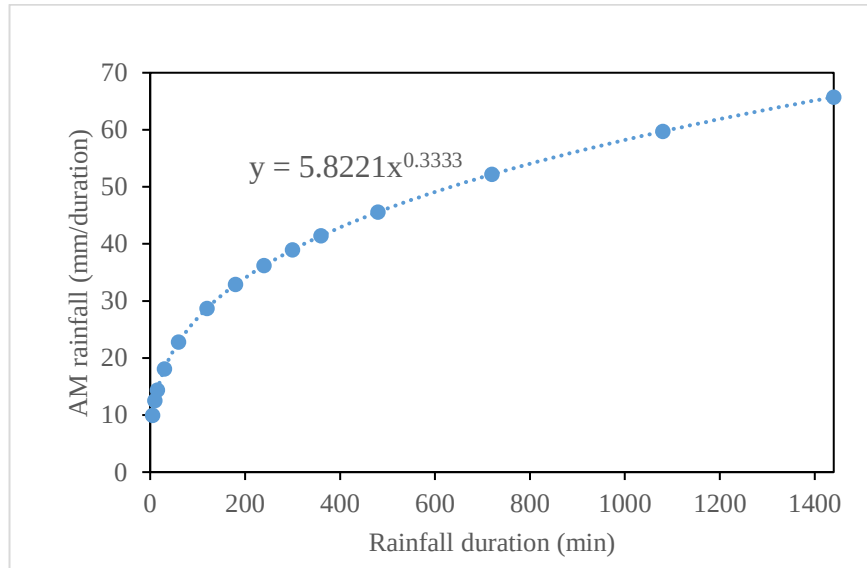


Figure 4.6 The shape of AM rainfall distribution using the IMD formula for Izmir station

The Temporal Distribution of Rainfall (TDR) is the ratio between mean values of the maximum rainfall in duration (d) to the maximum 24-hour rainfall amount. This

method was used as an alternative method to disaggregate 24-hr rainfall into standard short duration in this study. It is worth to mention here that this method can only be applied in case of a sufficient amount of observations are available.

Huff and Angel (1992) analyzed records of 34 rain gauges in Illinois, USA, then propose the empirical ratio for every duration for estimating short-duration rainfall. (Huff & Angel, 1992). Figure 4.7 illustrates the shape of rainfall distribution using Huff and Angel empirical ratio.

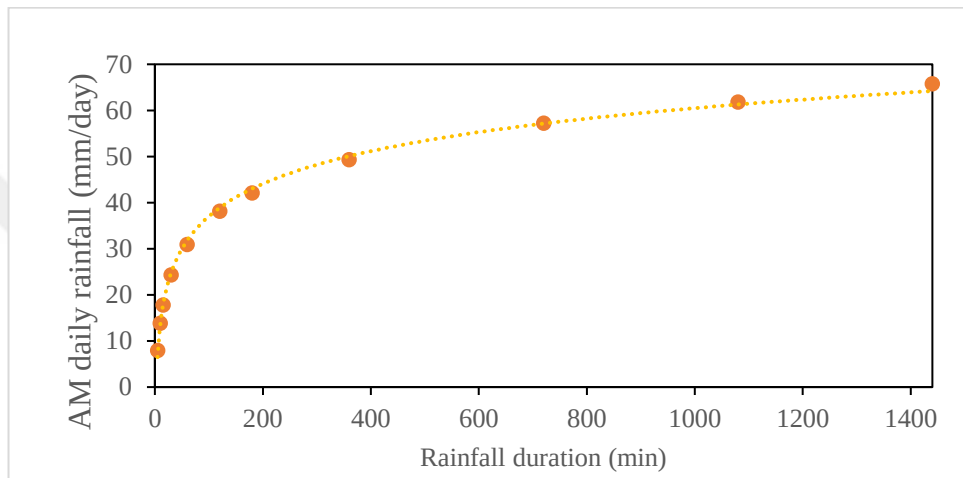


Figure 4.7 The shape of rainfall distribution using empirical ratio by Huff and Angel (1992)

In the presented study, the formula developed by The Indian Meteorological Department (IMD) is used to disaggregate the annual maximum daily rainfall to short durations. Also, the TDR ratio and the Huff and Angel empirical ratios are employed to evaluate and test the accuracy IMD formula.

4.6 Estimation IDF Curves

IDF curve concept is used to describe the relationship between basic hydrological components. Namely, rainfall intensity, storm duration, and the frequency of the extreme events. IDF curve implementation requires determining the annual maximum rainfall intensity from rainfall measurements for every year over specific durations. The establishment of the IDF curve requires selecting a suitable theoretical probability distribution to fit the annual maximum rainfall heights for each standard rainfall duration. Here, Gumbel distribution (Generalized extreme value distribution type-1)

was used to derive IDF curve. Then, the estimated annual maximum rainfall intensities with different durations of the same return period were plotted as curves like in Figure 4.8.

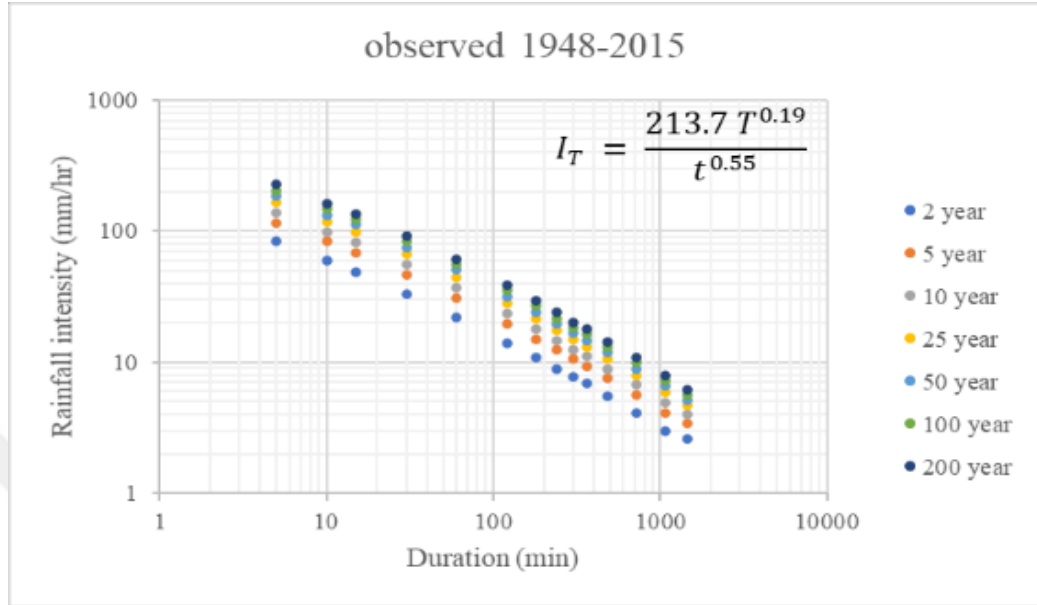


Figure 4.8 IDF curve

IDF curves can be expressed as an equation called "intensity-duration-frequency equation" to avoid reading the design rainfall intensity from a graph (Chow et al., 1988). IDF empirical equation estimates the maximum rainfall intensity for different durations and return periods. Different formulas have been proposed in the literature for deriving a relationship between the rainfall intensity and other effective rainfall variables (Chow et al., 1988; Ewea et al., 2018; Rashid et al., 2012). The most common formulas are Sherman, Bernard, Kimijima, and Talbot equations (Nhat et al., 2006). In this study, Bernard equation was used; as shown in Eq. (4.10):

$$I_T(mm/h) = \frac{k T^c}{t^b} \quad (4.10)$$

Where: I_T : intensity (mm/hr), T return period, t duration (min), k, c, b constant parameters.

Since the traditional approaches to develop IDF curves lean on the stationary assumption, which assumes the extreme precipitation characteristics (statistically) are unchangeable with time. However, it is scientifically proven that the non-stationary

assumption is more appropriate (Nguyen et al., 2007). In this regard and to cope with this challenge, Several studies proposed downscaling approach for updating IDF curves based on GCMs or RCMs (Agilan & Umamahesh, 2016; Hassanzadeh et al., 2014; Mirhosseini et al., 2013; Nguyen et al., 2007; Solaiman et al., 2011). These studies emphasize the drawbacks of the applied approaches as computational cost and using GCMs data directly without treating the bias in original models. Therefore, The proposed methodology built on the above-mentioned studies and used non-complex straightforward statistical approaches (downscaling, bias correction, and disaggregation) to generate the future IDF curve using GCMs.



CHAPTER 5

APPLICATION AND RESULTS

This chapter presents the applications and results in the same order in the methodology. The framework of the methodology consists of six steps, four of which are related to constructing a model to derive the IDF curve from the current climate using NCEP/NCAR dataset, and the remaining two steps are related to deriving the IDF curve for future climate conditions using GCMs outputs. Figure 5.1 summarizes the relationship between the steps of the methodology.

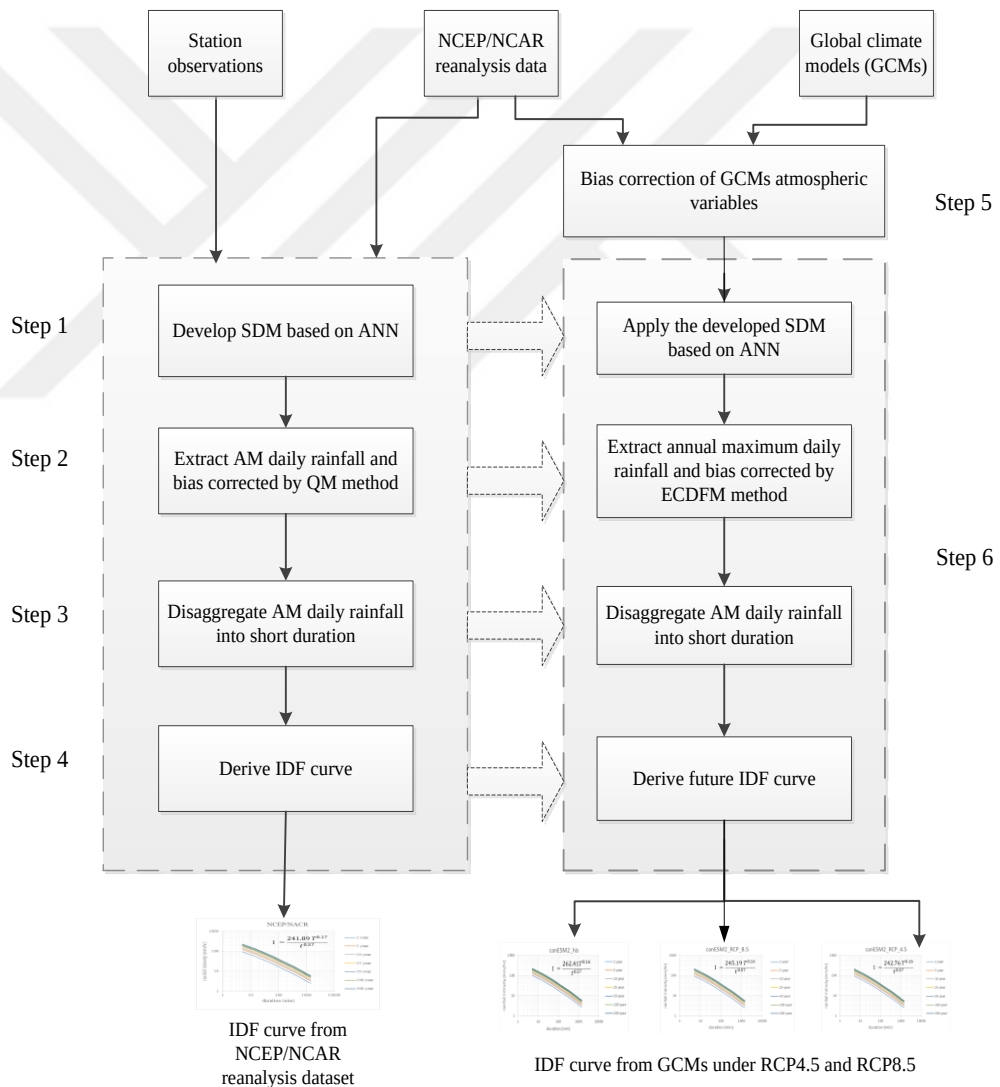


Figure 5.1 Summarized the methodology

5.1 Step 1: Building the Downscaling Model

ANN was used as a well-known machine learning technique to build a statistical downscaling model for estimating daily rainfall. The ANN was utilized as a practical black-box tool for developing a non-linear regression (Harpham & Wilby, 2005; Khan et al., 2006) between the large-scale atmospheric variables (predictors) and local weather variables such as temperature and precipitations (predictands).

In the presented study, the daily rainfall records of Izmir station were used as predictand, and the predictors were the atmospheric variables from NECP/NCAR Reanalysis dataset, which were air temperature, precipitation rate, sea level pressure and, v-wind speed. The predictand and predictors were used to build the statistical downscaling model in ANN. The data for the period of (1948–1990) was utilized for model training, and the period 1991- 2018 was employed for testing. In addition to that, for spatial validation, the model results were compared with the observed records of the five neighbor stations (for more details, see chapter 3).

The ANN structure here consisted of three layers: i) the input layer, which was the large-scale atmospheric variables, ii) the hidden layer contained several neurons which transform the inputs nonlinearly into another dimension, iii) the output layer contained the station-based daily precipitation in this study. The downscaling network is given in Figure 5.2. The hidden layer has a transfer function to translate the input signals to output signals. The most common transfer functions are tangent sigmoid, linear, and log-sigmoid. In this study, the tangent sigmoid function gave the best results.

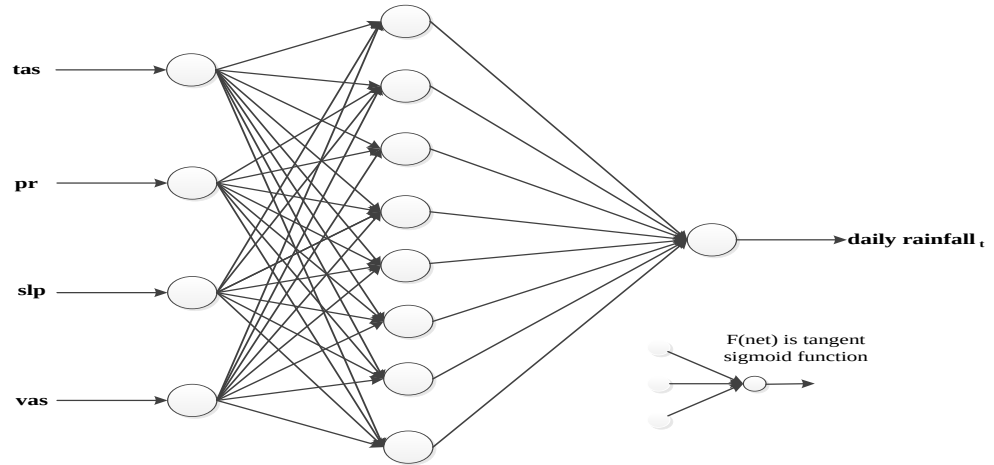


Figure 5.2 The structure of the downscaling model

Three statistical downscaling models were tested regarding the antecedent atmospheric conditions in this study. In the first model (ANN₁), the daily atmospheric variables on the day (t) of the study area were used as input (predictors) in order to estimate the daily rainfall on the day (t). In the second model (ANN₂), the atmospheric variables of the previous (t-1) and current (t) day were used as predictors, while the parameters of the two-day previous were added in the final model (ANN₃). Figure 5.3 shows the input and outputs of the three ANN-based downscaled models tested in this work.

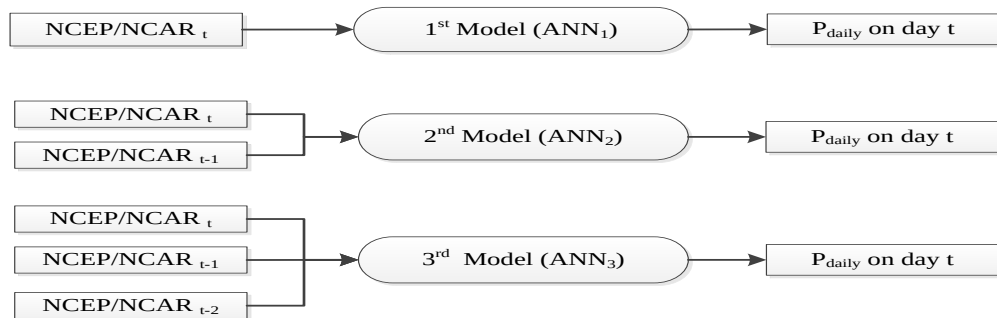


Figure 5.3 The tested ANN-based downscaling models

The determination coefficient (R^2) and the root mean squared errors (RMSE) were utilized to evaluate the performance of three downscaling models and to select the optimal model structure to be used for estimating the daily rainfall.

Figure 5.4 shows the overall performance of three models for the Izmir station in a scatter diagram. Table 5.1 summarizes the results of the three downscaling models of

the main station (Izmir) and its neighbor stations. Table 5.1 and Figure 5.3 clearly show that the second model (ANN₂) have better performance than the other models, where the model was taking into consideration the atmospheric variables of the previous day along with the current day. It was also evident that the performance of the first model (ANN₁) produced the worst results. In contrast, the third model (ANN₃) showed no significant difference relative to the optimal model.

Table 5.1 also highlights the performance of the models for each neighbor meteorological station as R^2 . The high correlations indicate that the ANN₂ based downscaled daily rainfall of the Izmir station is also spatially consistent with the other rainfall stations’.

Table 5.1 Summary of the three model results for the selected stations in the training and testing periods

Station	Period	Indicators	ANN ₁	ANN ₂	ANN ₃
Izmir	Train 1948-1990	R^2	0.36	0.55	0.54
		RMSE	5.256	4.410	4.46
Izmir	Test 1991-2018	R^2	0.33	0.46	0.45
		RMSE	5.91	5.250	5.330
Adnan Menderes	Test 2009-2018	R^2	0.37	0.51	0.49
Seferihisar	Test 1980-2011	R^2	0.26	0.35	0.35
Cesme	Test 1965-2018	R^2	0.27	0.33	0.32
Odemis	Test 1960-2011	R^2	0.30	0.41	0.37
Selcuk	Test 1965-2011	R^2	0.33	0.44	0.43

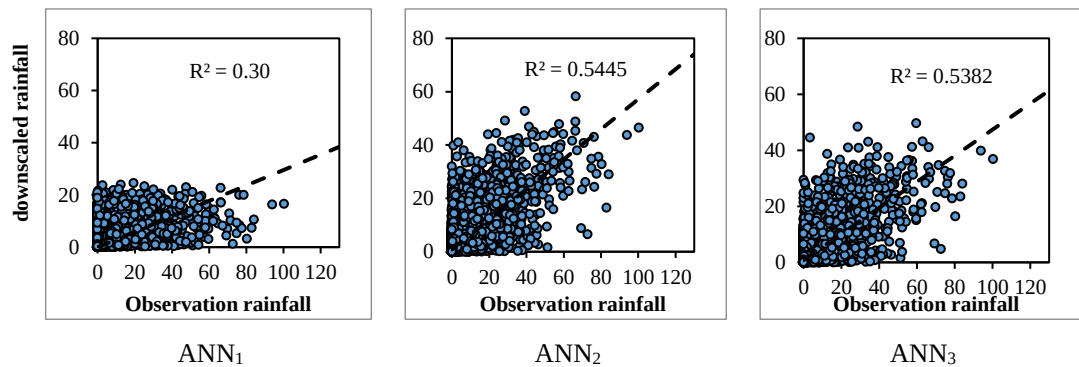


Figure 5.4 Comparing the observed and downscaled daily rainfall series resulted from three models of the Izmir station data for the period (1948-2018)

The results of the ANN₂ model reveals that the daily rainfall has a reasonable relationship with the model predictors, i.e., air temperature, precipitation rate, v-wind, and sea level pressure. This finding is similar to the results in several studies (Fistikoglu & Okkan, 2011; Vu et al., 2016). The results also reveal the large-scale atmospheric conditions of the day before and present day significantly influence the current local weather conditions, this result is consistent with the finding from other studies (Coulibaly et al., 2005).

5.2 Step 2: Bias Correction of Annual Maximum Daily Rainfall

The annual maximum (AM) daily rainfall ($P_{max,daily}$) is a sub-sample of the daily rainfall maximum value of each year was sampled to construct the AM daily rainfall estimations among the downscaled daily rainfall series, which refers in this study ($P_{max,daily}^{est.}$).

As the output of the downscaling model contains biases caused by the discrepancy (spatially and temporally) between the real and representative NCEP/NCAR atmospheric conditions and the inadequate model structure of the downscaling network (systematic errors), the biases must be removed from the AM daily rainfall values. The annual maximums sampled from the daily rainfall series are as accurate as the daily estimations.

.

In this section, the quantile mapping method (QM) was used to correct the distribution function of downscaled AM daily rainfall ($P_{max,daily}^{est.}$) to agree with the distribution function of the observed AM daily rainfall ($P_{max,daily}^{obs.}$) by creating a transfer function to shift the occurrence distributions.

The cumulative distribution functions (CDFs) were used in the bias correction process. The CDFs can be either empirical or fitted to some theoretical distribution. The Gamma distribution is frequently used for representing precipitations distribution (Ines & Hansen, 2006). In this work, the results of both chi-square and Anderson-

darling goodness of fit tests proven that Gamma distribution is accurately fitting the AM daily rainfall. See Figure 5.5.

The CDFs of Gamma distribution were constructed for both the observed and the downscaled AM daily rainfall time series of the period of (1948–2018); then, the value of the downscaled ($P_{max,daily}^{est.}$) was searched on the downscaled CDF to find its corresponding probability; then, the found probability was located on the observed CDF probability. Finally, the corresponding value was found; this value was used as the corrected value ($P_{max,daily}^{cor.}$). The procedure of the QM mapping also can be illustrated graphically in Figure 5.5 below. The QM method can be written mathematically using the Gamma distribution as Eq. (5.1):

$$P_{max,daily}^{cor.} = F_Y^{-1}\{F_Y(P_{max,daily}^{est.}|\alpha_{est.}, \beta_{est.})|\alpha_{obs.}, \beta_{obs.}\} \quad (5.1)$$

where;

$P_{max,daily}^{cor.}$: The corrected AM daily rainfall based on NCEP/NCAR datasets.

$P_{max,daily}^{est.}$: the estimated AM daily rainfall based on NCEP/NCAR datasets.

α, β : Shape and scale parameters of Gamma distribution.

F_Y : Cumulative distribution function (CDF)

F_Y^{-1} : Inverse of CDF

For example,

$$P_{max,daily}^{est.} = 40,$$

$$F_Y(50|\alpha_{est.}, \beta_{est.}) = 0.55,$$

$$F_Y^{-1}(0.53|\alpha_{obs.}, \beta_{obs.}) = 62,$$

$$P_{max,daily}^{cor.} = 62.$$

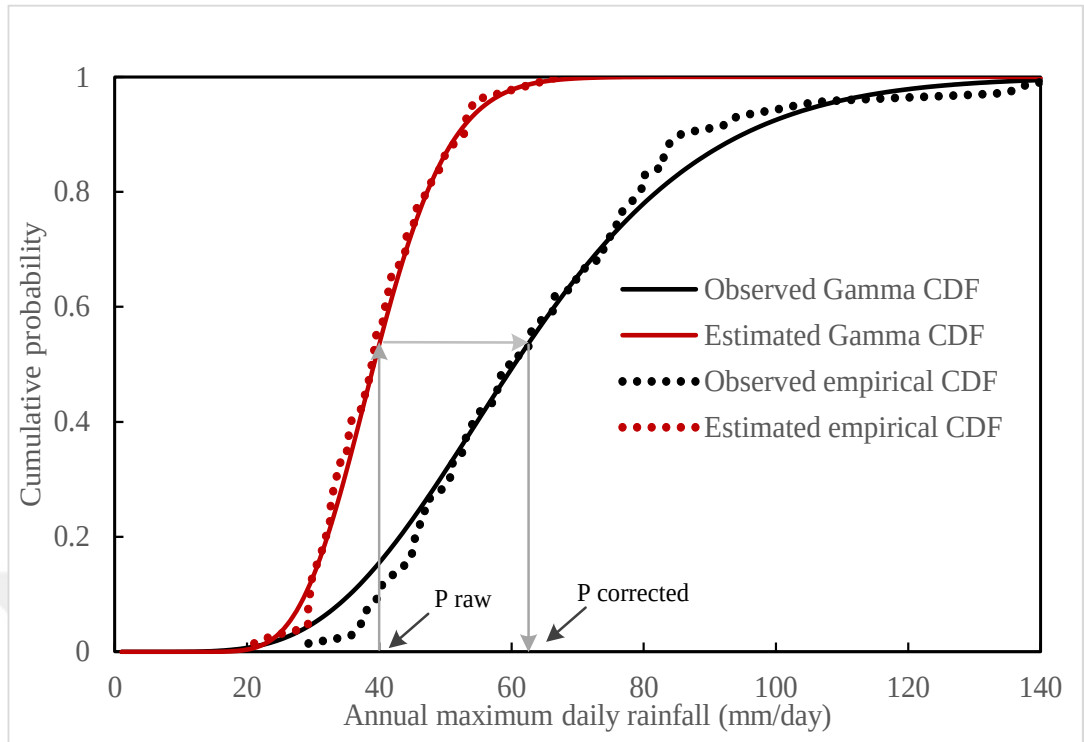


Figure 5.5 The empirical and Gamma CDF of AM daily rainfall for observed and estimated

For AM daily rainfall, the values of the α and β are 7.16, 8.84 for the observed, and 19.36, 2.06 for the downscaled values, respectively.

Figure 5.6 (b) exhibits the observed and bias corrected AM daily rainfall values of the Izmir station. The figure indicates that bias correction stretches and shifts the downscaled annuals regarding the mean value and the distribution of the observations properly. In Figure 5.6 (b), it is apparent that bias correction still preserves the trend mechanism in the maximum daily rainfall series. Table 5.2 also gives the statistics of the observed, downscaled (uncorrected), and bias corrected AM daily rainfall values of the Izmir station. In addition to Table 5.2, Figure 5.7 also shows the box plot diagrams of the observed, downscaled, and bias-corrected AM daily rainfall $P_{\max, \text{daily}}$ of the study area. Table 5.2 and Figure 5.7 indicate that the bias correction applies a decent correction to the downscaled maximums and the corrected maximums fairly fit to the observations.

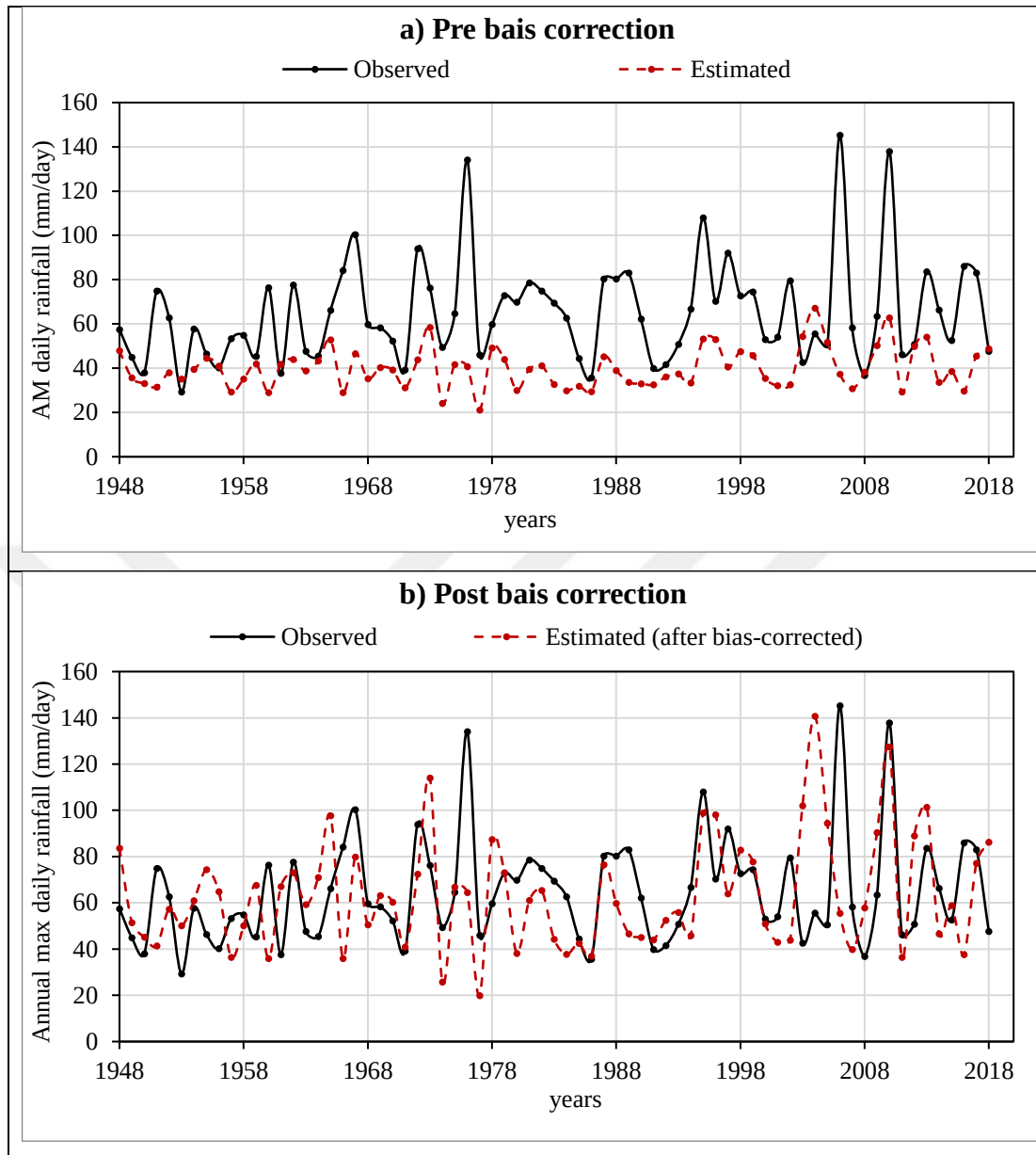


Figure 5.6 Variations of AM daily rainfall of a) the observed and the estimated (un-corrected) and (b) the observed and the estimated after bias-corrected

Table 5.2 Statistical description of AM daily rainfall of the observed and the estimated (pre and post-bias-corrected) (1948-2018)

	Observed	Pre bias corrected	Post bias corrected
mean	64.75	39.89	63.32
median	59.7	38.95	59.80
St. dev	23.12	9.07	23.88
RMSE		33.46	28.46

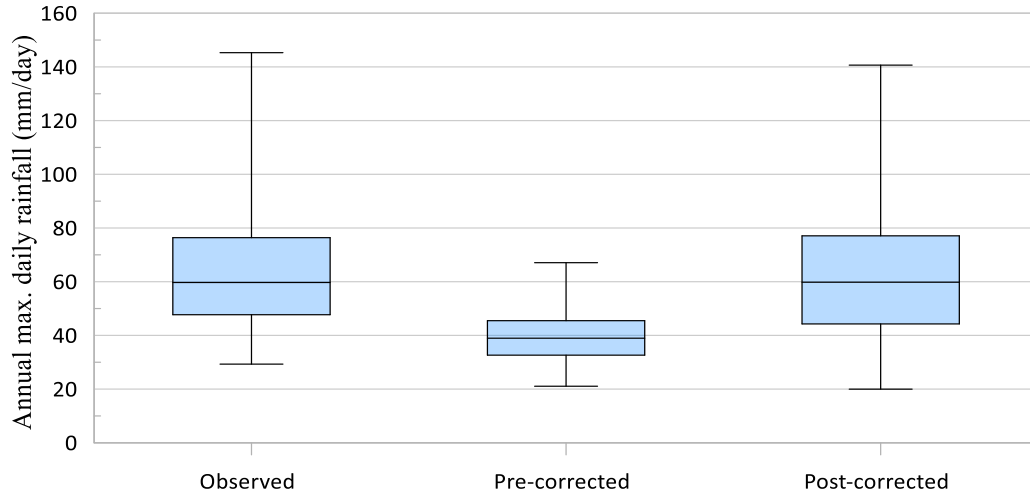


Figure 5.7 The box plot of the AM daily rainfall of the observed, estimated (pre-corrected), and corrected in the Izmir station.

5.3 Step 3: Disaggregation of AM 24-hr rainfall to Short Durations.

5.3.1 Estimation of the annual maximum 24-hour rainfall

The observed AM daily rainfall values were compared with observed AM 24-hour rainfall obtained from the station pluviograph records during 1948-2018. Figure 5.8 of the maximum daily and 24-hour rainfall demonstrates that most of the 24-hour rainfall event occurs in a calendar day and the 24-hour maximum precipitation is slightly higher than the maximum daily rainfall.

The regression equation between the observed daily and 24-hour rainfall observations given in Figure 5.9 and Eq. (5.2) (during the period 1948-2018.). This equation is used to estimate 24-hour maximum precipitation after bias corrected maximum daily rainfall is estimated.

$$P_{max,24}^{obs.} = r * P_{max,daily}^{obs.} \quad r \geq 1.0 \quad (5.2)$$

Where $r = 1.047$, this finding is consistent with the results of Huff & Angel (1992) findings, which show that the ratio between $P_{max,24}$ and $P_{max,daily}$ is slightly higher than 1.0 (ranging between 1.01 - 1.13 for the USA).

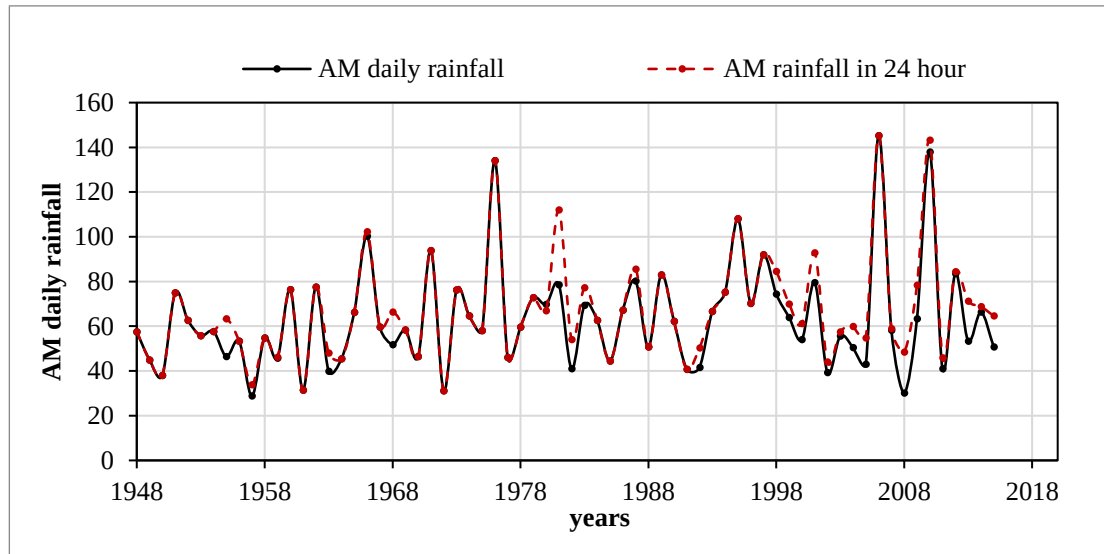


Figure 5.8 The differences between annual maximum daily rainfall and the maximum 24-hour rainfall over time

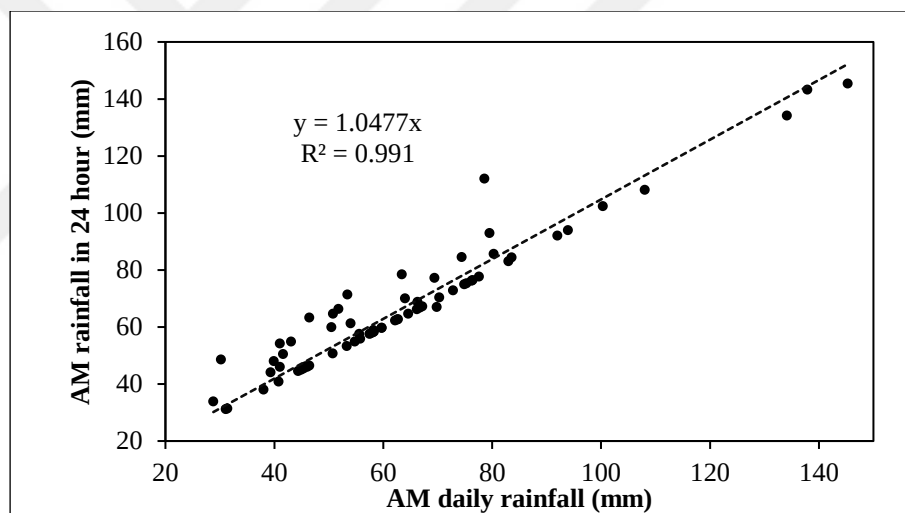


Figure 5.9 The relation between annual maximum daily rainfall and the maximum 24-hour rainfall

5.3.2 Disaggregation of AM 24-hr Rainfall to Standard Duration

The maximum rainfall intensities at standard durations generally occur during the maximum 24-hour rainfall event. Several studies (Al Mamun et al., 2018; Chowdhury et al., 2007; Jaharvi et al., 2014) used this assumption to formulate a correlation between the standard duration rainfall and 24-hour rainfall heights.

The Indian Meteorological Department (IMD) uses an empirical formula to estimate the short-duration rainfall heights from 24-hour rainfall if the observations do not exist. The presented study used this formula to estimate short-duration rainfall heights obtained. See Eq. (5.3).

$$P_{max,d}^{cor.} = P_{max,24hr}^{cor.} \left(\frac{d}{24} \right)^{(1/3)} \quad (5.3)$$

Where,

$P_{max,d}^{cor.}$: the corrected AM rainfall height based on NCEP/NCAR reanalysis data in duration d.

$P_{max,24hr}^{cor.}$: the corrected AM rainfall heights based on NCEP/NCAR data in 24-hour
d: rainfall duration in an hour.

In the presented study, the Temporal Distribution of Rainfall (TDR), which is the ratio between mean values of the maximum rainfall in d duration to the total rainfall amount (24 hr), was used as one of the alternative methods to disaggregate 24hr rainfall into standard short duration. Here, the TDR ratio was calculated using the historical data of the annual maximum series rainfall (1948-2015) as Eq. (5.4). Table 5.3 shows the obtained TDR ratios for the Izmir station.

$$TDR_d = \frac{(\sum_1^n P_{max,d})/n}{(\sum_1^n P_{max,24})/n} \quad (5.4)$$

Table 5.3 Temporal Distribution of Rainfall (TDR) ratio for Izmir station

Observation	Minute				Hour									
Year	5	10	15	30	1	2	3	4	5	6	8	12	18	24
2015	9.0	16.7	20.6	29.0	33.4	33.4	33.4	33.4	33.5	34.3	38.2	49.3	53.0	64.6
2014	8.5	11.2	17.9	28.0	39.8	45.7	49.3	51.3	57.9	63.8	65.4	66.3	66.3	68.8
2013	6.4	10.5	13.2	17.7	28.5	39.7	43.5	51.0	55.7	59.8	59.8	59.9	65.7	71.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
1950	10.2	14.3	17.0	19.7	20.5	21.3	24.3	28.9	29.2	29.7	29.8	30.1	30.2	38.0
1949	5.8	6.0	6.2	8.7	13.0	22.4	23.9	26.3	29.1	31.8	33.4	33.5	33.5	44.9
1948	5.0	8.3	10.6	12.1	12.1	12.1	14.8	18.2	23.8	27.8	33.3	35.5	36.0	57.5
Mean	7.7	10.9	13.5	18.2	24.2	30.2	35.3	38.7	42.0	44.8	48.2	53.4	58.3	64.5
TDR ratio (%)	0.12	0.17	0.21	0.28	0.37	0.47	0.55	0.60	0.65	0.69	0.75	0.83	0.90	1

Huff and Angel (1992) analyzed records of 34 rain gauges in Illinois, USA, then propose the empirical ratio for every duration to estimate short duration rainfall from daily rainfall (Huff & Angel, 1992). Table 5.4 shows that the empirical ratio proposed by Huff & Angel.

Table 5.4 The empirical ratio which was proposed by Huff and Angel

Durations (d)	5min	10min	15min	30min	1hr	2 hr	3 hr	6 hr	12 hr	18 hr
Ratio (d/24hr)	0.12	0.21	0.27	0.37	0.47	0.58	0.64	0.75	0.87	0.94

This study used the Indian Meteorological Department (IMD) formula to disaggregate $P_{max,24hr}^{cor.NCEP}$ into short durations. Furthermore, both the observed ratio (TDR) and the Huff and Angel empirical ratios were employed to evaluate and validate the IMD formula.

Table 5.5 shows the statistical characteristic of the observation data and the results from other disaggregation rainfall methods: IMD formula, TDR (observation ratio), and the empirical ratio by huff and angel.

Figure 5.11 compares the observation data and the disaggregation methods of IMD empirical method and empirical ratios by Huff and Angel's. The results are also provided in Figure 5.10 as box plots for comparing the observed and the disaggregated rainfall for all standard durations.

Table 5.5 The statistical characteristics of the annual maximum rainfall of standard durations from observation data, the IMF formula, observation ratio (TDR), and the empirical ratio (huff and angel)

	5-min	10-min	15-min	30-min	1-hr	2-hr	3-hr	4-hr	5-hr	6-hr	8-hr	12-hr	18-hr
Observed	Mean	7.45	10.67	13.02	17.66	23.46	29.07	33.55	36.62	39.66	42.13	45.23	54.57
	Median	7.10	9.60	12.45	15.85	20.85	25.95	30.75	34.25	37.60	39.10	44.10	53.90
	Std Dev	3.07	4.46	5.54	7.82	10.89	13.28	15.13	15.64	17.46	18.67	19.79	23.28
	Max	1.50	2.50	2.80	4.00	6.00	6.80	7.00	7.10	9.90	10.60	11.70	11.80
	Min	19.60	29.70	37.40	52.30	60.80	76.50	83.50	92.60	115.70	132.90	144.90	145.30
IMD formula	Mean	9.96	12.54	14.36	18.09	22.79	28.72	32.87	36.18	38.98	41.42	45.59	59.73
	Median	9.34	11.77	13.47	16.98	21.39	26.95	30.85	33.95	36.58	38.87	42.78	56.06
	Std Dev	3.44	4.34	4.97	6.26	7.88	9.93	11.37	12.52	13.48	14.33	15.77	20.66
	Max	4.71	5.93	6.79	8.56	10.78	13.58	15.55	17.11	18.44	19.59	21.56	28.26
	Min	22.00	27.72	31.73	39.98	50.37	63.47	72.65	79.96	86.14	91.53	100.75	132.01
TDR (observation ratio)	Mean	7.45	10.67	13.02	17.66	23.46	29.07	33.55	36.62	39.66	42.13	45.23	54.57
	Median	6.99	10.02	12.22	16.57	22.01	27.29	31.49	34.36	37.22	39.54	42.44	51.22
	Std Dev	2.58	3.69	4.50	6.11	8.11	10.06	11.61	12.67	13.72	14.57	15.64	18.88
	Max	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43
	Min	3.52	5.05	6.16	8.35	11.10	13.75	15.87	17.32	18.76	19.93	21.39	25.82
Empirical ratio (Huff and Angel)	Mean	7.89	13.81	17.75	24.33	30.90	38.13	42.08	-	-	49.31	-	61.80
	Median	7.40	12.96	16.66	22.83	29.00	35.79	39.49	-	-	46.28	-	58.00
	Std Dev	2.73	4.78	6.14	8.41	10.69	13.19	14.55	-	-	17.06	-	21.38
	Max	3.73	6.53	8.40	11.51	14.62	18.04	19.90	-	-	23.33	-	29.23
	Min	17.44	30.51	39.23	53.76	68.29	84.27	92.99	-	-	108.98	-	136.58

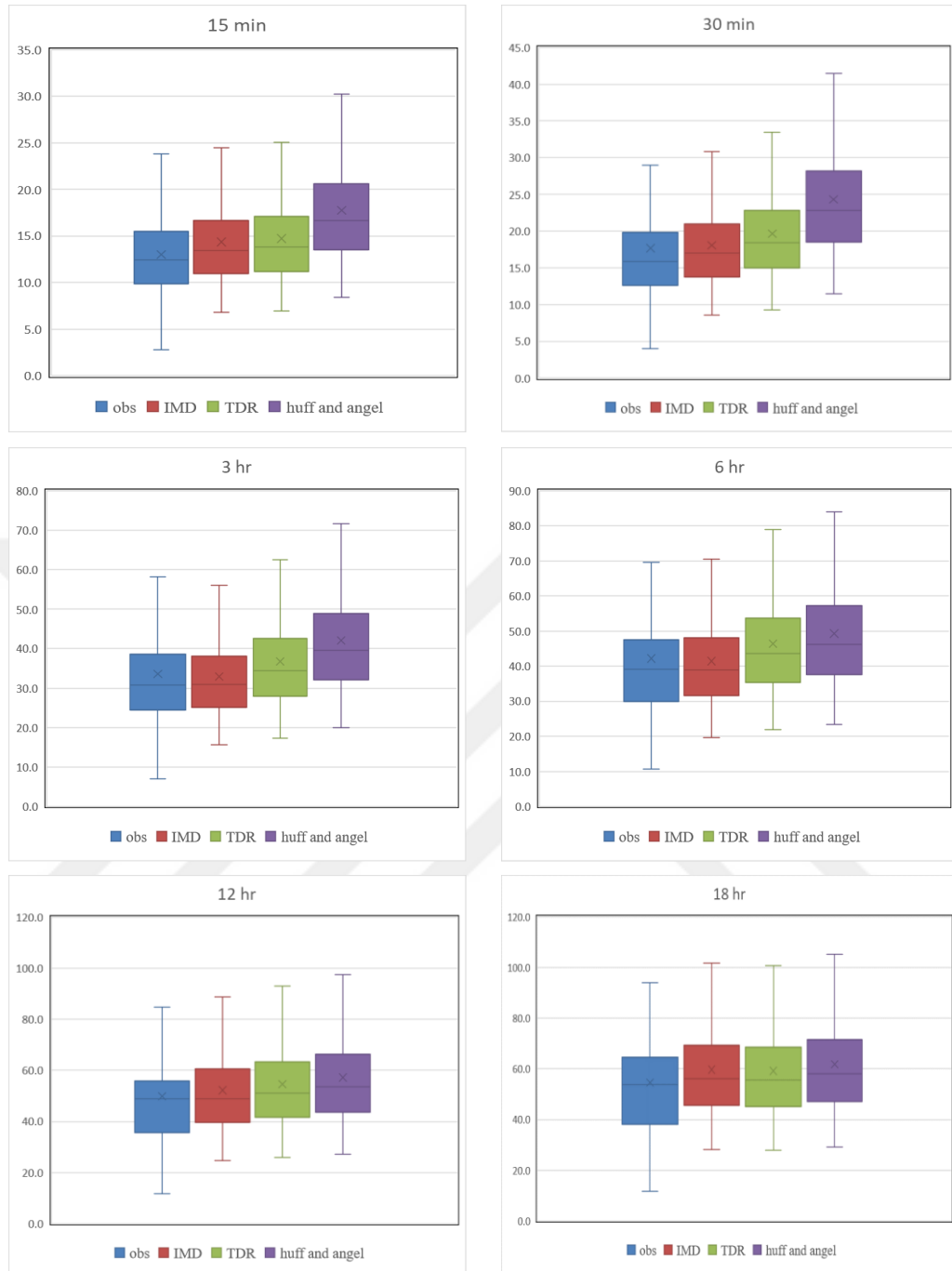


Figure 5.10 Box plots of AM rainfall of observed (obs) and the results of disaggregated methods: IMD formula, observation ratio (TDR), and Huff and Angel's empirical ratio

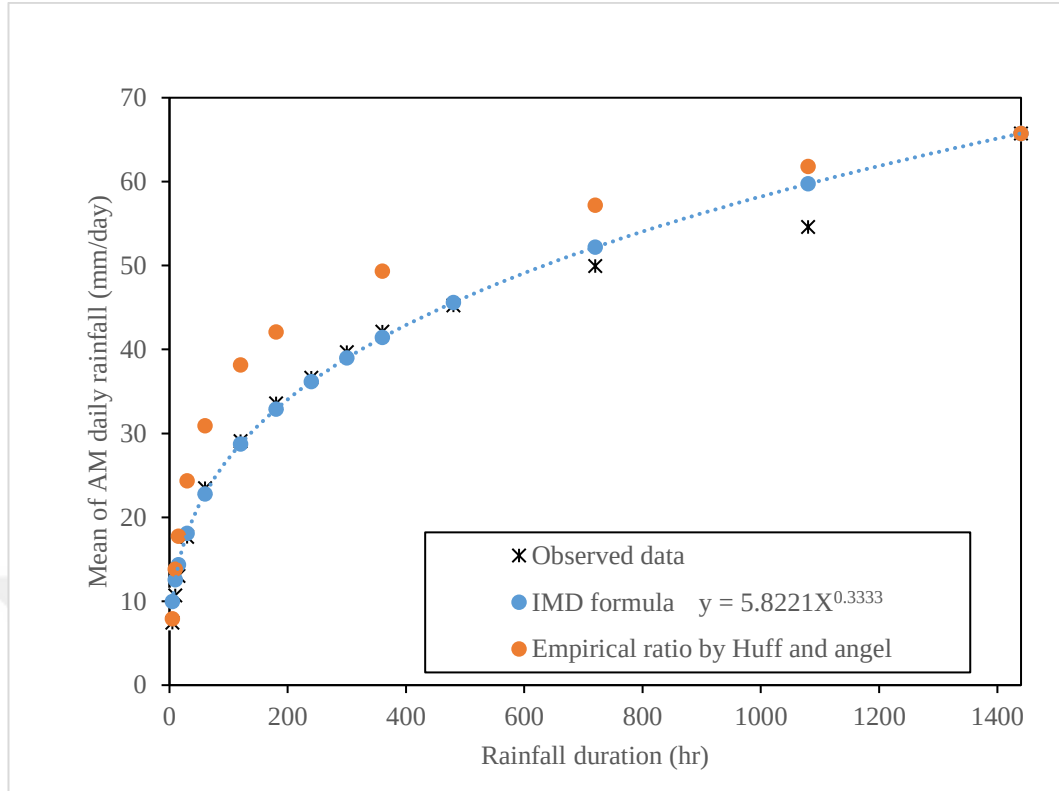


Figure 5.11 Comparison of the observed rainfall and the rainfall disaggregation methods: IMD formula, observed ratio (TDR), and Huff and Angel's empirical ratio

It can be seen that the obtained results based on IMD empirical formula, the observed ratios (TDR), and empirical ratios by Huff and Angel are almost similar. Therefore, the IMD formula is selected in this study for disaggregating $P_{max,24hr}^{cor}$ to standard short durations.

The disaggregated values (form using IMD formula) at standard durations (5, 10, 15, 30 mins, and 1, 2, 3, 4, 5, 6, 8, 12, 18 hr) were tested for their median and distribution properties using the Mann Whitney-U test. The Mann-Whitney test of the observed and disaggregated standard duration rainfall is tabulated in Table 5.6. The p-values of the Mann-Whitney-U tests revealed that the differences between the median value of the observed and all disaggregated standard durations of rainfall, except for the first two shortest durations (5 min, 10min), to be statistically insignificant at risk of 0.05, as shown in Table 5.6.

Table 5.6 Mann-Whitney U test for observed and disaggregated rainfall using IMD formula

Duration	P-value
5 min	0.001
10 min	0.040
15 min	0.335
30 min	0.959
1 hr	0.672
2 hr	0.785
3 hr	0.703
4 hr	0.612
5 hr	0.549
6 hr	0.509
8 hr	0.757
12 hr	0.768
18 hr	0.378
24 hr	0.417

*If the p-value is greater than the significance level (0.05), the decision fails to reject the null hypothesis that the median of the observations equals the median of the estimated values.

5.4 Step 4: Deriving IDF Curve for Observed and Estimated Rainfall

The observed annual maximum rainfalls for the standard durations (5, 10, 15, 30 min, 1, 2, 3, 4, 5, 6, 8, 12, and 24 hr) were analyzed to develop the IDF curves, and the 2-, 5-, 10-, 25-50- and 100-years rainfall intensities were calculated using the probability distribution function of the observed standard duration rainfalls as Gumbel distribution (Generalized extreme value distribution type-1).

Figure 5.12 (a) shows the IDF curves obtained from the observed rainfall records of the Izmir station. The IDF curves can be expressed as an equation, assuming logarithmic relationships between intensities, durations, and frequencies (AlHassoun, 2011), here Bernard equation was used. The equation is also shown in Figure 5.12 (a).

Similarly, the disaggregated estimations for standard duration rainfalls were also used to construct the estimated IDF curves using the same durations and occurrences. The Gumbel distribution was again selected as an appropriate probability distribution function for the estimated standard duration rainfall intensities. The estimated IDF

curves and their equation form of the Izmir station are also shown in Figure 5.12(b). It was noticed that the observed and estimated IDF curves and their simple forms of equations are not significantly different.

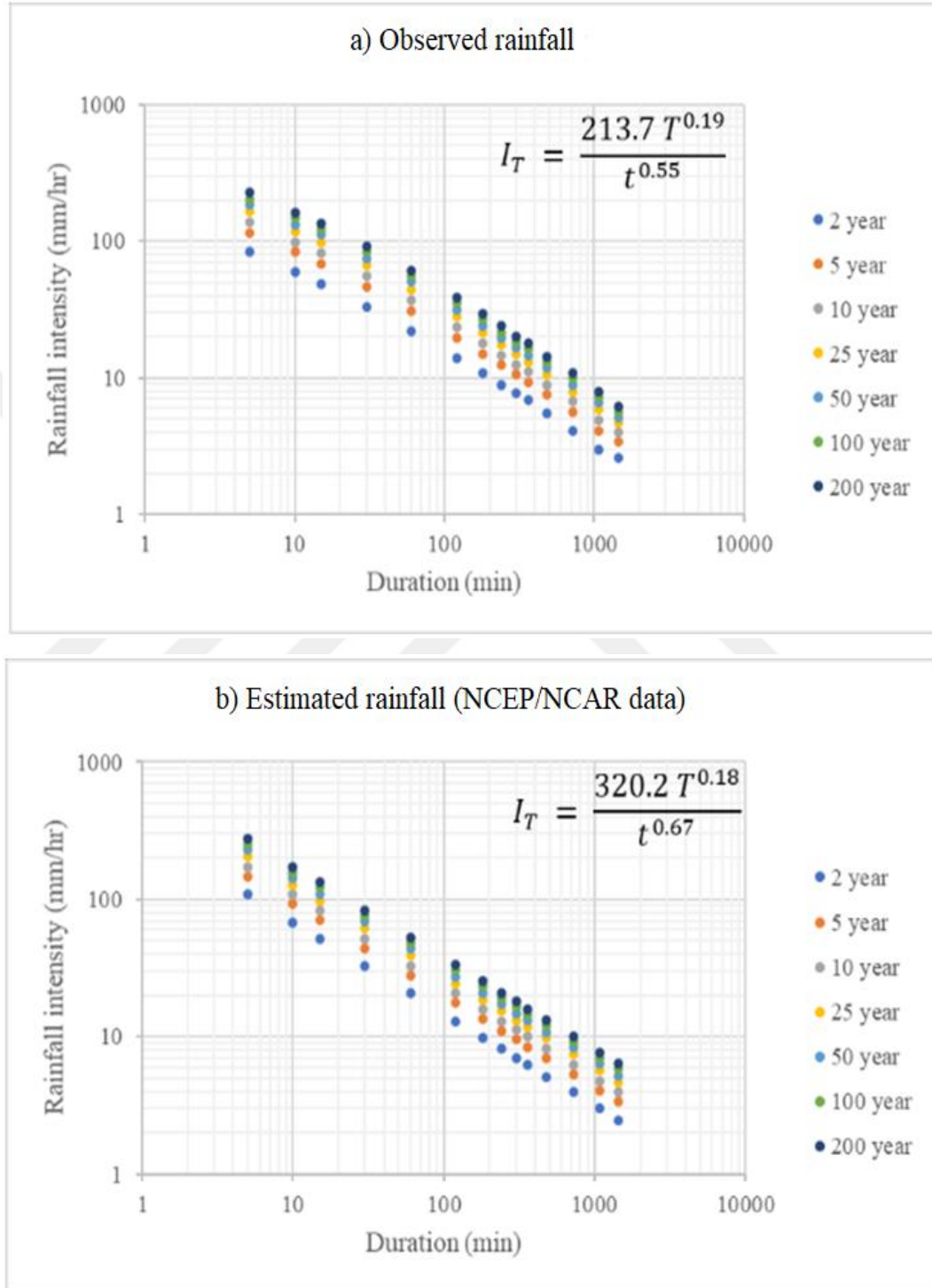


Figure 5.12 The IDF curve based on a) observation data, b) NCEP/NCAR reanalysis datasets

5.5 Step 5: Correction of Biases in GCMs Atmospheric Variables

As mentioned in the methodology chapter, GCMs have uncertain outputs in their historical data and future projections for climate change, so the raw data should be handled with caution and applying the necessary correction procedures (Christensen et al., 2008; Teutschbein & Seibert, 2012).

Bias correction processes were applied for all models for all selected variables (i.e., tas, pr, slp, vas). The historical and future variables are corrected in the different methods. In this section, only the HadGEM2-CC model was selected to apply the bias correction for presentation purposes.

5.5.1 Bias Correction of GCMs Historical Data

The quantile mapping (QM) method, which is the best correction method to correct the raw historical data, was used for correcting the bias in the atmospheric variables (i.e., tas, pr, slp, vas) of GCMs. In this study, the atmospheric variables of GCMs were corrected to correspond with NECP/NCAR data using the QM method.

The Gamma distribution was found suitable for representing the atmospheric variables such as tas, pr, and slp, while the normal distribution was found suitable for correction vas. Cumulative distribution functions (CDFs) of atmospheric variables were constructed for both the NECP/NCAR data and GCMs outputs using the historical data from 1970 to 2005. Quantile mapping (QM) procedures can be expressed mathematically as Eq. (5.5) for Gamma distribution, (5.6) for Normal distribution.

$$X_{corrected}(t) = F_Y^{-1}(F_Y(X_{raw}(t)|\alpha_{est}, \beta_{est.})|\alpha_{obs}, \beta_{obs}) \quad (5.5)$$

$$X_{corrected}(t) = F_N^{-1}(F_N(X_{raw}(t)|\mu_{est}, \sigma_{est.}^2)|\mu_{obs}, \sigma_{obs.}^2) \quad (5.6)$$

X_{raw} : The raw data of GCM atmospheric variables (tas, pr, slp, and vas)

$X_{corrected}$: The corrected data of the same variables.

F, F^{-1} : Cumulative distribution function (CDF), Inverse of CDF
 γ, N : Gamma distribution, normal distribution.
 α, β : Shape and scale parameters of Gamma distribution.
 μ, σ : Mean and Standard deviation.

Figure 5.13 explains the procedures of the quantile mapping for all atmospheric variables of the HadGEM2-CC model a) air temperature, b) precipitation rate, c) sea level pressure, and d) V-wind; the blue line refers to HadGEM2-CC variables, and the red line refers to NCEP/NCAR variables.

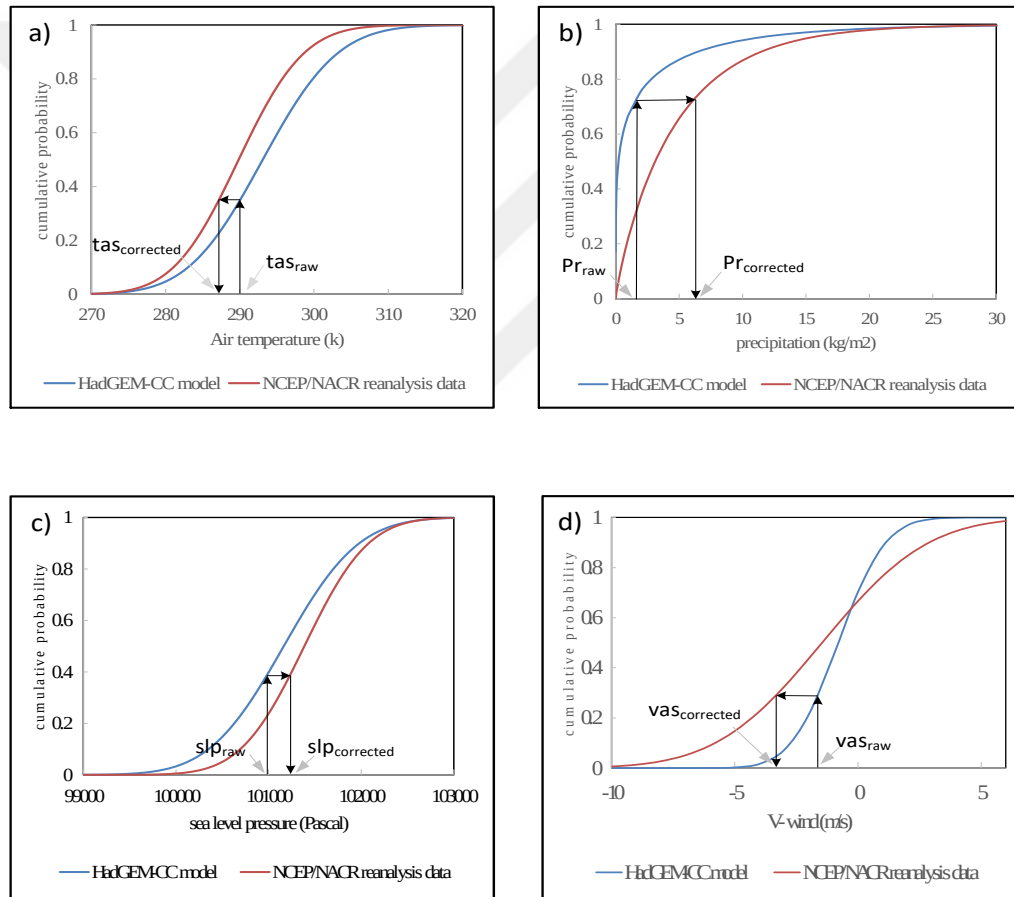


Figure 5.13 Exemplary procedure of the QM method for HadGEM2-CC model for a) air temperature (tas), b) precipitation rate (pr), c) sea level pressure (slp), and d) V-wind (vas)

Air Temperature Correction of GCMs Historical Data

Table 5.7 shows the statistical characteristic of the air temperature of NCEP/NCAR data and HadGEM2-CC data before and after the bias correction process. Figure 5.14 shows the statistics descriptive as a box plot. It was observed that the air temperature in the HadGEM2-CC model after bias correction has a similar distribution of air temperature of NCAP/NCAR data.

Table 5.7 The statistical characteristic of air temperature (tas) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data

	Tas of NCEP/NCAR reanalysis data	Tas of HadGEM2-CC raw	Tas of HadGEM2-CC corrected
Mean	289.89	293.15	289.88
Median	289.40	294.25	290.85
Std Dev	6.94	7.96	6.94
Min	269.21	273.20	272.45
Max	307.75	309.61	304.22

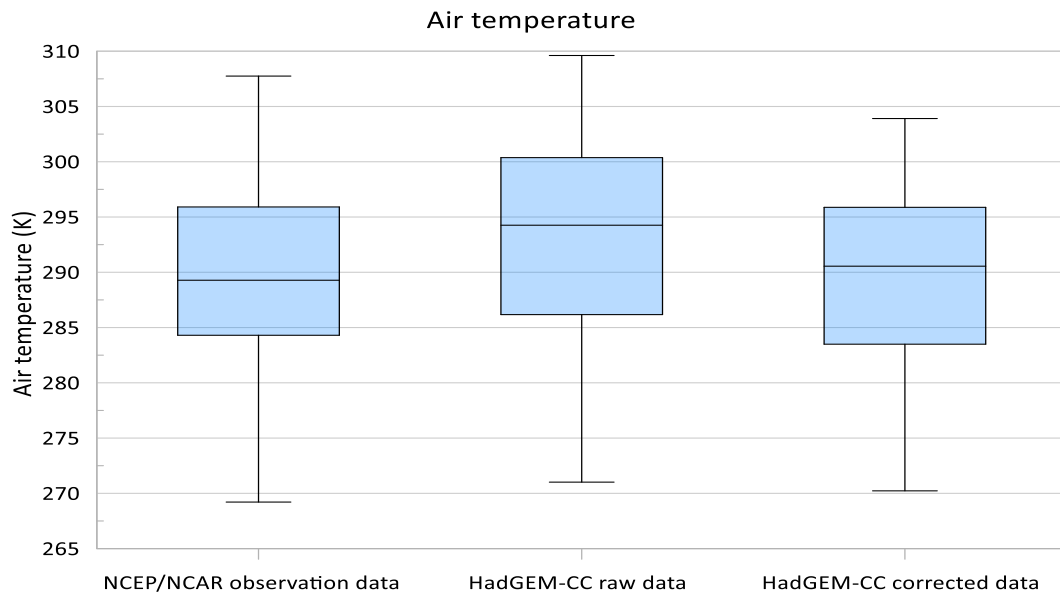


Figure 5.14 The box plots of air temperature (tas) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data

5.5.1.1 Precipitation Rate Correction of GCMs Historical Data

Table 5.8 shows the statistical characteristic of large-scale precipitation of NCEP/NCAR data and HadGEM2-CC data before and after the bias correction process; Figure 5.15 shows the statistics descriptive as box blot for the same variables. It was observed that the precipitation in the HadGEM2-CC model after bias correction has a similar distribution of precipitation of NCAP/NCAR data.

Table 5.8 The statistical characteristic of precipitation (pr) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data

	Pr of NCEP/NCAR reanalysis data	Pr of HadGEM2-CC raw	Pr of HadGEM2-CC corrected
Mean	1.42	1.82	1.13
Std Dev	3.57	4.55	3.13
Min	0.01	0.00	0.00
Max	39.12	65.09	48.15

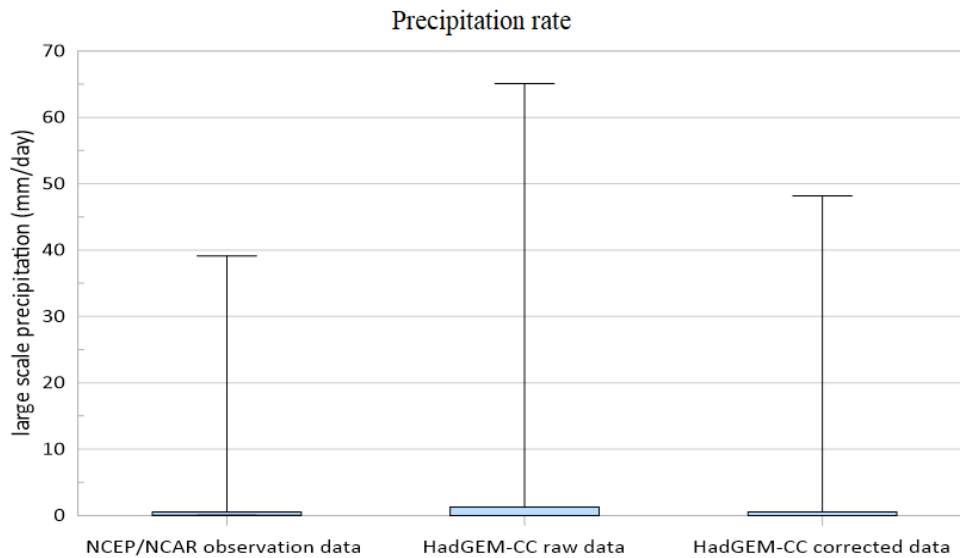


Figure 5.15 The box plots of precipitation rate (Pr) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data

5.5.1.2 Sea Level Pressure Correction of GCMs Historical Data

Table 5.9 shows the statistical characteristic of Sea level pressure NCEP/NCAR data and HadGEM2-CC data before and after the bias correction process; Figure 5.16 shows the statistics descriptive as box blot. It was observed that the Sea level pressure in the HadGEM2-CC model after bias correction has a similar distribution of precipitation of NCAP/NCAR data.

Table 5.9 The statistical characteristic of sea level pressure (slp) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CCcorrected data

	Slp of NCEP/NCAR Reanalysis data	Slp of HadGEM2-CC raw	Slp of HadGEM2- CCcorrected
Mean	101391.50	101164.56	101386.57
Median	101342.00	101105.00	101335.99
Std Dev	542.52	633.99	540.14
Min	99148.00	99579.00	100034.70
Max	103465.00	102999.00	102948.36

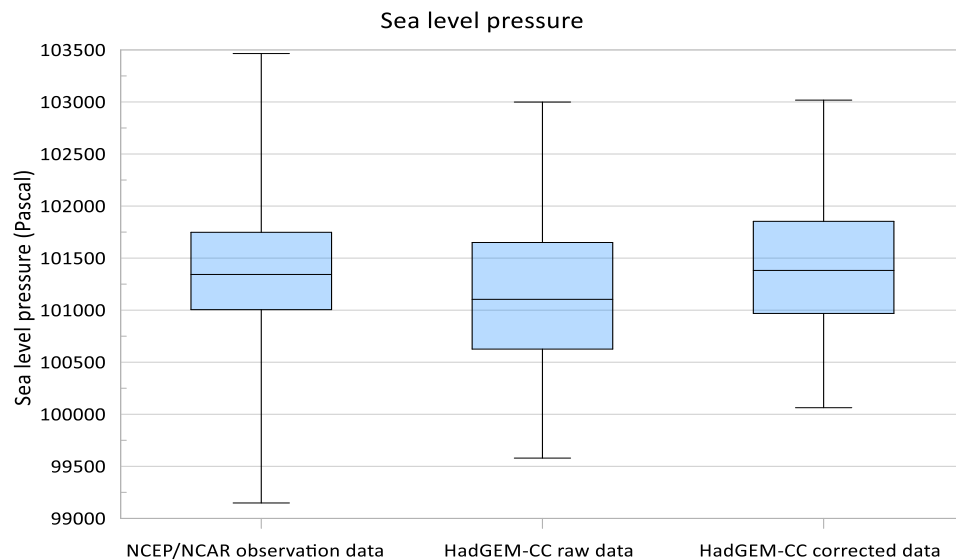


Figure 5.16 The box plots of sea level pressure (slp) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CC corrected data.

5.5.1.3 V-Wind Correction of GCMs Historical Data

Table 5.10 shows the statistical characteristic of V-wind before and after the bias correction process; Figure 5.17 shows the statistics descriptive as box blot. It was observed that the V-wind in the HadGEM2-CC model after bias correction has a similar distribution of precipitation of NCAP/NCAR data.

Table 5.10 The statistical characteristic of v-wind (vas) of NCEP/NCAR reanalysis data, HadGEM2-CCraw data, HadGEM2-CC corrected data

	Vas of NCEP/NCAR Reanalysis data	Vas of HadGEM2-CC raw	Vas of HadGEM2-CC corrected
Mean	-1.46	-0.80	-1.46
Median	-1.85	-0.89	-1.65
Std Dev	3.38	1.51	3.39
Min	-12.10	-7.35	-16.19
Max	10.43	7.34	16.85

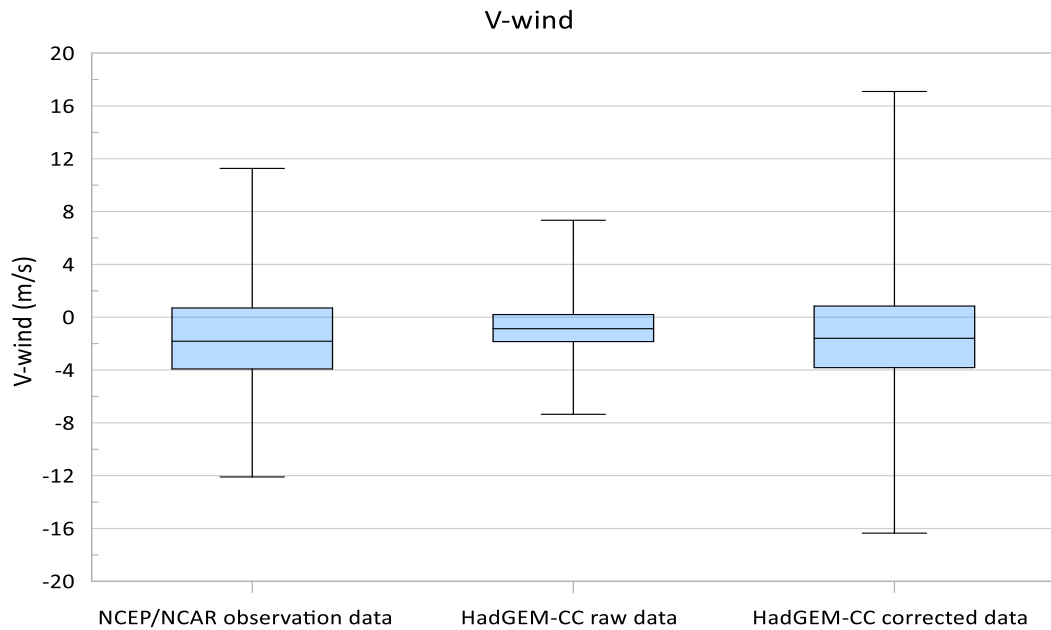


Figure 5.17 The box plots of v-wind (vas) of NCEP/NCAR reanalysis data, HadGEM2-CC raw data, HadGEM2-CCcorrected data

For all the results in this section, it was observed that the bias correction using quantile mapping (QM) applies a decent stretch to the downscaled maximums regarding the observed probability distribution, and the corrected variables fairly fit the observations. This result is compatible with many studies which indicate the QM is the best method to correct the historical data.

5.5.2 Bias Correction of GCMs Future Projections

The equidistant cumulative distribution function matching (EDCDFm) method was used in this section to correct the bias in GCMs variables for future climate projections. CDFs were constructed for both the NECP/NCAR atmospheric variables and GCMs atmospheric variables using the historical data from 1970 to 2005 and RCP scenarios (i.e., RCP4.5, RCP8.5) for 2005-2100.

This method can be illustrated graphically (Figure 5.18) with the following procedures: Firstly, CDFs for historical observation, the historically modeled, and the future modeled outputs should be constructed. Secondly, by following the selected distribution (e.g, Gamma distribution), the delta (Δ) can be calculated based on the differences CDF of both observed and model data for every point. Figure 5.18 (a) illustrates (an example with numbers) the procedures of the EDCDFm method as follow: $X_{G_f} = 298$, thus $F_{G_f}(298) = 0.62$. So $F_{obs_h}^{-1}(0.62) = 295$, and $F_{G_h}^{-1}(0.62) = 292$ can be determined. The difference between $F_{obs_h}^{-1}(0.62)$ and $F_{G_h}^{-1}(0.62)$ also can be defined as $\Delta = -3$. Finally, the correct value as adjusted $X_{G_f_adjust} = X_{G_f} + \Delta = 298 - 3 = 295$ can be calculated. The same procedure is repeated for every point for the future projection time series. Mathematically EDCDFm method can be written as an equation for Gamma Eq. (5.7) and normal distribution Eq. (5.8).

$$X_{G_f_cor} = X_{G_f} + F_Y^{-1}(F_Y(X_{G_f} | \alpha_{G_f}, \beta_{G_f}) | \alpha_{obs_h}, \beta_{obs_h}) - F_Y^{-1}(F_Y(X_{G_f} | \alpha_{G_f}, \beta_{G_f}) | \alpha_{G_h}, \beta_{G_h}) \quad (5.7)$$

$$X_{G_f_cor} = X_{G_f} + F_N^{-1}(F_N(X_{G_f}|\mu_{G_f}, \sigma_{G_f}^2)|\mu_{obs_h}, \sigma_{obs_f}^2) - F_N^{-1}(F_N(X_{G_f}|\mu_{G_f}, \sigma_{G_f}^2)|\mu_{G_h}, \sigma_{G_h}^2) \quad (5.8)$$

Where:

F, F^{-1}	CDF and inverse CDF
X	Atmospheric variable
obs_h	Observed data of the historical period.
G_h	Model outputs of the historical period.
G_f	Model outputs of the future projections.
G_f_cor	Model outputs corrected of the future projections

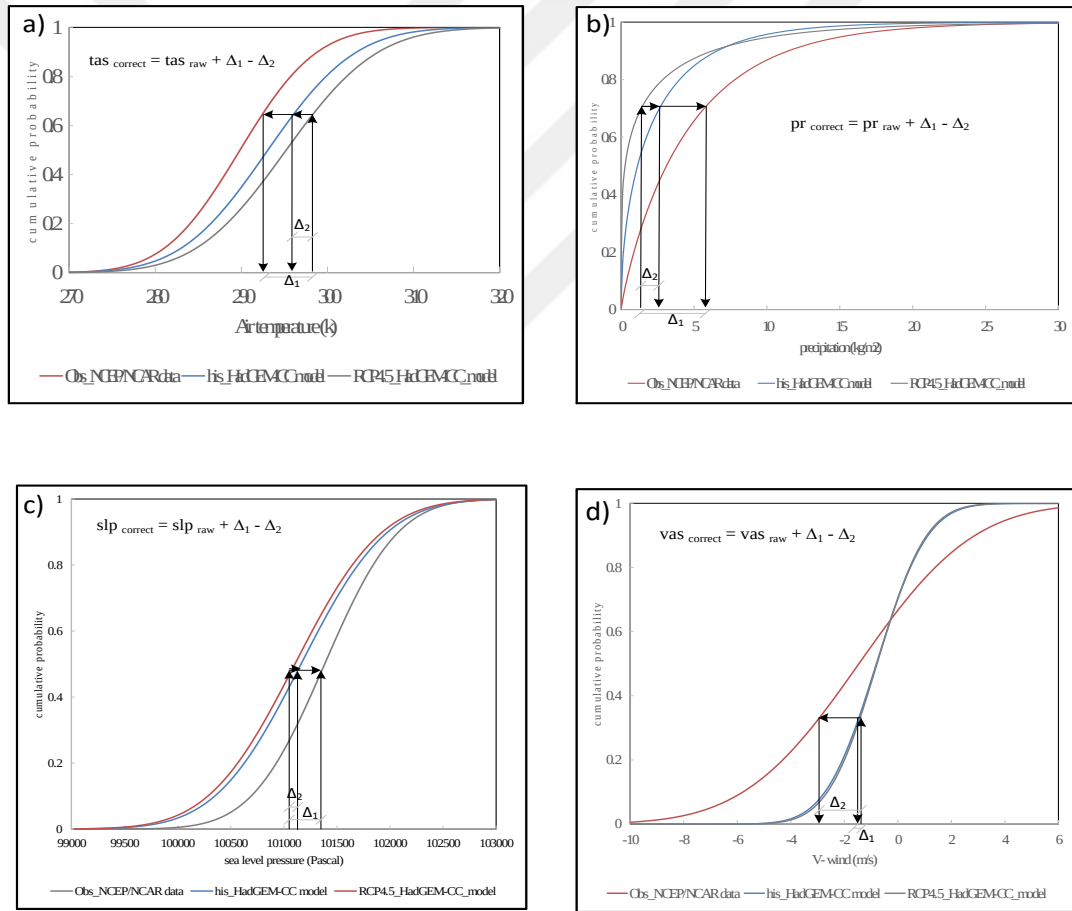


Figure 5.18 Exemplary procedure of the EDCDFm method for HadGEM2-CC model for a) air temperature, b) precipitation rate, c) sea level pressure, and d) V-wind

5.5.2.1 Air temperature correction of GCMs future projections

Table 5.11 shows the statistical characteristic of air temperature (tas) of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process). Also, Figure 5.19 shows the statistics descriptive as a box plot for the same variables.

Table 5.11 The statistical characteristics of the air temperature (tas) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process)

	Raw data			Corrected data		
	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5
Mean	293.20	295.28	297.18	289.62	291.65	293.57
Median	294.26	296.43	298.04	290.55	292.66	294.34
Std Dev	7.98	8.27	8.62	6.96	7.24	7.60
Min	271.01	274.00	274.96	270.22	272.96	273.95
Max	309.61	313.14	316.31	303.91	307.27	310.41

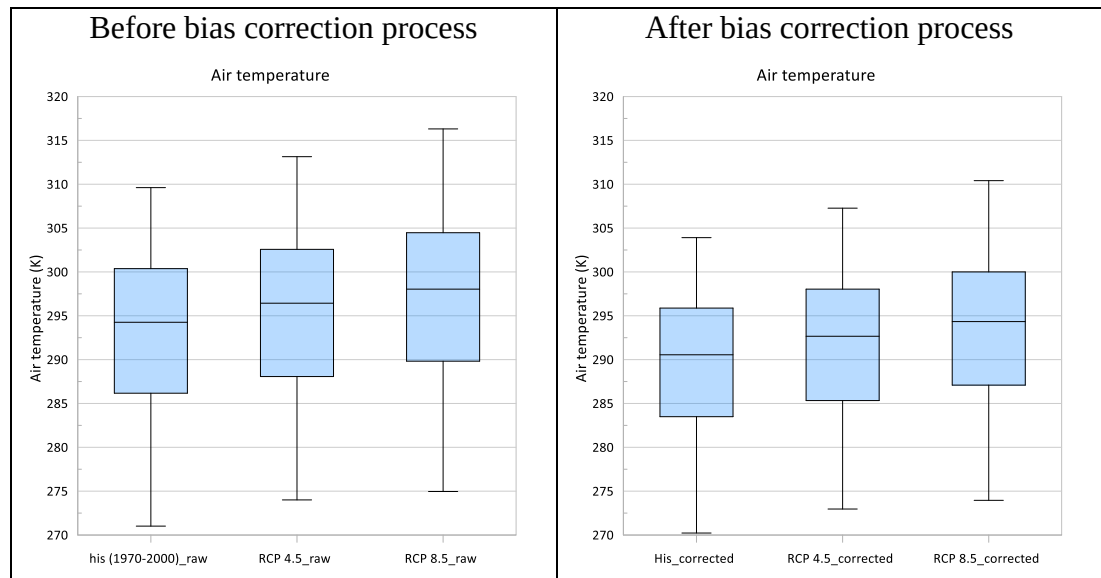


Figure 5.19 The box plots of the air temperature (tas) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases)

5.5.2.2 Precipitation rate correction of the future projections:

Table 5.12 shows the statistical characteristic of precipitation (pr) of the historical data and the future scenarios (before and after the bias correction process); Also, Figure 5.20 shows the statistics descriptive as a box plot for the same variables.

Table 5.12 The statistical characteristics of the precipitation (pr) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process)

	Raw data			Corrected data		
	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5
Mean	1.82	1.82	1.75	1.13	1.26	1.20
Std Dev	4.55	4.63	4.65	3.13	3.29	3.33
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	65.09	118.15	103.07	48.15	88.26	77.78

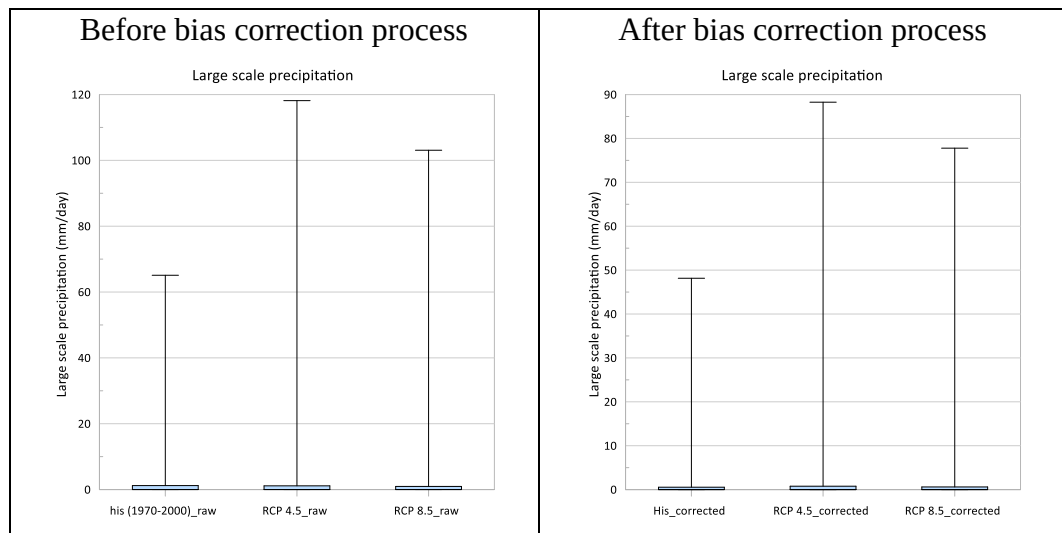


Figure 5.20 The box plots of the precipitation (pr) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases)

5.5.2.3 Sea level pressure correction of the future projections:

Table 5.13 shows the statistical characteristic of Sea level pressure (slp) of the historical data and the future scenarios (before and after the bias correction process); Figure 5.21 shows the statistics descriptive as a box plot for the same variables.

Table 5.13 The statistical characteristics of sea level pressure (slp) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process)

	Raw data			Corrected data		
	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5
Mean	101161	101125	101128	101431	101386	101392
Median	101104	101079	101092	101382	101346	101360
Std Dev	634.68	637.29	643.12	548.33	551.44	557.74
Min	99579	99572	99371	100063	100041	99867
Max	102999	103057	102952	103018	103057	102972

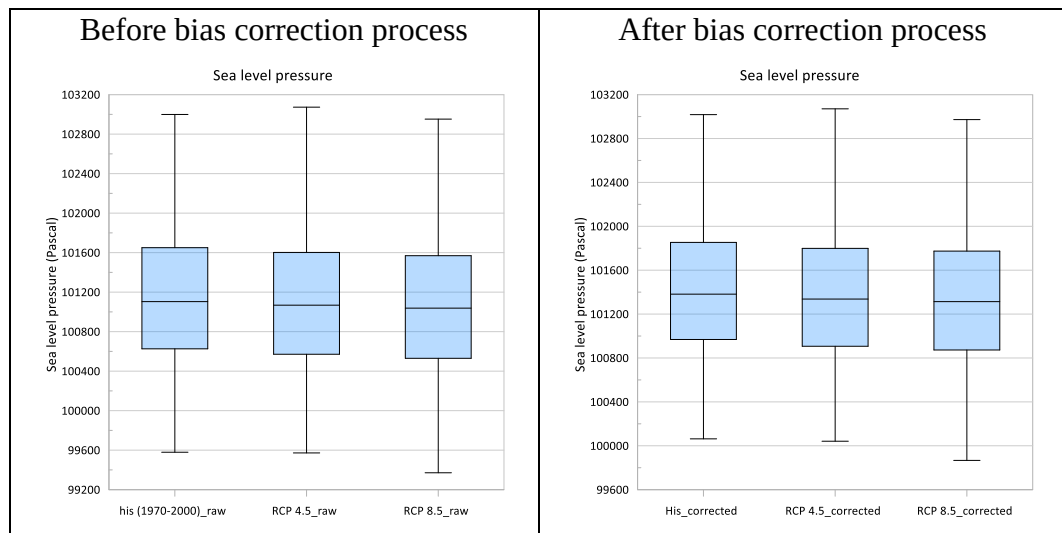


Figure 5.21 The box plots of the sea level pressure (slp) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases)

5.5.2.4 V-wind Correction of the Future Projections:

Table 5.14 shows the statistical characteristic of V-wind (vas) of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process); Figure 5.22 shows the statistics descriptive as a box plot for the same variables.

Table 5.14 The statistical characteristics of V-wind (vas) for the HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the bias correction process)

	Raw data			Corrected data		
	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5	HadGEM2-CC His.	HadGEM2-CC RCP_4.5	HadGEM2-CC RCP_8.5
Mean	-0.79	-0.78	-0.81	-1.41	-1.40	-1.43
Median	-0.87	-0.85	-0.88	-1.60	-1.56	-1.59
Std Dev	1.51	1.45	1.46	3.43	3.37	3.39
Min	-7.35	-5.73	-6.64	-16.36	-12.92	-14.95
Max	7.34	6.53	7.76	17.10	15.59	18.43

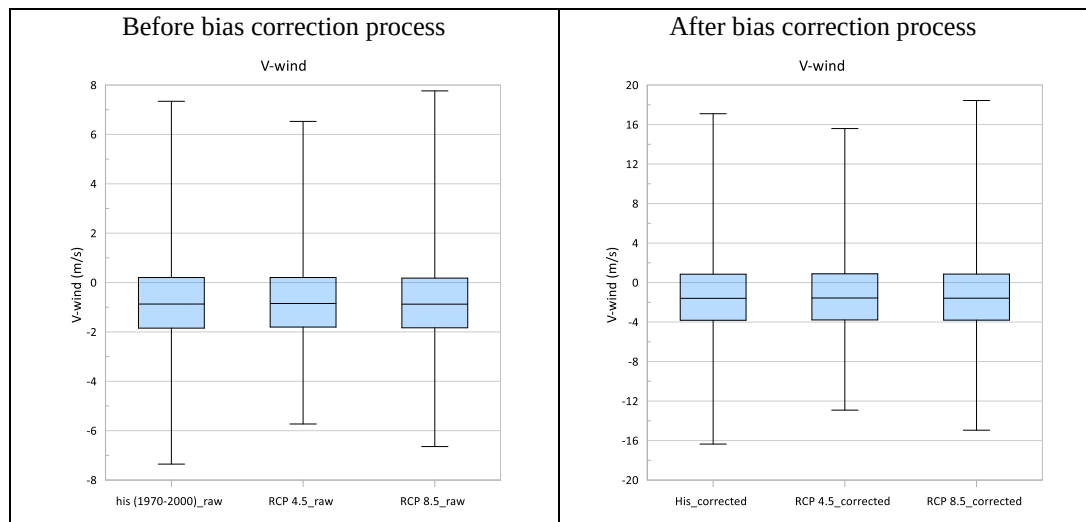


Figure 5.22 The box plots of the sea level pressure (slp) in HadGEM2-CC model of the historical data and the future scenarios RCP4.5 and RCP 8.5 (before and after the correction the biases)

5.6 Step 6: Deriving IDF Curve from Historical Data of GCMs and the Associated Future Scenarios (RCP4.5, RCP8.5)

In this section, the steps from 1 to 4 were repeated, using GCMs data instead of NCEP/NCAR Reanalysis data as following steps:

5.6.1 Step 6.1: Applying ANN₂ Using GCMs Data

The corrected Atmospheric variables from GCMs were served as the input in the optimal downscaling statistical model ANN₂, which was established by NCEP/NCAR reanalysis data, to produce the downscaled daily rainfall (output).

In this study, four GCMs were used: HadGEM2-CC, canESM2, MIROC-ESM-CHEM, and IPSL-CM5A-LR models. The atmospheric variables (tas, pr, slp, and vas) were used as input to downscaled daily rainfall for both the historical (1970 - 2005) and future projections (2005 – 2100) periods under RCPs 4.5 and RCPs 8.5. The output in this step was the downscaled daily rainfall based on GCMs $P_{daily}^{dow.GCM}$.

5.6.2 Step 6.2: Correction of Bias in the Annual Maximum Daily Rainfall

The AM daily rainfall based on GCMs was estimated from downscaled rainfall ($P_{daily}^{dow.GCM}$). Then this data was corrected to agree with the observation data, using the QM method for historical data and using EDCDFm method for future projections. The output in this step was corrected AM daily ($P_{max.daily}^{cor.GCM}$).

The "Delta change factor" approach was used to magnitude the changes under the future scenarios; this approach was applied to calculate the difference between future and historical climate by Eq. (5.9).

$$\Delta = \frac{\bar{X}_{future} - \bar{X}_{historical}}{\bar{X}_{historical}} * 100 \quad (5.9)$$

5.6.2.1 AM daily rainfall based on HadGEM2-CC model

The statistical descriptive in Table 5.15 and Figure 5.23 indicates that the corrected AM daily rainfall values based on HadGEM2-CC model ($P_{max.daily}^{cor.HadGEM}$), tend to increase in future projections (by 14.1% and 25.3% in RCP 4.5 and RCP8.5 scenarios, respectively); these increases are due to 1) increase in the mean values of air temperature by 2.1K, 4.5K in the RCP4.5, RCP8.5 respectively. 2) a decrease in sea level pressure values by 1% in both scenarios. 3) the changes in v-wind are small; therefore, it does not significantly affect the results. It was observed that air temperature played the main role in increasing AM daily rainfall for future scenarios.

Table 5.15 Statistical characteristics of AM daily rainfall of the observed data, and the HadGEM2-CC model results before and after applying the bias correction process

	observed	Historical 1970-2000		RCP4.5 2005-2095		RCP8.5 2005-2095	
		Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction
Mean	66.28	34.39	66.50	43.11	75.89	45.61	83.35
Median	65.65	34.16	65.30	41.31	72.50	43.92	79.99
Std Dev	21.10	8.83	22.93	14.32	26.70	17.48	34.12
Min	31.10	19.46	30.03	18.98	31.14	17.55	29.15
Max	134.10	61.28	139.32	116.33	212.85	131.76	252.34

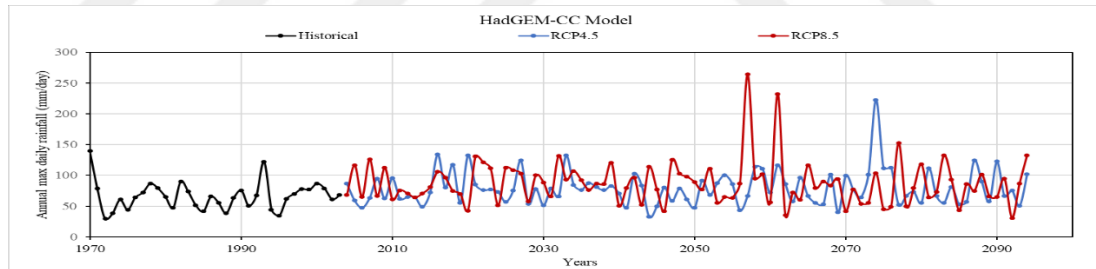


Figure 5.23 AM daily rainfall obtained from HadGEM2-CC model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)

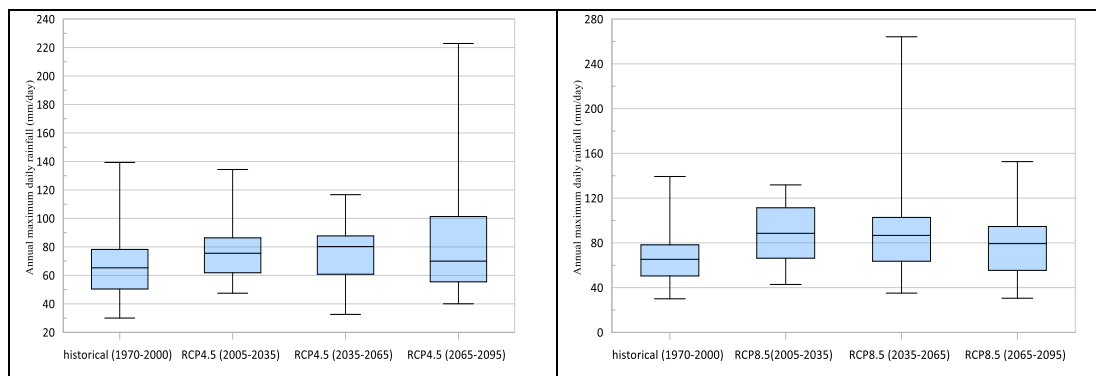


Figure 5.24 Box plots of annual maximum daily rainfall for HadGEM2-CC model for historical and future projections (left for RCP4.5, right for RCP 8.5)

5.6.2.2 AM Daily Rainfall Based on IPSL-CM5A-LR Model

The statistical characteristics in Table 5.16 indicate that the corrected AM daily rainfall values based on IPSL-CM5A-LR model ($P_{max.daily}^{cor.IPSL}$), also tend to increases in the future projections by 8.1% and 13.4% in RCP 4.5, RCP8.5 scenarios, respectively. Figure 5.25 shows the changes of AM daily rainfall with time from the historical period to future projections scenarios under RCP4.5 and RCP 8.5. These increases are due to 1) an increase in the mean values of air temperature by 2.2K, 3.6K in the RCP4.5, RCP8.5 respectively. 2) a slight decrease in large-scale precipitation rate was observed by 11%, 22.7% in the RCP4.5, RCP8.5 respectively. The air temperature and large-scale precipitation rate variables played a key role in increasing local precipitation in Izmir region.

Table 5.16 Statistical characteristics of AM daily rainfall of the observed data, and the IPSL-CM5A-LR model results before and after applying the bias correction process

	observed	Historical 1970-2000		RCP4.5 2005-2095		RCP8.5 2005-2095	
		Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction
Mean	66.28	39.25	66.65	44.72	72.07	47.57	75.56
Median	65.65	40.76	69.42	39.56	63.32	37.94	61.38
Std Dev	21.10	10.67	23.71	17.30	29.32	24.45	36.34
Min	31.10	20.97	28.36	23.82	36.70	17.32	29.20
Max	134.10	67.43	131.57	116.47	193.72	131.47	198.86

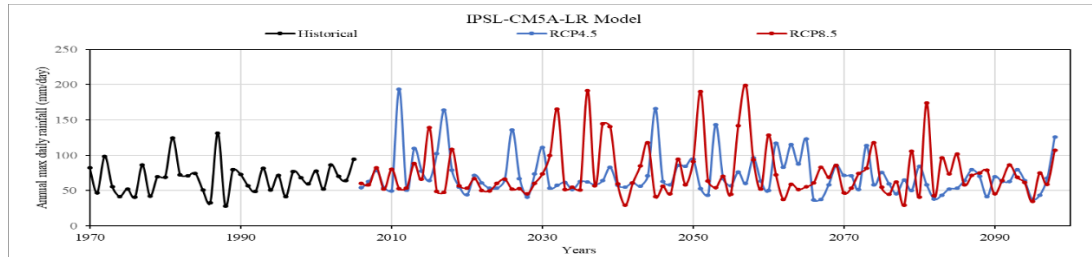


Figure 5.25 AM daily rainfall obtained from IPSL-CM5A-LR model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)

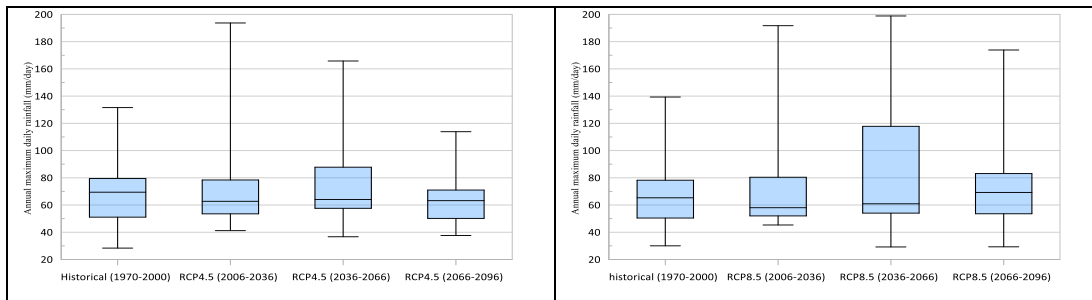


Figure 5.26 Box plots of AM daily rainfall for IPSL-CM5A-LR model for historical and future projections (left for RCP4.5, right for RCP 8.5)

5.6.2.3 AM Daily Rainfall Based on MIROC-ESM-CHEM Model

The results in Table 5.17 revealed that corrected AM daily rainfall based on the MIROC-ESM-CHEM model ($P_{max.daily}^{cor.MIROC}$) recorded a slight change in the future scenarios (RCP 4.5, RCP 8.5). Although there are increasing air temperature values in a future scenario, the precipitation rate decreased; therefore, no notable change was obtained.

Table 5.17 Statistical characteristics of AM daily rainfall of the observed data, and the MIROC-ESM-CHEM model results before and after applying the bias correction process

	observed	Historical 1970-2000		RCP4.5 2005-2095		RCP8.5 2005-2095	
		Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction
mean	66.28	37.78	67.49	37.37	66.65	33.43	62.67
median	65.65	35.21	62.40	36.25	64.29	31.06	57.98
st.dev	21.10	11.09	21.44	11.12	21.72	11.05	21.64
min	31.10	19.68	33.05	19.51	32.43	17.83	32.36
max	134.10	69.96	130.43	72.20	135.64	85.83	166.11

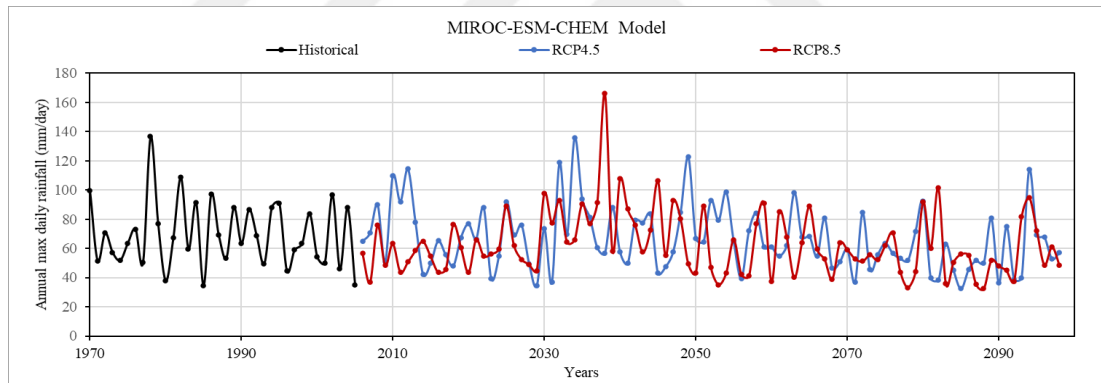


Figure 5.27 AM daily rainfall obtained from MIROC-ESM-CHEM model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)

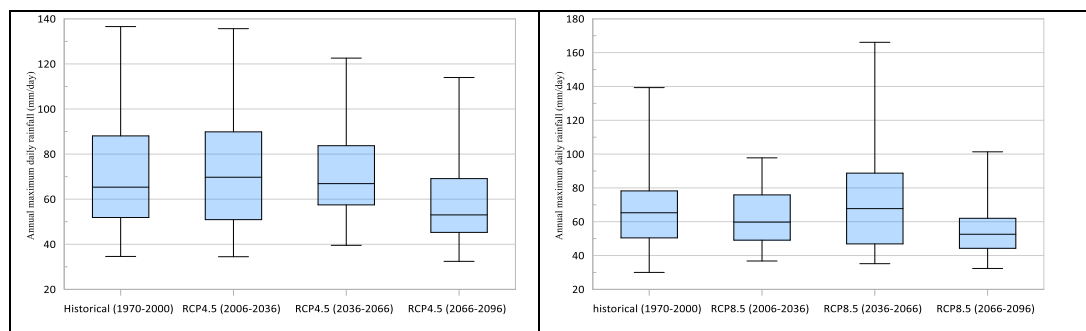


Figure 5.28 Box plots of AM daily rainfall for MIROC-ESM-CHEM model for historical and future projections (left for RCP4.5, right for RCP 8.5)

5.6.2.4 AM Daily Rainfall Based on CanESM2 Model

As shown in Table 5.18 and Figure 5.30, there are no significant changes in corrected AM daily rainfall based on the CanESM2 model ($P_{max.daily}^{cor.CanESM2}$). That because the air temperature values increase while the large-scale precipitation decrease in future scenarios. The results are nearly similar to the results obtained from the MIROC-ESM-CHEM model.

Table 5.18 Statistical characteristics of AM daily rainfall of the observed data, and the CanESM2 model results before and after applying the bias correction process

	observed	Historical 1970-2000		RCP4.5 2005-2095		RCP8.5 2005-2095	
		Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction	Pre- bias correction	Post-bias correction
mean	66.28	39.75	71.27	36.62	70.67	34.87	70.75
median	65.65	36.99	65.81	35.75	68.81	34.16	69.31
st.dev	21.10	11.28	22.00	11.25	22.99	8.14	16.56
min	31.10	23.71	40.54	21.30	39.71	17.49	35.39
max	134.10	82.23	154.84	77.42	154.53	66.46	134.94

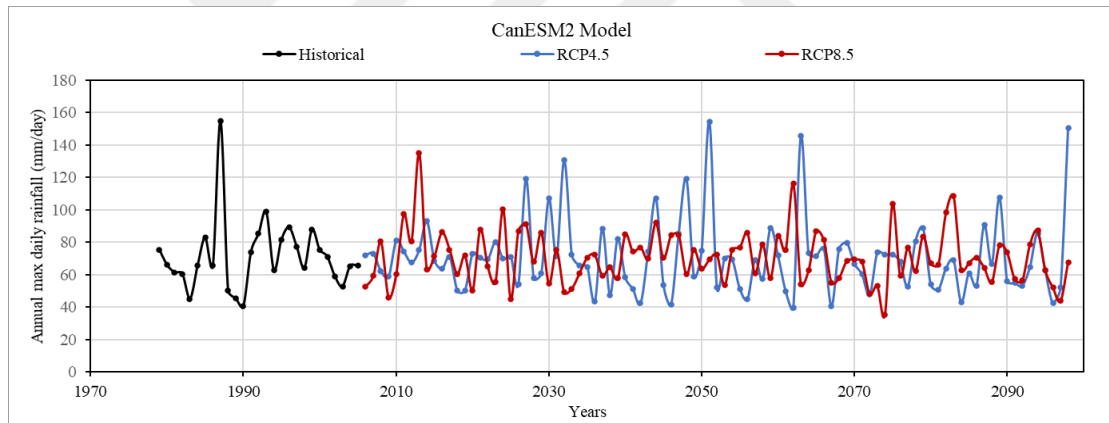


Figure 5.29 AM daily rainfall obtained from CanESM2 model with time for historical data (black line) and future projections (blue line for RCP4.5, and red line for RCP8.5)

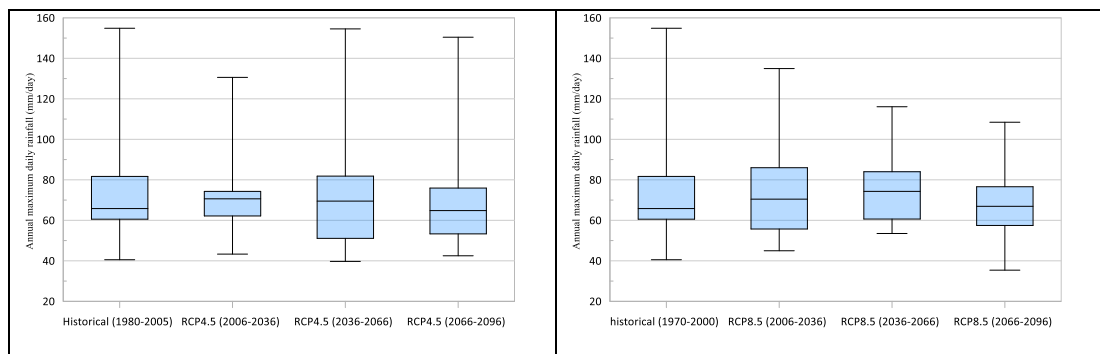


Figure 5.30 Box plots of annual maximum daily rainfall for CanESM2 model for historical and future projections (left for RCP4.5, right for RCP 8.5)

For all results in this section, in general, the AM daily rainfall has a reasonable relationship with the model predictors, i.e., air temperature, large-scale precipitation; this finding is similar to results in several studies (Fistikoglu & Okkan, 2011; Vu et al., 2016).

5.6.3 Step 6.3: Disaggregation of AM Daily Rainfall to Standard Durations

The AM daily rainfall from GCMs convert to AM 24-hr rainfall by empirical Eq. (5.2) then, The Indian Meteorological Department (IMD) formula (Eq. (5.3)) was used to disaggregate the AM daily rainfall to standard durations (for more information, see step 3).

5.6.4 Step 6.4: Generating GCM-based IDF Curves

The IDF curves were derived for GCMs and their projected scenarios Using the disaggregated AM daily rainfall. The current IDF curve was generated using the historical data in 1970-2005, while the future IDF curves used the projections for the period 2005-2100 under two scenarios (RCP4.5 and RCP 8.5).

5.6.4.1 IDF Curve Based on HadGEM2-CC Model

The results indicate that the IDF curves from the HadGEM2-CC model shifted up for the future projections, as shown in Figure 5.31 and Table 5.19. The rainfall intensity differs based on the return periods. For example, for a 2-year return period, the intensity increases by 13.7% and 24.1% for RCP 4.5, RCP 8.5.

Table 5.19 Intensity-duration-frequency values obtained from HadGEM2-CC model based on:

a) Historical data (1970 – 2005)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	119.66	75.38	57.52	36.24	22.83	14.38	10.97	9.06	7.81	6.91	5.71	4.36	3.32	2.74
5 years	158.8	100.04	76.34	48.09	30.3	19.09	14.57	12.02	10.36	9.18	7.57	5.78	4.41	3.64
10 year	184.72	116.37	88.81	55.94	35.24	22.2	16.94	13.99	12.05	10.67	8.81	6.72	5.13	4.24
25 years	217.47	137	104.55	65.86	41.49	26.14	19.95	16.47	14.19	12.57	10.37	7.92	6.04	4.99
50 years	241.77	152.3	116.23	73.22	46.13	29.06	22.18	18.3	15.77	13.97	11.53	8.8	6.72	5.54
100 years	265.88	167.5	127.82	80.52	50.73	31.96	24.39	20.13	17.35	15.36	12.68	9.68	7.39	6.1
200 years	289.91	182.63	139.37	87.8	55.31	34.84	26.59	21.95	18.92	16.75	13.83	10.55	8.05	6.65

b) RCP 4.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	136.1	85.74	65.43	41.22	25.97	16.36	12.48	10.3	8.88	7.86	6.49	4.95	3.78	3.12
5 years	177.89	112.06	85.52	53.87	33.94	21.38	16.32	13.47	11.61	10.28	8.48	6.47	4.94	4.08
10 years	205.55	129.49	98.82	62.25	39.22	24.7	18.85	15.56	13.41	11.88	9.8	7.48	5.71	4.71
25 years	240.5	151.51	115.62	72.84	45.88	28.91	22.06	18.21	15.69	13.9	11.47	8.75	6.68	5.51
50 years	266.43	167.84	128.09	80.69	50.83	32.02	24.44	20.17	17.38	15.39	12.71	9.7	7.4	6.11
100 years	292.17	184.05	140.46	88.48	55.74	35.11	26.8	22.12	19.06	16.88	13.94	10.63	8.12	6.7
200 year	317.81	200.21	152.79	96.25	60.63	38.2	29.15	24.06	20.74	18.36	15.16	11.57	8.83	7.29

c) RCP 8.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	148.49	93.54	71.39	44.97	28.33	17.85	13.62	11.24	9.69	8.58	7.08	5.4	4.12	3.4
5 years	201.43	126.9	96.84	61.01	38.43	24.21	18.48	15.25	13.14	11.64	9.61	7.33	5.6	4.62
10 years	236.49	148.98	113.69	71.62	45.12	28.42	21.69	17.91	15.43	13.66	11.28	8.61	6.57	5.42
25 years	280.78	176.88	134.99	85.04	53.57	33.75	25.75	21.26	18.32	16.22	13.39	10.22	7.8	6.44
50 years	313.64	197.58	150.78	94.99	59.84	37.7	28.77	23.75	20.46	18.12	14.96	11.42	8.71	7.19
100 years	346.26	218.13	166.46	104.86	66.06	41.62	31.76	26.22	22.59	20.01	16.52	12.6	9.62	7.94
200 years	378.75	238.6	182.09	114.71	72.26	45.52	34.74	28.68	24.71	21.88	18.07	13.79	10.52	8.68

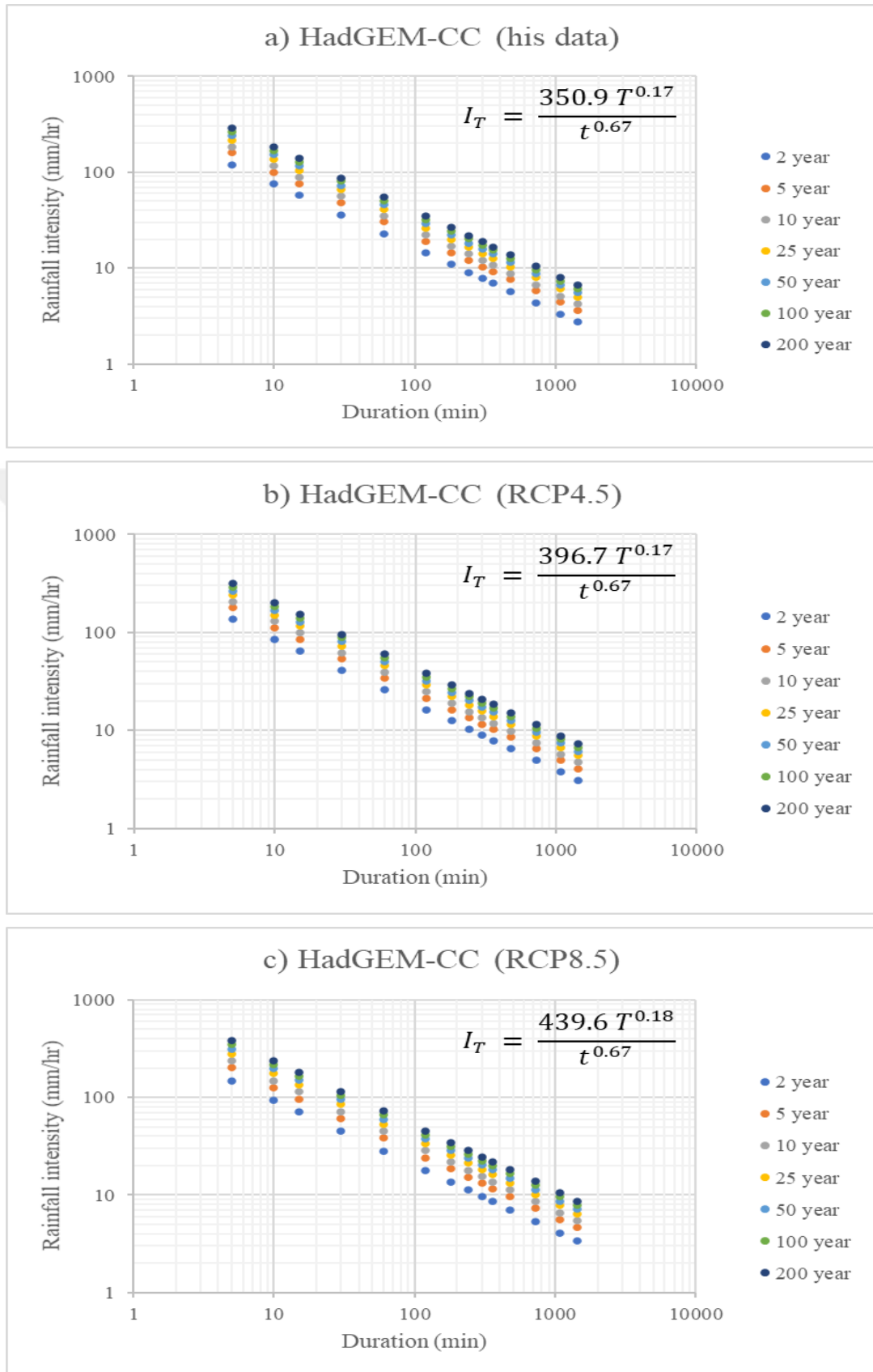


Figure 5.31 The IDF curves obtained from the HadGEM2-CC model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario

5.6.4.2 IDF Curve Based on IPSL-CM5A-LR Model

It was observed that the IDF curves generated from the IPSL-CM5A-LR model jumped up for the future projections, as shown in Figure 5.32 and Table 5.20. The rainfall intensity differs based on the return periods. For example, for a 2-year return period, the intensity increases by 5.0 % and 8.3% for RCP 4.5, RCP 8.5, respectively. This result is similar to the HadGEM2-CC results with a decrease in measurements.

Table 5.20 Intensity-duration-frequency values obtained from IPSL-CM5A-LR model based on a) historical data, b) RCP 4.5 scenario, and c) RCP 8.5 scenario

a) Historical data (1970 – 2005)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	121.36	76.45	58.35	36.76	23.15	14.59	11.13	9.19	7.92	7.01	5.79	4.42	3.37	2.78
5 years	161.62	101.81	77.7	48.95	30.83	19.42	14.82	12.24	10.55	9.34	7.71	5.88	4.49	3.71
10 years	188.27	118.6	90.51	57.02	35.92	22.63	17.27	14.25	12.28	10.88	8.98	6.85	5.23	4.32
25 years	221.94	139.81	106.7	67.21	42.34	26.67	20.36	16.8	14.48	12.82	10.59	8.08	6.17	5.09
50 years	246.92	155.55	118.71	74.78	47.11	29.68	22.65	18.69	16.11	14.27	11.78	8.99	6.86	5.66
100 years	271.71	171.17	130.63	82.29	51.84	32.66	24.92	20.57	17.73	15.7	12.96	9.89	7.55	6.23
200 years	296.42	186.73	142.5	89.77	56.55	35.63	27.19	22.44	19.34	17.13	14.14	10.79	8.23	6.8

b) RCP 4.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	127.45	80.29	61.27	38.6	24.32	15.32	11.69	9.65	8.32	7.36	6.08	4.64	3.54	2.92
5 years	166.96	105.18	80.27	50.57	31.85	20.07	15.31	12.64	10.89	9.65	7.96	6.08	4.64	3.83
10 years	193.12	121.66	92.84	58.49	36.85	23.21	17.71	14.62	12.6	11.16	9.21	7.03	5.36	4.43
25 years	226.17	142.48	108.73	68.5	43.15	27.18	20.74	17.12	14.76	13.07	10.79	8.23	6.28	5.19
50 years	250.69	157.93	120.52	75.92	47.83	30.13	22.99	18.98	16.36	14.48	11.96	9.13	6.96	5.75
100 years	275.03	173.26	132.22	83.29	52.47	33.06	25.23	20.82	17.95	15.89	13.12	10.01	7.64	6.31
200 years	299.28	188.54	143.88	90.64	57.1	35.97	27.45	22.66	19.53	17.29	14.27	10.89	8.31	6.86

c) RCP 8.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	131.43	82.8	63.19	39.8	25.08	15.8	12.06	9.95	8.58	7.59	6.27	4.78	3.65	3.01
5 years	180.29	113.58	86.67	54.6	34.4	21.67	16.54	13.65	11.76	10.42	8.6	6.56	5.01	4.13
10 years	212.64	133.95	102.23	64.4	40.57	25.56	19.5	16.1	13.87	12.29	10.14	7.74	5.91	4.88
25 years	253.51	159.7	121.87	76.78	48.37	30.47	23.25	19.19	16.54	14.65	12.09	9.23	7.04	5.81
50 years	283.83	178.8	136.45	85.96	54.15	34.11	26.03	21.49	18.52	16.4	13.54	10.33	7.88	6.51
100 years	313.93	197.76	150.92	95.07	59.89	37.73	28.79	23.77	20.48	18.14	14.97	11.43	8.72	7.2
200 years	343.91	216.65	165.34	104.16	65.61	41.33	31.54	26.04	22.44	19.87	16.4	12.52	9.55	7.89

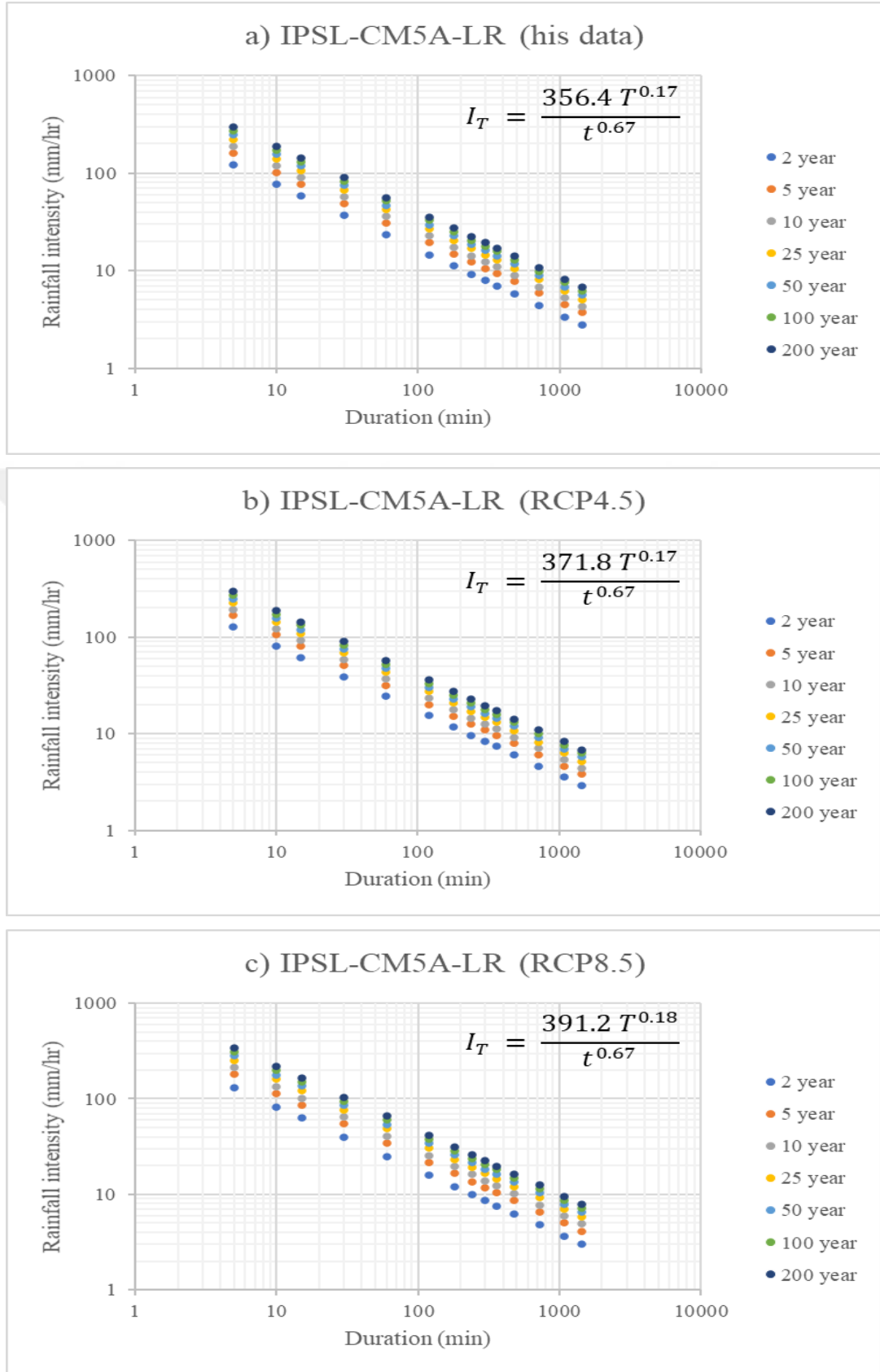


Figure 5.32 The IDF curves obtained from the IPSL-CM5A-LR model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario

5.6.4.3 IDF Curve Based on MIROC-ESM-CHEM Model

It was observed that the changes in rainfall intensity from RCPs to historical data are negligible in RCP 4.5 and are decreased slightly in the RCP 8.5 scenario. See table and figure below:

Table 5.21 Intensity-duration-frequency values obtained from MIROC-ESM-CHEM model based on a) historical data, b) RCP 4.5 scenario, and c) RCP 8.5 scenario

a. Historical data (1970 – 2005)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	119.57	75.32	57.48	36.21	22.81	14.37	10.97	9.05	7.8	6.91	5.7	4.35	3.32	2.74
5 years	157.52	99.23	75.73	47.71	30.05	18.93	14.45	11.93	10.28	9.1	7.51	5.73	4.38	3.61
10 years	182.66	115.07	87.81	55.32	34.85	21.95	16.75	13.83	11.92	10.55	8.71	6.65	5.07	4.19
25 years	214.41	135.07	103.08	64.93	40.91	25.77	19.67	16.23	13.99	12.39	10.23	7.8	5.96	4.92
50 years	237.97	149.91	114.4	72.07	45.4	28.6	21.83	18.02	15.53	13.75	11.35	8.66	6.61	5.46
100 years	261.35	164.64	125.64	79.15	49.86	31.41	23.97	19.79	17.05	15.1	12.47	9.51	7.26	5.99
200 years	284.65	179.32	136.84	86.21	54.31	34.21	26.11	21.55	18.57	16.45	13.58	10.36	7.91	6.53

b. RCP 4.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	119.81	75.48	57.6	36.29	22.86	14.4	10.99	9.07	7.82	6.92	5.71	4.36	3.33	2.75
5 years	156.78	98.77	75.37	47.48	29.91	18.84	14.38	11.87	10.23	9.06	7.48	5.71	4.36	3.6
10 years	181.26	114.19	87.14	54.9	34.58	21.79	16.63	13.72	11.83	10.47	8.65	6.6	5.04	4.16
25 years	212.19	133.67	102.01	64.26	40.48	25.5	19.46	16.07	13.84	12.26	10.12	7.72	5.89	4.87
50 years	235.13	148.12	113.04	71.21	44.86	28.26	21.57	17.8	15.34	13.59	11.21	8.56	6.53	5.39
100 years	257.91	162.47	123.99	78.11	49.21	31	23.66	19.53	16.83	14.9	12.3	9.39	7.16	5.91
200 years	280.6	176.77	134.9	84.98	53.53	33.72	25.74	21.25	18.31	16.21	13.38	10.21	7.79	6.43

c. RCP 8.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	112.24	70.71	53.96	33.99	21.41	13.49	10.29	8.5	7.32	6.49	5.35	4.09	3.12	2.57
5 years	145.93	91.93	70.16	44.2	27.84	17.54	13.38	11.05	9.52	8.43	6.96	5.31	4.05	3.35
10 years	168.24	105.98	80.88	50.95	32.1	20.22	15.43	12.74	10.98	9.72	8.02	6.12	4.67	3.86
25 years	196.42	123.74	94.43	59.49	37.47	23.61	18.02	14.87	12.82	11.35	9.37	7.15	5.46	4.5
50 years	217.33	136.91	104.48	65.82	41.46	26.12	19.93	16.45	14.18	12.56	10.37	7.91	6.04	4.98
100 years	238.09	149.98	114.46	72.1	45.42	28.61	21.84	18.03	15.53	13.76	11.36	8.67	6.61	5.46
200 years	258.76	163.01	124.4	78.37	49.37	31.1	23.73	19.59	16.88	14.95	12.34	9.42	7.19	5.93

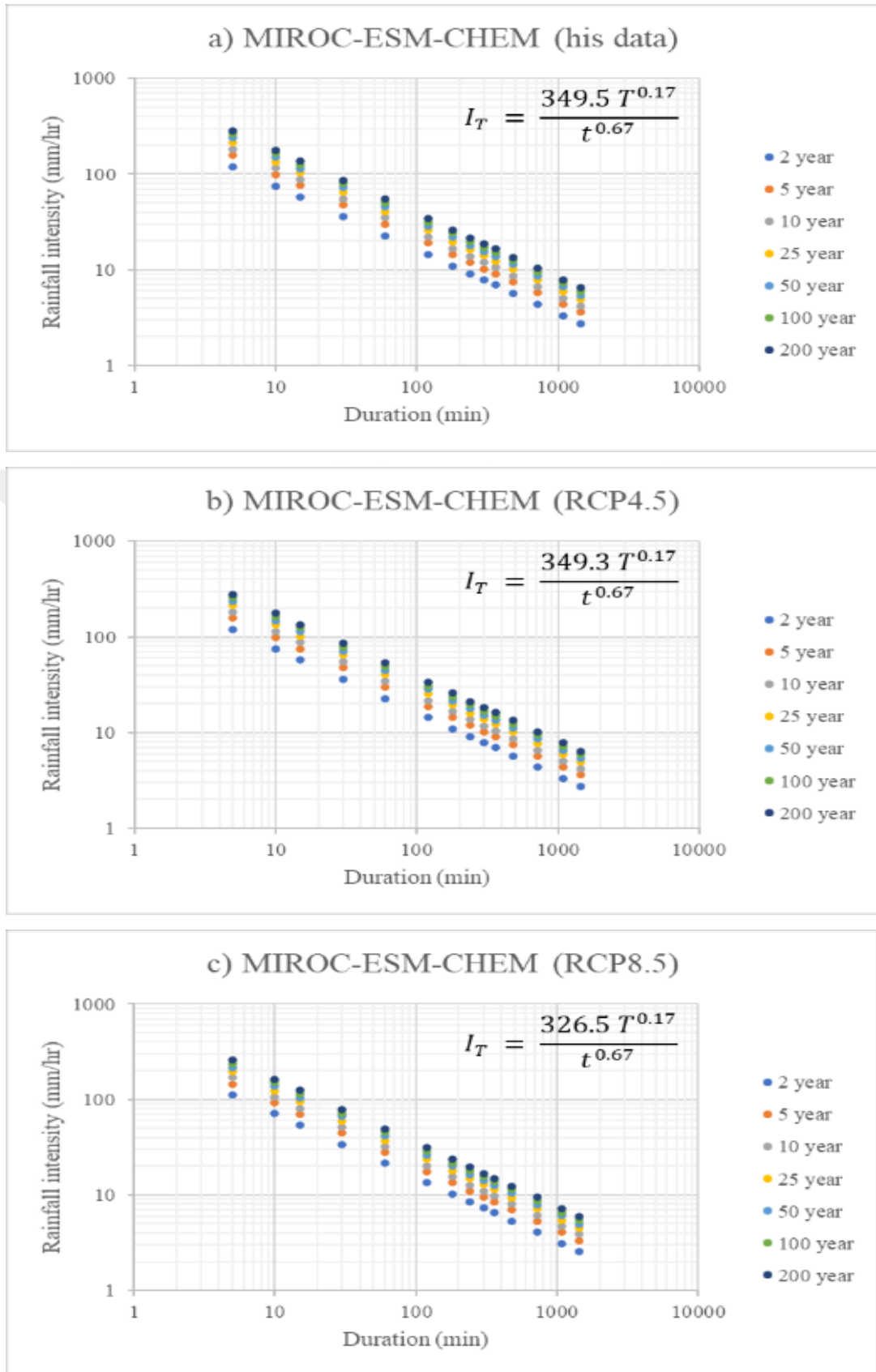


Figure 5.33 The IDF curves obtained from the MIROC-ESM-CHEM model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario

5.6.4.4 IDF Curve Based on CanESM2 Model

As shown in Table 5.22, it was observed that the IDF curves obtained from the CanESM2 model in the RCP 4.5 scenario are almost maintained the same behavior with the historical data, while IDF values are decreased slightly in the RCP 8.5 scenario.

Table 5.22 Intensity-duration-frequency values obtained from the CanESM2 model based on a) historical data, b) RCP 4.5 scenario, and c)RCP 8.5 scenario

a. Historical data (1970 – 2005)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 years	129.21	81.4	62.12	39.13	24.65	15.53	11.85	9.78	8.43	7.47	6.16	4.7	3.59	2.96
5 years	162.31	102.25	78.03	49.16	30.97	19.51	14.89	12.29	10.59	9.38	7.74	5.91	4.51	3.72
10 years	184.22	116.05	88.57	55.79	35.15	22.14	16.9	13.95	12.02	10.64	8.79	6.71	5.12	4.22
25 years	211.91	133.5	101.88	64.18	40.43	25.47	19.44	16.04	13.83	12.24	10.11	7.71	5.89	4.86
50 years	232.45	146.44	111.75	70.4	44.35	27.94	21.32	17.6	15.17	13.43	11.09	8.46	6.46	5.33
100 years	252.84	159.28	121.56	76.57	48.24	30.39	23.19	19.14	16.5	14.61	12.06	9.2	7.02	5.8
200 years	273.16	172.08	131.32	82.73	52.12	32.83	25.05	20.68	17.82	15.78	13.03	9.94	7.59	6.26

b. RCP 4.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 year	127.17	80.11	61.14	38.51	24.26	15.28	11.66	9.63	8.3	7.35	6.07	4.63	3.53	2.92
5 year	161.2	101.55	77.5	48.82	30.75	19.37	14.78	12.2	10.52	9.31	7.69	5.87	4.48	3.7
10 year	183.72	115.74	88.33	55.64	35.05	22.08	16.85	13.91	11.99	10.62	8.76	6.69	5.1	4.21
25 year	212.19	133.67	102.01	64.26	40.48	25.5	19.46	16.07	13.84	12.26	10.12	7.72	5.89	4.87
50 year	233.3	146.97	112.16	70.66	44.51	28.04	21.4	17.66	15.22	13.48	11.13	8.49	6.48	5.35
100 year	254.27	160.18	122.24	77.01	48.51	30.56	23.32	19.25	16.59	14.69	12.13	9.25	7.06	5.83
200 year	275.15	173.33	132.28	83.33	52.49	33.07	25.24	20.83	17.95	15.9	13.12	10.02	7.64	6.31

c. RCP 8.5 projections (2005 – 2095)

d (min)	5	10	15	30	60	120	180	240	300	360	480	720	1080	1440
2 year	129.73	81.73	62.37	39.29	24.75	15.59	11.9	9.82	8.46	7.5	6.19	4.72	3.6	2.97
5 year	159.39	100.41	76.62	48.27	30.41	19.16	14.62	12.07	10.4	9.21	7.6	5.8	4.43	3.65
10 year	179.02	112.77	86.06	54.22	34.15	21.52	16.42	13.55	11.68	10.34	8.54	6.52	4.97	4.1
25 year	203.82	128.4	97.99	61.73	38.89	24.5	18.69	15.43	13.3	11.78	9.72	7.42	5.66	4.67
50 year	222.23	139.99	106.84	67.3	42.4	26.71	20.38	16.83	14.5	12.84	10.6	8.09	6.17	5.1
100 year	240.49	151.5	115.62	72.83	45.88	28.9	22.06	18.21	15.69	13.9	11.47	8.75	6.68	5.51
200 year	258.69	162.97	124.37	78.35	49.35	31.09	23.73	19.59	16.88	14.95	12.34	9.42	7.19	5.93

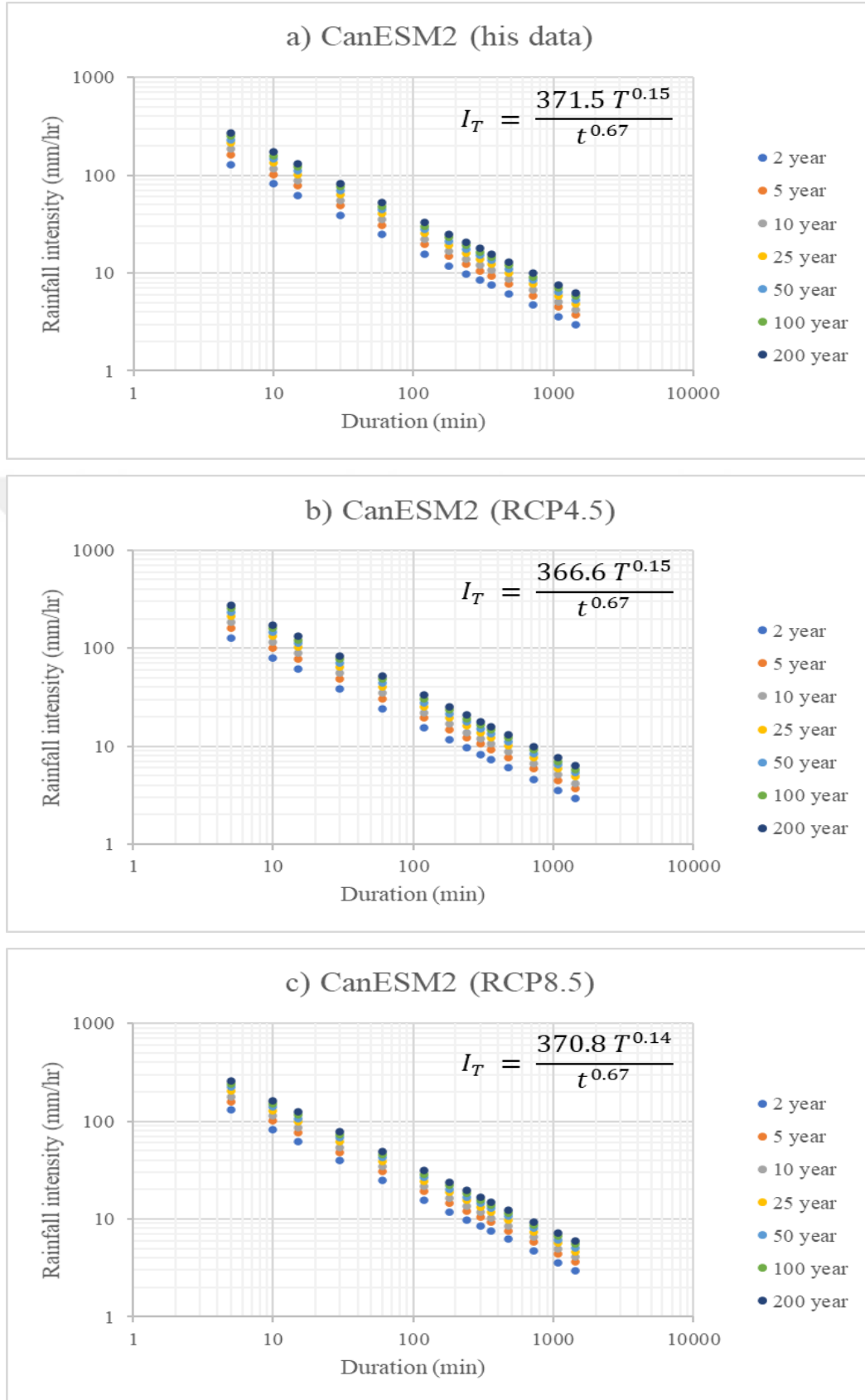


Figure 5.34 The IDF curves obtained from the CanESM2 model based on a) historical data, b) RCP4.5 scenario, c) RCP8.5 scenario

As the above results demonstrate, the four different models did not present identical results in the study region; this finding consistent with several studies several (Okkan & Kirdemir, 2016). Different results could be attributed to initial conditions and boundary conditions for each climate projection. The plots show that the IDF curves for the future climate are different from the currently employed IDF curves and that the extent of the difference between them varies depending on GCMs used.

The results indicate that the IPSL-CM5A-LR model shares the same behavior with the HadGEM2-CC model for generating IDF curves, whereas the *IDF* curve in both of them tends to increase (shifted up) under future scenarios. However, the HadGEM2-CC model recorded a higher increase rate. It was observed that there are no significant changes in future IDF curves in the MIROC-ESM-CHEM and the CanESM2 models under RCP 4.5, whereas the IDF curve in both of them tends to decrease slightly under RCP 8.5 scenarios.

5.7 Optimal Model for Representing Izmir Region to Estimate AM Daily Rainfall

Four criteria were used to determine which model best represents the region for estimating AM daily rainfall. The criteria are 1- the basic statistical characteristics, 2- Q-Q plots, 3- Mann-Whitney U test (similarity test), and 4- PBIAS values.

Table 5.23 and Figure 5.35 show the statistical characteristics of annual maximum daily rainfall based on observed data and corrected data from all GCMs. The results in this table revealed that GCMs provide acceptable output with respect to the observation data; however, the HadGEM2-CC model results are close to the observation data rather than other GCMs.

Table 5.23 The statistical characteristics of annual maximum daily rainfall (1970-2005) based on observed data, HadGEM2-CC, IPSL-CM5A-LR, MIROC-ESM-CHEM, CanESM2 models

	Observed	HadGEM2-CC	IPSL-CM5A-LR	MIROC-ESM-CHEM	CanESM2
Mean	66.28	66.50	66.65	67.49	71.27
Median	65.65	65.30	69.42	62.40	65.81
St.dev	21.10	22.93	23.71	21.44	22.00
Min	31.10	30.03	28.36	33.05	40.54
Max	134.10	139.32	131.57	130.43	154.84

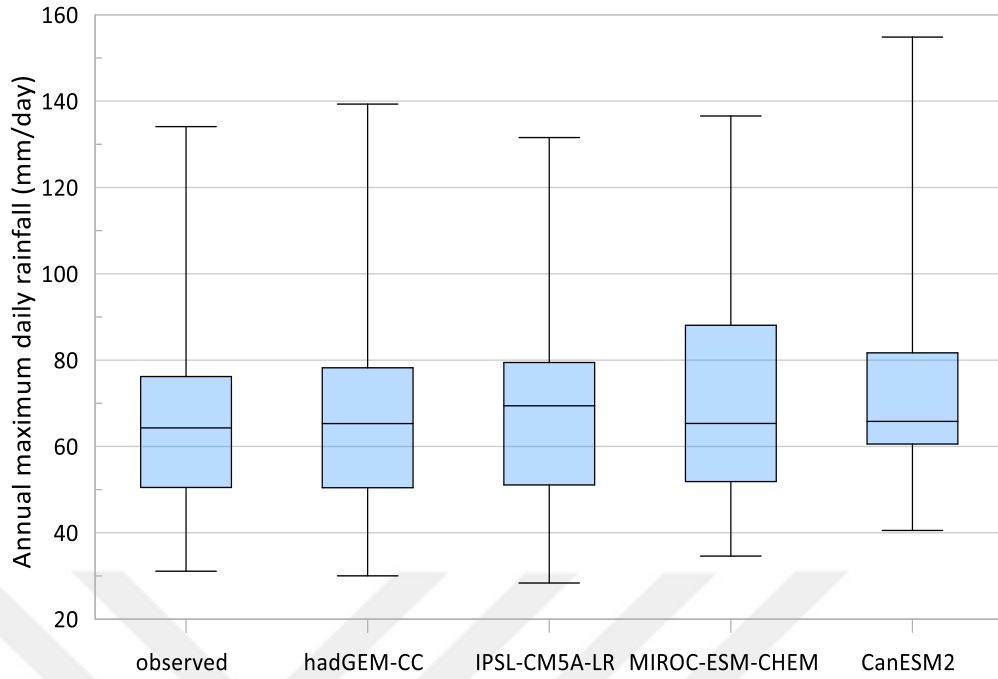


Figure 5.35 Box plot of AM daily rainfall from observed data and results from selected GCMs

Percent bias (PBIAS) measures the average tendency of the simulated values to be larger or smaller than their observed ones. PBIAS was calculated by Eq. (5.10). The optimal value of PBIAS was 0.0. The Positive (+) values indicate overestimation bias, while negative (-) values indicate model underestimation bias.

$$PBIAS = 100 \frac{\sum_{i=1}^N (Sim_i - Obs_i)}{\sum_{i=1}^N Obs_i} \quad (5.10)$$

Where: *Sim*: simulated data, *obs*: observation data.

Table 5.24 shows PBIAS values of AM daily rainfall based on all GCMs. The table shows that the IPSL-CM5A-LR, and MIROC-ESM-CHEM, HadGEM2-CC models have high PBIAS values, +0.7, +1.0, and -1.9, respectively.

Mann-Whitney U test was used to test whether two samples are likely to derive from the same population. Table 5.24 show the results of Mann-Whitney test of the Annual maximum daily rainfall between Observed data ($P_{max,daily}^{obs.}$) and estimated data from GCMs ($P_{max,daily}^{cor.GCM}$). The table revealed that AM daily rainfall of the observed and estimated from all GCMs are derived from the same population.

Table 5.24 Mann-Whitney test statistics and PBIAS ratios of AM daily rainfall (1970-2005)

Model	Mann-Whitney test (P-value)	PBIAS
HadGEM2-CC	0,773	-1,9%
IPSL-CM5A-LR	0,878	+0,7%
MIROC-ESM-CHEM	0,887	+1,0%
CanESM2	0,353	+9,1%

Figure 5.36 shows that the Q-Q plots of AM daily rainfall between observed and estimated from GCMs. The figure indicates that the best three models are HadGEM2-CC, IPSL-CM5A-LR, MIROC-ESM-CHEM models.

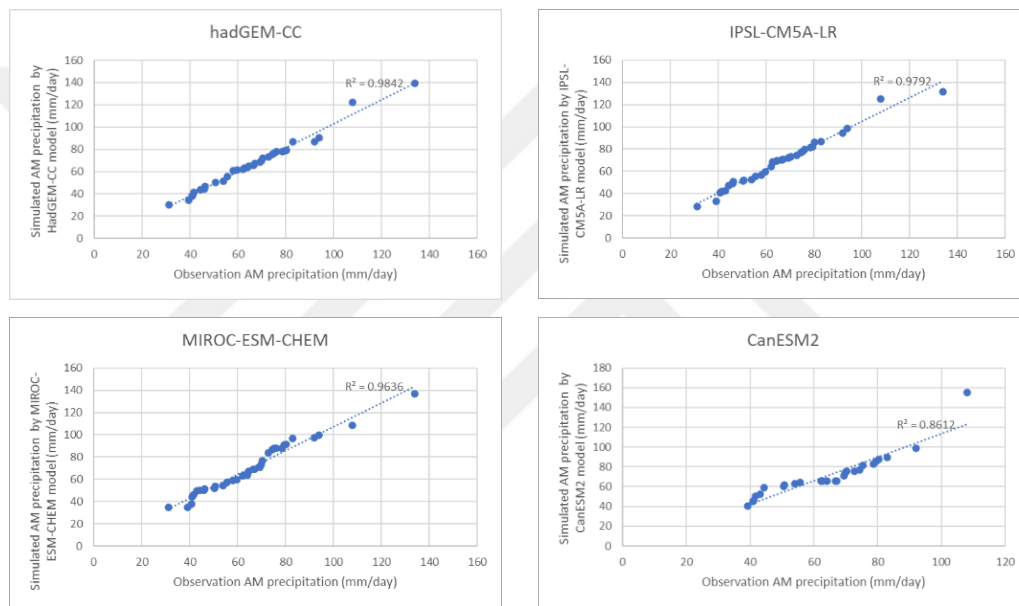


Figure 5.36 Q-Q Plot of AM daily rainfall between observed and estimated from the GCMs (1970-2005) a) HadGEM2-CC, b) IPSL-CM5A-LR, c) MIROC-ESM-CHEM, and d) CanESM2

According to the abovementioned criteria, the first three models (HadGEM2-CC, IPSL-CM5A-LR, and MIROC-ESM-CHEM) successfully represent the study region to estimate the AM daily rainfall; however, the HadGEM2-CC model provides the best representation.

CHAPTER 6

CONCLUSIONS

The extreme precipitation events have increased in many regions in the past century due to climate change. This casts doubt on the stationary assumption in urban infrastructure design and stormwater management. The IDF curves, which are commonly employed in hydrology for urban drainage design, are mainly based on the stationary assumption. Therefore, the current IDF curves should be updated by considering possible changes in extreme precipitation.

The presented study aimed to develop a new methodology that combined the process of statistical downscaling, bias correction, and sub-daily disaggregation of rainfall in order to derive future IDF curves based on global climate models (GCMs).

Statistical downscaling based on deep learning techniques using ANN structure was established to estimate the daily rainfall from the large-scale NCEP/NCAR atmospheric parameters over Izmir in the Aegean region. The atmospheric parameters selected as predictors were air temperature, sea level pressure, v-wind, and precipitation rate at the surface of the studied area. Scenario-based sets of analysis using varied ANN model structures were used to obtain the most explanatory parameters; in particular, three models were constructed. Here, the present and antecedent large-scale atmospheric variables were considered inputs for the daily downscaling networks. The statistical downscaling models used in this study i) the first model (ANN₁) used atmospheric variables on the current day (t) as predictors, ii) the second model (ANN₂) considered the atmospheric variables of previous (t-1) and current (t) day are used as predictors, iii) the last model (ANN₃) used the previous two-day atmospheric variables.

The models were trained for the period 1948–1990 using daily data and validated for 1991–2018. R^2 and RMSE statistical tests were used to determine the optimal model. The results show that the ANN₂ model, which used the current and previous days of NCEP/NCAR atmospheric variables as predictors, had better performance than

other models. The large-scale atmospheric conditions of the present and one antecedent day had a dominant role in the daily rainfall values of the present day in the study area. In addition, it was observed that the estimations of the model preserved the spatial properties of the rainfall distribution existing in the study area.

The annual maximum daily values were sampled from the downscaled daily rainfall series. The biases in the annual maximum daily values were removed using the distribution mapping approach. The results showed that the estimated annual maximum daily rainfall values were consistent with the observations in the study area, which led to the conclusion that the bias correction is a crucial step in a statistical downscaling approach.

The annual 24-hour maximum rainfall values were estimated using the regression equation formulated from observed data; The regression equation in the study area is consistent with the results of (Huff & Angel, 1992) study. Hence, the annual 24-hour maximum rainfall was disaggregated using the empirical formula IMD to the sub-daily standard-duration rainfall depths for deriving the IDF curve. The result of the disaggregation phase revealed that IMD empirical formula can be used to estimate the sub-daily rates of maximum rainfall because it proved to be effective in the estimate of maximum rainfall in the study region. Also, the Mann–Whitney U statistics revealed that the disaggregated and observed rainfalls share similar population characteristics.

The IDF curve derived from the proposed methodology was validated using the observed IDF curve. The results indicated that the proposed approach could develop reasonable IDF curves using large-scale atmospheric variables after downscaling, bias-correcting, and disaggregating processes.

The large-scale variables of GCMs were used as inputs in the proposed methodology in order to derive the future IDF curves under Representative Concentration Pathways (RCPs) scenarios. Atmospheric variables of four GCMs, which are HadGEM2-CC, IPSL-CM5A-LR, CanESM2, and MIROC-ESM-CHEM, under 4.5RCP and 8.5 RCP future scenarios were applied in this study.

Since the GCMs have uncertain/biased outputs in their historical and future projections, the GCMs' raw data should be handled cautiously by applying the necessary correction procedures. NCEP/NCAR reanalysis data were used to correct the raw data of GCMs. The quantile mapping (QM) approach was employed to eliminate the biases of historical data (1970–2005) of GCM atmospheric variables. While the equidistant cumulative distribution function matching (EDCDFm) method was employed for correcting the future period (2005 –2100) in this study.

The findings demonstrate that each model provides different results in the study region; these findings are consistent with several studies as different results could be attributed to initial conditions and boundary conditions for each climate projection (Okkan & Kirdemir, 2016).

The results revealed that the future IDF curves are different from the currently employed IDF curves and that the extent of the difference between them varies depending on GCMs selected.

The results indicate that IPSL-CM5A-LR model shares the same behavior as HadGEM2-CC model for generating IDF curves, whereas the IDF curve in both of them tends to increase (shifted up) under future scenarios. However, HadGEM2-CC model recorded a higher increase rate. In contrast, it was observed that there are no significant changes in IDF curves in the MIROC-ESM-CHEM and the CanESM2 models for both future scenarios. Although the IDF curves are different from one GCM to another, these results are consistent with Trzaska & Schnarr (2014) study, which said that different models might project opposite output in terms of rainfall amount for certain regions.

The study found that HadGEM2-CC, IPSL-CM5A-LR, and MIROC-ESM-CHEM models successfully present Izmir region in order to estimate annual maximum daily rainfall. Two of these models (HadGEM2-CC, IPSL-CM5A-LR) revealed that IDF curves tend to increase over time for future projections.

An increase in the intensity of extreme rainfall is likely to cause flooding in the studied area, which has strong implications for the Izmir region, which is highly vulnerable to climate change and needs suitable measures to mitigate it. According to the records from the Turkish State Meteorological Service, extreme rainfall was recorded on February 2nd, 2021, with the 109.6 mm of 4-hr accumulated rainfall observed at the Izmir station; an extreme rainfall event with a similar intensity did not record since 1938, while the previous extreme rainfall was observed in 4-hr 92.6 mm accumulated rainfall in 2006.

The Rational method is the most widely used method for the design of storm sewers (Chow et al., 1988); this method is commonly based on the current IDF curve to determine the rainfall intensity for each time of concentration and design storm frequency; this method can be expressed by Eq. (6.1).

$$Q = C I A \quad (6.1)$$

Where Q is peak discharge (m^3/s), C is the runoff coefficient, A is the watershed area (km^2), I is the rainfall intensity for a particular drainage basin.

It was assumed, the climate change phenomenon does not influence the C and A parameters, which means that the changes of Q just depend on the variation of I , ($Q = f(I)$). The change in the intensity depends on the design storm frequency (Return period) and time of concentration; therefore, any changes in climate conditions influence both the frequency and the intensity of the design storm.

According to the presented study, climate changes may lead to an increase in the future IDF curve, which subsequently increases the flood risk and failure risk in infrastructure systems. The main question here, what will happen in the existing infrastructure? We suggested the existing infrastructure can be redesigned with two alternatives scenarios; the first one is decreasing the return period, the second is increasing rainfall intensity.

As Figure 6.1 clearly revealed, the existing infrastructure (designed based on the reference climate change conditions), which is designed to accommodate the capacity of 6.1 mm/hr storm for 24-hr design rainfall duration associated with a 100-year return period, will be changed based on two options: 1) maintaining the storm intensity; here, the return period would decrease from 100- to 50- and 20-year for RCP4.5 and RCP8.5, respectively. 2) maintaining the return period, the rainfall intensity will be increased from 6.1 mm/hr to 6.8 mm/hr and 8 mm/hr for RCP 4.5 and RCP8.5 climate projection conditions, respectively.

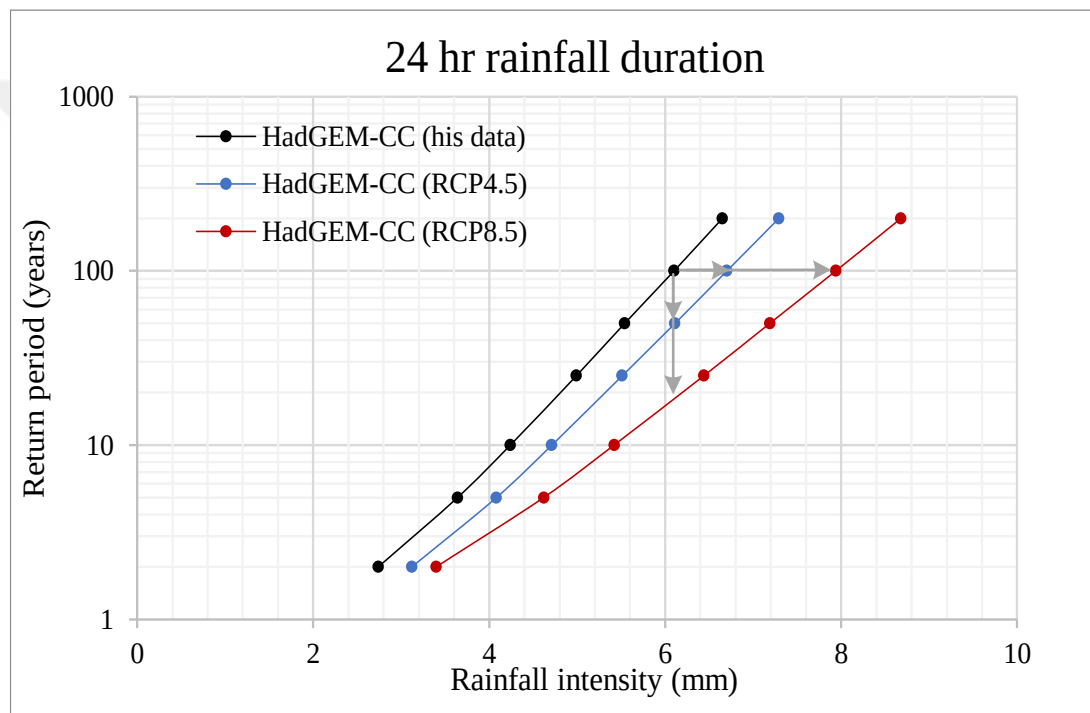


Figure 6.1 The relation between rainfall intensity and return period for the current IDF curve and the future IDF curves under RCP4.5 and RCP8.5 according to the HadGEM2-CC model

6.1 Challenges and Recommendations

It is critical to reconsider current IDF curve design guidelines based on the potential impacts of future climate change. Thus, collaboration between engineers and climate scientists is required for updating the IDF curves design strategies (Cheng & Aghakouchak, 2014; Yan et al., 2021).

There is a small agreement on the most appropriate selection of predictor variables for downscaling. Therefore, selecting the appropriate predictors is vital to receive reasonable results. More studies should be conducted in the future to determine the most appropriate predictors of each predictand for each region.

Climate impact assessments can be sensitive to biases in GCMs outputs (Stocker, 2014). Therefore, it is very important to apply bias correction perrier any downscaling application.



REFERENCES

- Agilan, V., & Umamahesh, N. V. (2016). Is the covariate based non-stationary rainfall IDF curve capable of encompassing future rainfall changes? *Journal of Hydrology*, 541, 1441–1455.
- Aichouri, I., Hani, A., Bougherira, N., Djabri, L., Chaffai, H., & Lallahem, S. (2015). River flow model using artificial neural networks. *Energy Procedia*, 74, 1007–1014.
- Al Mamun, A., bin Salleh, M. N., & Noor, H. M. (2018). Estimation of short-duration rainfall intensity from daily rainfall values in Klang Valley, Malaysia. *Applied Water Science*, 8(7), 203.
- AlHassoun, S. A. (2011). Developing an empirical formulae to estimate rainfall intensity in Riyadh region. *Journal of King Saud University - Engineering Sciences*, 23(2), 81–88.
- Anandhi, A., Srinivas, V. V., Kumar, D. N., & Nanjundiah, R. S. (2009). Role of predictors in downscaling surface temperature to river basin in India for IPCC SRES scenarios using support vector machine. *International Journal of Climatology*, 29(4), 583–603.
- Anilan, T., Yüksek, Ö., Saka, F., & Orgun, E. (2022). Rainfall Intensity-Duration-Frequency analysis in Turkey, with the emphasis of eastern black sea basin. *Teknik Dergi*, 33(4).
- ASCE. (2000). Artificial neural networks in hydrology. II: Hydrologic applications. *Journal of Hydrologic Engineering*, 5(2), 124–137.
- Bardossy, A., Bogardi, I., & Matyasovszky, I. (2005). Fuzzy rule-based downscaling of precipitation. *Theoretical and Applied Climatology*, 82(1–2), 119–129.
- Benestad, R. E., Hanssen-Bauer, I., & Førland, E. J. (2007). An evaluation of statistical models for downscaling precipitation and their ability to capture long-term trends.

International Journal of Climatology, 27(5), 649–665.

Brands, S., Gutiérrez, J. M., Herrera, S., & Cofiño, A. S. (2012). On the use of reanalysis data for downscaling. *Journal of Climate*, 25(7), 2517–2526.

Bureau, W. (1953). *Rainfall intensities for local drainage design in the united states*. Washington: United states weather bureau.

Chen, H., Guo, J., Xiong, W., Guo, S., & Xu, C.-Y. (2010). Downscaling GCMs using the Smooth Support Vector Machine method to predict daily precipitation in the Hanjiang Basin. *Advances in Atmospheric Sciences*, 27(2), 274–284.

Chen, H., Xu, C. Y., & Guo, S. (2012). Comparison and evaluation of multiple GCMs, statistical downscaling and hydrological models in the study of climate change impacts on runoff. *Journal of Hydrology*, 434–435, 36–45.

Cheng, L., & Aghakouchak, A. (2014). Nonstationary precipitation intensity-duration-frequency curves for infrastructure design in a changing climate. *Scientific Reports*, 4(1), 1–6.

Chow, T. V., Maidment, D. R., & Larry, W. M. (1988). *Applied hydrology*. New York: McGraw-Hill.

Chowdhury, R., Alam, M. J., Das, P., & Alam, M. A. (2007). Short duration rainfall estimation of Sylhet: IMD and USWB method. *Journal of the Indian Water Works Association*, 39(4), 285–292.

Christensen, J. H., Boberg, F., Christensen, O. B., & Lucas-Picher, P. (2008). On the need for bias correction of regional climate change projections of temperature and precipitation. *Geophysical Research Letters*, 35(20), L20706.

Cigizoglu, H. K., & Alp, M. (2004). Rainfall-runoff modelling using three neural network methods. *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*, 3070, 166–171.

Cook, L. M., McGinnis, S., & Samaras, C. (2020). The effect of modeling choices on

- updating intensity-duration-frequency curves and stormwater infrastructure designs for climate change. *Climatic Change*, 159(2), 289–308.
- Coulibaly, P., Dibike, Y. B., & Anctil, F. (2005). Downscaling precipitation and temperature with temporal neural networks. *Journal of Hydrometeorology*, 6(4), 483–496.
- Dayon, G., Boé, J., & Martin, E. (2015). Transferability in the future climate of a statistical downscaling method for precipitation in France. *Journal of Geophysical Research: Atmospheres*, 120(3), 1023–1043.
- Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., & Vitart, F. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 137(656), 553–597.
- Dogan, M., Ulke, A., & Cigizoglu, H. K. (2015). Trend direction changes of Turkish temperature series in the first half of 1990s. *Theoretical and Applied Climatology*, 121(1–2), 23–39.
- Druyan, L., & Fulakeza, M. (2013). Downscaling reanalysis over continental Africa with a regional model: NCEP versus ERA Interim forcing. *Climate Research*, 56(3), 181–196.
- Druyan, L. M. (2012). *Climate Models. BoD–Books on Demand*. Rijeka, Croatia: InTech.
- Ewea, H. A., Elfeki, A. M., Bahrawi, J. A., & Al-Amri, N. S. (2018). Modeling of IDF curves for stormwater design in Makkah Al Mukarramah region, the Kingdom of Saudi Arabia. *Open Geosciences*, 10(1), 954–969.
- Fistikoglu, O., & Okkan, U. (2011). Statistical downscaling of monthly precipitation using NCEP/NCAR reanalysis data for Tahtali river basin in Turkey. *Journal of Hydrologic Engineering*, 16(2), 157–164.

- Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., & Rummukainen, M. (2013). *Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (741-882). Cambridge: Cambridge university press
- Fu, G., Charles, S. P., Timbal, B., Jovanovic, B., & Ouyang, F. (2016). Comparison of NCEP-NCAR and ERA-Interim over Australia. *International Journal of Climatology*, 36(5), 2345–2367.
- Fu, G., Liu, Z., Charles, S. P., Xu, Z., & Yao, Z. (2013). A score-based method for assessing the performance of GCMs: A case study of southeastern Australia. *Journal of Geophysical Research: Atmospheres*, 118(10), 4154–4167.
- Ghenim, A. N., & Megnounif, A. (2016). Variability and trend of annual maximum daily rainfall in northern Algeria. *International Journal of Geophysics*, 2016, 1–11.
- Giorgi, F., Hewitson, B., Arritt, R., Gutowski, W., Knutson, T., & Landsea, C. (2001). Regional climate information—evaluation and projections. In *Climate change* (583–638). Cambridge: Cambridge University Press.
- Goly, A., Teegavarapu, R. S. V., & Mondal, A. (2014). Development and evaluation of statistical downscaling models for monthly precipitation. *Earth Interactions*, 18(18), 1–28.
- Govindaraju, R. S., & Ramachandra, A. (2013). Artificial neural networks in hydrology. In *Springer Science & Business Media* (Vol. 36) (287-311). Indiana: Springer Netherlands.
- Guo, L. Y., Gao, Q., Jiang, Z. H., & Li, L. (2018). Bias correction and projection of surface air temperature in LMDZ multiple simulation over central and eastern China. *Advances in Climate Change Research*, 9(1), 81–92.
- Hanssen-Bauer, I., Achberger, C., Benestad, R. E., Chen, D., & Forland, E. J. (2005).

- Statistical downscaling of climate scenarios over Scandinavia. *Climate Research*, 29(3), 255–268.
- Harpham, C., & Wilby, R. L. (2005). Multi-site downscaling of heavy daily precipitation occurrence and amounts. *Journal of Hydrology*, 312(1–4), 235–255.
- Hassanzadeh, E., Nazemi, A., & Elshorbagy, A. (2014). Quantile-based downscaling of precipitation using genetic programming: application to IDF Curves in Saskatoon. *Journal of Hydrologic Engineering*, 19(5), 943–955.
- Herath, S. M., Sarukkalige, R., & Nguyen, V. T. Van. (2018). Evaluation of empirical relationships between extreme rainfall and daily maximum temperature in Australia. *Journal of Hydrology*, 556, 1171–1181.
- Hu, Y., Maskey, S., & Uhlenbrook, S. (2013). Downscaling daily precipitation over the Yellow River source region in China: A comparison of three statistical downscaling methods. *Theoretical and Applied Climatology*, 112(3–4), 447–460.
- Huff, F. A., & Angel, J. R. (1992). *Rainfall frequency Atlas of the Midwest. (Bulletin 71)*. Illinois: Illinois State Water Survey.
- Hung, N. Q., Babel, M. S., Weesakul, S., & Tripathi, N. K. (2009). An artificial neural network model for rainfall forecasting in Bangkok, Thailand. *Hydrology and Earth System Sciences*, 13(8), 1413–1425.
- Ines, A. V. M., & Hansen, J. W. (2006). Bias correction of daily GCM rainfall for crop simulation studies. *Agricultural and Forest Meteorology*, 138(1), 44–53.
- IPCC. (2007). *Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (23-105)*. Geneva, Switzerland: IPCC.
- IPCC. (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (15-143)*. Geneva, Switzerland: IPCC.

- IZKA. (2015). *İzmir regional plan 2014-2023*. Izmir: Izmir development agency.
- Jahnvi, M., Bhatt, P., Gandhi, H. M., & Gohil, K. B. (2014). Generation of intensity duration frequency curve using daily. *Journal of International Academic Research for Multidisciplinary*, 2(2), 717–722.
- Jiang, D., Tian, Z., & Lang, X. (2016). Reliability of climate models for China through the IPCC Third to Fifth Assessment Reports. *International Journal of Climatology*, 36(3), 1114–1133.
- Jiang, H., & Cotton, W. R. (2004). Soil moisture estimation using an artificial neural network: A feasibility study. *Canadian Journal of Remote Sensing*, 30(5), 827–839.
- Johnson, F., & Sharma, A. (2011). Accounting for interannual variability: A comparison of options for water resources climate change impact assessments. *Water Resources Research*, 47(4), W04508.
- Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K. C., Ropelewski, C., Wang, J., Leetmaa, A., ... Joseph, D. (1996a). The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society*, 77(3), 437–471.
- Karl, T. R., Wang, W.-C., Schlesinger, M. E., Knight, R. W., & Portman, D. (1990). A Method of relating general circulation model simulated climate to the observed local climate. Part I: seasonal statistics. *Journal of Climate*, 3(10), 1053–1079.
- Katz, R. W. (1999). Extreme value theory for precipitation: Sensitivity analysis for climate change. *Advances in Water Resources*, 23(2), 133–139.
- Khan, M. S., Coulibaly, P., & Dibike, Y. (2006). Uncertainty analysis of statistical downscaling methods. *Journal of Hydrology*, 319(1–4), 357–382.
- Kidson, J. W., & Thompson, C. S. (1998). A comparison of statistical and model-based downscaling techniques for estimating local climate variations. *Journal of*

Climate, 11(4), 735–753.

Kilsby, C. G., Jones, P. D., Burton, A., Ford, A. C., Fowler, H. J., Harpham, C., James, P., Smith, A., & Wilby, R. L. (2007). A daily weather generator for use in climate change studies. *Environmental Modelling and Software*, 22(12), 1705–1719.

Koutsoyiannis, D., Kozonis, D., & Manetas, A. (1998). A mathematical framework for studying rainfall intensity-duration-frequency relationships. *Journal of Hydrology*, 206(1–2), 118–135.

Kusangaya, S., Warburton, M. L., Archer, E., Garderen, V., & Jewitt, G. P. W. (2014). Impacts of climate change on water resources in southern africa: A review. *Physics and Chemistry of the Earth*, 67-67, 47–54.

Laddimath, R. S., & Patil, N. S. (2019). Artificial neural network technique for statistical downscaling of global climate model. *Journal of Metrology Society of India*, 34(1), 121–127.

Lafon, T., Dadson, S., Buys, G., & Prudhomme, C. (2013). Bias correction of daily precipitation simulated by a regional climate model: A comparison of methods. *International Journal of Climatology*, 33(6), 1367–1381.

Li, H., Sheffield, J., & Wood, E. F. (2010). Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. *Journal of Geophysical Research Atmospheres*, 115(10), D10101.

Liu, J., Yuan, D., Zhang, L., Zou, X., & Song, X. (2016). Comparison of three statistical downscaling methods and ensemble downscaling method based on Bayesian model averaging in upper Hanjiang River Basin. *Advances in Meteorology*, 2016, 1–12.

Mailhot, A., Duchesne, S., Caya, D., & Talbot, G. (2007). Assessment of future change in intensity-duration-frequency (IDF) curves for Southern Quebec using the Canadian Regional Climate Model (CRCM). *Journal of Hydrology*, 347(1–2), 197–210.

- Maurer, E. P., & Pierce, D. W. (2014). Bias correction can modify climate model simulated precipitation changes without adverse effect on the ensemble mean. *Hydrology and Earth System Sciences*, 18(3), 915–925.
- McGinnis, S., Nychka, D., & Mearns, L. O. (2015). A new distribution mapping technique for climate model bias correction. *Machine Learning and Data Mining Approaches to Climate Science*. Switzerland: Springer International Publishing.
- Meehl, G. A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J. F. B., Stouffer, R. J., & Taylor, K. E. (2007). The WCRP CMIP3 multimodel dataset: A new era in climatic change research. *Bulletin of the American Meteorological Society*, 88(9), 1383–1394.
- Michelangeli, P. A., Vrac, M., & Loukos, H. (2009). Probabilistic downscaling approaches: Application to wind cumulative distribution functions. *Geophysical Research Letters*, 36(11), L11708.
- Minns, A. W., & Hall, M. J. (1996). Artificial neural networks as rainfall-runoff models. *Hydrological Sciences Journal*, 41(3), 399–417.
- Mirhosseini, G., Srivastava, P., & Stefanova, L. (2013). The impact of climate change on rainfall Intensity-Duration-Frequency (IDF) curves in Alabama. *Regional Environmental Change*, 13(1), 25–33.
- Moldovan, I. F. (2020). Calculation of the river flow with Different probabilities of occurrence using artificial neural network. *Geographia Technica*, 15, 172.
- Mooney, P. A., Mulligan, F. J., & Fealy, R. (2011). Comparison of ERA-40, ERA-Interim and NCEP/NCAR reanalysis data with observed surface air temperatures over Ireland. *International Journal of Climatology*, 31(4), 545–557.
- Murphy, J. (1999). An evaluation of statistical and dynamical techniques for downscaling local climate. *Journal of Climate*, 12(8), 2256–2284.
- NASA. (2021). Retrieved Feb 12, 2021 from <https://climate.nasa.gov/vital-signs/global-temperature/>

- Nguyen, V. T. V., Nguyen, T. D., & Cung, A. (2007). A statistical approach to downscaling of sub-daily extreme rainfall processes for climate-related impact studies in urban areas. *Water Science and Technology: Water Supply*, 7(2), 183–192.
- Nhat, L. M., Tachikawa, Y., & Takara, K. (2006). Establishment of intensity-duration-frequency curves for precipitation in the monsoon area of Vietnam. *Disaster Prevention Research Institute, Kyoto University*, 93–103.
- Nourani, V., Razzaghzadeh, Z., Baghanam, A. H., & Molajou, A. (2019). ANN-based statistical downscaling of climatic parameters using decision tree predictor screening method. *Theoretical and Applied Climatology*, 137(3–4), 1729–1746.
- Okkan, U., & Fistikoglu, O. (2014). Evaluating climate change effects on runoff by statistical downscaling and hydrological model GR2M. *Theoretical and Applied Climatology*, 117(1), 343–361.
- Okkan, U., & Kirdemir, U. (2016). Downscaling of monthly precipitation using CMIP5 climate models operated under RCPs. *Meteorological Applications*, 23(3), 514–528.
- Piani, C., Haerter, J. O., & Coppola, E. (2010). Statistical bias correction for daily precipitation in regional climate models over Europe. *Theoretical and Applied Climatology*, 99(1–2), 187–192.
- Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., & Hegewisch, K. C. (2015). Improved bias correction techniques for hydrological simulations of climate change. *Journal of Hydrometeorology*, 16(6), 2421–2442.
- Plummer, D. A., Caya, D., Frigon, A., Côté, H., Giguère, M., Paquin, D., Biner, S., Harvey, R., & De Elia, R. (2006). Climate and climate change over North America as simulated by the Canadian RCM. *Journal of Climate*, 19(13), 3112–3132.
- Rashid, M. M., Faruque, S. B., & Alam, J. B. (2012). Modeling of short suration rainfall intensity duration frequency (SDR- IDF) equation for Sylhet city in

Bangladesh. *ARNP Journal of Science and Technology*, 2(2), 92–95.

Requena, A. I., Nguyen, T. H., Burn, D. H., Coulibaly, P., & Nguyen, V. T. Van. (2021). A temporal downscaling approach for sub-daily gridded extreme rainfall intensity estimation under climate change. *Journal of Hydrology: Regional Studies*, 35, 100811.

Sachindra, D. A., & Perera, B. J. C. (2016). Statistical downscaling of general circulation model outputs to precipitation accounting for non-stationarities in predictor-predictand relationships. *PLOS ONE*, 11(12), e0168701.

Salimi, A. H., Masoompour Samakosh, J., Sharifi, E., Hassanvand, M. R., Noori, A., & von Rautenkranz, H. (2019). Optimized artificial neural networks-based methods for statistical downscaling of gridded precipitation data. *Water*, 11(8), 1653.

Schoof, J. T., Pryor, S. C., & Robeson, S. M. (2007). Downscaling daily maximum and minimum temperatures in the midwestern USA: a hybrid empirical approach. *International Journal of Climatology*, 27(4), 439–454.

Sennikovs, J., & Bethers, U. (2009). Statistical downscaling method of regional climate model results for hydrological modelling. *18 Th World IMACS / MODSIM Congress*, 3962–3968.

Seyam, M., & Mogheir, Y. (2011). Application of artificial neural networks model as analytical tool for groundwater salinity. *Journal of Environmental Protection*, 02(01), 56–71.

Seyam, M., S. Alagha, J., Abunama, T., Mogheir, Y., Affam, A. C., Heydari, M., & Ramlawi, K. (2020). Investigation of the influence of excess pumping on groundwater salinity in the Gaza coastal aquifer (Palestine) using three predicted future scenarios. *Water*, 12(8), 2218.

Singh, V. K., & Kumar, D. (2020). Downscaling daily precipitation over the Upper Shivnath basin: A comparison of three statistical downscaling techniques. *International Journal of Current Microbiology and Applied Sciences*, 9(1), 1676–

1688.

- Solaiman, T. A., King, L. M., & Simonovic, S. P. (2011). Extreme precipitation vulnerability in the Upper Thames River basin: uncertainty in climate model projections. *International Journal of Climatology*, 31(15), 2350–2364.
- Srivastav, R. K., Schardong, A., & Simonovic, S. P. (2014). Equidistance Quantile Matching Method for Updating IDFCurves under Climate Change. *Water Resources Management*, 28(9), 2539–2562.
- Srivastav, R. K., Schardong, A., & Simonovic, S. P. (2016). *Computerized Tool for the Development of Intensity-Duration-Frequency Curves under a Changing Climate. Technical Manual v.1.4*. London, Ontario, Canada: The University of Western Ontario.
- Statistical Institute Turkish. (2019). Retrieved May 3, 2021 from <http://www.izmir.gov.tr/istatistiklerle-izmir>
- Stocker, T. (Ed. . (2014). *Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge university press.
- Sudheer, K. P., Gosain, A. K., Mohana Rangan, D., & Saheb, S. M. (2002). Modelling evaporation using an artificial neural network algorithm. *Hydrological Processes*, 16(16), 3189–3202.
- Sun, L., & Lan, Y. (2020). Statistical downscaling of daily temperature and precipitation over China using deep learning neural models: Localization and comparison with other methods. *International Journal of Climatology*, 41(2), 6769.
- Sun, Y., Wendi, D., Kim, D. E., & Liong, S. Y. (2019). Deriving intensity–duration–frequency (IDF) curves using downscaled in situ rainfall assimilated with remote sensing data. *Geoscience Letters*, 6(1), 17.
- Tareghian, R., & Rasmussen, P. F. (2013). Statistical downscaling of precipitation

- using quantile regression. *Journal of Hydrology*, 487, 122–135.
- Tatli, H., Nüzhet Dalfes, H., & Sibel Menteş. (2004). A statistical downscaling method for monthly total precipitation over Turkey. *International Journal of Climatology*, 24(2), 161–180.
- Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of Hydrology*, 456–457, 12–29.
- Tolika, K., Maheras, P., Flocas, H. A., & Arseni-Papadimitriou, A. (2006). An evaluation of a general circulation model (GCM) and the NCEP–NCAR reanalysis data for winter precipitation in Greece. *International Journal of Climatology*, 26(7), 935–955.
- Tombul, M., & Oğul, E. (2006). Modeling of rainfall-runoff relationship at the semi-arid small catchments using artificial neural networks. In *International Conference on Intelligent Computing, ICIC 2006*. Kunming: Springer.
- Trzaska, Y., & Schnarr, E. (2014). *A Review of downscaling methods for climate change projections (USAID, 2014)*. Burlington, Vermont: Tetra Tech ARD.
- Turkish State Meteorological Service. (2019). Retrieved Jun 24, 2021 from <https://www.mgm.gov.tr/veridegerlendirme/havzalara-gore-yagis.aspx>
- Turkish State Meteorological Service Official. (2021). Retrieved Jun 24, 2021 from <https://www.mgm.gov.tr/veridegerlendirme/il-ve-ilceler-istatistik.aspx?k=A&m=IZMIR>
- USGCRP. (2018). *Impact, risks, and adaptation in United state : Fourth National climate Assessment, Volume 11*. Washington: U.S. Government Publishing Office.
- USGCRP, 2017: (2017). *Climate Science Special Report: Fourth National Climate Assessment, Volume I [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.)]*. Washington: U.S. Global Change

Research Program.

- Vu, M. T., Aribarg, T., Supratid, S., Raghavan, S. V., & Liong, S. Y. (2016). Statistical downscaling rainfall using artificial neural network: significantly wetter Bangkok? *Theoretical and Applied Climatology*, 126(3–4), 453–467.
- Wang, A., & Zeng, X. (2012). Evaluation of multireanalysis products with in situ observations over the Tibetan Plateau. *Journal of Geophysical Research Atmospheres*, 117(5) D05102.
- Watterson, I. G., & Dix, M. R. (2003). Simulated changes due to global warming in daily precipitation means and extremes and their interpretation using the gamma distribution. *Journal of Geophysical Research D: Atmospheres*, 108(13) D4379.
- Westra, S., Fowler, H. J., Evans, J. P., Alexander, L. V., Berg, P., Johnson, F., & Roberts. (2014). Future changes to the intensity and frequency of short-duration extreme rainfall, Reviews of Geophysics. *American Geophysical Union*, 52(3), 522–555.
- Wetterhall, F., Bárdossy, A., Chen, D., Halldin, S., & Xu, C. Y. (2009). Statistical downscaling of daily precipitation over Sweden using GCM output. *Theoretical and Applied Climatology*, 96(1–2), 95–103.
- Wilby, R. ., Troni, J., Biot, Y., Tedd, L., Hewitson, B. C., Smith, D. M., & Sutton, R. T. (2009). A review of climate risk information for adaptation and development planning. *International Journal of Climatology*, 29(9), 1193–1215.
- Wilby, R., Charles, S., Zorita, E., Timbal, B., Whetton, P., & Mearns, L. (2004). *Guidelines for use of climate scenarios developed from statistical downscaling methods*. New York: TGCIA.
- Wilby, R. L., Hay, L. E., & Leavesley, G. H. (1999). A comparison of downscaled and raw GCM output: Implications for climate change scenarios in the San Juan River Basin, Colorado. *Journal of Hydrology*, 225(1–2), 67–91.
- Wilby, R. L., & Wigley, T. M. L. (2000). Precipitation predictors for downscaling:

Observed and general circulation model relationships. *International Journal Of Climatology Int*, 20, 641–661.

Wilby, R. L., Wigley, T. M. L., Conway, D., Jones, P. D., Hewitson, B. C., Main, J., & Wilks, D. S. (1998). Statistical downscaling of general circulation model output: A comparison of methods. *Water Resources Research*, 34(11), 2995–3008.

Xu, C. Y. (1999). Climate change and hydrologic models: A review of existing gaps and recent research developments. *Water Resources Management*, 13(5), 369–382.

Yan, L., Xiong, L., Jiang, C., Zhang, M., Wang, D., & Xu, C. (2021). Updating intensity–duration–frequency curves for urban infrastructure design under a changing environment. *WIREs Water*, 8(3), e1519.