IMPACT OF CLIMATE CHANGE ON HYDRO-CLIMATOLOGICAL PARAMETERS IN NORTH CYPRUS: APPLICATION OF ARTIFICIAL INTELLIGENCE BASED STATISTICAL DOWNSCALING MODELS

A THESIS SUBMITTED TO THE INSTITUTE OF GRADUATE STUDIES OF NEAR EAST UNIVERSITY

By
OGODOR ELVIS

In Partial Fulfilment of the Requirements for the Award of Master of Science Degree

in

Civil and Environmental Engineering

NICOSIA, 2020

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Approval of Director of Institute of Graduate Studies

Prof. Dr. K. Hüsnü Can Başer

We certify this thesis is satisfactory for the award of the degree of Master of Science in Civil and Environmental Engineering

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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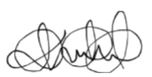
Signature: 

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In life there are friends that are closer than a brother, they have become a part of me, they have become my blood, my flesh and my bone. Thank you all!

To my parents…

ABSTRACT

In the 21st century, there are many environmental concerns in water scarce areas more especially in arid and semiarid regions due to climate change threat caused by greenhouse effect. To reduce the climate change impact and for suitable environmental planning, future predictions of hydro-climatological variables are highly significant. The aim of this study is to assess and evaluate the impact of climate change on hydro-climatological parameters through statistical downscaling and future projections of mean monthly precipitation and temperature over Famagusta, Nicosia and Kyrenia stations, north Cyprus. Thirteen predictors of the general circulation models (GCMs) for BNU-ESM from CMIP5 were used to achieve the study aim at a grid point located in Karfas region. In order to provide efficient and reliable downscaling modeling, initially, the GCM outputs were subjected to screening to determine the dominant predictors using mutual information (MI) and correlation coefficient (CC) feature extraction methods. Artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS) and multiple linear regression (MLR) models were then employed for the statistical downscaling using the selected predictors as inputs and observed data for the period 1995 – 2017 as output. The best downscaling model was then used as benchmark for the future projection of precipitation and temperature for the period 2018 – 2040 under RCP4.5 scenario. The results showed that both MI and CC methods were sufficient in the selection of dominant GCM outputs but MI method could be preferable because of the nonlinear and coarse nature of the large scale predictors. The statistical downscaling results showed that the artificial intelligence methods were more capable of reproducing the observed data than MLR method. The future projected results showed that there would be decrease and increase in precipitation and temperature trends towards the middle of the 21st century. A decrease in precipitation will be expected up to 22%, 4.8%, 42% and an increase in temperature up to 2.9%, 5%, 4.8% for Famagusta, Nicosia and Kyrenia stations, respectively. In general, the obtained results in this study could be useful in decision making, water resources management and climate change mitigation.

***Keywords*:** Predictors; global circulation models; statistical downscaling; precipitation; temperature

ÖZET

21. yüzyılda, sera etkisinin neden olduğu iklim değişikliği tehdidi nedeniyle su kıtlığı olan bölgelerde, özellikle kurak ve yarı kurak bölgelerde birçok çevresel kaygı yaşanmaktadır. İklim değişikliği etkisini azaltmak ve uygun çevresel planlama için, hidro-iklim değişkenlerinin gelecekteki tahminleri oldukça önemlidir. Bu çalışmanın amacı, iklim değişikliğinin hidro-klimatolojik parametreler üzerindeki etkisini istatistiksel ölçek küçültme yöntemiyle Kuzey Kıbrıs'ta; Gazimağusa, Lefkoşa ve Girne, istasyonları üzerindeki ortalama aylık yağış ve sıcaklığın gelecekteki projeksiyonları yoluyla değerlendirmektir. CMIP5'ten BNU-ESM için genel sirkülasyon modellerinin (GCM'ler) on üç öngörücüsü (predictors), Karfas bölgesinde bulunan bir grid noktasında çalışma amacına ulaşmak için kullanıldı. Etkili ve güvenilir ölçek küçültme modellemesi sağlamak için, başlangıçta GCM çıktıları, karşılıklı bilgi (MI) ve korelasyon katsayısı (CC) özellik çıkarma yöntemleri kullanılarak baskın öngörücüleri belirlemek için taramaya tabi tutuldu. Yapay sinir ağı (ANN), uyarlanabilir nöro bulanık çıkarım sistemi (ANFIS) ve çoklu doğrusal regresyon (MLR) modelleri için seçilen öngörücüler girdi olarak ve 1995 - 2017 dönemi için gözlemlenen veriler çıktı olarak kullanılmak suretiyle istatistiksel küçültme uygulandı. En iyi ölçek küçültme modeli daha sonra RCP4.5 senaryosu altında 2018-2040 dönemi için yağış ve sıcaklığın gelecekteki projeksiyonu için referans olarak kullanıldı. Sonuçlar, baskın GCM çıktılarının seçiminde hem MI hem de CC yöntemlerinin yeterli olduğunu, ancak büyük ölçekli öngörücülerin doğrusal olmayan ve kaba doğası nedeniyle MI yönteminin tercih edilebileceğini gösterdi. İstatistiksel ölçek küçültme sonuçları, yapay zeka yöntemlerinin, gözlenen verileri MLR yöntemine göre daha iyi yeniden üretebildiğini gösterdi. Gelecekte öngörülen sonuçlar, 21. yüzyılın ortalarına doğru yağış eğilimlerinde düşüş ve sıcaklıkta artış olacağını gösterdi. Gazimağusa, Lefkoşa ve Girne istasyonlarında sırasıyla yağışlarda% 22,% 4.8,% 42 azalma ve sıcaklıkta% 2.9,% 5 ve% 4.8'e varan artışlar beklenmektedir. Genel olarak, bu çalışmada elde edilen sonuçlar karar vermede, su kaynakları yönetiminde ve iklim değişikliği etkilerinin kontrolunda faydalı olabilir.

Anahtar Kelimeler: Öngörücüler; küresel dolaşım modelleri; istatistiksel ölçek küçültme; yağış; sıcaklık.

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AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
GCMs	Global Circulation Models
RCMs	Regional Climate Models
SDSM	Statistical Downscaling Model
GT	Gamma Test
CC	Correlation Coefficient
MI	Mutual Information
BNU-ESM	Beijing Normal University Earth System Model
DC	Determination Coefficient
RCP	Representation Concentration Pathway
MSD	Meteorological Subdivision
HadAM3P	Third Hadley Centre Atmospheric Model
NECP	National Energy and Climate Plan
FFNN	Feed Forward Neural Network
FG	Fuzzy Genetic
FIS	Fuzzy Inference System
IPCC	Intergovernmental Panel on Climate Change
GP	Genetic Programming
NCAR	National Center for Atmospheric Research
ECHAM5	Atmospheric Climate Model and the Extension to a Coupled Model
kNN	k-Nearest Neighbor
SRES	Special Report on Emissions Scenarios
CMIP5	Coupled Model Intercomparison Project Phase 5
LM	Levenberg-Marquardt
LSSVR	Least Square Support Vector Regression
PCA	Principal Component Analysis
M5tree	M5 Model Tree

MARS	Multivariate Adaptive Regression Splines
SOM	Self-Organizing Map
MCDA	Multiple-Criteria Decision Analysis
CGCM3	Third Generation Coupled Global Climate Model
RF	Random Forest
CanESM2	Second Generation Canadian Center for Climate Modeling
MLR	Multiple Linear Regression
WRF	Weather Research and Forecasting
CDF-t	Cumulative Distribution Function
MSE	Mean Square Error
NC	North Cyprus
TLFN	Time-Lagged Feed Forward Neural Network
TNN	Temporal Neural Network
LS	Least Squares
OLS	Ordinary Least Squares
SWAT	Soil and Water Assessment Tool
RMSE	Root Mean Square Error
MMEs	Multi-Model Ensembles
RVM	Relevance Vector Machine
LARS-WG	Long Ashton Research Station Weather Generator
RNN	Recurrent Neural Network
SFG	Sugeno fuzzy genetic
SVM	Support Vector Machine
SVR	Support Vector Regression
Tansig	Tangent Sigmoid
BP	Back Propagation
MF	Membership Function
P_R	Precipitation
T_{mean}	Mean Temperature
tasmax	Maximum Air Temperature
ts	Sea Surface Temperature
hurs	Relative Humidity

huss	Specific Humidity
psl	Sea Level Pressure
evspsbl	Water Evaporation
sfcwind	Wind Speed
ps	Surface Air Pressure
uas	Zonal Wind Speed
vas	Meridional Wind Speed
prw	Atmospheric Water Vapor Content
pr	Precipitation
clwvi	Cloud Condensed Water Content

CHAPTER 1

INTRODUCTION

1.1 Climate Change Impact on Hydro-Climatological Parameters

Water resources and many other life aspects are affected by the global change of climate in many developing and developed countries around the world (Alotaibi et al. 2018). Over the recent decades, research on climate change has achieved tremendous significance due to global warming. In several parts of the globe, the variations in rainfall and temperature differs owing to the consequence of climate changes (Peng et al. 2018). Therefore, droughts are expected to be experienced in some arid regions while heavy rainfalls might be expected in others. For instance, in China, the rates of sea level rise and warming are quicker than the mean global rate (Zhang et al. 2018). Peng et al., (2018) stated that the temperature variability increases by around 10% for every degree centigrade of temperature changes in Southeast Asia, India and Sahel and around 15% in Southern Africa and Amazonia. In hydro-environmental studies, the variables that are most effective are temperature and precipitation, hence for warning against future effect of global climate change and decision making in some problems (including flash floods, evaporation, drought, etc.), investigations into the future changes of temperature and precipitation are phenomenal (Nourani et al. 2019).

The general circulation models (GCMs) are used to study the future fluctuations of temperature and precipitation in such a way that up to the end of century, the large scale climate data is simulated under the greenhouse gases changes effect. In the local climate studies, the developed GCM outputs in coarse spatial resolution cannot directly be used. As a result, suitable techniques should be used to downscale the coarse spatial resolution of GCM outputs in to finer local climate data (Mora et al. 2014). The downscaling models are generally classified into: (a) dynamical downscaling method that uses regional climate models (RCMs) based on boundary condition set by GCMs data to extract local scale information (b) statistical downscaling method which is based on creating statistical relationship between the predictand (local scale weather data) and predictors (large scale climate variables). The methods used for statistical downscaling are simple to use and required little efforts for computations and can be applied in different regions for different for different GCM outputs (Timbal et al. 2003). Many methods of statistical downscaling can be found in the literature including statistical downscaling model (SDSM) (Samadi et al. 2013), correlation analysis (Landman et al. 2001), multiple linear regression (MLR) (Klein 1983), the nearest neighborhood (Zorita and Von Storch 1999), adaptive neuro fuzzy inference system (ANFIS) (Alotaibi et al. 2018) and artificial neural network (ANN) (Nourani et al. 2018) among others, have already been used to downscale statistically the GCM outputs.

In the past decades, nonlinear methods based on artificial intelligence (AI) including ANN and ANFIS have been applied successfully to capture the nonlinear aspect of downscaling GCM outputs in relation to the predictand and predictors (Chau 2017; Alotaibi et al. 2018). The capability of the AI based downscaling models for time-varying characteristics and nonlinear simulation of atmospheric variables considering different scales and their ability to determine the predictand/predictors relationship as well as their potential in extracting complex patterns have led to successful downscaling modeling using ANN as can be seen in several literature (e.g. Okkan and Kirdemir 2016; Nourani et al. 2018, 2019). However, apart from ANN, ANFIS another nonlinear downscaling model demonstrated an outstanding performance in climatic parameters' statistical downscaling modeling (e.g. Najafi et al. 2011; Hosseini et al. 2018; Alotaibi et al. 2018).

Focusing on the survey of literature on the consequence results achieved for statistical downscaling modeling of climatic parameters based on the application AI based methods e.g. ANNs, it was found that there are contradicting issues regarding their performance; while some studies show efficiency and superiority of ANNs, others demonstrate inferiority and drawback of ANNs over MLR based models (e.g. Abdellatif et al. 2013). The quantity and quality of the used data may contribute to these results' inconsistency. AI based modeling challenging issues for huge amount of data arise from noise presence in the data set and redundant information. While using the nonlinear models (such as ANN and ANFIS), over the simulation time, the noise present in the data set can be nonlinearly magnified. According to a study by Bowden et al. (2005), in ANN based hydro-climatic processes modeling, utilization of several input variables may lead to inefficient results owing to: (i) irrelevant input variables, which lead to difficulty in training process (ii) lack of convergence and low precision can be caused by the irrelevant input variables (iii) more time consuming and increase in computational memory (iv) it is more difficult to understand the complex models formed using huge inputs in comparable to simple models more especially when the results of the models are compared. As such, the AI based downscaling models' efficiency can be largely enhanced by input feature extraction methods as a preprocessing technique.

Some studies such as Babel et al., (2017) utilized data preprocessing techniques in addressing the complexity in statistical downscaling modeling of GCMs data through extraction of dominant predictors. However, feature extraction methods are the techniques employed for the selection of the dominant predictors for the downscaling modeling with maximum impact. Cheng et al., (2005) applied feature extraction methods for hydro-climatic variables modeling using fuzzy model and coupled genetic algorithm. Sachindra et al., (2013) selected dominant inputs using linear correlation coefficient (CC) for statistical downscaling modeling. Ahmadi et al., (2015) determined the dominant inputs using gamma test (GT) and CC for nonlinear statistical downscaling modeling based on support vector machine (SVM). Kang and Moon, (2017) performed feature extraction of input variables using the method of principal component analysis (PCA) for precipitation prediction using ANN under different scenarios. Pahlavan et al., (2017) employed feature extraction method via mutual information (MI) for predictors screening for downscaling modeling using SDSM. Okkan, (2015) applied data preprocessing methods of MI and CC for variables input selection. Among the several methods of data preprocessing for feature extraction of dominant predictors, MI and CC were found to be exceptional with remarkable performance, therefore, were used in this study for the selection of dominant predictors.

1.2 Problem Statement

Climate change has a significant effect on hydro-climatological parameters in Northern Cyprus (NC) being a semi-arid (water scarce) region. Studies have shown that precipitation has a decreasing trend, whereas the temperature trend is increasing in NC (Elkiran and Ergil, 2006). This led to over extraction of groundwater thereby jeopardizing one of the major sources of water in NC. Therefore, it is necessary to investigate the climate change effect on precipitation and temperature, in other to identify their future increase or decreasing trends to make necessary decisions.

1.3 Study Aim and Objectives

The main aim of this study is to investigate the impact of climate change on the hydro-climatological parameters through statistical downscaling modeling in three stations of Northern Cyprus. This can be achieved through the following objectives:

- Application of linear (CC) and nonlinear (MI) feature extraction methods to determine the dominant large scale predictors (variables).
- Application of ANN, ANFIS and MLR models for statistical downscaling modeling of precipitation and temperature from 1995-2017.
- Application of ANN, ANFIS and MLR models for statistical downscaling modeling to assess the future changes of precipitation and temperature from 2018-2040.

1.4 Hypothesis

Owing to the current literature, the following are the hypothesis in this study;

- The selected models ANN, ANFIS and MLR would be sufficient for the statistical downscaling modeling of precipitation and temperature in Northern Cyprus.
- Both MI and CC methods would lead to good selection of GCMs predictors.
- Due to climate change impact on semiarid regions, the future projection will show an increase in the mean temperature and decrease in annual precipitation in Northern Cyprus.

1.5 Novelty of the Study

The novelty of this study is that it will be the first study to perform statistical downscaling modeling of precipitation and temperature using artificial intelligence models in Nicosia, Kyrenia and Famagusta stations of Northern Cyprus.

1.6 Contributions of the Study to the Existing Knowledge

- This is the first study to be conducted in North Cyprus and it will serve as the basis for more studies in other areas to be performed.

- The data made available here will be useful to other researchers for further studies.
- This study will reveal the importance of continued application of global downscaling modeling for accuracy optimization in dealing with climatic and water resources problems.

1.7 Limitation(s) of the Study

This study is limited to the statistical downscaling modeling of GCM outputs from large scale data into regional or local scale data using ANN, ANFIS and MLR downscaling models for Famagusta, Nicosia and Kyrenia. A total of 13 atmospheric predictors generated from BNU-ESM GCM under RCP4.5 scenario at a grid point of latitude 35.53^0N and longitude 34.28^0E were usedss.

CHAPTER 2

LITERATURE REVIEW

Statistical downscaling modeling and future projection of climatic variables have been carried out in several studies by many researchers around the globe. As mentioned earlier, there are no studies published in the current literature on this topic in north Cyprus. Therefore, in this chapter, literature on the global studies of the statistical downscaling and future projection of precipitation and temperature are presented in three subsections viz; based on precipitation only, based on temperature only and based on both precipitation and temperature as follows;

2.1 Statistical Downscaling Modeling based on Precipitation

Wilby et al., (1998) performed statistical downscaling modeling of daily precipitation using ANN, Spell-length duration and WGEN standard methods of downscaling. The climate variables used were from 1980 – 1999 for present time and 2080 – 2099 for the future across six US regions. Difference skill levels were displayed by the different applied models. The difference between simulated and observed daily precipitation was yielded by the weather generated techniques. Because of its failure to adequately and statistically simulate wet-day occurrence, ANN displayed poor performance. The future and present precipitation results obtained by the applied statistical models have smaller difference than those generated by the GCM directly.

Ramirez et al., (2006) determined the relationship between observed rainfall and large scale GCM outputs using ANN and MLR over southeastern Brazil`s meteorological station. The results showed that in most season, ANN produced superior performance than MLR. The results also showed that due to less convection frequency, the prediction is more reliable in austral winter rainfall and consequently, instead of thermodynamic to occur, dynamic forcing occurs.

Tripathi et al., (2006) at monthly time scale proposed precipitation statistical downscaling using SVM. India's meteorological subdivision (MSD) determined the effectiveness of the SVM approach. Dry and wet seasons are the two groups formed by means of cluster analysis.

The conventional downscaling model (which uses ANN) was found to be inferior to the downscaling model proposed by the study. Consequently, the SVM approach was used to project the future precipitation. It was found that for precipitation statistical downscaling, SVM can serve as a productive alternative to ANN conventional technique.

Tolika et al., (2007) to determine the seasonal local changes between spring and winter as well as for rainy days in some stations selected over Greece applied ANN to statistically downscaled the precipitation. The predictors were selected in two sets that include 500 hPa based on circulation and combination of nonconventional predictor that comprises raw precipitation data and surface specific humidity. The employed model for the downscaling implied valuable performance for both rain days in winter and summer. The results revealed that the inclusion of nonconventional predictors have contributed to the simulation results improvement. However, HadAM3P was used to generate the future and present-day changes for the large-scale data on precipitation conditions. The signal for the downscale climate parameters for rainy days, precipitation, spring and winter showed similarity to HadAM3P with different changes amplitude.

Mendes and Marengo (2009) studied daily precipitation downscaling modeling using temporal neural networks over an Amazon basin for three scenarios of SRES comprises of A2, A1B and B1 as well as five twentieth century AOGCMs. Performance comparison based the ability of the statistical downscaling models to reproduce the tendency and variability of the observed climate data from 1970 – 1999 was made between autocorrelation and temporal neural networks models. For the daily precipitation, the results superiority and higher level of skill were produced by the temporal neural network model over the autocorrelation statistical model.

Chen et al., (2010) converted large scale weather variables in to local scale variable through statistical downscaling of daily precipitation in the basin of Taiwan's Shih-Men in two steps using SVM, SVC, SVR and SDSM models for large scale variables obtained from NECP. Multiple regression as well as discriminant analysis were also carried out. The daily precipitation's most reasonable properties were marched by SVM based of the revealed downscaling results. For daily precipitation usually less than 10 mm, mostly SDSM provided the best performance in comparison to the rest models. The study finally performed future projection suggested ways to improve the downscaling modeling.

Ghosh, (2010) determined the climate change impact on rainfall through statistical downscaling modeling over two meteorological subdivisions of Meghalaya and Assam located in northeastern India. Owing to its ability in understanding the nonlinear relationships of predictors and predictand more than transfer based function downscaling model of linear regression, SVM was employed for the monthly rainfall downscaling. Due to the overtraining and undertraining associated with SVM model, an optimization method was proposed in this study through computing the SVM's optimum parameters using PGSL. For multiple GCMs, hydrologic scenarios were computed based on local scale and large scale variables. Ensemble averaging method was used to model the uncertainty resulted from the multiple GCMs used. An improvement in the performance of the SVM developed downscaled rainfall was achieved by the application of the proposed model in the study.

Fistikoglu and Okkan (2011) performed large scale parameters conversion for statistical downscaling modeling of precipitation at Tahtali watershed in the republic of Turkey for data obtained from NCEP and NCAR. For each station's basin, ANN models were separately designed. As indicated by the obtained results, the most explanatory parameters for NCEP and NCAR were pressure levels, surface air temperatures, surface and sea level pressures and precipitation. The concluding remark by the study suggested that coarse scale parameters can be downscaled for monthly precipitation using ANN based models.

Hashmi et al., (2011) employed the services of ANN and GP for nonlinear downscaling modeling of precipitation in the New Zealands Clutha Watershed. The GP technique in comparison to ANNs has been rarely used for statistical downscaling modeling of precipitation despite being simpler and easy in application. The results showed that in the case of precipitation downscaling modeling, GP can provide efficient and simple solutions.

Najafi et al., (2011) applied two nonlinear and a linear downscaling model for precipitation modeling in the upper Willamette basin. Before the application of these models which include MLR, SVM and ANFIS, the predictor variables were first been subjected to screening using independent component analysis. Moreover, an ensemble of precipitation time series was developed of the assessment of hydrologic climate impact. For both seasonal and monthly time scales, the ICA was found to be successful for the selection of appropriate input predictors. It was also revealed by the study that with efficient input combination, MLR could be successfully apply for precipitation downscaling modeling.

Norton et al., (2011) performed statistical downscaling using ANN for daily precipitation extreme events and its future projection to determine possible changes in the future in Oahu, Hawaii. ECHAM5 A2 was chosen as the preferred method among the 2 methods recommended by IPCC for GCMs their scenarios of emission for Oahu extreme precipitation downscaling. In leeward, drier regions, ANN performance was found to be higher where extreme daily precipitation events are influenced the least by orographic uplift. The storm frequency of 95% interval was provided by a BCa method of resampling and the 3 sets of data (from present day to future projection). The obtained results revealed an expected increase in the events of heavy rainfall frequency and for the next 30 years from 2011 – 2040, there is tendency of decrease in the intensity of rainfall events for the Oahu southern shoreline.

Nasseri et al., (2013) performed daily precipitation downscaling using four nonlinear models GA-SVM, k-Nearest Neighbor (kNN), Model Tree (MT) and MARS for basins over different climates constituting of about twelve rain gauge stations in Iran. The employed downscaling models were also compared with NDMDM. The results implied that less absolute error of the daily precipitation values can be provided by the combined methods of MARS and MT. Also with these models, in both phases of training and validation, closer values to the historical data records based on skewness and standard deviation can be observed. The precipitation's future projection results showed statistical downscaling models and NDMDM significant uncertainties for the selected rain gauges stations based on B2 and A2 SRES scenarios.

Campozano et al. (2016) used ANN, SDSM and LSSVM monthly precipitation statistical downscaling at southern Ecuador's Paute River basin located in Andean Mountain region for 30 years observations data obtain from NCEP/NCAR reanalysis 1. Preliminary results comparison depicted that there was equality of performance by AI based ANN and LSSVM and in comparison, to SDSM, ANN and LSSVM led to better accuracy. Meanwhile, the estimates by SDSM in some months fitted better the monthly precipitation depth for the observed variance and median. Since local conditions are not always present for synoptic stations, especially for September to December period, refinement in the downscaling estimates for future studies is recommended.

Okkan and Kirdemir (2016) under RCPs for data extracted from CMIP5 datasets, a multi-GCM ensemble (combines ANN and LSSVM models) to statistically downscale monthly precipitation over Gezin basin, Turkey. Student t-test was used for the projection of the future changes in the mean precipitation from 2015 – 20150. The results showed that for RCP8.5 scenario, a significant decrease in the precipitation trend was observed, whereas for RCP6.0 and RCP4.5 scenarios, the decreasing trend is less significant.

Vu et al., (2016) for rainy season period, applied ANN as a means of downscaling of coarse variables of GCM in to finer local in Bangkok meteorological station of Thailand. To provides the best predictors for ANN training, PCA was employed. The results of the climate for present day demonstrated great level of skill for the produced model with efficiency for Nash-Sutcliffe of 0.65 and 0.8 correlation coefficient. The precipitation trend for rainy season is increasing towards the end of the 21st century over Bangkok for the four GCM grid points. Wetness increases strongly as shown by the statistical indices for the extreme precipitation values. The developed findings in the research could help in providing information mitigation measures and flood control.

Nourani et al., (2018) performed rainfall statistical downscaling from CMIP5 GCMs using ANN and LSSVM over two meteorological stations of Ardabil and Tabriz located in northwestern Iran. Self organizing map (SOM) and wavelet-entropy were the screening techniques developed to examine better predictors to input for the downscaling purpose. For comparison and to determine predictand/predictors linear relationship MLR was also employed in the study. The downscaling performance was then improved by employing ensemble approach. The proposed study results indicated rainfall alteration pattern under RCP8.5 and RCP4.5 an increase in Ardabil station of 5 – 13% and 6 – 12% and decrease at Tabriz station of 35 – 42% and 40 – 41%.

Sachindra et al., (2018) applied machine learning techniques to statistically downscale monthly precipitation in the Victoria state, Australia. A total of 48 stations data were used covering a period from 1950 – 1991 for calibration and from 1992 – 2014 for validation.

Four machine learning methods were employed for the purpose including ANN, RVM, GP and SVM. The results depicted recommended the use or application of ANN and RVM instead of GP and SVM for a study that requires a high extremes precipitation consideration such as flood. Compared to ANN, SVM or GP, consideration can be given to RVM for a study where low extremes precipitation is recommended such as analysis of drought. Using polynomial kernel, the precipitation downscaling modeling based on RVM and SVM showed the best performance irrespective of the regime climate.

Abbasian et al., (2020) analyzed the capability of a downscaling model in the spatial and temporal variability for the assessment of climate change impact. GHLM was the novel model utilized to downscale precipitation from multiple sites for general circulation models output. Precipitation variance was partition by the applied GHLM for information transfer between sites in such a way that the variability is between and within site for the precipitation downscaling. The applied methodology involved using eight GCMs output for the downscaling of the precipitation in Lake Urmia basin which is a basin that is located in the northwestern Iran. Equidistant quantile mapping and Bayesian model averaging were used for the bias correction and then the multi-model ensemble simulation was performed. The results for the projected precipitation from 2060 – 2080 showed a decreasing trend between 11.2% to 15.3% based on RCP4.5 and RCP8.5.

Homsi et al., (2020) assessed the possible changes in future precipitation over Syria. The predictor screening to determing the best GCM was conducted using MCDA and SU. Bias correction was performed using 4 methods including PT, LS, GEQM and GAQM for the assessment of the downscaled precipitation. The generation of MME was taken care of by RF using 4 emission scenarios from RCPs including RCP2.6, RCP4.5, RCP6.0 and RCP8.5 for the precipitation projection. The results demonstrated that the applied GCMs including CESM1-CAM5 CSIRO-Mk3-6-0, HadGEM2-AO, and NorESM1-M are capable of simulating the climate in Syria. Among the applied statistical downscaling models, LS provided the best performance. Based on the obtained results, a decrease in the annual precipitation is projected by < 0.0 to -30%, -30 to -85.2%, for RCP 2.6, RCPs 4.5, 6.0, and 8.5, respectively. During wet season, precipitation for some parts of the country is projected to be increased while for RCP6.0 decrease is expected for the entire country. A decrease in precipitation is expected from −12 to −93% for the dry season, and this explains expectation of a drier climate in Syria.

Lu et al., (2020) in an attempt to downscale large scale predictors in to regional or local scale applied statistical downscaling modeling of rainfall in summer periods for stations located in south China. A canonical correlation analysis was used for the statistical downscaling using ERA-Interim reanalysis data for relative humidity and zonal wind speed. In both the calibration and validation phases, the proposed method performed well in reproducing the observed variables. RMSE was 21% and the TCC at 14 stations was 0.52 for the validation period. For the rainfall seasonal forecasts from 1982–2018, version 2 of the Climate Forecast System was applied for the downscaling modeling. The results for the rainfall in South China, the CFSv2 improved by the downscaling model from 0.14 to 0.31 based on an average TCC. Also for South China rainfall, the region performance was improved from 0.11 to 0.53 an average TCC.

Pomee et al., (2020) due to inadequate observational coverage and regional complexity considered the Indus River basin of Pakistan to perform a regional precipitation statistical downscaling. Generalized linear models and K-means cluster analysis were employed for the modeling. The obtained results demonstrated that across the lower and upper Indus basin, the regional scale precipitation features can be understood by the applied models. However, the trans-Himalayans uncertain and northwestern regions illustrated adequate performance. Higher results predictability can be achieved by final statistical models in comparison to different lower Indus regions and wetter southern Himalayans. The achieved results could help in understanding the future climate changes of the region.

2.2 Statistical Downscaling Modeling based on Temperature

Huth, (2004) used 39 stations' data from western and central Europe to statistically downscale CCCM GCM outputs for daily temperature modeling using several models including gridded values MLR, Principal components MLR and canonical correlation analysis. The predictors used include thickness 1000–500-hPa, heights500- and 1000-hPa, temperature850-hPa and their combinations. A very wide difference was observed between the various methods used as well as between different predictors in their elevation independence, spatial and real mean in the Alpine region. The estimated warming was mainly determined by a number of PCs, the smaller the PCs number, the smaller the warming and vice versa. The results revealed that in the climate change estimation, the primary problem in the statistical downscaling applications is a shot time variability that the downscaling models appears to be fitted predominantly to, but with respect to climate change future predictions, a decadal or long-term time scales is required.

Tomozeiu et al., (2007) determined extreme temperature frequency of events Emilia-Romagna region of Italy through statistical downscaling modeling using CCA. At the station level, the predictands used include HWD, 10th percentile minimum temperature, 10th percentile maximum temperature, and number of frost days. To evaluate the large-scale predictors, NCEP/NCAR was used to obtain the large-scale predictors and using 32 stations observed data. For spring Tmin, MSLP was found to be the best in terms of performance whereas for spring Tmin90, Z500 displayed better skill level. Controlled experiments were used to test the temporal and special variability of HadAM3P for the simulation of present-day temperature. The results showed that for both minimum and maximum temperatures in both scenarios, temperature increase is expected to occur in both significantly. Meanwhile and expectant decrease in the frost days number is possible with an index indicating a heat wave duration increase. Compared to B2 scenario, the A2 scenario magnitude of change is more significant.

Hertig and Jacobeit (2008) to anthropogenically assess temperature in the Mediterranean regions forced by climate change conditions, between 1948 – 1998 a model called canonical correlation was employed to determine the correlation between North-Atlantic–European large-scale and Mediterranean temperatures that are highly resolved. The GCM outputs from HadCM3 and ECHAM4/OPYC3 were used under SRES B2 scenario to assess 21st century changes of the Mediterranean temperature. The revealed results identified the whole Mediterranean temperature increase between 2071 – 2100 for every month of the year in comparison to 1990 – 2019. Based on season and region, the rise in the temperature varies, but considering the general aspect, about more than 4 °C of the temperature in the Mediterranean regions is expected owing to warming conditions due to enhanced greenhouse effect.

Brands et al., (2011) performed downscaling modeling of minimum, maximum and mean daily air temperature by generating ensemble projections using analogue method NW Iberian Peninsula. The study also employed three more methods viz; pressure of the mean sea level and 850 hPa air temperatures from reanalysis data were used to estimate the error produced by the analogue method already applied. Predictors from global climate models including multi-initial-conditions, multi-model and control runs ensemble were applied to assess suboptimal conditions. The results showed that apart from warming by the mean relative humidity, higher accuracy increase is achieved in the reference period with less frequent event and within the scenario period, uncertainty interval increases. The trend is particularly more provoked in day time period than when compared with the corresponding heat/warm or night time events, and this led to tripling or even quadrupling of latter in the summer. Models error dominated the uncertainty intervals of the local projections.

Duhan and Pandey, (2015) for minimum and maximum monthly temperature downscaling modeling in Rewa, Satna and Allahabad in Tons River basin, a Ganges River's subbasin located at India's central region, MLR, LSSVM and ANN were employed for the projection of future temperature using CGCM3 from 2001 – 2100 simulated considering A2 emission scenario. Four performance indicators were used to evaluate the performance of the applies statistical downscaling models. The results displayed the capability of all the applied models for the downscaling of temperature. Moreover, a slightly better performance of LSSVM was discovered in comparison to ANN and MLR. As a result, the LSSVM that reproduced values close to the observed data was used for the future temperature projection. Based on the A2 scenario, future increasing trends of minimum and maximum temperatures are expected with higher rate of increase from minimum temperature.

Pang et al., (2017) proposed the application of Random Forest (RF) to statistically downscaled mean daily temperature over southern China and specifically Pearl River basin. Data derived from NCEP/NCAR reanalysis in form of large-scale variables for a series of observed temperature considering 61 national meteorological stations. Other statistical downscaling models including ANN, SVM and MLR were calibrated and validated for comparison with the proposed RF model. For comprehensive study and in order to provide efficient climate change assessment, partial correlation analysis and principal component analysis were employed for the selection of input predictors. The results showed that according to five applied performance criteria, RF led to better performance in comparison to the other three models developed. It was also discovered that without partial correlation analysis and principal component analysis, RF has the ability of selecting appropriate predictors. For temperature downscaling, the results implied the feasibility of using RF tool.

Baghanam et al., (2020) applied SDSM and LARS-WG models to statistically downscale temperature in Tabriz station, Iran. In order to assess the fluctuations of temperature in the future, Multi-GCM ensemble technique was employed as a function of the single GCMs from CMIP5 which include EC-EARTH, MPI-ESM, MIROC5, HadCM2 GCMs. For model validation for the assessment of climate change impact on the region, the baseline data were used from 1961 to 1990 and from 1991 to 2005. Multi-GCM ensemble showed superior performance as disclosed by the evaluation criteria for temperature prediction in comparison to single GCMs. The results also demonstrated that an increasing temperature trend will be experienced in the future between 2021 and 2080. Under RCP8.5 and RCP4.5, the temperature will increase for about 3.7 and 2.9 (°C).

Hassan and Hashim (2020) considered the period of study from 2020 to 2099 to determine maximum temperature changes over Iraq's 7 meteorological stations using CanESM2 and HadCM3 GCM models on the concept of RCP 8.5, RCP4.5, RCP2.6, A2 and B2 emission scenarios. SDSM model was used for the statistical downscaling of the daily maximum temperature. The results showed that among all stations, CanESM2 was found to be the best in performance under RCP2.6 scenario. Maximum temperature increase was also demonstrated by the study for all stations towards the end of 21st century with values ranging from 0.3 to 1.2 °C. Water resources is affected by this maximum temperature increase owing to increase in surface water evaporation which in turns aggravate water scarcity. HadCM3 model showed more of the maximum temperature increase for all stations in comparison to CanESM2 model.

Liu et al., (2020) proposed and used the method of stepwise cluster analysis to statistically downscaled minimum, maximum and mean temperature for Nur Sultan city Kazakhstan capital. Evaluations were made between the current period temperatures 1979 – 2004 and the projected changes for the future 2075 – 2100. The results showed a projected increase in the temperatures (minimum, maximum and mean) trends consistently, implying that for the

21st century warming is expected in the Nur Sultan city, emissions scenarios as well as GCMs have significant effects on the variability in temperature projection. The changes observed due to monthly temperature projection are lower in magnitudes between April and October and higher between November and March. The findings can be useful in the adaptation and mitigation of climate change in Nur Sultan city.

Pryor and Schoof (2020) applied resilient generalized linear model and robust model in form of a transfer function to statistically downscale the anomalies of maximum and minimum daily temperature using GCMs outputs and ERA-Interim reanalysis for 10 stations. The temperature indices for the extreme climate to derive relevant impact for models credibility were categorized into two based on (i) GCMs large scale relevant predictors to reproduce the observed data (ii) downscaled series observation reproduction to determine the degree of variance after inflation technique application. The results showed variation in credibility for the two GCMs for the temperature downscaling across the study stations with minimum temperature result from better credibility than the maximum temperature. It is flexible and easy to assess the credibility of the model as demonstrated by the proposed framework in this study. The method can be used to provide information to the decision makers and can be prolonged to contain other transfer function components and to weight members.

Sa’adi et al., (2020) studied and evaluated the future temperature changes using an ensemble GCMs for statistical downscaling modeling under RCPs emission scenarios Borneo Island. From a pool of 20 GCMs from CMIP5 GCMs, GCM ensemble variables were selected based on envelope and past-performance approaches. Using entropy-based method, feature selection of GCMs were carried out for every grid point separately. The observed temperature data used ranged from 1961 – 2005. For the generation of the multi-model ensemble projections, the services of regression based on RF was employed and for bias removal in GCMs, method of linear scaling was used. Temperature increase is expected based on the revealed results for Borneo Island for the selected GCMs temperature projection especially in the southwest regions. More temperature increase is expected for minimum temperature than maximum temperature with values of 3.3 to 4.7 °C and 3.0 to 4.6 °C, respectively. Thus, until the end of the 21st century, gradual decrease in diurnal temperature was expected. For southwest monsoon, the projected maximum average temperature increases more in comparison to northeast monsoon. bio-environment and ecology of the island will be greatly impacted by decreasing diurnal temperature and increasing temperature trends.

Sekiyama et al., (2020) applied convolutional neural networks to downscale large scale predictors to smaller ones for every 6 hours of temperature measurements. Temperatures and surface winds were used as inputs to train the deep learning model for gridded global analysis of 22 km operation. The results demonstrated that with great detail, the mountain ridges and coastline locations can be estimated efficiently using the DCNN. For examples for altitudes greater than 100 m and the RMSE between regional and global analyses is averaged as 2.7 K, then the surrogate model RMSE will be dropped to 1.0 K with improvement from 0.6 up to 0.9 of the correlation coefficients. Although only surface temperature was used to evaluate the surrogate model, the vertical profiles and downscaling variable augmentation can be probably improved. Once their training is concluded, computational power with less effort is required by the DCNN surrogate model. Hence, at short time intervals, with implementation of the surrogate model, guidance in weather forecasts high resolution will be provided and at low cost, environmental agency alerts.

Wang et al., (2020) used high resolution dynamical and hybrid statistical/dynamical methods to downscale maximum, minimum and mean air temperatures for local scale quality estimation developed by downscaling modeling near western Finland's coastal region. The observed air temperature data used for the study were obtained from Finnish Meteorological Institute. WRF was used to perform the dynamical downscaling while CDF-t was the method employed to perform statistical downscaling. The CDF-t training was performed using data from WRF for a 20-year duration. Qualitatively the performance of the two applied downscaling models were assessed by using root-mean-square error, Cramer-von Mises, mean absolute error and quantile-quantile plots. Significant level of skill was provided by the hybrid model for the maximum and mean daily air temperatures. Better forecasting accuracy was demonstrated by the hybrid model with less computational difficulty.

2.3 Statistical Downscaling Modeling based on Precipitation and Temperature

Coulibaly et al., (2005) proposed the downscaling modeling of daily minimum, maximum temperatures and daily precipitation for Serpent River watershed which is located in north of Quebec, Canada using feed forward time-lagged neural network (TLFN) using large scales data from NCEP/NCAR reanalysis which include geopotential height, wind velocity and specific humidity determined as the most relevant downscaling atmospheric predictors. SDSM was also used to be compared with the downscaling TLFN model. The provided results by the study showed that both temperatures and daily precipitation time series can be efficiently downscaled using TLFN. However, the results indicated an increasing peak flow in early spring and as well as in mean annual flow.

Dibike and Coulibaly (2006) for a GCM outputs obtained from NCEP reanalysis, applied the method of temporal neural network (TNN) model for the downscaling of temperature and daily precipitation over a northern Quebec, Canada. Regression models were also used to compare the downscaling performance of TNN. The efficiency of TNN has been demonstrated from the base results obtained for the period 1961 – 2000 for both daily minimum, maximum temperatures and daily precipitation statistical downscaling modeling. The results also showed that the regression models' performance is outsmarted by TNN model for the variable and extremes daily precipitation downscaling.

Khan et al., (2006) compared the performance of ANN, LARS-WG and SDSM models for statistical downscaling methods' uncertainty analysis of minimum and maximum temperatures and daily precipitation. Data from National Center for Environmental Prediction spanning from 1961 – 2000 (40 years). The results of the uncertainty assessment suggested that with 95% confidence interval, the downscaling model capable of matching the characteristics of the observed data is SDSM, where ANN exhibited the 2nd best performance, the LARS-WG performed in between the 1st and 2nd (SDSM and ANN) most productive downscaling models.

Hessami et al., (2008) employed the services of regression based automated statistical downscaling (ASD) method to convert the coarse resolution data to finer resolution using temperature and precipitation as predictands. The ASD is inspired by SDSM for the statistical downscaling in Canada. Partial correlation coefficient as well as backward stepwise regression methods were the techniques employed for the selection of dominant predictors from 10 meteorological stations from present period of 1961 – 1990. The results showed that the most sensitive predictors to precipitation downscaling were specific and relative humidity, geopotential height, zonal velocity and surface airflow strength. In case of temperature, the variables with more efficient downscaling were mean sea level pressure, geopotential height, surface vorticity and temperature. The results demonstrated that different seasons and stations lead to different downscaling results and the downscaling performance depends on used input predictors. The results also implied that for every months and seasons, neither SDSM nor ADC were capable of providing efficient results.

Hundecha and Bárdossy, (2008) compared the constructive ability of two statistical downscaling models for the conversion of large-scale atmospheric variables into local scales for precipitation and temperatures. One method generated daily series of temperature and precipitation through stochastic modeling, while the other method focused on constructing extremes of temperature and precipitation for seasonal indices. While in winter season, in reproducing precipitation indices, a fairly well performance was generally achieved by both models, whereas a nonattractive performance was demonstrated in summer season. For temperature indices, both the two models provided more efficient performance than the ones they provided for precipitation while a less prominent performance was shown for seasonal variation. HadAM3P GCM was used under SRES emission scenarios. In all seasons for scenarios of the future climate change, maximum and minimum daily mean temperatures both increases. Temperatures increase of the inter-annual variability accompanied the summer increase. The inter-model uncertainty revealed by the two models indicate the existence of disparity for the future climate change prediction.

Tolika et al., (2008) compared statistical downscaling models in two approaches for the temperature and rainfall extreme conditions over a Greek area for the simulation of future changes. The two downscaling models used were ANN and MLR on a circulation based approach (MLRct). The results demonstrated that better simulation of temperature indices was obtained in comparison to precipitation indices. However, highest skill in the downscaling was shown by winter season. Four ensemble members in form of control runs examined the rainfall and temperature extreme events for future and present-day conditions. Between the period 2070–2100 in the future, increase in extreme temperature values are expected as demonstrated by the MLRct model. The signals provided by ANN models were not impressive which showed opposite direction in some cases.

Jeong et al., (2012) compared the performance of a nonlinear model and three linear models for the identification of the most desirable downscaling functions to statistically downscale daily precipitation and minimum, maximum daily temperatures over five provinces including Ontario, Manitoba, Québec, Saskatchewan and British Columbia, which combined together and produced over twenty-five meteorological stations. Precisely, the models used precisely were ridge regression, MLR, OLS, robust regression and ANN. Mutual information and correlation coefficient were also employed as feature extraction techniques to screen and select the best predictors to be used for the downscaling modeling. The result showed that a monthly MLR can outperformed annual MLR slightly considering extreme events. Nevertheless, recommendation can also be placed on annual MLR for the four predictands` transfer function because despite the mathematical simplicity it possesses, its performance is similar to that of monthly MLR. Based on the annual ANN model performance among others, it is only recommended for minimum temperature.

Flaounas et al., (2013) compared the two downscaling models (dynamic and statistical) and their combination to simulate the space-time rainfall and temperature variability in the near future and also their extremes across the region of Mediterranean. WRF was the employed dynamical model using different resolution from 20 km to 50 km and land-surface models and transform of Cumulative Distribution Function was the statistical tool employed. The dataset for European Climate Assessment was over the Mediterranean to achieve resolved spatial downscaling. The results showed that downscaled time-variability, CDF-t does not indicate any added value while as bias correction tool, it displayed promising efficiency.

Pierce et al., (2013) considered 16 predictors from GCM to determine the future changes in temperature and precipitation through statistical downscaling over California. Statistical downscaling models (two types) and dynamic downscaling models (three nested type) were used for the modeling. Both temperature and precipitation timescale changes (daily and monthly) were addressed. The results presented better agreement of temperature to reproduce observed data than precipitation. For the projected future temperature, decrease in temperature will lead to cooler July unlike is used to witness based on monthly average. Still in 2060s, temperature will be as cold as it used to be in January but monthly average temperatures based on maximum and median scale will be increased. Small amount of changes can be witnessed for precipitation in seasonal and annual scale in comparison with intermodel or interannual variability. In the southeastern California, dynamic downscaling models showed decreasing precipitation trend affected by north American monsoon a feature which statististical downscaling failed to capture.

Samadi et al., (2013) analyze the uncertainties related to statistical downscaling modeling of temperature and daily precipitation over a semiarid catchment area, an area that is highly vulnerable situated in the west of Iran. ANN and SDSM were the two downscaling models employed for the study purpose. Data from 1961 – 1990 (30 years) obtained from NCEP were also used. The results obtained revealed that there is high uncertainty in the precipitation downscaled, but in an accurate manner, the extreme events can be reproduced via daily temperature simulations. With the confidence level of 95%, the results revealed that SDSM provided the better characteristics that matched the ones by observed data, whereas the performance of ANN was inferior.

Asong et al. (2016) used 120 sites observation data for minimum, maximum temperatures and precipitation for a multisite multivariate analysis using a Generalized Linear Model downscaling approach across Manitoba, Saskatchewan and Alberta, the Canadian Prairie Provinces. For the GCMs calibration, observed precipitation and temperature data from 1971–2000 were used as the predictands while data from NCEP Reanalysis-I were used as predictors. Using CMIP5, the future climate variables from 2006 – 2100 were projected under RCP2.6, RCP4.5 and RCP8.5 emission scenarios. The obtained results revealed that the observed temperature and precipitation data spatiotemporal characteristics can be captured by the GCMs. Decrease and increase in the mean precipitation for winter and summer is projected for the future, while the maximum temperature is predicted to warm slower than minimum temperature. With increasing radiative forcing, extreme climates are expected to intensify.

Ba et al., (2018) assessed climate change effect on temperature and precipitation for Kaidu River Basin, which is located in Xinjiang, China for future projections from 2020–2029 and 2040–2049 through dynamic and statistical downscaling. The used reference period was from 1990–1999. RCP4.5 and RCP8.5 were the emission scenarios used for the future temperature and precipitation projection. The results showed that there will be increase in both temperature and precipitation under different scenarios with respect to the reference period and there are about 38.4% and 2.4°C increase in the mean annual precipitation and annual mean temperature which are also found to be the largest increment for both precipitation and temperature. The results showed better accuracy in temperature compared to precipitation.

Feyissa et al., (2018) evaluated the climate change impact of extremes of daily precipitation and minimum, maximum daily temperature in Addis Ababa, Ethiopia through statistical downscaling modeling. Two GCMs were considered including CanESM2 and CGCM3 under two future climate projections method with two scenarios each including RCP4.5, RCP8.5 and A1B, A2 from RCPs and SRES. For the calibration and validation of the models, data from two meteorological stations were used including Addis Ababa downtown and Entoto. To assess precipitation extremes and temperature changes, 12 core indices were selected. The results showed that for the largest changes, maximum and minimum temperature increase for Addis Ababa were 0.9 °C and 0.3 °C using CGCM3A2 in 2020 and 2.1 °C and 1.0 °C in 2080 using CGCM3A1B for RCP4.5. Both the highest minimum and the highest maximum temperatures were obtain for Addis Ababa station. For winter by 2080, 29% for RCP4.5 represent the highest precipitation increase while in summer, the highest precipitation increase was 20.9% for RCP8.5.

Ali et al., (2019) performed analysis to determine future events of extreme temperature and precipitations regions of southern Punjab, north Pakistan, Sindh, Monsoon region and Balochistan for climate change between the present time 1976 – 2005 and the future changes in different categories up to 2095 from CMIP5 under RCP4.5 and RCP8.5 scenarios. For the future projection, SDQDM while extremes climate changes were determined by ETCCDI. Increase in temperature frequency was determine for the future and warm extremes magnitudes, while for the 21st century for cold extremes, the temperature is decreasing. The mean temperature trend is less than the corresponding extremes of the minimum and maximum temperature trends while using both RCPs, the extremes minimum temperature's magnitude and frequency are more compared to north of Pakistan's extremes maximum temperature trend for the 21st century. Across most subregions in Pakistan, the study showed annul precipitation increase higher increase with Sindh region showing the least increase.

Nourani et al., (2019) applied ANN for mean monthly temperature and precipitation statistical downscaling modeling over northwest of Iran, a synoptic station in Tabriz. Selection of the best predictors to be used for calibrating and validating the downscaling models were made using MI and CC which were used as nonlinear and linear feature extraction methods. ANN based simulation carried out the projection of temperature and precipitation for the future from 2020 – 2060. For different scenarios and different GCMs, different results were obtained. Decrease in annual precipitation up to 29.78% was received based on RCP8.5 from Can-ESM2 while increase in annual precipitation up to 1.06% was achieved based on B1 from CGCM3. With respect to annual mean temperature projection, an increase is expected with the mean temperature wider increase demonstrated under RCP8.5 from BNU-ESM model.

Wu et al., (2019) quantified the propagation effects on temperature and precipitation downscaling. The proposed method feasibility was determine using the case study approach that was applied. H3A2a with A2 emission scenario were downscaled using SDSM. The downscaled results obtained were entered as input to SWAT model (a distributed hydrological model). 2016 – 2020 was considered for the prediction of surface runoff by using temperature and precipitation downscaled. Through the application of studies on hydrological modeling, the uncertainties were evaluated for the downscaling via simulation of surface run off.

Ahmed et al., (2020) evaluated the reliability and proposed the application of multi-model ensembles (MMEs) for statistical downscaling of minimum, maximum temperatures and precipitation for winter and monsoon over Pakistan using ANN, KNN, SVM and RVM. For individual variables and seasons, Taylor skill score was used to rank the GCMs and then each GCM’s overall rank was determined by comprehensive rating metrics. The results showed that the least and most skilled GCMs in simulating the climate variables were IPSL-CM5B-LR and HadGEM2-AO, respectively. Comparison of the performance of the developed MMEs based on the individual models showed higher reliability with MMEs developed using KNN and RVM. ANN showed large performance fluctuations in comparison to KNN. It was therefore concluded that for determining the future climate change over Pakistan using MMEs, KNN and RVM are preferable.

Birara et al., (2020) employed SDSM and LARS-WG models the most widely applied methods for statistical downscaling to simulate climate change for Tana basin in current and future periods over Ethiopia. For LARS-WG model, four GCMs were employed including NCCCS, MPEH5, GFCM21, and HadCM3 while for SDSM model, two GCMs were used including CanESM2 and HadCM3. Different emission scenarios were also used for the future projections. The general results disclosed the capability of CanESM2 and HadCM3 models to reproduce the observed climatic variables with acceptable response. Three of the four GCMs used for LARS-WG model showed rainfall increasing trend while decreasing trend was demonstrated by the other GCMs with reduction between − 9.6% to 45.2%. An increasing rainfall trend was shown by the applied ensemble for values between 3.9% to 18.8%. For all periods of time, minimum and maximum temperature increase was shown by the downscaled results of the four GCMs for LARS-WG model with values ranging from 0.6 °C to 2.5 °C and 0.9 °C to 2.9 °C. Comparison between the downscaled results for daily and monthly rainfall showed that for both LARS-WG and SDSM models performed less for daily rainfall than monthly rainfall series. Also, temperature was much better simulated by the models than rainfall.

Phuong et al., (2020) applied statistical downscaling methods for daily minimum and maximum temperatures and daily rainfall using SDSM for different scenarios in a River basin located in Vietnam called Vu Gia Thu Bon. A dimensionless and dimensioned statistical Taylor diagrams were employed to determine the models' performance. For seasonal rainfall and extreme temperatures, all models demonstrated good ability to downscaling. HadCM3 and CanESM2 were the GCMs used to extract the predictors. Under all emission scenarios, a consistent increase in extreme temperatures was observed. The changes for the worst-case scenarios within the reference period and 2080s, the greater increase was found to be 1.24–1.96 °C for minimum temperature and 2.67–3.9 °C for maximum temperature. For rainfall projections, different results were obtained based on the stations used and the applied scenarios. For most stations, towards the period 2099, rainfall is expected to decrease significantly up to 11.57%–17.68%.

Saddique et al., (2020) assessed the precipitation and temperature trends for present day observations from 1961 – 1990 and future projection 2061 – 2090 for downscaling modeling between large scales and local scale variables at the Jhelum River Basin. Three GCM models estimated the future trends of temperature and precipitation under RCP8.5 and RCP4.5 emission scenarios. RClimdex package was used for calculating temperature and precipitation indices for 15 stations. To detect the extreme climate trends, Sen's slope and Man-Kendall tests were applied. The general results discovered the patterns for temperature and precipitation changes significantly for projected as well as for observed data values and also for extreme events. In ascending order, the precipitation increases from the emission scenario RCP4.5 to emission scenario RCP8.5. For the 21st century, a significant level rise in trends of up to 95% for temperature and precipitation can be found for all stations. Decision-makers can be benefitted substantially from this study for adaptation and mitigation measures.

Wang et al., (2020) employed recurrent neural network (RNN) and compare it with the traditional ANN for statistical downscaling of precipitation and temperature whereas SWAT model was used to evaluate the downscaled meteorological data response to hydrology. Comparison of the downscaling performance between the northwestern and southeastern China showed that less performance of the temperature downscaling was obtained in northeastern China, while the opposite results were obtained regarding precipitation. About 10% and 6% increment in performance was achieved for minimum and maximum temperature downscaling by RNN model over ANN model. For extreme conditions, RNN model simulates the temperature better. For precipitation simulation, RNN and ANN displayed similarity in performance. For wet and dry days, the use of RNN made significant improvement. To increase performance, RNN-RandExtreme model was introduced. The RNN-RandExtreme when compared with the developed single RNN and ANN, the efficiency and reliability of precipitation extreme were increased up to 16.56% and 28.32% over the single RNN and ANN, respectively.

CHAPTER 3

MATERIAL AND METHODS

3.1 Study Location

Cyprus is located in the Mediterranean region and it constitutes a Mediterranean climate. The Eastern Mediterranean's third largest island is characterized by rainfall occurrence mostly spanning from November through March. A mild wet winters with dry hot summers are experienced in the region. The island's average precipitation as a whole is annually around 500 mm. Around 1200 mm average rainfall could be found in Trodos mountain which is the highest point, whereas around 300 – 400 mm average rain falls in the central plain (Elkiran and Ergil, 2006). Northern Cyprus, average temperature in January falls around 5 to 15 ^{0}C whereas in July it rises higher. In this thesis, the study stations are Famagusta, Nicosia and Kyrenia. Detail information about these stations can be found in the following subsections.

3.1.1 Famagusta stations

Famagusta is a coastal city, located at a latitude 35.12^0 N, longitude 33.94^0 E and altitude 25 m. The category of Famagusta climate is warm and temperate with around 19.3 ^{0}C of average temperature and around 407 mm average rainfall annually.

3.1.2 Nicosia station

Nicosia is the capital city of both south and north Cyprus. Nicosia is also called Lefkoşa in Turkish language. The Mediterranean Sea effect is less in Nicosia than the coastal cities being an inland city. Nicosia is characterized by hot summers and wet winters and as such, daytime maximum temperature and night minimum temperature difference is greater than in the coastal cities. By comparing the other coastline cities' daytime temperature with Nicosia, there is a difference of up to 4 ^{0}C or 7 ^{0}C for the hottest months of July and August. In the coldest months of January and February, up to 2 ^{0}C or 3 ^{0}C lower daytime temperature difference is witnessed in Nicosia than other coastal cities.

3.1.3 Kyrenia station

Kyrenia is a coastal city in Northern Cyprus. The city is situated at latitude of 35.34^0 N, longitude of 33.32^0 E and altitude of 3 m. Temperature in the hottest month of July has an average of 29^0 C and coldest month of January 10^0 C. Rainfall in hilly areas varies from 750 mm to as low as 500 mm, falls mostly in winter and in rare occasion in summer. Due to elevation, the highest rainfall is experienced in Kyrenia Mountains at a rate which ranges between 750 to 1110 mm. Figure 3.1 describes Cyprus map and locations of the study and the selected grid point.

Figure 3. 1: Study location and the selected grid point

3.2 Study Data

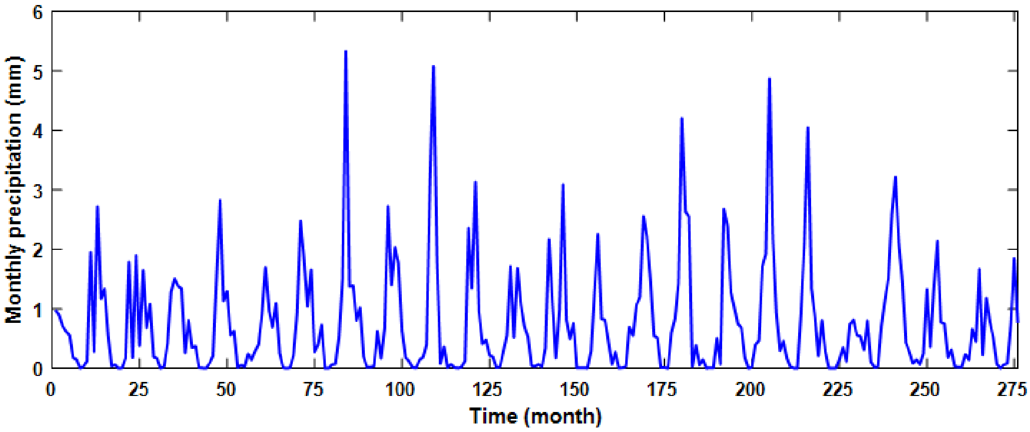
The mean monthly predictands data of precipitation and temperature used in this thesis from 1995 -2017 (23 years) were obtained from North Cyprus Meteorological Organization. A total of 13 number of GCM predictors for a grid point located at Karfas (shown in Figure 3.1) for BNU-ESM GCM under Representation Concentration Pathways (RCPs) from

CMIP5 were downloaded from http://cera-www.dkrz.de for large scale predictors from 1995 – 2040 for the statistical downscaling and future projection of the predictands. Table 3.1 gives the descriptive statistics of the predictands.

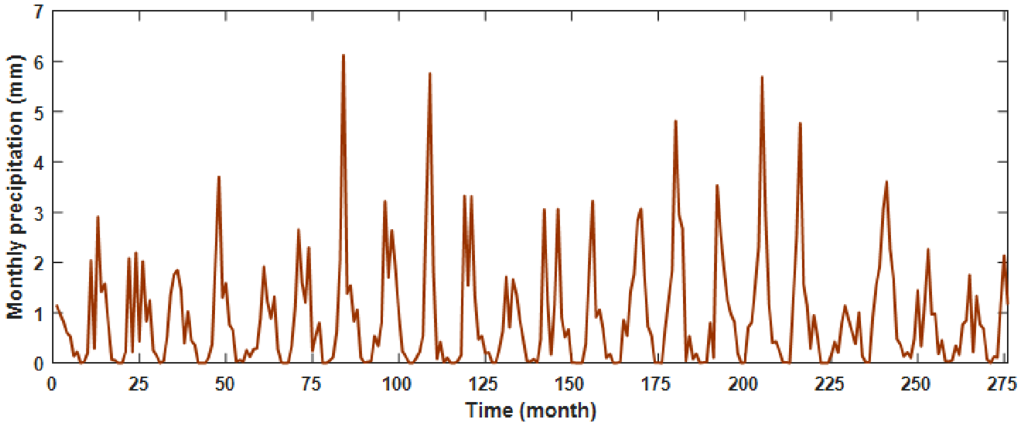
Table 3. 1: Data description for predictands

Station	Parameters	Unit	Min	Max.	Average	St. Deviation
Famagusta	Precipitation (P_R)	mm	0	5.33	0.77	0.93
	Mean Temperature (T_{mean})	^0C	12.37	31.23	21.47	5.88
Kyrenia	Precipitation (P_R)	mm	0	189.69	27.69	33.13
	Mean Temperature (T_{mean})	^0C	11.16	30.96	20.61	6.11
Nicosia	Precipitation (P_R)	mm	0	5.83	0.94	1.11
	Mean Temperature (T_{mean})	^0C	10.76	33.26	24.17	6.85

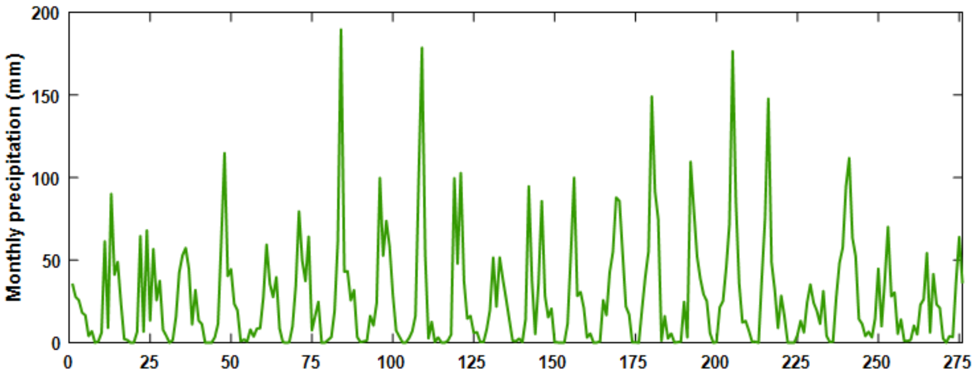
It can be seen from Table 3.1 that in terms of precipitation, all stations have minimum value as low as 0 mm which indicates a month(s) with no precipitation received. But considering maximum amount of precipitation, Kyrenia show highest rate of precipitation with about 189.69 mm while the second station with highest precipitation is Nicosia with 5.83 mm and lastly Famagusta with 5.33 mm. For average value of precipitation, the case is similar with 27.69 mm, 0.94 mm and 0.77 mm for Kyrenia, Nicosia and Famagusta, respectively. With respect to the mean temperature, the maximum temperature is found to be 33.26 ^0C and maximum average temperature is found to be 24.17 ^0C all at Nicosia station due to its inland location while the coastal breezes lessen the rise of temperature in Famagusta and Kyrenia stations. A difference in average temperature of about 3 ^0C could be spotted between Nicosia and Kyrenia stations, which confirms the earlier statement in subsection 3.1.2 regarding difference of daytime temperature between Nicosia and other coastal stations. Figure 3.2 shows precipitation distribution from 1995 – 2017 for all stations.



(a) Famagusta



(b) Nicosia



(c) Kyrenia

Figure 3. 2: Distribution of precipitation across study stations from 1995 – 2017

From the displayed precipitation time series in Figure 3. 2 it can be deduced that, the precipitation patterns for Famagusta, Nicosia and Kyrenia are similar, which might be due to their identical semiarid climate. Despite this development, difference in the amount or rate of precipitation can be seen from the highest precipitation station (Kyrenia) to the lowest precipitation station (Famagusta). These are in agreement with the characteristics of the data shown in Table 3.1. In spite the coastal location of Famagusta station, which by virtue of the larger evaporation body (e.g. sea) would experience higher precipitation than inland (Nicosia) station, the time series data plotted in Figure 3.2 show precipitation was received by Nicosia than Famagusta. This might be because both Nicosia and Kyrenia are surrounded by mountains and the energy reaching the earth surface which helps in evaporation and eventual precipitation will reach the mountains faster and as such, may aggravate precipitation which may lead to receiving more in mountainous areas. Moreover, from water cycle concept, water is in constant movement from the earth to the atmosphere and due to such movement, the water that evaporates from a given area may fall at another area. This is implying that water that large quantity of water that evaporates from Famagusta may not fall in Famagusta, rather small quantity of water that evaporates from another area may fall in Famagusta due to the continuous movement of the water in the atmosphere. Table 3.2 describes the GCM data employed for the study.

Table 3. 2: Data descriptions of large scale GCM predictors

S/N	Predictors	Description	Height
1	tasmax	Maximum air temperature	Surface
2	ts	Sea surface temperature	Surface
3	hurs	Relative humidity	Near surface
4	huss	Specific humidity	Near surface
5	psl	Sea level pressure	Surface
6	evspsbl	Water evaporation	Surface
7	sfcwind	Wind speed	Near surface
8	ps	Surface air pressure	Surface
9	uas	Zonal wind speed	Near surface
10	vas	Meridional wind speed	Near surface
11	prw	Atmospheric water vapor content	Surface
12	pr	Precipitation	Surface
13	clwvi	Cloud condensed water content	Surface

As seen in able 3.2, the predictors used for the purpose of the study include variables that are related to the factors influencing both precipitation and temperature such as wind speed, relative humidity, temperature, precipitation etc. at surface and near surface heights.

3.2.1 Data normalization and performance criteria

Mostly in AI based studies, for all variables to receive equal attention and for their dimensions elimination, data normalization is usually applied. The data normalization comes with two major benefits: (1) the disadvantage of larger numeric ranges to overshadow the smaller ones is eliminated using data normalization (2) data normalization minimizes computational difficulties (Abdullahi and Elkiran, 2017). Hence, the data were normalized as follows;

$$P_n = \frac{P_i - P_{min}}{P_{max} - P_{min}} \tag{3.1}$$

Where P_n, P_i, P_{max} and P_{min} are the normalized value, ith observed value, maximum value and minimum value, respectively.

To determine models performance, to widely acceptable performance indicators of determination coefficient (DC) and root mean square error (RMSE) regarded by Legates and McCabe (1999) as sufficient indicators for determining the performance of any hyroclimatic models. The following equations were used for determining the models performance.

$$DC = 1 - \frac{\sum_{i=1}^{N}(P_i - \hat{P}_i)^2}{\sum_{i=1}^{N}(P_i - \bar{P})^2} \tag{3.2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - \hat{P}_i)^2}{N}} \tag{3.3}$$

Where P_i is the observed i^{th} value, $\bar{P}$ represents mean of the observed values, $\hat{P}_i$ is the predicted i^{th} value and N stands for number of observations. The DC has a values which range between –infinity to 1 ($-\infty < DC \leq 1$) and the model is more efficient with a value close to 1 while RMSE lies between 0 to infinity ($0 \geq RMSE < \infty$) with the efficiency of the model increases with RMSE towards 0 (Nourani et al. 2020).

3.3 Model Validation

In this thesis, k-fold cross validation technique was utilized to validate the models. With k-fold technique, the data set are divided randomly into certain number of equal subsamples regarded as k-number subsamples. The model is trained with the k-number subsamples minus 1 (k-1) and remaining k-subsample is used for validation. The process is repeated continuously with k-1 and k different subsamples for training and validation of the model, until the subsamples are used once in both training and validation of the model. The final results are then obtained by averaging the k-fold results. The advantage of k-fold validation technique is that for model training and validation, every observation is used once (Nourani et al. 2019).

In this thesis, the k-fold random division of the data set was done for k=4 (4-fold) subsamples. In this way, ¾ of the subsample were utilized for training and ¼ remaining subsample utilized for model validation. The process was repeated for 4 consecutive times, with different ¾ and ¼ subsamples for training and validation.

3.4 Proposed Methodology

In this thesis, downscaling modeling as well as future projection of precipitation and temperature were performed using ANN, ANFIS and MLR downscaling models. Therefore the proposed methodology is in three steps as follows;

3.4.1 Step 1: feature extraction of dominant predictors

For different GCMs, there are different methods of obtaining outputs due to different resolutions, as a result, the reliability of the different GCMs determines the projection efficiency for future. Therefore, GCM performance assessment and determination of the most dominant GCMs become important (Nourani et al. 2019). In this way, CC and MI feature extraction methods were used to calculate predictands (precipitation and temperature) and predictors (GCM outputs) relationships in form of linear and nonlinear approaches, which led to selection of dominant predictors used as inputs for the downscaling modeling.

3.4.2 Step 2: Statistical downscaling modeling of precipitation and temperature

The statistical downscaling of precipitation and temperature using ANN and ANFIS models was performed in this step considering the dominant predictors determined by feature extraction methods in step 1.

In accordance with the technical literature survey that was conducted, it was found that the evaluation of the AI based models downscaling efficiency has been carried out mostly using classic models such as SDSM. In statistical downscaling modeling, SDSM is a commonly applied method which determines predictant and predictors statistical relevance through utilization of MLR method. Hence, MLR model was also employed for the statistical downscaling of the predictands to compare and evaluate the performance of AI based (ANN and ANFIS) downscaling models. The reason why MLR was preferred over SDSM downscaling model is that in any time scale, MLR can use predictors, whereas predictors can only be used in daily scale using SDSM model. In view of this study's monthly time scale, working with the model that uses only daily time scale is not possible. In the next step (step 3), the downscaling model that produced highest efficiency was used as benchmark for the projection of future precipitation and temperature.

3.4.3 Step 3: Future projection of precipitation and temperature

The future projection of monthly precipitation sum and mean temperature for the future from 2018 – 2040 was conducted using the best downscaled model as benchmark output. It is important of mention that due to social, population, energy extension and economic growth rate, future anthropogenic functions are admissibly plausible, which have an impact on greenhouse gas production. In accordance with future status mentioned, RCPs represent emission scenario and radiative forcing pathways, was used for precipitation and temperature future projection. Detail information regarding RCPs and emission scenarios are given in section 3.10. Figure 3.3 shows the schematic procedure developed for the proposed modeling. This should be noticed that the proposed methodology is same for both precipitation and temperature and are applied for all stations.

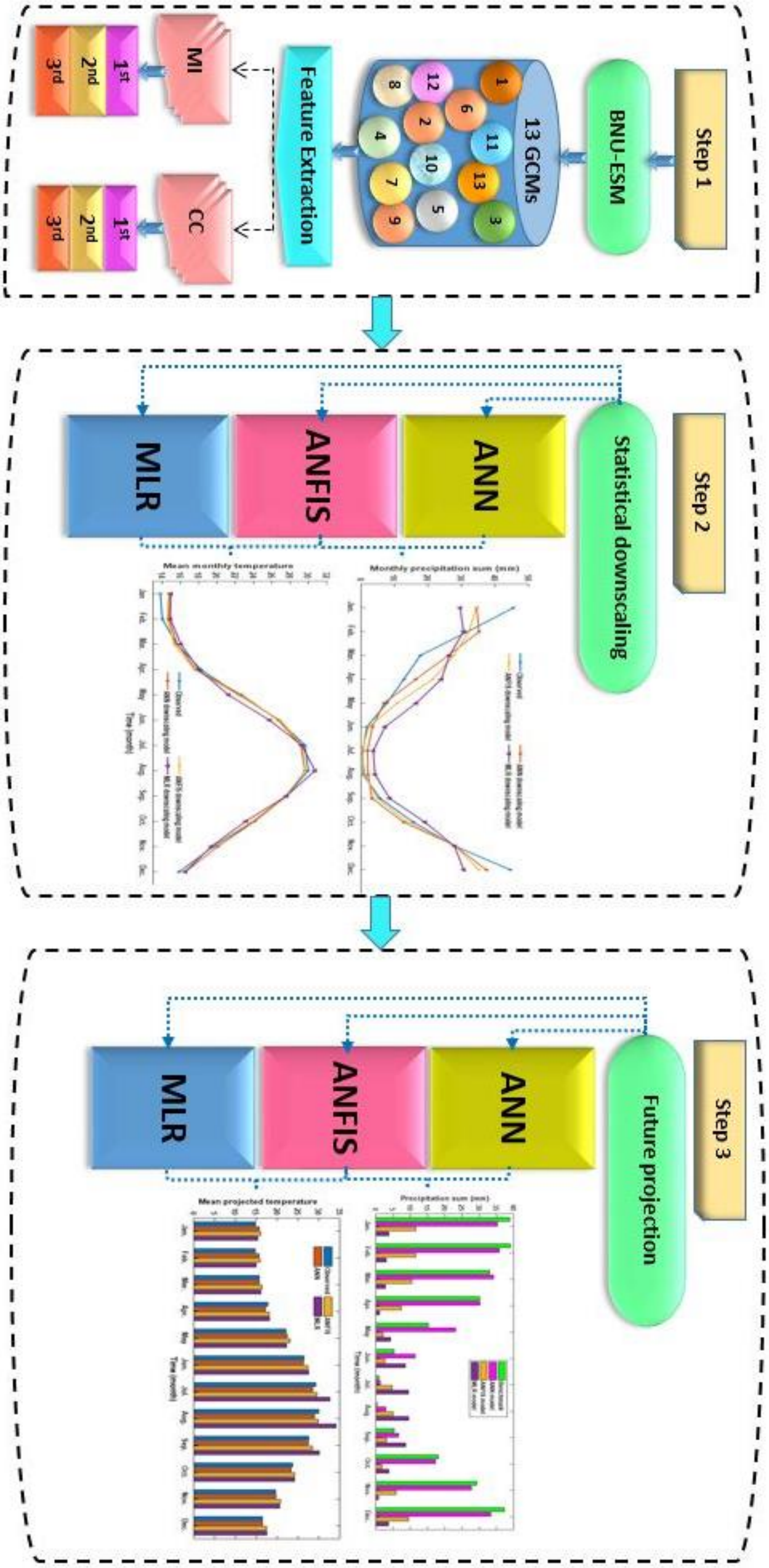


Figure 3. 3: The applied study methodology

3.5 Artificial Neural Network (ANN)

Amongst AI techniques, ANN is a convincing approach that has the potential of handling noisy, nonlinearity and data dynamism, more specifically when there is insufficient understanding of the underlying physical relationships. This emphasizes the ANN as an important data driven tool for time series modeling (Nourani et al., 2020).

ANN comprises of neurons or nodes interconnected by a number of simple processing elements with processing characteristics of attractive peculiarity of information including generalization capability, nonlinearity, learning, parallelism and noise tolerance. For handling many problems in engineering, FFNN model equipped with an algorithm called back propagation (BP), amongst neural network methods, are mostly used (Hornik et al. 1989). The method of FFNN constitutes layers of neurons of parallel processing elements, whereby weights are used to connect fully every layer to the proceeding layer. The BP algorithm is generally used to accomplish such ANNs learning (Hornik et al. 1989).

Levenberg-Marquardt (LM), amongst several algorithms for neural networks training, was preferred in this study owing to its ability to converge quickly (Sahoo et al. 2005). As a hybrid technique and for optimal convergence of solution, LM algorithm utilizes Gauss-Newton and steepest descent together. The hybrid approach to solve problems of wide margins, usually, different algorithms' best characteristics are used for trade off. For example, the approach of Gauss-Newton is quicker when the optimal solution is relatively close to the initial guess, consequently, LM algorithm is utilized. Contrarily, the approach of steepest descend is used by LM algorithm to find area of potential solution and traverse the design space and then determine the optimum. This technique is especially important for providing solutions to nonlinear equations (Wilson and Mantooth, 2013). Nevertheless, tangent sigmoid (Tansig) was utilized as the transfer function of both layers (hidden and output). To ensure hidden layer neurons of optimum number and also to generate efficient epochs for calibration, process of trial and error was followed. The ANN schematic structure is given in Figure 3.4.

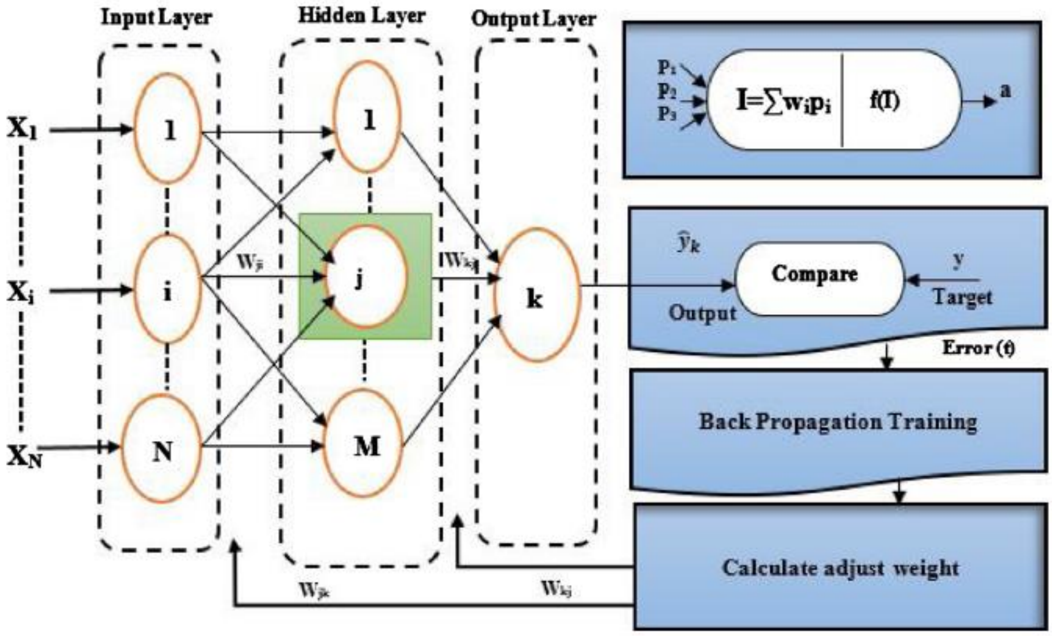


Figure 3. 3: The schematic diagram of ANN model

3.6 Adaptive Neuro Fuzzy Inference System (ANFIS)

Neuro fuzzy in neural network technical literature refers to the approaches of fuzzy logic modeling that comprise of distinctive learning algorithm application to the system of fuzzy inference (FIS). In the development of Neuro fuzzy system, ANFIS is a peculiar approach that Jang (1993) initially introduced. It utilizes the learning algorithm of the neural network.

In every fuzzy system there constitutes three major parts, namely; fuzzifier, defuzzifier and fuzzy database (Nourani et al. 2015). Inference engine and fuzzy rule base are fuzzy database's two essential parts. Rules related to fuzzy propositions are comprised in fuzzy rule base as Jang et al. (1997) revealed. Therefore, in fuzzy inference, operational analysis is administered. The fuzzy inference engines that are most commonly applied are Mamdani and Sugeno which both could produce a desired goal on application.

For overall real continuous functions, ANFIS being a universal approximator is capable of impacting accuracy to a higher degree. As Jang et al (1997) stated, functionally, ANFIS is equivalent to FIS. Thus, specifically the ANFIS system is equal to first order Sugeno fuzzy model. Figure 3.5 shows ANFIS general structure. As seen in the mentioned Figure, the

ANFIS model has *x* and *y* inputs with *f* considered as output. There two if-then sets of rules constituted in the first order Sugeno model, demonstrated as:

$$\text{Rule (1): If } \mu(x) \text{ is } A_1 \text{ and } \mu(\text{y}) \text{ is } B_1\text{; the } \mathfrak{f}_1 = p_1 x + q_1 y + r_1 \quad (3.4)$$

$$\text{Rule (2): If } \mu(x) \text{ is } A_2 \text{ and } \mu(\text{y}) \text{ is } B_2\text{; the } \mathfrak{f}_2 = p_2 x + q_2 y + r_2 \quad (3.5)$$

Where *x* inputs MFs are represented by A_1 *and* A_2, while *y* inputs MFs are represented by B_1 and B_2. p_1, q_1, *r1* and p_2, q_2, r_2 are output function parameters. Each ANFIS layer has the following functions:

Layer 1: Input variable membership grades are produced by each node in this layer. The i^{th} node output of the k layer is denoted by Q_i^k. Assuming as a generalized bell function of a MF (gbellmf), Jang and Sun (1995) stated that the output (Q_i^1), can be determine from:

$$Q_i^1 = \mu_{A_i}(x) = \frac{1}{1+((x-c_i)/a_i))^{2b_i}} \quad (3.6)$$

Where a_i, b_i, c_i are adaptable variables called premise parameters.

Layer 2: In this layer, the incoming signals are multiplied by each node:

$$Q_i^2 = w_i = \mu_{A_i}(x).\mu_{B_i}(y) \; i = 1, 2, \ldots \quad (3.7)$$

Layer 3: In this layer, the ith node calculated the normalized firing strength:

$$Q_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1, 2 \quad (3.8)$$

Layer 4: In this layer, node i calculated the contribution given by the ith rule to the model output:

$$Q_i^4 = \bar{w}_i(p_i x + p_i y + r_i) = \bar{w}_i \mathfrak{f}_i \quad (3.9)$$

Where, p_1, q_1, r_1 is the perimeter set, $\bar{w}_i$ is the output of layer 3.

Layer 5: In this layer, single node calculated the overall output of the ANFIS (Jang and Sun, 1995).

$$Q_i^5 = \sum_i \bar{w}_i \mathfrak{f}_i = \frac{\sum_i w_i \mathfrak{f}_i}{\sum_i w_i} \quad (3.10)$$

ANFIS hybrid learning algorithm is formed by a combination of least-squares and gradient descent methods. The consequent parameters are represented by p_i, q_i, r_i while the optimization parameters known as premise parameters are represented by a_i, b_i, c_i. Least-square technique identified the consequent parameter in the hybrid learning approach towards forward pass until the 4th layer where the output node goes forward. There is propagation of the error signals backward in the backward pass and the gradient descent updated the premise parameters (Nourani and Komasi, 2013). Figure 3.5 shows the ANFIS general structure.

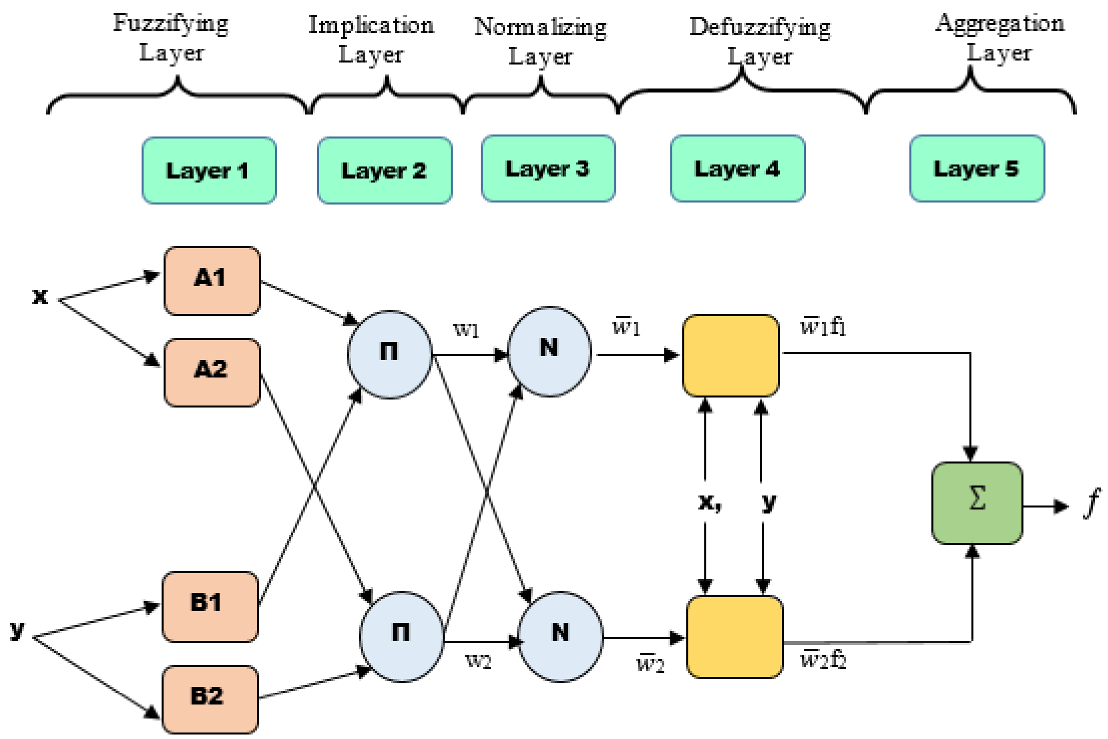


Figure 3. 4: The ANFIS general structure

3.7 Multiple Linear Regression (MLR)

MLR is a conventional technique that modeled mathematically the linear relevancy between two or more predictors (independent variables) and a predictand (dependent variable). In general, the n and y representing predictors and dependent variables might have relation, given by (Nourani et al. 2019):

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_ix_i + \xi \tag{3.11}$$

Where the i^{th} predictor value is x_i, the constant of regression is b_0, the i^{th} predictor coefficient is b_i and the error term is ξ. Figure 3.6 shows visual MLR model.

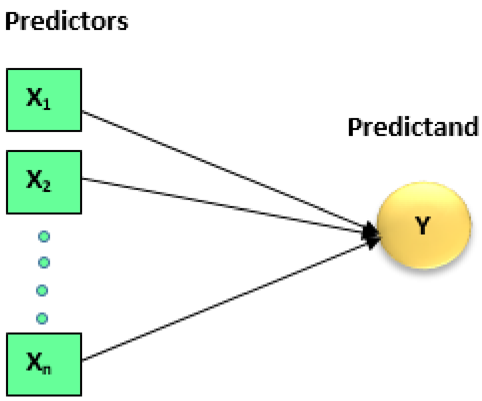


Figure 3. 5: MLR graphical representation

3.8 Correlation Coefficient (CC)

The method of CC has been applied as a common metric for understanding the linear behavior between variables (predictand and predictors), its values fall between +1 and -1. When the value is +1, it denotes that the linear relationship is strongly positive while when the value is -1, it means that the linear relationship is strongly negative, whereas 0 value indicates that the variables have no linear relationship. Baghanam et al., (2019) defined two variables relationship based on CC as:

$$CC = \frac{\sum(R-\bar{R})-\sum(Z-\bar{Z})}{\sqrt{\sum(R-\bar{R})^2\sum(Z-\bar{Z})^2}} \tag{3.12}$$

Where $\bar{Z}$, $\bar{R}$, Z and R imply the predictor mean value, predictand mean value, predictor value and predictand value, respectively.

3.9 Mutual Information (MI)

Using data probability distribution, mathematically the information and entropy content have been measured and formulated (Shannon 1948). As a measurement of uncertainty, turbulence and criterion of disorder, it has been introduced. The Shannon theory of information content generally is applied in the continuous or discrete form based on the nature of problem and data. Owing to the discrete nature of the data in this study, for a random variable X the Shannon entropy is calculated with n length and $X_1, X_2, \ldots, X_n$ values with correspondence probabilities of $P_1, P_2, \ldots, P_n$ as demonstrated by Shannon, (1948).

$$H(X) = -\sum_{i=1}^{N} P(X_i) \log [P(X_i)] \tag{3.13}$$

Yang et al., (2000) defined MI between X and Y random variables as:

$$MI(X,Y) = H(X) + H(Y) - H(X,Y) \tag{3.14}$$

Where X and Y entropies are $H(X)$ and $H(Y)$, while X and Y common entropy is $H(X,Y)$ and is calculated as Gao et al., (2008) as:

$$H(X,Y) = -\sum_{i=1}^{N} \sum_{i=1}^{N} P(X_i, Y_i) \log [P(X_i, Y_i)] \tag{3.15}$$

In this thesis, the feature selection of dominant predictors (GCM outputs) for predictands (precipitation and temperature) was performed using the method of MI.

3.10 Emission Scenarios

In the early 1990s, six emission scenarios were developed by IPCC to assess climate changes called IPCC Scenarios 92 (IS92) (Sanderson et al. 2017). As time went by, there was research advancement in assessment method and on emission driven forces. Four new sets of emission scenarios were published based on socioeconomic storylines described by IPCC in the Special Report on Emissions Scenarios (SRES) (Moss et al. 2010). Representative Concentration Pathways (RCPs) are other sets of emission scenarios that were emerged based on radiative forcing. The RCPs include RCP8.5 (very high emission), RCP6.0 (medium stabilization), RCP 4.5 and RCP2.6 (very low radiative forcing level). Thorough results comparison and the survey of technical literature of several sets of scenarios indicate the similarity of RCP8.5 and SRES A1F1, whereas in between RCP6.0 and RCP8.5 results, are results produces by SRES A2, while the climate changes produced by SRES A1B scenario are comparable to SRES B1 and RCP6.0 scenarios and are similar to that of RCP4.5. Compared to any of the SRES scenarios, RCP2.6 projected temperature changes are found to be lower. Couple Model Inter-comparison Project 5 (CMIP5) are formed on the basis of four RCPs climate projections. In the IPCC fifth assessment report, these projections were extensively analyzed (Moss et al. 2010). There is no preference regarding the sets of emission scenarios of RCPs or SRES. In other words, there is no disliking or liking attached to RCPs or SRES (Sanderson et al. 2017). Rather, both are credibly representations of future emissions. Hence, various activities in life and different policy options can be explored under RCPs or SRES group of scenarios for future precipitation and temperature projections. Therefore, in this study, RCP4.5 scenario was considered for the projection of precipitation and temperature for future.

CHAPTER 4

RESULTS AND DISCUSSION

This study was performed in 3 steps. In the first step, the most appropriate downscaling predictors were determined using the methods of MI and CC in order to have better downscaling modeling of precipitation and temperature. Statistical downscaling modeling was performed in the second step through the application of ANN and ANFIS nonlinear downscaling models and compared with linear MLR downscaling model. In the final step (step 3) of this study, future projection of precipitation and temperature was conducted. Therefore, the results in this study were presented accordingly.

4.1 Step 1 Results (Selection of Downscaling Predictors for Predictands)

Selection of the dominant predictors is essential for downscaling modeling especially in the fields that are related to climate change (such as precipitation and temperature) due to greenhouse effect. According to Nourani et al. (2019), to achieve optimum performance by data driven model, dominant predictors' selection should follow assignment of GCM. In this regards, a total of 13 atmospheric predictors generated from BNU-ESM GCM at a grid point of latitude 35.53^0N and longitude 34.28^0E were subjected to MI and CC input screening techniques for Famagusta, Nicosia and Kyrenia stations. The results of the applied MI feature extraction technique are presented in Tables 4.1 and 4.2. It should be understood that predictor with higher MI signifies dominant predictor for the predictand.

Table 4. 1: Step 1 results across the study stations for MI input screening

		Precipitation		Temperature	
Station	**Predictor**	**MI**	**Rank**	**MI**	**Rank**
Famagusta	Tasmax	1.6374	6	1.5568	6
	Ts	1.6293	8	1.5403	8
	Hurs	1.6460	5	1.5687	5
	Huss	1.6735	1	1.5972	2
	Psl	1.6604	4	1.5480	7
	Evspsbl	1.6069	9	1.5253	10
	Sfcwind	1.6633	3	1.5850	4
	Ps	1.6297	7	1.5272	9
	Uas	1.6698	2	1.5968	3
	Vas	1.6015	10	1.5188	11
	Prw	1.4028	12	1.3135	13
	Pr	1.5086	11	1.4112	12
	Clwvi	1.3674	13	1.6035	1
Nicosia	Tasmax	1.6335	6	1.5868	7
	Ts	1.6261	7	1.5645	8
	Hurs	1.6783	3	1.6059	6
	Huss	1.7020	1	1.6316	1
	Psl	1.6732	5	1.6168	5
	Evspsbl	1.5368	10	1.4711	11
	Sfcwind	1.6776	4	1.6213	3
	Ps	1.6071	8	1.5476	9
	Uas	1.6951	2	1.6189	4
	Vas	1.5866	9	1.5342	10
	Prw	1.3786	13	1.3169	13
	Pr	1.4906	11	1.4218	12
	Clwvi	1.3891	12	1.6311	2
Kyrenia	Tasmax	1.6902	9	1.6161	9
	Ts	1.7483	4	1.6622	2
	Hurs	1.7367	7	1.6362	7
	Huss	1.7468	5	1.6484	6
	Psl	1.7621	3	1.6567	3
	Evspsbl	1.7393	6	1.6289	8
	Sfcwind	1.7707	2	1.6492	5
	Ps	1.7149	8	1.6031	10
	Uas	1.7727	1	1.6648	1
	Vas	1.6661	10	1.5503	11
	Prw	1.4755	12	1.3610	13
	Pr	1.5585	11	1.4506	12
	Clwvi	1.4386	13	1.6566	4

As depicted by MI results in Table 1, different predictors characterize different performance for certain predictant for different stations. For Famagusta station, the results show that Huss (1.6735), Uas (1.6698) and Sfcwind (1.6633) are respectively ranked as the 1st, 2nd and 3rd most dominant predictors with respect to precipitation predictand. These are relative humidity and wind speed related predictors. According to the results provided by Allen et al. (1998) study, relative humidity and wind speed are important parameters hydrologic water cycle whereas precipitation is among the most significant parameters. This shows that the relationship and bonding (between precipitation, relative humidity and wind speed) are not affected by local-scale climate but they are strong for large-scale climate. For temperature, the most dominant predictors are Clwvi (1.6035), Huss (1.5972) and Uas are the 1st, 2nd and 3rd most dominant predictors. This shows that both Huss and Uas have strong nonlinear relationship with the predictands (precipitation and temperature). This may be because Famagusta is semiarid coastal station which is both affected by the characteristics of hot temperature and insufficiency of rainfall.

For Nicosia station, the first 2 dominant predictors are same as for Famagusta station with respect to precipitation and Hurs appears to be the 3rd most dominant predictor. The main reason that lead to this might be the difference between the two stations being Nicosia as an inland station and Famagusta as coastal station. For temperature, Huss (1.6316), Clwvi (1.6319) and Sfcwind (1.6213) are the best, second and third most influential predictors. Wind speed related predictors are found to be most effective owing to the vulnerability to semiarid climate and being Nicosia as inland station.

For Kyrenia station, the feature extraction technique by MI shows in ascending order the performance of the predictors in terms of precipitation as Uas (1.7727), Sfcwind (1.7707) and Psl (1.7621). It is obvious from the results obtained for Kyrenia station MI has higher values than when compared to Famagusta and Kyrenia station. The third most dominant predictor in Kyrenia has a MI value of 1.7621 which is better than the one obtained for the best performance in Famagusta with MI 1.6735 and the best performance in Nicosia which has MI of 1.6313. This implies that the uniqueness of Kyrenia station that characterizes by more frequent precipitation and unstable elevation which comprises of hilly and valley areas also affected the feature extraction of the input variables (predictors). In case of temperature, Uas was found to be the most dominant predictor with MI value of 1.6648, followed by Ts with 1.6622 MI value and Psl is the third most dominant predictor with 1.6567 MI value. Comparing the performance of the two predictands it can be deduced that precipitation with its more frequency and higher storm could be predicted more efficiently by MI method of feature extraction than temperature.

Despite the nonlinearity effect displayed by predictors, it is a well-known fact that time series data may contain both linear and nonlinear aspects not only for local scale data but for large scale data. Therefore, in order to determine the linear relationship between the predictors and the predictands, CC method of input screening was performed. The results of the applied CC method of feature extraction are presented in Table 4.2.

Table 4. 2: Step 1 results across the study stations for CC input screening

		Precipitation		**Temperature**	
Station	**Predictor**	**CC**	**Rank**	**CC**	**Rank**
Famagusta	Tasmax	-0.6220	13	0.9686	1
	Ts	-0.4911	10	0.9379	3
	Hurs	-0.2787	7	0.1731	7
	Huss	-0.5641	12	0.9459	2
	Psl	0.6356	1	-0.8804	13
	Evspsbl	0.5168	5	-0.4202	8
	Sfcwind	-0.3216	8	0.5200	5
	Ps	0.5473	4	-0.6790	9
	Uas	-0.3523	9	0.2119	6
	Vas	0.5482	3	-0.8714	12
	Prw	-0.5378	11	0.8505	4
	Pr	0.5162	6	-0.7246	10
	Clwvi	0.5781	2	-0.7493	11
Nicosia	Tasmax	-0.6230	13	0.9677	1
	Ts	-0.4956	11	0.9304	3
	Hurs	-0.3636	9	0.5010	5
	Huss	-0.5689	12	0.9611	2
	Psl	0.5832	1	-0.7114	11
	Evspsbl	0.2197	6	0.0349	7
	Sfcwind	-0.0862	7	0.0042	8
	Ps	0.5168	4	-0.6915	9
	Uas	-0.1020	8	0.0838	6
	Vas	0.5563	3	-0.8640	13
	Prw	-0.4651	10	0.8102	4
	Pr	0.4995	5	-0.7094	10
	Clwvi	0.5750	2	-0.7584	12

Kyrenia	Tasmax	-0.6184	13	0.9732	1
	Ts	-0.5153	11	0.9400	3
	Hurs	0.6448	1	-0.8769	13
	Huss	-0.5814	12	0.9551	2
	Psl	0.6209	3	-0.7112	8
	Evspsbl	0.1475	7	0.0296	7
	Sfcwind	-0.0963	8	0.0871	5
	Ps	0.6233	2	-0.8763	12
	Uas	-0.2456	9	0.0501	6
	Vas	0.5004	6	-0.8757	11
	Prw	-0.4651	10	0.7664	4
	Pr	0.5295	5	-0.7217	9
	Clwvi	0.6184	4	-0.7636	10

In the results shown by Table 4.2, it can be seen that some variables have negative relationship with the predictands while some have positive values. For Famagusta station considering precipitation as the predictand, the pressure related predictor (Psl) was found to be most effective followed by wind speed related predictors (Clwvi and Vas). By comparing with the results achieved by MI method, in Famagusta station, it is obvious that due to the linear and nonlinear nature of the feature extraction methods, distinct results were obtained. For examples, Clwvi is found to be the least effective predictor variable using MI method, while CC method showed Clwvi as the most dominant predictor. However, as shown in Table 4.2, Tasmax, Huss, and Ts are respectively the best, 2nd and 3rd most sensitive predictors with temperature as the predictand. This demonstrates that the linear correlation is stronger towards temperature variable.

Considering Nicosia station, due to the similarity of the climate to that of Famagusta station, the first 3 most effective parameters are same. Moreover, despite the slight difference in the degree or strength of the correlation that exists between the predictors and precipitation, they possess same negative values for Tasmax, Ts, Hurs, Sfcwind, Uas, Prw and same positive values of Psl, Evspsbl, Ps, Vas, Pr and Clwvi. With respect to temperature as predictand, the sensitivity analysis method by CC in Table 4.2 showed similar results to that of Famagusta but with less improve relations. This is because Nicosia as inland station heats and cools faster than Famagusta as coastal station, which heats and cools slowly and this increases the nonlinear characteristics of the predictors in Nicosia due to the uncertainty in the inland station. With regards to temperature, Tasmax is the most effective predictor while Vas has the least correlation with temperature of Nicosia with weak negative value of -0.8640.

Considering Kyrenia station in terms of precipitation, it is expected to obtain entirely different results, because the frequency of occurrence of the precipitation as well as the average, minimum and maximum amount of precipitation in Kyrenia differ with that of the other 2 stations. As shown in Table 4.2, Hurs, Ps, and Psl are the 3 most dominant predictors. The predictor that is less correlated with the precipitation is Tasmax, which implies that rhe relationship between them is mostly nonlinear. It is worth explaining that the nature of the rocks surrounding Kyrenia helps in attaining higher frequency of precipitation which in turns correlated more linearly with atmospheric predictors such as Ps. With respect to temperature, the climate of both the 3 stations is semiarid Mediterranean climate, which makes the predictors possess similar linear relationship with temperature. With the determination of the significant predictors, the statistical downscaling modeling was then perform and the results are presented in the next section.

4.2 Step 2 Results (Statistical Downscaling Modeling)

This section presents the statistical downscaling modeling results of precipitation and temperature that was performed using ANN, ANFIS and MLR models. It should be noted that the first 3 predictors revealed by the results of MI and CC feature extraction methods (see Tables 4.1 and 4.2) were used as inputs for the downscaling models. The validating method applied in this study was k-fold validation. The data for the selected predictors were divided into 4-fold, with ¾ used for calibration and ¼ for validation. In this way, precipitation and training were split in to 75% for training the downscaling models and 25% for validating the downscaling models.

For ANN downscaling, several modeling algorithms were considered in order to come up with the most effective and most reliable performance. Trial and error procedure was applied for the selection of hidden neuron numbers which are important in AI based downscaling modeling. The network parameters used to develop the ANN model including learning algorithm, transfer function type, training function etc. for the two predictands under study for all stations are presented in Table 4.3.

Table 4. 3: ANN network parameters for statistical downscaling modeling

		Precipitation		Temperature	
Station	Model Function	MI	CC	MI	CC
Famagusta	Type of network used	FFNN	FFNN	FFNN	FFNN
	Learning algorithm	LM	LM	LM	LM
	Training Function	TrainLM	TrainLM	TrainLM	TrainLM
	Number of input layer neurons	3	3	3	3
	Number of hidden layer neurons	8	6	12	10
	Number of output layer neurons	1	1	1	1
	Transfer function type	TANSIG	TANSIG	TANSIG	TANSIG
	Maximum epochs	1000	1000	1000	1000
	Number of iterations	236	198	70	150
Nicosia	Type of network used	FFNN	FFNN	FFNN	FFNN
	Learning algorithm	LM	LM	LM	LM
	Training Function	TrainLM	TrainLM	TrainLM	TrainLM
	Number of input layer neurons	3	3	3	3
	Number of hidden layer neurons	7	7	7	7
	Number of output layer neurons	1	1	1	1
	Transfer function type	TANSIG	TANSIG	TANSIG	TANSIG
	Maximum epochs	1000	1000	1000	1000
	Number of iterations	300	276	300	276
Kyrenia	Type of network used	FFNN	FFNN	FFNN	FFNN
	Learning algorithm	LM	LM	LM	LM
	Training Function	TrainLM	TrainLM	TrainLM	TrainLM
	Number of input layer neurons	3	3	3	3
	Number of hidden layer neurons	10	7	6	6
	Number of output layer neurons	1	1	1	1
	Transfer function type	TANSIG	TANSIG	TANSIG	TANSIG
	Maximum epochs	1000	1000	1000	1000
	Number of iterations	120	96	120	96

In the Table, FFNN, LM and TANSIG represent feed forward neural network, Levenberg Marquardt and tangent sigmoid, respectively.

For ANFIS downscaling modeling, hybrid optimization algorithm was used for the calibration of Sugeno type fuzzy inference system. Several membership functions were used including Trapezoidal, Triangular and Gaussian. To achieve best ANFIS construction, trial and error procedure was employed for the network selection. The parameters used in developing ANFIS downscaling modeling are presented in Table 4.4.

Table 4. 4: ANFIS network parameters for statistical downscaling modeling

		Precipitation		Temperature	
Station	Model Function	MI	CC	MI	CC
Famagusta	Learning algorithm	Hybrid	Hybrid	Hybrid	Hybrid
	Fuzzy inference algorithm	Sugeno	Sugeno	Sugeno	Sugeno
	Structure formulation	TA	TA	TA	TA
	Membership function type	Triangular	Trapezoidal	Gaussian	Triangular
	Generated FIS	GP	GP	GP	GP
	Number of membership functions	3	3	3	3
	Output type	Constant	Constant	Constant	Constant
	Error tolerance	0.0005	0.0005	0.0005	0.0005
	Epochs	53	29	60	77
Nicosia	Learning algorithm	Hybrid	Hybrid	Hybrid	Hybrid
	Fuzzy inference algorithm	Sugeno	Sugeno	Sugeno	Sugeno
	Structure formulation	TA	TA	TA	TA
	Membership function type	Trapezoidal	Trapezoidal	Gaussian	Gaussian
	Generated FIS	GP	GP	GP	GP
	Number of membership functions	3	3	3	3
	Output type	Constant	Constant	Constant	Constant
	Error tolerance	0.0001	0.0001	0.0001	0.0003
	Epochs	70	102	39	82
Kyrenia	Learning algorithm	Hybrid	Hybrid	Hybrid	Hybrid
	Fuzzy inference algorithm	Sugeno	Sugeno	Sugeno	Sugeno
	Structure formulation	TA	TA	TA	TA
	Membership function type	Triangular	Gaussian	Gaussian	Trapezoidal
	Generated FIS	GP	GP	GP	GP
	Number of membership functions	3	3	3	3
	Output type	Constant	Constant	Constant	Constant
	Error tolerance	0.0005	0.0005	0.0005	0.0005
	Epochs	88	110	90	68

GP and TA represent grid partitioning and trial and error

By reviewing statistical downscaling modeling literature, MLR method which captures the statistical correlation between predictand and predictors was also applied in this study to measure the statistical downscaling performance of the ANN and ANFIS models. It is important to state that since the study is concerned with statistical downscaling modeling of precipitation and temperature, the results are presented in different subsections for all stations.

4.2.1 Statistical downscaling of precipitation

The results of the downscaling modeling of precipitation using the ANN, ANFIS and MLR downscaling models for both MI and CC predictor screening methods across the study stations are provided in Table 4.5. It is worthy to clarify that the results are presented for the best downscaling performance.

Table 4. 5: Statistical downscaling results for precipitation

				Training		Validation	
Station	Input screening method	Downscaling model	Inputs	DC	*RMSE	DC	*RMSE
Famagusta	MI	ANN	Huss, Uas, Sfcwind	0.589	0.097	0.554	0.121
		ANFIS	Huss, Uas, Sfcwind	0.546	0.101	0.518	0.126
		MLR	Huss, Uas, Sfcwind	0.404	0.116	0.377	0.143
	CC	ANN	Psl, Clwvi, Vas	0.438	0.136	0.360	0.120
		ANFIS	Psl, Clwvi, Vas	0.507	0.106	0.497	0.129
		MLR	Psl, Clwvi, Vas	0.433	0.137	0.355	0.121
Nicosia	MI	ANN	Huss, Uas, Hurs	0.408	0.116	0.404	0.142
		ANFIS	Huss, Uas, Hurs	0.450	0.127	0.286	0.137
		MLR	Huss, Uas, Hurs	0.337	0.150	0.291	0.126
	CC	ANN	Psl, Clwvi, Vas	0.570	0.121	0.404	0.116
		ANFIS	Psl, Clwvi, Vas	0.563	0.122	0.394	0.117
		MLR	Psl, Clwvi, Vas	0.457	0.136	0.368	0.119
Kyrenia	MI	ANN	Uas, Sfcwind, Psl	0.556	0.099	0.487	0.130
		ANFIS	Uas, Sfcwind, Psl	0.532	0.102	0.581	0.118
		MLR	Uas, Sfcwind, Psl	0.435	0.137	0.413	0.114
	CC	ANN	Hurs, Ps, Psl	0.522	0.126	0.371	0.118
		ANFIS	Hurs, Ps, Psl	0.562	0.120	0.492	0.106
		MLR	Hurs, Ps, Psl	0.475	0.132	0.469	0.108

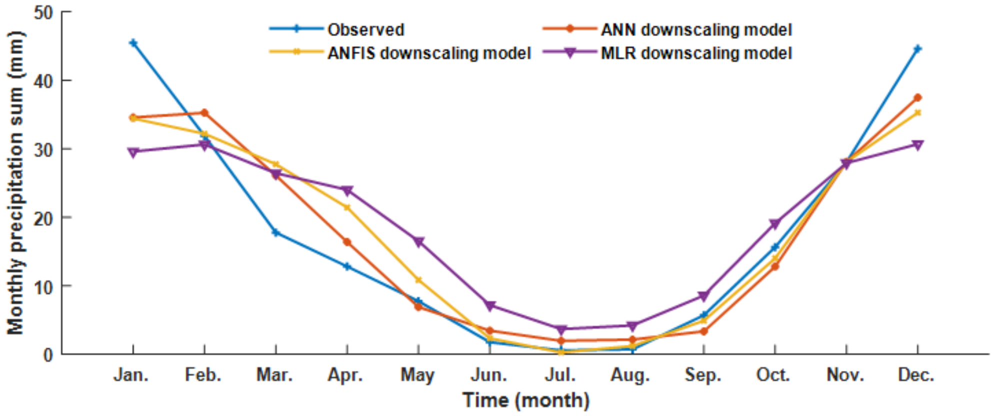
*RMSE: Being normalized data, RMSE is unitless

As given in Table 4.5, the downscaling performances of the models are evaluated according to DC and RMSE performance indicators. Considering Famagusta station, it can be seen that the AI downscaling models performed better than MLR downscaling model with respect to both MI and CC predictors screening methods. In terms of DC and based on validation results, ANN is found to be more efficient downscaling model with 4% and 17% over ANFIS and MLR respectively, based on MI feature extraction. Whereas, in terms of CC, ANFIS outperformed the other models with 14% and 15% over ANN and MLR respectively.

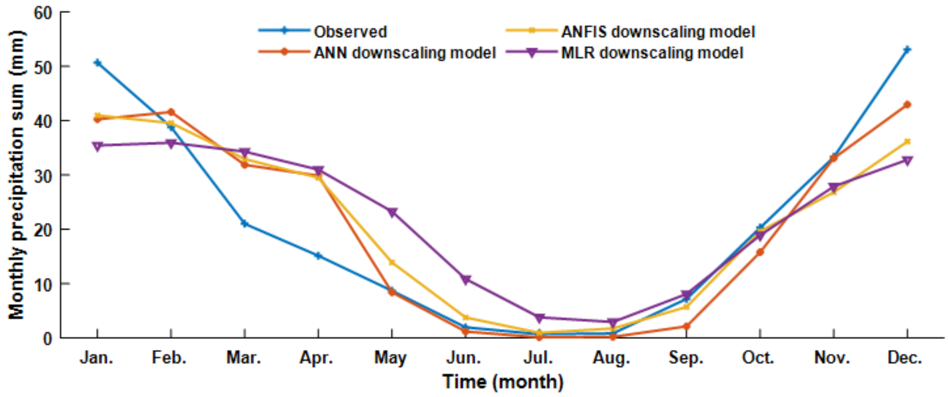
For Nicosia station, the general performance of the downscaling models is lower in comparison to Famagusta station especially that obtained by MI method. This could be because of the difference in location of the two stations (inland for Nicosia and coastal for Famagusta). The better performance of models produced by the CC method could be because of the direct effect the environment has on precipitation aspect, in a sense that the energy reaching the area causes direct increase in temperature and is easily predictable with less fluctuations which result in almost constant amount of evaporation and transpiration and hence precipitation. These processes lead to easy perception of the climate in the region and thereby creating more linear relationship and less nonlinear phenomenon is generated. In the validation phase, ANN improved performance of ANFIS by 12% and MLR by 11%. A slight improvement of MLR around 0.5% can be seen over ANFIS model. This also affirmed the observation earlier made in the Nicosia station that the nature and climate of the region make the relationship between the predictors and precipitation more linear in nature.

For Kyrenia station, it is expected that the performance of the statistical downscaling models would be higher than in Famagusta and Nicosia stations. This is as a results of higher amount and frequency of precipitation experienced in Kyrenia station. As the results in Table 4.5 received, high amount of precipitation received in an area signifies better downscaling capabilities and of course better performance and vice versa. Similar to the coastal station (Famagusta) ANFIS is found to be more efficient than the rest of the downscaling models. Better performance is achieved up to 10% over ANN and 17% over MLR in terms of MI method, 3% and 12% in terms of CC method. Looking at the performances of the downscaling models in the 3 stations under study, it can be seen that the nature and climate of a region influence downscaling efficiency of precipitation. For instance, Famagusta and Kyrenia are coastal stations while Nicosia is inland station. The results revealed better performance for former than latter. This is because evaporation and transpiration have direct effect on precipitation, as more evaporation source is present (sea in coastal stations) the higher evaporation which in turns results in better downscaling modeling of precipitation.

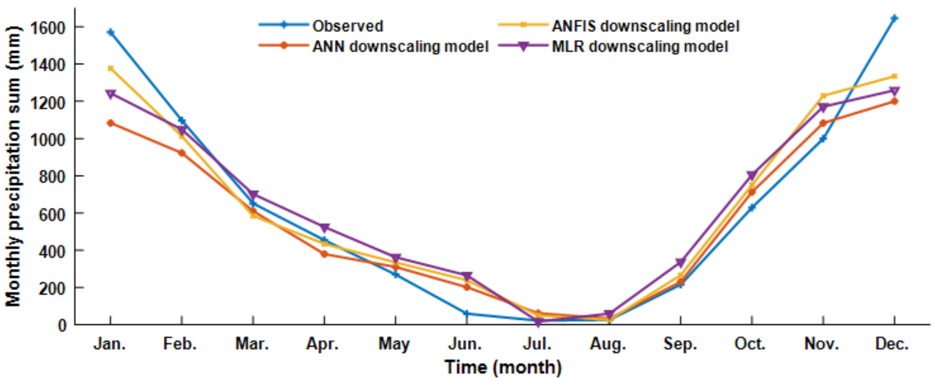
To evaluate the monthly precipitation downscaling performance of the applied models, the observed monthly precipitation sum is compared with the downscaled precipitation sum by the applied downscaling models and presented in Figure 4.1.



(a) Famagusta



(b) Nicosia



(c) Kyrenia

Figure 4. 1: Comparison of monthly precipitation between observed and downscaling models

It can be seen from Figure 4.1 that December and January are the months with highest precipitation amount and the months span from June until August are periods with little or no rainfall amount across all the study stations. In view of the closeness and fitness of the downscaled models toward the observed precipitation between June and August it can be deduced that the downscaling models are more reliable within that period. In other words, with less precipitation, the linear and nonlinear underlying processes of precipitation are easier to be monitored and captured, whereas, increase amount of precipitation lead to difficulty in understanding the phenomenon of precipitation which results in more fluctuations and eventually less efficiency in the downscaling of the precipitation.

4.2.2 Statistical downscaling of mean temperature

Similarly to precipitation, the results of the downscaling modeling of temperature using the ANN, ANFIS and MLR downscaling models for both MI and CC predictors screening methods across the study stations are provided in Table 4.6. However, the results are presented for the best downscaling performance.

Table 4. 6: Statistical downscaling results for temperature

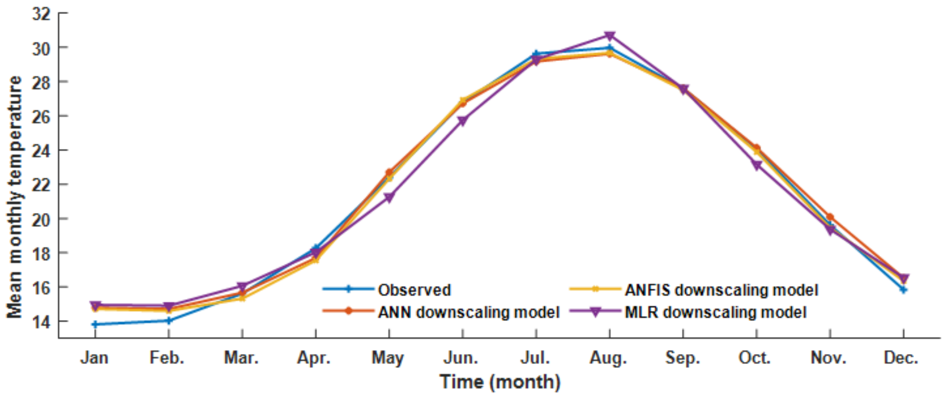
				Training		Validation	
Station	Input screening method	Downscaling model	Inputs	DC	*RMSE	DC	*RMSE
Famagusta	MI	ANN	Clwvi, Huss, Uas	0.948	0.069	0.940	0.077
		ANFIS	Clwvi, Huss, Uas	0.951	0.067	0.943	0.075
		MLR	Clwvi, Huss, Uas	0.923	0.085	0.914	0.092
	CC	ANN	Tasmax, Huss, Ts	0.976	0.047	0.976	0.049
		ANFIS	Tasmax, Huss, Ts	0.972	0.052	0.969	0.053
		MLR	Tasmax, Huss, Ts	0.954	0.067	0.951	0.067
Nicosia	MI	ANN	Huss, Clwvi, Sfcwind	0.945	0.071	0.944	0.073
		ANFIS	Huss, Clwvi, Sfcwind	0.965	0.056	0.959	0.063
		MLR	Huss, Clwvi, Sfcwind	0.950	0.067	0.941	0.076
	CC	ANN	Tasmax, Huss, Ts	0.970	0.052	0.970	0.054
		ANFIS	Tasmax, Huss, Ts	0.968	0.054	0.968	0.056
		MLR	Tasmax, Huss, Ts	0.953	0.065	0.951	0.069
Kyrenia	MI	ANN	Uas, Ts, Psl	0.958	0.062	0.954	0.066
		ANFIS	Uas, Ts, Psl	0.962	0.058	0.959	0.063
		MLR	Uas, Ts, Psl	0.927	0.081	0.926	0.084
	CC	ANN	Tasmax, Huss, Ts	0.966	0.058	0.963	0.058

ANFIS	Tasmax, Huss, Ts	0.970	0.053	0.967	0.055
MLR	Tasmax, Huss, Ts	0.953	0.067	0.953	0.065

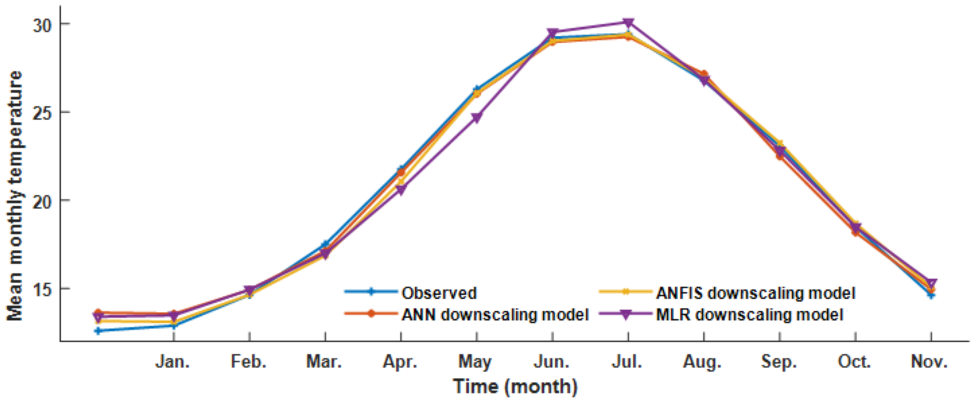
*RMSE: Being normalized data, RMSE is unitless

By visual inspection of Tables 4.5 and 4.6 it can be understood that the general performance of the downscaling models are superior in temperature downscaling than precipitation downscaling. This may be because of the distinct characteristics of the predictands in the study stations. Being a semiarid Mediterranean climate, the stations under study are subjected to high temperature and scarce water resources (less or little rainfall). The harsh weather coupled with uncertainty in factors affecting hydrologic cycle lead to more stochastic nature of precipitation and hence, difficult to be downscaled. The results in Table 4.6 show better downscaling capability of AI models than MLR model across all stations. This is also in agreement with the results revealed in precipitation downscaling, but the gap difference created over the MLR model is less in temperature downscaling. This could be because of the stochastic nature of precipitation, the relationship between the predictand (precipitation) and GCM variables is detected more nonlinearly, which is why nonlinear downscaling models performed better while linear downscaling model struggles.

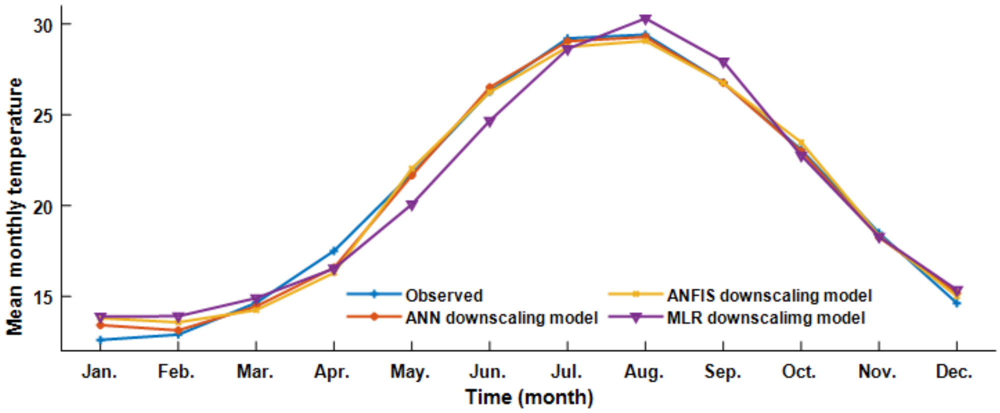
For Famagusta station in the validation phase based on DC performance indicator, the results in Table 4.6 revealed that ANFIS produced the best performance in terms of MI. ANFIS improved performance in the mean temperature downscaling modeling up to 1% and 3% over ANN and MLR, respectively. Regarding CC feature screening method, ANN propelled as the best performing downscaling model with an improvement of 1% over ANFIS and 3% over MLR. For Nicosia station, ANFIS has the best performance with DC 0.959, followed by ANN with 0.944 and finally MLR with 0.941 with respect to MI, whereas, ANN slightly edged ANFIS with DC of 0.970 and 0.968 and MLR followed with DC of 0.951. For Kyrenia station, ANFIS is narrowly the best downscaling model with DC = 0.959 and RMSE = 0.063, followed by ANN with DC = 0.954, RMSE = 0.066. MLR downscaling model perform the least in performance with DC = 0.926 and RMSE = 0.084. To ascertain the performances of the downscaling models for mean temperature in the period of this study (1995 – 2017), monthly average of the statistically downscaled temperature for each month are compared with the observed mean temperature as shown in Figure 4.2.



(a) Famagusta



(b) Nicosia



(c) Kyrenia

Figure 4. 2: Comparison of monthly mean temperature between observed and downscaling models

Graphical illustration of Figure 4.2 shows the downscaling models are very close to the observed values which ultimately confirmed the performance illustrated by DC and RMSE efficiency criteria. However, when the downscaling results of Figures 4.1 and 4.2 are compared, it can be deduced that values in Figure 4.2 are more fitted to observed values. This indicates better downscaling modeling is achieved with temperature as predictand than with precipitation. Moreover, Figure 4.2 indicates that temperature within the study region is higher in hot months (most especially the hottest months of June, July, August and September) and lower in cold months(December, January, February and March).

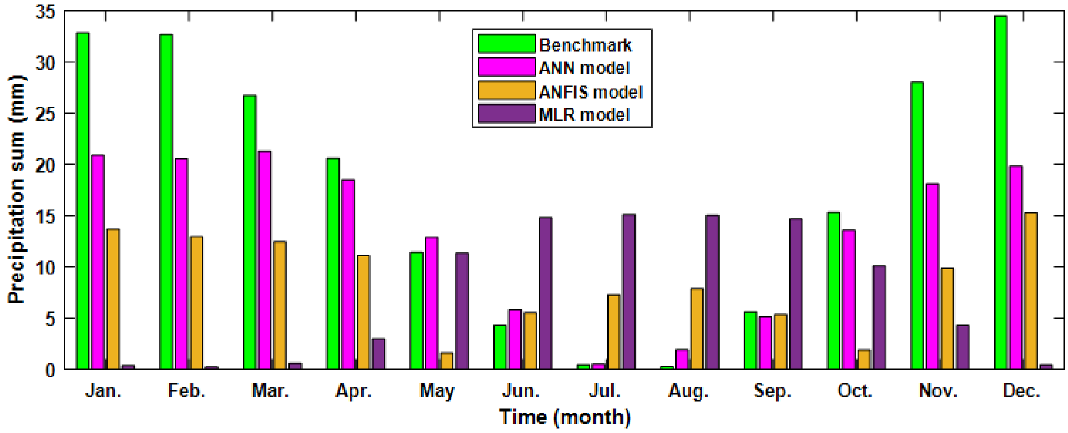
In general, the obtained results demonstrate that all the applied models (ANN, ANFIS and MLR) are sufficient statistical downscaling of precipitation and mean temperature across Famagusta, Nicosia and Kyrenia stations of north Cyprus. Moreover, both MI and CC feature extracting methods could be employed to determine the dominant GCM variable for a successful statistical downscaling modeling of precipitation and temperature. The results also indicate that where the relationship between the predictands and the GCM variables are more linear in nature, statistical downscaling models performed better with CC method, whereas MI method performed better for nonlinear relationships. It is therefore important for downscaling modeling of precipitation and temperature in the study station to use both screening methods. But MI method is preferable if a choice has to be made because of the coarse nature of large scale predictors results in more nonlinear relationship than linear relationship.

4.3 Step 3 Results (Future Projection of Precipitation and Temperature)

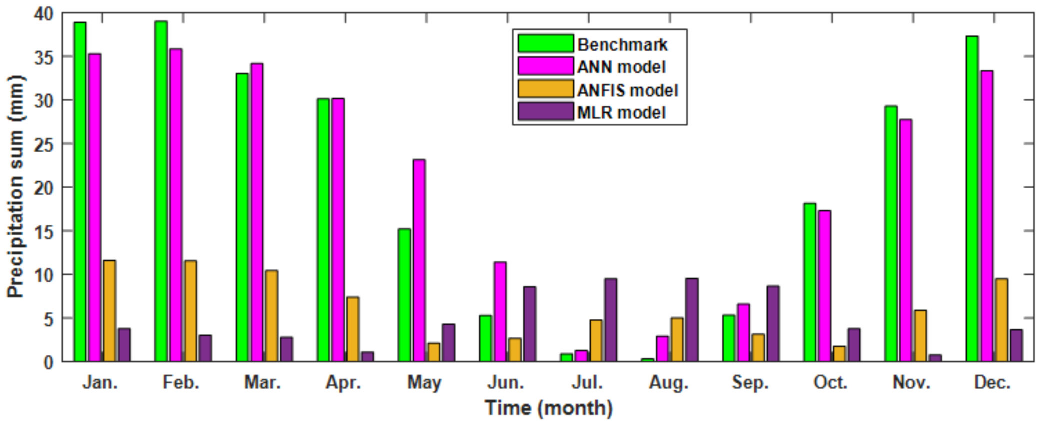
In this section of the study, the projection of precipitation and temperature for the future from 2018 – 2040 was performed which is a useful factor to consider for decision making, water resources management and climate change warning. Like in the case of statistical downscaling, MI and CC feature extraction methods are used in the selection of predictors for predictands. Moreover, the performances of ANN, ANFIS and MLR models are evaluated using DC and RMSE efficiency criteria. The results for the future projection of precipitation and temperature are provided in 2 subsections.

4.3.1 Results of precipitation projection for the future

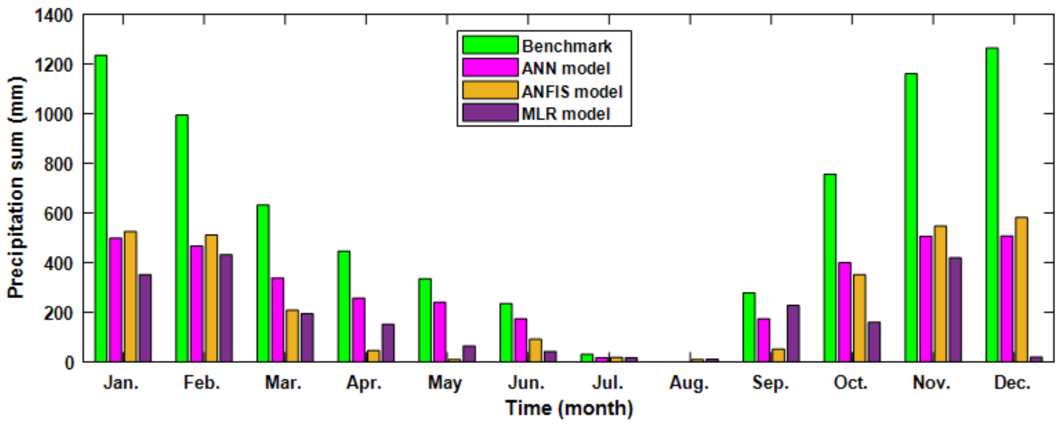
It can be seen from Table 4.5 that in most cases ANN provided the best performance for the downscaling modeling using MI feature extraction method, while ANFIS mostly performed better for CC method. Therefore, for future projection of precipitation, ANN was used as the benchmark model for projection made based on MI method and ANFIS was used as the benchmark model for projection based on CC method. According to the results obtained for the future projection of the predictands, different models yielded different results (Figure 4.3). For Famagusta station ANN reproduced the benchmark precipitation much better than other models. This followed by ANFIS with 0.25% less efficient and MLR which is 0.6% less efficient than ANN. MLR model performs the least in all stations in this study. For Nicosia station, ANN outperformed the other models with a higher gap increments of 20% and 43% over ANFIS and MLR models. For Kyrenia station, the projected precipitation results show the superiority of ANN over other model with MI and CC as input selection methods. A performance increment of up to 9% and 9% over ANFIS model based on MI and CC methods are achieved by ANN model. Figure 4.3 compares the benchmark monthly precipitation sum and future projection by the applied models.



(a) Famagusta



(b) Nicosia



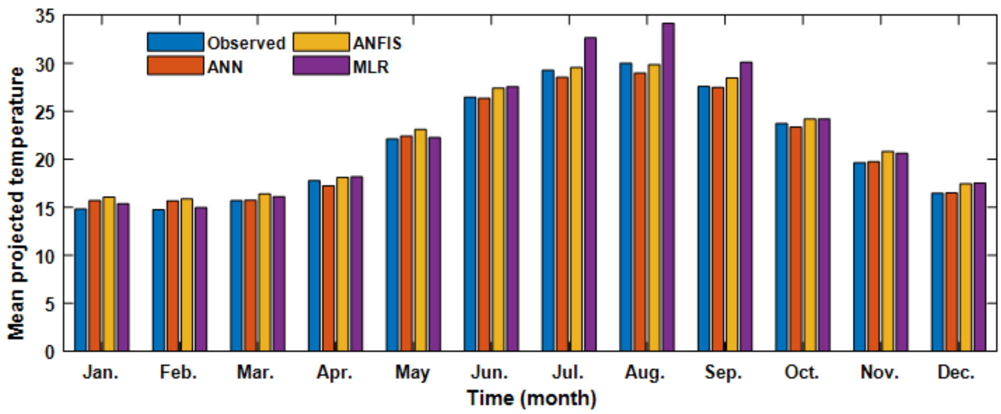
(c) Kyrenia

Figure 4. 3: Monthly projected precipitation sum for future (2018-2040)

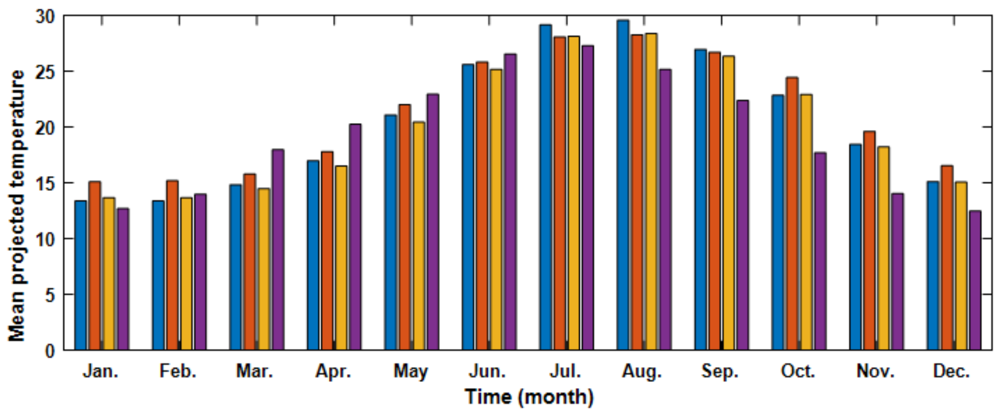
Since the projection results showed that ANN model performed better for the projection of precipitation for the future, the discussion on the section are made through comparison between benchmark precipitation and future projection by ANN model only. Considering projected precipitation sum for Famagusta station it can be seen that, almost in every month, there would be decrease in precipitation amount with exception May and August. This could be because the two months serve as strategic points for entrance to summer and entrance to winter. It can be seen that periods with higher precipitation including November, December, January, February and March will experience more decrease in precipitation than months with less frequency and amount of precipitation. For instance, a decrease of about 8% could be noticed in November, 14% in December, 12% in January and February and 5% in March. The results in Figure 4.3 show different pattern of precipitation in Nicosia with respect to Famagusta. The precipitation trend shows an increase in precipitation in summer period (March, May, June, July, August, September) and decreasing trend in October, November, December, January and February while April remain same. However, the precipitation decrease is very low in Nicosia compared to Famagusta. For instance, a decrease of 0.5%, 1%, 2%, 2% and 2% are observed for October, November, December, January and February whereas an increase in precipitation values of up to 0.5%, 4%, 4%, 0.2%, 2% and 1% are witnessed for March, May, June, July, August and September, respectively. For Kyrenia station, despite having different amount of precipitation sum compared to Famagusta, they have similar % decrease in precipitation. Their only difference is that throughout the period, there is no increasing trend for precipitation in any month and a large percentage will be decreased in every year.

4.3.2 Results of temperature projection for the future

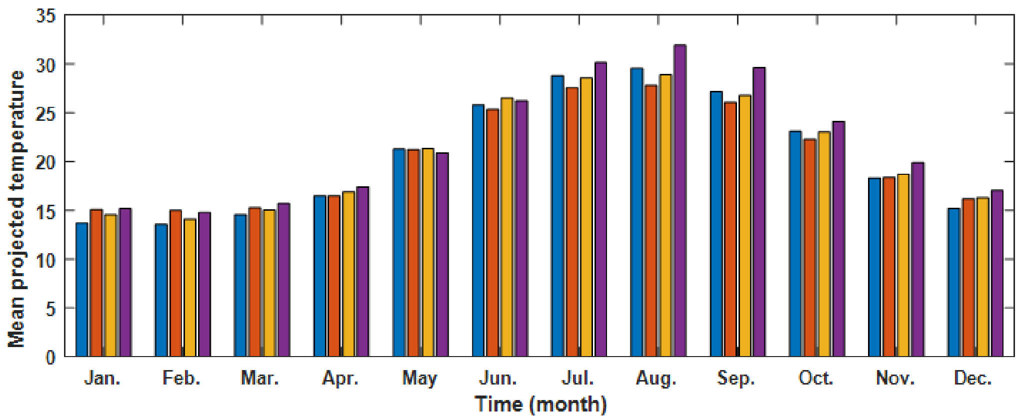
As depicted by Table 4.6, both AI downscaling models performed efficiently and at one point in certain station and certain input screening method, ANN provided the most reliable performance whereas in another circumstance, ANFIS is most significant. Moreover, their difference in performance is very little to the extent that any of them could be selected efficiently for the future projection of temperature. In view of this, ANN statistical downscaled values were selected as the benchmark temperature for all stations. The performance of the models for the future projection of temperature in most cases is higher in Nicosia station for both MI and CC input selection methods. This could be because of a little bit higher temperature that Nicosia is experiencing in comparison to Famagusta and Kyrenia stations (see Table 3.1). However, this results show that with higher temperature, the models for future projection of temperature are more productive because of the higher radiant that is received. Comparing the performances across the stations, it can be seen that for Famagusta, ANN provided the best performance based on MI, whereas for CC method, ANFIS led to better performance. For Nicosia station, slight differences in reproducing the benchmark temperature for MI and CC methods based on ANN and ANFIS models can be seen (Figure 3.4). For Kyrenia station, ANFIS performed the best for MI whereas in the case of CC, both ANN and ANFIS models produced the same, followed by MLR model which happens to be the least. Since all the three models have shown accuracy in the future projection of temperature, the temperature values produced by the models are compared with the benchmark temperature and presented in Figure 4.4 to determine the trend of decrease or increase in temperature between 2018 – 2019.



(a) Famagusta



(b) Nicosia



(c) Kyrenia

Figure 4. 4: Monthly projected mean temperature for future (2018-2040)

The close temperature trend shown by the models in Figure 4.4 affirmed the reliable performance of the models indicated by DC and RMSE evaluation criteria in Table 4.8. However, the future projection of higher mean temperature produced by MLR model shown in Figure 4.4 could be due to error produced by the model as can be seen in Table 4.8. Since ANN and ANFIS models are found to be more robust models as shown in both Table 4.8 and Figure 4.4, the discussion regarding the mean temperature for the future are made based on the two models.

For Famagusta station, both ANN and ANFIS models show an increase in the future temperature of less than 1% in January and February months. March, May, June, September, November and December show no difference (decrease or increase) in the mean temperature by ANN model but for ANFIS model, the months with no difference are April and August only. A decrease in the temperature would be noticed in April, July, August and October. For Nicosia station, an increase in the mean temperature will occur from January through June. This may be because with continues greenhouse effect, the temperature of hot weather climate increases and gradually even the temperature in cold weather changes. A short decrease of usually less than 1% of mean temperature will occur in from July to September while October, November, and December will also witness rise in temperature. What this is implying is that the future temperature for Nicosia will increase in winter season and slightly increase in summer season. For Kyrenia station, the increase and decrease in the mean temperature is similar to Nicosia station. From November through March the temperature is expected to rise. While April and May show a balance between previous and future mean temperature, June, July, August, September and October will experience slight decrease.

The general results of the projected precipitation and mean temperature showed that there will be decrease in precipitation amount in Kyrenia station in every month of the year from 2018 – 2040, while decrease in precipitation is also expected for Nicosia and Famagusta stations for all months with exception of May where the results showed an expected increase in precipitation. With regards to mean temperature, both increase and decrease are possible due to the effect of greenhouse gases. The increase will occur mostly in winter periods while summer periods will experience decrease in temperature. The results also showed that in terms of percentage, higher percentage of precipitation would be lost compare to an increment or decrease percentage of mean temperature.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, the Impact of Climate Change on Hydro-climatological Parameters especially precipitation and temperature in North Cyprus was evaluated for a period from 2018 - 2040. At a grid point located in Karfas, thirteen predictors from BNU-ESM GCM based on CMIP5 under RCP4.5 were used for statistical downscaling and future projection of mean precipitation and temperature over Famagusta, Nicosia and Kyrenia stations using ANN, ANFIS and MLR models. Although, the climate over the selected stations can be affected by several variables, some are more effective than others. Hence, to ensure efficiency and more reliable study, initially, MI and CC feature extraction methods were used to determine both nonlinear and linear relationship between the predictors/predictands and later, the most dominant predictors were used as inputs variables for the downscaling modeling. The results of the best downscaling model was then used as benchmark for the future projection of the hydro-climatological parameters.

The results of the feature extraction methods showed that for both precipitation and temperature, different predictors led to different performance. For Famagusta station based on precipitation, combination of Huss, Uas, Sfcwind for MI and Psl, Clwvi, Vas for CC provided the best performance, while Clwvi, Huss, Uas for MI and Tasmax, Huss, Ts led to better accuracy based on Temperature. For Nicosia station based on precipitation, combination of Huss, Uas, Hurs for MI and Psl, Clwvi, Vas for CC provided the best performance, while Huss, Clwvi, Sfcwind for MI and Tasmax, Huss, Ts led to better accuracy based on Temperature. For Kyrenia station based on precipitation, combination of Uas, Sfcwind, Psl for MI and Hurs, Ps, Psl for CC provided the best performance, while Uas, Ts, Psl for MI and Tasmax, Huss, Ts led to better accuracy based on Temperature. The results of the downscaling modeling showed that the AI based models performed better than MLR model. For instance in terms of precipitation, ANFIS outperformed the other models with 14% and 15% over ANN and MLR respectively. In terms of temperature, more reliable downscaling was achieved by ANFIS which has 1.5% and 1.8% higher accuracy than ANN and MLR, respectively. The future projection of the predictands showed a decreasing trend in the annual precipitation and an increasing trend in temperature. This suggest that the greenhouse effect will continue to escalate in the future years to come and thus increase the global warming with precipitation decrease of up to 22%, 4.8%, 42% and temperature increase up to 2.9%, 5%, 4.8% for Famagusta, Nicosia and Kyrenia stations, respectively.

5.2 Recommendations

Owing to the results achieved in this thesis, there are several observations made which would improve the statistical downscaling modeling results of this study. Hence, the following suggestions are given for future studies;

1. The statistical downscaling models showed better skill for temperature than precipitation. Ensemble model that combines other models shows superior performance in statistical downscaling modeling such as in the case of Nourani et al., (2018) study, therefore, for future studies, ensemble model should be employed to improve the downscaling performance of precipitation.
2. Previous studies show that performance of downscaling models could be affected by the distance between grid points and the stations under study and by different grid points, similar studies should be carried out in the future by adding more grid points (2, 3 or more) to verify whether this statement holds for semiarid Mediterranean region of north Cyprus.
3. In this thesis, BNU-ESM GCM was used but several GCMs can also be used including Can-ESM2, INM-CM4, CGCM3, etc. and according to the technical literature, different types of GCMs give different downscaling results. As such, different type of GCM (from the one used in this study) should be employed in the future studies and compare their results with that of the current study to select the best downscaling model for the predictands.
4. For the future projection of precipitation and temperature, RCP emission scenario (RCP4.5) was used in this study. There are several RCPs that can also be applied including RCP2.6, RCP6.0 and RCP8.5. However, SRES emission scenarios that include A1, A2, A1B, B1 and B2 could equally be employed. Therefore, one or more of these scenarios should be used in the future studies to ascertain whether the emission scenarios could affect the future predictions of the predictands.

This thesis is limited to Famagusta, Nicosia and Kyrenia stations of north Cyprus and there are many areas that could be affected by climate change. It is therefore, recommendable to perform statistical downscaling and future predictions of precipitation and temperature in other stations of the island.

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