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REGIONAL CLIMATE SCENARIOS USING A STATISTICAL DOWNSCALING APPROACH

(SENARIO CUACA KAWASAN MENGGUNAKAN KAEDAH PENURUNAN SKALA STATISTIK)

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ABSTRACT

REGIONAL CLIMATE SCENARIOS USING A STATISTICAL DOWNSCALING APPROACH

(Keywords: precipitation, downscaling, climate change)

The climate impact studies in hydrology often rely on climate change information at fine spatial resolution. However, General Circulation Models (GCMs), which are among the most advanced tools for estimating future climate change scenarios, operate on a coarse scale. Therefore the output from a GCM has to be downscaled to obtain the information relevant to hydrologic studies. The results presented in this report have indicated that it is feasible to link large-scale atmospheric variables by GCM simulations from Hadley Centre 3rd generation (HadCM3) outputs with daily precipitation at a local site. Statistical Downscaling Model (SDSM) was applied using three set of data; daily precipitation data for the period 1961-1990 corresponding to Endau rainfall (Station no. 2536168) and Muar (Station no. 2228016) located in Johor at the Southern region of Peninsular Malaysia; The observed daily data of large-scale predictor variables derived from the National Centre for Environmental Prediction (NCEP) and GCM simulations from Hadley Centre 3rd generation (HadCM3). The HadCM3 data from 1961 to 2099 were extracted for 30-year time slices. The result clearly shows increasing increment of daily mean precipitation of most of the months within a year in comparison to current 1961-1990 to future projections 2020's, 2050's and 2080's considering SRES A2 and B2 scenarios developed by the Intergovernmental Panel on Climate Change (IPCC). Frequency analysis techniques were carried out using the observed annual daily maximum precipitation for period 1961-1990 and downscaled future periods 2020's, 2050's and 2080's. Therefore, it does appear that SDSM can be considered as a bench mark model to interpret the impact of climate change.

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ABSTRAK

SENARIO CUACA KAWASAN MENGGUNAKAN KAEDAH PENURUNAN SKALA STATISTIK

(Kata kunci: hujan, penurunan skala, perubahan cuaca)

Kajian-kajian kesan iklim dalam hidrologi selalu bergantung pada maklumat perubahan iklim di resolusi ruang yang baik. Bagaimanapun, General Circulation Models (GCMs) yang wujud di kalangan paling maju peralatan menganggarkan akan datang senario-senario perubahan iklim, menjalankan pembedahan terhadap satu skala yang kasar. Oleh itu, keluaran daripada GCM perlu dikecilkan untuk mendapatkan maklumat yang relevan untuk kajian-kajian hidrologi. Hasil laporan ini telah menunjukkan adalah munasabah untuk menghubungkan pembolehubah atmosferik berskala besar oleh simulasi GCM daripada Hadley Centre 3rd Generation (HadCM3) pengeluaran dengan presipitasi tempatan. Statistical Downscaling Model (SDSM) digunakan 3 set data ; presipitasi harian dari 1961 – 1990 merujuk kepada curahan hujan Endau (No. Stesen 2536168) dan Muar (No. Stesen 2228016) yang terletak di Johor, Selatan Semenanjung Malaysia ; Diperhatikan data harian yang di cerap daripada peramal skala besar dari National Centre for Enviromental Prediction (NCEP) dan simulasi GCM dari Hadley Centre 3rd Generation (HadCM3). Data HadCM3 daripada tahun 1961 untuk 2099 adalah di ekstrak untuk 30 kepingan masa. Hasil menunjukkan dengan jelas pertambahan presipitasi purata harian bagi kebanyakkan bulan dalam tahun semasa dijangkakan teknik analisis frekuensi dijalankan digunakan presipitasi cerapan harian tahun maksimum bagi jangka masa 1961-1990 dan diunjurkan masa depan 2020’s, 2050’s, 2080’s. Oleh itu, di dapati SDSM boleh dipertimbangkan sebagai model tanda aras untuk menilai impak perubahan cuaca.

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GCM	-	General Climate Model
RCM	-	Regional Climate Model
HadCM3	-	Hadley Centre 3rd generation
SD	-	Statistical Downscaling

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Precipitation is a key component of the hydrological cycle and one of the most important parameters for a range of natural, water resources management, and agriculture and flood protection. The study of consequences of global climate change on these systems requires scenarios of future precipitation change as input to climate impact models.

General Circulation Models (GCM's), based on mathematical representations of atmosphere, ocean, and land surface processes, are considered the only credible tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. Direct application of output from General Circulation Models (GCMs) is often inadequate because of the limited representation of meso-scale atmospheric processes, topography and land-sea distribution in GCMs (e.g. Cohen, 1990; Storch et al., 1999).

Techniques have been developed to downscale information from GCMs to regional scales. These can be categorized into two approaches: "Dynamical downscaling" uses Regional Climate Models (RCMs) to simulate finer-scale physical processes consistent with the large-scale weather evolution prescribed from a GCM (Giorgi et al., 2001; Mearns et al., 2004). "Statistical downscaling", adopts statistical relationships between the regional climate and carefully selected large-scale parameters (Storch et al., 1993; Wilby et al., 2004; Goodess et al., 2005). Dynamical downscaling methods are extremely computationally intensive and have data requirements which may not be easily available.

The methods dealt with in this study are statistical downscaling. The main strength of statistical downscaling are computationally cheap and only requires very few parameters compare to dynamical downscaling (Fowler et al., 2005). Statistical Downscaling Model (SDSM) which is regression-based method developed by (Wilby et al. 1999) was used as the basic model to present the initial view of how significant the projections of climate change scenarios will affect the precipitation variability for the sites under study. SDSM is well documented and has been successfully tested in numerous studies (Wilby et al., 2003; Nguyen et al., 2005; Diaz-Nieto and Wilby, 2005; Haylock et al., 2006; Khan et al., 2006). The model permits the spatial downscaling of daily predictor-predictand relationships using multiple linear regression techniques and generates “synthetic predictand” that represents the generated local climate scenario.

1.2 Research Background

Precipitation is the main cause of variability in the water balance over space and time on the earth surface, and changes in precipitation have important implications for hydrology and water resources. Precipitation varies in space and time as result of the general circulation pattern of atmospheric circulation and local factors. Therefore in this study, Statistical Downscaling Model (SDSM) was applied using three set of data. Daily precipitation data for the period 1961-1990 corresponding to Endau rainfall (Station no. 2536168) and Muar (Station no. 2228016) located in Johor at the Southern region of Peninsular Malaysia. The observed daily data of large-scale predictor variables representing the current climate condition is derived from the National Centre for Environmental Prediction (NCEP) and GCM simulations from Hadley Centre 3rd generation (HadCM3) coupled oceanic-atmospheric general circulation model.

The HadCM3 data starts from 1961 to 2099 were extracted for 30-year time slices, GCM simulations from Hadley Centre namely HadCM3 A2 and B2 scenarios developed by the Intergovernmental Panel on Climate Change (IPCC). Emission scenarios, are considered as A2 (Medium–High Emissions and B2 Medium–Low Emissions scenarios) of the IPCC Special Report on Emission Scenarios (SRES). These scenarios cover a range of future socioeconomic, demographic and technological storylines.

1.3 Problem Statement

According to Intergovernmental Panel on Climate change assessment report (IPCC, 2001), global climate changes is expected to alter precipitation and run-off patterns, exerting significant pressure on water resources on a regional and global scale. Thus potential impacts of climate change on hydrologic extremes, like floods, in small and medium sized watersheds, have not received significant attention. Consequently, there is lack of sufficient development and application of suitable water resources design techniques in the context of climate change.

The specific regional projections about the impact of climate change are hampered by the limited spatial resolution of global circulation models. The spatial resolution of GCMs remains quite coarse, in the order of (250 km x 250 km), and at that scale, the regional and local details of the climate are lost. GCMs are therefore unable to provide local climate information. Alternatively, Statistical Downscaling Model is used to simulate the climate impacts on smaller scale.

1.4 Research Objectives

The main objectives of this report were to investigate the feasible to link large-scale atmospheric variables from Hadley Centre 3rd generation (HadCM3) outputs with daily precipitation at a local site. The more specific goals of the study are given below:

i. To investigate the possibility of linking daily precipitation at a local scale, directly with large scale atmospheric variables using statistical downscaling method.
ii. To evaluate and investigate the performance of statistical downscaling model in the simulation of daily precipitation series of single station.
iii. To perform scenarios development analysis using accurate statistical downscaling method.
iv. To carry out Frequency analysis of extreme values using the daily annual maximum observed precipitation and downscaled GCMs precipitation.

1.5 Scope of the Research

This study comprises of a series of precipitation analysis. Daily Precipitation for period 1961-1990 was used. This study covers:

i. Daily time series for the period 1961 to 1990 corresponding to two rainfall stations namely Endau (Station no. 2526168) and Muar (Station no. 2228016) situated in Johor state at the Southern region of Peninsular Malaysia. For each station, thirty years (1961 to 1990) high reliable daily precipitation records have been used as predicatnds.

ii. Gridded atmospheric variables were obtained from the NCEP (National Centre for Environmental Prediction reanalysis project (Kalnay et al., 1996). Reanalysis data are outputs from a high resolution atmospheric mode that known as Numerical Weather Prediction model. The model has been run using data assimilated from surface observation stations, upper-air stations, and satellite-observing platforms and the data kept unchanged over the analysis period and constrained by observations.

iii. GCM simulations used for this report are from Hadley Centre 3rd generation (HadCM3) coupled oceanic-atmospheric general circulation model (Wilby et al., 2001). The Hadley circulation provides a useful framework for understanding the nature of large scale flow, the actual circulation in the tropics involves substantial zonal and regional variations (Manton and Bonell, 1995). The HadCM3 data from 1961 to 2099 were extracted for 30-year time slices. For consistency description the scenarios data will be named as follow; the baseline period, 1961-1990 (current), 2010 to 2039 (the 2020s), 2040 to 2069 (the 2050's) and 2070 to 2099 (the 2080's).

1.6 Report Outline

This report consists of six main chapters. Chapter 1 begins with an introduction, as well as provides an outline of the study background, problem statement, objectives and scope of research. Chapter 2 describes, general climate models, downscaling techniques and applications and case study of similar research. Chapter 3 discusses the overall methodological framework of this study; this chapter is divided into two main parts. Section one reviews different Statistical Downscaling Techniques. Section two reviews SDSM and elaborates the methods that were applied in this study. Descriptions of study area and data collection are presented in Chapter 4. Results are discussed in Chapter 5. Conclusion and recommendation remarks are provided in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews previous attempts at dealing with general circulation models and downscaling techniques and applications. The literature is discussed in subject areas rather than by specific studies. Section 2.2 defines General Circulation Models (GCMs) and its applications; history of GCMs is demonstrated in Section 2.2.1. Features of GCMs are described in Section 2.2.3. Section 2.3 discusses downscaling techniques and applications. Section 2.3.1 illustrates dynamical downscaling method Statistical downscaling method is explained in Section 2.3.2. Section 2.3.3 elaborates statistical-dynamical method. Section 2.3.4 refers to previous research of statistical downscaling method. Finally, section 2.4 summarizes this chapter.

2.2 General Circulation Models

The mathematical models used to simulate the present climate and project future climate with forcing by greenhouse gases and aerosols are generally referred to as General Circulation Models or Global Climate Models (GCMs). GCMs are the most advanced tools available for accurate simulation of the current global climate and future climate scenario projections. Their formulation usually takes in to account the behaviour and interaction of flow systems in the biosphere, hydrosphere, atmosphere and geosphere in the climate system. GCMs are Cartesian point models and are run at different horizontal and vertical resolutions for use in different parts of the world.

The main objective of a typical general circulation model is to predict climate having a spatial coverage with a temporal scale of years, having a very coarse spatial resolution, low relevance of initial conditions, having a high relevance of clouds, radiation, surface, ocean dynamics, and model stability.

The spatial resolution of GCMs remains quite coarse, in the order of 250 x 250 km, and at that scale, the regional and local details of the climate which are influenced by spatial heterogeneities in the regional physiography are lost. GCMs are therefore inherently unable to represent local sub-grid scale features and dynamics, such as local topographical features and convective cloud processes. Therefore, there is the need to convert the GCM outputs into at least a reliable daily rainfall time series at the local scale.

2.2.1 History of GCMs

The idea of mathematically simulating atmospheric motion, to aid the forecast of weather, was first started in the 1 920s. But the numerical weather forecasting became very practical in the 1 950s using electronic digital computers. Towards the end of the 1 950s weather forecasters in United States and some parts of Europe incorporated computer-generated weather maps into their work on a routine basis. In the 1 960s, with the increase in the computer power, it was possible to go beyond regional weather simulations to model the global general circulation. This helped scientists to simulate climate over very long periods.

By the 1970s, General Circulation Models (GCMs) had become a very important tool of climate science. During that time, scientists became concerned about the long term possible effects of carbon dioxide accumulation in the atmosphere, which resulted in the study of anthropogenic (human-induced) global climate change. GCMs simulations provided a crucial means of analyzing the effects of climate change. Meanwhile, ocean modelers started to build similar computer simulations of the Oceanic General Circulation Models (OGCMs). Since oceans are a major component of the overall climate system, climate modellers began trying to "couple" OGCMs with 19 atmospheric GCMs. Although there were some difficulties in coupling these models, by the middle of the 1980s, these coupled models had established a new standard for climate modelling.

In the 1 980s, scientific concerns led to international political negotiations over how to respond to the possible climatic changes. A global body of climate scientists, the Intergovernmental Panel on Climate Change (IPCC), was formed to provide scientific advice to these negotiations. GCMs have thus played a major role not only in advancing the atmospheric science but also in creating global awareness of a possibly serious threat to human civilization.

2.2.2 Features of GCMs

The main features of General Circulation Models are as following:

i. The main goal is to predict the future climate.
ii. They have a global spatial coverage.
iii. They have a temporal range of years to centuries.
iv. They have a very coarse resolution of several hundreds of kilometres.
v. They are based on the conservation laws for mass, momentum, energy and water vapour.
vi. They are controlled by spatial resolution.
vii. The method used to run GCMs is finite difference expression of continuous time and space equations, or a spectral representation.

Global climate models are the only powerful tools currently available for simulating the response of the global climate system to the increasing greenhouse gas concentrations. These three-dimensional models of the atmosphere and ocean have been used to investigate the effects of changes in the atmospheric composition on the global climate. The more recent GCMs are able to differentiate between the warming effect of greenhouse gases and the regional cooling effect of sulphate aerosols. Many GCM experiments are now available for use in climate change studies. There is a large library of equilibrium GCMs experiments available for use (http://ipccddc.cru.uea.ac.uk).

2.3 Downscaling Techniques and Applications

Outputs from general circulation models (GCMs) can be useful in getting an overview of possible climate scenarios, but are typically too coarse in scale to be useful in practical comprehensive water resource planning situations. (Durman et al., 2001).

In many hydrological applications, extreme precipitation patterns such as a number of consecutive rainy days and prolonged dry spells must be well described. Simulations of multisite precipitation series that are to be used in climate change impact studies should thus reproduce the important patterns in the observed precipitation. One possible solution to overcome this problem is to downscale the output from GCMs to a higher resolution in space or time, thereby making use of scenario outputs in local water management.

Downscaling techniques has been developed tested and used through the efforts on many climatologists and hydrologists .More recently, downscaling has found wide application in hydro-climatology for scenario of construction, simulation and prediction of (i) regional precipitation (Kim et al., 2004);(ii) low-frequency rainfall events (Wilby, 1998); (iii) Mean, minimum and maximum air-temperature (Kettle and Thompson, 2004); (iv) Soil moisture (Georgakakos and Smith, 2001 and Jasper et al., 2004); (v) runoff (Arnell et al., 2003) and stream flows(Cannon and Whitfield, 2002); (vi) Ground water levels (Bouraoui et al., 1999); (vii) Transpiration (Misson et al., 2002), Wind speed (Faucher et al., 1999) and potential evaporation rates (Weisse and Oestreicher, 2001); (viii) soil erosion Zhang et al., 2004); and crop yield (ix) Landslide occurrence Buma and Dehn, 2000 and Schmidt and Glade, 2003) and (x) water quality (Hassan et al., 1998).

The approaches, illustrated in Figure 2.1 which have been proposed for downscaling GCMs, could be broadly classified into two categories: dynamic downscaling and statistical downscaling.

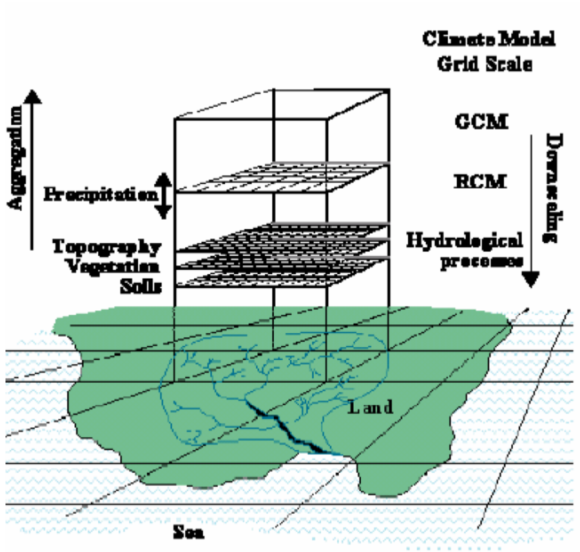

Figure 2.1: A schematic illustrating the general approach to downscaling.

2.3.1 Dynamical Downscaling Method

Dynamical Downscaling (DD) method involves the development of the regional climate model which required the user to highly understanding of the atmospheric physical behaviour and local or regional interactions and feedback. Generally, DD method is used for regions of complex topography, coastal or island locations in the regions of highly heterogeneous land cover.

The advantages cited for are dynamical downscaling are, respond in physically consistent ways to different external forcing, resolve the atmospheric process such as topographic precipitation and consistency with GCM. The disadvantages of dynamical downscaling are that it requires significant computing resources, dependent on the realism of GCM boundary forcing and initial boundary conditions affects results.

One of the most important aspects of dynamical downscaling techniques is determining whether the high resolution scenarios actually lead to significantly different calculations of impacts compared to the coarser resolution GCM from which the high resolution scenario was partially derived.

2.3.2 Statistical Downscaling Method

Statistical downscaling or empirical downscaling is a tool for downscaling climate information from coarse spatial scales to finer scales. Statistical downscaling methods rely on empirical relationships between local-scale predictands and regional-scale predictors to downscale GCM scenarios Successful statistical downscaling is thus dependent on long reliable series of predictors and predictands. Statistical Downscaling (SD) methods are used to achieve the climate change information at the fine resolution through the development of direct statistical relationships between large scale atmospheric circulation and local variables (such as precipitation and temperature).

Compared to other downscaling methods (e.g. dynamical downscaling), the statistical method is relatively easy to use and provides station-scale climate information from GCM-scale outputs (Wilby et al., 2002). Thus, statistical downscaling methods are the most widely used in anticipated hydrologic impact studies under climate-change scenarios.

The main advantages of statistical downscaling are that they are cheap, computationally undemanding and readily transferable, providing local information most needed in many climate change impact applications and ensembles of climate scenarios permit risk or uncertainty analyses.

The disadvantages of statistical downscaling are, requires highly quality data for model calibration, predictor-predictand relationships are often non-stationary and it is empirically-based techniques does not account for possible systematic changes in regional forcing conditions or feedback processes.

Statistical Downscaling Methods are particularly useful in heterogeneous environmental with complex physiography or steep environment gradients (as in island, mountainous, land and sea contexts) where there are strong relationships to synoptic scale forcing. A further justification for statistical downscaling is the need for better sub-GCM grid-scale information on extreme events such as heavy precipitation (Diez et al, 1999).

A very real pragmatic reason is when there are severe limitations on computational resources, especially in developing nations where the greatest need exists. It has been widely recognized that Statistical Downscaling Methods offer several practical advantages over Dynamical Downscaling procedures, especially in terms of flexible adaptation to specific study purposes, and inexpensive computing resource requirements (Wilby and Wigley, 1997 and Xu, 1999).

2.3.3 Statistical-Dynamical Downscaling

Statistical-dynamical downscaling links global and regional model simulations through statistics derived for large-scale weather types. The regional simulations are initialized using representative vertical profiles for each weather type and then run for a short period without lateral forcing by the global model (Heinmann and Sept, 1998). The statistical-dynamical approach combines advantages of the other two methods. As in dynamical downscaling, a regional model is used; and as in statistical-empirical downscaling, the computational effort does not depend on the length of the period to be downscaled. Statistical-dynamical downscaling consists of three steps which are described below.

i. A multi-year time series from a GCM simulation is classified into an adequate amount of large-scale weather type's characteristic for the region of interest. These weather types are defined on a scale which is well resolved by the GCM. The frequency of the weather types is used as the probability of their occurrence in the climate simulated by the GCM.

ii. Regional model simulations are carried out once for each weather type. The regional model calculates the mesoscale deviations from the large-scale state due to the impact of the regional topography. The model domain is situated within the area in which the frequencies of the large-scale weather types are derived.

iii. The regional model output is weighted with the respective frequencies of the weather types and then is statistically evaluated to yield regional distributions of climatological parameters (mean values, or frequency distributions) corresponding to the global climate represented by the GCM data.

2.3.4 Research of Statistical Downscaling Methods

Using thirty years of five-minute precipitation data for sites in the Ruhr valley, that the probability of a wet hour and number of wet spells in a day are conditional on the season and prevailing circulation pattern. Precipitation scenarios at a fine temporal and spatial resolution are needed in order to improve the design and evaluate the future performance of urban drainage systems (Bardossy et al, 2005).

Statistical downscaling method is the only method that requires very few parameters and this makes it attractive for many hydrological applications (Wilby et al., 1999). Statistical downscaling techniques were applied based on the daily precipitation series and downscaled the HadCM2 greenhouse experiment results to a scale relevant for hydrologic impact empirical methodology based on modelled monthly changes from for the time of horizon 2050’s. Their research aimed at a problem faced by hydrologists undertaking impact studies on flooding at Severn at Haw Bridge, a catchments of 9895 km2 situated in Wales in western England due to the inappropriate scales of the climatic output provided by Current GCMs. It is found that these scenarios show an overall change of the flood regime both in terms of increase of magnitude and frequency of the extreme events (Prudhomme et al., 2002).

Downscaled the GCMs output from The HadCM3 using statistical techniques to provide precipitation for the baseline period of 1961-1990 and two future scenarios; 2041-2070 and 2061-2090. Monthly climate data of 570 precipitation stations and 65 temperature station was used in Republic of Ireland. The results proved that the statistical downscaling technique is able to give significant result for climate change impact assessment on water supply and flood hazard. The results of these simulations indicate a decrease in annual runoff that is most marked in the east and southeast of the country, whereas an increase is likely for extreme northwest. It is also found that increasing trend in runoff is suggested for the western half of country which could have implication for flood frequency (Charlton et al., 2006).

Evaluated local daily temperature produced by two GCMs, several statistical downscaling methods and a weather generator; the former study in terms of lag-1 autocorrelations, distribution of day-to-day temperature changes and characteristics of heat and cold waves, while the latter in terms of extreme value distributions and return periods. It is also shown that the spatial behaviour of precipitation is dependent of time scale, precipitation is more intermittent for shorter time periods (Huth et al., 2000).

Three downscaling models namely Statistical Downscaling Model (SDSM), Long Ashton Neutral Network (ANN) model were used and compared the in terms various uncertainty assessments exhibited in their downscaled results of daily precipitation, daily maximum and minimum temperatures. The study has been carried out using 40 years of observed and downscaled daily precipitation, daily maximum and minimum temperature data using NCEP (National Centre for Environmental Prediction) reanalysis predictors starting from 1961 to 2000. The uncertainty assessment results indicate that the SDSM is the most capable of reproducing various statistical characteristics of observed data in its downscaled results with 95% confidence level , the ANN is the least capable in this respect, and the LARS-WG is the between SDSM and ANN (Khan et al., 2006).

2.4 Summary

General Circulation Models (GCMs) have been recognised to be able to represent reasonably well the main features of the global distribution of basic climate parameters, but outputs from these models are usually at resolution that is too coarse for many impact studies. Hence, there is a great need to develop tools for downscaling GCM prediction of climate variability and change to regional and local scales. In recent years, different downscaling techniques have been developed (dynamical and statistical).

Dynamical downscaling methods are extremely computationally intensive and have data requirements which may not be easily available. Another way which is much more computationally efficient is Statistical Downscaling method which is commonly used in practice to link the climate change scenarios given by GCMs to rainfall at a local site with grid-resolution daily GCM climate simulation outputs.

Therefore in this report Statistical Downscaling Model (SDSM) which is regression based method developed by Wilby et al. (1999) was used as the basic model to present the initial view of how significant the projections of climate change scenarios will affect the precipitation variability for the site under study. SDSM is well documented and has been successfully tested in numerous studies (Wilby et al., 2003; Nguyen et al., 2005; Diaz-Nieto and Wilby, 2005; Haylock et al., 2006; Khan et al., 2006).

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This report is based on statistical downscaling method which is used to link large-scale climate variables as provided by Global Climate Models (GCMs) simulations with daily precipitation at local site using the popular Statistical Downscaling Model (SDSM).

In this chapter the overall methodological framework of the research is presented. The chapter is divided into two main parts. Section 3.2 reviews different Statistical Downscaling Techniques. Sections 3.3 and 3.4 explain procedure of Statistical Downscaling Model (SDSM), which was used for the research. Section 3.5 describes criteria of scenarios development. Finally, section 3.6 summarizes the chapter.

3.2 Statistical Downscaling Methods

Statistical downscaling involves developing quantitative relationships between large-scale atmospheric variable (predictors) and local surface variable (predictands). In its most general form the downscaling model is

$R_t = F(X_T)$ for $T \leq t$ (3.1)

where R_t represents the local-scale predictand at single or multiple sites at time t, X_T is the predictor set (e.g. a collection of current and past values of large- scale atmospheric variables up to time t) and *F* represents the techniques used to quantify the relationship between two disparate spatial scales.

Most statistical downscaling work has focused on daily site precipitation as the predictand because it an important input variable for any natural systems models. There is a variety of statistical downscaling techniques in the literature, but three major approaches can be identified at this research, namely, weather typing approaches, regression methods, and stochastic weather generators.

3.2.1 Weather-Pattern Methods

Weather-pattern methods involve linking observational station data to given weather classification schemes. These classification schemes can be either subjectively or objectively derived but they are pre-supposed to be internally consistent and synoptic. This can be represented by

$R_T = F_R(S_t)$ (3.2)

$S_t = F_R(X_T)$ for $T \leq t$ (3.3)

where S_t is the weather state at time *t*. typically, weather state definition F_R is archived directly by applying methods such a cluster analysis to atmospheric fields (Huth, 2000) or using subjective circulation classification schemes (e.g. Bardossy and Hundecha, 2000).

An advantage of the weather pattern methods is its simplicity and that it is easy to apply to different areas simultaneously as the circulation pattern remains the same for large regions. The main limitation of such procedures is that precipitation changes produced by changes in the frequency of weather patterns could be inconsistent with the changes produced by the host GCM (Wilby, 1994).

3.2.2 Regression Methods

A definition of regression methods is given by Wilby and Wigley (1997). “generally involves establishing linear or nonlinear relationships between sub grid- scale (e.g. single-site) parameters and coarser-resolution (grid-scale) predictor variables”. The linear or nonlinear relationships between *R* and *X*:

$$R_T=F_Y\ (X_T;\ \theta)\ \text{for}\ T\leq t \tag{3.4}$$

where θ is the parameter and F_Y is the linear or nonlinear regression function. The regression-based downscaling methods are mainly relied on the empirical statistical relationships between large-scale predictors and local-scale parameters (Burger, 1996).

In general, the main advantage of the regression downscaling procedures is that these methods are simple and less computationally demanding as compared to other downscaling methods. However, the application of regression-based procedures is limited to the locations where good predictor-predictand relationships could be found.

3.2.3 Stochastic Weather Generators

The stochastic weather generators have been used extensively in the planning, design, and management of water resources systems (Hughes and Guttorp, 1994). Stochastic weather generators method share many attributes to circulation based methods, but differ in the way that predictor variables are conditioned directly on predictands instead of using weather patterns. This can be represented by using equation 3.5 or 3.6.

$$R_T = F_W(\theta | X_T) \text{ for } T \leq t \tag{3.5}$$

$$R_T = F_W(\theta | S_t) \tag{3.6}$$

where θ is the parameter set of the weather generator represented by F_W. There are two fundamental types of daily weather generators, the Markov chain approach and spell-length approach. In either case, the statistical parameters extracted from observed data are used along with some random components to generate a similar time series of any length. The resulting weather generator models are then used to simulate daily series of indefinite lengths representative of the altered climate.

In general, the principal advantage of the stochastic weather generator procedures is that they are able to reproduce many observed statistical characteristics of daily weather variables at a particular site. In addition, the stochastic weather generators could generate a large number of different climate scenarios for risk assessment studies. However, the main disadvantage of these procedures is related to the arbitrary manner of determining the model parameters for future climate conditions.

3.3 Statistical Downscaling Model (SDSM)

The Statistical Downscaling Model (SDSM) is a windows-based decision support tool for regional and local scale climate change impact assessments. SDSM is best described as a hybrid of the stochastic weather generator and regression-based downscaling methods. This is because large-scale circulation patterns and atmospheric moisture variables are used to linearly condition local-scale weather generate parameters (Wilby et al, 2004).

The version 4.1 of SDSM, shown in Figure 3.1 will be selected in this research generally reduces the task of downscaling daily climate from a global model in to seven discrete processes, namely: quality control and data transformation; predictor variable(s) screening; model calibration; weather generation; statistical analyses; graphing model output; and scenario generation. SDSM is a free available from (https://co-public.lboro.ac.uk/cocwd/SDSM/). Schematic diagram of SDSM analysis is shown in Figure 3.2.

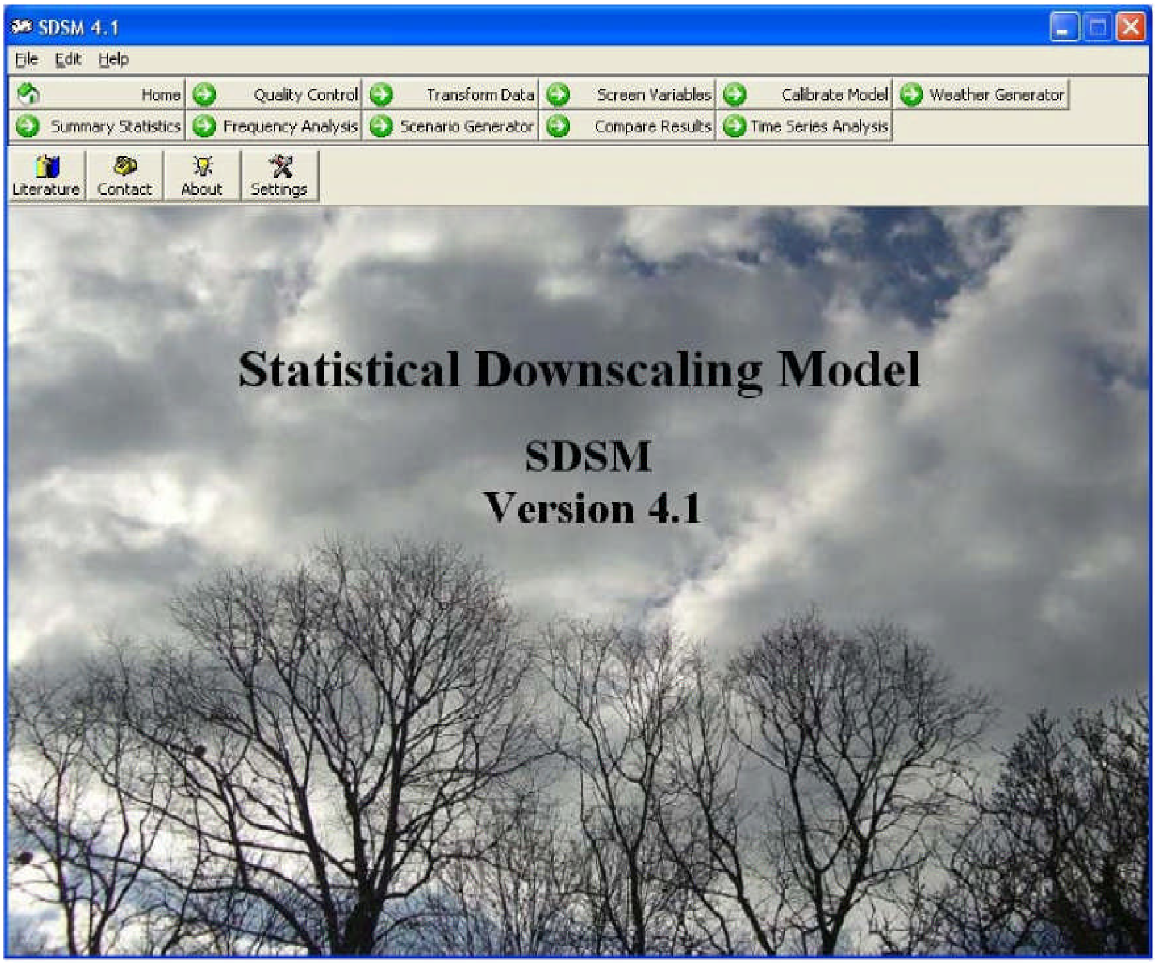

Figure 3.1: Main menu of Statistical Downscaling Model (SDSM)

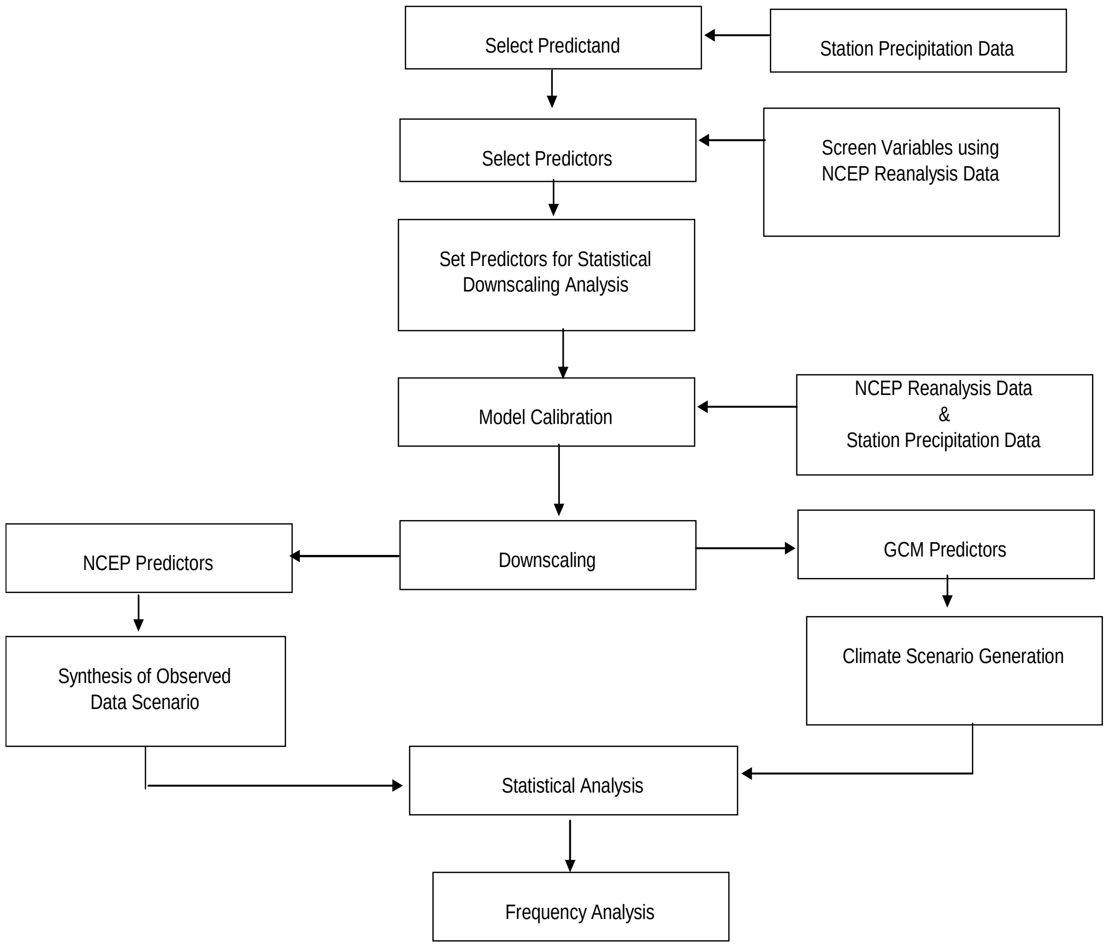

Figure 3.2: A schematic illustrating of statistical downscaling mechanisms.

3.3.1 Quality Control and Data Transformations

In the quality control process, input file formats are verified, the total numbers of values in a file are counted, and the numbers of values "ok" are displayed. The difference between the total and "ok" values in a file is the missing data. The user then must trace all dates with missing values from the input file and pad them with -999 before moving to the stage of the analysis. The default model settings specified by Wilby et al. (2002) are used in all the quality control checks, except for the observed daily precipitation, where a 4th root model transformation are transformed by fourth root to normalize the distribution and make it less skewed to low precipitation values.

3.3.2 Screening Variables

Identifying empirical relationships between gridded predictors (such as mean sea level pressure) and (such as station precipitation) is central to all statistical downscaling methods. The main purpose of the 'Screen Variables' operation is to assist the user in the choice of appropriate downscaling predictor variables. This remains one of the most challenging stages in the development of any statistical downscaling model since choice of the predictors largely determines the character of the downscaled climate scenario.

3.3.3 Model Calibration

The model calibration process uses a specified predictand and predictors to construct downscaled models, based on multiple linear regression equations. The model processes, conditional and unconditional respectively. A conditional process for precipitation is used as its local amount depends on wet/dry-day occurrence, which, in turn, depends on regional-scale predictors, such as humidity and atmospheric pressure. In unconditional process a direct link is assumed between the predictors and predictand. For precipitation, the statistics performed in SDSM are mean, median, max, sum, and variance, dry and wet spells length, and average wet days. Minimum precipitation is always zero, so it was not analyzed.

3.3.4 Synthesize of Observed Data

The 'Synthesize' operation generates ensembles of synthetic daily weather series given daily observed or re-analysis atmospheric predictor variables. The procedure enables the verification of calibrated models (ideally using independent data) as well as the synthesis of artificial time series for subsequent impacts modeling.

3.3.5 Data Analysis

The data analysis screen in SDSM provides a means for performing statistical tests on both the generated climate sets and the observed station data. The model default statistics, namely, monthly / seasonal / annual means, maxima, minima, sums The outputs of these statistical analyses are imported to MS Excel for computation of calibration and model errors, as well as to generate graphical comparisons.

3.3.6 Scenario Generation

The 'Scenario generation' operation produces ensembles of synthetic daily weather series given observed daily atmospheric predictor variables supplied by a GCM (either for current or future climate experiments).The procedure is identical to that of the 'Synthesize' operation in all respect except that it may be necessary to specify a different convection for the model dates.

3.4 General Method of Precipitation Downscaling

The general method in precipitation downscaling takes the form described by (Wilby, et al. 1999).

$$\omega_i = \alpha_o + \sum_{j=1}^{n} \alpha_j \mu_i^{(j)} \qquad (3.7)$$

where ω_i is the conditional probability of precipitation occurrence on day $_i$, μ^i are the normalized predictors and ctj are the estimated regression coefficients. Precipitation occurs if $\omega_i \leq r_j$, where r_j is a computer-generated uniformly distributed stochastic number.

The precipitation amount given that precipitation occurs is modelled by:

$$Z_i = \beta_o + \sum_{j=1}^{n} \beta_j \mu^{i(j)} + \varepsilon \tag{3.8}$$

where Z_i is the z-score for day *t*, β_j are estimated regression coefficients calculated for each month, ε is a normally distributed stochastic error term, and

$$Z_t = \phi^{-1}\left[F\left(y_i\right)\right] \tag{3.9}$$

where *F* is the normal cumulative distribution function and *F* is the empirical type equation here, distribution function of the y_i daily precipitation amounts.

3.4.1 Coefficients and Error Terms

The choice of predictor variable(s) is one of the influential steps in the development of SD scheme because the decision largely determines the character of the downscaled scenario. The NCEP reanalysis data set (1961-1990) is used to investigate the predictand-predictor relationships. The predictor variables were selected based on the criteria such as physically related to the predictand, produce the highest explained variance (r^2) and the lowest standard error (*SE*). The high correlation values indicate that the there is strong predictor predictand relationship of all the twelve months. Therefore the analysis output can provide a more accurate simulation of daily precipitation.

The significant test explained variance (r^2), standard error (*SE*) and correlations are indicated in Equation (3.10 and 3.11). The explained variance (r^2) identified the variance of predictand explained by the predictor and can be written as:

$$r^2 = 1 - \frac{\sum_{t=1}^{n}\left(y_i - p_i\right)^2}{\sum_{t=1}^{n}\left(y_i - \bar{y}\right)} \tag{3.10}$$

where y_t is the observed rainfall occurrence at day t, y is the average y_t of the values (fraction of wet days), pt is the estimated rainfall probability for day t and n is the number of days in the record. This is allowed because the average of the values is almost equal with the values. Then, the residual autocorrelation refers to the lag-1 autocorrelation coefficient of the residuals.

The standard error measure the index of the difference between the predictand and the actual value of the criterion variable. Therefore, the smallest *SE* identified that the predicted value *y'* will equal or at least close to the actual score on that variable and can be defined as;

$$SE = \tilde{S}\ \sqrt{\left[\frac{n-1}{n-2}\right]}\left[1 - r^2\right] \tag{3.11}$$

where $\tilde{S}$ is the adjusted standard error of estimate values and n is the number of data.

Then, the correlation coefficient is used to assess how well the linear model fits the data using the equations;

$$r_{XY} = \frac{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)/(n-1)}{S_X S_Y} \tag{3.12}$$

where S_x and S_Y are the sample standard deviations. The correlation falls between - 1 and +1, the zero corresponds to the situation where there is no linear association.

Once the predictor variables are selected, the same predictor sets were consistently applied at each site. SDSM is said to be calibrated when the predictor-predictand relationships are finalized, and a parameter file is created.

3.4.2 Model Evaluation

In SDSM probability scores (RPS) are commonly used to evaluate forecasts and are calculated by classifying a random variable *X* with $k > 2$ thresholds, x1<x2<... xk, That defines the events $A_k = \{X \leq x_k\}$ for $k=1, 2, K$ with the forecast probabilities ($p_1, p_2, ..., p_k$). The binary indicator variable fort the K^{th} event is donated 'ok' and defined as '*ok*'= 1 if A_k occurs and 0 otherwise 1.

$$RPS = \frac{1}{N}\frac{1}{K}\sum_{n=1}^{n}\sum_{k=1}^{k}\left(P_k - O_K\right)^2 \tag{3.13}$$

$$CRPS = \frac{1}{N}\sum_{N=1}^{N}\int_{-\infty}^{\infty}\left[F(x) - H(x - x_o)^2\right]dx \tag{3.14}$$

where, *N* is the number of forecast. *CPRS* is the continuous extensions of *RPS* were *F(x)* is the cumulative distribution function $F(x) = p\ (X \leq x)$ and $H(x - x_0)$ is the Heaviside function, that has the value 0 when x - $x_0 < 0$ and 1 otherwise.

The probability scores are commonly used to evaluate forecasts (Jolliffe and Stephenson, 2003) and are calculated by classifying a random variable *X* with $K > 2$ thresholds, $x1 < x2 <. . .<$ xk, that defines the events $A_k = \{X \leq x_k\}$ for $k=1, 2, K$ with the forecast probabilities ($p_1, p_2, ..., p_k$). The binary indicator variable for the kth event is denoted ok and defined as '*ok*'= 1 if A_k occurs and 0 otherwise 1

In order to quantify the skill of the probability score, the skill score (*SS*) is calculated as

$$SS\left(C\right)RPS = 1 - \frac{\left(C\right)RPS_{FP}}{\left(C\right)RPS_{RP}} \qquad (3.15)$$

where, *(C)* RPS_{FP} denotes the forecast score and *(C)* RPS_{RP} is the score of a reference forecast of the same predictand. The *SS(C) RPS* is the validation tool that compares how the distribution of an ensemble of forecasts predicts the observed value, and it is sensitive to bias as well as variability in the forecasted values. A skill score *SS(C) RPS* close to unity means a successful simulation; if the skill score is negative, the method is performing worse than the reference forecast.

3.4.3 Validation Methods

The classifications are evaluated using measures of their ability to classify Patterns with large differences in precipitation structure. These measures are designed for precipitation occurrence I1 and amount I2.

$$I_1 = \frac{1}{T}\sum\sqrt{\left(\left(P\left(CP(t) - \overline{P}\right)\right)\right)} \qquad (3.16)$$

$$I_2 = \frac{1}{T}\sum_{t=1}^{T}\left|\ln\left(\frac{z\left[CP\left(T\right)\right]}{z}\right)\right| \qquad (3.17)$$

where *T* is the number of classified days, *P(CP (t))* is the probability of the precipitation on day *t* and *z* is the mean precipitation amount in day t with classification *CP* and *p* is the probability of precipitation for all days. Along with these also frequency were evaluated.

3.4.4 Model Performance

Performance evaluation, the statistical parameters such as mean, standard deviation, percentage of wet days, dry-and wet- spell length are compared.

$$x*u = \chi_u + \Delta\chi_i \tag{3.18}$$

Where *x*u* is the value of the i_{th} predictor for day t in the period Δx_i, is the change in the mean of between the periods.

3.4.5 Frequency Analysis

In SDSM, Frequency Analysis option allows the User to plot various distribution diagnostics for both modelled and observed data. The available distributions are Generalized Extreme Value (GEV) and Gumbel.

3.4.5.1 Generalised Extreme Value (GEV)

This fits a three-parameter (ξ, β, and k) Generalised Extreme Value (GEV) distribution to the data of the form:

$$F(x) = \exp\left(1 - \left(1 - k\frac{x-\xi}{\beta}\right)\frac{1}{k}\right) \tag{3.19}$$

The parameters (ξ, β, k) are estimated using the method of *L* moments in which the first three moments are estimated from the data (Kysely, 2002).The parameters are then calculated according to:

$$k = 7.8590z + 2.955z^2 \tag{3.20}$$

$$\beta = \frac{l_2 k}{\left(1 - 2^{-k}\right)\Gamma(1+k)} \tag{3.21}$$

$$\xi = l_2 - \beta\,\frac{\Gamma(1+(k-1))}{k} \tag{3.22}$$

in which,

$$z = \left(\frac{2}{3 + {l_3}/{l_2}} - \frac{\ln 2}{\ln 3} \right) \tag{3.23}$$

3.4.5.2 Gumbel

SDSM Fits a Gumbel Type 1 distribution to the data using the annual maximum series after the method of (Shaw 1994).

$$F(x) = 1 - e^{-e^{e^{-(x-\mu)/\sigma}}} \tag{3.25}$$

Thus, the annual maximum for a return period of T-years can be calculated from:

$$Q_T = \overline{Q} + K(T)S_Q \tag{3.26}$$

$$K(T) = -\frac{\sqrt{6}}{\pi}\left(\gamma + \ln\ln\left[\frac{T(X)}{T(X)-1}\right]\right) \tag{3.27}$$

in which Q is the mean of the annual maximums, S_Q is the standard deviation of these maximums, *K (T)* is a frequency factor, *T(X)* is the return period in years, and γ is a constant equal to 0.5772. To access this facility select Frequency Analysis from any of the main screens. Figure 3.3 illustrates the screen appears in the SDSM modeling.

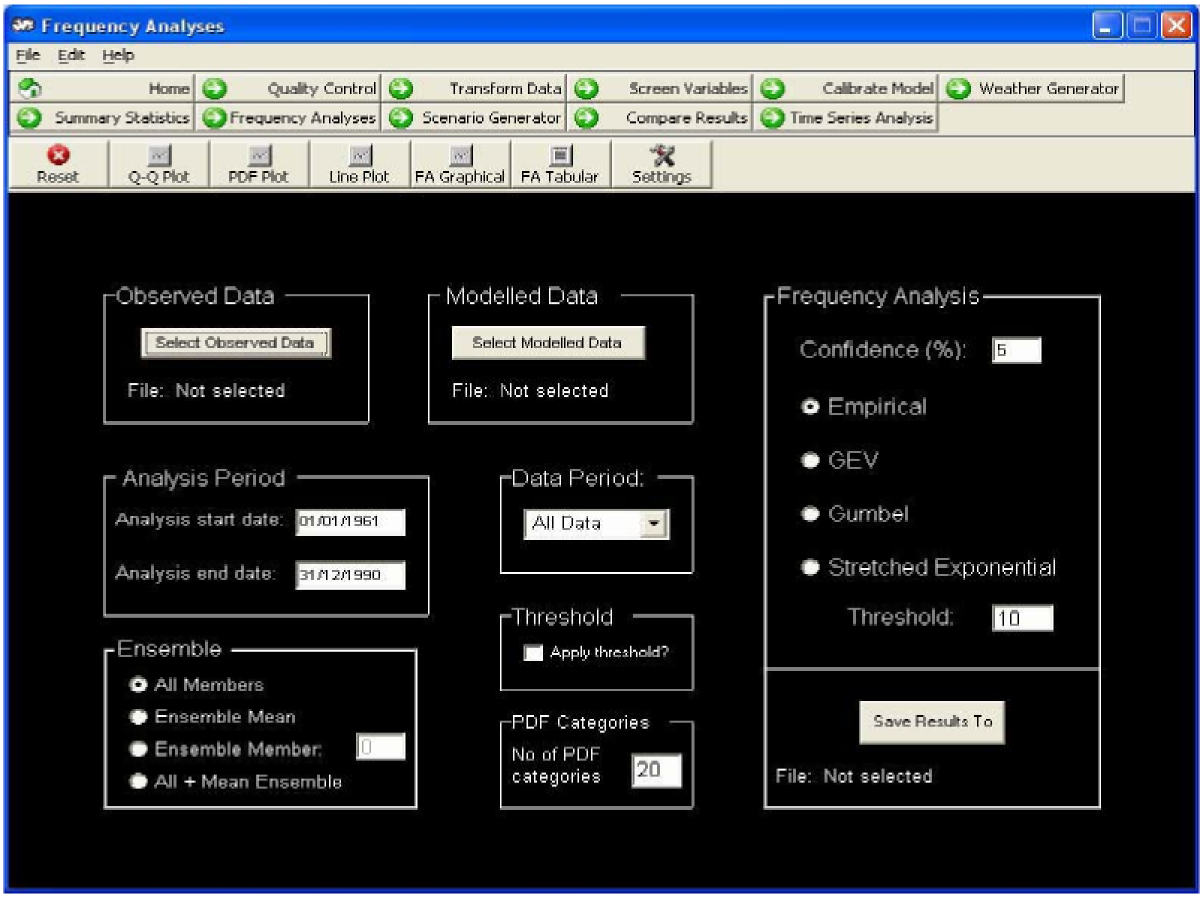

Figure 3.3: Frequency Analysis Screen of SDSM

3.5 Criteria for Scenarios Development

A number of factors need to be considered in choosing a driver GCM to specify lateral and surface boundary conditions and free-atmosphere composition changes: availability of suitable experiments; availability of data with suitable temporal resolution; quality of the GCM; and parameterization bias. Five criteria that should be met by climate scenarios if they are to be useful for impact researchers and policy makers are suggested:

i. Consistency with global projections. They should be consistent with a broad range of global warming projections based on increased concentrations of greenhouse gases. This range is variously cited as 1.4°C to 5.8°C by 2100, or 1.5°C to 4.5°C for a doubling of atmospheric CO2 concentration (otherwise known as the "equilibrium climate sensitivity").

ii. Physical plausibility. They should be physically plausible; that is, they should not violate the basic laws of physics. Hence, changes in one region should be physically consistent with those in another region and globally. In addition, the combination of changes in different variables (which are often correlated with each other) should be physically consistent.

iii. Applicability in impact assessments. They should describe changes in a sufficient number of variables on a spatial and temporal scale that allows for impact assessment. For example, impact models may require input data on variables such as precipitation, solar radiation, temperature, humidity and wind speed at spatial scales ranging from global to site and at temporal scales ranging from annual means to daily or hourly values.

iv. Representative. They should be representative of the potential range of future regional climate change. Only in this way can a realistic range of possible impacts be estimated.

v. Accessibility. They should be straightforward to obtain, interpret and apply for impact assessment.

3.6 Summary

This chapter has described a number of Statistical downscaling (SD) methods. First it classified SD into three categories according to the computational techniques used: weather typing approaches; regression methods; and stochastic weather generators. Secondly, it described Statistical Downscaling Method (SDSM). As a decision support tool for assessing local climate change impacts; and based on a multiple regression-based methods and last criteria for scenarios development needed to be considered in choosing a driver GCM outputs simulations was discussed.

CHAPTER 4

DESCRIPTION OF STUDY AREA AND DATA

4.1 Introduction

This chapter starts by describing Hydro-Climatologically regime of study area Johor state in Section 4.2. Section 4.3 reviews the sites under study. The Empangan Labong Endau rainfall (station no. 253618) and Muar (station no 2228016) located in the state of Johor at the Southern region of Peninsular Malaysia. The daily rainfall data for these stations was provided by the Department of Irrigation and Drainage (DID). Section 4.4.1 describes re-analyses data from Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR). Sections 4.4.2 and 4.4.3 describe data collection for Global Circulation Models (GCMs) output. Finally, Section 4.5 summarizes the chapter.

4.2 Hydro-Climatological Regime of Johor State

The state of Johor with an area of 19,984 km^2 is situated at the southern end of Peninsular Malaysia. The state is blessed with a uniform temperature, pressure, high humidity and abundant rainfall all the year round. The average annual temperature is about 26°C and the annual average rainfall is around 2000 mm.

The climate of the state is equatorial and the year can be divided into two main seasons, the northeast monsoon (December to March) and the southwest monsoon (June to September) separated by two relatively short inter monsoon periods. During the northeast monsoon season, northeast winds prevail with speed reaching 20 km/hr. Cloudy conditions in December and January with frequent afternoon showers, spells of widespread moderate to heavy rain can last for a duration of 1 to 3 days continuously. During the southwest monsoon, southwest winds tend to prevail. However, relatively speaking the state does not experience southwest monsoon rains in abundance.

4.3 Description of Study Area

The study areas selected in this report are Empangan Labong Endau rainfall (station no. 2536168) and Muar (station no. 2228016) located in the state of Johor at the Southern region of Peninsular Malaysia. The daily rainfall data for these stations was provided by the Department of Irrigation and Drainage (DID). The data was properly checked for quality and any doubtful values are thus omitted. The overall length of the data is between 1961 to 1990 years. The study area is shown in Figure 4.1 and a summary of the stations data is given in Table 4.1.

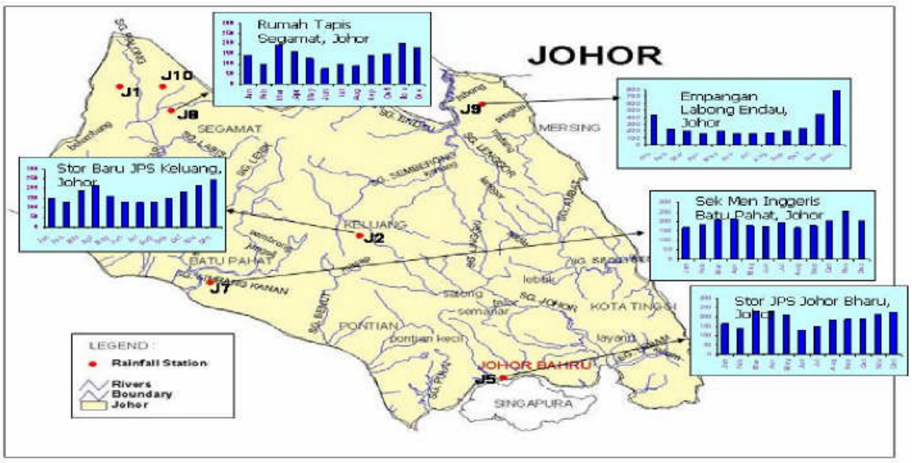

Figure 4.1: Location of Empangan Labong Endau rainfall station

Table 4.1: Selected rainfall stations in Johor Malaysia.

Station name	Station number	Longitude	Latitude
Empangan Labong Endau	2536168	103.666•	2.5833•
Muar	2228016	103˙ 12•	2.55•

4.4 Data Collection for Large-scale Predicator Variables

4.4.1 NCEP/NCAR Reanalysis Data

All atmospheric predictor variables used to calibrate the SDSM model originate from the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis project (Kalnay et al.1996). The NCEP/NCAR reanalysis dataset is produced by state-of-art assimilation of all available observed weather data into a global climate forecasting model that produces interpolated grid output of many weather variables. These data are gridded at a horizontal resolution of 2.5 x 2.5, with daily output on multiple atmospheric levels. NCEP re-analysis data are composed of 25 daily atmospheric variables for the same period which are selected at grid box covering each of the stations.

On entering the location of selected site, the correct grid box is calculated and a zip file is made available for download. The web-site is accessed from htttp://www.cics.uvic.ca/scenarios/index.cgi. The predictor variables are supplied by grid box basis as shown Figure 4.2 Summary of large atmospheric variable composed of 24 is given in Table 4.2.

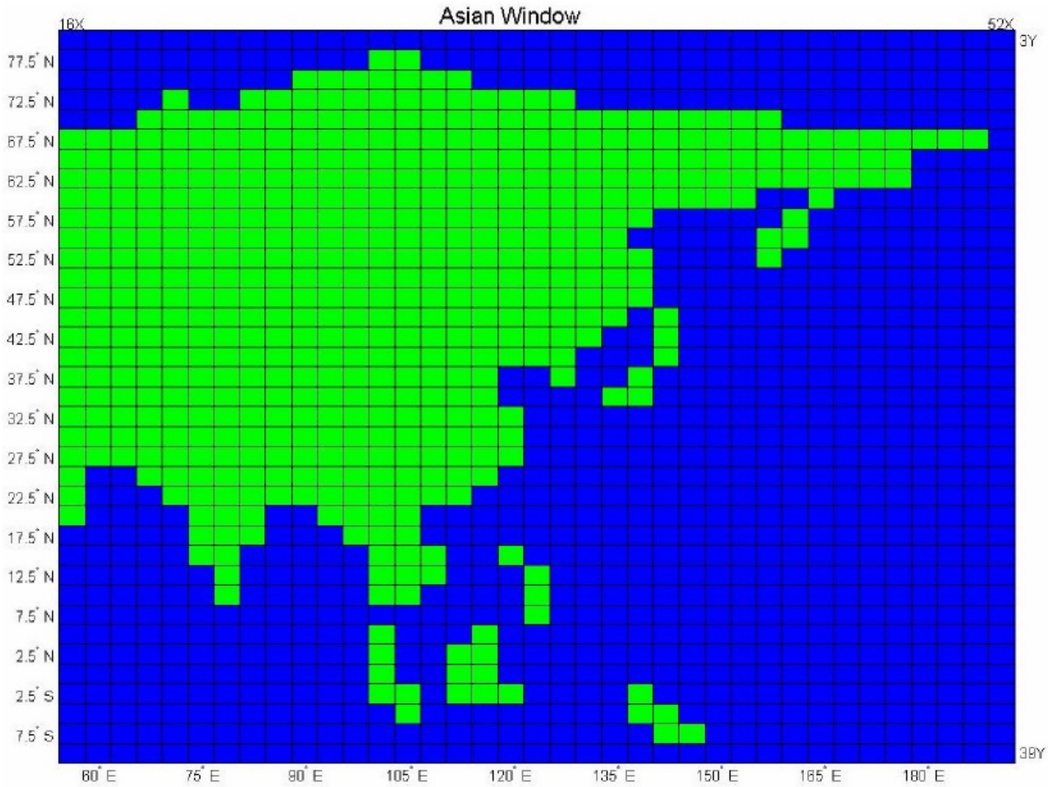

Figure 4.2: Grid box of the selected region of this study

Table 4.2: Predictor variables and their conventional file name in SDSM

Number	Predictor file name	Description
1	Ncepmslpna.dat	Mean sea level pressure
2	Ncepp-fna.dat	Surface airflow strength
3	Ncepp_una .dat	Surface zonal velocity
4	Ncepp_vna.dat	Surface meridional velocity
5	Ncepp_zna .dat	Surface vorticity
6	Ncepp_thna .dat	Surface wind direction
7	Ncepp_zhna .dat	Surface divergence
8	Ncepp5_fna .dat	500 hpa zonal velocity
9	Ncepp_una. dat	500 hpa meridional velocity
10	Ncepp_vna .dat	500 hPa meridional velocity
11	Ncepp_zna .dat	500 hpa vorticity
12	Ncepp500na. dat	500 hpa geopotential height
13	Ncepp5thna .dat	500hpa geopotentail height
14	Ncepp5zhna.dat	500hpa wind direction
15	Ncepp8_fna .dat	850hpa divergence
16	Ncepp8_una.dat	850hpa airflow strength
17	Ncepp8_vna .dat	850 hpa meridional velocity
18	Ncepp_zna .dat	850 hpa vorticity
19	Ncepp850na.dat	850hpa geopotential height
20	Ncepp8thna.dat	850hpa wind direction
21	Ncepp8zhna.dat	850hpa divergence
22	Nceps500na .dat	Specific humidity at 500 hpa
24	Ncepsphuna. dat	Near surface specific humidity

4.4.2 Global Circulation Model Output

For the purpose of regional modeling, data has been downloaded from General circulation Model (http://iipcc-ddc.cru.uea.ac.uk/dkrz_index.html).
It consists of parameter files with a “.par” extension, historic data files with a “.dat” extensions, source code, executable files, etc. The GCM simulations used for this study are from Hadley Centre 3rd generation (HadCM3) coupled oceanic-atmospheric general circulation model .The GCM simulations output from Hadley Centre Third Generation (HadCM3) equates from a moderate to high Greenhouse Gaseous resulted from population growth and fairly slow introduction of alternative technologies.

The HadCM3 simulation outputs are the divided based on Special Report on Emission Scenarios (IPCC, 2001) in to four types namely A1, B1, A2 and B2. A1 is used for a country with a very rapid economic growth but low on population growth. B 1 is used for a country with a low population growth but more on environmentally sustainable development. A2 is a characteristic of scenarios with higher rates of GHG emissions in combination with higher Sulfate and other Aerosol emissions and B2 is a lower rate of emissions. The Hadley circulation provides a useful framework for understanding the nature of large scale flow, the actual circulation in the tropics involves substantial zonal and regional variations.

The atmospheric component of the model has 19 levels with a horizontal resolution of 2.5 degrees of latitude by 3.75 degrees of longitude, which produces a global grid of 96 x 73 grid cells. This is equivalent to a surface resolution of about 417 km x 278 km at the Equator, reducing to 295 km x 278 km at 45 degrees of latitude (comparable to a spectral resolution of T42). The transient simulations form HadCM3 span the period 1961 to 2099. Monthly time series are available for 1961-1990 (the baseline period), 2010-2039 (the 2020’s), 2040-2069 (the 2050’s) and 2070-2099 (the 2080’s).

4.4.3 Sources of Cimate Change Scenarios

The IPCC-DDC (http://ipcc-ddc.cru.uea.ac.uk) archives climate change scenarios constructed from the GCMs experiments undertaken at seven international modelling centres as following list.

i. Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO)
ii. Deutsches Klimarechenzentrum DKRZ, Germany
iii. Hadley Center for Climate Prediction and Research HCCPR, UK
iv. Canadian Center for Climate Modeling and Analysis (CCCMA)
v. Geophysical Fluid Dynamics Laboratory GFDL, USA
vi. National Center for Atmospheric Research (NCAR), USA
vii. Centre for Climate Research Studies (CCSR), Japan

Steps involving how to excess the data distribution centres are mentioned is summarized in Figure 4.3.

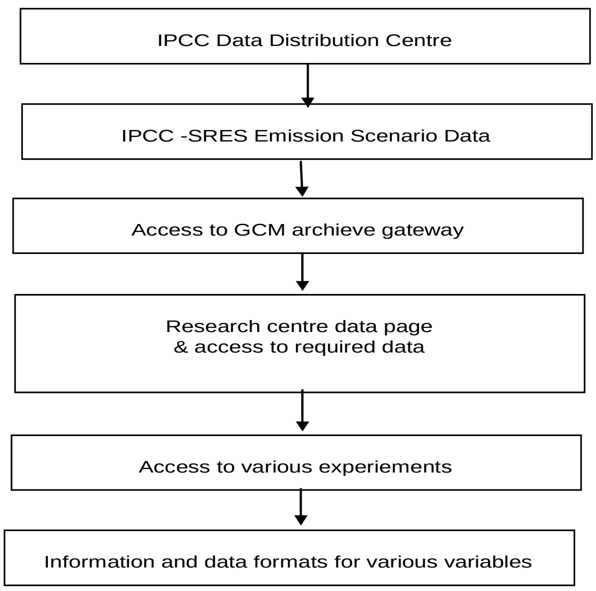

Figure 4.3: Steps involved in accessing required in the process of downloading the data for different weather variables from the IPCC website.

4.5 Summary

This chapter has described the study area and data collection. First it characterised Hydro-Climatological regime of Johor state. Secondly, it reviewed Thirty years of daily precipitation data for the period 1961 to 1990 corresponding to a two selected rainfall station namely Empangan Labung Endau (station no. 2536168) and Muar (station no. 2220816) .Observed large-scale NCEP (National Centre for Environmental Prediction) reanalysis atmospheric variables (kalnay et al., 1996) representing the current climate condition for the period 1961 to 1990. Finally, illustrated different sources of climate change scenarios derived from the GCM output, from IPCC data distribution centre, the HadCM3 data from 1961 to 2099 were extracted for 30-year time slices of 2020’s, 2050’s and 2080’s .

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Introduction

The precipitation analysis is based on daily time series for the period 1961 to 1990 corresponding to two rainfall station namely Endau (Station no. 2536168) Muar (Station no. 2228016) situated in Johor at the Southern region of Peninsular Malaysia. In this chapter, Section 5.2 will present basic statistical characteristics of daily precipitation data, means, standard deviation and maximum were calculated for basic statistical analysis. Section 5.3 will illustrate precipitation downscaling using (SDSM). Sections 5.4 and 5.5 will present the statistical downscaled precipitation corresponding to the selected rainfall stations Endau and Muar for the observed 1961-1990 as well as future periods 2020's, 2050's, and 2080's. Section 5.6 describes frequency analysis of annual daily maximum the observed precipitation and generated precipitation for the period 1961-1990 as well as for some future periods 2020's, 2050's and 2080's, in order to interpret extreme events.

5.2 Basic Statistical Analyses

For the basic analysis of statistical characteristics of daily rainfall for the period of 1961-1990 corresponding to precipitation stations namely Endau (Station no. 2536168) and one precipitation station namely Muar (Station no. 2228016) were conducted using Ms Excel. The analysis aims to provide a comprehensive comparison of the important statistical precipitation characteristics. Table 5.1 shows average daily mean rainfall of Endau (Station no. 2536168). Daily standard deviation rainfall is presented in Table 5.2 and Table 5.3, shows the maximum amounts of daily rainfall for a period of 1961-1990.

Table 5.1: The statistical characteristics of average mean daily rainfall of Endau (Station no. 2536168) for the period 1961-1990.

YEAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961	20.3	33.0	83.5	65.7	76.1	55.8	28.4	26.6	33.2	22.8	50.7	66.8
1962	10.1	38.0	76.1	41.9	79.2	54.6	27.9	90.1	55.8	111.7	40.1	53.3
1963	24.6	25.3	0.0	34.2	60.9	17.2	30.9	40.6	77.9	43.1	55.8	50.7
1964	52.0	50.7	100.3	58.4	77.4	41.9	69.8	106.6	113.0	50.7	81.2	82.5
1965	0.0	51.8	60.9	25.3	41.9	23.8	44.1	71.6	71.8	159.2	43.4	109.7
1966	33.5	42.4	28.9	68.5	23.6	33.2	26.6	53.3	31.4	36.0	27.9	58.4
1967	69.3	115.5	11.6	52.3	15.4	54.1	21.5	84.3	23.8	90.4	49.2	154.4
1968	24.8	6.8	71.6	39.3	41.1	38.6	65.0	13.9	48.5	46.4	20.3	50.7
1969	55.8	30.4	25.3	83.8	58.4	76.7	38.0	29.9	24.3	80.7	42.6	124.4
1970	23.3	25.6	43.4	39.6	62.2	22.3	79.2	33.0	78.7	63.4	41.9	44.1
1971	130.3	25.9	27.9	71.1	29.7	56.1	14.2	38.0	33.5	51.8	48.2	79.2
1972	30.4	46.9	21.3	37.0	17.5	26.4	29.2	17.7	36.0	33.7	38.6	35.5
1973	50.2	58.1	56.6	52.5	38.3	17.2	25.9	62.7	33.5	50.5	66.0	113.7
1974	16.0	59.9	30.0	36.0	33.5	15.5	62.5	39.5	52.5	17.5	83.5	23.0
1975	42.5	49.0	44.5	37.5	29.5	51.5	63.5	43.5	37.5	47.0	40.5	39.5
1976	0.0	20.5	112.5	136.5	26.5	37.5	38.0	41.5	45.0	46.5	25.5	61.0
1977	23.0	43.5	10.5	35.0	50.5	37.5	27.5	30.5	45.0	31.0	40.0	25.0
1978	43.0	34.5	60.5	47.5	79.0	30.5	45.0	34.0	16.5	46.0	25.0	64.5
1979	65.5	15.0	41.5	67.0	20.5	62.5	26.0	31.0	31.0	51.0	105.0	23.5
1980	73.5	24.5	34.5	62.5	43.5	14.0	28.0	30.5	36.5	50.0	86.5	50.0
1981	24.0	42.0	78.0	73.0	32.0	51.5	35.0	11.5	26.0	53.0	56.0	60.5
1982	0.0	32.5	27.5	55.0	34.5	21.0	17.0	10.0	33.0	60.0	50.0	39.0
1983	22.0	27.5	21.0	20.5	38.0	40.0	45.0	36.0	23.5	40.0	20.5	40.0
1984	39.0	155.0	22.0	29.0	41.5	25.0	43.0	31.0	30.0	40.0	30.0	75.0
1985	95.0	35.0	57.0	36.0	47.0	7.5	34.0	37.5	75.0	32.5	92.5	123.0
1986	36.0	15.0	132.0	18.0	50.0	38.5	34.0	38.0	39.0	64.0	45.5	40.0
1987	43.5	0.0	30.0	36.5	34.5	40.0	46.0	49.5	45.5	47.0	39.0	50.0
1988	48.0	110.0	65.0	31.5	32.0	36.0	13.0	45.5	80.0	16.5	80.0	20.5
1989	32.0	45.5	21.5	48.5	38.0	13.5	20.0	35.0	48.0	51.0	61.5	28.5
1990	18.5	30.0	49.0	48.5	30.0	74.0	46.0	14.0	35.8	30.0	50.0	60.0

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Table 5.2: The statistical characteristics of average standard deviation daily rainfall of Endau (Station no. 2536168) for the period 1961-1990.

YEAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961	31.9	19	14.9	13.8	18.5	2	3	7.6	8.1	13.5	20.2	37.4
1962	47.5	10	23.5	12.7	16.2	11	8	15.8	10.7	17.0	28.9	37.9
1963	23.8	5	2.3	6.7	8.0	11	13	15.1	9.1	12.4	11.1	26.9
1964	21.6	32	14.1	6.5	8.1	9	12	9.8	15.8	9.5	18.5	64.6
1965	1.9	14	10.1	5.0	14.5	10	10	6.1	11.3	15.5	16.1	19.4
1966	39.6	23	11.7	5.2	13.7	7	5	13.2	13.1	15.7	12.8	13.4
1967	50.2	66	30.2	7.2	17.1	10	10	10.1	10.2	10.3	32.7	54.2
1968	11.9	2	7.8	5.8	15.5	5	5	9.3	12.0	20.5	14.6	26.7
1969	16.2	22	6.3	9.2	14.2	12	11	14.8	7.2	17.2	16.9	59.3
1970	15.8	5	24.5	25.9	19.4	14	12	13.2	11.9	15.1	16.3	89.9
1971	60.6	6	12.3	0.9	6.5	12	7	10.1	12.6	10.7	15.2	56.7
1972	7.2	10	0.5	15.3	11.7	7	6	9.2	17.7	6.2	23.9	33.4
1973	40.2	15	15.5	5.7	21.6	19	8	7.2	13.6	8.8	30.0	37.6
1974	6.6	18	2.2	12.4	14.3	11	12	13.8	15.2	13.4	27.7	33.2
1975	13.1	21	17.1	16.4	13.8	7	12	11.1	16.8	17.9	44.9	22.4
1976	1.3	2	11.9	15.7	16.4	20	10	15.1	9.4	11.3	20.8	62.2
1977	4.1	44	1.2	0.1	15.6	11	10	9.9	9.2	21.9	34.8	46.0
1978	42.1	24	6.7	14.3	7.4	7	2	12.3	7.0	15.7	14.4	21.4
1979	41.1	4	18.9	11.2	18.0	7	7	2.8	13.8	10.4	25.8	23.6
1980	36.2	3	24.6	11.8	17.5	20	8	11.1	10.1	18.9	22.5	15.6
1981	21.1	29	15.2	6.9	18.2	6	11	6.4	10.3	10.9	35.4	64.6
1982	11.6	1	4.2	13.2	11.7	14	11	13.9	7.0	13.4	6.3	78.9
1983	9.9	2	0.0	3.0	9.6	11	10	10.0	10.9	14.5	38.9	55.0
1984	41.8	35	11.3	7.1	14.0	18	9	9.5	12.3	14.8	18.5	16.7
1985	34.2	11	19.2	12.5	8.7	6	10	24.0	5.4	13.5	15.7	38.6
1986	14.8	2	18.1	14.4	11.3	5	4	10.1	7.5	10.1	16.2	53.7
1987	39.7	4	8.8	9.8	12.0	4	12	7.7	13.4	22.0	17.7	78.4
1988	16.1	16	44.3	11.0	12.0	7	8	20.1	12.0	9.1	31.4	20.7
1989	21.5	8	12.3	7.4	9.7	11	7	7.0	10.3	13.5	29.9	52.4
1990	42.2	44	3.1	10.1	6.9	11	9	12.0	10.6	17.9	37.7	36.4

Table 5.3: The statistical characteristics of maximum daily rainfall of Endau (Station no. 2536168) for the period 1961-1990.

YEAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961	119.6	81.7	65.0	55.8	88.9	12.1	19.5	35.0	36.0	62.7	59.4	157.4
1962	211.8	55.8	77.7	50.0	87.8	57.1	38.3	63.4	38.0	78.7	134.6	180.5
1963	124.2	27.9	12.6	28.7	25.9	57.1	53.0	62.7	34.0	47.2	38.0	116.5
1964	102.1	125.4	68.3	26.4	35.5	43.1	59.6	44.9	66.8	38.6	69.0	212.0
1965	10.1	66.0	54.6	20.8	79.5	40.6	38.0	25.9	46.9	60.9	54.6	59.6
1966	138.6	119.3	50.0	21.8	73.1	24.3	18.7	69.8	42.9	53.8	46.4	54.6
1967	237.4	280.6	130.8	38.6	75.6	42.6	43.6	35.0	42.1	37.5	141.7	208.5
1968	65.0	15.2	24.8	21.3	67.8	24.6	23.3	38.0	59.9	83.8	49.0	99.0
1969	78.7	104.3	24.1	49.7	61.7	62.9	46.9	56.1	28.1	84.0	56.3	317.7
1970	69.3	18.7	113.7	124.9	82.0	62.4	43.4	48.7	39.3	50.5	61.2	385.5
1971	246.8	31.7	49.2	4.0	27.1	40.8	27.4	40.8	56.1	39.3	53.3	255.0
1972	36.8	36.8	2.2	54.6	55.8	33.0	22.3	42.4	82.5	30.4	108.4	148.0
1973	160.0	60.9	57.1	21.5	83.8	82.8	27.6	31.2	41.4	33.5	132.5	157.4
1974	36.8	75.7	10.0	52.5	63.0	34.5	50.0	50.0	55.0	47.0	124.0	145.0
1975	60.0	90.0	86.0	67.5	65.0	34.5	55.0	43.0	60.0	79.0	200.0	88.0
1976	3.1	12.0	42.0	65.0	60.0	55.0	35.0	69.0	45.0	25.0	76.0	240.0
1977	20.0	233.0	2.8	0.5	68.0	40.0	37.0	40.0	37.5	90.0	180.0	151.0
1978	170.0	130.0	25.5	60.0	30.0	35.5	11.0	67.0	30.0	54.0	45.5	100.0
1979	210.0	21.0	70.0	37.0	95.0	39.0	37.0	9.5	47.5	37.0	93.0	100.5
1980	150.0	15.0	119.0	37.0	75.0	95.0	45.0	57.5	33.5	71.5	71.0	51.0
1981	90.0	143.0	78.0	28.0	63.0	23.0	47.0	25.0	37.0	48.5	190.0	256.0
1982	55.0	6.0	15.0	46.0	46.0	60.5	53.5	62.0	32.5	56.5	30.5	312.5
1983	35.0	12.5	0.0	10.2	44.5	45.0	38.5	39.0	45.5	54.5	148.0	216.0
1984	202.5	150.0	45.0	28.5	62.5	94.0	43.5	40.0	43.0	76.0	84.0	63.5
1985	162.0	48.5	68.5	61.5	34.0	34.0	34.5	91.5	22.5	47.5	54.0	141.0
1986	46.5	11.0	90.0	76.5	52.5	25.0	16.5	41.5	22.0	38.0	72.0	289.5
1987	175.5	21.5	40.0	35.5	60.5	16.5	61.5	27.0	60.5	91.5	75.5	353.5
1988	67.5	68.0	225.0	44.5	50.5	32.0	35.0	81.5	44.5	38.5	122.5	91.5
1989	82.5	42.5	48.5	26.5	43.0	45.0	28.5	25.5	45.5	57.5	139.0	283.5
1990	208.5	213.5	11.5	30.5	32.0	46.5	43.5	64.5	56.5	69.5	156.5	126.5

Similarly, the statistical basic characteristics were computed Muar rainfall (Station no. 2228016). Table 5.4 gives all the basic statistical characteristics of daily mean rainfall. Daily standard deviation rainfall is presented in Tables 5.5 and Table 5.6, shows the maximum amounts of daily rainfall for a period of 1961-1990. The unit of all basic statistical characteristics is mm / day.

Table 5.4: The statistical characteristics of average mean daily rainfall of Muar (Station no. 2228016) for the period 1961-1990.

YEAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961	1.2	3.3	9.1	7	5	5.0	4.7	2.1	3.8	2.9	7.5	5.6
1962	1.9	2.6	11.4	5	8	7.0	2.6	9.3	3.8	9.2	5.1	3.4
1963	1.2	2.7	0.0	2	8	1.7	2.7	3.1	5.9	4.7	7.6	3.8
1964	5.8	9.7	10.6	7	5	4.1	8.8	8.9	7.4	4.9	8.9	6.3
1965	0.0	5.3	6.6	4	4	2.2	2.6	6.1	4.8	13.3	6.1	10.4
1966	3.3	3.7	4.0	12	2	2.9	4.7	7.4	4.9	6.3	5.0	4.6
1967	7.2	14.7	0.7	8	2	6.7	2.5	5.8	3.7	8.0	9.7	17.7
1968	2.2	0.3	6.1	4	3	2.4	6.6	1.4	5.9	8.7	3.1	5.9
1969	4.8	1.9	3.4	8	9	6.5	1.4	5.3	1.9	12.8	5.3	7.9
1970	2.8	1.3	6.1	5	5	1.2	6.7	2.6	6.8	7.1	5.5	8.1
1971	8.8	1.6	2.0	5	3	3.4	1.4	5.2	3.3	7.8	5.7	10.6
1972	1.2	4.8	2.4	8	1	4.9	2.2	1.9	7.2	5.0	7.1	3.3
1973	4.9	4.1	6.1	9	5	2.9	2.1	10.2	4.4	6.4	6.5	7.4
1974	1.3	6.5	2.6	4	6	2.0	8.0	5.2	9.2	1.7	7.2	2.0
1975	4.2	4.1	5.4	5	4	5.6	7.3	5.9	2.3	2.6	7.8	5.0
1976	0.0	2.3	10.9	12	2	2.7	5.3	4.3	7.9	6.8	3.0	6.3
1977	0.9	4.1	0.5	4	5	4.7	3.4	2.7	8.7	1.0	5.6	2.2
1978	4.9	3.7	6.4	5	9	3.0	5.4	4.2	3.2	5.5	6.0	6.3
1979	2.9	2.1	5.3	7	2	3.7	3.7	4.2	3.9	4.9	12.4	1.0
1980	4.9	2.1	5.0	7	3	2.1	2.5	3.0	6.0	8.7	11.0	4.1
1981	0.0	3.3	2.7	10	6	2.4	3.9	1.6	7.2	5.3	8.6	3.5
1982	1.5	1.7	6.7	11	4	8.1	3.2	1.0	4.2	5.3	8.5	8.4
1983	1.8	2.1	0.8	2	3	3.2	5.0	4.6	4.4	4.7	3.1	2.4
1984	5.3	14.9	2.5	4	5	2.1	3.9	1.9	3.5	3.5	6.3	8.1
1985	4.7	2.6	5.4	2	6	0.6	2.7	5.0	11.3	7.3	6.7	5.7
1986	7.1	1.3	9.6	1	3	2.2	1.8	2.1	8.3	6.5	6.4	4.4
1987	10.2	0.0	3.8	6	3	3.9	5.7	8.6	8.2	9.9	4.1	3.6
1988	3.1	7.2	6.7	4	3	4.1	1.8	8.7	10.5	2.5	9.3	1.8
1989	4.1	2.8	3.7	5	2	1.1	2.3	4.3	5.1	7.0	8.5	3.6
1990	1.8	3.4	4.3	3	3	3.9	7.4	0.6	4.2	4.9	5.0	5.5

Table 5.5: The statistical characteristics of average standard deviation daily rainfall of Muar (Station no. 2228016) for the period 1961-1990.

YEAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961	4.0	7.7	17.6	16.6	14.4	12.3	8.5	6.5	8.1	5.6	14.0	13.5
1962	3.4	8.0	18.9	10.9	19.4	14.5	6.4	18.6	11.9	22.5	9.9	10.4
1963	4.6	6.6	0.0	7.2	14.9	3.5	6.2	8.4	15.2	9.4	12.9	10.1
1964	13.1	13.9	23.0	14.2	17.0	10.6	16.6	22.0	21.3	12.0	19.0	15.8
1965	0.0	12.1	13.3	7.5	9.5	5.4	8.6	14.3	13.7	31.0	10.0	23.0
1966	7.1	9.5	7.2	18.6	6.0	6.9	7.5	12.2	8.6	10.3	7.5	11.3
1967	16.7	30.4	2.3	14.6	4.0	12.2	5.3	15.8	7.3	17.3	13.5	36.3
1968	5.8	1.3	13.6	8.8	9.1	8.0	13.7	3.7	12.9	12.6	5.6	12.4
1969	12.1	7.1	6.8	19.7	17.3	16.3	6.8	9.2	5.1	19.9	11.5	27.0
1970	6.4	5.2	13.2	9.3	13.2	4.3	15.7	7.0	16.3	15.1	10.7	13.2
1971	28.6	5.4	5.6	14.6	6.6	10.6	3.2	8.8	8.6	14.0	9.9	20.3
1972	5.6	10.8	5.5	11.7	4.1	8.0	6.6	4.6	10.1	9.0	9.4	8.0
1973	11.8	13.0	11.4	16.1	10.8	5.1	6.0	18.7	8.1	11.3	13.9	22.1
1974	3.6	15.4	6.9	9.3	9.7	4.4	16.2	11.2	13.0	4.6	17.4	5.4
1975	10.1	9.6	10.3	9.6	7.3	11.6	14.8	11.7	7.3	8.6	11.3	10.6
1976	0.0	6.2	25.7	27.4	7.6	8.3	11.2	9.8	13.0	13.2	6.2	14.2
1977	4.1	10.9	1.9	9.1	12.3	9.3	7.5	7.8	13.6	11.1	11.2	5.5
1978	10.0	7.6	14.7	10.2	18.1	8.0	10.1	8.4	5.1	11.4	7.9	13.9
1979	11.8	4.3	9.2	13.2	5.4	12.6	7.3	7.5	8.1	10.1	24.4	4.3
1980	14.8	6.2	9.2	14.8	8.0	3.9	5.2	7.0	9.8	12.8	21.4	10.4
1981	0.0	7.3	5.6	14.2	10.0	5.6	6.2	2.8	10.5	12.1	13.8	7.6
1982	4.5	8.0	16.1	17.9	9.0	11.6	8.1	2.4	6.6	11.8	12.8	16.4
1983	5.1	6.0	3.8	4.7	7.8	8.0	11.1	9.2	6.9	9.7	5.8	7.7
1984	10.8	37.5	5.2	9.4	10.7	5.1	9.1	6.1	8.3	9.2	8.4	16.7
1985	17.4	7.2	12.1	7.2	12.3	1.9	6.5	10.3	19.5	11.6	17.6	22.9
1986	12.2	3.8	25.2	4.3	9.5	7.6	6.3	7.3	11.6	14.2	13.3	10.8
1987	16.6	0.0	7.3	10.4	8.4	9.1	11.8	14.8	12.5	13.8	10.1	10.1
1988	9.0	21.2	13.4	8.0	7.2	8.1	3.8	12.8	17.3	4.7	18.6	5.6
1989	8.0	9.5	6.7	11.3	7.1	3.2	4.8	8.6	10.0	12.1	16.1	6.8
1990	4.7	7.8	10.6	9.7	6.3	13.7	13.5	2.6	7.9	8.8	11.4	14.1

Table 5.6: The maximum amount of daily rainfall of Muar (Station no. 2228016) for a period 1961-1990.

YEAR	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961	20.3	33.0	83.5	65.7	76.1	55.8	28.4	26.6	33.2	22.8	50.7	66.8
1962	10.1	38.0	76.1	41.9	79.2	54.6	27.9	90.1	55.8	111.7	40.1	53.3
1963	24.6	25.3	0.0	34.2	60.9	17.2	30.9	40.6	77.9	43.1	55.8	50.7
1964	52.0	50.7	100.3	58.4	77.4	41.9	69.8	106.6	113.0	50.7	81.2	82.5
1965	0.0	51.8	60.9	25.3	41.9	23.8	44.1	71.6	71.8	159.2	43.4	109.7
1966	33.5	42.4	28.9	68.5	23.6	33.2	26.6	53.3	31.4	36.0	27.9	58.4
1967	69.3	115.5	11.6	52.3	15.4	54.1	21.5	84.3	23.8	90.4	49.2	154.4
1968	24.8	6.8	71.6	39.3	41.1	38.6	65.0	13.9	48.5	46.4	20.3	50.7
1969	55.8	30.4	25.3	83.8	58.4	76.7	38.0	29.9	24.3	80.7	42.6	124.4
1970	23.3	25.6	43.4	39.6	62.2	22.3	79.2	33.0	78.7	63.4	41.9	44.1
1971	130.3	25.9	27.9	71.1	29.7	56.1	14.2	38.0	33.5	51.8	48.2	79.2
1972	30.4	46.9	21.3	37.0	17.5	26.4	29.2	17.7	36.0	33.7	38.6	35.5
1973	50.2	58.1	56.6	52.5	38.3	17.2	25.9	62.7	33.5	50.5	66.0	113.7
1974	16.0	59.9	30.0	36.0	33.5	15.5	62.5	39.5	52.5	17.5	83.5	23.0
1975	42.5	49.0	44.5	37.5	29.5	51.5	63.5	43.5	37.5	47.0	40.5	39.5
1976	0.0	20.5	112.5	136.5	26.5	37.5	38.0	41.5	45.0	46.5	25.5	61.0
1977	23.0	43.5	10.5	35.0	50.5	37.5	27.5	30.5	45.0	31.0	40.0	25.0
1978	43.0	34.5	60.5	47.5	79.0	30.5	45.0	34.0	16.5	46.0	25.0	64.5
1979	65.5	15.0	41.5	67.0	20.5	62.5	26.0	31.0	31.0	51.0	105.0	23.5
1980	73.5	24.5	34.5	62.5	43.5	14.0	28.0	30.5	36.5	50.0	86.5	50.0
1981	24.0	42.0	78.0	73.0	32.0	51.5	35.0	11.5	26.0	53.0	56.0	60.5
1982	0.0	32.5	27.5	55.0	34.5	21.0	17.0	10.0	33.0	60.0	50.0	39.0
1983	22.0	27.5	21.0	20.5	38.0	40.0	45.0	36.0	23.5	40.0	20.5	40.0
1984	39.0	155.0	22.0	29.0	41.5	25.0	43.0	31.0	30.0	40.0	30.0	75.0
1985	95.0	35.0	57.0	36.0	47.0	7.5	34.0	37.5	75.0	32.5	92.5	123.0
1986	36.0	15.0	132.0	18.0	50.0	38.5	34.0	38.0	39.0	64.0	45.5	40.0
1987	43.5	0.0	30.0	36.5	34.5	40.0	46.0	49.5	45.5	47.0	39.0	50.0
1988	48.0	110.0	65.0	31.5	32.0	36.0	13.0	45.5	80.0	16.5	80.0	20.5
1989	32.0	45.5	21.5	48.5	38.0	13.5	20.0	35.0	48.0	51.0	61.5	28.5
1990	18.5	30.0	49.0	48.5	30.0	74.0	46.0	14.0	35.8	30.0	50.0	60.0

5.3 Precipitation Downscaling using SDSM

Due to the coarse resolution of the General Circulation Model (GCM), the Statistical Downscaling Model (SDSM), fully described in Wilby and Dawson (2004), was used. SDSM is software that enables the construction of climate change scenarios for individual sites at daily time scales, using a grid resolution GCM output. The version

4.1 of SDSM, used in this report, generally reduces the task of downscaling daily climate from a global model into seven discrete processes, namely: quality control and data transformation; predictor variables screening; model calibration; weather generation; statistical analyses; scenario generation; and graphing model output.

The procedure for SDSM analysis always starts with the preparation of coincident predictor and predictand data sets. The predictor data set is obtained from the HadCM3 output in the grid corresponding to the local study area, whereas the predictand is a long series of observed daily precipitation at the two rainfall station namely Endau (Station no. 2526168) and Muar (Station no. 2220816) representing the local study area. The predictand data used in this report is the observed daily precipitation data series for the thirty years 1961-1990. Both the predictor and predictand data are supplied by the user for SDSM analysis.

SDSM uses the information to develop a set of parameters, relating the predictors to the predictand, for deriving local current and future weather data, based on the output of the HadCM3 time periods. The SDSM has been reported to have some problems in downscaling daily precipitation amounts at individual stations. This is due to the generally low predictability of daily precipitation amounts at local scales by regional forcing factors. This unexplained behaviour is currently modelled stochastically (within SDSM itself) by artificially inflating the variance of the downscaled precipitation series to fit with daily observations. Ongoing research is attempting to address this problem (Wilby and Dawson, 2004).

Regardless of this deficiency, the model is the most viable downscaling tool in the public domain. The daily precipitation data from Endau (Station no. 2536168) and Muar (Station no.2220168) station was also reformatted to the SDSM requirements. Once all input data files are ready, the SDSM analyses could be performed as detailed below.

5.3.1 Quality Control and Data Transformations

In the quality control process, input file formats are verified, the total number of values in a file are counted, and the number of values “ok” are displayed. The difference between the total and “ok” values in a file is the missing data. The user then must trace all dates with missing values from the input file and pad them with -999 before moving to the stage of the analysis. Zero missing values were encountered during the analysis of the observed daily precipitation data corresponding to two rainfall stations Endau and Muar. The precipitation values are transformed by fourth root transformation to normalize the distribution and make it less skewed to low precipitation values. A summary of the quality control results and modified model settings are presented in Table5.7 for Endau and Muar stations, respectively.

Table 5.7: Quality control results and modified model settings.

Stations	Precipitation					
	Number of record	Missing Values	Bias Correction	Variance Inflation	Transformation	Event Threshold (mm)
Endau	10976	0	1	12	Fourth root	0.3
Muar	10957	0	1	12	Fourth root	0.3

5.3.2 Selection of Predictors

Selecting the appropriate predictor variables is viewed as the most challenging aspect of the entire downscaling procedure, because the choice of predictors largely determines the character of the downscaled climate. The predictor variables are meteorological variables generated from Hadley Centre 3rd generation coupled oceanic-atmospheric general circulation model (HadCM3) model runs for the selected grid square.

The process is carried out by using the predictand (i.e., the observed precipitation) to screen all the 25 predictor variables for SDSM use, as provided by re-analyses data set (Kalnay et al., 1996). Monthly regressions of the predictors with the predictand variable are run, a correlation matrix and explained variance produced, and the predictor variables that are the most correlated with the predictand (and are statistically significant, low p-value, $p < 0.05$) are selected. The selected predictor variables are strongly correlated with the predictand.

The results of the variable screening analyses show that the variables of ncepmslpna.dat, ncep850na.dat, nceprhumas.dat and ncepshumas.dat are more suitable in predicting the precipitation. The predictor variables identified for downscaling experiments conducted in this study are summarized in Tables 5.8, 5.9 and 5.10. Large scale predicator variables obtained from the HadCM3 SRES A2 and B2 emission scenario were used to force the observed precipitation-hydro meteorological relationships for the selected time slices.

Table 5.8: Selected large-scale predictor variables at Endau (Station no.2536168) and Muar (Station no.222289)

No	Predictors	Definition
1	Ncepmslpna.dat	Mean sea level pressure
2	Ncepp500na.dat	500hPa geopotential height
3	Ncepp800na.dat	850hpa geopotentail height
4	Nceprhumas.dat	Near surface relative humidity
5	Ncepshumas.dat	Near surface specific humidity

Table 5.9: Cross-correlation between predictand (daily precipitation) and predictors variables of Endau (Station no. 2536168)

Variable name	Variable no	Variable					
		1	2	3	4	5	6
Daily precipitation	1	1	0.187	0.152	0.099	0.066	-0.177
Mean sea level pressure	2	0.187	1	0.943	0.000	0.077	-0.762
500 hPa geopotential height	3	0.152	0.943	1	-0.152	-0.022	-0.544
850 hpa geopotential height	4	0.099	0.000	-0.159	1	0.495	-0.093
Near surface relative humidity	5	0.066	0.077	-0.020	0.495	1	-0.002
Near surface specific humidity	6	-0.177	-0.762	-0.544	-0.093	-0.002	1

Table 5.10: Cross-correlation between predictand (daily precipitation) and predictors variables of Muar (Station no. 22208168).

Variable name	Variable no	Variable 1	2	3	4	5	6
Daily precipitation	1	1	0.049	0.031	0.031	-0.006	-0.079
Mean sea level pressure	2	0.049	1	0.947	0.072	0.072	-0.079
500 hPa geopotential height	3	0.031	0.947	1	-0.219	-0.032	-0.490
850 hpa geopotential height	4	0.031	-0.072	-0.219	1	0.476	-0.037
Near surface relative humidity	5	-0.006	0.072	-0.032	0.476	1	-0.015
Near surface specific humidity	6	-0.079	-0.709	0.490	-0.037	-0.015	1

5.3.3 Model Calibration

The model calibration process uses a specified predictand and predictors to construct downscaled models, based on multiple linear regression equations. The precipitation data series of two rain fall stations namely of Endau (Station no. 2536168) and Muar (Station no. 22208168) are used for the downscaling experiments. For each station, 30 years (1961–1990) of daily precipitations have been used as predictands.

The thirty year daily precipitation data used was divided into a calibration data set (1961–1 976) and an independent verification set for (1977 to 1990). In this context, atmospheric data for the period 1961 to 1990 from National Centre for Environmental Prediction (NCEP) re- analyses data set (Kalnay et al., 1996) have been identified using empirical relationships with station data. The best performance predictors were selected based on higher correlation and lowest standard errors for every month between a year.

The five selected predictor variables have shown in Table 5.8, from the variable screening process. The annually model type is used in calibrating for precipitation predictor variables, using the conditional model processes, respectively. A conditional process for precipitation is used as its local amount depends on wet¬/dry-day occurrence, which, in turn, depends on regional-scale predictors, such as humidity and atmospheric pressure (Wilby et al., 2002). In order to indentify how accurately the model is likely to downscale future climate variables the calibrated model must be tested. Testing compares output from the calibrated model against known data from normalized period 1961-1990 and presented using the variation analysis on box and whisker plots.

Figures 5.1 and 5.4 show the histogram intervals and frequency of each interval for y mean daily of observed and simulated. The average daily mean and monthly standard deviation variations for observation (local stations) and simulation NCEP re-analysis data. Figures 5.2, 5.3, 5.5 and 5.6 show that the observed and simulated precipitation varies little in the preservation of average daily mean and standard deviations. From this Box and Whisker plots analysis, it indicates that the model can preserve the basic statistical properties.

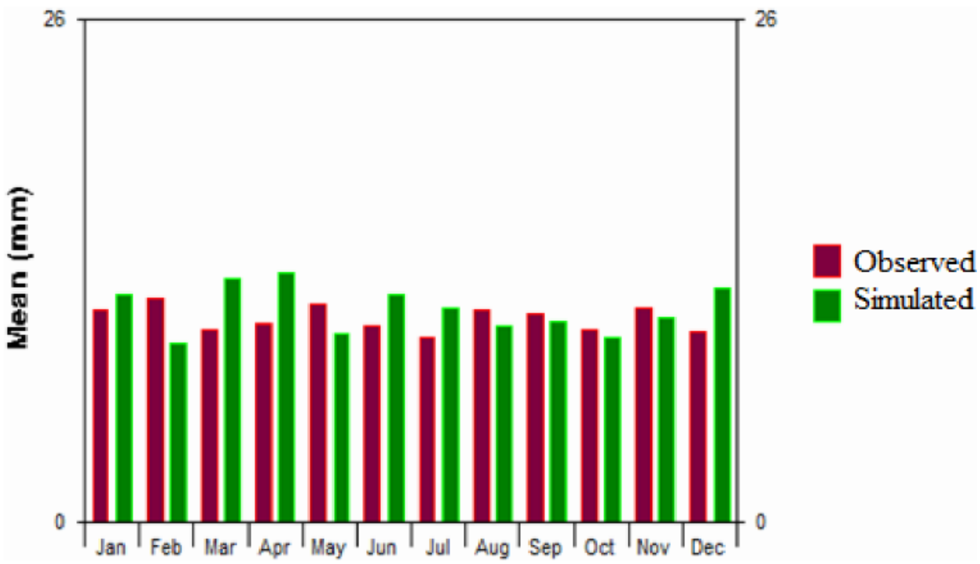

Figure 5.1: Mean daily precipitation between observed and simulated for Endau.

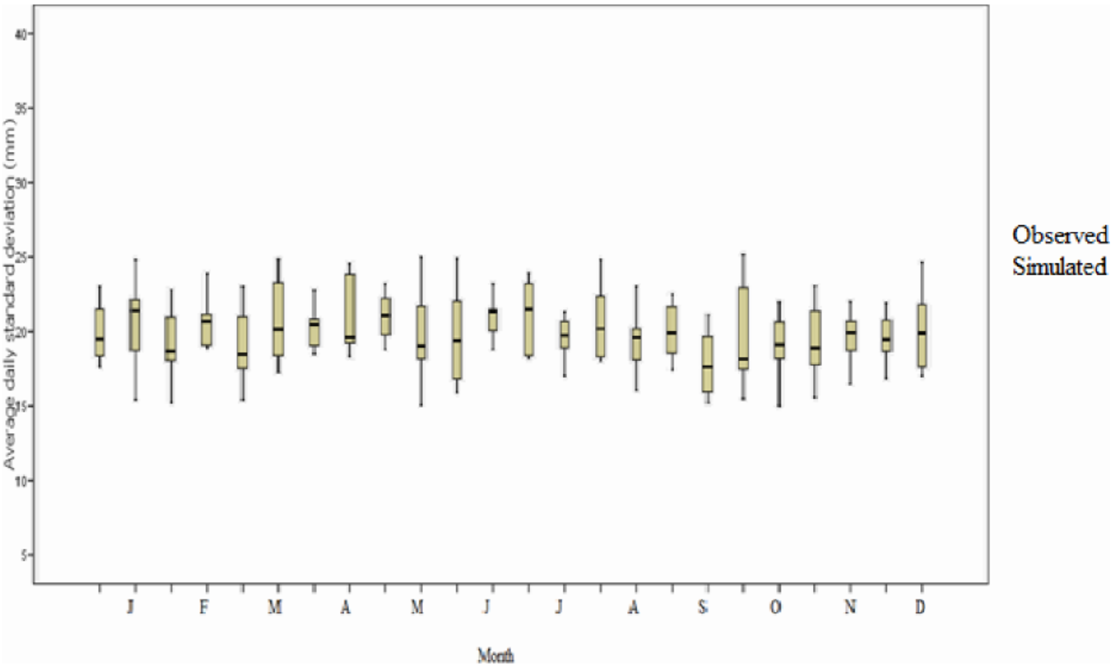

Figure 5.2: Average daily mean precipitation distribution between observed and simulated (Endau).

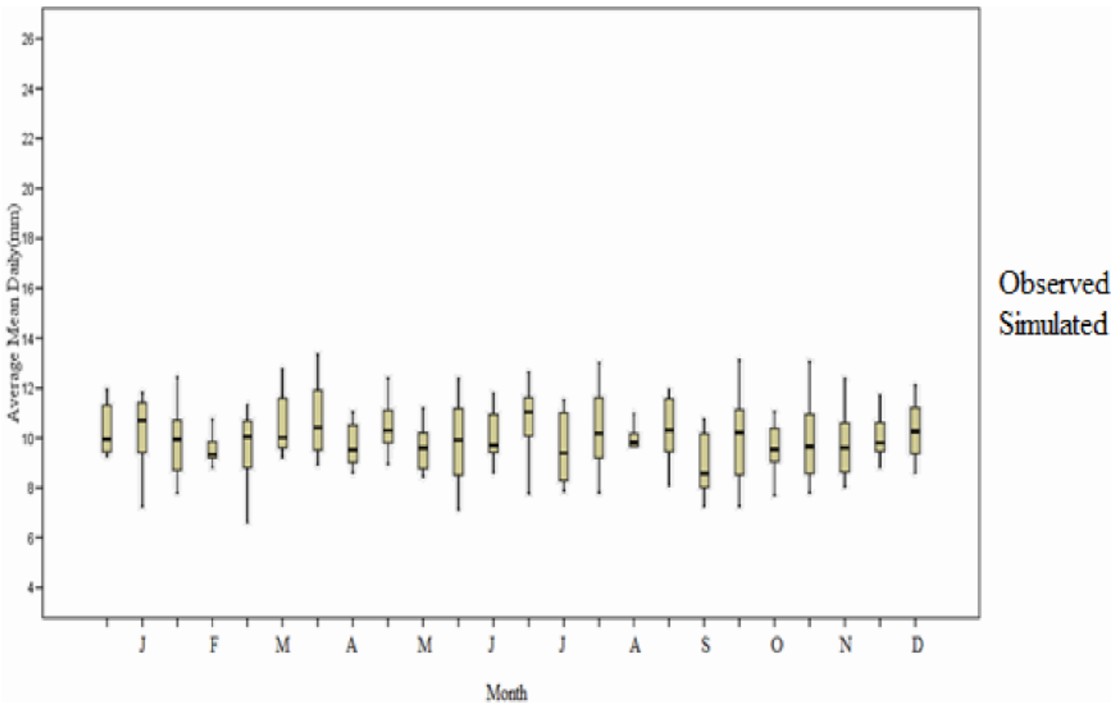

Figure 5.3: Average daily standard deviation precipitation distribution between observed and simulated (Endau).

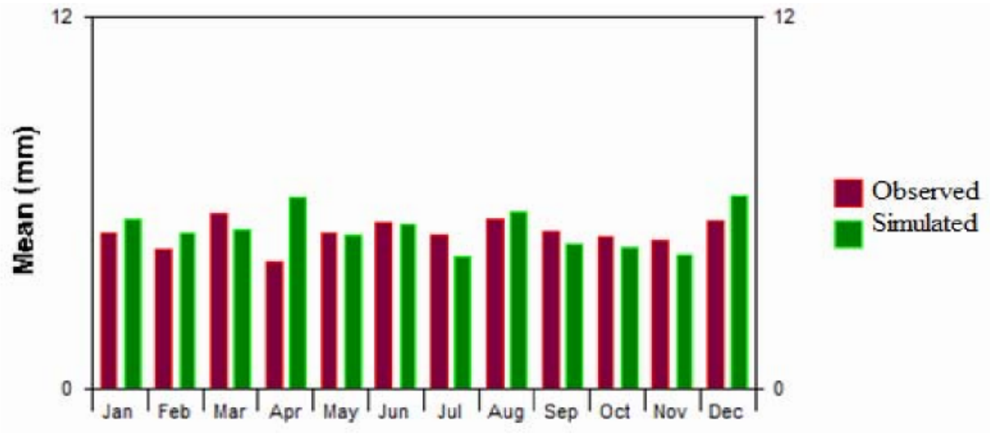

Figure 5.4: Mean daily precipitation between observed and simulated for Muar.

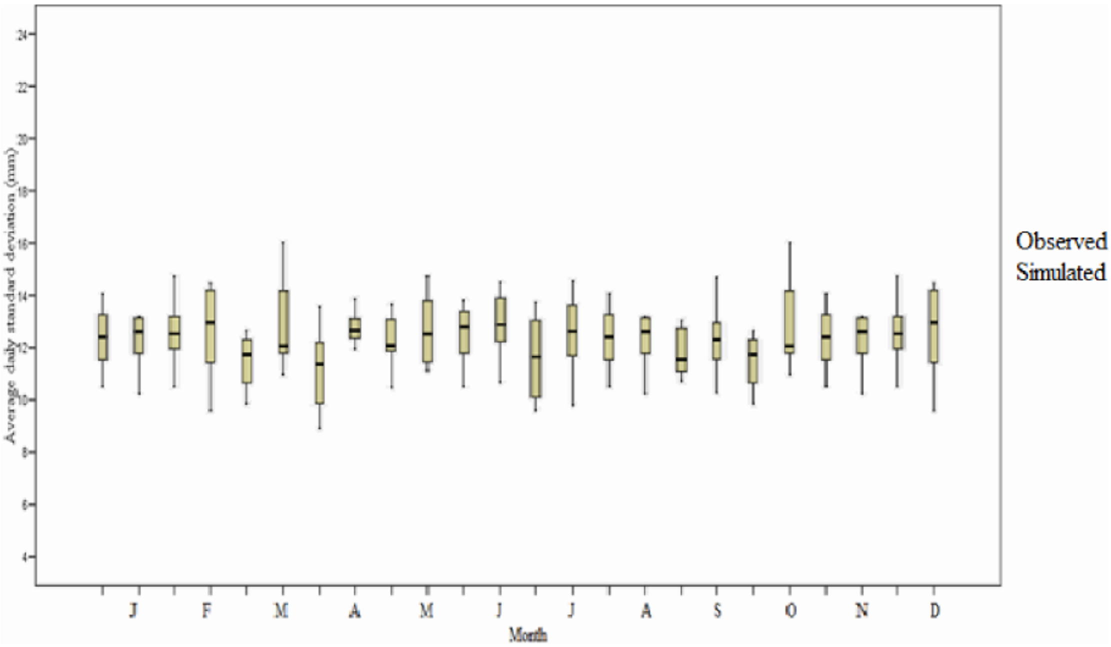

Figure 5.5: Average daily mean precipitation distribution between observed and simulated (Muar).

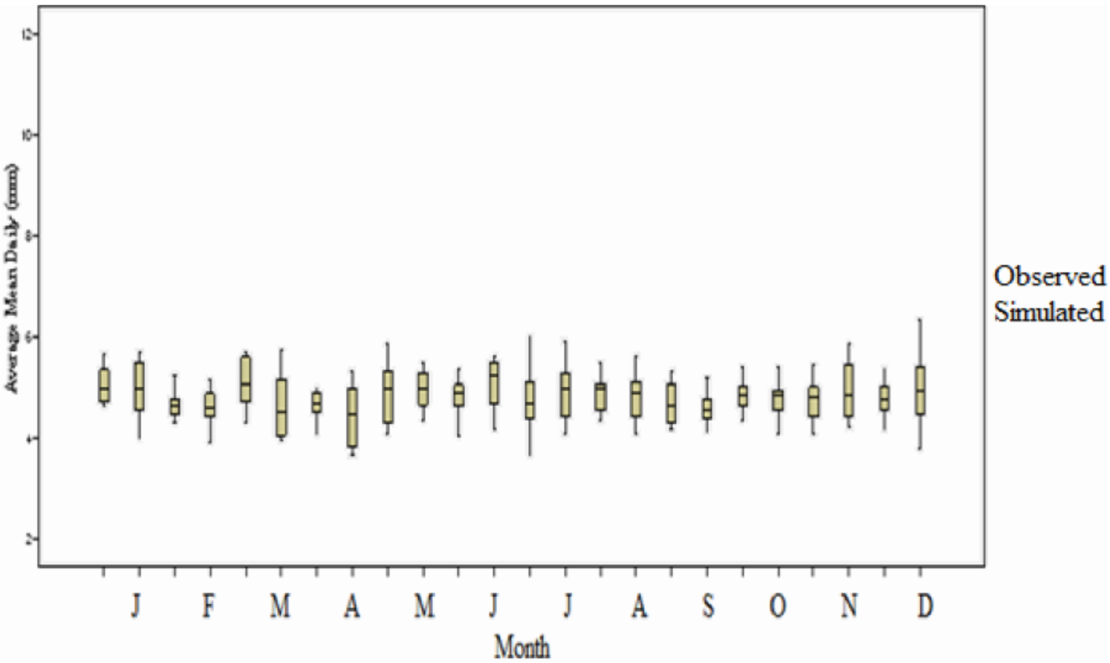

Figure 5.6: Average daily standard deviation precipitation distribution between observed and simulated (Muar).

5.3.4 Model Validation

For precipitation, the statistics performed in SDSM are mean, average wet days, max, sum, dry and wet spells length, minimum precipitation is always zero, so it was not analyzed. During validation, mean and variance of downscaled daily precipitation are adjusted by bias correction and variance inflation factor to force the model to replicate the observed data. Bias correction compensates for any tendency to over or under estimates the mean of downscaled variables. After the statistical downscaling model performance has been checked, the GCM simulations from HadCM3 of represent future climate were used to generate synthetic daily precipitation series.

With the aim to highlight the climate change in local daily precipitation series. For each application 100 simulations were performed to produce 100 synthetic series of daily precipitation. To have complete performance evaluation, the statistical parameters such as mean, standard deviation , average wet days, dry- spell length and wet-spell length of observed and simulated were compared as listed in Tables 5.11 to 5.14.

Table 5.11: Comparison of mean and standard deviation for observed and simulated average daily precipitation of Endau using SDSM model.

Month	Daily Rainfall (mm)			
	Average Mean Daily		Average Daily Standard Deviation	
	Observed	Simulated	Observed	Simulated
January	19.06	23.00	10.97	11.82
February	18.07	22.80	11.57	9.30
March	17.61	23.27	9.98	12.64
April	22.23	19.47	10.29	11.90
May	23.19	18.52	11.31	9.75
June	18.51	23.20	10.19	11.79
July	23.92	17.03	9.60	11.07
August	22.44	20.20	10.95	10.18
September	21.11	16.39	10.76	10.34
October	17.33	20.63	9.95	9.54
November	17.77	21.90	11.03	10.59
December	20.39	21.81	9.81	10.11

Table 5.12: Comparison of precipitation statistical properties of observed and simulated daily precipitation of Endau using SDSM model.

Months	Observed Daily Precipitation (mm)					Synthesized Daily Precipitation (mm)				
	Mean	Max	Average Wet-days	Dry-spell length	Wet-spell length	Mean	Max	Wet-days	Dry-spell length	Wet-spell length
Jan	19.06	248.07	47	4.00	3.36	23.00	214.34	52	1.82	2.05
Feb	18.07	186.69	33	4.46	2.32	22.80	145.47	49	1.86	1.80
Mar	17.61	175.45	33	4.55	2.43	23.27	254.34	51	1.93	1.96
Apr	22.23	148.03	39	3.07	1.94	19.47	249.31	54	1.76	2.08
May	23.19	136.56	42	2.50	1.88	18.52	193.40	50	1.99	1.99
June	18.51	250.59	38	2.78	1.77	23.20	168.64	55	1.71	2.04
July	23.92	166.27	38	2.90	1.87	17.03	112.88	49	1.98	1.88
Aug	22.44	231.75	40	2.78	1.97	20.20	132.73	47	2.19	1.94
Sept	21.11	177.59	41	2.60	1.84	16.39	145.79	48	1.99	1.83
Oct	17.33	211.19	53	2.14	2.35	20.63	139.36	49	1.96	1.94
Nov	17.77	201.43	67	1.64	3.10	21.90	139.86	52	1.84	1.99
Dec	20.39	150.45	67	2.07	3.90	21.81	184.91	53	1.90	2.18

Table 5.13: Comparison of mean and standard deviation for observed and simulated average daily precipitation of Muar using SDSM model.

Month	Daily Rainfall (mm)			
	Average Mean Daily		Average Daily Standard Deviation	
	Observed	Simulated	Observed	Simulated
January	13.05	13.10	5.04	5.50
February	13.08	13.25	4.62	4.89
March	9.96	12.22	5.07	4.63
April	8.91	13.85	4.62	4.98
May	11.01	12.42	4.40	4.34
June	12.74	13.03	4.64	4.72
July	9.61	13.62	4.41	4.38
August	13.12	12.74	4.55	5.08
September	11.33	12.66	4.19	4.58
October	9.86	12.45	4.34	4.96
November	11.73	12.78	4.34	5.00
December	12.75	13.07	4.21	5.39

Table 5.14: Comparison of precipitation statistical properties of observed and simulated daily precipitation of Muar using SDSM model.

Months	Observed Daily Precipitation (mm)					Synthesized Daily Precipitation (mm)				
	Mean	Max	Average Wet-days	Dry-spell length	Wet-spell length	Mean	Max	Wet-days	Dry-spell length	Wet-spell length
Jan	13.05	130.30	23	6.52	2.24	13.10	204.97	30	3.48	1.54
Feb	13.08	155.00	24	4.83	1.74	13.25	98.47	28	3.62	1.43
Mar	9.96	132.00	33	3.57	1.91	12.22	154.08	28	3.44	1.44
Apr	8.91	136.50	39	2.83	1.91	13.85	179.90	31	3.02	1.44
May	11.01	79.20	33	3.14	1.62	12.42	148.08	29	3.56	1.49
June	12.74	76.70	25	3.65	1.33	13.03	112.73	27	3.52	1.43
July	9.61	79.20	30	3.36	1.59	13.62	75.29	29	3.07	1.35
Aug	13.12	106.60	32	3.39	1.65	12.74	172.46	26	3.40	1.30
Sept	11.33	113.00	39	2.67	1.77	12.66	113.90	28	3.27	1.32
Oct	9.86	159.20	43	2.63	2.02	12.45	101.61	24	3.66	1.27
Nov	11.73	105.00	43	2.60	2.02	12.78	82.12	28	3.38	1.40
Dec	12.75	154.40	32	3.71	1.84	13.07	104.46	24	3.81	1.38

5.4 Downscaling Climate Variables Corresponding to Future Climate Change A2 and B2 Scenarios of Endau

Change Considering A2 and B2 Scenarios of Endau (Station no. 2536168)
After the statistical downscaling model performance has been checked, the GCM simulations from HadCM3 SRES A2 and B2 scenarios of represent future climate is used to generate synthetic daily precipitation series. With the aim to highlight the climate change in local daily precipitation series.

Figure 5.7 indicates increasing increment mean daily precipitation of most of the months with in year of future generated precipitation for 2020's, 2050's and 2080's, in comparison to observed precipitation of 1961-1990 due to climate change A2 scenario. Also, similar increasing increment in precipitation for all months within a year is predicted for all future time periods relative to current (Figure 5.8) due to climate change B2 scenarios.

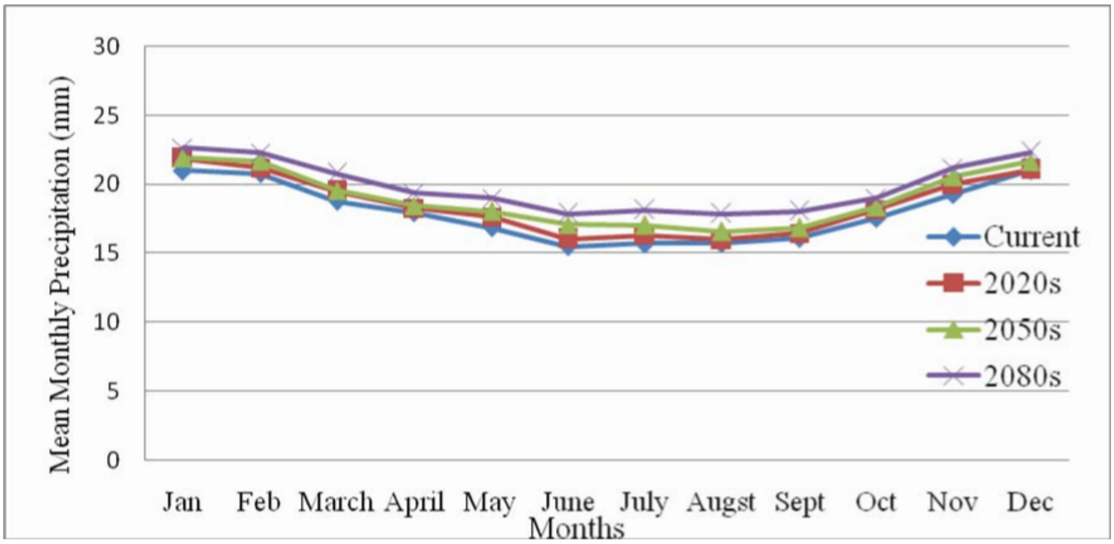

Figure 5.7: Average daily mean precipitation between current and the future climate periods forcing A2 scenario (Endau).

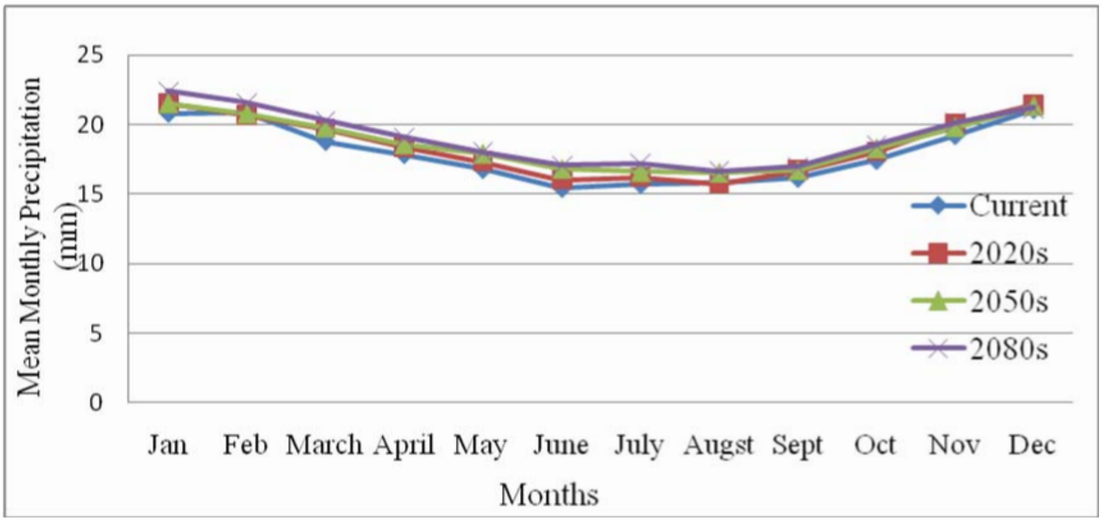

Figure 5.8: Average daily mean precipitation between current and the future climate periods forcing B2 scenario (Endau).

5.4.1 Average Wet Days

Daily Average wet days are indication of how often it rains in a month, and is an indirect measure of precipitation frequency and duration. SDSM downscaled daily average wet days results are shown in Figure 5.9 to 5.10.

Downscaled daily average wet days, in the Figure 5.9 shows that the model generally downscaled the future projection scenarios very well in comparison to observed. The model's prediction of average wet days in all months of year indicates slight increasing increment of future periods 2020's, 2050's and 2080's under climate change scenarios A2. There is slight increment in average daily wet days for the most months into the future period (Figure 5.10) due to climate change scenarios of B2.

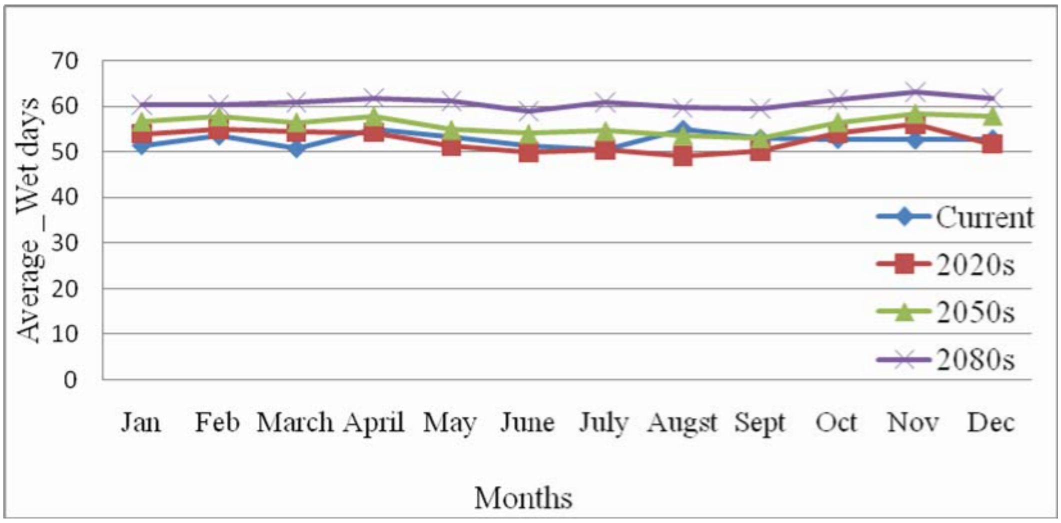

Figure 5.9: Average wet days precipitation between current and the future climate periods forcing A2 scenario (Endau).

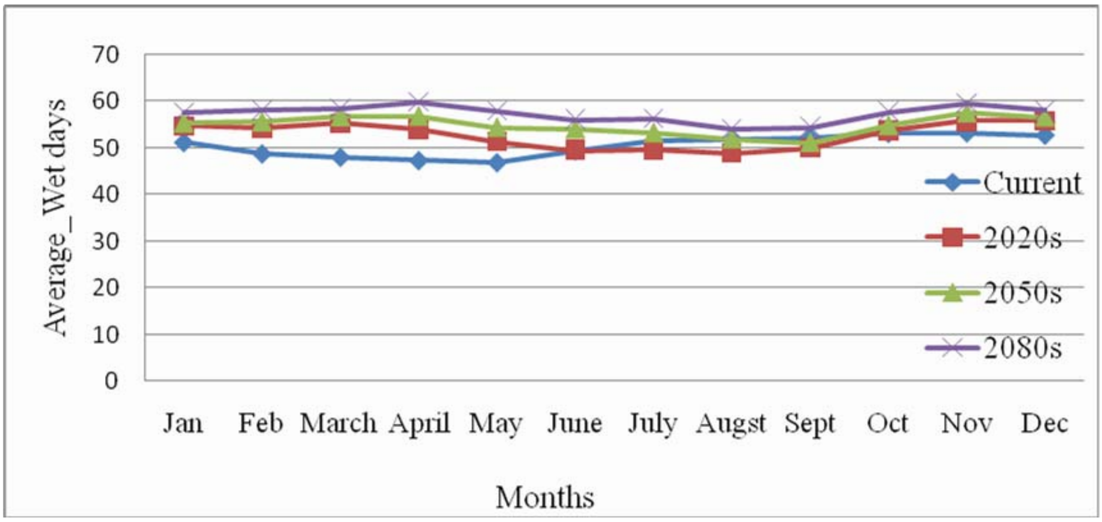

Figure 5.10: Average wet days precipitation between current and the future climate periods forcing B2 scenario (Endau).

5.4.2 Wet Spell Length

SDSM downscaling results of wet spell lengths are shown in (Figures 5.11 and 5.12). The wet spell length refers to the number of consecutive days with non zero or, at least higher than zero, precipitation. SDSM downscales fairly consistently throughout the months of a year, the wet spell length increased by approximately half day from the current to the future period, 2080's. Due to climate change A2 scenarios an increasing average wet spell length was predicted for most of the month within year between observed and Future projections periods 2020's, 2050's and 2080's under climate change B2.

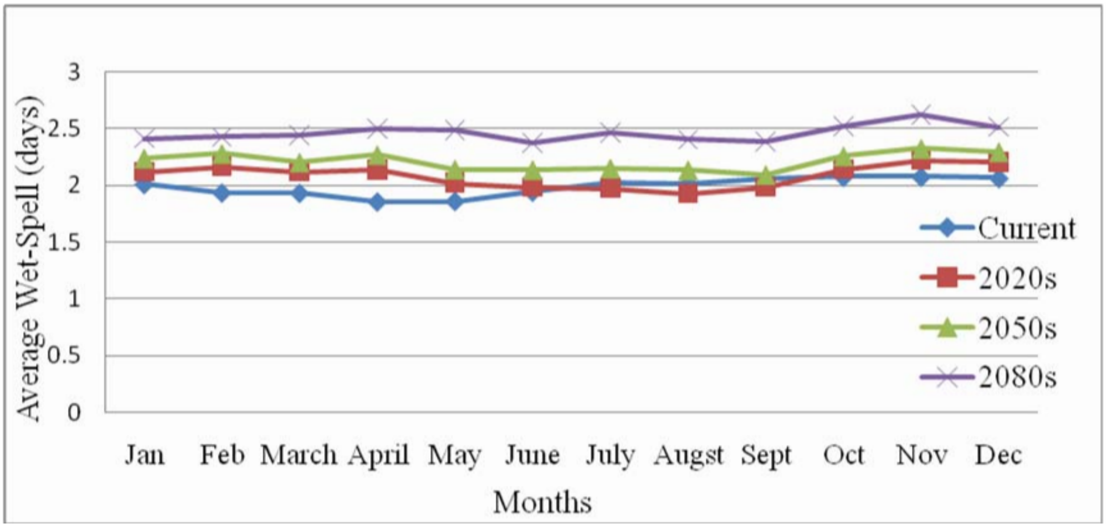

Figure 5.11: Average daily wet-spell precipitation between current and the future climate periods forcing A2 scenario (Endau).

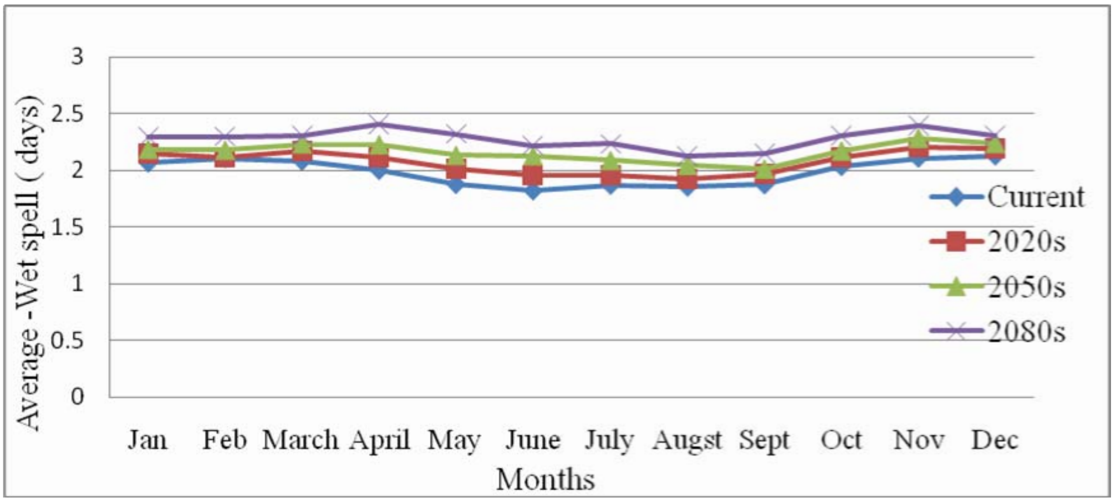

Figure 5.12: Average daily wet-spell precipitation between current and the future climate periods forcing B2 scenario (Endau).

5.4.3 Dry Spell Length

Dry spell length indicates the number of consecutive days without precipitation. The generated future dry spell lengths in (Figures 5.13 and 5.14), show decrease for the future projection periods in comparison to current, except 2020's months where the simulated future dry spells are slightly near to the current under climate scenarios A2 and B2.

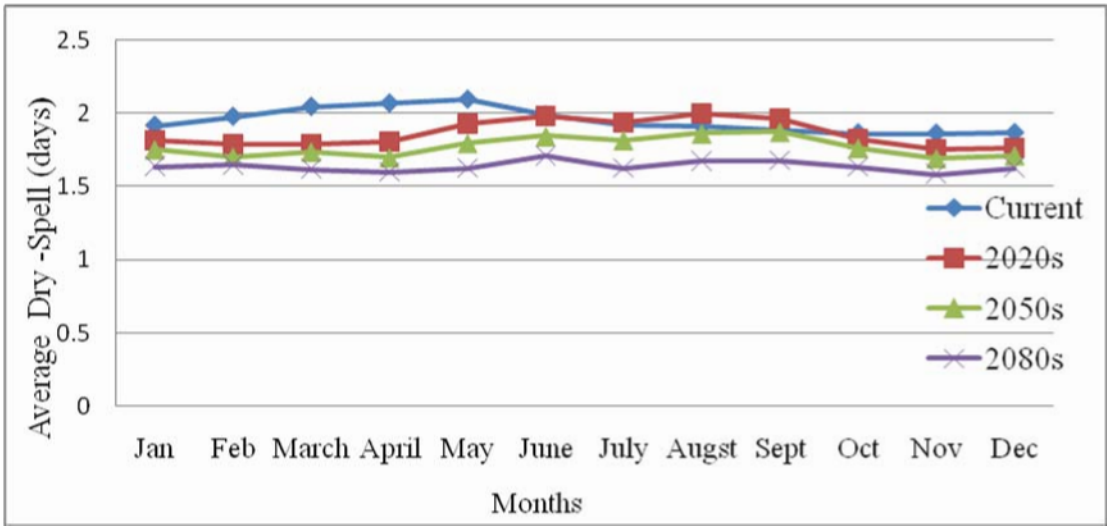

Figure 5.13: Average daily dry-spell length precipitation between current and the future climate periods forcing A2 scenario (Endau).

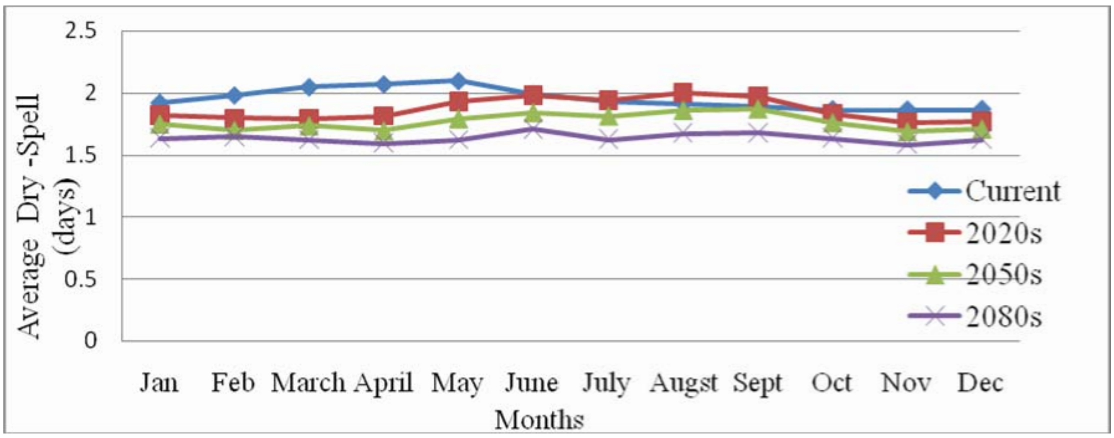

Figure 5.14: Average monthly dry-spell length precipitation between current and the future climate periods forcing A2 scenario (Endau).

5.5 Downscaling Climate Variables Corresponding to Future Climate Change A2 and B2 Scenarios of Muar

Change Considering A2and B2 Scenarios of Muar (Station no. 2536168).
The performance of SDSM in downscaling daily mean precipitation of Muar, as shown in Figure 5.15, indicates a slight increasing of the mean daily precipitation of future climate change periods 2020's, 2050's and 2080's in the month of January ,February November and December and little decreases in the month of June, July and August , as compared to current period 1961 to 1990 under climate change A2 scenarios. Same result was obtained under climate change B2 scenario (refer Figure 5.16). Figure 5.17 shows increase of average wet-days in the projection period 2020's, 2050's and 2080's of all the month within a year under climate change A2 scenarios. No significant changes were obtained under climate change B2 scenario as illustrated in Figure 5.18.

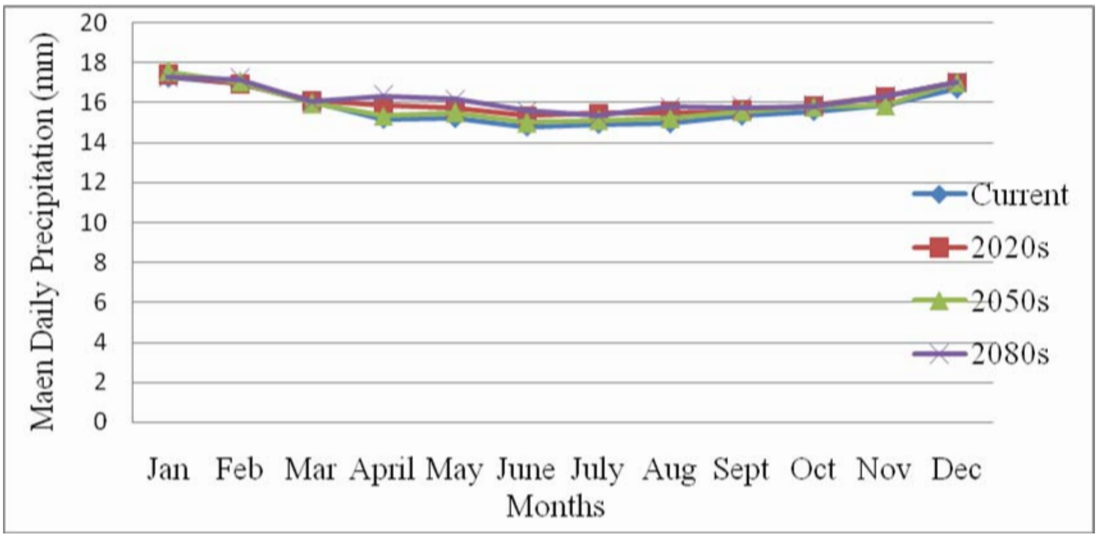

Figure 5.15: Average monthly mean precipitation of the differences between current climate and the future climate periods forcing A2 scenario (Muar)

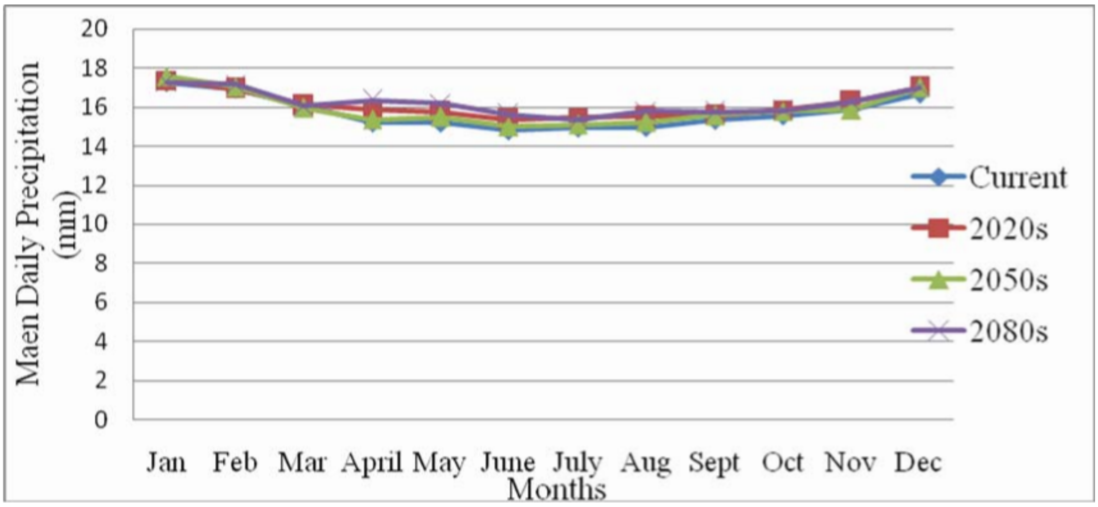

Figure 5.16: Average monthly mean precipitation between current and the future climate periods forcing B2 scenario (Muar).

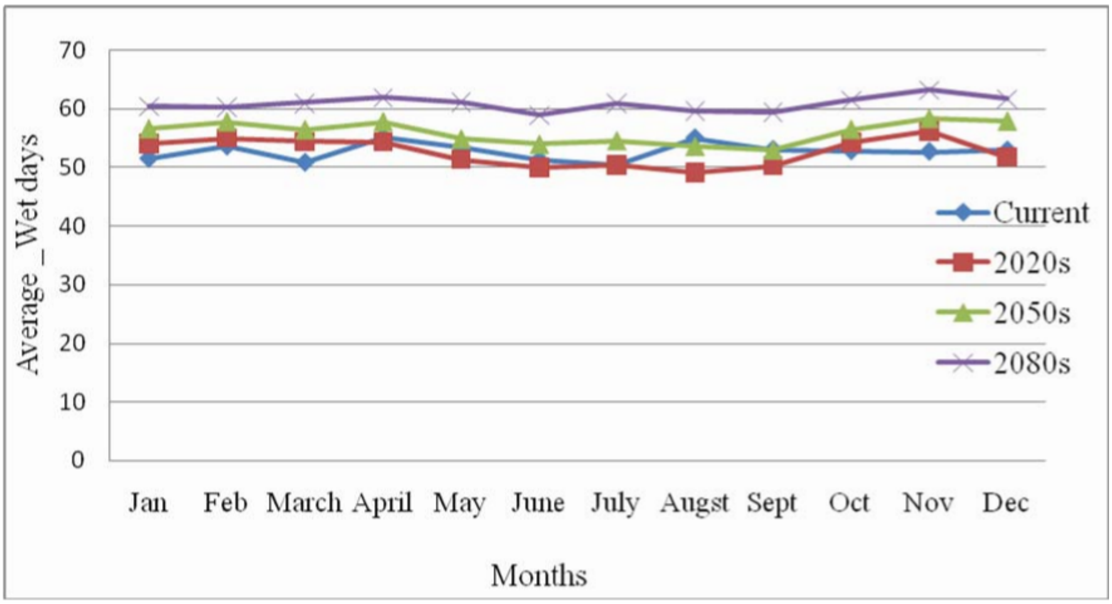

Figure 5.17: Average monthly wet-days precipitation between current and the future climate periods forcing A2 scenario (Muar).

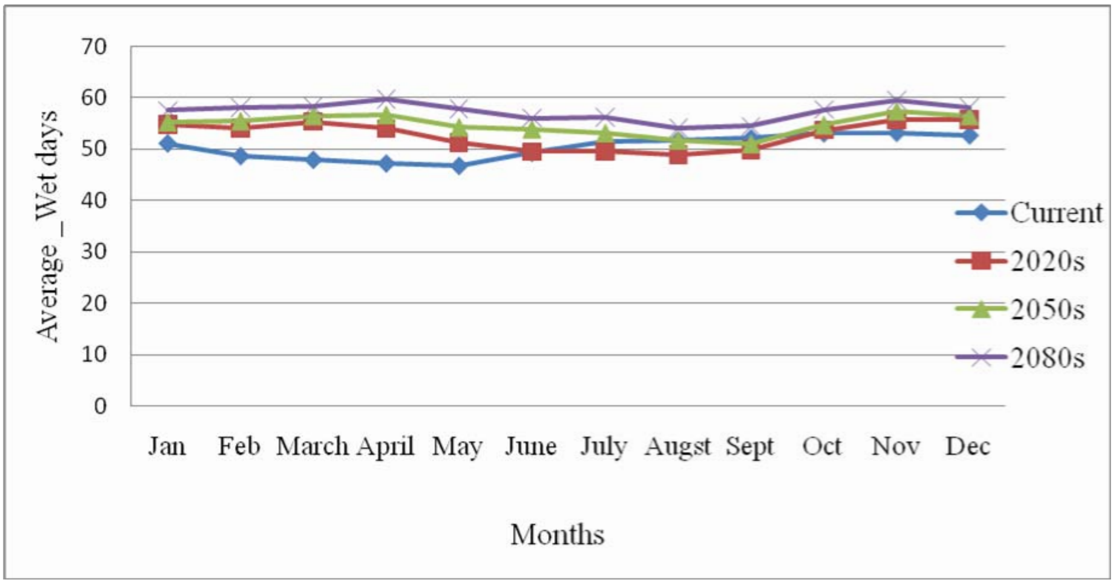

Figure 5.18: Average monthly wet-days precipitation between current and the future climate periods forcing B2 scenario (Muar).

Additionally, Figure 5.19 shows an increase in average wet-spells durations for the month of a year projections with the future periods 2020's, 2050'sand 2080's as compared to current (1961-1990) under climate change A2 scenarios. Similar result was obtained in Figure 5.20, under climate change scenario B2. There are consistent decreasing trends of average dry-spells length throughout the year for all time slices future projections under climate changes A2 and B2 scenarios as observed in Figures 5.21 and 5.22, respectively.

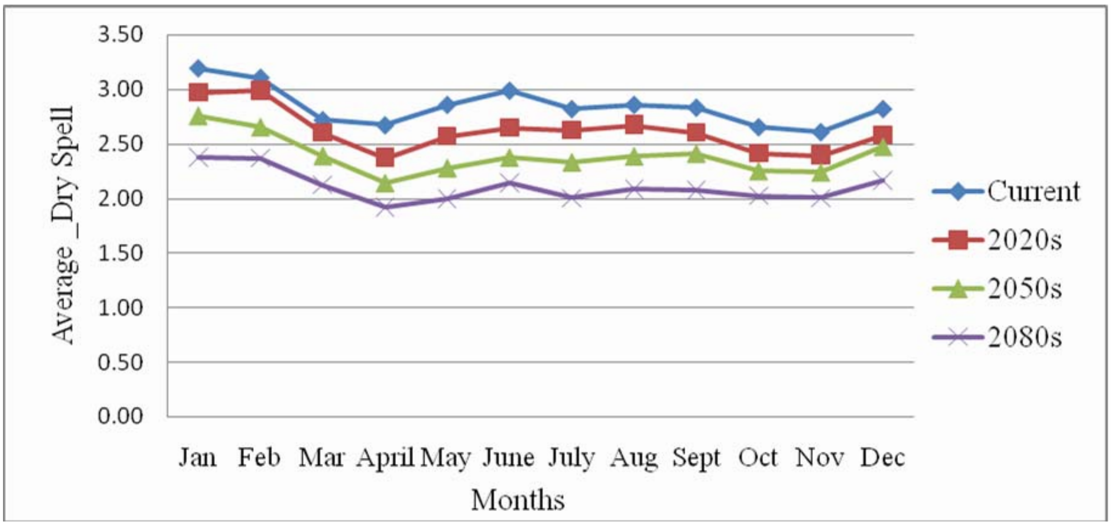

Figure 5.19: Average monthly dry-spell length precipitation between current and the future climate periods forcing A2 scenario (Muar).

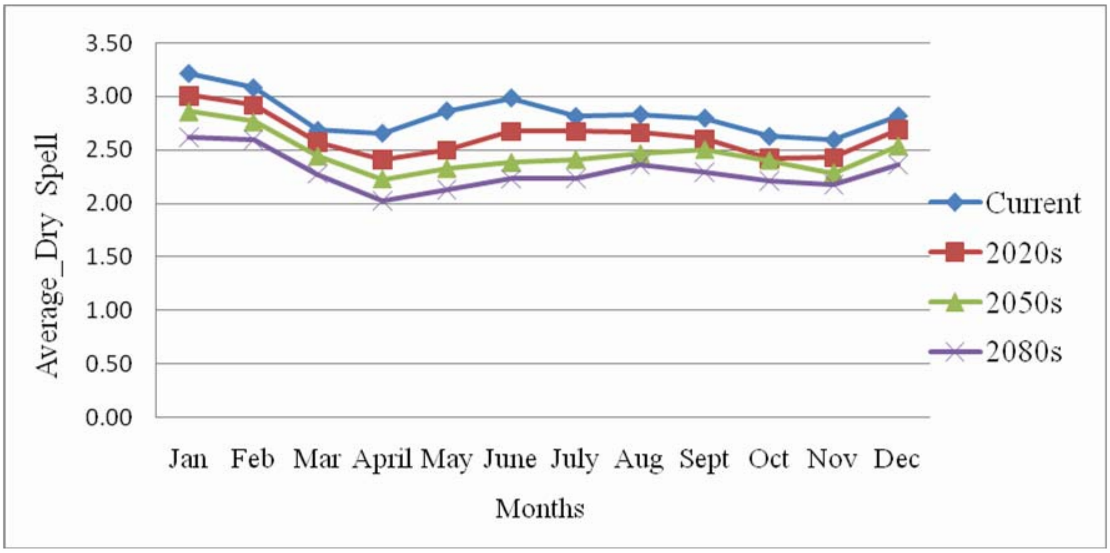

Figure 5.20: Average monthly dry-spell length precipitation between current and the future climate periods forcing B2 scenario (Muar).

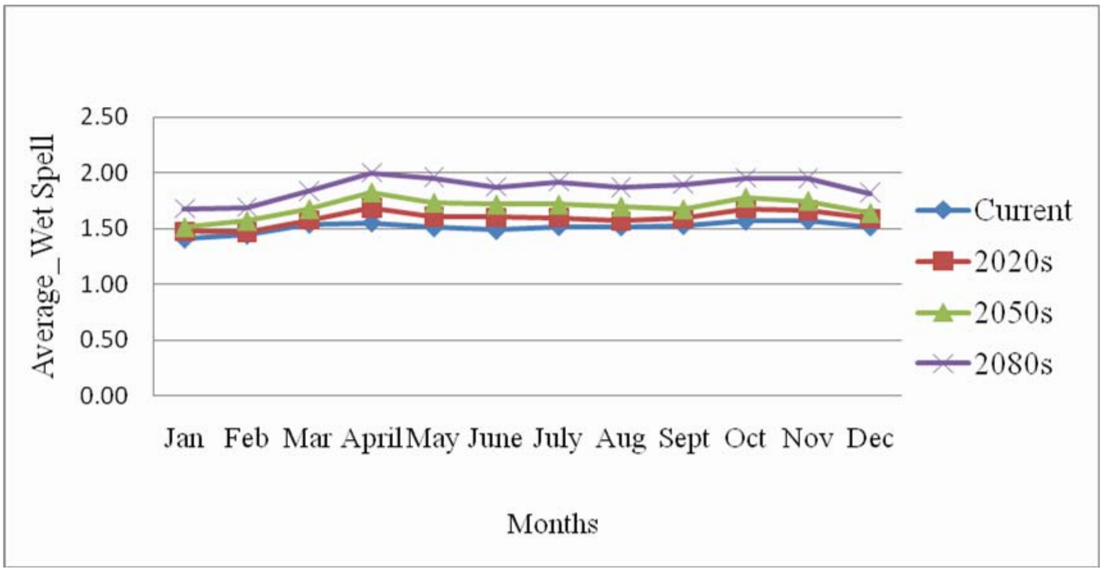

Figure 5.21: Average monthly wet-spell length precipitation between current and the future climate periods forcing A2 scenario (Muar).

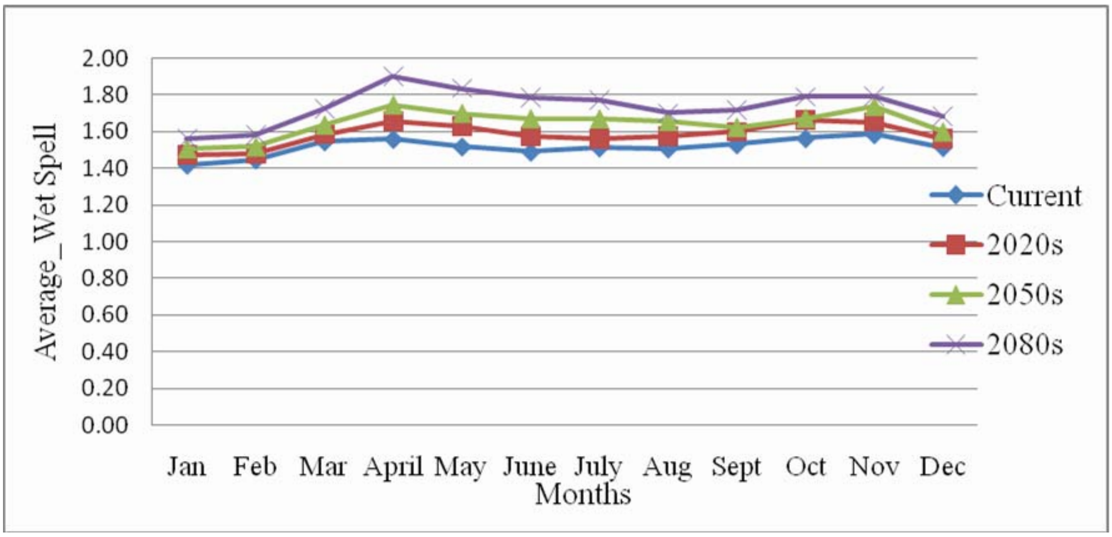

Figure 22: Average monthly wet spell length precipitation of between current and the future climate periods forcing B2 scenario (Muar).

5.6 Frequency Analysis

Key focus of this study was to evaluate the impact of climate change on the occurrence of floods in the study area. Since the occurrence of this extreme event is intrinsically linked to extreme storm depths, it is important to determine the probabilities of exceedence of different storms depths.

Frequency analysis is a technique of fitting a probability distribution to a series of observations for defining the probabilities of future occurrences of some events of interest, e.g., an estimate of a flood magnitude corresponding to a chosen risk of failure. The use of this technique has played an important role in engineering practice. The maximum rainfall amount for a given duration and for selected return period is often required for the planning and design of urban drainage systems. There are two basic approaches to determining the return periods of extreme values.

The Gumbel and Generalized Extreme Values (GEV) distributions are particularly convenient for extreme value distribution purposes and has been commonly used for the estimation of precipitation quantiles. Therefore, the Gumbel and GEV distributions and is assumed as the underlying probability distributions for next 50–100 return periods Extreme precipitation events of were analysed using annual daily maximum precipitation observed data at two selected rainfall station Endau and Muar and climate scenarios downscaled results denoted by for future 2020s,2050s, and 2080s period.

Table 5.15 listed results for 50 and 100 years return periods associated with observed and generated depths. Results of frequency analysis clearly indicate that future generated 2020’s, 2050’s and 2080’s, representing the increasing precipitation scenario. For example, consider a storm depth of 335 mm. Similar increasing trends were observed for other storm depths, the numerical storm depth values are the highest for Endau and the lowest for Muar. The message of these results is that, there is positively correlation with the increasing precipitation trends obtained from the statistics performed in SDSM such as mean, wet spells length, and average wet days.

Table 5.1.5: 50 and 100 years return periods associated with observed and generated rainfall series.

Station Name	Return Period	Distributions	Observed (mm)	Generated (mm)		
				2020's	2050's	2080's
Endau	50	Gumbel	220	260	260	275
		GEV	210	295	300	310
	100	Gumbel	235	280	280	300
		GEV	220	320	320	335
Muar	50	Gumbel	100	135	145	180
		GEV	110	135	155	190
	100	Gumbel	110	145	160	195
		GEV	115	147	165	210

For illustrative purpose, Figure 5.23 to 5.34 presents the probability plots of annul daily maximum precipitations of observed for the period (1961-1990) and three future projection generated scenarios for the periods 2020's, 2050's and 2080's of generated precipitation The plots indicate that Gumbel and Generalized Extreme Events distributions are good fit with observed and generated extreme events.

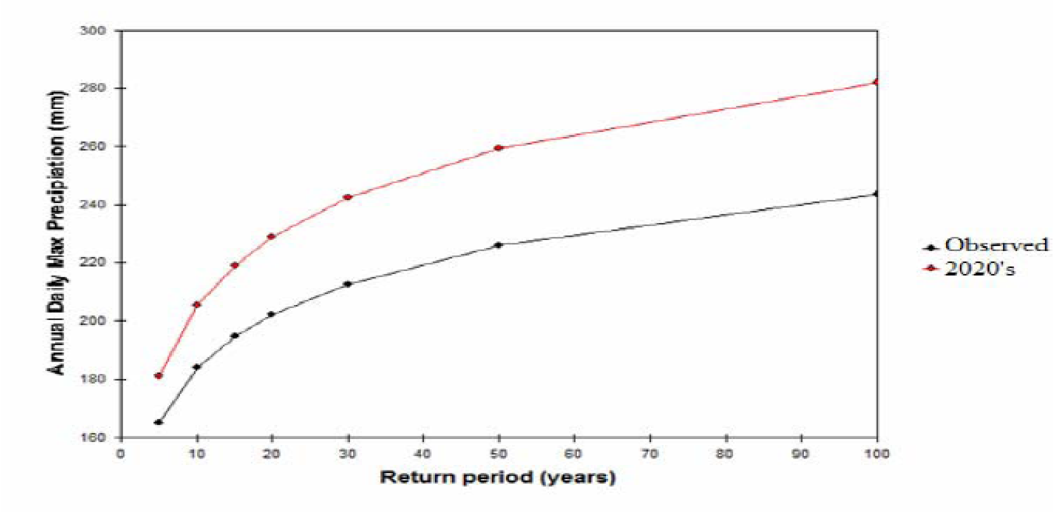

Figure 5.23: Gumbel distribution of annual daily maximum precipitation between o observed and2020's (Endau).

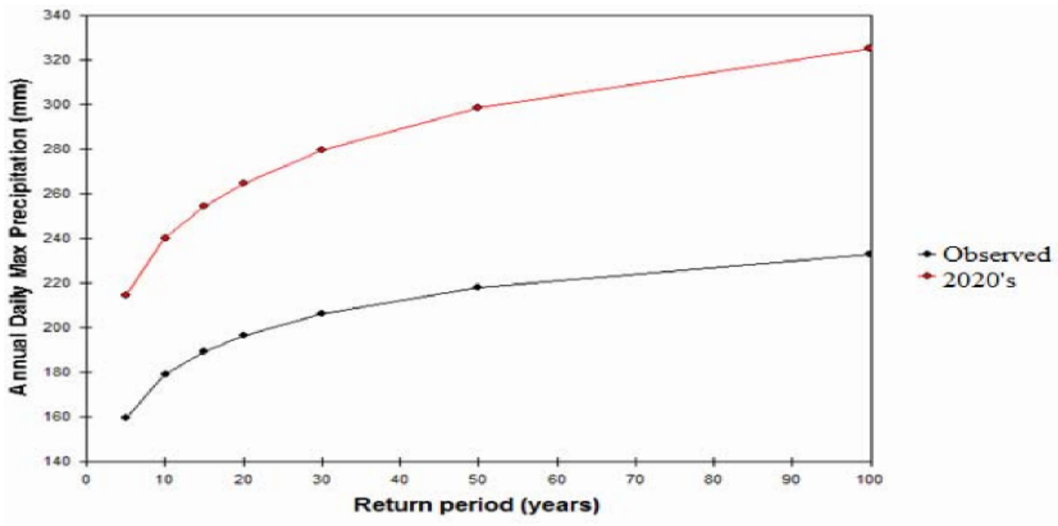

Figure 5.24: GEV distribution of annual daily maximum precipitation between of observed and 2020’s (Endau).

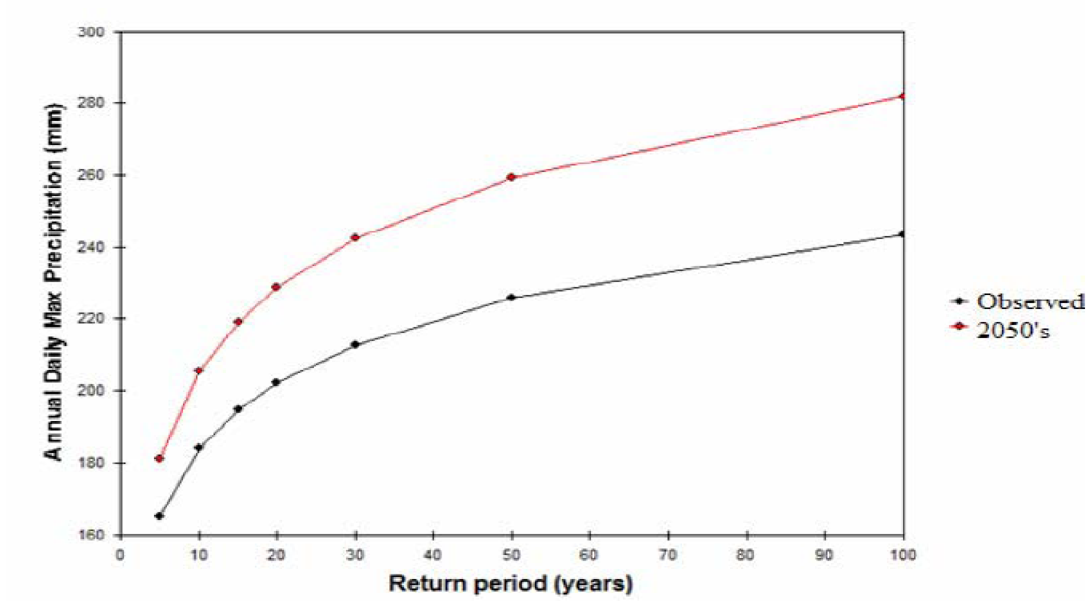

Figure 5.25: Gumbel distribution of annual daily maximum precipitation between of observed and 2050’s (Endau).

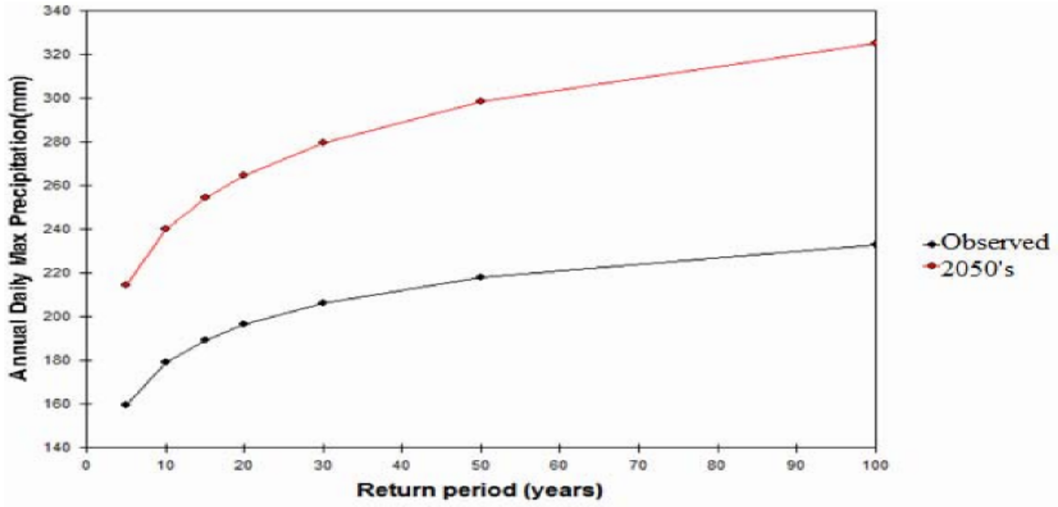

Figure 5.26: GEV distribution of annual daily maximum precipitation between of observed and 2050’s (Endau).

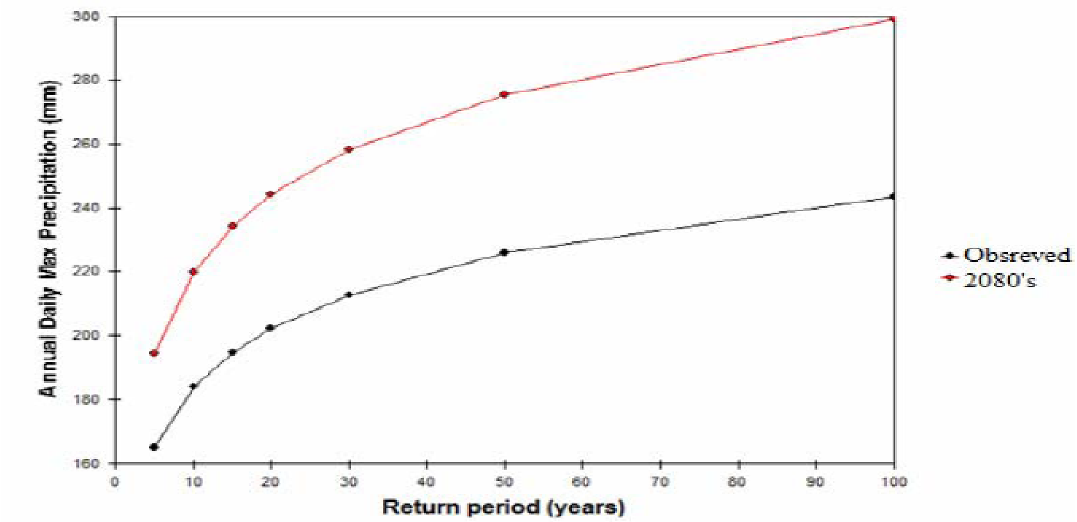

Figure 5.27: Gumbel distribution of annual daily maximum precipitation between of observed and 2080’s (Endau).

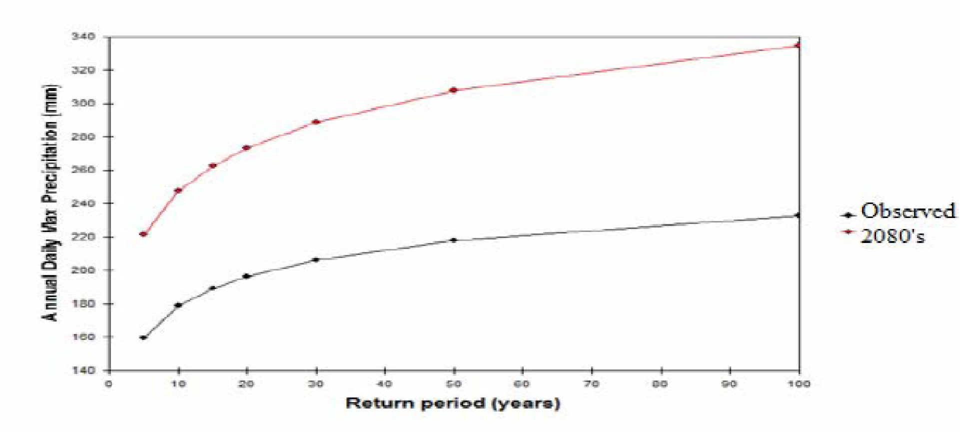

Figure 5.28: GEV distribution of annual daily maximum precipitation between of observed and 2080's (Endau).

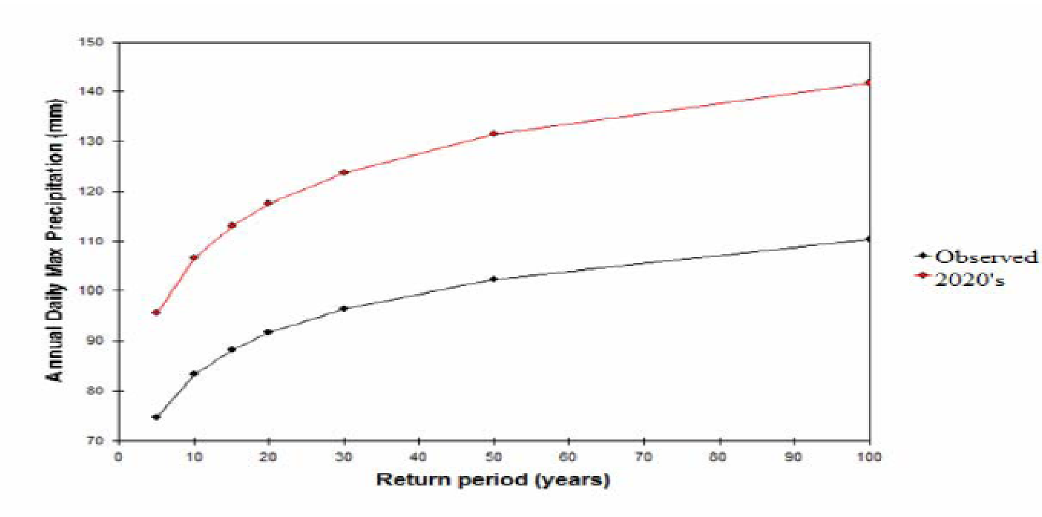

Figure 5.29: Gumbel distribution of annual daily maximum precipitation between of observed and 2020's (Muar).

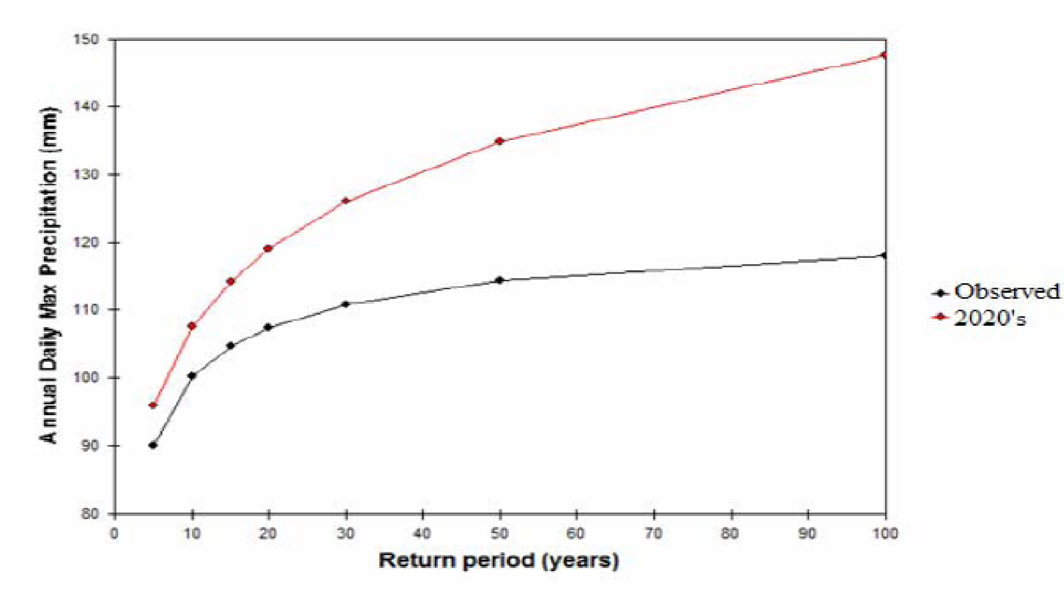

Figure 5.30: GEV distribution of annual daily maximum precipitation between of observed and 2050's (Muar).

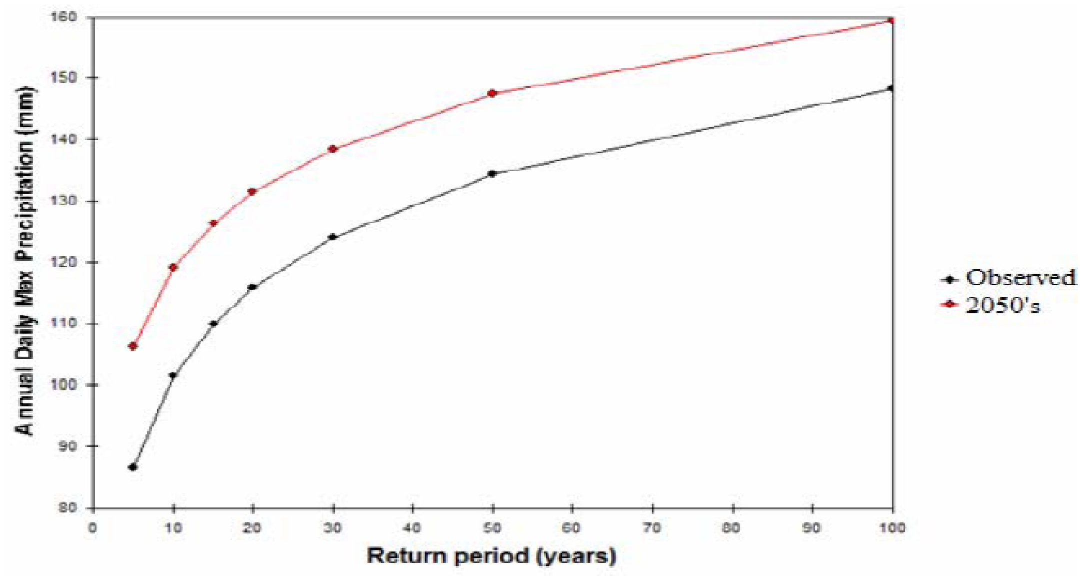

Figure 5.31: Gumbel distribution of annual daily maximum precipitation between of observed and 2050's (Muar).

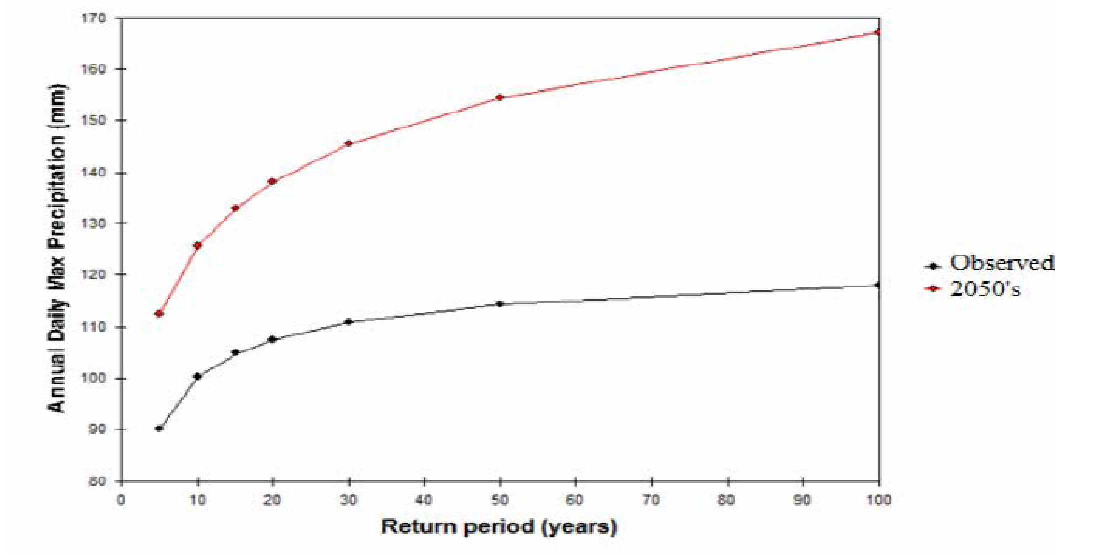

Figure 5.32: GEV distribution of annual daily maximum precipitation between of observed and 2050's (Muar).

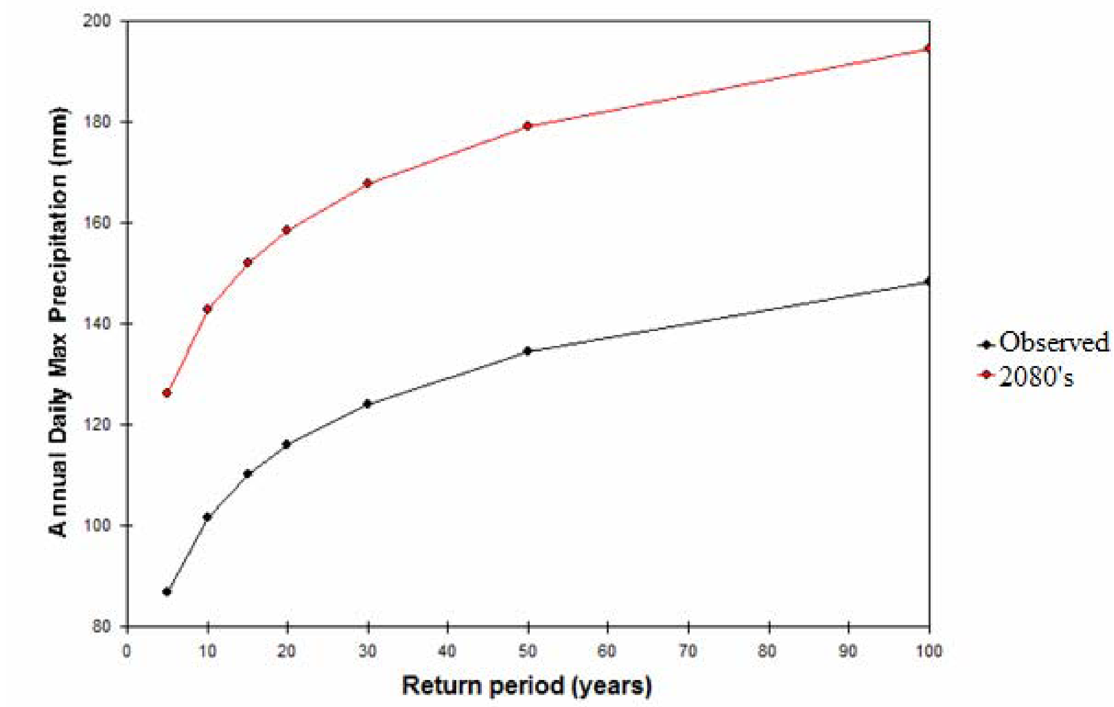

Figure 5.33: Gumbel distribution of annual daily maximum precipitation between of observed and 2080's (Muar).

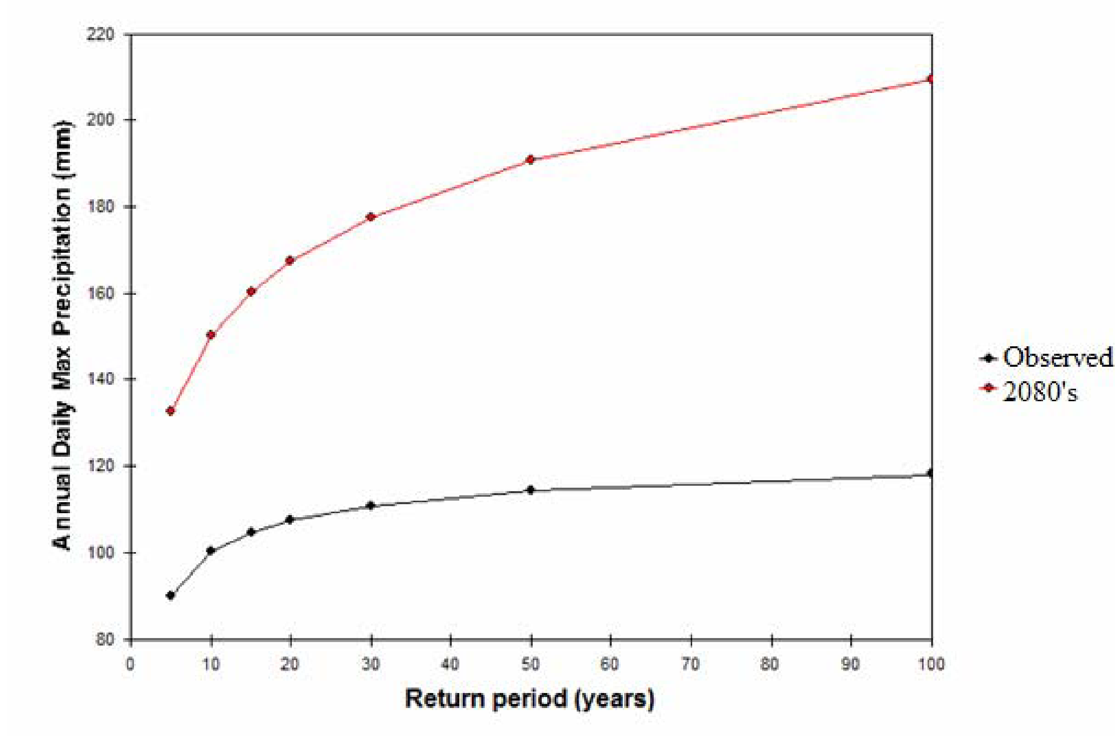

Figure 5.34: GEV distribution of annual daily maximum precipitation between of observed and 2080's (Muar).

CHAPTER 6

CONCLUSIONS

6.1 Conclusions

The potential impact of climatic change on the occurrence of extreme precipitation events in the two rainfall station Endau (station no. 2536168) Muar (station no. 2228016) situated in Johor at the Southern region of Peninsular Malaysia has been investigated.

Statistical Downscaling Model (SDSM) was applied using three set of data; observed daily precipitation for the period of 1961-1990, two rainfall station Endau and Muar and NCEP re-analysis data composed of 24 daily atmospheric variables for the same period which are selected at grid box covering each of the stations considered and HadCM3 SRES A2 and B2 emission scenarios SDSM have used NCEP reanalysis data of gridded large atmospheric variables as predictors and station data as predictands.

The results of the variable screening analyses show that the variables of ncepmslpna.dat, ncep850na.dat, nceprhumas.dat and ncepshumas.dat are more suitable in predicting the precipitation. The observed data for the 1961-1976 period were used for models calibration step, and those of 1977-1990 for models validation, at the validation step, the calibrated model was run with model’s parameter and climate conditions for the period 1977-1990 to generate 100 series of daily precipitation. The outputs were statistically analyzed and compared to statistics of observed data for the same period to evaluate the model's performance. The Box and Whisker plot analysis of average daily and standard deviation indicates that the model can preserve the basic statistical properties.

Three future periods 2020's, 2050's and 2080's were compared to the observed precipitation for the period 1961 to 1990. The intent was to create an ensemble of scenarios that can be used for the evaluation, especially the extremes events. The SDSM downscaled results predicted increasing increment for the mean daily precipitation of Endau station for the most months within a year. Due to A2 climate change scenario similar increasing trend for mean daily precipitation was obtained to B2 scenario.

Average wet days which are indicated how often it rains in a month and is in direct measure of precipitation frequency and duration, reveal that the future periods (2020's 2050's and 2080's) is expected to slightly increase, the average daily wet days in all the months with in year under climate change A2 scenario. An increasing average wet spell length was predicted for most of the month within year between observed and future projections periods 2020's, 2050's and under climate change A2 and B2. The result of generated future dry spell lengths indicted decrease of future projection periods in comparison to current.

The downscaled results of Muar also shows slight increasing increment of mean daily precipitation of future climate change periods 2020's, 2050's and 2080's in most of the months within a year of as compared to current under climate change A2 scenarios. Similar result was obtained under climate change B2 scenarios. Similarly consistent increasing trends was predicted to average wet-days and average wet spell length in the projection period 2020's, 2050's and 2080's in all month under climate change A2 and B2 emission scenario.

Frequency analysis of annual daily maximum of observed for the period 1961 to 1990 and three future scenarios 2020's , 2050's and 2080's was carried out to determine the impact of potential climate change on the occurrence of storm depths of any given magnitude revealed for the increasing extreme precipitation values for future projection periods. The return periods of 50 to 100 years storm depths were found to be the slightly higher in GEV distributions. The results obtained indicate that the increasing precipitation scenario is the critical scenario associated with the occurrence of floods in the study area.

The conclusion drawn from the study can be summarized as following:

i. It is feasible to link large-scale atmospheric variables by GCM simulations from Hadley Centre 3rd generation (HadCM3) outputs with daily precipitation at a local site.
ii. The Statistical Downscaling Model (SDSM) is capable of simulating present climate to investigate the future climate change due to the atmospheric projections.
iii. The SDSM can be considered as a bench mark model to interpret the impact of climate changes.

6.2 Recommendations

Based on this study, it is suggested to use downscaled precipitation series in runoff modeling, evaluating the effects of the future climate change on local surface hydrology. This demands that other hydro-meteorological variables, such as temperature, stream flow.

Further study is need on other sites as well as to use other methods such as Long Ashton Research Station Weather Generator (LARS-WG) and Artificial Neural Networks in order to indentify the robust method in Malaysia.

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APPENDIX A

SDSM Statistical Output Results (Endau)

Summary of Statistics for Observed Precipitation for a Period 1961-1990

Month	Mean	Maximum	Minimum	Variance	Sum	ACF	Skewness
January	9.44	152.23	0.00	330.85	292.66	0.10	3.09
February	10.53	144.04	0.00	396.20	297.59	0.01	3.16
March	10.26	103.34	0.00	321.02	318.17	-0.03	2.43
April	11.69	262.86	0.00	613.14	350.65	0.02	4.33
May	10.15	171.73	0.00	424.75	314.50	0.03	3.40
June	10.87	307.59	0.00	572.42	325.98	0.00	5.74
July	11.05	154.17	0.00	409.98	342.61	-0.04	2.96
August	10.96	248.83	0.00	487.29	339.63	-0.04	4.70
September	10.08	141.37	0.00	359.63	302.34	-0.05	3.22
October	11.14	282.60	0.00	589.19	345.43	0.05	5.41
November	11.33	154.09	0.00	501.48	339.83	0.02	2.97
December	12.33	164.08	0.00	521.49	342.83	0.02	3.27

Summary of Statistics for Observed Precipitation for a Period 1961-1990

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.47	4.00	3.36	25.00	15.00	3.12	4.68	62.00
February	0.33	4.46	2.32	23.00	12.00	2.00	4.69	32.00
March	0.33	4.55	2.43	31.00	23.00	2.63	4.56	31.00
April	0.39	3.07	1.94	26.00	11.00	1.49	3.73	12.00
May	0.42	2.50	1.88	13.00	10.00	1.34	2.20	30.00
June	0.38	2.78	1.77	16.00	9.00	1.30	2.52	12.00
July	0.38	2.90	1.87	18.00	14.00	1.54	2.60	7.00
August	0.40	2.78	1.97	17.00	9.00	1.54	2.50	19.00
September	0.41	2.60	1.84	12.00	9.00	1.30	2.04	10.00
October	0.53	2.14	2.35	10.00	16.00	2.04	1.57	28.00
November	0.67	1.64	3.10	6.00	16.00	3.14	1.01	76.00
December	0.67	2.07	3.90	11.00	21.00	3.56	1.74	168.00

Summary of Statistics for Simulated Precipitation for a Period 1961-1990

Month	Mean	Maximum	Minimum	Variance	Sum	ACF	Skewness
January	18.69	176.65	0.30	536.47	296.97	0.01	2.64
February	17.45	175.43	0.30	504.97	243.31	0.01	2.92
March	16.55	170.82	0.30	465.91	248.96	0.01	2.87
April	15.94	165.13	0.30	434.05	225.04	0.01	2.90
May	16.03	151.73	0.30	423.14	232.36	0.01	2.67
June	16.67	163.78	0.30	461.46	246.75	0.01	2.76
July	17.75	178.74	0.30	515.51	281.42	0.01	2.84
August	18.59	181.32	0.30	550.36	295.56	0.01	2.76
September	19.71	180.68	0.30	596.53	308.17	0.02	2.61
October	19.53	191.80	0.30	589.95	319.40	0.01	2.78
November	19.87	192.14	0.30	599.65	314.95	0.02	2.74
December	19.53	185.59	0.30	583.84	317.95	0.02	2.71

Summary of Statistics for Simulated Precipitation for a Period 1961-1990

Month	Wet-days%	Dry-spell	Wet-spell	Max_dspel	Max_wspel	SD_Wet Spell	SD_Dry Spell	POP
January	0.52	1.82	2.05	7.00	8.00	1.43	1.29	0.43
February	0.49	1.86	1.80	8.00	8.00	1.18	1.28	0.33
March	0.51	1.93	1.96	7.00	10.00	1.55	1.21	0.45
April	0.54	1.76	2.08	10.00	8.00	1.45	1.47	0.42
May	0.50	1.99	1.99	6.00	10.00	1.42	1.18	0.33
June	0.55	1.71	2.04	7.00	7.00	1.50	1.09	0.40
July	0.49	1.98	1.88	7.00	10.00	1.48	1.43	0.42
August	0.47	2.19	1.94	12.00	9.00	1.32	1.80	0.39
September	0.48	1.99	1.83	8.00	8.00	1.33	1.43	0.38
October	0.49	1.96	1.94	7.00	8.00	1.33	1.28	0.33
November	0.52	1.84	1.99	13.00	7.00	1.30	1.50	0.34
December	0.53	1.90	2.18	7.00	13.00	1.82	1.27	0.46

Summary of Statistics for Simulated Precipitation for future period 2010-2039 (2020's)

Month	Mean	Maximum	Minimum	Variance	Sum	ACF	Skewness
January	21.88	204.09	0.30	694.62	354.81	0.02	2.62
February	21.17	193.64	0.30	647.07	349.57	0.02	2.58
March	19.50	190.48	0.30	586.87	318.11	0.00	2.76
April	18.28	171.93	0.30	516.21	298.01	0.01	2.64
May	17.62	167.83	0.30	493.33	271.51	0.01	2.67
June	16.03	159.31	0.30	433.17	240.52	0.01	2.82
July	16.30	159.76	0.30	441.86	246.38	0.00	2.74
August	16.00	157.39	0.30	425.99	235.61	0.01	2.77
September	16.44	162.12	0.30	441.17	247.90	0.02	2.76
October	18.17	178.51	0.30	527.15	295.51	0.01	2.73
November	20.00	196.08	0.30	607.62	337.41	0.00	2.79
December	21.04	201.30	0.30	660.44	352.83	0.01	2.72

Summary of Statistics for Simulated Precipitation for future period 2010-2039 (2020's)

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.54	1.82	2.12	8.12	9.94	1.53	1.22	0.45
February	0.55	1.79	2.16	7.86	10.34	1.59	1.20	0.44
March	0.54	1.79	2.12	7.97	9.92	1.54	1.20	0.41
April	0.54	1.81	2.13	7.94	10.08	1.56	1.21	0.38
May	0.51	1.93	2.02	9.49	9.69	1.43	1.38	0.38
June	0.50	1.98	1.98	9.34	9.56	1.41	1.43	0.35
July	0.50	1.94	1.97	9.06	9.09	1.38	1.36	0.35
August	0.49	2.00	1.93	9.51	8.79	1.34	1.44	0.34
September	0.50	1.97	1.98	9.18	9.33	1.40	1.39	0.34
October	0.54	1.83	2.14	8.10	10.33	1.57	1.23	0.39
November	0.56	1.76	2.22	7.67	10.15	1.64	1.15	0.41
December	0.52	1.77	2.20	7.58	10.40	1.62	1.16	0.43

Summary of Statistics for Simulated Precipitation for future period 2040-2069 (2050's)

Month	Mean	Maximum	Minimum	Variance	Sum	ACF	Skewness
January	21.91	198.43	0.30	694.08	371.65	0.01	2.56
February	21.68	197.27	0.30	666.04	375.44	0.01	2.54
March	19.55	184.49	0.30	581.83	330.87	0.01	2.65
April	18.46	176.09	0.30	523.68	319.74	0.01	2.63
May	18.05	178.44	0.30	523.50	296.67	0.01	2.79
June	17.10	171.29	0.30	483.84	276.56	0.01	2.77
July	17.04	167.87	0.30	473.55	278.70	0.01	2.74
August	16.58	169.07	0.30	454.51	266.45	0.02	2.84
September	16.84	166.10	0.30	469.91	267.39	0.02	2.77
October	18.36	180.05	0.30	534.90	310.85	0.02	2.71
November	20.55	189.13	0.30	625.10	359.40	0.01	2.59
December	21.66	198.65	0.30	679.50	376.07	0.01	2.60

Summary of Statistics for Simulated Precipitation for future period 2040-2069 (2050's)

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.57	1.75	2.24	7.72	10.42	1.65	1.15	0.44
February	0.58	1.70	2.28	7.25	11.03	1.72	1.08	0.44
March	0.56	1.74	2.20	7.47	10.65	1.63	1.14	0.40
April	0.58	1.70	2.27	7.17	11.06	1.73	1.08	0.38
May	0.55	1.80	2.14	7.87	9.87	1.57	1.21	0.37
June	0.54	1.84	2.14	8.32	10.89	1.60	1.27	0.36
July	0.55	1.82	2.15	8.32	10.31	1.59	1.24	0.36
August	0.54	1.86	2.14	8.79	10.29	1.57	1.30	0.34
September	0.53	1.88	2.09	8.45	9.81	1.51	1.30	0.35
October	0.56	1.77	2.26	8.00	11.04	1.72	1.17	0.38
November	0.58	1.69	2.32	7.18	11.37	1.76	1.08	0.42
December	0.58	1.71	2.30	7.41	10.97	1.74	1.11	0.44

Summary of Statistics for Simulated Precipitation for future period 2070-2099 (2080's)

Month	Mean	Maximum	Minimum	Variance	Sum	ACF	Skewness
January	22.64	217.57	0.30	735.98	409.92	0.01	2.68
February	22.28	204.49	0.30	718.44	402.29	0.02	2.60
March	20.79	194.26	0.30	638.02	379.83	0.01	2.63
April	19.36	183.33	0.30	560.13	359.01	0.01	2.63
May	18.99	193.83	0.30	565.19	348.04	0.01	2.82
June	17.88	178.85	0.30	523.76	315.74	0.02	2.78
July	18.13	185.04	0.30	517.34	331.27	0.01	2.76
August	17.87	186.12	0.30	523.91	319.66	0.01	2.86
September	18.03	181.42	0.30	520.18	321.23	0.01	2.78
October	18.99	181.50	0.30	548.91	349.62	0.02	2.65
November	21.19	196.18	0.30	643.41	401.35	0.01	2.56
December	22.34	209.49	0.30	718.89	412.87	0.01	2.62

Summary of Statistics for Simulated Precipitation for future period 2070-2099 (2080's)

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.60	1.64	2.42	6.97	11.55	1.83	1.03	0.43
February	0.60	1.65	2.43	6.95	11.77	1.87	1.04	0.43
March	0.61	1.62	2.45	7.09	12.03	1.89	1.01	0.40
April	0.62	1.60	2.50	6.48	12.27	1.94	0.97	0.38
May	0.61	1.62	2.49	7.10	12.42	1.95	1.03	0.37
June	0.59	1.71	2.38	7.61	11.70	1.84	1.12	0.36
July	0.61	1.62	2.47	6.70	11.72	1.90	1.00	0.36
August	0.60	1.68	2.41	7.35	12.40	1.89	1.08	0.36
September	0.59	1.68	2.39	7.35	11.64	1.83	1.08	0.36
October	0.61	1.63	2.53	6.86	12.47	1.98	1.02	0.37
November	0.63	1.58	2.63	6.69	13.46	2.10	0.98	0.41
December	0.62	1.63	2.52	6.82	12.23	1.97	1.01	0.43

Appendix B

SDSM Statistical Output Results (Muar)

Summary of Statistics for Observed Precipitation for a Period 1961-1990

Month	Mean	Maximum	Minimum	Variance	Sum	ACF	Skewness
January	17.30	116.54	0.31	303.13	166.47	0.00	2.17
February	16.96	113.43	0.30	288.38	162.07	0.00	2.16
March	16.20	114.79	0.30	272.60	178.96	0.00	2.23
April	15.73	112.11	0.30	258.98	192.76	0.00	2.21
May	15.93	110.31	0.30	261.14	180.41	0.00	2.18
June	15.23	106.16	0.30	250.32	168.22	0.01	2.16
July	15.38	105.15	0.30	252.17	170.39	0.02	2.19
August	15.52	110.90	0.30	258.58	167.67	0.00	2.24
September	15.68	107.47	0.30	252.69	174.80	0.01	2.17
October	15.77	112.44	0.30	265.56	191.38	0.02	2.21
November	16.41	117.42	0.30	283.19	198.46	0.00	2.23
December	16.89	113.10	0.30	287.12	188.98	0.00	2.12

Summary of Statistics for Observed Precipitation for a Period 1961-1990

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.32	2.97	1.47	14.98	5.65	0.84	2.45	33.01
February	0.32	2.99	1.47	15.00	5.71	0.83	2.44	32.26
March	0.37	2.60	1.57	12.54	6.30	0.95	2.03	33.08
April	0.41	2.37	1.69	11.67	7.20	1.08	1.80	35.78
May	0.38	2.57	1.60	13.49	6.67	0.99	2.07	32.71
June	0.37	2.64	1.60	14.15	6.83	0.99	2.16	30.57
July	0.37	2.62	1.60	13.35	6.72	0.99	2.10	30.48
August	0.36	2.67	1.57	14.47	6.57	0.95	2.19	30.52
September	0.37	2.60	1.59	12.81	6.78	0.98	2.07	31.48
October	0.40	2.41	1.68	12.30	7.39	1.09	1.89	35.52
November	0.40	2.40	1.66	11.93	7.09	1.05	1.83	38.32
December	0.37	2.58	1.59	13.00	6.88	0.99	2.03	36.40

Summary of Statistics for Simulated Precipitation for a Period 1961-1990

Month	Mean	Maximu	Minimum	Variance	Sum	ACF	Skewness
January	17.35	116.45	0.30	299.26	180.03	0.00	2.14
February	16.88	117.40	0.30	293.87	184.05	0.01	2.21
March	15.87	111.77	0.30	261.41	193.12	0.00	2.19
April	15.28	112.31	0.30	251.35	209.40	0.01	2.24
May	15.66	111.92	0.30	255.74	201.26	0.01	2.22
June	15.12	109.26	0.30	249.32	187.77	0.01	2.24
July	15.06	106.01	0.30	241.23	189.19	0.00	2.19
August	15.27	111.38	0.30	248.28	187.80	0.01	2.24
September	15.39	106.40	0.30	245.19	186.52	0.01	2.13
October	15.57	111.18	0.30	252.78	203.78	0.00	2.22
November	16.22	115.60	0.30	273.47	210.58	0.00	2.23
December	16.89	112.38	0.30	286.26	198.63	0.01	2.12

Summary of Statistics for Simulated Precipitation for a Period 1961-1990

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.35	2.76	1.52	13.66	6.17	0.88	2.19	36.33
February	0.36	2.65	1.57	13.39	6.57	0.96	2.12	36.99
March	0.41	2.39	1.68	12.40	7.41	1.08	1.87	36.88
April	0.46	2.14	1.82	10.38	8.57	1.25	1.57	38.63
May	0.43	2.28	1.73	10.90	7.54	1.12	1.73	37.71
June	0.41	2.37	1.72	12.03	7.53	1.13	1.87	34.18
July	0.42	2.33	1.72	11.81	7.71	1.13	1.82	34.38
August	0.41	2.39	1.70	12.56	7.26	1.10	1.89	34.39
September	0.40	2.41	1.67	12.29	7.23	1.08	1.88	34.07
October	0.44	2.25	1.78	11.08	8.23	1.21	1.72	38.27
November	0.43	2.24	1.75	10.62	7.86	1.16	1.68	40.35
December	0.39	2.47	1.64	12.69	7.00	1.03	1.94	39.87

Summary of Statistics for Simulated Precipitation for future period 2020-2039 (2020's)

Month	Mean	Maximu	Minimum	Variance	Sum	ACF	Skewness
January	17.30	119	0.30	297.65	209.23	0.00	2.23
February	16.90	114	0.30	285.26	208.41	0.01	2.11
March	16.13	113	0.30	257.82	217.85	0.01	2.19
April	16.19	114	0.30	251.25	232.86	0.00	2.28
May	16.29	107	0.30	242.75	224.02	0.01	2.15
June	15.34	109	0.30	232.32	203.97	0.01	2.24
July	15.49	108	0.30	234.86	214.74	0.00	2.23
August	15.84	112	0.30	244.16	211.04	0.01	2.27
September	15.81	114	0.30	246.83	217.37	0.00	2.24
October	15.79	114	0.30	245.88	222.42	0.01	2.27
November	16.27	119	0.30	270.48	235.77	0.01	2.25
December	16.94	118	0.30	281.16	225.76	0.00	2.18

Summary of Statistics for Simulated Precipitation for 2010-2039 (2020's)

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.30	0.41	2.38	1.68	7.54	1.09	1.84	43.29
February	0.30	0.41	2.37	1.69	7.52	1.09	1.86	43.38
March	0.30	0.46	2.13	1.84	8.66	1.27	1.58	41.53
April	0.30	0.51	1.92	2.00	9.22	1.42	1.33	44.13
May	0.30	0.49	2.00	1.96	9.24	1.39	1.42	41.99
June	0.30	0.46	2.14	1.87	8.88	1.32	1.63	37.27
July	0.30	0.49	2.01	1.92	8.85	1.34	1.45	39.53
August	0.30	0.47	2.09	1.87	8.66	1.32	1.54	39.21
September	0.30	0.48	2.07	1.90	8.77	1.32	1.53	41.19
October	0.30	0.49	2.03	1.96	9.24	1.38	1.47	41.64
November	0.30	0.49	2.01	1.95	9.22	1.38	1.45	46.28
December	0.30	0.45	2.17	1.82	8.41	1.25	1.63	46.74

Summary of Statistics for Simulated Precipitation for future period 2040-2069 (2050's)

Month	Mean	Maximu	Minimum	Variance	Sum	ACF	Skewness
January	17.26	112.72	0.30	296.85	152.00	0.01	2.12
February	16.96	113.20	0.30	298.00	158.59	0.01	2.16
March	16.06	109.10	0.30	264.91	171.52	0.00	2.15
April	15.20	110.91	0.30	271.80	177.00	0.00	2.14
May	15.21	114.67	0.30	279.81	163.08	0.01	2.28
June	14.80	104.45	0.30	256.23	150.46	0.01	2.14
July	14.93	103.77	0.30	246.44	155.74	0.01	2.12
August	14.96	112.76	0.30	266.33	159.01	0.01	2.25
September	15.34	107.39	0.30	253.07	162.02	0.01	2.11
October	15.56	109.00	0.30	258.32	172.71	0.00	2.15
November	15.89	110.62	0.30	268.70	181.92	0.00	2.14
December	16.69	111.15	0.30	283.82	173.51	0.01	2.08

Summary of Statistics for Simulated Precipitation for 2040-2069 (2050's)

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.29	3.21	1.42	16.90	5.33	0.78	2.69	30.13
February	0.31	3.08	1.45	15.73	5.79	0.81	2.54	30.93
March	0.36	2.68	1.55	13.83	6.36	0.93	2.16	31.55
April	0.36	2.66	1.56	13.40	6.48	0.94	2.14	33.25
May	0.34	2.87	1.52	14.71	6.12	0.89	2.37	30.68
June	0.32	2.99	1.49	15.74	6.01	0.87	2.51	26.97
July	0.34	2.81	1.51	14.67	6.09	0.89	2.30	27.46
August	0.34	2.83	1.51	14.65	6.13	0.88	2.33	28.72
September	0.34	2.80	1.53	14.19	6.18	0.91	2.27	29.04
October	0.36	2.63	1.56	13.36	6.29	0.95	2.09	30.66
November	0.37	2.60	1.59	12.81	6.63	0.97	2.04	33.51
December	0.34	2.82	1.52	15.23	6.06	0.89	2.34	33.53

Summary of Statistics for Simulated Precipitation for future period 2070-2099 (2080's)

Month	Mean	Maximu	Minimum	Variance	Sum	ACF	Skewness
January	17.57	114.73	0.31	308.04	177.10	0.00	2.11
February	17.05	116.36	0.30	292.50	176.31	0.00	2.14
March	15.97	112.41	0.30	265.30	188.76	0.00	2.19
April	15.35	108.57	0.30	252.69	200.23	0.01	2.20
May	15.51	108.29	0.30	249.12	193.64	0.00	2.17
June	15.01	110.41	0.30	244.23	183.34	0.00	2.26
July	15.11	108.36	0.30	249.96	182.85	0.00	2.25
August	15.22	106.93	0.30	247.25	180.35	0.01	2.19
September	15.58	105.23	0.30	246.30	180.90	0.01	2.09
October	15.78	109.65	0.30	259.03	191.58	0.01	2.17
November	15.85	112.09	0.30	260.88	202.50	0.01	2.19
December	17.01	116.69	0.30	294.92	193.48	0.00	2.18

Summary of Statistics for Simulated Precipitation for 2070-2099 (2080's)

Month	Wet-days%	Dry-spell	Wet-spell	Max_dry spell	Max_ Wet spell	SD_Wet Spell	SD_Dry Spell	POP
January	0.34	2.86	1.51	14.43	5.98	0.88	2.34	36.54
February	0.34	2.77	1.52	13.95	6.10	0.89	2.23	36.67
March	0.39	2.44	1.64	12.28	6.81	1.02	1.90	35.74
April	0.43	2.23	1.75	10.61	7.85	1.16	1.65	36.61
May	0.42	2.33	1.70	11.21	7.37	1.10	1.79	35.07
June	0.41	2.38	1.67	11.82	7.46	1.07	1.84	33.40
July	0.40	2.41	1.67	12.62	7.01	1.07	1.92	33.28
August	0.39	2.47	1.66	12.72	6.82	1.05	1.94	32.66
September	0.39	2.51	1.63	12.68	7.09	1.02	1.96	33.52
October	0.40	2.40	1.68	12.01	7.36	1.08	1.86	35.93
November	0.43	2.29	1.74	11.63	7.77	1.16	1.75	37.76
December	0.38	2.54	1.60	12.20	6.89	1.00	1.97	38.62