ASSESEMENT OF THE PROJECTION OF THE FUTURE CHANGES IN CLIMATE BY RCP 2.6, RCP4.5, RCP8.5

BASRI BIN ABDUL

B. ENG (HONS.) CIVIL ENGINEERING

UNIVERSITI MALAYSIA PAHANG

UNIVERSITI MALAYSIA PAHANG

DECLARATION OF THESIS AND COPYRIGHT

Author's Full Name : BASRI BIN ABDUL

Date of Birth : 10 DECEMBER 1996

Title :

Academic Session :

I declare that this thesis is classified as:

☐	CONFIDENTIAL	(Contains confidential information under the Official Secret Act 1997)*
☐	RESTRICTED	(Contains restricted information as specified by the organization where research was done)*
☑	OPEN ACCESS	I agree that my thesis to be published as online open access (Full Text)

I acknowledge that Universiti Malaysia Pahang reserves the following rights:

1. The Thesis is the Property of Universiti Malaysia Pahang
2. The Library of Universiti Malaysia Pahang has the right to make copies of the thesis for the purpose of research only.
3. The Library has the right to make copies of the thesis for academic exchange.

Certified by:

(Student's Signature)

961210-12-5067
New IC/Passport Number
Date:

(Supervisor's Signature)

DR NURUL NADRAH AQILAH BINTI TUKIMAT
Name of Supervisor
Date:

NOTE : * If the thesis is CONFIDENTIAL or RESTRICTED, please attach a thesis declaration letter.

STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

____

(Student's Signature)

Full Name : BASRI BIN ABDUL

ID Number : AA15093

Date : 31 MAY 2019

ASSESSMENT OF THE PROJECTION OF FUTURE CHANGES IN CLIMATE VARIABLE BY RCP 2.6, RCP4.5, RCP8.5

BASRI BIN ABDUL

Thesis submitted in partial fulfillment of the requirements
for the award of the degree of
B. Eng (Hons.) of Civil Engineering

Faculty of Civil Engineering & Earth Resources

UNIVERSITI MALAYSIA PAHANG

MAY 2019

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude towards my supervisor Dr Nurul Nadrah Aqilah Binti Tukimat for her guidance, ideas, continuous encouragement and support in making this research possible. She was helpful in many ways in my research, from bright ideas towards consulting on how to approach problems to solve them. Also, she gave me an insight towards what should be called life-long learning experience. She had strict principles and a firm belief on what she was doing. I really appreciate the help that she has given to me and my teammates in completing our study. Without her progressive thinking and progressive attitude, I would never made it towards the end of the Bachelor's Degree I'm currently pursuing.

A special gratitude I would like to forward towards my family especially my father, Mr Abdul and also my sister for their support through my ups and downs, making sure that they have my back whenever I needed them and plus, encouraging me to go further and surpass myself in all kinds of aspects. They're also my backbone towards me finishing this study and helped me in understanding, having patience and finally, being the ones I can turn back to if I am in need of help.

My sincere thanks towards my teammates, Fatin, Izhar and also to my best friend Abdul Rahman Bin Alimuddin in helping me finish this research and the cooperation in making the study more understandable, viable to simulate and support in me finishing the research.

I would like to acknowledge my housemates, especially Ismat, Ibrahim Adham and Azizi, for their tremendous support and confidence in me towards concluding my life here in UMP. I also would like to acknowledge their suggestions and comments, which was crucial for in completing the study

ABSTRAK

Peningkatan dalam suhu permukaan global memberi impak signifikan kepada perubahan iklim. Keadaan ini menjurus kepada keperluan untuk mentaksir kesan – kesan perubahan iklim yang serantau. Perisian Statistical Downscaling Model (SDSM) telah digunakan sebagai model untuk simulasi trend ramalan iklim di negeri Melaka dan negeri Sembilan. Simulasi ini dijalankan di tiga stesen untuk setiap negeri iaitu Ranc. Tali Air, Ladang Sing Lian di Bhg Garing dan Pintu Pasang Surut Duyong bagi Negeri Melaka, sementara JPS Tampin, Kg. Chennah dan Politeknik Port Dickson bagi negeri Sembilan. berdasarkan jumlah hujan harian. Model SDSM ialah terbitan daripada National Centre for Environmental Prediction (NCEP) dan pemerhatian pembolehubah – pembolehubah yang tempatan metodologikal yang telah menyelaras menggunakan besar – berskala pembolehubah peramal. Pengesahan model SDSM telah dilakukan oleh tempoh bebas analisis semula NCEP. Data yang diperolehi dignakan untuk menjana trend ramalan iklim dibawah berbagai senario – senario Representative Concentrations Pathways (RCP), RCP 2.6, RCP 4.5 dan RCP 8.5 disediakan oleh Canadian Centre for Climate Modelling and Analysis (CanESM2) di negeri Melaka dan negeri Sembilan.

ABSTRACT

The increase in global temperature give significantly impact on the climate changes. This situation will lead to the need for an assessment of regional climate change impacts. The application of Statistical Downscaling Model (SDSM) were used to simulate the projection of future climate trend in Melaka and Negeri Sembilan. The simulation was taken at three stations for each state which is Ranc. Tali Air, Ladang Sing Lian di Bhg Garing and Pintu Pasang Surut Duyong for Melaka, while JPS Tampin, Kg. Chennah and Politeknik Port Dickson for Negeri Sembilan. The SDSM model is the derivation of National Centre for Environmental Prediction (NCEP) reanalysis data and observation of locally methodological variables that have been calibrated using large – scale predictors variables. The SDSM model validation has been done by independent period of NCEP reanalysis. The result obtained was used to generate the future climate trend under various scenarios Representatives Concentration Pathways (RCP), RCP 2.6, RCP 4.5 and RCP 8.5 provided by the Canadian Centre for Climate Modelling and Analysis (CanESM2) at Melaka and Negeri Sembilan.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

%	Percentage
r	Correlation coefficient value
MAE	Mean Absolute Error

LIST OF ABBREVIATIONS

RCP	Representative Concentration Pathways
CanESM2	Canadian Centre for Climate Modelling and Analysis
HadCM3	Hadley Center Coupled Model
IPCC	Intergovernmental Panel on Climate Change
GCM	General Circulation Model
AR5	Fifth Assessment Report
AR4	Fourth Assessment Report

CHAPTER 1

INTRODUCTION

1.1 Introduction

Climate change or also known as global warming, refers to the rise in average surfaces temperature on Earth. The primary cause of climate change is the burning of the fossil fuels such as oil and coal, which emits greenhouse gases into the atmosphere primarily carbon dioxide. Furthermore, human influence on the climate system is clear and recent anthropogenic emissions of greenhouse gasses are the highest in history (IPCC, 2014). According to the recently published report of Intergovernmental Panel on Climate Change (IPCC) 2013, the rise in temperature from the year 1990 to 2100 is approximately 1.4°C to 5.8°C [1] (Tahir, Hashim, & Yusof, 2018). To predict the climate change in the future, the General Circulation Models (GCMs) were introduced by early 1970's and are widely used by many researches to project the future trend and variation of climate at global and continental scale. The current IPCC Valuation Report used a numeral GCMs to evaluate upcoming climate with different emission scenarios and concluded that the it is very likely that trends in extreme precipitation will continue to increase (Tahir et al., 2018). To describe the climate futures, four different Representative Concentration Pathways (RCPs) which are RCP2.6, RCP4.5, RCP 6.0 and RCP8.5 have been selected for climate modelling and research. The RCPs are the amount of greenhouse gas concentration trajectory adopted by the IPCC for its fifth Assessment Report (AR5) in 2014.

In this study, the Statistical Downscaling Model (SDSM) is used to downscale the GCMs because the model results are built on a larger grid scale (250 to 600 km) (Tahir et al., 2018). Therefore, due to its coarse resolution, the results are not fine enough to evaluate the variation of hydrological impacts of local or regional scales.

1.2 Statement of the problems

According to the IPCC Fifth Assessment Report 2014, the globally averaged combined land and ocean surface temperature data as calculated by a linear trend show a warming of 0.85 [0.65 to 1.06]°C over the period 1880 to 2012 (IPCC, 2014). The data collected was based on GCMs method approach at global scale which provide clear resolution. Besides global warming, the projection of hydrological impact such as rainfall, temperature on specific regions also are hampered with limited spatial resolution of global climate model. The spatial resolution of GCMs remain quite coarse which limited at global and continental scale of (250 to 600 km) and at that scale, the details of climate change on the specific regions are lost.

GCMs are therefore unable to provide local climate information for the future prediction of hydrological impact. To convert the coarse resolution of GCMs into fine resolution, the SDSM is used to stimulate the climate impacts on smaller scale.

1.3 Objectives

The main aim of this study is to project the future changes in local climate in Melaka and Negeri Sembilan states by RCP 2.6, RCP 4.5 and RCP 8.5. The objectives of this study are outlined as follows:

1. To identify the best RCPs and GCMs group for these regions

2. To generate the future trend of climates variables for year in 2020,2050,2080

1.4 Scope of the study

The study will be focused on identifying the best RCPs and GCMs group for Melaka and Negeri Sembilan states. The calibration and simulation of the climate models will use the SDSM to generate the future trend of climate variables for year in 2020,2050 and 2080.

1.5 Significant of the study

This study will be significant in promoting the downscaling approach in predicting the future climate change at a regional scale. The topography, atmospheric behaviour and local or regional interactions will be differed in comparing with other regions. In this study, the Statistical Downscaling (DS) approach will be use. However, SD may not be suit in some places and Dynamical Downscaling approach (DD) may be used to evaluate the future climate data.

It is very important for public or authorities to know this method in assessing the future climate change by using the best and accurate method to predict the future climate changes and can prepare for it.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The observation of climate system is based on direct measurements and remote sensing from satellites and other platforms. According to Working Group I (WGI) contribution to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) 2013, the globally averaged combined land and ocean surface temperature data as calculated by a linear trend, show a warming of 0.85 [0.65 to 1.06] ^{o} C, over the period 1880 to 2012, when multiple independently produced datasets exist. The total increase between the average of the 1850 -1900 period and the 2003-2012 period is 0.78[0.72 to 0.85] ^{o} C, based on the single longest dataset available (**Figure 2.1**) (Physical & Basis, 2013). Since the start of Industrial Revolution in 18th century, human activities such as the burning of fossil fuels, coal and oil as source, have dramatically increased the concentration of greenhouse gases in our atmosphere. Hence, it tends to increase rapidly as are result of climate change (Hassan, Shamsudin, & Harun, 2014). The atmospheric concentrations of the greenhouse gases, carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) have all increased since 1750 due to human activity (Physical & Basis, 2013). The enhanced of greenhouse effect is expected to change many of the basic weather patterns that make up our climate. Scientists have high confidence that global temperature will continue to rise for decades, largely due to greenhouse natural and anthropogenic substances. The Intergovernmental Panel on Climate Change (IPCC), which includes more than 1300 scientists from United States and other countries, forecast a temperature rise of 2.5 to 10 degrees Fahrenheit over the next century.

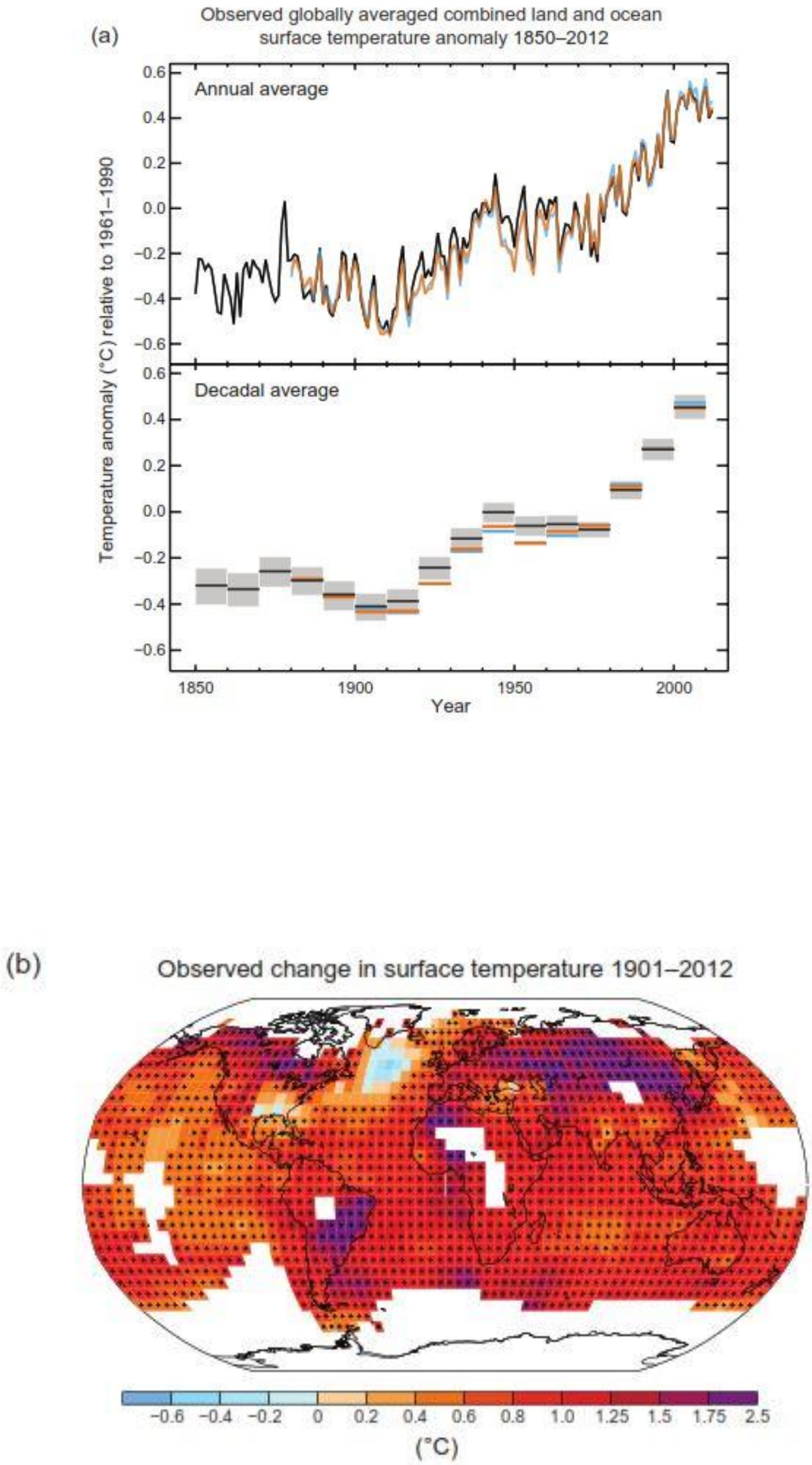

Figure 2. 1 : Observed surface temperature over period of time

According to IPCC 2013 in Summary for Policymakers (SPM), the ocean warming dominates the increase in energy stored in the climate system

2.2 General Circulation Models (GCMs)

GCMs are used to estimate the future climate change resulted from the continuous increment of greenhouse gas concentration in the atmosphere. This method was proposed by Norman Philips in the year 1956 as other alternative for the failed numerical approach. It displays a mathematical model of a planetary atmosphere or ocean. The GCMs and global climate models have been used to the transition of the climate trend affected by the continuous increment of greenhouse gas concentration in the atmosphere. This mathematical model was developed by Norman Philips in year 1956 that could depict monthly and seasonal patterns in the troposphere. GCMs representing physical processes in the atmosphere, ocean, cryosphere and land surface, are the most advanced tools currently available for stimulating the response of the global climate system to increasing greenhouse concentration (Yan, Werners, Ludwig, & Huang, 2015). For projecting the global climate into the future, GCMs are forced to with various scenarios of future greenhouse gas (GHG) emissions (Sachindra & Perera, 2016). However, GCMs have limitation in representing the models due to limitation of resources or input data because the simulation of GCMs at global climate produced coarse spatial resolution in the order of few hundred kilometres.

So, because of the coarse spatial resolution, they cannot adequately simulate the catchment scale climate at the regional or small area, which is largely influenced by the sub grid-scale features such as topography, land use, and convective processes (Tahir et al., 2018). Most of the catchment scale applications need hydroclimatic data at a much finer spatial resolution than that of GCMs outputs. Therefore, to bridge the spatial scale gap between the coarse resolution GCM outputs and the fine resolution hydroclimatic information required for catchment scale applications and at the same time to convert the coarse spatial resolution of the GCMs output into a fine resolution, which may involve the generation of data of a specific area by using GCMs climatic output variables the downscaling techniques is used dynamic and statistical downscaling approaches are used (Nottingham, 2014).

2.2.1 Types of GCMs

The Earth's climate system is incredibly complicated, to begin with, models must portray the physical interactions between the atmosphere, the oceans, land surfaces, and sea ice with respect to a multitude of processes operating on many different space and time scales. Different models have different details in projecting the future climate activity. For example, the atmospheric models (ADMS, AERMOD, ATSTEP etc.), global weather models (FIM, GFS, MPAS etc.), climate models (HadCM3, HadGEM2, CGSM, CanSM2 etc).

Useful climate projections depend on having the most comprehensive and accurate models of the climate system (Hadgem et al., 2011). However, any single model will still have limitations and it is increasingly apparent that we need a range of models to address the variety of applications. The HadGEM2 are models that can address different aspects of the climate projecting problem. MET Office Hadley Centre had adopted a flexible approach to climate modelling based on model "families" of HadGEM2. The members of such family may differ in a number of way: resolution, vertical extend, region (e.g. limited area or global), complexity (e.g. atmosphere-only, coupled atmosphere-ocean, inclusion of earth system feedbacks) (Hadgem et al., 2011). The HadGEM2 model family comprises configurations made by combining model components which facilitate the representation of many different purposes within climate system, as illustrated in **Figure 2.2**. These combinations have different levels of complexity for application to a wide range of science questions, although clearly many of the processes are independent.

The shaded trapezoids illustrate the stages by which the full Earth system configuration can be built. Starting with the Atmosphere-only (A) configuration (with or without a well-resolved stratosphere, S), the addition of ocean and sea ice components constitute the coupled Atmosphere-Ocean configuration, to which the carbon cycle processes can be added to form the coupled Carbon Cycle (CC) configuration, and finally the addition of tropospheric chemistry completes the full Earth System (ES) configuration (Hadgem et al., 2011). **Table 2.1** shows the current HadGEM2 configuration.

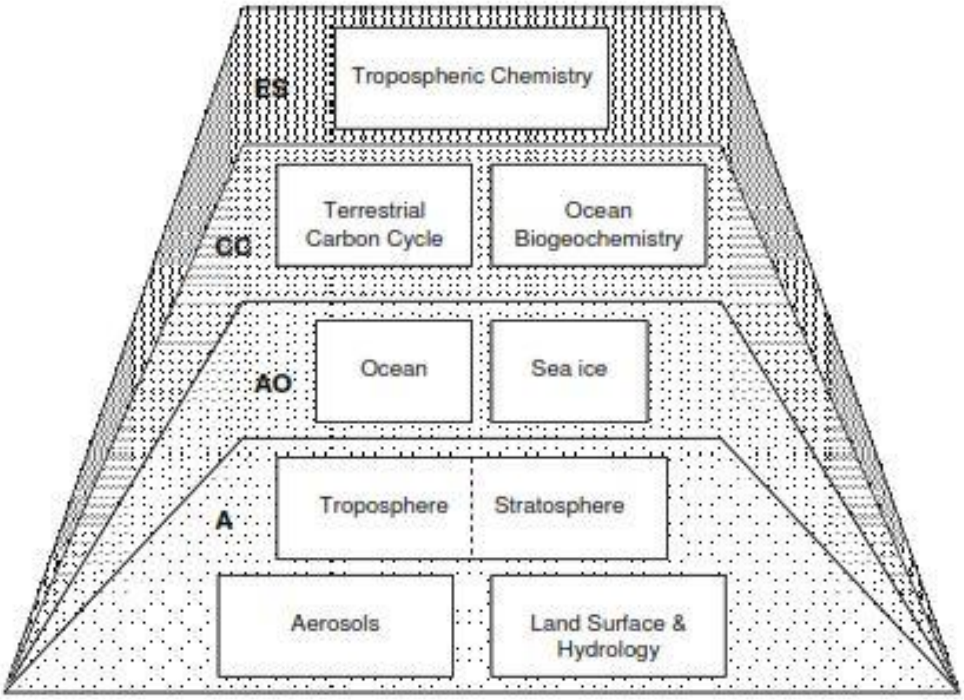

Figure 2. 2 : Processes included in the HadGEM2 model family

Configuration	Process Included
HadGEM2-A	Troposphere, Land Surface & Hydrology, Aerosols
HadGEM2-O	Ocean and Sea-ice
HadGEM2-AO	Troposphere, Land Surface & Hydrology, Aerosols, Ocean & Sea-ice
HadGEM2-CC	Troposphere, Land Surface & Hydrology, Aerosols, Ocean & Sea-ice, Terrestrial Carbon Cycle, Ocean Biogeochemistry
HadGEM2-CCS	Troposphere, Land Surface & Hydrology, Aerosols, Ocean & Sea-ice, Terrestrial Carbon Cycle, Ocean Biogeochemistry, Stratosphere
HadGEM2-ES	Troposphere, Land Surface & Hydrology, Aerosols, Ocean & Sea-ice, Terrestrial Carbon Cycle, Ocean Biogeochemistry, Chemistry

Table 2.1: HadGEM2 configuration

2.2.1.1 HadGEM2 Earth System (ES)

The HadGEM2-ES is used to evaluate the response to historical and projected future greenhouse gas forcing that follow Representative Concentration Pathways (RCP). HadGEM2-ES (Hadgem et al., 2011) is a coupled atmosphere-ocean GCM with interactive land and ocean carbon cycles and dynamic vegetation. The atmospheric resolution is N96(1.875^o x 1.25^o), with 38 levels in the vertical, and the resolution is 1^o (1/3^o at the equator), with 40 levels in the vertical. The experimental setup followed the CMIP5 protocols (Jones et al. 2011.). It has a climate sensitivity estimated at 4.6^{o}C (Andrews et al. 2012a). as already noted, and an estimated transient climate response of 25^{o}C (Andrews et al. 2012b). The simulations comprise a historical period from 1860 to 2005 driven by historical greenhouse gases, aerosols, and natural forcings, including solar and volcanic influences, described in detail in Jones et al. (2011), with the atmospheric CO_2 concentrations shown in **Figure 2.3**.

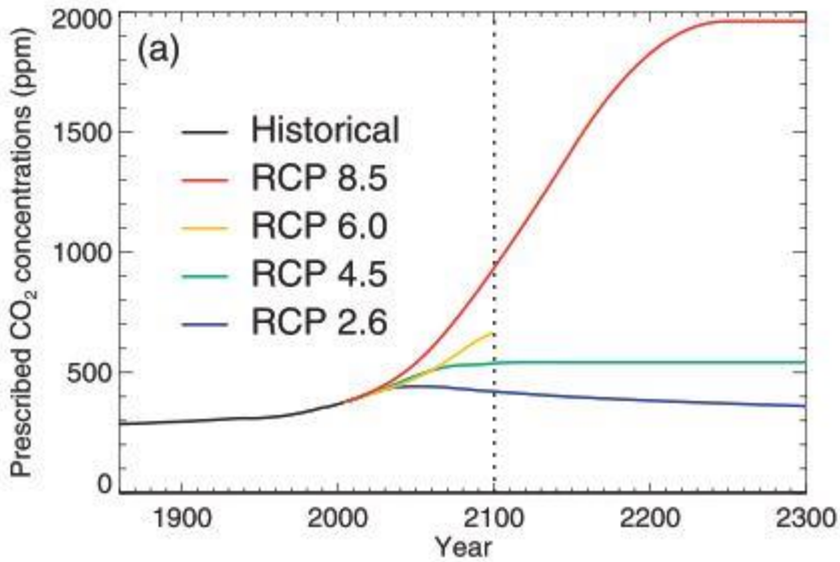

Figure 2. 3: Prescribed CO_2 Concentrations

Figure 2.3 shows the historical simulation and future projections for the RCP scenarios from 1860 to 2300 for a prescribed CO_2 concentration.

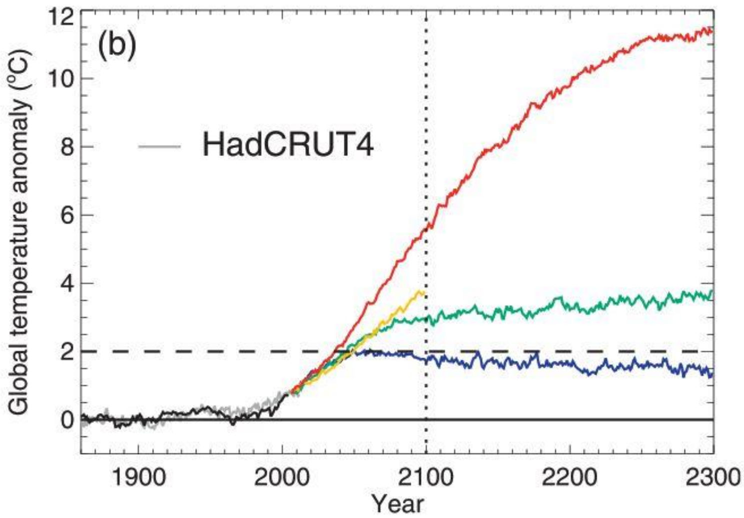

Figure 2. 4: Global Temperature anomaly

Figure 2.4 shows the mean global temperature anomaly relative to 1861-90, with 2^{o}C anomaly represented by the horizontal dashed line and the ensemble median HadCRUT4 (Morice et al. 2012). The graph shows that in the future, with aggressive mitigation under RCP2.6, projected global mean surface air temperature peaks during 2040s (at a level of just over 2^{o}C above preindustrial , defined as 1861-90) and then slowly declines over the following two centuries, remaining below 2^{o}C after 2100 (Al, 2013). These changes are coincident with the graph pattern of gradual reduction of CO_2 concentration as shown in **Figure 2.4.** Under RCP2.4, the temperature anomaly increases to around 3^{o}C above preindustrial during the 2070s and then increases at a slower rate to just below 4^{o}C by 2300. However, under RCP8.5, the largest temperature increase occurred. The temperature anomaly rising above 2^{o}C around the year 2037 and reaching almost 6^{o}C by 2100. The temperature continues increasing and round the mid twenty-second century, the rate of increase begins to decline, again coincident with a reduction in the rate of increase CO_2 concentrations.

2.3 The Downscaling Method for The Local climate Prediction

Downscaling is a method for obtaining high-resolution climate or climate change information from relatively coarse-resolution global climate models (GCMs). Typically, GCMs have a resolution of 150-300 km by 150-300 km. It is important to understand that the downscaling process adds information to the coarse GCM output so that information is more realistic at a finer scale, capturing sub-grid scale contrasts and inhomogeneities (Methods & Projections, 2014).

In the last 20 years, several downscaling techniques have been developed, which were able to reduce the mismatch between spatial and temporal local and coarse scale (Tahir et al., 2018). Downscaling can be performed on spatial and temporal aspects of climate projections. Spatial downscaling refers to the methods used to derive finer-resolution spatial climate information from coarser-resolution GCM output, e.g., 500 kilometres grid cell GCM output to a 20 kilometres resolution, or even a specific location. Many processes that control local climate, e.g., topography, hydrology and vegetation, are not included in coarse-resolution GCMs.

The development of statistical relationship between the local and large scales may include some of these processes implicitly as shown in **Figure 2.5.** Temporal downscaling refers to the derivation of fine-scale temporal information from coarser-scale temporal GCM output (e.g., daily rainfall sequences from monthly or seasonal rainfall amounts). Both approaches detailed below can be used to downscale monthly GCM output to localized daily information. The two sets of techniques that can be used for downscaling were dynamical downscaling (DD) and statistical downscaling (SD). DD involved a nested regional climate model (RCM) while SD involved statistical relationship between the large-scale climatic state and the local variations derived historical data (Hassan and Harun, 2015). SD and DD have their own strength and weakness as shown in **Table 2.2**.

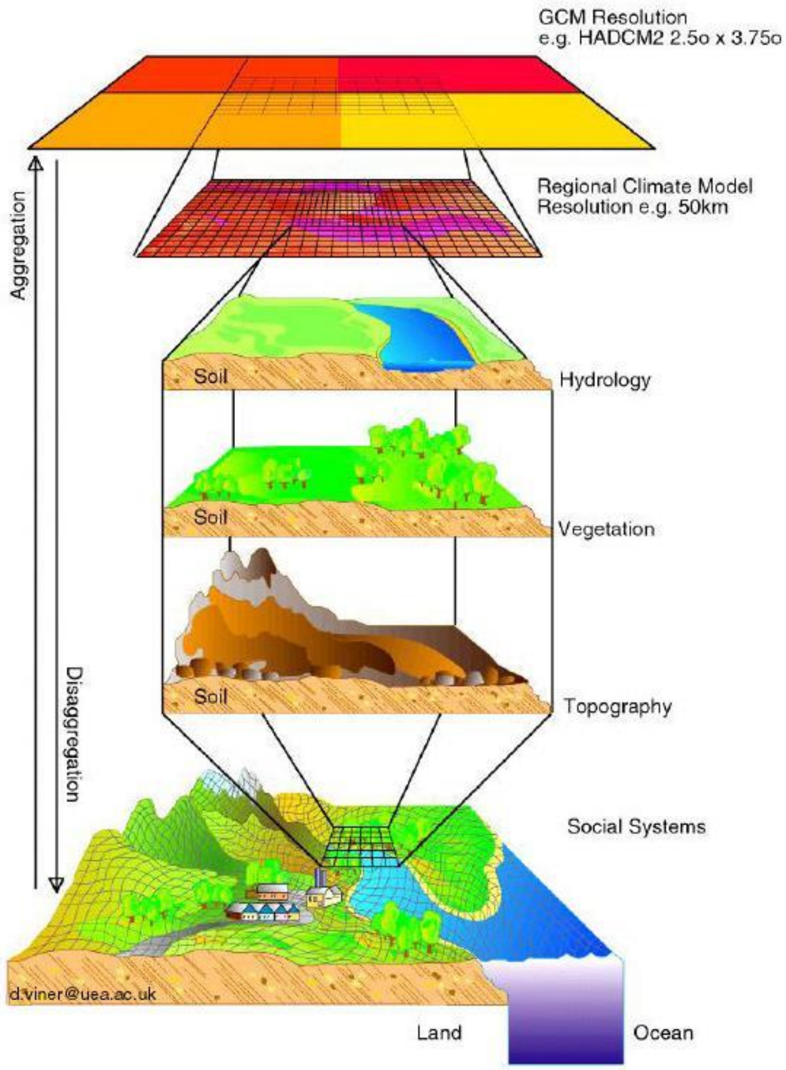

Figure 2. 5: The concept of spatial downscaling

The downscaling climate models is classified into five main groups (Hassan et al., 2014) there are; i) dynamical climate modelling, ii) statistical downscaling, iii) synoptic weather typing, iv) stochastic weather generation and v) regression-based approaches. The description for each group is explained as follow:

2.3.1 Dynamical Downscaling (DD)

Dynamical downscaling relies on the use of a regional climate model (RCM), similar to a GCM in its principles but with high resolution to stimulate regional climate. RCMs take the large-scale atmospheric information supplied by GCM output at the lateral boundaries and incorporate more complex topography, the land-sea contrast, surface heterogeneities, and detailed descriptions of physical processes in order to generate realistic climate information at a spatial resolution of approximately 20–50 kilometres as shown in **Figure 2.6** (Methods & Projections, 2014).

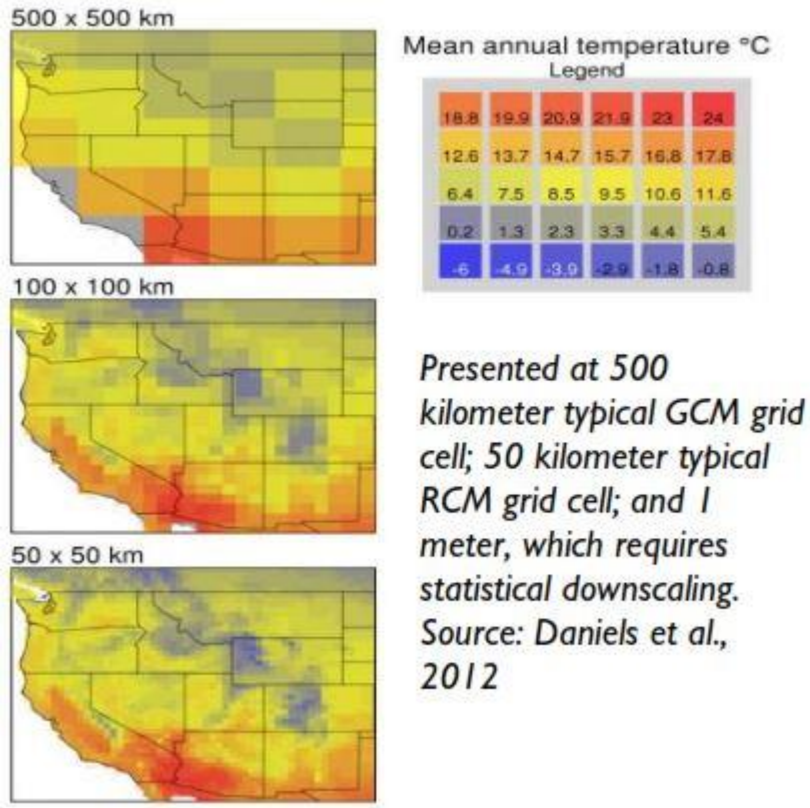

Figure 2. 6: The mean annual temperature (1961 -1990)

The primary advantage of RCMs is their ability to model atmospheric processes and land cover changes explicitly. However, the grid-box size of an RCM is typically greater than 10 kilometres, which is still too coarse for hydrological and agricultural impact studies that require more local- or station-scale climate information (Benestad, 2009). To obtain higher resolution results, statistical methods are used in lieu of RCMs, or RCM output is further downscaled via statistical means. The quality of RCM results depends on the driving GCM information. For example, if the GCM misplaces storm tracks, there will be errors in the RCM’s precipitation climatology (Wilby et al., 2009). Additionally, different RCMs contain distinct dynamical schemes and physical parameters, which means that RCMs driven by the same GCM can produce different results as shown in **Figure 2.7.**

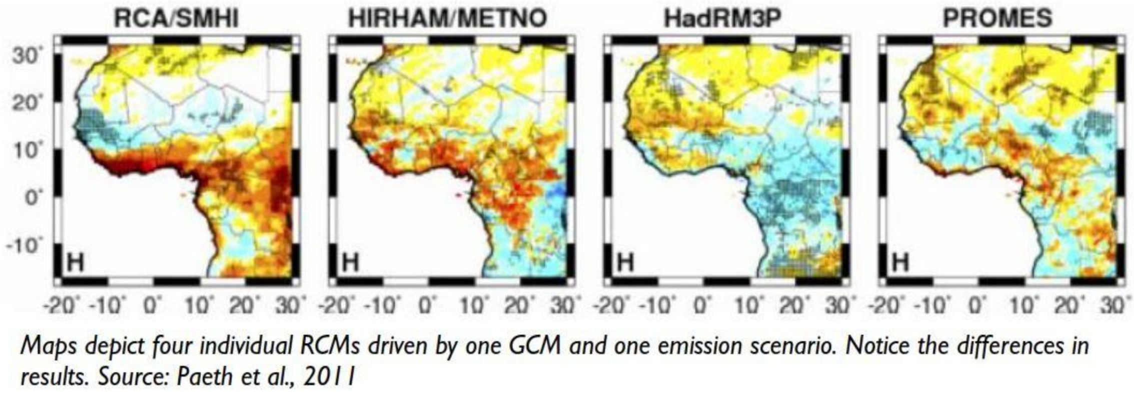

Figure 2. 7: Projected Changes in Annual Precipitation During The 2001-2050 Period

2.3.2 Weather Typing Schemes

Weather typing approaches involve grouping local, meteorological data in relation to current patterns of atmospheric circulation. The observed data distribution will be re-sampling to construct future regional climate. By using Monte Carlo techniques can generate the sequences of weather patterns. It is founded on sensible linkages between climate on the large scale and weather at the local scale is the main appeal of circulation-based downscaling. The technique is also valid for a wide variety environmental variable. However, the weather typing schemes are often parochial and entirely dependent on stationary circulation-to-surface climate relationships. The most serious limitations in weather typing is that the precipitations changes produced by changes in the frequency of weather patterns are seldom consistent with the changes produced by the host GCM unless additional predictors are employed.

Weather typing can be used in a similar manner to transfer function methodology to observe station meteorological data is statistically related to a weather classification scheme. In this case the starting point is the identification of the weather types - this may be by using an objective methodology, or they may be subjectively derived. Once the classification scheme has been selected and the weather types derived, relationships between the type and local weather variables are calculated. For climate change studies, pressure fields from a GCM are used to drive the model. The weather types are calculated based on these pressure fields and the relationships derived using observed data are then implemented to derive site information for, say, temperature and precipitation for some point in the future.

The relationships between weather type and local climate variable will continue to be valid under future radiative forcing. The advantage of weather typing is founded on sensible physical linkages between climate on the large scale and weather on the local scale. The disadvantages of weather typing are the fundamental assumption may have differences in relationship between weather type and local climate have occurred at some sites during the observed record and scenarios produced are relatively insensitive to future climate forcing. Although this method is founded on sensible physical linkages between large-scale climate and local weather, there are some concerns. It has been demonstrated that the fundamental assumption may not be stationary the relationship between weather type and site weather.

2.3.3 Stochastic Weather Generators (WGs)

Stochastic downscaling approaches usually involve in modifying the parameters of conventional weather such as WGEN or LARS-WG. The WGEN model stimulates precipitation occurrence using two-state. Climate change scenarios are generated stochastic using revised parameter sets scaled in direct proportion to the corresponding parameter changes in a GCM. This technique can exactly reproduce many observed climate statistics and has widely used. Besides, the efficient production of large ensembles of scenarios is enabling in stochastic weather generators for risk analysis. But it also has its own disadvantages which are related to the arbitrary manner in precipitation parameters that adjusted for future climate change and need secondary variables to avoid this effect.

The stochastic weather generator is a statistical model of observed weather variables, with those variables generally conditioned on the occurrence of rainfall. It is possible to use stochastic weather generators to downscale large – scale climate by running a weather generator at both the site and area scales. The statistical correlations between climatic variables derived from observed data are assumed to be valid under a changed climate.

The advantages of stochastic weather generator are the ability to generate time series of unlimited length, opportunity to obtain representative weather time series in regions of data sparsity, by interpolating observed data and the ability to alter the WG's parameters in accordance with scenarios of future climate change in variability as well mean changes. This model also has its own disadvantages which is seldom able to describe all aspects of climate accurately especially persistent event, rare events and decadal-or century-scale variations.

2.3.4 Regression Model

Regression-based downscaling method is an empirical relationship between local scale predictands and regional scale predictor(s). To differentiate between linear and non-linear regression, artificial neural networks (ANN), canonical correlation and principal components analyses is used to derive predictor-predictand relationships. The main advantages of regression downscaling is the relative ease of application, coupled with their use of observable trans-scale relationship. The main disadvantages of regression downscaling is the models often explain only a fraction of the observed climate variability. Besides, the downscaling future extreme events using regression methods is problematic since these phenomena, by definition, tend to lie at the limits or beyond the range of the calibration data set.

2.3.5 Statistical Downscaling (SD)

The basic idea of SD is to define a relationship between the large-scale model (either GCM or RCM) and the local climate. SD or also known as empirical downscaling is a tool for downscaling climate information from coarse spatial scales to finer scales. SD methods rely on empirical relationships between local-scale predictands and regional-scale predictors to downscale GCM scenarios. Successful SD is thus dependent on long reliable series of predictors and predictands. 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).

A large number of researches had been done to compare the performance between statistical and dynamical climate model. **Table 2.2** shows the advantages and weakness of each climate model.

SD		DD
1. SD methods are computationally inexpensive 2. Climate information from GCM in station scale-scale station 3. Applicable to unusual predictand	Strength	1. Climate information from GCM in 10-50 km range 2. Physically respond in consistent way to different external forcing 3. Resolve atmospheric process consistency with GCM
1. Requires highly quality data for model calibration 2. Predictor-predictand relationships are often non-stationary 3. Successful statistical downscaling depends on long, reliable, observational series of predictors and predictand	Weaknesses	1. Requires significant computing resources 2. Depends on boundary conditions supply from some other sources 3. The dynamical downscaling model may miss the most extreme data

Table 2.2: HadGEM2 configuration

Statistical downscaling (SD) is easier to be used because it focuses on its station scale while dynamical downscaling (DD) has a range between 10-50km resolutions. Besides, the SD use computational understanding compared to DD. DD is difficult to be used because it is a combination of climate scenarios that seldom produce due to the climate is always change from time to time while SD have ensembles of climate scenarios permit risk. SD also readily to be transferable to new regions or domains contrast to DD which is not readily to be transferred to new regions or domains. Even though, DD is consistence with GCM, but the result does not always feedback into the host GCM because typically applied online compare to SD computationally undemanding.

2.3.5.1 Statistical Downscaling Model (SDSM)

SDSM is introduced by Wilby et al. (2002). SDSM is a software to Downscaling Global Climate Model (GCMs) and it is coded in Visual Basic 6.0 (Hassan et al., 2015). It is built up the relationship between the GCMs variables that known as predictors and the local-scale variables known as predictands. The data of GCM will be downscaling in SDSM using multiple linear regressions by daily predicator-predictand relationships. The predictor variable describes the daily information in the large-scale state of the atmosphere, while the predictand provides the condition at the site scale. In SDSM the parameter of the regression equation is estimated using an ordinary Least Squares algorithm. The local rainfall is classified as the conditional process because the local weather is correlated with the occurrence of wet days. The fourth root transformation is applied to the original series as the distribution of precipitation is skewed to convert it to the normal distribution, and then used in the regression analysis. Temperature is modelled as the unconditional process, where a direct link is assumed between the large-scale predictors and local scale predictand.

SDSM are divided into three major methods, which are; i) regression models, ii) stochastic weather generator and iii) weather typing schemes. In this study, it is focused on one downscaling method which is regression model. The SDSM model is a popular statistical downscaling model to downscale the GCMs model. Therefore, many recent studies focused on the ability to stimulate the mean and extreme rainfall frequency using parametric distribution at a watershed scale.

A large number of researches had been done to compare the performance between SDSM model with others model. **Table 2.3** shows the comparison of SDSM model with the other model that have made by past researchers.

Table 2.3: Comparison of SDSM with another model

Author	Comparison
Gagnon et al, 2013	Comparison between SSARR and SDSM in three river basinslocated in the province of Québec: Vermillon, Sainte- Marguerite and Grande-Baleine. Results show that SDSM provides adequate downscaled temperature and precipitation data using observed current climate (NCEP predictors).
Hua Chen et al, 2012	SSVM and SDSM was used as hydrological models toperformed in upper Hanjiang basin in China. It is proved that SDSM has better performance than SSVM in simulating rainfall in the calibration and validation periods.
Jing Zhou, 2015	Integrated SWAT and SDSM was used for estimating streamflow response to climate change in Lake Dianchi watershed, China. Based on result, SDSM capture the statistical relationships between the large-scale climate variables and the observed weather at the regional scale, except less satisfactory with maximum monthly precipitation compared to SWAT.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The main aim of this study is to study the future climate trend at local state in Malaysia in interval year of 2020, 2050, and 2080 and to identify the best RCPs and GCM group for Melaka and Negeri Sembilan states using the popular SDSM. The SDSM model is used to generate the climate trend for the future. Currently, an annual temperature of 32ºC per year. In this research, the selected station of rainfall and temperature in Melaka and Negeri Sembilan were selected as the case study. The framework of this study consists of four steps, which are : 1) download and screen the GCM data for under different scenarios which are HadGEM2-A, HadGEM2-CC, HadGEM-ES and CanESM2. 2) downscale the GCM data using the SDSM. 3) calibrate and validate the SDSM with the observed data and 4) project the future rainfall and temperature. In this following section, the study area, data and models, method are described.

There were seven steps of SDSM which are 1. Quality control and transformation, 2. Screening of predictor variables, 3. Model calibration, 4. Weather Generator, 5. Statistical analysis 6. Graphing model output and 7. Scenario generation. The function of quality control identifies gross data error, outline prior to model calibration and specification of missing data codes, therefore transformation function will be applied to the selected transformations for selected data files because for practical situations, handling of missing and imperfect data is necessary. Screening of predictor variables is identifying relationships between the predictors and predictand is important to all statistical downscaling methods. In selecting the appropriate downscaling predictor variables, screen variable can assist it. Next, model calibration takes user-specified along with the set of predictors and estimates the parameter of multiple regression equation through an optimization algorithm by either ordinary least square method or dual simple. Before proceeding to the next step, it is needed to specify the model structure whether monthly, seasonal or annual sub-models and whether the process is unconditional or conditional. Direct link is assumed between the predictors and predictand in unconditional models while in conditional model, there is an intermediate process between regional forcing and local weather. Weather generator ensembles of synthetic daily weather series given observed (or NCEP re-analysis) atmospheric predictor variables where this procedure enables the verification of calibrated models and synthesis of artificial time series for present climate conditions. Statistical analysis provides means of interrogating both downscaled scenarios and observed climate data with summary statistics and frequency analysis that will allow user to specify the outputfile name, sub-period and chosen statistics. The graphing model is the procedure of analysing the data using the graphical method, comparing the results and time series analysis. The operation of produces ensembles of synthetic daily weather variables given atmospheric predictor variables supplied by a climate model rather than observed predictors known as scenario generation. In this research rainfall and temperature data besides the GCM group are needed for climate modelling in three type of scenarios. These were used in SDSM to project the climate in year 2020, 2050, and 2080. Hence, the best RCP determined in climate analysis. Figure 3.1 shows the schematic diagram of methodology of the study.

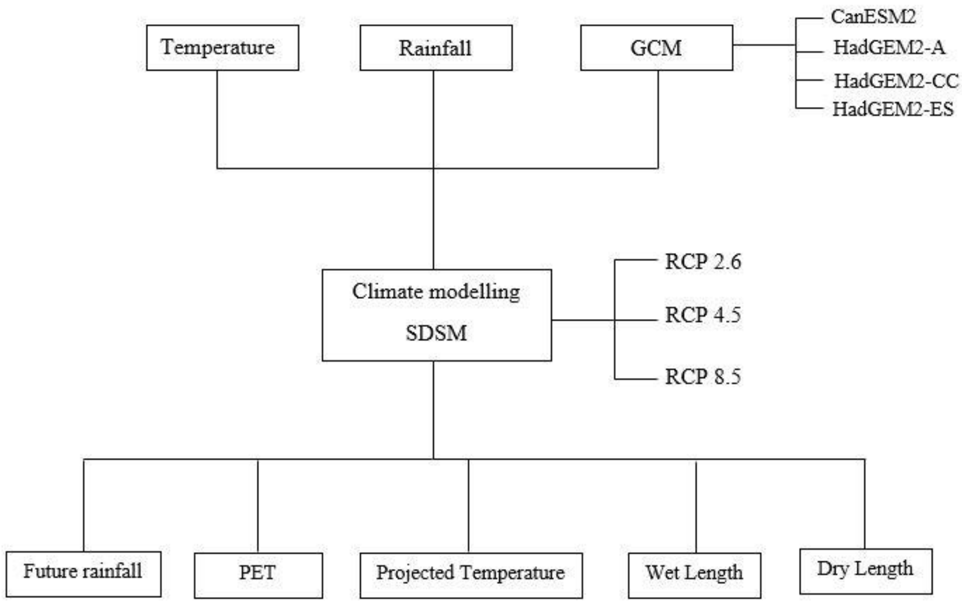

Figure 3. 1: The schematic diagram of methodology of the study.

3.2 Statistical Downscaling Modelling (SDSM)

SDSM 4.2 is one of the downscaling models that applied linear regression analysis to interpret the relationship between GCMs characteristics with local climate records. The daily local precipitation and temperature data are required for generating the future climate trend during interval year 2020, 2050, and 2080 based on the emission level in the region. SDSM 4.2 facilitates the rapid development of multiple, low cost, single size scenarios of daily surface weather variables under present and future climate forcing. This model is widely used in the hydrological issue due to various climate scenarios. This is because, this model provides station scale climate information from the grid resolution GCM-scale outputs using multiple regression techniques. Its build up the relationship between GCM's variable which is predictors and the local scale variable acts as predictand (Chu et al,. 2010).

SDSM is categorized as a hybrid model which utilized a linear regression method and a stochastic weather generator. The SDSM method consists of two steps. The first step determines whether rainfall occurs on each day or not and the second step is to determine the estimated value of rainfall on each rainy day. Rainfall is a condition process, and it is modelled using stochastic weather generator conditioned based on the chosen predictor. The large-scale predictors for the meteorological prediction employing the SDSM model used in this study based on the outputs from the NCEP reanalysis for calibration, as well as HadGEM2 for future generation.

The SDSM model implies that the statistical relationship to downscale the large-scale resolution of GCMs denoted as predictors into the local climate variables known as predictand. It allowed the raw data to transform into standard predictor variables to produce nonlinear regression models before applying the calibration and validation. The data series can also be shifted forward or backward by any number of time steps to produce lagged predictor variables.

Figure 3.1 illustrates the methodology of SDSM model. To downscale the local climate change two types of data are required and those included the rainfall and temperature stations known as predictand and two sets of predictors. In this study, temperature recorded at Melaka station and historical rainfall at several stations at Melaka and Negeri Sembilan states were used as predictand. The lesser percentage of missing data is considered during selection of rainfall station in order to control the quality and originality of data set. These data were presented in daily time series and were converted into month and annual period for the analysis purposes. The predictors set were provided by National Centre for Environment Prediction (NCEP) reanalysis data to be used for calibration and validation process and GCMs-variables to generate the future climate trend based on the expected increment of greenhouse gases at the region.

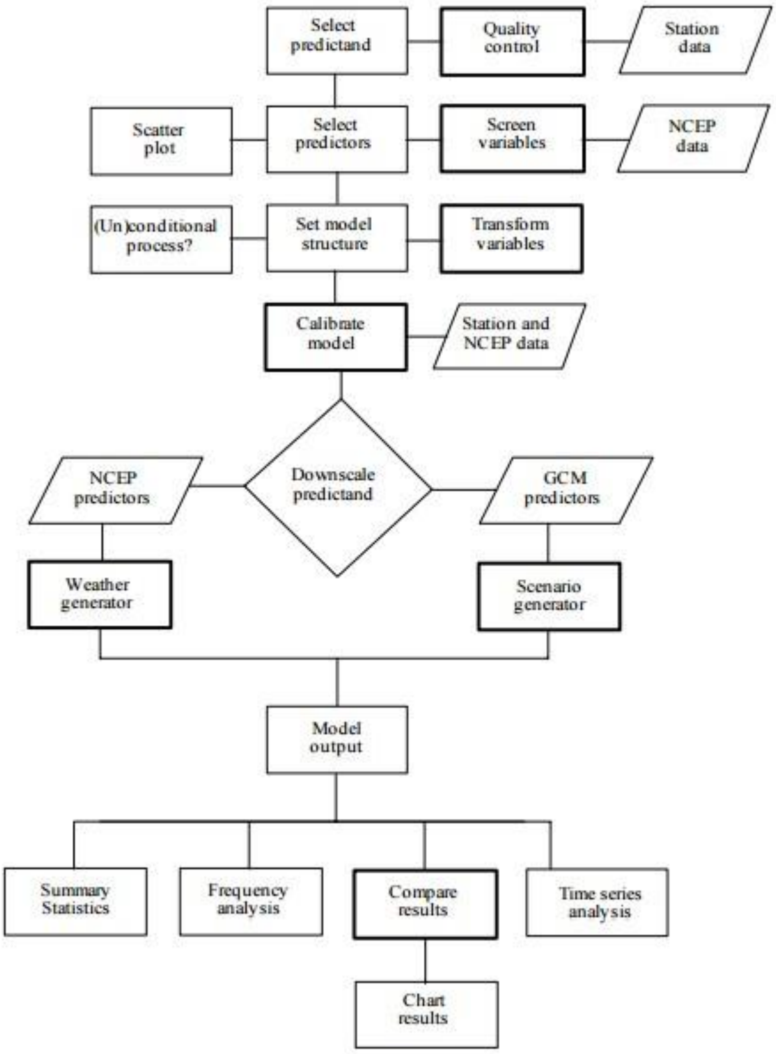

Figure 3. 2: Schematic diagram of SDSM

3.2.1 Selection of Predictors

One of the major challenges on climate downscaling extreme rainfall is the selection of appropriate predictors. It is expected that predictors should be highly correlated with extreme rainfall indices. Furthermore, the predictors should be accurately projected by available GCMs for the future projection climate. There are no general guidelines for the selectin of predictors in different parts of the world, therefore a comprehensive search of predictors is necessary. There are 26 NCEP variables that are usually projected by various climate models, including the Hadley Centre Climate Model (HadCM) were used ini the present study for the selection of predictors. The description of 26 NCEP various is given in Table 3.1.

The climate system is influenced by the combined actions of multiple atmospheric variables in a wide tempo-spatial space. Any single circulation predictor and small tempo-spatial space are unlikely to be sufficient for climate projection, as they fail to capture key rainfall mechanism based on thermodynamics and vapour content. The regional synoptic circulation patterns that contributed to the anomalous rainfall pattern in Malaysia were considered in the selection of the spatial domain of each predictor, represented as 42 grid points surrounding the study area.

All 26 daily NCEP variables at one NCEP grid points surrounding the study area were individually correlated with local extreme rainfall events. The correlation coefficient was used to measure the degree of association between NCEP variables and local extreme rainfall events. Finally, the NCEP variables that have strong correlation with a particular rainfall station were used for the selection of the final set of predictors through stepwise regression processes to downscale the corresponding rainfall event at that station.

No	Predictor Variable	Predictor Description	No	Predictor Variable	Predictor Description
1	mslp	mean sea level pressure	14	p5zh	500 hpa divergence
2	p_f	surface air flow strength	15	p8_f	850 hpa airflow strength
3	p_u	surface zonal velocity	16	p8_u	850 hpa zonal velocity
4	p_v	surface meridional velocity	17	p8_v	850 hpa meridional velocity
5	p_z	surface vorticity	18	p8_z	850 hpa vorticity
6	p_th	surface wind direction	19	p850	850 hpa geopotential height
7	p_zh	surface divergence	20	p8th	850 hpa wind direction
8	p5_f	500 hpa airflow strength	21	p8zh	850 hpa divergence
9	p5_u	500 hpa zonal velocity	22	p500	relative humidity at 500 hpa
10	p5_v	500 hpa meridional velocity	23	p850	relative humidity at 850 hpa
11	p5_z	500 hpa vorticity	24	rhum	near surface relative humidity
12	p500	500 hpa geopotential height	25	shum	surface specific humidity
13	p5th	500 hpa wind direction	26	temp	mean temperature at 2m

Table 3.1: List of Predictors

3.2.2 Calibration & Validation Process in SDSM

Before performing the analysis, first performed calibration between runoff and rainfall that occurred in the Liliba Watershed in the city of Kupang and surrounding areas, so that the results of the analysis are expected to be like the real situation. From. (Sidharno, 2016).The calibration and validation in SDSM are important procedure during projecting climate. The mathematical equation from Croarkin and Tobias (2012) the calibration is a process that measures the assigned values to the property of the artifact or the response of a in instrument relative to reference standards or to designate measurement process. The calibration precisely referred to the design/build among local data and the selected regional atmospheric variables based on multiple regression equations (Wilby and Dawson, 2007). The calibration was formulated using specific period as the basis to estimate the combination of predictor variable values in validation process. The main objective is to know the fundamental rules and the predictand-predictor relationship that is adequate to be as an original data.

The calibration and validation model is constructed from multiple screening processes aimed at determining the best predictors that corresponds towards the climate trend of the area. the calibration and validation must not exceed an error amount of more than 20% when compared with the historical data obtained. This is to avoid and mitigate the inaccuracy of predictors as a different graph of calibration and validation would project a different projection when compared with the historical projection hence making the projection unusable for the research purposes.

The calibrated model is used to build the predictand-predictor relationships in the analysis of SDSM. The relationships are used to stimulated and generated synthetic daily weather series by using weather generator. Therefore, the temperature is calibrated for the time period from 19XX-20XX which is the same for the calibration for the rainfall. By using the same GCM predictors variables in the calibration, the ensembles of synthetic daily weather series during the years are generated using scenario generator in the SDSM model.

After the calibration and validation of the model constructed with the screened predictors, the model is made sure to not have error percentage more than 20. The model which fulfil the criteria would be further processed within SDSM model in order to project the climate of the area. then the projected climate is compared with historical data to account the differences in temperature and rainfall of the area.

3.2.3 Location of Study Area

The location of study area is at Melaka and Negeri Sembilan states. In Malaysia, the climate is hot and humid, so the expected weather is to be either sunny or rain and since Malaysia is also influenced by the Monsoon thus making most parts of Malaysia receiving heavy downpour (Wang et. al, 2003; Kale and Hire, 2004; Sultan et. al. 2005; Colin et. al.;2010, Pai and Al-Tabba, 2010; Pattanaik and Rajeevan, 2010). The inter annual monsoon variations can be shown in the variation of climate that was present in the year to year variation of climate of the seasonal transition. Since Malaysia was a hot and humid country, the climate is mainly affected by the four seasons that happen across the world.

Both Melaka and Negeri Sembilan are located near to the South China Sea. Therefore, the climate of these two areas are influenced by the northeast monsoon wind flow pattern. The monsoon season is from November to March, which is also known as the wet season of these two states. With the country developing at a fast rate and the monsoon sweeping over 1/3 of the total months in a year, the temperature and the rainfall of the area should be affected by the amount of development that is currently ongoing. By referring to data that were historical, the rainfall distribution stations were not uniform but the rainfall pattern was similar throughout these two counties. Making it easier to get a hold of the circulation models with the rainfall data set.

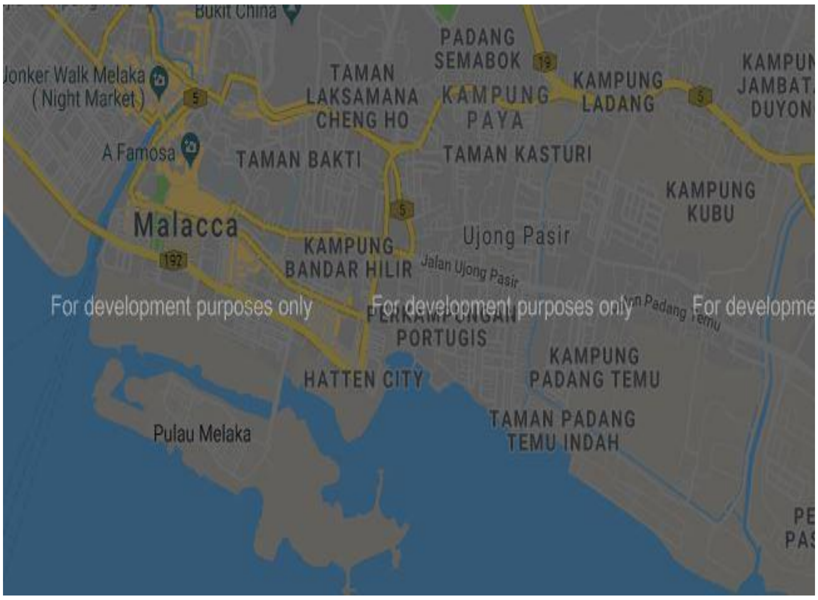

Figure 3. 3: Location of Melaka

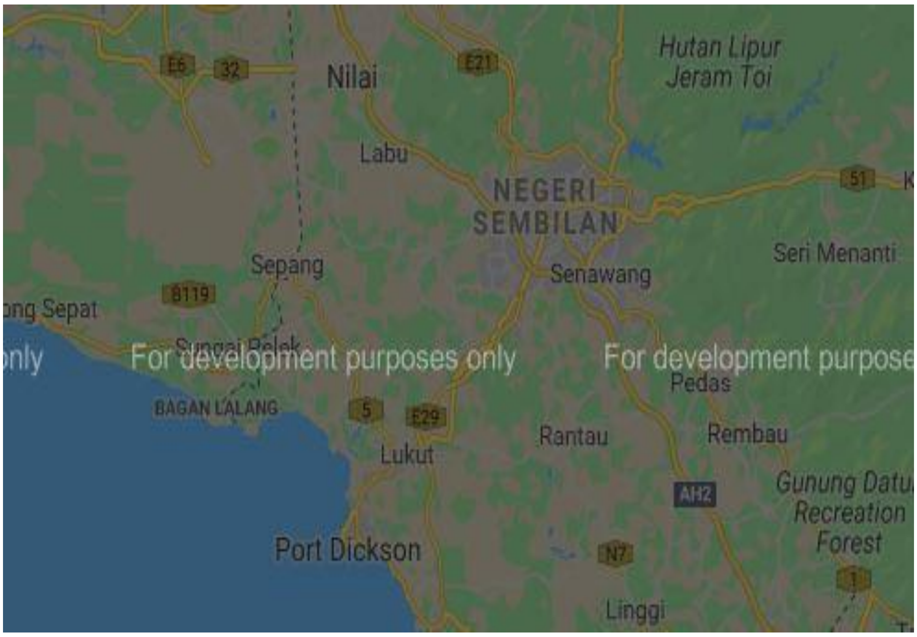

Figure 3. 4: Location of Negeri Sembilan

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The results of the study are presented and discussed in three main parts there are:

i. The selection of predictors in Statistical Downscaling Model (SDSM)

ii. Analysis of best RCP in the region

iii. Projection of future trend of hydrological variable which are rainfall and temperature in the year interval 2020, 2050, and 2080.

In this study, the historical years for temperature (1984 – 2013) and rainfall (2007-2016) determine the changes trend of climate in the year 2010 – 2099. The SDSM model was applied to generate the change of climate trend which considered the Green House Gases.

4.2 Selected Predictor Variables

In selecting the predictor variables, the screening process in the SDSM model was applied to calculate the correlation coefficient (partial r) value to measure the predictors-predictand relationship following by preliminary analysis of predictor-predictand performances. The purpose of the screening process is to assist in the choice of appropriate downscaling predictor variables for model calibration. The selected predictors are primary important to ensure the accuracy and reliability of projected rainfall and temperature. Based on the results, 5 predictors for rainfall variable and 3 predictors for temperature variable were selected to be used in the simulation of SDSM model based on local climate change characteristics.

The local predictand was calibrated (2007 - 2011 for rainfall and 1984 – 1998 for temperature) and validated (2012 – 2016 for rainfall and 1999 – 2013 for temperature) with the selected NCEP predictors previously after the screening variable process to evaluate the simulated result compared to the historical data. The GCM predictors were used to generate the daily weather series using equal NCEP predictor variables for the future year.

4.2.1 Temperature Simulation

The simulation of temperature data refers to the meteorological station at Bandaraya Melaka. It is assumed that the recorded temperature at Melaka station could represent the temperature trend for Melaka state. As mentioned previously, the predictors selection was based on the correlation evaluation among predictor – predictand relationship. The temperature data is correlated to the atmospheric characteristics and hence the selection of predictor for temperature is easy to be done.

There are five predictors that have been selected for temperature trends at Melaka which are 500 hpa geopotential height (*p_500),* surface specific humidity (*shum)* and mean temperature at 2m (*temp).* The geopotential height of the 500 hpa shows approximately the actual height of a pressure surface above mean sea-level. Therefore, the geopotential height observation represents the height of the pressure surface on which of the observation was taken. Surface specific humidity is the ratio of the masse of water vapor to the masse of water vapor and dry air. It is to describe the moist air at the surface.

Table 4.1: Performances of calibrated and validated results for temperature using SDSM model

	Maximum		Mean		Minimum	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
r	0.976	0.951	0.981	0.960	0.977	0.953
% Error	0.386	0.405	0.613	0.645	1.401	1.351

The performances of calibration and validation results were presented in Table 4.1 which consist of correlation coefficient (r) and percentage of error (% Error). Based on the results, the % Error values were slightly small in the whole analysis ranged from 0.0 to 10.0 %. The error of calibrated and validated for minimum temperature recorded the highest among the maximum and mean temperature. The correlation values in the calibrated and validated results for maximum, mean and minimum temperature are higher with closer to 1.0. It indicates a strong correlation, that the calibrated and validated values were in good results compared to historical records.

Figure 4.1 to 4.3 shows the simulated results produced calibration (1984 – 1998) and validation (1999 – 2013) processes using predictors set from NCEP for three conditions which are maximum, mean and minimum temperature. The constant predictors were used to project the future temperature trend in the same grid box provided by CanESM2.

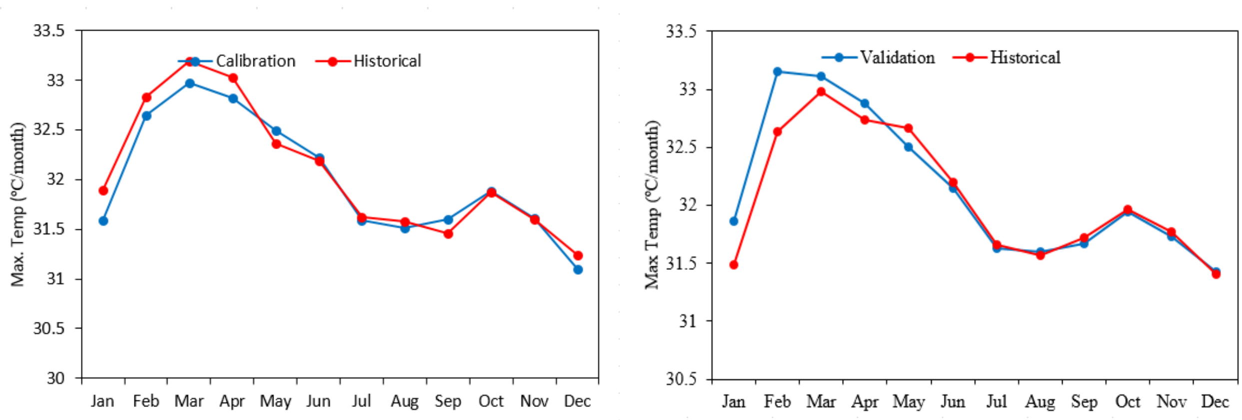

Figure 4. 1: Calibrated and validated result for Maximum Temperature at Melaka using SDSM model

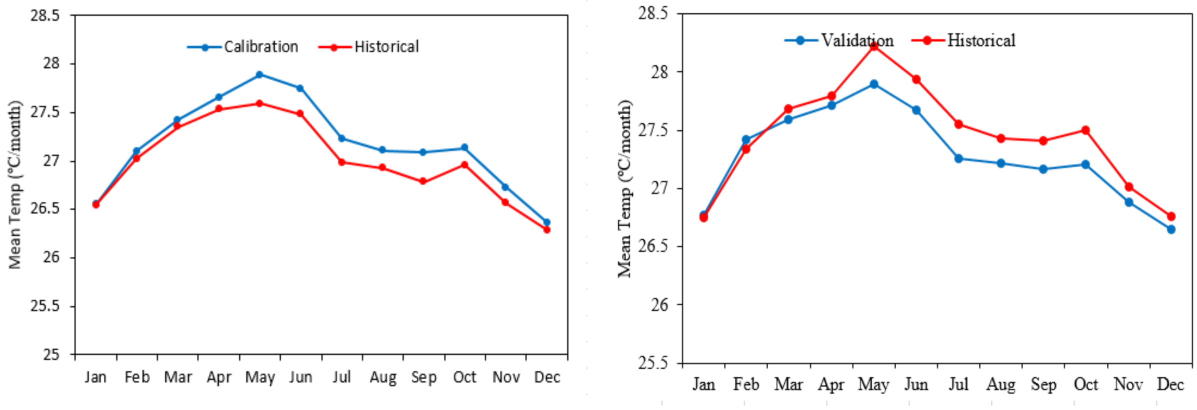

Figure 4. 2: Calibrated and validated result for Mean Temperature at Bandaraya Melaka using SDSM model

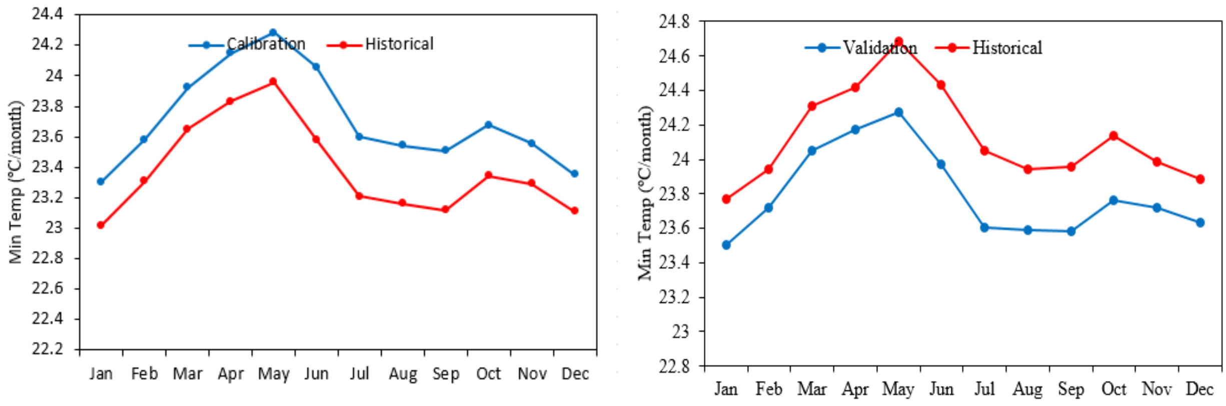

Figure 4. 3: Calibrated and validated result for Minimum Temperature at Bandaraya Melaka using SDSM model

4.2.2 Rainfall Simulation

In the rainfall simulation, two states were chosen as study of area to predict the rainfall trend which are Melaka state and Negeri Sembilan state. Three stations were chosen from each state. Station 1 to Station 3 for Melaka states are Ranc. Taliair Telok Rimba, Pintu Pasang Surut Duyong and Ladang Sing Lian Di Bhg. Garing respectively. While Station 1 to Station 3 for Negeri Sembilan are Politeknik Port Dickson, JPS Tampin, and Kg. Chennah. The analysis started with the selection of predictors using correlation relationship in the screening process. Then, the calibration and validation process were conducted to examine the performance of the model using predictor selection and the rainfall station. The GCMs predictors were used to project the local climate trend in the future year 2010-2099. This process considers the future potential level of greenhouse gases.

4.2.2.1 Predictors selection

The selection of predictors is important to calibrate the model as it will develop the predictand – predictor relationship to obtain the analysis result and for evaluation performances purposes. In this study, 10 years observed historical datasets of 2007 – 2016 were used where the first five years (2007 – 2011) were used for calibration and the remaining five years (2012 – 2016) were used for validation purposes. Before performing the calibration process, predictor variables from NCEP data were selected through a screening process in SDSM using the values of the explained variances and scatter plots in the predictand – predictor relationship.

Five out of 26 predictors were selected for each station at Melaka and Negeri Sembilan states. Table 4.2 shows the station of each states and their respective predictors selection. Note that, for Melaka state, the predictors for stations Pintu Pasang Surut Duyong and Ldg Sing Lian di Bhg Garing are same and only station Ranc. Taliair Telok Rimba have different predictors. While for Negeri Sembilan state, all stations have similar predictors. The predictors selection are affected by the climate change and location of studies.

Table 4.2: Predictors selection on each station for Melaka and Negeri Sembilan states

States	Station	Predictors
Melaka	2125002 Ranc. Taliair Telok Rimba	1. mslp 2. p50 3. p850 4.shum 5.temp
	2223023 Pintu Pasang Surut Duyong	1. p_f 2.r500 3. r850 4. shum 5. temp
	2323007 Ldg Sing Lian di Bhg Garing	1. p_f 2. r500 3. r850 4. shum 5. temp
Negeri Sembilan	2418034 Politeknik Port Dickson	1. mslp 2. p_f 3. r500 4. r850

	5. shum
2422062 JPS Tampin	1. mslp 2. p_f 3. r500 4. r850 5. shum
3020016 Kg. Chennah	1. mslp 2. p_f 3. r500 4. r850 5. shum

4.2.2.2 Result of Calibration and Validation Processes for Rainfall

In this study, 10 years of historical observed data were divided into two period of times, for calibration (2007 – 2011) and validation (2012 – 2016). After the model was calibrated, the validation process must be performed. The model structures of calibration have been categorized as condition for rainfall. Table 4.3 and Table 4.4 shows the performances of calibrated and validated results for each station at both states.

Table 4.3 consist of correlation coefficient (r) and percentage (% Error). Based on the result, the % Error values were small for station 2 and 3 ranging from 0.00 to 20.00% but for station 1, the % Error is higher than 20.00%. This is due to the selection of predictors. The NCEP data for Melaka at Grid box 2.5 North and 102.5 East only has nine predictors available which are mslp, p_f, p500, p850, r500, r850, rhum, shum, and temp. The remaining 17 predictors have missing data. The chances to have the suitable predictors at Station 1 is decreased since only nine predictors were available. The correlation value for all stations were close to 1.0 indicating a strong correlation which means the calibrated and validated values were in good result compared to historical records.

Table 4.4 shows the performances of calibrated and validated results for rainfall at Negeri Sembilan. The % Error for all stations were below 20%. The correlation coefficient (r) value for all stations were closer to 1.0 indicating a strong correlation which means the calibrated and validated values were in good result compared to historical records.

Table 4.3: Performances of calibrated and validated results for rainfall at Melaka using SDSM model

	Station 1		**Station 2**		**Station 3**	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
r	0.847	0.767	0.906	0.963	0.934	0.955
% Error	25.949	24.322	9.472	9.720	11.515	10.706

Table 4.4: Performances of calibrated and validated results for rainfall at Negeri Sembilan using SDSM model

	Station 1		**Station 2**		**Station 3**	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
r	0.933	0.978	0.968	0.978	0.956	0.961
% Error	11.160	12.579	5.239	7.706	12.944	10.803

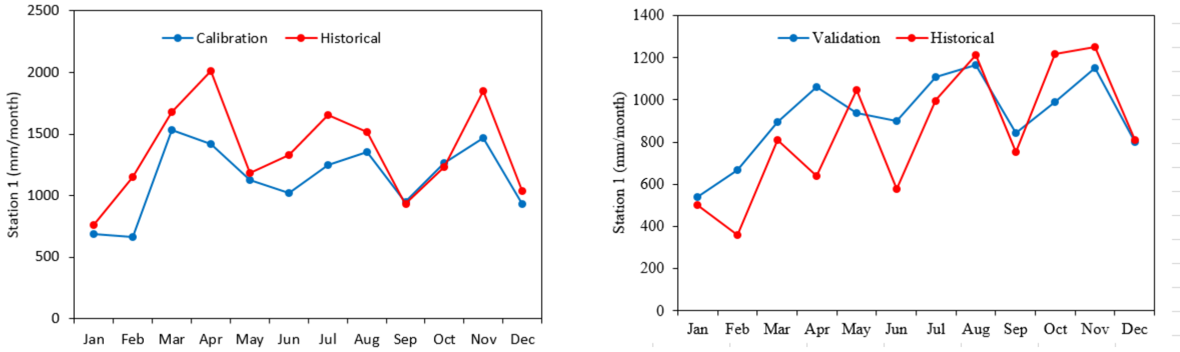

Figure 4. 4: Calibrated and Validated result for Station 1 at Melaka

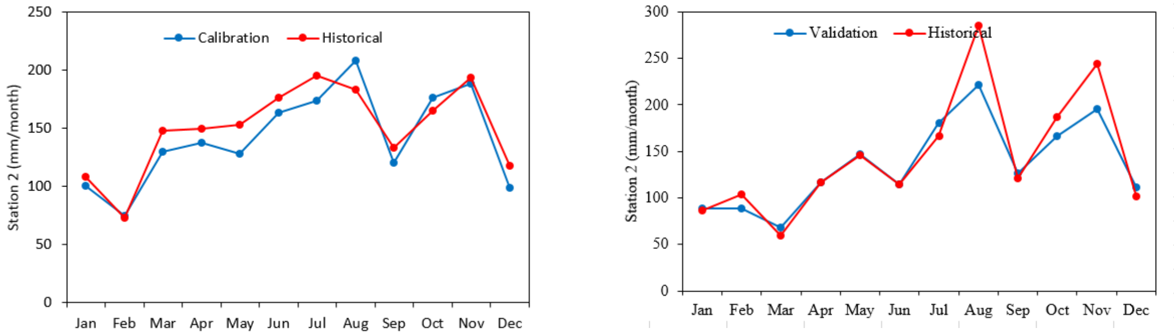

Figure 4. 5: Calibrated and Validated result for Station 2 at Melaka

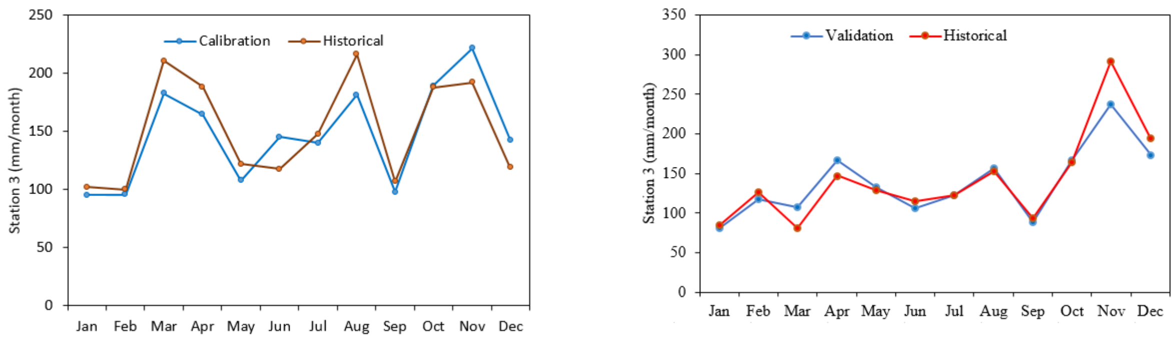

Figure 4. 6: Calibrated and Validated result for Station 3 at Melaka

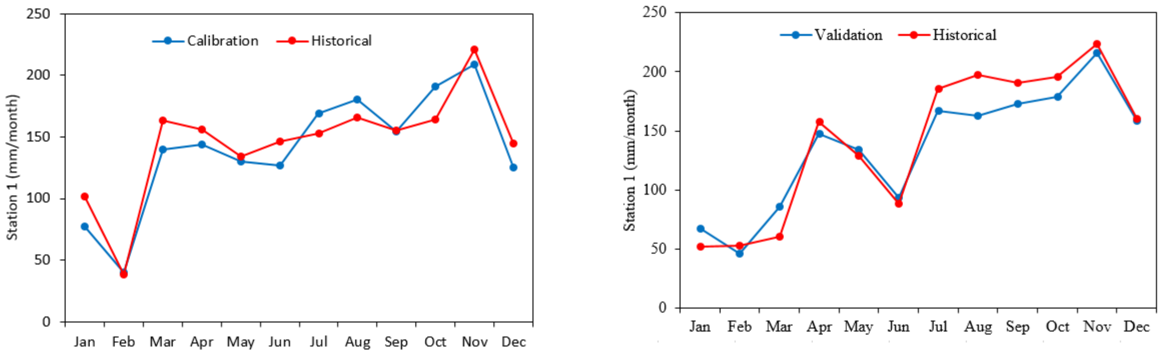

Figure 4. 7: Calibrated and Validated result for Station 1 at Negeri Sembilan

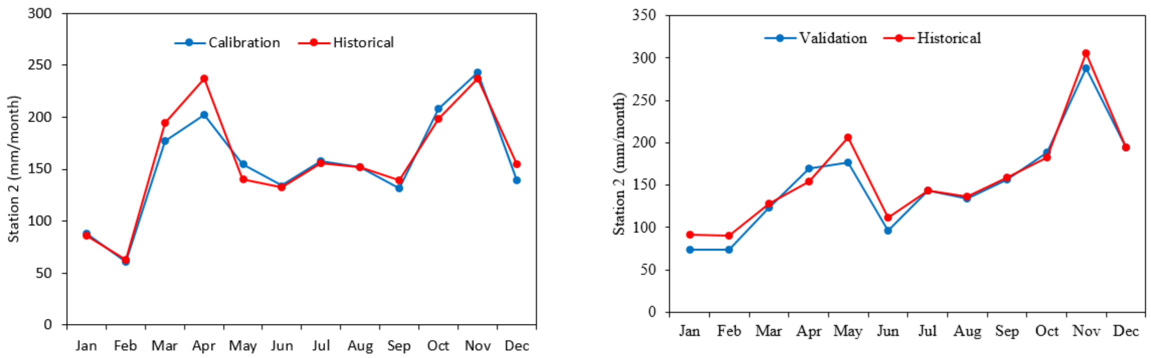

Figure 4. 8: Calibrated and Validated result for Station 2 at Negeri Sembilan

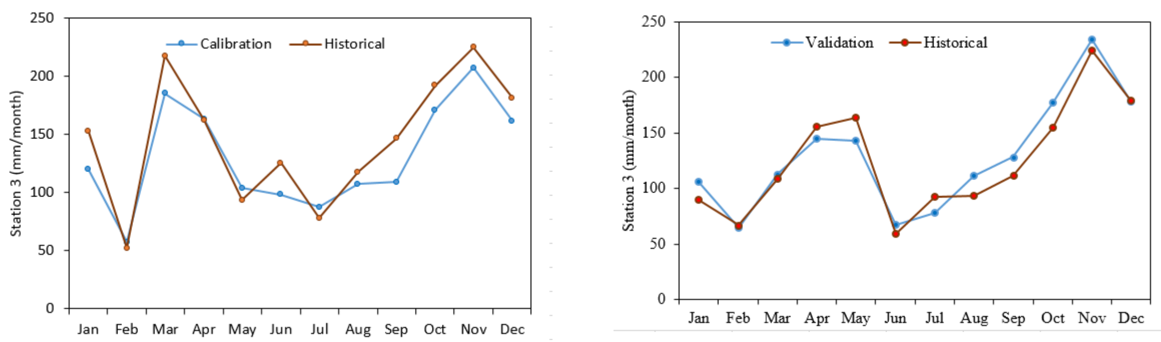

Figure 4. 9: Calibrated and Validated result for Station 3 at Negeri Sembilan

Figure 4.4 to 4.6 shows the calibrated and validated result for Station 1 to Station 3 in Melaka state. The calibration and validation result have the same trend with historical data. Although Station 1 as shown in Figure 4.4 shows a huge difference between calibration and historical data in April, but generally, it has the same pattern and it was still in good result since the correlation coefficient value (r) is close to 1.0 as shown in Table 4.3, which indicates, there are strong relationship between predictors chosen and the predictand.

Figure 4.7 to 4.9 shows the calibrated and validated result for Station 1 to Station 3 in Negeri Sembilan state. The calibration and validation result have the same trend with historical data and the performances of calibration and validation shows the correlation value (r) was closer to 1.0 which means there are strong relationship between predictors chosen and the predictand.

4.3 Analysis of Best RCP

Under CanESM2 model, three different scenarios RCP 2.6, RCP 4.5 and RCP8.5 which were modelled in the SDSM were carried out to find out the future temperature and rainfall under various carbon emissions. To determine which was the best RCP for each station, the value was considered. The historical temperature data as provided in CanESM2 model for three RCPs and the GCM data chosen for analysis were in year 2006 – 2013, where the historical data as a predictand and GCM data as predictors.

Table 4.5 shows the analysis of best RCP based on the %MAE. The %MAE for RCP 2.6 recorded the lowest for maximum temperature and minimum temperature which is 0.382 and 0.228 respectively. For RCP 4.5, the lowest is mean temperature with 0.212. For RCP 8.5, the lowest is minimum temperature with 0.216. Since, RCP 2.6 recorded two types of temperature with the lowest % MAE compare to RCP 4.5 and RCP 8.5, therefore, it was concluded that the best RCP for Temperature is RCP 2.6.

Temperature	RCP 2.6		RCP 4.5		RCP 8.5	
	%MAE	Correlation	%MAE	Correlation	%MAE	Correlation
Maximum	0.382	0.986	0.394	0.985	0.385	0.986
Mean	0.208	0.976	0.212	0.976	0.216	0.977
Minimum	0.228	0.988	0.228	0.988	0.216	0.989

Table 4.5: Analysis of best RCP of Temperature

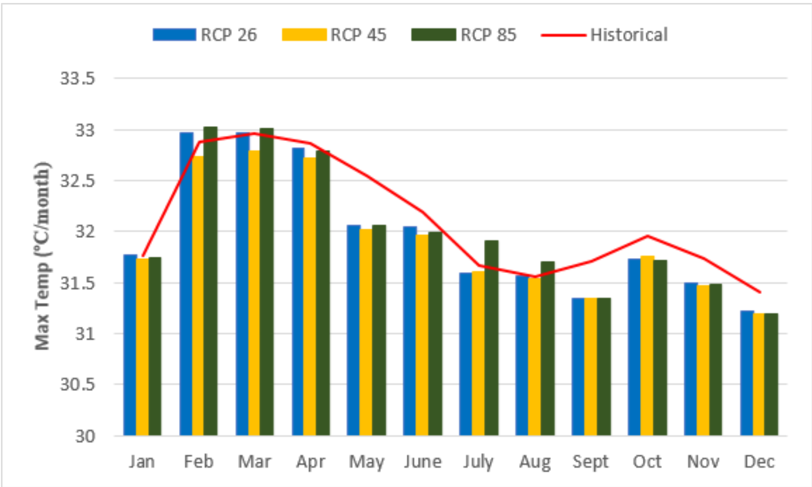

Figure 4. 10: Result of Maximum Temperature under RCP 2.6, RCP 4.5, RCP 8.5

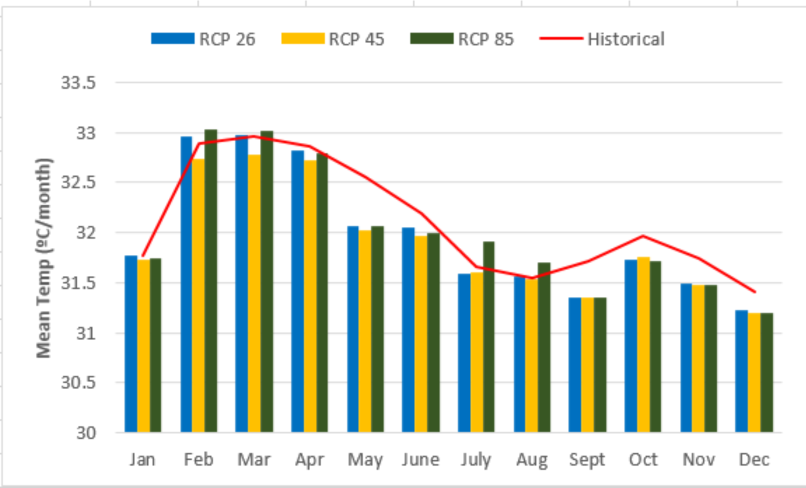

Figure 4. 11: Result of Mean Temperature under RCP 2.6, RCP 4.5, RCP 8.5

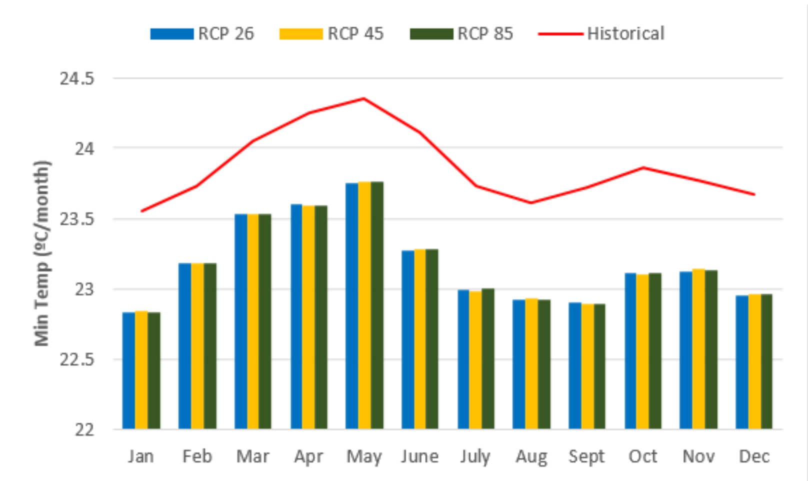

Figure 4. 12: Result of Minimum Temperature under RCP 2.6, RCP 4.5, RCP 8.5

Table 4.6 shows the analysis of best RCP based on the %MAE. The %MAE for RCP 8.5 recorded the lowest for Station 1 and Station 3 which is 2.709 and 1.830 respectively. For RCP 4.5, the lowest is Station 3 with 2.105. For RCP 2.6, the lowest is Station 3 with 1.953. Since, RCP 8.5 recorded two stations of rainfall with the lowest % MAE compared to RCP 2.6 and RCP 4.5, therefore, it was concluded that the best RCP for rainfall at stations in Melaka is RCP 8.5.

Table 4.6: Analysis of best RCP for rainfall in Melaka

Melaka	**RCP 2.6**		**RCP 4.5**		**RCP 8.5**	
	%MAE	Correlation	%MAE	Correlation	%MAE	Correlation
Station 1	3.189	0.990	3.140	0.993	2.709	0.994
Station 2	2.183	0.9	6.684	0.988	7.424	0.964
Station 3	1.953	0.995	2.105	0.997	1.830	0.998

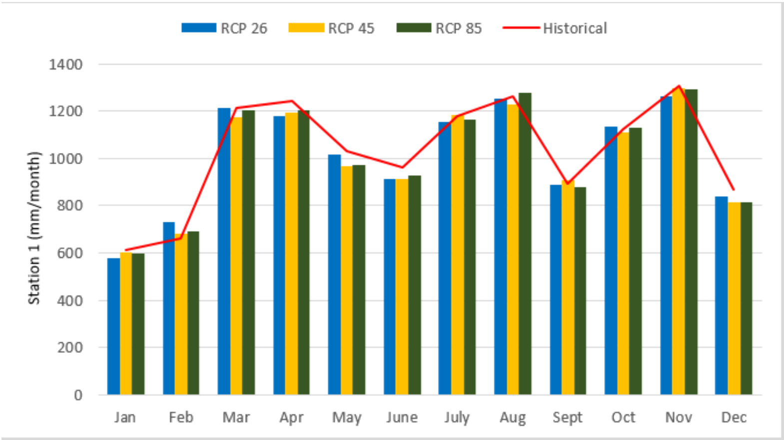

Figure 4. 13: Result of rainfall in Melaka for Station 1 under three RCPs

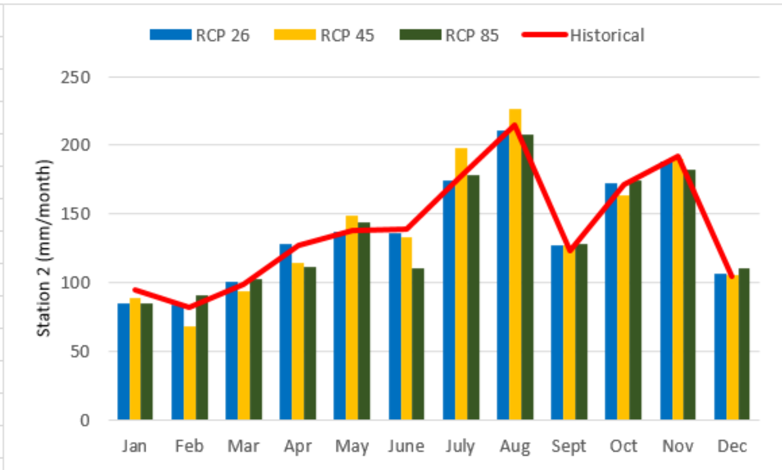

Figure 4. 14: Result of rainfall in Melaka for Station 2 under three RCPs

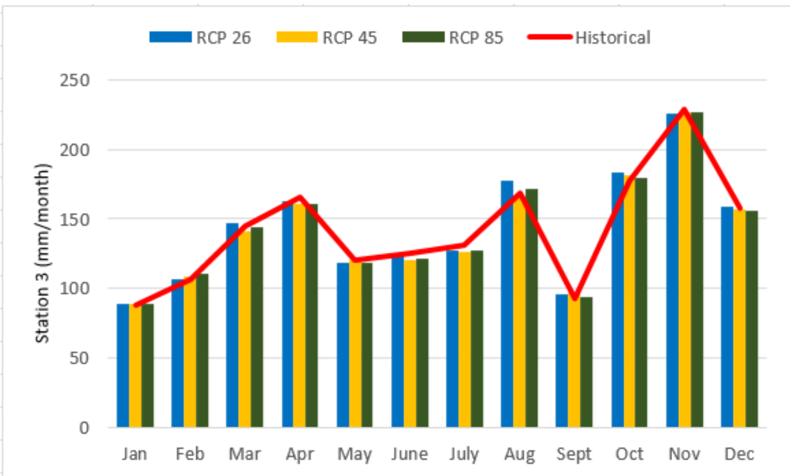

Figure 4. 15: Result of rainfall in Melaka for Station 3 under three RCPs

Table 4.7 shows the analysis of best RCP based on the %MAE. The %MAE for RCP 8.5 recorded the lowest for Station 2 and Station 3 which is 1.353 and 1.662 respectively. For RCP 4.5, the lowest is Station 1 with 1.383. For RCP 2.6, the lowest is Station 1 with 1.132. Since, RCP 8.5 recorded two stations of rainfall with the lowest % MAE compared to RCP 2.6 and RCP 4.5, therefore, it was concluded that the best RCP for rainfall at stations in Negeri Sembilan is RCP 8.5.

Table 4.7: Analysis of best RCP for rainfall in Negeri Sembilan

Melaka	**RCP 2.6**		**RCP 4.5**		**RCP8.5**	
	%MAE	Correlation	%MAE	Correlation	%MAE	Correlation
Station 1	1.132	0.999	1.383	0.999	1.770	0.999
Station 2	1.874	0.998	1.638	0.999	1.353	0.999
Station 3	1.936	0.999	1.920	0.999	1.662	0.999

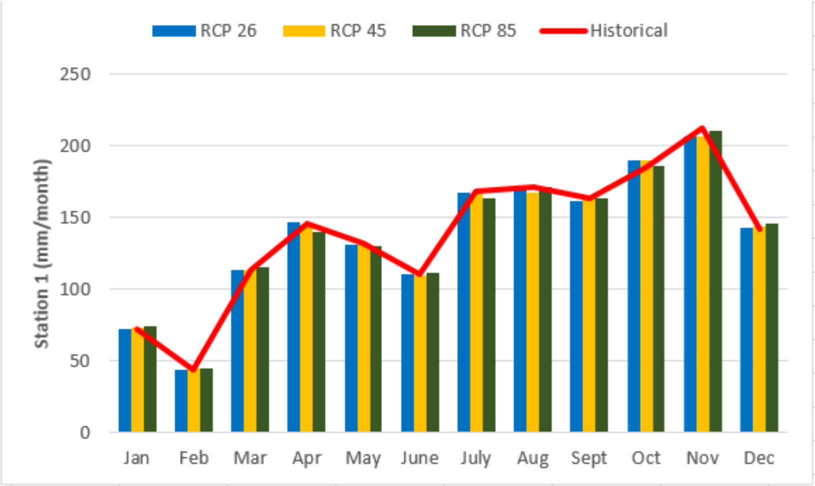

Figure 4. 16: Result of rainfall in Negeri Sembilan for Station 1 under three RCPs

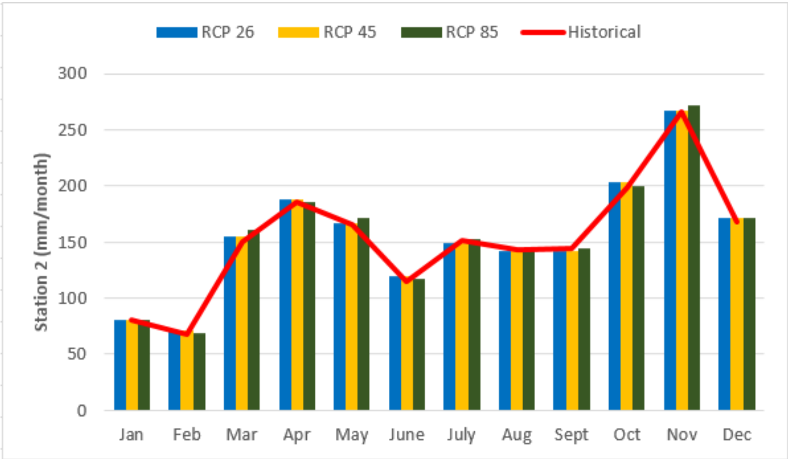

Figure 4. 17: Result of rainfall in Negeri Sembilan for Station 2 under three RCPs

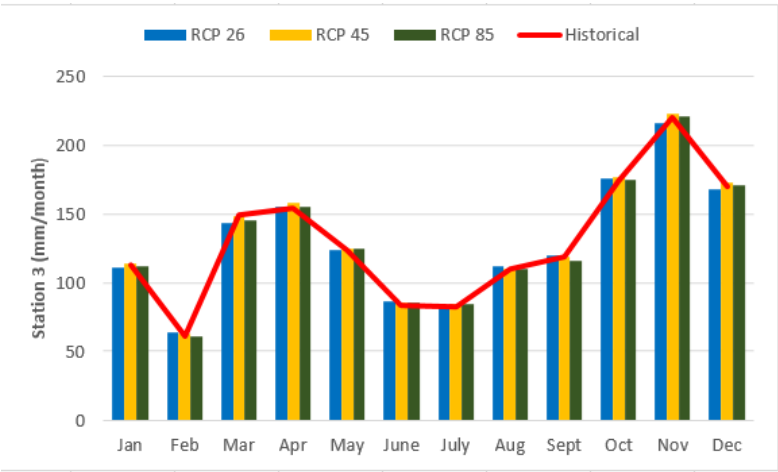

Figure 4. 18: Result of rainfall in Negeri Sembilan for Station 3 under three RCPs

4.4 Projection of Future Trend for Temperature and Rainfall

In this study, the changes of climate in the future in local region chosen which is Melaka and Negeri Sembilan states were projected using SDSM. This study investigated the future trend of temperature and rainfall in year interval 2020, 2050 and 2080.

The CanESM2 model provides data for RCP 2.6, RCP 4.5 and RCP 8.5 from 2006 until 2100 was sorted to generate the future trend for 30 years in year 2010–2039, 2040-2069 and 2070-2099. The location of study area is in Melaka

4.4.1 Projection of Temperature

Figure 4.19 to 4.21 shows the result of maximum temperature in the interval year 2020, 2050 and 2080 respectively. Generally, the temperature trend does not change in the future. The temperature pattern remains the same where the highest temperature in the maximum temperature future projection is in March which recorded in RCP 4.5 with 33.1 ºC for all projections. The trend of temperature is fluctuated and decreasing when approach the end of year. The percentage error for maximum temperature is 0.17% for year 2020, 2050 and 2050.

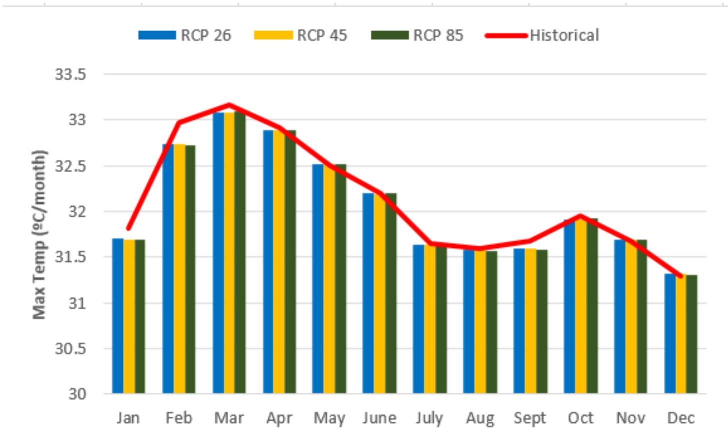

Figure 4. 19: Result of Maximum Temperature for interval year 2020

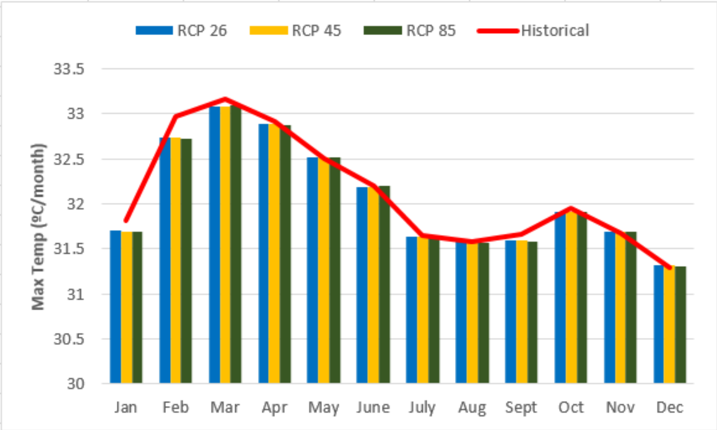

Figure 4. 20: Result of Maximum Temperature for interval year 2050

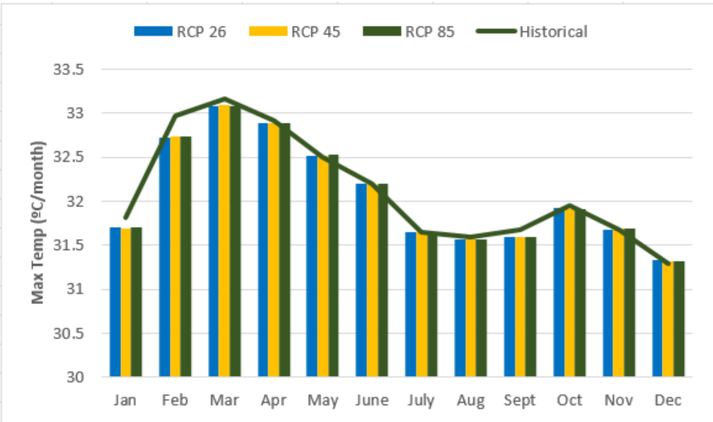

Figure 4. 21: Result of Maximum Temperature for interval year 2080

Figure 4.22 to 4.24 shows the result of mean temperature in the interval year 2020, 2050 and 2080 respectively. Generally, the temperature trend does not change in the future. But there is huge gap between the historical data and future projection. The future projection recorded lower emission of carbon under three RCPs compared to historical data. In Figure 4.22, the projection of mean temperature recorded the highest temperature will be in February with 27.40 ºC under RCP 2.6 at 2020. In 2050, the highest temperature is in May with 27.43 ºC under RCP 4.5. In 2080, the highest temperature is in February with 27.53 ºC under RCP 8.5. The percentage error for mean temperature for year 2020 and 2080 is 1.49% while for year 2050, the percentage error is 1.34%. Despite the future trend is same, the prediction of future change for mean temperature is not very accurate because the error is more than 1%

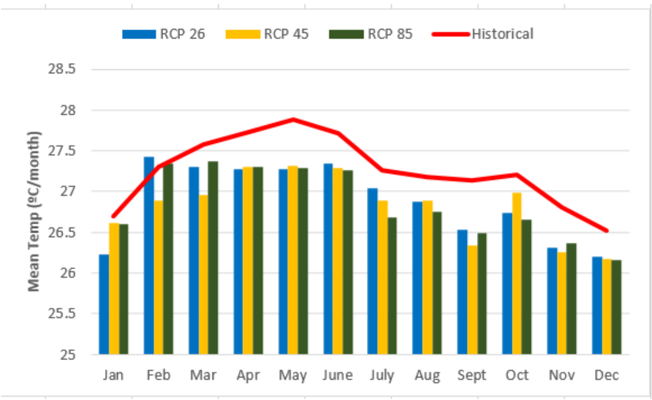

Figure 4. 22: Result of Mean Temperature for interval year 2020

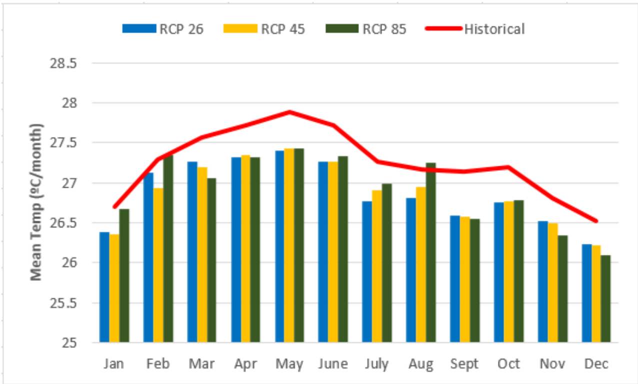

Figure 4. 23: Result of Mean Temperature for interval year 2050

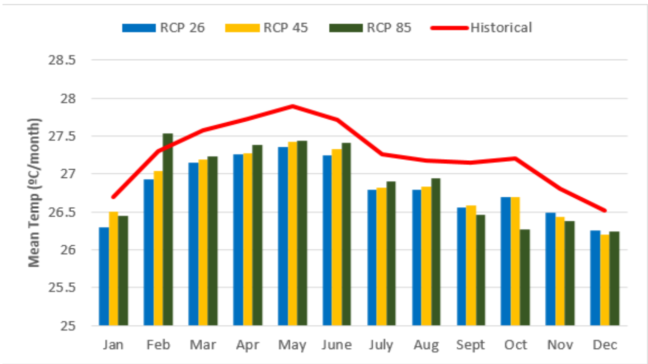

Figure 4. 24: Result of Mean Temperature for interval year 2080

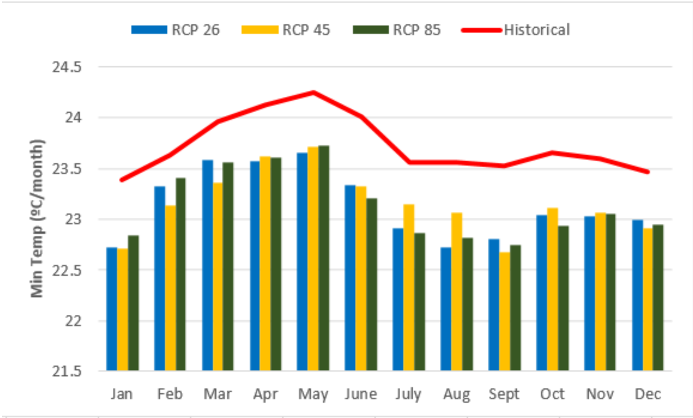

Figure 4. 25: Result of Minimum temperature for interval year 2020

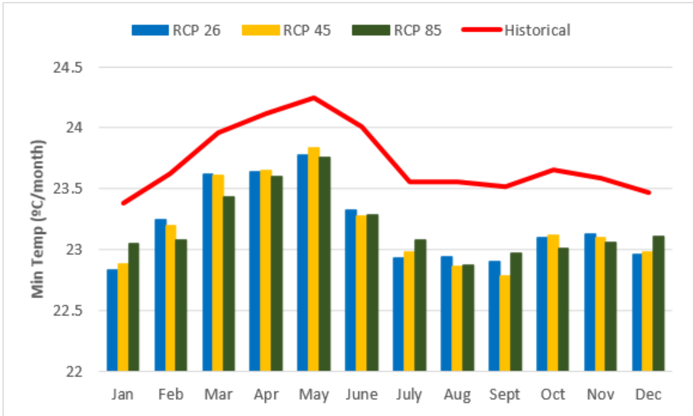

Figure 4. 26: Result of Minimum temperature for interval year 2050

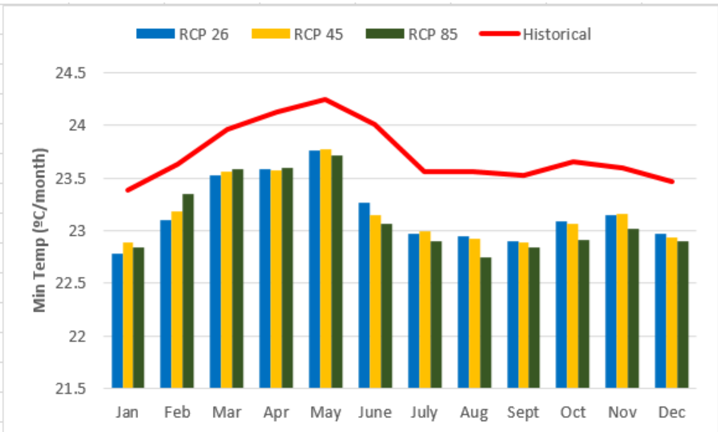

Figure 4. 27: Result of Minimum temperature for interval year 2080

Figure 4.25 to 4.27 shows the result of projection of minimum temperature for interval year 2020, 2050, and 2080 respectively. Generally, the temperature trend does not change in the future. Similar with the projection of mean temperature, there is huge gap between the historical data and future projection. The future projection recorded lower emission of carbon under three RCPs compared to historical data. The projection of minimum temperature recorded the highest temperature will be in May for all interval year. In 2020, the highest temperature recorded 23.73 ºC under RCP 8.5. In 2050, the highest temperature recorded 23.84 ºC under RCP 4.5. In 2080, the highest temperature recorded 23.77ºC under RCP 4.5. The percentage error for mean temperature for year 2020 and 2080 is 2.4% while for year 2050, the percentage error is 2.23%. Despite the future trend is same, the prediction of future change for mean temperature is not very accurate because the percentage error is more than 2%

4.4.2 Projection of Rainfall

The projection of rainfall was performed at Melaka and Negeri Sembilan states. This projection was performed using the data provided by CanESM2 model under RCP 2.6, RCP 4.5 and RCP 8.5.

4.4.2.1 Projection of Rainfall at Melaka

Figure 4.28 to 4.30 shows the projection of rainfall at Melaka for Station 1 in year 2020, 2050 and 2080. From the graph, the projected rainfall pattern is roughly similar compared to historical for year 2020,2050 and 2080. The projection of rainfall in year 2020 recorded the highest precipitation will occur in March with 1593.46 mm per month under RCP 4.5. In year 2050, the highest precipitation will occur in November with 1491.49 mm per month for both RCP 2.6 and RCP 4.5. In year 2080, again, the highest precipitation will occur in November with 1561.16 mm per month for both RCP 2.6 and RCP 4.5. The percentage error % for station 1 for 2020, 2050, and 2050 is below 20%. In year 2020, the percentage error is 19.23%, 17.93% for year 2050 and 13.05% for year 2080. Therefore, this projection is accurate and reliable compared with historical rainfall.

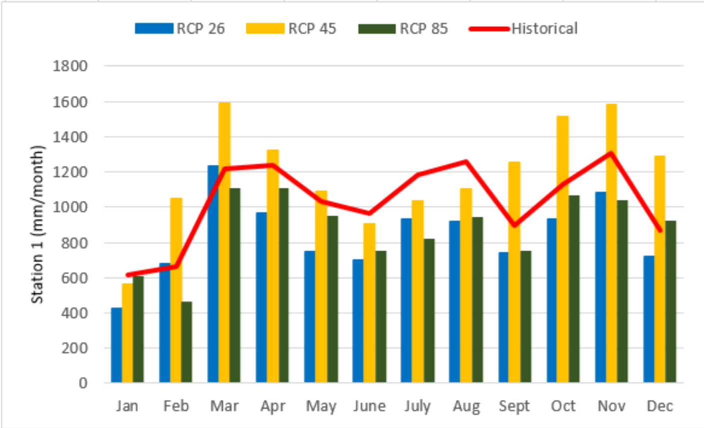

Figure 4. 28: Projection of Rainfall for Station 1 at Melaka in year 2020

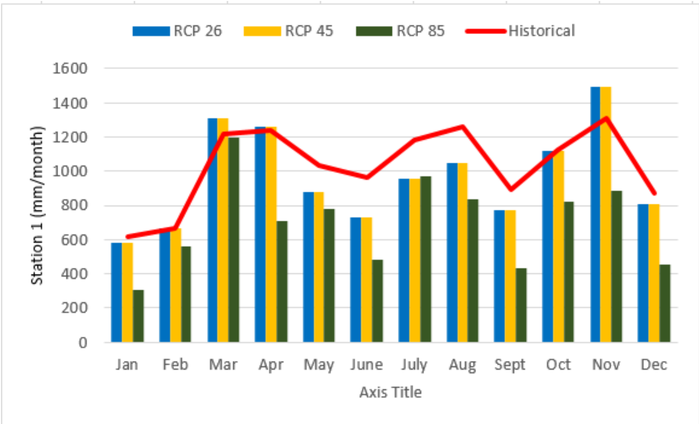

Figure 4. 29: Projection of Rainfall for Station 1 at Melaka in year 2050

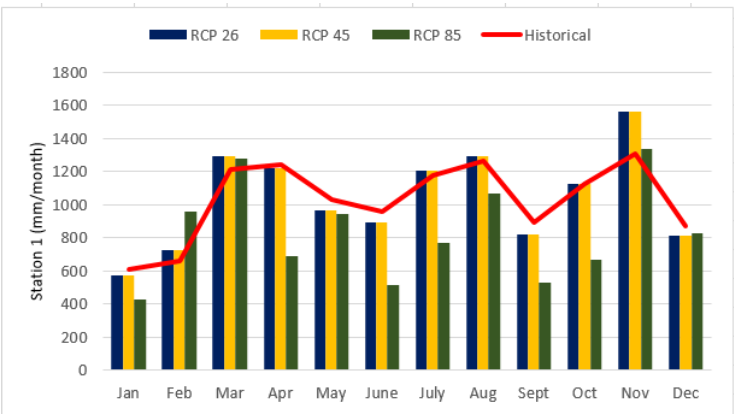

Figure 4. 30: Projection of Rainfall for Station 1 at Melaka in year 2080

Figure 4.31 to 4.32 shows the result of projection of rainfall for Station 2 at Melaka for year interval 2020, 2050 and 2080. From the graph, the projected rainfall pattern is roughly similar compared to historical for year 2020,2050 and 2080. The projection of rainfall in year 2020 recorded the highest precipitation will occur in August with 271.56 mm per month under RCP 4.5. In year 2050, the highest precipitation will occur in November with 219.61 mm per month under RCP 2.6. In year 2080, the highest precipitation will occur in November with 295.7 mm per month under RCP 8.5. The percentage error % for station 1 for 2020, 2050, and 2050 is below 20%. In year 2020, the percentage error is 10.94%, 10.21% for year 2050 and 8.16% for year 2080. Therefore, this projection is accurate and reliable compared with historical rainfall.

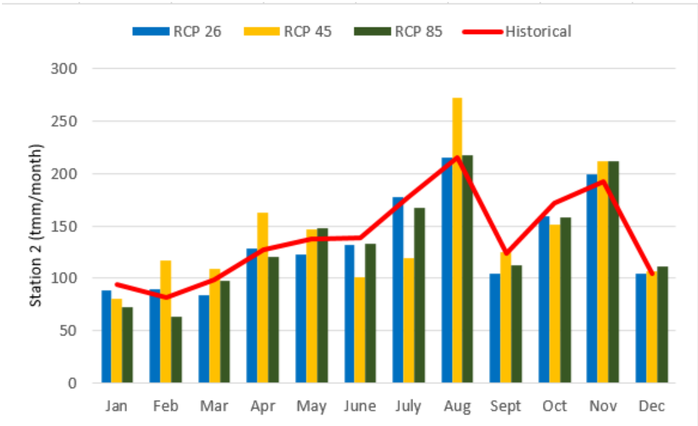

Figure 4. 31: Projection of rainfall for Station 2 at Melaka in year 2020

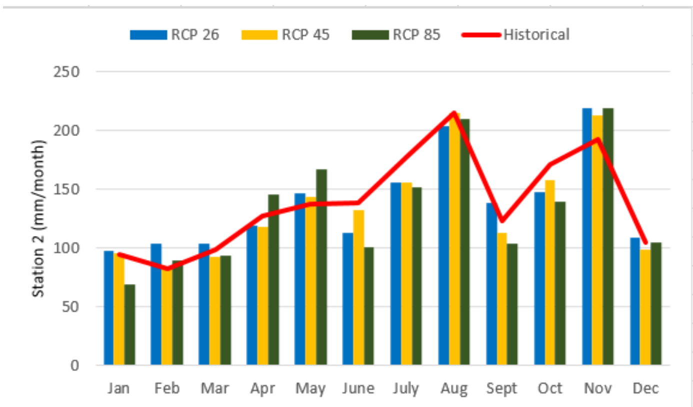

Figure 4. 32: Projection of rainfall for Station 2 at Melaka in year 2050

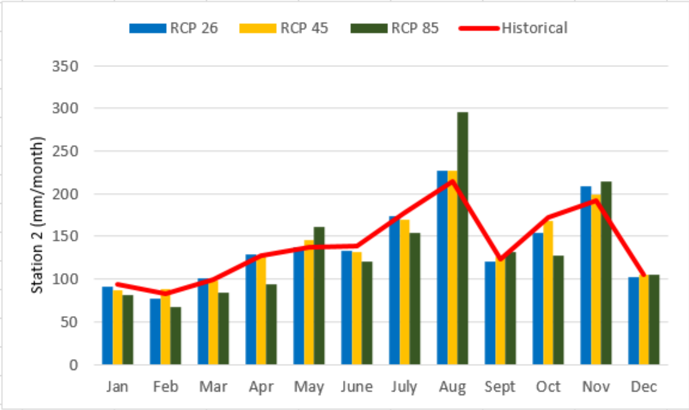

Figure 4. 33: Projection of rainfall for Station 2 at Melaka in year 2080

Figure 4.34 to 4.36 shows the result of projection of rainfall for Station 3 at Melaka in the year 2020, 2050 and 2080. From the graph, the projected rainfall pattern is roughly similar compared to historical for year 2020,2050 and 2080. The projection of rainfall in year 2020 recorded the highest precipitation will occur in November with 249.79 mm per month under RCP 4.5. In year 2050, the highest precipitation will occur in November with 255.81 mm per month under RCP 8.5. In year 2080, the highest precipitation will occur in November with 270.53 mm per month under RCP 8.5. The percentage error % for station 1 for 2020, 2050, and 2050 is below 20%. In year 2020, the percentage error is 10.30%, 9.51% for year 2050 and 8.77% for year 2080. Therefore, this projection is accurate and reliable compared with historical rainfall.

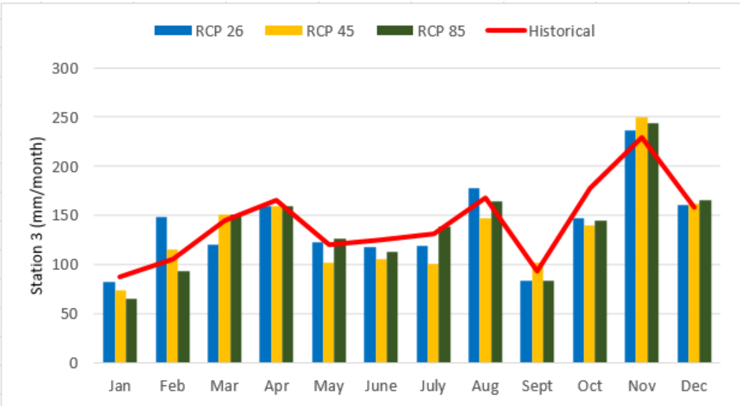

Figure 4. 34: Projection of Rainfall for Station 3 at in year 2020

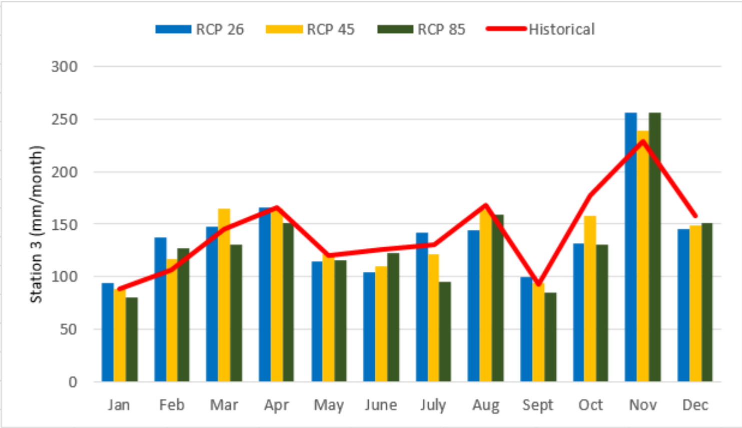

Figure 4. 35: Projection of Rainfall for Station 3 at in year 2050

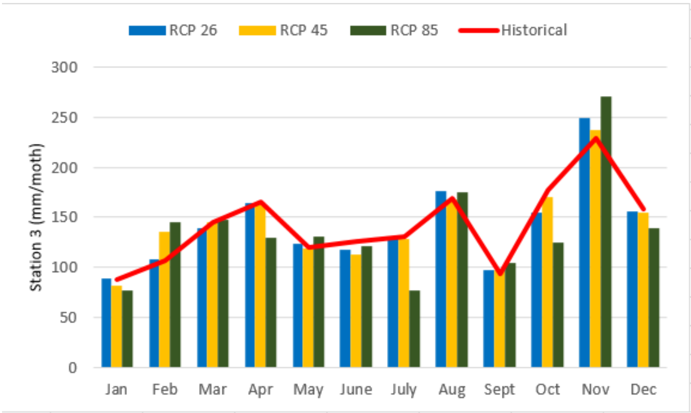

Figure 4. 36: Projection of Rainfall for Station 3 in year 2080

4.4.2.2 Projection of Rainfall in Negeri Sembilan

Figure 4.37 to 4.39 shows the projection of rainfall for Station 1 at Negeri Sembilan for year 2020, 2050 and 2080. From the graph, the projected rainfall pattern is roughly similar compared to historical for year 2020,2050 and 2080. The projection of rainfall is recorded the highest precipitation will occur in November for all interval year. In the year 2020, the precipitation is 226.76 mm per month under RCP 8.5. In year 2050, the precipitation is 297.64 mm per month under RCP 8.5. In year 2080, the precipitation is 226.32 mm per month under RCP 4.5. The percentage error % for station 1 for 2020, 2050, and 2050 is below 20%. In year 2020, the percentage error is 4.35%, 4.90% for year 2050 and 5,04% for year 2080. Therefore, this projection is accurate and reliable compared with historical rainfall.

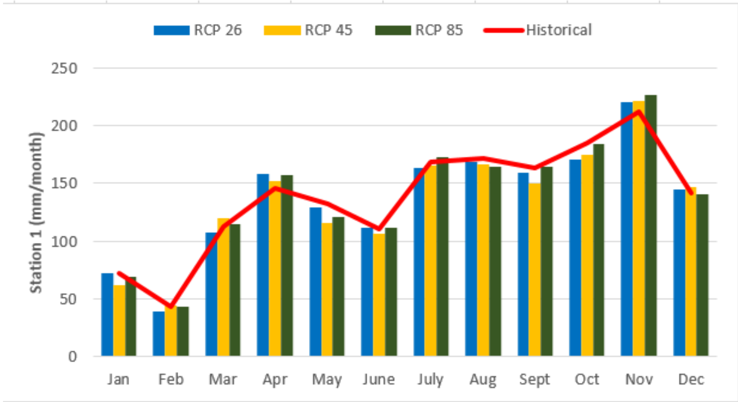

Figure 4. 37: Projection of rainfall for Station 1 in year 2020

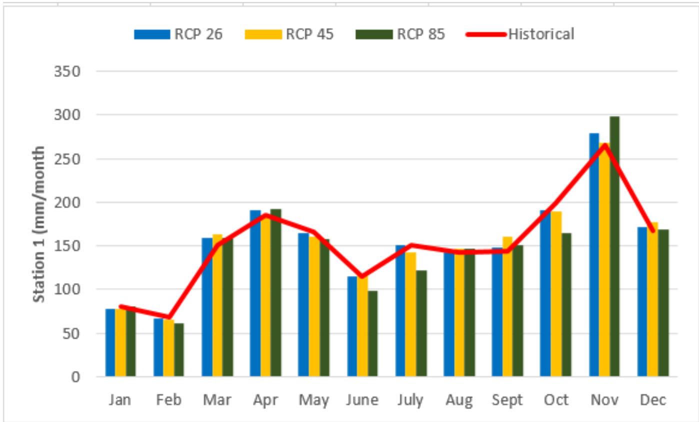

Figure 4. 38: Projection of rainfall for Station 1 in year 2050

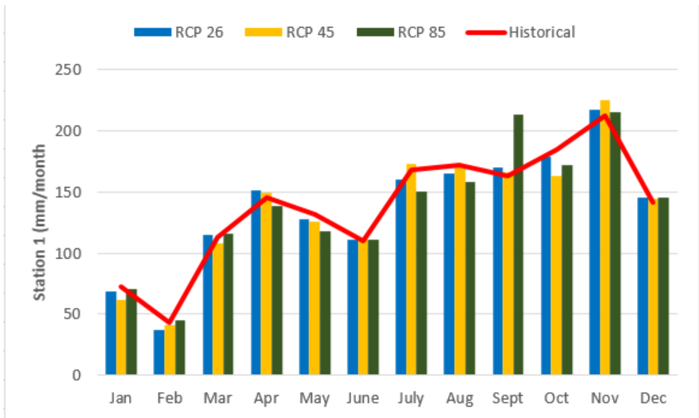

Figure 4. 39: Projection of Rainfall for Station 1 in year 2080

Figure 4.40 to 4.42 shows the result of projection of rainfall for Station 2 in year 2020, 2050 and 2080. From the graph, the projected rainfall pattern is roughly similar compared to historical for year 2020,2050 and 2080. The projection of rainfall is recorded the highest precipitation will occur in November in the year 2020 with 284.92 mm per month under RCP 8.5. In year 2050, the precipitation is 237.54 mm per month under RCP 8.5. In year 2080, the precipitation is 264.47 mm per month under RCP 4.5. The percentage error % for station 1 for 2020, 2050, and 2050 is below 20%. In year 2020, the percentage error is 4.58%, 5.25% for year 2050 and 2.72% for year 2080. Therefore, this projection is accurate and reliable compared with historical rainfall.

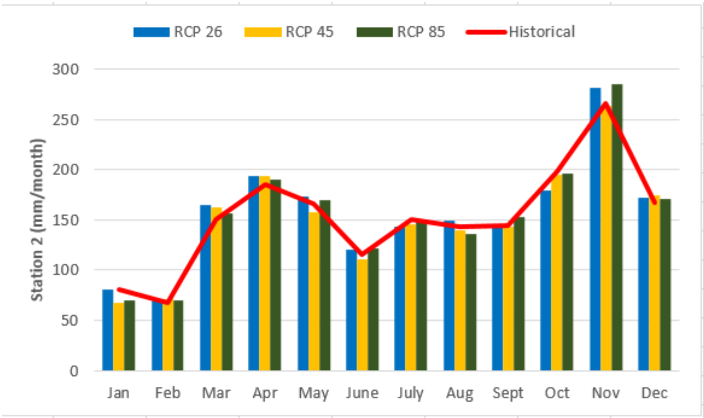

Figure 4. 40: Projection of Rainfall for Station 2 in year 2020

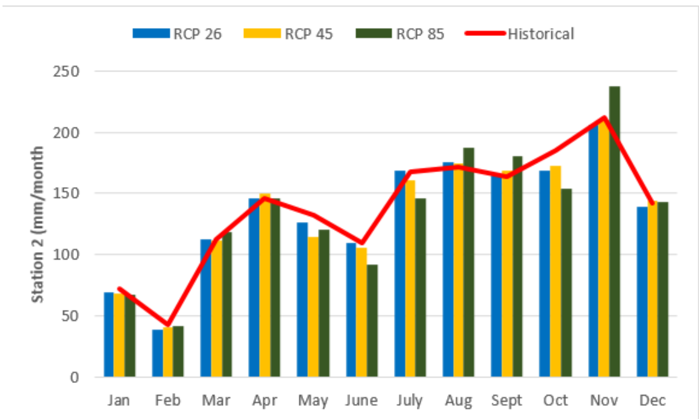

Figure 4. 41: Projection of Rainfall for Station 2 in year 2050

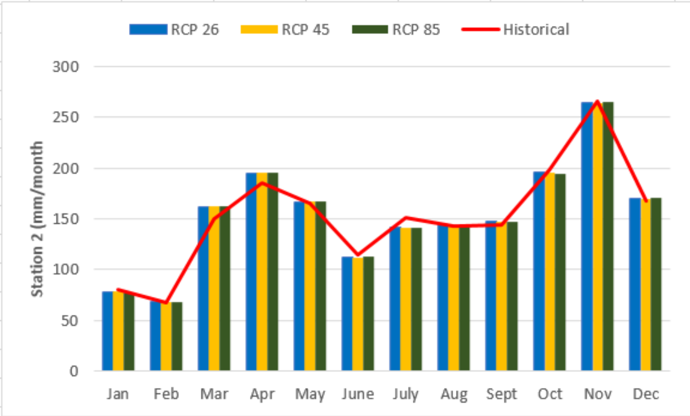

Figure 4. 42: Projection of Rainfall for Station 2 in year 2080

Figure 4.43 to 4.45 shows the result of projection of rainfall for Station 3 in year 2020, 2050 and 2050. From the graph, the projected rainfall pattern is roughly similar compared to historical for year 2020,2050 and 2080. The projection of rainfall is recorded the highest precipitation will occur in November in the year 2020 with 226.32 mm per month under RCP 8.5. In year 2050, the precipitation is 233.59 mm per month under RCP 8.5. In year 2080, the precipitation is 226.32 mm per month under RCP 4.5. The percentage error % for station 1 for 2020, 2050, and 2050 is below 20%. In year 2020, the percentage error is 5.77%, 5.97% for year 2050 and 5.04% for year 2080. Therefore, this projection is accurate and reliable compared with historical rainfall.

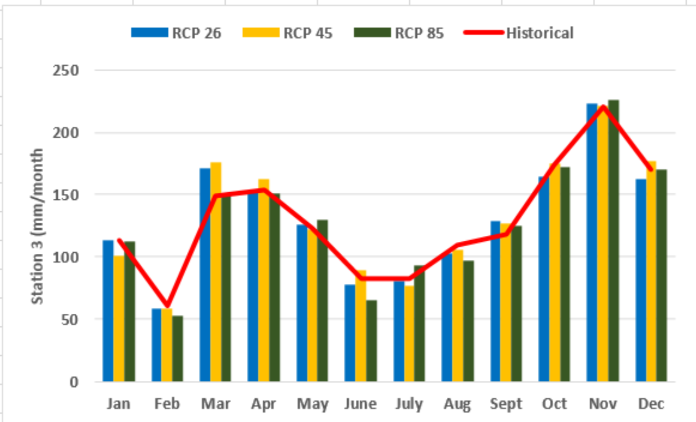

Figure 4. 43: Projection of Rainfall at Station 3 in year 2020

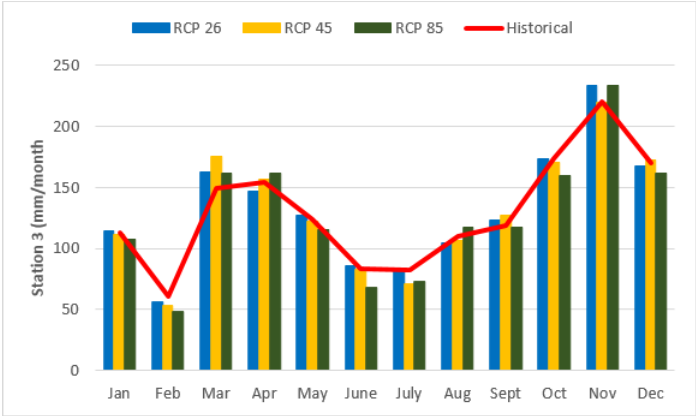

Figure 4. 44: Projection of Rainfall at Station3 in year 2050

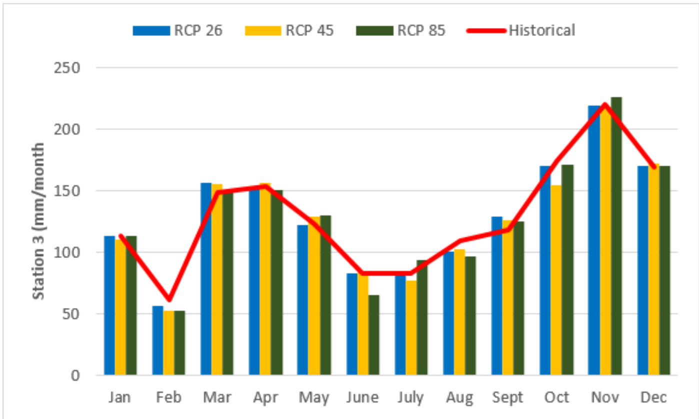

Figure 4. 45: Projection of Rainfall at Station 3 in year 2080

CHAPTER 5

CONCLUSION

5.1 Introduction

This study attempts to analyse the performance of SDSM in generating the future temperature and rainfall trend. The results will contribute to the improvement of planning and managing the water resources, and flood mitigation mainly in local region at Melaka and Negeri Sembilan. In SDSM model, the correlation relationship is proposed as a method to manage the complexity of predictor selections. The General Circulation Model (GCMs) parameters were employed to project the climate trend which considered the estimated emission level projection in the future year. The results of climate trend projection were used as the input data for the hydrological model. In general, the wet and warm climates would result in significant changes in the decreasing of daily river catchment. The lower depth of future rainfall and insignificance of temperature effect projected lower runoff, and those events can contribute to future drought events in the catchment area. Therefore, water and flood management planning is key challenges faced by the local authorities.

This chapter conclude the results and discussion in the previous chapter. The study has drawn several specific conclusions as listed in the following sections:

5.1.1 Analysis of Best RCP for Temperature and Rainfall

a) The best RCP for temperature at Melaka is RCP 2.6 while the best RCP for Rainfall for both Melaka and Negeri Sembilan states is RCP 8.5

5.1.2 Projection of Future Temperature and Rainfall Pattern

a) The SDSDM model is recognized as the relevant climatic projection model to produce good agreement between simulated and historical values during the calibration and validation process.

b) The average temperature in the future are expected to maintain with 33.1ºC for the maximum temperature while for mean and minimum temperature, the temperature will decrease to 1.44% and 2.4% of the historical data respectively.

c) By considering the maximum temperature to be taken as the average temperature, the highest temperature by the end of the century year March 2080s.

d) Based on the results, the future rainfall pattern in Melaka for Station 1, the highest rainfall will occur in March in the interval year (2010-2039) and the highest rainfall will occur in November after period (2010-2039) to the end of century year (2040-2099) with 1491.49 mm and 1561.16 mm per month for both year 2050 and 2080 respectively. The rainfall pattern for Station 2 achieve highest rainfall in the month of August with 271.56 mm per month in year 2020 while in year 2050 and 2080, the highest precipitation occurs in November with 291.61 mm and 295.7 mm per month respectively. The rainfall pattern for Station 3 achieve highest precipitation in November for all projection's year 2020,2050 and 2080 with 226.32 mm, 233.59 mm, 226.32 mm respectively.

e) For future rainfall pattern in Negeri Sembilan for Station 1, the highest precipitation will occur in November for all projection 's year 2020, 2050 and 2080 with 226.76 mm, 297.64 mm and 226.32 mm per month respectively. For Station 2, the highest precipitation occurs in November for all projection's year 2020, 2050 and 2080 with 284.92 mm, 237.54 mm and 264.47 mm per month respectively. For Station 3, the highest precipitation also occurs in November for all projection's year 2020, 2050 and 2080 with 226.32 mm, 233.59 and 226.32 mm per month respectively.

REFERENCES

Al, C. E. T. (2013). *Response of the HadGEM2 Earth System Model to Future Greenhouse Gas Emissions Pathways to the Year 2300 **. (2009), 3275–3284. https://doi.org/10.1175/JCLI-D-12-00577.1

Hadgem, T., Team, D., Bellouin, N., Collins, W. J., Culverwell, I. D., & Halloran, P. R. (2011). *Model Development The HadGEM2 family of Met Office Unified Model climate configurations*. 723–757. https://doi.org/10.5194/gmd-4-723-2011

Hassan, Z., Shamsudin, S., & Harun, S. (2014). *Application of SDSM and LARS-WG for simulating and downscaling of rainfall and temperature*. (April). https://doi.org/10.1007/s00704-013-0951-8

IPCC. (2014). *Summary: Synthesis*. https://doi.org/10.1017/CBO9781107415324

Methods, D., & Projections, C. C. (2014). *A REVIEW OF DOWNSCALING METHODS FOR CLIMATE CHANGE PROJECTIONS*. (September).

Nottingham, T. (2014). *ASSESSMENT OF CLIMATE CHANGE IMPACT ON RUNOFF AND PEAK FLOW – A CASE STUDY ON KLANG WATERSHED IN WEST MALAYSIA Reza Kabiri Thesis submitted to the University of Nottingham for the degree of Doctor of Philosophy April 2014*. (April).

Physical, T., & Basis, S. (2013). *CLIMATE CHANGE 2013 The Physical Science Basis*.

Sachindra, D. A., & Perera, B. J. C. (2016). *Statistical Downscaling of General Circulation Model Outputs to Precipitation Accounting for Non-Stationarities in Predictor-Predictand Relationships*. 1–21. https://doi.org/10.1371/journal.pone.0168701

Sidharno, W. (2016). *STUDY of CLIMATE CHANGE IMPACT on WATER AVAILABILITY in OEBOBO LILIBA WATERSHED*. (July), 29–31.

Tahir, T., Hashim, A. M., & Yusof, K. W. (2018). Statistical downscaling of rainfall under transitional climate in Limbang River Basin by using SDSM. *IOP Conference Series: Earth and Environmental Science*, *140*(1). https://doi.org/10.1088/1755-1315/140/1/012037

Yan, D., Werners, S. E., Ludwig, F., & Huang, H. Q. (2015). Hydrological response to climate change: The Pearl River, China under different RCP scenarios. *Journal of Hydrology: Regional Studies*, *4*(PB), 228–245. https://doi.org/10.1016/j.ejrh.2015.06.006

Hannah, L. (2015). *The Climate System and Climate Change*. *Climate Change Biology*.

https://doi.org/10.1016/B978-0-12-420218-4.00002-0

Jalota, S. K., Vashisht, B. B., Sharma, S., & Kaur, S. (2018). *Climate Change Projections*. *Understanding Climate Change Impacts on Crop Productivity and Water Balance*. https://doi.org/10.1016/B978-0-12-809520-1.00002-1

Ayugi, B. O., Wang, W., & Chepkemoi, D. (2016). Analysis of Spatial and Temporal Patterns of Rainfall Variations over Kenya. *Environment and Earth Science*, *6*(11), 69–83.

Sachindra, D. A., Huang, F., Barton, A., & Perera, B. J. C. (2014). Statistical downscaling of general circulation model outputs to precipitation – part 2 : bias-correction and future, *3303*(January), 3282–3303. https://doi.org/10.1002/joc.3915

Sidharno, W. (2016). STUDY of CLIMATE CHANGE IMPACT on WATER AVAILABILITY in OEBOBO LILIBA WATERSHED, (July), 29–31.

Thompson, J. E. (2017). Survey data reflecting popular opinions of the causes and mitigation of climate change. *Data in Brief*, *14*, 412–439. https://doi.org/10.1016/j.dib.2017.07.060

Jian-Bin, H., Shao-Wu, W., Yong, L., Zong-Ci, Z., & Xin-Yu, W. (2012b). The Science of Global Warming. *Advances in Climate Change Research*, *3*(3), 174–178. https://doi.org/10.3724/SP.J.1248.2012.00174

Jalota, S. K., Vashisht, B. B., Sharma, S., & Kaur, S. (2018). *Climate Change Projections*. *Understanding Climate Change Impacts on Crop Productivity and Water Balance*. https://doi.org/10.1016/B978-0-12-809520-1.00002-1

Le Roux, R., Katurji, M., Zawar-Reza, P., Quénol, H., & Sturman, A. (2018). Comparison of statistical and dynamical downscaling results from the WRF model. *Environmental Modelling and Software*, *100*, 67–73. https://doi.org/10.1016/j.envsoft.2017.11.002

Najafi, M. R., Asce, S. M., Moradkhani, H., Asce, M., Wherry, S. A., & Asce, S. M. (2011). Statistical Downscaling of Precipitation Using Machine Learning with Optimal Predictor Selection, (August), 650–664. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000355.