ASSESSMENT OF THE BEST REPRESENTATIVE CONCENTRATION PATHWAYS (RCPs) FOR NORTHERN MALAYSIA

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ABSTRAK

Akibat dari perubahan iklim di Malaysia telah membawa kepada bencana banjir di Perlis yang berlaku pada tahun 2010 yang melibatkan 50,000 mangsa perlu berpindah dari rumah mereka ke kawasan penempatan sementara selain menyebabkan kematian 6 mangsa. Oleh itu, ramalan cuaca pada tahun yang akan datang menjadi perlu dalam merancang dan mengurus sumber air dan pencegahan bencana. Walau bagaimanapun, isu utama dalam ramalan iklim jangka panjang ialah radiasi tahap yang sesuai di rantau tempatan yang dibentangkan dalam Laluan Konsentrasi Perwakilan (RCPs). RCP telah diperkenalkan oleh Project Interconduct Coupling Model Fasa 5 (CMIP5) dan dibentangkan dalam tiga tahap radiasi yang dikenali sebagai RCP2.6, RCP4.5 dan RCP8.5. Setiap RCP mempunyai lintasan pelepasan tertentu dan kemudian memancarkan radiasi seterusnya dalam mengubah keseimbangan tenaga masuk dan keluar ke dalam sistem Bumi. Ia menganggap keseluruhan radiasi memaksa sehingga tahun 2100. Oleh itu, objektif kajian ini adalah untuk mengenal pasti RCP terbaik untuk Utara Malaysia (Perlis dan Pulau Pinang) dan untuk menghasilkan trend iklim jangka panjang di rantau ini. Berdasarkan hasilnya, terdapat 5 prediktor yang paling dipilih; ncepr850, nceptemp, nceprhum, ncepr500 dan ncepp500. Keputusan yang diselaraskan dan disahkan menunjukkan bahawa RCP2.6 adalah yang terbaik untuk membentangkan tahap pemantauan radiasi di negeri Utara dengan ralat peratusan yang sangat rendah iaitu 0.208% dan korelasi ditutup kepada 1. Iklim yang diunjurkan menunjukkan suhu dijangka meningkat pada tahun yang akan datang dan mencapai 35˚C dengan kenaikan 0.01%. Selain itu, Mei dijangka sebagai bulan yang menerima suhu tertinggi sepanjang tahun ini. Sementara itu, hujan dijangka berkurangan sebanyak 7.2% (2020), 12% (2050) dan 15% (2080).

ABSTRACT

Consequence from the climate change in Malaysia had leads to flood disaster in Perlis that happened in year 2010 that involved 50 000 victims need to evacuate from their house to temporary settlement areas besides caused death of 6 victims. Thus, the climate prediction in the future year become necessary in planning and managing the water resources and disasters prevention. However the main issue in the long term climate prediction was the appropriate level radiation of the local region which presented in the Representative Concentration Pathways (RCPs). The RCP has been introduced by Coupled Model Intercomparison Project Phase 5 (CMIP5) and presented in three radiation levels known as RCP2.6, RCP4.5 and RCP8.5. Every RCP had its own specific emissions trajectory and subsequent radiative forcing in altering the balance of incoming and outgoing energy into the Earth system. It considers the total radiative forcing until year 2100. Therefore, the objective of this study was to identify the best RCPs for the Northern Malaysia (Perlis and Pulau Pinang) and to generate the long term climate trend at these regions. Based on the results, there were 5 predictors which the most been selected ; ncepr850, nceptemp,nceprhum,ncepr500 and ncepp500. The calibrated and validated results shows the RCP2.6 was the best to present the radiation forcing level at Northern state with very low percentage error which 0.208% and correlation closed to 1. The projected climate revealed the temperature is expected to increase in the future year and reaches 35˚C with 0.01% increment. Besides that, May is expected as the month which receiving the highest temperature through the year. Meanwhile, the rainfall is estimated to reduce 7.2% (2020), 12% (2050) and 15% (2080).

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Global warming can be classified as general increase in the earth's near-surface air temperature and sea water temperatures which affected the earth populations and pollution. This phenomenon remains a pressing issue in a society which consistent to the expanded its industrial use since the mid-20th century. Moreover, the global warming is a result of the increase in changes climate system due to the enhanced anthropogenic emissions of greenhouse gases (GHGs) with carbon dioxide (CO2) that primarily released into the atmosphere. Due to human activities, atmosphere concentration of CO2 had increase more than 40% during year 1750 and 2011(Shukla et al, 2017). The scientists around the world agreed and claimed the global temperatures will continue to rise for decades to come, largely due to GHGs produced by human activities.

The unpredicted rainfall amount nowadays is one of the impacts or sources of climate change on hydrological process, especially in extreme event that generate peak runoff flow. According to (Strauch *et al.*, 2015), changes in the magnitude and frequency of rainfall events includes watershed function are projected of large impacts of climate change. For example, in year 2014, heavy rain occurred in December caused extreme flood in some states especially in east of Malaysia. Officially, more than

100,000 flood victims involved and evacuated from their houses during the flood disasters (Muzzamil *et al.*, 2017). Besides that, the floods happened in December 2006 are also considered the most damaging floods in history of Malaysia. The water level recorded during these floods reached 2.75 meters which is the highest level observed since 1950. In Perlis, the worst flood happened during year 2010 that involved 50 000 victims need to evacuate from their house to temporary settlement areas besides caused death of 6 victims. In March 2016, drought phenomena occurred in Northen Malaysia especially Perlis and Pulau Pinang. The highest temperature is 39˚C recorded at Chuping, Perlis effect of the El-Nino phenomenon and north-eastern monsoon winds experienced by the country since October 2015.

Since the world became warmer day by day due to increase of global temperature, climate change assessment is important to predict the long term weather characteristic and short term weather extreme in future. Range of possible future climate is needed to be considered since we do not know the future climate that will affect the world especially in term of disasters. Therefore, by doing the climate assessment, it can help the scientist and populations around the world be prepared for the future disasters besides created awareness among the people.

To project future climate change resulting from the continuous increase of GHGs concentration in the atmosphere, the Representative Concentration Pathway (RCP) reanalysis data are used. RCP contains a set of starting values and the estimated emissions up to 2100 for each category of emissions (Wayne, 2013). These estimated are based on assumptions about economic activity, energy sources, population growth and other socio-economic factors. RCPs are divided into four pathways which are RCP2.5, RCP 4.5, RCP 6 and RCP8.5 and each RCP was developed by an Integrated Assessment Modelling (IAM) group, whose published scenario papers were consistent with the base criteria for a particular RCP.

For the climate projection, two main approaches for downscaling that can be used, which are dynamical downscaling (DD) that involves a nested regional climate model (RCM) and statistical downscaling (SD) that employs a statistical relationship between a large scale climatic state and the local variations derived from historical data.

In this study, statistical downscaling techniques has been chosen and the universally multiple linear regression models called Statistical Downscaling Model (SDSM).

1.2 Statement of the Problem

Climate change is a change in the statistical distribution of weather patterns when that change lasts for an extended period of time which decades to millions of years. Climate change may refer to a change in average weather conditions, or in the time variation of weather around longer-term average conditions that is more or fewer extreme weather events. Climate change is caused by factors such as biotic processes, variations in solar radiation received by earth. Certain human activities have also been identified as significant causes of recent climate change, often referred to as global warming.

In terms of rainfall, there are also have a change, but not all areas have data over long periods. Rainfall has increased in the mid-latitudes of the northern hemisphere since the beginning of the 20th century. Historical rainfall trend in Malaysia have shown that it is affected by the climate change. For example, rainfall trend in Northern Malaysia during 2007- 2016 showed the fluctuated trend where 2007 to 2009 rainfall trend were in decreased condition and 2010 to 2012 in increased pattern followed by decreased pattern during 2013-2016 (Mohd Zizi *et al.*, 2018).

Consequence from the climate change in Malaysia had leads to flood disaster in Perlis that happened in year 2010 that involved 50 000 victims need to evacuate from their house to temporary settlement areas besides caused death of 6 victims. Besides that, flood disaster that occurred in Penang town was inundated by up 4m water level after 18-hour storm causes seven people died and thousands evacuated in December 2017. Besides the flood disaster, drought phenomena occurred in Northern Malaysia especially Perlis in March 2016 where the highest temperature is 39˚C recorded at Chuping, Perlis effect of the El-Nino phenomenon and north-eastern monsoon winds experienced by the country since October 2015. These disasters proved that the climate change was a major factor leading to floods and drought in Malaysia. Besides that, Perlis and Pulau Pinang were located at the Northern Malaysia that growing rapidly with industrialization. The main economy sources were focused on industrial such as food manufacturing. The manufacturing was one of the contributors of GHGs emission in Malaysia. Therefore, GHGs emission in manufacturing area had brought to climate change in Northern Malaysia.

The understanding of past, present and future climate changes are very important in preparing the long term precaution in facing disaster. Therefore, many climate modellings have been develop and widely used among researchers in predicting the climatic trend in the context of climate change. Simulations of global climate are conducted with Global Climate Model (GCMs), which are designed to balance model resolution and physics with computational requirements and limitations. Hence, long climate simulations have necessarily been run at relatively coarse spatial resolutions, which are on the order of a few degrees in latitude and longitude.

The trend of global warming has been exacerbated by the heat island effect in the urban environment due to flash flood and heat energy in urban saturated surfaces (Md Hashim et al., 2010). Increasing in urban temperatures compared to rural areas has long been observed whether in the country or abroad as well as in the country simple climate even in tropical country. Climate parameters like temperature, rainfall and humidity are expected to change with global climate and thus may affect the ranging patterns of the rainfall intensity and temperature average of Malaysia.

The SDSM model is applied to downscale GCMs into catchment scale. The SDSM models have several advantages and disadvantages. Some advantages of SDSM are SDSM the user-friendly software that largely self explanatory which it comes with comprehensive instructions for use. Besides that, SDSM model need less technically demanding, it can possibly to tailor the scenarios for specific localities, scales and problem. The SDSM model is more accurate compared to regional modelling. Although, SDSM is the best model in downscaling, yet it also has its limitation which is SDSM should has same resolution with NCEP and can use only one of Canadian model. SDSM cannot add any others files for downscaling even though it can run step by step in clear way.

Besides that, the problem in RCPs performance that may be effected accuracy of rainfall projection. This is because every RCP had its own specific emissions trajectory and subsequent radiative forcing which a measure of the influence a factor has in altering the balance of incoming and outgoing energy in the Earth-atmosphere system, measured in watts per square metre.

1.3 Objectives of the study

The main aim of this study was to assess the best RCPs for Northern Malaysia refer to Perlis and Pulau Pinang. The objectives of this study were as follow:-

i. To identify the best RCPs for Northern Malaysia refer to Perlis and Pulau Pinang using statistical downscaling model.

ii. To generate the future trend of rainfall and temperature for the interval year 0f 2020, 2050 and 2080.

iii. To analyse the performances different between RCPs

1.4 Scope of Research

This study was conducted at Northern Malaysia especially Perlis and Pulau Pinang. The data were taken from Malaysian Meteorological Department (MMD). The study focused on the selection of the best RCPs selection for Northern Malaysia. There were three types of RCPs selected which have different of performances which are RCP 2.6, RCP 4.5 and RCP 8.5. Thus, data analysis can be done and the future data can be estimate based on the historical data obtained where the future trend of rainfall and temperature at these state can be generated.

The climate tools used in this study is Statistical Downscaling Model (SDSM). The function of the downscaling models is to downscale the coarse spatial resolution from grid resolution GCM-scale to the finer scale variation that will focused on the specific regional climate in 10 km. This model is widely used in the hydrological issue due to climate scenarios (Tukimat *et al.*, 2018). Besides that, the accuracy of the SDSM simulation is depended on the appropriate selections of predictor variables that should have better correlation relationship with the predictand site in the equal sub-grid scale.

In this case study, the CanESM2 was used as a Global Climate Model (GCM) which consider expecting GHGs emission in the atmospheric variables.

1.5 Significance of Study

Identification of the best RCPs was the fundamental stage in the climate prediction. It is important to choose appropriate RCPS in term of accuracy and reliability in the climate assessment. Besides that, the predictions of rainfall and temperature trend at Northern Malaysia are very useful information to the stakeholder about the statistical modelling are very important. This is because there still lack of studies in rainfall prediction. The result from this study can be as reference and guidance for the other stakeholder or authorities in preparing long term management.to propose better water resources planning and management in the long term. Data will produce in the future, knowledge and deep understanding

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Nowadays, climate change is not a new issue and has been the subject of intense debate around the world. Climate changes or known as global warming is alludes to an increment of global temperatures caused by emission of heat trapping gases due to human activities such as deforestation, industrial processes, power plants and vehicles. These phenomena include the changes of sea level rise and increased temperature trends that worrying population around the world. In Peninsular Malaysia, the prediction of highest and lowest projected seasonal average temperature towards the end of the century was found to be 3.7˚C during the months of December, January and February, 3.3˚C during September, October and November respectively (MMD, 2009). The current warming trend is of particular significance because it is greater than 95% probability to be the result of human activity since the mid-20th century.

According to European Commission (Commission, 2015) stated that the current global average temperature is 0.85˚C which is higher than that was recorded during late 19th century. These higher global temperature affected the environment that will cause flooding, disappeared of glaciers and ocean acidity continued rising besides affect the health of populations. Moreover, scientists have high confidence that global temperatures will continue to rise for decades to come, largely due to GHG produced by human activities nowadays that supported by Intergovernmental Panel on Climate Change (IPCC) forecasts a temperature will rise of 2.5 to 10˚F over the next century.

Changes in climate also can affect the changes in rainfall trends as according to average precipitation in Malaysia has showing fluctuated trend since 2004 with some areas recorded increase trend which greater than the national average. However, some areas showed decrease trend. This can be supported by data of the precipitation for the 10 years which the highest average recorded 542.90mm and the lowest with 63.62mm. However, an extreme of rainfall cause by changes in precipitation can bring to the flood. For example, the worst flood in world history that happened in August 1931 sacrificed 3.7 million victims. Considered to be the worst flood disaster in human history, Yangtze River flood 1931 happened after long period of extreme rainfall cause Yangtze River with high population began to flood and spread to cover over 500-squares-miles area and forced half millions of people to evacuate. (Wang et al, 2018).

Climate change is also affects the sea level which arising due to melt of glaciers and ice sheets. Global sea level has risen about 8 inches since reliable record keeping began in 1880. It is projected to rise another 1 to 4 ft by year 2100 as the oceans are absorbing over 90% of the increased atmospheric heat that contributed by human activities. Refer to thermal expansion, water expands as it warms up like mercury in a thermometer causing sea levels arise (Whitehead *et al.*, 2018). Climate changes in Malaysia are contributed by emission of Greenhouse gases emission (GHGs).

Rising of the global temperature and climate change were contributed by GHGs emission in the atmosphere influenced the patterns of absorption of incoming radiation from the sun and affected the circulation patterns in the atmosphere and oceans. Therefore, changes in land and ocean topography had major influences on global climate at time scales of 50 million to 150 million years. For example, since the end of the last ice age (14,000-10,000 years ago) globally an average temperatures have fluctuated over arrange of up to 2˚C on time scales of centuries or more.

2.2 Types of GHGs

GHG is a gas that absorbs and emits radiant energy within the thermal infrared range. There are many compounds present in atmosphere that allow direct sunlight to reach the earth’s surface unhindered where natural characteristic of GHGs is absorbing this energy, thereby allowing less heat to escape back to space, and trapping it in the lower atmosphere. The primary GHGs in Earth's atmosphere are water vapour, carbon dioxide, methane, nitrous oxide and ozone. GHGs act as the shortwave energy that visible and ultraviolet portion of the spectra will heat the surface while infrared energy act as longer wave is reradiated to the atmosphere.

Many GHGs exist naturally in the atmosphere, such as methane (NH4), carbon dioxide (CO2), nitrous oxide (N2O) and water vapour while the others are synthetic. CO2 formed 81% from all the gas emission, 10% of CH4 gases , 6% of N2O gases and 3% of Fluorinated gases (F). Those gases exist because of man-made that can stay in the atmosphere for centuries and contribute to a global greenhouse effect include the chlorofluorocarbons (CFCs), Perfluorocarbons (PFCs) and hydrofluorocarbons (HFCs) as well as sulfur hexafluoride (SF6). Without the GHGs in atmosphere, the average temperature of earth surface become lower compare to the atmosphere with GHGs present. This is because of the atmosphere contain the GHGs, they will radiate energy in all directions and parts of it directed to the earth surface and cause the earth surface warming. Thus,the temperature is increased. Besides that, atmospheric concentrations are determined by the balance between emissions of the gas from human activities and natural systems and the removal of the gas from the atmosphere by conversion to a different chemical compound or absorption by bodies of water.

Atmospheric concentrations for both of the natural and man-made gases have been rising over the last few centuries due to the industrial revolution. Since the global population has increased and our need of fossil fuels such as oil, natural gas and coal have been firmly solidified to fulfil the request, so emissions of these gases have risen. While gases such as CO2 occur naturally in the atmosphere, through our interference with the carbon cycle (through burning forest lands, mining and burning coal), we artificially move carbon from solid storage to its gaseous state, thereby increasing atmospheric concentrations. In order to overcome the GHG problem, Malaysia has declared to reduce its greenhouse gas emissions by up to 40% by the year 2020 as comparable with 2005 levels to implement the Cancun agreements and the Bali declaration of joint efforts of emission reduction by both developed and developing countries.

According to EPA (2018), in United State (US), CO2 gases is the largest contribution to the GHG in 2016 followed by CH4 with 10.1%, 5.7% N2O and the lowest emission is F (HFCs, PFCs, SF4 and NF3) gases with 2.7%. These emission of gases come from the several of primary sources which the largest source of GHG emission is from human activities in the US is from burning fossil fuels for electricity, heat, and transportation. Based on (EPA, 2018), transportation and electricity recorded as the highest with 28% of the total gas emission followed by industry sector with 22%, commercial and residential 11%. Besides that, agriculture recorded the lowest with 9%. The transportation sector generates the largest share of greenhouse gas emissions. GHG emissions from transportation primarily come from burning fossil fuel for our cars, trucks, ships, trains, and planes.

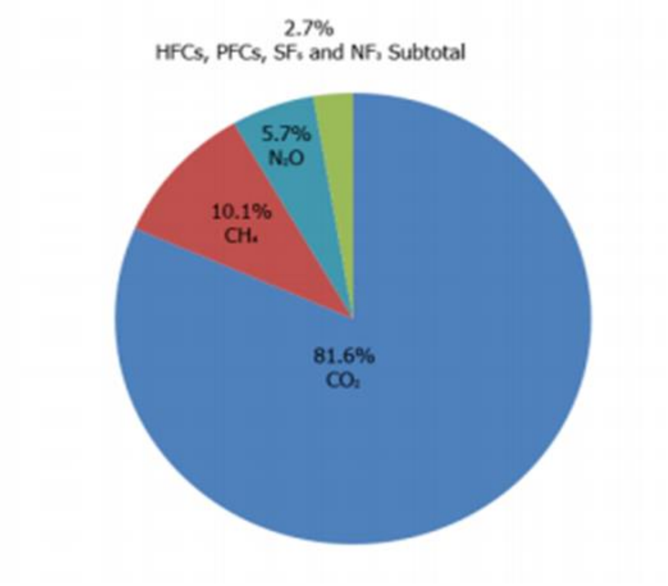


Figure 2.1 types of GHGs in 2016 (EPA,2018)

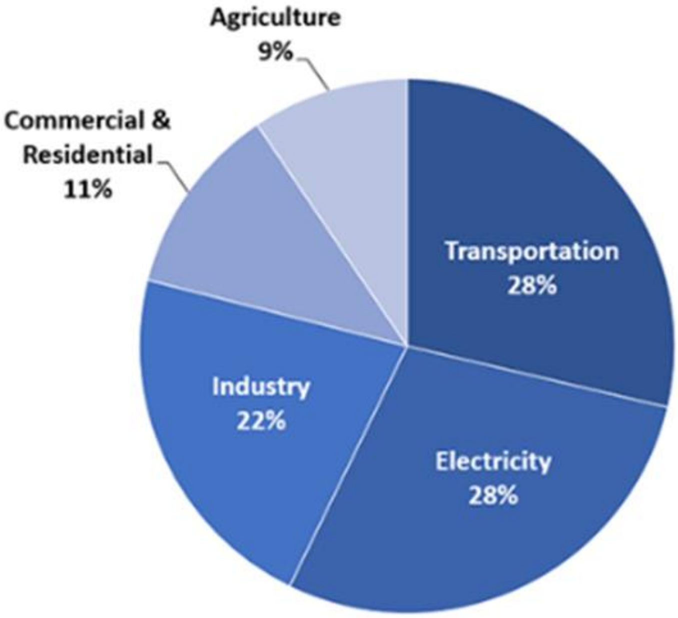


Figure 2.2 GHGs distribution in 2016 (EPA, 2018

In Malaysia, the total emission of GHGs is on the rise with the energy industries leading the emission. In 2011, energy sector contributed to 76% of the total emission, followed by waste disposal (12%) and industrial processes (6%). The agricultural sector contributed 5% of the total GHGs emission (Tang Kuok Ho, 2018). GHGs emitters of the energy sector were included road transportation, power generation, fuel manufacturing and processing, and activities of other sectors involving energy production, while those of the industrial processes were cement production, limestone and dolomite use, as well as iron and steel industry. For waste disposal, solid waste disposal sites and treatment of wastewater from palm oil mills were the major contributors of GHGs, particularly methane. Agricultural soil was the primary source of nitrous oxide.

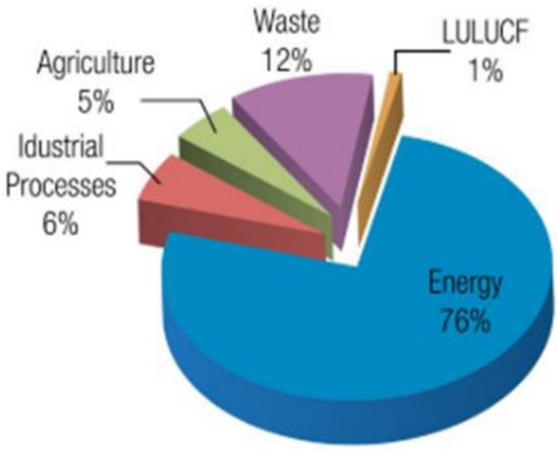


Figure 2.3 GHGs distributors in Malaysia

2.2.1 CO_2 Dispersion

Based on EPA (2018), CO_2 is the primary GHGs contributors through human activities. In year 2016, CO_2 represented 81% from all the gas emission and recorded 6,511million metrics tons. Figure 2.4 shows global CO_2 gas emission in 2006-2018 that shows increasing trend from 2006 and the highest CO_2 recorded was 414 ppm in year 2018 which 18% from safe limt. By increasing trade globalization and global structural changes especially in the manufacturing industry and international trade flows since 1990s, have caused the researchers from all over the world devoted to study the CO_2 emissions. Naturally, CO_2 enters the atmosphere through burning fossil fuels, solid waste, trees and wood products. Chemical reactions like manufacture of cement also contribute to carbon dioxide emission to atmosphere. However, CO_2 is an important variable because the positive effects of CO_2 on plants growth were discovered 200 years ago(Li et al., 2018). The CO_2 will be absorbed by plants as a part of the biological carbon cycle thus CO_2 can be removed from the atmosphere.

In Malaysia, the energy consumed by commercial and residential buildings accounted for about 13% and 48% of the total energy and electricity consumption (Wan Omar, 2018). Thus the emission of CO_2 potentially to increase due to increasing of energy consumed. The energy consumption was increasing rapidly because of economic growth and development between year 2000 and 2010. Figure 2.5 shows

Malaysia CO2 gas emission in 1970-2016 that shows increasing trend from 1970. This is because Malaysia is among the fastest developed countries in the Asian region and rapid urbanisation is the main target for the Malaysia Government in order to achieve developed country status in 2020. Thus the emission of CO_2 is expected to increase due to increasing of energy consumed (Li *et al.*, 2018).

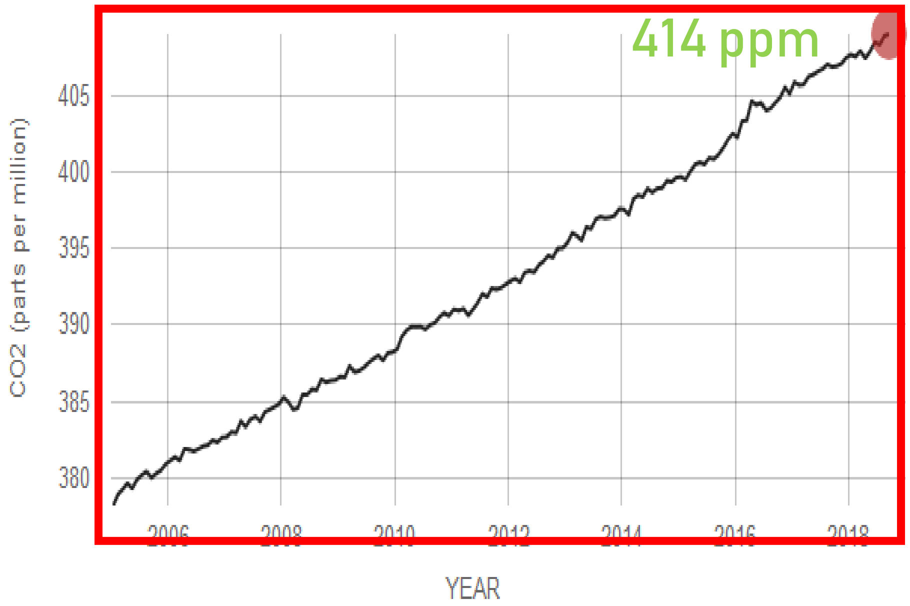


Figure 2.4 Global CO_2 gases emission in year 2006 -2018

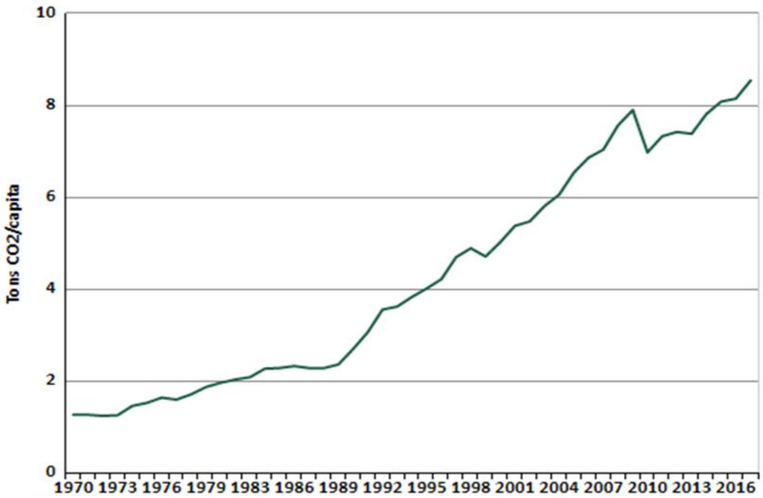


Figure 2.5 Malaysia CO_2 gas emission in 1970-2016

2.2.2 CH_4 Dispersion

CH_4 is the secondary higher gas emission after CO_2 gases with 10% from the total gas exist in atmosphere recorded in United State greenhouse gas emission in year 2016. CH_4 was emitted during the production and transport of coal, natural gas, and oil. Methane emissions also result from livestock and other agricultural practices and by the decay of organic waste in municipal solid waste landfills. Methane acts as the main natural gas component that released into the atmosphere by several industries. However, methane emissions cause serious environmental damages and safety risks (Farzaneh-Gord *et al.*, 2018). Formed of methane poses an explosion hazard which can result in evacuation of areas over old landfills or mines thus it can bring to safety risks for the people around.

In Malaysia, emission of CH_4 contributed by the main sector, agricultural soil which is flooded rice cultivation and this GHG responsible for global warming (Pardis Fazli, 2014). CH_4 that is produced and released into the atmosphere is taken up by methane sinks which include soil and the process of methane oxidation in the troposphere (the lowest atmospheric region).

Most methane produced naturally in the atmosphere contribute to the greenhouse effect, whereby greenhouse gases absorb infrared radiation which net heat energy and reradiate it back to Earth's surface, potentially trapping heat and producing substantial changes in climate. Increased atmospheric methane also adds to the greenhouse effect indirectly. For example, in methane oxidation hydroxyl radicals (OH−) remove methane by reacting with it to form CO2 and water vapour, and as concentrations of atmospheric methane increase, concentrations of hydroxyl radicals decrease, effectively prolonging the atmospheric lifetime of methane.

2.2.3 F Dispersion

Dissimilar to numerous other greenhouse gases, F gases have no characteristic sources and just originate from human-related activities. These gases are discharged through an assortment of mechanical procedures, for example, aluminium and semiconductor fabricating. Numerous fluorinated gasses have high global warning potentials (GWPs) with respect to other greenhouse gasses, so little air fixation can affect global temperatures. Like other extensive greenhouse gasses, F gases are very much blended in the climate, spreading the world over after they have discharged.

The main uses of F gases are in stationary and mobile refrigeration and air-conditioning systems, fire protection, high voltage switch gear, semiconductor production as well as in foams, aerosols and metered dose inhalers. In many cases, HFCs have been used to replace ozone depleting substances such as CFCs and HCFCs in refrigeration and air conditioning systems and halons in fire protection systems.

2.2.4 N_2O Dispersion

In year 2016, N_2O emission is around 6% of all U.S greenhouse gas emission from human activities. Nitrous oxide is emitted during agricultural and industrial activities, as well as during combustion of fossil fuels and solid waste. Nitrous oxide particles stay in the air for a normal of 114 years before being uprooted by a sink or decimated through compound responses. According to EPA, this nitrous oxide gas is 310 times more effective than carbon dioxide in trapping the heat (EPA , 2012).

In Malaysia, a total of 13,574 Gg (1 k tonne) CO_2 equivalent of N_2O were emitted recorded during 2011(Zaid *et al.*, 2015). These emissions were primarily from the agriculture sector which is growing rapidly nowadays and the agriculture soils contributed 81% of the emissions of nitrous oxide in Malaysia. Figure 2.6 shows the major sources of N_2O in 2011.

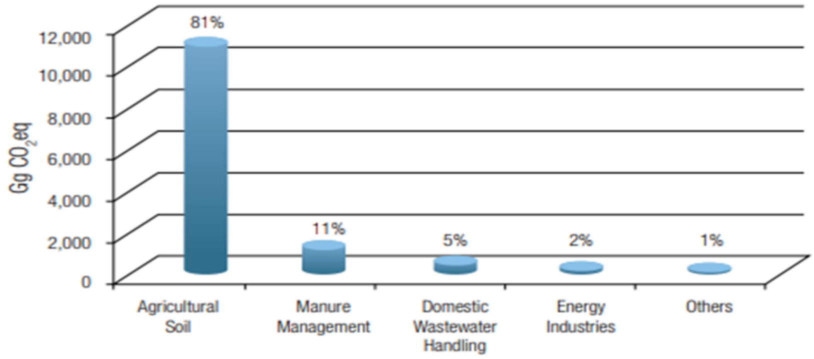


Figure 2.6 Malaysia major sources of NO_2 in 2011

2.3 Sources of GHGs

Table 2.1 sources of GHGs

Greenhouse gas	Sources
Carbon dioxide (CO_2)	• Decomposition of organic matter, animal and plant respiration • Deforestation • Burning of fossil fuel
Chlorofluorocarbons (CFC)	• Leaking of old air conditioners and refrigerators • Production of plastic foams • propellants in spray can
Methane (CH_4)	• Solid waste dumping grounds and landfills • Burning of forest • Agricultural waste.
Nitrous oxide (N_2O)	• Nylon production • Decomposition of nitrogen fertilizers • Burning of fossil fuels.

The sources of natural CO_2 include decomposition of organic matter, animal and plant respiration, deforestation, and emissions from vehicles. However, there are also naturally occurring CO_2 deposits found in formation layers within the Earth's crust that could serve as CO_2 sources. Emission of CFC also uncontrolled because of some human activities and the main sources of CFC emission are leaking of old air conditioners and refrigerators that not manage well, production of plastic foams and uses of the polystyrene in food packaging. Besides that, propellants in spray cans also contributed to CFC emission. Solid waste dumping grounds and landfills contributes to CH_4 emission to the atmosphere besides burning of forest and agricultural waste. The sources of N_2O were nylon production, decomposition of nitrogen fertilizers and burning of fossil fuels.

2.4 Impacts of GHGs to the climatic trend

GHGs move freely in the atmosphere and absorb the heat from the sunlight that passes through the atmosphere, then the heat is emitted. In sunny day, we can feel the effect by holding our hand over dark asphalt or our car's body. Besides that, GHGs absorb heat energy rising from the Earth's surface and re-emit some of that heat back down towards the ground. The effect is similar to how an actual greenhouse works but with different sources of heat absorbed. All GHGs were trapped the trap heat in the atmosphere and with their higher-than-natural concentrations, they lead to unnatural warming. In other word, GHGs act like the windows of a greenhouse, allowing light through but trapping heat inside (Jiang and Green, 2017).

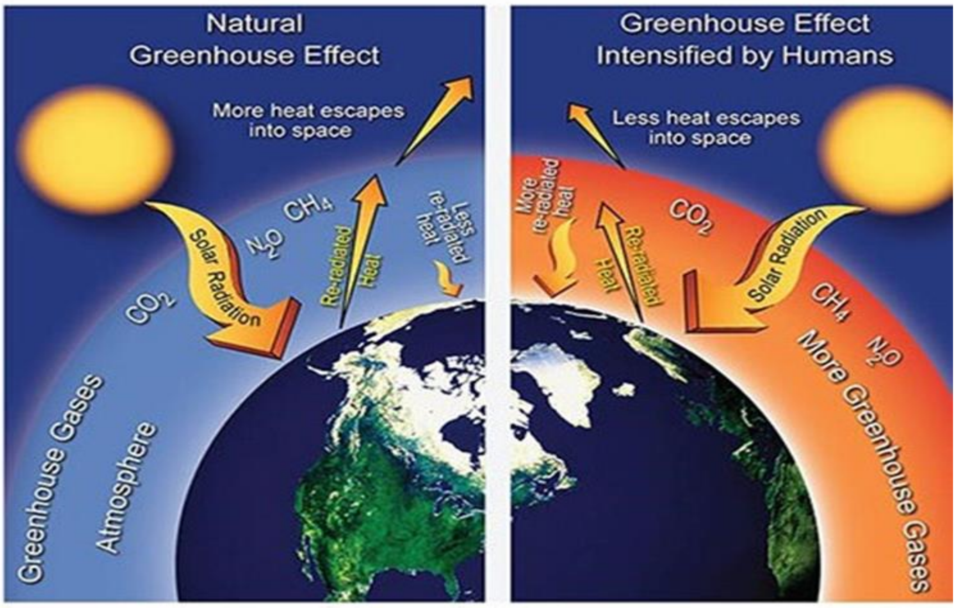


Figure 2.7 Human Influenced on the Greenhouse Effect

According to the near – universal consensus of scientists, these phenomena was expected to have profound implications in the future when the level of GHGs combined with greenhouse effect which resulting the global warming. NASA and EPA stated that if the global warming continues uncontrolled, it will cause worse climate change globally, rising in sea levels, increasing ocean acidification and extreme weather events (Ranveer et al , 2015). The CO2 emission also effect the marine life as the ocean also absorbs a lot, but not all. Unfortunately, the increased of CO2 in the ocean changes the water, making it more acidic. Thus, it can cause marine life such as fish harmful as not enough oxygen for breathe and produce unhealthy coral.

More droughts and flooding will happen when the weather gets warmer as the evaporation from both land and sea increases. For the areas with less rainfall per year, evaporation effect from the warmer weather can cause drought and in some regions of the world, this will result in crop failure and famine especially in areas where temperatures are already high. Malaysia had experienced one of the most devastating floods in decades(Ruiz Estrada *et al.*, 2017). Last four years, Kelantan had occured a huge flood that in year 2014 where 200,000 people are affected while 21 were killed.

Floods are by far the most common natural hazard in causing loss of life, human suffering inconvenience and widespread damage to building, structures, crops and infrastructure. In October 2003, major flooding affected a large area in Peninsular Malaysia, including the states of Kedah, Penang and Northern Perak.

Scenes of flooding and storms show us just how much weather and climate change can affect our lives. Understanding and predicting what the coming winter might bring, or predicting how climate will change over the next century is of vital importance for our economy and society. Climate can be thought of as the average or typical weather conditions we experience. Weather and climate can affect almost all aspects of our lives (NCAS, 2015). This is why prediction of climate was important.

2.5 Assessment Report (AR)

The drastic changes in global climate over the past decades are unpredicted and cannot be ignored as this phenomenon is likely to be worse in the future. These changes are well documented in the Assessment Reports (ARs) of the Intergovernmental Panel on Climate Change (Minx *et al.*, 2017). The main cause of this change is the rapid rise of atmospheric Greenhouse Gas (GHG) concentrations and in its periodic assessment, IPCC has become gradually more certain that global warming underway, and this rapid warming rate is attributed to human activities (EPA, 2014)

According to United Nations Intergovernmental Panel on Climate Change (IPCC), Climate Change 2007 known as the Fourth Assessment Report (AR4) is the fourth in a series of reports intended to assess scientific, its potential effect, technical and socio-economic information concerning climate change and options for mitigation and adaptation. This report is the largest and most detailed summary of the climate change situation produced by thousands of authors, editors, and reviewers from dozens of countries with citing over 6,000 peer-reviewed scientific studies (Vasileiadou et al, 2011).

From the AR4, summary finding can be made which is observational evidence from all continents and most oceans shows that many natural systems are being affected by regional climate changes, particularly temperature increases reported by Rosenzweig et al. (2007). In that particular, they highlighted several areas with the conclusion that supported by some evidences. First evidence, changes in snow, ice, and frozen ground that caused of increased ground instability in mountains and other permafrost regions. Thus, these changes had led to changes in some Arctic and Antarctic ecosystems and produced increases in the number and size of glacial lakes. Some hydrological systems had been affected by increased runoff and earlier spring peak discharges therefore in particular many glacier- and snow-fed rivers and lakes had warmed, producing changes in their thermal structures and water quality had been the evidence for the conclusion made in AR4. Besides that, these shifts in plant and animal ranges were attributed to recent warming because of spring events that had appeared earlier in the year so that terrestrial ecosystems had moved pole ward and upward. Shifts in ranges and changes in algal, plankton, and fish abundance as well as changes in ice cover salinity, oxygen levels, and circulation had been associated with rising water temperatures in some marine and freshwater systems are one of the evidence of conclusion in AR4.

Comprehensive scientific assessments on anthropogenic climate change have been produced by the Intergovernmental Panel on Climate Change (IPCC) since 1988. In November 2014, the Synthesis to the Fifth IPCC Assessment Report (AR5) was finalized. To access on a comprehensive, objective, open, and transparent basis the scientific, technical, and socioeconomic information on climate change, its impacts, and options for adaptation and mitigation are the IPCC's mandate. Hundreds of authors and thousands of reviewers contribute their expertise in this assessment process on a voluntary basis without any form of remuneration. A few dozen paid professional scientific and technical staff at the Technical Support Units (TSUs), led by the Co-Chairs of their respective Working Groups (WGs) support this massive community.

2.6 Representative Concentration Pathway (RCPs)

A Representative Concentration Pathway (RCP) is a greenhouse gas concentration trajectory adopted by the IPCC for its AR5 (Shrestha et al, 2016) which is a set of greenhouse gas concentration and emissions pathways designed to support research on the impacts of and potential policy responses to climate change. The RCPs include impacts from land use and land cover (LULC) changes as well, in contrast to the SRES scenarios that include only the forcing by greenhouse gas and aerosol from artificial climate change factors. RCPs are important in order to improve understanding of the complex linkages between human activities and the climate system (Chuwah *et al.*, 2013).

The RCP set consists of four scenarios which are RCP2.6, RCP4.5, RCP6.0 and RCP8.5 where each of RCPs describes a different trajectory for emissions of long-lived GHGs and short-lived air pollutants, the corresponding concentration levels, land use and radiative forcing. Figure 2.8 shows projected greenhouse gas concentration for four different emissions pathways. The top pathway assumes that greenhouse gas emissions will continue to rise throughout the current century. The bottom pathway assumes that emissions reach a peak between 2010 and 2020, declining thereafter.

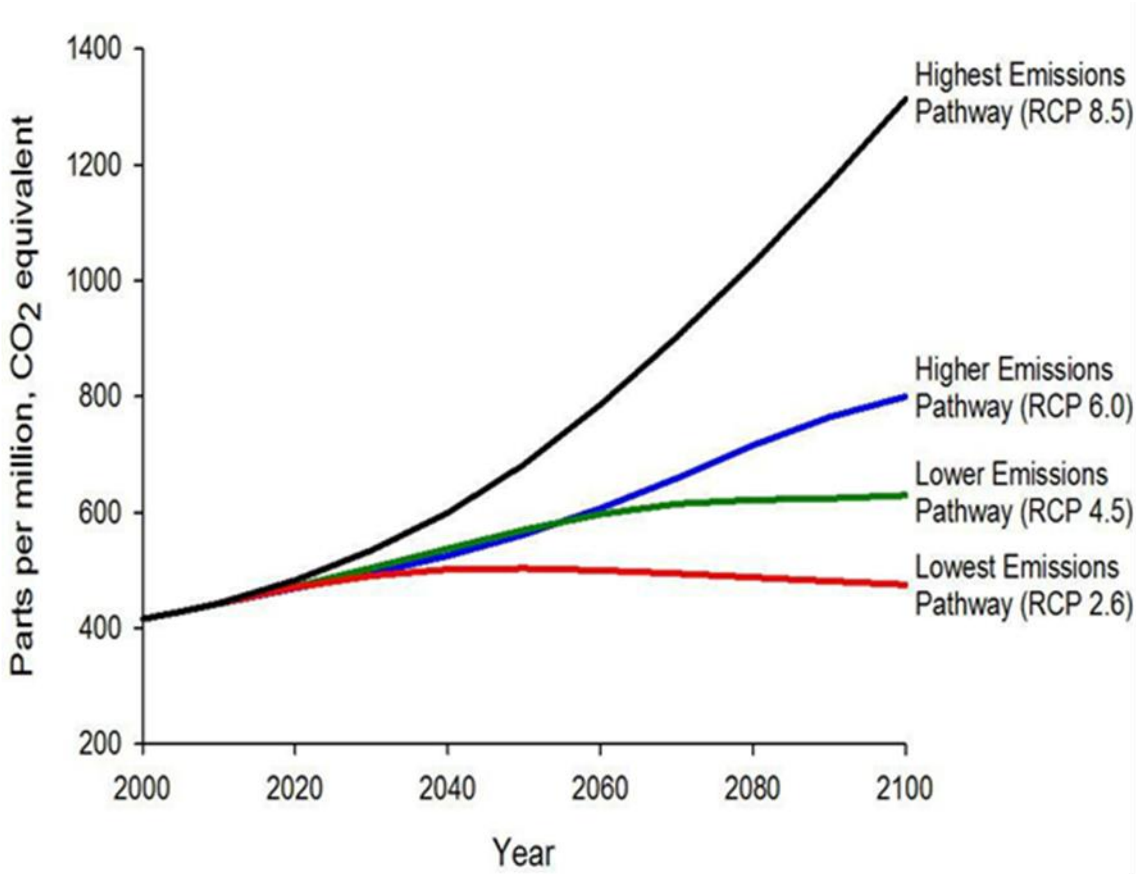


Figure 2.8 The projected greenhouse gas concentration for four different emissions pathways (www.epa.gov/climatechange/)

However, the best RCPs where the higher and lower RCPs will be chosen to capture this range for impact assessments if full range of RCPs used are not possible. Therefore, the best RCPs used in this research are RCP 2.6, RCP 4.5 and RCP 8.5. The global climate implications of the forcing of the scenarios used can be seen in the projected changes in the global mean surface air temperature by 2100 as simulated by global climate models for two emissions scenarios, RCP2.6 (lower) and RCP8.5 (higher) compared to the historical period baseline (1986–2005). Figure 2.9 shows the comparison of RCPs with the historical.

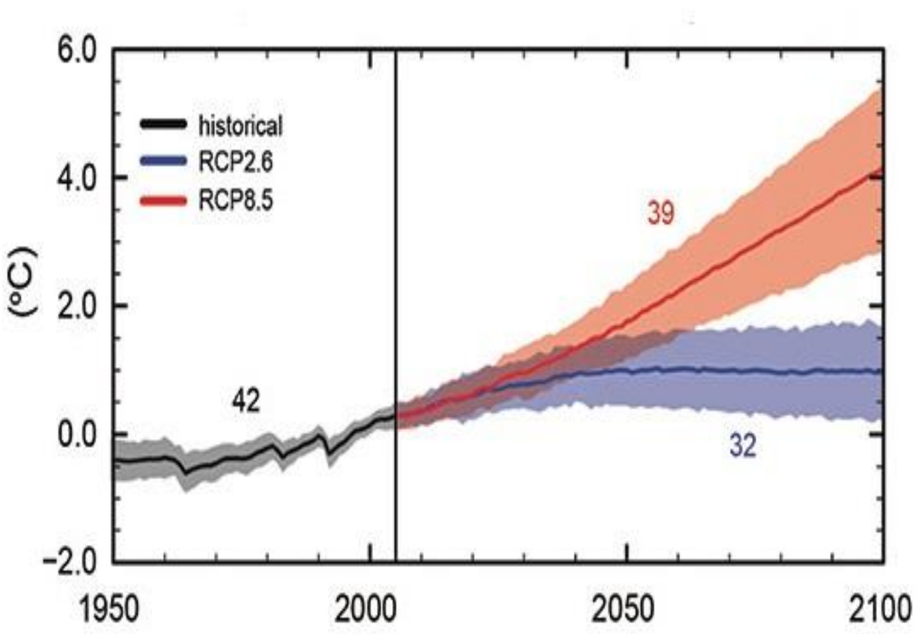


Figure 2.9 Comparison RCPs with the historical

RCP8.5 was developed using the MESSAGE model and the IIASA Integrated Assessment Framework by the International Institute for Applied Systems Analysis (IIASA), Austria. This RCP is characterized by increasing GHGs over time, representative of scenarios in the literature that lead to high GHGs concentration levels in the atmosphere and was categorized as the highest emission pathway. RCP 4.5 is a stabilization scenario in which total radiative forcing is stabilized shortly after year 2100 without overshooting the long-run radiative forcing target level. This RCP was categorized as lower emissions pathway. The lowest of emissions pathway was RCP2.6 as it was representative of scenarios in the literature that lead to very low GHGs concentration levels. This is because of reducing immediately that leading to slight reduction on today's level by year 2100.

Each RCP could result from different combinations of economic, technological, demographic, policy, and institutional futures. For example, the second-to-lowest RCP could be considered as a moderate mitigation scenario. However, it is also consistent with a baseline scenario that assumes a global development that focuses on technological improvements and a shift to service industries but does not aim to reduce greenhouse gas emissions as a goal in itself. Besides that, RCP is provided by the four GCM groups which are CanESM2, HadGEM2-A, HadGEM2-CC and HadGEM2-ES

2.7 Global Circulation Model (GCM)

Global Circulation Models (GCMs), represent physical processes in the atmosphere, ocean, and land surface. These models are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations (Corbeels *et al.*, 2018). GCMs present the climate using a three dimensional grid over the globe typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere. Their resolution is thus quite coarse relative to the scale of exposure units in most impact assessments. Moreover, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modelled. Instead, properties must be averaged over the larger scale in a technique known as parameterization.

This is one source of uncertainty in GCM-based simulations of future climate. Others relate to the simulation of various feedback mechanisms in models concerning, for example, water vapour and warming, clouds and radiation, ocean circulation and ice and snow albedo. For this reason, GCMs may simulate quite different responses to the same forcing, simply because of the way certain processes and feedbacks are modelled.

GCMs are the most complex of climate models, since GCMs can represent the main components of the climate system in three dimensions (3D). The historical evolution of GCMs, computing resources and the nature of climate change experiments are necessarily linked.

There are several types GCMs which 1) HadGEM 2- ES 2) HadGEM 2-A 3) HadGEM 2-CC 4) CanESM22. The Hadley Centre Global Environmental Model version 2 (HadGEM2) family of models has been designed for the specific purpose of simulating and understanding the centennial scale evolution of climate including biogeochemical feedbacks (Collins *et al.*, 2011). The HadGEM2-ES model was developed from HadGEM, that represent improvements in the physical model and the addition of earth system components and coupling. HadGEM2 is the product of two development projects which are improving the physical climate and adding earth system components. HadGEM2-ES is the first Met Office Hadley Centre, earth system model to run without the need for flux corrections not as previous carbon cycle model in the Hadley Centre (HadCM3LC) that had to use artificial correction terms to keep the model state from drifting uncontrollably.

The HadGEM2-A model is a configuration of the HadGEM2 model which is an atmosphere only simulation with other component interfaces replaced with ancillary file input. HadGEM2-CC is a specific configuration of HadGEM2 for the CMIP5 project using a 60 level atmosphere. Major differences from HadGEM2-ES are the inclusion of a non-orographic gravity wave drag scheme, production of stratospheric water vapour from methane oxidation, and the removal of the UKCA interactive tropospheric chemistry component. Chemical oxidants are prescribed using decadal averages from the equivalent HadGEM2-ES simulations

However, GCMs also have their limitation such as it fail to account properly for certain multiplier effects that may significantly amplify the initial impacts of various biospheric processes. For example, several multiplier effects may significantly amplify the initial perturbation although the absolute variations associated with some solar-related phenomena are small. The major of imperfections in the GCMs prevent proper simulation of important elements of the climate system including wind, clouds, pressure, temperature and precipitation. When comparing these elements, huge differences between model predictions and observations frequently exist and some cases computer models fail to simulation.

GCMs can be categorized into three main types there are; (1) atmospheric GCMs coupled with a simple slab ocean and simple land-surface parameterization schemes, (2) atmospheric GCMs coupled to a three-dimensional representation of the ocean system and with simple land-surface parameterization schemes and (3) atmospheric GCMs coupled to a three-dimensional representative of the ocean and a three dimensional terrestrial biosphere model. Example of types one are UKLO and UKHI, form type two is UKTR and example of type three are HadCM2 and HadCM3.

2.8 Climate Modelling

Climate models are fundamental tools used for studying the potential impacts of climate change, including changes in temperature, rainfall, and sea level. The National Oceanic and Atmospheric Administration (NOAA),Climate Prediction Centre defines a climate model as a mathematical model used for quantitatively describing, simulating, and analyse the interactions between the atmosphere and underlying surface such as ocean, land and ice which based on the laws of physics and run on of powerful computers. They represent fundamental physical processes in the atmosphere, ocean, land surface and cryosphere. Even though there is some chaotic behaviour involved at small scales, in theoretically, these physical processes can be represented mathematically. There are some of the challenges in developing an Earth system model such as many processes making up the Earth's climate operate on different temporal and spatial scales from a few metres and seconds to thousands of kilometres and thousands of years and these processes interact with each other across different time and space scales. This means that even though a global climate model is mainly used for decadal-to-century long projections, they seek to incorporate as many short-term and small scale processes as possible since these also interact with the larger scales.

The climate models project possible future climate shifts under the conditions of the specific scenarios. Various scenarios of future conditions, such as population levels and anticipated emissions of CO2 or other GHGs are run by these models in multiple times. Each GCM is distinct and has a different sensitivity to GHGs emissions. Sense of the uncertainty surrounding possible future events given a particular scenario and period provided by researchers and GCM is important to them. Ensembles of multiple global climate model simulations are often used to capture this range and make sure the complements of projections(Laflamme, Linder and Pan, 2016).

Climate models are the best devices for reproducing the future climate situations. However, variety inside and among alternate climate models postures issues for ends users attempting to distinguish ideal models from which to obtain simulations (Collins *et al.*, 2011). There is no clear direction or guidance of the best way to choose the most proper simulations for a given application. There may be a final conclusion effected by the data collected and little objective in selecting climate models for effect displaying. Consideration should be taken to the choice of climate models for impacts evaluation.

Some region will be represented to inadequately by climate model for example, mountainous regions, zones influenced with urban heat island impact, beach front areas (Beaumont et al, 2008, Martinez et al,2015). Through simulation, computerized climate models consolidate and formulize our understanding of the many natural region that form systems that together comprise Earth's climate.

Climate models are important for scientists in order to understand the complexities of Earth's climate. With this models, the climate projection are more fast and effective as these computer simulations incorporate both direct observations and theory of the past and present in order to project climate into the future. Because of this synthesizing role, and because their output takes the recognizable shape of maps, these models lay an important foundation for political action on climate change.

2.8.1 Downscaling Models

Global climate models (GCMs) are the best tools for providing climate projections and climate model classified as a mathematical representation of the climate system where mathematical equations are solved on a super-computer at points on a 3-dimensional grid in the ocean and atmosphere, over a number of time-steps. Downscaling is the process by which coarse-resolution GCM outputs are translated into finer resolution climate information, so that they better account for regional climatic influences, such as local topography.

Atmosphere-ocean general circulation models, or AOGCMs, are coupled atmosphere and ocean models that simulation weather global scale. AOGCMs are the main component of global climate models (GCMs) which are the primary tools used to quantify and assess climate change impacts. However, because global weather simulation is so computationally expensive, these models provide predictions at an extremely coarse scale (250 km by 250 km, in most cases).

GCM outputs can be translated to finer resolutions or even point locations in many different ways and as a general guide, downscaling methods can typically be categorised into three groups which are change factor methods, statistical downscaling and dynamical downscaling(Sachindra *et al.*, 2018). There were two downscaling models which are statistical downscaling and dynamical statistical tha have to look forward because statistical and dynamical downscaling are more technical processes than change factor methods, and have the potential to reveal new and plausible regional detail in the climate change signal.

2.8.2 Dynamical Downscaling (DD)

Dynamical downscaling has the same ultimate goal as statistical downscaling – a finer resolution climate scenario but employs a regional climate model forced at the boundaries by the large-scale climate model rather than relying on statistical relationships. Dynamical downscaling for Alaska has been conducted using lateral boundary forcing from reanalysis output (Bieniek et al., 2016; Bhatt et al., 2007) as well as historical and future output from climate models (Zhang et al., 2007; Lader et al., 2017). Dynamical downscaling provides physically consistent projections of many variables, and therefore sufficient data to explore future climate variability mechanisms. This method is computationally expensive, limiting the number of different models/scenarios that can be downscaled. Dynamical downscaling is also a complex process requiring a relatively high level of modelling expertise to conduct. Biases and other errors in the models are also problematic in dynamical downscaling.

Dynamical downscaling is a widely applied approach for high resolution climate prediction. Every model has its limitation. In dynamical downscaling, a Regional Climate Model (RCM) is employed on a limited area of interest and it implies that vertical resolution is affordable and higher horizontal. In the horizontal resolutions of the atmosphere part of the GCM employed were 250-300km while RCM employed with approximately 50km resolution although some climate simulations were performed on much finer resolution (Andreas et al, 2012). Therefore, RCMs clearly increase the resolution compared to GCMs. This increased resolution is a potential source for better description of the climate system by better resolving the dynamics of the system and better description of surface forcing such as topography, land-sea and vegetation contrasts.

Four types of dynamic downscaling had been proposed by Rockel et al.,(2008) which type 1, used for numerical weather prediction, remembers its real-world initial conditions, as do the lateral boundary conditions. In Type 2, the initial conditions in the interior of the model are forgotten but the lateral boundary conditions feed real-world data into the regional model. In Type 3, a global model prediction is used to create the lateral boundary conditions. These internal climate system components are assigned and not predicted. This constrains the global model predictions such that some real-world data is still fed into the regional model through the lateral boundary conditions. In Type 4, a global model is run in which there are no prescribed internal climate system forcing. The coupling interfacial fluxes among the ocean-land-continental ice atmosphere are all predicted

2.8.3 Statistical Downscaling (SD)

One of the primary methods of transforming coarse-resolution climate information to high resolution is statistical downscaling with the goal to reproduce local climate averages. This requires long-term high quality observational data to develop ‘training’ relationships between coarser-resolution model-derived variables and local conditions. Temperature, winds and precipitation over a training period are local variables of statistical that established relationship with large-scale climate. Downscaling to a local point at whatever time step is resolved by local observations either monthly or daily allowed by this method (Sachindra *et al.,* 2018).

Although winds, relative humidity, ocean water temperature and snow water downscaled statistically downscaled, the most common statistically downscaled variables are temperature and precipitation (Sachindra *et al.*, 2018). One of the SD methods is including several variants of quantile-mapping. The characteristic of statistical downscaling that most sensitive to the driving GCM, secondly to statistically method and evaluation metric were found by Hayhoe (2010) and (Sachindra *et al.*, 2018). Statistical downscaling is relatively computationally inexpensive, allowing many models or scenarios to be downscaled, and the methods are generally friendly used.

Statistical downscaling can be divided into three categories, 1) regression-based approaches, 2) approached based on weather generators and 3) weather classification-based approaches. Regression-based statistical downscaling approaches have gained popularity out of the above three categories owing to their simplicity in application. The regression techniques widely used in statistical downscaling include Multi Linear Regression (Sachindra *et al.*, 2018).

Essentially, statistical downscaling is consisting two-step process where the development of statistical relationships between local climate variables and large scale predictors, and the application of such relationships to the output of large scale output to simulate local climate characteristics in the future (Hoar et al, 2008). Besides that, it able to approach and develop a specific, local-level climate prediction as statistical downscaling is realistic. Typically, statistical downscaling methods are applied to GCM projections besides may also be applied to RCM output as these results may not be representative for the local climate. Furthermore, RCM output may simply have in-adequate spatial resolution for some impact studies, and hence additional statistical downscaling must be applied to the dynamical model results (Sachindra *et al.*, 2018).

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

Table 2.2 Strengths and weakness of Downscaling Models

Statistical downscaling		Dynamical downscaling
• GCM produces information in station-scale-scale-output • User-friendly, affordable and computationally undemanding • Ensembles of climate scenarios permit risk • Applicable to unusual predictants	Strengths	• Climate information from GCM in 10-50km range of resolution-scale output • predicting spatial-temporal rainfall variation due to a finer resolution of regional climate models • Consistency with GCM • Resolve atmospheric process
• Model calibration and validation required to produce unsatisfactory results that lead to uncertainty in the model outputs. • SDSM showed insensitivity of selected large-scale atmospheric predictors • performance of statistical downscaling was not satisfactory in projecting future rainfall	Weakness	• Dynamical Downscaling depends on boundary conditions supply from some other sources • The dynamical downscaling model may miss the most extreme rainfall data

Statistical downscaling (SD) is friendly user as it is easy to use compare to Dynamical downscale (DD) because it is focuses on its station scale while DD has climate information from GCM in 10-50km range in resolution. Moreover, SD use computational demanding compared to DD. DD is difficult to use because its depends on boundary conditions supply from some other source which it is a combination of climate scenarios that seldom produce due to climate that always change from time to time while SD have ensembles of climate scenarios permit risk. SD also showed insensitivity of selected large-scale atmospheric predictors thus it is good compared to DD that may miss the most extreme rainfall data.

SD has more superiority than DD but it also has its own limitations. SD is depending on the realism of GCM boundary forcing. The result of SD depends on the choice of domain size and location. Its mean the result will be different depend on the choice. SD also needs high quality of data for model calibration otherwise the model will not run. In conclusion, SD has more advantages in form of technology, affordable and user friendly compared to DD modelling, a multiple regression-based method was chosen as the basis of the decision support tool which is SDSM.

The consensus of model inter–comparison studies is that dynamical and statistical methods have comparable skill at estimating surface weather variables under present climate conditions. However, because of recognised inter–variable biases in host GCMs, assessing the realism of future climate change scenarios produced by statistical downscaling methods is problematic. This is because uncertainties exist in both GCM and downscaled climate scenarios. For example, precipitation changes projected by the U.K. Met Office's coupled ocean–atmosphere model HadCM2, were found to be over–sensitive to future changes in atmospheric humidity. Overall, the greatest obstacle to the successful implementation of both statistical and dynamical downscaling is the realism of the GCM output used to drive the schemes.

2.9 Statistical Downscaling Model (SDSM)

SDSM methodologies have several pragmatic advantages over dynamical downscaling approaches. In situations where a minimal effort, fast assessment of highly restricted climate change impacts required, statistical downscaling represents the all alternatives. The software is named Statistical Downscaling Model (SDSM) and is coded in Visual Basic 6.0.

SDSM is a user-friendly as it comes with comprehensive instructions for use software package designed to implement statistical downscaling methods to produce high-resolution monthly climate information from coarse-resolution climate model (GCM) simulations. The software also uses weather generator methods to produce multiple realizations of synthetic daily weather sequences. The advantage is SDSM can be used if daily GCM outputs for large-scale climate variables are available while impact assessments require small-scale climate scenarios and provided quality observational data.

SDSM model was created by Robert L. Wilby and Christian W. Dawson in year 2000 from United Kingdom and it uses weather generator system to create different acknowledgement of synthetic every day weather sequence. This software calculates the statistical relationship based on different regression techniques between large scale and local climate. Using an observed weather data through relationship of GCM-determined indicator was created. This relationship create a minimum and greatest temperature, precipitation and humidity of site specific day by day scenarios for selected district and scope of statistical parameter such as fluctuation and frequencies of extreme. SDSM model allows diverse types of data to be transformed into standard indicator variables before being downscaled and aligned to deliver nonlinear regression models. To produce delayed predictor variables, data series can also be shifted forward or backward by any number of time steps and regressions models can also be built on a monthly or annual basis. SDSM can reduce the standard error of estimate and increase the number of explained variance using variance inflation techniques or using bias correction in order to generate the most ideal downscaled model (Tukimat *et al.*, 2018).

SDSM are divided into three major methods, which are a) regression models, b) weather typing schemes and c) stochastic weather generation. 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.

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

Table 2.3 Comparison of SDSM performances with the other model

Author	Comparison
(Zehtabian et al., 2016)	Comparison of performance between SDSM and CLIMGEN models in simulation of climatic variables in Qazvin Plain. Result shows The results showed that CLIMGEN outperform in rainfall data generation while SDSM outperforms in simulating average temperatures.
Chen et al,2012	Comparison between SDSM and SSVM as hydrological models to perform in upper Hanjing basin in China. It is proved that SDSM has better performances compare to SSVM in simulating rainfall.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The main aim of this study is to study the future climate trend at northern Malaysia in interval year of 2020, 2050 and 2080 and to identify the best RCPs and GCM group for Northern Malaysia (Perlis and Pulau Pinang) using SDSM. The SDSM model is used to generate the climate trend for the future. Currently, an annual rainfall in northern Malaysia is between 2,000 - 4,000 mm with has uniform maximum temperature of 32˚C per year. In this research, the selected station of rainfall and temperature in Perlis and Pulau Pinang were selected as a case study. The framework of this study consists of four steps, which are: 1) download and screen the GCM data for the under different scenarios which are HadGEM2-A, HadGEM2-CC, HadGEM-ES and CanESM 2) downscale the GCM data using the SDSM, 3) 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 step of SDSM which are 1. Quality control and data transformation 2. Screening of predictor variables 3. Model calibration 4. Weather Generator 5. Statistical analyses 6. Graphing model output and 7. Scenario generation. The function of quality control identifies gross data error, outlines prior to model calibration and specifications of missing data codes, therefore transformation function will be applied to the selected transformation 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 variables operation can assist it. Next, model calibration takes user-specified along with the set of predictors andestimates the parameter of multiple regression equation through an optimization algorithm by either ordinary least square method or dual simplex. Before proceed 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 models, 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 output file 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 types 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.

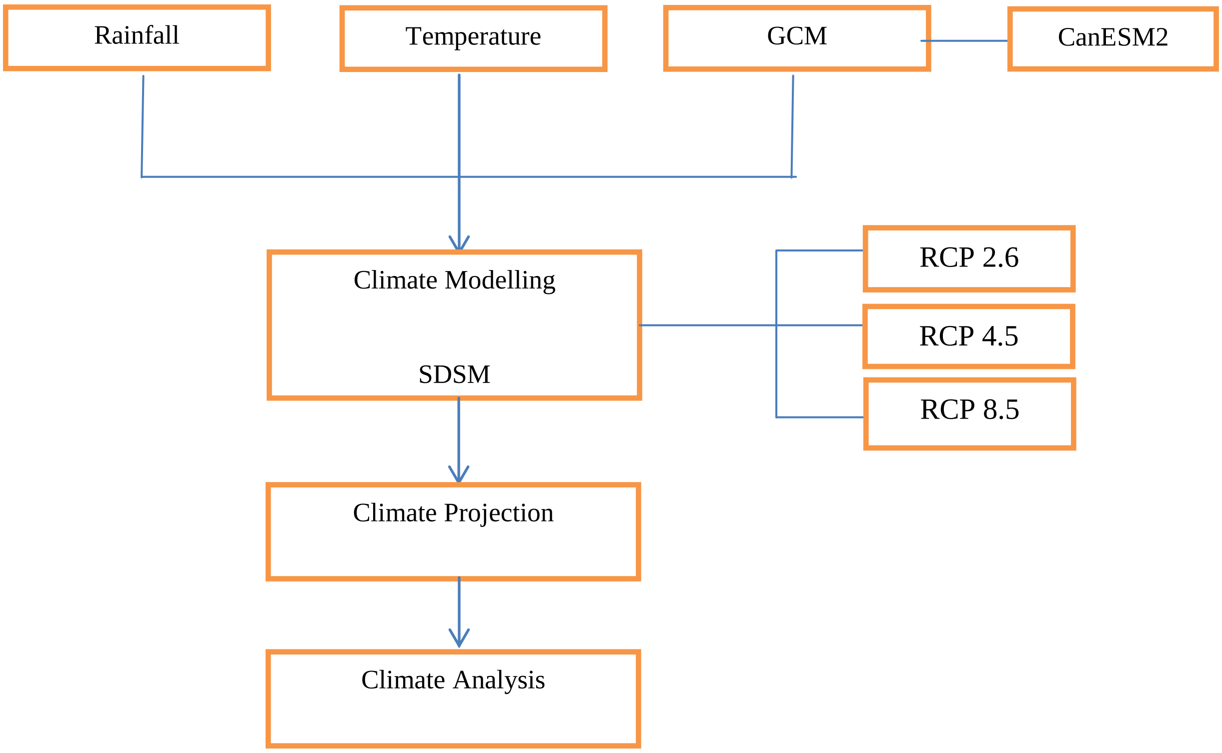


Figure 3.1 The schematic diagram methodology of the study

3.2 Statistical Downscaling Model (SDSM)

SDSM 4.2 is one of the downscaling models that applied the linear regression analysis to interpret the relationship between GCMs characteristics with local climatic 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 site 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 output using multiple regression techniques. Its build up the relationship between GCMs' variable which is predictors and the local scale variable acts as predictants (Chu et al., 2010), the relationship between predictand – predictor can be determined by:

$$Y = F(X) \quad 3.1$$

which Y means the local predictand and, X(x1, x2,…xn) represents n large-scale atmospheric predictors, and F is the built quantitative statistical relationship.

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 determines the estimated value of rainfall on each rainy day. Rainfall is a condition process, and it is model 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 output from the NCEP reanalysis for calibration, as well as HadGEM2 for future generation

The SDSM model implies that the statistical relationships to downscale the large-scale resolutions 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 numbers 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 station known as predictand and two set of predictors. In this study, temperature recorded at Northern Malaysia stations and historical rainfall at several stations in Northern Malaysia 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 Environmental 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.

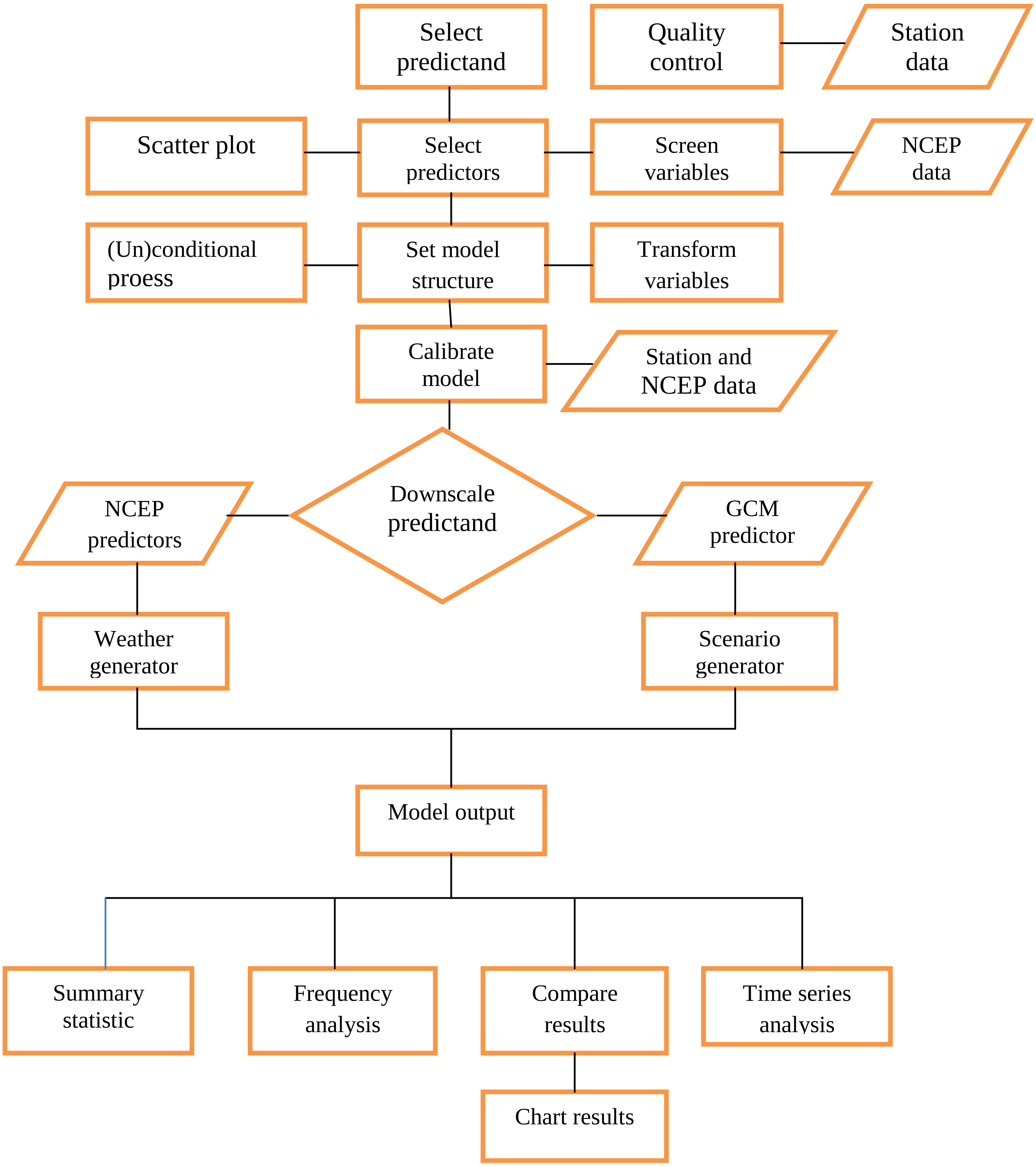


Figure 3.2 Schematic Diagram of SDSM

3.2.1 Selection of the Predictors

One of the major challenges in climate downscaling especially in 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 of climate. There are no general guidelines for the selection of predictors in different parts of the world, therefore a comprehensive search of predictors is necessary. Twenty-six NCEP variables that are usually projected by various climate models, including the Hadley Centre Climate Model (HadCM) were used in the present study for the selection of predictors. The description of 25 NCEP variables is given in tables 3.1.

The climatic system is influenced by the combined action 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 surrounding the study area were individually correlated with local extreme rainfall events. The non-parametric Kendall correlation coefficient was used to measure the degree of association between NCEP variables and local extreme rainfall events. Finally, the NCEP variables that have a 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 (Hadipour,2014)

Table 3.1 : List of 26 Predictors

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	humidity
13	p5th	500 hpa wind direction	26	temp	mean temperature at 2m

3.2.2 Calibration and Validation Process

The calibration and validation processes are important procedures during predicting stage. The calibration of downscaling models was based on solving multiple regression equations, by given daily weather data as the predictand and regional–scale atmospheric act as predictor variables. The mathematical interpretation by Croarkin and Tobias (2012), the calibration is a measurement process that assigned values to the property of an artifact or to the response of an instrument relative to reference standards or to designate measurement process. In this case study, the term of calibration precisely referred to the build/design relationship among local data (predictand) and selected regional atmospheric variables (predictors) based on multiple linear regression equations (Wilby and Dawson, 2007). The calibration results were formulated using specific period as foundation to estimate another combination of predictor variable values in validation process. The goal was to identify the fundamental rules and the predictand-predictors relationships that were able to be adequate as original data.

The calibrated model is used to build predictand-predictor relationships in the SDSM analysis. These predictor-predictand relationships are simulated to generate synthetic daily weather series using weather generator. Therefore, the temperature is calibrated for the time period 1984 – 1998 and validated for the period of 1999 - 2013 The rainfall is calibrated for the time period 1979 – 1993 and validated for the time period 1994 - 2008. Using the same GCMs predictors' variables in the calibration, the ensembles of synthetic daily weather series during year 2010 to 2099 are generated using scenario generator in the SDSM model.

3.3 Representative Concentration Pathway Assessment

Due to inability of prediction in how the greenhouse gas and concentrations in the atmosphere, a range of RCPs should be considered when developing the climate projection. In this study, 3 RCPs were selected which are RCP2.6, RCP 4.5 and RCP 8.5 that defined by their total radiative forcing pathway which is cumulative measure of human emissions of GHGs from all sources expressed in Watts per square meter and level by 2100. These RCPS were chosen because of some criteria where each RCP is based on an internally consistent set of socioeconomic assumption where the four RCPs cannot be treated as a set with consistent internal socioeconomic logic. For example, RCP8.5 cannot be used as a no-climate-policy socioeconomic reference scenario for the other RCPs because RCP8.5's socioeconomic, technology, and biophysical assumptions different from those of the other RCPs.

Figure 3.3 shows the comparison of all types of RCPs in term of radiative forcing trajectories for the four RCPs. The radiative forcing trajectories are consistent with socio-economic projections unique for each RCP. For example, RCP2.6 assumes that through drastic policy intervention, greenhouse gas emissions are reduced almost immediately, leading to a slight reduction on today's levels by 2100.

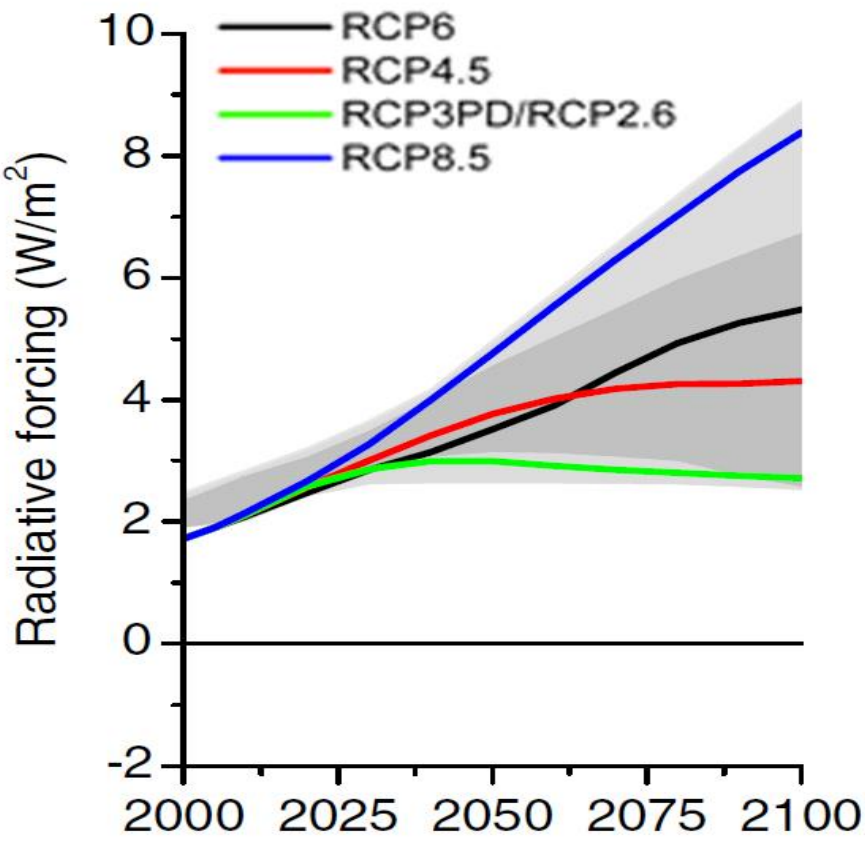


Figure 3.3 comparison types of RCPs

3.4 Climate Projection

In order to downscale the future emission scenarios, the SDSM software of the scenario generator was used to produce ensembles of synthetic daily weather time series given a daily atmospheric predictor variable supplied by the GCM .The climate projection of the future is using the scenario of CanESM2, HadGEM2-A, HadGEM2-CC and HadGEM-ES. These scenarios have been chosen because of some characteristics.

The developed SDSM model is applied to downscale and generate future scenarios of daily temperature (TMax and TMin) and precipitation from predictors of second generation Canadian Earth System Model (CanESM2). CanESM2 is under the

CMIP5 experiments that consists of the physical coupled atmosphere-ocean model CanCM4 coupled to a terrestrial carbon model (CTEM) and an ocean carbon model (CMOC). The ocean and land carbon cycle components of CanESM2 are essentially the same as those in CanESM1 and are represented by the Canadian Model of Ocean Carbon (CMOC) (Christian et al., 2010) and the Canadian Terrestrial Ecosystem Model (CTEM) (Arora et al., 2009) respectively.

Hadley Centre Global Environment Model version 2 or known as HadGEM2 is the model that comprises a range of specific model configurations incorporating different levels of complexity but with a common physical framework. There are three version of HadGEM2 which are HadGEM2-A, HadGEM2-CC and HadGEM-ES. The HadGEM2-A is a model which is an atmosphere that simulation only with the other component interfaces replaced with ancillary file input. The HadGEM2-ES model was a two stage development from HadGEM1, representing improvements in the physical model (leading to HadGEM2-AO) and the addition of earth system components and coupling that leading to HadGEM2-ES. In HadGEM2-ES the vegetation cover is better than in the previous HadCM3LC model especially for trees, and the productivity is better than in the non-interactive HadGEM2-AO model.

HadGEM2-CC is a specific configuration of HadGEM2 for the CMIP5 project using a 60 level atmosphere. Major differences from HadGEM2-ES are the inclusion of a non-orographic gravity wave drag scheme, production of stratospheric water vapour from methane oxidation, and the removal of the UKCA interactive tropospheric chemistry component. Chemical oxidants are prescribed using decadal averages from the equivalent HadGEM2-ES simulations

3.5 Statistical Analysis

Statistical tests between observed and downscaled weather data have been done to control the accuracy and reliability of the SDSM. There are some errors in the SDSM which are mean absolute error (MAE), Correlation value R2 and Nash–Sutcliffe model efficiency coefficient (NSE). In statistics, mean absolute error (MAE) is a measure of difference between two continuous variables. It can be illustrated by assuming X and Y as variables of paired observations that express the same phenomenon. For examples of

Y versus X include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement. Consider a scatter plot of n points, where point i has coordinates (xi, yi). Therefore, Mean Absolute Error (MAE) is the average vertical distance between each point and the identity line besides the average horizontal distance between each point and the identity line.

The Mean Absolute Error is given by:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |xi - x| \qquad 3.2$$

Correlation value R2 is the proportion of the variance in the dependent variable that is predictable from the independent variable. It is a statistic used in the context of statistical models whose main purpose is either the prediction of future outcomes or the testing of hypotheses, on the basis of other related information. is used to evaluate the correlation between the simulated and observed flow data, with a range from -1 to 1 It provides a measure of how well by the model, based on the proportion of total variation of outcomes explained by the model. The correlation value R is given by:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \qquad 3.3$$

The Nash–Sutcliffe model efficiency coefficient (NSE) is used to assess the predictive power of hydrological models and widely used in hydrological studies, measures how well the plot of simulated versus observed data fit the 1:1 line. Values of NSE closer to 1 indicate better model performance as NSE can range from −∞ to 1. It is defined as:

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_m^t - Q_o^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q_o}\right)^2} \qquad 3.4$$

where Qo is the mean of observed discharges and Qm is modeled discharge. Qot is observed discharge at time, t. An efficiency of 1 (NSE = 1) corresponds to a perfect match of modeled discharge to the observed data. An efficiency of 0 (NSE = 0) indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero (NSE < 0) occurs when the observed mean is a better predictor than the model or, in other words, when the residual variance is larger than the data variance. Values of NSE closer to 1 indicate better model performance as NSE can range from $-\infty$ to 1. Essentially, the closer the model efficiency is to 1, the more accurate the model is. Threshold values to indicate a model of sufficient quality have been suggested between 0.5 < NSE < 0.65.

3.6 Location of Study Area

The studies were focused at North of Malaysia which are Perlis and Pulau Pinang. These locations were selected because of their flood and disaster history happened for past few years. For example, flood disaster happened in Pulau Pinang during year 2017 caused 7 death and over 3000 people evacuated. In Pulau Pinang and Perlis, the average temperature are 30˚C with 400mm annual rainfall for Pulau Pinang and 245mm in Perlis. The average wind speed in Pulau Pinang recorded 11.5 kmph while 14.4 kmph in Perlis. The average temperature recorded in Perlis. In more detail, in the table below, there are list of the stations selected.

Table 3.2: List of selected stations in Perlis and Pulau Pinang

No	Station name	Types of station
1	Ladang Perlis Selatan	Rainfall
2	Ulu Pauh	Rainfall
3	Gua Nangka	Rainfall
4	Sungai Simpang Ampat	Rainfall
5	Kolam Bukit Air Berapit	Rainfall
6	Pintu Air Bagan	Rainfall
7	Chuping	Temperature

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, the results were discussed according to the calibration, validation and projection of future climate trend. About three parts that were presented and discussed in this study as follow:

I. The best RCPs for Pulau Pinang and Perlis were identified using Statistical Downscaling Model (SDSM).

II. The future trend for interval 2020, 2050 and 2080 in Pulau Pinang and Perlis were generated.

III. The performances of different RCPs were discussed.

The study of climate change in Perlis for the historical years of rainfall was 2001-2016 while in Pulau Pinang 1984-2009. Meanwhile, historical years of temperature in Perlis were 1984-2013. Besides that, the prediction of future trends for 2010-2099 were produced by the applicability of mathematical model simulation to get correlation between local climate trend and information of atmospheric circulations at specified sub-grid using SDSM.

The process for each station was divided into calibration and validation. For temperature in Perlis, the calibration process was performed in the year (1984-1998) which represented first half of the period range while the validation process was performed in year (1999-2013). Meanwhile, for the rainfall in Perlis the calibration process was performed in first 8 years which is in year (2001-2008) and the validation process was performed in year (2009-2016) which count of second half of 16 years. For the rainfall in Pulau Pinang, the calibration was performed in year (1995-2005) and the validation was in year (2006-2016).

This process was to obtain reliable projected results and can be compared with the historical data itself. Three different years periods were chosen due to the data availability, the calibration and validation periods of all the stations shown in Table 4.1. Subsequently, the best RCP between RCP 2.6, RCP4.5 and RCP8.5 were selected for each station where the historical curve will be the bench mark for choosing the best RCP. Climate projection for all stations were generated from 2010 to 2099 using GCM predictors.

Table 4.1 Detail information about local climate stations

Types of station	Data year	Name of station	Calibration year	Validation year
Temperature (Perlis)	1984-2013	Chuping	1984-1998	1999-2013
Rainfall (Perlis)	2001-2016	6503001- Ldg. Perlis Selatan	2001-2008	2009-2016
		6403001- Ulu Pauh		
		6402006 Guar Nangka		
Rainfall (Pulau Pinang)	1984-2009	5204048 Sg. Simpang Ampat	1984-1991	1992-2009
		5304045 Kolam Air Bkt. Berapit / Pusat Kesihatan Bukit Berapit		
		5302002 Pintu Air Bagan di Air Itam		

4.2 Predictors Selection

In SDSM, screening process was important in order to produce reliable climate projection where before the calibration starts, several predictors were selected based to the correlation value which the best five predictors were chosen for the calibration. The main purpose of the screen variables operation was assisting to decide and select appropriate downscaling predictor variables. After the screening process, several predictors were selected based on the correlation value and strength of the predictors to each other in order to form as factors to climate change on local region because a single predictor could not possible for being a factor to climate change. Therefore, the predictors were obtained from NCEP with a total of 26 predictors with specific function that produce different correlation value with local region. The reliability of the results in climate projection refers to the workability of the selected atmospheric variables with all the local climates in Perlis. Table 4.2 shows the predictor used in this study for all stations.

Based on the 26 predictors, four predictors were chosen for all three categories of temperature in Perlis that divided into maximum, mean and minimum temperature. Meanwhile, five different predictors were used for all the stations in Perlis which were Ladang Perlis Selatan station, Ulu Pauh station and Guar Nangka station. In Pulau Pinang, the predictors used for Sg Simpang Ampat was four predictors included r850, temp, r500 and rhum. Besides that, four predictors were used for Kolam Air Bukit Berapit station while three predictors in Pintu Air Bagan station.

Table 4.2 List of predictors selection for each station

Predictors	Temperature			Rainfall			Rainfall		
	max	mean	min	Ldg. Perlis Selatan	Ulu Pauh	Guar Nangka	Sg.Simpang Ampat	Kolam Air Bukit Berapit	Pintu Air Bagan
ncepp500	√	√	√	√					
ncepr850	√	√		√	√		√	√	√
ncepshum	√	√	√						
nceptemp	√		√	√			√		√
ncepr500				√	√	√	√	√	
ncepp8_u					√				
nceprhum				√	√	√	√	√	√
ncepp_v						√			
ncepp5_u						√			
ncepp850					√	√		√	

4.3 Calibrated and Validated Performances

4.3.1 Temperature Result

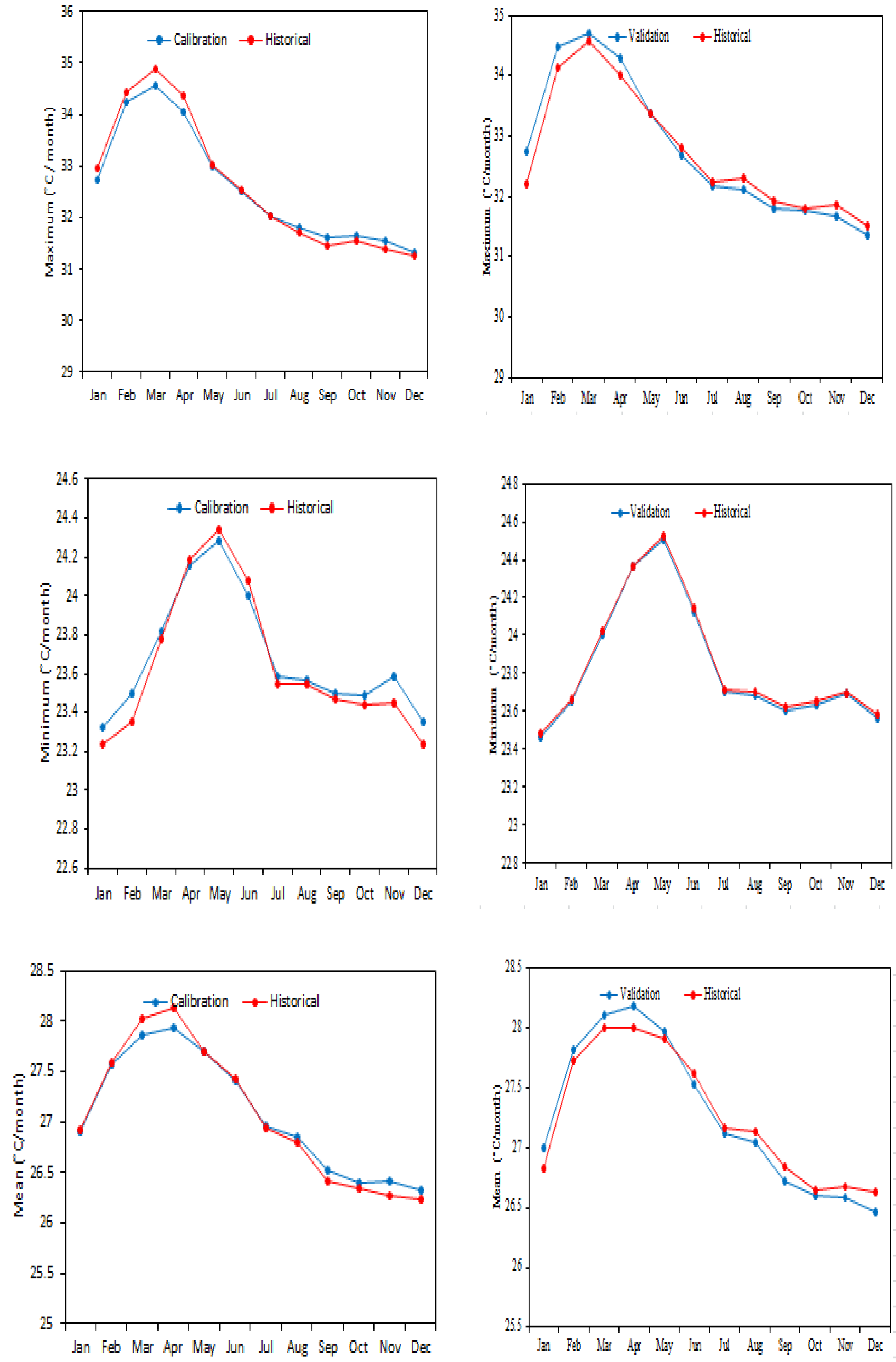
The temperature data recorded in Perlis for 30 years referred as predictand that used to represent temperature trend in Perlis. The temperature was divided into three categories which are maximum, minimum and mean. Based on correlation value, four predictors value used for maximum temperature were geopotential height (p500), relative humidity at 850hpa (r850), surface specific humidity (shum) and mean temperature (temp). For minimum temperature, the predictors used for were geopotential height (p500), surface specific humidity (shum) and mean temperature (temp). geopotential height (p500), relative humidity at 850hpa (r850) and surface specific humidity (shum) were used as predictors for mean temperature. The performances of the calibration (1984-1998) and validation (1999-2013) result in three conditions were tabled in table 4.3 below.

Table 4.3 Statistical Analysis for Temperature

Temperature	%MAE		Correlation	
	Calibrated	Validated	Calibrated	Validated
Maximum	0.438	0.546	0.998	0.985
Mean	0.295	0.588	0.993	0.989
Minimum	0.281	0.052	0.997	0.999

As shown in Table 4.3, it can conclude that in temperature analysis, %MAE for calibrate and validate were rather low for all temperature. In maximum temperature, %MAE for calibrated result as expected has lower error than validated result which recorded only 0.44% compared to 0.55% and recorded small percentage different between calibrate and validate of maximum temperature which is 0.9%. For mean temperature, validated result recorded quite higher compared to calibrate which is 0.58% for validate and 0.28% for calibrate. This different recorded among calibrate and validate was 0.30% and recorded the highest among three temperatures. In minimum temperature however, it can be seen that %MAE in validation recorded the lowest value among the other two which was recorded 0.05% only and had big different with calibrate value. Moreover, as shown in Table 4.3, it clearly can be seen that correlation value for all conditions does not exceed ($r \leq 1$). For the calibration, the result for all the conditions almost perfect to 1.0 which are recorded 0.99% while the validation has no different with calibration with the result recorded almost perfect to 1.0 and same with calibration.

Based on the graph, the pattern for temperature remain high in Perlis especially in February to May and remains lower during October to December. The highest temperature recorded in Perlis was 34.6 ˚C and the lowest was 24˚C. Looking at the minimal percentage different between model simulation and historical data, this can be concluded that projection analysis for future projection of temperature trend was acceptable and reliable.



a) Calibration b) Validation

Figure 4.1 Comparisons Performances of Max, Min and Mean Temperature in calibration and validation processes

4.3.2 Rainfall Analysis Result in Perlis

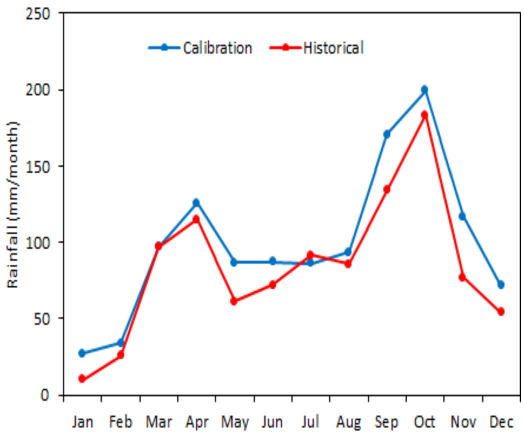
For Perlis state, three rainfall stations were selected for performing the rainfall analysis and calibration and validation process were performed with the selected predictors that had been chosed through screening process. The rainfall station involved in this projection were Ladang Perlis Selatan station, Ulu Pauh station and Guar Nangka station while the predictors used were mean temperature (temp), 500 hpa geopotential height (p500), relative humidity at 850 Hpa (r850), relative humidity at 500 Hpa (r500), 850 hpa zonal velocity (p8_u), 500 Hpa zonal velocity (p5_u), relative humidity at 500 hpa (p500), surface meridional velocity (p_v) and near surface relative humidity (rhum). Figure 4.2 shows the calibration and validation results for three rainfall stations.

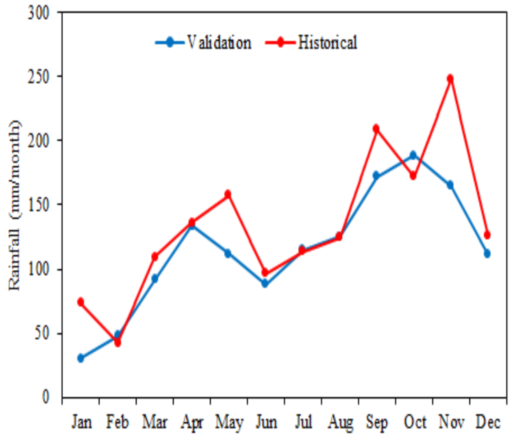
Based on the graph, the pattern of calibration analysis for three stations can be concluded that during March and April, the rainfall was in higher point and recorded the highest pattern in October for Ladang Perlis Selatan and Ulu Pauh station while in Guar Nangka station, September was the highest rainfall. For Validation, the pattern of rainfall was in fluctuated pattern. Looking at the minimal percentage difference between model simulation and historical data, this can be concluded that the projection analysis for the rainfall projection is reliable. In this stage, the performance of the predictors selected can be evaluated based on the result of calibration and validation. The standard deviation, %MAE and correlation value for all the stations have been analysed as shown in Table 4.4.

Table 4.4 Statistical Analysis for Rainfall in Perlis

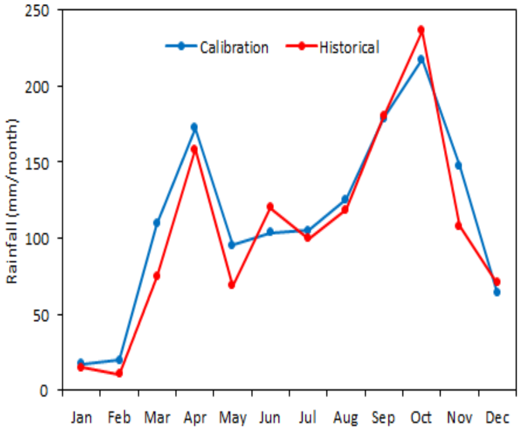
Stations	Std Deviation		%MAE		Correlation	
	Calibrated	Validated	Calibrated	Validated	Calibrated	Validated
Ladang Perlis Selatan	0.440	0.378	20.000	16.795	0.962	0.867
Ulu Pauh	0.512	0.411	21.010	12.278	0.959	0.975
Guar Nangka	0.403	0.406	20.020	18.275	0.929	0.932

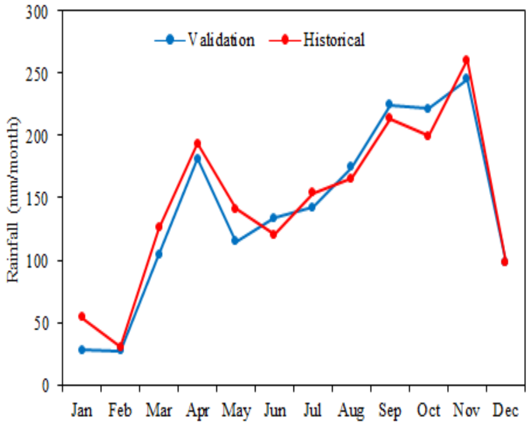
Ladang Perlis Selatan



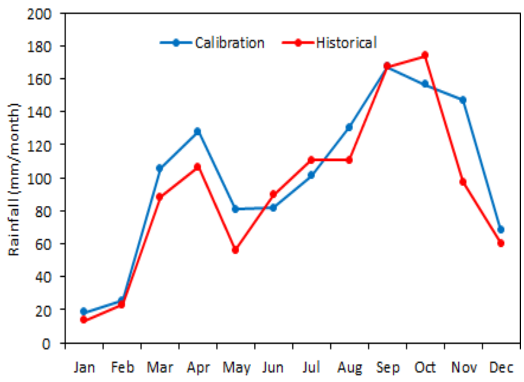


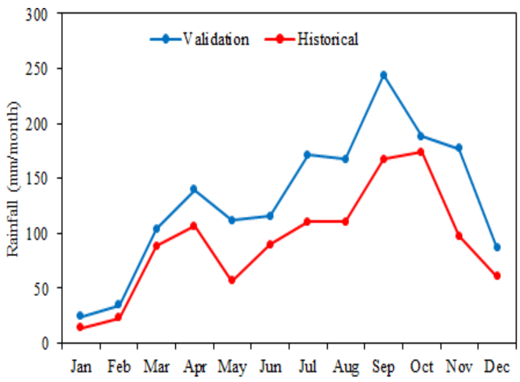
Ulu Pauh





Guar Nangka





a) Calibration b) Validation

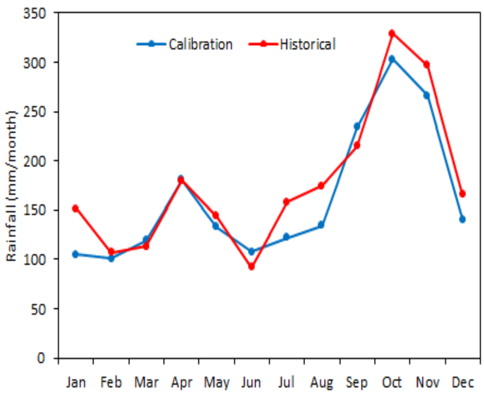
Figure 4.2 Comparison performances between historical with calibrated and validated results at Perlis

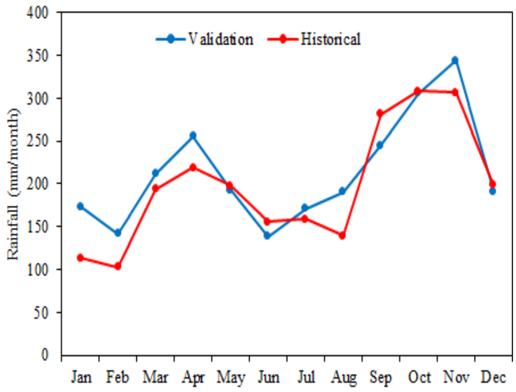
As shown in Table 4.4, it can be seen that the percentage error of calibrated for all stations exceed 20% which Ladang Perlis Selatan and Guar Nangka recorded as 20% and the highest %MAE is 21%. This however, does not affect much the correlation value although all the stations have higher of mean absolute erroy. For validation, %MAE for all the stations are lower than calibration which is recorded below 20% with the highest 18.3% in Guar Nangka station and 12.3% recorded in Ulu Pauh that represent the lowest of %MAE in Validation. In Correlation value, the value for both calibration and validation do not exceed 1.0. in calibration, the correlation value for all stations almost perfect 1.0 with the highest is 0.962 and the lowest is 0.929. This analysis is no different with the correlation value for validation which recorded almost 1.0 for all the stations with the highest is 0.975 and the lowest is 0.867. As for the error and correlation value, the result generated may be influenced by the predictors selected and the selecting of predictors are primary important to ensure the accuracy and reliabilty of projected rainfall.

4.3.3 Rainfall Result in Pulau Pinang

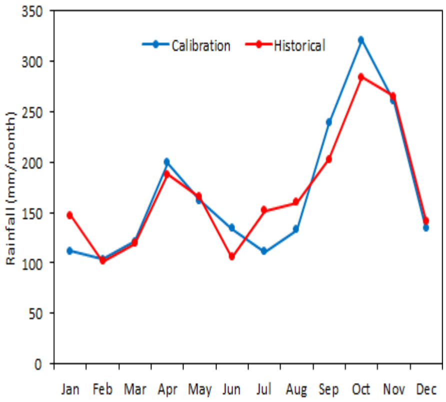
Calibration and Validation have been performed with the selected predictors that have been believed to be the most perfect group of predictors to be used for the future rainfall trend projection. The predictors used were relative humidity at 850 hpa (r850), mean temperature at 2m (temp), relative humidity at 500 hpa (r500), 850 hpa geopotential height (p50) and near surface relative humidity (rhum). Due to identify by researchers of rainfall is one of the most problematic variables unlike the temperature, because the projection of rainfall depend on another process such as occurrence of humidity and wet-days. Figure 4.3 shows the results of calibration and validation of the rainfall stations in Pulau Pinang.

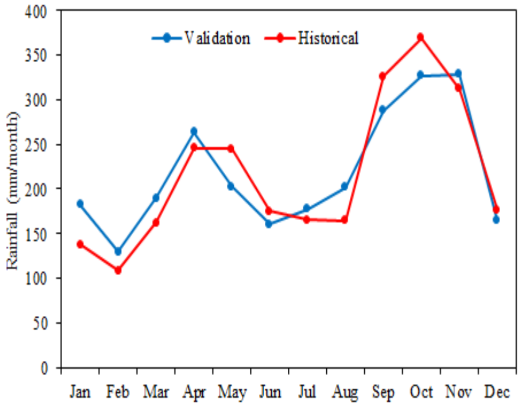
Sg Simpang Ampat



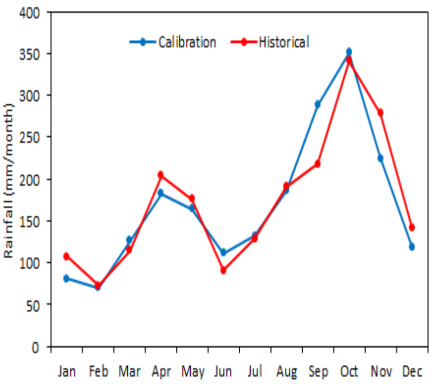


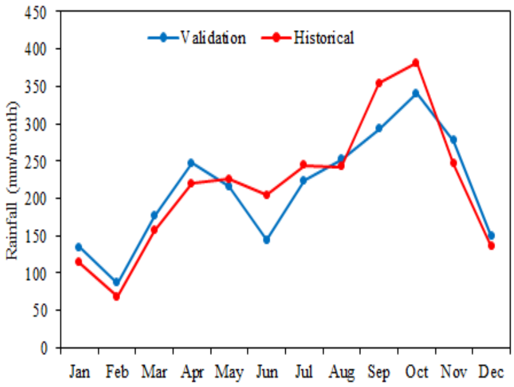
Kolam Air Bukit Berapit





Pintu Air Bagan





a) Calibration b) Validation

Figure 4.3 Comparison performances between historical with calibrated and validated results at Pulau Pinang

Based on Figure 4.3, for calibration the highest rainfall is was October for all stations which recorded 300 mm per month and the lowest rainfall was in Febuary which recorded lower than 100 mm per month. For validation, there was no different with the calibration where the highest was in October and the lowest is in Febuary. This because of the predictors selected and the performances of predictors can be evaluated based on the result of the calibration and validation. The analysis of the calibration and validation were standard deviation, %MAE and correlation value are been analysed in calibration and validation. The statistical analysis of calibration and validation for three stations are shown in Table 4.5 below.

Table 4.5 Performances of Calibrated and Validated Results based on the Statistical Analysis

Stations	Std Deviation		%MAE		Correlation	
	Calibrated	Validated	Calibrated	Validated	Calibrated	Validated
Sg Simpang Ampat	0.527	0.538	15.454	22.480	0.951	0.755
Kolam Air Bukit Berapit	0.564	0.513	11.997	13.988	0.937	0.935
Pintu Air Bagan	0.481	0.432	11.997	10.053	0.932	0.936

The selected predictors was primary important to ensure the accuracy and reliability of projected rainfall in Pulau Pinang. As presented by the analysis, most rainfall stations were estimated small of percentage MAE for calibration which recorded under 20%. The highest percentage of MAE was 15% in Sg Simpang Ampat station while Kolam Air Bukit Berapit and Pintu Air Bagan rainfall station recorded same %MAE with 12%. For the validation, Sg Simpang Ampat rainfall station also recorded the highest %MAE with 22% that exceed 20%. However, it does not effect its correlation value since the value almost 1.0. For Kolam Air Bukit rainfall station, percentage of MAE is 14% and the lowest is 10% which is in Pintu Air Bagan station.

In Pintu Air Bagan station, the percentage of mean absolute error for validation was the lowest, its correlation recorded as the higher among three stations for validation and the lowest for calibration. For calibration , the highest correlation value is 0.951 in Sg Simpang Ampat followed by Kolam Air Bukit Berapit with 0.937 and 0.932 for Pintu Air Bagan. However, the difference of the correlation value for all the stations was in small value. In validation, the correlation value for Sg Simpang Ampat station was the lowest which recorded 0.755 and the others were exceed 0.90 and almost perfect to 1.0.

4.4 The Best RCP Selection

RCPs were described as the scenarios that describe alternative trajectories for carbon dioxide emissions and the resulting atmospheric concentration from 2000 to 2100. The best Rcp analysis were being done on each of station in order to choose the best RCP for the future projection. The RCPs involved in this analysis were RCP2.6, RCP4.5 and RCP8.5. Each RCP was developed independently by a modelling team whose previous work was a close match to the starting requirements for the new scenarios. Moreover, each RCP has its own primary characteristic. For example, RCP 8.5 was characterized by representative of scenarios in the literature and increasing greenhouse gas emissions over time, that caused high greenhouse gas concentration levels. RCP2.6 was representative of scenarios in the literature that lead to very low greenhouse gas concentration levels among the others. For RCP4.5, it is a stabilization scenario in which total radiative forcing was stabilized shortly after 2100, without overshooting the long-run radiative forcing target level. Therefore, the best RCP for every station is important since every station has different GHGs concentration.

4.4.1 Temperature Analysis

The historical temperature and GCM data chosed for the analysis were in year 2006-2013 where the historical data as a predictand and GCM data as predictors. Table 4.6 shows the Statistical Analysis for the temperature. From the graph, a small different between the three RCPs with the historical data recorded and as shown in Table 4.6 the percentage error for maximum temperature showed the RCP 2.6 recorded the lowest value with 0.382% followed by RCP 8.5 with 0.385 and the highest value recorded by RCP 8.5. However, the correlation value of all the stations recorded the strong relationship since the value of correlation was almost perfect to 1.0. Therefore, the best RCP for the maximum temperature is RCP 2.6.

Table 4.6 Statistical Analysis of the Temperature

Temperature	**RCP2.6**		**RCP4.5**		**RCP8.5**	
	%MAE	Correlation	%MAE	Correlation	%MAE	Correlation
Maximum	0.382	0.986	0.394	0.985	0.385	0.986
Minimum	0.208	0.976	0.212	0.976	0.216	0.977
Mean	0.228	0.988	0.228	0.988	0.216	0.989

In perspective of minimum temperature, the lowest of percentage error was from RCP2.6 with 0.208% while the percentage error for RCP 4.5 and RCP8.5 were 0.212% and 0.216%. These three RCPs only recorded small different of percentage error with the almost same and perfectly to 1.0 of correlation value. However, the best RCP for minimum temperature was RCP2.6. For the mean temperature, the lowest percentage error was from RCP 8.5 with 0.216% and the correlation value was 0.989. Meanwhile, the percentage error and correlation of RCP2.6 and RCP 4.5 recorded the same value with 0.228% and 0.988. Therefore, the best RCP for the mean temperature was rcp 8.5 .

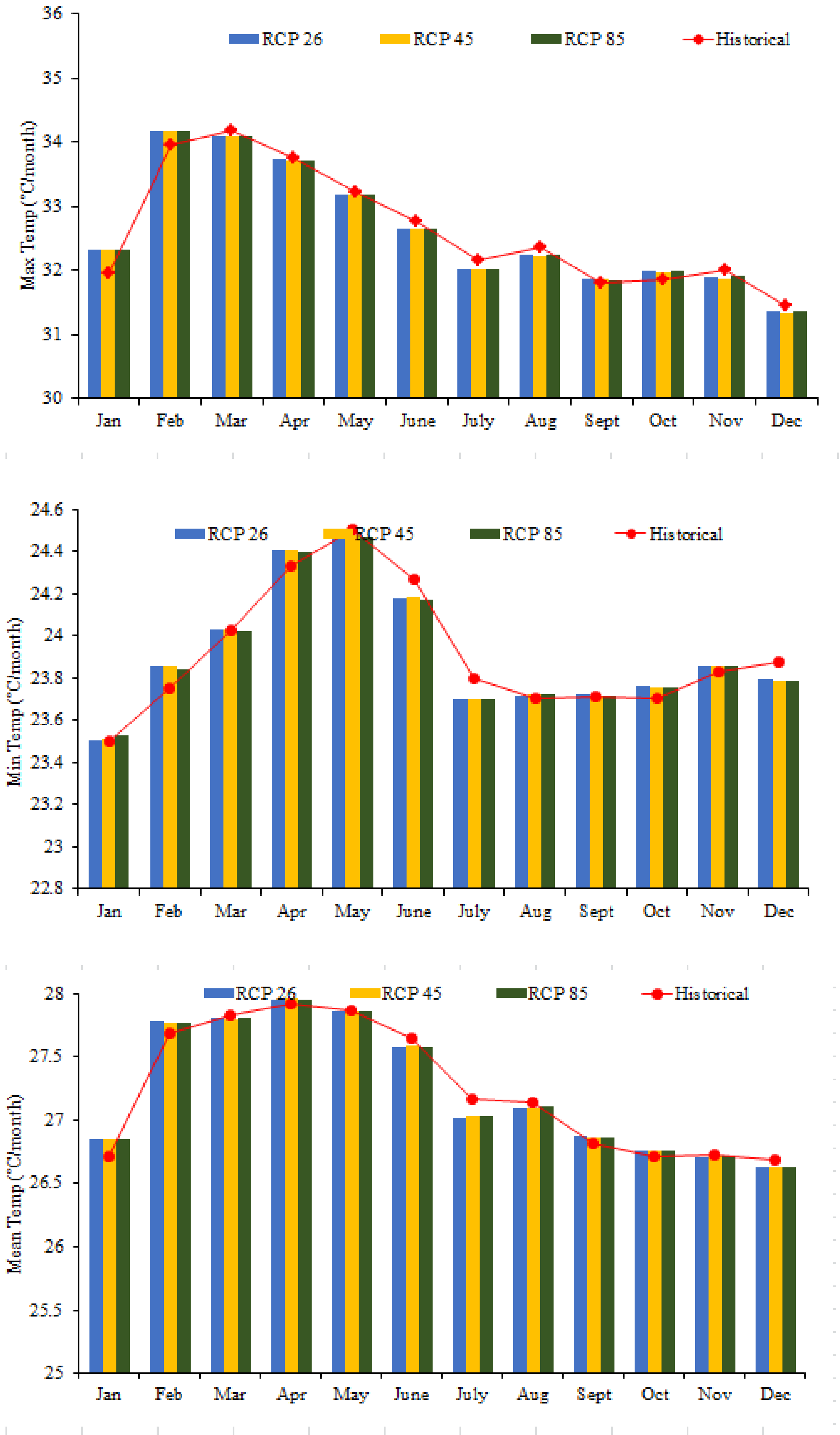


Figure 4.4 RCP analysis of Temperature

As a conclusion, the best RCP for Temperature in Perlis was RCP 2.6 since majority of the temperature recorded RCP 2.6 as the best RCP. However, the graph in Figure 4.4 showed a same pattern of three RCPs with small different with the historical data. Therefore, the statistical analysis of percentage error and correlation value were important in order to measure the accuracy and relationship between the historiocal data and downscaled data.

4.4.2 Rainfall Analysis in Perlis

The historical rainfall data and GCM data chosed for the analysis were in year 2006-2016 where the historical data as a predictand and GCM data as predictors. In order to determine the best RCP, the statistical analysis generated for the station since the different of three RCPs with the historical data in Figure 4.5. Therefore, table 4.7 shows the Statistical analysis of rainfall in Perlis. From the table, Ladang Perlis Selatan station stated the percentage error of RCP 2.6 was 15.824% followed by RCP4.5 with 16.462% and RCP8.5 with 11.983%. In this station, RCP 8.5 recorded the lowest error compared to the others. Since the lowest percentage erro of Ladang Perlis Selatan was RCP 8.5 with the correlation value 0.973 that almost same with the other RCPs, therefore the best RCP for Ladang Perlis station was RCP 8.5.

Table 4.7 Statistical Analysis of the Rainfall in Temperature

Rainfall station	**RCP2.6**		**RCP4.5**		**RCP8.5**	
	%MAE	Correlation	%MAE	Correlation	%MAE	Correlation
Ldg Perlis Selatan	15.824	0.974	16.462	0.977	11.983	0.973
Ulu Pauh	6.748	0.991	8.499	0.988	15.880	0.961
Guar Nangka	11.375	0.988	12.156	0.988	15.887	0.963

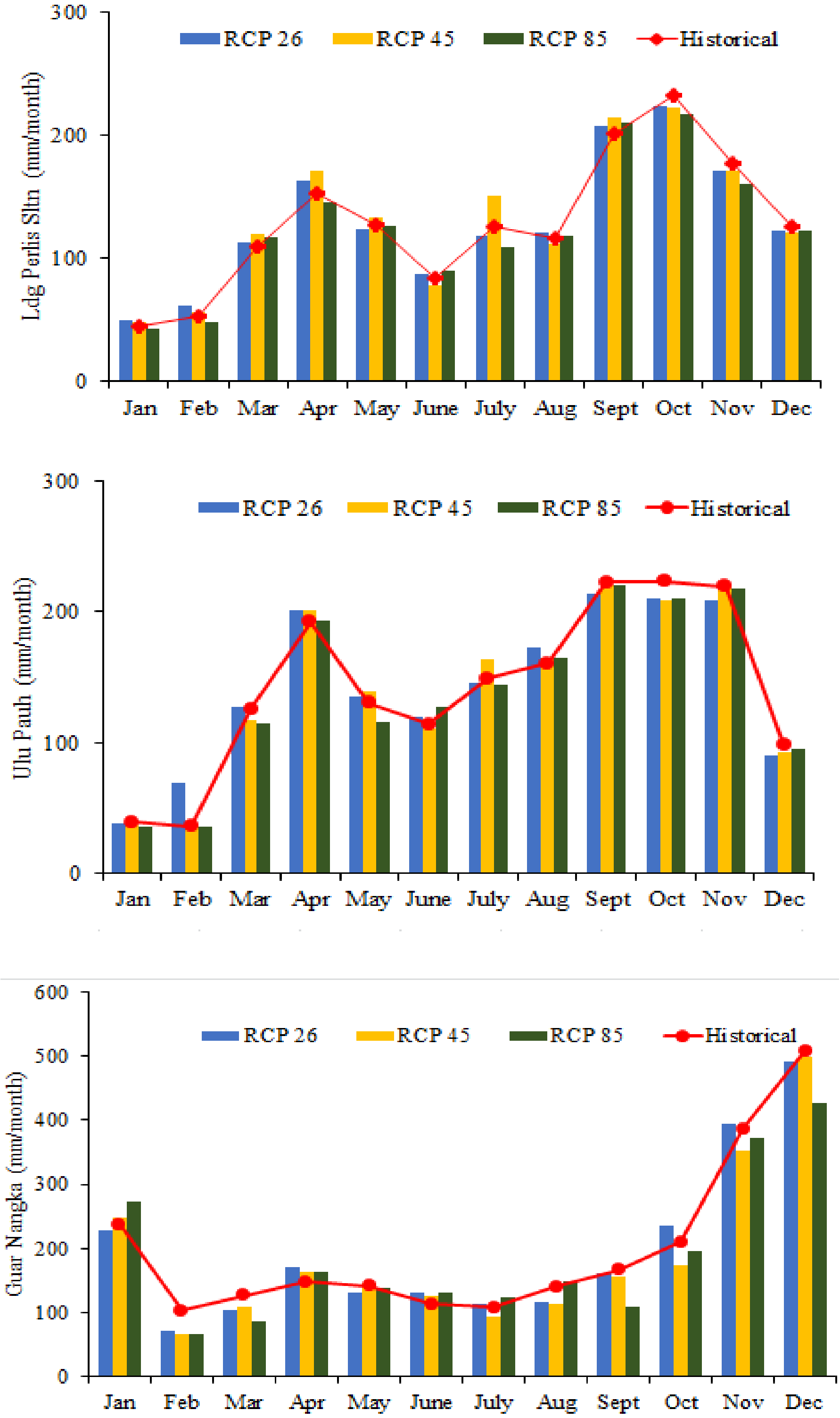


Figure 4.5 RCP Analysis of Rainfall in Perlis

4.4.3 Rainfall Analysis in Pulau Pinang

The historical rainfall data and GCM data chosed for the analysis were in year 2009-2016 where the historical data as a predictand and GCM data as predictors. For the Sg Simpang Ampat, the graph in Figure 4.6 shows the pattern of the RCP with the historical rainfall data. From that, it can be concluded that RCP8.5 has a small different with the historical data compared to the RCP4.5 and RCP2.6. Besides that, the lowest percentage error of Sg Simpang Ampat was RCP4.5 with 7.644% followed by RCP 8.5 with 7.732% and RCP 4.5 with 8.727% . Therefore, the best RCP for Sg Simpat Ampat was RCP 8.5 since it had the lowest of percentage error.

Table 4.8 Statistical Analysis of the Rainfall

Rainfall station	**RCP2.6**		**RCP4.5**		**RCP8.5**	
	%MAE	Correlation	%MAE	Correlation	%MAE	Correlation
Sg Simpang Ampat	8.727	0.983	7.644	0.991	7.732	0.973
Kolam Bukit Air Berapit	7.035	0.992	5.772	0.992	8.663	0.989
Pintu Air Bagan	9.823	0.988	6.669	0.993	6.315	0.995

For Kolam Bukit Air Berapit, the pattern of graph RCP2.6 shows a small different with the graph line of historical data. However, RCP 8.5 also show a small different with the historical data. These can be proved by the percentage error where the lowest of percentage error for RCP 2.6 was 7.035%, RCP4.5 with 5.772% and RCP8.5 with 8.663%. These value recorded RCP4.5 had the lowest of percentage value with the correlation value perfect to 1.0. Therefore, the best RCP for Kolam Bukit Air Berapit was RCP4.5.

The best RCP for Pintu Air Bagan was RCP8.5 since the pattern of the graph in figure 4.6 has small different with the historical line graph. This can be supported by the percentage error from the analysis where the lowest percentage error recorde was in

RCP 8.5 with 6.315. In conclusion, the percentage error and correlation value were a benchmark for choosing the best RCP for rainfall. Since the best RCP Sg Simpang Ampat and Pintu Air Bagan station are RCP8.5 while RCP 4.5 for Kolam Bukit Air Berapit station, we can conclude that the best RCP for the rainfall station in Pulau Pinang was RCP8.5.

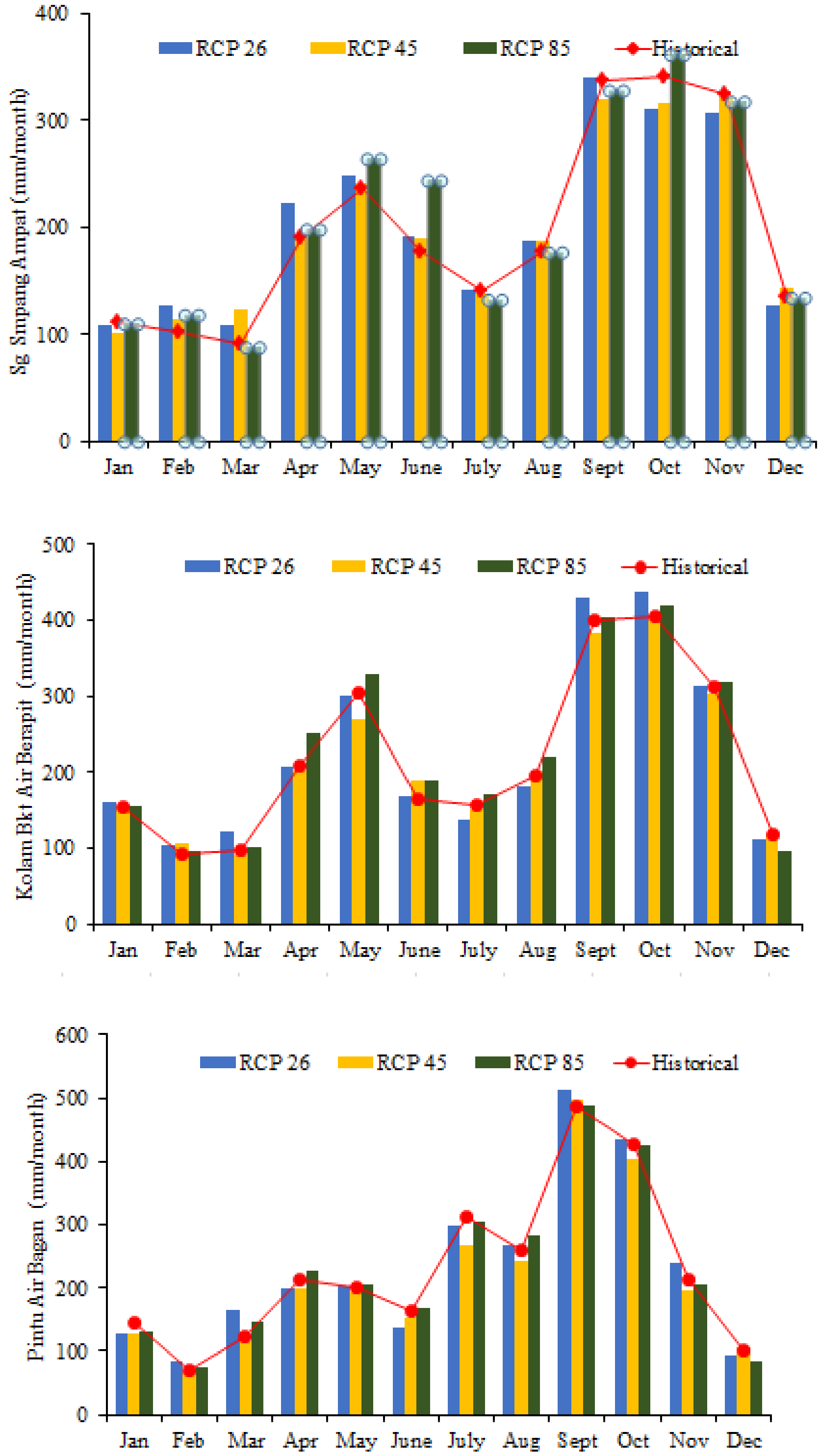


Figure 4.6 RCP Analysis for Rainfall in Pulau Pinang

For the Ulu Pauh station the correlation value for three RCPs recorded the value with almost perfect to 1.0 that showed the strong relationship between the historical an downscaled data. However, the percentage error of three RCPs showed a big different which the lowest error was from RCP2.6 with 6.748% and the highest was from RCP8.5 with 15.880%. Therfore, the best RCP for Ulu Pauh station was RCP 2.6. in Guar Nangka station , the lowest percentage error was RCP2.6 with 11.375% followed by RCP 4.5 and Rcp 8.5. Therefore, the best RCP for Guar Nangka station was RCP2.6.

As conclusion, the lower of percentage error in statistical analysis, the more accurate downscaled data to the historical data. Thus, the best RCP for rainfall in Perlis was RCP 2.6 since the best RCP of two out of three stations were RCP 2.6.

4.5 GCM Projection

The projection year of 2010-2099 were done after result obtained from calibration and validation with less than 20% of MAE with the correlation value below 1.00. Projection for year Δ2020, Δ2050, and Δ2080 were be done in order to achieve the objectives of this study. In scenario projection, the third generation of scenario projection which is RCP has taken over in the previous scenario projection SRES after AR5 was released. RCP projection consists of three different scenarios which are RCP2.6, RCP4.5 and RCP 8.5. Therefore, in this projection, the future trend will be projected in all of the different scenrios.

4.5.1 GCM Projection for Temperature

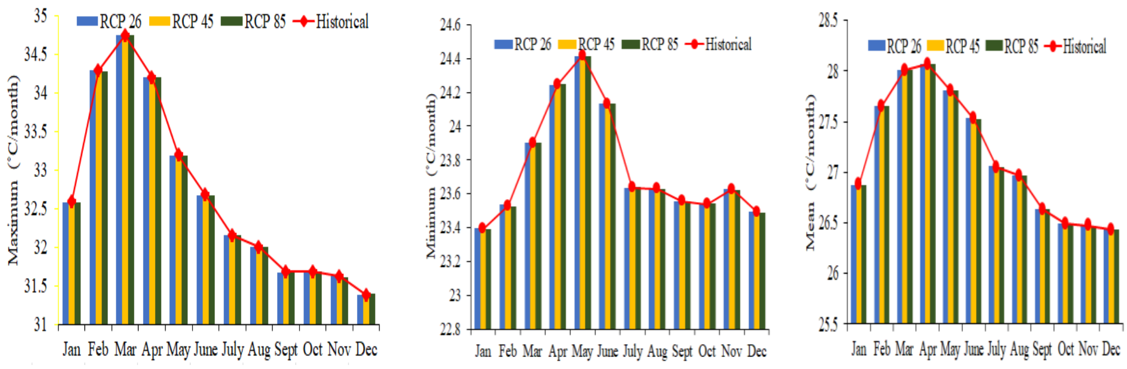
In achieving the objective of the study, the projection for maximum, mean and minimum temperature were be done for year Δ2020. In Figure 4.7 below shows the RCP projection in temperature for Δ2020. As shown in figure, the temperature trend does not change in future where the temperature pattern for RCP2.6, RCP4.5 and RCP 8.5 remain the same. For the record, the highest temperature for three RCPs are same with historical where recorded 34.7˚C for maximum temperature. Besides that, it can be seen from the Table below, increment and deacrement were in lowest and almost 0%. based on three projection of RCPs in the graph below, the pattern difference is obvious when in the first half year, the projection is increasing but in the second half year the projection is deacreasing.

Based on the Table 4.9 below, maximum temperature showed deacrement pattern for RCP 2.6 in projection year∆2020, ∆2050 and showed increment pattern for year ∆2080. For the minimum temperature, the pattern of the projection increase for year ∆2020 and deacrease for year ∆2050 and ∆2080. In the mean temperature,the pattern of the projections were in increasing pattern. For the RCP 4.5, in maximum temperature, the pattern in increasing for the ∆2020 and deacrease for year ∆2050 and ∆2080. The pattern of the projection minimum and mean temperature were same with deacreasing for year ∆2020 and ∆2080. Same as RCP 8.5, the pattern of the projection was only having small different with the historical which recorded the percentage of different below 1%. In maximum temperature, the pattern showed increment in year ∆2020 and ∆2080 while ∆2050 had decrement in year ∆2050 while for minimum the pattern of the projections were in deacresing pattern as shown in table below.

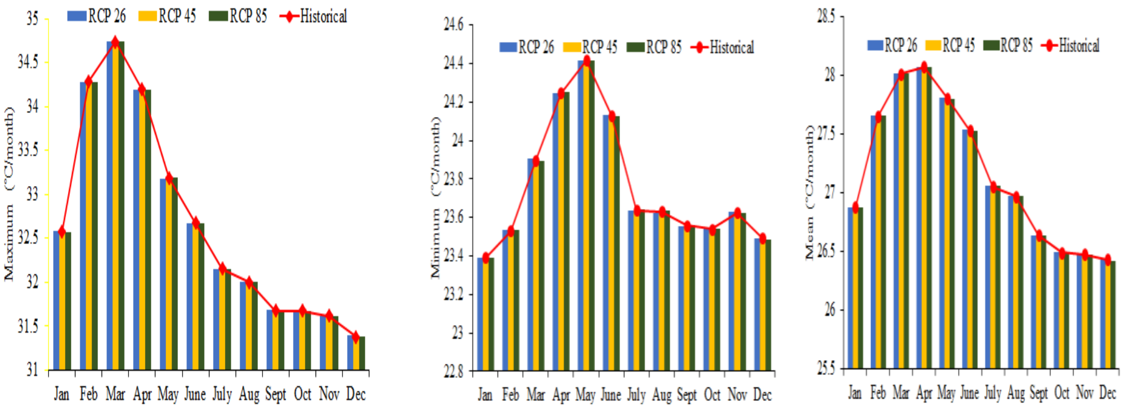
Table 4.9 Analysis of Temperature Projection

Rainfall station	RCP2.6 (%)			RCP4.5 (%)			RCP8.5 (%)		
	∆2020	∆2050	∆2080	∆2020	∆2050	∆2080	∆2020	∆2050	∆2080
Ldg Perlis Selatan	-0.010	-0.020	+0.020	+0.020	-0.020	-0.020	+0.010	-0.010	+0.010
Ulu Pauh	+0.010	-0.010	-0.010	-0.010	+0.020	-0.010	-0.010	-0.010	-0.010
Guar Nangka	+0.010	+0.010	+0.010	-0.010	+0.020	-0.010	+0.010	+0.010	-0.010

Year Δ2020



Year Δ2050



Year Δ2080

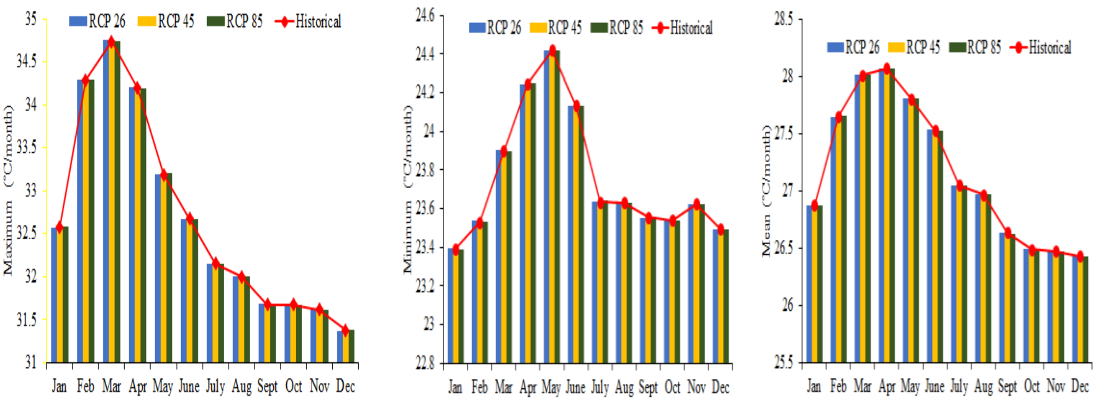


Figure 4.7 RCP Projections in Temperature

4.5.2 GCM Projection for Rainfall in Perlis

The GCMs data were used as predictors to project and generate the local climate trend in the future year with the consideration of future potential greenhouse gas. Three RCPs were used in projection of the rainfall trend of in year Δ2020, Δ2050 and Δ2080 for three stations in Perlis. Figure 4.8 shows the projected rainfall in the year Δ2020, Δ2050 and Δ2080 for stations in Perlis. Obviously from the graph, the rainfall pattern projected was fluctuated for all the stations with increment and decrement from the historical data . However, projected of Guar Nangka station in year 2020 recorded quite similar with the historical. Besides that, from the figure 4.8, it can be concluded that the pattern of the projected years for all stations were similar at early of the year where recorded the lowest of rainfall.

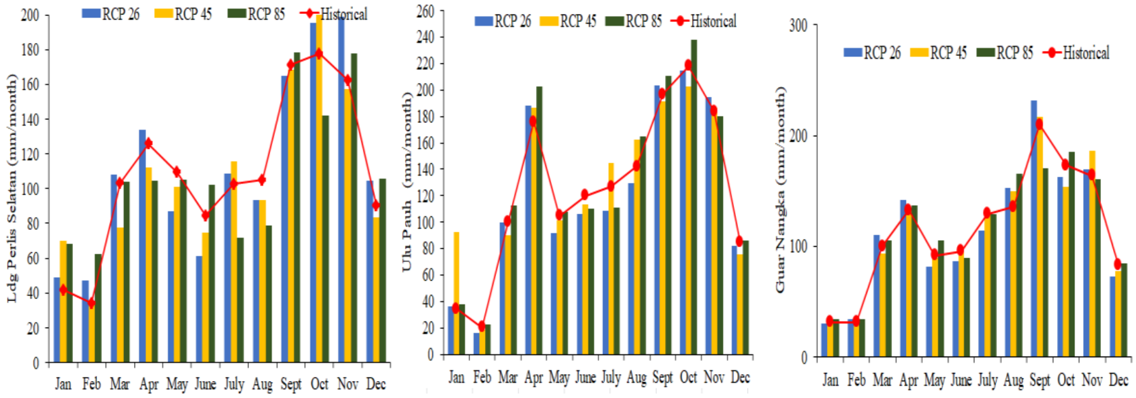
In year Δ2050, the projected of rainfall in Guar Nangka was recorded the highest for RCP 8.5 in September compared to others RCPs besides recorded highest increment with the historical data as shown in Figure 4.8. Analysis of rainfall projection was being done to analysis the pattern of the projected rainfall accurately as shown in Table 4.9. The table below shows the increment or decrement of projected rainfal from the historical data. For the year Δ2020 in RCP2.6, Ladang Perlis Selatan station had an increment with 15.270% the highest between three stations as Ulu Pauh station faced decrement and increment pattern for Guar Nangka with only 8.999%. Besides that, all the stations had increment in year Δ2050 with Guar Nangka station recorded the highest different with 12.34% followed by Ulu Pauh station with 9.30% and Ladang Perlis Selatan with 7.59%. In year Δ2080, same as year Δ2050 the pattern of rainfall for three stations had increment with the highest was 6.36% from Guar Nangka station. Therefore, the pattern of the graph for this station showed quite high different with the historical data compared to the other stations.

For the RCP 4.5, the projected pattern of the all stations increase for year Δ2020 and Δ2050 with Ulu Pauh recorded the highest increment with 21.09% followed by Ladang Perlis Selatan with 15.90% in year Δ2020. A small different can been seen in the graph Guar Nangka station in year Δ2050 as the increment of projected pattern was too small with 0.190% only. Next, for the RCP8.5, Ladang Perlis Selatan had a decrement with 24.54% while the others station increased in pattern. As a conclusion, RCP2.6 has the highest average annual rainfall for all the stations among others RCPs.

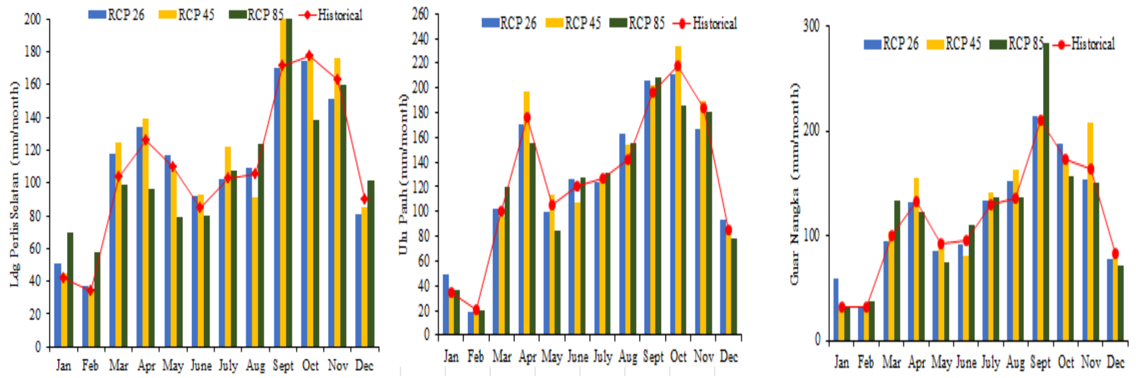
Table 4.9 Analysis of Rainfall Projection in Perlis

Rainfall station	RCP2.6 (%)			RCP4.5 (%)			RCP8.5 (%)		
	Δ2020	Δ2050	Δ2080	Δ2020	Δ2050	Δ2080	Δ2020	Δ2050	Δ2080
Ldg Perlis Selatan	+15.270	+7.590	+4.280	+15.900	+10.840	+5.010	-24.540	+25.410	+15.550
Ulu Pauh	-7.999	+9.300	+3.210	+21.090	+6.740	+8.690	+8.920	-9.120	-5.680
Guar Nangka	+8.999	+12.340	+6.360	+5.210	+0.190	-3.120	+8.920	+14.250	+7.810

Δ2020



Δ2050



Δ2080

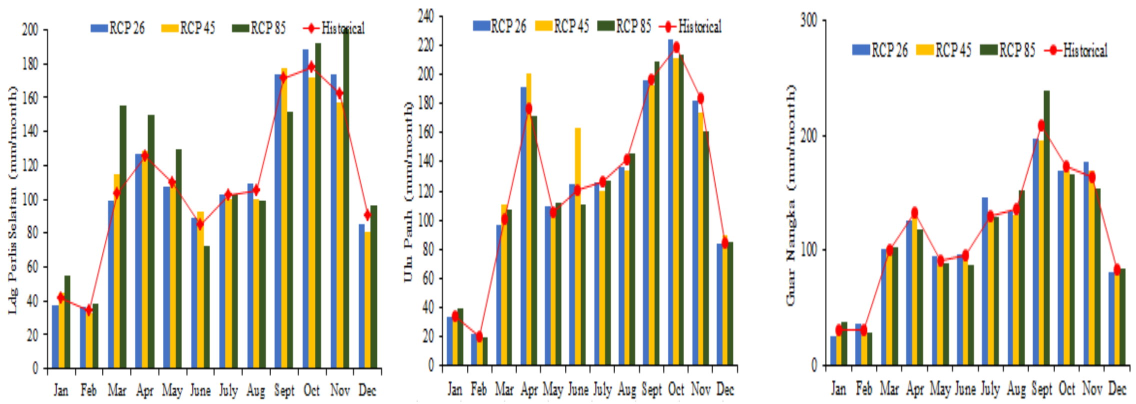


Figure 4.8 RCP Projections of Rainfall in Perlis

4.5.3 GCM Projection for Rainfall in Pulau Pinang

The selected predictors was primary important to ensure the accuracy and realibilty of projected rainfall. Applying method of analysis could be made as a guideline to the analyst. Therefore, the analysis for the rainfall in Pulau Pinang was being done as shown in Table 4.10 and Figure 4.9. From the graph in Figure 4.9, the pattern of the projected rainfall for three RCPs was fluctuating with high increment and decrement. For the pattern of Kolam Bukit Air Berapit, the pattern of the projected had small different for RCP 4.5 and RCP 8.5 except RCP2.6 that had high of annual rainfall in November and Disember recorded almot 700 mm/year. Besides that, the pattern of the graph in year ∆2050 shows quite similar pattern for three stations with small different increment and decrement.

To support the analysis of graph pattern , increment and decrement of of annual pattern have been observed. Therefore, the Table 4.10 shows the analysis of rainfall projection in Pulau Pinang. From the table, in year ∆2020 for RCP 2.6, the pattern of the projected rainfall was in increment pattern for Sg Simpang Ampat and Kolam Bukit Air Berapit stations with 10.02% and 20.2% while Pintu Air Bagan station in decrement pattern with 7.23%. The pattern of the projected in year ∆2050 having decrement in all stations with the highest was 12.610% in Kolam Bukit Air Berapit followed by Pintu Air Bagan with 5.54% and Sg Simpang Ampat with 4.69%. Same as in year ∆2050, the pattern of the projected rainfall in year ∆2080 was in decrement pattern for all stations with the highest was 15.910% in Sg Simpang Ampat followed by Pintu Air Bagan with 5.030%.

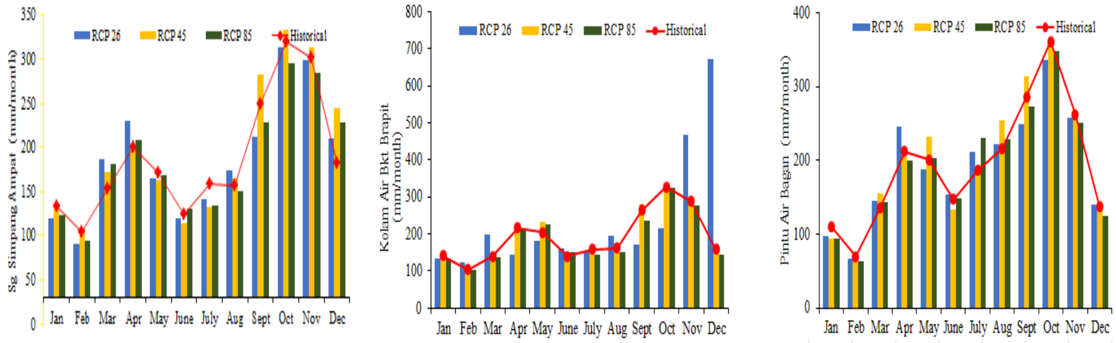
For the RCP 4.5, year ∆2020 the projected were recorded a quite different with the historical since the analysis showed an increment with Sg Simpang Ampat had the bigger increment than the other stations with 8.970% followed by Pintu Air Bagan for 7.720%. The value of decrement in year ∆2050 had a small different to each other where the stations recorded 5.25% for Sg Simpang Ampat, 4.62% for Kolam Bukit Air Berapit and 4.36% for Pintu Air Bagan. Therefore, it can be seen the different between the stations was very small. Same as year ∆2050, the pattern of projected in year ∆2080 was in decrement pattern.

In RCP 8.5, the pattern of the projected in year Δ2020 was in decrement pattern with high different with the historical was 20.63% from Kolam Bukit Air Berapit followed by Sg Simpang Ampat with 9.45% and 7.56% for Pintu Air Bagan. For the year Δ2050, the projected pattern for all the stations were in increment with the high different between RCPs and historical data

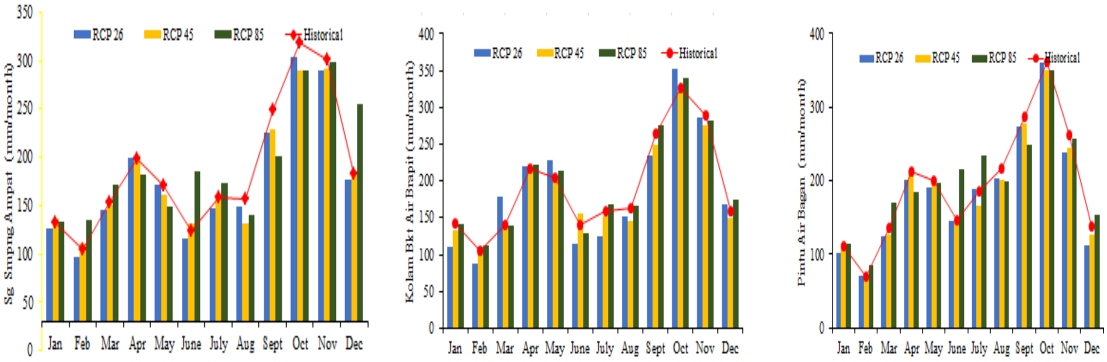
Table 4.10 Analysis of Rainfall Projection in Pulau Pinang

Rainfall station	RCP2.6 (%)			RCP4.5 (%)			RCP8.5 (%)		
	Δ2020	Δ2050	Δ2080	Δ2020	Δ2050	Δ2080	Δ2020	Δ2050	Δ2080
Sg Simpang Ampat	+10.020	-4.690	-5.100	+8.970	-5.250	-4.330	-9.450	+16.730	-4.160
Kolam Bkt Air Berapit	+20.200	-12.610	-15.910	+5.260	-4.620	-5.040	-20.630	+4.320	-4.940
Pintu Air Bagan	-7.230	-5.540	-7.030	+7.720	-4.360	-4.300	-7.560	+14.610	-5.870

Δ2020



Δ2050



Δ2080

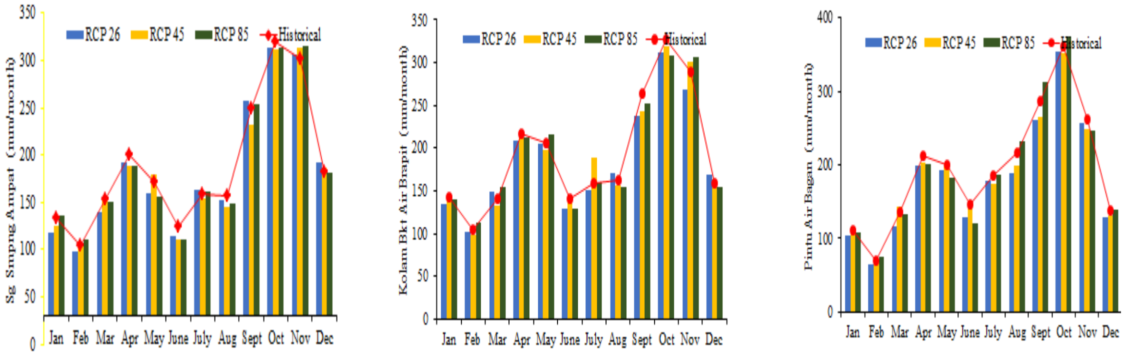


Figure 4.9 RCP Projections of Rainfall in Pulau Pinang

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

SDSM software was used to downscale the climatic data for temperature and rainfall in Northern Malaysia. Results obtained show use of suitable predictors from NCEP influenced adequate downscaled of temperature and rainfall data by SDSM. Moreover, SDSM was the best tool to find the best RCP of temperature and rainfall station besides acts as climate agent for projecting the future climate. In this study, SDSM managed to project future clinmate with close result of pattern like historical.

5.1.1 Performances of the SDSM Accuracy

I. The most predictors used in analysis affect the accuracy of the modelling. For example the predictors used in analysis of rainfall in Perlis more than the predictors used in Pulai Pinang. Therefore, it can be seen the accuracy of modelling in Perlis more accurate than Pulau Pinang.

II. In calibration and validation result for temperature, the %MAE recorded for calibration of maximum temperature was 0.438% that lower than validated value that was 0.546%. For the minimum temperature, the %MAE was 0.295% of calibrated and 0.588% of validated. The lowest %MAE for calibrated and validated are from mean temperature that recorded 0.281% and 0.052. The correlation for these three were perfectly to 1.00.

III. For rainfall result in perlis, the %MAE for Ladang Perlis Selatan station, the validated was 16.8%. The analysis shows Ulu Pauh station has the lowest %MAE with 12.3%. The correlation value for Ulu Pauh and Guar Nanka recoreded almost 1.00 with 0.975 and 0.932 while Ladang Perlis Selatan was 0.867.

IV. The percentage error of the calibrated and validated of rainfall in Pulau Pinang were quite high with all the stations recorded above 10% for three RCPs. The highest percentage error of calibrated and validated were recorded was in Sg Simpang Ampat with 15.454% for calibrated and 20.480% for validated.

5.1.2 The Selected RCPs Radiation for the Region

The best RCP was choosen based on percentage error and correlation value that measured the accuracy and relationship between historical data and downscaled data. The lower the percentage error, the higher of accuracy of the downscaled data. Therefore, the choosing of the best RCP was depending on the lower of percentage error with the limit 20% and correlation value 1.0.

I. the best RCP for Temperature in Perlis was RCP 2.6 since majority of the temperature recorded RCP 2.6 as the best RCP. However, the graph in Figure 4.4 showed a same pattern of three RCPs with small different with the historical data. Therefore, the statistical analysis of percentage error and correlation value were important in order to measure the accuracy and relationship between the historiocal data and downscaled data

II. As conclusion, the lower of percentage error in statistical analysis, the more accurate downscaled data to the historical data. Thus, the best RCP for rainfall in Perlis was RCP 2.6 since the best RCP of two out of three stations were RCP 2.6.

III. Since the best RCP Sg Simpang Ampat and Pintu Air Bagan station are RCP8.5 while RCP 4.5 for Kolam Bukit Air Berapit station, we can conclude that the best RCP for the rainfall station in Pulau Pinang was RCP8.5.

5.1.3 The Climate Projection Considered with the GHGs Emission

I. For maximum, mean and minimum temperature projection, the result shows that it constantly deacreasing from historical to different RCPs. In maximum temperature the highest value was 34.7˚C with the decrement less than 1%. In maximum temperature, the pattern showed increment in year Δ2020 and Δ2080 while Δ2050 had deacrement in year Δ2050 while for minimum the pattern of the projections were in deacreasing pattern.

II. Projected of Guar Nangka station in year 2020 recorded quite similar with the historical data with small increment or decrement.Besides that, it can be concluded that the pattern of the projected years for all stations were similar at early of the year where recorded the lowest of rainfall.

III. In RCP 4.5, small increment and decrement recorded for all the years with the values were below 10% where in year Δ2020 the projected were recorded a quite different with the historical since the analysis showed an increment with Sg Simpang Ampat had the bigger increment than the other stations with 8.970% followed by Pintu Air Bagan for 7.720%

5.6 Recommendations

There are several recommendations that could be implemented for better future climate projections results:

I. In selecting the predictors, the selection must be done with statistical method such as multi-correlation matrix (MCM) to produce highly correlation value in multiple variables since the selection of the predictors affect the projection results.

II. The RCPs for other states is recommended to be identified whereby each region having different radiation forcing and GHGs level.

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