PREDICTION OF WATER STREAM FLOW IN THE CONTEXT OF CLIMATE CHANGE

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PREDICTION OF WATER STREAM FLOW IN THE CONTEXT OF CLIMATE CHANGE

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Dedicated to mak and ayah.

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ABSTRACT

The increase in global surface temperature in response to the changing composition of the atmosphere will significantly impact upon local hydrological process and water sources. This situation will lead to the need for an assessment of regional climate change impacts. The application of Statistical Downscaling Model (SDSM) and Identification of Unit Hydrograph and Component Flows from Rainfall, Evaporation and Streamflow Data (IHACRES) were used as rainfall runoff models to stimulate streamflow event in Sungai Kecau, Kuala Lipis, Pahang catchment based on daily rainfall. The rainfall station is taken at Kampung Bandar at Ulu Kechau. The SDSM model is the derivation of National Centre for Environmental Prediction (NCEP) reanalysis data and observation of locally methodological variables that have been calibrated using large – scale predictors variables. The SDSM model validation has been done by independent period of NCEP reanalysis. The outcome obtained was used to generate the possible future scenarios of meteorological variables and then the input is used to the IHACRES model. Stimulation of corresponding future streamflow changes was stimulated by IHACRES model and the observed station data in the catchment Sungai Kecau, Kampung Dusun.

ABSTRAK

Peningkatan dalam suhu permukaan global sebagai tindak balas kepada perubahan komposisi atmosphere ketara memberi kesan kepada proses hidrologi dan sumber air. Keadaan ini menjurus kepada keperluan untuk mentaksir kesan – kesan perubahan iklim yang serantau. Perisian Statistical Downscaling Model (SDSM) dan Identification of Unit Hydrograph and Component Flows dari Rainfall, Evaporation and stream flow Data (IHACRES) telah digunakan sebagai model untuk mengkaji jumlah hujan yang merangsang aliran air sungai dan kawasan tadahan hujan di Sungai Kecau, Kuala Lipis, Pahang. berdasarkan jumlah hujan harian. Stesen hujan diambil di Kampung Bandar di Ulu Kechau. Model SDSM ialah terbitan daripada National Centre for Environmental Prediction (NCEP) dan pemerhatian pembolehubah – pembolehubah yang tempatan metodologikal yang telah menyelaras menggunakan besar – berskala pembolehubah peramal. Pengesahan model SDSM telah dilakukan oleh tempoh bebas analisis semula NCEP. Data yang diperolehi dignakan untuk meramal senario – senario masa hadapan yang mungkin memberi kesan kepada meteorology dan kemudian data yang diperolehi akan digunakan untuk model IHACRES. Perubahan aliran sungai pada masa hadapan diramal menggunakan model IHACRES dan stesen kawasan tadahan yang digunakan ialah di Sungai Kecau, Kampung Dusun.

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INTRODUCTION

1.1 INTRODUCTION

Rainfall runoff model is the standard tools designed for hydrological investigations. It is used for many purposes such as for detecting climate change towards catchment response, design floods calculation, water resources management, flood forecasting, estimation of land use change impact, and stream flow prediction. Since various interacting processes that involve in the transformation of rainfall into runoff are complex, therefore stimulating the real-world relationship using rainfall-runoff model is a difficult task. To overcome the difficulty on stimulation, rainfall-runoff models have been classified into three types there are the physically-based model, conceptually-based model and metric-based model. Physically-based model and conceptual-based models describes the real system of hydrological system of the catchment based on physical equations. Both models require extreme data demand and large number of parameters. Therefore, these models are difficult to be calibrate and facing over parameterization. Another rainfall-runoff model that has been used widely is Metric-based model. This model is based on extracting information that is simplicity contained in the hydrological data without directly taking into the physical laws that underline the rainfall-runoff process. The model uses undemanding complex data and simple calculation that more suitable to apply at areas which have insufficient or very limit data record.

The unpredicted rainfall amount nowadays, is one of the impacts of climate change on hydrological process, particularly in extreme event that generate peak runoff flows. International Governmental Panel on Climate Change (IPCC, 2007) proved the that climate change lead to changes in rainfall and streamflow. Heavy and extreme runoff flows will increase as the mean of the total rainfall increase (Dore et al., 2005). Climate change has begun to transform rainfall pattern in Malaysia and extreme flood becomes more severe in several states (Ghani et al., 2012). In year 2014, heavy rain occured in December has caused severe flooding and this flood has been described as the worst floods in decades. Changing trend in rainfall distribution and the streamflow trend also gives an effect in hydrological analysis related to historical rainfall record. These events have raised concern in researcher on the behavior of daily rainfall such as the frequency of wet days, the mean intensity of rain during wet days, the mean amount for extreme events, and the mean lengths of wet and dry spells, which have gradually changed over the years, possibly due to global climatic change and it will affect the trend of streamflow in the future.

In this study, Identification of unit Hydrograph and Component flow from Rainfall, Evaporation and Stream flow data (IHACRES) (Jakeman et al., 1990) has been applied the model is classified in the metric-based model. In recent year, IHACRES has been successfully used as a rainfall-runoff model. In this study, IHACRES has advantages over the physical and conceptual model, since it able to stimulate non-linearity in a system. IHACRES also effectively distinguish between relevant from irrelevant data characteristics. In addition, IHACRES is non-parametric techniques. The model does not require the assumptions of constraints. The relationship between climate and stream flow can be investigated and study by hydrological model which need an output from the downscaling method to became an input to hydrological model. In this study, SDSM has been applied to converting the coarse spatial resolution of Global Climate Models (GCMs) output into fine resolution which involve of generating station data of a specific area (Hashmi et al., 2009).

1.2 STATEMENT OF THE PROBLEMS

The Intergovernmental Panel on Climate Change (IPCC) reported that the global temperature surface has been increased by 0.74°C in 1906 – 2005, with the increment rate is about 0.13°C per 100 years in the next 20 years (IPCC, 2007). The temperature would increase by about 1.1–4.4°C during the next century as stated in IPCC. It will have an impact on hydrological cycles and subsequent changes in river stream flow, and toward production of agriculture. Historical trends in streamflow around the world have shown that it is affected by climate change. Streamflow plays a vital role in water resources management such as assessing the impact of past, ongoing and future climate or land use change, operational purposes like flood forecasting, dam and hydroelectric management, integration with other models like designing flood or drought control structures using a hydraulic model, prediction in ungagged basin by generating flow data at basins without monitoring station and to improve our understanding of hydrological possess at specific region. Based on the past researcher it has shown that in Pahang the streamflow during the month September and October show that the minimum streamflow while during November and December is the maximum streamflow (Syazwan et al., 2006).

Sungai Kecau, Kampung Dusun in Kuala Lipis, Pahang was selected for this research area due to its historical data of flood recurrence, its rainfall recorded and its recent flood disaster. Town of Kuala Lipis is sited at the confluence of Sungai Jelai and Sungai Lipis. In January 1971, the town and the areas alongside of the river experienced the worst flood. The flood lasted for 12 days and it inundated depth of approximately 3 meter (Ghani et al., 2015). During the end of 2013 and 2014, the flood occurred again at Kuala Lipis. Kuala Lipis records among the highest number of evacuees among other states in Pahang. The extensive rainfall in high intensity is the main reason of flooding Kuala Lipis. For the past two decades, Pahang has been experiencing with land development and economic growth rapidly. The increment of population in Pahang state may causes the problem of water supply and water pollution from the industries (Tan et al., 2009).

The understanding of past, present and future changes of water stream flow are very important in preparing the long term effective management of water resources. Therefore, the various climate modeling have been developed and widely used among researchers in predicting the climatic trend in the context of climate change. Simulations of global climate are conducted with general circulation models (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. GCMs are now being run for shorter time periods at finer resolution. However, the prevailing approach for obtaining finer spatial resolution climate information is to apply techniques for downscaling GCM output.

The SDSM model is applied to downscale GCMs into catchment scale. The SDSM models have several advantages and disadvantages (Dibike and Coulibaly, 2005). Some advantages of SDSM are SDSM model need less technically demanding, it can possibly to tailor the scenarios for specific localities, scales and problems and SDSM includes an evaluation of GCM performance in stimulating the climate of a specific area where as the disadvantages of SDSM model are the assumption that observed links between local predictant and large-scale predictors will persist in a changed climate, successfully of SDSM model depends on reliable observational series of predictors and predictants and the problem when applying SDSM to daily values is the observed autocorrelation between the weather at consecutive time is not reproduced. The SDSM model is more accurate compared to regional modeling. SDSM can downscale from several GCMs and several different emission scenarios relatively quickly and inexpensively compared to regional modeling. 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.

The hydrologic impacts of climate change are analyzed by using conceptual-based and/or physically-based hydrological models (Dibike and Coulibaly, 2005). In this study, it will focus on metric-based model which has more accurate result than the other model. The expertise of the modeler with prior knowledge of the information input being modeled is the result in the IHACRES model. Sometimes, due to the subjective factors involved, the tedious nonlinear structure calibration process may produce uncertainty results. Therefore, the study also focuses on developing an effective and efficient calibration procedure. Based on the past research, the performance of IHACRES model is the best prediction result was achieved in term of accuracy prediction of stream flow compared with other hydrological model such as autoregressive integrated moving average (ARIMA), deseasonalized autoregressive moving average (DARMA) and simulator for water resources in rural basins (SWRRB) has been proved by Mahdi Zarei, 2014.

1.3 OBJECTIVES OF THE STUDY

The main aim of this study is to generate the streamflow characteristics in the context of the climate change impact. The objectives of the study are outlined as follows:

1. To generate the future rainfall and temperature pattern during year 2010 to 2099.
2. To estimate the future trend of water streamflow in the context of climate change.

1.4 SCOPE OF THE STUDY

The study is focused on the calibration and simulation of the climate models by using the SDSM models for the future rainfall. The projected result of the climate trend in the future year 2010 – 2099, will be used as data input to the hydrological models. IHACRES model has been used to study the rainfall-runoff relationship and to obtain the streamflow characteristics with consider the climate change response. The study is focused on Kuala Lipis, Pahang and station number 4320066 is selected as the rainfall stations in the Kampung Bandar at Ulu Kechau while the streamflow station is selected in Sungai Kecau watershed with station number 4320401 in Kampung Dusun. The location is selected because of rapid urbanization occur in that area is affect the trend of streamflow. Sungai Kecau is also one of the well-known places in Pahang that occur flood every year.

1.5 SIGNIFICANT OF THE STUDY

This study will be significant endeavor in promoting the stream flow for the future. Identification of the climate change is vital to determine the streamflow along the river using rainfall data. With the changing of climate, the water levels of the rivers become fluctuated. Thus, this data analysis is important for the authorities to know the flow of the water in the future. There are several benefit and significant of the study, there are: i) to manage water level effectively, ii) design the future plan of food mitigation, iii) to determine the trend of future rainfall and temperature.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The water stream flow is important to conduit in water cycle. The main factors that contribute to the hydrodynamic change on the river flow is the change pattern of seasonal climate. Human activities such as land use changes and rapid development along the river bank or within the river basin might change in the drastic river flow (Walter and Tullos, 2010). In this study, considered the extreme weathers have great impact to hydrodynamic change of Sungai Kecau, Kampung Dusun, in Kuala Lipis, Pahang. The extreme rainfall in northeast monsoon season will caused the overflowing of Sungai Kecau, while in the drought season it will caused to the lowest flow of the Sungai Kecau. Monsoon rain and winds are the end result of heating patterns produced by the sun and the distribution of land and ocean (John, 1987). Normally, Malaysia received the highest rainfall in November to December in average 40% from the total annual rainfall especially in Pahang state (Suhaila et al., 2010). The main factor that resulted to the high river flow is due to the extreme rainfall that triggered during northeast monsoon (DID, 2009). The erosion would probably happened that may change the width and depth of river size (Anderson et al., 2006; Kamarudin et al,. 2009; Jung et al., 2011; Hoyle et al., 2012).

Hydrological cycle has nine major processes there are precipitation, evaporation, infiltration, transpiration, runoff, stream flow, interception and evapotranspiration. In this study, it is focused hydrological cycle on precipitation which is rainfall and stream flow. The change in rainfall pattern due to warmer climate in the future is estimated leading to alter the stream flow characteristics. The hydrological processes reflect combined effects of climate, vegetation and soil, resulting in changes of streamflow at the basin scale. Changes in climate combined with the human activities have led to massive changes in hydrological process in many basins. These changes have caused a series of water resource problem in some region such as the Murray-Darling basin in Australia (Petheram et al., 2010), the Mississippi River basin in America (Ziegler et al., 2005) and the Yellow River basin in China (Liu and Cheng, 2000). To understand the influence of climate change on streamflow, many of studied have been performed. This is to investigate the response of hydrological processes to climate changes for example in Malaysia (Hassan and Harun, 2012, Tukimat and Harun, 2014), China (Li et al., 2007, Liu et al., 2009), in Australia (Jones et al., 2006; Hicked and Zhang, 2006) and in Mexico (Gochis et al., 2006).

Climate change is one of the significant impacts on water basin and region, such as runoff and hydrological system. Changing in climate causes the decreasing or increasing of volume of flow. Therefore, there is a need to study the relationship between climate change and water basin stream flow. To estimate the future stream flow downscaling method is used. The downscaling method is the projection from annually rainfall data thirty (30) years ago into future rainfall data. The future stream flow is affected by the change in climate. Climate change is affected by the continuous increase of greenhouse gas concentration in the atmosphere. To estimate this relationship, Global Climate Change models (GCMs) are used. Due to their coarse spatial resolution, GCMs output cannot directly use for hydrological assessment (Hassan and Harun, 2012). Process of converting the coarse spatial resolution of the GCMs output into a fine resolution, downscaling model is used. This process involve generating the station data of a specific data by using GCM climatic output variables (Nguyen et al., 2005; Wilby and Wigley, 1997; Dawnson et al., 2007; Fowler et al., 2007; Hashimi et al., 2009; Hassan and Harun, 2012).

The history the past decades it is found that the Earth’s climate has changed. According to American Association for the Advancement of Science human activity is the major caused of global climate changed that occurring now and it is a growing threat to society (AAAS, 2006). Climate change is real. There is strong evidence that shows the phenomenon of climate change such as the rising surface air temperature, rising in global temperature, warming ocean, shrinking ice sheets, and snow cover decreasing and declining arctic sea ice. It is the warning in recent decades can attributes to human activity (IPCC, 2001). Increased atmospheric carbon dioxide (CO_2) concentration and climate change may significantly impact the hydrological and meteorological processes of a watershed system. Global atmospheric concentration of CO_2 have markedly as a result of human activities since year 1750 and now far exceed pre-industrial values determined from ice cores spanning many thousands of year (IPCC, 2007). The elevation of atmospheric CO_2 concentration not only raises mean air temperature but also changes the temporal and spatial distribution of rainfall, causing an increased risk of both heavy rainfall events and drought (Eckhardt and Ulbrich, 2003).

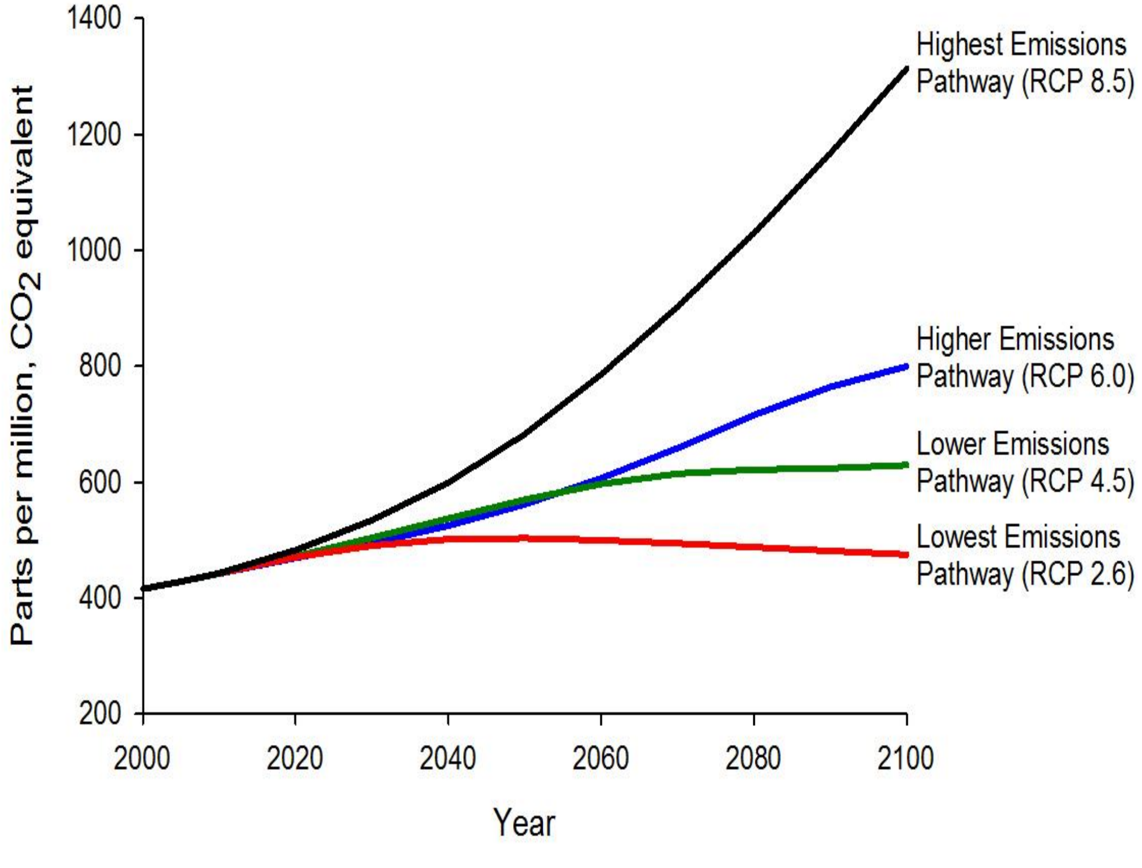

Figure 2.1: The projected greenhouse gas concentration for four different emissions pathways (www.epa.gov/climatechange/)

Figure 2.1 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.

Since, the past few decades, researchers found that the effect of climate change upon the areas of hydrology and water resources is one of important topic to be discussed on. The changes in the mean and/or the variability of climate's properties that persists for an extended time duration, typically decades or longer, due to natural variability or as a result of human activity is referred to the meaning of climate change (IPCC, 2007; Hassan et al.,2013). The uncertainty of climate change may impacts on the environment, ecosystems, water resources and all aspects of human life (Jiang et al., 2007). Human activities like the burning of fossil fuels and changes in land cover and use are one of the major factors to increase the atmospheric concentrations of greenhouse gases. Therefore, the result of climate change tends to increase rapidly. In term of hydrology, climate change can cause significant impact on water resources. In the result, changing in the hydrological cycle will happen. Temperature and rainfall are the relevant parameters that influence hydrological cycle. Increase in air temperature will accelerate the global hydrological cycle (Oki and Kanae, 2006). The most affected components that will influence regional water availability are precipitation and evapotranspiration (Milly et al., 2005). Therefore, the expected changes of hydrological changes are essential to develop adaptation to current water resources systems.

A lot of catchments in Malaysia have experienced the increased sediment loading and water quality declination over the years. In Malaysia, the study about the future pattern of water stream flow in the context of climate change is very limited. Thus only a few attempts have been carried out on understanding the water stream, flow due to climate change. Nowadays, this study became important to understand any factors that will degenerate the quality of freshwater to ensure the sustainability of fresh water in this changing world. Theoretically, stream flow is a flow of water that moves over a designated point over a fixed period of time and it is a major element in hydrological cycle. It is one of the main mechanisms for water movement from the land to the oceans. Stream flow is always changing from time to time. In Malaysia, stream flow is affected by weather, increasing during rainstorms and decreasing during dry period. The Sungai Jelai watershed in Pahang receives mean annual rainfall of 2057.91 mm and the mean monthly rainfall was 169.41 mm with the maximum (507.29 mm) occurring in the North-east monsoon season (Chin, 1987). The past researcher Chin has found that the streamflow followed the rainfall trend closely. Mean monthly streamflow was recorded at 61.98 mm, maximum flow occurred in November and minimum flow in August. The mean annual streamflow was 742.86 mm. Rapid physical development in the study area had given the negative impacts towards the rate of stream flow into the water body system. Consequently with that situation, it will affect the water level at certain location in the river basin like Sungai Kecau and subsequently may lead to flood.

Therefore, the hydrological model is used to study the impacts of weather, climate change and characteristics of stream flow in a specific watershed. Understanding the characteristics of stream flow change due to the hydrological budget is crucial in order to assess the future water availability.

2.2 GENERAL CIRCULATION MODELS (GCMs)

GCMs are used to estimate the future climate change resulted from the continuous increment of greenhouse gas concentration in the atmosphere. This method was proposed by Norman Philips in the year 1956 as other alternative for the failed numerical approach. For investigating the physical and dynamic processes of the earth-atmosphere system, GCMs are considered as compressive models as well as providing plausible patterns of global climate change (Jiang et al. 2007). GCMs indicate a significant skill at the continental and hemisphere scales and incorporate a large amount of the complication of the global system, an inherently unable to represent local subgrid-scale features and dynamics (Wigley et al., 1990; Carter et al., 1994, Hassan et al., 2013). The GCMs output cannot be used directly for climate change study and do not provide direct estimation of the hydrological response towards climate change (Dibike and Coulibaly, 2005). It is due to the mismatch in the spatial resolution between the GCMs and hydrological models and large coarse in resolution. Therefore, to convert the coarse spatial resolution of the GCMs output into a fine resolution, which may involve the generation of data of a specific area by using GCMs climatic output variables the downscaling techniques is used (Xu, 1999; Wilby and Dawnson, 2012; Fowler et al., 2007; Dibike and Coulibaly, 2005; Hashimi et al., 2009).

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. Table 2.1 show the evolution of the Hadley Centre models can be viewed in a historical context.

Table 2.1: Evolution of the Hadley Centre GCMs (http://www.cru.uea.ac.uk/)

Model Name and Experiments	Year	Ocean	Resolution lat. x long.
UKLO • Equilibrium 10 year integration	1987	Slab-ocean	5.0 x 7.5
UKHI • Equilibrium 10 year integration	1990	Slab-ocean	2.5x3.75
UKTR • Transient cool start • Multi-decadal integrations	1992	20 layer full ocean	2.5x3.75
HadCM2 • Transient warm start • Historically forced • Multi gas • Multi-century integrations • Multi-member ensembles	1995	20 layer full ocean	2.5x3.75
HadCM3 • Transient warm start • Historically forced • Multi gas • Multi-century integrations • Multi-member ensembles • Including gas life cycle models and any early version of a biosphere model • No flux correction	1998	20 layer full ocean at 1.25°x1.25° resolution	2.5x3.75

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).

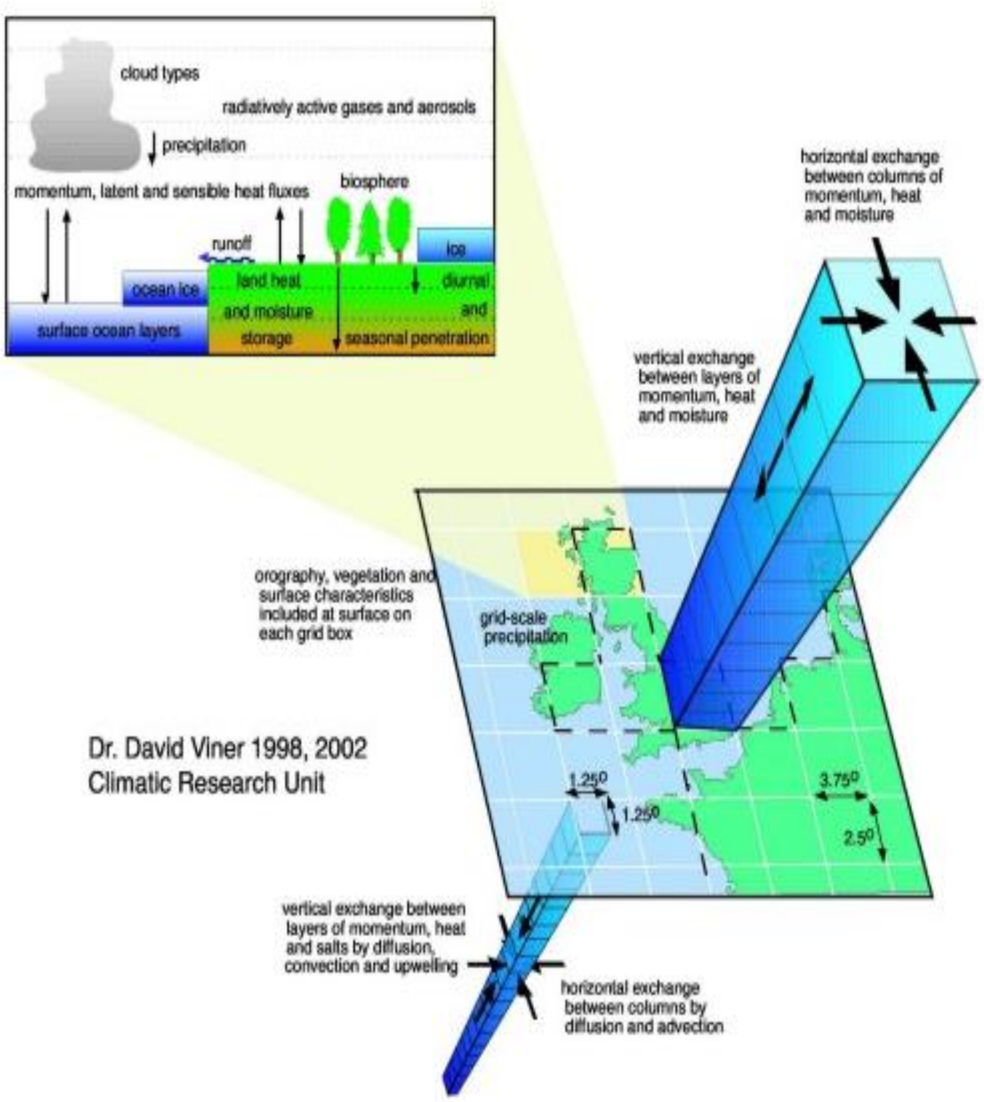

Figure 2.2: A conceptual structure of a coupled ocean-atmosphere GCM (www.ipcc.data.org/)

The results of climate change have been used widely to investigate how the ecosystems will respond. The spatial resolution of GCMs is relatively coarse, of the order of 2.5° (latitude) x 3.75° (longitude). The impacts assesements that carried out at resolution of 50 km or less usually leads to a mismatch. To overcome this different in scales there is a need to construct scenarios. Figure 2.3 show the GCMs resolution. Figure demonstrates the complexity of the downscaling process.

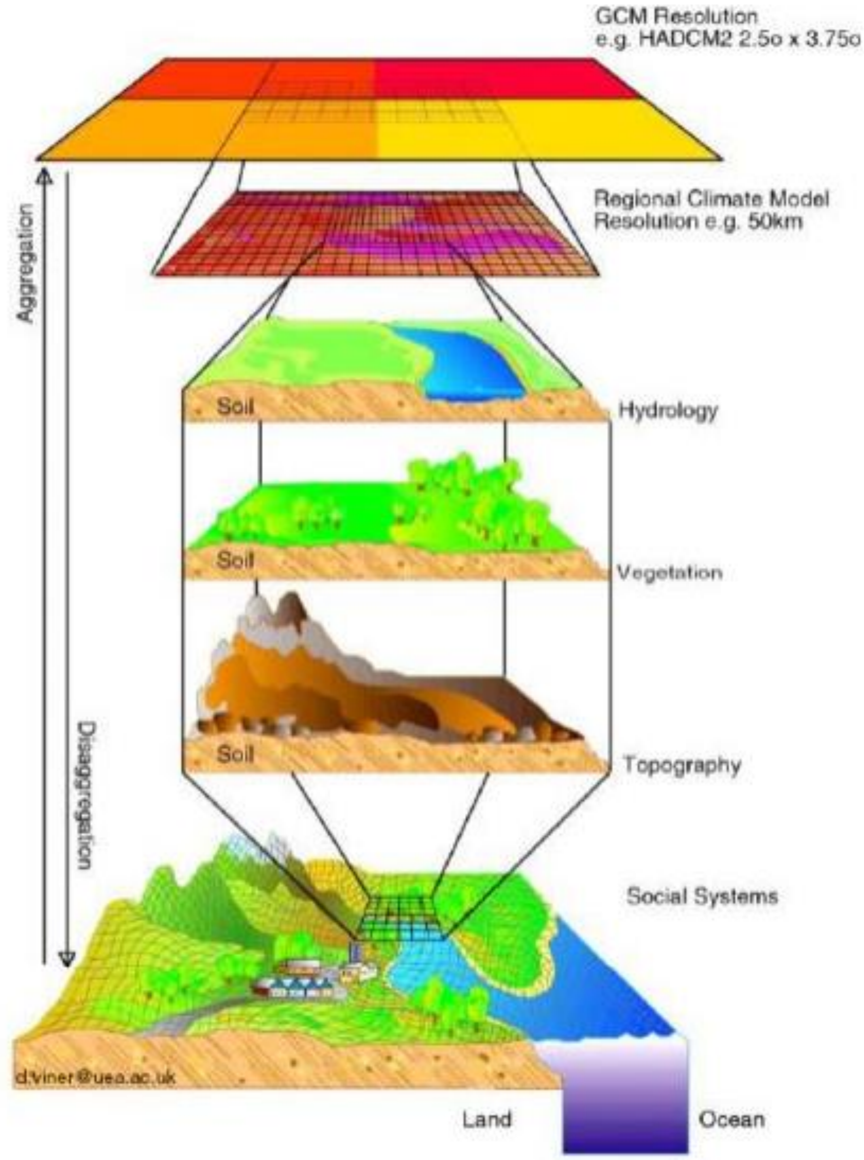

Figure 2.3: GCMs resolution in represent the local climate

2.3 THE DOWNSCALING METHOD FOR CLIMATE MODEL PROJECTION

The two sets of techniques that can be used for downscaling are dynamical downscaling (DD) and statistical downscaling. Dynamical downscaling involved a nested regional climate model (RCM) while statistical downscaling involved statistical relationship between the large scale climatic state and the local variations derived historical data (Wilby and Dawnson, 2012; Hassan and Harun, 2015). In this study, statistical downscaling has been chosen. The universally multiple linear regression model called Statistical Down-Scaling Model (SDSM) has applied. Statistical downscaling model have several advantages compare to dynamical model (Wilby and Dawnson, 2013). Statistical downscaling is more low-cost, rapid assessments of local climate change impacts are required and represents the more promising options. In addition, compare to other model that widely used in the hydrological and agriculture community such as LARS-WG, WGEN and CLIGEN, do not directly utilize GCM output in the scenario construction process. The study of hydrological model can investigate the relationship between climate and stream flow (Xu, 1999), which the output of downscaled can become an input to hydrological model (Hassan and Harun, 2015). There are three type of hydrological model which are physically-based model, conceptual-based model and metric-based model (Nguyen, 2005; Guero, 2006).

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

2.3.1 Dynamical Downscaling

The nesting of higher resolution Regional Climate Model (RCM) within a coarser resolution GCM is involved in dynamical downscaling. The RCM uses the GCM to define time-varying atmospheric boundary conditions around a finite domain, within the grid spacing of 20-50km. Every model has its limitations. RCM main limitation is RCM are as computationally demanding as GCMs. The scenarios produced by RCMs are also sensitive to choice the boundary conditions. The main advantage of RCMs is it can resolve smaller-scale atmospheric features. Besides, RCMs can be used to explore the relative significant of different external forcing.

The use of dynamical downscaling in long-range climate projections has accelerated with the growth of computing resources. At present, many large collaboration projects are generating databases of downscaled climate output for model intercomparison and impacts assessment. The North Regional Climate Change Assessment Progam (NARCCAP), begun in 2006, has generated high resolution 50km climate projections for the United States, Canada and Northern Mexico. In 2009, as a successor to the projects the World Climate Research Program (WRCP) began the international Coordinated Regional Climate Downscaling Experiment (CORDEX) to produce similar output for all continents. The level of effort invested in dynamical downscaling warrants a proper evaluation of its benefits for impacts assessments.

Castro et al. (2005) has proposed four types of dynamic downscaling. Type 1, which is used for numerical weather prediction, remembers its real-world initial conditions, as do the laterally boundary conditions. In types 2, the initial conditions in the interior of the models are forgotten but the lateral boundary conditions feed real – world data into the regional model. In types 3, a global model prediction, rather than a reanalysis, is used to create the lateral boundary condition. These internal climate system components are assigned and not predicted. In type 4, a global model is run in which there is no prescribed internal climate system forcing. The coupling among the ocean – land – continental ice-atmosphere is all predicted.

2.3.2 Weather Typing Schemes

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

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

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

2.3.3 Stochastic Weather Generators (WGs)

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

The stochastic weather generator is a statistical model of observed weather variables, with those variables generally conditioned on the occurrence of rainfall. It is possible to use stochastic weather generators to downscale large – scale climate (Wilks, 1999), by running a weather generator at both the site and area scales. The statistical correlations between climatic variables derived from observed data are assumed to be valid under a changed climate.

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

2.3.4 Regression Model

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

2.3.5 Statistical Downscaling (SD)

SD is categorized as a hybrid model, which utilized a linear regression method and a stochastic weather generator. The predictors are used to a linearly condition and non-condition of the local-scale weather generator parameters at single stations. Rainfall is in the condition process. It is modeled using a stochastic weather generator conditioned on the predictor variable. During the model calibration, some parameters bias correction and variance inflation were adjusted in order to obtain the best statistical result between observed and stimulated climate variables (Hassan et al., 2013). Therefore, Tukimat and Harun, 2013 suggested to apply Multi – Correlation Matrix (MCM) in the predictors selection to ensure the accuracy of the calibrated and validated result.

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

Table 2.2: Mains strength of statistical-versus-dynamical model (wilby et al.)

Statistical downscaling		Dynamical downscaling
• Climate information from GCM in station-scale-scale output • Easy to transferable, cheap 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 • Physically respond in consistent way to different external forcing • Resolve atmospheric process • Consistency with GCM

• The statistical downscaling is the assumptions that observed links between large scale-predictors and local predictand will persist in a change • The daily value is that the observed autocorrelation between the weather at consecutive time steps is not necessarily reproduced • Statistical downscaling does not necessarily reproduce a physically sound relationship between different climate element • Successful statistical downscaling depends on long, reliable observational series of predictors and predictants.	**Weakness**	• Dynamical downscaling depends on boundary conditions supply from some other sources • The dynamical downscaling models may miss the most extreme rainfall data

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

Kidson and Thompson (1998) used the RAMS dynamical model to downscale reanalysis data (ECMWF) over New Zealand to a grid resolution of 50 km. The statistical downscaling used a screening regression technique to predict local minimum and maximum daily temperature, and daily rainfall. The regression technique limits each regression equation to 5 predictors selected from EOFs of 1000 hPa and 500 hPa geopotential height fields, local scalar wind speed and anomalies of geostrophic wind speed at 500 hPa and 1000 hPa, anomalous 1000 hPa–500 hPa thickness and relative vorticity, and terms of vorticity advection. The results indicated little difference in skill between the two techniques, and Kidson and Thompson suggest that, subject to the assumption of statistical relationships remaining viable under a future climate, the computational requirements do not favor the use of the dynamical model, although it is noted that the dynamical model performed better with convective components of the rainfall.

SD has more superiority than DD, yet it does also have 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 need high quality of data for model calibration otherwise, the model will not run. The result of SD is also depending on the choice of predictor variable. In conclusion, because of the niggardliness and lower technology advantages of SD methods over DD modeling, a multiple regression-based method was chosen as the basis of the decision support tool which is SDSM.

2.3.5.1 Statistical Downscaling Model (SDSM)

SDSM is introduced by Wilby et al. (2002). SDSM is software to Downscaling Global Climate Model (GCMs) and it is coded in Visual Basic 6.0 (Hassan et al., 2015). It is a tool that has been developed by Dawson and Wilby that freely offered and used to the border climate change impacts (Dawson and Wilby, 2007). It is build up the relationship between the GCMs variables that known as predictors and the local-scale variables known as predictants (Chu et al., 2009). The data of GCM will be downscaling in SDSM using multiple linear regressions by daily predicator-predictand relationships. The predictor variable describes the daily information in the large-scale state of the atmosphere, while the predictand provides the condition at the site scale. In SDSM the parameter of the regression equation is estimated using an ordinary Least Squares algorithm. The local rainfall is classified as the conditional process because the local weather is correlated with the occurrence of wet days. The forth root transformation is applied to the original series as the distribution of precipitation is skewed to convert it to the normal distribution, and then used in the regression analysis. Temperature is modeled as the unconditional process, where a direct link is assumed between the large scale predictors and local scale predictand.

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

A large number of researches had been done to compare the performance between SDSM model with others model. Table 2.4 shows the comparison of SDSM model with the other model that have made by past researchers.

Table 2.3: Comparison of SDSM performances with the other model

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

2.4 RAINFALL-RUNOFF MODELING

In this study, the metric-based model is used. However, metric based model contain parameters that involve physical characteristic that allow the modeling of input-output patterns based on empiricism. Furthermore, these models are established on the mathematical link between input and output series considering the catchment as a lumped unit, with no spatial in homogeneities of the basin (Hassan and Harun, 2015). This method has been widely and successfully used by the researches. Examples of this approach are Unit Hydrograph and Rational Method. In this study, Unit Hydrograph (UH) theory is used and it been categorized as metric based-model. Sherman introduced UH theory in 1932 and it has been widely used over the past decades. The concept of UH theory is the hydrograph that results from one (1) unit of excess rainfall uniformly over the watershed for the entire specified period of time. There are many models that have been developed using UH theory including a rainfall separation model and the conversion of effective rainfall into stream flow. This study focused on the IHACRES model (Identification of unit Hydrograph and Component flows from Rainfall, Evaporation and Stream flow data) for the runoff modeling. Hydrological model can be classified into three model according to; i) physically based-model, ii) conceptually based-model and iii) metric-based-model.

2.4.1 Physically based model

The hydrological process of water movement are modeled either by the finite difference approximation of the partial differential equation is called physically-based model (Abbott et al., 1986). The primary components of hydrological cycle usually related to the land phase. The hydrological components are interception, snowmelt, evapotranspiration, sub-surface runoff, groundwater flow, surface runoff and channel routine (Zahidul, 2011).

In physically based hydrologic modeling the hydrologic process of water movement are modeled either by the finite difference approximation of the partial differential equation representing the mass, momentum and energy balance or by empirical equations (Abbott et al., 1986b). Typically the primary components of hydrologic cycle related to the land phase are taken into consideration. These are interception, snowmelt, evapotranspiration, sub-surface runoff, groundwater flow, surface runoff and channel routing. Figure 2.4 shows a schematic representation of components of a physically based distributed hydrologic model MIKE SHE (Refsgaard and Stron, 1995). A number of physically based hydrologic models have been reviewed and modeling concepts of these physical processes used by various hydrologic models will be discussed in the following sections. This model demonstrates the channel flow.

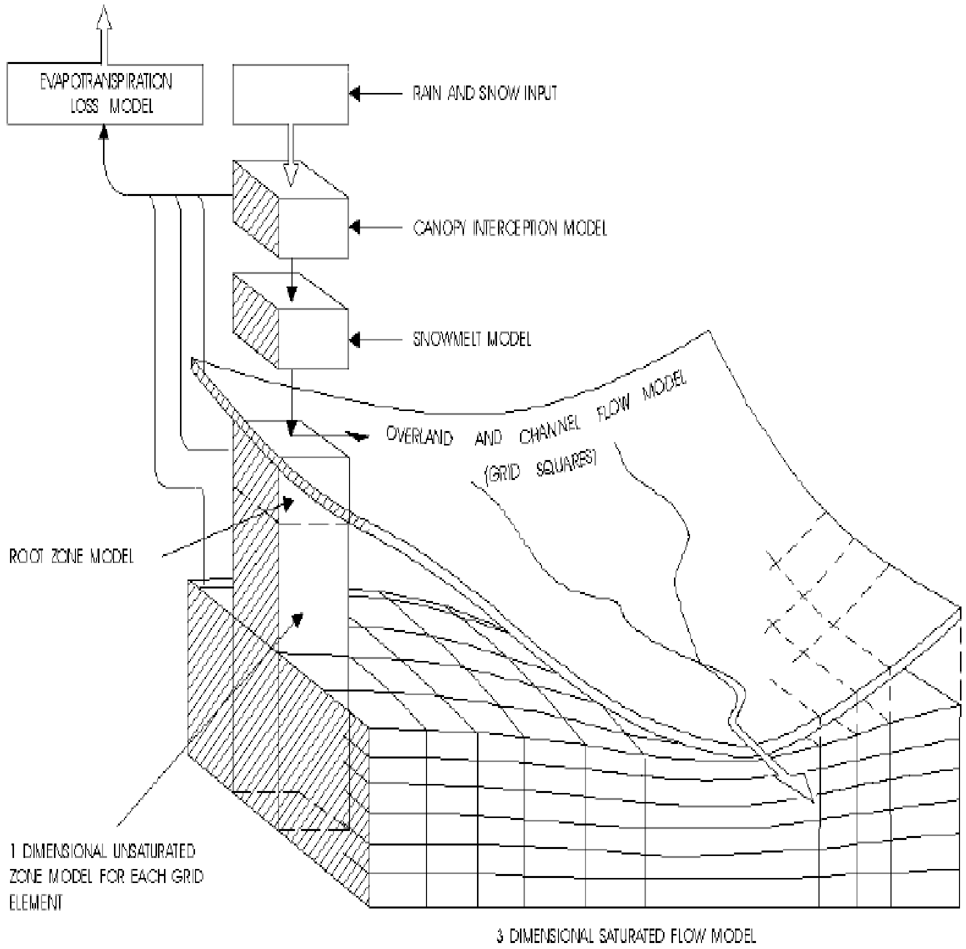

Figure 2.4: A schematic representation of components of a physically based distributed hydrological model MIKE SHE

2.4.2 Conceptually Based Model

A conceptual based-model is a representative of the hydrological units and the flow system of groundwater. A conceptual model is necessary to obtain a numeric model. The hydrological systems are very complex causes the many aspects are not possible to represent in numerical model (Wagener et al., 2007). There are three main aspects that are considers in this models which are processes, scale and objectives (Gosain, 2009; Sivakumar 2007). A conceptual model is a pictorial representation of the flow system of groundwater (Andersson and Woessner, 1992). The conceptual models also include the characteristics of the hydraulic parameters of each unit, the positions of the phreatic and piezometric surface and also groundwater flow conditions (Teresita et al., 2011). A conceptual model gives the basic idea of how of the systems and processes operate (Bredehoeft, 2005).

2.4.3 Metric Based Model

Metric based-model or the named is empirical hydrological models. Metric based-model does not attempt to explain the driving process. It is simply transform an input of result based on statistical analysis of previous results. It can provide reliable results if used within the constraints of the original data. The data usually provide bounds of applicability based on factors like location, rainfall or land use. Metric based-model is the simplest and robust models.

2.5 IDENTIFICATION OF UNIT HYDROGRAPH AND COMPONENT FLOWS FROM RAINFALL, EVAPORATION AND STREAM FLOW DATA (IHACRES)

IHACRES is conducted using conceptual based model. The simplicity of the metric model is used to reduce the parameter uncertainty inherent in hydrological model. It often requires six (6) parameters to be calibrated and it performed well on variety catchment sizes and areas. The main objective of IHACRES is to characterize catchment-scale hydrological behavior (Abushandi and Merkel, 2013).

The IHACRES Classic Plus (Croke et al., 2006; Jakeman and Hornberger, 1993) has been used in this study. This model is based on the concept of modeling identifiable catchment-scale rainfall-runoff behavior that causes runoff (Hassan et al.,, 2015). It includes the two types of module which are the non-linear loss module and linear unit hydrograph. This transformation is similar to the concept of Unit Hydrograph (UH) theory, which is configuration of catchment in series and/or parallel acting on linear storage. The non-linear module is used to calculate the effect of antecedent weather condition, by considering the current status of soil moisture and vegetation conditions and evapotranspiration effects (Hassan et al, 2015). In order to obtain effective rainfall, a catchment wetness index, representing catchment saturation, is calculated for each time step. The linear module is used to allow effective rainfall to pass through any combination of storage, in parallel and series, in order to become runoff.

IHACRES is selected because of several factors. It is because IHACRES is a simple model. It has efficient parameters and statistically meticulous. In addition, the IHACRES results are data-based and do not required any estimated parameter values. The model provides a unique identification of system response even with only a few year data input (Hassan and Harun , 2015). Input data of IHACRES model are simple. The example of input data comprises only precipitation, stream flow and temperature. Furthermore, the model stimulation is quickly set up and computational demand is low. Besides, IHACRES model can be run on any size of catchments. Catchment area up to 1km^2 hourly time steps are recommended, while for larger catchment area a daily time step are recommended (Jakeman and Hornberger, 1993). Moreover, IHACRES model can be used to assess changes in stream flow following a change of land-use in the catchment area. The model efficiently describes the response to dynamic characteristics of catchments. Last but not least, statistical relationship may be developing relating the dynamic response characteristics to physical catchment descriptors.

The advantage of the IHACRES approach is it requires only six (6) parameters, three in the non-linear module from model rainfall to rainfall excess and three in a linear module from rainfall excess to stream flow. A model with a few well-defined parameters gives better statistical relationships. Generally, the IHACRES is the data based mechanistic type (Young, 2002) and hence is able to make efficient use of existing data set. For calibration, the model requires time series of rainfall, stream flow and temperature data. Its parametric efficiency makes it easy to link. Despite its structural simplicity, the IHACRES model has been applied successfully to a wide range of catchment type studies (Tukimat, 2014; Kokkonen et al., 2003; Hassan et al., 2015; Hamidon et al., 2015).

A large number of researches had been done to compare the performance between IHACRES model with others model. Table 2.4 shows the comparison of IHACRES model performance with the other model that have made by past researchers.

Table 2.4: Comparison of IHACRES model performance with the other model

Author	Comparison
Neil McIntyre et al, 2009	KIneros2 and IHACRES was applied in an arid catchment in Oman. Kineros2 performed more poorly overall than IHACRES especially for flow peaks. Kineros2 is a complex model both conceptually and numerically. The simple semi distributed version of IHACRES was preferred over the other approaches for predicting flow peaks and volumes.
Abushandi and Merkel, 2013	The HEC-HMS and IHACRES rainfall runoff models were applied to simulate a single streamflow event in Wadi Dhuliel arid catchment. It is proved that the IHACRES rainfall-runoff model is applicable in the Jordanian arid area compared to HEC-HMS model.
Hassan et al, 2015	This study is to determine current and future climate change scenarios using SDSM and to assess climate change impact on river runoff using ANN and IHACRES models. The result revealed that the ANN and IHACRES were able to capture the observed runoff. However, compared to the IHACRES model, the ANN model was unable to provide an identical trend for daily and annual runoff series.

In addition, IHACRES model is also an extension of the original non-linear loss module to include ephemeral catchment (Ye et al. 1997). IHACRES also visualization tools including zoom able and 3D plots and a cross correlation tools.

IHACRES has been successfully applied to over 100 catchments worldwide. These cover a wide range of catchment size 490m^2 to 1500km^2 and climatologies (Littewood and Jakeman, 1994). Recently, a snow accumulation and melt module has been incorporated by Schreider et al. (1996) into the loss model and applied successfully to large catchments in the Kiewa and Mitta Basins of Southeastern Australia (Ye et al., 1997).

2.6 SUMMARY OF THE LITERATURE REVIEW

The study is about the ability of IHACRES models to reproduce levels of present and future runoff using the input from the downscaled rainfall from the SDSM models. In general, the wet and warm would result in significant changes in the increase of daily river runoff. Changes in climate will give significant impacts on water resources and hydrological regimes. In order to determine the impact of climate changes, especially regarding changes in runoff, the relationship between them are analyzed using the general circulation models (GCMs) output. The downscale rainfall and temperature from GCMs are conducted by applying downscaling approaches. In this study, statistical downscaling approaches are utilized. These approaches use a method which derives local-scale information from GCMs through inference from the cross-scale relationship by using some random deterministic functions (Coulibaly and Dibike, 2005). The main approaches are that there are: (1) inexpensive, (2) computationaly undemanding, and (3) readily transferable. This means that it is able to provide the local information that is most needed in many climate change impact applications. Further, ensembles of climate scenarios permit the use of risk or uncertainty analyses.

In this study, it is proposed to apply identification of unit hydrographs and component flows from rainfall, evaporation and streamflow data (IHACRES). IHACRES is a hybrid rainfall-runoff model in which metric and conceptual model are utilized (Croke and Jakeman, 2004). It has been reported that it can be applied to a catchment with a wide range of sizes and climatologies. IHACRES has been used to predict runoff in the un-gauged catchment, as well as to investigate dynamic response characteristics and physical catchment (Kokkonen et al., 2003). Due to minimal data requirement, IHACRES has been successfully used in many catchment and responses (Bernard et al., 2013) as well as in the climate change assessment such as Karamouz et al. (2012).

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

The main aim of this study is to generate the future rainfall and temperature pattern for year 2010 – 2099 and to estimate the future trend of water in the context of climate change and streamflow.

The framework of this study consists of four steps, which are: (1) download and screen the GCM data for the under different scenarios, (2) downscale the GCM data using the Statistical Downscaling Models (SDSM), (3) validate the statistical downscaling models with the observed data, and (4) project the rainfall, maximum (T_{max}) and minimum (T_{min}) temperatures corresponding to the climate change scenarios for the next 30 years on the streamflow using IHACRES. In the following sections, the study area, data and models, method are described.

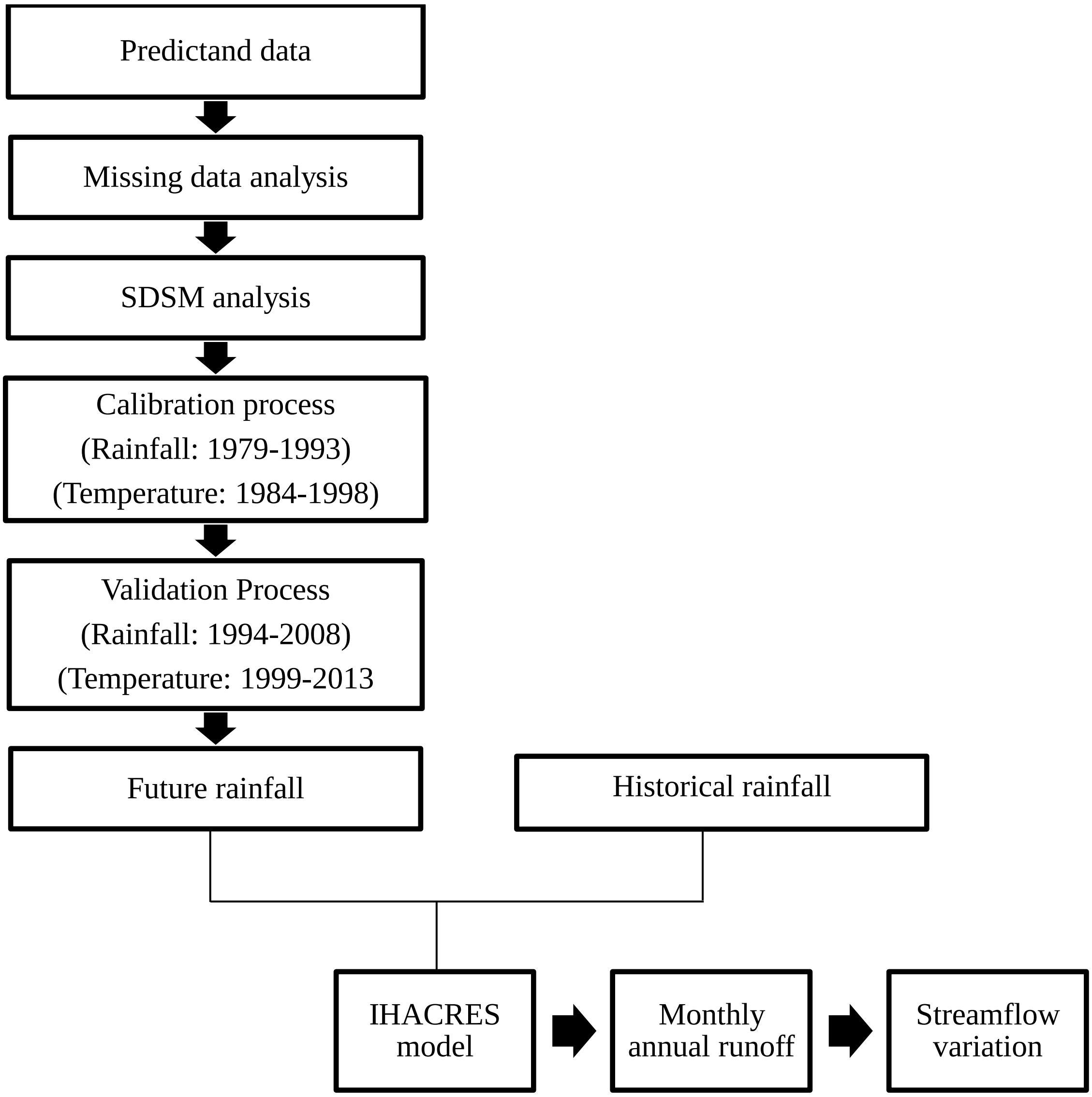

Figure 3.1: The schematic diagram of methodology of the study

3.2 STATISTICAL DOWNSCALING MODEL (SDSM)

The Statistical Downscaling model (SDSM) is introduced by Wilby et al. (2002). SDSM is the first tool of its type freely offered to study climate stimulation analysis. 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), as:

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

in which Y means the local predictand and, $X(x_1, x_2, \ldots x_n)$ represents *n* large-scale atmospheric predictors, and F is the built quantitative statistical relationship. Besides, the SDSM models are low cost, simple, computationally undemanding and easily accessible.

SDSM is categorized as a hybrid model. It 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 determines the estimated value of rainfall on each rainy day. Rainfall is a condition process, and it is modeled 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 Had-CM3 A2 for future generation. Figure 3.2 shows the sequences step of SDSM.

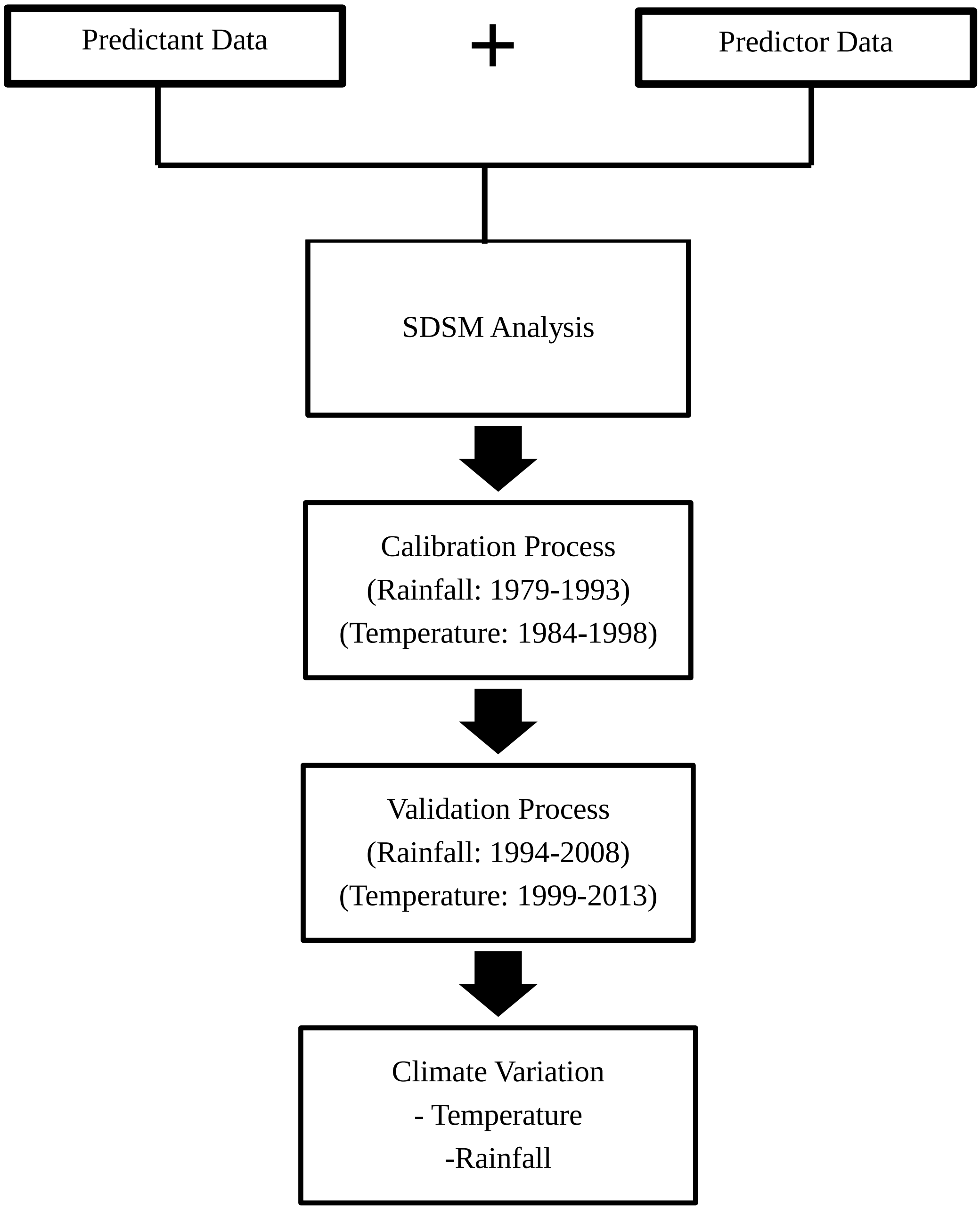

Figure 3.2: The sequence step of SDSM model

The regressions models are presented in monthly or annual period depended on the analysts demand. To generate the most ideal downscaled model, SDSM can reduce the standard error of estimate and increase the number of explained variance using bias correction and variance inflation techniques (Wilby *et al.*, 2001; Paulin *et al.*, 2005). Besides, the SDSM model does not require high computational demand to view the simulation results but has ability to produce high quality of projection results. These advantages, as a whole, had made SDSM a reliable tool for climate downscaling (Muluye, 2012, Samadi *et al.*, 2013, Tukimat and Harun, 2015) and was selected as a downscaling tool to generate the future climate trend at the study site.

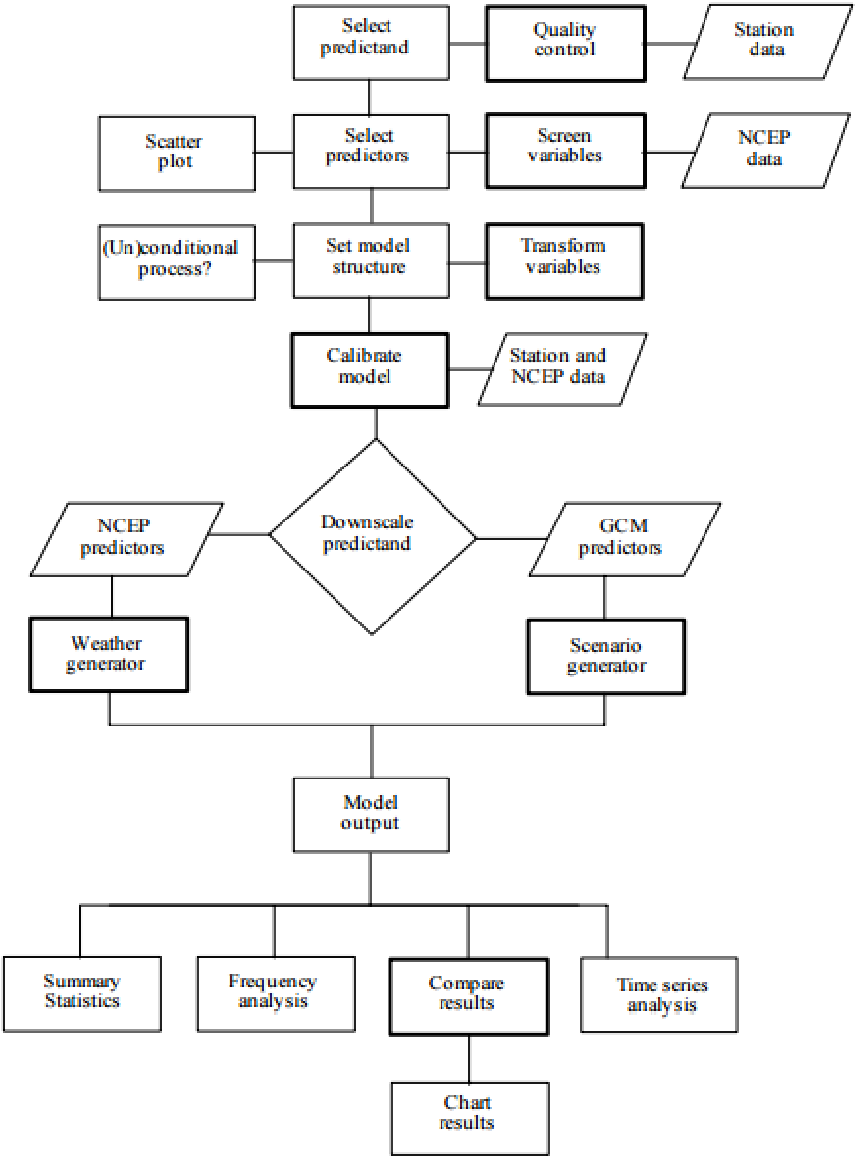

Figure 3.3: Schematic diagram of SDSM

Figure 3.3 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, the temperature recorded at Kuantan station and historical rainfall stations at Kuala Lipis were used as predictand. The selection of rainfall stations was based on the lesser percentage of missing data to control the quality and originality of data set. These data was presented in daily time series and was converted into month and annual period for the analysis purposes. The predictors set were provided by National Center 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.

3.2.1 Atmospheric Characteristics in GCMs

HadCM3 has been choosing as predictor variable in Peninsular Malaysia. It is provided on a grid box by grid box basis of size 2.5° latitude and 3.75° longitudes. The watershed area is lies in 3.93° latitude and 103.06° longitudes as shown in Figure 2.5. NCEP and HadCM3 both data sets contain predictor variable, which is used as an input in SDSM.

Selection of predictor variables from 26 variables is as shown in Table 3.1. These predictors were derived from the daily reanalysis data set of the National Centers of Environmental Prediction (NCEP). The selection is the most difficult part of SDSM. Different atmospheric predictors control different local variables and will affect predictant outcomes. Therefore, the predictor is selected from sensible, strongly and consistence correlated with predictand, and accurately modeled by GCMs (Wilby and Dawnson, 2007). Scenarios that been chosen for Peninsular Malaysia is A2 of HadCM3. Scenario A2 is defines as the cultural identities that separate the different regions, making the world more heterogeneous and international cooperation is less likely. It is an emphasizing of family values, local traditional and high populations growth and it is less focused on economic growth and material wealth. The NCEP data was interpolated in order to adjust its resolution to same as the A2 scenarios of HadCM3 model. The study found that some predictors of HadCM3 were not available to be used at some grid lines. Therefore, it increased a difficulty to select the best choice of predictors.

Table 3.1: The Predictor Variable

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

3.2.2 Construction of the Climate Change Scenarios

The perturbing parameters of the distribution for a site with the predicted changes of climate change using the GCM output is made to generate daily meteorological based on the climate scenarios for the study area. The different in the emission predicted by a GCM is the changing parameter for future and baseline period is the observation of weather. Scenarios files presenting relative changes with respect to the current in the different statistical parameters are prepared for each period from the GCM outputs.

3.3.3 Calibration and Validation Process in SDSM Model

The calibration and validation process is important procedure during predicting procedure. 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 IHACRES MODEL

IHACRES is selected because of several factors. It is because IHACRES is a simple model. It has efficient parameters and statistically meticulous. In addition, the IHACRES results are data-based and do not required any estimated parameter values. The model provides a unique identification of system response even with only a few year data input (Hassan and Harun , 2015). Input data of IHACRES model are simple. The example of input data comprises only precipitation, stream flow and temperature. Furthermore, the model stimulation is quickly set up and computational demand is low. Besides, IHACRES model can be run on any size of catchments. Catchment area up to

$1km^2$ hourly time steps are recommended, while for larger catchment area a daily time step are recommended (Jakeman and Hornberger, 1993). Moreover, IHACRES model can be used to assess changes in stream flow following a change of land-use in the catchment area. The model efficiently describes the response to dynamic characteristics of catchments. Statistical relationship may develop relating the dynamic response characteristics to physical catchment descriptors.

IHACRES is a modeling identifications catchment-scale rainfall-runoff behavior, which causes streamflow (Littlewood et al., 1997). IHACRES only require three set of data which are rainfall, temperature and stream flow per time unit. Concept of IHACRES model can be shown in Figure 3.3, show the flow of non-linear loss module. It is configuration of linear storage acting in series and/or parallel in the catchment.

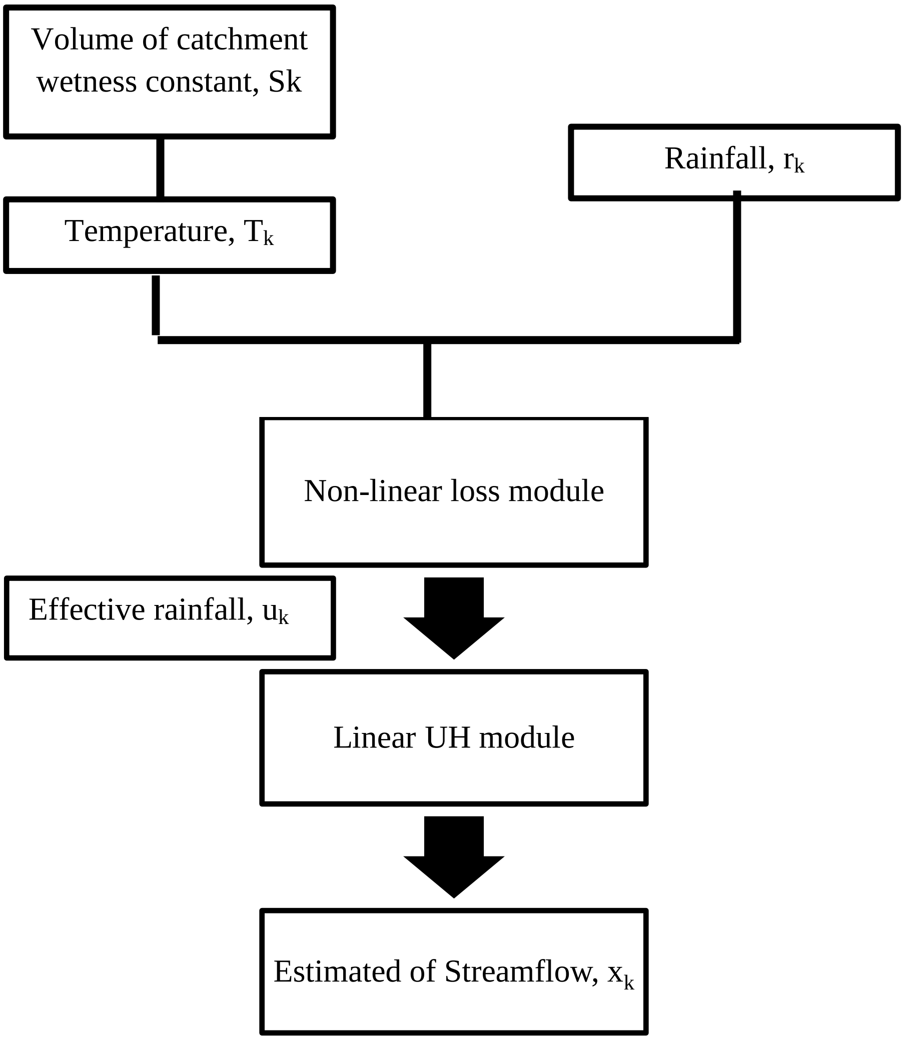

Figure 3.4: IHACRES module structure

The IHACRES Classic Plus (Croke et al., 2006) model applied in this study to provide an enchantment of the IHACRES_PC software (Littlewood et al., 1997). The concept of IHACRES is to model identification catchment-scale rainfall-runoff behavior that causes runoff. IHACRES only requires three (3) sets of data per unit time. The sets of data are temperature, rainfall and streamflow. The IHACRES model consists of two modules which are: i) non-linear loss module and ii) linear unit hydrograph module (Croke and Jakeman, 2004). Non-linear loss module transformation of rainfall (r_k) due to time step (k) to effective rainfall (u_k) while linear unit hydrograph module is a transformation of effective rainfall (u_k) into runoff (x_k). In this study, the data of rainfall, temperature and runoff series become inputs to the IHACRES model, with similar time period (Croke and Jakeman, 2004).

The behind concept of IHACRES model is that catchment wetness varies with recent past rainfall and with evapotranspiration which catchment wetness index, s_k is computed at each time step, k based on recent rainfall and temperature (Hassan, 2015). As the catchment wetness index, s_k lies between zero and unity, the percentage of rainfall varies linearly between 0% and 100% which becomes effective rainfall in any time. Figure 2.7 is actually the total parameter that used inside IHACRES model which are six (6) parameters. Figure 2.8 shown three (3) parameters in the non-linear loss module and another three (3) in the linear module.

3.3.1 Calibration and Validation Process of IHACRES Model

IHACRES model is an assessment for quality and accuracy of predictive. The model requires adjustment of the model parameters to calibrate match model output with the measured data for the selected period and scenarios. The model will be tested at the validation period to test model simulation capability, which is not use during calibration. If during validation process the model not performed, calibration will be repeating again with different period of time until the model performance in calibration and validation.

In this study, calibration and validation of 30 years (1970-2000) are used. This period of time is choose because available data and higher quality of observed rainfall, temperature and streamflow. From this period, 1970 is used as a warm up to initialize the model before calibration. The latest IHACRES software has capabilities to automated calibration in order to determine a practical range of the parameter values for IHACRES model and minimum error in volume error in volumes. It also has a statistical analysis withheld user to compare model output.

The best calibration was based on the higher value of Coefficient of Determination (R^2) with lower percentage of Average Relative Parameter Error (%ARPE) using following equations:

$$R^2 = 1 - \frac{\sum_I \left(X_{obs_i} - X_{est_i}\right)^2}{\sum_i \left(X_{obs_i} - X_{obs}\right)^2} \tag{3.2}$$

$$\% \, ARPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left(X_{est_i} - X_{obs_i}\right)}{X_{obs_i}} \times 100 \tag{3.3}$$

where x refers to the observed streamflow, $\bar{x}$ is the mean of observed streamflow, and *n* is the total number of streamflow. A high D and low % ARPE indicated that the model had been well calibrated and validated. The projected rainfall and temperature during year 2010 to 2100 from SDSM analysis were used to simulate the streamflow in the future projection.

3.3.2 Model Simulation Correspond to Future Climate Change Scenarios

The simulation of streamflow due to climate change is done after the hydrological model undergo calibration and validation process. Maximum temperature, minimum temperature and rainfall which has been generated by using SDSM are used as the input for IHACRES to stimulate streamflow for future. The analysis of the stimulated streamflow is carried out for one group in the future, which is 2015-2045.

3.4 DESCRIPTION OF THE STUDY AREA

Malaysia is tropical country located at Southeast Asia close to the equator. Being one of the tropical countries, Malaysia gets heavy rainfall all the year round. Monsoon influence many parts of the world including Malaysia (Wang et Al., 2003; Kale and Hire., 2004; Sultan et al., 2005; Colin et al,. 2010; Pal and Al- Tabba, 2010; Pattanaik and Rajeevan, 2010). The inter-annual variations of monsoon can be shown in the variation of climatic trend in the year-to-year variation of the seasonal transition and the inter-annual variation of amplitudes of the intra-seasonal oscillations (Chen et al., 1992). . Malaysia is a country that having wet and dry season every year. In Peninsular Malaysia, the climate is mainly affected by four seasons. The mainly season happened are namely two season which is the northeast and southwest monsoons and two inter-monsoon seasons (Suhaila et al., 2010). The two season usually is called wet season. There are two types of wet season that occur in Malaysia which are Southwest Monsoon that having in west coast of peninsular Malaysia and Northeast Monsoon that having in east coast of peninsular Malaysia. The influence of the monsoons in the Peninsular is characterized by higher total monthly rain. The consequences of extreme rainfall has an impact on river in Malaysia where in result higher river flow and water level (DID, 2005, 2009)

Pahang is located near to South China Sea. Therefore, the climate at this area is influenced by the northeast monsoon wind flow pattern. Northeast monsoon season prevails in November to March, also known as wet season. Monsoon season as well as the swift physical development will lead to the change of stream flow at the study area. Referring to the historical data, the daily main rainfall distribution in the study area was non-uniform at this area. However, the rainfall pattern was almost similar for every year. The rainfall intensity increased from November to March

Kuala LIpis is located at East Coast of Peninsular Malaysia in Pahang. Kuala Lipis is a small town in Pahang with a population of 20,000. Kuala Lipis is one of the developed towns in Pahang. Kuala Lipis has been undergoing rapid development and thus the water quality in that area will be affected. As the human activities are being related to huge impacts to environment, it is undeniable that it will cause abundant changes to the collection and biodiversity of the river fauna Kuala Lipis had experience this phenomenon for a few decades. Malaysia receives about 3500 mm of annual rainfall in average each year (Muhammad Hazwan, 2010). Indirectly with this phenomenon, Malaysia had recorded as one of the riches country with water sources. In Malaysia, river play important role compare to groundwater. Its usage approaching to 98% and 2% in daily activity (Ismail, et al, 2010).

In this study, the Sungai Kecau, Kuala Lipis that located in East Coast Peninsular Malaysia was selected. It runs along Jelai watershed. From the upper slopes of Titiwangsa Mountains at Cameron Highlands, Jelai river flows in a southeasterly direction, passing through Padang Tengku and Kuala Lipis before merging with

Tembeling river. Tembeling River which begins at Pahang andTerengganu state border at Ulu Tembeling, flows in a southwesterly direction passing through Kuala Tahan. Pahang River flows in a southerly direction passing through Jerantut Feri, Kuala Krau, Kerdau and Temerloh. At Mengkarak, the river turns to the northeast, passing through Chenor and then turning east at Lubuk Paku and Lepar into the floodplain of Paloh Hinai, Pekan and Kuala Pahang before draining into the South China Sea.

Sungai Kecau was selected due to its important role in supplying water to almost population in the Kuala Lipis District. Rapid physical grow in this area has influence the negative impacts towards the rate of water surface runoff level into the body system. This will affected the certain level of water stream flow at certain area in the river basin. This watershed is unique because its location in the monsoon influenced area and is susceptible to storm events. During northeast monsoon period usually in December-January-February, the Eastern part of Peninsular Malaysia receives abundance amount of rainfall. This causes the validation and calibration of a hydrological model extremely challenging.

The area of basin is approximately 709.628 km^2. Sungai Kecau is located in Sungai Jelai sub basin. The length of Sungai Kecau is approximately 61.5 km. The station that had used for rainfall is Kampung Bandar at Ulu Kechau with station ID 4320066 and for streamflow is Sungai Kecau at Kampung Dusun with station ID 4320401. The coordinate of Sungai Kecau, Kampung Dusun is around 4°19’′N latitude and 102°10′ longitude. Figure 3.5 shows the location of rainfall and streamflow station at Sungai Kecau, Kuala Lipis.

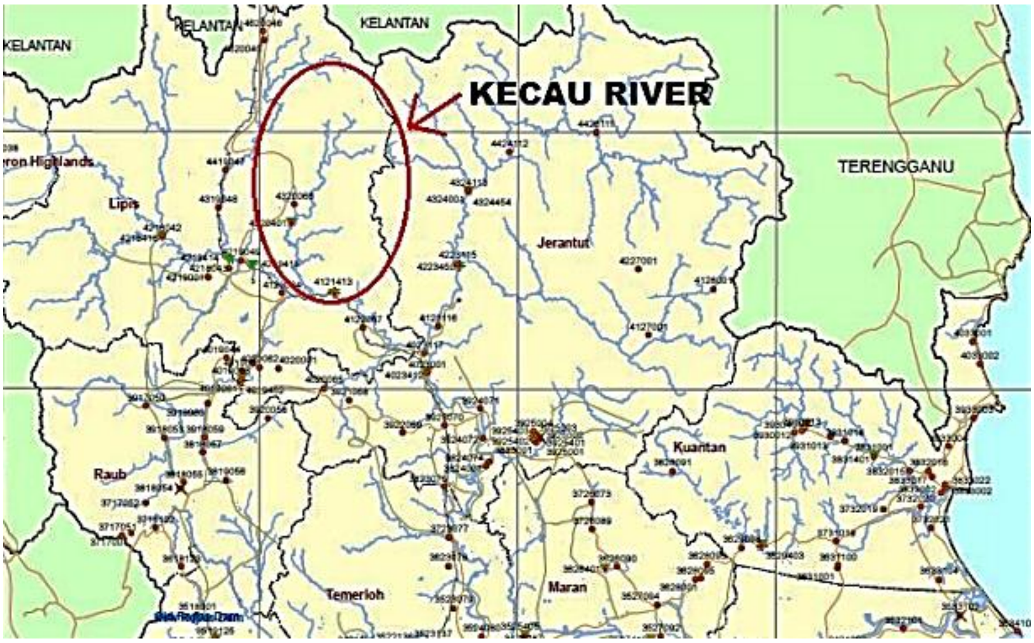

Figure 3.5: The location of rainfall and streamflow station of Sungai Kecau

CHAPTER 4

RESULT AND DISCUSSION

4.1 INTRODUCTION

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

i. The selection of predictors in Statistical Downscaling Model (SDSM).
ii. Projection of future climate variation using hydrological variable there are rainfall and temperature.
iii. The selection of parameter for Identification of unit Hydrograph and Component flow from Rainfall, Evaporation and Stream flow data (IHACRES).
iv. Projection of future trend of water stream in the context of climate change.

In this study, the historical years for temperature (1984 – 2013) and rainfall (1979 – 2008) determine the changes trend of water stream year 2010 – 2099. The SDSM model has been used to generate the change of climate trend with considered the Green House Gases.

Then, the prediction of future trend of water stream for future years (2010-2099) were obtains using the IHACRES model.

4.2 CLIMATE SIMULATION USING SDSM MODEL

The SDSM model started with the screening process variables to measure the performance in terms of correlation among predictors-predictand relationships. The correlation relationship was used to the association between predictors and predictand. The purpose of this process is to screen all the predictor-predictand performances in a one-shot analysis. Based on the results, 5 predictors were selected to be simulated based on local climate change characteristics. Correlation relationship was used for the rainfall station because the relationship between rainfall predictand and atmospheric parameters which is predictors are more sensitive and complex if compare with temperature.

The local predictand was calibrated (1979-1993 for rainfall and 1984-1998 for temperature) and validated (1994-2008 for rainfall and 1999-2013 for temperature) with the selected NCEP predictors to evaluate the performance of the simulated result compared to the observed data. The GCM predictors were used to generate the daily weather series using equal NCEP predictor variables for the future year.

4.2.1 Temperature Simulation

The simulation of temperature data refers to the meteorological station at Kuantan, Pahang. It is assumed that the recorded temperature at Kuantan station could represent the temperature trend for Pahang state. During temperature analysis, the predictors selection was based on the correlation among predictor – predictand relationship. Based on temperature in Malaysia, the monthly temperature is very small. Moreover, the temperature data is correlated to the atmospheric characteristics. The selection of predictor for temperature can be easily being done.

There are five predictors that have been selected for temperature trends at Kuantan: surface vorticity (p__z), 500 hpa geopotential height (p500), relative humidity at 500 hpa (r500), relative humidity at 850 hpa (r850) and mean temperature at 2m (temp). The surface vorticity is refers to the rotation of the fluid. Everything on the Earth rotates with the Earth. These result were supported by the Department of Oceanography, Texas which it state that every ocean, rotation and conservation of vorticity influence flow over distance exceeding a few tens of kilometers. The geopotential height of the 500 hpa shows approximately the actual height of a pressure surface above mean sea-level. Therefore, the geopotential height observation represents the height of the pressure surface on which of the observation was taken. Relative humidity is the amount of water vapor present in air expressed as a percentage of the amount needed for saturation at the same temperature. The temperature in Pahang was influenced by relative humidity at the height of 500 hpa and 850 hpa.

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

	Maximum		Mean		Minimum	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
r	0.99	0.99	0.99	0.99	0.99	0.97
% Error	0.02	0.29	0.01	1.25	0.01	1.99

The performances of calibration and validation results were presented in Table 4.1 consist of correlation coefficient (r) and percentage of error (% Error). Based on the result, the % Error values were slightly small in the whole analysis, with range from 0.0 to 5.0 %. The correlation values were estimated higher in the calibrated and validated results for maximum, mean and minimum temperature with closer to 1.0. It shows that the calibrated and validated values were in good results compared to historical records.

Figure 4.1 to 4.3 show the simulated results produced for calibration (1984-1998) and validation (1999-2013) processes using predictors set from NCEP for three condition which are maximum, mean and minimum temperature. The constant predictors were used to project the future temperature trend in the same grid box provided by HadCM3 type A2 scenario.

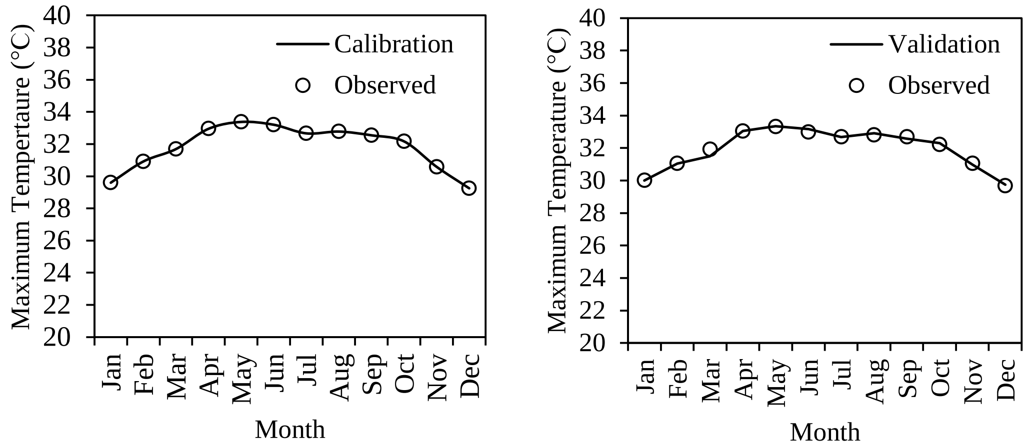

Figure 4.1: Calibrated and validated results for maximum temperature at Kuantan using SDSM model

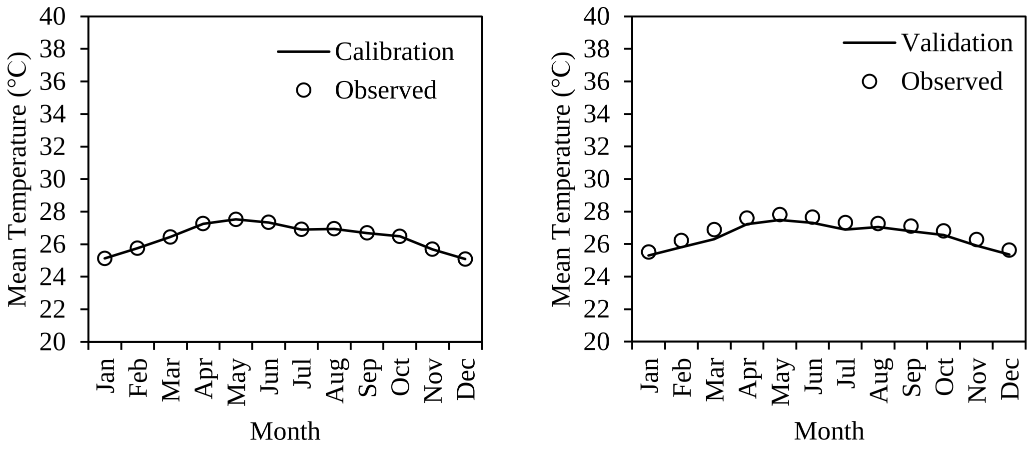

Figure 4.2: Calibrated and validated results for mean temperature at Kuantan using SDSM model

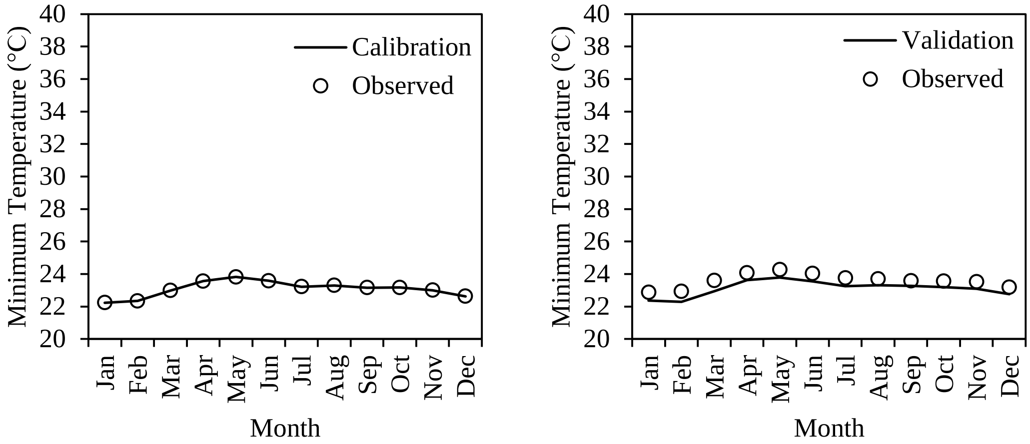

Figure 4.3: Calibrated and validated result for minimum temperature at Kuantan using SDSM model

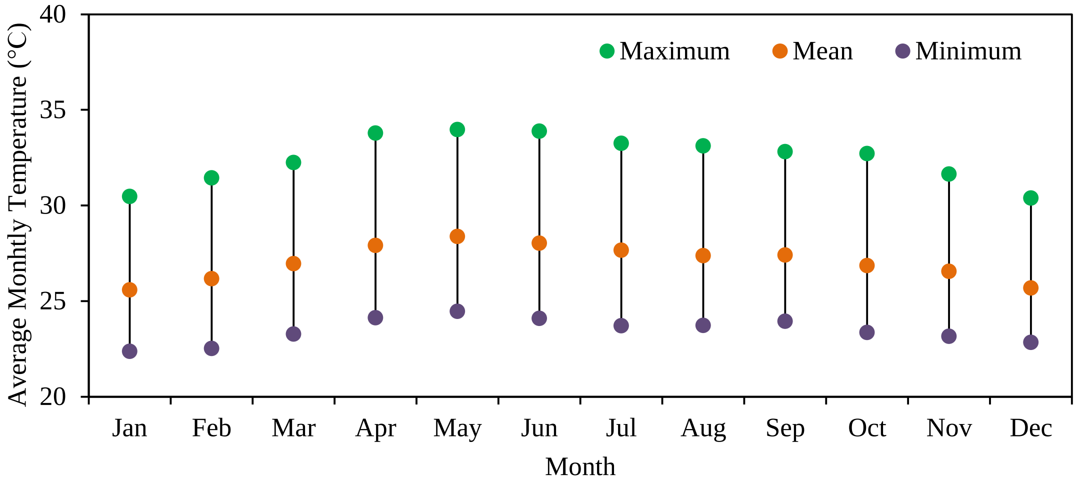

Figure 4.4: Projection of average monthly temperature trend for year 2010 to 2039 using SDSM model

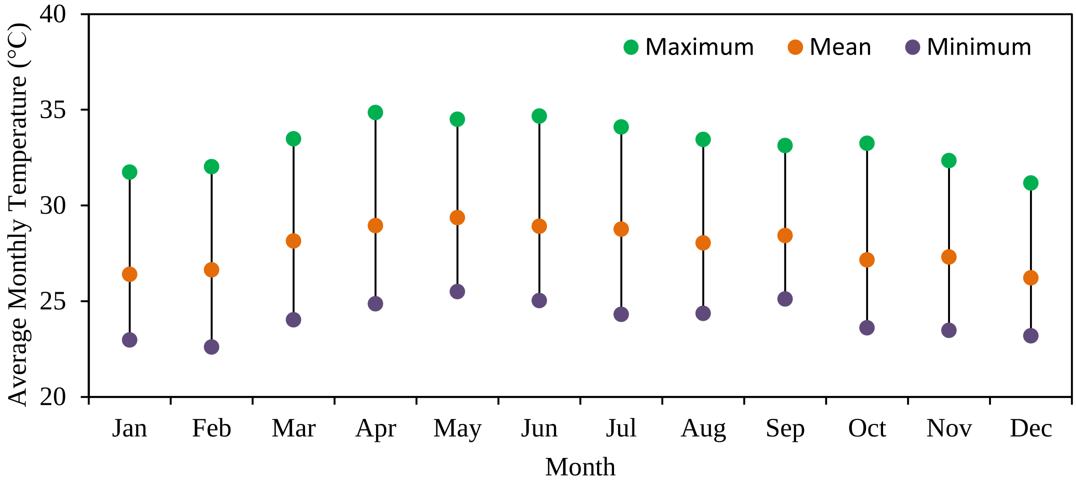

Figure 4.5: Projection of average monthly temperature trend for year 2040 to 2069 using SDSM model

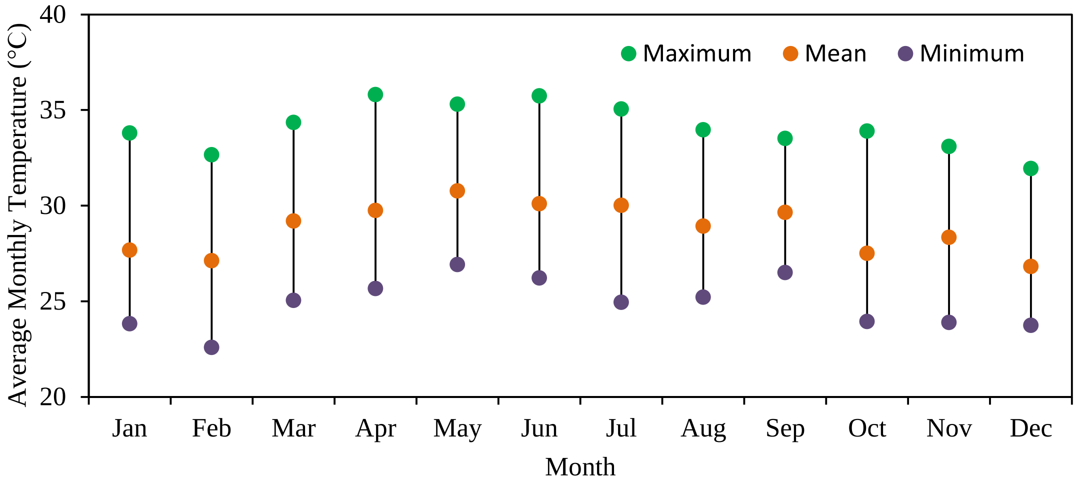

Figure 4.6: Projection of average monthly temperature trend for year 2070 to 2099 using SDSM model

Figure 4.4 to 4.6 indicate the generated temperature in terms of maximum, mean and minimum during year 2010 until 2099. The results present in the average monthly temperature for every interval year period there are 2010-2039, 2040-2069, and 2070-2099. The results show that the average temperature will arise during January to May achieve 41.5%, 41.9% and 42.0% and will drop during June to December achieve

58.5%, 58.2% and 58.0% for year 2020s, 2050s and 2080, respectively. The temperature is expected to increase in every decade achieve 38.9%. The highest maximum temperature at the end of the century achieved 35.8°C year April 2080s. The mean temperature is consistently in between 25°C-31°C. The lowest temperature is expected recorded in year January 2020s achieved 22.4°C. For maximum, mean and minimum temperature, shows a continuous increment achieve 32.5%, 33.3% and 34.2% during year 2020s, 2050s and 2080s, respectively. A higher temperature is predicted to occur on March to May that may be influenced by interchange of the monsoon.

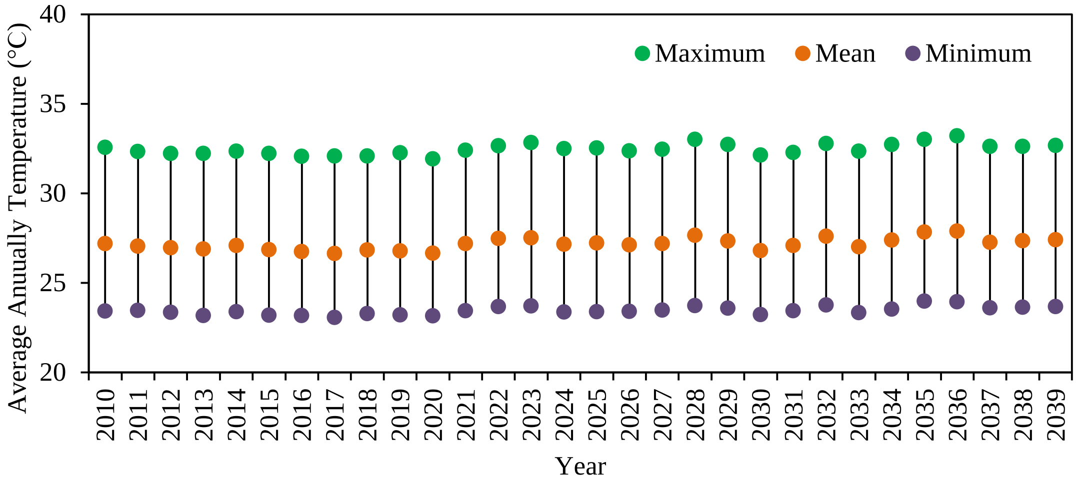

Figure 4.7: Projection of average annually temperature trend for year 2010 to 2039 using SDSM model

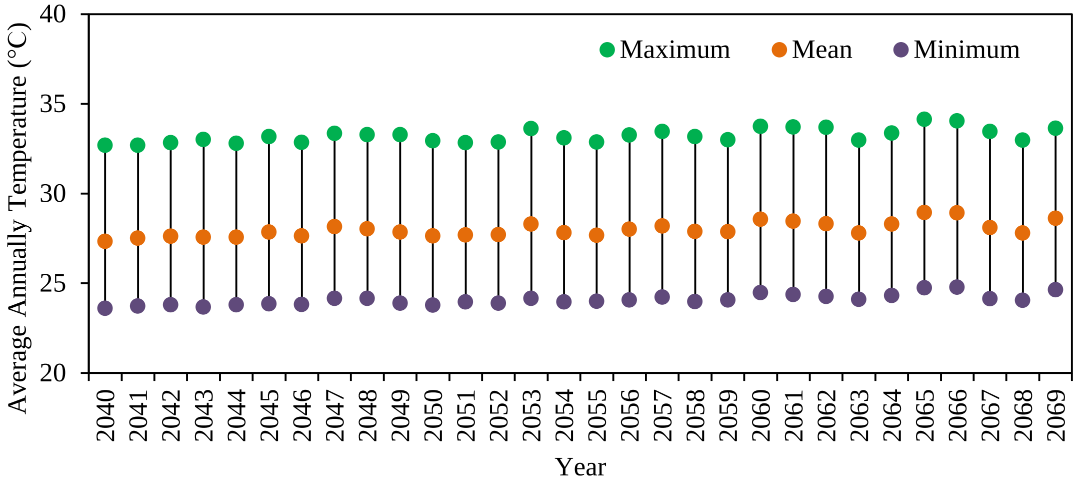

Figure 4.8: Projection of average annually temperature trend for year 2040 to 2069 using SDSM model

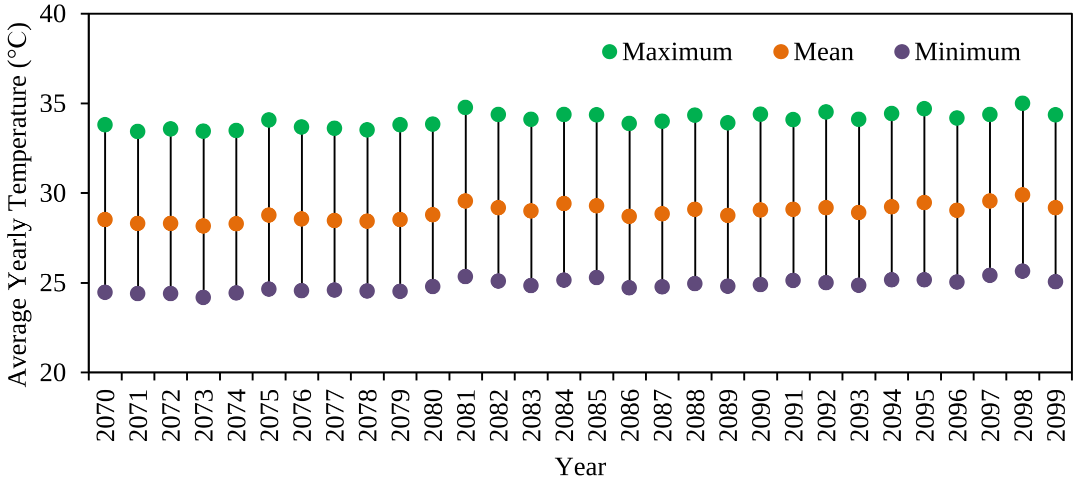

Figure 4.9: Projection of average annually temperature trend for year 2070 to 2099 using SDSM model

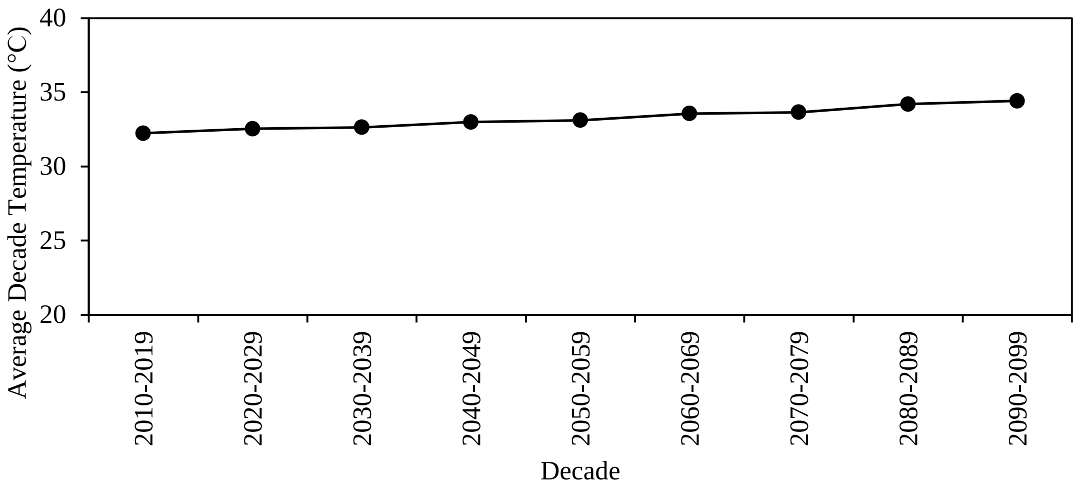

Figure 4.10: Prediction of decade average maximum temperature at Kuantan using SDSM model

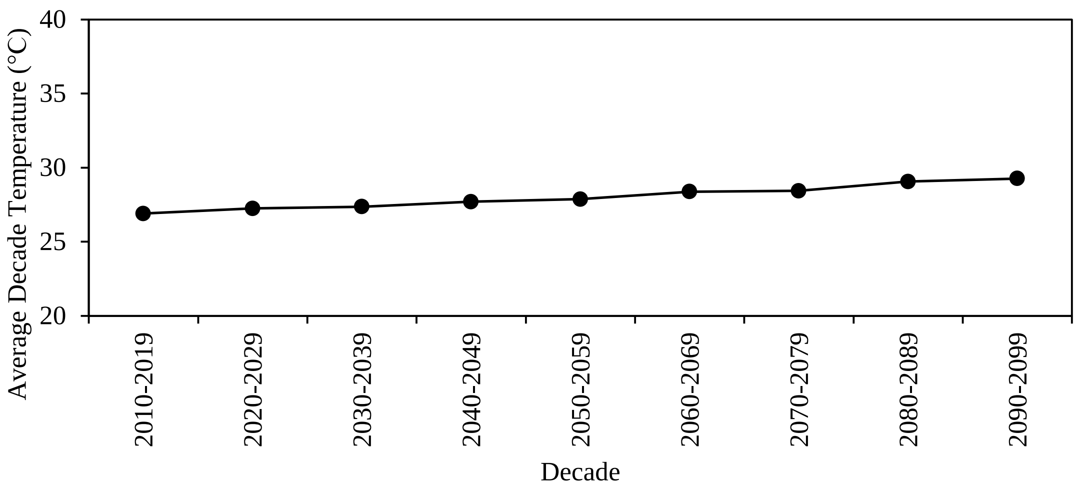

Figure 4.11: Prediction of decade average mean temperature at Kuantan using SDSM model

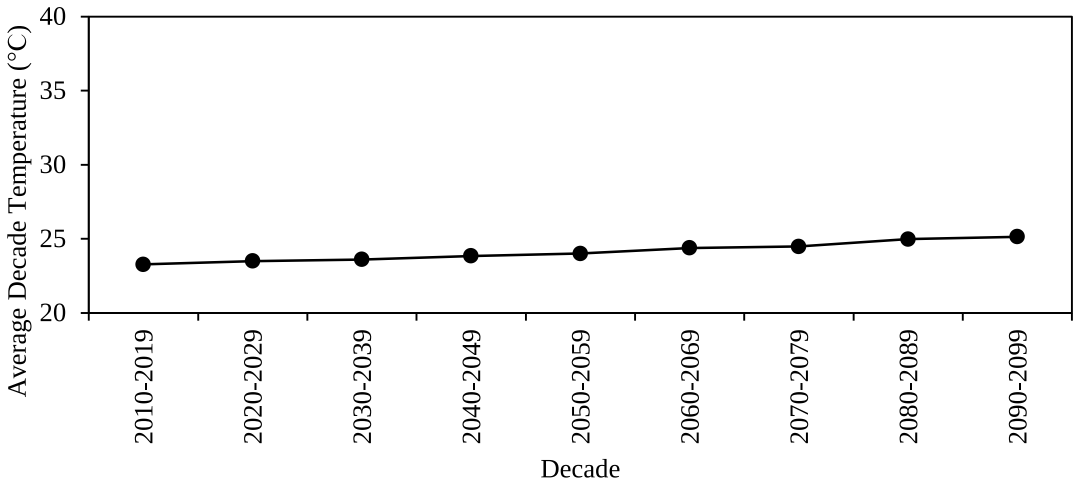

Figure 4.12: Prediction of decade average minimum temperature at Kuantan using SDSM model

Figure 4.7 to 4.9 indicate the generated annual temperature in terms of maximum, mean and minimum during year 2010 to 2099. The results present the average annual temperature for year 2010 – 2099. The results revealed the temperature trend are expected to be increase inconsistently reaching 35°C. However, the mean temperature and minimum temperature are expected to achieve 30°C and 25°C, respectively. The highest temperature is expected to occur on 2098 with 35.01°C and minimum temperature occurs on 2013 with 23.2°C.

Figure 4.10 to 4.12 indicate the change of temperature trend for every 10 years. As general, the results show the average temperature is estimated to rise decade by decade. The temperature is expected to increase in every decade. A higher temperature is predicted to occur at the end of the century. Based on the result, the temperature expected to be increase between 0.1°C to 1.5°. These results were supported by the Malaysian Meteorological Department, Malaysia report (MMD, 2009), which said that the increment of projected temperature in Peninsular Malaysia in between 1.1 °C to 3.0 °C at the end of the century.

The temperature results show the increment in the minimum, mean and maximum temperature readings. Precaution is highly recommended even though the estimated temperature in the future year not extremely high. It is because the temperature raises may encourage the loss of volume of soil moisture and evapotranspiration rate especially at open surface like paddy fields. Thus, the irrigated demand is expected to inconsistent and possibly increase affected by changes of climate variability in the future year. This result can be supported from Intergovernmental Panel on Climate Change report in 2007 stated that the increase in temperature is expected to continue, and by 2100 the average global temperature is likely to be 1.4–5.8 °C warmer.

4.2.2 Rainfall Simulation

The rainfall simulation was directed at station number 4320066 Kampung Bandar at Ulu Kechau, Pahang. The analysis started with the selection of predictors using correlation relationship in the screening process. Then, the calibration and validation process were conducted to examine the performance of the model using predictor selection and the rainfall station. The GCMs predictors were used to project the local climate trend in the future year 2010-2099. This process considers the future potential level of greenhouse gases.

4.2.2.1 Predictors Selection

The success of the SDSM model-based downscaling is dependent on the selection of predictor variables while developing the predictant-predictor relationship. Thus, the first step to calibrate the model starts from the selection of the predictor variables. From the 30 years observed historical datasets of 1979-2008, the first 15 years (1979-1993) were used for calibration and the remaining 15 years (1994-2008) were used for validation purposes. Before performing the calibration process, predictor variables from NCEP data were selected through a screening process in SDSM using the values of the explained variances and scatter plots in the predictant-predictor relationship.

Five out of 27 predictors were selected for station Kampung Bandar. The predictors are 500 hpa geopotential height (p500), 850 hpa geopotential height (p850), relative humidity at 850 hpa (r850), near surface relative humidity (rhum) and mean temperature at 2m (temp). The geopotential height of the 500 hpa and 850 hpa shows approximately the actual height of a pressure surface above mean sea-level. Therefore, the geopotential height observation represents the height of the pressure surface on which of the observation was taken. Relative humidity is the amount of water vapor present in air expressed as a percentage of the amount needed for saturation at the same temperature. The temperature in Pahang was influenced by relative humidity at the height 850 hpa.

4.2.2.2 Results of the Calibration and Validation Processes

In this study, 30 years observed data was divided into two period of times, for calibration (rainfall: 1979 – 1993 and temperature: 1984 – 1998) and validation (rainfall: 1994 – 2008 and temperature: 1999 – 2013). After the model is calibrated, validation process is needed. Validation process enables to produce synthetic current daily weather data based on inputs of the observed time series data and the multiple linear regression parameters produced using independent observed data, which not used during calibration procedure.

The calibration model process constructs downscaling models based on MC-M analysis, given the observed daily rainfall and NCEP-reanalysis. The model structures of calibration have been categorized as condition for rainfall. Table 4.2 exhibits the calibration and validation result of the SDSM model of daily rainfall. Tables 4.2 consist of correlation coefficient (r) and percentage of error (% Error). Based on the result, the % Error values were very small in the whole analysis, ranging from 0.0 to 50.0 %. The graph of rainfall variance, there is underestimating for simulation in several months. The correlation values were estimated higher in the calibrated and validated results for station Kampung Bandar, Ulu kechau which is closer to 1.0. It shows that the calibrated and validated values were in a good result compare to historical records.

Table 4.2: Performance of calibrated and validated results of station 4320066 Kampung Bandar, Ulu Kechau, Pahang using SDSM model

	4320066	
	Calibration	Validation
r	0.99	0.85
% Error	1.99	48.12

Figure 4.13 show the simulated results produced for calibration (1979-1993) and validation (1994-2008) processes using predictors set from NCEP for station Kampung Bandar, Ulu Kechau. Result of calibration and validation indicate that the observed and stimulated rainfalls are in good results. The combination of five selected predictors was successfully able to model relationships with the local stations. The finding confirms the works of Wilby and Wigley (2000).

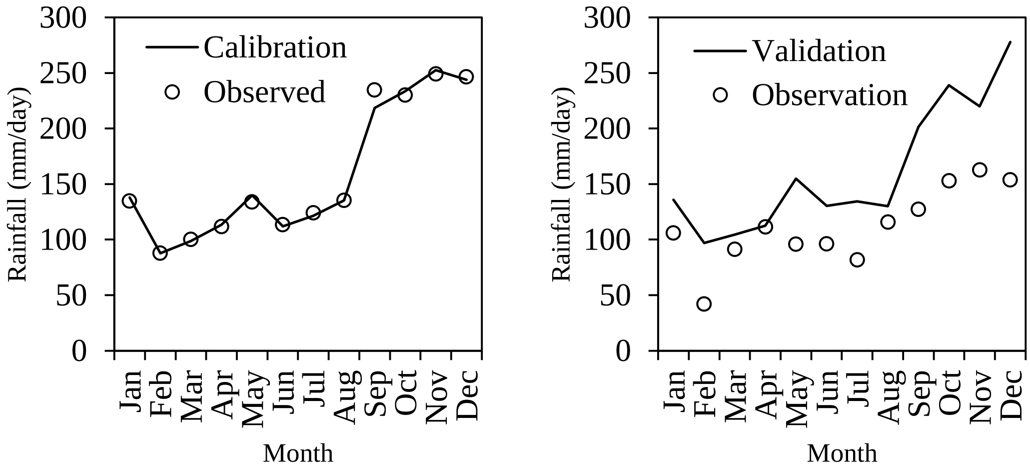

Figure 4.13: Calibration and validation rainfall station at 4320066 Kampung Bandar, Ulu Kechau, using SDSM model

4.2.2.3 Downscaling for Future Emission

The regression weighted produced during the calibration process to the time series output of the GCM output and assumption that relationship between predictor and predictant under the observed conditions remain valid under the future climate conditions is used. 100 ensembles of synthetic daily time series are produced for HadCM3 A2. Outcome will be average and divided into three period there are 2020s (2010 – 2039), 2050s (2040 – 2069) and 2080s (2070 – 2099) for IHACRES analysis. The result of downscaling for future emission is shown in Figure 4.14 to Figure 4.16.

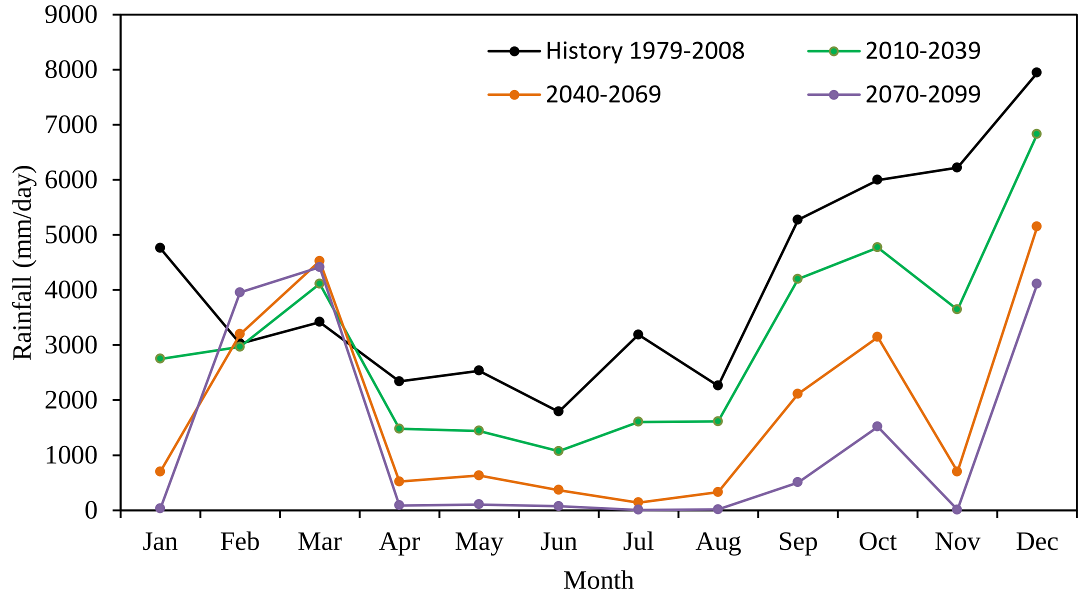

Figure 4.14: Prediction of monthly average rainfall at station 4320066 Kampung Bandar, Ulu Kechau, using SDSM model

Figure 4.14 shows the prediction of monthly average rainfall at station Kampung Bandar, Ulu Kechau, Lipis. The figure it shows that there is an increasing thread in all future time horizons for rainfall in month except on April to August and November. The rainfall intensity achieving 19.8%, 9.2% and 1.9% for April to August while for November achieving 10.0%, 3.3% and 0.1% in year 2020s, 2050s and 2080s, respectively. The heaviest rainfall is expected occur on December during Northeast season. However, the rainfall intensity is predicted to become lesser in year 2020s, 2050s and 2080s achieve 14%, 35% and 48% respectively compare with historical rainfall.

Figure 4.15 presented the prediction of annual average rainfall at station Kampung Bandar, Ulu Kechau, Lipis. From the graph, it shows that the decreasing amount of rainfall until the end of the century. The highest rainfall trend will be in year 2017 which is 2.34% while the lowest rainfall trend will be in year 2081 which is 0.40%.

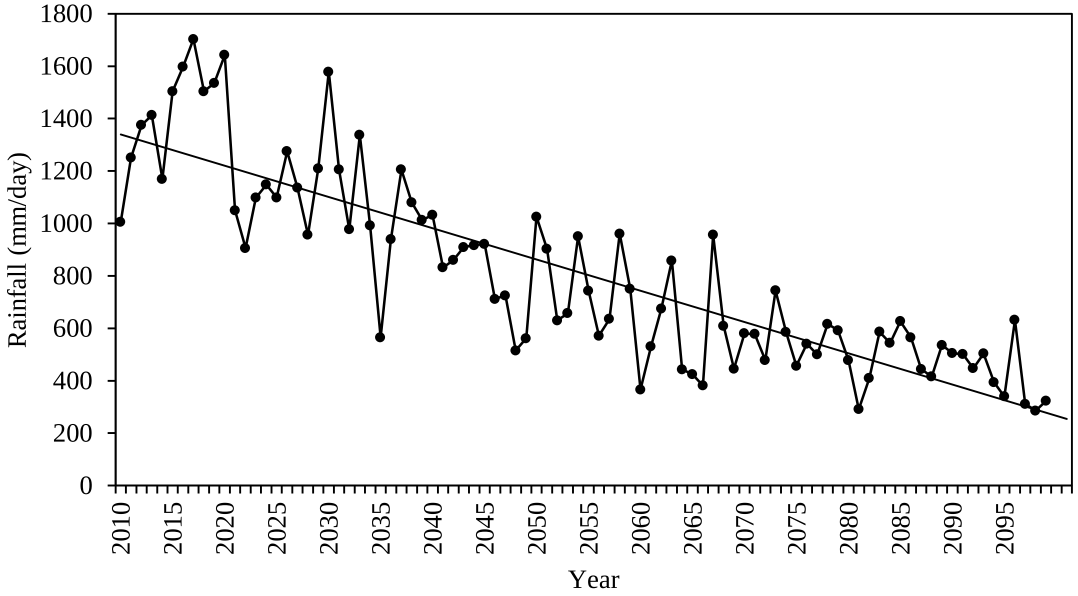

Figure 4.15: Prediction of annually average rainfall at station 4320066 Kampung Bandar, Ulu Kechau, using SDSM model

Figure 4.16 indicate the change of future rainfall trend for every 10 years. The results show that the total rainfall will decrease achieving 5.8% for year 2090 – 2099 at the end of the century. The rainfall is expected to decrease in every decade. A lower rainfall is predicted to occur at the end of the century.

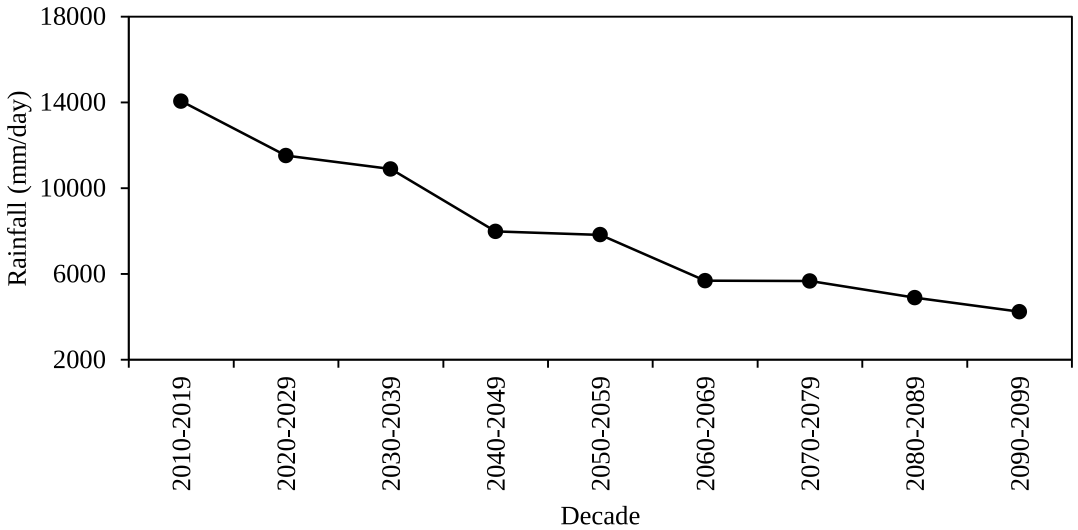

Figure 4.16: Prediction of decade average rainfall at station 4320066 Kampung Bandar, Ulu Kechau,using SDSM model

4.3 STREAM FLOW PREDICTION USING IHACRES MODEL

The IHACRES model was chosen in this analysis as it takes into account the effect of rainfall and temperature at the study area. IHACRES model is the metric-based model which needs minimum input to operate, which sets of time series data of observed rainfall, temperature and observed streamflow. In addition, catchment area is required. Table 4.3 shows the parameter values that been used in this study. The parameter was selected by trial and error using IHACRES model. Based on the result, it shows the good agreement because it has higher Correlation Coefficient (r) and has lower Average Relative Parameter Error (%ARPE).

Table 4.3: Calibrated model parameters value for IHACRES model

Parameter	Value
Mass Balance (c)	0.001
Drying Rate at Reference Temperature (t_w)	5.0
Temperature Dependence of Drying Rate (f)	3.8
Reference Temperature (t_{ref})	20
Moisture Threshold for Producing Flow (l)	0.0
Power on Soil Moisture (ρ)	0.3
Correlation Coefficient (r)	0.97
Average Relative Parameter Error (%ARPE)	0.13

4.3.1 Calibrated and Validated Results of IHACRES Model

IHACRES model is an assessment for quality and accuracy of predictive. For calibration stage, the model requires adjustment of the model parameters to match model output with measured data for selected period and situation entered to the model. After getting the good result for IHACRES parameters, the model will be tested at the validation period to the model simulation capability, which using independent data and period of times, which are not used during calibration. If during validation the model not performed, calibration will be repeating again with different period of time until the model performs in both of calibration and validation. Three years length period have been used to calibrate year 2001 and validate year 2002 – 2003. The period selection based on the availability data and high quality of historical rainfall, temperature and streamflow. The IHACRES model has the capabilities to automated calibration in order to determine a practical range of the parameter values for IHACRES model and minimum error in volume error in volumes. In addition, it has a statistical analysis which held to compare model output. The chosen of the model is depending in which model give higher of R squared and lower of relative bias. In this study, calibration model has been choosing from several periods of time.

The performance of calibrated and validated has been arranged in table 4.4. in general, the validation results showed that the model performance is reasonably well in stimulating flows for periods outside of the calibration period.

The good performance of IHACRES model runoff modeling is witnessed by the closed result between the results of observed and stimulated runoff. The value of Correlation Coefficient (r) predicted higher in the calibration and validation results with 0.99 and 0.96 respectively. The Percentage of Error (% Error) is in good result which is between 0 % – 5 %. It is show that the result is in a good agreement.

Table 4.4: Result for calibrated and validated process using IHACRES model

Result	Parameter	
	r	% Error
Calibrate	0.99	4.22
Validate	0.96	4.42

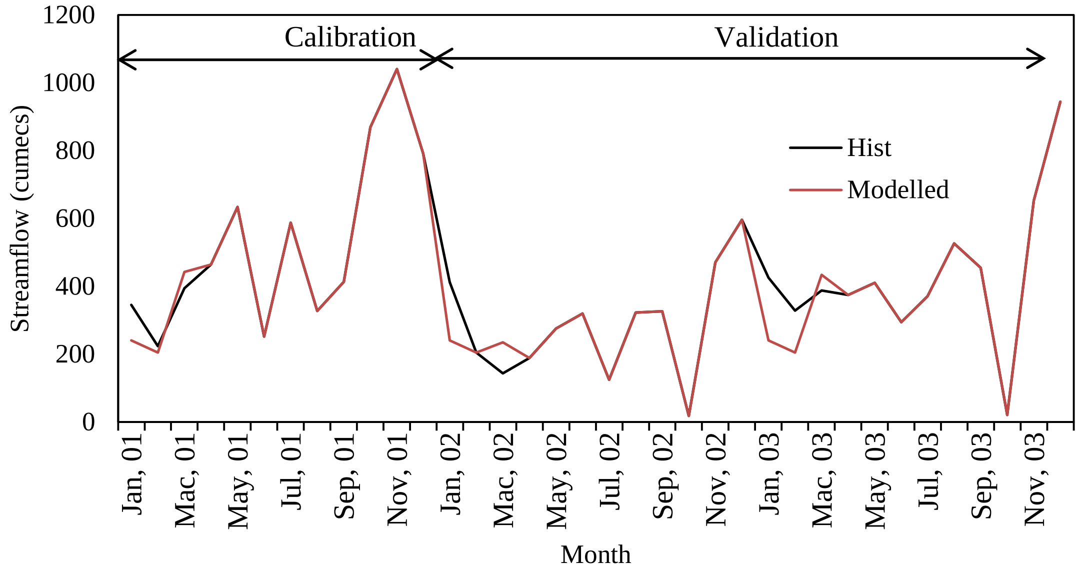

Figure 4.17: Result of calibration (Jan,2001 to Dec,2001) and validation (Jan, 2002 to Dec, 2003) for streamflow simulation using IHACRES model

Figure 4.17 shows the association between observed and stimulated streamflow for calibrated (Jan, 2001 – Dec 2001) and validated (Jan, 2002 – Dec, 2003) results. Generally, the accuracy model prediction is good except January to March in every year that was slightly different than historical record.

4.3.2 Model Simulation Corresponding to Future Climate Change Scenarios

After the hydrological model is form after calibration and validation by using IHACRES as discussed previously, then, the simulation of streamflow due to climate change is done. The mean temperature and rainfall that have been generated using SDSM model are used as the input for IHACRES model to stimulate streamflow trend in the context of climate change. The analysis of the simulated streamflow is carried out for three period range there are 2010 – 2039, 2040 – 2069, and 2070 – 2099. The analysis consist of change in average monthly mean flows, annual mean flow and decade mean flow in Sungai Kechau of future due to scenarios A2 at streamflow station Kampung Dusun, Pahang.

The generated inflow time series was dependent on the future trend of rainfall and local temperature at Kuantan station produced by SDSM model. The inflow trend is estimated to become decrease at the end of the century. It is consistent with the future rainfall pattern due to the climate change impact. The monthly inflow volume is non – uniform influenced by the local monsoon disturbance.

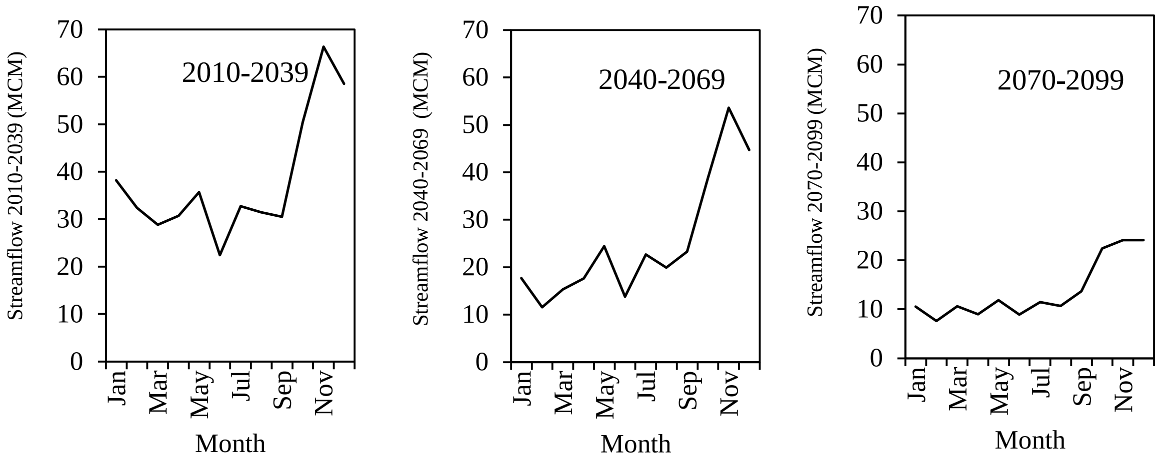

Figure 4.18: Monthly inflow during year 2010 to 2099 using IHACRES model

Figure 4.18 shows a graph of change in mean flow. There is an increasing and decreasing thread in every month. The figure it shows that there is an increasing thread in all future time horizons for streamflow in month except on January to August. The streamflow achieving increasing 44.9%, 52.8% and 51% for September to December while for January to August achieving decreasing 55.1%, 47.2% and 48.9% year 2020s, 2050s and 2080s, respectively. This result can be supported from United States Environmental Protection Agency (EPA) stated that the warmer temperatures increase the rate of evaporation of water into the atmosphere, in effect increasing the atmosphere's capacity to "hold" water. Increased evaporation may dry out some areas and fall as excess rainfall on other areas and may reduce the water flow at that area.

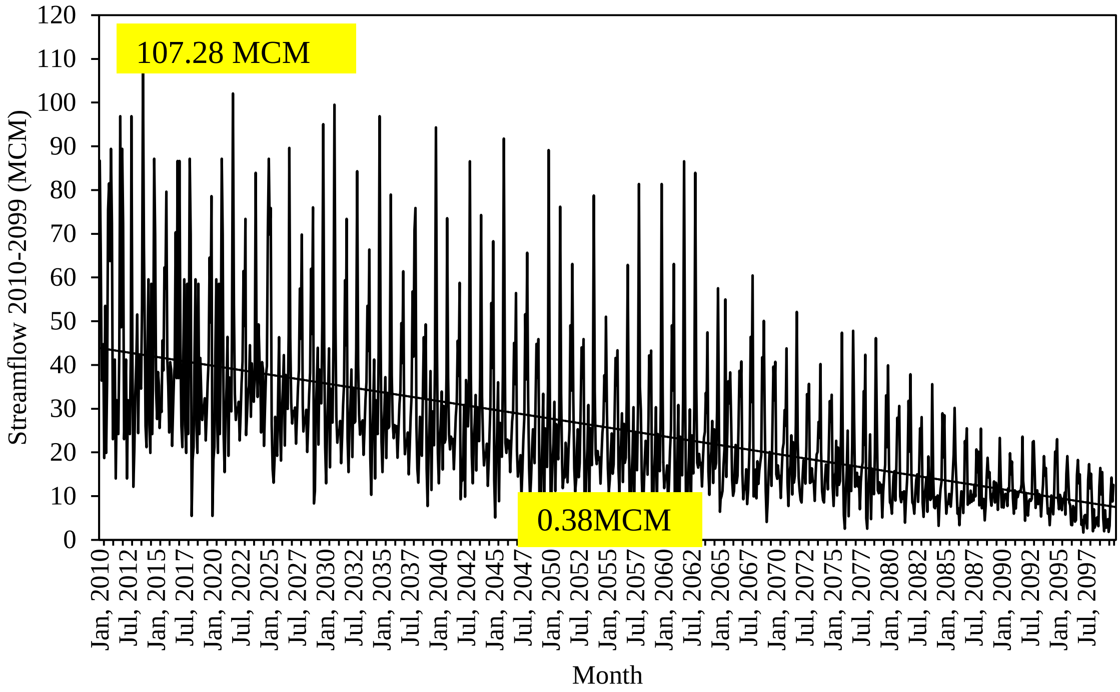

Figure 4.19: Generated monthly inflow time series during year 2010 to 2099 using IHACRES model

Figure 4.19 presents the generated inflow series that could happen in the future year. The highest volume is predicted on November 2013 reaches 107.28 MCM and the lowest volume is expected on February 2061 reaches 0.38 MCM. The result was generated based on the data collection at rainfall station at Kampung Bandar, Ulu Kechau.

Figure 4.20 shows the generated inflow time series during year 2010 until 2099. The average annual inflow was estimated to decrease in every year. The water flow will decrease consistently until the end of the century. The highest water flow was during 2020 which is 622.39 MCM and the lowest water flow was during 2099 which is 75.31 MCM. The results show that the streamflow will decrease achieves 49.4%, 32.7% and 17.8% during year 2020s, 2050s and 2080s, respectively.

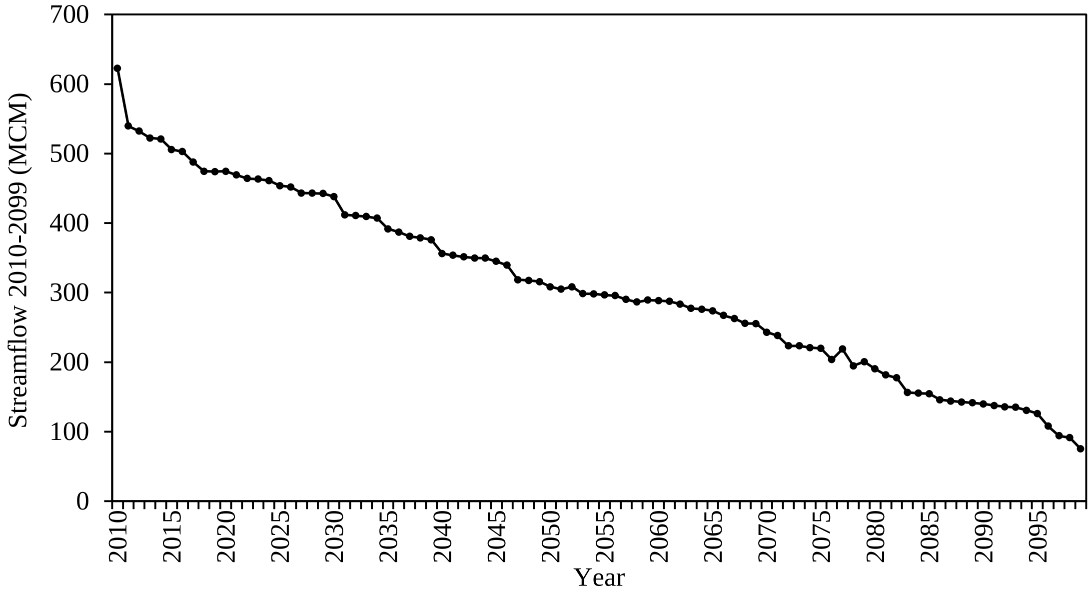

Figure 4.20: Generated annually inflow time series during year 2010 to 2099 using IHACRES model

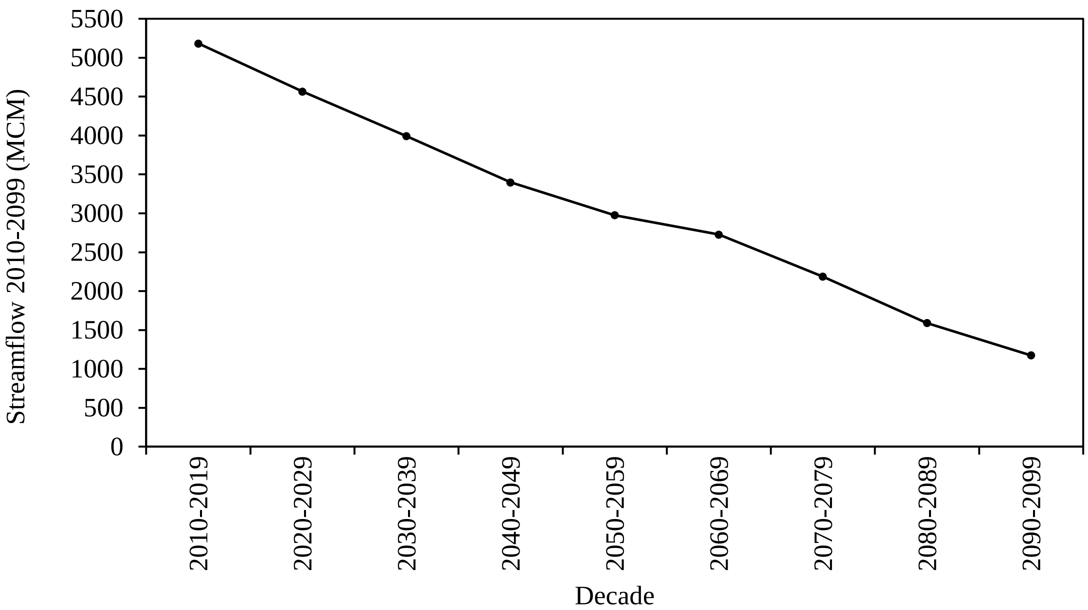

Figure 4.21: Generated decade inflow time series during year 2010 to 2099 using IHACRES model

Figure 4.21 present the generated decade inflow time series during year 2010 – 2099. Based on the generated inflow result using IHACRES model, the inflow trend was experiences to decrease through these years. The highest inflow volume was estimated during decade 2010 – 2019 which is 5182.73 MCM and the lowest inflow volume was estimated during decade 2090 – 2099 which is 1174.19 MCM. The results show that the streamflow will decrease achieves 4.22% during year 2090 – 2099.

This result can be supported form Intergovernmental Panel on Climate Change (IPCC) report in 2007 stated that by the 2050s, freshwater availability, particularly in large river basins, is projected to be decrease. Coastal areas, especially South – East Asia, will be at the greatest risk due to increased flooding from the sea. Climate change in projected to compound the pressures on natural resources and the environment associated with rapid urbanization, industrialization and economic develop

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSIONS

This study contributes towards ability of the IHACRES model to reproduce levels of present and future runoff using the input from the downscaled rainfall and temperature values from the SDSM model. In SDSM model, the correlation relationship is proposed as a method to manage the complexity of predictor selections .The General Circulation Model (GCMs) parameters were employed to project the climate trend which considered the estimated emission level projection in the future year. The results of climate trend projection were used as the input data for the hydrological model. In general, the wet and warm climates would result in significant changes in the decreasing of daily river catchment. The lower depth of future rainfall and insignificance of temperature effect projected lower runoff, and those events can contribute to future drought events in the catchment area. Therefore, water and flood management planning is key challenges faced by the local authorities.

This chapter presents the main conclusions from the discussions in the preceding chapters. The study has drawn several specific conclusions as listed in the following sections

5.1.1 Projection of Future Temperature and Rainfall Pattern

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

b) The average temperatures in the future are expected to increase continuously between 0.1°C - 1.5°C.

c) The average temperature will arise during January to May achieve 41.5%, 41.9% and 42.0% and will drop during June to December achieve 58.5%, 58.2% and 58.0% for year 2020s, 2050s and 2080, respectively.

d) The highest maximum temperature at the end of the century achieved 35.8°C year April 2080s

e) The rainfall in the future is expected to decrease continuously achieving 5.8% per decade.

f) Rainfall is expecting to have an increasing thread in all future time horizons in month except on April to August and November. The rainfall intensity achieving 19.8%, 9.2% and 1.9% for April to August while for November achieving 10.0%, 3.3% and 0.1% in year 2020s, 2050s and 2080s, respectively.

g) The heaviest rainfall is expected occur on December during Northeast season. However, the rainfall intensity is predicted to become lesser in year 2020s (14%), 2050s (35%) and 2080s (48%) respectively compare with historical rainfall.

h) The highest rainfall trend will be in year 2017 which is 2.34% while the lowest rainfall trend will be in year 2081 which is 0.40%.

5.1.2 Projection of Future Trend of Water Flow

a) The flow generated by IHACRES model is found to be reliable and the model successfully simulated a likely similar pattern to the historical value.

b) The water stream is estimated to become lesser at the end of the century. It is consistent with the future rainfall pattern due to the climate change impact. The monthly inflow volume is non – uniform influenced by the local monsoon disturbance.

c) There is an increasing thread in all future time horizons for streamflow in month except on January to August. The streamflow achieving increasing

44.9%, 52.8% and 51% for September to December while for January to August achieving decreasing 55.1%, 47.2% and 48.9% year 2020s, 2050s and 2080s, respectively.

d) The highest water flow was during 2020 which is 622.39 MCM and the lowest water flow was during 2099 which is 75.31 MCM. The results show that the streamflow will decrease achieves 49.4%, 32.7% and 17.8% during year 2020s, 2050s and 2080s, respectively.

e) This result can be supported form Intergovernmental Panel on Climate Change (IPCC) report in 2007 stated that by the 2050s, freshwater availability, particularly in large river basins, is projected to be decrease. Coastal areas, especially South – East Asia, will be at the greatest risk due to increased flooding from the sea. Climate change in projected to compound the pressures on natural resources and the environment associated with rapid urbanization, industrialization and economic develop.

5.2 RECOMMENDATION IN FUTURE

Several recommendations are provided in enhancing the reservoir operation management for irrigation purpose:

a) Applying the General Circulation Models (GCMs) for generating future climate trends using Statistical Downscaling Model (SDSM).

b) Applying the Identification of Unit Hydrographs and Component Flow from Rainfall, Evaporation and stream flow Data (IHACRES) is recommended to project runoff or discharge in the climate change assessment.

c) It is expected that future studies can be performed concerning the exploration of the impact of climate change on various sectors including crop production and reservoir assessment. Hence, a list of adaption factors for climate change can be proposed.

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