APPLICATION OF BIAS CORRECTION IN CLIMATE PREDICTION

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APPLICATION OF BIAS CORRECTION IN CLIMATE PREDICTION

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ABSTRAK

Isu perubahan iklim dan kesannya terhadap banyak aspek alam sekitar menjadi lebih cabaran kepada masyarakat. Pelepasan dan kepekatan karbon dioksida dan gas rumah hijau memberi kesan kepada peningkatan suhu, dan dengan itu membawa kepada pemanasan global. Oleh itu, adalah penting dan wajar untuk menganalisis dan meramalkan perubahan pembolehubah iklim terutamanya untuk hujan. Kajian ini memberi tumpuan kepada analisis ramalan corak hujan Lubuk Paku dan Temerloh di negeri Pahang berdasarkan hujan bersejarah. Corak hujan boleh menganggarkan perubahan iklim masa depan, model edaran umum (GCMS) digunakan. Oleh itu, Statistik penskalaan rendah Model (SDSM) digunakan untuk menukar resolusi spatial kasar output GCMS ke dalam resolusi halus. Walau bagaimanapun, terdapat bias dalam hasil SDSM dan hasilnya GCMS. Oleh itu, dua kaedah pembetulan bias yang Linear Scaling (LS) dan Intensiti Tempatan Penskalaan (lokus) digunakan untuk mengurangkan bias sebelah dari model hidrologi dan prestasi mereka yang dibandingkan.

ABSTRACT

The issue of climate change and its effects on many aspects of the environment become more challenges for society. The emission and concentration of carbon dioxide and greenhouse gases give impact to the increase in temperature, and thus leading to global warming. It is important and desirable to analyze and predict the changes of climatic variables especially for rainfall. However, the accuracy in the climate simulation is becomes significant to ensure the reliability of the projection results. Thus, the bias correction (BC) methods were suggested to imply to treat the gaps between observed and simulated results. This study is focus on analysis the prediction patterns of rainfall in Lubuk Paku and Temerloh in Pahang state based on the historical rainfall. The rainfall pattern can be estimate the future climate change, general circulation models (GCMs) are applied. Therefore, Statistical Downscaling Model (SDSM) is applied in order to convert the coarse spatial resolution of the GCMs output into a fine resolution. However, there are biases in SDSM result and GCMs result. Therefore, two bias correction methods which are Linear Scaling (LS) and Local Intensity Scaling (LOCI) are applied to reduce the bias of those model and the performance of those methods are being compared.

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LIST OF ABBREVIATIONS

SDSM	Statistical Downscaling Model
DD	Dynamical Downscaling
SD	Statistical Downscaling
BC	Bias Correction
GCM	Global Circulation Model
RCM	Regional Circulation Model
NCEP	National Centers for Environmental Prediction
MMD	Metrology Malaysia Department
DID	Department of Irrigation and Drainage
LP	Lubuk Paku
TEM	Temerloh
LS	Linear Scaling
LOCI	Local Intensity Scaling
MAE	Mean Absolute Error
mlsp	mean sea level pressure
p_f	surface airflow strength
p_u	surface zonal velocity
p_v	surface meridional velocity
p_z	surface vorticity
p_th	surface wind direction
p_zh	surface divergence
p5_f	500hpa airflow strength
p5_u	500hpa zonal velocity
p5_v	500hpa meridional velocity
p5_z	500hpa vorticity
p500	500hpa geopotential height
p5th	500hpa wind direction
p5zh	500hpa divergence
p8_f	850hpa airflow strength
p8_u	850hpa zonal velocity
p8_v	850hpa meridional velocity
p8_z	850hpa vorticity
p850	850hpa geopotential height

p8th	850hpa wind direction
p8zh	850hpa divergence
r500	relative humidity at 500hpa
r850	relative humidity at 850hpa
rhum	near surface relative humidity
shum	surface specific humidity
temp	mean temperature

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Climate change is the most serious environmental threats of the 21st centuries and become a very serious global issue. Extreme or severe climate change can lead to natural disaster. Factors such as global factor, national factor and localized factor could be the cause and influences climate changes. The emission and concentration of carbon dioxide and greenhouse gases give impact to the increase in temperature, and thus leading to global warming. Global warming, open burning (haze) are some of the good examples of global factor leads from human activities in industrialization and clearing land illegally.

Malaysia is one of the countries in the world that experiences a warming trend for the past few decades. According to Intergovernmental Panel on Climate Change **(**IPCC) in year 2001, the global land precipitation has raising about 2% since the early of the 20th century. It is also reported in year 2007, the extremely hot temperature, heat waves and heavy precipitation events will become more frequent. In the past few years, the frequency of long dry period tended to be higher with significant increase in the mean and variability of the length of the dry spells. All the indices of wet in these areas show a decreasing trend. Increasing temperature with long dry periods would give variable result of weather and climate (Deni et al., 2008).

Generally, Malaysia is considered as a free zone from climate related disaster. However, mild climate-disasters are quite frequent to happen lately. These refer to the occurrence of floods and droughts that caused significant socio-economic impacts to the nation. Not only that, the occurrence of landslides due to excessive rainfall and strong winds happened at the hilly and coastal areas had caused minimal damage. The excessive rainfall causing the floods incidence happened in the southern states of Malaysia, such as Negeri Sembilan and Johor.

Realizing the importance of reducing the impact of climate change and Greenhouse Gas's emissions, the Malaysia government has taken concerted efforts towards this issue by introducing the mitigation programs in the Ninth Malaysian Plan. There has been a rapid change in climate in response to human influences caused by local, national and global social, economic, industrial, and land use developments. These changes continue to have impacts on different aspects of society, including health, agriculture, water resources, and energy demand (Raneesh KY, 2013) Therefore, it is important to investigate observed changes in the present climate so that future climate predictions can be validated and put into context.

There are many climatic models were introduces to project the long term climate information with considered the estimation of the Greenhouse Gas such as General Circulation Models (GCMs) and Regional Climate Models (RCMs). However, the output of those models are still afflicted with biases to a degree that precludes its direct use, especially in climate change impact studies. To overcome this problem, bias correction has now become a significant procedure in climate change impact studies. Hence, it is important to know the methodologies of bias correction and their performances and to treat reliability result in calibration and validation process.

1.2 Problem Statement

Nowadays, Malaysia experienced extreme climate change which is considered quite unusual. This extreme change can be seen by the major flood due to heavy rainfall with during monsoon northeast and cold temperature which is 19°C happened in Kelantan in the early years. The flood was reported as the warming effect in Siberia worsen with poor drainage systems. These occurrence of floods cause displacement of people, damaged infrastructures and losses of property. Besides, the occurrence of a tornado often occurs at the end of 2014 as well as the El-Nino phenomenon resulting in more floods, droughts, and heat waves.

Extreme climate is referred to the unexpected and unusual weather trend such as drought, flood, tornadoes and hurricane. Drought event associated with reducing of water resources supply. The drought normally occurred when happening rain decrement to a period where well off sources of water under normal level. Based on historical drought event in Malaysia, extreme drought were recorded happened in year 1991 at Malacca that resulting Durian Tunggal dam dropped until critical level and water rationing at most of the state. In year 1998, El Nino that caused extensive impact to environment. Selangor, Sarawak and Sabah most exposed with the effect of this phenomena due to wild forest fire happened during dry weather condition. That situation had resulted months of hazy atmosphere and are threatened the citizen's health.

As climate change give significant impact to human and earth, it is very important to predict future climate change information as it can provides information that helps all public people and policy makers to develop an innovative idea in storage and productivity in response to climate change risks and make decisions accordingly. Many of climate model were introduces to project the long term climate information with considered the estimation of the Greenhouse Gases (GhGs) in the future. General Circulation Model (GCMs) is a complex mathematical model that attempts to provide information about the global climate. GCMs usually include equations that describe the energy changes that occur when regions of different temperature, pressure, chemical composition, velocities, and accelerations interact with each other. However, GCMs' outputs cannot be directly used to force hydrological models for assessing the hydrological impacts of climate change (Sharma et al., 2007), because GCMs do not provide reliable information. Therefore, dynamical and statistical downscaling were introduced to transfer the climate information from GCMs into the finer scales.

Even though, these climatic model are still subjected to consider the biases treatment to ensure the accuracy and reliability of the result. For example, most Regional Climate Models (RCMs) which is also a climatic model tend to overestimate the frequency of precipitation and the occurrence of light precipitation, while they underestimate the heavy precipitation (Murphy, 1999; Fowler et al., 2007). To overcome this problem, post-processing of the climatic output by correcting with and towards observations has become a standard procedure in climate change impact studies. This BC procedure significantly alters the model output and therefore influences all CCIS relying on bias corrected data. (Ehret, 2012).

1.3 Objective of Study

The objective of this study is:

i. To evaluate the performances of two different methods of the bias corrections which are Linear Scaling and Local Intensity Scaling.
ii. To determine the reliability of the climate projection results using bias corrections.

1.4 Scope of Study

The study focused on the methods of bias correction available and widely used in climate model. The historical daily rainfall and temperature were provided by Malaysia Meteorological Department (MMD and Drainage Malaysia (DID) respectively. Bias correction methods were compared based on their performances in treating the biases. The methods used are linear scaling (LS) and local intensity scaling (LOCI). The study treat the biases projected result at two stations in Pahang state there are Lubuk Paku and Temerloh.

1.5 Significant of Study

The study is very important to enhance the accuracy and the reliability of the future climatic trend result and can be used as very important information in preparing and managing the long term water resources for Pahang state.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Climate change is defined as any significant change in the measures of climate for long lasting period of time. This climate change includes major changes in temperature, precipitation and wind pattern among other effect that occur over several decades or longer. Climate change gives a significant effect on Malaysia's climate such as increasing flooding risks and leading to large droughts.

As located near the equator, Malaysia's climate is categorized as being hot and humid throughout the year. Malaysia is exposed to the El Nino effect, which reduces rainfall in the dry season. Malaysia faces two monsoon winds seasons, the Southwest Monsoon (SWM) from late May to September, and the Northeast Monsoon (NEM) from October to March. The NEM which originating from China and the north Pacific brings more rainfall while the SWM originates from the deserts of Australia. During the NEM, the exposed areas on the eastern part of the Peninsula to receive heavier rainfall than other months. On the other hand, the areas which are sheltered by the mountain ranges (the Titiwangsa Range) are more or less free from its influence. The period of the SWM is a drier period for the whole country, particularly for

One of the greatest challenge in the facing modern society is the management of risk due to climate change such as extremes event of floods and droughts. (Vorosmarty et al., 2000; Oki and Kanae, 2006). Risk is a concept representing in the statistical terms, hence, proper risk management must consider the climatic forecasting to prepare an effective long term plan. Ordinarily, output fields from climate models, regional or global, are used to force future hydrological simulations. It is well known that some form of pre-processing is necessary to remove biases present in the simulated climate output fields before they can be used for this purpose (Sharma et al., 2007; Hansen et al., 2006; Christensen et al., 2008)

Most of the global climate models have good production for the predicted temperature trend but not in precipitation. The difficulty arises due to the high degree of complexity and non-linearity of the microphysical and 5 thermodynamic response of the climate system, which drives the hydrological cycles, to changes in the boundary conditions such as atmospheric greenhouse gas loading. For example, under conditions of constant relative humidity but warmer temperatures, the atmosphere should be able to hold more moisture and consequently produce more extreme precipitation events (Trenberth et al., 2003; Emori and Brown, 2005; Lenderink and Meijgaard, 2008; Berg et al., 2009). The effects that causes from the boundary forcings the precipitation are under debate. Radiative balance arguments have been made in favor of a slowing-down of the hydrological cycle (Held and Soden, 2006; Allen and Ingram, 2002). This could explain a weaker increase of mean precipitation with temperature than the rate given by the Clausius-Clapeyron equation for 15 saturation specific humidity.

In the simplest formulations of bias correction which is linear scaling (LS), only the changes in a specific statistical aspect of the simulated fields is used. The change is applied directly to present day observations to obtain a field which is then used to force the hydrological models. Often the change in mean value or the variance is employed. More advanced bias correction methodologies correct for more than one explicitly chosen statistical aspect (Leander and Buishand, 2007 Hurkmans et al., 2010). Hydrological processes depend on the entire distribution function of the precipitation intensity and temperature. Hence, the reliability result can be made when adjusting the entire probability density function (pdf) of the simulated fields to that of the observations.

2.2 Importance of Accuracy in Estimation

Accuracy is only one of the dimensions in the broader context of quality that has been articulated in recent years. Yet it remains as critical importance. Inaccuracy in estimation and forecasting will causes by error in sampling measurement and processing. It is important to estimate accurately from the beginning of the procedure of any process. Estimate accurately can avoid from any errors in any process. Researchers have to know the importance of accurate estimation especially for the long term climate prediction. However, the biases are still exist due to the weaknesses of the climate model.

The General Circulation Models (GCMs) outputs could not be directly used for assessing the hydrological impacts of climate change (Sharma et al., 2007)]. It is because GCMs do not provide reliable information on scales below 200 km for most hydrological-relevant variables (Maraun et al., 2010). Therefore, downscaling techniques are needed to transfer the information from GCMs to finer scales by applying a higher-resolution regional climate model (RCM) over a limited area with initial and boundary conditions.

2.3 Problem of Calibration and Validation Processes in Modelling

Calibration is the activity of checking the accuracy of a measuring instrument of any type. It may also include adjustment of the instrument to bring it into alignment with the standard. While validation is assessing the degree to which instrument accurately measures what it purpose to measure or a statistical technique or test that predicts a value accurately. Validation is an extension from the calibration process. Its purpose is to assure that the calibrated model properly assesses all the variables and conditions which can affect model results, and demonstrate the ability to predict field observations for periods/conditions separate from the calibration effect.

According to International Atomic Energy Agency (1982) defines a validation as one of the process to provide a good representation of the actual process occurring in a real system. Vogel and Sankarasubramanian (2003) stated that model hypothesis testing (validation) should be performed prior to and independent of parameter estimation (calibration). Thus without validation, calibration is worthless and so is uncertainty estimation. Klemes (1986) stated a hierarchical scheme for the validation of hydrologic models to tests model ability to make predictions based on the calibration period (split-sample), on different basins (proxy-basin), and under different climate regimes (differential split-sample). Verification is the first step that only deal with numerical resolution of the equation in the model. It is not deal with the agreement between model and reality but deal with no coding errors and accurate numerical method to solve model equations. There are different methods are available to achieve this goal of verification. One of them which is the standard one is to compare the numerical solution with the analytical one for highly idealized test cases for which an exact solution is available. It is also possible to formally state that some parts of the code are correct.

The next step which is the validation process, which the process to evaluate the performances of the calibrated result. Validation must be first performed on the representation of individual physical processes. Therefore, model results have to be compared with observations obtained in the same conditions. The boundary conditions and forcings must be correctly specified to represent the observed situation. This is generally achieved for particular locations, during field campaigns specifically designed to study this process. On a larger scale, the different components of the model have to be tested independently, ensuring that the boundary conditions at the interface with the other components are well defined. Finally, the results of the whole coupled model have to be compared with observations. All those steps are necessary because there are always exist possibility after the different elements are coupled together, due to non-linear interactions between the components. Several problems might cause by the formulation of the boundary conditions when components are run individually. However, having a coupled model providing reasonable results is not enough. In order to test whether the results occur for the correct reason, it is necessary to check that all the elements of the model are doing a good job, and that the satisfactory overall behaviour of the model is not due to several errors in its various elements cancelling each other.

The verification and validation should be considered as processes that never lead to a final product. The model should be continuously retested as new data or experimental results become available. The building of a model could then be viewed in the same way as a scientific theory. Hypotheses are formulated and a first version of the model developed. The results of the model are then compared to observations. If the model results are in good agreement with the data, the model could be said as to be confirmed for those conditions, so increasing its credibility. However, this does not mean that the model is validated for all possible cases. If the model results do not compare well with observations, the model should be improved. Model developers and users also may decide if the model could not reproduce the observations in some special cases, this indicates that it is not valid for such conditions, although it can still be used in other situations where the tests indicate better behavior.

A disagreement between model and observations can be related to an inadequate selection of the value of some parameters that are not precisely known. This is the meaning of calibrate of model which is adjusting those parameters. The calibration of physical parameters is generally required and is justified as there is no a prior reason to select one particular value in the observed range of the parameters. To obtain the most accurate numerical solution of the equations, it is valid to calibrate the numerical parameters. However, care has to be taken to ensure that the calibration is not a way of s masking some deficiencies in the model. If this does occur, there is a high probability that the selected parameters will not provide satisfactory results for other conditions (e.g. the climate at the end of the 21st century). Performing many tests for widely different situations and for various elements of the model should limit the risk, but the number of observations is often too small to ensure that the problem has been completely avoided. An additional problem with the constant improvement of the model and of its calibration as soon as new data becomes available is the absence of independent data to really test the performance of the model. Ideally, some of the available information should be used for the model development and calibration, and some should be kept to assess its accuracy. Another good model practice is to choose or design models components for which the selection of one particular value of the parameters has only a small impact on model results, so reducing importance of the calibration.

2.4 Comparison of Bias Correction Performances

Climate change is widely used as the most pressing global issue facing society (*Mitchell and Jones,* 2005). Climate change has attracted attention its effects on biological, physical, and socioeconomic processes cannot be avoided. Thus, global climate models (GCMs) become a primary tool for understanding and modelling physical processes underlying climate system for climate change research. GCMs can simulate the present-day climate and project future climate conditions under different scenarios (*Miao et al.,* 2013).

However, there are bias in regarding the GCMs output due to their representation of the intensity and frequency of meteorological variables. The bias is caused by limited computational resources, incomplete understanding of the way the climate reacts, simplified assumptions in model construction and uncertainties in model parameterization. Moreover, current GCMs have insufficient spatial resolution to resolve many important processes or provide the spatial details required for impact studies (*White and Toumi,* 2013). Researchers generally employ a downscaling technique to generate a representation of climatic variables at a finer spatial scale (*Shrestha et al.,* 2014) but both statistical and dynamic downscaling techniques exhibit considerable bias, as shown by comparing the simulated climate for a reference period with observations from the same period (*Miao et al.,* 2015).

Highlight the above limitations, a number of statistical methodologies have been proposed to correct GCM outputs and their application to downscaling so that the results can be used for impact studies (*Giorgi and Mearns*, 1991). The underlying idea is the identification of possible biases between observed and GCM-simulated variables, which form the basis for correcting both current and future GCM simulations (*Mehrotra and Sharma,* 2015). Some commonly used correction techniques are based on the equalization of statistical characteristics between modeled and observed variables, such as the mean and the variance(*Ho et al.,* 2011).

Scientists were using these methodologies to treat bias all over the world. Piani et al. (2010) validated a bias correction method (distribution mapping based on the gamma distribution) for correcting RCM-simulated daily precipitation over Europe. The results showed that this method performed reasonably well, not only at the mean but also at other moments (drought index and heavy precipitation) of intensity distribution. Terink et al. (2009) corrected RCM-simulated precipitation by fitting the mean and coefficient of variation of the observation, and corrected RCM-simulated temperature by fitting the mean and standard deviation of the observation. This bias correction process led to satisfactory results as precipitation and temperature differences between RCM data and observations decrease significantly.

Bennett et al. (2011) tested the performance of a quantile mapping bias correction method (based on an empirical distribution) for use in hydroclimatological projections in Australia. The bias correction improved the spatial correlation between modelled and observed seasonal and annual rainfall. This method can effectively couple RCM outputs to a hydrological model for assessing the hydrological impact in a changing climate. Lafon et al. (2012) compared the performance of four bias correction methods (linear, nonlinear, gamma, and empirical distribution-based quantile mapping) in the reduction of biases in RCM-simulated precipitation for seven catchments spread across Great Britain. The results showed that the mean and standard deviation of daily precipitation can be corrected robustly while the correction of skewness and kurtosis of daily precipitation are much more sensitive to the choice of a bias correction method and the selection of a particular calibration period. If both precipitation data sets (modelled and observed) can be approximated by a gamma distribution, the gamma-based quantile mapping method offers the best combination of accuracy and robustness. Otherwise, the nonlinear method is more effective at reducing the bias.

Gudmundsson et al. (2012) compared the performance of distribution-derived transformations, parametric transformations, and nonparametric transformations at downscaling precipitation for 83 stations in Norway. Nonparametric transformations gave the best performance in the reduction of systematical biases in RCM-simulated precipitation. The above mentioned comparisons were only conducted on the construction of climate projection, which is the first step for impact studies. Themel et al. [2010] compared an ensemble of seven statistical and bias correction approaches in downscaling RCM daily precipitation over the historical period in the Alps region. The results showed that bias correction approaches such as quantile mapping and local intensity (LOCI) scaling displayed significant advantages compared to the traditional multiple linear regression methods.

There are another methods to correct the bias of GCMs output and their application to downscaling so that the results can be used for impact studies. Some commonly used correction techniques are based on the equalization of statistical characteristics between modeled and observed variables, such as the mean and the variance (*Ho et al.,* 2011*; Li et al.,* 2012; *Fang et al.,* 2015). The methods are linear scaling (LS) and Local Intensity Scaling (LOCI).

Table 2.1: The Advantages and Disadvantages of the Two Bias Correction Methods

Method	**Classification**	**Advantages**	**Disadvantages**
Linear scaling (LS)	Mean Based	• A mean monthly correction factor is applied to the RCM-simulated daily precipitation in a month. It is the simplest bias correction method in a month. It is the simplest bias correction method	• The daily precipitation sequence is the same as that of the RCM - simulated data (usually too many wet days compared to the observation). • It does not account for the changes in the frequency distribution of precipitation. • No adjustment is made to the temporal structure of daily precipitation occurrence.
Local intensity scaling (LOCI)	Mean-based	• The wet-day frequency is corrected. A mean monthly correction factor is applied to the RCM-simulated daily precipitation in a month.	• It does not account for the different changes in the frequency distribution of precipitation. • No adjustment is made to the temporal structure of daily precipitation occurrence.

2.5 Climate Modelling

Climate models are computer programs that simulate how the climate has changed in past and how it will change in the future. In general terms, a climate model could be defined as a mathematical representation of the climate system based on physical, biological and chemical principles. The equations derived from these laws are so complex that they must be solved numerically. As a consequence, climate models provide a solution which is discrete in space and time, meaning that the results obtained represent averages over regions, whose size depends on model resolution, and for specific times. For instance, some models provide only globally while others have a numerical grid whose spatial resolution could be less than 100 km. The time step could be between minutes and several years, depending on the process studied. Statistical downscaling (SD) and dynamical downscaling (DD) are used for downscaling outputs of a GCM. SD methods are much simpler than DD methods to downscale the outputs of a GCM. Using SD methods, global-scale climate variables such as mean sea level pressure, zonal wind, temperature, geo-potential height are linked with local-scale variables such as observed temperature, precipitation and humidity. This is done by producing some statistical/empirical relationships (Wetterhall et al. 2008). To date, many statistical models have been developed and are available.

2.5.1 Dynamical Downscaling (DD)

In dynamical downscaling, a high-resolution numerical model, or Regional Climate Model (RCM), with a resolution of about 5 to 50 km (Chu et al. 2010) is coupled with the GCM. The RCM drives the lateral and large-scale boundary condition from the GCM and provides detailed information or high-resolution outputs at the regional level. The GCM responds to large-scale forces such as greenhouse gases, atmospheric circulation, and oceanic circulation etc. On the other hand, the RCM simulates small-scale climatic variables such as extreme climate events, orographic precipitation, and regional-scale anomalies. Since the RCM is dependent on the GCM’s boundary conditions, it is exposable to any systematic errors which belong to the GCM’s driving fields. The skill of the RCM is strongly dependent on both, the GCM’s driving forces and information about regional-scale forcing. Regional-scale forcing such as land use data and land sea. There must be a strong co-ordination between the global and regional climate modeling groups to ensure that the appropriate data is available. The RCMs are computationally intensive, depending upon the resolution and domain size (Wilby and Wigley 1997; Hay and Clark 2003; Fowler et al. 2007).

2.5.2 Statistical Downscaling (SD)

SD methods are much simpler than DD methods to downscale the outputs of a GCM. Using SD methods, global-scale climate variables such as mean sea level pressure, zonal wind, temperature, geo-potential height, etc. are linked with local-scale variables (regional-scale variables) such as observed temperature and precipitation, and this is done by producing some statistical/empirical relationships (Wetterhall et al. 2006). SD is not only useful in numerical weather prediction and synoptic climatology, but is also applied for a wide range of climate applications. The main advantage of SD is that it provides local-scale information, which is very useful in climate change impact assessment studies (Giorgi et al. 2001). On the downside, the main disadvantage of this approach is that it requires long historical meteorological weather station data to construct an appropriate link with large-scale variables. The main assumption of SD is that the empirical relationship between larger and small scales is temporally stationary (Hay and Clark 2003). DD is a good alternative for SD in the case of basins which have no historical data (Benestad et al. 2008).

2.6 Statistical Downscaling Model (SDSM)

The main tools to predict the variability and changes in climate variables such as temperature, rainfall and humidity on global and continental levels, are Global Climate Models that are also called General Circulation Models (GCMs). However, as the output of this model are based on large grid scale (250 to 600km), the output cannot be used successfully to investigate the environmental and hydrological impacts of climate change. In practice, the choice of downscaling method not only hinges on the time, data and technical resources available, but also the intended application (Wilby et al. 2010). The Statistical Downscaling Model (SDSM) has been identified as one of the leading statistical downscaling techniques and was recommended as an appropriate downscaling model by the Canadian Climate Impacts and Scenarios project (CCIS, 2006). The SDSM is a useful downscaling technique and able in reproducing observed climatic variability compared with other statistical downscaling methods as demonstrated by (Khan et al., 2006; Dibike and Coulibaly, 2005). Numerous studies have also assessed the SDSM for downscaling GCM output to be used in many hydrological applications (Khan et al., 2006; Gagnon et al., 2005; Diaz-Nieto and Wilby, 2005).

2.6.1 Calibration and Validation Processes in the SDSM

SDSM is being used widely throughout the world to downscale the important climate variables such as temperature, precipitation, and evaporation for assessing hydrologic responses in climate change scenarios. This SDSM model is developed through a combination of multiple linear regression and the stochastic weather. SDSM developed by Wilby et al. is a hybrid of multiple linear regression (MLR) and the stochastic weather generator (SWG). SDSM involved steps of screening, calibrate and validate. Screening process is crucial for the creation of credible downscaling scenarios. SDSM provides quantitative tools to assist in choosing a realistic set of predictors. Monthly percentages of explained variance show the capability of a given predictor to explain local climate variability.

The calibration and validation process are become important during forecasting/predicting procedure. The calibration step involves the establishment of statistical relationships between the selected predictors and the surface predictands (Gagnon, 2005). Furthermore, the SDSM is capable of modelling both conditional processes, such as precipitation, and unconditional processes using the regression relationships. The term of calibration refers to build relationship among local data (predictands) and selected regional atmospheric variables (predictors) based on multiple linear regression equations (Wilby and Dawson, 2007). The calibration results formulated by using specific period is used to estimate another combination of predictor variable values in validation process. The goal is to identify the fundamental rules and the predictand-predictors relationships. In the SDSM analysis, the calibrate model used to build predictand-predictors relationship and proceed to the weather generator to produce an ensembles of synthetic daily weather series at that region.

Once the SDSM has been calibrated, model calibrations must be verified through synthesizing daily time series using predictand and predictor variables. However, there is still have an error in estimating the mean and the variance. Hence, the user's choice of reanalysis product for calibration of the SDSM affects the downscaled data produced. Therefore, users need to be aware that the National Centers for Environmental Prediction (NCEP) reanalysis used throughout the literature to calibrate the SDSM.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The main purpose of this study is to develop two bias correction methods from the climatic model output for two hydrological stations. The methodology was constructed to achieve the objectives of the study. Rainfall data were used to develop the future rainfall pattern in two respective stations. At the beginning of analysis, climate model will be used to project the current and future climate trend at site study. The function of climate model is to analyse the pattern of local climate (rainfall, temperature, period of dry and wet spell) which affected by the transition of greenhouse emission in the atmosphere during future years. In this study, SDSM 4.2.9 was applied to downscale the raw atmospheric resolutions turn to smaller climatic information scale that focus on the local station by using regression analysis. Then, the projection of local climate trend will be used to simulate and generate the monthly inflow time series via Global Climate model. Two bias correction method which are Linear Scaling (LS) and Local Intensity Scaling (LOCI) are applied to correct bias of the climate models' output. This research focus on two stations in Pahang state LP and TEM to determine climate change scenarios on a daily, monthly and yearly. The certain period times and under the climate change scenario projections using rainfall and output from selected Global Climate Models selected (GCMs). Figure 3.1 shows a methodological project which involved with 2 stages in achieving the objectives of study.

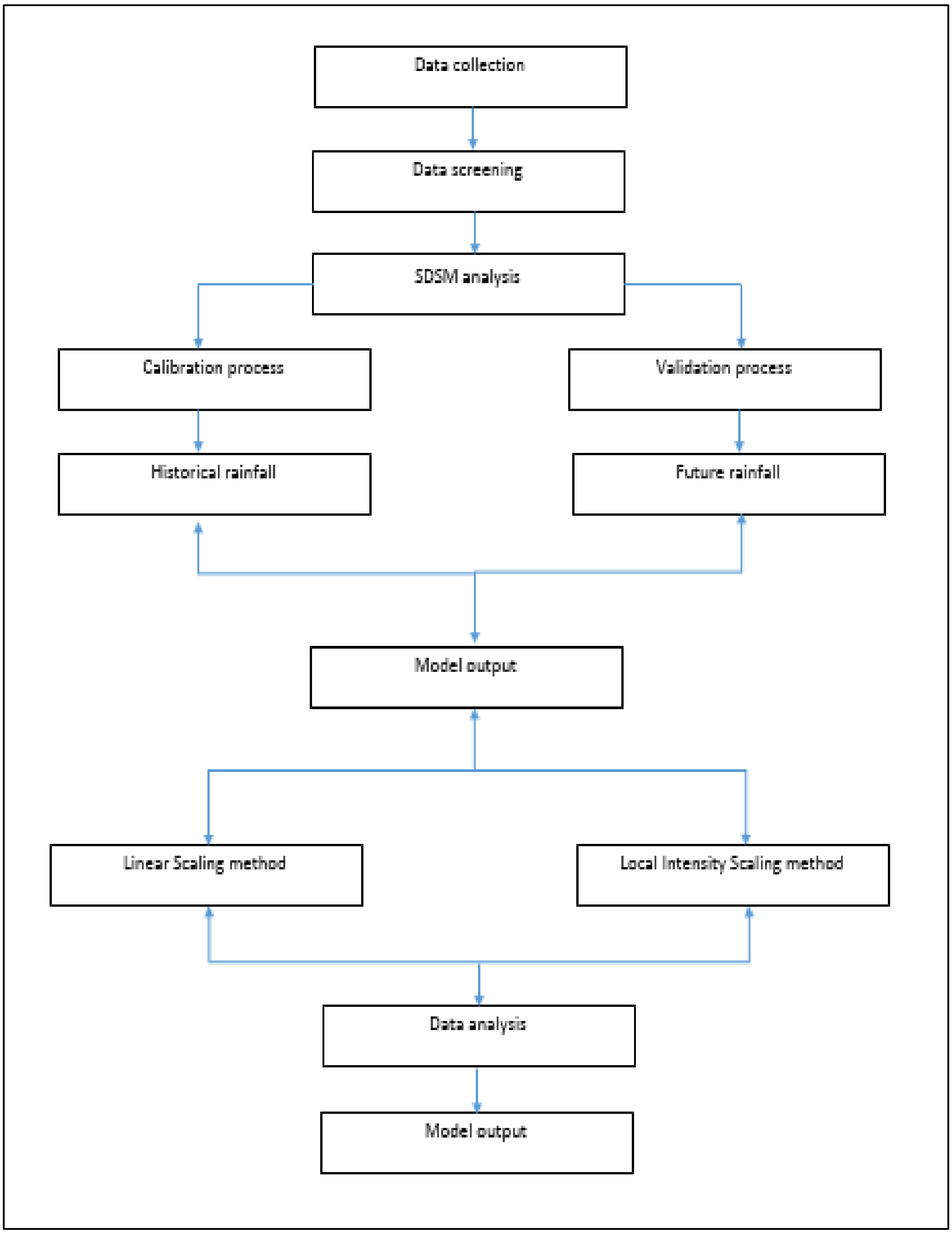


Figure 3.1: Flow Chart of Research Methodology

This study has two stages. Climate models which is Global Climate Model is applied to investigate the nature of distribution of rainfall in the future for LP and TEM. Hence, rainfall data for Pahang state is obtained from particular agencies that responsible in preparing the original and reliable data. The MMD and DID is responsible for agency review, store information and data about the distribution of rainfall.

In order to have more precise and accurate data, checking had be done to the data received from MMD and DID. This is done by checking for any defect in filtering and analyzing process. Besides, there also have some missing data for certain period of times for some stations. Hence, a method named arithmetic mean method is applied to find missing data for upcoming steps. Data that has been refined to be used as input to ensure that each model is able to process weather data with accurately and efficiently. All those checking and finding missing data are important as any input into the model must be correct to ensure that the results obtained in range. Besides, to prevent unreliable results as well as to ensure that results obtained can minimize disability.

In order to get result/output in line with this study, the data that has been processed is analyzed. This is to ensure that the results obtained can be presented in a more simple and convenient. In addition, this analysis process is important to ensure that the results to achieve the goal of the research objective of the study. The results should be in line with the study. After get satisfactory results, these data will be compiled in a more organized and structured. The discussions should be achieved with the results. The report in full should be updated to reference by the authorities and can be useful for benefits in the future.

3.2 Climate Model

In this study, the Statistical Downscaling Model (SDSM) version 4.2 (Wilby et. al. 2007) was used and applied to downscale the GCM output to a regional scale as well as to project the rainfall 2040-2069. The variables of GCMs are represents the physical process of atmosphere, ocean, cryosphere, and land surface in the numerical model with considering the greenhouse gasses in the future (IPCC, 2011). Unquestionably, these model have credibility in projecting climate simulation (Ghosh and Mujumdar, 2007; Anandhi et. al. 2008). However, the spatial resolution presented are coarse (250km - 600 km). Besides, the GCMs' ability may be suspicious because some critical climatic conditions like rain well correlated with atmospheric conditions in a particular sub-grid scale (Wilby and Wigley, 2000).

SDSM model had implies the statistical relationships between large-scale resolutions of GCMs (predictors) with local climate variables (predictands) based on multiple linear regression techniques. Different types of data is allowed to be converted into standard predictor variables before being downscaled down and calibrated to produce non-linear regression models. 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. 2002; Paulin et al., 2005) made SDSM a reliable tool for climate downscaling (Samadi et al., 2013; Muluye, 2012).

There are two types of data required in SDSM downscaling process which are predictand and predictor. In the present study, historical rainfall (1982-2011) and (1975-2004) are recorded at LP and TEM accordingly. Besides, the National Center for Environmental Prediction (NCEP) reanalysis data of the study area for the time period of 1948-2015 were used as the predictor for this study.

3.2.1 Predictors Selection

To obtain the good statistic relationship between predictors and predictands, the SDSM proposed screening process in the Screen Variables stage to measure the performance level of selected predictors with the single-site of predictand. The simulation performances are presenting in seasonal and partial correlation analysis in range 0 to 1 in positive or negative relationship; as guidance to the decision makers in identifying the behavior of each variable while reacting to local climatic variables.

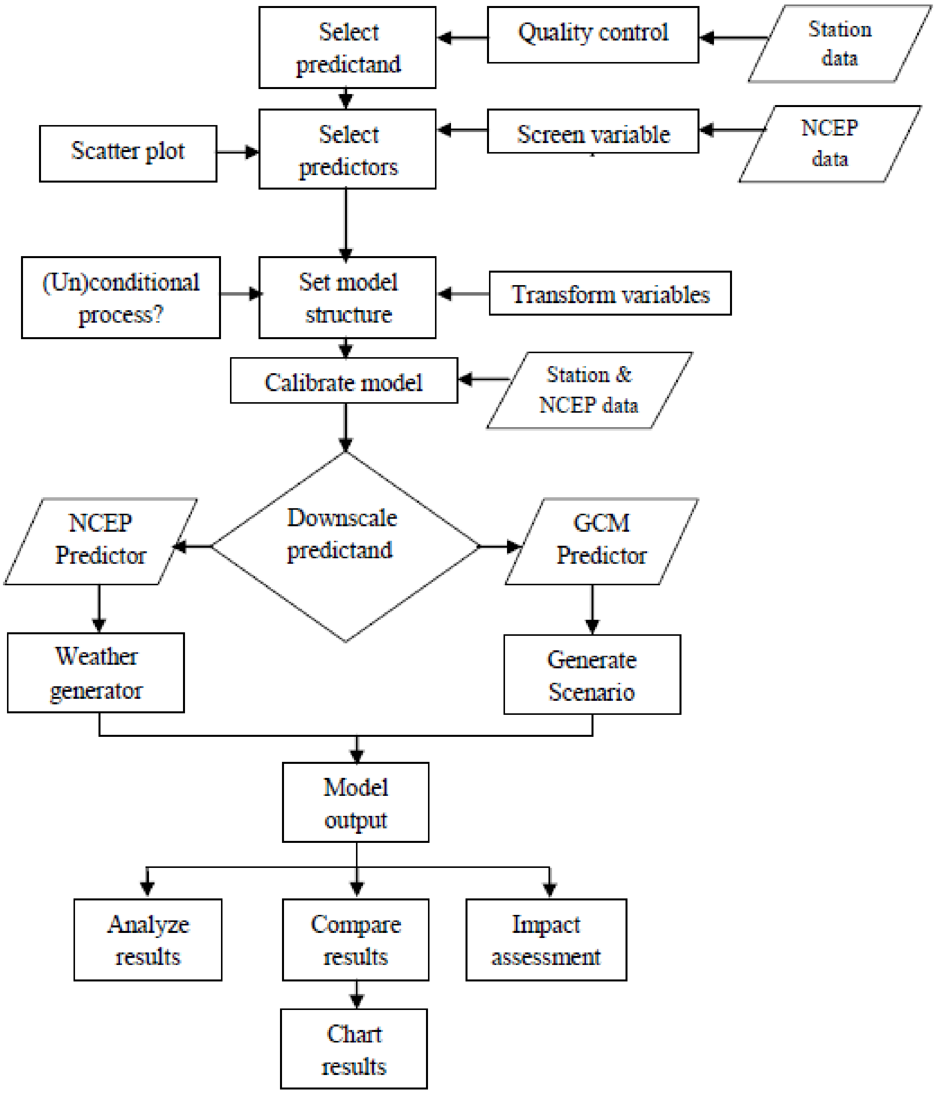


Figure 3.2: Schematic diagram of SDSM analysis

Table 3.1: List of predictors in the SDSM analysis

No	Predictors variable	Predictors description
1	mlsp	mean see level pressure
2	p_f	surface airflow strength
3	p_u	surface zonal velocity
4	p_v	surface meridional velocity
5	p_z	surface vorticity
6	p_th	surface wind direction
7	p_zh	surface divergence
8	p5_f	500hpa airflow strength
9	p5_u	500hpa zonal velocity
10	p5_v	500hpa meridional velocity
11	p5_z	500hpa vorticity
12	p500	500hpa geopotential height
13	p5th	500hpa wind direction
14	p5zh	500hpa divergence
15	p8_f	850hpa airflow strength
16	p8_u	850hpa zonal velocity
17	p8_v	850hpa meridional velocity
18	p8_z	850hpa vorticity
19	p850	850hpa geopotential height
20	p8th	850hpa wind direction
21	p8zh	850hpa divergence
22	r500	relative humidity at 500hpa
23	r850	relative humidity at 850hpa
24	rhum	near surface relative humidity
25	shum	surface specific humidity
26	temp	mean temperature

However, the difficulty happened in finding the best set of predictors representing for multi-site of predictands. The analysis may take longer time and complicated procedure to screen the predictors-predictands relationship because SDSM tool could be done by single-site predictand.

The generated correlation value shows the percentage of variance that can be explained in the form of multi dependent variable, by using the multi independent variable and also giving the criterion variables (product innovation variables) for each of them. The formula for the correlation matrix r_{xy} is

$$\mathrm{Cov(xy)} = \frac{1}{N}\sum(x_i y_i - xy)$$

$$r_{xy} = \frac{\mathrm{Cov(xy)}}{\sqrt{s^2x+s^2y}}$$

where x_i and y_i refer to the predictands and predictors data, is mean value of both variables, while and refer to their standard deviation. Basically, the capability among variables will be interpreted as values between -1 to 1 which shows the positive/negative association relation.

3.2.2 Model calibration and validation

The calibration and validation process are become necessity during forecasting/predicting procedure. In the mathematic interpretation, "*calibration is a measurement process that assigns values to the property of an artifact or to the response of an instrument relative to reference standards or to designated measurement process"* (Croarkin and Tobias, 2012). The term of calibration refers to build/design relationship among local data (predictands) and selected regional atmospheric variables (predictors) based on multiple linear regression equations (Wilby and Dawson, 2007). The calibration results formulated by using specific period are as foundation to estimate another combination of predictor variable values in validation process. The goal is to identify the fundamental rules and the predictand-predictors relationships are able to adequate as original data.

In the SDSM analysis, the calibrate model used to build predictand-predictors relationship and proceed to the weather generator to produce an ensembles of synthetic daily weather series at that region. Therefore, the local rainfall stations were calibrated for the time period of 1961-1975 and validated for the period of 1976-1990. The temperature was calibrated for the time period of 1972-1999 and validated for the period of 2000-2008. By using the same GCMs predictors' variables in model calibration, the ensembles of synthetic daily weather series during year 2010 to 2099 were generated in the scenario generation process.

3.3 Bias Correction Methods

Climate models subjected to systematic errors in their output. These errors cause by limited spatial resolution (horizontal and vertical), simplified physics and thermodynamic processes, numerical schemes and incomplete knowledge of climate system processes. Such errors can and generally should be corrected for, before using climate model data in impact studies. The main assumptions of bias correction methods are quality of the observations database limits the quality of the correction, it is assumed that the bias behaviour of the model does not change with time and for limitation is temporal errors of major circulation systems could not be corrected. To correct these biases, several methods exist, such as delta change approach, multiple linear regression, analogue methods, linear scaling, local intensity scaling and quantile mapping. In this study, two bias correction methods were used for precipitation. These bias correction methods were conducted on a monthly basis from 1982 to 2011 for LP and 1975 to 2004 for TEM.

3.3.1 Linear scaling (LS) of precipitation

The LS method aims to perfectly match the monthly mean of corrected values with that of observed ones (Lenderink et al., 2007). It operates with monthly correction values based on the differences between observed and raw data (raw RCM simulated data in this case). Precipitation is typically corrected with a multiplier.

3.3.2 Local Intensity Scaling (LOCI) of precipitation

The LOCI method (Schmidli et al., 2006) corrects the wet-day frequencies and intensities and can effectively improve the raw data which have too many drizzle days (days with little precipitation). It normally involves two steps: firstly, a wet-day threshold for the mth month Pthres,m is determined from the raw precipitation series to ensure that the threshold exceedance matches the wet-day frequency of the observation; secondly, a scaling factor is calculated and used to ensure that the mean of the corrected precipitation is equal to that of the observed precipitation

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Climate Trend at Lubuk Paku and Temerloh

The IPCC in the special report of The Regional Impacts of Climate Change stated three of hydrological variables get involves indirectly due to the climate impact there are soil moisture, ground water recharge and runoff. The prediction of climate trend at site study for the historical year (1982-2011) and (1975-2004) for respectively two stations and future year (2040-2069) are produced by the simulated of mathematical relationship between the local climate pattern and information of the atmospheric circulation at specific sub-grid. The climate is predicted in synthetic daily and monthly precipitation at 2 of rainfall station at LP and TEM station by using multi-regression techniques in the SDSM model.

In the SDSM model, the climate simulation is started with the screening of variables performance which has better association to the local rainfall stations (predictand). This analysis is only prefer to the rainfall station due to the two reasons; 1) The selection of rainfall station that been used in this analysis is more than 1 and 2) The rainfall predictand is more sensitive and complicated to the atmospheric parameters rather than the temperature. Since the screening involve 26 of NCEP predictors and 2 of local predictands, therefore the multi-correlation matrix (M-CM) been used to analyze many-to-many relationships resulted in the form of correlation matrix. The purpose of this analysis is to screen all the predictand-predictors performance. Based on the results, 3 of predictors were selected to simulate with local climate characteristics at LP and 5 predictors for TEM. Then, each local predictand calibrated (1982-1996) and validated (1997-2011) and predictands calibrated (1975-1989) and validated (1990-2004) for respective stations to these predictors set from NCEP data to evaluate the performance of the simulated result compared to the observed data. The GCM-derived predictors were then used to generate the daily weather series based on re-analysis predictor variables for the future year.

4.1.1 Rainfall simulation results

4.1.1.1 The calibrated and validated performance

Using the selected predictors set, LP station was calibrated (1983-1998) and validated (1999-2011) with the NCEP data. For TEM station was calibrated (1975-1989) and validated (1990-2004). Figure 4.1 and figure 4.2 shows the calibration results between observed and simulated data for LP and TEM rainfall stations meanwhile Figure 4.3 and 4.4 present the validation result for LP and TEM respectively.

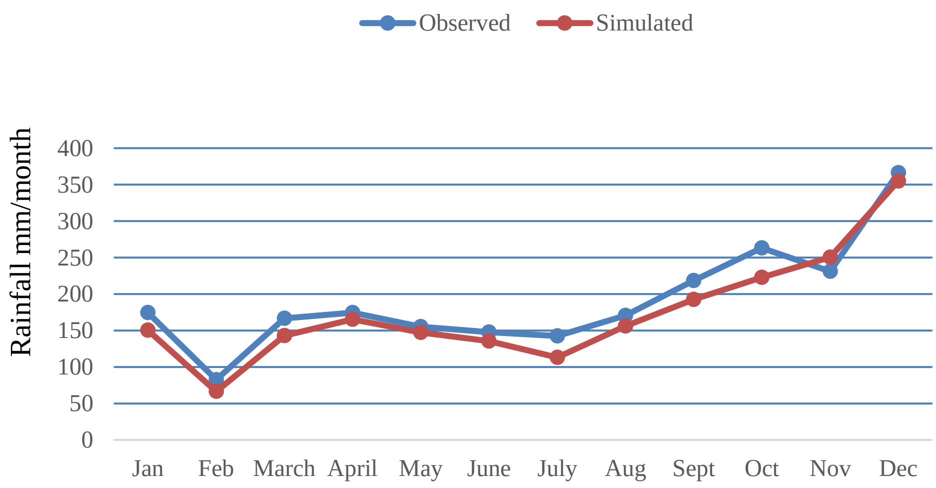


Figure 4.1: Calibrated results between observed and simulated for LP station

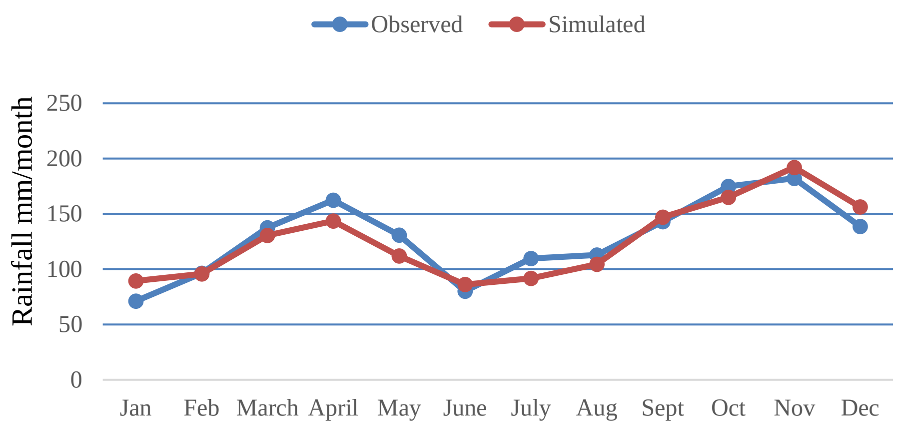


Figure 4.2: Calibrated result between observed and simulated for TEM station

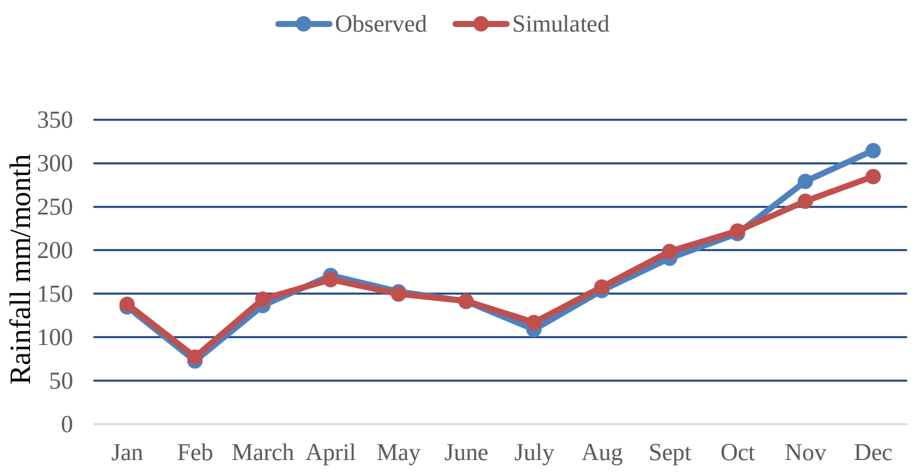


Figure 4.3: Validated result between observed and simulated for LP station

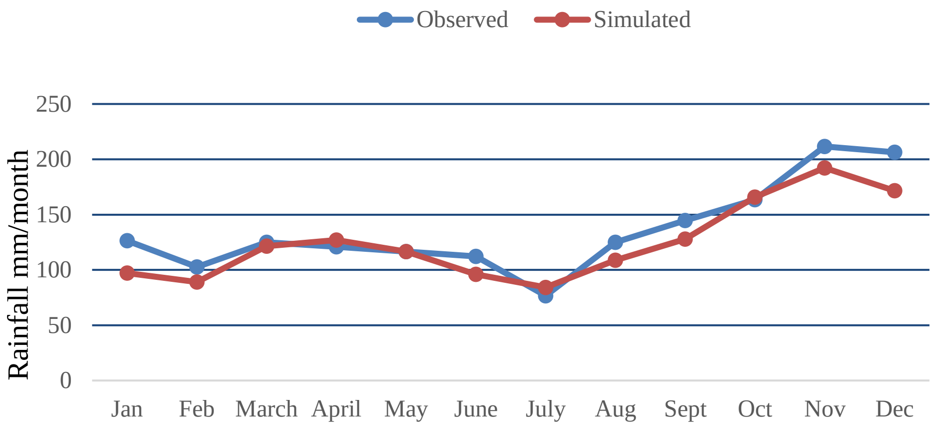


Figure 4.4: Validated result between observed and simulated for TEM station

Table 4.1: MAE results for monthly mean precipitation

	MAE (%)	
Month	**LP**	**TEM**
Jan	5.8	5.9
Feb	5.7	7.8
Mar	4.5	4.2
Apr	3.9	4.7
May	3.2	8.2
June	3.7	5.5
July	6.5	6.1
Aug	2.5	11.5
Sept	3.4	4.7
Oct	6.7	2.4
Nov	1.8	2.5
Dec	6.5	5.2

Based on MAE result, prediction is expected well simulated throughout the year for both stations. Although the error for TEM in August is quite big, but it is still well simulated

Table 4.2: Correlation value for precipitation

CORRELATION (%)		
Month	**LP**	**TEM**
Jan	1.0	0.3
Feb	1.0	0.6
Mar	1.0	0.1
Apr	1.0	0.2
May	1.0	0.2
June	1.0	0.7
July	1.0	0.3
Aug	1.0	0.7
Sep	1.0	0.7
Oct	0.6	1.0
Nov	1.0	0.7
Dec	0.6	0.6

From the correlation value, it can be said that there are well relationship between the predictands and predictors for both hydrological stations.

4.1.2 Rainfall trend in the future year 2040 to 2069

The rainfall trend in the future year at the site study was projected using the GCMs model that is representing the physical atmospheric in the form of numerical number. The future trending was generated at every 2 rainfall stations using the same predictors selected. The future year was in year period 2040-2069.

Figure 4.5 and figure 4.6 show the projection of rainfall trend in interval year 2040-2069 in LP for monthly and annually respectively. Generally, the pattern and intensity of rainfall in average is expected to be not much different from the historical data.

The annually rainfall graph showed that the rainfall pattern expected is fluctuated and constant throughout the 30 years. The error between projection and observation is small for every year except for 2056, the observation rainfall seems to be higher than projection one in average

The monthly rainfall graph in LP showed the rainfall intensity is expected highest in month November with 300mm/month compared to observation data which December is estimated to be the highest rainfall with 325mm/month. However, the decrement is predicted to occur on June, July and August compared to the observation record. While an increment is predicted to occur in May compared to observation record. For the rest month which are January, February, March, April, September and October, the predicted rainfall are same as the observation record. As overall, the pattern and intensity of rainfall in average is expected to be not much different from the observation record for monthly prediction.

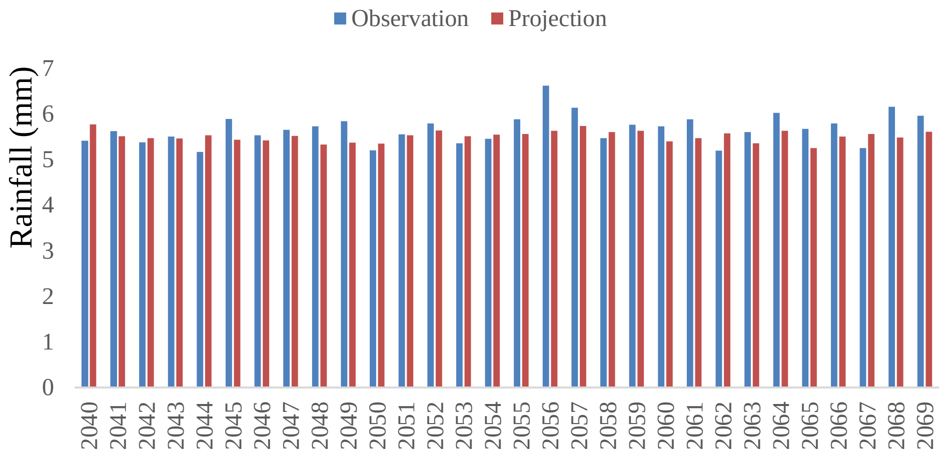


Figure 4.5: Projection of rainfall trend for 2040-2069

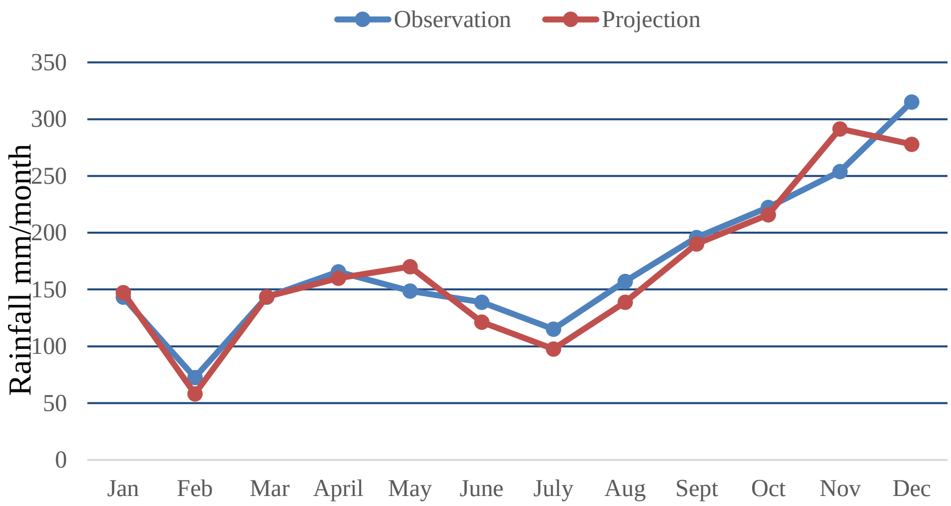


Figure 4.6: Projection of rainfall trend in interval year 2040-2069

Figure 4.7 and figure 4.8 show the projection of rainfall trend in interval year 2040-2069 in TEM for monthly and annually respectively. Generally, the pattern and intensity of rainfall in average is expected to be not much different from the historical data.

The annually rainfall graph showed that the rainfall pattern expected is fluctuated and constant throughout the 30 years. The error between projection and observation is large for every year, the projection rainfall seems to be higher than observation one in average. It can be said that the unsuitable predictors selected for GCM affect the result and give much error.

The monthly rainfall graph in TEM showed the rainfall intensity is expected highest in month June with 300mm/month compared to observation data which November is estimated to be the highest rainfall with 200mm/month. Not suitable predictors selected in GCM affect the result and cause noticeable error.

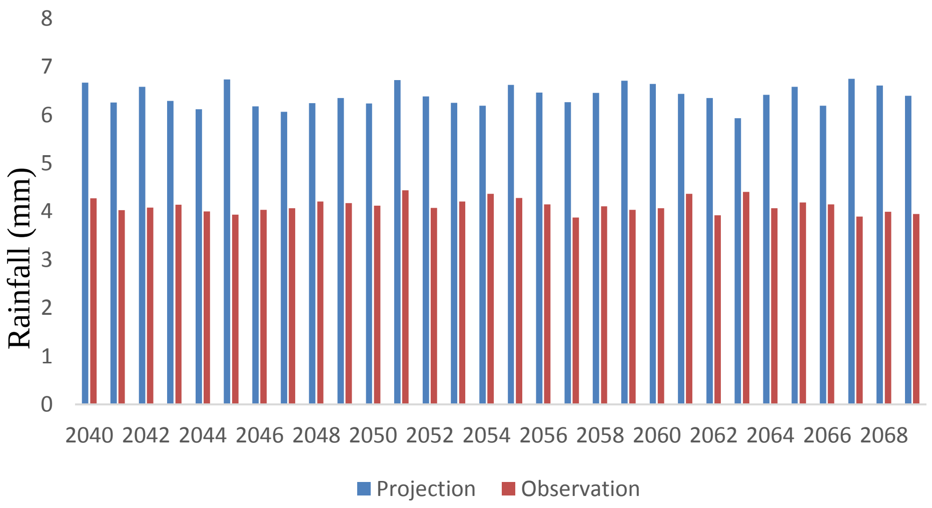


Figure 4.7: Projection of rainfall trend for 2040-2069

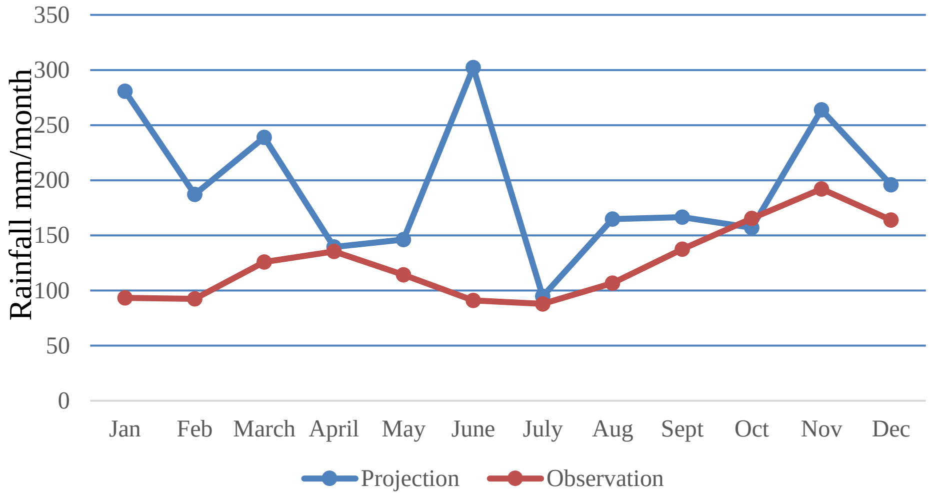


Figure 4.8: Projection of rainfall trend in interval year 2040-2069

4.2 Application of LS

LS is applied to correct the bias in calibrate, validate and project for two hydrological stations. As LS is responsible in correcting the bias in precipitation, result showed a very good for all the processes for corresponding stations.

Figure 4.9 and figure 4.10 showed how LS treated the bias for calibrate and followed by validate for LP. As there is bias between the raw data and the simulated data during calibrate, it can be seen that LS correct the bias successfully and make it closer. Same goes to validate, during validation process in SDSM, there is an error for September and October. LS correct the bias between those months and make the error become smaller. However, a small error between the raw data and the corrected one still exist on December with 6.1 % during calibration. While for validation, there is a small error of 5.9% between raw data and the corrected one during October.

Table 4.3 showed the correction factor for observation and raw data. This correction factor is used for the corrected purposes. It can be seen that all the correction factors for all months is less than 1.0.

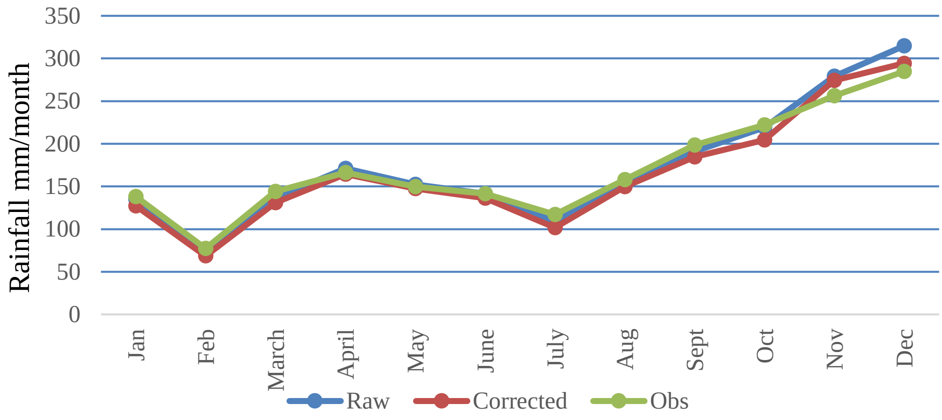


Figure 4.9: Application of LS for calibration (1982-1998)

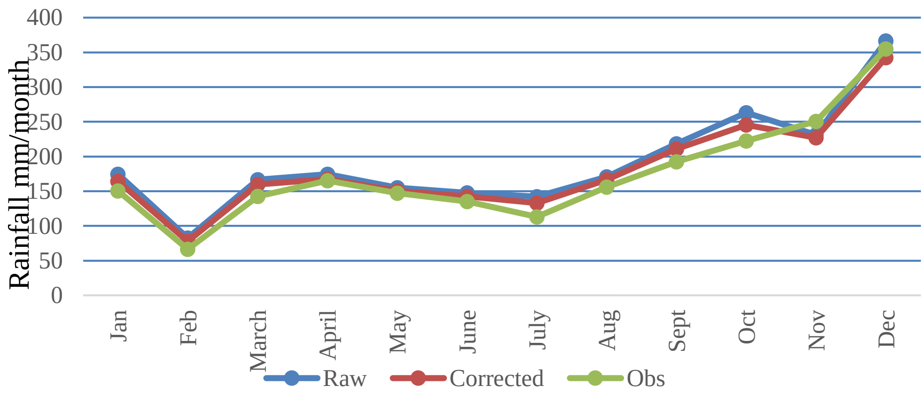


Figure 4.10: Application of LS for validation (1999-2011)

Table 4.3: Correction factor of LS for LP

Month	Observe	Raw	Corrected
January	4.330	4.908	0.882
February	2.734	2.726	1.003
March	4.748	4.828	0.983
April	5.475	5.751	0.952
May	4.788	4.955	0.966
June	4.526	4.806	0.942
July	3.867	3.980	0.972
August	5.145	5.195	0.990
September	6.635	6.763	0.981
October	7.210	7.686	0.938
November	8.875	8.616	1.030
December	9.630	10.873	0.886

Figure 4.11 and figure 4.12 showed how LS treated the bias for calibrate and followed by validate for TEM. As there is bias between the raw data and the simulated data during calibrate, it can be seen that LS correct the bias successfully and make it closer. Same goes to validate, during validation process in SDSM, there is an error for September and October. LS correct the bias between those months and make the error become smaller. However, a small error between the raw data and the corrected one still exist on August with 3.4 during calibration. Table 4.4 showed the correction factor for observation and raw data. This correction factor is used for the corrected purposes. It can be seen that all the correction factors for all months is less than 1.0. Table 4.5 showed the error between raw data and corrected data that has been treated.

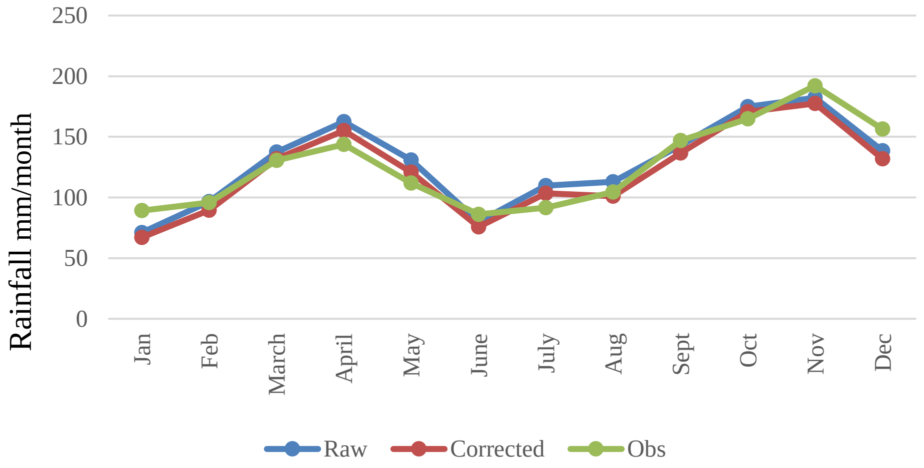


Figure 4.11: Application of LS for calibration (1982-1998)

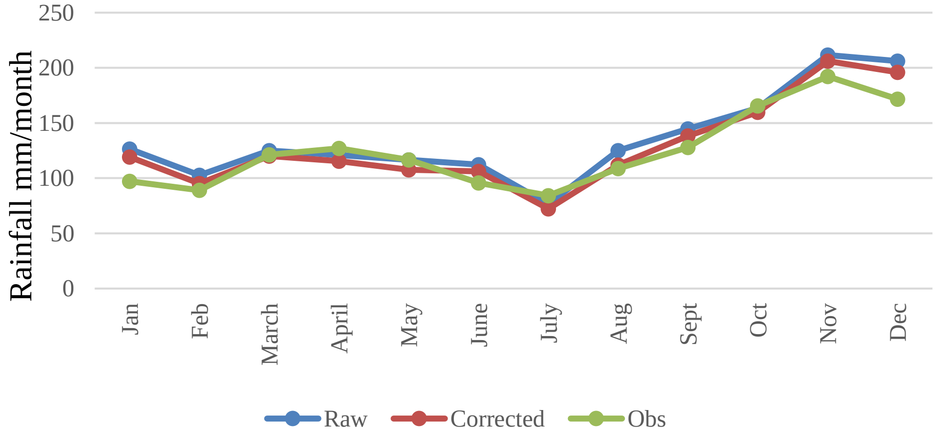


Figure 4.12: Application of LS for validation (1999-2011)

Table 4.4: Correction factor of LS for TEM

Month	Observe	Raw	Corrected
January	3.007	3.192	0.942
February	3.268	3.522	0.928
March	4.063	4.233	0.960
April	4.510	4.723	0.955
May	3.688	3.990	0.924
June	3.034	3.203	0.947
July	2.836	3.008	0.943
August	3.438	3.835	0.896
September	4.582	4.796	0.955
October	5.329	5.460	0.976
November	6.393	6.563	0.974
December	5.288	5.562	0.951

Table 4.5: MAE results for LS treatment

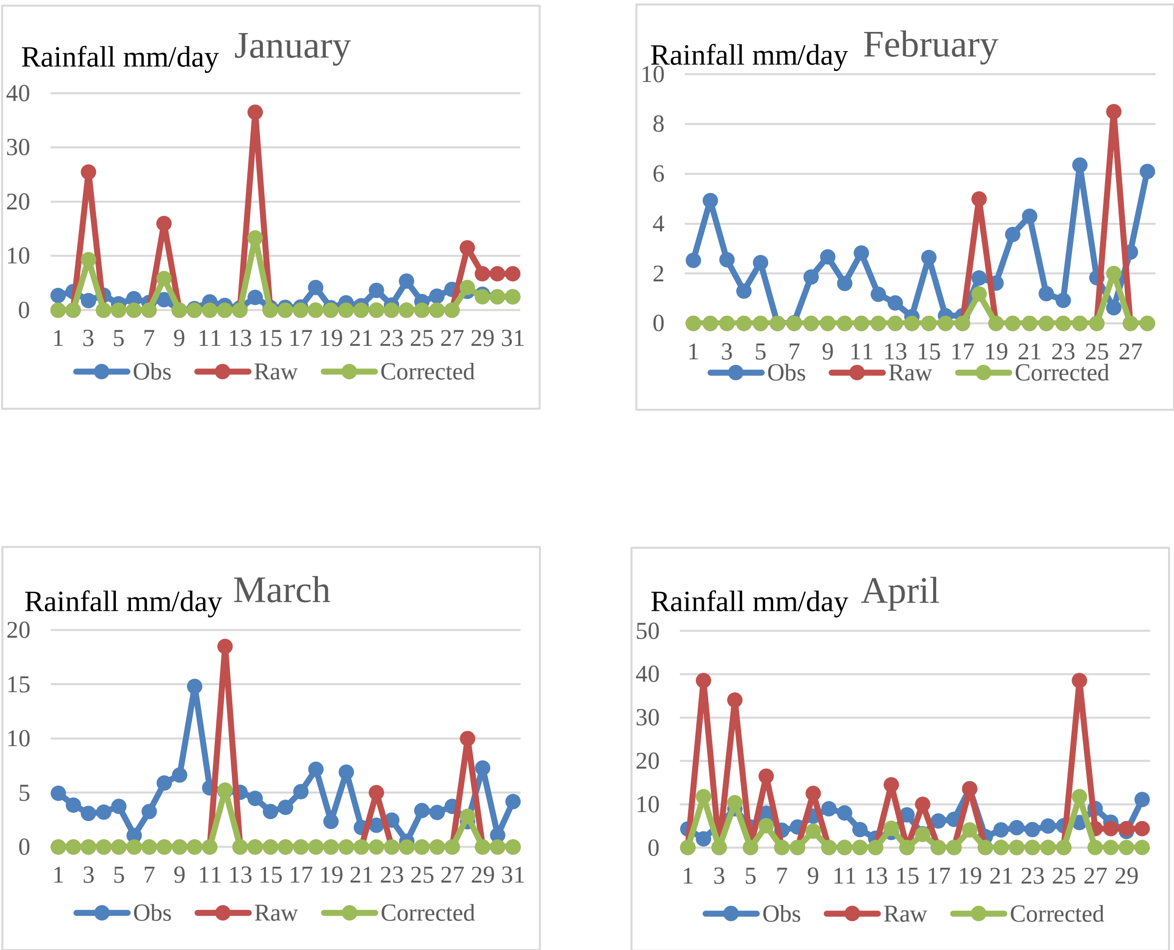
	MAE (%)			
Month	**LP**		**TEM**	
	Calibrated	**Validated**	**Calibrated**	**Validated**
Jan	5.8	5.8	5.6	5.6
Feb	5.7	5.7	7.3	7.3
March	4.2	4.2	4.0	4.0
Apr	3.9	3.9	4.5	4.5
May	3.2	3.2	7.6	7.6
June	3.7	3.7	5.3	5.3
July	6.5	6.5	5.7	5.7
Aug	2.5	2.5	10.4	10.4
Sept	3.4	3.4	4.5	4.5
Oct	6.7	6.7	2.4	2.4
Nov	1.8	1.8	2.6	2.6
Dec	6.5	6.5	4.9	4.9

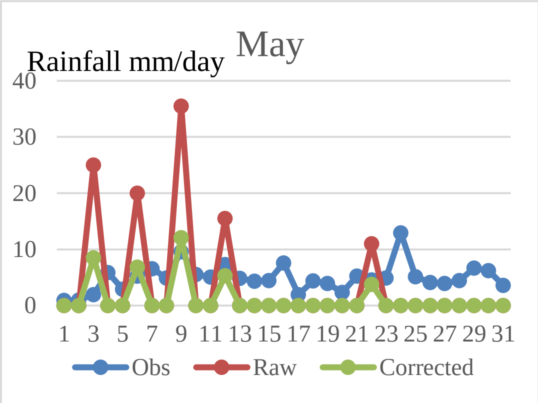
4.3 Application of LOCI

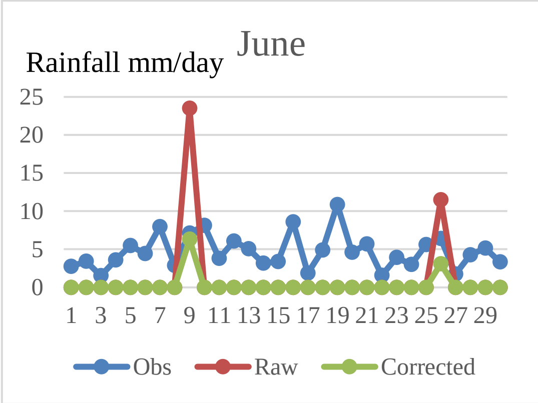
LOCI is applied to correct the calibration, validation and projection precipitation for LP and TEM. However, the ability of LOCI to correct monthly precipitation is not satisfying and the result is not logical. Thus, LOCI only has the performance towards daily precipitation.

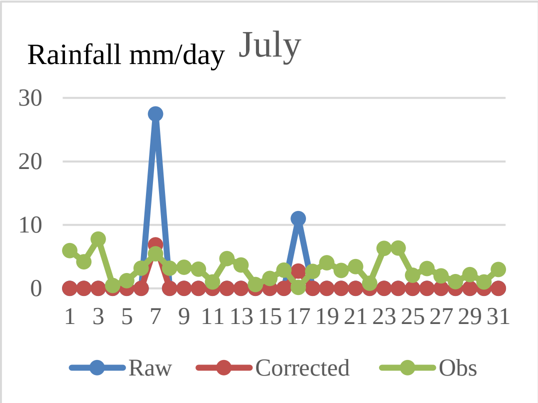
Figure 4.13 shows the result of application of LOCI in daily precipitation for LP from January to June in 1982. From the result, it can be seen that LOCI perform in correct the bias between raw and observed data. However, there still error exist between those particular data especially in February and June.

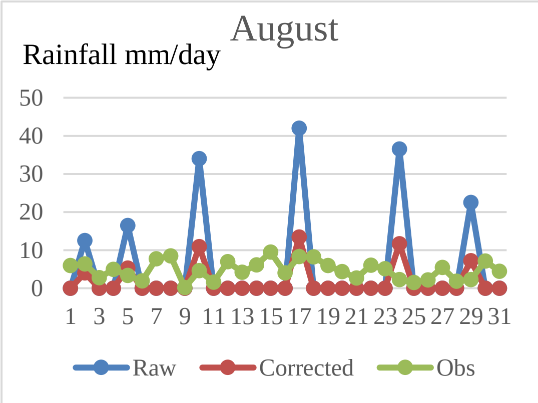
Table 4.6 showed the correction factor of LOCI for LP station.

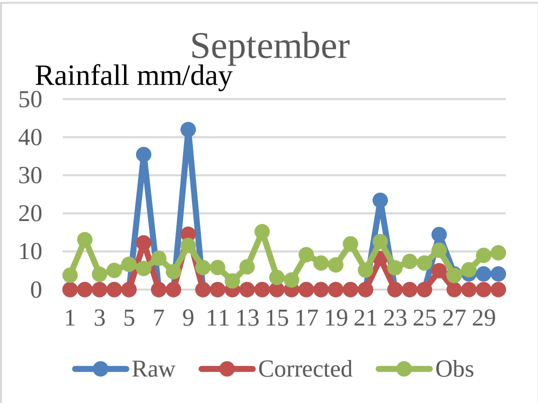


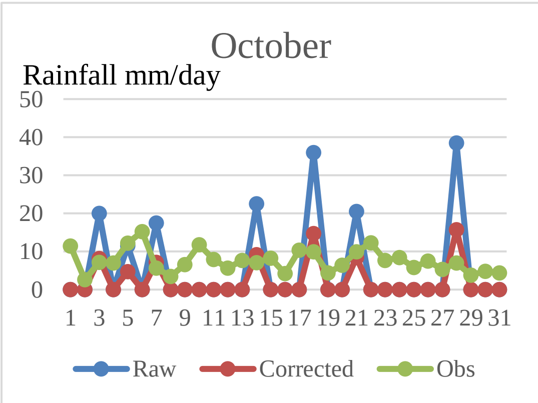

May
Rainfall mm/day
40
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Obs
Raw
Corrected

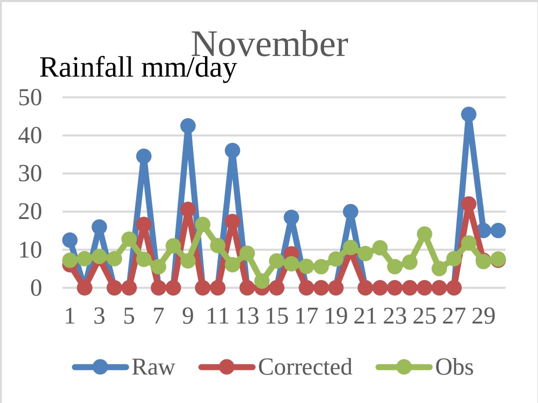

June
Rainfall mm/day
25
20
15
10
5
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29
Obs
Raw
Corrected


July
Rainfall mm/day
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Raw
Corrected
Obs


August
Rainfall mm/day
50
40
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Raw
Corrected
Obs


September
Rainfall mm/day
50
40
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29
Raw
Corrected
Obs


October
Rainfall mm/day
50
40
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Raw
Corrected
Obs



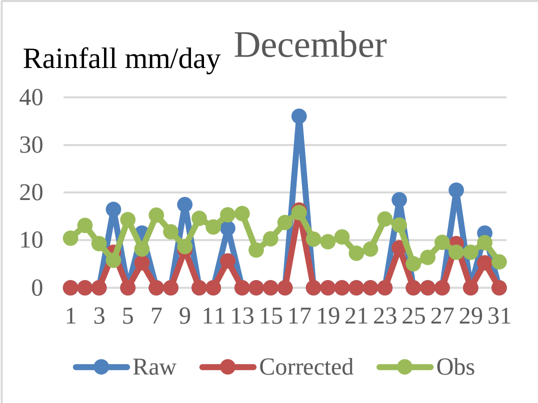


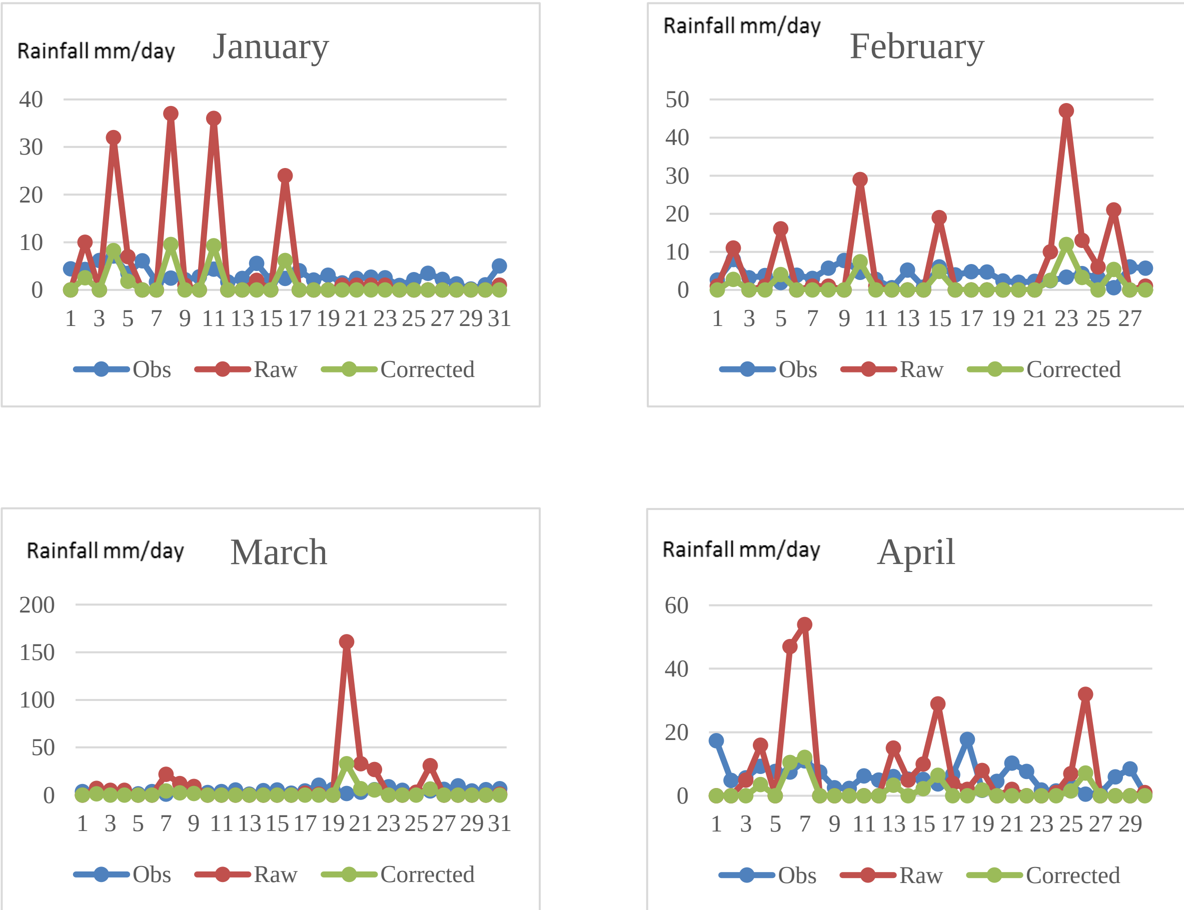
Figure 4.13: Simulated results after treated by LOCI for January to December in 1982

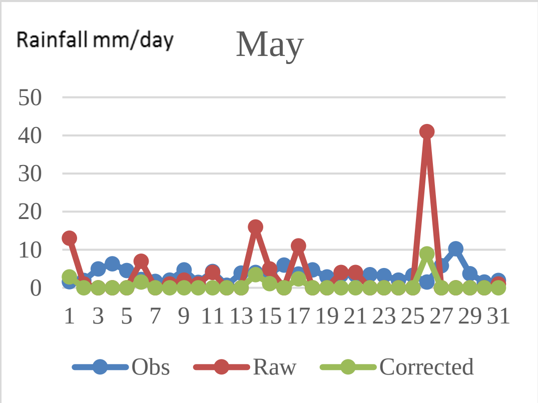
Table 4.6: Correction factor of LOCI for LP

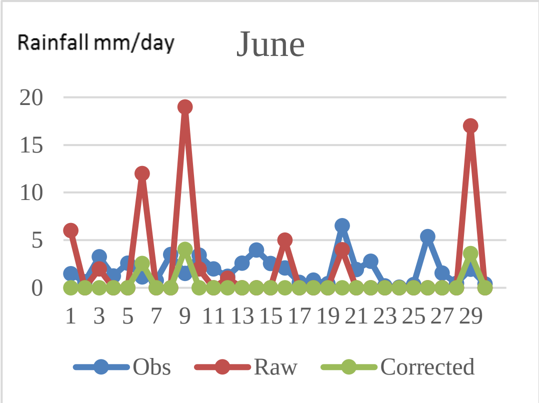
Month	Observe	Raw	Corrected
January	9.779	6.691	3,273
February	8.232	5.010	4.477
March	11.599	7.390	5.122
April	12.626	7.764	5.218
May	10.959	6.872	5.330
June	12.964	7.009	6.387
July	11.154	6.365	5.264
August	11.658	7.394	5.124
September	13.521	9.017	4.992
October	12.587	9.353	4.109
November	13.097	10.573	3.454
December	15.524	12.614	2.455

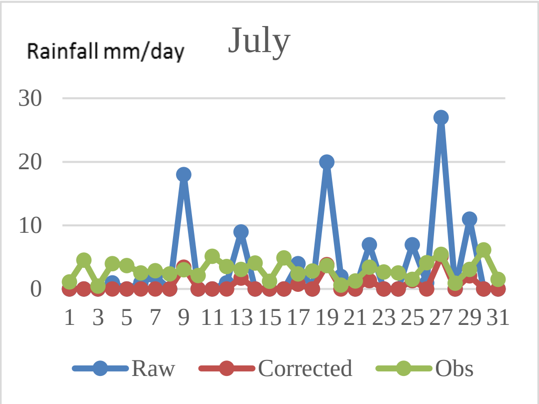
Figure 4.14 shows the result of application of LOCI in daily precipitation for TEM from January to June in 1975. From the result, it can be seen that LOCI perform in correct the bias between raw and observed data. Besides, LOCI had correct all the biases between these months in daily basis.

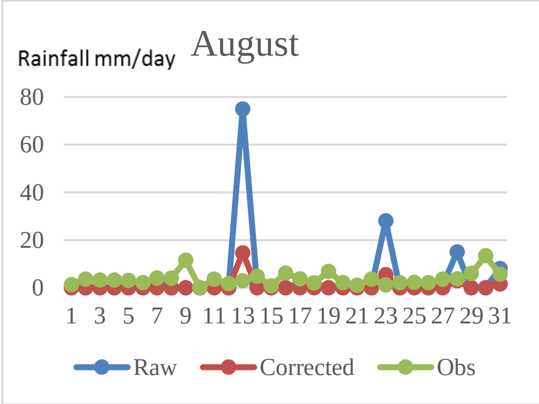
Table 4.7 showed the correction factor of LOCI for TEM station.

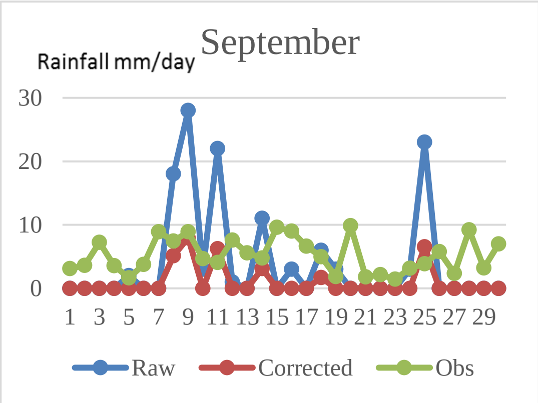


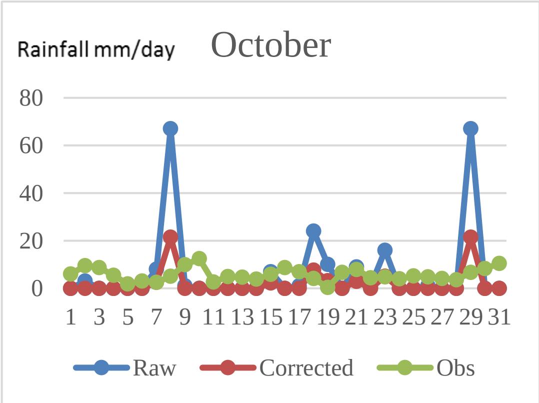

Rainfall mm/day
May
50
40
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Obs Raw Corrected

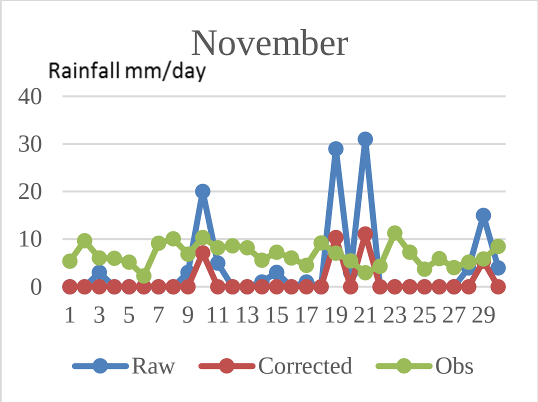

Rainfall mm/day
June
20
15
10
5
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29
Obs Raw Corrected


Rainfall mm/day
July
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Raw Corrected Obs


Rainfall mm/day
August
80
60
40
20
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Raw Corrected Obs


Rainfall mm/day
September
30
20
10
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29
Raw Corrected Obs


Rainfall mm/day
October
80
60
40
20
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31
Raw Corrected Obs



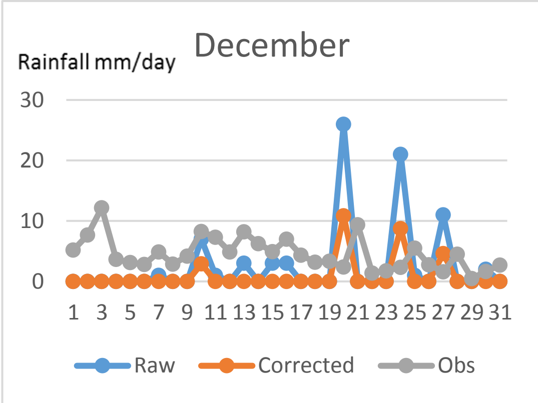


Figure 4.14: Simulated results after treated by LOCI from January to December for 1975

Table 4.7: Correction factor of LOCI for TEM

Month	Observe	Raw	Corrected
January	8.977	3.016	0.000
February	10.641	5.622	6.370
March	14.191	7.230	6.550
April	14.161	7.783	5.578
May	11.699	6.113	6.150
June	11.667	5.937	5.772
July	11.081	5.273	7.083
August	12.746	6.229	6.693
September	12.170	7.134	5.319
October	13.634	7.769	5.647
November	13.816	8.601	5.458
December	10.828	7.346	4.349

4.4 Generated treatment

4.4.1 Application of LS for future period 2040 to 2069

LS is applied to treat the bias between the simulation rainfall data and the generated data from GCM. It is because, only LS can treat monthly precipitation for historical data. The accurateness of LS treatment make the projection of future rainfall trend is reliable. As compared the result between simulation data (1982-2011) for LP and GCM projection data, it can be seen that there is bias and error occurred. Same goes to TEM which the bias between simulation data (1975-2004) and GCM projection data produce too much error. LS give a good performance in correcting those biases. Figure 4.15 and figure 4.16 showed how LS treat the projection of rainfall trend for both LP and TEM.

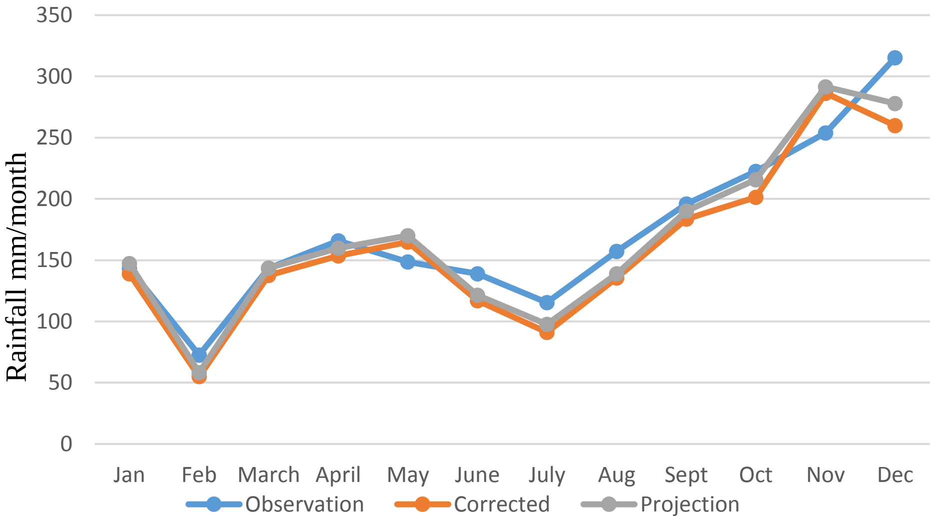


Figure 4.15: Application of LS for rainfall projection in LP

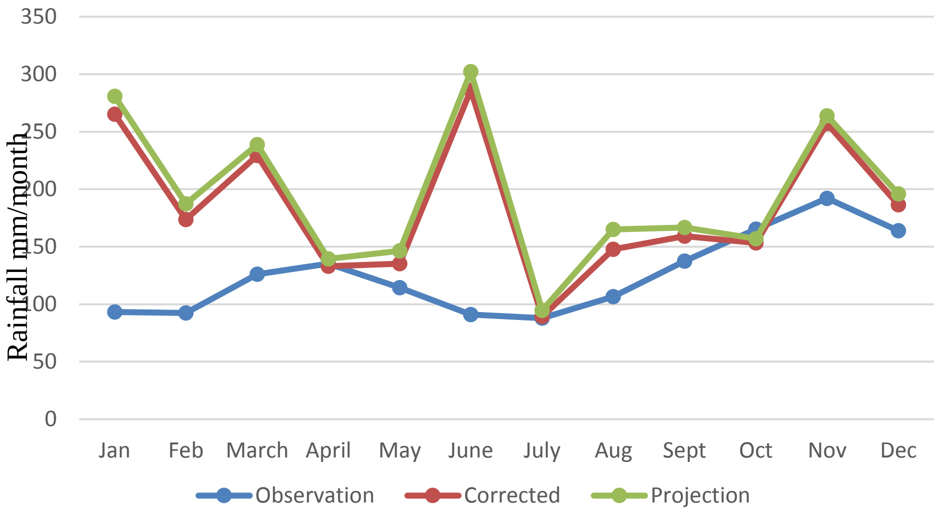


Figure 4.16: Application of LS for rainfall projection in TEM

From the graph above, it is clearly seen that the bias between those data from simulation and GCM had been corrected by using LS. LS correct the bias until no error need to be calculated.

In the last decade, several bias correction methods have been proposed to downscale climate model outputs (usually precipitation and temperature), and ultimately, for use in assessing climate change impacts. This study evaluates and compares the performance of two bias correction methods for two hydrological stations which are LP and TEM. The performance is based on the ability to reproduce precipitation with the use of a hydrology model. The performance for precipitation simulation depends on the choice of a bias correction method. LS is the simplest bias correction method, which adjusts monthly mean precipitation. It can be clearly seen that LS perform very well in correcting the bias of calibration and validation rainfall from SDSM analysis. It is obvious that LS reduce the error form those historical data and simulation data as well as GCM data.

CHAPTER 5

CONCLUSION

5.1 Conclusion

This study evaluated the performance of two bias correction methods in reproducing precipitation in two hydrological stations which are LP and TEM. The performance of these bias correction methods was assessed via their correction of SDSM simulated precipitation driven by NCEP reanalysis data. The following conclusions can be drawn:

SDSM simulated daily precipitation is always biased which precludes its direct use with hydrological models. The direct use of SDSM data with a specific calibration of the hydrological model somewhat improves the hydrological simulation, indicating bias can be overcome by the hydrological model.

LS bias correction methods are able to improve the SDSM simulated precipitation. Performance depends on the choice of a correction method. Bias correction methods will be invalid if the temporal structure of precipitation is not well-reproduced by the climate models, especially at the daily scale. This is more likely to happen when less forcing is exerted on the climate model, in flatter regions or away from the model computational boundaries. This problem should be less severe in snow-dominated regions because the winter hydrology is less sensitive to the precipitation occurrence and mostly conditioned on temperature, which is much better simulated by climate models than precipitation (Shicklomanov, and E. Stakhiv, 2001). While for LOCI, the ability of this bias correction method is only for predict daily rainfall/precipitation not for monthly basis. The performance of LOCI in correcting the daily precipitation is quite satisfying.

Bias correction methods should be validated over the “recent past” prior to any climate change impact study. If such a validation is not possible, impact studies should rely on simpler methods that correct the observed time series. Finally, this study further emphasizes the importance of using several climate models and bias correction methods to include the overall uncertainty for hydrological impact studies. In particular, for climate change impact studies, the use of only one model or method could give misleading results.

5.2 Recommendation

This study showed and evaluated the performances of two bias correction method to correct precipitation of hydrological stations. Both bias correction methods which are LS and LOCI has its own advantages and disadvantages. However, they help in treating the bias comes from the hydrological model. But it really recommended for further studies to evaluate the other bias correction method available in hydrological field to get most reliable result in predicting the climate. Other bias correction methods that available to correct the bias are daily translation, daily bias correction and quantile mapping based on empirical distribution.

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APPENDIX A

Calibrate rainfall for LP			
Month	ob-82 lubuk paku.TXT : Mean	mo-82 lubuk paku.TXT : Mean	MAE (%)
Jan	135.050	137.938	2.1
Feb	72.691	77.297	6.3
March	136.633	143.947	5.4
April	171.139	166.106	2.9
May	152.372	149.794	1.7
June	141.382	141.480	0.1
July	108.853	117.096	7.6
Aug	153.706	157.986	2.8
Sept	191.018	198.552	3.9
Oct	219.292	222.239	1.3
Nov	279.235	256.475	8.2
Dec	314.754	284.816	9.5

Validate rainfall for LP			
Month	ob-99 lubuk paku.TXT : Mean	mo-99 lubuk paku.TXT : Mean	MAE (%)
Jan	174.50	150.43	13.8
Feb	82.58	66.41	19.6
March	166.69	142.76	14.4
April	174.36	165.36	5.2
May	155.22	147.25	5.1
June	147.85	135.43	8.4
July	142.35	112.94	20.7
Aug	170.65	155.91	8.6
Sept	218.42	192.52	11.9
Oct	263.10	222.65	15.4
Nov	231.31	250.51	8.3
Dec	366.25	354.99	3.1

APPENDIX B

Calibrate rainfall for TEM			
Month	ob-75 temerloh.TXT : Mean	mo-75 temerloh.TXT : Mean	MAE (%)
Jan	71.067	89.264	25.6
Feb	96.467	95.674	0.8
March	137.467	130.565	5.0
April	162.533	143.687	11.6
May	130.867	111.982	14.4
June	80.067	86.124	7.6
July	109.800	91.584	16.6
Aug	112.867	104.484	7.4
Sept	143.000	146.977	2.8
Oct	174.933	164.955	5.7
Nov	182.200	192.094	5.4
Dec	138.600	156.335	12.8

Validate rainfall for TEM			
Month	ob-90 temerloh.TXT : Mean	mo-90 temerloh.TXT : Mean	MAE (%)
Jan	126.400	97.147	23.1
Feb	102.667	89.063	13.3
March	125.000	121.361	2.9
April	120.867	126.938	5.0
May	116.533	116.650	0.1
June	112.133	95.905	14.5
July	76.667	84.237	9.9
Aug	124.933	108.701	13.0
Sept	144.733	127.923	11.6
Oct	163.600	165.695	1.3
Nov	211.600	192.210	9.2
Dec	206.267	171.545	16.8

APPENDIX C

Simulated and projection result for LP		
Month	Observation	Projection
Jan	143.352	147.345
Feb	72.580	58.267
March	143.435	143.585
April	165.783	159.925
May	148.691	170.134
June	138.857	121.352
July	115.295	97.539
Aug	157.088	138.989
Sept	195.938	190.212
Oct	222.417	215.801
Nov	253.889	291.503
Dec	315.224	277.810

Simulated and projection result for TEM		
Month	Observation	Projection
Jan	93.205	280.829
Feb	92.369	187.238
March	125.963	238.908
April	135.313	139.392
May	114.316	146.325
June	91.014	302.189
July	87.910	94.675
Aug	106.592	164.919
Sept	137.450	166.645
Oct	165.325	157.015
Nov	192.152	263.925
Dec	163.940	196.017

APPENDIX D

Corrected result for calibrated period for LP using LS				
Month	Raw	Corrected	Obs	MAE (%)
Jan	135.05	127.2447	137.9379	5.779595
Feb	72.69118	68.54035	77.29738	5.710224
March	136.6329	130.9506	143.9469	4.158851
April	171.1394	164.4411	166.1064	3.913964
May	152.3724	147.4961	149.7937	3.200251
June	141.3824	136.1599	141.4797	3.693834
July	108.8529	101.7306	117.0961	6.543082
Aug	153.7059	149.9243	157.9863	2.460277
Sept	191.0176	184.469	198.5525	3.428316
Oct	219.2918	204.698	222.2392	6.654953
Nov	279.2353	274.2894	256.4745	1.771228
Dec	314.7535	294.3548	284.8164	6.480856

Corrected result for calibrated period for LP				
Month	Raw	Corrected	Obs	MAE (%)
Jan	135.05	127.2447	137.9379	5.779595
Feb	72.69118	68.54035	77.29738	5.710224
March	136.6329	130.9506	143.9469	4.158851
April	171.1394	164.4411	166.1064	3.913964
May	152.3724	147.4961	149.7937	3.200251
June	141.3824	136.1599	141.4797	3.693834
July	108.8529	101.7306	117.0961	6.543082
Aug	153.7059	149.9243	157.9863	2.460277
Sept	191.0176	184.469	198.5525	3.428316
Oct	219.2918	204.698	222.2392	6.654953
Nov	279.2353	274.2894	256.4745	1.771228
Dec	314.7535	294.3548	284.8164	6.480856

APPENDIX E

Corrected result for validated period for LP using LS				
Month	Raw	Corrected	Obs	MAE (%)
Jan	174.5	164.4146	150.4311	5.779595
Feb	82.57692	77.8616	66.41009	5.710224
March	166.6923	159.7598	142.7646	4.158851
April	174.3615	167.5371	165.3593	3.913964
May	155.22	150.2526	147.248	3.200251
June	147.8462	142.385	135.4283	3.693834
July	142.3462	133.0323	112.9389	6.543082
Aug	170.6538	166.4553	155.9127	2.460277
Sept	218.4231	210.9348	192.5179	3.428316
Oct	263.0962	245.5872	222.6487	6.654953
Nov	231.3077	227.2107	250.5071	1.771228
Dec	366.25	342.5139	354.9871	6.480856

Corrected result for calibrated period for TEM using LS				
Month	Raw	Corrected	Obs	MAE (%)
Jan	71.07	67.09	89.26	5.598785
Feb	96.47	89.49	95.67	7.229494
March	137.47	131.95	130.56	4.016053
April	162.53	155.21	143.69	4.507622
May	130.87	120.94	111.98	7.586203
June	80.07	75.83	86.12	5.292334
July	109.80	103.53	91.58	5.709367
Aug	112.87	101.18	104.48	10.35144
Sept	143.00	136.62	146.98	4.460287
Oct	174.93	170.72	164.96	2.409118
Nov	182.20	177.47	192.09	2.596174
Dec	138.60	131.77	156.33	4.925672

APPENDIX F

Corrected result for validated period for TEM using LS				
Month	Raw	Corrected	Obs	MAE (%)
Jan	126.4	119.323136	97.14653	5.598785
Feb	102.6667	95.2443857	89.06307	7.229494
March	125	119.979934	121.3612	4.016053
April	120.8667	115.418455	126.9382	4.507622
May	116.5333	107.692878	116.65	7.586203
June	112.1333	106.198862	95.90453	5.292334
July	76.66667	72.2894852	84.23673	5.709367
Aug	124.9333	112.00093	108.7006	10.35144
Sept	144.7333	138.277811	127.9227	4.460287
Oct	163.6	159.658683	165.6952	2.409118
Nov	211.6	206.106496	192.2096	2.596174
Dec	206.2667	196.106648	171.545	4.925672

APPENDIX G

Corrected result using LOCI from January to December for LP

Jan			
Day	Raw	Corrected	Obs
1	0	0	2.7094
2	0	0	3.3769
3	25.5	9.31	1.7579
4	0	0.00	2.7293
5	0	0.00	1.1774
6	0	0.00	2.0753
7	0	0.00	1.41095
8	16	5.84	1.92705
9	0	0.00	0
10	0	0.00	0.2468
11	0	0.00	1.5359
12	0	0.00	0.86725
13	0	0.00	0.3976
14	36.5	13.32	2.3121
15	0	0.00	0.50655
16	0	0.00	0.48385
17	0	0.00	0.54375
18	0	0.00	4.161
19	0	0.00	0.44485
20	0	0.00	1.35535
21	0	0.00	0.8118
22	0	0.00	3.64225
23	0	0.00	0.91585
24	0	0.00	5.33355
25	0	0.00	1.5727
26	0	0.00	2.5989
27	0	0.00	3.81815
28	11.5	4.20	3.4545
29	6.7	2.45	2.91215
30	6.7	2.45	2.48285
31	6.7	2.45	2.4614

Feb			
Day	Raw	Corrected	Obs
1	0	0	2.52795
2	0	0	4.93285
3	0	0	2.5574
4	0	0	1.30245
5	0	0	2.4459
6	0	0	0
7	0	0	0.02505
8	0	0	1.8633
9	0	0	2.6721
10	0	0	1.60675
11	0	0	2.8303
12	0	0	1.1734
13	0	0	0.82265
14	0	0	0.2672
15	0	0	2.65065
16	0	0	0.3093
17	0	0	0.31285
18	5	1.18286779	1.8222
19	0	0	1.6253
20	0	0	3.5769
21	0	0	4.2988
22	0	0	1.19495
23	0	0	0.9301
24	0	0	6.35075
25	0	0	1.8429
26	8.5	2.01087524	0.6255
27	0	0	2.86885
28	0	0	6.1046

APPENDIX H

March			
Day	Raw	Corrected	Obs
1	0	0	4.94185
2	0	0	3.8465
3	0	0	3.0884
4	0	0	3.22015
5	0	0	3.7431
6	0	0	1.05795
7	0	0	3.2788
8	0	0	5.8879
9	0	0	6.6194
10	0	0	14.8169
11	0	0	5.46065
12	18.5	5.25156479	5.16595
13	0	0	5.0479
14	0	0	4.4634
15	0	0	3.26985
16	0	0	3.64795
17	0	0	5.08495
18	0	0	7.1739
19	0	0	2.34135
20	0	0	6.9079
21	0	0	1.78285
22	5	0	1.99085
23	0	0	2.4644
24	0	0	0.5111
25	0	0	3.3448
26	0	0	3.1777
27	0	0	3.7371
28	10	2.83868367	2.3376
29	0	0	7.27425
30	0	0	1.0798
31	0	0	4.18045

April			
Day	Raw	Corrected	Obs
1	0	0	4.2892
2	38.5	11.7090251	2.03795
3	0	0	5.3253
4	34	10.3404378	8.96735
5	0	0	4.74775
6	16.5	5.01815362	7.9413
7	0	0	3.9758
8	0	0	4.77195
9	12.5	3.80163153	7.27915
10	0	0	8.9297
11	0	0	7.9768
12	0	0	4.1241
13	0	0	2.14215
14	14.5	4.40989257	3.51425
15	0	0	7.5756
16	10	3.04130522	3.2054
17	0	0	6.16415
18	0	0	6.50165
19	13.5	4.10576205	13.5715
20	0	0	2.5243
21	0	0	4.0619
22	0	0	4.58425
23	0	0	4.1182
24	0	0	4.99235
25	0	0	5.03355
26	38.5	11.7090251	5.7458
27	4.4	0	9.0055
28	4.4	0	5.85365
29	4.4	0	3.66915
30	4.4	0	11.06795

APPENDIX 1

May			
Day	Raw	Corrected	Obs
1	0	0	0.89875
2	0	0	0.9775
3	25	8.52660483	1.9535
4	0	0	5.8584
5	0	0	2.9001
6	20	6.82128386	5.23335
7	0	0	6.5364
8	0	0	4.91135
9	35.5	12.1077789	9.55285
10	0	0	5.55765
11	0	0	5.0665
12	15.5	5.28649499	7.32895
13	0	0	4.84205
14	0	0	4.31805
15	0	0	4.47545
16	0	0	7.57265
17	0	0	1.93345
18	0	0	4.4033
19	0	0	3.94455
20	0	0	2.3588
21	0	0	5.23735
22	11	3.75170612	4.58715
23	0	0	4.93605
24	0	0	12.9614
25	0	0	5.1163
26	0	0	4.1129
27	0	0	3.9573
28	0	0	4.4515
29	0	0	6.6992
30	0	0	6.2402
31	0	0	3.60685

June			
Day	Raw	Corrected	Obs
1	0	0	2.76685
2	0	0	3.4365
3	0	0	1.5289
4	0	0	3.59995
5	0	0	5.49275
6	0	0	4.4298
7	0	0	7.94355
8	0	0	2.86885
9	23.5	6.30993047	7.1033
10	0	0	8.13105
11	0	0	3.8174
12	0	0	6.0503
13	0	0	5.0705
14	0	0	3.1788
15	0	0	3.38125
16	0	0	8.5851
17	0	0	1.85605
18	0	0	4.87915
19	0	0	10.876
20	0	0	4.5811
21	0	0	5.70055
22	0	0	1.56585
23	0	0	3.9402
24	0	0	3.0026
25	0	0	5.62395
26	11.5	3.08783832	6.38725
27	0	0	1.73515
28	0	0	4.28355
29	0	0	5.13245
30	0	0	3.3296

APPENDIX J

July			
Day	Raw	Corrected	Obs
1	0	0	5.96425
2	0	0	4.205
3	0	0	7.7869
4	0	0	0.4515
5	0	0	1.22305
6	0	0	3.1897
7	27.5	6.871304	5.48335
8	0	0	3.18235
9	0	0	3.3552
10	0	0	3.0538
11	0	0	1.04055
12	0	0	4.71835
13	0	0	3.69245
14	0	0	0.6309
15	0	0	1.56915
16	0	0	2.8683
17	11	2.748522	0.153
18	0	0	2.70315
19	0	0	4.06485
20	0	0	2.82015
21	0	0	3.45665
22	0	0	0.8385
23	0	0	6.33645
24	0	0	6.38295
25	0	0	2.06525
26	0	0	3.1477
27	0	0	1.99165
28	0	0	1.0577
29	0	0	2.2077
30	0	0	1.0153
31	0	0	2.98865

Aug			
Day	Raw	Corrected	Obs
1	0	0	5.96665
2	12.5	4.002286	6.3693
3	0	0	2.7845
4	0	0	4.9625
5	16.5	5.283017	3.3224
6	0	0	1.95355
7	0	0	7.741
8	0	0	8.46695
9	0	0	0.18155
10	34	10.88622	4.63275
11	0	0	1.58685
12	0	0	6.9301
13	0	0	4.16795
14	0	0	6.09475
15	0	0	9.4724
16	0	0	4.049
17	42	13.44768	8.29025
18	0	0	8.21565
19	0	0	5.9597
20	0	0	4.3685
21	0	0	2.70625
22	0	0	6.0746
23	0	0	5.1141
24	36.5	11.68667	2.24075
25	0	0	1.52965
26	0	0	2.16535
27	0	0	5.4943
28	0	0	1.84555
29	22.5	7.204114	2.22555
30	0	0	7.14545
31	0	0	4.4295

APPENDIX K

Sept			
Day	Raw	Corrected	Obs
1	0	0	3.76225
2	0	0	13.115
3	0	0	4.03035
4	0	0	5.10105
5	0	0	6.6968
6	35.5	12.28831	5.59245
7	0	0	8.25855
8	0	0	4.6997
9	42	14.53828	11.59755
10	0	0	5.8222
11	0	0	5.8561
12	0	0	2.28965
13	0	0	6.0041
14	0	0	15.18815
15	0	0	3.21925
16	0	0	2.52415
17	0	0	9.1575
18	0	0	6.96745
19	0	0	6.5285
20	0	0	12.0397
21	0	0	5.13715
22	23.5	8.134515	12.6571
23	0	0	5.7594
24	0	0	7.3981
25	0	0	7.02635
26	14.5	5.019169	10.34765
27	4.1	0	3.67855
28	4.1	0	5.19615
29	4.1	0	8.995
30	4.1	0	9.724

Oct			
Day	Raw	Corrected	Obs
1	0	0	11.43405
2	0	0	2.59465
3	20	8.190333	7.1743
4	0	0	7.02035
5	11.5	4.709441	12.1701
6	0	0	15.2216
7	17.5	7.166541	5.638
8	0	0	3.48005
9	0	0	6.56275
10	0	0	11.75565
11	0	0	7.89745
12	0	0	5.64235
13	0	0	7.63225
14	22.5	9.214124	7.05245
15	0	0	8.24395
16	0	0	4.2249
17	0	0	10.342
18	36	14.7426	9.9072
19	0	0	4.35575
20	0	0	6.42785
21	20.5	8.395091	9.8996
22	0	0	12.32495
23	0	0	7.6891
24	0	0	8.45025
25	0	0	5.8128
26	0	0	7.49135
27	0	0	5.29635
28	38.5	15.76639	6.97415
29	0	0	3.78415
30	0	0	4.84645
31	0	0	4.424

APPENDIX L

Nov			
Day	Raw	Corrected	Obs
1	12.5	6.041825	7.2224
2	0	0	7.67265
3	16	7.733537	8.2235
4	0	0	7.6543
5	0	0	12.77275
6	34.5	16.67544	7.4832
7	0	0	5.54695
8	0	0	10.97265
9	42.5	20.54221	7.0356
10	0	0	16.6572
11	0	0	11.0922
12	36	17.40046	6.0513
13	0	0	9.06535
14	0	0	1.73275
15	0	0	7.04945
16	18.5	8.941902	6.3194
17	0	0	5.6247
18	0	0	5.5401
19	0	0	7.55425
20	20	9.666921	10.59035
21	0	0	8.9818
22	0	0	10.49435
23	0	0	5.5616
24	0	0	6.70335
25	0	0	14.08495
26	0	0	5.0378
27	0	0	7.6163
28	45.5	21.99224	11.74505
29	15	7.250191	6.9161
30	15	7.250191	7.5329

Dec			
Day	Raw	Corrected	Obs
1	0	0	10.40805
2	0	0	13.11745
3	0	0	9.25695
4	16.5	7.4834	5.78275
5	0	0	14.3003
6	11.5	5.215703	8.13545
7	0	0	15.24505
8	0	0	11.7864
9	17.5	7.936939	8.70205
10	0	0	14.55325
11	0	0	12.79865
12	12.5	5.669242	15.2975
13	0	0	15.5981
14	0	0	7.92025
15	0	0	10.27575
16	0	0	13.7011
17	36	16.32742	15.80505
18	0	0	10.20925
19	0	0	9.6953
20	0	0	10.6791
21	0	0	7.26465
22	0	0	8.1467
23	0	0	14.44695
24	18.5	8.390479	13.15575
25	0	0	5.0168
26	0	0	6.3555
27	0	0	9.55885
28	20.5	9.297557	7.46895
29	0	0	7.4899
30	11.5	5.215703	9.4591
31	0	0	5.46785

APPENDIX M

Corrected result using LOCI from January to December for TEM

Jan			
Day	Raw	Corrected	Obs
1	0	0	4.41
2	10	2.787641	4.304
3	0	0	6.174
4	32	8.920452	7.122
5	7	1.951349	3.474
6	0	0	6.073
7	0	0	1.702
8	37	10.31427	2.457
9	1	0	2.174
10	0	0	2.759
11	36	10.03551	4.352
12	0	0	1.662
13	0	0	2.408
14	2	0	5.587
15	0	0	1.947
16	24	6.690339	2.412
17	0	0	3.997
18	0	0	2.105
19	0	0	3.065
20	1	0	1.501
21	1	0	2.44
22	1	0	2.671
23	1	0	2.55
24	0	0	0.934
25	0	0	2.15
26	0	0	3.456
27	0	0	2.198
28	0	0	1.264
29	0	0	0.2
30	0	0	1.084
31	1	0	5.024

Feb			
Day	Raw	Corrected	Obs
1	1	0	2.63
2	11	3.049203	7.928
3	0	0	3.209
4	1	0	3.752
5	16	4.435205	1.922
6	0	0	3.861
7	1	0	2.98
8	1	0	5.682
9	0	0	7.693
10	29	8.038808	4.603
11	1	0	2.761
12	0	0	0.552
13	0	0	5.211
14	0	0	0.709
15	19	5.266805	6.002
16	0	0	3.926
17	0	0	4.773
18	0	0	4.667
19	0	0	2.343
20	0	0	2.037
21	0	0	2.279
22	10	2.772003	2.441
23	47	13.02841	3.358
24	13	3.603604	4.304
25	6	1.663202	3.217
26	21	5.821206	0.582
27	0	0	6.065
28	1	0	5.684

APPENDIX N

March			
Day	Raw	Corrected	Obs
1	0	0	3.804
2	7	1.417579	2.927
3	5	0	3.925
4	5	0	1.16
5	0	0	1.49
6	0	0	3.815
7	22	4.455247	0.982
8	12	2.430135	3.017
9	9	1.822601	3.756
10	0	0	2.768
11	0	0	3.823
12	0	0	5.329
13	0	0	0.986
14	0	0	4.732
15	0	0	5.609
16	0	0	1.938
17	2	0	4.438
18	1	0	10.613
19	0	0	6.184
20	161	32.60431	1.655
21	33	6.682871	2.994
22	27	5.467804	5.936
23	0	0	8.743
24	0	0	5.194
25	3	0	2.439
26	31	6.277848	4.45
27	0	0	6.089
28	0	0	9.778
29	0	0	4.467
30	0	0	5.894
31	1	0	6.823

APPENDIX O

April			
Day	Raw	Corrected	Obs
1	0	0	17.346
2	0	0	4.903
3	5	0	5.644
4	16	3.53238	9.295
5	0	0	7.72
6	47	10.37637	7.446
7	54	11.92178	10.968
8	0	0	7.482
9	0	0	2.562
10	0	0	2.302
11	0	0	6.27
12	0	0	4.945
13	15	3.311606	6.062
14	5	0	5.245
15	10	2.207737	5.199
16	29	6.402438	3.769
17	4	0	6.678
18	2	0	17.782
19	8	1.76619	1.705
20	0	0	4.604
21	2	0	10.304
22	0	0	7.639
23	0	0	1.803
24	1	0	1.502
25	7	1.545416	3.076
26	32	7.06476	0.502
27	0	0	0.857
28	0	0	6.005
29	0	0	8.452
30	1	0	0.65

APPENDIX P

May			
Day	Raw	Corrected	Obs
1	13	2.929248	1.635
2	1	0	1.974
3	0	0	4.924
4	0	0	6.332
5	0	0	4.549
6	7	1.577287	2.197
7	0	0	1.669
8	1	0	2
9	2	0	4.715
10	1	0	1.452
11	4	0	4.276
12	0	0	0.67
13	0	0	3.832
14	16	3.605228	4.064
15	5	1.126634	3.718
16	0	0	5.997
17	11	2.478595	3.584
18	0	0	4.674
19	0	0	2.863
20	4	0	3.371
21	4	0	3.389
22	0	0	3.475
23	0	0	3.189
24	0	0	2.041
25	0	0	3.261
26	41	9.238398	1.542
27	0	0	5.803
28	0	0	10.224
29	0	0	3.698
30	0	0	1.553
31	1	0	1.968

APPENDIX Q

June			
Day	Raw	Corrected	Obs
1	6	1.307476	1.482
2	0	0	0.649
3	2	0	3.258
4	0	0	1.25
5	0	0	2.603
6	12	2.614952	1.148
7	0	0	0.787
8	0	0	3.486
9	19	4.140341	1.503
10	2	0	3.433
11	0	0	1.976
12	1	0	1.207
13	0	0	2.595
14	0	0	3.962
15	0	0	2.564
16	5	1.089563	2.073
17	0	0	0.569
18	0	0	0.799
19	0	0	0.431
20	4	0	6.53
21	0	0	1.9
22	0	0	2.795
23	0	0	0.213
24	0	0	0.061
25	0	0	0.341
26	0	0	5.389
27	0	0	1.541
28	0	0	0.478
29	17	3.704516	1.961
30	0	0	0.399

APPENDIX R

July			
Day	Raw	Corrected	Obs
1	0	0	1.143
2	0.000	0.000	4.559
3	0.000	0.000	0.474
4	1.000	0.000	4.018
5	0.000	0.000	3.723
6	1.000	0.000	2.533
7	2.000	0.000	2.875
8	0.000	0.000	2.378
9	18.000	3.447	3.044
10	0.000	0.000	2.144
11	0.000	0.000	5.188
12	1.000	0.000	3.526
13	9.000	1.724	3.087
14	0	0	4.11
15	0	0	1.255
16	0	0	4.9
17	4	0.7660121	2.383
18	0	0	2.821
19	20	3.8300605	3.697
20	2	0	0.611
21	0	0	1.286
22	7	1.3405212	3.461
23	0	0	2.695
24	0	0	2.528
25	7	1.3405212	1.521
26	1	0	4.176
27	27	5.1705817	5.475
28	0	0	0.913
29	11	2.1065333	3.074
30	0	0	6.154
31	0	0	1.511

APPENDIX S

Aug			
Day	Raw	Corrected	Obs
1	0	0	1.247
2	0	0	3.643
3	0	0	3.134
4	0	0	3.15
5	0	0	3.068
6	0	0	2.042
7	4	0	4.031
8	0	0	3.998
9	0	0	11.477
10	0	0	0.151
11	2	0	3.58
12	0	0	1.689
13	75	14.663568	2.98
14	1	0	4.859
15	0	0	0.774
16	0	0	6.101
17	2	0	3.744
18	2	0	1.998
19	0	0	6.803
20	0	0	2.111
21	0	0	1.1
22	0	0	3.595
23	28	5.4743988	1.111
24	0	0	2.128
25	0	0	2.202
26	0	0	2.149
27	1	0	3.554
28	15	2.9327137	3.717
29	0	0	6.055
30	0	0	13.34
31	8	1.564114	5.608

APPENDIX T

Sept			
Day	Raw	Corrected	Obs
1	0	0	3.084
2	0	0	3.606
3	0	0	7.218
4	0	0	3.534
5	2	0	1.649
6	0	0	3.778
7	0	0	8.888
8	18	5.1163434	7.437
9	28	7.9587564	8.895
10	3	0	4.673
11	22	6.2533086	4.062
12	1	0	7.6
13	0	0	5.56
14	11	3.1266543	4.764
15	0	0	9.629
16	3	0	8.997
17	0	0	6.619
18	6	1.7054478	4.958
19	3	0	1.863
20	0	0	9.85
21	0	0	1.784
22	0	0	2.124
23	0	0	1.428
24	3	0	3.178
25	23	6.5375499	3.886
26	0	0	5.79
27	0	0	2.337
28	0	0	9.192
29	0	0	3.198
30	0	0	7.007

APPENDIX U

Oct			
Day	Raw	Corrected	Obs
1	0	0	5.979
2	3	0	9.445
3	0	0	8.618
4	0	0	5.411
5	0	0	1.864
6	0	0	2.983
7	8	2.5564625	2.548
8	67	21.410373	5.107
9	1	0	9.934
10	0	0	12.392
11	0	0	2.695
12	0	0	4.916
13	0	0	4.596
14	0	0	3.871
15	7	2.2369046	5.925
16	0	0	8.639
17	1	0	6.886
18	24	7.6693874	4.161
19	10	3.1955781	0.368
20	0	0	6.615
21	9	2.8760203	7.856
22	1	0	4.368
23	16	5.1129249	4.728
24	0	0	4.014
25	0	0	5.237
26	1	0	4.774
27	0	0	4.064
28	0	0	3.591
29	67	21.410373	6.608
30	0	0	8.25
31	0	0	10.385

APPENDIX V

Nov			
Day	Raw	Corrected	Obs
1	0	0	5.381
2	0	0	9.663
3	3	0	6.033
4	0	0	5.97
5	0	0	5.199
6	0	0	2.262
7	0	0	9.144
8	0	0	10.112
9	3	0	6.834
10	20	7.1501614	10.318
11	5	0	8.204
12	0	0	8.589
13	0	0	8.227
14	1	0	5.553
15	3	0	7.231
16	0	0	6.073
17	1	0	4.473
18	0	0	9.201
19	29	10.367734	7.034
20	3	0	5.447
21	31	11.08275	2.961
22	0	0	4.287
23	0	0	11.325
24	0	0	7.268
25	0	0	3.678
26	0	0	5.889
27	0	0	4.027
28	4	0	5.191
29	15	5.3626211	5.869
30	4	0	8.457

APPENDIX W

Dec			
Day	Raw	Corrected	Obs
1	0	0	5.173
2	0	0	7.666
3	0	0	12.188
4	0	0	3.678
5	0	0	3.106
6	0	0	2.801
7	1	0	4.873
8	0	0	2.85
9	0	0	4.158
10	7	2.9153065	8.253
11	1	0	7.299
12	0	0	4.865
13	3	0	8.2
14	0	0	6.256
15	3	0	4.915
16	3	0	6.978
17	0	0	4.328
18	0	0	3.17
19	0	0	3.33
20	26	10.828281	2.369
21	0	0	9.389
22	0	0	1.377
23	0	0	1.751
24	21	8.7459196	2.324
25	1	0	5.526
26	0	0	2.739
27	11	4.581196	1.567
28	0	0	4.485
29	0	0	0.498
30	2	0	1.623
31	0	0	2.698