POTENTIAL IMPACTS OF CLIMATE CHANGE ON WATER RESOURCES IN LOMBOK, INDONESIA

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POTENTIAL IMPACTS OF CLIMATE CHANGE ON WATER RESOURCES IN LOMBOK, INDONESIA

By

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ABSTRACT

Climate change is an issue of current debate around the world. The changes of climatic conditions are evidenced by changes in temperatures and precipitations that may lead to increased risks of floods, droughts, food shortages, diseases, and species extinction. Lombok, a small island in Indonesia and a part of the Nusa Tenggara Barat (NTB) Province, is predicted to suffer extensively in various ways due to climate change. To study the impacts of climate change on water resources on Lombok Island, the Jangkok River with a drainage area of approximately 180 km² has been chosen as a representative catchment for a case study. To date, no research has been conducted in this region to better understand the myriad of climate change impacts especially as it relates to the Island's water resources. In light of these challenges, this thesis aims to address the following five major objectives which are all related to the potential impacts of climate change on Lombok Island, Indonesia: (1) to develop a new downscaling model to provide a higher quality of finer resolution simulated local climatic variables, (2) to modify the commonly used Non Recorded Catchment Area (NRECA) rainfall-runoff model to take climate change into account, (3) to develop a new water index criterion to provide a more accurate assessment of water balance, (4) to develop a water balance optimization model based on the new water index criterion developed in the third objective for water balance assessment of the Jangkok River Basin in Lombok Island, Indonesia for climate change scenarios in the future, and (5) to recommend agriculture and animal farm development policies based on optimum consumptive water uses to sustain future water resources in Lombok due to likely climate change scenarios in Lombok.

Required data for this research included historical local runoff, rainfall, and climatic data as well as GCM outputs from CGCM2, CSIRO-mk2, and NIES99. Regarding the first objective, results showed that the new downscaling model proposed which is based on a **hy**brid of **a**lgebraic and **s**tochastic approaches (called the HYAS model) is superior to currently used methods. The HYAS model which incorporates multiple variables, successfully simulated realistic values and reproduced changing variance of predicted local hydrological and climatic variables. It is found that impacts of climate change on water resources in the Jangkok River Basin in future include: increases in air humidity, rainfall, as well as air temperature; but decreases in sunshine duration and evapotranspiration. For the second objective, the NRECA model was successfully modified to incorporate climate change in its model input so that it can be used to evaluate the impacts of climate change on the future water availability of the Jangkok River Basin. For the third objective, a new and more realistic water index criterion called the Remaining Water Index Criterion (*RWI*) which takes minimum water services and the priority of water uses into account was successfully developed to replace the Critical Water Index (*CWI*), the current criterion, to assess the future water balance of the Jangkok River Basin. Regarding the fourth objective, a water balance optimization model was successfully developed using a Response Surface Methodology (*RSM*) based on Central Composite Design (*CCD*). This model applied the *RWI* criterion. For the final objective, the optimization analysis showed that the population growth rate will be a significant factor in the water balance status after 2050 but the area of agricultural farm development will become a less significant factor in the water balance of the basin after 2080 due to less agricultural water demands and more abundance of water. The development of livestock farms is not a significant factor of the water balance model. Therefore, it is suggested that the Government of NTB Province should: 1) pay more attention to the population growth rate and to strictly maintain the rate at a level of 1.5 % or less from now; 2) keep the area of agricultural farms at the level of 51 % of the total land or 2295 ha until 2050. This agricultural farm can be developed to approximately 55 % of the total land or 2475 ha from 2051 to 2080. It can be further developed in 2081 to approximately 67% or 3000 ha, and finally approximately 81% or 3645 ha can be developed in 2100; and keep the development of livestock farms at a level of 2 % per year.

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Statement of Originality

The originality and scientific contributions of this research can be summarised as follows:

(1) In downscaling modeling, a new model was developed based on a hybrid of algebraic and stochastic approaches. This technique was developed to enhance the performance of currently available approaches. Results showed that the proposed technique is superior to the currently available approaches.

(2) The Non Recorded Catchment Area (NRECA) model, a well-known rainfall-runoff model in Indonesia was successfully modified to take climate change effects into account to simulate future local runoffs. The NRECA model was originally developed with the assumption that climate variables do not change in future.

(3) An improved water assessment criterion was proposed to enhance the performance of water balance assessments. This new and more accurate water index criterion was developed based on the amount of remaining water and the priorities of water demands to meet future water demands that was not accounted for in the currently used index.

(4) The impacts of climate change on water resources on Lombok Island have never been assessed before and this study has provided a better understanding of the impacts of climate change on water resources in the region. This new information will provide the

local government with vital information in their efforts to better prepare for climate change adaptation.

(5) In water balance optimization, a new optimization model for obtaining the best combination of water uses was developed. The model is based on 10-year period evaluations of water balance statuses using a new water index criterion. The optimization was performed using the Response Surface Methodology based on Central Composite Design. The optimization results will be very useful to provide guidance to the Government of NTB Province, on implementation policies of population growth rate as well as agricultural and animal farm developments to sustain the future of water resources under climate change projections in Lombok.

Table of Contents

List of Tables

List of Figures

List of Symbols

A	=	Population Growth Rate (%)
ANN	=	Artificial Neural Networks
B	=	Agricultural Farm Area Development (%)
C	=	Livestock Development (%)
$CCAM$	=	Conformal Cubic Atmospheric Model
$CCCma$	=	Canadian Centre for Climate Modelling and Analysis
CCD	=	Central Composite Design
CF	=	Change Factor Method
CGCM1	=	First Generation Coupled Global Climate Model
CGCM2	=	Second Generation Coupled Global Climate Model
CGCM3	=	Third Generation Coupled Global Climate Model
CGCM4	=	Fourth Generation Coupled Global Climate Model
CSIRO	=	Commonwealth Scientific and Industrial Research Organisation
CWI	=	Critical Water Index
$c^{\#}$	=	Seasonal Factor
DMI	=	Domestic-Municipal-Industry
DR	=	Direct Runoff (mm)
DWD	=	Domestic Drinking Water Demands (lt/day)
DWR	=	Domestic Water Requirement (lt/day/person)
d_1, d_2, d_n	=	Residuals

δ	=	Residual Rescaling Coefficient
ET_c	=	Crop Evapotranspiration = Consumptive Uses (mm/day)
Exm	=	Excess Moisture (mm)
ea	=	Actual Vapour Pressure (mbar)
es	=	Saturation Vapour Pressure (mbar)
ε_i	=	Generated Model Residuals with Changing Mean and Variance
FAO	=	Food and Agriculture Organization
f(GWF)	=	Function of Groundwater Flow (mm)
$f(I)$	=	Function of Infiltration (mm)
$f(O)$	=	Function of Water Uses And Water Release (mm)
$f(P)$	=	Function of Precipitation (mm)
$f(PET)$	=	Function of Evapotranspiration (mm)
$f(u)$	=	Wind Speed Factor (knots, m/sec/, km/hour)
$f(x_i)$	=	Simulated Value
GCM	=	General Circulation Model
GF	=	Base Flow or Groundwater Flow (mm)
GS	=	Groundwater Storage (mm)
GWF	=	Percentage of Groundwater Flows into a River (%)
HYAS	=	Hybrid of Algebraic and Stochastic
H_0	=	Hypothesis
I	=	Infiltration (mm)
IGS	=	Initial Groundwater Storage (mm)

IMS	=	Initial Moisture Storage (mm)
IPCC	=	Intergovernmental Panel on Climate Change
i	=	Simulated Variables
j	=	Baseline Variables
K	=	Standardized GCM Variables Rescaling Coefficient
K_c	=	Crop Coefficients
LP	=	Water Uses at Land Preparation (mm/day)
LP_T	=	Duration for Land Preparation (days)
LWD	=	Livestock Water Demands (lt/day)
LWR	=	Livestock Water Requirement (lt/day)
M	=	Water Required To Maintain Saturation (mm/day)
MS	=	Moisture Storage (mm)
$\mathrm{Med}(Z_{j(i)})$	=	Median of Future Standardized GCM Variables
$\mathrm{Med}(Z_{j(Yi)})$	=	Median of Baseline Standardized GCM Variables
$Med(\hat{Y}_{(i)})$	=	Median of Simulated Local Variables
$\mathrm{Med}(Y_{(i)})$	=	Median of Baseline Local Variables
Mk2	=	Second version of Mark Model
μ_1, μ_2, μ_3	=	Means of Group 1, Group 2, and Group 3
NIES99	=	Climate Change Model developed in 1999 by the National Institute for Environmental Studies
NL	=	Number of Livestock (animal unit)
NRECA	=	Non Recorded Catchment Area

NSE	=	Nash-Sutcliffe Model Efficiency Coefficient
NTB	=	Province of Nusa Tenggara Barat
n	=	Number of Data, the Number of GCM Variables
O	=	Observed Local Variables
$\bar{O}$	=	Mean of Observed Local Variables
P	=	Rainfall (mm)
Pc	=	Percolation (mm/day)
PET	=	Potential Evapotranspiration (mm, mm/day)
Pp	=	Population (person)
$PSUB$	=	Percentage of Water Losses Due To Subsurface Flows (%)
Q	=	Soil Moisture Storage (mm)
RCM	=	Regional Climate Model
R_n	=	Net Radiation (mm/day)
RSM	=	Response Surface Methodology
RWI	=	Remaining Water Index
$Sign[r]$	=	Sign of Correlation
S	=	Simulated Local Variables
Sat	=	Water Required in the Process of Saturation (mm)
σ	=	Standard Deviation of GCM Variables
W	=	Temperature Factor (^{o}C)
X, X_i	=	GCM Variables
X1	=	Mean 2m Wind Speed (m/s)

X2	=	Evaporation (mm/day)
X3	=	Precipitation (mm/day)
X4	=	Screen (2m) Temperature (°C)
X5	=	Screen Specific Humidity (kg/kg)
X6	=	Sea Level Pressure (hPa)
X7	=	Skin (surface) Temperature (°C)
X8	=	Solar Flux at Surface (W/m^2)
X9	=	Surface Pressure (hPa)
$\bar{X}$	=	Average (mean) of GCM Variables
$\hat{Y}_i$	=	Downscaled Local Variable
Y^*_i	=	Calculated Local Variables before Being Added To Generated Residuals
Y_i	=	Baseline Local Variable
Y	=	Local Variables
y_i	=	Observed Variables
Z_i	=	Standardized Values
$Z_{j_{(i)}}$	=	Standardized GCM Variable of *i* in the Next *j* Year (future period)
$Z_{j_{(Yi)}}$	=	Standardized GCM Variable of *i* in the Baseline Period

Chapter 1

Introduction

This study of the possible impacts of climate change on the water resource system of a river basin in Lombok, Indonesia is an effort to support the Government of Nusa Tenggara Barat (NTB) Province, Indonesia, to have the best preparation for the adaptation to climate change in the Province (see letter of support from the Government of NTB Province in Appendix A).

1.1. Background

Recently, many natural disasters around the globe, such as storms, floods and droughts had destroyed residences, dams, roads, bridges, farms and many other facilities and have caused huge of financial losses around the world. These disasters have brought crucial questions as to what factors have triggered, and how to adapt to these disasters. It is believed that some of the recent disasters were related to climate change (Ylvisaker, 2003 and Quaile, 2009).

Many people are concerned about climate change as climate information plays an important role in answering questions such as, how large should agricultural land be developed in a particular basin?, how many hours of wind are required to sustain a wind-driven generator?, and what is the designed height of embankments to protect a town from floods? In the past, designs were based on the assumption that the elements of climate would not change. However, current records of climate and hydrological conditions show that these conditions are currently undergoing changes (IPCC, 2007). Therefore, the designs in the future should allow for the possible effects of climate change.

In water resource studies, designs of water structures are directly dependent on the following climatic information: precipitation, temperature, humidity, wind, net radiation, groundwater, and streamflows. These variables control water availability (Dingman, 2002; Viessman, 2003; Tallaksen and Van Lanen, 2004; and Majone et al., 2012). Many researchers have attempted to study the implications of climate change on a water resources system through a water balance analysis. Inflows to and outflows from the water balance model, which are the available stream-flows and water uses, respectively, depend on several factors, such as topography, soil properties, hydrometeorologic variables, and types of water uses. In fact, these hydrometeorologic variables are under the influence of climate. It has been reported by IPCC (2007) that climate change will likely affect the annual average, the intensities, and the patterns of precipitation during the 21st century. In addition, according to Brinkman and Sombroek (1996), increasing air temperatures will significantly raise soil temperatures and evaporation which can reduce soil moisture content and this condition will rapidly increase the need for water by vegetation.

In a water balance analysis, water uses are mostly defined as the demand of water from domestic, agricultural farms, and industries. With an increasing population, a changing climate, and the expansion of human activity, water resource management has unique and evolving challenges. These challenges are more obvious as observational records provide abundant evidence of climate change with wide-ranging consequences for human societies and ecosystem predictions. It is reported in IPCC (2007) that about 250 million people across the world are projected to be exposed to increased water stress due to climate change. Rain-fed water supplies for agricultural farms might be decreased by up to 50% and lead to food reserves to be at high risk in some countries. Many experts maintain a link between climate change and the rapid decrease of food stocks, as prolonged drought is the most common cause of harvest failure. Further, increased sea levels around the world are projected towards the end of the 21st century.

Many countries have been projected to experience the impacts of climate change. Indonesia, a Southeast Asia and Oceania country comprises five main islands and approximately 17,500 small islands spread along 90°30' E to 140° 10' E and 5°00' N to 10°05' S with an estimated population of around 237 million people, is expected to suffer from the effects of climate change impacts. Water scarcity, prolonged droughts, sudden floods, food shortages, rise of sea water level, changes of rainfall pattern, and increase in air temperature have been projected (Sari, 2002). These effects of climate change are predicted to lead to impacts, such as unsuccessful harvests, severely reduced number of livestock, lack of food stock, increase in tropical diseases, and the loss of many small islands. These impacts are likely to be worse for small islands. Lombok, one of small islands in Indonesia, is also predicted to experience climate change catastrophes.

Information about global climate change based on emission scenarios has been simulated using General Circulation Models (GCMs); however, given the coarse resolutions, an enormous challenge is posed in utilizing these long-term outputs for any meaningful local climate change studies. In light of this shortcoming, it becomes necessary to deploy downscaling models to simulate future climate change scenarios at finer spatial scales, which are more adaptable for useful local climate change studies.

Many researchers including Schnur and Lettenmaier (1998); Wilby et al., (2004); Cannon (2006); Lopes (2009); Olsson et al. (2012); among others, have investigated and applied currently available approaches to GCM downscaling modelling such as dynamical and statistical methods. None of the current approaches has been found to be always the best in all cases. Some of the disadvantages of current approaches include high cost of operations, inability to present changing variability in the future, inability to avoid producing some unrealistic values, inability to produce fine resolution for small drainage area (basin), and difficulty in satisfying essential assumptions (Von Storch et al., 2000; Wilby et al, 2004; Katzfey et al., 2010; Sulistiyono and Lye, 2011). As such, one of purposes of this study is therefore to examine the current downscaling approaches, and if none of the currently existing approaches is appropriate for the region of interest, a new downscaling model needs to be developed for simulating local hydrologic and climatic variables for the Jangkok River Basin.

Presently recommended procedures by the Government of Indonesia to be used in water balance analysis in Indonesia include the uses of: the Non Recorded Catchment Area (NRECA) model for simulating runoff, the Modified Penman model by the FAO (Food and Agricultural Organization, United Nations) for calculating potential evapotranspiration to estimate irrigation water use, and Domestic-Municipal-Industry (*DMI*) tables produced by the government for estimating other water uses (SNI 03-1724-1989; and Ministry of Environmental the Republic of Indonesia, 2005). However, the NRECA model does not consider climate change in its algorithm. Therefore, the NRECA model needs to be modified in order that the effects of climate change can be considered. Finally, some inconsistency has been found in the use of the Critical Water Index (CWI) (PT. Tataguna Patria Jaya, 2004), the commonly used water balance assessment criterion in Indonesia. Therefore a new water index criterion that considers the exact amount of remaining water has to be developed to enhance the performance of the previously used criterion.

The Jangkok River Basin has been chosen as a representative catchment for a case study to evaluate the potential impacts of climate change on water resources in the Lombok Island as it is classified as the first priority basin to be rehabilitated in Lombok (Dept of Forestry, 2009). This approximately 170 km^2 of the drainage (basin) area is very fertile and there are about 4,500 ha of agricultural farms to be developed (Anonymous 9, 2008). About 50% of the basin area is still covered by tropical rain forest, and the remaining areas have been developed as municipal and industrial areas, as well as agricultural farms (Anonymous 6, 2002). In addition, water from the Jangkok River Basin is intended to supply the water use for the 4,500 ha of agricultural farms as well as about 100,000 units of livestock (Anonymous 1, 2008) and supply drinking water to around 150,000 people with an average population growth of about 2.61% per year (Anonymous 3, 2008). An average annual rainfall of 2400 mm provides the major water source in this area (Anonymous 4, 2007). The variation in rainfall in this region is linked with the tropical monsoon season. Generally, the dry season is from April to September which is influenced by the Australian continental air masses, and the rainy season is from October to March as the result of the mainland Asia and Pacific Ocean air masses. Incidentally, to date, no research has been conducted in this region to better understand the myriad of climate change impacts, especially as it relates to water resources in the island. Figure 1.1 and Figure 1.2 show the location map of Lombok Island and the Jangkok River Basin, respectively.

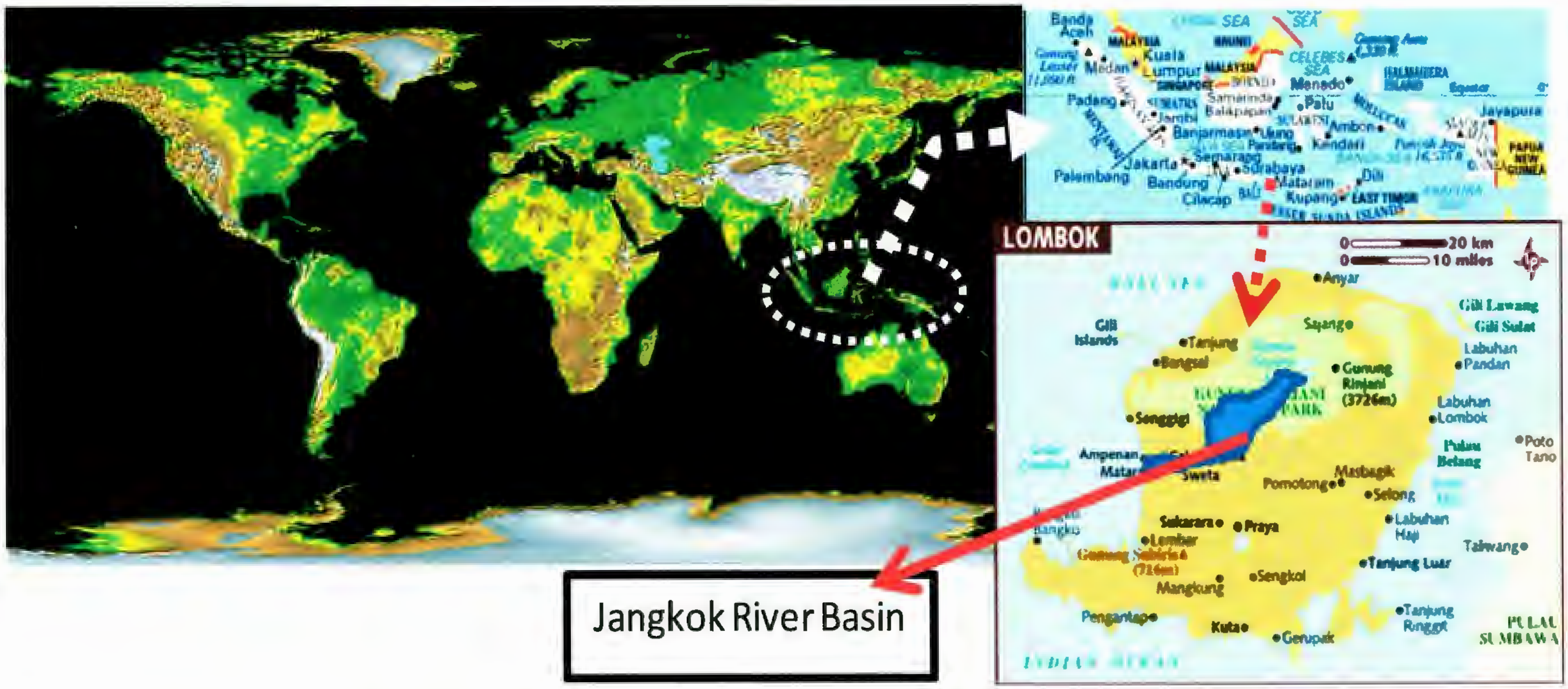

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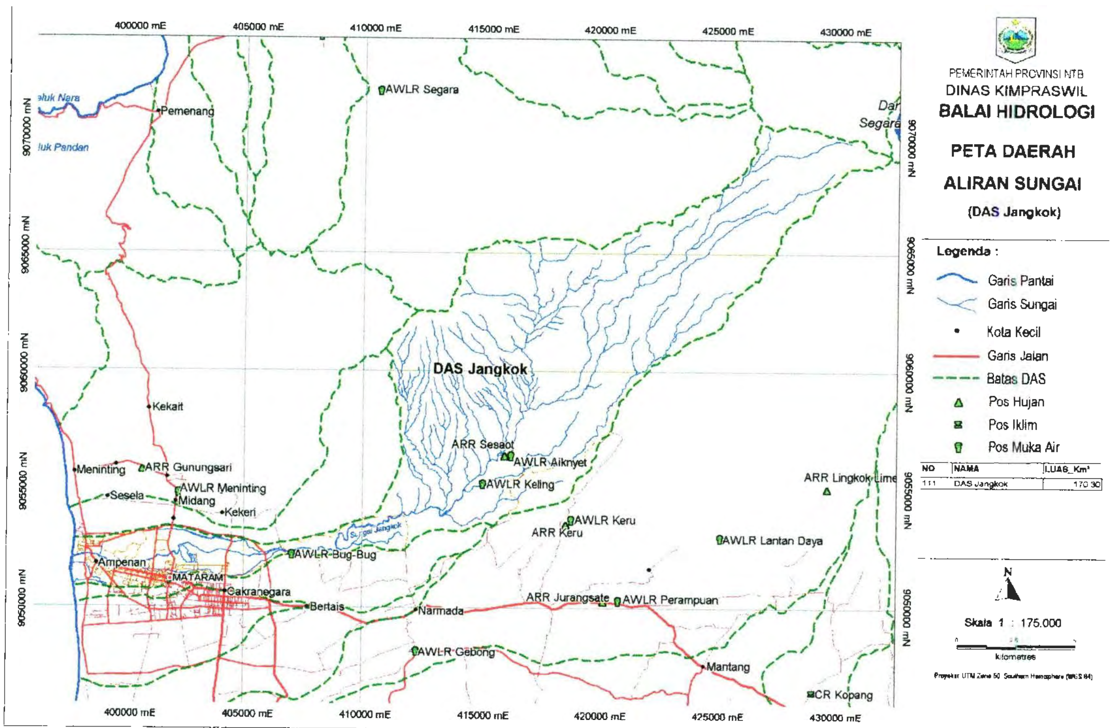
Figure 1.1 Location Map of the Study

1.2. Study Location

Figure 1.1 shows Lombok, a small island in Indonesia located at 115° 46' E to 116° 44' E and 8°15' S to 8° 55' S. Lombok with a population of 2,950,105 in 2005 is an island in West Nusa Tenggara Province (Nusa Tenggara Barat = NTB), Indonesia. It is about 70 km across the Island and the total island area of about 4,725 km² (1,825 sq mi). The provincial capital and the largest city on the island is Mataram.



Source: Balai Hidrologi,-.

Figure 1.2 The Jangkok River Basin

Figure 1.2 shows the Jangkok River Basin. It is located in the western part of Lombok Island. The upstream of this basin is vulcan tropical forests with an average elevation about 1,290 m above the sea level. The downstream of this basin, which has an average elevation about 20 m above the sea water level, is Mataram, the capital of NTB Province.

1.3. Research Objectives

Keeping in perspective the research intentions, this study has the following broad objectives:

1. To develop a new downscaling model in order to provide a better quality of finer resolution simulated local climatic variables,
2. To modify the NRECA model to take climate change into account,
3. To develop a new water index criterion to provide more accurate assessments of water balance,
4. To develop a water balance optimization model based on the new water index criterion developed in the third objective for the water balance assessment of the Jangkok River Basin in Lombok Island, Indonesia due to climate change scenarios in the future, and
5. To recommend population growth rate, agricultural and animal farm development policies based on optimum consumptive water uses in order to sustain the future of water resources due to the possible occurrence of climate change in Lombok.

1.4. Research Procedures

To accomplish the study, the schematic diagram shown in Figure 1.3 is presented to give a better understanding of the links among the various procedures. Figure 1.3 shows the five major areas of work in this research. These include the development of a new downscaling model, the modification of the NRECA model, the development of a new water index criterion, the development of a new water balance optimization model for the assessment of water balance and the optimization of water uses due to climate change scenarios in the future, and the recommendations to the Government regarding agricultural and livestock farm development policies in the Jangkok River Basin.

Required data for this research included historical local runoff, rainfall, and climatic data as well as GCM outputs from CGCM2, CSIRO-mk2, and NIES99. Next will be the investigation of currently used dynamical and statistical downscaling models. Two dynamical models: CCAM-CSIRO and RCM-Lombok, as well as, three well known statistical models: Artificial Neural Networks (ANN), Change Factor (CF), and Linear Regression will be investigated. This will then be followed by the development of a new downscaling model, which will be developed based on a hybrid of algebraic and stochastic approaches and then used to simulate future local climatic and runoff variables. Subsequently, an uncertainty analysis will be conducted to study the influence of: GCM outputs, emission scenarios, methods of residual generation, and applying outputs of regional climate models. Quartile plots as well as a statistical approach based on confidence intervals will be performed to evaluate the model uncertainty.

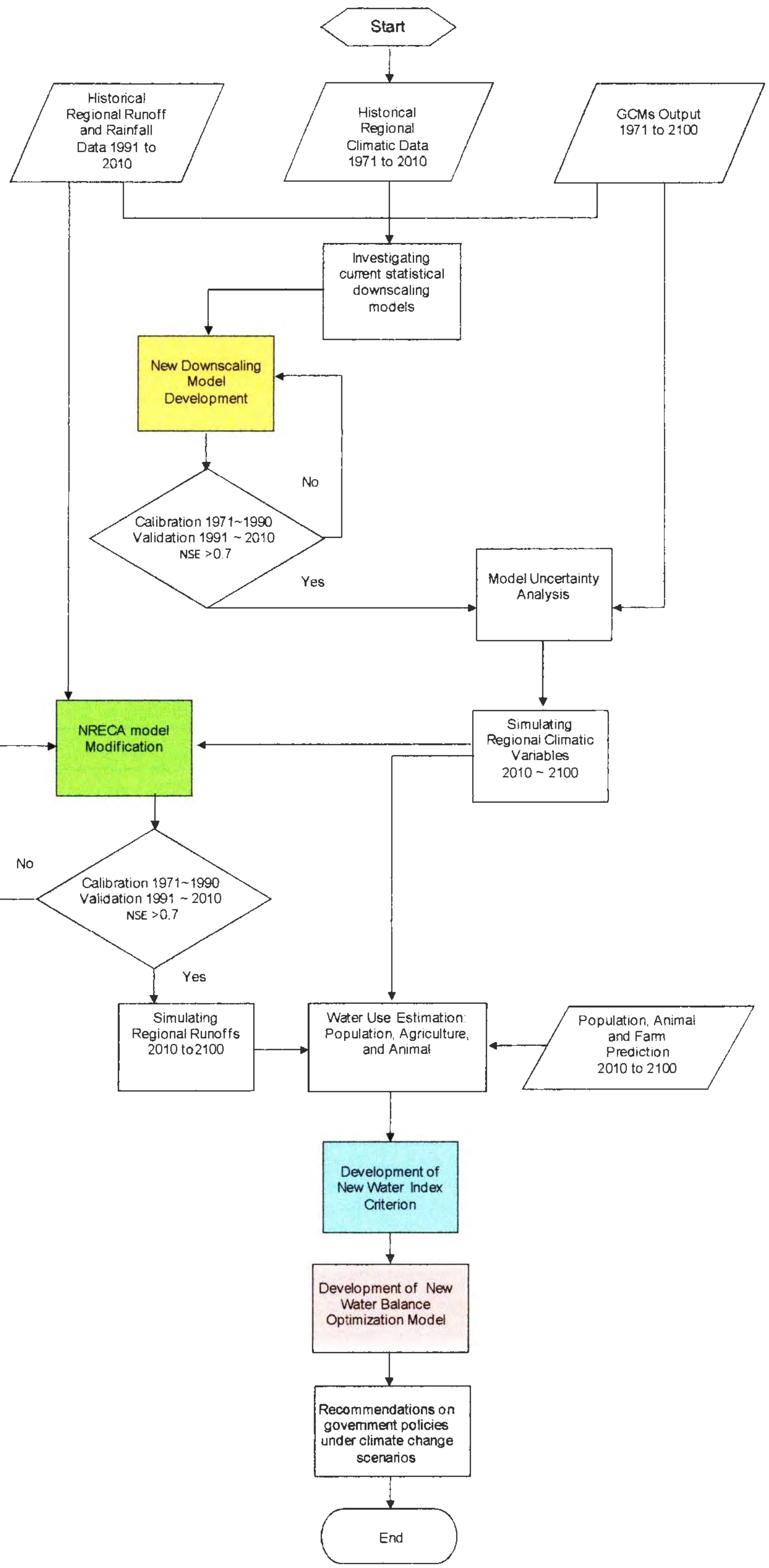


Figure 1.3 Schematic Diagram of the Research.

In the context of water availability analysis, the Non Recorded Catchment Area (NRECA) model, one of the commonly used rainfall-runoff models in Indonesia that does not incorporate climate change in its calculation will be modified to take climate change effects into account in the simulation of monthly runoff from 2010 to 2100. This simulation reflects impacts of climate change on water availability in the future. In this research, the modification of NRECA will be applied only to its inputs to maintain its significance of application in Indonesia. Inputs of the modified NRECA model in this research will be derived from the outputs of the HYAS models. Next, future water uses will be estimated based on the prediction of future population, livestock, and agricultural farm developments using a standard table of water requirements and irrigation water use calculations. These water use tables were recommended by the various departments of the Government of Indonesia. Furthermore instead of using a presently used water balance assessment method, a new approach called the Remaining Water Index Criterion (*RWI*) that considers more parameters, such as remaining water, minimum water services and water use priorities will be developed to provide a more reliable index to assess and optimize the water balance of The Jangkok River Basin. Finally from the result of this research, recommendations to government agencies will be provided regarding future allowable population growth rate, agricultural and animal farm developments policies in the face of climate change.

1.5.Outline of the Thesis

The thesis consists of eight chapters and a list of references. Chapter 1 describes the background, statement of problems, research objectives, research procedures, and outline of the thesis. Chapter 2 provides reviews of the prediction of climate change impacts around the world, general circulation models, downscaling techniques, runoff models, water balance assessments, and uncertainty and sensitivity analyses. Chapter 3 presents the selection of likely emission scenario, the selection of sensitive GCM variables for the simulation local climatic variables, and the investigation of currently existing downscaling techniques. Chapter 4 describes the development of a new downscaling model and the model uncertainty analysis. Chapter 5 explains the NRECA model modification to take climate change effects into account. Chapter 6 describes the development of a new water index criterion and the development of a new water balance optimization model as well as the assessment of water balance and the optimization of water uses of the Jangkok River Basin. Chapter 7 presents recommendations to the government in their effort to adapt to impacts of climate change. And, Chapter 8 presents conclusions and recommendations for future works.

Chapter 2

Literature Review

This chapter provides general reviews of the literature relating to the impacts of climate change. Reviews start from the prediction of climate change impacts around the world followed by General Circulation Models and downscaling techniques, which are described in Subsections 2.2 and 2.3. Reviews of runoff models and water balance assessments will be presented in Subsections 2.4 and 2.5, respectively. The last subsection reviews uncertainty and sensitivity analyses.

2.1. The Prediction of Climate Change Impacts around the World

Climate change refers to the permanent change of statistical characteristics of climate factors such as solar radiation, temperature, wind, humidity, precipitation, air pressure, and so forth, over long periods of time such as decades to millions of years (IPCC, 2001; and Pryor, 2009). It can be a change in the average, the extreme amounts, the pattern, and/or the distribution of climate factors. Climate change may refer to changes happening within a specific region, whereas global climate change refers to changes that occur around the World. Global climate change will likely begin to happen within the next several decades or even earlier (Gleick, 1997). This can be caused by solar output variations, Earth's orbital variations, volcanic activities, plate tectonic movements, ocean variability, and human influences (IPCC, 2007). Moreover, according to the United Nations Framework Convention on Climate Change

(UNFCCC) in Kyoto, Japan, 11 December 1997, the change in global atmosphere composition as a part of climate change was primarily caused by human activities that produce and store greenhouse gases (GHGs) such as carbon dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O) in the atmosphere over long periods of time. A wide range of human activities such as burning fossil fuels, destruction of forests, and the use of many chemical products are believed to have emitted the GHGs. These GHGs stay for a very long time in the Earth's atmosphere and lead to the global climate change (IPCC, 2007).

Myriad of climate change impacts are predicted to cause many detrimental effects around the world. Sea level rise is expected to exacerbate inundation, storm surge, erosion and other coastal hazards, thus threatening vital infrastructure, settlements and facilities that support the livelihood of island communities (IPCC, 2007). Flora and fauna are becoming vulnerable under climate change. The Botanic Gardens Conservation International has warned that many medicinal plants are nearly to vanish due to climate change (Gutierrez, 2008). Climate change will also cause the extinction of some animal species and the persistent habitat migration of some other species (Hryciuk, 1999). The uphill movement of animal habitation is a predicted response to the increase of temperatures (Dodd, 2008). Some bird and fish species will vanish as they are included in the category of animals at risk due to climate change (Black, 2008; and Renton, 2008). For that reason, the UNFCCC encourages all countries to mitigate the climate change and to force all industrialized countries to reduce their global greenhouse gas emissions by an average of 20 % below 1990 levels by 2012 (IPCC, 2007; and Spencer, 2008).

African countries are expected to suffer negative impacts of climate change such as the reduction of agricultural yields caused by the decrease of rainfall by 50 %, and sea level rise in low-lying coastal areas with large populations (Anuforom, 2009). In Europe, negative impacts will include an increased risk of floods and erosions, reduced snow covers, and species extinctions (Arnell, et al., 2005). Furthermore, there is an increased risk of animal and plant species extinction in many areas of tropical Latin America (IPCC, 2007). Climate change also impinges on the decrease in agricultural and livestock productions, with adverse consequences for food security. Changes in precipitation patterns and the disappearance of glaciers are estimated to significantly affect water supplies for domestics, agricultural farms, industries, and energy productions. Many cities that currently experience heat waves are also expected to have even more intense heat waves (US. EPA, 2010).

In Polar Regions, it is predicted that the average temperatures have risen at almost twice the rate as temperatures in the rest of the world over the past few decades (IPCC, 2007). This increase in temperature can lead to the widespread melting of glaciers and sea ice. Furthermore, specific ecosystems and habitats such as those of polar bears, ice-dependent seals, and local people, are estimated to be vulnerable due to the increase in environmental temperatures, the decrease in food sources and the shrinkage of polar ice (US. EPA, 2010). Climate change is also blamed as the number one threat to the 22,000 polar bears that remain in the world (Young, 2002). The sea ice in the northern pole regions has declined by 3.6 percent per decade since 1961. Most of the sea ice decline has occurred in the Barents, Kara and East Siberian (Johnston and Santillo, 2005).

Asia and Australia will also face natural catastrophes. Over 3 billion people will face the impact of climate change. Temperatures in several regions and countries from Southern India to Siberia will increase approximately 1 to 2 degree Celcius and will cause the melting of glaciers. Some unusual storms such as El Nino, sea water level rising and coral bleaching are expected to happen in Bangladesh, China, and the Indian Ocean (Mendelsohn, 2005). Further, some parts in the Western regions of Australia will have an increase in rainfall up to 50 mm (approximately 30% per year), while some parts in the Eastern regions of Australia will face a decrease in rainfall of 50 mm per year (Preston and Jones, 2006; and Clarke, 2009).

In Indonesia, many farmers and fishermen have complained about difficulties in predicting the recent weather. Farmers were confused on the choice of the best period to start planting crops. Fishermen cannot go sailing due to unexpected sea waves and streams. Moreover, large islands such as Sumatra, Jawa (Java), Kalimantan (Borneo), and Sulawesi (Celebes) experienced irregular heavy rains. Irregular storms have occurred in Java Sea and South China Sea with unexpected sea waves up to 5 m of height. Furthermore, sea water temperatures have also increased and have led the detriment of corals (Karim, 2009). Recent issues according to the Meteorology and Geophysics Agency in Indonesia include: the increase in average air temperatures from January 1971 to December 2006 of 0.5 degree Celsius; the increase in maximum air temperatures of 0.7 degree Celsius; the decrease in minimum air temperatures of approximately 1.2 degree Celsius; the change of maximum rainfall season from January – March to October – December; and the occurrence of droughts in some regions. In addition, many small islands, such as Lombok, Sumbawa, Flores, Sumba, Timor, Solor, and Alor will be more vulnerable to the change of climate compared to larger islands (Hilman et al, 2010).

2.2. General Circulation Models

General Circulation Models (GCMs), also called Global Climate Models, are mathematical models that are developed for high-level supercomputers or massively parallel computers. These models are based upon the working of earth and climate systems to represent the global circulation of atmosphere and ocean in relation to the sphere rotation and emission scenarios (IPCC, 2001). All global climate models must include the representations of ocean, sea ice, land surface, troposphere, stratosphere, important physical processes, radiation, cloud formation, turbulence, and solar radiation. The model should also consider the spectral and time scales of primary interest ranging from seasonal cycle, to annual variations, to decadal variability, and to century-scale climate change (Weart, 2009).

Large scale simulations of oceanic and atmospheric variables have been developed using General Circulation Models (GCMs) based on the change in Carbon Dioxide (CO_2) concentration. The change in Carbon Dioxide (CO_2) concentration is used in the simulation model to represent greenhouse gas forcing. According to Timbal et al. (2009), up to 23 GCMs have been developed in Australia, Canada, European, Japan, the United Kingdom, and the United States of America to simulate the changing of both atmospheric and oceanic variables. It has been reported by IPCC that none of the GCMs is better than another. Moreover, it is stated in the IPCC report (2007) that reliability of estimating future climate change depends on factors including the approach of downscaling method, the quality of regional information, and the size of catchment area.

GCMs can provide longer prediction data than any other weather prediction models. Therefore, GCMs are preferably used to predict climate while weather prediction models are used to forecast weather (McGuffie and Sellers, 1997). GCMs simulate oceanic and atmospheric factors based on the assumptions of future global population, future technology, future economic conditions, and emission scenarios (Environment Canada, 2005). In 1990 the IPCC released the first four emission scenarios called the Scientific Assessment 1990 (SA90a, SA90b, SA90c, and SA90d) to be used for driving global circulation models to develop climate change scenarios. The scenarios cover the emissions of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), chlorolluorocarbons (CFCs), carbon monoxide (CO), and nitrogen oxides (NO_x) from present up to the year 2100. Emissions of those GHGs were estimated based on the predicted growth of world population which is assumed to approach 10.5 billion by 2050. Economic growth was assumed to be 2-3% annually in the coming decade in the Organisation for Economic Co-operation and Development (OECD) countries and 3-5 % in the Eastern European and developing countries. The economic growth levels were assumed to decrease thereafter. The levels of technological development and environmental controls were varied. In 1992 the IPCC released the second set of six alternative scenarios called the IPCC Scenarios 1992 (IS92 a-f). This set is the update of the first set of emission scenarios. The IS92a-f scenarios represent a wide array of assumptions affecting how future greenhouse gas emissions might evolve in the absence of climate policies beyond those already adopted.

In 1994, IS92 scenarios have been reviewed (IPCC, 2001). It was found that for the purposes of driving atmospheric and climate models, the CO_2 emissions trajectories did not equate it with being the most likely scenario. Income gaps between developed and developing countries significantly affect the results of CO_2 emissions were not considered in the scenarios. Therefore, in the IPCC Third Assessment Report (IPCC, 2001), the third set of IPCC scenarios was commissioned to replace the six IS92 emission scenarios. The third set of emission scenarios called the Special Report on Emission Scenarios 2001 (SRES2001) are grouped into the following four families: A1, A2, B1, and B2 with storylines as follow:

The A1 storyline describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity-building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B; where balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end use technologies).

The A2 storyline describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing population. Economic development is primarily regionally oriented and per capita economic growth and technological change more fragmented and slower than other storylines.

The B1 storyline describes a convergent world with the same global population that peaks in mid-century and declines thereafter, as in the A1 storyline, but with rapid change in economic structures toward a service and information economy, with reductions in material intensity and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social and environmental sustainability, including improved equity, but without additional climate initiatives.

The B2 storyline describes a world in which the emphasis is on local solutions to economic, social and environmental sustainability. It is a world with continuously increasing global population, at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. While the scenario is also oriented towards environmental protection and social equity, it focuses on local and regional levels.

Based on those storylines, assumptions required in the four families of emission scenarios discussed in the IPCC's Third Assessment Report (TAR) and Fourth Assessment Report (AR4) (IPCC, 2001; and IPCC, 2007) are

- The A1 scenario assumes:
  - A global rapid economic growth,
  - The global population will reach 9 billion in 2050 and then gradually declines,
  - A quick spread of new and efficient technologies,
  - A convergent world - income and way of life converge between regions, and
  - Extensive social and cultural interactions worldwide.

There are subsets to the A1 scenario based on their technological emphasis:

A1FI - An emphasis on fossil-fuels,

A1B - A balanced emphasis on all energy sources, and

A1T - Emphasis on non-fossil energy sources.

- The A2 scenario assumes:
  - A world of independently operating, self-reliant nations,
  - Continuously increasing population,
  - Regionally oriented economic development, and
  - Slower and more fragmented technological changes and improvements to per capita income.

- The B1 scenario assumes:
  - A rapid global economic growth as in A1, however with rapid changes towards a service and information economy,
  - The population will reach 9 billion in 2050 and then declining as in A1,
  - The development of clean and efficient resource technologies, and
  - An emphasis on global solutions to economic, social and environmental stability.

- The B2 scenario assumes:
  - A continuously increasing global population, but at a slower rate than in A2,

- An emphasis on regional rather than global solutions to economic, social and environmental stability,
- The intermediate levels of economic development, and
- A less rapid and more fragmented change of technology than in A1 and B1.

In the IPCC-WGIII (2012), the climate modelling community requested for an extended climate change projections to 2300 in order to explore the long term response of the climate system to greenhouse gas forcing. It is also mentioned in the IPCC-WGIII (2012) that criteria used in evaluating extension options include:

- Relevance for exploring long-term dynamics of the climate system;
- Relevance for exploring ranges of possible impacts;inclusion of long-term features not previously included in model comparison exercises, such as peak-and-decline behavior;
- Facilitation of comparison across the different extensions;
- Use of simple rules to avoid interpretation as scenarios.

Simple rules that are used to produce pathways beyond 2100 include:

1) Constant emissions (emissions are held fixed at their 2100 level)
2) Constant forcing (radiative forcing is held fixed at its 2100 level)
3) Adapted emissions (changing emissions/forcing subject to a simple rule, e.g., constant percentage annual change)

In 2011, the IPCC approved a new set of the fourth IPCC scenarios called the Representative Concentration Pathways (RCPs) (IPCC-WGIII, 2012). The four RCPs are RCP3/2.6, RCP4.5, RCP6, and RCP8.5.

- Under RCP3/2.6, the assumption is radiative forcing reaching the peak by 2050 at ~3 W/m^2, and decreases to 2.6 W/m^2 by 2100. Thus, emissions are negative after 2100, and radiative forcing is declining. Options include holding radiative forcing constant, holding emissions constant or developing an intermediate pathway in which radiative forcing continues to decline for some time beyond 2100 but eventually stabilizes further in the future. This additional option was proposed to reflect the possibility of limits on negative emissions.
- Under RCP4.5, radiative forcing reaches 4.5 W/m^2 in 2100, and then stably goes on. CO_2 concentrations and radiative forcing are held constant after 2100.
- Under RCP6, radiative forcing increases slowly over time and reaches approximately 6 W/m^2 by 2100. CO_2 concentrations and radiative forcing are also held constant after 2100.
- Under RCP8.5, radiative forcing is still increasing in 2100, and emissions are still high. An assumption of constant emissions would result in very high radiative forcing (above approximately 16 W/m^2 under default assumptions), with indefinite increase (and concentrations in 2300 of ~3000ppm CO_2).

Up until now, the simulation of climate change based on the RCPs is not yet finished to cover a whole surface of the Earth. IPCC therefore still impose the simulation results of the second and third generations of GCMs that use the SRES2001 (IPCC-WGIII, 2012).

With these large-scale atmospheric models, it is possible to produce long-term temporal and spatial information of simulated atmospheric variables, which are usable for climate change studies and its impacts on water resources systems (National Research Council, 2001). However, the outputs of GCMs cannot be directly used in the local environmental applications as their information resolutions are coarse as it covers approximately 100 km to 600 km range of area. The amount of GCM outputs might be very small compared to the amount of relevant local variables, for example: the amount of monthly precipitation of GCM output (PCP) for Mataram on January 1971, 1.23 mm/month is very small compared to the amount of relevant local precipitation on the same month, 179 mm/month. Therefore, this large scaled information has to be downscaled to achieve finer resolutions (Lopes, 2009).

2.3. Downscaling Techniques

Downscaling techniques are strategies for generating locally relevant data from GCMs. Up to now downscaling can be done in three ways, applying either dynamical models, statistical models, or Change Factor method (Wilby et al., 2004). Dynamical models also called Regional Climate Models (RCMs) are technologically equal to GCM models that are composed of three layers (Hay and Clark, 2003; and McDaniels and Dowlatabadi, 2008). The first layer is driven by the GCM outputs, the second layer consists of some local information such as topography and land covers, and the third layer is utilized with climatic and meteorological equations to generate the simulated local information based on data from the previous two layers. Presently, RCM's downscaled climatic data for Indonesia are available. However, the downscaling resolution of 60 km or 3600 km^2 from RCMs (Katzfey et al., 2010) is still coarse for the Jangkok River Basin, which has an approximately 170 km^2 of drainage basin; therefore, RCMs are not appropriate for downscaling local variables for the Jangkok River Basin.

Another downscaling technique is using statistical models. There are three types of statistical models (Wilby et al., 2004): Weather Classification (Typing), Regression, and Weather Generator (Stochastic) methods. In the use of Weather Classification (Typing) Methods, climatic data are grouped into weather types. Next, the predictands (local information) are assigned to the existing weather state. Finally, simulated local information is generated using the replication of changed climate. The method has been successfully applied to climate simulations by Zorita and Von Storch (1999) as well as Schuol and Abbaspour (2007).

In regression methods, there are a variety of such methods ranging from simple linear to non linear regressions, and even more complex regressions such as neural networks (Cannon, 2006). The general strategy of these methods is to establish the relationship between large scale variables from GCMs that are defined as the regression predictors, and local level climate information that is defined as the regression predictand (Wilby et. al., 2004).

In weather generator (stochastic) methods, local information series are generated based on stochastic process that involves both GCM and local information. According to Scibek et al.

(2008), weaknesses of this method include simulated streamflows has lower baseflows than historical data, this method requires longer periods of historical data compared to other techniques, and the simulated hydrographs have different time of peak. In weather generator methods, Koenig (2008) explained that local variables could be simulated using available software packages such as the Long Ashton Research Station Weather Generator (LARS-WG) and the Weather Generator (WGEN).

Up to now, all downscaling models unfortunately produce discrepancies between the simulated and observed data (Huth et al., 2001 and Wilby et al., 2004). The possible causes of discrepancies might come from (i) the absence of some unknown physical processes in the downscaling models, (ii) inadequacies of physical processes in the GCMs, (iii) violation of regression assumptions, and (iv) properties of the underlying statistical model of the weather generator.

In Prudhomme et al., (2002), GCM outputs are currently still not considered to be reliable for any time scales shorter than 1 month. In addition, the empirical (statistical) methods are still more reliable than other methods unless the next generation of GCMs can generate more reliable variance estimates, in which case the application of weather generators is perhaps more appropriate than empirical methods. Moreover according to Wilby et al. (2004), based on the comparison study of six statistical downscaling approaches (two neural nets, two weather generators, and two regressions), the regression method performed the best. Furthermore, Goyal and Ojha (2011) reported that the regression method gave a better explanation of daily variance in precipitation anomalies compared to the dynamical model.

As stated in Wilby et al. (2004), a GCM downscaling model can be developed based on a relationship between predictors (GCM variables) and predictands (local variables). In Wilby et al. (2004), all previous statistical downscaling models are based upon a single driving GCM. Although using a single GCM variable can simplify the development of downscaling models; however, this will lead to a lack of statistical information from other GCM outputs. Therefore, a new proposed downscaling model in this thesis will use three GCM variables as be described in the next chapter. The GCM variables that are involved in each downscaling model of local variable will be selected based on their significant contribution to the model of each local variable. Contribution of each GCM variable will be analysed in a sensitivity analysis process using a method of standardized regression coefficients.

The Change Factor (CF) method is the most straightforward downscaling technique (Wilby et al., 2004; Chen et al., 2011; and Walsh, 2011). It only uses a single driving GCM, typically variables of temperature. This method utilizes the difference between mean of simulated GCM and mean of baseline GCM to be added to individual baseline local variables.

Disadvantages of presently existing downscaling models that have led to a development of a new proposed model in this thesis, include (Wilby et al., 2004; Heimann and Zemsch, 2011; Sulistiyono and Lye, 2011):

- High cost of operations as in the use of dynamical models,
- vulnerability to the appearance of outliers as in the use of ordinary least square regression models,
- inability to avoid the result of unrealistic values as in the use of neural network,

- inability to reflect the future change of variation as in the use of change factor method, and
- inability to include multiple variables as also in the use of change factor method.

2.4. Runoff Models

Surface runoff, commonly called runoff, is a flow of water that occurs on the surface when the excess of water from rainfall over the land after the soil has reached the maximum capacity of infiltration (Dingman, 2002). According to Longobardi et al. (2004), climate and catchment area represent the main factors dominating the proportion of rainfall that becomes runoff. Naturally, runoff flow toward the seas, lakes, or other depletion storages. Runoff is very important for environmental systems as it not only keeps rivers and lakes full of water, but it also changes the landscape by the action of erosion (Beven, 2008). Moreover in some regions, runoff is significant for determining water availability in order to calculate water balance. The magnitude of runoff is defined as the discharge of a stream and is ideally measured and recorded using an Automatic Water Level Recorder (AWLR). For some cross sections of stream unequipped with AWLR, runoff data are estimated using runoff models. The calculation of runoff needs hydrologic, climatologic, and land information (Beven, 2008).

As the major hydrologic element (precipitation) to cause runoff is rainfall; therefore, it is also called rainfall-runoff models. Not every cross section of stream has been equipped with AWLR, in Indonesia. Therefore, the estimated runoff is simulated using rainfall-runoff models. The local regulation in Indonesia (Anonymous 8, 2004) requires the use of either

NRECA model or Mock model for estimating rainfall-runoff. Both models were specifically developed in Indonesia for use in the Indonesia, as not many catchment parameters are available. NRECA and Mock models have 4 and 6 model parameters, respectively. According to Setiawan et al., 2005, the NRECA model is preferable to the Mock model, as the NRECA model has fewer model parameters compared to the Mock model. Therefore, the NRECA model is utilized in this research.

The NRECA model is one of well known models that are prominently applied in Indonesia as they were developed specifically for the use of runoff analysis in Indonesia (SNI 03-1724-1989; and Ministry of Environmental the Republic of Indonesia, 2005). According to Yazid (2010), the NRECA model is more applicable for regions with low to medium rainfall intensity such as in Lombok, Nusa Tenggara and other regions in the eastern part of Indonesia. Although, the model has been successfully applied by researchers including Sahan (2006), Legowo et al. (2006), Sulistiyono and Lye (2010), among others; unfortunately, the NRECA model does not take into account the change of climate in its calculations. Its calculations are only based upon the average of historical local climatic variables. Therefore in Chapter 5, a spreadsheet based NRECA model needs to be modified to involve climate change in their calculations to simulate future runoff.

2.5. Water Balance Assessments

A water resource system is defined as a human-made system of water use. It could be a simple single purpose water use or a very complex multi-purpose water use. It interrelates with human and physical systems, and this leads to innumerable financial, economic, social and political considerations (Simonovic, 2009). The two most important elements of water resource system assessment are water quality and water quantity. The system could be at high risk when it is confronted with shortage of water and/or excess water. Shortage of water can cause detrimental effects, such as unsuccessful harvests, failures of electricity demand fulfilment, and deficiencies of drinking water. Excess of water can also cause detrimental effects, such as floods, inundations, broken dams caused by overtopping. In general, sustainability of a water resource system is based on its best management. A key success of water resource management is to optimize its water balance (Binder et al., 1997).

A water balance is an accounting of water availability as the inputs, and water uses as the outputs of water in storage of water resource system over a particular period of time. In a river basin, water availability can be defined as the runoff, while water uses might be defined as the released water into a downstream as well as water supplies for domestic, industries, hydroelectric, agricultural farms, and animal farms. A water balance equation can be used to describe the flow of water in and out of a system, and can help manage water supply and predict water shortages. It is also used in irrigation, flood control and pollution control (Xu and Singh, 1998). Water balance of a water resource system is assessed periodically such as every 5 or 10 years for many purposes. A water balance assessment can be used to analyze impacts of climate change on a water resource system. According to Combalicer et al. (2010), the impacts of climate change on water balance might be reflected in the increase in evaporation, the decrease in runoff, and the dramatic fluctuations of hydrologic events.

While several commercial software packages are available for water balance analysis, these packages are not easily accessible in Indonesia due to cost, applicability, and language issues. In addition, recommended procedures and techniques used in Indonesia are not implemented in these software packages. On the other hand, spreadsheet software such as Excel is widely available and used by engineers in Indonesia. In addition, developing a spreadsheet based water balance model is inexpensive, flexible, can be easily disseminated, and can help engineers gain a better insight into the operating policies of the weirs. However, the drawback is that the user interface is usually not as "pretty" as commercially developed software. The water balance model involving all elements will be described in Chapter 5.

The currently used technique for assessing a water balance in Indonesia is using a Critical Water Index (*CWI*) criterion (Setiawan et al., 2005 and Sulistiyono and Lye, 2010) as shown in Table 2.1. In Sulistiyono and Lye (2010), it has been used to assess a water balance system in the Reak Basin in Lombok Island. The CWI is given by

$$CWI = \frac{\sum water\ uses}{\sum water\ availability} * 100\% \quad \text{..............................} \quad (2.1)$$

Table 2.1 Critical Water Index

	Critical Water Index	Category
	$CWI \leq 50\ \%$	Surplus
	$50\ \% < CWI < 70\ \%$	Critical
	$CWI \geq 70\ \%$	Deficit

Source: Sulistiyono and Lye, 2010

However, as the *CWI* uses a percentage ratio of water uses over available water, this assessment might be spurious and inaccurate to represent the status of a water resource system as water uses only represent the amount of water that was used and does not represent the whole amount of water that should be used to achieve a particular level of prosperity. Therefore, this water index needs to be enhanced to reflect the water balance more accurately. Besides assessing the water balance, another effort is to optimize the water uses using the water balance model.

The currently used technique for optimizing water uses in the location of study is using a Trial and Error method (Setiawan et al., 2005). In Lye (2009), this method has several disadvantages which include

- time consuming,
- may not be able to obtain the true optimum result,
- deterministic solution which cannot provide variability of result
- cannot provide effects of parameter interaction

In this study, a Water Balance Optimization Model based on Spreadsheets and Response Surface Methodology (RSM) based on Central Composite Design (CCD) was developed in Chapter 6. The model is used to obtain the best combination of water uses for sustaining water resources in the location of study under possible climate change impacts in the future. In Sulistiyono (1999), the RSM was successfully used to optimize the six parameters of Mock Rainfall-Runoff Model in the calibration process.

RSM integrates mathematical and statistical techniques, (Myers and Montgomery, 1995; Sulistiyono, 1999; and Lye, 2009) and was essentially developed from numerical methods. The mathematical techniques are objective function development, build polynomial models, and optimise the model-parameters. The statistical techniques are to test the significance of results. Response Surface Designs include Central Composite, Box-Behnken, Three-Level Factorial, Hybrid, D-Optimal, Distance-Based, and Modified-Distance, can be used for model development and optimization (Myers and Montgomery, 1995; Sulistiyono, 1999; and Lye, 2009). Central Composite Design (CCD) is the most frequently used to fit second-order models (Myers and Montgomery, 1995). CCD is created from either factorial or fractional factorial designs.

The benefits of using RSM (Myers and Montgomery, 1995; Sulistiyono, 1999; and Lye, 2009) are:

1. It does not need a lot of time to finish its iterations and simulations,
2. It can provide many possible results of parameter combination to produce the optimum result,
3. It can determine the effects of parameter-interactions on the response,
4. It is more systematic and accurate in guiding researchers to obtain the optimum result, and
5. The design and analysis can be conducted using standard statistical software without the need to write custom programs for a particular model.

2.6. Summary

Climate change has been predicted to have many negative impacts on ecosystems around the world. Therefore, IPCC has provided the projections of climate change information using GCMs. As the resolution of GCMs is too coarse for direct applications of local climate change studies, downscaling techniques are used to obtain the finer resolutions. Some researchers have come up with several downscaling techniques. Those existing downscaling techniques will be investigated in Chapter 3. Rainfall-runoff models were also reviewed which includes the analysis of local climate variables, runoff, and water balance due to possible impacts of climate change. The NRECA model and the CWI criterion are the recommended procedure in Indonesia. But, the NRECA model does not include climate change information in its simulations. Moreover, the CWI criterion white simple does not take the priority of water uses into account. Consequently, the inputs of NRECA model need to be modified to be able to take climate change information into account and a new water index criterion has to be developed to take the priority of water uses into account. The modification of a spreadsheet based NRECA model and the development of new water index criterion will be described in Chapters 5 and 6, respectively.

Chapter 3

Investigation of Existing Downscaling Models

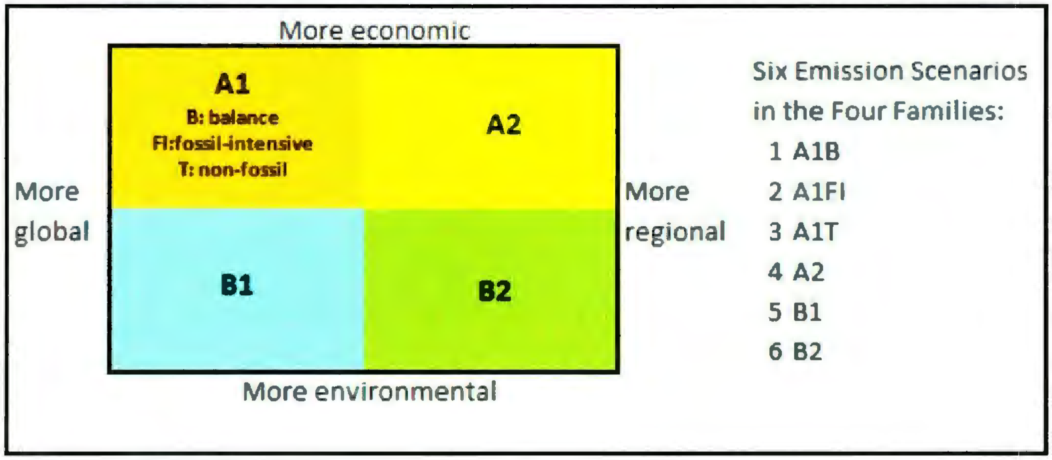
This chapter describes the investigation of existing downscaling models. This will include the background, selection of the most likely emission scenario, selection of GCMs, selection of sensitive GCM variables, performance evaluation of existing downscaling models, and finally a summary.

3.1. Background

Climate change has been studied for many years based on simulated variables using GCMs, which are numerical models representing physical processes in the atmosphere, ocean, cryosphere and land surface. These are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. In this thesis, the results of simulated GCM are called GCM variables. These GCM variables cannot be directly applied in a local setting as its resolution is very coarse. This is because GCM variables cover a very wide area of the Earth's surface. In the Website of Environment Canada (2012), the first, second and third generation of Coupled General Circulation Models or CGCM1, CGCM2, and CGCM3 from the CCCma-Canada cover the area of grid spacing approximately 3.7° x 3.7° or approximately 411.4 km x 411.4 km. This equals to approximately 170,000 km^2. The fourth generation of Coupled General Circulation Models or CGCM4 introduced in 2008 covers the area of grid spacing approximately 1.41° in longitude and 0.94° in latitude or approximately 160 km x 100 km. This equals to approximately 16,000 km^2. As the covered area is very large, it may include many types of Earth's surfaces such as ocean, lakes, land, mountains, and forests. Therefore, it is necessary to downscale the GCM variables to obtain finer scaled variables that can be used for a smaller region. Downscaling models can be grouped into dynamical models, statistical models, and a change factor method (Wilby et al., 2004). So far, there is no official suggestion as to the best GCM model as well as downscaling models for use in all cases. Disadvantages of current downscaling models include high cost of operations, inability to incorporate changing variability in the future, inability to avoid producing some impossible variables, inability to include multiple variables, and difficulty in satisfying essential assumptions (Pfizenmayer and von Storch , 2001; Wilby et al, 2004).

3.2. Selection of the most likely Emission Scenario

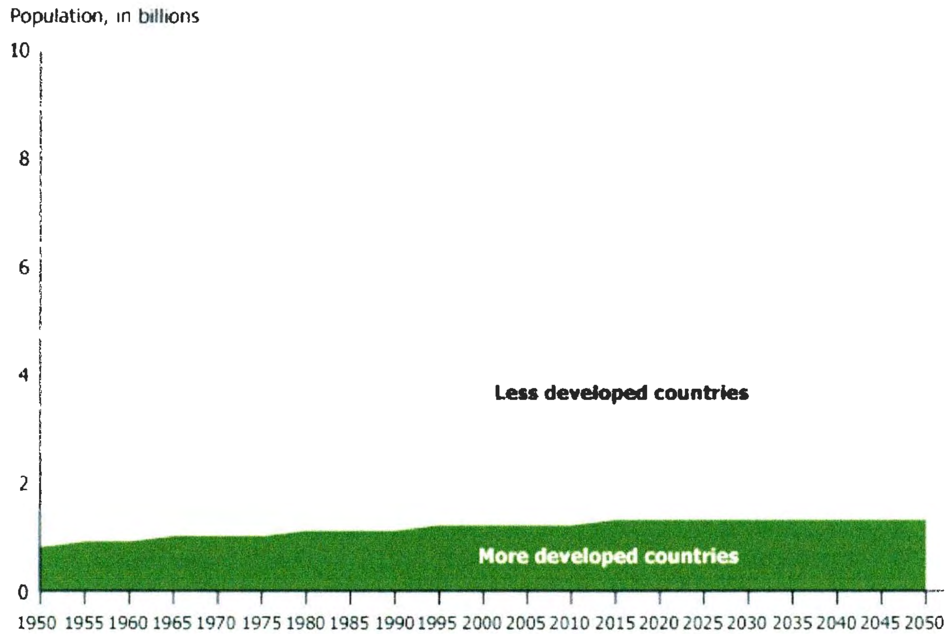
In IPCC (1992), emission scenarios describe future releases into the atmosphere of greenhouse gases, aerosols, and other pollutants and, along with information on land use and land cover, provide inputs to climate models. They are based on assumptions about driving forces such as patterns of economic and population growth, technology development, and other factors. Levels of future emissions are highly uncertain, and so scenarios provide alternative images of how the future might unfold. As mentioned in Chapter 2, there are six emission scenarios in the four families discussed in the IPCC reports. None of them has been officially recommended as the most reliable emission scenario. Any of them might be useful as long as it is supported by adequate assumptions of global population growth, economic growth, and technology developments. Figure 3.1 shows the matrix guidance to select an emission scenario that might match assumptions according to conditions of global population growth, economic growth, and technology developments.



(Source: CCCSN, 2011)

Figure 3.1 The Four Families of Six Emission Scenarios

Figure 3.1 explains that if the condition of economic growth and technology development in the future is more global, then the emission scenario likely to be selected is A1B, A1FI, A1T, or B1. However if the condition of economic growth and technology development in the future is more regional, then the emission scenario likely to be selected is A2 or B2. Moreover, if the economic growth and technology development emphasize on environmental safety, then the emission scenario likely to be selected is B1 or B2; otherwise the emission scenario likely to be selected is A1 or A2.



(Source: UN Population Division, 2008)

Figure 3.2 Estimated Global Population Growth Up to 2050

According to IPCC (2001), population projections could be considered as the backbone of the greenhouse gas (GHG) emission scenarios. Population projections are one of the most frequently cited indicator of the future state of the world. Figure 3.2 shows the estimated world's population growth to approximately 9 billion by 2050 (UN, 2008).

In the IPCC-WGIII (2000), it has been stated that technology development is also an important driving force of Green House Gases (GHG) in the atmosphere. The increase in GHG is significantly related to the world's technological development. In the Synthesis Report (IPCC, 2007), technology is defined as the practical application of knowledge to achieve particular tasks that employ both technical artefacts, such as hardware, equipment, and social information. According to Padmanabhan (2010), new technologies cannot be easily and directly applied in some countries or particular regions due to cost, means of support, applicability, local policies, and language issues.

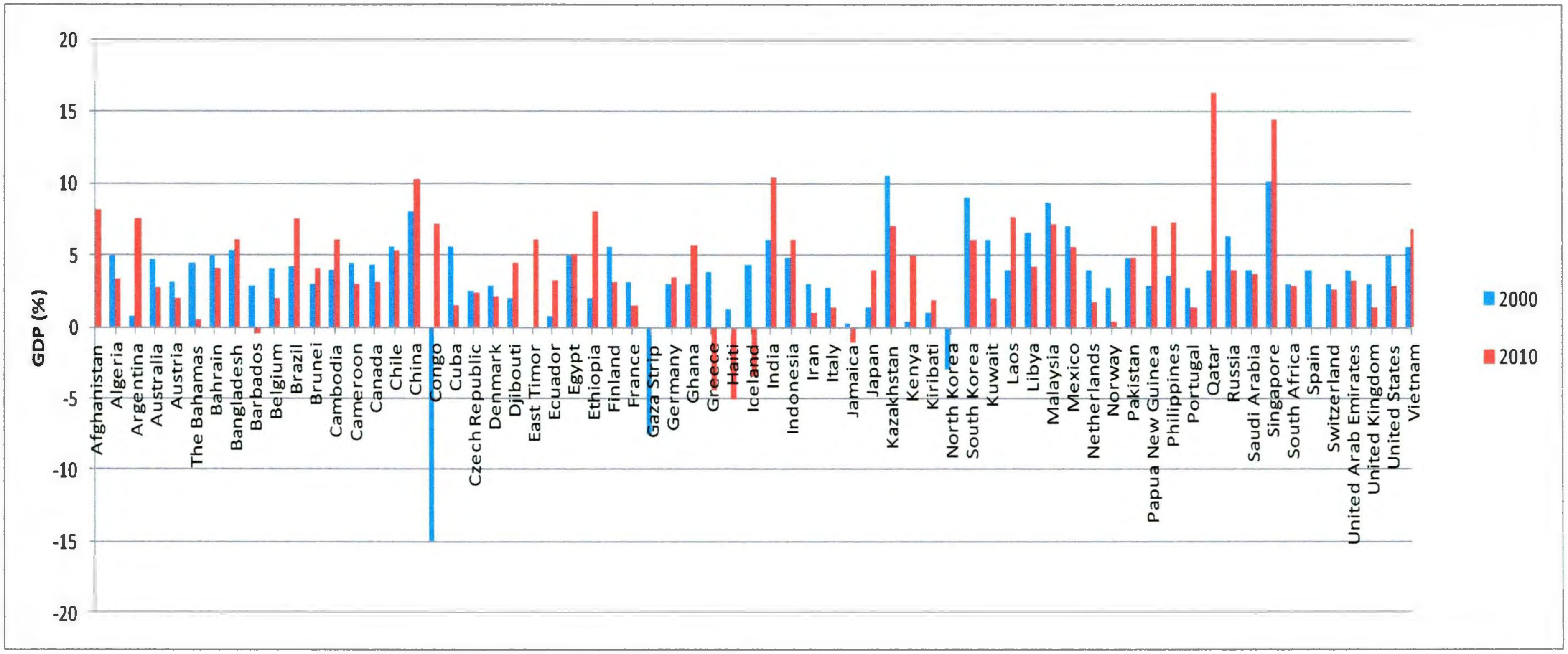
In Weil (2008), the economic growth of a country is defined as an increasing capacity of economy in the country to satisfy the demands of goods and services of people. The comparison of economic growth among countries is a complex study. As a real relationship of economic growth of countries around the world is difficult to be comprehensively analyzed, this research utilizes a matrix economic growth correlation coefficient of 67 represented countries around the world to obtain whether economic growth of countries around the world is regional or global. Correlation coefficient larger than 0.6 is considered to the satisfactory of acceptance (Soewarno, 1995 and Prak, 2011), therefore, this research uses a correlation coefficient of larger than 0.6 to indicate global economic growth, otherwise it will be considered as regional economic growth. Table 3.1 shows a part of correlation coefficients of 67 representative countries' growth rates. The remaining correlation coefficients are attached in Appendix C. Figure 3.3 shows barcharts of economic growths of some representative countries around the world.

Table 3.1 A part of correlation coefficient of 67 representative countries' growth rates

	Chile	China	Congo
China	0.240		
Congo	0.089	0.481	
Cuba	0.309	0.462	0.094
Czech Rep	0.815	0.454	0.359
Denmark	0.695	0.178	-0.005
Djibouti	-0.158	0.470	0.176
East Timor	0.032	-0.197	0.026
Ecuador	0.626	0.059	0.304
Egypt	0.236	0.614	0.222
Ethiopia	0.306	0.283	0.376
Finland	0.658	0.210	-0.048
France	0.508	0.215	-0.168
Gaza Strip	0.023	0.845	0.481
Germany	0.682	0.247	-0.022
Ghana	0.242	0.608	0.776
Greece	0.229	0.130	-0.003
Haiti	-0.339	0.174	-0.135
Iceland	0.444	0.038	-0.108
India	0.290	0.900	0.525
Indonesia	0.675	0.535	0.302
Iran	0.432	0.500	0.468
Italy	0.611	0.075	-0.161
Jamaica	0.625	-0.051	0.199
Japan	0.794	0.223	0.255
Kazakhstan	0.681	-0.255	-0.179
Kenya	0.414	0.603	0.573
Kiribati	0.023	-0.080	-0.058
North Korea	-0.086	0.035	0.648
South Korea	0.098	0.295	-0.264
Kuwait	0.685	0.142	0.13
Laos	0.241	0.612	0.782
Libya	0.842	0.289	0.056
Malaysia	0.687	0.485	0.007
Mexico	0.675	0.247	-0.129
Netherlands	0.485	0.230	-0.172
Norway	0.683	0.448	0.198
Pakistan	0.544	0.355	0.212
PNG	0.044	0.648	0.25
Philippines	0.726	0.544	0.498
Portugal	0.299	0.114	-0.274
Qatar	0.341	0.402	0.516
Russia	0.722	0.339	0.2
Saudi Arabia	0.774	0.287	0.239
Singapore	0.597	0.560	0.049
South Africa	0.835	0.253	0.232
Spain	0.501	0.221	-0.041
Switzerland	0.699	0.421	-0.021
UAE	0.723	0.106	0.281
UK	0.671	0.208	0.052
US	0.536	0.187	-0.111
Vietnam	0.674	0.661	0.639

Results:

Corr. Coeff	# Corr. Coeff.	Percentage
< 0.6	1590	74.23 %
> 0.6	552	25.77 %
total =	2142	100.00 %



(Data Source: CIA World Factbook, January 2011)

Figure 3.3 The Comparison of Countries' Economic Growth 2000 and 2010

Table 3.1 shows that most or 74.23 % of economic growth correlation coefficients are smaller than 0.6. This indicates that economic growths of countries around the world are probably more regional than global. Figure 3.3 shows economic growth rates of countries around the world. Some countries are more developed than others. In addition, some countries have negative economic growth.

From the literature review, such characteristics as global population, economic, and technology growths as described above meet the assumptions of the A2 emission scenario. Therefore, this research applies the A2 emission scenario. Some researchers including Mahmud (2006), Lapp and Barrow (2008), and Bates (2009) also agree that the A2 emission scenario is a likely emission scenario for simulating future climate variables. The A2 world has less international cooperation than the A1 or B1 worlds. People, ideas, and capital are less mobile so that technology diffuses more slowly than in the other scenario families. International disparities in productivity, and hence income per capita, are largely maintained or increased in absolute terms. With the emphasis on family and community life, fertility rates decline relatively slowly, which makes the A2 population the largest among the storylines of emission scenarios (9 billion by 2050 and 15 billion by 2100). Global average per capita income in A2 is low relative compared to other storylines. Technological change in the A2 scenario world is also more heterogeneous (IPCC, 2007). The second likely emission scenario is the B2. The difference between A2 and B2 is the population growth. B2 assumes the population reaches 7 billion by 2050 with economic growth rates more stable but slower than A2. Therefore, the B2 scenario will also be used in this study to complete the uncertainty analysis of the HYAS model.

3.3. Selection of General Circulation Models (GCMs)

In the Data Distribution Centre (IPCC – DDC, 2010), there are 19 agencies around the world that can provide simulated GCM variables. Up to now, almost all of the 19 agencies have developed the fourth generation of GCMs. However, the latest available climate change information that covers the location of study was simulated based on the third IPCC emission scenarios using the second and the third generations of GCMs.

The third generation of GCMs that also simulate climate change information based on the third IPCC emission scenarios provide finer resolution (up to 350 km) of simulated GCM variables from 2000 to 2100; however, the author could not choose the third generation of GCMs as the length of historical local data for this research spans from 1970 to 2010. The author thus chose the second generations GCMs as these models provide simulated GCM variables from 1900 to 2100, even though their resolution of 1000 km is coarser than resolutions of newer generations. This option allows the author to prepare 20 years of data for the calibration process and other 20 years of data for the validation process instead of only 5 years for calibration and other 5 years for validation.

This research utilized three models of the second generation of GCMs. The three models are the Mk2 from the Commonwealth Scientific and Industrial Research Organization (CSIRO-Australia), the NIES99 from the National Institute for Environmental Studies (NIES-Japan), and the CGCM2 from the Canadian Centre for Climate Modelling and Analysis (CCCma-Canada). The reason for choosing the three agencies is because NIES-Japan and CSIRO-

Australia are close to the study location which is Lombok Island in Indonesia, and since this research is conducted at the Memorial University of Newfoundland, Canada; a Canadian developed model was also chosen.

3.4. Selection of Sensitive GCM Variables

According to Wilby et al. (2004), one GCM variable is sufficient enough to simulate local variables. However in statistics, applying only one independent variable to simulate dependent variables will probably lead to a lack of information. Other independent variables might have some other information that can support and explain the observations. This research applies three of the most sensitive GCM variables as the independent variables to simulate local climatic variables. Unless three independent GCM variables cannot fit the observations, five, seven, or nine independent GCM variables might be fitted. Therefore in this research, a total of nine GCM variables will be made available for selection, as shown in Table 3.2.

Table 3.2 GCM Variables Available for Selection

Notation	Description	Units
X1	Mean 2m Wind Speed	m/s
X2	Evaporation	mm/day
X3	Precipitation	mm/day
X4	Screen (2m) Temperature	°C
X5	Screen Spec. Humidity	kg/kg
X6	Sea Level Pressure	hPa
X7	Skin (surface) Temperature	°C
X8	solar flux at surface	W/m^2
X9	Surface Pressure	hPa

The selection or screening process of the top three most sensitive GCM variables was conducted using a sensitivity analysis approach. As the selection or screening process is not a core of this research, three methods of sensitivity analysis will be used. These are Neural Networks, Standardized Regression Coefficients, and Correlation Coefficients. These will be used to select sensitive GCM variables that will be involved in the development of a new downscaling model. The descriptions of neural networks, standardized regression coefficients, and correlation coefficients have been explained in detail in many text books, and applications can also be found in many journals including in McCuen (1993), Stergiou and Siganos (1996), Ji (2004), and Kralisch et al., 2005, Pacelli et al., 2011, Kim, 2011, and Prak, 2011; therefore they are not described in this thesis. Table 3.3 and Table 3.4 show the results of the screening process for local humidity.

Table 3.3 Results of Screening Process of GCM variables for the Local Humidity Model

REGIONAL HUMIDITY MODEL								
	ANN		SRC		CC		**Average**	**Rank of**
Inputs	Importance	Ranking	Coefficient	Ranking	Coefficient	Ranking	**Ranking**	**Av. Rank**
X1	0.027	4	-0.353	6	-0.091	6	5.33333	**4**
X2	0.019	5	0.412	5	-0.023	8	6	**6.5**
X3	0.004	8	0.0508	9	0.149	5	7.33333	**8**
X4	0.319	2	1.85	2	0.222	2	2	**2**
X5	0.127	3	0.935	3	0.231	1	2.33333	**3**
X6	0.005	6	0.449	4	-0.088	7	5.66667	**5**
X7	0.493	1	-2.64	1	0.215	3	1.66667	**1**
X8	0.001	9	-0.0849	8	-0.08	9	8.66667	**9**
X9	0.004	7	-0.314	7	-0.17	4	6	**6.5**

In Table 3.3, GCM variables are ranked based on their sensitivity to the change of model outputs. Their sensitivity is recognized from importance in the ANN method, and from coefficients of standardized regression (SRC) and correlation (CC). The average of the three rankings is used as the grand rank of GCM variables. The top three most sensitive GCM variables are then selected for modelling the local humidity variables. Table 3.3 shows that the top three most sensitive GCM variables for modelling local humidity model are X4, X5, and X7 which are Screen (2m) Temperature, Screen Spec. Humidity, and Skin (surface) Temperature, respectively. The top three most sensitive GCM variables for modelling other local variables are presented in Table 3.4.

Table 3.4 Results of Screening Process of GCM Variables for Local Rainfall, Sunshine, Air Temperature, and Wind Speed

The Average Ranking of significant GCM Variables				
GCM Var	Rainfall	Sunshine	Air Temperature	Wind Speed
X1	8	6	5	6.5
X2	6.5	5	4	3
X3	9	9	9	8
X4	1	1	2	6.5
X5	3	2	3	1
X6	4.5	7	7.5	5
X7	2	3	1	4
X8	6.5	8	7.5	9
X9	4.5	4	6	2

Table 3.4 shows that the top three most sensitive GCM variables for modelling local rainfall, sunshine and air temperature are X4, X5, and X7 which are Screen (2m) Temperature, Screen

Spec. Humidity, and Skin (surface) Temperature, respectively. However, the top three most sensitive GCM variables for modelling local wind speed are X2, X5, and X9 which are Evaporation, Screen Spec. Humidity, and Surface Pressure, respectively. These three GCM variables were also used in the investigation of existing downscaling models as described in the following subsection.

3.5. Evaluation of Existing Downscaling Models

Wilby et al. (2004) describes two groups of downscaling models: dynamical and statistical models. Dynamical downscaling models are models which apply different equations regarding the change of time. Mathematically, dynamical models apply differentials of time (Gamkrelidze, 2011). In climate change downscaling modelling, dynamical models refer to regional climate models (RCMs) that apply in mesoscale weather systems. In this model, hydrodynamic Euler equations and Lagrangian numerical integrations are used to simulate atmospheric variables at all spatial scales (Caya and Laprise, 1999).

RCMs that cover the Lombok Island include the Conformal-Cubic Atmospheric Model (CCAM) from CSIRO (Katzfey et al., 2010) and the RCM-Lombok (Hilman et al., 2010) however, both resolutions of 60 km are still too coarse and cannot be directly applied for the basin of interest at the study location. Therefore, results of CCAM from Katzfey et al., (2010) and RCM-Lombok were downscaled again to obtain finer local climatic variables for the relevant region for the purpose of uncertainty analysis.

Four well known statistical downscaling techniques: Artificial Neural Networks (ANN) models, Change Factor (CF) method, Linear Regression (LR), and Nonlinear Regression (NLR) approaches were evaluated. Other statistical techniques, such as the Weather Generator (WG) and Weather Typing (WT) cannot be applied in this research as both WG and WT are based on the distribution of daily data. Unfortunately, daily data is not available in this region, only monthly data are available.

Artificial Neural Networks (ANN) Models

Artificial Neural Networks (ANN) models are basically advanced multiple nonlinear regression based approaches. Currently, a back-propagation is the most popular architecture of neural networks (Stergiou and Siganos, 1996; Kralisch et al., 2005; and Cannon, 2006). According to Stergiou and Siganos, a typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers. An example illustration of Back-propagation Network is shown in Figure 3.4

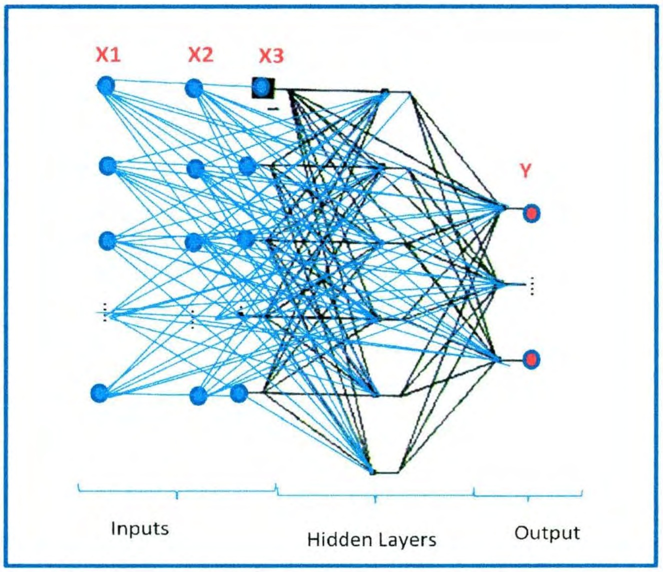


Figure 3.4 An Example Illustration of Back-Propagation Network

Figure 3.4 shows an example of Back-Propagation Network. The responses of the ANN model are local variables, while independent variables are the three most sensitive GCM variables. This network needs 139 hidden layers to produce R^2 of 0.80 in the calibration process. Using software to obtain ANN models is quite easy and quick; however, no equation will be provided by the software. One has to record (save) and copy the network instead of writing a final equation to solve other tasks. In addition, ANN will produce deterministic results.

<u>Change Factor (CF) Method</u>

CF methods are the simplest technique of downscaling (Wilby et al., 2004). They are single independent variable (simple) models. The equation of CF method (Wilby et al., 2004) is expressed as

$$\hat{Y}_{(i)} = Y_{(j)} + \left(\frac{\sum_{i=1}^{n}(X_{(i)}) - \sum_{j=1}^{n}(X_{(j)})}{n} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where:

i = future simulated variables

j = baseline variables

n = number of data

X = GCM variables

Y = Local variables

A CF method applies original unit scales; therefore, independent and dependent (response) variables must be the same variable. A CF method does not consider any statistical relationship between independent and dependent variables. It works based on the summation of the difference between the average of GCM data in the baseline period and the simulation period or so called "the delta change" to the local climatic data in the baseline period. In addition, a CF method produces deterministic results since it does not deal with residuals for variations. The workings of CF method are illustrated in Figures 3.5, and 3.6.

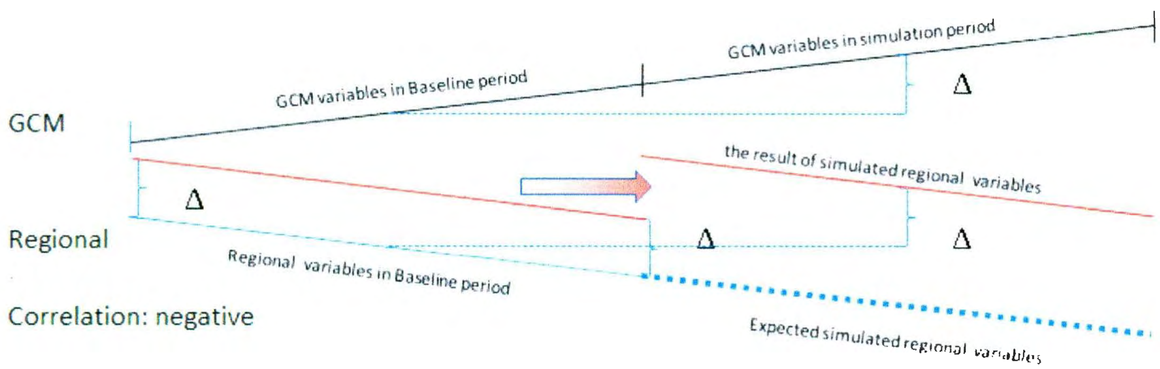


Figure 3.5 An Illustration of CF Method in a Negative Correlation Case

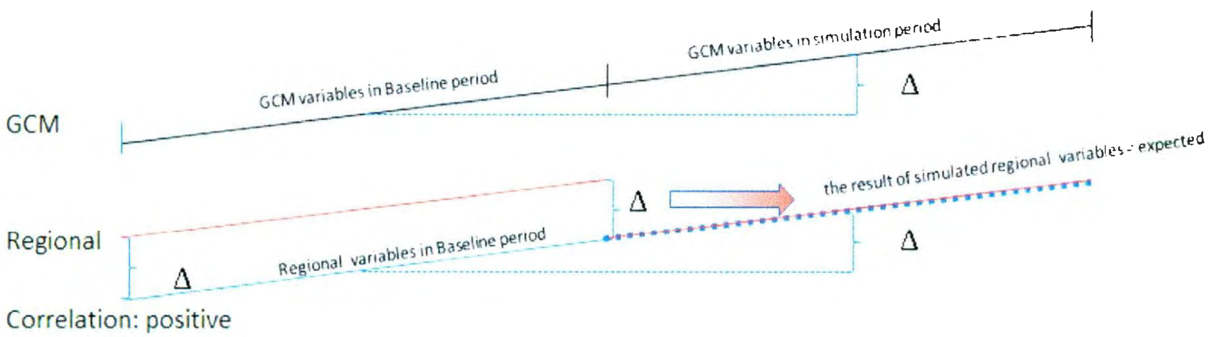


Figure 3.6 An Illustration of CF Method in a Positive Correlation Case

Figure 3.5 shows the result of simulated local variables is not the same as expected local variables. However, Figure 3.6 shows the result of simulated local variables is exactly the same as expected local variables. Therefore, a CF method will only well produce a realistic simulation when the correlation between GCM and local data is positive.

<u>Linear Regression (LR) Approach.</u>

Similar to ANN models, the response of the regression is local variables, while independent variables of regression were the three most sensitive GCM variables. The equation of regression is expressed as

$$\hat{Y} = aX_1 + bX_2 + cX_3 + \ldots + \varepsilon \quad (3.2)$$

Where:

X = GCM variables

$\hat{Y}$ = Local variables

ε = Residuals

A statistical software package, such as Minitab can be used to obtain the linear models. In regression approaches, the following assumptions of Ordinary Least Square (OLS): linearity of model parameters, normality, independency, and constant variance of residuals must be maintained.

Nonlinear Regression (NLR) Approach

Some models which cannot be transformed into linear models can only be estimated through nonlinear models (Lye, 1996; and Lye, 2008). Nonlinear regression (NLR) is a form of regression analysis in which observational data are modeled by a function which is a nonlinear combination of the model parameters such as polynomial, power, exponential, logarithmic, logistic, or Gaussian function (Motulsky and Christopoulos, 2004). The example forms of nonlinear equation are expressed as

Polynomial: $f(x) = \sum_1^n(a_n x^n + a_{n-1}x^{n-1} + \cdots + a_2x^2 + a_1\mathrm{x}) + a_0 + \varepsilon$ .... (3.3)

Power: $f(x) = \sum_1^n(a_n {x_n}^{b_n}) + \mathrm{a}_0 + \varepsilon$ .... (3.4)

Exponential: $f(x) = \sum_1^n(a_n e^{b_n x_n}) + \mathrm{a}_0 + \varepsilon$.. (3.5)

Logarithmic: $f(x) = \sum_1^n(a_n \ln(\mathrm{x}_n)) + \mathrm{a}_0 + \varepsilon$ .... (3.6)

Logistic: $f(x) = \sum_1^n\left(\frac{1}{1+e^{-x_n}}\right) + a_0 + \varepsilon$ .... (3.7)

Gaussian: $f(x) = \sum_1^n a_i\, e^{\left[-\left(\frac{x-b_i}{c_i}\right)^2\right]} + a_0 + \varepsilon$ .... (3.8)

The goal of nonlinear regression is to fit a model to observed data (Press et al., 2002). A statistical software package, such as Datafit software from Oakdale Engineering can be used to obtain nonlinear models. The program finds the best-fit values of the variables in the model. Although, some software packages might automatically fit data to hundreds or thousands of nonlinear equations; however, the software has no understanding of the scientific context of physical processes. Understanding of physical processes is a required scientific decision. It is useful information to support the decision of choosing a type of nonlinear model. Choosing a type of model is not solely based on the shape of the graph.

Results of the four statistical downscaling methods were analyzed in terms of their maximum and minimum values are presented in Table 3.5.

Table 3.5 Results of the Four Statistical Downscaling Methods

Regional	Ranges		ANN		CF		LR		NLR	
Variables	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min
Humidity (%)	100	0	178.9	64.2	88.7	85	85	75	91.1	76.4
Rainfall (mm)	+inf	0	1700.5	-1500.4	590	7	363.1	-7	516.5	-7.4
Sunshine (%)	100	0	164	-159	96	38	96	38	89	58
Air Temp. (°C)	+inf	-inf	37.8	8.7	29.9	22.8	30	23	29.7	24.8
Wind Speed (knots)	+inf	0	12	-6	9	2.1	9	3	6	6

Table 3.5 shows that only CF method produced realistic results. ANN models produced unrealistic values of simulated local rainfall (-1500.4 mm), sunshine (-159 %), and wind speed (-6 knots); LR and NLR approaches also produced unrealistic values of simulated local rainfall. This indicates that only the CF model can produce realistic values of all local variables of the region of interest; however, it has several disadvantages as described in Chapter 2. In addition, as a deterministic model, the CF method cannot provide variability of results and does not produce the change of variance in the future as shown in Figure 3.7.

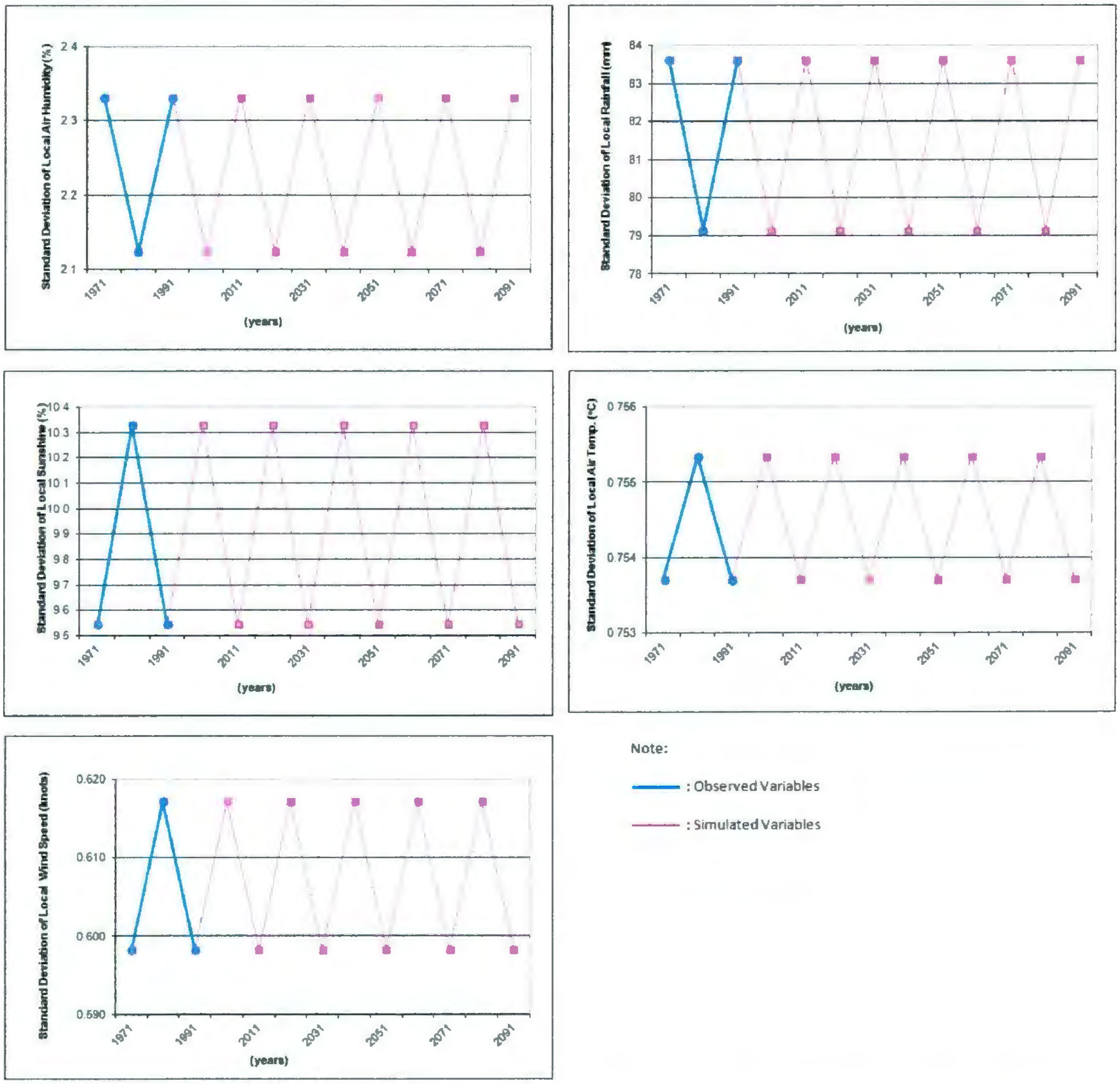


Figure 3.7 Standard Deviations of Simulated Local Climatic Variables from 1971~2100 Produced by the CF Method

Figure 3.7 shows that all local climate variables simulated using a CF method have a repetition of standard deviations. Each standard deviation is actually the standard deviation of the historical data. This means that a CF method cannot produce the change of variance in the future. A CF method can only produce the change of mean of data in the future. Therefore, a CF method will not be used to downscale climatic variables in the region of interest, either. However, as CF is the only method that can produce realistic simulated values of local climatic variables among currently used models, therefore, its concept will be used in the development of a new climatic downscaling model for the region of interest.

3.6. Summary

Impacts of climate change can be studied based on the results of GCMs. However, the problem is that resolution of GCMs; approximately 360 km to 1000 km is coarse for hydrology study on river basin basis. Even though some regional (dynamical) climate models are available for regions in Indonesia, their resolution of 60 km is still coarse for direct applications. Downscaling techniques are appropriate approaches to obtain finer resolution to overcome the problem. One GCM variable might be able to simulate downscaled local climatic variables. However, applying only one GCM variable can lead to lack of some other information. The following top three most sensitive GCM variables: Screen (2m) Temperature, Screen Specific Humidity, and Skin (surface) Temperature were selected through sensitivity analysis to simulate local climatic variables on the Jangkok River Basin.

Currently used downscaling techniques of dynamical models including CCAM-CSIRO, RCM-Lombok, as well as statistical models including Artificial Neural Networks (ANN) models, Change Factor (CF) method, linear regression, and nonlinear regression approaches were investigated in this research. It was found that the resolution of available dynamical models is still too coarse and cannot be directly applied for the basin of interest at the study location. Moreover among the four currently used statistical techniques, only the CF method produces realistic simulated values. However, it cannot provide variability of results and produce the change of variance in the future. Therefore, a new climatic downscaling model has to be developed for the region of interest in order to provide finer simulated local climatic variables. The development of a new model discussed in the next chapter, will be based on the concept of CF method.

Chapter 4

New Downscaling Model

This chapter describes the development of a new downscaling model to facilitate the simulation of local climatic variables for the Jangkok River Basin. This chapter includes background, review of the change factor method, the development of a new downscaling model, the generation of model residuals, the analysis of model uncertainties, and summary.

4.1. Background

Downscaling techniques are required to provide finer scale simulated local climatic variables. Existing downscaling techniques, including dynamical and statistical models as well as the change factor method have been investigated in this research to provide simulate local climatic variables. From the investigation, it is found that the existing downscaling models have the following disadvantages: coarse scale of resolution, unrealistic simulated values, and unchanged statistical characteristic of simulated values. These disadvantages were also reported in Wilby et al. (2004). They also include a high cost of operation and inability to provide variability in simulations as disadvantages. Among the existing downscaling techniques investigated in the previous chapter, the Change Factor (CF) method was found to be able to simulate realistic values of local climatic variables for the Jangkok River Basin. However, it has several drawbacks that need to be overcome. In the next section, modifications to the CF method that will overcome the listed drawbacks will be described.

4.2. Modifications to the Change Factor Method

From the results of Chapter 3, a new and better model based on modifications to the CF method is possible. However, since the CF method has several disadvantages namely the use of a single variable model with prerequisite only for the same type of variables between GCM and local, the disregard for any correlations between GCM and local variables, the inability to represent changes in statistical characteristics of simulated future values, and the inability to provide variability of the simulated values, the new downscaling model that will be developed based on the basic concept of CF method, must overcome the disadvantages of the CF method. It must be able to:

1. take into account correlations between GCM and local variables,
2. deal with multiple GCM variables,
3. represent the change in statistical characteristics of the simulated future values, and
4. provides variability of the simulated values.

4.3. Development of a New Downscaling Model

A new downscaling model will be developed based on a hybrid of algebraic and stochastic approaches, so named the "HYAS" model which employs the differences between simulated future variables and baseline variables, and are added to generated residuals that have changing mean and variance. An algebraic process is basically a mathematical process which deals with the rules to develop equations of relationships between predictor (independent) variables and predictant (dependent) variables (Michael, A., 1991). A Stochastic process is a process which deals with variable values or non deterministic values, and might deal with random numbers (Salas et al., 1985; and Devore, 1995).

The development of a new downscaling model was inspired by the concept of the CF method that considers a delta (difference) between both means of future values and of baseline values of GCM variables for obtaining the change of values from historical to predicted local variables. The differences between the CF method and the new downscaling (HYAS) model are:

1. The CF method works based on the mean (average), while the HYAS model works based on individual values; therefore, the CF method cannot represent the change of other statistical characteristics except the mean, while the HYAS model can represent the change of all statistical characteristics,
2. The CF method does not take into account any correlations between GCM and local variables, while the HYAS model takes into account the sign of correlation between GCM and local variables; hence the CF method might produce unexpected results (see explanation in Figures 3.4 and 3.5),
3. The CF method uses original units of GCM variables, while the HYAS model applies standardized units of GCM variables; therefore, the CF method can only apply one GCM variable (a single variable model) which must be similar to the local variable, while the HYAS model can apply any multiple GCM variables,
4. The CF method cannot apply variability in their input, while the HYAS model can apply variability in its input; therefore, the CF method is a deterministic model, while the HYAS model is a stochastic model.

Referring to point 1 above, $\frac{\sum_{i=1}^{n}(X_{(i)})}{n}$ and $\frac{\sum_{j=1}^{n}(X_{(j)})}{n}$ in Equation 3.1 has to be changed to $\frac{\sum_{j=1}^{n}(Z_{j_{(i)}})}{n}$ and $\frac{\sum_{j=1}^{n}(Z_{j_{(Yi)}})}{n}$. With regards to point 2, a new term "sign[r]" is added to the model. With regards to point 3, $\left(\frac{\sum_{i=1}^{n}(X_{(i)})}{n} - \frac{\sum_{j=1}^{n}(X_{(j)})}{n}\right)$ in Equation 3.1 has been changed to become $\frac{\sum_{j=1}^{n}(Z_{j_{(i)}} - Z_{j_{(Yi)}})}{n}$ where Zs are standardized GCM variables. Because Zs have a standardized unit, a rescaling coefficient (K) is required to change the standardized unit to a similar unit with the original unit of the local variables. The standardized values can be obtained using Equation 4.1

$$Z_i = \frac{X_i - \bar{X}}{\sigma} \quad \text{...} \quad (4.1)$$

Where:

Z_i = standardized values

X_i = GCM variables

$\bar{X}$ = the average (mean) of GCM variables

σ = the standard deviation of GCM variables

The rescaling coefficient, K is obtained using calibration. However, its initial estimate can be determined using Equation 4.2.

$$K = \frac{\left(Med(Z_{j_{(i)}}) - Med(Z_{j_{(Yi)}})\right)}{\left(Med(\hat{Y}_{(i)}) - Med(Y_{(i)})\right)} \quad \text{..................................... (4.2)}$$

Where:

K = standardized GCM variables rescaling coefficient,

$Med(Z_{j(i)})$ = median of future standardized GCM variables,

$Med(Z_{j(Yi)})$ = median of baseline standardized GCM variables,

$Med(\hat{Y}_{(i)})$ = median of future (simulated) local variables,

$Med(Y_{(i)})$ = median of baseline (historical) local variables.

Therefore the final equation of the HYAS model is

$$\hat{Y}_i = Y_i + sign[r] * K * \frac{\sum_{j=1}^{n}(Z_{j_{(i)}} - Z_{j_{(Yi)}})}{n} + \delta * \varepsilon_{(i)} \quad \text{..................... (4.3)}$$

$$\text{If } \frac{\sum_{j=1}^{n}(Z_{j_{(i)}} - Z_{j_{(Yi)}})}{n} = G_i, \text{ then}$$

$$\hat{Y}_i = Y_i + sign[r] * K * G_i + \delta * \varepsilon_{(i)} \quad \text{............................ (4.4)}$$

If $Y^*_i = Y_i + sign[r] * K * G_i$, then

$$\hat{Y}_i = Y^*_i + \delta * \varepsilon_{(i)} \quad \text{...................................... (4.5)}$$

Where:

$\hat{Y}_i$ = downscaled local variable,

δ = residual rescaling coefficient,

Y^*_i = calculated local variables before being added to generated residuals,

Y_i = baseline local variable,

r = sign of correlation between the baseline of GCM and local variables,

K = standardized GCM variables rescaling coefficient,

$Z_{j_{(i)}}$ = standardized GCM variable of i in the next j year (future period),

$Z_{j_{(Yi)}}$ = standardized GCM variable of i in the baseline period,

ε_i = generated model residuals with changing mean and variance,

n = the number of GCM variables.

The purpose of the residual rescaling coefficient (δ) is to adjust the range of the predicted local variables so that it will not go beyond the limit of possible values. If none of the predicted local variables lies beyond the boundary, $\delta = 1$; if at least one of the predicted local variables lie beyond the boundary, the value of δ will be between 0 (zero) and 1 (one) and can be obtained by calibration. Model acceptance criteria are used to judge whether the new model can satisfactorily replace the currently used models. The new climatic downscaling model will be accepted only if it satisfies certain criteria proposed to be discussed in Section 4.6.

4.4. Generation of Model Residuals

Climate change can be recognized from the change in statistical characteristics of long term recorded climatic variables. The change is not always in all statistical characteristics. It may occur only in one or two statistical characteristics (IPCC, 2001; and Pryor, 2009). Two important statistical characteristics are mean and variance (Inouye, 2005). As global future climate change has been simulated using GCMs, the change in statistical characteristics of future climatic variables can be investigated in GCM variables. In this research, the change of average and the inconstancy of variance are investigated to confirm the existence of climate change in the future. The change in statistical characteristics of GCM variables is then reproduced in the simulated future local climatic. In this research, model residuals are purposely generated to mimic these inconstancies. The analysis of the change in mean and the inconstancy in variance of climatic variables are described below.

The Analysis of Changing Mean in GCM Variables

The change of mean can be recognized using standard statistical methods such as two sample t, ANOVA, or some non parametric tests (Lye, 1996 and Lye, 2008). A significant change in mean of GCM variables in this research is tested using ANOVA for parametric data or Kruskal-Wallis for non parametric data, and Interval Plots. As an illustration of these tests, the top three most sensitive GCM variables of CGCM2 for modelling local climatic variables were divided into three sets of data which are: A1 commences from 1971 to 1995, A2 commences from 2019 to 2043, and A3 commences from 2067 to 2091. In both analyses: ANOVA and Kruskal-Wallis, the null hypothesis is that the three sample means are identical, and the alternative hypothesis is that at least one of the means is different from others. A significance level (α) of 0.05 is assumed.

$$H_0: \mu_1 = \mu_2 = \mu_3$$

Ha: at least one mean is different.................................. (4.6)

Where:

H_0 = the null hypothesis (the hypothesis of equality of the means),

Ha = alternative hypothesis,

μ_1, μ_2, μ_3 = means of group 1, group 2, and group 3.

In this test, the p-value less than α indicates the rejection of the null hypothesis. Normality tests have to be conducted to decide whether using ANOVA or Kruskal-Wallis as shown in Figure 4.1.

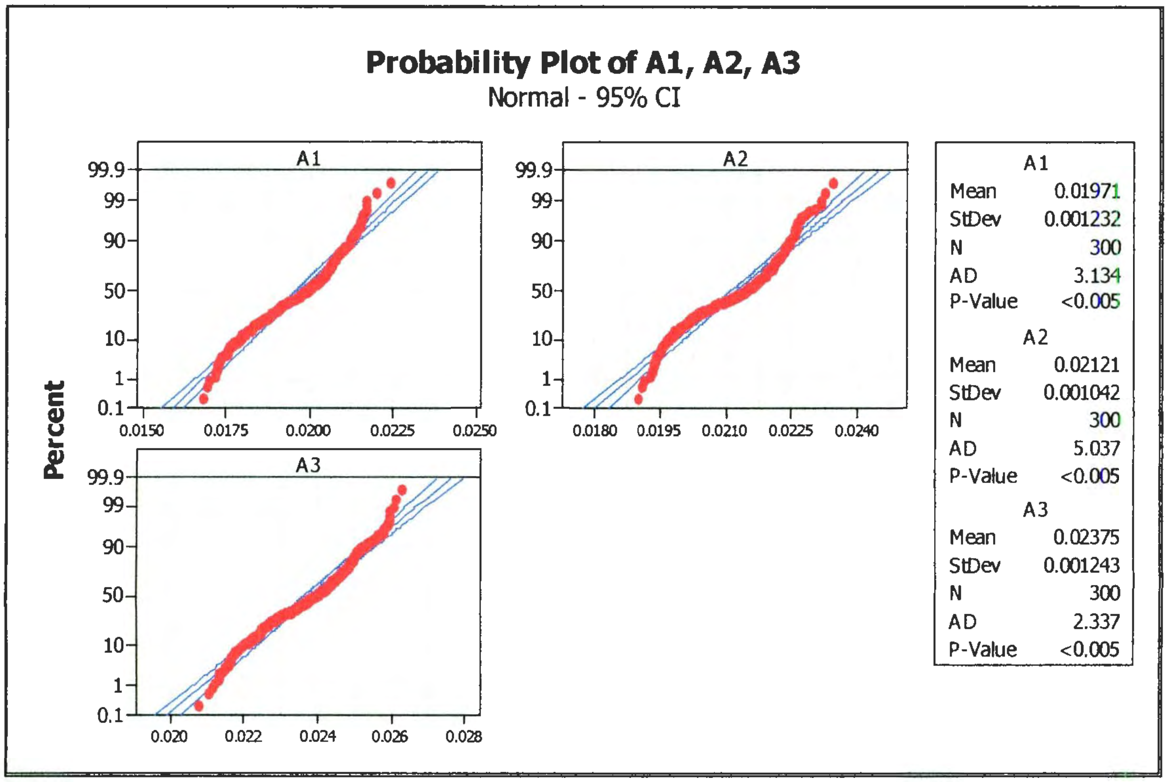


Figure 4.1 Normality Tests for A1, A2, and A3

Figure 4.1 shows that data of A1, A2, and A3 do not follow normal distributions as their P-values are smaller than 0.05. Next, a Kruskal-Wallis is used to examine differences in their means. The result of a Kruskal-Wallis test for GCM Screen (2m) Air Temperature is shown in Table 4.1.

Table 4.1 Results of the Analysis of GCM Screen (2m) Air Temperature using a Kruskal-Wallis Test

Kruskal-Wallis Test:

```
Kruskal-Wallis Test

Subscripts    N  Median  Ave Rank       Z
A1          300   27.34     221.9  -18.65
A2          300   28.46     413.9   -2.99
A3          300   30.15     715.6   21.64
Overall     900             450.5

H = 549.99  DF = 2  P = 0.000
H = 549.99  DF = 2  P = 0.000  (adjusted for ties)
```

Table 4.1 shows that the sample medians for the three treatments were calculated 27.34, 28.46, and 30.15. The z-value for A1, -18.65 is smaller than zero. This size indicates that the mean rank for A1 differed from the mean rank for all observations. The mean rank for A2, -2.99 is also smaller than zero to indicate lower mean of A2 compared to the mean of all observations. The mean rank for A3 is higher than the mean rank for all observations, as the z-value is positive (z = 21.64). The test statistic (H) had a p-value of 0.00, both unadjusted and adjusted for ties, indicating that the null hypothesis can be rejected in favour of the alternative hypothesis of at least one difference among the treatment groups.

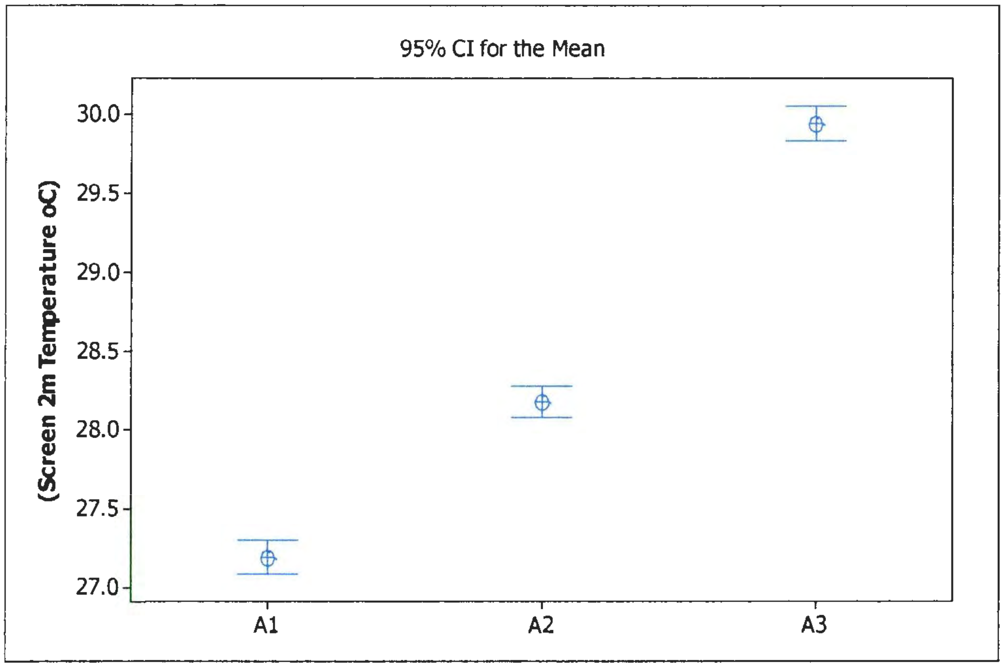


Figure 4.2 The Interval Plot of GCM Screen (2m) Air Temperature (^{o}C)

Figure 4.2 shows three interval plots of GCM Screen 2m Air Temperature commencing from 1971 to 1995 (A1), 2019 to 2043 (A2), and 2067 to 2091 (A3) that do not overlap each other. This explains that the means are significantly different from each other.

The Analysis of Inconstant Variance in GCM Variables

In this study, a Test for Equal Variances will be used to identify inconstant variances of GCM climatic variables. The result of a test for Equal Variances is shown in Figure 4.3.

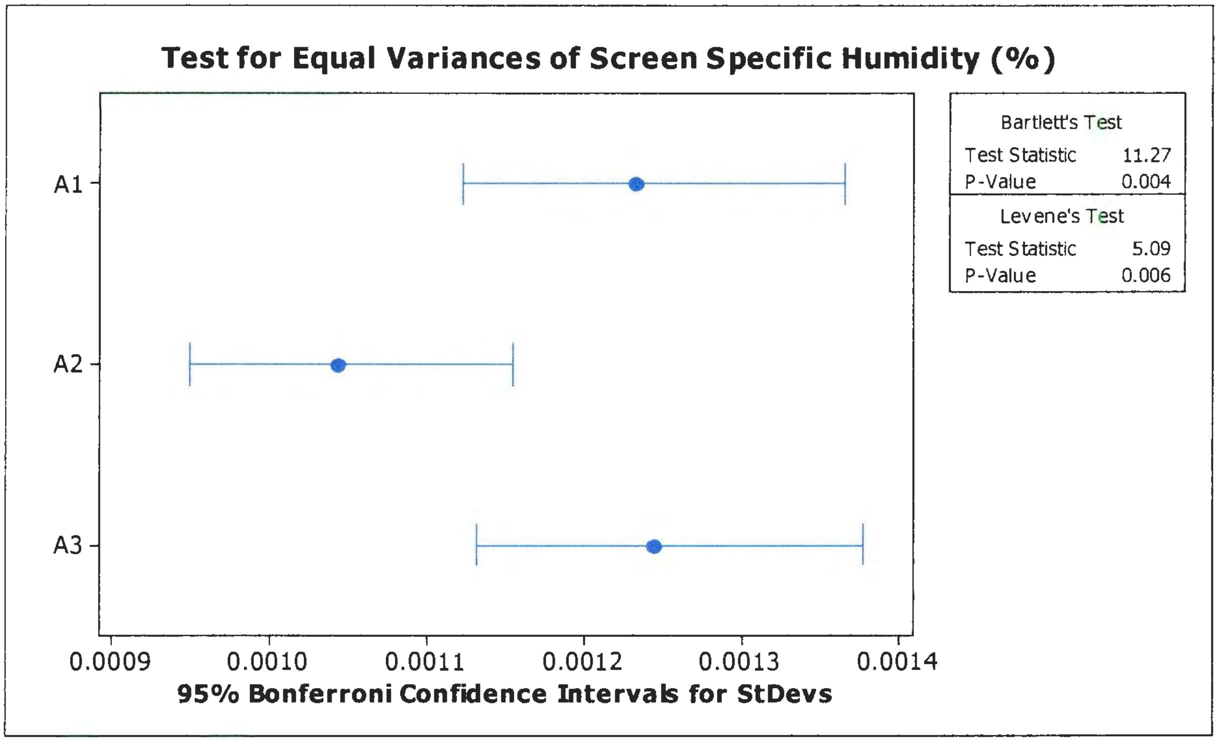


Figure 4.3 Test for Equal Variances of Screen Specific Air Humidity (%)

Figure 4.3 also shows that the p-values of 0.004 from a Barlett`s test and 0.006 from a Levene`s test are smaller than 0.05. P-value smaller than 0.05 indicates the null hypothesis can be rejected in favor of the alternative hypothesis of at least one difference among the treatment groups. The Analysis for the change in mean and inconsistency in variance of other significant GCM Variables is attached in Appendix B.

Two methods of residual generations: artificial neural networks (ANN) and a cluster based approach developed as a part of HYAS model will be performed to generate residuals to produce a varying mean and variance. Both results will also be used in the analysis of model uncertainty.

4.4.1. ANN Based Model Residual Generation

An important application of neural networks is pattern recognition (Stergiou and Siganos, 1996, and Pacelli et al., 2011). The patterns of historical data in ANN can be recognized through training. During training, the network learns any possibilities of association patterns between outputs and input. Unsupervised learning and supervised learning processes are two types of training in neural networks. However, this research only applies a supervised learning process.

In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This is called a "Back-Propagation" algorithm (Rumelhart et al., 1986, and Alpaydın, 2010). This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is called the "training set." The current commercial network development packages provide tools to monitor how well an artificial neural network is converging on the ability to predict the right answer. Many layered networks with multiple nodes are capable of memorizing data. To monitor the network to determine if the system is simply memorizing its data in some insignificant way, supervised training needs to hold back a set of data to be used to test the system after it has undergone its training. Generally summary has to be done on reviewing the input and outputs, the number of layers, the number of elements per layer, the connections between the layers, the summation, transfer, and training functions, and even the initial weights themselves. The other type of training is called unsupervised training. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features should be used to group the input data. This is often referred to as self-organization or adaption.

The behaviour of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories: Linear, Threshold, or Sigmoid. ANN produces simulated outputs based on minimizing errors of historical outputs. ANN calculates error derivative for the weights (EW) using an algorithm in order to change the weight by an amount that is proportional to the rate at which the error changes as the weight is changed.

This residual generation requires information of GCM variables, normal random variates, calculated local variables before being added to generated residuals (Y*), and historical residuals as shown in Table 4.2. Historical residuals are set as responses, then GCM variables, calculated local variables before being added to generated residuals (Y*), and normal random variates (NR) are set as input variables. Historical residuals are the differences between Y* and observed variables. Normal random variates that will be converted to the same distribution of GCM variables are applied to generate variation in its simulations. The outputs of ANN are simulated residuals. In this approach, either the original unit of GCM variables or standardized GCM variables can be used. In this research, the ANN needs 80 to 150 hidden layers. Table 4.2 shows an illustration of this method using the GCM variables of CGCM2.

Table 4.2 Input Variables and Responses

	X4	X5	X7	NR	Y*	Res
1	-0.157675338	-0.40283	-0.102777725	0.276440545	82	0
2	-0.28448299	-0.37327	-0.371944268	-0.820454276	85	0
3	-0.440619971	-0.66748	-0.378412563	0.61898607	83	0
4	-0.350657223	-0.54776	-0.284247595	-0.760963927	84	0
5	-0.941953581	-1.16034	-0.861620796	-1.343989508	81	0
6	-1.551873374	-1.62661	-1.492568541	-1.428225882	80	0
7	-1.889734451	-1.98632	-1.889595367	0.895418059	79	0
8	-2.311894412	-2.23832	-2.271353154	1.087833849	76	0
9	-1.852236381	-2.04701	-1.980911582	-0.119046825	78	0
10	-1.180290448	-1.71876	-1.317307902	2.87354285	78	0
...	...	...	...	...	...	...
475	-1.556801781	-1.25832	-1.577658598	1.66517321	78	2
476	-1.711339383	-1.38585	-1.737768957	-1.571706796	80	4
477	-1.521039115	-1.33717	-1.512324871	2.446771408	80	2
478	-1.050074669	-0.87912	-1.053512751	-0.181375775	81	-1
479	-0.334132131	-0.39011	-0.270595625	0.146419902	79	9
480	0.170297593	0.025094	0.208803222	-0.318549449	81	5
481	0.293973623	-0.23856	0.14393561	0.592277467	82	
482	0.247336656	0.241922	0.096935723	0.048170275	85	
483	-0.002236211	-0.02263	0.011792126	0.535213846	83	
484	-0.091528007	-0.12852	-0.06713661	1.25987918	84	
485	-0.200041278	-0.47799	-0.084149792	0.555329989	81	
...	...	...	...	...	...	
1559	2.061660177	2.359719	2.087478044	0.716761834	82	
1560	2.393402938	2.446708	2.430383005	-1.628804185	81	

The Plot between actual values (historical residuals) versus ANN based predicted values (simulated residuals) is shown in Figure 4.4

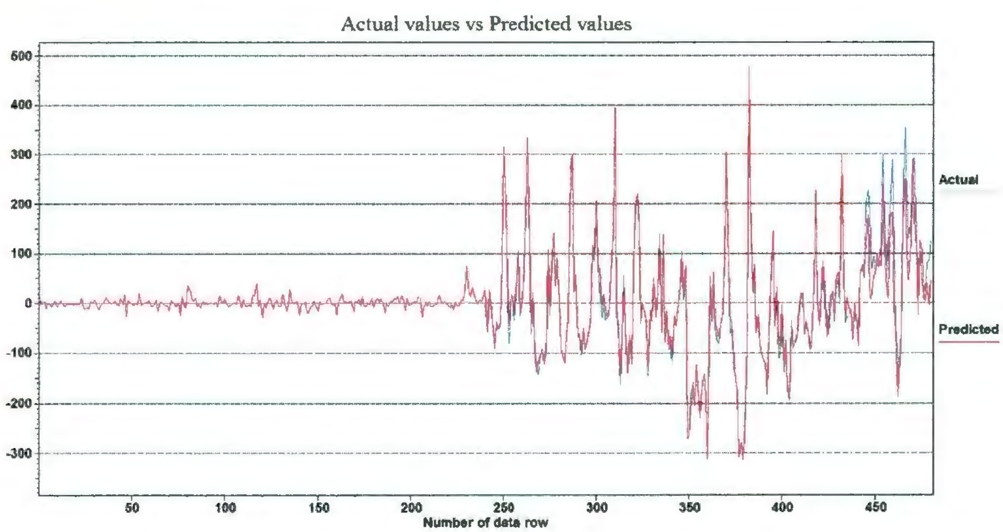


Figure 4.4 The Graph of Actual Values Versus Predicted Values During Learning Processes

Figure 4.4 shows a very good performance of ANN to simulate residuals. It has a R^2 of 0.86. The result of ANN based residual generation is shown in Table 4.3.

Table 4.3 The Results of ANN Based Residual Generation

No	Simulated Residuals
1	-0.372316
2	-0.012521
3	-0.521682
4	-0.599105
5	-0.205851
6	-0.213866
7	-0.282264
8	0.646114
9	0.317468
10	-0.383155
...	...
1551	9.361881
1552	11.74759
1553	8.597907
1554	13.21694
1555	7.692856
1556	7.655729
1557	8.235731
1558	10.70147
1559	10.67492
1560	14.78044

Table 4.3 shows that the results of simulated residuals (predictions). These simulated residuals are then put in the equation (4.5) to produce downscaled local variables ($\hat{Y}_i$).

4.4.2. Cluster Based Model Residual Generation

It is explained in many statistical text books that clustering also known as classification, numerical taxonomy, botryology, or typological analysis refers to one of sampling techniques which is the task of assigning a set of objects or data into groups (called **clusters**). It is done to arrange the objects or data in the same cluster are more similar (in some sense for example: geography, time period, age, level of education) to each other than to those in other clusters (Kriegel et al., 2011). The objective of clustering in this new model is to assign observations into groups so that observations within each group are more similar to one another.

Cluster approach is applied here as hydrologic and climatic data follow seasonal or monthly patterns. In monthly data, variation of data cannot be analyzed among months. They can only be analyzed within a month. Therefore, a clustering approach in this new downscaling model was conducted based on months: January to December. Data are clustered into 12 groups. Each of the groups is analyzed separately.

Procedures applied in the generation of model residuals based on cluster approach include

1. Clustering the residuals found in the calibration process based on a monthly order to eliminate the time dependency of residuals;
2. Regressing the clustered residuals to time to obtain the slope of the change of residuals;
3. Determining the new residuals obtained from the regression in step 2;
4. Transforming the new residuals into a normally distributed variate;

5. Determining the parameters (μ, σ) of the normally distributed residuals found in step 4;
6. Generating a new random variable based on a normal distribution with mean zero and standard deviation of σ which was found in step 5;
7. Inverse transforming the normally distributed variables based on the type of transformation used in step 4;
8. Adding the transformed residuals to the regression equation of step 2; and
9. Anti-clustering the results of step 8 into the original sequences.

These procedures can be explained using the following illustrations starting from the pattern of residuals as illustrated in Figure 4.5 that is similar to the pattern of residuals shown in Figure 4.1.

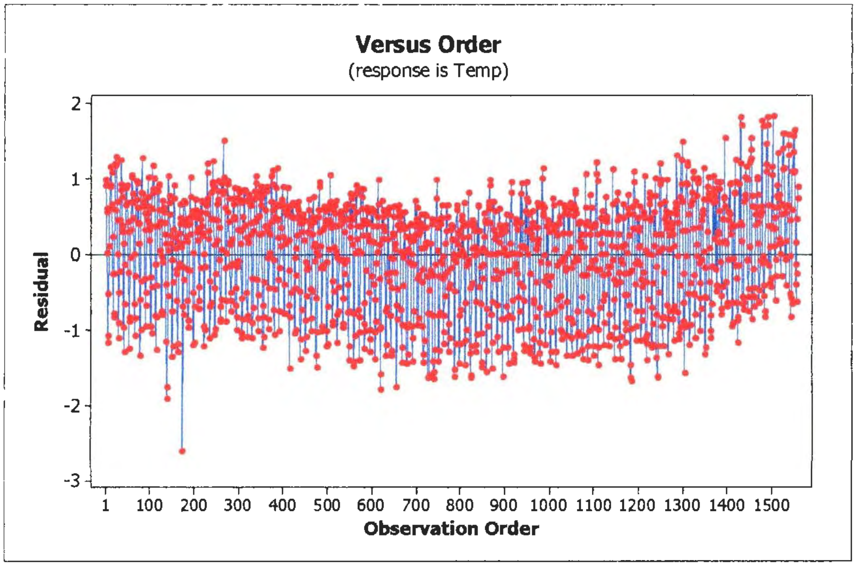


Figure 4.5 The Plot of Residuals Versus Observation Order

After monthly clustering (step 1), the plot of residuals are shown as in Figure 4.6.

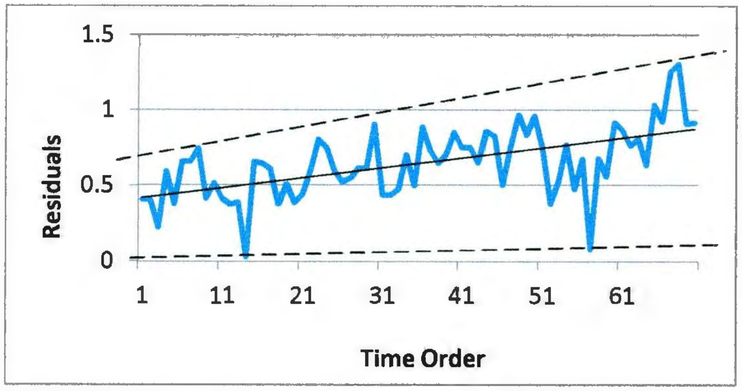


Figure 4.6 The Plot of Residuals of Local Air Humidity in January Versus Time Order

Figure 4.6 shows that the residuals do not follow normal distribution, have a non constant variance, and a non constant mean; however, they are now random independent since there is no curvature pattern in the plot of residuals. After conducting a regression between the clustered residuals and the independent variable of time (step 2), new residuals were shown in Figure 4.7.

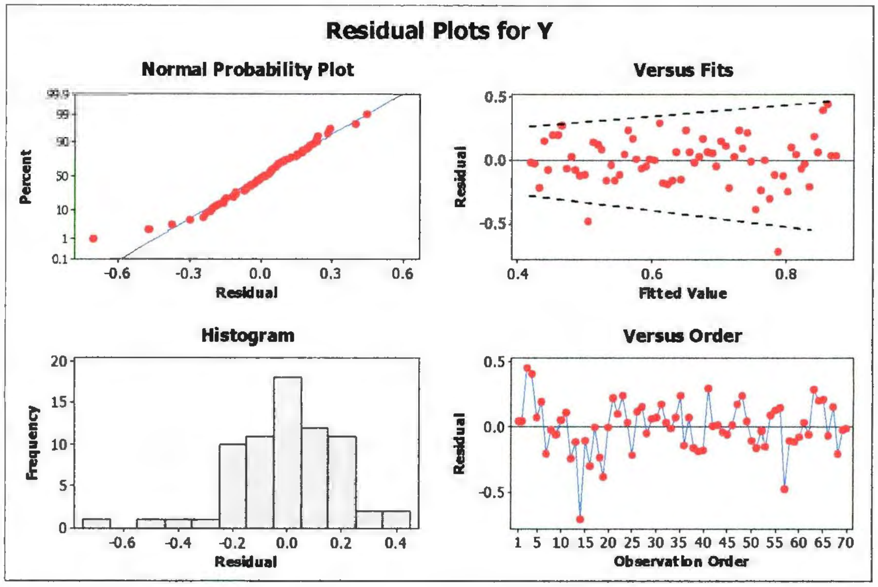


Figure 4.7 The Residual Diagnostics of Air Humidity in January After Regression Against Time

Figure 4.7 shows that even though, new residuals still do not follow normal distribution and have a non constant variance; however, they have a constant mean equal to zero. The regression equation in this example case is Y = 0.880 - 0.00659 x. New residuals can be found through the subtraction of the clustered residuals by the predicted Y from the equation above (step 3). After transforming the new residuals using a "natural logarithmic" function (step 4), the transformed new residuals follow a normal distribution as shown in a normal probability plot in Figure 4.8.

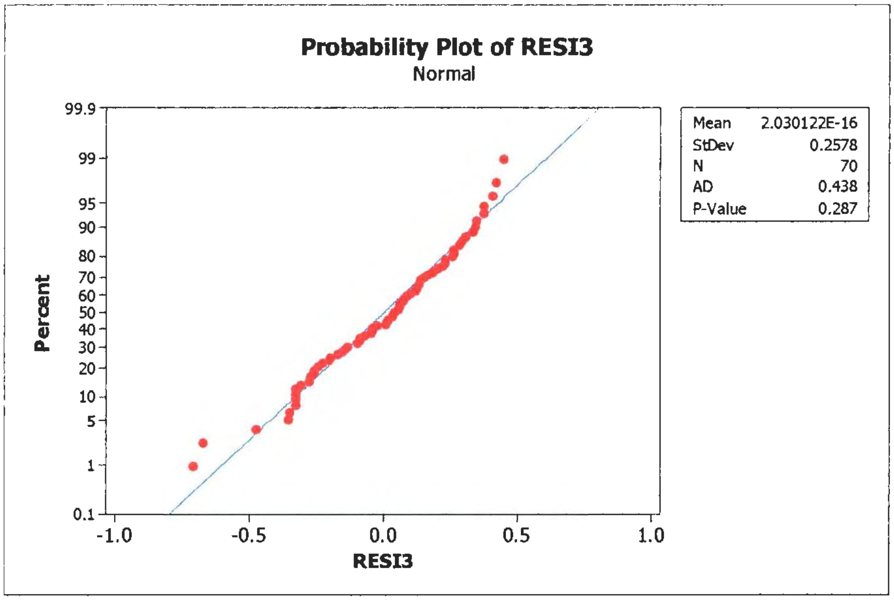


Figure 4.8 A Normal Probability Plot of Residuals After a Natural Logarithmic Transformation

Figure 4.8 shows that the P-Value of 0.287 is larger than 0.05. This indicates that the transformed new residuals follow approximately a normal distribution after a natural logarithmic transformation. From the descriptive statistics in this example case, it is found that the mean (μ) and standard deviation (σ) of the transformed residuals are zero and 0.3, respectively (step 5). Finally, by following steps 6 to 9 in the procedures of cluster based residual generation above, the residuals of new downscaling model can be determined.

These residuals are important factors in the new downscaling model to adjust the final simulated results to be always inside the boundary of realistic values and to have variability. Therefore pursuant to the important tasks of model residuals, residuals require a coefficient for adjusting the range of predicted local climatic variables ($\hat{Y}_i$) so that they will not lie beyond the limit of realistic values. The coefficient (C) is called the coefficient of residual correction. If none of the predicted local variables ($\hat{Y}_i$) lies beyond the boundary, C = 1 (one); if at least 1 (one) of predicted local variables ($\hat{Y}_i$) lies beyond the boundary, the value of C will be between 0 (zero) and 1 (one) and can be obtained using calibration. The boundary is based on characteristic of local variables, for example: lower and upper boundaries of local Air Humidity are 0 (zero) % and 100 % as Air Humidity variables cannot be smaller than 0 (zero) % or larger than 100 %.

4.5. Model Fitting

Model fitting is a process of constructing a model that has the best fit to a series of observed data points. Model fitting in this research refers to a process of best matching the new downscaling model to a series of observed local climatic variables. The technique of model fitting used in this research is a least square technique. The method of least squares assumes that the best-fit curve of a given type is the curve that has the minimal sum of the deviations squared (least square error) from a given set of data.

Suppose that the data points are (x_1, y_1) , (x_2, y_2), ..., (x_n, y_n) where x is the independent variable and y is the dependent variable. The fitting curve $f(x)$ has the deviation (residual) d from each data point, i.e., $d_1 = y_1 - f(x_1)$, $d_2 = y_2 - f(x_2)$, ..., $d_n = y_n - f(x_n)$. According to the method of least squares, the best fitting curve has the property that:

$$Minimize \prod = {d_1}^2 + {d_2}^2 + \cdots + {d_n}^2 = \sum_{i=1}^{n} {d_i}^2 = \sum_{i=1}^{n} [y_i - f(x_i)]^2 \quad \text{...... (4.7)}$$

Where:

d_1, d_2, d_n	=	residuals,
y_i	=	observed value
$f(x_i)$	=	simulated value
n	=	number of simulations

4.6. Model Acceptance Criteria

Model acceptance criteria are used to judge whether the new downscaling model can satisfactorily replace currently used models. A new downscaling model will be accepted only if it satisfies the criteria proposed in Table 4.4.

Table 4.4 Model Acceptance Criteria

No	Criteria	Range of Acceptance
1	Goodness of fit model validation	NSE > 0.7
2	Realistic range of simulated results	Local Air Humidity (%) = 0 ~ 100 Rainfall (mm) = 0 ~ + infinity Sunshine (%) = 0 ~ 100 Air Temperature (°C) = – infinity ~ + infinity Wind Speed (knots) = 0 ~ + infinity
3	Statistical characteristics	Presence of changing future means and variances.

In the development of a model, model goodness of fit tests is an important step both in calibration and in validation processes. Model goodness of fit tests in this study refers to how well a model fits a set of observations. Measures of goodness of fit will summarize the discrepancy between observed values and the values expected from the model (Sorooshian and Gupta, 1995; and Sulistiyono, 1999). The goodness of fit test that will be used in this study is the Nash Sutcliffe Model Efficiency Coefficient (NSE) (Nash and Sutcliffe, 1970). The equation of NSE is expressed as:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (O - S)^2}{\sum_{i=1}^{n} (O - \overline{O})^2} \qquad (4.6)$$

where:

NSE = The Nash-Sutcliffe Model Efficiency Coefficient

O = Observed local variables

S = Simulated local variables

$\overline{O}$ = The mean of observed local variables

NSE measures the experimental errors of simulated values to the grand mean of observed values. The value of NSE is a fraction between - infinity and one, and has no units. According to Nash and Sutcliffe (1970), NSE equal to one corresponds to a perfect match of modelled to the observed data; NSE equal zero indicates that the model predictions are as accurate as the mean of the observed data; and NSE less than zero indicates that the observed mean is better predictor than the model. However in a more recent research by Gupta, H. V. and H. Kling, (2011), in general model simulation can be judged as satisfactory if NSE larger than 0.7.

4.7. Model Uncertainty Analysis

Model uncertainty in this research referred to model output variability due to lack of and difference of information in the development of a new model. In fact, variability in a non deterministic (stochastic) model always exists (Mukhtasor, 2001). Lack of and difference of information in the model development might include given information on population, economy, and technology of a particular region. Moreover, different period of time also leads to different choices of emission scenario. In addition, the use of different GCMs and methods for generating residuals also give different results.

In this research, the purpose of uncertainty analysis was to obtain the degree of model uncertainty based on several possible variations of model inputs and assumptions. Model uncertainty analysis applied referred to the change in application of General Circulation Models (GCMs), emission scenarios, and methods of residual generation. GCMs employed in the uncertainty analysis were the Second Generation Coupled Global Climate Model from Canadian Centre for Climate Modelling and Analysis (CGCM2-CCCma); the Second version of Mark Model from Australia's Commonwealth Scientific and Industrial Research Organisation (Mk2-CSIRO); and the Climate Change Model developed in 1999 by the National Institute for Environmental Studies (NIES99) from the collaboration between the Center for Climate System Research (CCSR) and Japan's National Institute of Environmental Studies (NIES). Emission scenarios employed were A2 and B2 as both scenarios are the most probable to happen in the region of interest. Furthermore, the methods of normal random with neural network and normal random with cluster generations were performed to generate different residuals to complete the uncertainty analysis in this research. In addition, the simulated local climatic variables of two different regional climate models: Conformal – Cubic Atmospheric Model from CSIRO (CCAM-CSIRO) and Regional Climate Model for Lombok (RCM-Lombok) (Hilman et al., 2010) were applied in model inputs to complete the model uncertainty analysis.

The uncertainty analysis determined how far the new model produces differences in statistical characteristics of model outputs including median, mean, standard deviation, maximum, and minimum. Quartile plots as well as a numerical approach were used to analyze uncertainties of model. Quartile (Q1, median, and Q3) plots were used to see the change of statistical characteristics in the future. In addition, numerical uncertainties based on 95% confidence interval were used to precisely determine the degree of model uncertainty.

4.8. Results

The goodness of fit model calibration and validation of the HYAS model is presented in Figure 4.9 to Figure 4.13.

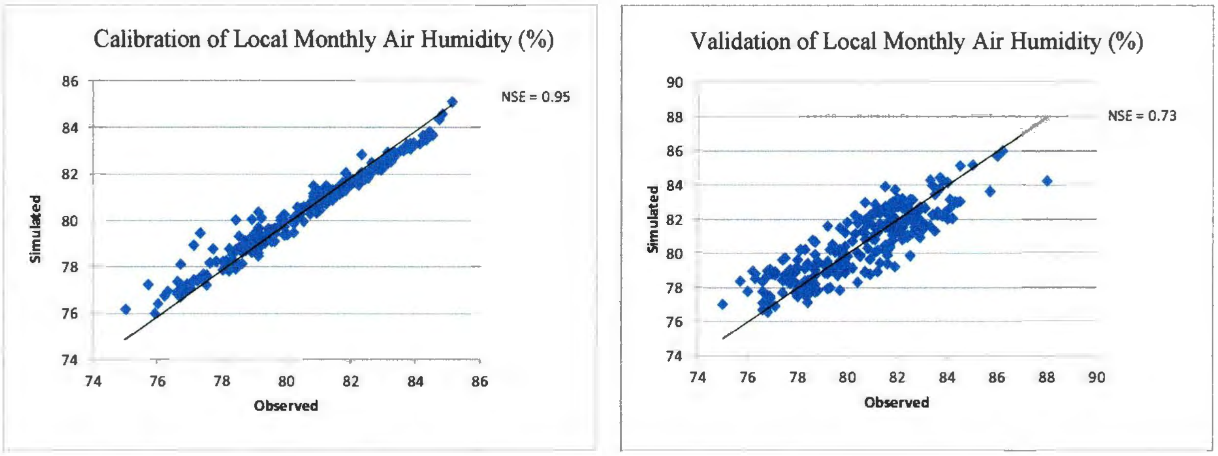


Figure 4.9 Plot of Observed Versus Simulated Local Monthly Air Humidity (%)

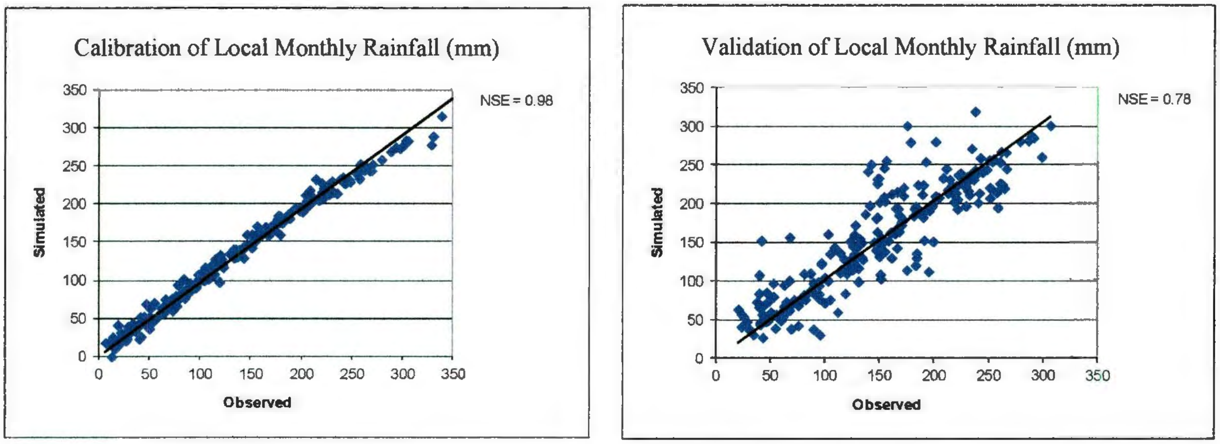


Figure 4.10 Plot of Observed Versus Simulated Local Monthly Rainfall (mm)

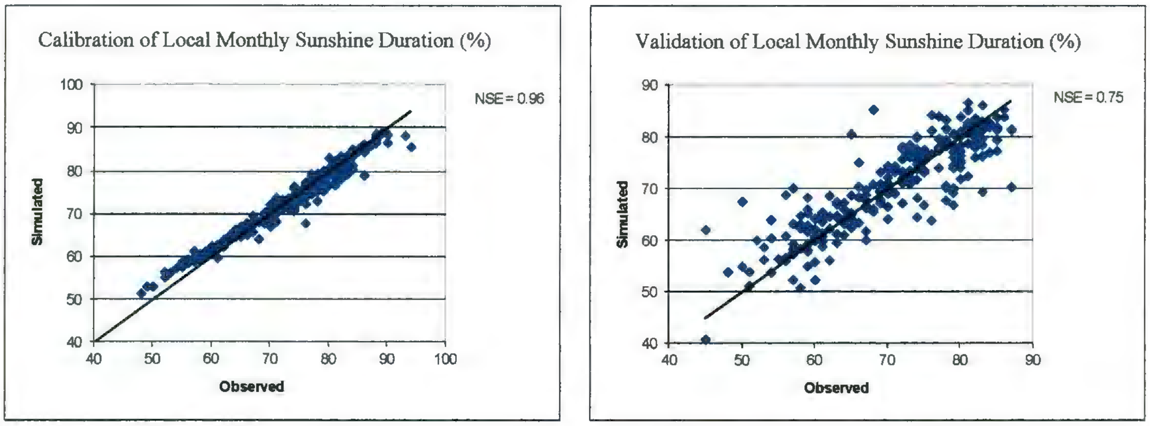


Figure 4.11 Plot of Observed Versus Simulated Local Monthly Sunshine (%)

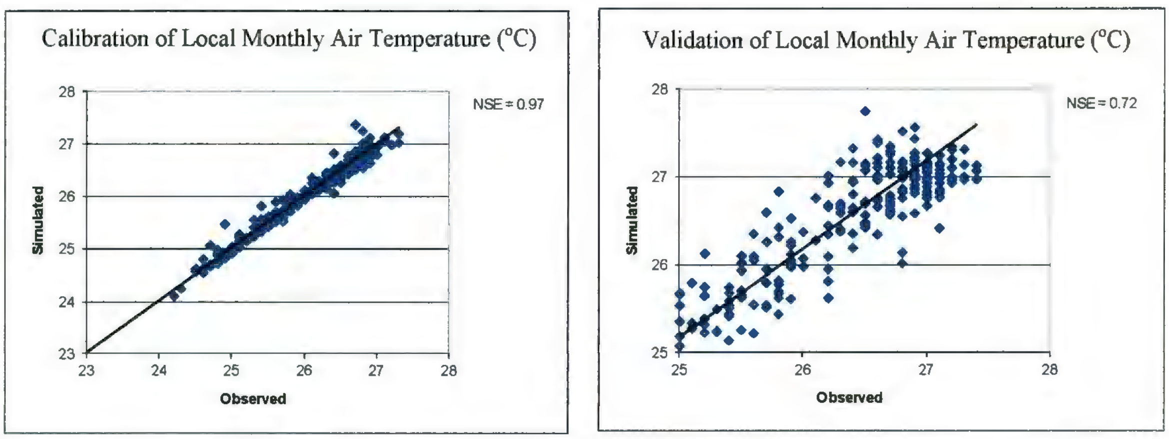


Figure 4.12 Plot of Observed Versus Simulated Local Monthly Air Temperature (°C)

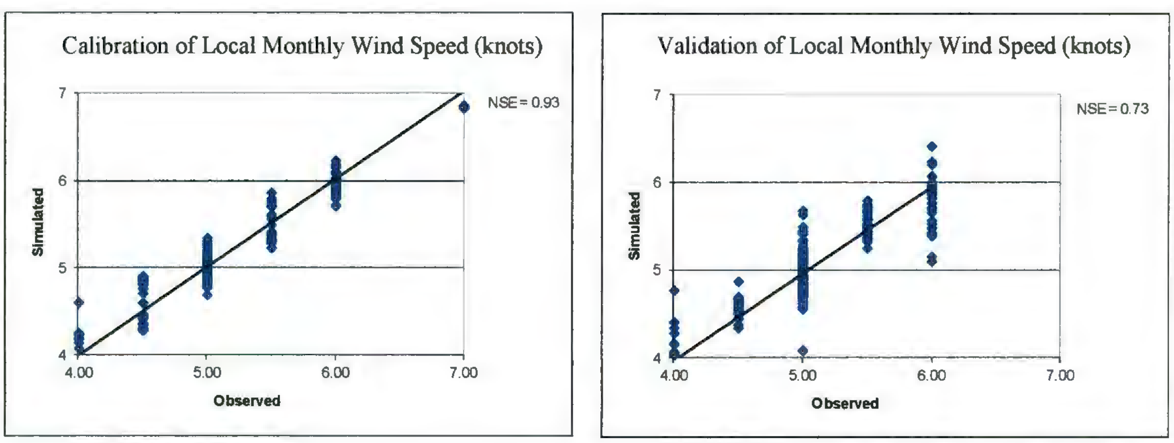


Figure 4.13 Plot of Observed Versus Simulated Local Monthly Wind Speed (knots)

Figures 4.9 to 4.13 show very good performances of the HYAS model to mimic the observed values of the five local climatic variables. It is indicated by all NSE values are higher than 0.70 in calibration and validation processes, respectively.

Table 4.5 Range of Simulated Local Climatic Variables Produced by the New Proposed Downscaling Model applied in the Region of Interest from 1971~2100

Local Variables	Ranges		HYAS	
	Max	Min	Max	Min
Air Humidity (%)	100	0	97	76
Rainfall (mm)	+ inf	0	619	7
Sunshine (%)	100	0	98	33
Air Temp(^{o}C)	+ inf	- inf	33	24
Wind Speed (knots)	+ inf	0	13	3

Table 4.5 shows that HYAS can successfully simulate realistic values of local climatic variables as all maximum values and minimum values of local variables are inside the boundaries.

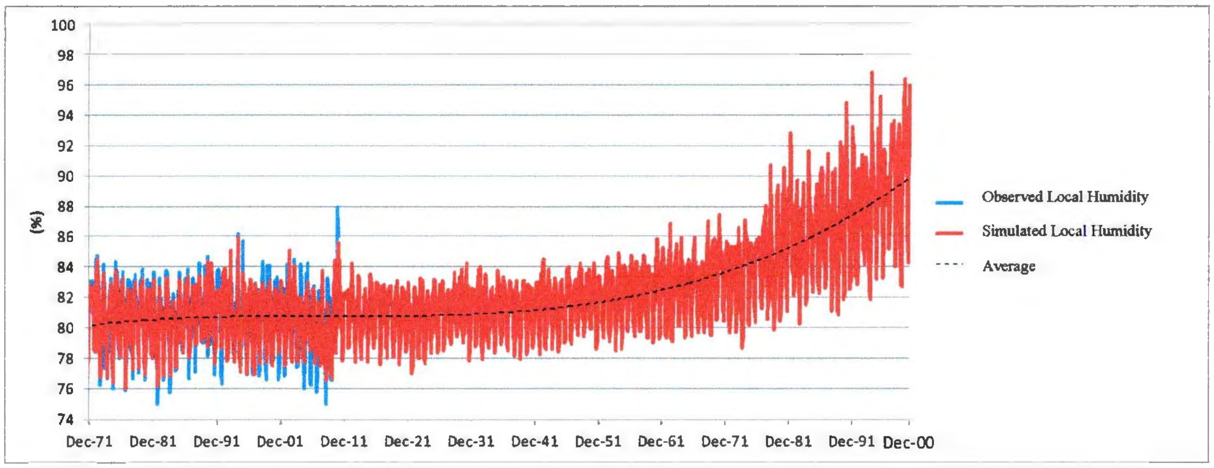


Figure 4.14 Plot of Observed Versus Simulated Local Monthly Air Humidity (%)

Figure 4.14 shows the results of simulated local monthly air humidity using the new downscaling model. An increase in average and variance of local air humidity was expected in the future under climate change conditions.

Table 4.6 One Way ANOVA for Uncertainty Analysis of Local Air Humidity

One-way ANOVA: CCCma A2, CCCma B2, CSIRO A2, CSIRO B2, NIES99 A2, ...

```
Source     DF        SS    MS     F      P
Factor      8     50.86  6.36  0.64  0.744
Error    9819  97380.53  9.92
Total    9827  97431.39

S = 3.149   R-Sq = 0.05%   R-Sq(adj) = 0.00%


                                  Individual 95% CIs For Average Based on
                                  Pooled StDev
Level           N  Average  StDev  -----+---------+---------+---------+----
CCCma A2     1092   82.222  2.984    (-----------*-----------)
CCCma B2     1092   82.258  3.043      (-----------*-----------)
CSIRO A2     1092   82.373  3.273              (-----------*-----------)
CSIRO B2     1092   82.281  3.100        (-----------*----------)
NIES99 A2    1092   82.190  3.095  (-----------*-----------)
NIES99 B2    1092   82.304  3.124         (-----------*-----------)
NR           1092   82.281  3.059        (-----------*----------)
CCAM-CSIRO   1092   82.444  3.572                  (-----------*----------)
RCM-Lombok   1092   82.303  3.052         (-----------*-----------)
                                   -----+---------+---------+---------+----
                                    82.08     82.24     82.40     82.56

Pooled StDev = 3.149
```

Table 4.6 shows 0.744 of P-value. This indicates that their differences of averages are insignificant. This also indicates that the HYAS model is consistent against the change of GCMs, emission scenarios, and method of residual generations to simulate local monthly air humidity in the Jangkok River Basin.

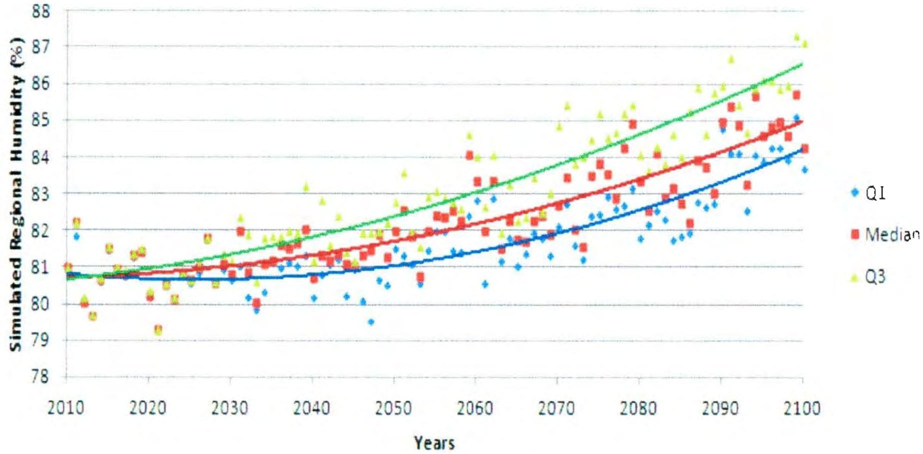


Figure 4.15 Plot of Simulated Local Air Humidity (%) from 2010 to 2100

Figure 4.15 shows the gaps between first (Q1) and third (Q3) quartiles is getting larger over years. This indicates that the variance of simulated local air humidity is getting larger in the future. Figure 4.16 shows that there is an increase in the air humidity of approximately 0.01 % from 2010 to 2011. The increase in air humidity gradually increases every year to achieve approximately 0.10 % in the change of air humidity from 2099 to 2100. Or, it is approximately 1.8 % increase in air humidity in 50 years (2010 to 2060) and 3.4 % increase in air humidity in the next 40 years (2060 to 2100). In general, there will be an increase approximately 5.3 % in air humidity over 90 years from 2010 to 2100.

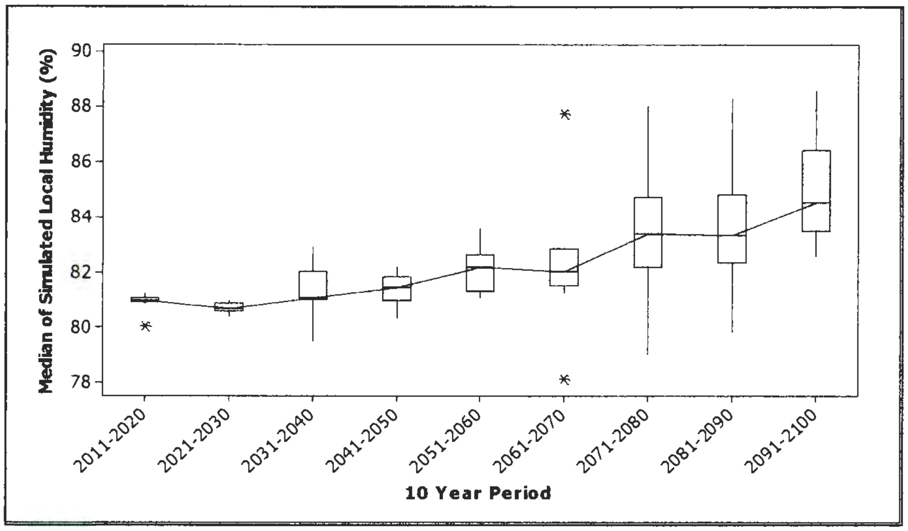


Figure 4.16 Box Plots of Median of 10 Year Period of Simulated Local Air Humidity (%)

Figure 4.16 shows in general, the median and the inter quartile range of 10 year period of simulated local air humidity increases in the future.

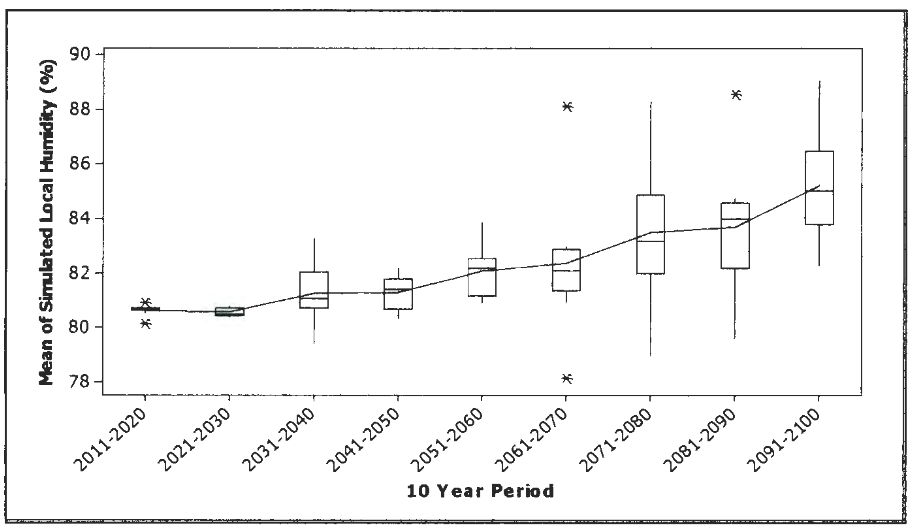


Figure 4.17 Box Plots of Average of 10 Year Period of Simulated Local Air Humidity (%)

Figure 4.17 shows in general, average and variance of 10 year period of simulated local air humidity increases in the future.

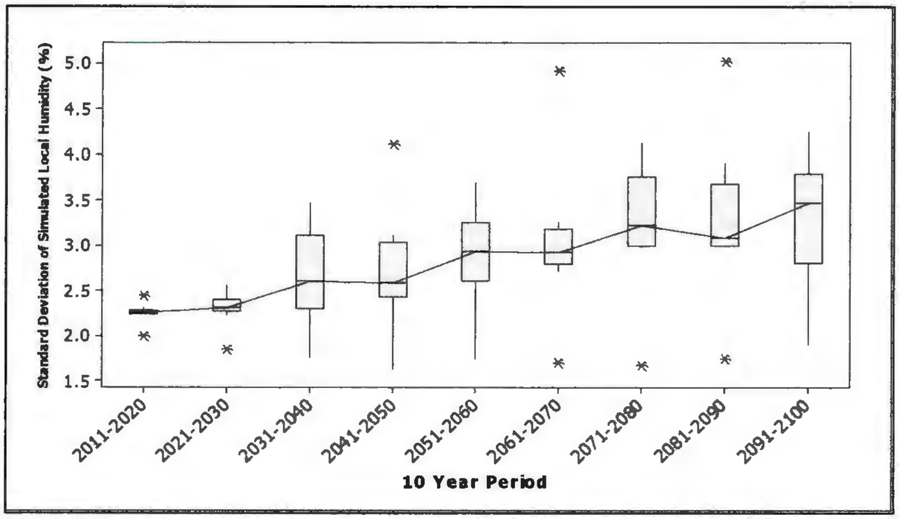


Figure 4.18 Box Plots of Standard Deviation of 10 Year Period of Simulated Local Air Humidity (%)

Figure 4.18 shows in general, the standard deviation of 10 year period of simulated local air humidity increases in the future.

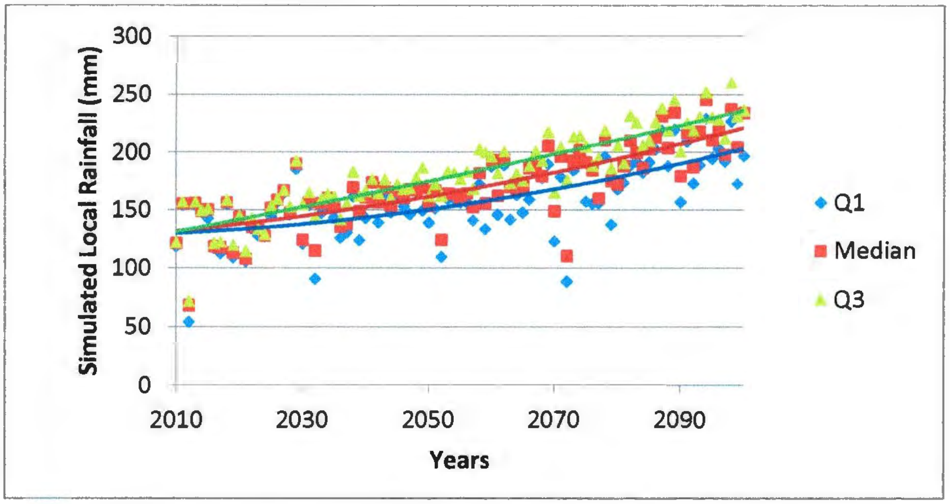


Figure 4.19 Plot of Simulated Local Rainfall (mm) from 2010 to 2100

Figure 4.19 shows the gaps between first (Q1) and third (Q3) quartiles of the simulated local rainfall increases over years. This indicates that the variance of simulated local rainfall increases in the future. Figure 4.19 shows an increase in the median of monthly rainfall of approximately 85 mm or 57 % with an Inter Quartile Range (IQR) approximately 39 mm in 2100.

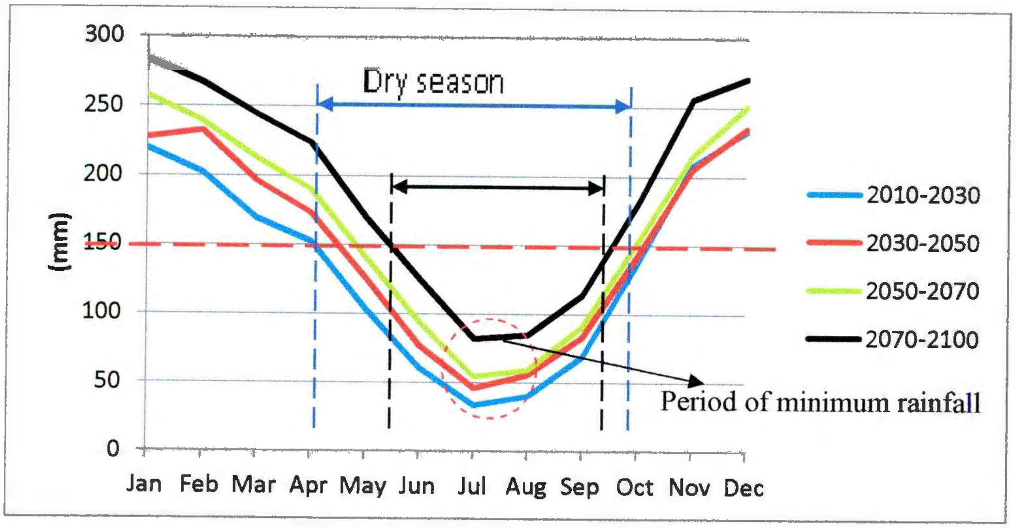


Figure 4.20 Plot of Median of Simulated Local Rainfall (mm) from 2010 to 2100

Figure 4.20 shows that there is an expected reduction of the length of dry season in the future. Moreover, Figure 4.20 shows that until 2030, the median of monthly local rainfall pattern in the region is expected to remain the same as the past pattern in which the 6-month length of dry season starts from April and finishes on October. However in the future, the length of dry seasons gradually reduces. The length of median of dry season pattern shrinks in the future into approximately 4 months during 2070 to 2100. Minimum monthly rainfall is expected to occur in the same months which are between July and August, and is expected to increase in the future. In addition, the peak of monthly rainfall is also expected to occur always in the same months which are between December and January.

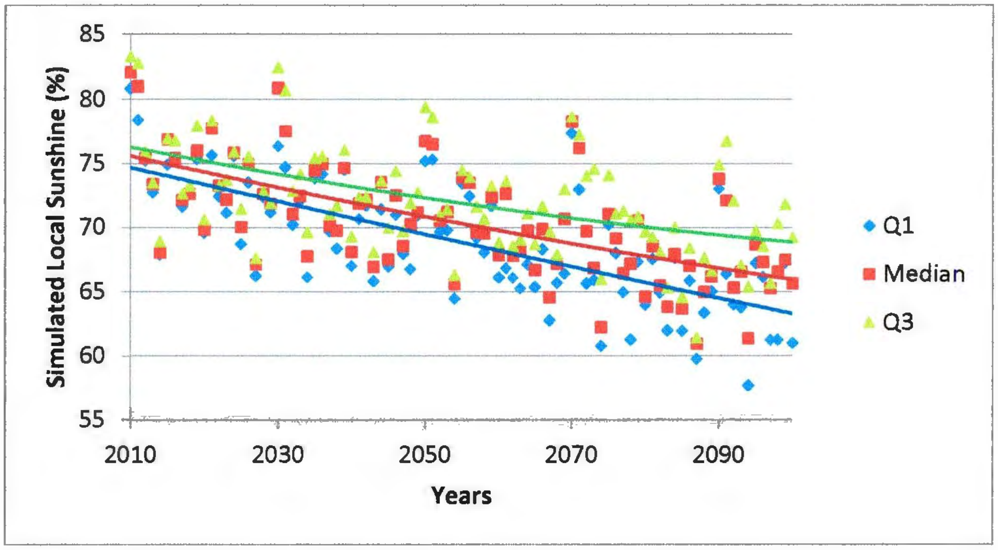


Figure 4.21 Plot of Simulated Local Sunshine Duration (%) from 2010 to 2100

Figure 4.21 shows the gaps between first (Q1) and third (Q3) quartiles of sunshine duration increases over years. This indicates that the variance of simulated local sunshine duration increases in the future. Moreover, Figure 4.21 shows that a decrease in median of monthly sunshine duration of approximately 10 % with an IQR approximately 8.2 % from 2010 to 2100 will occur in the region.

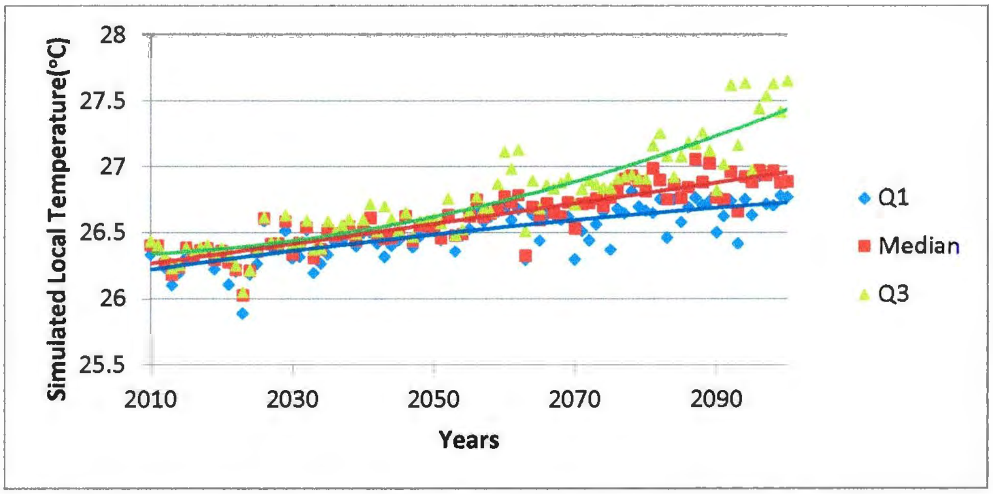


Figure 4.22 Plot of Simulated Local Air Temperature (°C) from 2010 to 2100

Figure 4.22 shows the gaps between first (Q1) and third (Q3) quartiles of local air temperature increases over years. This indicates that the variance of simulated local air temperature increases in the future. Moreover, Figure 4.22 shows that an increase in median of monthly air temperature of approximately 1.0 °C with an IQR approximately 1.0 °C from 2010 to 2100 will occur in the region.

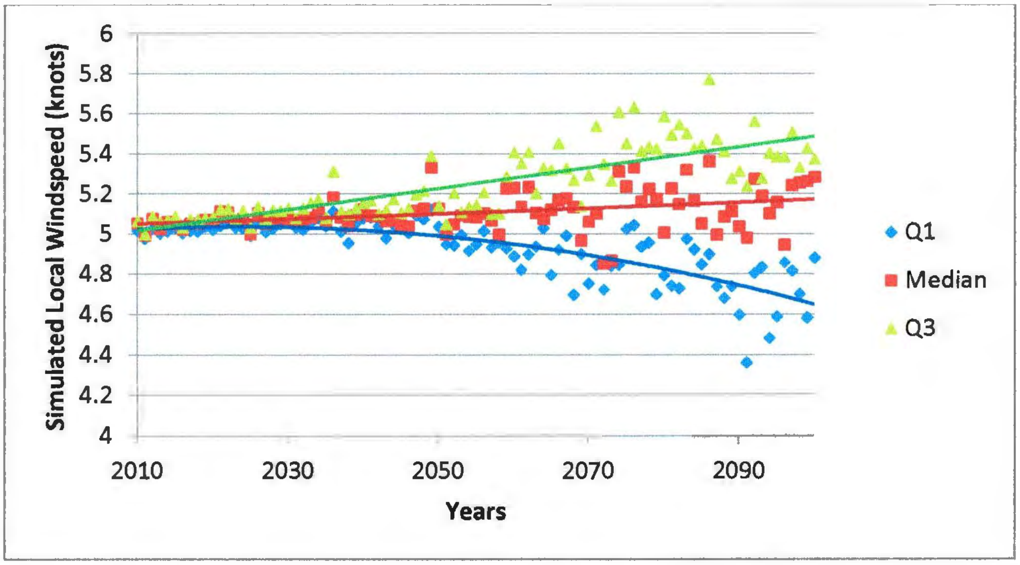


Figure 4.23 Plot of Simulated Local Wind Speed (knot) from 2010 to 2100

Figure 4.23 shows the gaps between first (Q1) and third (Q3) quartiles of local wind speed increases over years. This indicates that the variance of simulated local wind speed increases in the future. Moreover, Figure 4.23 shows that an increase in the median of monthly wind speed of approximately 0.25 knots with an IQR approximately 0.5 knots from 2010 to 2100 will occur in the region. In Figure 4.23, while median and third quartile increase, the first quartile of monthly wind speed decreases approximately 0.2 knots.

4.9. Summary

A new downscaling model based on a hybrid of algebraic and stochastic (HYAS) approaches was developed for simulating local climatic variables. HYAS model was inspired by the basic concept of the Change Factor method. Specific residuals that have inconstant mean and variance were systematically generated to support HYAS models to accurately produce realistic local climatic variables. The HYAS model is shown to successfully replace the existing downscaling models including the Change Factor method to simulate local climatic variables of the Jangkok River Basin.

From uncertainty analysis, it is found that the HYAS model is consistent against the change of GCMs, emission scenarios, and method of residual generations to simulate local climatic variables. In addition, the uncertainties of simulated local climatic variables are becoming larger following years to the future.

From simulations using the HYAS model based on GCM variables of CGCM2, it is predicted that:

1. Local monthly Air Humidity of the Jangkok River Basin increases approximately by 4.3 % from 80.7 % in 2010 to 85 % in 2100 with possible maximum air humidity approximately 87 % in 2100.
2. In general, rainfall patterns do not change in the future. A change occurs in the amounts of minimum and maximum monthly rainfall. Local monthly Rainfall increases approximately by 95 mm from 130 mm in 2010 to 225 mm 2100 with possible maximum monthly rainfall might be 251 mm.
3. Local monthly Sunshine Hours decreases approximately by 10 % from 75 % in 2010 to 65 % in 2100 with possible minimum Sunshine Hours 55.5 %.
4. The average of local monthly Air Temperature increases approximately by 1.0 ^{o}C from 26 ^{o}C in 2010 to 27 ^{o}C in 2100 with the increase in maximum Air Temperature from 27 ^{o}C in 2010 to 32 ^{o}C in 2100.
5. Local monthly wind speed slightly increases approximately by 0.2 knots from 5 knots in 2010 to 5.2 knots in 2100 with possible maximum wind speed might achieve 5.8 knots.
6. As it has been explained in the uncertainty analysis, these results are expected to be insignificantly different from the results of applying GCM variables of the same generation models from other GCMs with the same emission scenario.

Chapter 5

Modification of the NRECA Model

This chapter describes the modification of the NRECA model inputs to take climate change into account for the water balance analysis on the Jangkok River Basin. This chapter includes background, water balance models, the NRECA model and modifications, water demand estimations, and summary.

5.1. Background

It is common in water resource studies to use a water balance to analyze the condition of water resource systems. In this thesis, water balance analysis refers to an analysis of available water as it inflows to, water demands as outflow from, and storage in a hydrologic unit. Water balance analysis uses water availability and water demands for its input and output system processes, respectively. In addition, storages are accounted as water that is left in the systems.

One of the most well-known models in Indonesia to simulate surface water is the Non Recorded Catchment Area (NRECA) model. The NRECA model was modified from the Explicit Soil Moisture Accounting (ESMA) models in the era of 1960s for the use in Indonesia (Setiawan et al., 2005 and Sulistiyono and Lye, 2010). The NRECA model originally assumes that climatic variables will always be the same every year; and it simply requires the average of climatic variables and a set of historical rainfall data to simulate future runoff. Therefore, modifications need to be made to the NRECA model to take the effects of climate change into account.

Water demands are one of the most important factors in water balance calculations. The water demands can be defined as the total amount of water required for ecosystem functions as well as in stream uses such as adequate base flows required to support fish and other lifeforms; and out-of-stream uses such as domestic uses, irrigation, industrial activities, and energy production. Generally in water demand estimations, utilities and water managers consider population data (current population and population growth projections) for domestic usage, agricultural and livestock farms usage, public utility usage, and industrial usage. Water demands vary from location to location and from day to day within a location. In this study, water demands of agricultural, domestic, and livestock in the Jangkok River System are described in the following subsections.

5.2. Water Balance Model

This study is expected to give a better understanding of the potential impacts of climate change on the development of domestic, agriculture, and livestock in a particular region. As previously defined, the inflows of a water balance is a function of precipitation and groundwater flow; while, the outflow of water balance is a function of infiltration, evapotranspiration, water uses, and released water; and the storage of water balance is water from inflow that is left after outflow; therefore the basic water balance equation can be expressed as (Dingman, 2002):

$$\Delta S = \Sigma \text{ Inflow} - \Sigma \text{ Outflow } = [f(P)+f(GWF)] - [f(I)+f(PET)+f(O)] \text{ ....(5.1)}$$

Where

$f(P)$ = function of precipitation,

f(GWF) = function of groundwater flow,

$f(I)$ = function of infiltration,

$f(PET)$ = function of evapotranspiration, and

$f(O)$ = function of water uses and water release

By rearranging Equation (5.1), water balance can be rewritten as

$$\Delta S = [f(P)+f(GWF) - f(I) - f(PET)] - [f(O)] \text{ ...or}$$

$$\Delta S = f(P, PET, I, GWF) - f(O)$$

$$\Delta S = Q - f(O) \text{ ....(5.2)}$$

According to Equation (5.2), the water balance can be understood as a subtraction of water uses from the runoff. Therefore in this study, the inflow of a water balance model is simulated runoff which was obtained using the NRECA model as described in Subsection 5.3, and the outflow of a water balance model is a summation of water uses from agricultural farms, livestock farms and domestic as well as water releases. They will be described in Subsection 5.4, except water releases. In water resource management, water releases refer to water that are intentionally released for purposes such as flood damage reduction of dam, river navigation, hydropower production, water quality control, water supply managements, groundwater level control, river biotic managements, and recreation (Hancock and Skinner, 2000). Proper analysis of water releases requires adequate parameters from the various purposes which are beyond scope of this research. In this study, the amount of water releases is set to follow the local government regulation which is 10 % (Anonymous 8, 2004). It is understandable as a ratio between the average of stream discharge in dry season and the average of annual stream discharge in the study location is approximately 10 %.

5.3. NRECA model and Modifications

NRECA model

The NRECA model consists of the following main calculations: monthly evapotranspiration, model parameter calibration, model validation, and simulations of monthly (Setiawan et al., 2005; Sulistiyono and Lye, 2010). The calculation of monthly evapotranspiration is usually based on the average of historical local climatic variables. Moreover, there is no official recommendation regarding the length of time for the parameter model calibration or for the validation.

This model has four model parameters that need calibration: initial moisture storage (IMS), initial groundwater storage (IGS), percentage of water losses due to subsurface flows (PSUB), and percentage of groundwater flows into a river (GWF). The original NRECA model is schematically explained in Figure 5.1. The ranges of the model parameters: *PSUB*, *GWF*, *IMS*, and *IGS* are presented in Table 5.1.

Table 5.1 The ranges of NRECA model parameters

Parameters		Unit	Low Level	High Level
Initial Moisture Storage	*IMS*	mm	150	900
Initial Groundwater Storage	*IGS*	mm	50	500
percentage of water lost due to subsurface	*PSUB*	-	10 %	90 %
percentage of water flows to the river	*GWF*	-	10 %	90 %

(Source: Sulistiyono and Lye, 2010)

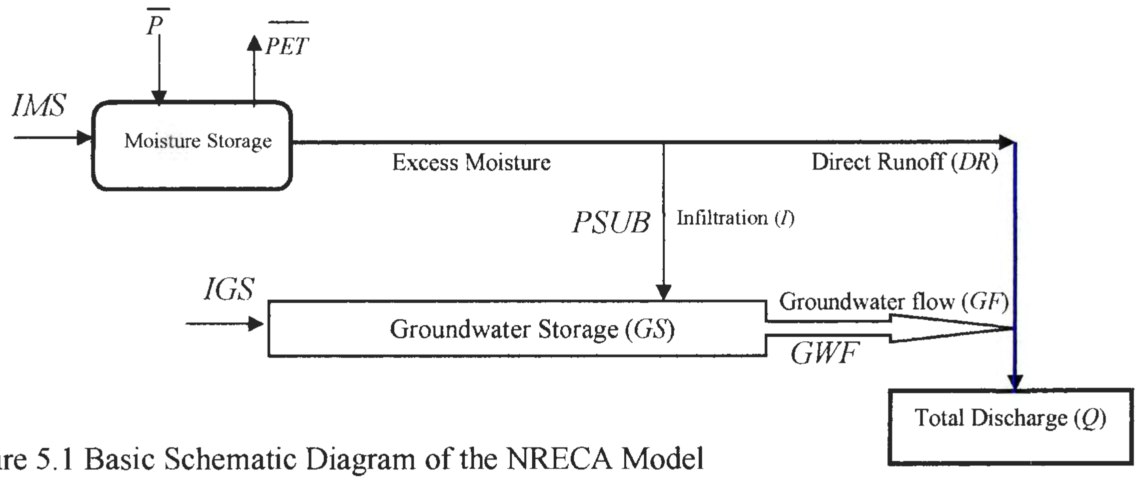


Figure 5.1 Basic Schematic Diagram of the NRECA Model

In Figure 5.1, it is understood that besides the four parameters, the model has two input variables: rainfall or precipitation (P) and potential evapotranspiration (PET).

Runoff or total discharge is a function of direct runoff (DR) and base flow or groundwater flow (GF). It is expressed (Setiawan et al., 2005; Sulistiyono and Lye, 2010) as

$$Q = DR + GF \qquad (5.3)$$

Where:

Q = Total Discharge (mm)

DR = direct runoff (mm)

GF = base flow or groundwater flow (mm)

Direct flow is the water from excess moisture (Exm) after subtracting infiltration, and can be expressed as

$$DR = Exm - I \quad \text{.....................................} \quad (5.4)$$

Where:

Exm = excess moisture (mm)

I = infiltration (mm)

Base flow or groundwater flow is a percentage of groundwater water that flows into a river and is a function of infiltration (I) and groundwater storage. Infiltration is a recharge to groundwater. Groundwater flow (GF) can be expressed as

$$GF = GWF * GS \quad \text{.....................................} \quad (5.5)$$

Where:

GWF = percentage of groundwater flows into a river (%)

GS = groundwater storage (mm)

Groundwater storage is a summation of initial groundwater storage and infiltration. Groundwater storage can be expressed as

$$GS = IGS + I \quad (5.6)$$

Where:

IGS = initial groundwater storage (mm)

I = infiltration (mm)

Infiltration is the water from excess moisture (Exm) that is absorbed by soil and is expressed as

$$I = Exm * PSUB \quad (5.7)$$

Where:

Exm = excess moisture (mm)

$PSUB$ = percentage of water losses due to subsurface flows

Excess moisture is a function of moisture storage (MS), rainfall (P), and potential evapotranspiration (PET). Excess moisture can be expressed as

$$Exm = MS + P - PET \quad (5.8)$$

Where:

MS = moisture storage (mm)

P = rainfall (mm)

PET = potential evapotranpiration (mm)

Moisture storage (MS) is a function of initial moisture storage (IMS) and excess moisture. Moisture storage can be expressed as

$$MS = IMS + Exm \quad (5.9)$$

Where:

MS	=	moisture storage (mm)
IMS	=	initial moisture storage (mm)
Exm	=	excess moisture (mm)

Therefore generally in the NRECA model, runoff is a function of rainfall (*P*), potential evapotranspiration (*PET*), infiltration (*I*), and base flow or groundwater flow (*GWF*); and can be expressed as

$$Q = f(P, PET, I, GWF) \quad (5.10)$$

Where:

Q	=	Total Discharge (mm)
P	=	rainfall (mm)
PET	=	potential evapotranpiration (mm)
I	=	infiltration (mm)
GWF	=	percentage of groundwater flows into a river (%)

Modified NRECA model

In a modified NRECA model, sets of future local climatic and rainfall variables that are obtained from the climatic downscaling processes were considered completely. This requires longer calculation tables and larger files than what the original model has. Therefore in this study, the development of a modified NRECA model in spreadsheet software was split into several files. Every file only simulates a 10 year runoff period. Consequently, 11 spreadsheet files were developed for this modified model including two files for parameter model calibration and validation to cover the runoff simulation from 1991 to 2100. Every file consists of 10 worksheets of runoff simulation, and 7 additional worksheets of catchment area information, observed runoff data, simulated rainfall, simulated climatic variables, evapotranspiration calculation, and recapitulation of simulated runoff. These sheets are shown in Figure 5.3.

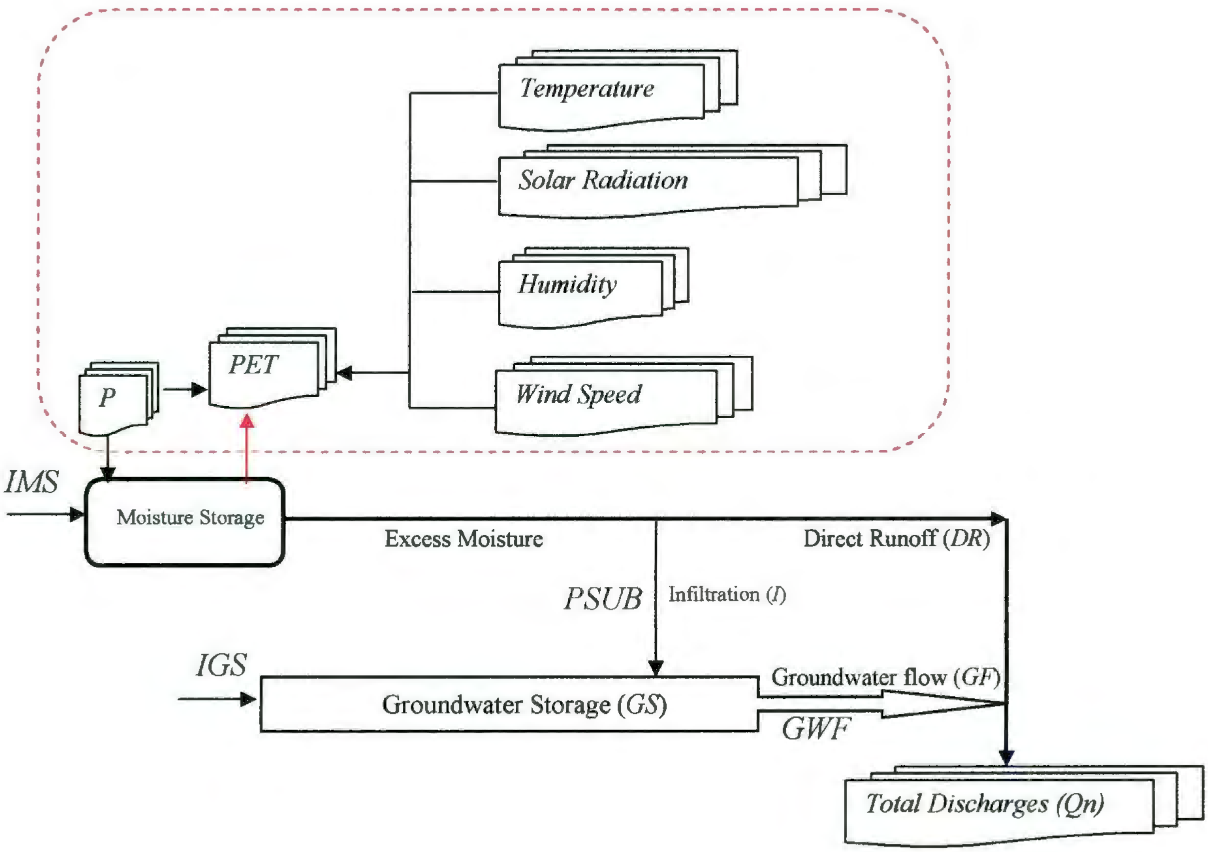


Figure 5.2 Schematic Diagram of the Modified NRECA Model

Figure 5.2 shows that the modification was done only in the model inputs to consider all simulated rainfall and other climatic variables to simulate the total discharges. Based on the modifications of inputs, a modified NRECA model will always produce different total discharges for every month. Therefore, by involving effects of climate change, a modified NRECA model can simulate changing simulated runoff in the future. Figures 5.3 to 5.8 show how a modified NRECA model is written in an excel spreadsheet.

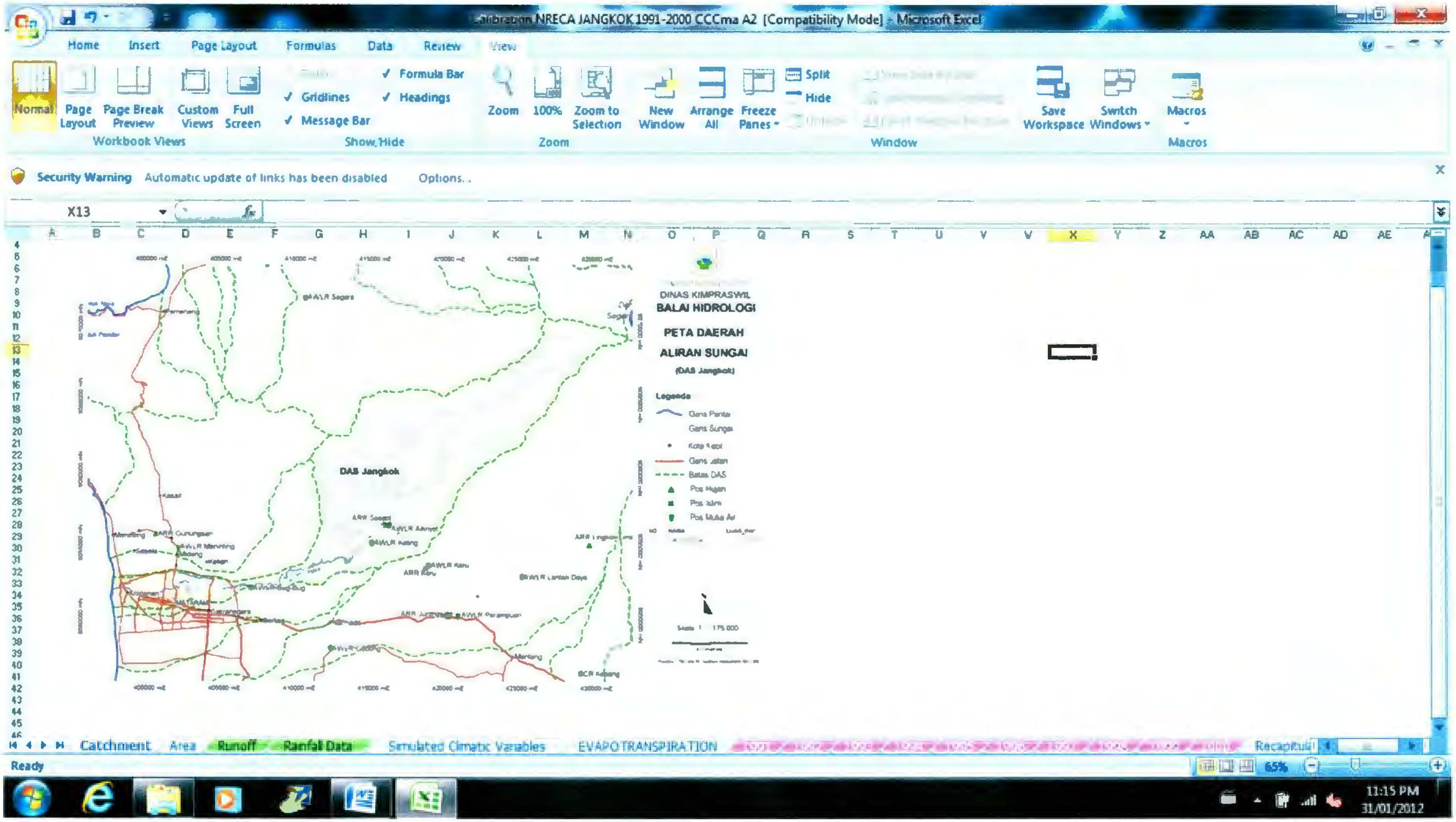
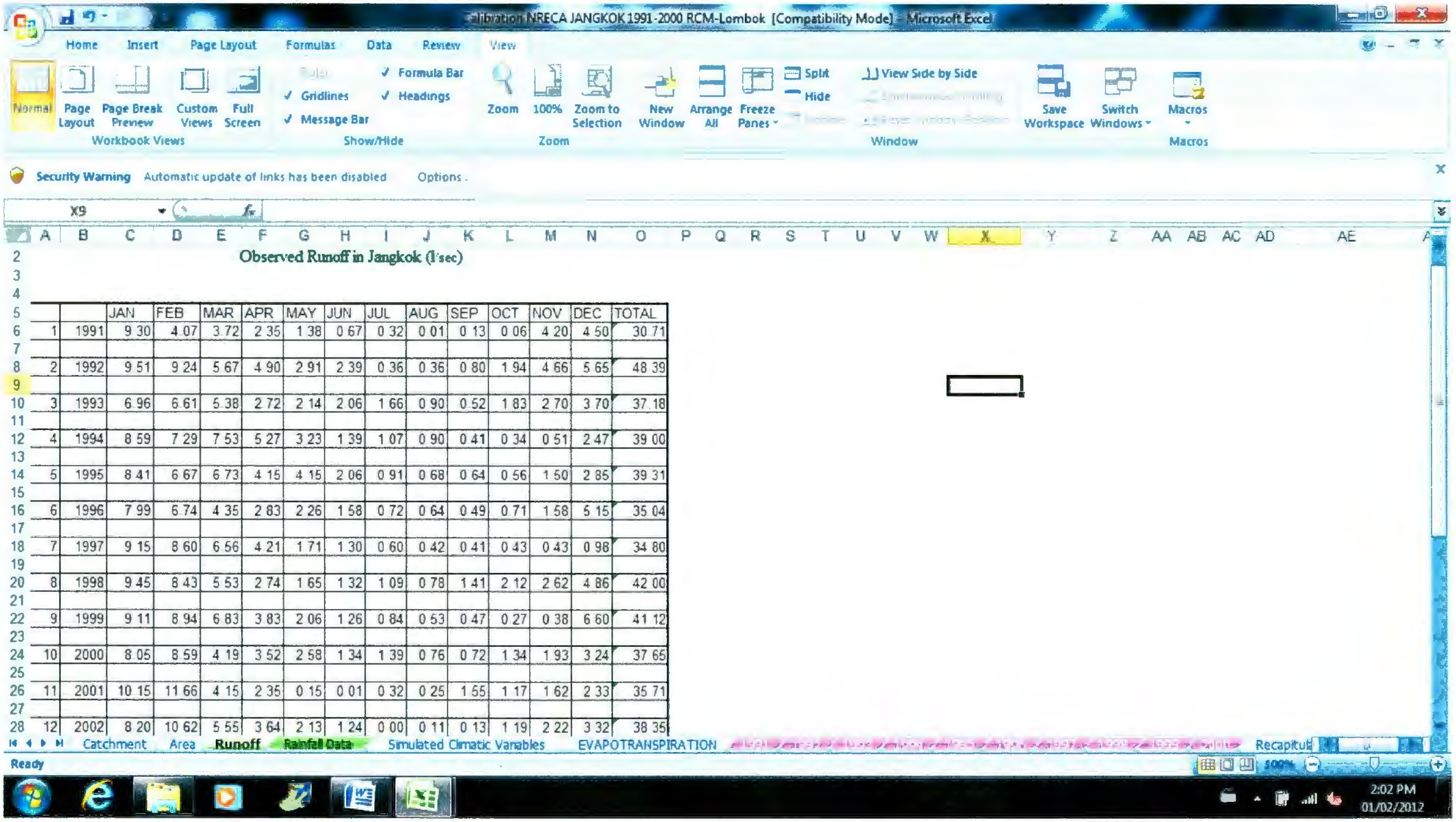


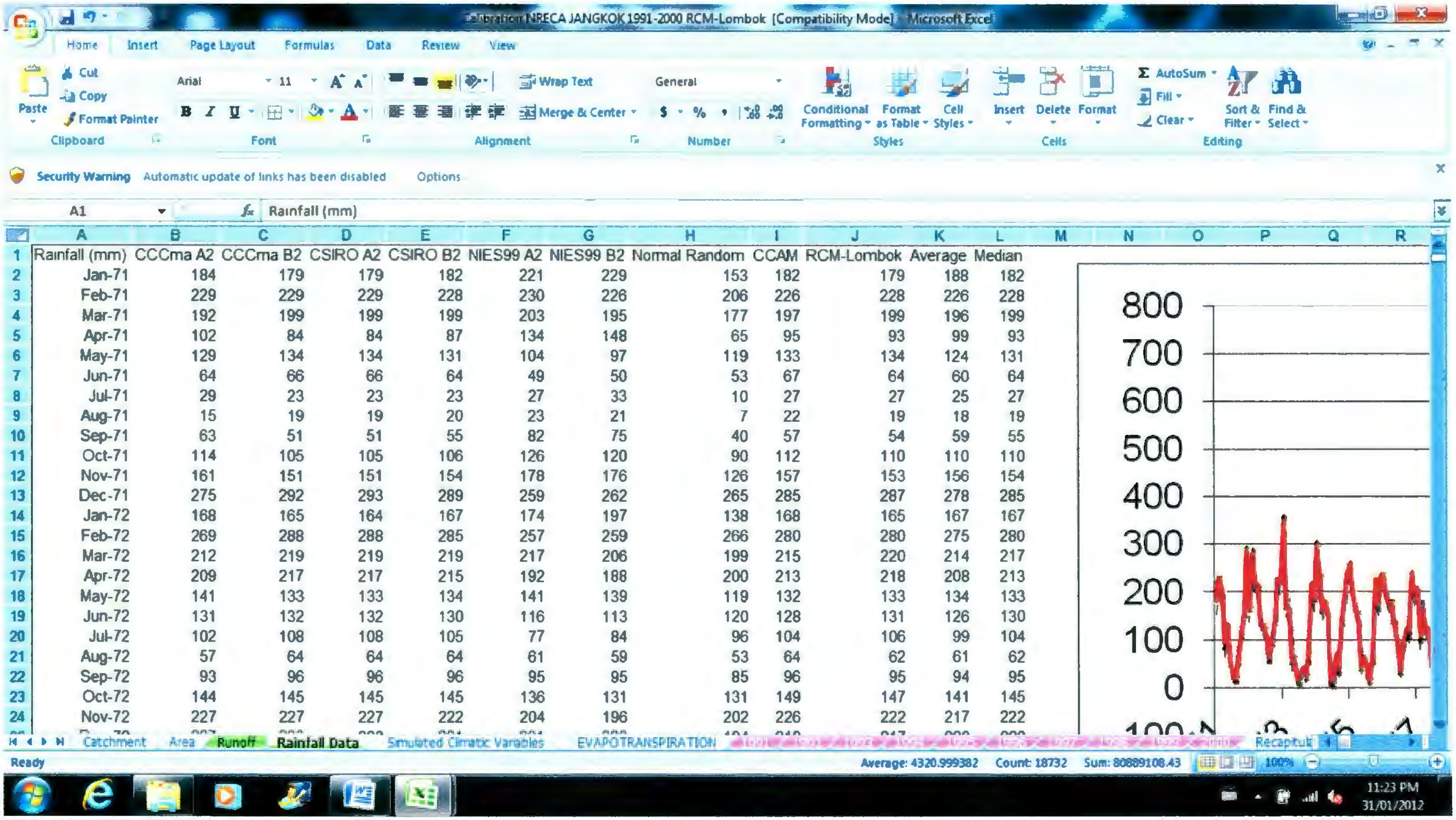
Figure 5.3 A Spreadsheet of Catchment Area of Interest



Observed Runoff in Jangkok (l/sec)

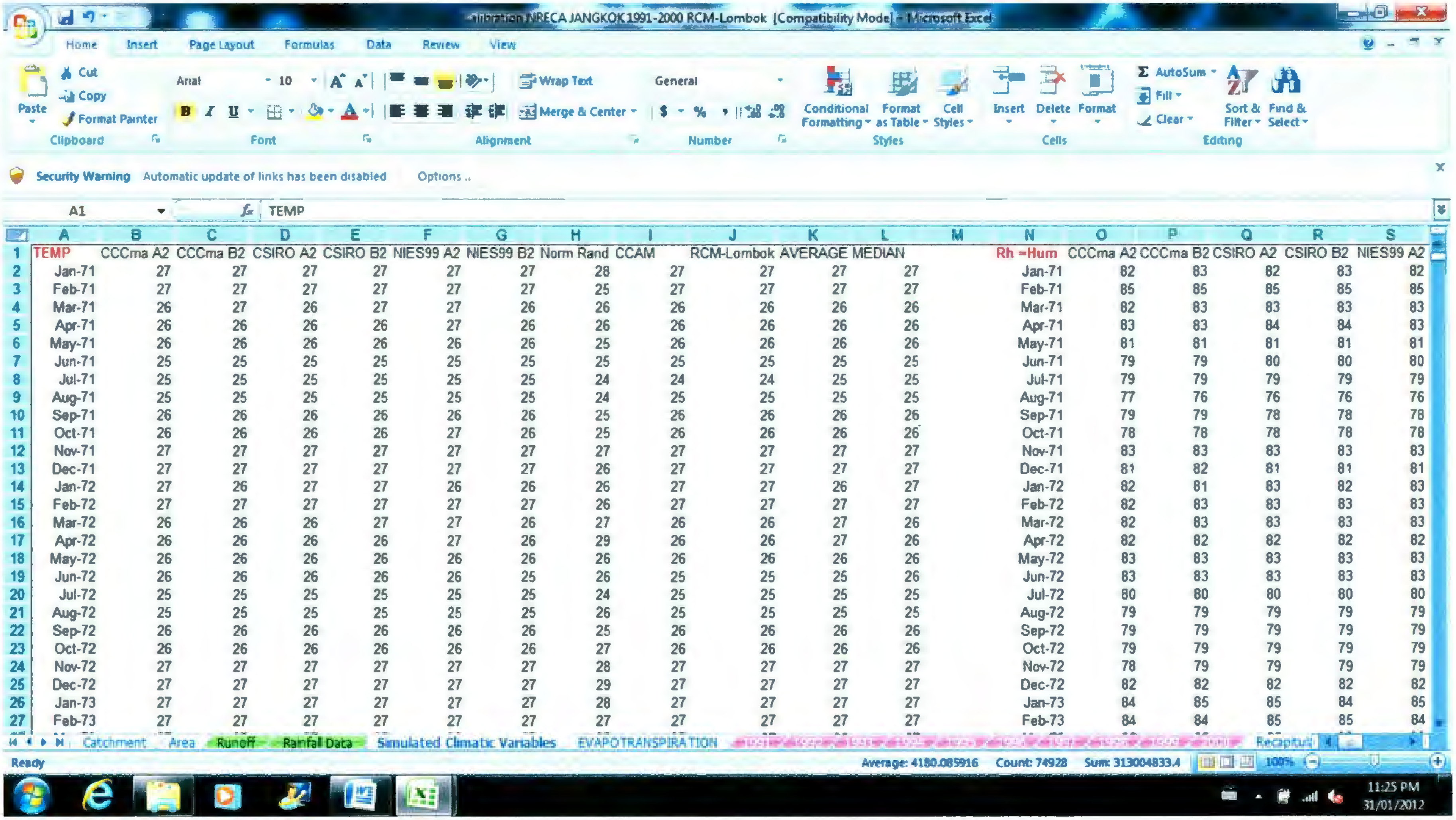
		JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	TOTAL
1	1991	9.30	4.07	3.72	2.35	1.38	0.67	0.32	0.01	0.13	0.06	4.20	4.50	30.71
2	1992	9.51	9.24	5.67	4.90	2.91	2.39	0.36	0.36	0.80	1.94	4.66	5.65	48.39
3	1993	6.96	6.61	5.38	2.72	2.14	2.06	1.66	0.90	0.52	1.83	2.70	3.70	37.18
4	1994	8.59	7.29	7.53	5.27	3.23	1.39	1.07	0.90	0.41	0.34	0.51	2.47	39.00
5	1995	8.41	6.67	6.73	4.15	4.15	2.06	0.91	0.68	0.64	0.56	1.50	2.85	39.31
6	1996	7.99	6.74	4.35	2.83	2.26	1.58	0.72	0.64	0.49	0.71	1.58	5.15	35.04
7	1997	9.15	8.60	6.56	4.21	1.71	1.30	0.60	0.42	0.41	0.43	0.43	0.98	34.80
8	1998	9.45	8.43	5.53	2.74	1.65	1.32	1.09	0.78	1.41	2.12	2.62	4.86	42.00
9	1999	9.11	8.94	6.83	3.83	2.06	1.26	0.84	0.53	0.47	0.27	0.38	6.60	41.12
10	2000	8.05	8.59	4.19	3.52	2.58	1.34	1.39	0.76	0.72	1.34	1.93	3.24	37.65
11	2001	10.15	11.66	4.15	2.35	0.15	0.01	0.32	0.25	1.55	1.17	1.62	2.33	35.71
12	2002	8.20	10.62	5.55	3.64	2.13	1.24	0.00	0.11	0.13	1.19	2.22	3.32	38.35

Figure 5.4 A Spreadsheet of Observed Runoff



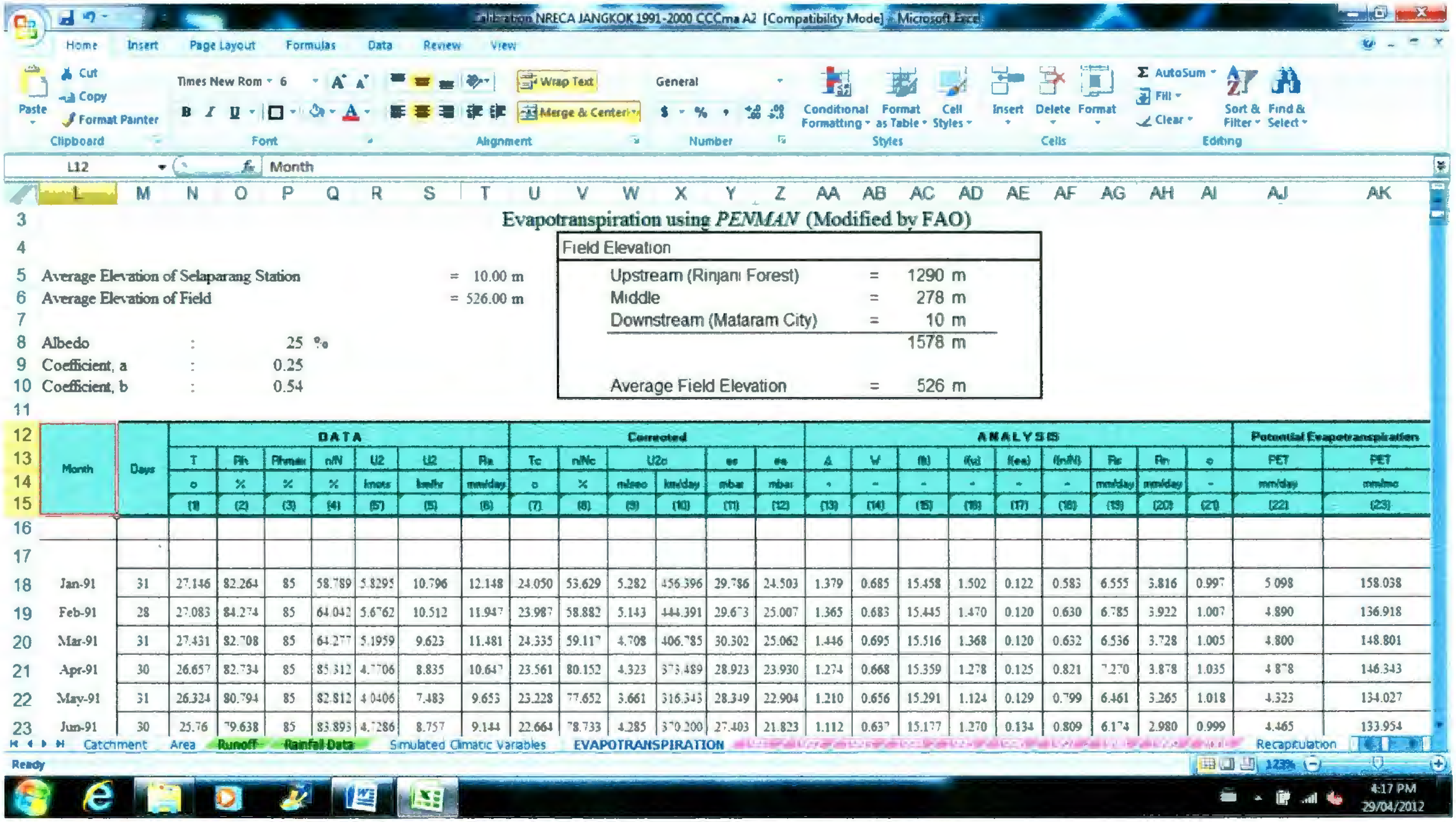
Rainfall (mm)	CCCma A2	CCCma B2	CSIRO A2	CSIRO B2	NIES99 A2	NIES99 B2	Normal Random	CCAM	RCM-Lombok	Average	Median
Jan-71	184	179	179	182	221	229	153	182	179	188	182
Feb-71	229	229	229	228	230	226	206	226	228	226	228
Mar-71	192	199	199	199	203	195	177	197	199	196	199
Apr-71	102	84	84	87	134	148	65	95	93	99	93
May-71	129	134	134	131	104	97	119	133	134	124	131
Jun-71	64	66	66	64	49	50	53	67	64	60	64
Jul-71	29	23	23	23	27	33	10	27	27	25	27
Aug-71	15	19	19	20	23	21	7	22	19	18	19
Sep-71	63	51	51	55	82	75	40	57	54	59	55
Oct-71	114	105	105	106	126	120	90	112	110	110	110
Nov-71	161	151	151	154	178	176	126	157	153	156	154
Dec-71	275	292	293	289	259	262	265	285	287	278	285
Jan-72	168	165	164	167	174	197	138	168	165	167	167
Feb-72	269	288	288	285	257	259	266	280	280	275	280
Mar-72	212	219	219	219	217	206	199	215	220	214	217
Apr-72	209	217	217	215	192	188	200	213	218	208	213
May-72	141	133	133	134	141	139	119	132	133	134	133
Jun-72	131	132	132	130	116	113	120	128	131	126	130
Jul-72	102	108	108	105	77	84	96	104	106	99	104
Aug-72	57	64	64	64	61	59	53	64	62	61	62
Sep-72	93	96	96	96	95	95	85	96	95	94	95
Oct-72	144	145	145	145	136	131	131	149	147	141	145
Nov-72	227	227	227	222	204	196	202	226	222	217	222

Figure 5.5 A Spreadsheet of simulated Local Rainfall Data



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	TEMP	CCCma A2	CCCma B2	CSIRO A2	CSIRO B2	NIES99 A2	NIES99 B2	Norm Rand	CCAM	RCM-Lombok	AVERAGE	MEDIAN		Rh =Hum	CCCma A2	CCCma B2	CSIRO A2	CSIRO B2	NIES99 A2
2	Jan-71	27	27	27	27	27	27	28	27	27	27	27		Jan-71	82	83	82	83	82
3	Feb-71	27	27	27	27	27	27	25	27	27	27	27		Feb-71	85	85	85	85	85
4	Mar-71	26	27	26	27	27	26	26	26	26	26	26		Mar-71	82	83	83	83	83
5	Apr-71	26	26	26	26	27	26	26	26	26	26	26		Apr-71	83	83	84	84	83
6	May-71	26	26	26	26	26	26	25	26	26	26	26		May-71	81	81	81	81	81
7	Jun-71	25	25	25	25	25	25	25	25	25	25	25		Jun-71	79	79	80	80	80
8	Jul-71	25	25	25	25	25	25	24	24	24	25	25		Jul-71	79	79	79	79	79
9	Aug-71	25	25	25	25	25	25	24	25	25	25	25		Aug-71	77	76	76	76	76
10	Sep-71	26	26	26	26	26	26	25	26	26	26	26		Sep-71	79	79	78	78	78
11	Oct-71	26	26	26	26	27	26	25	26	26	26	26		Oct-71	78	78	78	78	78
12	Nov-71	27	27	27	27	27	27	27	27	27	27	27		Nov-71	83	83	83	83	83
13	Dec-71	27	27	27	27	27	27	26	27	27	27	27		Dec-71	81	82	81	81	81
14	Jan-72	27	26	27	27	26	26	26	27	27	26	27		Jan-72	82	81	83	82	83
15	Feb-72	27	27	27	27	27	27	26	27	27	27	27		Feb-72	82	83	83	83	83
16	Mar-72	26	26	26	27	27	26	27	26	26	27	26		Mar-72	82	83	83	83	83
17	Apr-72	26	26	26	26	27	26	29	26	26	27	26		Apr-72	82	82	82	82	82
18	May-72	26	26	26	26	26	26	26	26	26	26	26		May-72	83	83	83	83	83
19	Jun-72	26	26	26	26	26	25	26	25	25	25	26		Jun-72	83	83	83	83	83
20	Jul-72	25	25	25	25	25	25	24	25	25	25	25		Jul-72	80	80	80	80	80
21	Aug-72	25	25	25	25	25	25	26	25	25	25	25		Aug-72	79	79	79	79	79
22	Sep-72	26	26	26	26	26	26	25	26	26	26	26		Sep-72	79	79	79	79	79
23	Oct-72	26	26	26	26	26	26	27	26	26	26	26		Oct-72	79	79	79	79	79
24	Nov-72	27	27	27	27	27	27	28	27	27	27	27		Nov-72	78	79	79	79	79
25	Dec-72	27	27	27	27	27	27	29	27	27	27	27		Dec-72	82	82	82	82	82
26	Jan-73	27	27	27	27	27	27	28	27	27	27	27		Jan-73	84	85	85	84	85
27	Feb-73	27	27	27	27	27	27	27	27	27	27	27		Feb-73	84	84	85	85	84

Figure 5.6 A Spreadsheet of Simulated Local Climatic Variables



Evapotranspiration using *PENMAN* (Modified by FAO)

Average Elevation of Selaparang Station	=	10.00 m
Average Elevation of Field	=	526.00 m
Albedo	:	25 %
Coefficient, a	:	0.25
Coefficient, b	:	0.54

Field Elevation		
Upstream (Rinjani Forest)	=	1290 m
Middle	=	278 m
Downstream (Mataram City)	=	10 m
		1578 m
Average Field Elevation	=	526 m

Month	Days	DATA							Corrected						ANALYSIS									Potential Evapotranspiration	
		T	Rh	Rhmax	n/N	U2	U2	Ra	Tc	n/Nc	U2c		es	ea	Δ	W	f(t)	f(u)	f(ea)	f(n/N)	Rs	Rn	c	PET	PET
		o	%	%	%	knots	km/hr	mm/day	o	%	m/sec	km/day	mbar	mbar	-	-	-	-	-	-	mm/day	mm/day	-	mm/day	mm/mo
		(1)	(2)	(3)	(4)	(5)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Jan-91	31	27.146	82.264	85	58.789	5.8295	10.796	12.148	24.050	53.629	5.282	456.396	29.786	24.503	1.379	0.685	15.458	1.502	0.122	0.583	6.555	3.816	0.997	5.098	158.038
Feb-91	28	27.083	84.274	85	64.042	5.6762	10.512	11.947	23.987	58.882	5.143	444.391	29.673	25.007	1.365	0.683	15.445	1.470	0.120	0.630	6.785	3.922	1.007	4.890	136.918
Mar-91	31	27.431	82.708	85	64.277	5.1959	9.623	11.481	24.335	59.117	4.708	406.785	30.302	25.062	1.446	0.695	15.516	1.368	0.120	0.632	6.536	3.728	1.005	4.800	148.801
Apr-91	30	26.657	82.734	85	85.312	4.7706	8.835	10.647	23.561	80.152	4.323	373.489	28.923	23.930	1.274	0.668	15.359	1.278	0.125	0.821	7.270	3.878	1.035	4.878	146.343
May-91	31	26.324	80.794	85	82.812	4.0406	7.483	9.653	23.228	77.652	3.661	316.343	28.349	22.904	1.210	0.656	15.291	1.124	0.129	0.799	6.461	3.265	1.018	4.323	134.027
Jun-91	30	25.76	79.638	85	83.893	4.7286	8.757	9.144	22.664	78.733	4.285	370.200	27.403	21.823	1.112	0.637	15.177	1.270	0.134	0.809	6.174	2.980	0.999	4.465	133.954

Figure 5.7 A Spreadsheet of Evapotranspiration Calculation

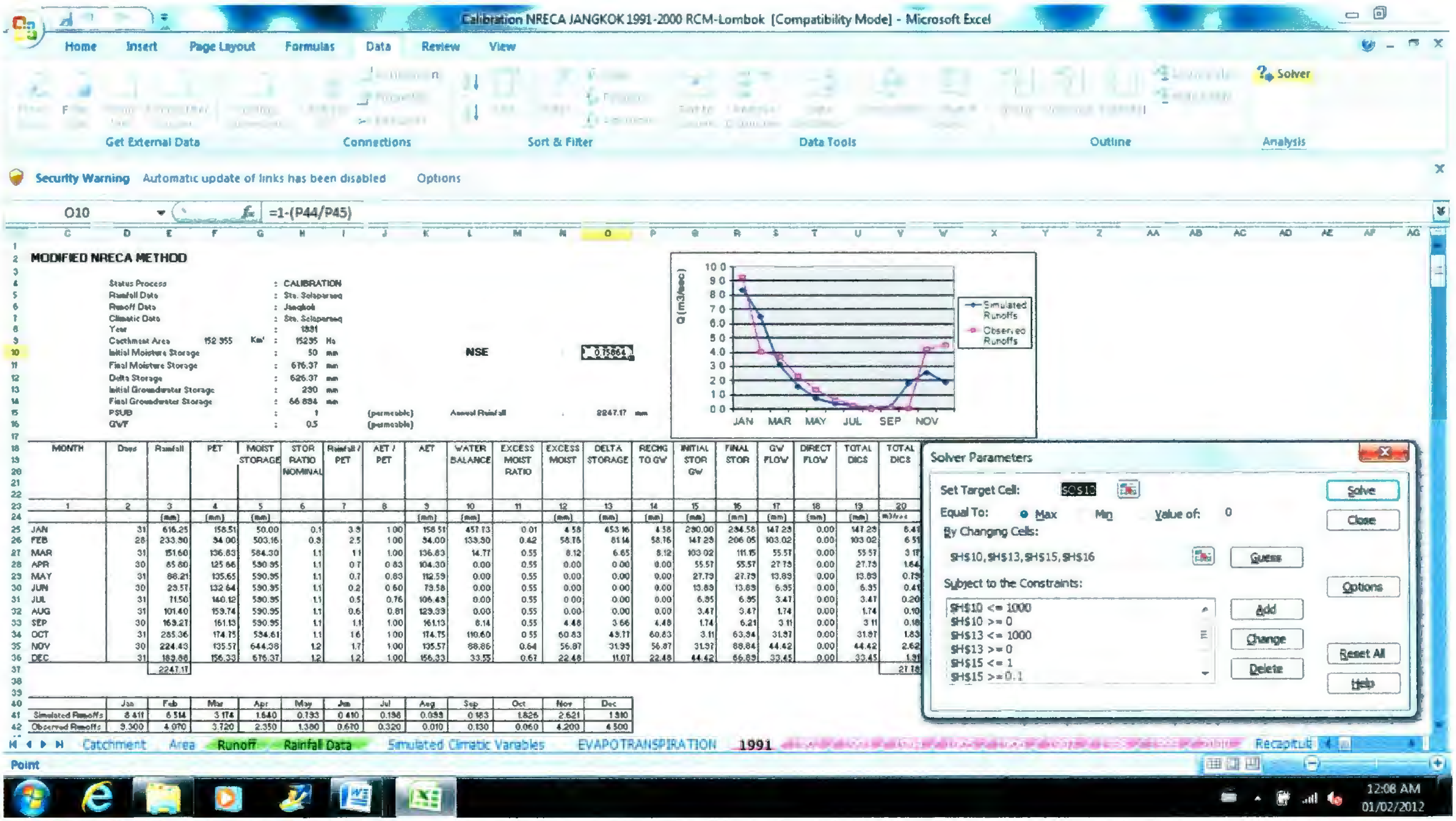


Figure 5.8 A Spreadsheet of Runoff Simulation

Figure 5.3 shows a file of the modified NRECA model for the Jangkok River basin using simulated local rainfall and other climatic variables for a period of 1991 to 2000 based on GCM of CCCma A2. The 17 connected worksheets of the modified NRECA model are listed in the bottom of the spreadsheet. The NRECA model is written in sheets: 1991 to 2000.

Figure 5.4 shows the observed runoff. This observed runoff is connected to sheets: 1991 to 2000 and is used to calibrate the four parameters of the NRECA model. In this modified NRECA model, the model is calibrated each year along a 10 year period (1991 to 2000). The calibrated parameters are the average of the model calibration for 10 years. Commonly, a regular NRECA model calibration needs only one year period of calibration (Sulistiyono and Lye, 2010).

Figure 5.5 shows the following nine sets of simulated rainfall: CCCma A2, CCCma B2, CSIRO A2, CSIRO B2, NIES99 A2, NIESS B2, Normal Random, CCAM, and RCM-Lombok. These rainfall variables were simulated using the HYAS model and are connected to sheets: 1991 to 2000 as the inputs of NRECA model. A regular NRECA model uses only one set of observed rainfall.

Figure 5.6 shows simulated climatic variables. nine sets of four climatic variables: Air Temperature, Air Humidity, Sunshine, and Wind Speed were simulated using the HYAS model as explained in Chapter 4. In this modified NRECA model, all simulated climatic variables are used as the inputs of the calculation of evapotranspiration; therefore, every year has different results of evapotranspiration. A regular NRECA model uses only one year evapotranspiration as it assumes that the evapotranspiration is always the same every year.

Figure 5.7 shows the modified PENMAN model by FAO (Allen et al., 1998). All equations and parameters of this model are described in Subsection 5.4.1. This sheet is connected to sheets: 1991 to 2000 as the inputs of the modified NRECA model.

Figure 5.8 shows the calculation of simulated runoff using the modified NRECA model. All equations were previously described in Subsection 5.3. The calibration can be done using several methods; however in this research, the NRECA model calibration is done using the solver function of Excel software, as it is available provided in the spreadsheet. Therefore, it is easier and more convinient to use the solver function of Excel software. The four calibrated NRECA model parameters were obtained after maximizing the NSE between observed and simulated runoff. Constraints used in this calibration are the ranges of model parameters defined in Table 5.1.

5.4. Water Uses

5.4.1. Agricultural Water Demands

The agricultural water demand was calculated using the "Van De Goor and Ziljstra" approach based on multiplication of net field requirements (*NFR*) and total irrigation efficiency (Van De Goor and Ziljstra, 1982; Anonymous 7, 1986). The *NFR* was calculated based on agricultural water losses that relates to the potential evapotranspiration. The potential evapotranspiration was calculated using the equation of Modified Penman Method that is expressed as

$$PET = c^{\#}\left[W.R_n + (1-W).f(u).(es - ea)\right] \text{ .... } (5.11)$$

Where:

PET	=	potential evapotranspiration (mm/day),
$c^{\#}$	=	seasonal factor,
W	=	temperature factor,
R_n	=	net radiation (mm/day),
$f(u)$	=	wind speed factor,
es	=	saturation vapour pressure (mbar), and
ea	=	actual vapour pressure (mbar).

Net field water requirement (NFR) equals to agricultural water losses (ET_C) subtracted by rainfall (R). It is expressed as

$$NFR = ET_C - R \text{ .... } (5.12)$$

Agricultural water losses can be calculated using crop evapotranspiration (ET_c) or using land preparation (LP). ET_c is used when the land is in the period of planting, while LP is used when the land is in the period of preparation, and their equations are expressed as (Van De Goor and Ziljstra, 1982; Anonymous 7, 1986)

$$ET_C = K_C \times PET \text{ .... } (5.13)$$

$$LP = \frac{Me^k}{(e^k - 1)} \text{ .... } (5.14)$$

$$M = (1.1PET + P_C) \quad (5.15)$$

$$k = \frac{M(LP_T)}{Sat} \quad (5.16)$$

Where:

ET_c = the crop evapotranspiration = consumptive uses (mm/day)

K_c = crop coefficients

PET = Potential Evapotranspiration ≈ the Reference Crop Evapotranspiration (mm/day)

LP = water uses at land preparation (mm/day)

M = water required to maintain saturation (mm/day)

LP_T = duration for land preparation (days)

Pc = percolation = 2.00 mm/day (Van De Goor and Ziljstra, 1982; Anonimous 7, 1986)

Sat = water required in the process of saturation = 250 (mm) per month (Van De Goor and Ziljstra, 1982; Anonymous 7, 1986)

Some crop coefficients (K_c) are shown in Table 5.2. These crop coefficients change in accordance with the age of the plants.

Table 5.2 Cropping Coefficient (K_c)

Monthly Period	Rice	Vegetables
1	1.10	0.51
2	1.05	0.85
3	0.95	0.95

Source: Allen et. al., 1998.

Total irrigation water demand equals to the multiplication of total net field water requirement and total irrigation efficiency. The total irrigation efficiency consists of three efficiencies, which are of primary, secondary, and tertiary conveyances. According to the Indonesian Irrigation Design Standard (Anonymous 7, 1986), those efficiencies are

- between 90% to 95% for primary conveyances
- between 80% to 90% for secondary conveyances
- between 75% to 80% for tertiary conveyances and fields

The total irrigation efficiency is the multiplication of all efficiencies. For an irrigation system which consists of three types of water conveyances: primary, secondary, and tertiary, the irrigation efficiency will be equal to 95% * 85% * 80% = 64.6%. This research used the irrigation efficiency of 65% as this research was applied on the Jangkok water resource system that has a complete irrigation system (primary, secondary, and tertiary conveyances). Tables 5.3 shows the Agricultural Water Demand Calculation written in Excel.

Table 5.3 The Agricultural Water Demand Calculation Table in Excel

Crop Starting period		:	JAN											
NFR		:	1.081	1.463	1.399	1.331	1.181	1.526	1.509	1.439	1.278	1.226	1.084	1.114
The Minimum NFR		:	MIN											
Water Requirement in the year		:	30957.70231											
Crop Pattern		:	Rice - (Rice & Vegetables) - Vegetables											
Area		:	4500	ha										
NFR		:	1.081	1 sec.ha										
Year			2001											
S =	250	mm		Eo = 1.1 x ETo	convertion from mm day to l sec ha =					0.116			effisiency =	0.65
NO	Discription		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
			1	2	3	4	5	6	7	8	9	10	11	12
1	Crop Pattern		LP		Rice 100%		LP Break		Rice 50% Vegetables 50 %			Vegetables 100		
2	Days		31	28	31	30	31	30	31	31	30	31	30	31
3	Pot Evapotranspiration (PET)	mm day	4.969	5.067	5.227	5.029	5.335	5.343	5.695	5.994	5.782	5.738	5.241	5.278
4	Evaporation due to Land Preparation	mm day	2.733	2.534			2.000	0.668						
5	Percolation (P)	mm day	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000
6	Replacing Water due to Land Preparation (M)	mm day	4.733	4.534			4.000	2.668						
7	k	mm day	0.587	0.508			0.496	0.320						
8	Water Requirement due to Land Preparation (LP)	mm day	10.662	11.387			10.230	9.739						
9	Rainfall	mm	7.408	6.949	7.128	6.036	4.833	5.211	1.010	1.588	2.556	4.112	7.491	5.951
10	Rainfall	mm	7.408	6.949	7.128	6.036	4.833	5.211	1.010	1.588	2.556	4.112	7.491	5.951
11	Effective Rainfall for Rice	mm day	5.186	4.864	4.990	4.225	3.383	3.648	0.707	1.112	1.789	2.879	5.243	4.166
12	Effective Rainfall for Vegetables	mm day	5.186	4.864	4.990	4.225	3.383	3.648	0.707	1.112	1.789	2.879	5.243	4.166
	First period of changing water	mm day			3.300				3.300					
	Second period of changing water	mm day				3.300				3.300				
13	Average of changing water (WLR)	mm day			1.650	1.650			1.650	1.650				
	Crop coefficient of Rice =1		LP	1.100	1.050	0.950	LP	1.100	1.050	0.950				
	Crop coefficient of Rice =2			LP	1.100	1.050	0.950	LP	1.100	1.200				
14	Average of crop coefficient of Rice			0.550	1.075	0.881	0.119	0.413	0.544	0.419	0.000			
	Crop coefficient of Vegetables =1							0.510	0.850	0.950	0.510	0.850	0.950	
	Crop coefficient of Vegetables =2								0.510	0.850	0.950	0.510	0.850	0.950
15	Average of crop coefficient of Vegetables							0.191	0.298	0.438	0.374	0.680	0.900	0.475
16	Water Recharge for Rice (ETc1)	mm day	10.662	14.174	5.619	4.432	10.864	12.965	4.791	5.132	2.161	3.902	4.717	2.507
17	Water Recharge for Vegetables (ETc2)	mm day	0.000	0.000	0.000	0.000	0.000	1.022	1.694	2.622	2.161	3.902	4.717	2.507
18	NFR for Rice	mm day	5.476	9.310	4.279	3.857	7.481	9.317	7.734	7.670	2.372	3.023	1.474	0.341
19	NFR for Vegetables	mm day	0.000	0.000	0.000	0.000	0.000	0.000	0.987	1.510	0.372	1.023	0.000	0.000
20	NFR for Rice	l sec.ha	0.635	1.080	0.496	0.447	0.868	1.081	0.897	0.890	0.275	0.351	0.171	0.040
21	NFR for Vegetables	l sec.ha	0.000	0.000	0.000	0.000	0.000	0.000	0.115	0.175	0.043	0.119	0.000	0.000
	Total NFR	l sec.ha	0.635	1.080	0.496	0.447	0.868	1.081	1.012	1.065	0.318	0.469	0.171	0.040
22	Water Requirement in the intake for Rice	l sec.ha	0.977	1.662	0.764	0.688	1.335	1.663	1.380	1.369	0.423	0.540	0.263	0.061
23	Water Requirement in the intake for Vegetables	l sec.ha	0.000	0.000	0.000	0.000	0.000	0.000	0.176	0.270	0.066	0.183	0.000	0.000
24	Water Requirement in field for Rice	m3 ha	1701.44	2612.74	1329.60	1159.57	2324.16	2801.48	2402.92	2383.10	713.17	939.33	443.09	106.07
25	Water Requirement in field for Vegetables	m3 ha	0.00	0.00	0.00	0.00	0.00	0.00	306.78	469.27	111.83	317.94	0.00	0.00
26	Water Requirement in intake for Rice	m3 ha	2617.60	4019.61	2045.54	1783.95	3575.63	4309.97	3696.80	3666.31	1097.19	1445.12	681.68	163.18
27	Water Requirement in intake for Vegetables	m3 ha	0.00	0.00	0.00	0.00	0.00	0.00	471.97	721.96	172.04	489.14	0.00	0.00

5.4.2. Domestic Drinking Water Demands

Domestic Drinking Water Demands (*DWD*) might be affected by many factors. Based on the standard of water consumption in Indonesia, the *DWD* was calculated using equation (5.16) (Anonymous 2, 1990):

$$DWD = Pp \times DWR \qquad (5.16)$$

Where:

DWD = the domestic drinking water demands (lt/day)

Pp = the population (person)

DWR = the domestic water requirement (lt/day/person)

The other water demands, which were from municipalities and industries, were approximated using the DMI (Anonymous 2, 1990) water demand table as shown in Table 5.4. All these procedures and water demand tables are recommended by the various departments of the Government of Indonesia.

Table 5.4 The Indonesian Standard of Water Requirement for Domestics, Municipalities, and Industries (DMI)

No	Type of Consumers	Water Requirements of (l/day/person)				
		Metropolitans, population > 1 million	Big cities, population 0.5 ~ 1.0 million	Medium cities, population 0.1 ~ 0.5 million	Small cities, population 20,000 ~ 100,000	Suburban, population 3,000 ~ 20,000
1	Domestics (= DWR)	120	100	90	60	45
2	Municipalities	35% DWR	25 % DWR	10% DWR	5% DWR	5% DWR
3	Industries	25% DWR	20% DWR	20% DWR	10% DWR	10% DWR

Source: Anonymous 2, 1990

The prediction of population in the region of study was estimated using the following two growth rates: the growth rate based on censuses in 2000, 2005, and 2010 which is r_1 = 2.5 %; and the expected population growth rate for Indonesia if the family planning program works well which is r_2 = 1.5 % (Sinuraya, 1990).

5.4.3. Livestock Water Demands

Livestock Water Demands (*LWD*) was calculated using the equation

$$LWD = NL \times LWR \quad (5.17)$$

Where:

LWD = Livestock Water Demands (lt/day)

NL = Number of Livestock (animal unit)

LWR = Livestock Water Requirement (lt/day)

Livestock Water Requirement (*LWR*) depends on the type of animal and is found in Table 5.5.

Table 5.5 The Standard of Water Requirement for Livestock.

No.	Type of Animal	Water Requirements (lt/day/animal unit)
1	Cows / Buffalo / Horses	40
2	Sheep / Goats	4
3	Pigs	6
4	Poultry	0.6

Source: Anonymous 5, 1990.

In this study, the growth rate of livestock is assumed similar to the growth rate of population. The estimate number of livestock to 2100 is shown in Figure 5.6.

5.5. Results

<u>Modified NRECA model:</u>

The four calibrated NRECA model parameters are shown in Table 5.6

Table 5.6 The Results of Calibration

Calibrated NRECA model parameters				
Initial Moisture Storage	:	602	mm	
Initial Groundwater Storage	:	356	mm	
PSUB	:	0.817		(permeable)
GWF	:	0.347		(permeable)
NSE	:	0.845876		

Table 5.6 shows that the results of calibration are acceptable as the calibration produced NSE of 0.85. The comparison between observed and simulated runoff in the calibration and validation processes are shown in Figures 5.9 and 5.10, respectively.

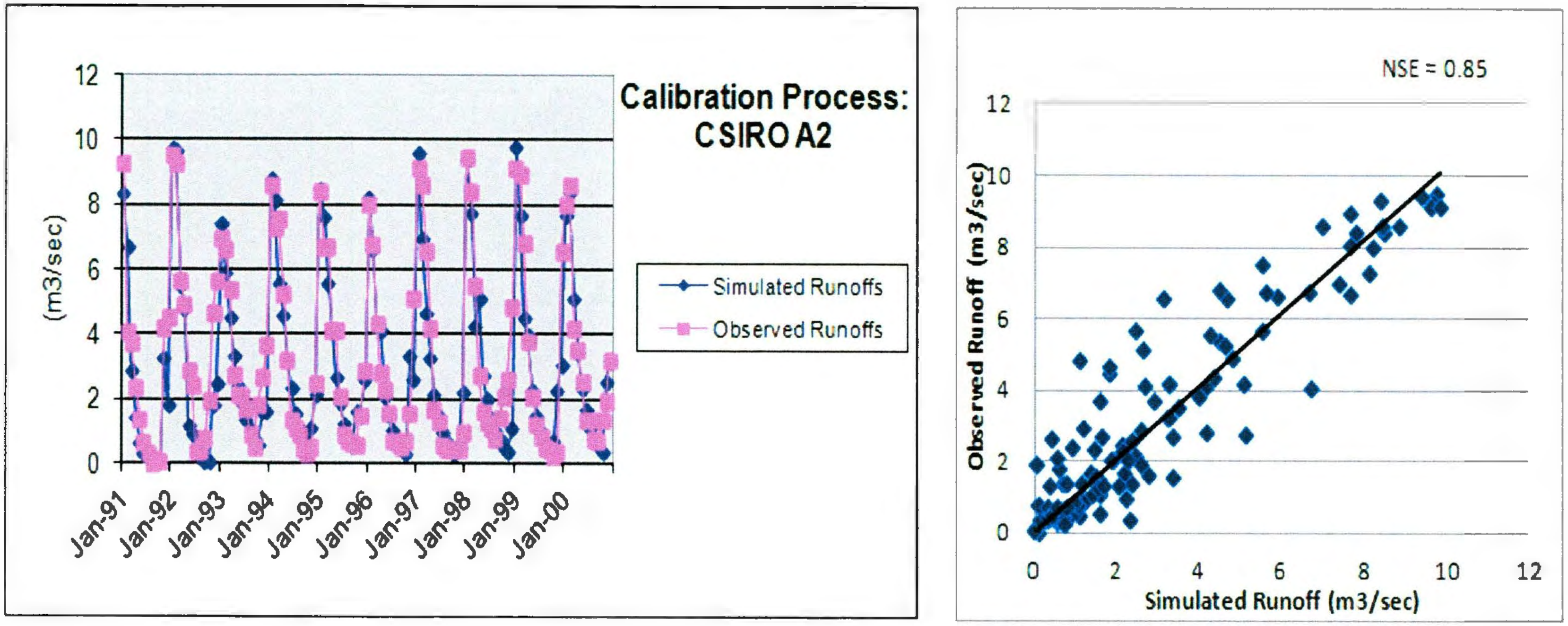
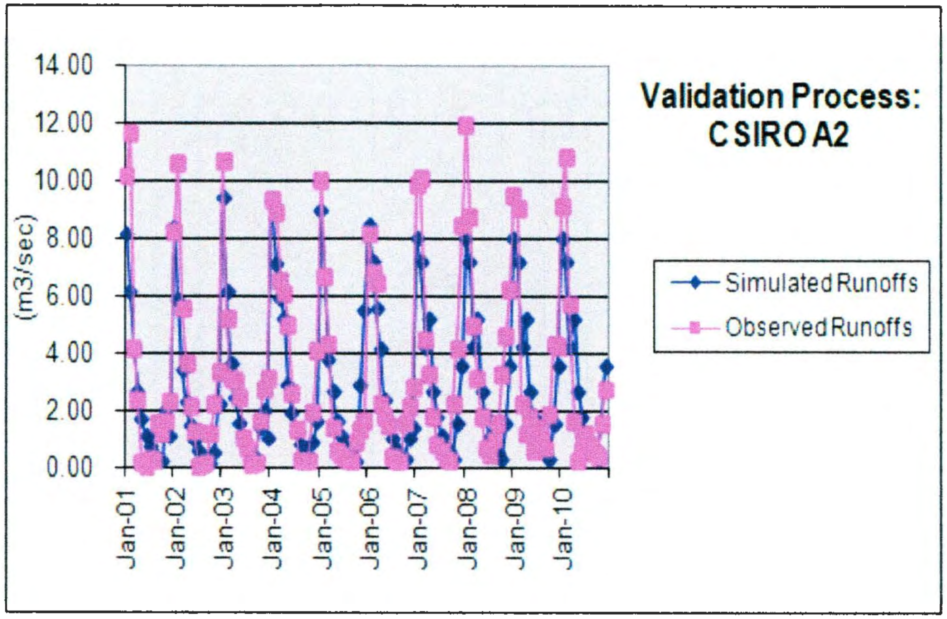


Figure 5.9 Plot of Observed and Simulated Runoff of Calibration Process



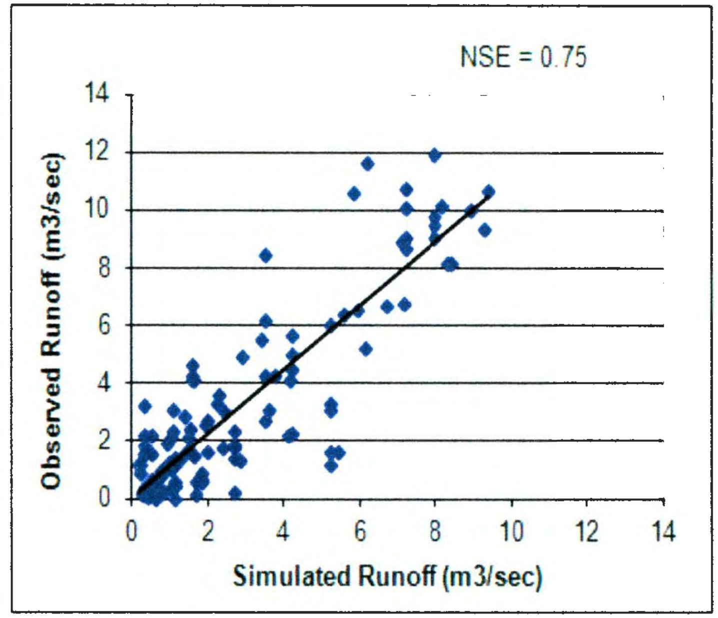


Figure 5.10 Plot of Observed and Simulated Runoff of Validation Process

Future Runoff

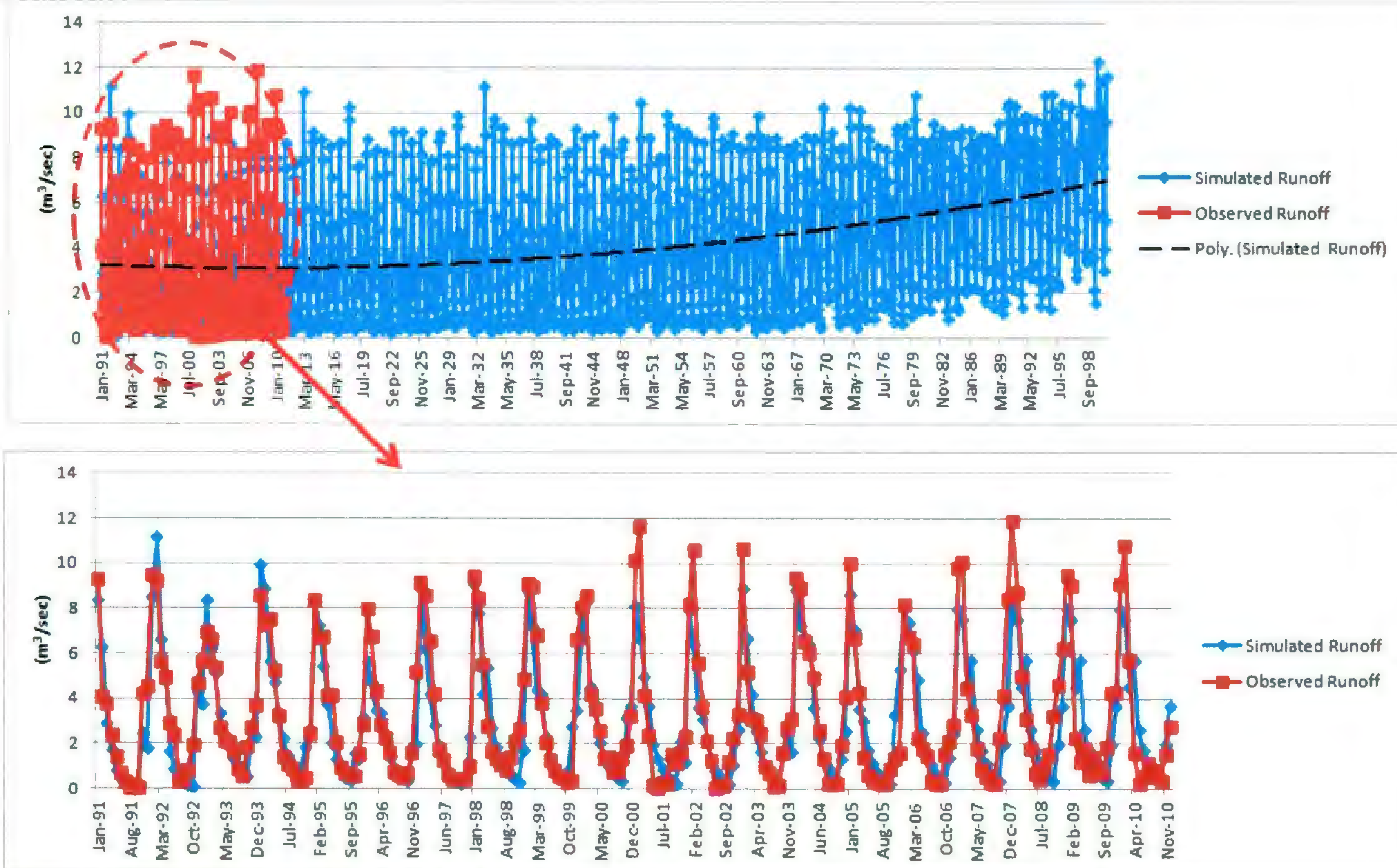


Figure 5.11 Plot of Observed and Simulated Runoff

Figures 5.9 to 5.11 show that the Modified NRECA model can simulate runoff that is relatively similar to the observed runoff. The NSEs in calibration and validation processes were 0.85 and 0.75, respectively. Moreover, Figure 5.11 also shows the increasing trend line of simulated runoff. It indicates that simulated runoff increases in the future.

Table 5.7 One Way ANOVA for Uncertainty Analysis of Local Rainfall-Runoff

One-way ANOVA: CCCma A2, CCCma B2, CSIRO A2, CSIRO B2, NIES99 A2, ...

```
Source      DF        SS   MS     F      P
Factor       8      31.9  4.0  0.46  0.885
Error    11871  102822.8  8.7
Total    11879  102854.7

S = 2.943   R-Sq = 0.03%   R-Sq(adj) = 0.00%


                                       Individual 95% CIs For Average Based on
                                       Pooled StDev
Level              N   Mean  StDev  ----+---------+---------+---------+-----
CCCma A2        1320  4.105  2.950          (----------*---------)
CCCma B2        1320  4.054  2.909      (---------*----------)
CSIRO A2        1320  4.080  2.928       (----------*----------)
CSIRO B2        1320  4.067  2.918       (---------*----------)
NIES99 A2       1320  4.076  2.926       (----------*---------)
NIES99 B2       1320  4.105  2.950          (----------*---------)
Normal Random   1320  4.003  2.882  (----------*---------)
CCAM-CSIRO      1320  4.207  3.070                   (---------*----------)
RCM-Lombok      1320  4.105  2.950          (----------*---------)
                                    ----+---------+---------+---------+-----
                                      3.90      4.05      4.20      4.35

Pooled StDev = 2.943
```

Table 5.7 shows 0.885 of p-value. This indicates that their differences of averages are statistically insignificant. This also indicates that the Modified NRECA model is consistent against the change of GCMs, emission scenarios, and method of residual generations to simulate the local monthly runoff of the Jangkok River.

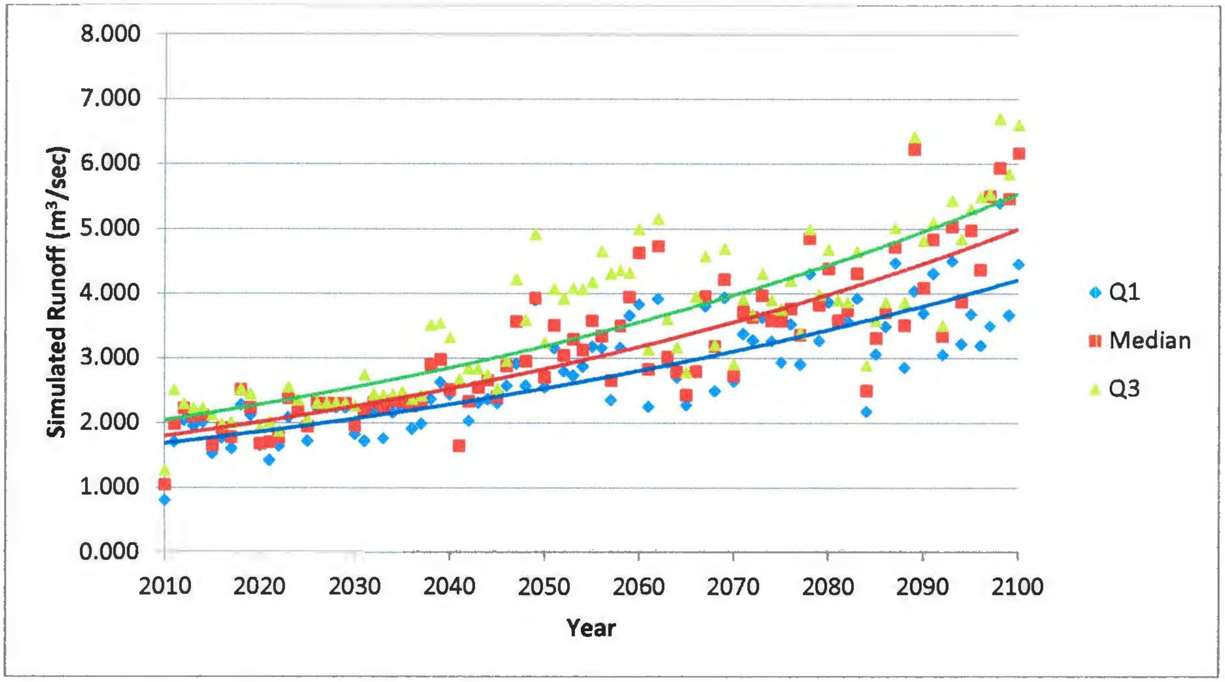


Figure 5.12 Plot of Simulated Runoff (m^3/sec) from 2010 to 2100

Figure 5.12 shows the increase in the average of simulated monthly runoff from approximately 2 m^3/sec in 2010 to 5 m^3/sec in 2100. Here, the gaps between first (Q1) and third (Q3) quartiles of simulated monthly runoff is getting larger over years. This indicates that the variance of simulated runoff increases in the future. This situation is also confirmed in Figure 5.15. In addition, the predicted runoff increases in the future. The increase in future runoff is also confirmed by Figures 5.13 and 5.14.

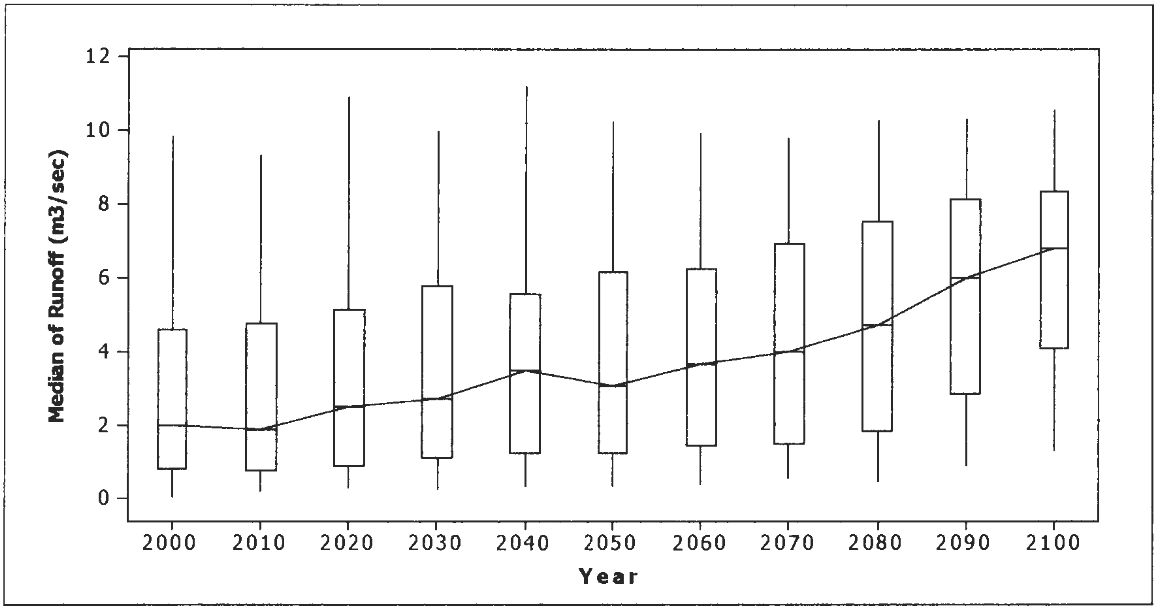


Figure 5.13 Box Plots of Median of 10 Year Period of Simulated Runoff (m^3/sec)

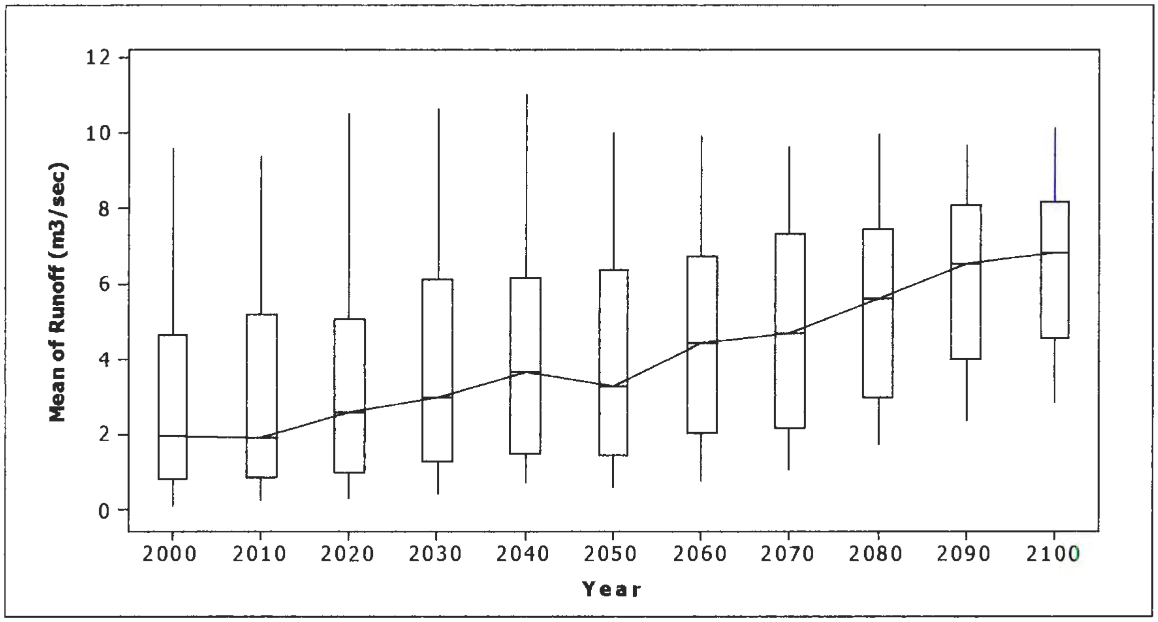


Figure 5.14 Box Plots of Average of 10 Year Period of Simulated Runoff (m^3/sec)

Figures 5.13 and 5.14 show that the average and median of 10 year period of simulated runoff gradually increases in the future.

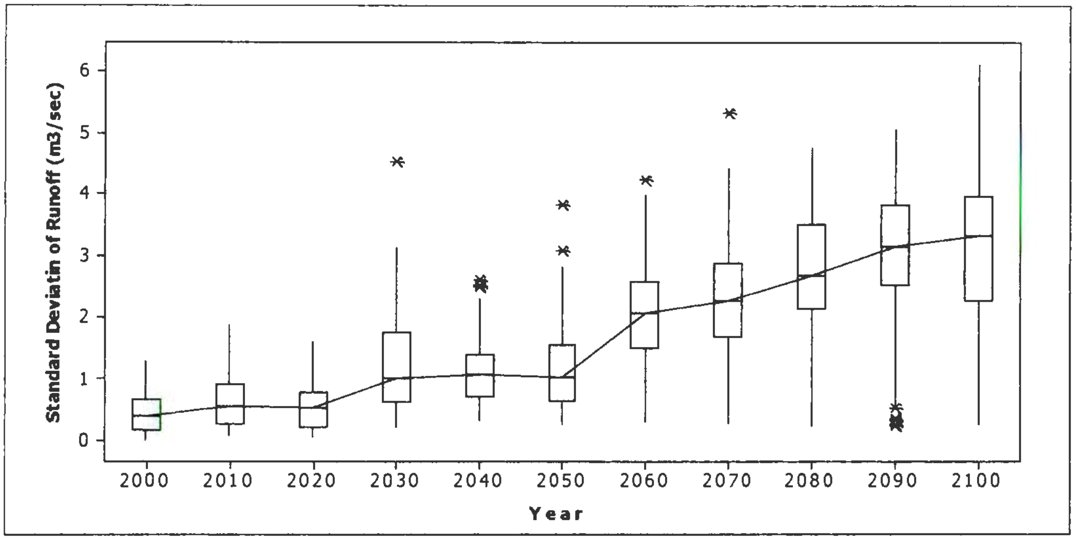


Figure 5.15 Box Plots of Standard Deviation of 10 Year Period of Simulated Runoff (m^3/sec)

Future Evapotranspiration

Table 5.8 One Way ANOVA for Uncertainty analysis of Simulated Evapotranspiration

One-way ANOVA: CCCma A2, CCCma B2, CSIRO A2, CSIRO B2, NIES99 A2, ...

```
Source     DF       SS     MS     F      P
Factor      8    0.531  0.066  0.34  0.949
Error    1071  207.598  0.194
Total    1079  208.129

S = 0.4403   R-Sq = 0.26%   R-Sq(adj) = 0.00%


                                   Individual 95% CIs For Average Based on
                                   Pooled StDev
Level         N    Mean   StDev   --------+---------+---------+---------+-
CCCma A2    120  4.9333  0.3928               (-----------*----------)
CCCma B2    120  4.8913  0.3970         (-----------*----------)
CSIRO A2    120  4.9014  0.5349           (----------*----------)
CSIRO B2    120  4.9087  0.4210            (----------*-----------)
NIES99 A2   120  4.8767  0.4284       (-----------*----------)
NIES99 B2   120  4.8767  0.4284       (-----------*----------)
NR          120  4.8494  0.4362   (----------*----------)
CCAM        120  4.8968  0.3927          (-----------*----------)
RCM-Lombok  120  4.8841  0.5077        (-----------*----------)
                                  --------+---------+---------+---------+-
                                        4.830     4.900     4.970     5.040

Pooled StDev = 0.4403
```

Table 5.8 shows 0.949 of P-value. This indicates that their differences of averages are statistically insignificant. This also indicates that the Modified PENMAN method is consistent against the change of GCMs, emission scenarios, and method of residual generations to simulate the local monthly evapotranspiration in the Jangkok River Basin.

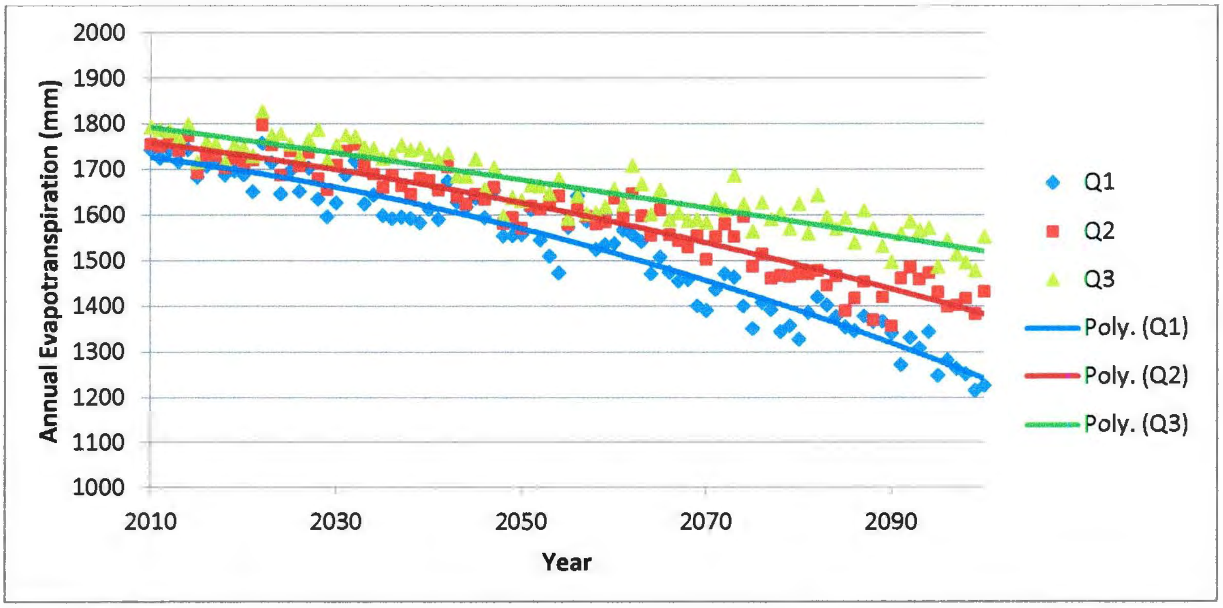


Figure 5.16 Plot of Estimated Annual Evapotranspiration at The Jangkok River Basin Under Climate Change Scenarios

Figure 5.16 shows the predicted annual local potential evapotranspiration decreases by approximately 360 mm from 1760 mm in 2010 to 1400 mm in 2100. The gap between first (Q1) and third (Q3) quartiles of estimated annual evapotranspiration increasing over years. This indicates that the variance of simulated runoff is getting larger in the future. Moreover in general, the amount of annual evapotranspiration decreases in future years.

Future Irrigation Water Requirement

Table 5.9 One Way ANOVA for Uncertainty Analysis of Simulated Irrigation Water Requirement

One-way ANOVA: CCCma A2, CCCma B2, CSIRO A2, CSIRO B2, NIES99 A2, ...

```
Source    DF           SS        MS     F      P
Factor     8     60885390   7610674  0.22  0.987
Error    891  30275758492  33979527
Total    899  30336643881

S = 5829   R-Sq = 0.20%   R-Sq(adj) = 0.00%


                                Individual 95% CIs For Average Based on
                                Pooled StDev
Level         N   Mean  StDev  --------+---------+---------+---------+-
CCCma A2    100  19867   5801    (-------------*--------------)
CCCma B2    100  20462   5596           (-------------*-------------)
CSIRO A2    100  20164   5607        (-------------*-------------)
CSIRO B2    100  20191   5165        (-------------*--------------)
NIES99 A2   100  20029   5396      (-------------*--------------)
NIES99 B2   100  20353   5132          (-------------*--------------)
NR          100  19705   6347  (-------------*--------------)
CCAM-CSIRO  100  20571   6791              (-------------*-------------)
RCM-Lombok  100  20138   6393       (--------------*-------------)
                               --------+---------+---------+---------+-
                                   19200     20000     20800     21600

Pooled StDev = 5829
```

Table 5.9 shows 0.987 of p-value. This indicates that their differences of averages are statistically insignificant. This also indicates that the "Van De Goor and Ziljstra" approach is consistent against the change of GCMs, emission scenarios, and method of residual generations to calculate irrigation water requirement in the Jangkok River Basin. The future irrigation water requirement is shown in Figure 5.17.

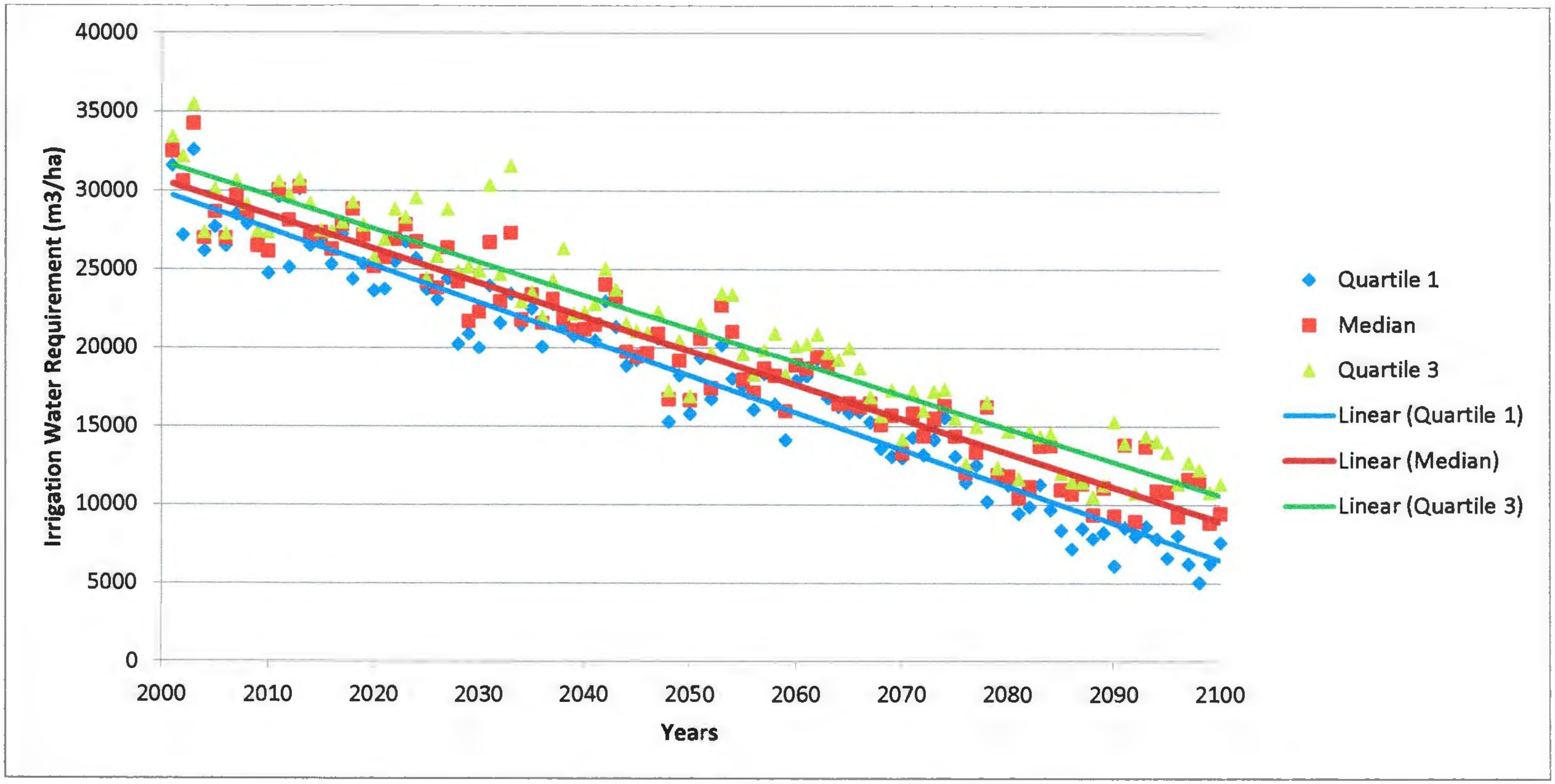


Figure 5.17 Plot of Predicted Irrigation Water Requirement Under Climate Change Scenarios

Figure 5.17 shows the decrease of future irrigation water requirement. However, the variance of irrigation water requirement in the future increases as it is indicated by the increase in gap between first (Q1) and third (Q3) quartiles of predicted irrigation water requirement in the future.

Future Domestic Water Demand

The prediction of population and the prediction of domestic water demand in the region of study are presented in Figures 5.18 and 5.19, respectively.

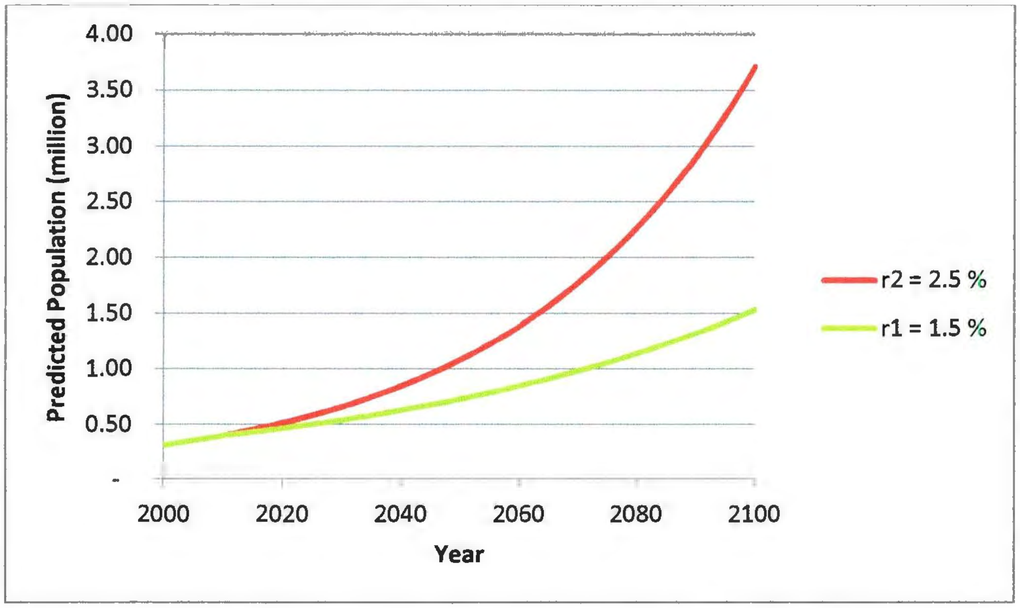


Figure 5.18 The Prediction of Population in the Region of Study until 2100

Figure 5.18 shows the two rates of predicted population in the region of study until 2100. Next, the prediction of domestic water demand was calculated based on these two predicted population growths.

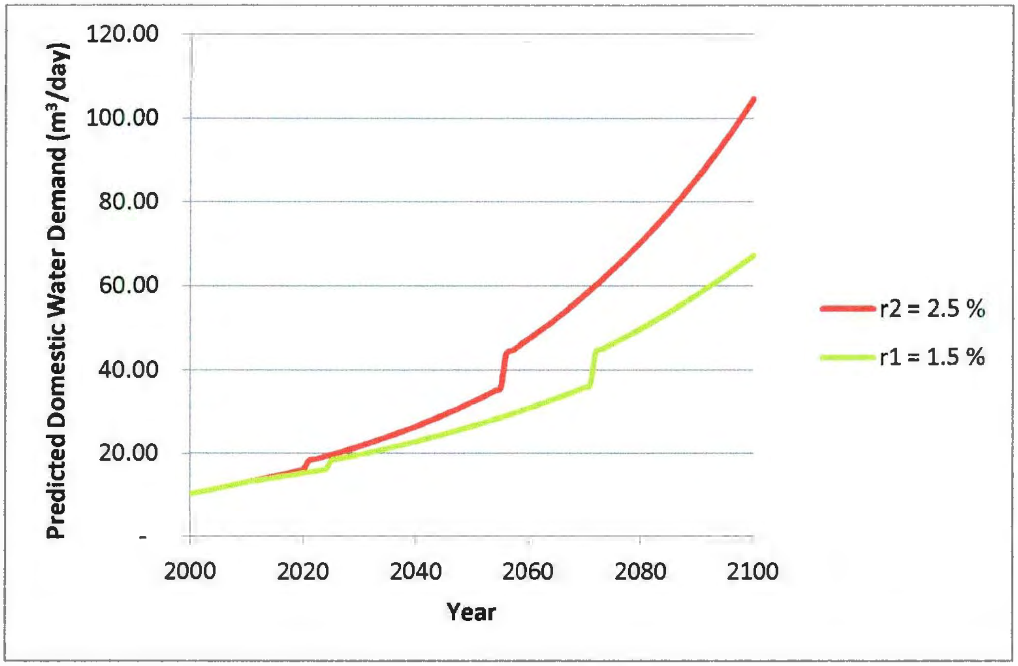


Figure 5.19 The Prediction of Domestic Water Demand

Figure 5.19 shows the two growth rate of domestic water demand calculated based on two scenarios of population growths. Here, sudden increases in domestic water demand occur from time to time because of a change of daily water requirement per person following the change of city status based on population as described in Table 5.6. In addition, the difference was very significant in the future between the two predicted domestic water demands.

Future Livestock Water Demand

From a prediction of livestock population, the estimate of livestock water demand until 2100 is presented in Figure 5.20.

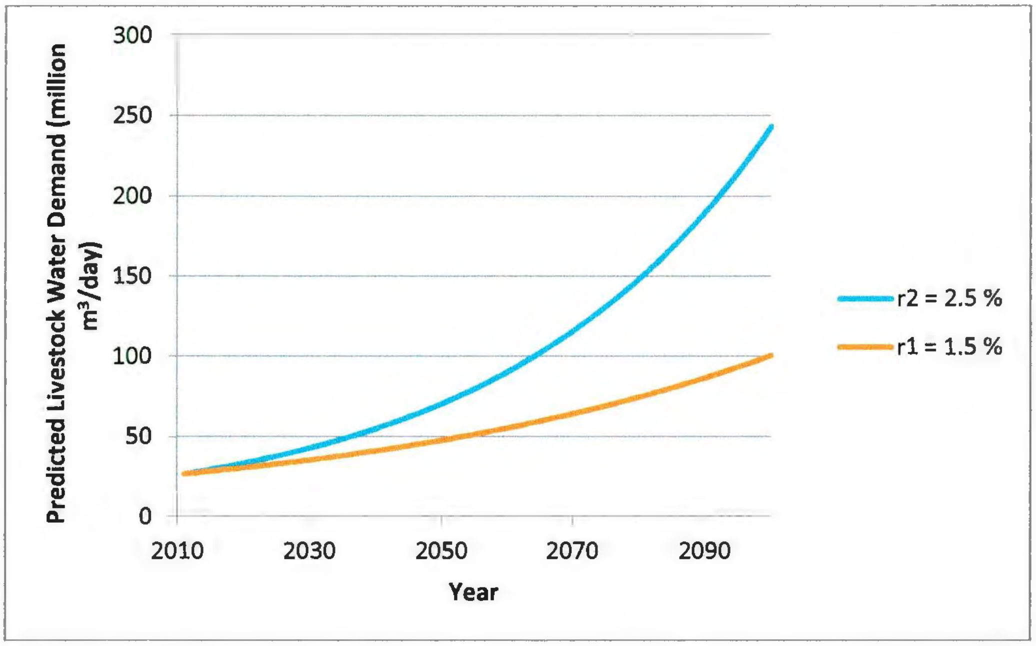


Figure 5.20 The Estimate of Livestock Water Demand until 2100

Figure 5.20 shows two curves of future livestock water demand calculated based on two growth rates: $r_1 = 1.5\%$ and $r_2 = 2.5\%$. The two livestock growth rates are expected to follow the two population growth rates.

5.6. Summary

In this study, the NRECA model's inputs were successfully modified to take climate change into account. The modified NRECA model is shown to be consistent in producing simulated runoff using inputs of climatic variables from different GCMs, RCMs, emission scenarios, and residual generation methods from the HYAS models. It is also found that the average of predicted monthly runoff increases from approximately 2 m^3/sec in 2010 to 6 m^3/sec in 2100 due to climate change effects.

From the calculation of evapotranspiration, it was found that climate change will decrease future evapotranspiration in the location of study. This makes sense because evapotranspiration is affected by factors including precipitation and temperature. As described in Chapter 4, climate change is expected to increase in the average of monthly precipitation and temperature in the location of study. Even though the average of monthly temperature increases in the location of study, however it is found from the result of evapotranspiration calculation that the increase in the average of precipitation dominantly causes evapotranspiration to decrease in the location of study.

From the calculation of water demands, it was found that Net Field Irrigation Water Requirement (NFR) decreases in the future due to climate change effects. This also makes sense because NFR is affected by the amount of precipitation and evapotranspiration. As increasing precipitation is followed by decreasing evapotranspiration, then the amount of water required for irrigation is decreasing or NFR decreases.

From the calculation of predicted population, it was found that there is a big difference of population comparison in 2100 between populations based on the growth rates of 1.5 % and 2.5 % which are approximately 1.5 million and 3.75 million, respectively. If the population growth rate is 2.5 %, population in the region of interest will be as large as population in a big city in 2020 and will become as large as population in a metropolitan in 2047. It is a very rapid increase in population compared to if the population growth rate is 1.5 % which population will be longer or approximately in 2070 to be as large as population in a metropolitan. The domestic water demand was calculated based on water demand of person and lifestyle: metropolitan, big city, medium city, small city, or suburban. The population growth rate of 2.5 % will result in a very large amount of domestic water demand which is approximately 160 million m^3/day in 2100 compared to domestic water demand from the population of growth rate of 1.5 % which is approximately 65 million m^3/day.

Chapter 6

Developments of New Water Index Criterion And Water Balance Optimization Model

This chapter describes the development of a new water index criterion to provide a more realistic assessment of water balance, and the development of a water balance optimization model for optimal development alternatives. This chapter includes background, the development of a new water index criterion, water balance assessments, the development of water balance optimization model, and summary.

6.1. Background

It is common in water resource studies to use a water balance to analyze the condition of a water resource system. In hydrology, input and output of a water balance can be defined as water availability and water uses; therefore, a water balance equation can be used to describe the flow of water in and out of a system and to help manage water supply and predict where there may be water shortages. It is also used in irrigation designs and evaluations, flood control and pollution control. Water balance studies are also important analysis for evaluating the impacts of climate change on water resource systems. In this research, water demand is water required by agricultural farms, livestock farms, and domestic uses as described in Chapter 5. In Indonesia, water balance of a water resource system is usually assessed periodically every 5 or 10 years (Sulistiyono and Lye, 2010).

Water balance assessment is an important tool in the evaluation of current status and trends of a water resource system in an area over a specific period of time. Water balance assessments can strengthen decision-making and improve the validity of visions, scenarios and strategies in water management. A water balance assessment is generally prepared for the following major purposes (Majkic, et al, 2008):

1. Systematic monitoring of quantity and quality variations in available surface water and groundwater resources, and of water abstractions and discharges for and by all users;
2. Updating, to reflect current knowledge and international trends;
3. Systematic monitoring of changes in water resources and provision of reliable data for the preparation of water regime management plans and water management master plans, and for timely undertaking of measures aimed at the conservation, protection and development of water resources;
4. Evaluation of current methods and procedures for collection of data for all elements of the water management balance and for recommending data acquisition and archiving improvements;
5. Definition of principles to be used in the selection of balance profiles and the territorial division of the country for purposes of management of available water resources;
6. Assessment of the availability and quality of water resources within various territories; and
7. Making recommendations for inter-institutional integration of all factors relevant to the water balance.

Water balance assessment in this research refers to the evaluation of effects of components or factors involved in a water resource system to maintain the sustainability of water in a water resource system. So far, a methodology of a comprehensive water balance assessment is difficult to be developed due to a number of practical problems. A comprehensive methodology should apply to current conditions, and should be adjustable to changes over space and time.

Currently, the Critical Water Index (CWI) is used to assess water balance in Lombok, Indonesia including an assessment of the water balance in the Reak Basin in Lombok Island (Sulistiyono and Lye, 2010). Considering water uses without priorities, prosperity or possible future water demands, the CWI might lead to inaccurate assessment of water balance; therefore, a new water index criterion is developed herein to provide more realistic assessments.

A currently used technique to optimize water uses in the location of study is using a Trial and Error method (Setiawan et al., 2005). However, as this method has disadvantages that have been described in Chapter 2, a new water balance optimization model will be developed as will be described in Subsection 6.3.

6.2. New Water Index Criterion

The evaluation of potential impacts of climate change on a water resource system can be done using a water balance assessment. In order to evaluate the future water resource availability to meet different domestic and agricultural utilizations under the climate change scenario, this research will assess a future water balance based on a 10-year period starting from 2010 to 2100. In this research, a new Water Index Criterion proposed is based on the remaining water uses and water demand priorities. This new criterion is better than the previous one that was proposed in 2005 to the Department of Public Work in Indonesia (see Equation 2.2) as it considers more parameters namely the remaining water, minimum water services and water use priorities. The proposed new water index criterion will be called the Remaining Water Index or RWI as is given by

$$RWI = \frac{(annual\ water\ availability - annual\ water\ uses)}{(first\ priority\ services\ of\ a\ system)} \quad \ldots\ldots\ldots\ldots\ldots \text{(6.1)}$$

Where:

RWI = Remaining Water Index

The first priority services of a system include first priorities of agricultural and minimum services for a system. In this research, the first priority of agricultural water demand is defined as the minimum water required supplying a minimum area of agricultural farm to meet a local demand for agricultural production. The minimum services for a system such as a city are municipal services and home based industries, which are equal to 25 % and 20 % of annual domestic water uses in big cities, respectively (see Table 5.4). The water balance status related to RWI is shown in Table 6.1.

Table 6.1 Water Balance Status

No.	**Condition**	**Category**	**Index**	**Annotation**
1	$RWI > 1.2$	Surplus	1	Allowed
2	$1.2 > RWI > 1.0$	Critical	1	Allowed
3	$RWI < 1.0$	Deficit	0	Not allowed

In Table 6.1, it is proposed that the index for surplus and critical is 1; and the index for deficit is 0. This means that the status of a water balance is only allowed to be in surplus or critical. It is not allowed to be in deficit. If the status of water balance is in surplus, then the area of agricultural farm can be developed. If the status of water balance is in critical, then the area of agricultural farm cannot be developed further. If the status of water balance is in deficit, then the area of agricultural farm has to be reduced. The range of water balance condition in the category of critical is set to 20 % or 1.0 to 1.2, following the range of critical condition in the CWI criterion. Therefore, RWI > 1.2 is considered in the category of surplus.

6.3. Water Balance Optimization Model

Optimization, in this research refers to choosing the best development alternatives for domestic, agriculture, and livestock. Response Surface Methodology based on a Central Composite Design was used in the development of the water balance optimization model.

RSM combines some use of statistical experimental design fundamentals, regression modelling techniques, and optimization methods. RSM optimises processes based on polynomial response surface analysis (Myers and Montgomery, 1995; Sulistiyono, 1999; and Lye, 2009). Although the RSM has many advantages as described in Chapter 2, the important reasons to utilize the RSM in this research were because of the abilities to reduce the number of experiments, to provide a systematic procedure, and to provide many possible alternative results.

A central composite design (CCD) of RSM is used in this research to optimize three factors: the growth rate of population, the percentage of irrigation area in the Jangkok River Basin, and the growth rate of livestock (see Table 6.2) with one response variable which is average status of water balance (see Table 6.3). This CCD-RSM utilizes a face centered option of axial points and one center point; therefore $15 = (2^3+2*3+1)$ runs are involved in this optimization.

Table 6.2 Factors and Factor Levels

No	Factor	Symbol	Low Level	High Level
1	The Growth Rate of Population	A	1.5 %	2.5 %
2	The Percentage of Irrigation Area	B	50%	100%
3	The Growth Rate of Livestock	C	1.5 %	2.5 %

The procedure of conducting optimization using RSM includes:

1) Setting experiments following a guided combination of factors (Yates' order), as shown in Table 6.3.

Table 6.3 Experimental Runs

Std	Run	Factor 1 A:Population %	Factor 2 B:Agricultural %	Factor 3 C:Livestock %	Response 1 Ave. Status of WB
7	1	1.50	100.00	2.50	
10	2	2.50	75.00	2.00	
1	3	1.50	50.00	1.50	
3	4	1.50	100.00	1.50	
14	5	2.00	75.00	2.50	
2	6	2.50	50.00	1.50	
4	7	2.50	100.00	1.50	
11	8	2.00	50.00	2.00	
8	9	2.50	100.00	2.50	
9	10	1.50	75.00	2.00	
15	11	2.00	75.00	2.00	
12	12	2.00	100.00	2.00	
13	13	2.00	75.00	1.50	
5	14	1.50	50.00	2.50	
6	15	2.50	50.00	2.50	

2) Running experiments following a guided combination of factors (Yates' order) and obtain the results of average status of water balance based on the RWI model as shown in Table 6.4

Table 6.4 The Spreadsheet Based Water Balance Model using the RWI Criterion

WATER AVAILABILITY (NRECA SIMULATED RUNOFF)

	1	2	3	4	5	6	7	8	9	10
	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Jangkok										
(m3/sec)	3.30	2.70	3.25	3.61	3.27	3.58	3.53	4.02	3.80	4.35
(m^3)	104,165,601.53	84,994,006.26	102,356,134.28	113,789,983.47	103,102,557.72	112,800,203.89	111,439,451.56	126,798,404.38	119,738,466.84	137,145,158.07

WATER REQUIREMENT IN INTAKE

	1	2	3	4	5	6	7	8	9	10
	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Jangkok										
(m3/ha)	25,781.01	26,930.63	27,861.89	26,768.26	24,240.99	23,163.69	26,399.07	24,235.55	21,712.64	22,301.10

WATER DEMANDS

		2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
	Jangkok										
B = 50	Irrigation (m^3)	58.007.281.25	60,593.927.56	62.689.263.27	60.228.578.83	54.542.219.03	52.118.306.18	59.397.906.73	54.529.987.76	48.853.435.84	50.177.463.85
C = 2.5	Livestocks (m^3)	94,835.71	97,206.60	99,636.77	102,127.69	104,680.88	107,297.90	109,980.35	112,729.86	115,548.10	118,436.81
A = 2.5	Domestics (m^3)	19,266,525.00	19,748,325.00	20,241,805.00	20,748,060.00	21,266,725.00	21,798,530.00	22,343,475.00	22,901,925.00	23,474,610.00	24,061,530.00
	Released runoff (m^3)	10,416,560.15	8,499,400.63	10,235,613.43	11,378,998.35	10,310,255.77	11,280,020.39	11,143,945.16	12,679,840.44	11,973,846.68	13,714,515.81
	Total Water Demand (m^3)	87,785,202.12	88,938,859.79	93,266,318.47	92,457,764.87	86,223,880.68	85,304,154.47	92,995,307.23	90,224,483.05	84,417,440.62	88,071,946.46
	Remaining Water (m^3)	16,380,399.42	(3,944,853.53)	9,089,815.81	21,332,218.61	16,878,677.04	27,496,049.42	18,444,144.32	36,573,921.33	35,321,026.21	49,073,211.61
	Reserved water for Municipals and Industries = 25%+20%	10,596,588.750	10,861,578.750	11,132,992.750	11,411,433.000	11,696,698.750	11,989,191.500	12,288,911.250	12,596,058.750	12,911,035.500	13,233,841.500

WATER BALANCE

			2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
X1 = pop	1.5, 2, 2.5	2.5	**Average Status**									
X2= agr	50, 75, 100	50	**80%**	**1**	**0**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
X3=livs	1.5, 2, 2.5	2.5	**Category**	**Surplus**	**Deficit**	**Deficit**	**Surplus**	**Surplus**	**Surplus**	**Surplus**	**Surplus**	**Surplus**	**Surplus**
			RWI	**1.55**	**-0.36**	**0.82**	**1.87**	**1.44**	**2.29**	**1.50**	**2.90**	**2.74**	**3.71**

Table 6.4 shows a spreadsheet based water balance model using the RWI Criterion to assess a water balance of the Jangkok River Basin for the period of 2021 to 2030. Black and red numbers in the yellow box indicate levels of each factor and combinations that were applied to calculate RWI, respectively. These are the same as in the upper boxes next to the Water Demands' table. With A, B, and C equal to 2.5 %, 50.0 %, and 2.5 %, respectively; the average status of water balance from 2021 to 2030 shows the response was 80% or only two RWIs of 2022 and 2023 were smaller than 1 or in the category of "deficit". This calculation was repeated until all treatment combinations were done.

3) filling up all average statuses of water balance as responses based on all treatment combinations as shown in Table 6.5

Table 6.5 An Example of Water Balance Status of The Jangkok River Basin from 2021 to 2030

Std	Run	Factor 1 A:Population %	Factor 2 B:Agricultural %	Factor 3 C:Livestock %	Response 1 Status of Water Balance
7	1	1.50	100.00	2.50	0
10	2	2.50	75.00	2.00	0.1
1	3	1.50	50.00	1.50	0.9
3	4	1.50	100.00	1.50	0
14	5	2.00	75.00	2.50	0.1
2	6	2.50	50.00	1.50	0.8
4	7	2.50	100.00	1.50	0
11	8	2.00	50.00	2.00	0.8
8	9	2.50	100.00	2.50	0
9	10	1.50	75.00	2.00	0.2
15	11	2.00	75.00	2.00	0.1
12	12	2.00	100.00	2.00	0
13	13	2.00	75.00	1.50	0.1
5	14	1.50	50.00	2.50	0.9
6	15	2.50	50.00	2.50	0.8

Table 6.5 shows responses from 15 runs of factor level combination. Each response is an average status of water balance of the Jangkok River Basin from 2021 to 2030 based on all combinations of factor levels. For example: the response of the first run based on 1.5 %, 100 %, and 2.5 % of Factors A, B, and C, respectively is 0. This means that all years from 2021 to 2030 are in deficit water status if the growth rate of population is 1.5 %, the irrigation area in the Jangkok River Basin has been developed 100 %, and the growth rate of livestock is 2.5 %; however, the response of the third run based on 1.5 %, 50 %, and 1.5 % of Factors A, B, and C, respectively is 0.9. This means that there are 9 years from 2021 to 2030 which are in surplus or critical water statuses if the growth rate of population is 1.5 %, the irrigation area in the Jangkok River Basin has been developed 50 %, and the growth rate of livestock is 1.5 %; etc.

4) Developing the best model for optimization

The best optimization model can be obtained using ANOVA as shown in Table 6.6

Table 6.6 The ANOVA of Selected Model

Response 1 RWI

ANOVA for Response Surface Reduced Quadratic Model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	2.90	5	0.58	2150.58	< 0.0001	significant
A-Population	0.01	1	0.01	33.35	0.0003	
B-Agricultural	2.21	1	2.21	8186.29	< 0.0001	
AB	0.01	1	0.01	18.53	0.002	
A^2	3.57E-03	1	3.57E-03	13.24	0.0054	
B^2	0.53	1	0.53	1969.94	< 0.0001	
Residual	2.43E-03	9	2.70E-04			
Cor Total	2.90	14				

Std. Dev.	0.02	R-Squared	0.999
Mean	0.32	Adj R-Squared	0.999
C.V. %	5.13	Pred R-Squared	0.997
PRESS	0.01	Adeq Precision	99.210

Table 6.6 explains that the selected model in significant as it has a"P-value of Prob.>F" < 0.0001 smaller than 0.05, it means that the probability of the selected model wrong is very small (<0.0001). The "Pred R-Squared" of 0.9965 is in reasonable agreement with the "Adj R-Squared" of 0.9982. "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 89.584 indicates an adequate signal. This model can be used to navigate the design space.

The coded factor model is expressed as

$$RWI = 0.106 - 0.03\,A - 0.42\,B + 0.025\,AB + 0.036\,A^2 + 0.286\,B^2$$

Whereas the actual factor model is expressed as

$$RWI = 4.93 - 0.78\,A - 0.09\,B + 0.002\,AB + 0.143\,A^2 + 0.0005\,B^2$$

Where:

RWI	=	Remaining Water Index
A	=	population growth rate (%)
B	=	agricultural farm area development (%)

This model is used to develop a response surface graph that is used to obtain the optimum response. The response surface graph is shown in Figure 6.1

5) Optimization Processes

The optimization process searches for possible combinations of factor levels that simultaneously satisfy the requirements of the optimum responses. Optimization was performed numerically by choosing the desired goal for each factor and response from the menu. The goals were to set all factors within their ranges and to set the response at a value target of 0.8. A minimum and a maximum level were provided for each parameter included. A weight was assigned to each goal to adjust the shape of its particular desirability function. Desirability is an objective function that ranges from zero outside of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. The "importance" of each factor's goal was set to the default of 3 pluses (+++). The goal of response was set to 5 pluses (+++++) to indicate the most important in this process. A 3D surface shown in Figure 6.1 was used to explore the function in the factor space.

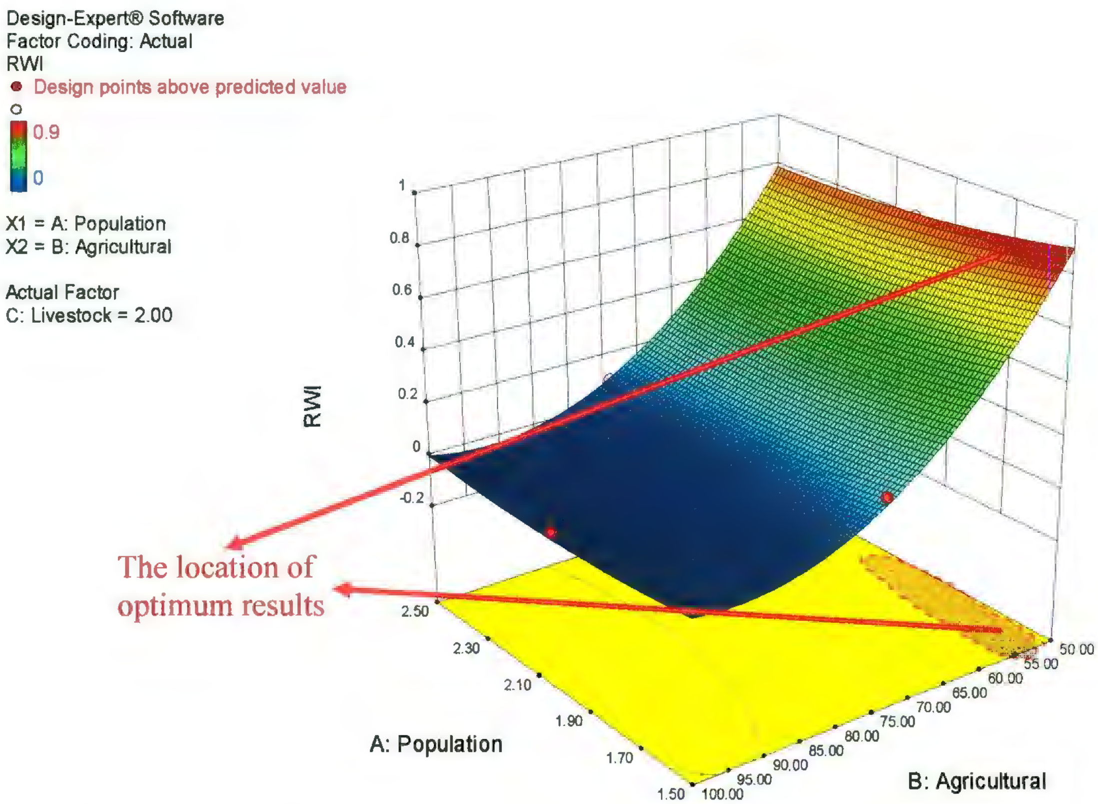


Figure 6.1 A Response Surface Graph of RWI for the Period of 2021 to 2030

Figure 6.1 shows the location of optimum results for the period of 2021 to 2030 which is in the top 90% highest contours of the response surface graph. This response surface graph is developed based on a fixed value (2 %) of factor C (the growth rate of livestock). That is because factor C is insignificant factor of the model; therefore, it is still fine to set the factor C in a maximum value. It can be seen that possible optimum results for the period of 2021 to 2030 are located between 1.5 % and 2.3 % of Factor A as well as between 53 % and 59 % of Factor B. All possible values of Factors A and B for all periods from 2011 to 2100 are plotted in Figure 6.2.

Periods	Intercept	Coeff of A	Coeff of B
2011 ~ 2020	0	0	-0.45
2021 ~ 2030	0.106	-0.03	-0.42
2031 ~ 2040	0.006	-0.03	-0.47
2041 ~ 2050	0.409	-0.2	-0.29
2051 ~ 2060	0.146	-0.29	-0.23
2061 ~ 2070	0.367	-0.36	-0.17
2071 ~ 2080	0.04	-0.34	-0.16
2081 ~ 2090	0.16	-0.44	-0.09
2091 ~ 2100	0.02	-0.46	-0.05

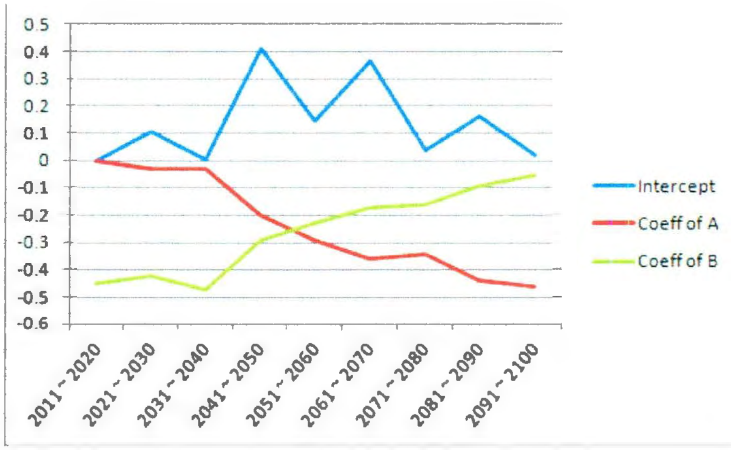


Figure 6.2 Intercept and Coefficients of the Response Surface Models

Figure 6.2 shows in general that the coefficient of Factor A starts from 0 in the period of 2011 ~ 2020 and decreases to -0.46 in the period of 2091 ~ 2100; while the coefficient of Factor B starts from -0.45 in the period of 2011 ~ 2020 and increases to approximately zero in the period of 2091 ~ 2100. This means that Factor A started from as an insignificant factor of the water balance status model in the period of 2011 ~ 2020 since it is zero to a significant factor in the period of 2091 ~ 2100 since it is further from zero. Oppositely, Factor B started from as a significant factor of the water balance status model in the period of 2011 ~ 2020 since it is further from zero to an insignificant factor in the period of 2091 ~ 2100 since it is closed to zero.

6.4. Results of Optimization

A complete result of optimization in this research is to summarize all possible expected combinations of factors: the growth rate of population (A), the development of agricultural farm (B), and the growth rate of livestock (C) from 2011 to 2100.

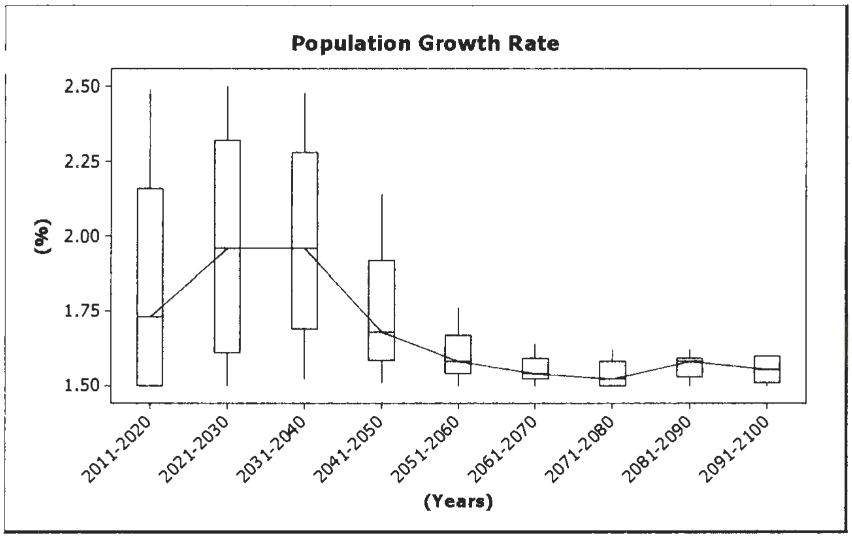


Figure 6.3 The Box Plot of Population Growth Rate in The Jangkok River Basin from 2011 to 2100

Figure 6.3 shows the expected population growth rates from 1.75 % in the period of 2011 – 2020 to 1.55 % in the period of 2091 – 2100. It is also clearly shown in Figure 6.3 that the variance of expected population growth rate decreases in the future as indicated in Figure 6.3 by the decrease in the size of boxes from the period 2011 – 2020 to the period of 2091 – 2100. This indicates that during the periods of 2011 to 2040, the population growth rate is more flexible. It can be allowed to be between 1.5 % and 2.3 %; however, it must be limited to approximately 1.55 % in the future. This means that although rainfall is predicted to be higher in the future; however, it cannot meet the demand of domestic water supply if the population grow faster than 1.55 % in the future.

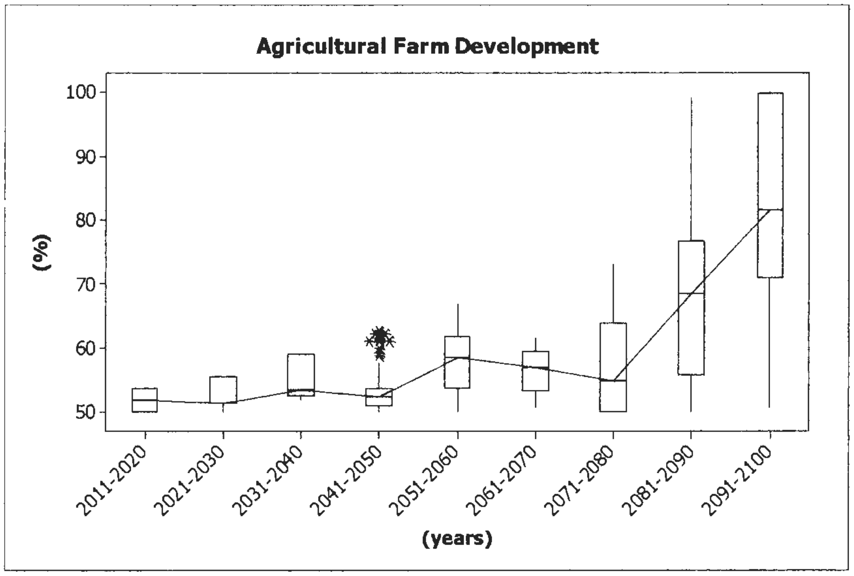


Figure 6.4 The Box Plot of Expected Agricultural Farm Developments in The Jangkok River Basin from 2011 to 2100

Figure 6.4 shows the increase in the percentage of agricultural farm area development from approximately 52 % in the period of 2011 – 2020 to approximately 81 % in the period of 2091 – 2100. Figure 6.4 also shows the increase in variance of expected percentage of agricultural farm area development in the future as indicated by the increase in the size of boxes. This means that during the period of 2011 to 2050, the area of agricultural farm cannot be developed more than 52 %; however, it can be developed to reach 81 % in the future as there will be benefit of climate change impacts. The increase in the percentage of agricultural farm development is possible since there is more rainfall and less evapotranspiration as described in Chapters 4 and 5.

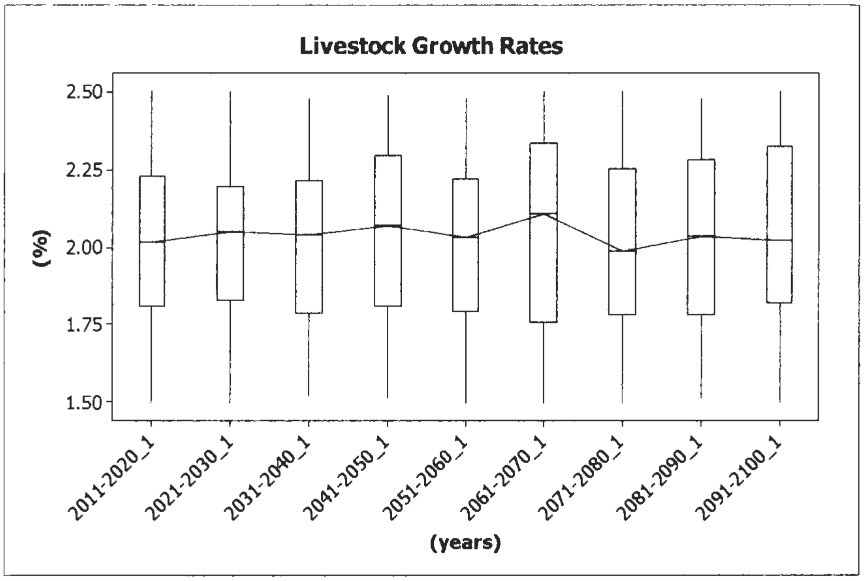


Figure 6.5 The Box Plot of Expected Livestock Growth Rates in The Jangkok River Basin from 2011 to 2100

Figure 6.5 shows the expected rate of livestock growth in The Jangkok River Basin from 2011 to 2100 based on the optimization to be constant at approximately 2 %.

6.5. Summary

From the results of optimization, it can be summarized that

- The livestock growth rate is an insignificant factor of the water balance status. It is indicated by the consistency of size and central point of box plots from 2011 to 2100, also by the absence of Factor C in the response surface model. Therefore, it is reasonable to set the livestock growth rate at 2 % in the future;
- In the beginning periods (2011 to 2040), the population growth rate is an insignificant factor to the water balance status; however in the future, it is a significant factor of the

water balance status. It is indicated by a larger size of box plots in the periods of 2011 to 2040 and a smaller size of box plots in the future, also by the values of coefficient of Factor A in the response surface models went from 0 to -0.45. Moreover as the growth rate of population is a significant factor in the water balance status; therefore, it is recommended to the Government of NTB province to pay attention and to restrict the growth rate at 1.5 %;

- In the beginning periods (2011 to 2040), the area of agricultural farm development is a significant factor of the water balance status; however in the future, it is becoming an insignificant factor in the water balance status. It is indicated by a smaller size of box plots in the periods of 2011 to 2040 and a larger size of box plots in the future, also by the values of coefficient of Factor B in the response surface models started going from -0.45 to -0.05. In addition, the agricultural farm area can be expected to grow until 81 % of the whole agricultural land (4500 ha) or 3645 ha.

Chapter 7

Possible Impacts of Climate Change and Recommendations to the Government

Climate change is currently an important issue which makes many people are worried about because of its possible negative impacts. For that reason, efforts have been made by governments to plan adaptation and mitigation measures due to possible climate change. The necessary efforts should also consider the local capabilities and the types of impacts in the region of interest. Climate change studies would thus be an initial and important step for planning adaptation and mitigation measures.

The fourth assessment report published mid-April 2007 by the IPCC-Working Group II has strengthened its belief in the impacts of climate change threats to mankind on this earth. Threats certainly have negative consequences on the environment, infrastructure, society and economy. Among them is the increase in average air temperature, sea water level rise which can lead to the sinking of the coastal zones and small islands, the change in rainfall pattern and intensity, and the melting of snow cover and thickness. Climate change is projected to not only increase temperatures, but also increase the intensity of the hydrologic cycle and change in seasonal precipitation patterns, leading to more intense flooding.

Presently no climate change studies have ever been specifically conducted for the Jangkok River basin, Lombok – Indonesia. Even though, the Jangkok river basin is included in the first priority basin rehabilitation program. Therefore, this research supports the Government efforts regarding the rehabilitation program based upon possible impacts of climate change in the future.

7.1 Possible Impacts of Climate Change on the Jangkok River Basin

- Increase in Air Humidity

Results from this research show that local monthly air humidity is estimated to increase by approximately 4.3 % from 80.7 % in 2010 to 85 % in 2100 with a possible maximum air humidity of approximately 87 % in 2100.

- Increase in Monthly Rainfall

Results of this research show that in general, rainfall patterns may not change in the future. However, there may be a change in the amounts of minimum and maximum monthly rainfall. Local monthly rainfall increases by approximately 95 mm, from 130 mm in 2010 to 225 mm 2100 with possible maximum monthly rainfall of up to 250 mm. This increase in monthly rainfall will increase water availability in the region of interest. If not carefully managed, the increase in water availability may lead to the abundance of water that may cause floods, areal inundations, decrease in the quality of agricultural productions, and other property losses.

- Increase in Air Temperature

Results of this research show that the average local monthly air temperature may increase by approximately 1.0 °C from 26 °C in 2010 to 27 °C in 2100 with the increase in maximum air temperature from 27 °C in 2010 to 32 °C in 2100.

- Increase in Wind Speed

Results of this research show that local monthly wind speed may slightly increase by approximately 0.2 knots from 5 knots in 2010 to 5.2 knots in 2100 with possible maximum wind speed of up to 5.8 knots. This increase is very small and might not have any significant effects.

- Decrease in Evapotranspiration

Results of this research show that annual local potential evapotranspiration may decrease by approximately 360 mm from 1760 mm in 2010 to 1400 mm in 2100. Decreases in potential evapotranspiration may lead to decreases in the amount of agricultural water demands. This may be beneficial for developing the area of agricultural farms. More area of agricultural lands can thus be developed.

- Increase in Runoff

Results of this research show that the average of predicted monthly runoff increases from approximately 2 m^3/sec in 2010 to 6 m^3/sec in 2100. This increase in runoff is caused by the increase in rainfall and by the decrease in sunshine duration. Similar to the increase in rainfall, the increase in runoff may lead to the increase in water availability. This increase in runoff is possibly followed by increasing flood and areal inundations.

- Rapid Increase in Population

Results of this research show that if the population growth rate is about 2.5 % then the population in the Jangkok River basin will be approximately 3.75 million in 2100. This is a very rapid increase in population growth compared to if the population growth rate can be controlled at 1.5 % in which case the population will be only 1.5 million in 2100. Moreover, if the population growth rate is 2.5 %, the region of interest will very soon become a big city in 2020 and will become a metropolitan in 2047. Furthermore, domestic water demand will reach approximately 160 million m^3/day in 2100. It is a very large amount compared to domestic water demand from the population of growth rate of 1.5 % which is approximately 65 million m^3/day.

7.2 Recommendations to the Government

Based on these possible effects described above, it is suggested that the government develop the following programs:

1. Water resource program

a. To protect sustainable water resources in river basins,

b. To control the utilization of water resource systems,

c. To monitor, evaluate, and enhance availability and quality of water,

d. To monitor, evaluate, and anticipate risk of existing dams from failures,

e. To develop rain water collection through reservoirs and dams, and

f. To provide education and technical support to local governments on engineering solutions to water storage, waste and flood management, including existing dam evaluations and rehabilitations.

2. Population control program

a. To pay attention and control on the population growth rate at level 1.5 % to avoid overpopulation through the National Population and Family Planning Board (*Badan Kependudukan dan Keluarga Berencana Nasional* = BKKBN),

b. To limit birth rates through legal regulations,

c. To educate people regarding family planning,

d. To increase access to birth control and contraception, and

e. To conduct resettlement and transmigration to mitigate overpopulation in the future.

3. Forests, land use and public housing program

a. To regulate infrastructure and sanitation facilities;

b. To rehabilitate forest and land use,

c. To conduct conservation of protected forests and nature reserves,

d. To regulate public housing, and

e. To monitor, evaluate, as well as to protect from the risk of landslides and infrastructural damages.

4. Public health program

a. To develop medical care,

b. To educate people on hygienic life style,

c. To develop proper sewage treatment,

d. To enhance sanitation and waste management programs, and

e. To develop disease control schemes.

5. Agricultural and Livestock Farm Development to support Food Security Programs

a. To provide technical assistance in the development of agricultural sector,

b. To guide farmers on the right crop pattern following rainfall patterns,

c. To keep the area of agricultural farm at 51 % of the total land or 2295 ha until 2050, as agricultural water demand is still a significant factor of the water balance model of the Jangkok River Basin until 2050. This area of agricultural farm can be developed starting from 2051 to reach approximately 55 % of the total land or 2475 ha by 2080 and to reach approximately 81 % or 3645 ha in 2100, as it becomes a less significant factor of the Jangkok River Basin in the future,

d. To guide and regulate the development of livestock farm to support local economic and food security programs,

e. To develop fresh water fisheries due to the possible abundance of surface water to support food production,

f. To enhance food security,

g. To develop agribusiness prospects,

h. To improve farmer welfare, and

i. To establish a research centre of water, agricultural, livestock, and health resources for

    1) Studying possible impacts of increasing in local air humidity of the Jangkok River Basin with regard to social activities, as well as quantity and quality of agricultural and livestock productions in the region.

    2) Studying possible impacts of increasing rainfall with regard to water management, failure risk of existing water structures such as dams, irrigation, and drainage systems in the region.

    3) Studying possible impacts of increasing local air temperature with regard to human, vegetation, and animal health.

    4) Studying impacts of increasing local monthly runoff on flood occurrences and areal inundations as well as on the existing infrastructures of public services in the region.

    5) The development of Agricultural Land Resources,

6) The development of Socio-Economic Policies in Agricultural Land Resource,
7) The development of agribusiness innovation based models,
8) The development of Science and Technology for agricultural information, communication, dissemination and Feedback, and
9) The development of Institutional Capacity Building for Agricultural Research.

Chapter 8

Conclusions

In this chapter, a summary of the study and recommendations for future work will be presented in the relation to the scope and purpose of the research which was to study the Potential Impacts of Climate Change on Water Resources in Lombok, Indonesia. The study was carried out by integrating the investigation of existing downscaling models and subsequent development of a new proposed downscaling model, the modification of the NRECA model, the development of RWI criterion, the development of a new RSM-CCD based water balance optimization model, the assessment of local water balance under climate change scenarios, and providing recommendations to the Government of NTB with regards to the control of population growth rate, the development of agricultural lands and livestock farms.

8.1. Summary of the Study

Keeping in perspective the objectives of this research, it can be concluded that:

1. This study has successfully developed a new downscaling model based on a hybrid of algebraic and stochastic approaches, so named the"HYAS" model. This model employs the differences between simulated future variables and baseline variables, and then added to generated residuals that have changing mean and variance. This model has overcome some of the disadvantages of existing downscaling techniques to provide finer resolution simulated local climatic variables. The HYAS model worked

well based on a single or multiple variables. The results of simulated monthly local climatic variables by the HYAS model were well fitted to the observed variables and were able to simulate local climatic variables to assess and predict future status of water balance in the Jangkok River Basin. From model uncertainty analysis, it was found that the HYAS model was consistent against the change of model assumptions including the changes of GCMs, RCMs, emission scenarios, and the method of residual generation.

From the climate change analysis of the local simulated climatic variables using the HYAS model based on the CGCM2, it was found that the impacts of climate change on water resources in the Jangkok River Basin include:

a. Local monthly Air Humidity of the Jangkok River Basin is estimated to increase approximately 4.3 % from 80.7 % in 2010 to 85 % in 2100 with possible maximum air humidity reaching approximately 87 % in 2100.
b. In general, rainfall patterns will not change in the future. However, a change may occur in the amounts of minimum and maximum monthly rainfall. Local monthly Rainfall is estimated to increase by approximately 95 mm from 130 mm in 2010 to 225 mm 2100 with possible maximum monthly rainfall up to about 250 mm.
c. Local monthly Sunshine Hours is estimated to decrease by approximately 10 % from 75 % in 2010 to 65 % in 2100 with possible minimum Sunshine Hours of about 55 %.

d. The average of local monthly Air Temperature is estimated to increase by approximately 1.0 °C from 26 °C in 2010 to 27 °C in 2100 with the increase in maximum Air Temperature from 27 °C in 2010 to 32 °C in 2100.

e. Local monthly wind speed is estimated to increase slightly by about 0.2 knots from 5 knots in 2010 to 5.2 knots in 2100 with possible maximum wind speed of up to 5.8 knots.

2. One of the most well-known models in Indonesia to simulate surface water, the Non Recorded Catchment Area (NRECA) model was successfully modified to take climate change effects into account. The input modified NRECA model was consistent against the change of model assumptions such as the changes of GCMs, RCMs, emission scenarios, and the method of residual generation to simulate the monthly local rainfall-runoff process.

   From the modified NRECA model, it was found based on the estimated changes of the various climatic variables as described in 1.a to 1.e that the predicted increase in the average of monthly runoff is from approximately 2 m^3/sec in 2010 to 5 m^3/sec in 2100.

3. A new water index criterion named RWI was developed to provide a more accurate assessment of water balance of a water resource system. This new water index criterion was based on the ratio between the remaining water and the reserved water based on minimum water services. This new approach was found to be more logical

and effective for assessing the water balance than the currently used index as it considers more parameters and priorities of water usage.

4. A new water balance optimization model using RSM based on CCD was successfully developed in this research to obtain the best combination of water uses in the Jangkok River Basin to sustain the future of water resource system.

From the water balance optimization analysis in this research, it was found that:

   a. Population growth rate will start out as an insignificant factor in the water balance status during the beginning period (2011 ~ 2020) but will become a significant factor during the latter period (2021 – 2100). It is thus critical to limit population growth during this period.
   b. Agricultural farm development, other the other hand, will start off as a significant factor in the water balance status during the beginning period (2011 ~ 2020) but will become a less significant factor during the latter period (2021 – 2100). This is because during this period, there is more rainfall and less loss, leading to less water requirement for agricultural needs.

8.2. Recommendations for Future Works

1. Based on the availability of observed local data (1971 to 2010) in this research, CGCM2 from CCCma-Canada that provides GCM simulations from 1900 to 2100 was used in this research. This allowed 20 years (1971 to 1990) of GCM outputs to be used

in the calibration process and other 20 years (1991 to 2010) of GCM outputs to be used for model validation. This research cannot utilize the newer GCMs as the newer GCMs only provide GCM simulations from 2000 to 2100 thus giving only 5 years of GCM outputs for calibration and other 5 years of GCM outputs for validation. Therefore it is recommended that when local observed data are enough to provide at least 15 years of data for calibration and other 15 years data for validation, the newer GCMs that have finer resolutions should be used;

2. It is recommended that the study carried out herein be periodically updated as GCM data available as GCM agencies are constantly being reviewed and updated to accommodate new methods and information;

3. This research has utilized GCM simulations from three agencies: the Commonwealth Scientific and Industrial Research Organization (CSIRO-Australia), the National Institute for Environmental Studies (NIES-Japan), and the Canadian Centre for Climate Modelling and Analysis (CCCma-Canada); it is recommended that GCM data from other agencies around the world be also utilized to provide more variability and additional information;

4. This research did not investigate some existing downscaling climate change models, such as the Statistical Downscaling Model (SDSM) by Wilby et al. (2002), Ozclim by CSIRO (2007), the Long Ashton Research Station Weather Generator (LARS-WG) by Semenov and Barrow (1997), or MAGICC/SCENGEN by Wigley (2008) as these

models are based on daily data. The available local data used in this research are monthly data; therefore, it is recommended that these models be investigated if daily data are available in future;

5. In this research, only the inputs to the NRECA model was modified to take climate change into account so that it is able to simulate runoff in the future under climate change scenarios; it is recommended to modify the other commonly used runoff model in Indonesia which is the Mock model to take climate change effects into account so that their results can be compared to those of the NRECA model;

6. This research only investigated the change of local climate elements such as air humidity, rainfall, sunshine duration, air temperature, and wind speed, on their effects on potential evapotranspiration, and runoff. However, the impacts of climate change on local water quality, on agricultural and livestock productions, on human health, on local economic growth, as well as on social and political issues were not considered. Therefore, it is recommended that to gain a fuller picture of climate change impacts in the region the above issues would need to be investigated with associated adaptation and mitigation measures.

References

Allen, R.G., L.S. Pereira, D. Raes, M. Smith, 1998: Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements. FAO Irrigation and drainage paper 56. Rome, Italy. Food and Agriculture Organization of the United Nations. ISBN 92-5-104219-5.

Anonymous 1, 2008: Livestock Data. Dept. of Animal, the Province of NTB.

Anonymous 2, 1990: Clean Water and Rural Residency Sanitation. Dept. of Public Works, Directorate General of Housing, Building, Planning and Urban Development (*Air bersih dan penyehatan lingkungan permukiman perdesaan. Departemen Pekerjaan Umum, Direktorat Jenderal Cipta Karya*). The Government of the Republic of Indonesia.

Anonymous 3, 2008: Central Bureau of Statistics and Demography, the Province of NTB.

Anonymous 4, 2007: Data. Meteorological and Geophysical Agency.

Anonymous 5, 1990: The Guideline for Animal Farms Development in Indonesia, (*Petunjuk Pelaksanaan Pengembangan Peternakan Di Indonesia*). Dinas Peternakan. The Government of Republic of Indonesia.

Anonymous 6, 2002: Data and Information of Forestry, The Province of NTB (*Data dan Informasi Kehutanan Propinsi NTB*). Department of Forestry, NTB.

Anonymous 7, 1986: Irrigation Design Standard. Design Criteria of Irrigation Network. Directorate General of Irrigation. Department of Public Works. The Republic of Indonesia

(*Standard Perencanaan Irigasi. Kriteria Perencanaan Bagian Jaringan Irigasi (KP-01). Direktorat Jenderal Pengairan. Departemen Pekerjaan Umum. Republik Indonesia*).

Anonymous 8, 2004: The Regulations of the Republic of Indonesia No. 7, Year: 2004 on Water Resources (*Undang-Undang Republik Indonesia Nomor 7 Tahun 2004 Tentang Sumber Daya Air*). The Government of the Republic of Indonesia.

Anonymous 9, 2008: Data. Dept. of Agriculture, the Province of NTB.

Anuforom, A. C., 2009: Climate Change Impacts in Different Agro-ecological Zones of West Africa – Humid Zone, Paper presented at the International Workshop on Adaptation to Climate Change in West African Agriculture at Ouagadougou, Burkina Faso from 27 – 30 April 2009.

Alpaydın, E., 2010: Introduction to machine learning (2nd edition). Cambridge, Mass.: MIT Press. ISBN 978-0-262-01243-0.

Arnell, N., E. Tompkins, N. Adger, and K. Delaney, 2005: Vulnerability to abrupt climate change in Europe. Technical Report, Tyndall Center for Climate Change Research. Report to ESRC Environment and Human Behaviour Programme Project RES-221-25-0011.

Balai Hidrologi, -: Peta Daerah Aliran Sungai (*Watershed Map*). DAS Jangkok (*Jangkok River Basin*). Dinas KIMPRASWIL. NTB.

Bates, B.C., 2009: Climate Activities in Australia. Seminar Proceeding in the CSIRO Climate Adaptation Flagship. Australia.

Beven, K.J., 2008: Rainfall-Runoff Modelling: The Primer. John Wiley & Sons, Ltd.

Binder, C., R. Schertenleib, J. Diaz, H.P. Bader, and P. Baccini, 1997: Regional Water Balance as a Tool for Water Management in Developing Countries. International Journal of Water Resources Development, Volume 13, Issue 1 March 1997, pages 5 – 20.

Black, R., 2008: Fast fall of Mediterranean sharks, Journal of Climate Change. UK.

Brinkman, R. and W.G. Sombroek, 1996: Global climate change and agricultural production. Direct and indirect effects of changing hydrological, pedological and plant physiological processes. John Wiley and Sons Ltd, West Sussex, England.

Cannon, A.J., 2006: A Hybrid Neural Network/Analog Model for Climate Downscaling. International Joint Conference on Neural Networks. Vancouver, BC, Canada.

Caya, D. and R. Laprise, 1999: A Semi-Implicit Semi-Lagrangian Regional Climate Model: The Canadian RCM. Mon. Wea. Rev., 127, 341-362.

CCCSN, 2011. Introduction to Climate Change Concepts. Environment Canada.

Chen, J., F. P. Brissette, and R. Leconte, 2011: Uncertainty of Downscaling Method in Quantifying the Impact of Climate Change on Hydrology. Journal of Hydrology 401 (2011) 190-202. Elsevier.

CIA, 2011: GDP-Real Rate %. World Factbook. https://www.cia.gov/library/publications/theworld-factbook/ . http://www.indexmundi.com/g/g.aspx?v=66&c=bx&l=en

Clarke, D., 2009: Greenhouse/Climate Change and Australia, Geocities journals.

Combalicer, E.A., R.V.O. Cruz, S. Lee, and S. Im, 2010: Assessing climate change impacts on water balance in the Mount Makiling forest, Philippines. Journal of Earth System Science. 2010.

CSIRO, 2007: Welcoming to OZCLIM. Exploring climate change scenarios for Australia. CSIRO website: http://www.csiro.au/ozclim/home.do

Department of Forestry, 2009: Rehabilitation of Lands and Forests. Government of Indonesia.

Devore, J.L., 1995: Probability and Statistics for Engineering and the Sciences. Duxbury Press. USA.

Dingman, S. L., 2002: Physical Hydrology. ISBN: 0-13-099695-5. Prentice Hall. USA.

Dodd, G., 2008: Reptiles, amphibians flea uphill from Gobal Warming, BioOne Online Journal.

Environment Canada, 2005: The Canadian Centre for Climate Modelling and Analysis. University of Victoria. British Columbia. Canada.

Environment Canada, 2012: Climate Modelling and Analysis. http://www.ec.gc.ca/ccmac-cccma/default.asp?lang=En.

Gleick, P. H., 1997: Journal Of The American Water Works Association: Water Planning and Management under Climate Change.

Gamkrelidze, R.V., 2011: Encyclopaedia of Mathematical Sciences. Springer. ISSN: 0938-0396

Goyal, M.K. and C.S.P. Ojha, 2011: Evaluation of Linear Regression Methods as Downscaling Tools in Temperature Projections Over the Pichola Lake Basin in India. Reasearch Article. Hydrological Process. Vol 25 Issue 9. OI: 10.1002/hyp.7911

Gupta, H. V. and H. Kling, 2011: On typical range, sensitivity, and normalization of Mean Squared Error and Nash-Sutcliffe Efficiency type metrics, *Water Resour. Res.*, 47, W10601, doi: 10.1029/2011WR010962.

Gutierrez, D., 2008: 400 Medicinal Plants on Verge of Extinction Warn Researchers. Article. http://www.naturalnews.com/023402.html.

Hancock, P. and B.J. Skinner, 2000: River Management. The Oxford Companion to the Earth. Scientific Article. http://www.encyclopedia.com/doc/1O112-rivermanagement.html

Hay, L.E. and M.P. Clark, 2003: Use of statistically and dynamically downscaled atmospheric model output for hydrologic simulations in three mountainous basins in the western United States. Journal of Hydrology 282:56-75.

Heimann, H. D. and M.J.C. Zemsch, 2011: Statistical-Dynamical Downscaling. Institut für Physik der Atmosphäre, DLR Oberpfaffenhofen, D-82234 Weßling, Germany.

Hilman, M., G.M. Hatta, D. Hilman, A. Gunawan, Y Suryani, S. Irwani, G. Setiawan, H. Von Luepke, T. Hertz, C. Panjiwibowo, K. Pasaribu, S.A. Suroso, T.W. Hadi, I. Sofian, H. Latief, O. Abdurahman, Halil, H. Julianto, E. Riawan, A. Muhammad, and L. Anggraini, 2010: A Synthesis Report: Risk and Adaptation Assessment to Climate Change in Lombok Island, West Nusa Tenggara Province. Ministry of Environment of the Republic of Indonesia.

Hryciuk, D., 1999: Endangered Species of Canada Stories, Edmonton Journal.

Huth, R., J. Kysely, and M. Dubrovsky, 2001: Time Structure of Observed, GCM-Simulated, Downscaled, and Stochastically Generated Daily Temperature Series. Journal of Climate, Vol. 14, 4047-4061. ISSN: 0894-8755. American Meteorological Society, Boston, MA

Inouye, B.D., 2005: The Importance of the Variance around the Mean Effect Size of Ecological Processes. Journal Ecology, 86(1), 2005, pp. 262–265. The Ecological Society of America.

IPCC, 1990: Climate Change 1990. The IPCC Scientific Assessment. The First Assessment Report (AR1). The World Meteorological Organization / the United Nations Environment Programme. ISBN: 0-521-40720-6.

IPCC, 1992: Climate Change 1992. The Suplementary Report to The PCC Scientific Assessment. The World Meteorological Organization / the United Nations Environment Programme. ISBN: 0-521-43829-2.

IPCC, 2001: Climate Change 2001: The Scientific Basis; Impacts, Adaptation, and Vulnerability; Mitigation; and Model Evaluation. The Third Assessment Report (TAR) of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, U.K. and New York, N.Y., U.S.A.

IPCC, 2007: Climate Change 2007: The Synthesis Report and The Physical Science Basis - Summary for Policymakers. IPCC Plenary XXVII. Valencia, Spain

IPCC – DDC, 2010: The IPCC – Data Distribution Centre. http://www.mad.zmaw.de/IPCC_DDC/html/SRES_AR4/index.html

IPCC-WGII, 2007: The Fourth Assessment Report (AR4). "Impacts, Adaptation and Vulnerability". Contribution of Working Group II to the Fourth Assessment Report of the IPCC.

IPCC-WGIII, 2000: IPCC Special Report. Emissions Scenarios. Summary for Policymakers. ISBN: 92-9169-113-5

IPCC-WGIII, 2012:IPCC Special Report. Renewable Energy Sources and Climate Change Mitigation. Cambridge University Press. ISBN 978-1-107-60710-1 Paperback.

Ji, X., 2004: Comparison of Methods for Sensitivity and Uncertainty Analysis of Signalized Intersections Analyzed with HCM. Department of Civil and Environmental Engineering University of Hawaii, Honolulu.

Johnston, P., and D. Santillo, 2005: The Canadian Seal Hunt: No Management and No Plan. Technical Note. Greenpeace International.

Karim, M., 2009: Perubahan Iklim Global Ancam Perikanan Kita (*The Global Climate Change Endanger Us*). http://www.p2sdkpkendari.com

Katzfey, J., J. McGregor, K. Nguyen, and M. Thatcher, 2010: Regional Climate Change Projection Development and Interpretation for Indonesia. The Centre for Australian Weather and Climate Research.

Kim, R.S., 2011: Standardized Regression Coefficients as Indices of Effects Sizes in Meta-analysis. Doctoral Thesis. The Graduate School. The Florida State University.

Koenig, K.A., 2008: An Evaluation of Statistical Downscaling Methods in Central Canada for Climate Change Impact Studies. Master Thesis. The University of Manitoba.

Kralisch, S., M. Fink, and C. Beckstein, 2005: Neural Network Based Sensitivity Analysis of Natural Resource Models. Friedrich-Schiller-University Jena, Germany.

Kriegel, H.P., P. Kröger, J. Sander, and A. Zimek, 2011: Density-based Clustering. WIREs Data Mining and Knowledge Discovery 1 (3): 231–240. doi:10.1002/widm.30.

Lapp, S. and E. Barrow, 2008: Scenarios of Future Hydroclimatic Variability from Global Climate Models (GCMs). Presentation for Prairie Adaptation Research Collaborative. Canada.

Legowo, S., I.K. Hadihardaya, and S. Rabuanawati, 2006: Pengoperasian dan Umur Guna Waduk_Studi Kasus: Waduk Cimeta Padalarang (Operation and Lifetime of Cimeta Dam). Jurnal Teknik Sipil. V_13N_04. ITB.

Longobardi, A., P. Villania, R.B. Graysonb, and A.W. Westernb, 2004: Online Journal:http://www.mssanz.org.au/MODSIM03/Volume_02/A17/04_Longobardi.pdf

Lopes, P., 2009: Assessment of statistical downscaling methods - application and comparison of two statistical methods to a single site in Lisbon. IOP Conf. Series: Earth and Environmental Science 6.

Lye. L.M., 1996: Statistical Modelling. Memorial University.

Lye. L.M., 2008: Eng 9622: Environmental Statistics. Memorial University of Newfoundland.

Lye. L.M., 2009: Eng 9516: Similitude, Modelling, and Data Analysis. Memorial University of Newfoundland.

Mahmud, 2006: Skenario Perubahan Variabilitas Iklim Indonesia. Proceeding in The National Seminar of Climate and Environmental Change, Indonesia. ISBN : 978-979-17490-0-8.

Majkic, B., S. Prohaska, and D. Isailovic, 2008: Basic concept for water balance assessment in Serbia. BALWOIS 2008 – Ohrid, Republic of Macedonia,-27, 31 May 2008.

Majone, B., C. I. Bovolo, A. Bellin, S. Blenkinsop, and H. J. Fowler, 2012: Modeling the impacts of future climate change on water resources for the Gállego river basin (Spain), *Water Resour. Res.*, 48, W01512, doi:10.1029/2011WR010985.

McCuen, R. H., 1993: Microcomputer Applications in Statistical Hydrology. Prentice Hall. New Jersey. ISBN: 0-13-585290-0.

McDaniels, T. and H. Dowlatabadi, 2008: How does downscaling work?. University of British Columbia. Canada.

McGuffie, K. and A. H. Sellers, 1997: A Climate Modelling Primer. Wiley: Chichester.

Mendelsohn, R., 2005: Climate Change Impacts on Southeast Asian Agriculture. Paper. Yale University.

Michael, A., 1991: Algebra. Prentice Hall, ISBN 978-0-89871-510-1.

Ministry of Environment the Republic of Indonesia, 2005: Peraturan Menteri Negara LH Republik Indonesia No. 308 Tahun 2005. Kerangka Acuan Analisis Dampak Lingkungan Hidup Pembangunan Waduk. (*The Recomendation from the Ministry of Environmental, the Republic of Indonesia No. 308, 2005: a Reference for Environmental Assessments in Dam Constructions*) http://know. brr.go.id/dc/manuals/20070100_KA_ANDAL_Cover _Waduk_Idi.pdf

Motulsky, H. and A. Christopoulos, , 2004: Fitting Models to Biological Data using Linear and Nonlinear Regression. Oxford University Press, Oxford.

Mukhtasor, 2001: Hydrodynamic Modeling And Ecological Risk-Based Design Of Produced Water Discharge From An Offshore Platform. PhD Thesis. Memorial University of Newfoundland.

Myers, R. H. and D.C. Montgomery, 1995: "Response Surface Methodology: Process and Product Optimisation Using Designed Experiments", John Wiley & Sons, INC.

Nash, J. E. and J.V. Sutcliffe, 1970: River flow forecasting through conceptual models part I - A discussion of principles. Journal of Hydrology. 10 (3), 282–290.

National Research Council, 2001: Climate Change Science: An Analysis of Some Keys Questions. National Academy Press. Washington, D.C.

Oakley, J. and A. O'Hagan, 2004: Probabilistic sensitivity analysis of complex models: a Bayesian approach. *J. Royal Stat. Soc. B* **66, 751–769.**

Olsson, J., U. Willen, A. Kawamura, 2012: Downscaling Extreme Short-Term Regional Climate Model Precipitation for Urban Hydrological Applications. Hydrology Research. An International Journal. IWA Publishing. ISSN: 0029-1277.

Pacelli, V., V. Belilacqua, and M. Azzollini, 2011: An Artificial Neural Network Model to Forecast Exchange Rates. Journal of Intelligent Learning Systems and Applications. DOI: 10.4236/jilsa.2011.32008.

Padmanabhan, A., 2010: Increasing Global Access to Medicines through Technology. E-Articles for WHO. WordPress & Green Park 2. http://endtheneglect.org/2010/11/increasing-global-access-to-medicines-through-technology/

Palmer, W.C., 1965: Meteorological Drought. Research Paper no. 45. Weather Bureau. US. Department of Commerce. Washington D.C.

Pfizenmayer, A. and H. Von Storch, 2001: Anthropogenic climate change shown by local wave conditions in the North Sea. pfizenmayer http://coast.gkss.de/staff/storch/pdf/pfizenmayer.pdf.

Prak, J.L., 2011: An Empirical Research on the Reliability of Correlation Coefficients. British Journal of Psychology, Vol. 21, Issue 4. DOI: 10.1111/j.2044-8295.1931.tb00602 .x

Preston, B.L. and R.N. Jones, 2006: Climate Change Impacts on Australia and the Benefits of Early Action to Reduce Global Greenhouse Gas Emissions. The Report of CSIRO Marine and Atmospheric Research, PMB No 1, Aspendale, Victoria, 3195, Australia.

Press, W.H., S.A. Teukolsky, W.T. Vetterling, and B.P. Flannery, 2002: Numerical Recipe in C++. The Art of Scientific Computing, Second Edition. Cambridge Univessity Press. UK.

Prudhomme,C., N. Reynard, and S. Crooks, 2002: Downscaling of global climate models for flood frequency analysis: where are we now? HYDROLOGICAL PROCESSES. 16, 1137–1150. Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/hyp.1054.

Pryor, S. C., 2009: Understanding Climate Change: Climate Variability, Predictability, and Change in the Midwestern United States. Bloomington : Indiana University Press.

PT. Tataguna Patria Jaya, 2004: *Laporan Akhir Proyek Studi Pengembangan Daerah Irigasi Sub SWS DAS Putih dan DAS Menanga. Indonesia.* (The Final Project Report of Irrigation Development Study for Sub Basin Putih and Menanga. Indonesia).

Quaile, I., 2009: More natural disasters due to climate change? Electronic Media. News. http://www.dw-world.de/dw/article/0,,4598063,00.html

Renton, A., 2008: How the world's oceans are running out of fish. Guardian. UK.

Rumelhart, E. David, Hinton, E. Geoffrey, Williams, J. Ronald, 1986: Learning representations by back-propagating errors. *Nature* **323** (6088): 533–536.

Sahan, R.T., 2006: Studi Potensi Dan Pemanfaatan Sungai Oba Halmahera Untuk Menunjang Kota Sofifi Sebagai Ibukota Propinsi Maluku Utara. Master Theses from JBPTITBPP. ITB Central Library.

Salas, J.D., J.W. Delleur, V. Yevjevich, and W.L. Lane, 1985: Applied Modeling Of Hydrologic Time Series. Water Resources Publications. Colorado. USA.

Sari, I.P., 2002: Indonesia Harus Waspada, Dampak Perubahan Iklim Sudah di Depan Mata (*Indonesia must be attentive; the climate change impacts have been ahead*).

Schnur, R. and D.P. Lettenmaier, 1998: A case study of statistical downscaling in Australia using weather classification by recursive partitioning. Journal of Hydrology 212-213 (1998) 362-379. Elsevier.

Schuol, J. and K.C. Abbaspour, 2007: Using monthly weather statistics to generate daily data in a SWAT model application to West Africa. Ecological Modelling 2 0 1 (2 0 0 7) 301–311. Elsevier. journal homepage: www.elsevier.com/locate/ecolmodel.

Scibek, J., D.M. Allen, and P.H. Whitfield, 2008: Quantifying the impacts of climate change on groundwater in an unconfined aquifer that is strongly influenced by surface water.

Geological Society, London, Special Publications; 2008; v. 288; p. 79-98; DOI: 10.1144/SP288.7

Setiawan, E., H. Sulistiyono, M.B. Budianto, and Amirullah, 2005: Efek Pemberian Nilai Awal Parameter Model NRECA Terhadap Konsistensi Hasil Kalibrasi dan Verifikasi (*The Effect of Initial Assessment of NRECA Model Parameters to the Consistency of Calibration and Verification Result*). Jurnal Teknik: Rekayasa. Vol. 6. No. 1. ISSN: 1411-5565.

Semenov, M.A, E.M. Barrow, 1997: Use of a stochastic weather generator in the development of climate change scenarios. Climate Change 35(4):397–414.

Simonovic, S.P., 2009: Managing Water Resources: Methods And Tools For A Systems Approach. Department of Civil and Environmental Engineering, the University of Western Ontario, London, ON, Canada N6A 5B9.

Sinuraya, G., 1990: The role of family planning programs in population development and national resilience in Indonesia (*Peranan program keluarga berencana Pemerinatah Republik Indonesia terhadap kependudukan dalam ketahanan nasional Indonesia*). USU Press. Medan. Indonesia. ISBN 10: 9794580228.

SNI 03-1724-1989: Tata Cara Perencanaan Hidrologi Dan Hidraulik Untuk Bangunan Sungai (Indonesian National Standard: Procedures of Hydrology and Hydraulic Designs for River Structures).

Soewarno, 1995: Hidrologi: Aplikasi Metode Statistik untuk Analisa Data (*Hydrology: the application of statistic methods for Data Analysis*). Nova. Bandung.

Sorooshian, S. and V. K. Gupta (edited by V. P. Sigh), 1995: Model Calibration: Computer Models of Watershed Hydrology, Water Resources Publications, Colorado, USA.

Spencer, R.W., 2008: Climate Confusion; How Global Warming Hysteria leads to Bad Science, Pandering Politicians, and Misguided Policies That Hurt the Poor. Encounter Books, New York.

Stergiou, C. and D. Siganos, 1996: Neural Networks. Electronic Report. http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html

Sulistiyono, H. 1999: Rainfall-Runoff Model Calibration Using Experimental Designs And Response Surface Methodology. Master Thesis. The Memorial University of Newfoundland. Canada.

Sulistiyono, H. and L.M. Lye, 2010: A Spreadsheet Based Water Balance Model for the Reak River Basin, Lombok, Indonesia. CSCE Conference. Winnipeg, June 2010.

Sulistiyono, H. and L.M. Lye, 2011: Predicted Regional Hydrologic and Climatic Variables under Climate Change Scenarios using Statistical Downscaling Techniques for Future Water Resource Studies in Lombok, Indonesia. Proceedings of the 64th CWRA Conference. St. John's, June 2011.

Tallaksen, L.M. and H.A.J. Van Lanen, 2004: Developments in Water Science 48. Hydrological Drought: Processes and Estimation Methods for Streamflow and Groundwater. ELSEVIER. ISBN: 0-444-51688-3.

Timbal, B., E. Fernandeza, and Z. Li, 2009: Generalization of a statistical downscaling model to provide local climate change projentions for Australia. Journal Environmental Modelling & Software. www. elsevier.com/locate/envsoft.

UN Population Division, 2008: World Population Prospects. http://www.un.org/esa/population/publications/wpp2008/wpp2008_highlights.pdf

US. EPA, 2010: Climate Change. http://www.epa.gov/climatechange/

Van De Goor, G. A. W. and G. Zijlstra, 1982: Irrigation Requjrements For Double Cropping Of Lowland Rice In Malaya. International Institute for Land Reclamation and Improvement ILRt, Wageningen. The Netherlands.

Van Nguyen, V.T., 2005: Downscaling Methods for Evaluating The Impacts Of Climate Change and Variability on Hydrological Regime At Basin Scale. McGill University. Department of Civil Engineering and Applied Mechanics. Montreal, Quebec, Canada.

Viessman, W. Jr., 2003: Introduction to Hydrology, Fifth Edition. ISBN: 0-67-399337-X. Prentice Hall. NJ 07458.

Von Storch, H., H. Langenberg and F. Feser, 2000: A spectral nudging technique for dynamical downscaling purposes. Mon. Wea. Rev. 128: 3664-3673.

Walsh, J., 2011: Statistical Downscaling. NOAA Climate Services Meeting, March 2011.

Weart, S., 2009: General Circulation Models of Climates.

Weil, D. N., 2008: Economic Growth 2nd edition. Addison Wesley. USA.

Wigley, T.M.L., 2008: MAGICC/SCENGEN 5.3 (version 2). National Center for Atmospheric Research, Boulder, CO 80307

Wilby, R.L., C.W. Dawson, and E.M. Barrow, 2002: SDSM - a decision support tool for the assessment of regional climate change impacts, Environmental Modelling & Software, 17, 147– 159.

Wilby, R.L., Charles, S.P., Zorita, E., Timbal, B., Whetton, P., Mearns, L.O., 2004: Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods. Supporting Material of the IPCC. http://www.ipcc-data.org/guidelines/dgm_no2 v1_09_2004.pdf.

Wilhite, D.A. and M.D. Svoboda, 2000: Drought Early Warning Systems in the Context of Drought Preparedness and Mitigation. Paper published on the Expert Group Meeting on Early Warning Systems for Drought Preparedness and Drought Management, Nebraska, USA.

Xu, C.Y. and V.P. Singh, 1998: "A Review on Monthly Water Balance Models for Water Resources Investigations". *Water Resources Management* **12** (1): 31–50.

Yazid, R., 2010: Perhitungan Potensi Debit Aliran Rendah (*the Calculation of Potential lowflow discharge*).

Ylvisaker, A., 2003: Natural Disasters: Droughts. Capstone Press. Minnesota. ISBN:0-7368-1505-8

Young, E., 2002: Climate change threatens polar bears. http://www.newscientist.com/article /dn2285-climate-change-threatens-polar-bears.html.

Zorita E.E and H. Von Storch, 1999: The Analog method as a simple statistical downscaling technique: comparison with more complicated methods. J. of Climate, 12, 2474–2489.

Appendix A:

Letter of Support from the Government of NTB Province

PEMERINTAH PROVINSI NUSA TENGGARA BARAT

BADAN LINGKUNGAN HIDUP DAN PENELITIAN

(B L H P)

Jalan Majapahit Nomor 56, Telepon (0370) 621784, 628647, fax. 644782

REKOMENDASI

No. 050.7/321/III/BLHP/2010

Sehubungan dengan rencana research untuk penyelesaian program Doktor (S3) yang akan dilakukan oleh :

Nama	: Ir. Heri Sulistiyono, M.Eng.
Pekerjaan	: Dosen Fakultas Teknik Universitas Mataram
Topik/Judul Penelitian	: Pengaruh Perubahan Iklim Global terhadap Sumberdaya Air di Pulau Lombok : Memodelkan Iklim Regional Lombok (*The Effects of Global Climate Change on Water Resources in Lombok Island : Lombok Regional Climate Modeling)*.

Kami sampaikan bahwa topik/judul penelitian tersebut yang terkait dengan *Global Climate Change* adalah sangat relevan dan dibutuhkan bagi daerah, khususnya Pulau Lombok, mengingat Pulau lombok dengan sejumlah pulau-pulau kecil di sekelilingnya rentan terhadap dampak perubahan iklim global.

Demikian rekomendasi ini dibuat untuk mendapat perhatian dan dipergunakan sesuai keperluan.

Mataram, 2 Maret 2010

Kepala BLHP
Provinsi Nusa Tenggara Barat

PEMERINTAH PROVINSI NUSA TENGGARA BARAT
BADAN LINGKUNGAN HIDUP DAN PENELITIAN

for Ir. Tadjuddin Erfandy,M.Sc
NIP. 19581129 198402 1 001

Translation:

RECOMMENDATIONS

No: 050.7/321/III/BLHP/2010

Regarding to the research for the completion of the doctoral program that will be conducted by:

Name : Ir. Heri Sulistiyono, M. Eng.

Occupation : Lecturer at the Faculty of Engineering, University of Mataram

Topic / Title of research : Effect of Global Climate Change on Water Resources in Lombok Island

We consider that the topic / title of research that relates to Global Climate Change is very relevant and necessary for the region, particularly the island of Lombok, given the island of Lombok with a number of small islands around it vulnerable to the impacts of global climate change.

The recommendation is made to get attention and be used as necessary.

Mataram, March 2nd, 2010
The Chief of Environmental and Research Agency
The Province of NTB

Ir. Tadjuddin Erfandy, M.Sc.
NIP. 19581129 198402 1 001

Appendix B:

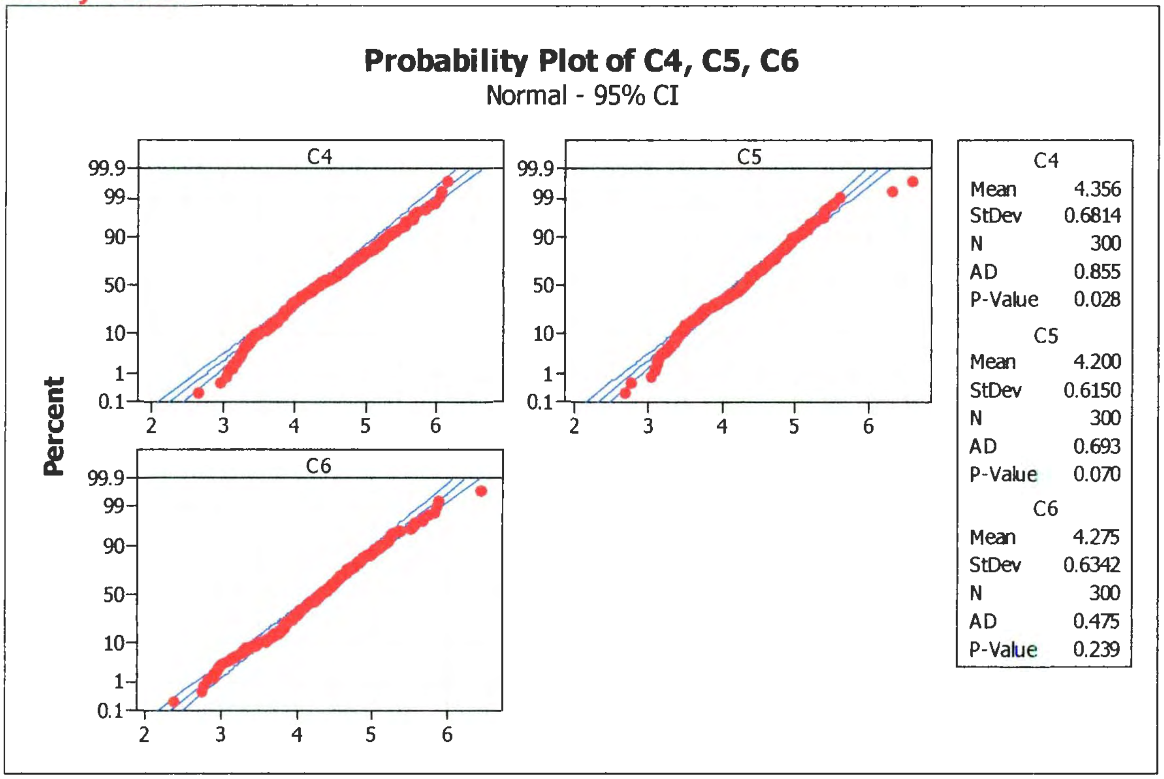
The Analysis of Mean and Variance of GCM Variables

EVAPORATION:

Descriptive Statistics: C4, C5, C6

Variable	Mean	StDev	CoefVar	Median	Skewness	Kurtosis
C4	4.3560	0.6814	15.64	4.3055	0.22	-0.47
C5	4.1998	0.6150	14.64	4.2386	0.21	0.21
C6	4.2753	0.6342	14.83	4.2965	0.01	0.39

Normality Tests:



Explanation:

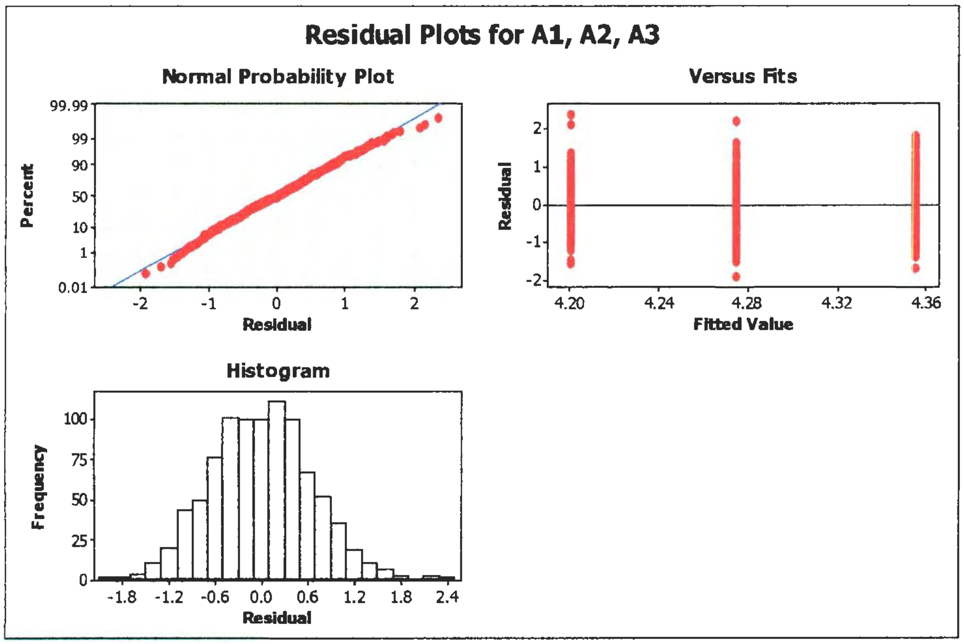
Evaporation data are spitted into three sets of time period data: A1 commences from 1971 to 1995, A2 commences from 2019 to 2043, and A3 commences from 2067 to 2091 and are put in three columns C4, C5, and C6; respectively. From a normality test, it is found that a set of data that commences from 1971 to 1995 does not follow a normal distribution as its P-value, 0.028 is smaller than 0.05.

Tests for Mean:

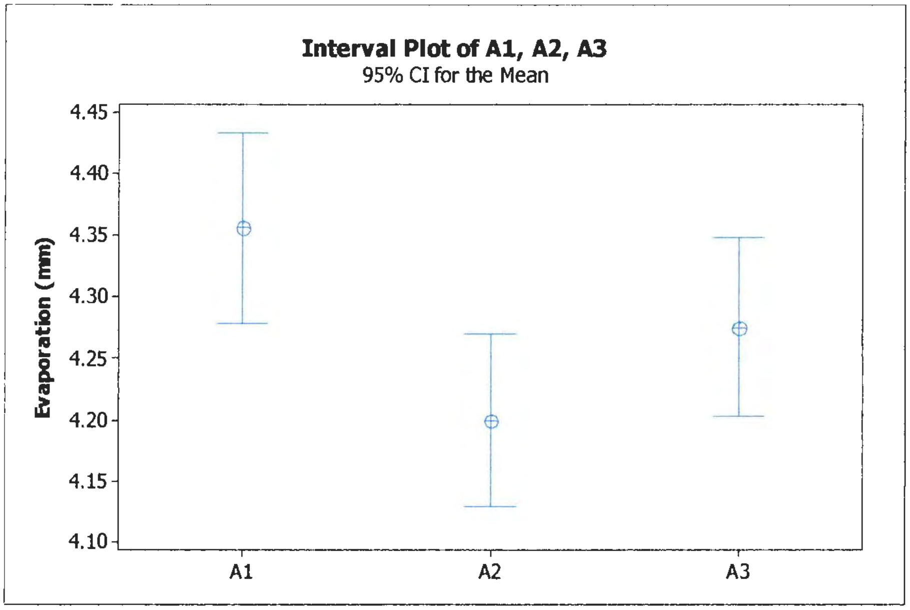
One-way ANOVA: A1, A2, A3

```
Source   DF       SS     MS     F      P
Factor    2    3.660  1.830  4.41  0.012
Error   897  372.200  0.415
Total   899  375.859

S = 0.6442   R-Sq = 0.97%   R-Sq(adj) = 0.75%


                                  Individual 95% CIs For Mean Based on
                                  Pooled StDev
Level    N    Mean   StDev   ----+---------+---------+---------+-----
A1     300  4.3560  0.6814                       (--------*---------)
A2     300  4.1998  0.6150   (--------*--------)
A3     300  4.2753  0.6342            (--------*---------)
                             ----+---------+---------+---------+-----
                               4.160     4.240     4.320     4.400

Pooled StDev = 0.6442
```

Explanation:
From ANOVA test, it is found that at least one of the three means differs from others as P-value of the test, 0.012 is smaller than 0.05.

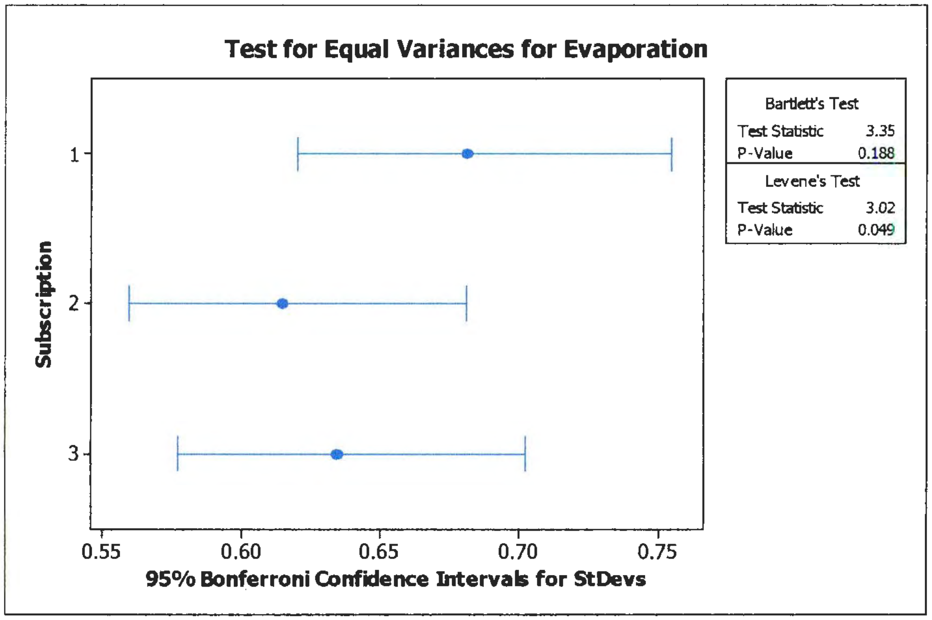


Explanation:
From residual plots, it is found that all assumptions of ANOVA: a normal distribution and a consistent variance of residuals are satisfied.

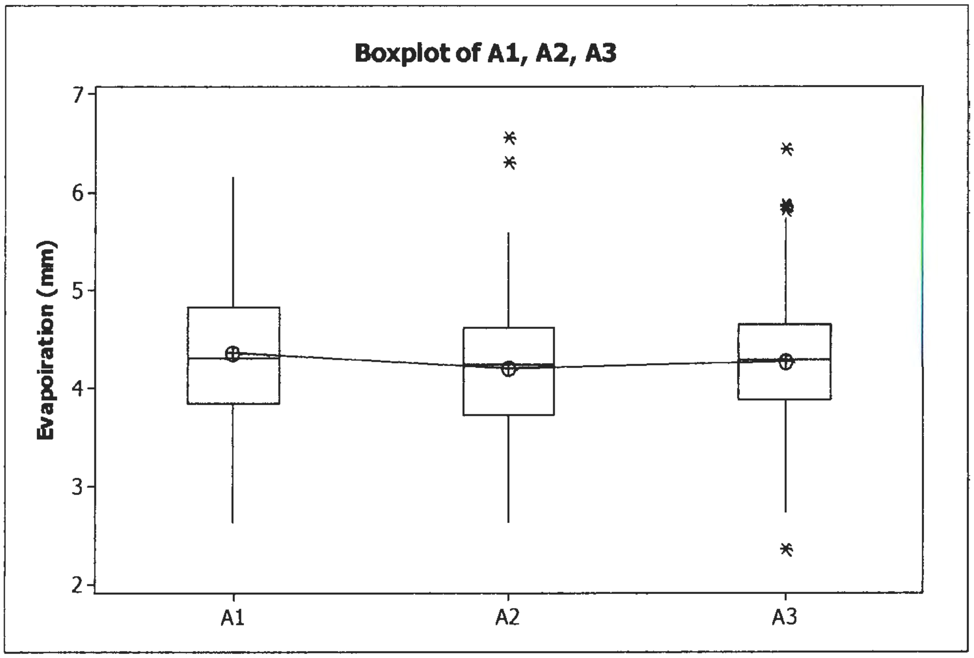


Explanation:
From interval plot, it is found that mean of A1 is not the same as mean of A2 as their intervals do not overlap. However, mean of A3 might be the same as mean of A1 or A2 as the interval of A3 overlaps with intervals of A1 and A2.

Tests for Variance:



Explanation:
From a Barlett's test which assumes that all sets of data follow normal distributions, it is found that all variances are equal as its P-value 0.188 is greater than 0.05. However according to a Levene's test which does not assumes data follow normal distributions, it is found that at least one of the three variances is different from others as its P-value 0.049 is smaller than 0.05.

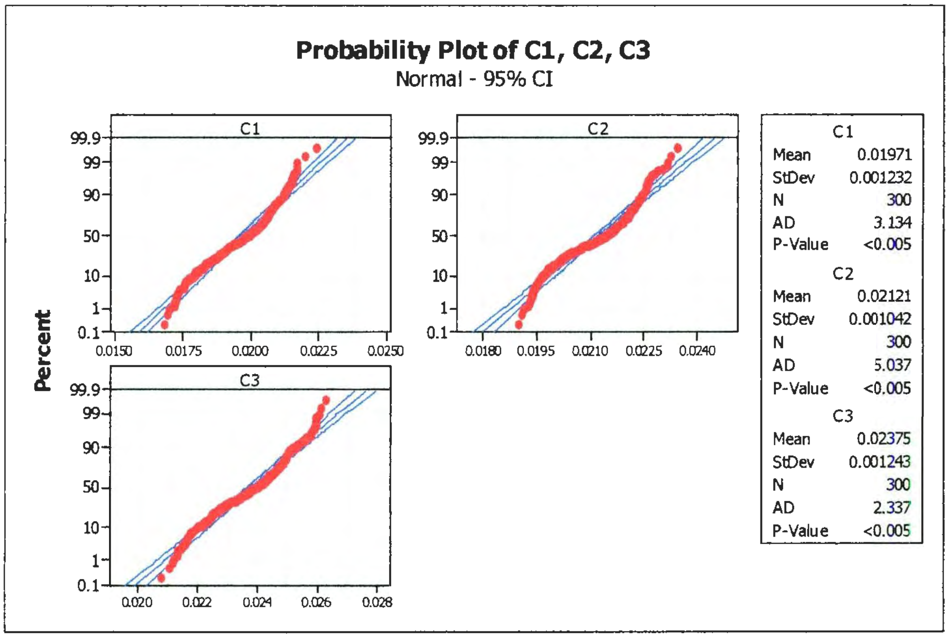


Explanation:
From a boxplot, it is found that the size of three boxes is not exactly the same; however, the difference is not larger than three times. This indicates that at least one of them might have a different variance.

Screen Specific Humidity:

Descriptive Statistics: C1, C2, C3

Variable	Mean	StDev	CoefVar	Median	Skewness	Kurtosis
C1	0.019709	0.001232	6.25	0.019934	-0.35	-0.80
C2	0.021210	0.001042	4.91	0.021425	-0.28	-1.07
C3	0.023755	0.001243	5.23	0.023905	-0.23	-0.84

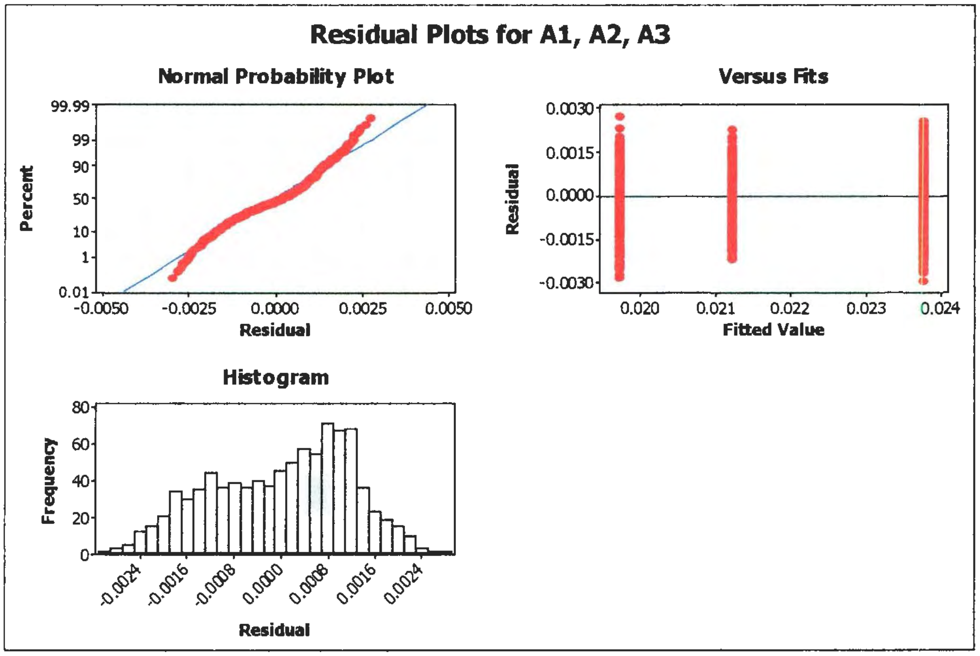


Explanation:
Evaporation data are spitted into three sets of time period data: A1 commences from 1971 to 1995, A2 commences from 2019 to 2043, and A3 commences from 2067 to 2091 and are put in three columns C1, C2, and C3; respectively. From a normality test, it is found that the three sets of data do not follow normal distributions as its P-values are smaller than 0.05.

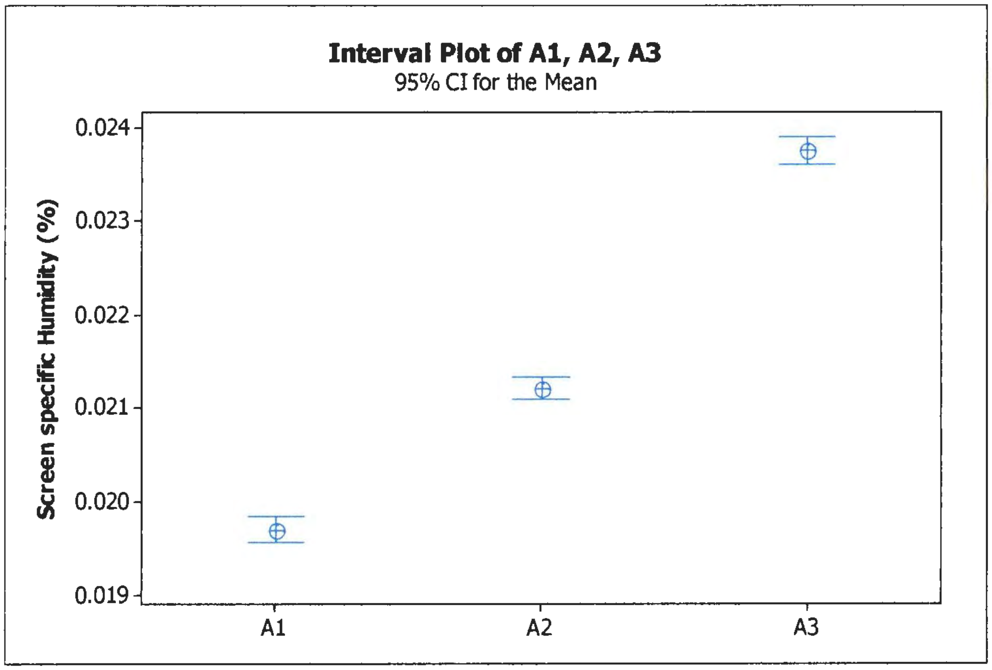
One-way ANOVA: A1, A2, A3

```
Source   DF         SS         MS       F      P
Factor    2  0.0025104  0.0012552  907.62  0.000
Error   897  0.0012405  0.0000014
Total   899  0.0037509

S = 0.001176   R-Sq = 66.93%   R-Sq(adj) = 66.85%


                                    Individual 95% CIs For Mean Based on
                                    Pooled StDev
Level    N      Mean     StDev   -------+---------+---------+---------+--
A1     300  0.019709  0.001232   (*)
A2     300  0.021210  0.001042               (*)
A3     300  0.023755  0.001243                                   (*)
                                 -------+---------+---------+---------+--
                                     0.0204    0.0216    0.0228    0.0240

Pooled StDev = 0.001176
```

Explanation:
From ANOVA test, it is found that at least one of the three means differs from others as P-value of the test is smaller than 0.05.

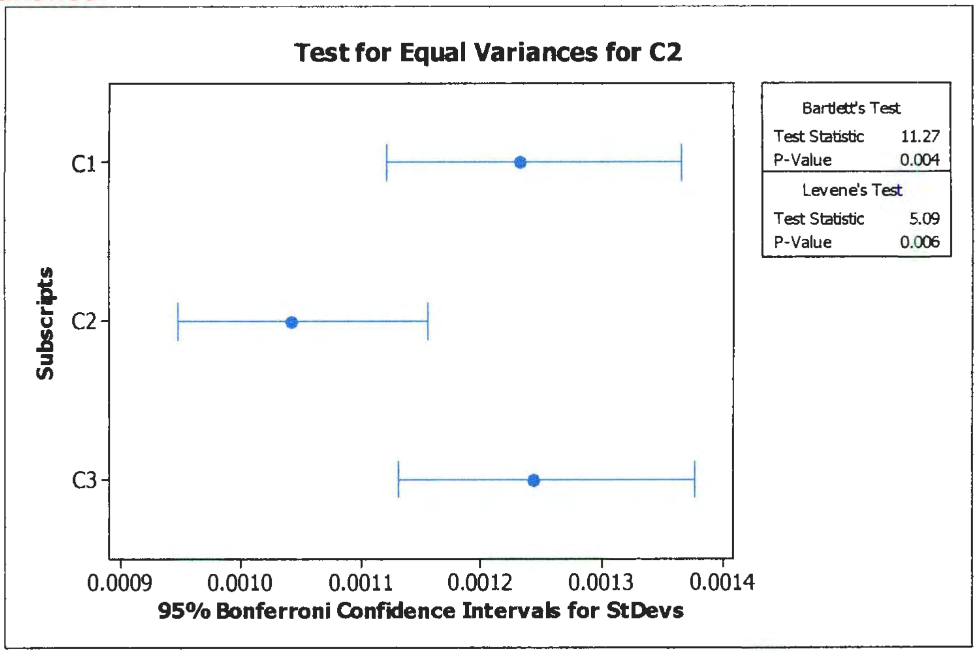


Explanation:
From residual plots, it is found that assumptions of ANOVA: a normal distribution and a consistent variance of residuals are not satisfied.

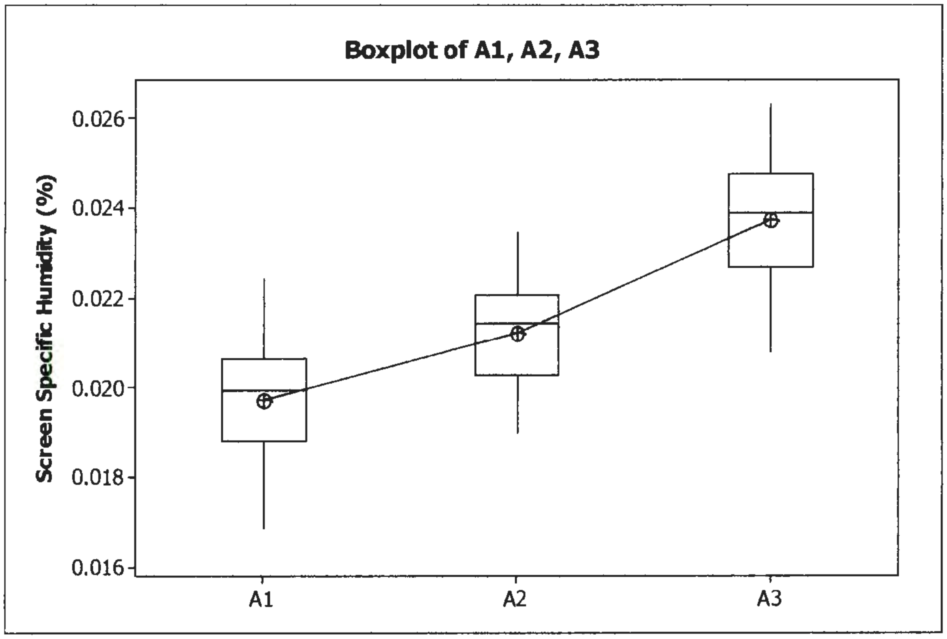


Explanation:
From interval plot, it is found that the three means are not the same as their intervals do not overlap each other.

Tests for Variance:



Explanation:
From both tests: Barlett's and Levene's tests, it is found that at least one of variances is not equal as its P-values are smaller than 0.05.



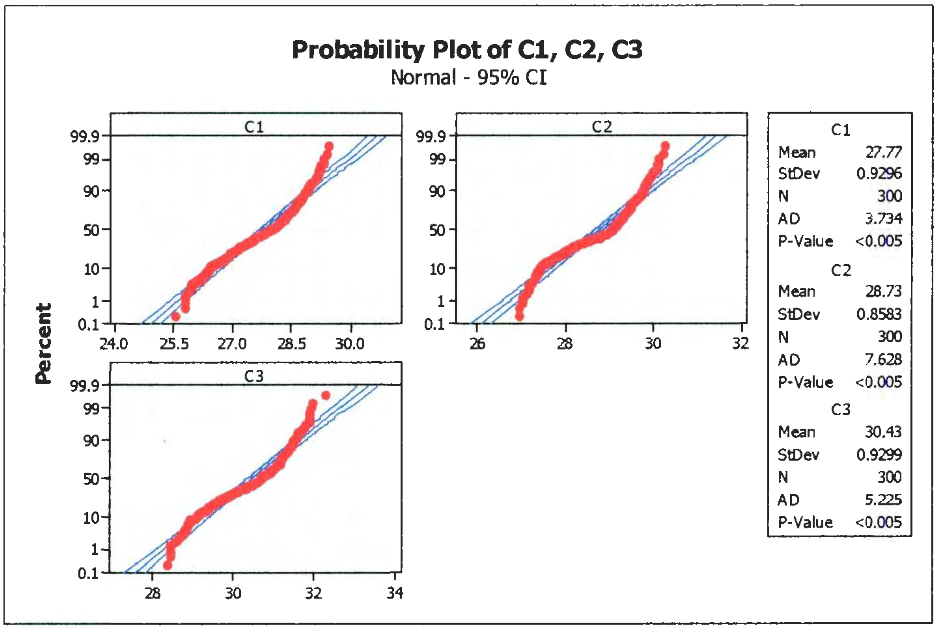
Explanation:

From a boxplot, it is found that the size of three boxes is not exactly the same; however, the difference is not larger than three times. Therefore, at least one of them might have a different variance.

Skin Surface Temperature:

Descriptive Statistics: C1, C2, C3

Variable	Mean	StDev	CoefVar	Median	Skewness	Kurtosis
C1	27.772	0.930	3.35	27.928	-0.40	-0.83
C2	28.734	0.858	2.99	29.024	-0.45	-1.04
C3	30.431	0.930	3.06	30.652	-0.43	-0.91



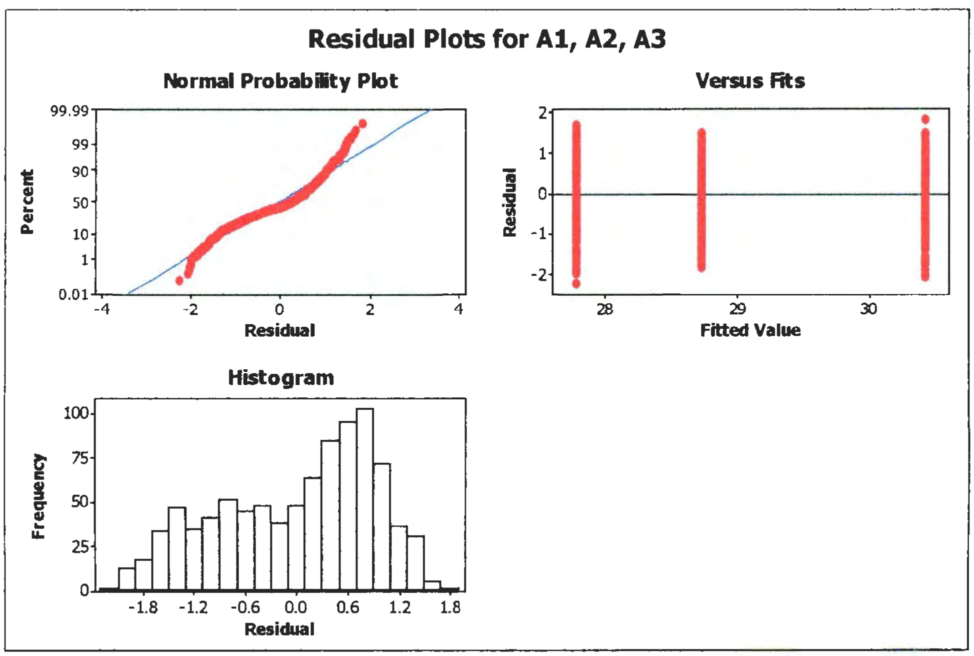
Explanation:

Evaporation data are spitted into three sets of time period data: A1 commences from 1971 to 1995, A2 commences from 2019 to 2043, and A3 commences from 2067 to 2091 and are put in three columns C1, C2, and C3; respectively. From a normality test, it is found that the three sets of data do not follow normal distributions as its P-values are smaller than 0.05.

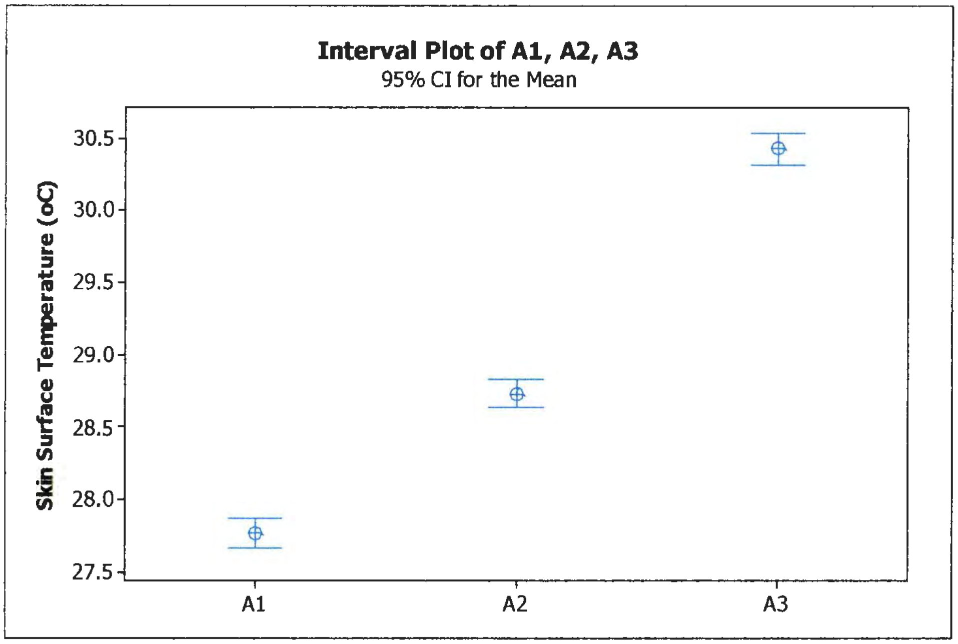
One-way ANOVA: A1, A2, A3

```
Source   DF        SS       MS       F      P
Factor    2  1087.770  543.885  661.80  0.000
Error   897   737.174    0.822
Total   899  1824.944

S = 0.9065   R-Sq = 59.61%   R-Sq(adj) = 59.52%


                             Individual 95% CIs For Mean Based on
                             Pooled StDev
Level    N    Mean  StDev    ----+---------+---------+---------+-----
A1     300  27.772  0.930    (*)
A2     300  28.734  0.858                (*)
A3     300  30.431  0.930                                    (*-)
                             ----+---------+---------+---------+-----
                              28.00     28.80     29.60     30.40

Pooled StDev = 0.907
```

Explanation:
From ANOVA test, it is found that at least one of the three means differs from others as P-value of the test is smaller than 0.05.

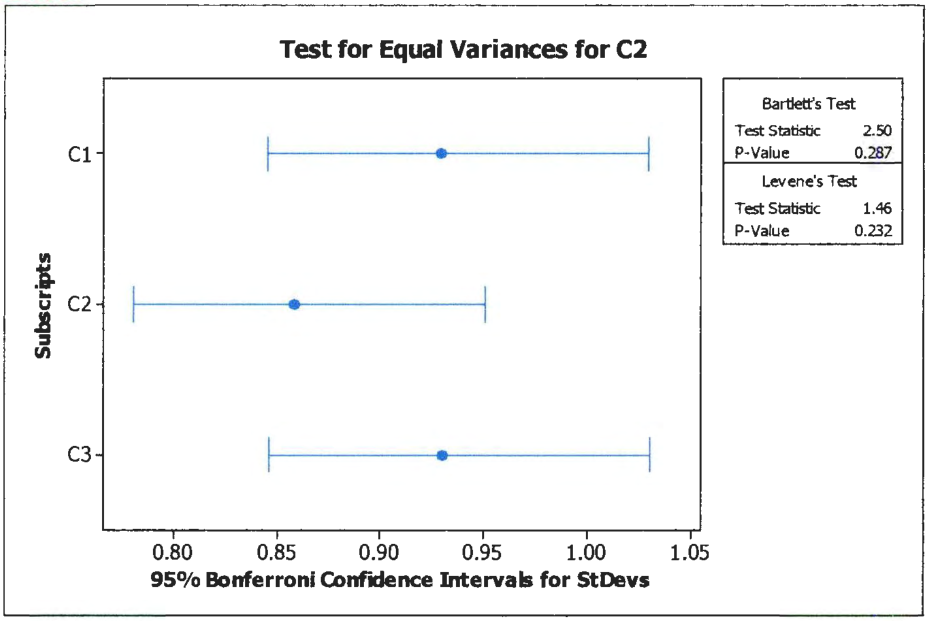


Explanation:
From residual plots, it is found that assumptions of ANOVA: a normal distribution and a consistent variance of residuals are not satisfied.

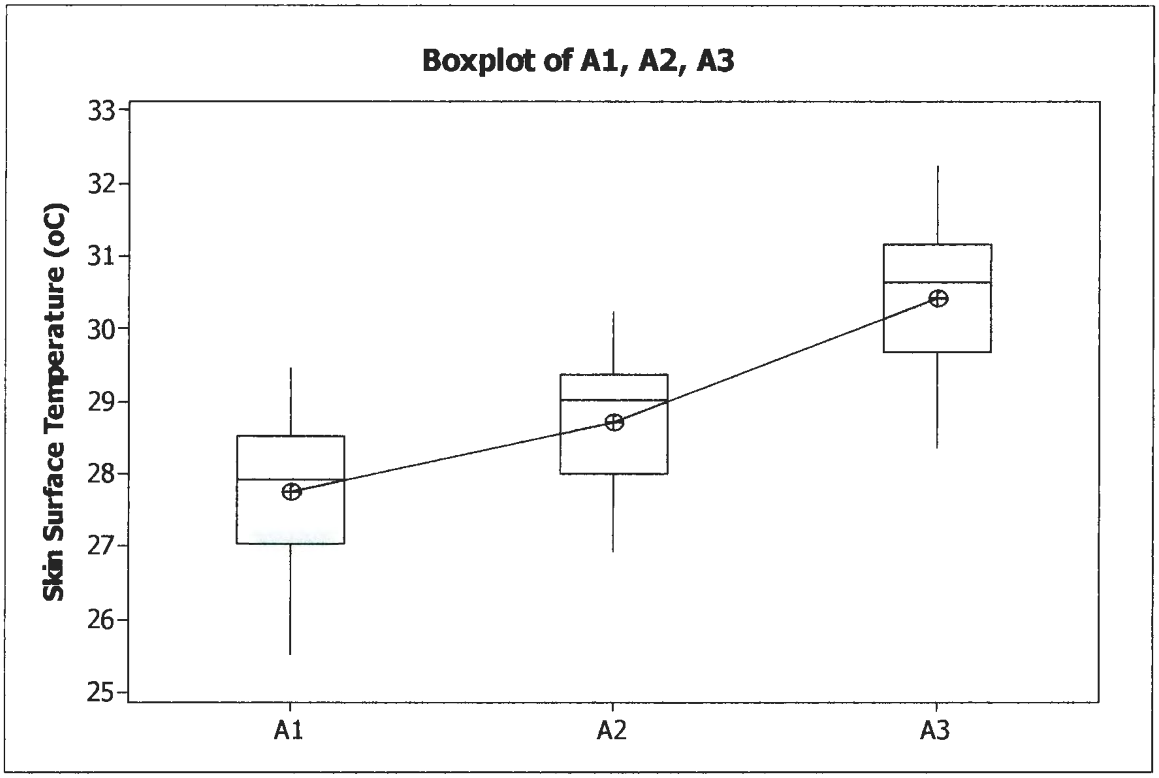


Explanation:
From interval plot, it is found that the three means are not the same as their intervals do not overlap each other.

Tests for Variance:



Explanation:
From both tests: Barlett's and Levene's tests, it is found that all variances are equal as its P-values are greater than 0.05.

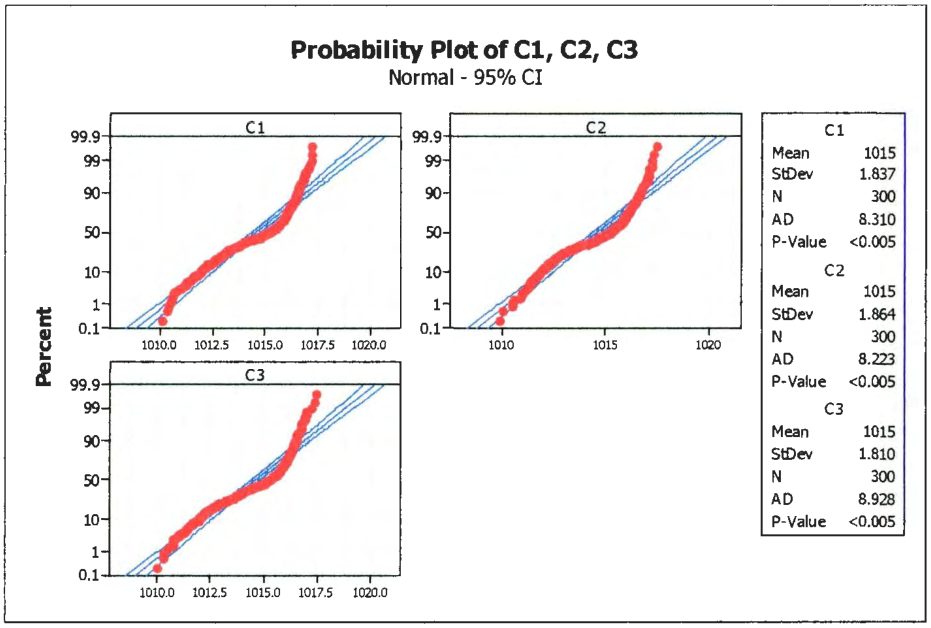


Explanation:
From a boxplot, it is found that the three boxes have the same size. This indicates that their variances are the same.

Surface Pressure:

Descriptive Statistics: C1, C2, C3

Variable	Mean	StDev	CoefVar	Median	Skewness	Kurtosis
C1	1014.5	1.84	0.18	1015.1	-0.55	-0.90
C2	1014.5	1.86	0.18	1015.2	-0.51	-0.97
C3	1014.6	1.81	0.18	1015.2	-0.64	-0.76

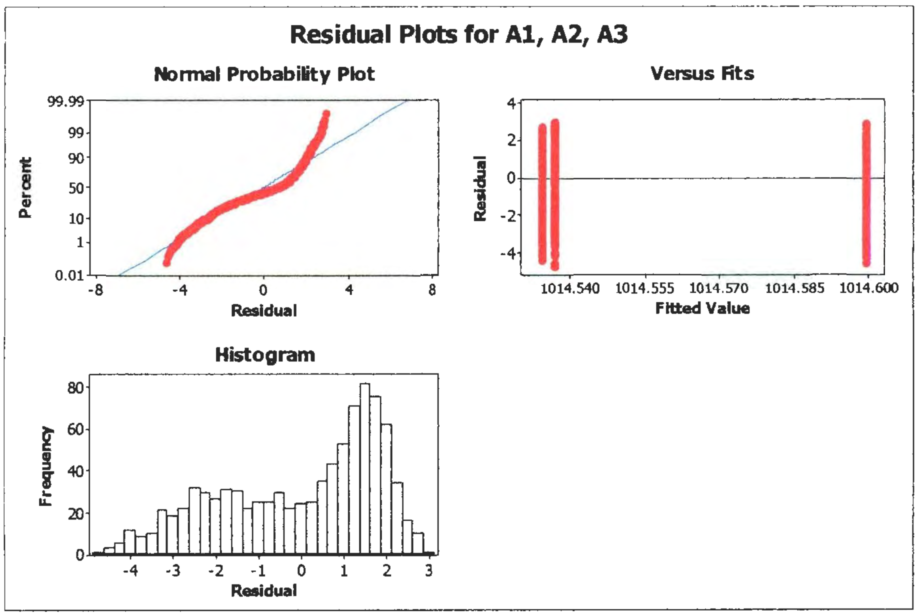


Explanation:
Evaporation data are spitted into three sets of time period data: A1 commences from 1971 to 1995, A2 commences from 2019 to 2043, and A3 commences from 2067 to 2091 and are put in three columns C1, C2, and C3; respectively. From a normality test, it is found that the three sets of data do not follow normal distributions as its P-values are smaller than 0.05.

One-way ANOVA: A1, A2, A3

```
Source   DF       SS    MS     F      P
Factor    2     0.82  0.41  0.12  0.886
Error   897  3027.04  3.37
Total   899  3027.86

S = 1.837   R-Sq = 0.03%   R-Sq(adj) = 0.00%


                               Individual 95% CIs For Mean Based on
                               Pooled StDev
Level    N     Mean  StDev  --------+---------+---------+---------+-
A1     300  1014.53   1.84  (-------------*------------)
A2     300  1014.54   1.86  (-------------*-------------)
A3     300  1014.60   1.81      (-------------*-------------)
                            --------+---------+---------+---------+-
                               1014.45   1014.60   1014.75   1014.90

Pooled StDev = 1.84
```

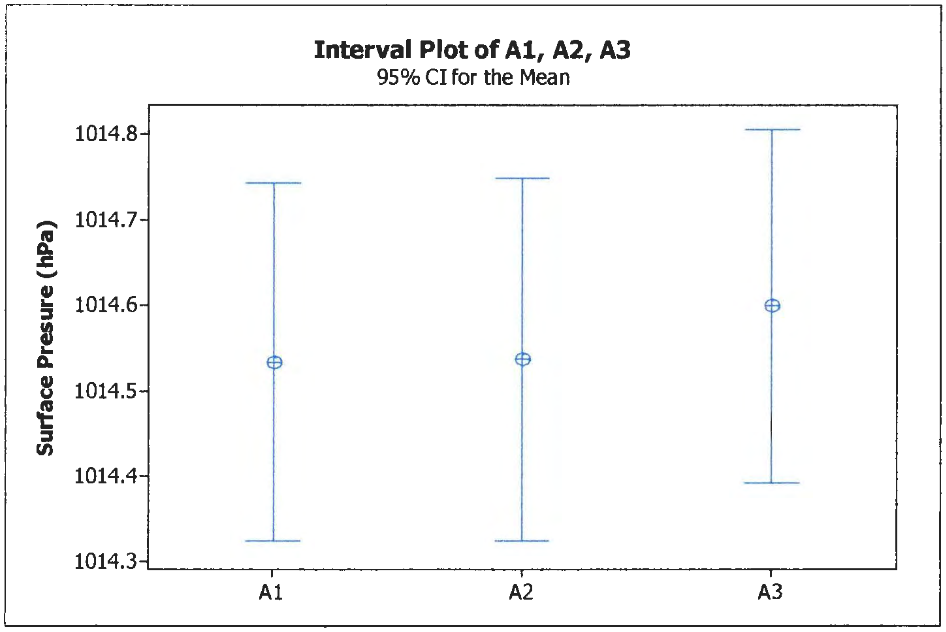
Explanation:
From ANOVA test, it is found that the three means are the same as P-value of the test is greater than 0.05.



Explanation:
From residual plots, it is found that assumptions of ANOVA: a normal distribution and a consistent variance of residuals are not satisfied.

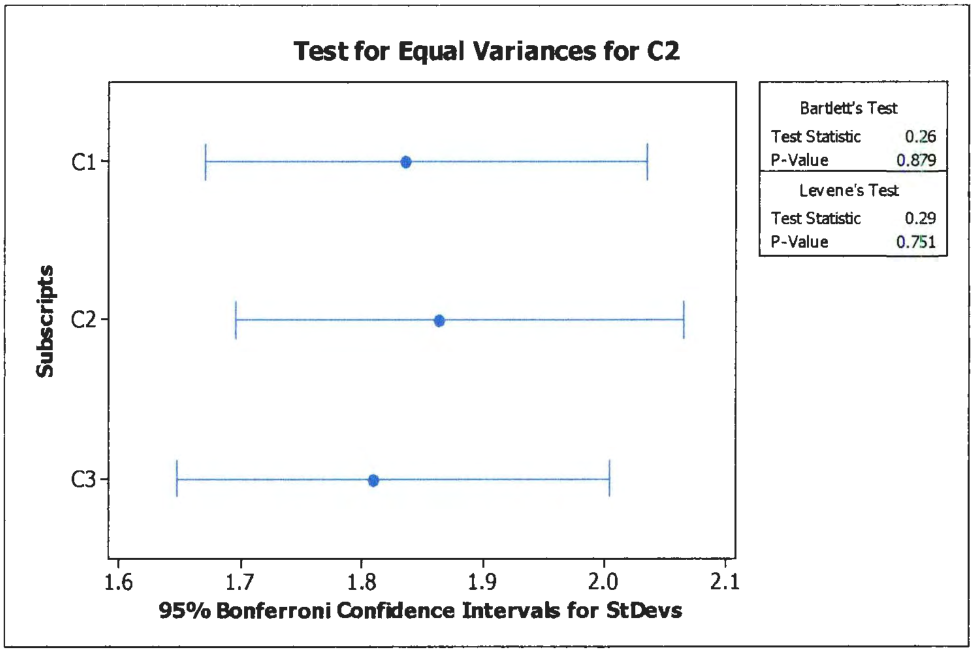
```
Kruskal-Wallis Test on C2

Subscripts     N  Median  Ave Rank      Z
C1           300    1015     448.5  -0.16
C2           300    1015     447.4  -0.25
C3           300    1015     455.6   0.41
Overall      900             450.5

H = 0.17  DF = 2  P = 0.917
```

Explanation:
As data do not follow normal distributions, a Kruskal-Wallis test is used to analyze their medians. From a Kruskal-Wallis test, it is found that their medians are the same as its P-value, 0.917 is greater than 0.05.

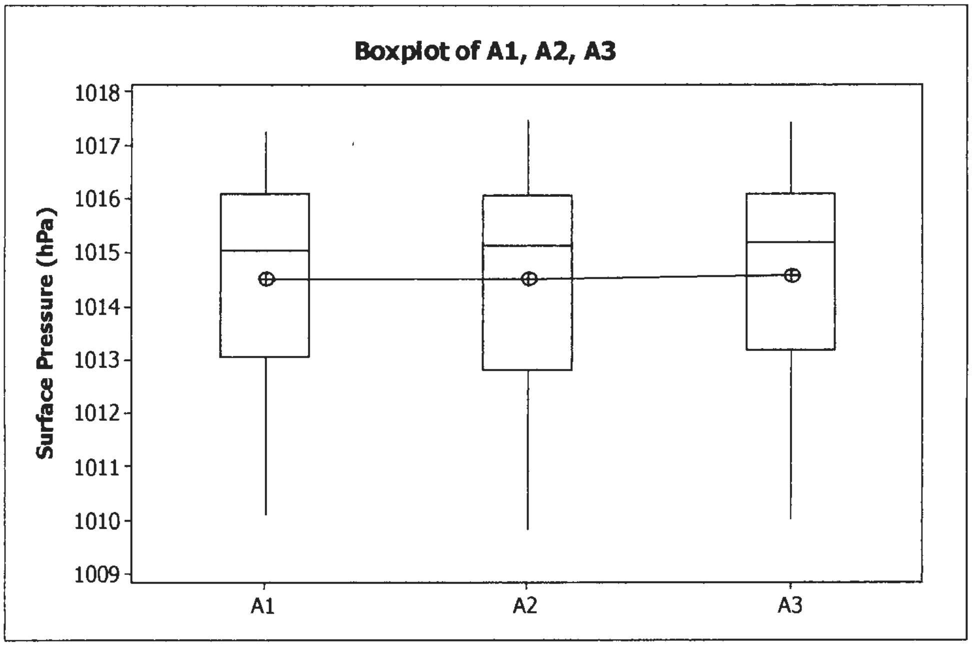


Explanation:
From interval plot, it is found that the three means are the same as their intervals overlap each other.

Tests for Variance:



Explanation:
From both tests: Barlett's and Levene's tests, it is found that all variances are equal as its P-values are greater than 0.05.



Explanation:
From a boxplot, it is found that the three sets of data have the same means and medians. Moreover, they might have the same variances as their sizes of box are similar.

Appendix C:

The correlation coefficient of 67 representative countries' growth rates

	Afghanistan	Algeria	Argentina
Algeria	0.328		
Argentina	0.441	0.434	
Australia	-0.170	0.325	-0.06
Austria	-0.443	0.308	0.314
The Bahamas	-0.508	0.348	0.158
Bahrain	-0.034	0.214	0.62
Bangladesh	0.241	-0.085	0.613
Barbados	-0.192	0.534	0.376
Belgium	-0.377	0.397	0.302
Brazil	-0.326	-0.048	0.462
Brunei	-0.315	0.317	-0.268
Cambodia	-0.182	0.361	0.403
Cameroon	-0.551	0.292	-0.387
Canada	-0.456	0.316	-0.078
Chile	-0.129	0.495	0.564
China	0.324	0.007	0.379
Congo	0.402	0.063	0.398
Cuba	-0.082	0.139	0.476
Czech Rep	-0.076	0.419	0.546
Denmark	-0.465	0.324	0.121
Djibouti	-0.002	-0.479	-0.068
East Timor	-0.126	-0.32	0.146
Ecuador	0.065	0.128	0.362
Egypt	-0.008	-0.154	0.62
Ethiopia	-0.208	-0.415	0.297
Finland	-0.413	0.397	0.25
France	-0.506	0.333	0.09
Gaza Strip	0.466	0.229	0.489
Germany	-0.490	0.219	0.259
Ghana	0.022	-0.101	0.281
Greece	-0.067	0.533	0.04
Haiti	0.148	-0.142	0.056
Iceland	-0.286	0.593	0.2
India	0.488	0.090	0.608
Indonesia	0.235	0.032	0.604
Iran	0.172	0.454	0.217
Italy	-0.457	0.389	0.115
Jamaica	-0.036	0.625	0.331
Japan	-0.088	0.587	0.48
Kazakhstan	-0.160	0.390	0.078
Kenya	0.215	-0.078	0.596
Kiribati	-0.475	-0.143	0.086
North Korea	-0.038	-0.042	0.131
South Korea	-0.441	0.104	-0.244
Kuwait	-0.161	0.359	0.644
Laos	0.234	-0.261	0.552
Libya	-0.241	0.390	0.62
Malaysia	-0.243	0.456	0.306
Mexico	-0.450	0.345	0.247
Netherlands	-0.592	0.143	0.167
Norway	-0.282	0.265	0.39
Pakistan	0.428	0.467	0.865
PNG	0.25	-0.198	0.579
Philippines	-0.019	0.262	0.432
Portugal	-0.693	0.041	-0.108
Qatar	0.358	-0.056	0.617
Russia	-0.178	0.589	0.359
Saudi Arabia	0.174	0.784	0.714
Singapore	-0.218	0.115	0.336
South Africa	-0.318	0.276	0.374
Spain	-0.333	0.489	0.152
Switzerland	-0.454	0.125	0.406
UAE	-0.198	0.393	0.555
UK	-0.329	0.55	0.222
US	-0.344	0.556	0.114
Vietnam	0.315	0.388	0.655

	Australia	Austria	The Bahamas
Austria	0.635		
The Bahamas	0.354	0.736	
Bahrain	0.256	0.698	0.442
Bangladesh	-0.159	0.203	0.312
Barbados	0.696	0.858	0.717
Belgium	0.712	0.955	0.766
Brazil	0.230	0.618	0.263
Brunei	0.220	0.325	0.296
Cambodia	0.228	0.637	0.59
Cameroon	0.272	0.408	0.445
Canada	0.798	0.825	0.683
Chile	0.226	0.666	0.562
China	0.563	0.300	-0.176
Congo	-0.085	0.008	-0.292
Cuba	0.440	0.630	0.535
Czech Rep	0.404	0.804	0.567
Denmark	0.558	0.857	0.833
Djibouti	0.063	-0.174	-0.556
East Timor	-0.418	-0.104	-0.103
Ecuador	-0.375	0.066	-0.061
Egypt	0.251	0.466	0.092
Ethiopia	-0.275	0.057	-0.034
Finland	0.645	0.977	0.804
France	0.775	0.917	0.798
Gaza Strip	0.546	0.23	-0.19
Germany	0.567	0.954	0.693
Ghana	0.122	0.292	-0.243
Greece	0.526	0.490	0.443
Haiti	0.120	-0.036	0.013
Iceland	0.580	0.747	0.783
India	0.359	0.277	-0.177
Indonesia	-0.076	0.210	-0.098
Iran	0.378	0.313	0.001
Italy	0.623	0.914	0.818
Jamaica	0.186	0.581	0.693
Japan	0.411	0.784	0.632
Kazakhstan	0.007	0.402	0.655
Kenya	0.072	0.323	0.19
Kiribati	0.123	0.414	0.088
North Korea	-0.223	0.078	-0.225
South Korea	0.867	0.628	0.476
Kuwait	0.111	0.719	0.592
Laos	-0.154	0.119	-0.251
Libya	0.283	0.764	0.597
Malaysia	0.788	0.884	0.55
Mexico	0.655	0.935	0.742
Netherlands	0.666	0.947	0.73
Norway	0.474	0.784	0.614
Pakistan	0.058	0.290	0.384
PNG	0.145	0.146	-0.277
Philippines	0.418	0.675	0.34
Portugal	0.701	0.807	0.733
Qatar	-0.311	-0.058	-0.445
Russia	0.625	0.895	0.583
Saudi Arabia	0.268	0.51	0.337
Singapore	0.602	0.693	0.466
South Africa	0.289	0.799	0.649
Spain	0.725	0.876	0.776
Switzerland	0.572	0.923	0.673
UAE	0.115	0.737	0.606
UK	0.673	0.924	0.747
US	0.748	0.817	0.712
Vietnam	0.274	0.473	0.262

	Bahrain	Bangladesh	Barbados
Bangladesh	0.459		
Barbados	0.667	0.250	
Belgium	0.611	0.159	0.821
Brazil	0.457	0.231	0.261
Brunei	-0.332	-0.386	0.126
Cambodia	0.615	0.485	0.677
Cameroon	-0.044	-0.617	0.311
Canada	0.287	-0.010	0.75
Chile	0.591	0.323	0.486
China	0.452	0.274	0.327
Congo	0.323	0.211	0.112
Cuba	0.769	0.582	0.786
Czech Rep	0.869	0.423	0.759
Denmark	0.486	0.226	0.751
Djibouti	-0.105	0.024	-0.255
East Timor	0.074	0.227	-0.253
Ecuador	0.414	0.061	-0.165
Egypt	0.701	0.496	0.427
Ethiopia	0.436	0.306	-0.136
Finland	0.610	0.184	0.866
France	0.444	0.049	0.837
Gaza Strip	0.354	0.211	0.449
Germany	0.530	0.179	0.71
Ghana	0.534	0.044	0.221
Greece	0.576	-0.153	0.7
Haiti	0.318	0.336	0.249
Iceland	0.554	0.128	0.925
India	0.444	0.488	0.316
Indonesia	0.545	0.419	-0.006
Iran	0.567	-0.138	0.421
Italy	0.443	0.072	0.762
Jamaica	0.640	0.206	0.65
Japan	0.478	0.267	0.693
Kazakhstan	0.302	0.201	0.254
Kenya	0.571	0.846	0.348
Kiribati	0.136	-0.086	0.261
North Korea	0.327	-0.184	0.103
South Korea	0.043	-0.137	0.61
Kuwait	0.889	0.385	0.656
Laos	0.491	0.546	0.06
Libya	0.787	0.416	0.693
Malaysia	0.502	0.033	0.758
Mexico	0.479	0.132	0.763
Netherlands	0.572	0.164	0.817
Norway	0.893	0.304	0.758
Pakistan	0.542	0.712	0.435
PNG	0.3	0.435	0.129
Philippines	0.521	0.307	0.494
Portugal	0.258	0.021	0.685
Qatar	0.165	0.272	-0.242
Russia	0.696	0.056	0.845
Saudi Arabia	0.503	0.196	0.595
Singapore	0.321	0.337	0.514
South Africa	0.793	0.357	0.648
Spain	0.633	0.099	0.946
Switzerland	0.664	0.370	0.73
UAE	0.864	0.381	0.697
UK	0.590	0.022	0.86
US	0.353	-0.09	0.805
Vietnam	0.753	0.528	0.541

	Belgium	Brazil	Brunei
Brazil	0.596		
Brunei	0.362	0.153	
Cambodia	0.509	0.348	0.039
Cameroon	0.407	-0.025	0.695
Canada	0.850	0.345	0.546
Chile	0.690	0.681	0.228
China	0.311	0.404	-0.371
Congo	-0.147	0.139	-0.269
Cuba	0.582	0.194	-0.394
Czech Rep	0.729	0.519	-0.007
Denmark	0.856	0.435	0.424
Djibouti	-0.273	0.263	-0.336
East Timor	-0.223	0.312	-0.226
Ecuador	0.022	0.399	-0.104
Egypt	0.389	0.574	-0.507
Ethiopia	-0.032	0.561	-0.55
Finland	0.960	0.506	0.44
France	0.948	0.462	0.442
Gaza Strip	0.236	0.163	-0.333
Germany	0.927	0.729	0.496
Ghana	0.105	0.391	-0.26
Greece	0.481	-0.197	-0.082
Haiti	-0.084	-0.392	-0.677
Iceland	0.720	0.043	0.167
India	0.267	0.393	-0.283
Indonesia	0.197	0.638	-0.299
Iran	0.258	0.084	-0.213
Italy	0.936	0.470	0.595
Jamaica	0.560	0.071	0.165
Japan	0.778	0.539	0.527
Kazakhstan	0.460	0.151	0.387
Kenya	0.229	0.432	-0.412
Kiribati	0.251	0.454	0.232
North Korea	-0.138	-0.013	-0.126
South Korea	0.691	0.209	0.435
Kuwait	0.654	0.443	-0.08
Laos	-0.050	0.470	-0.475
Libya	0.712	0.590	-0.033
Malaysia	0.934	0.621	0.423
Mexico	0.963	0.619	0.509
Netherlands	0.903	0.571	0.278
Norway	0.735	0.458	-0.201
Pakistan	0.373	0.271	-0.29
PNG	0.1	0.48	-0.404
Philippines	0.633	0.724	0.265
Portugal	0.813	0.454	0.417
Qatar	-0.123	0.576	-0.127
Russia	0.851	0.457	0.346
Saudi Arabia	0.515	0.384	0.135
Singapore	0.762	0.733	0.283
South Africa	0.709	0.566	0.092
Spain	0.858	0.205	0.231
Switzerland	0.901	0.796	0.155
UAE	0.605	0.417	-0.007
UK	0.917	0.432	0.461
US	0.881	0.313	0.534
Vietnam	0.431	0.388	-0.275

	Cambodia	Cameroon	Canada
Cameroon	-0.010		
Canada	0.515	0.485	
Chile	0.710	0.054	0.485
China	0.221	-0.484	0.26
Congo	0.360	-0.272	-0.114
Cuba	0.538	-0.161	0.416
Czech Rep	0.862	0.047	0.565
Denmark	0.712	0.406	0.908
Djibouti	-0.018	-0.560	-0.201
East Timor	0.102	-0.244	-0.44
Ecuador	0.326	-0.116	-0.194
Egypt	0.247	-0.384	0.053
Ethiopia	0.258	-0.382	-0.259
Finland	0.632	0.484	0.887
France	0.470	0.535	0.927
Gaza Strip	0.105	-0.37	0.178
Germany	0.557	0.419	0.835
Ghana	0.413	-0.158	0.097
Greece	0.391	0.409	0.423
Haiti	0.041	-0.360	-0.177
Iceland	0.664	0.429	0.686
India	0.263	-0.574	0.18
Indonesia	0.371	-0.530	-0.085
Iran	0.509	0.015	0.234
Italy	0.508	0.603	0.898
Jamaica	0.678	0.398	0.449
Japan	0.686	0.320	0.726
Kazakhstan	0.499	0.318	0.404
Kenya	0.643	-0.602	0.125
Kiribati	0.144	0.259	0.151
North Korea	0.169	0.203	-0.132
South Korea	0.139	0.415	0.874
Kuwait	0.594	0.164	0.322
Laos	0.418	-0.603	-0.163
Libya	0.768	-0.000	0.468
Malaysia	0.469	0.337	0.865
Mexico	0.507	0.444	0.895
Netherlands	0.519	0.402	0.799
Norway	0.727	0.099	0.555
Pakistan	0.389	-0.391	0.074
PNG	0.006	-0.604	-0.118
Philippines	0.644	0.030	0.57
Portugal	0.345	0.506	0.851
Qatar	0.093	-0.515	-0.312
Russia	0.698	0.420	0.76
Saudi Arabia	0.629	0.006	0.35
Singapore	0.380	-0.016	0.724
South Africa	0.864	0.168	0.572
Spain	0.640	0.473	0.832
Switzerland	0.599	0.134	0.719
UAE	0.822	0.191	0.376
UK	0.634	0.568	0.863
US	0.433	0.586	0.916
Vietnam	0.732	-0.308	0.295

	Chile	China	Congo
China	0.240		
Congo	0.089	0.481	
Cuba	0.309	0.462	0.094
Czech Rep	0.815	0.454	0.359
Denmark	0.695	0.178	-0.005
Djibouti	-0.158	0.470	0.176
East Timor	0.032	-0.197	0.026
Ecuador	0.626	0.059	0.304
Egypt	0.236	0.614	0.222
Ethiopia	0.306	0.283	0.376
Finland	0.658	0.210	-0.048
France	0.508	0.215	-0.168
Gaza Strip	0.023	0.845	0.481
Germany	0.682	0.247	-0.022
Ghana	0.242	0.608	0.776
Greece	0.229	0.130	-0.003
Haiti	-0.339	0.174	-0.135
Iceland	0.444	0.038	-0.108
India	0.290	0.900	0.525
Indonesia	0.675	0.535	0.302
Iran	0.432	0.500	0.468
Italy	0.611	0.075	-0.161
Jamaica	0.625	-0.051	0.199
Japan	0.794	0.223	0.255
Kazakhstan	0.681	-0.255	-0.179
Kenya	0.414	0.603	0.573
Kiribati	0.023	-0.080	-0.058
North Korea	-0.086	0.035	0.648
South Korea	0.098	0.295	-0.264
Kuwait	0.685	0.142	0.13
Laos	0.241	0.612	0.782
Libya	0.842	0.289	0.056
Malaysia	0.687	0.485	0.007
Mexico	0.675	0.247	-0.129
Netherlands	0.485	0.230	-0.172
Norway	0.683	0.448	0.198
Pakistan	0.544	0.355	0.212
PNG	0.044	0.648	0.25
Philippines	0.726	0.544	0.498
Portugal	0.299	0.114	-0.274
Qatar	0.341	0.402	0.516
Russia	0.722	0.339	0.2
Saudi Arabia	0.774	0.287	0.239
Singapore	0.597	0.560	0.049
South Africa	0.835	0.253	0.232
Spain	0.501	0.221	-0.041
Switzerland	0.699	0.421	-0.021
UAE	0.723	0.106	0.281
UK	0.671	0.208	0.052
US	0.536	0.187	-0.111
Vietnam	0.674	0.661	0.639

	Cuba	Czech Rep	Denmark
Czech Rep	0.640		
Denmark	0.498	0.743	
Djibouti	-0.060	-0.104	-0.349
East Timor	-0.175	-0.008	-0.326
Ecuador	-0.140	0.450	0.088
Egypt	0.714	0.453	0.094
Ethiopia	0.141	0.299	-0.003
Finland	0.579	0.771	0.914
France	0.538	0.596	0.875
Gaza Strip	0.527	0.289	0.032
Germany	0.441	0.698	0.859
Ghana	0.265	0.519	0.155
Greece	0.528	0.555	0.414
Haiti	0.610	0.047	-0.218
Iceland	0.684	0.664	0.706
India	0.485	0.451	0.151
Indonesia	0.172	0.561	0.105
Iran	0.286	0.659	0.271
Italy	0.402	0.642	0.905
Jamaica	0.402	0.765	0.674
Japan	0.332	0.762	0.83
Kazakhstan	0.037	0.534	0.636
Kenya	0.557	0.618	0.317
Kiribati	0.117	0.092	0.042
North Korea	0.093	0.194	-0.047
South Korea	0.378	0.202	0.639
Kuwait	0.686	0.792	0.563
Laos	0.310	0.436	-0.004
Libya	0.681	0.851	0.65
Malaysia	0.464	0.693	0.801
Mexico	0.493	0.655	0.892
Netherlands	0.643	0.630	0.766
Norway	0.758	0.901	0.719
Pakistan	0.584	0.507	0.29
PNG	0.418	0.128	-0.186
Philippines	0.235	0.773	0.657
Portugal	0.449	0.378	0.759
Qatar	-0.125	0.168	-0.209
Russia	0.499	0.879	0.788
Saudi Arabia	0.390	0.682	0.452
Singapore	0.415	0.507	0.711
South Africa	0.510	0.948	0.791
Spain	0.689	0.752	0.829
Switzerland	0.646	0.743	0.777
UAE	0.601	0.896	0.622
UK	0.468	0.79	0.883
US	0.440	0.56	0.857
Vietnam	0.543	0.863	0.49

	Djibouti	East Timor
East Timor	0.432	
Ecuador	-0.003	0.225
Egypt	0.391	0.278
Ethiopia	0.361	0.520
Finland	-0.320	-0.218
France	-0.292	-0.289
Gaza Strip	0.296	-0.322
Germany	-0.149	-0.078
Ghana	0.414	0.000
Greece	-0.355	-0.305
Haiti	0.199	0.123
Iceland	-0.368	-0.227
India	0.366	-0.213
Indonesia	0.363	0.300
Iran	0.101	-0.176
Italy	-0.422	-0.240
Jamaica	-0.659	-0.182
Japan	-0.369	-0.233
Kazakhstan	-0.584	-0.059
Kenya	0.273	0.253
Kiribati	0.388	0.506
North Korea	-0.009	-0.076
South Korea	-0.051	-0.49
Kuwait	-0.357	-0.045
Laos	0.508	0.312
Libya	-0.034	0.040
Malaysia	-0.121	-0.360
Mexico	-0.258	-0.291
Netherlands	-0.050	-0.015
Norway	-0.110	-0.096
Pakistan	-0.315	-0.132
PNG	0.609	0.221
Philippines	0.053	0.061
Portugal	-0.117	-0.127
Qatar	0.449	0.289
Russia	-0.223	-0.206
Saudi Arabia	-0.130	-0.177
Singapore	0.046	-0.247
South Africa	-0.127	0.109
Spain	-0.339	-0.310
Switzerland	0.043	0.049
UAE	-0.243	0.134
UK	-0.378	-0.256
US	-0.435	-0.56
Vietnam	-0.011	-0.073

	Egypt	Ethiopia	Finland
Ethiopia	0.488		
Finland	0.301	-0.093	
France	0.262	-0.141	0.945
Gaza Strip	0.607	-0.026	0.164
Germany	0.365	0.061	0.943
Ghana	0.456	0.507	0.165
Greece	0.102	-0.187	0.512
Haiti	0.449	-0.033	-0.091
Iceland	0.195	-0.241	0.787
India	0.625	0.159	0.208
Indonesia	0.484	0.622	0.103
Iran	0.158	0.201	0.269
Italy	0.120	-0.182	0.969
Jamaica	-0.043	-0.004	0.654
Japan	0.123	-0.065	0.837
Kazakhstan	-0.326	-0.011	0.51
Kenya	0.591	0.522	0.259
Kiribati	0.452	0.079	0.299
North Korea	0.150	0.229	0.004
South Korea	0.119	-0.378	0.67
Kuwait	0.528	0.280	0.671
Laos	0.620	0.672	-0.016
Libya	0.554	0.316	0.703
Malaysia	0.341	-0.084	0.885
Mexico	0.298	-0.083	0.954
Netherlands	0.513	0.034	0.908
Norway	0.528	0.407	0.727
Pakistan	0.449	0.168	0.298
PNG	0.844	0.291	-0.002
Philippines	0.309	0.305	0.653
Portugal	0.264	-0.078	0.814
Qatar	0.392	0.464	-0.169
Russia	0.282	-0.049	0.897
Saudi Arabia	0.268	0.006	0.504
Singapore	0.409	0.127	0.684
South Africa	0.329	0.392	0.77
Spain	0.255	-0.175	0.907
Switzerland	0.632	0.289	0.86
UAE	0.416	0.306	0.696
UK	0.174	-0.113	0.959
US	0.064	-0.312	0.886
Vietnam	0.426	0.396	0.442

	France	Gaza Strip	Germany
Gaza Strip	Strip	0.198	
Germany	0.897	0.130	
Ghana	0.038	0.471	0.231
Greece	0.475	0.200	0.241
Haiti	-0.085	0.294	-0.274
Iceland	0.755	0.171	0.57
India	0.133	0.854	0.255
Indonesia	-0.080	0.205	0.22
Iran	0.158	0.373	0.136
Italy	0.948	0.017	0.928
Jamaica	0.496	-0.072	0.46
Japan	0.720	0.195	0.826
Kazakhstan	0.366	-0.491	0.423
Kenya	0.138	0.435	0.296
Kiribati	0.290	0.038	0.431
North Korea	-0.125	0.162	-0.006
South Korea	0.835	0.32	0.644
Kuwait	0.491	0.145	0.593
Laos	-0.165	0.463	0.111
Libya	0.555	0.205	0.668
Malaysia	0.880	0.412	0.886
Mexico	0.944	0.188	0.963
Netherlands	0.919	0.193	0.9
Norway	0.639	0.276	0.629
Pakistan	0.209	0.438	0.227
PNG	-0.013	0.706	0.138
Philippines	0.547	0.308	0.739
Portugal	0.931	0.081	0.827
Qatar	-0.317	0.307	0.052
Russia	0.780	0.293	0.809
Saudi Arabia	0.368	0.381	0.441
Singapore	0.727	0.408	0.797
South Africa	0.598	0.001	0.734
Spain	0.881	0.243	0.733
Switzerland	0.835	0.274	0.919
UAE	0.481	0.058	0.608
UK	0.906	0.169	0.869
US	0.922	0.241	0.795
Vietnam	0.283	0.501	0.377

	Ghana	Greece	Haiti
Greece	0.160		
Haiti	-0.053	0.422	
Iceland	0.019	0.805	0.309
India	0.557	-0.033	0.122
Indonesia	0.491	-0.089	-0.097
Iran	0.652	0.695	0.11
Italy	0.001	0.431	-0.235
Jamaica	0.131	0.697	-0.043
Japan	0.234	0.256	-0.433
Kazakhstan	-0.203	0.306	-0.3
Kenya	0.455	-0.063	0.203
Kiribati	0.201	-0.075	0.044
North Korea	0.742	0.2	-0.063
South Korea	-0.054	0.278	-0.016
Kuwait	0.352	0.509	0.115
Laos	0.789	-0.224	0.055
Libya	0.361	0.417	0.089
Malaysia	0.266	0.398	-0.235
Mexico	0.122	0.322	-0.246
Netherlands	0.159	0.423	0.105
Norway	0.487	0.670	0.21
Pakistan	0.008	0.124	0.126
PNG	0.373	-0.284	0.288
Philippines	0.503	0.096	-0.397
Portugal	-0.045	0.271	-0.045
Qatar	0.529	-0.521	-0.359
Russia	0.409	0.659	-0.103
Saudi Arabia	0.306	0.359	-0.152
Singapore	0.183	-0.073	-0.305
South Africa	0.448	0.474	-0.068
Spain	0.156	0.796	0.197
Switzerland	0.277	0.243	-0.025
UAE	0.444	0.553	0.089
UK	0.212	0.631	-0.166
US	0.053	0.528	-0.224
Vietnam	0.592	0.376	0.044

	Iceland	India
India	0.007	
Indonesia	-0.136	0.568
Iran	0.414	0.333
Italy	0.708	0.059
Jamaica	0.716	-0.032
Japan	0.567	0.346
Kazakhstan	0.391	-0.229
Kenya	0.129	0.679
Kiribati	0.195	-0.046
North Korea	0.034	0.088
South Korea	0.511	0.175
Kuwait	0.615	0.247
Laos	-0.195	0.691
Libya	0.658	0.352
Malaysia	0.602	0.445
Mexico	0.650	0.258
Netherlands	0.729	0.167
Norway	0.699	0.328
Pakistan	0.305	0.544
PNG	-0.146	0.756
Philippines	0.266	0.533
Portugal	0.610	-0.003
Qatar	-0.463	0.587
Russia	0.770	0.315
Saudi Arabia	0.551	0.425
Singapore	0.270	0.571
South Africa	0.613	0.217
Spain	0.941	0.138
Switzerland	0.569	0.392
UAE	0.688	0.177
UK	0.804	0.154
US	0.752	0.154
Vietnam	0.374	0.670

	Iran	Italy	Jamaica
Italy	0.139		
Jamaica	0.520	0.622	
Japan	0.288	0.823	0.686
Kazakhstan	0.194	0.581	0.769
Kenya	0.213	0.115	0.233
Kiribati	-0.155	0.243	-0.201
North Korea	0.390	-0.11	0.193
South Korea	-0.019	0.699	0.056
Kuwait	0.395	0.542	0.706
Laos	0.298	-0.186	-0.027
Libya	0.462	0.557	0.564
Malaysia	0.375	0.854	0.437
Mexico	0.146	0.945	0.478
Netherlands	0.136	0.851	0.377
Norway	0.654	0.590	0.686
Pakistan	0.125	0.205	0.435
PNG	-0.046	-0.153	-0.429
Philippines	0.407	0.617	0.466
Portugal	-0.083	0.837	0.235
Qatar	0.101	-0.255	-0.233
Russia	0.625	0.823	0.739
Saudi Arabia	0.545	0.392	0.531
Singapore	0.017	0.671	0.139
South Africa	0.554	0.68	0.76
Spain	0.465	0.842	0.722
Switzerland	0.181	0.785	0.365
UAE	0.525	0.562	0.8
UK	0.445	0.94	0.752
US	0.277	0.896	0.566
Vietnam	0.692	0.301	0.619

	Japan	Kazakhstan	Kenya
Kazakhstan	0.579		
Kenya	0.381	0.100	
Kiribati	0.108	-0.330	-0.008
North Korea	0.063	-0.246	0.023
South Korea	0.405	-0	-0.043
Kuwait	0.592	0.431	0.345
Laos	0.164	-0.226	0.811
Libya	0.641	0.405	0.456
Malaysia	0.809	0.324	0.212
Mexico	0.829	0.428	0.195
Netherlands	0.596	0.228	0.241
Norway	0.548	0.414	0.485
Pakistan	0.486	0.261	0.594
PNG	-0.008	-0.588	0.511
Philippines	0.817	0.408	0.632
Portugal	0.512	0.188	0.095
Qatar	0.182	-0.203	0.424
Russia	0.835	0.478	0.261
Saudi Arabia	0.704	0.296	0.28
Singapore	0.700	0.197	0.471
South Africa	0.723	0.659	0.528
Spain	0.662	0.432	0.189
Switzerland	0.687	0.290	0.487
UAE	0.657	0.517	0.452
UK	0.851	0.551	0.178
US	0.779	0.401	-0.011
Vietnam	0.613	0.355	0.781

	Kuwait	Laos	Libya
Laos	0.277		
Libya	0.867	0.326	
Malaysia	0.528	0.041	0.656
Mexico	0.592	-0.039	0.676
Netherlands	0.583	0.019	0.673
Norway	0.806	0.320	0.834
Pakistan	0.581	0.321	0.553
PNG	0.151	0.635	0.276
Philippines	0.395	0.509	0.512
Portugal	0.286	-0.183	0.391
Qatar	0.148	0.737	0.238
Russia	0.699	0.119	0.74
Saudi Arabia	0.642	0.222	0.788
Singapore	0.316	0.248	0.506
South Africa	0.761	0.351	0.826
Spain	0.631	-0.116	0.651
Switzerland	0.650	0.274	0.791
UAE	0.909	0.356	0.86
UK	0.631	-0.064	0.648
US	0.487	-0.255	0.531
Vietnam	0.578	0.640	0.63

	Malaysia	Mexico
Mexico	0.938	
Netherlands	0.795	0.884
Norway	0.652	0.630
Pakistan	0.326	0.305
PNG	0.191	0.09
Philippines	0.709	0.638
Portugal	0.717	0.838
Qatar	0.060	-0.055
Russia	0.862	0.808
Saudi Arabia	0.614	0.513
Singapore	0.828	0.822
South Africa	0.625	0.66
Spain	0.769	0.790
Switzerland	0.834	0.886
UAE	0.488	0.546
UK	0.877	0.887
US	0.895	0.908
Vietnam	0.481	0.349

	Norway	Pakistan	PNG
Pakistan	0.433		
PNG	0.097	0.366	
Philippines	0.558	0.347	0.201
Portugal	0.474	-0.001	0.03
Qatar	-0.041	0.295	0.626
Russia	0.777	0.292	0.002
Saudi Arabia	0.536	0.618	0.215
Singapore	0.461	0.435	0.391
South Africa	0.876	0.34	-0.046
Spain	0.790	0.262	-0.111
Switzerland	0.754	0.390	0.372
UAE	0.823	0.438	0.03
UK	0.733	0.257	-0.14
US	0.575	0.257	-0.134
Vietnam	0.737	0.660	0.242

	Philippines	Portugal	Qatar
Portugal	0.408		
Qatar	0.403	-0.376	
Russia	0.719	0.553	0.002
Saudi Arabia	0.483	0.104	0.377
Singapore	0.720	0.679	0.242
South Africa	0.741	0.441	0.095
Spain	0.459	0.727	-0.414
Switzerland	0.689	0.790	0.121
UAE	0.539	0.294	0.122
UK	0.683	0.723	-0.196
US	0.486	0.764	-0.281
Vietnam	0.749	0.042	0.359

	Russia	Saudi Arabia	Singapore
Saudi Arabia	Arabia	0.694	
Singapore	0.521	0.398	
South Africa	0.819	0.549	0.465
Spain	0.875	0.483	0.456
Switzerland	0.724	0.470	0.825
UAE	0.784	0.649	0.242
UK	0.952	0.561	0.585
US	0.805	0.536	0.665
Vietnam	0.629	0.629	0.442

	South Africa	Spain
Spain	0.707	
Switzerland	0.748	0.700
UAE	0.897	0.683
UK	0.775	0.92
US	0.521	0.853
Vietnam	0.728	0.460

	UAE	UK
United	0.698	
United	0.444	0.901
Vietnam	0.667	0.501

Corr. Coeff.	# Corr. Coeff.	Percentage
< 0.6	1590	74.23%
> 0.6	552	25.77%
Total =	2142	100.00%