STATISTICAL DOWNSCALING USING REGRESSION-BASED TECHNIQUE IN PENINSULAR MALAYSIA

KHO PUI KIM

UNIVERSITI TEKNOLOGI MALAYSIA

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KHO PUI KIM

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ABSTRACT

General Circulation Models (GCMs) are important in projecting future climate change. Due to its coarse spatial resolution, downscaling methods are used to obtain local climate information from GCM. This study presents an application of statistical downscaling to assess rainfall changes in Peninsular Malaysia during the months of November to February. Statistical downscaling models are developed using the reanalysis output from the National Center for Environmental Prediction/ National Center for Atmospheric Research (NCEP/NCAR) to test the ability in simulating the daily time series of local rainfall. In the pre-processing step, Principal Component Analysis (PCA) and Self-Organizing Map (SOM) are used to reduce the dimensionality of the dataset. Eight variables are considered from the NCEP/NCAR reanalysis output including sea level pressure (SLP), geopotential height at 500hPa and 850hPa (P500 and P850), relative humidity at 500hPa and 850hPa (R500 and R850), near surface relative humidity (RHUM), near surface specific humidity (SHUM) and mean temperature (TEMP). Potential predictors are selected based on the correlations of NCEP reanalysis with observed rainfall. The predictors are ranked based on the strength of correlations and the model is built with high correlated predictors until the model is optimized. The humidity appears to be the most suitable predictors with the highest correlations to the observed rainfall. Eight models are developed: four with single variable (SLP) and four with combined variables (SHUM + SLP), to form Principal Component Analysis and Regression model (PCA-REG), Principal Component Analysis and Canonical Correlation Analysis Model (PCA-CCA), Self-Organizing Map and Regression model (SOM-REG) and Self-Organizing Map and Canonical correlation Analysis model (SOM-CCA). Results show that the best downscaling model is SOM-REG with combined predictors (SHUM + SLP). The calibration and validation of the best downscaling model determined in this study has shown that the (SOM-REG) model is able to adequately capture the trend of the observed rain series. This model is also capable to project future climate with GCM outputs. The overall results have shown that the future climate is predicted to be having an increasing trend.

ABSTRAK

General Circulation Models (GCMs) adalah penting dalam meramal perubahan iklim masa hadapan. Oleh kerana resolusi reruangnya yang kasar, kaedah penurunan skala telah digunakan untuk mendapatkan maklumat iklim tempatan daripada GCM. Kajian ini membentangkan aplikasi penurunan skala statistik untuk menilai perubahan hujan di Semenanjung Malaysia daripada bulan November hingga Februari. Model penurunan skala statistik telah dibangunkan dengan menggunakan keluaran analisis semula daripada *National Centers for Prediction/ National Center for Atmospheric Research* (NCEP / NCAR) untuk menguji keupayaan mensimulasi siri hujan harian tempatan. Dalam langkah pra-proses, Analisis Komponen Utama (PCA) dan Peta Penyusun Sendiri (SOM) digunakan untuk mengurangkan dimensi data. Lapan pembolehubah telah dipertimbangkan daripada keluaran analisis semula NCEP / NCAR termasuk tekanan paras laut (SLP), ketinggian geopoten pada 500hPa dan 850hPa (P500 dan P850), kelembapan relatif pada 500hPa dan 850hPa (R500 dan R850), berhampiran kelembapan relatif permukaan (RHUM), berhampiran kelembapan khusus permukaan (SHUM) dan suhu purata (TEMP). Peramal yang berpotensi telah dipilih berdasarkan korelasi analisis semula NCEP dengan amaun hujan yang dicerap. Peramal telah diperingkat berdasarkan kekuatan korelasi antara model yang dibina dengan peramal berkorelasi tinggi sehingga model dioptimumkan. Kelembapan merupakan peramal yang paling sesuai dengan korelasi tertinggi kepada amaun hujan yang dicerap. Lapan model telah dibangunkan: empat dengan pembolehubah tunggal (SLP) dan empat dengan pembolehubah gabungan (SHUM + SLP) untuk membentuk model Analisis Komponen Utama dan Regresi (PCA-REG), model Analisis Komponen Utama dan Analisis Korelasi Kanonik (PCA-CCA), model Peta Penyusun Sendiri dan Regresi (SOM-REG) dan model Peta Penyusun Sendiri dan Analisis Korelasi Kanonik (SOM-CCA). Hasil kajian menunjukkan bahawa model penurunan skala terbaik ialah SOM-REG dengan pembolehubah gabungan (SHUM + SLP). Penentukuran dan pengesahan model penurunan skala terbaik yang ditentukan dalam kajian ini telah menunjukkan bahawa model SOM-REG ini dapat mengekalkan trend aliran siri hujan yang mencukupi. Model ini juga mampu meramal iklim masa hadapan dengan keluaran GCM. Hasil keseluruhan telah menunjukkan bahawa iklim masa hadapan diramalkan mempunyai trend yang semakin meningkat.

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LIST OF ABBREVIATIONS

CCA	–	Canonical Correlation Analysis
CMIP3	–	Coupled Model Intercomparison Project phase 3
Corr		Correlation coefficient
CP	–	Component plane
ECHAM5	–	Max Plank Institute for Meteorology, Germany
ESRL	–	Earth System Research Laboratory
GCM	–	General Circulation Model
MAE	–	Mean Absolute Error
ME	–	Mean Error
MSE	–	Mean Square Error
NCEP	–	National Centre for Environmental Prediction
NDJF	–	November-December-January-February
NOAA	–	National Oceanic & Atmospheric Administration
NSout	–	Nash-Sutcliffe Efficiency Index
P500	–	500hPa geopotential height
PCA	–	Principal Component Analysis
P850	–	850hPa geopotential height
R500	–	relative humidity at 500hPa
R850	–	relative humidity at 850hPa
RMSE	–	Root Mean Square Error
RHUM	–	relative humidity
SHUM	–	specific humidity
SLP	–	Sea level pressure
SOM	–	Self-Organizing Map
SRESA2	–	SRES A2 experiments

SSE	–	Standard Error of Estimation
TEMP	–	temperature
WCRP	–	World Climate Research Programme
nt	_	Number of target
np	_	Number of predictors
20c3m	–	20^{th} century experiments

LIST OF SYMBOLS

s_y	–	standard deviation of forecast fields
s_o	–	standard deviation of observations
r_{yo}	–	anomaly correlation coefficient between forecast field and observations
r	–	Correlation
$\bar{x}$	–	mean
std	–	Standard deviation
σ	–	variance
Σ	–	Variance-covariance matrix
λ_j	–	eigenvalues
e_m	–	Eigenvector of x
f_m	–	Eigenvector of y
a_m	–	Canonical vector for x
b_m	–	Canonical vector for y
v_m	–	Canonical variates for x
w_m	–	Canonical variates for y
y_o	–	Observed rainfall
y_s	–	Simulated rainfall
$\bar{y}_o$	–	Mean of observed rainfall
$\bar{y}_s$	–	Mean of simulated rainfall

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CHAPTER 1

INTRODUCTION

1.1 Background of study

Over the last century the facts that the Earth has warmed is generally acknowledged. Climate for a specified geographical region is generally defined as the average state of the atmosphere for a given time scale (hour, day, month, season, year, decade and so forth). In other word, climate is the average weather for a specific time and area. The average-state statistics for a given time scale including all deviations from the mean are obtained from the ensemble of conditions recorded for many occurrences for the specified period of time (Couissi, 2017).

According to the summary of climate change 2014 synthesis report, the observed climate changes were the warming of atmospheric and ocean, diminishing of the snow and ice amount and risen of the sea level. The report showed three observations of a changing global climate system - the globally averaged combine land and ocean surface temperature anomaly, the globally averaged sea level change and the globally averaged greenhouse gas concentrations showed an increasing trend form 1950 to 2010 (IPCC, 2014).

Malaysia has experienced a dramatic change in climate for the last few years (Tang, 2018; Haliza, 2018). Direct observations of climate change were the increasing occurrence of the drought and flood in Malaysia. Drought and flood are the extremes associated with rainfall variability. With high variability in extreme rainfall, flood occurred (Guhathakurta *et al*., 2011). In contrast, drought occurred when the extreme rainfall variability is low. And hence, rainfall is an important tool to study the climate change impacts.

In climate change impacts study, General Circulation models (GCMs) are wisely projected climate change for future. Climate change is able to assess from GCMs as they provide considerable potential in the study of climate variability and climate change (Fowler *et al.*, 2007). Therefore, they can be used to simulate current and future time series of climate variables. These models are numerically coupled climate models for various earth systems representative such as atmosphere, oceans, land surface and sea-ice.

Typically, GCMs run on a large 150-300 km by 150-300 km resolution and are not able to significantly describe the sub grid scale features. Unfortunately, they cannot be used in the local impact studies as many impacts models require information at scales of 50 km or less. This implies that GCMs do not give local climate a realistic description (Benestard *et al.*, 2008). Therefore, downscaling method is developed to overcome these limitations (Schubert, 1998).

Downscaling is used to obtain high-resolution scenarios of climate change as a procedure where large scales information is used to make predictions at local scales. In other words, downscaling is a method used to reduce the large scale information into small scale information that is to downscale the output of GCM predictors to the local predictands. With the downscaling method, predictions of rainfall trend for current and future can be done by submitting the output of GCM into the model built by the NCEP variables with rainfall.

1.2 Statement of problem

There is a systematic procedure for selecting and constructing a downscaling model from GCM outputs to generate a set of climate change scenarios for assessing regional climate impact. Downscaling method consist of dynamical downscaling and statistical downscaling. Dynamical downscaling is able to describe mesoscale atmospheric circulation accurately than its original driving GCM. However, it is expensive to construct long-term or multiple regional scenarios. Therefore, statistical downscaling is an alternative way to study current and future regional climate change. To have a better understanding of statistical downscaling model, the factors that affect the performance of downscaling is introduced.

First of all, GCMs are rarely able to reproduce the observed climate very well at regional scales. GCMs act as an important tool to assess climate change for studying our climate. However, they tend to have a coarse spatial resolution and not able to resolve features of the sub grid scale significantly. A distinct problem for the impact assessment of climate change is bridging the gap between the resolution of climate models and regional and local scale processes. And hence the development of techniques to bridge the gap has been focused by the climate community and the most popular known technique is known as downscaling. Downscaling is possible to model the resolution of climate and establish relationships between local climate and atmospheric conditions.

The second issue focus on predictor selection since it will affect the performance of downscaling. Normally, the selection of the optimum combination of predictors in downscaling is solely based on the historical observed data (rainfall) or reanalysis data such as NCEP reanalysis. When applying to GCMs, the hypothesis that the essence of the large-scale changes is captured by the chosen predictors. However, the hypothesis is usually beyond the scope of downscaling studies. Therefore, predictor selection is important to optimized downscaling model.

Lastly, there is a lack of consistency in evaluating the performance of downscaling method. There have been several downscaling techniques proposed with advantages and shortcomings. However, the performance of downscaling model is not clear to provide which downscaling technique is reliable to simulate climate variables. Hence, evaluation of downscaling techniques must be performed.

1.3 Objectives

The purpose of this study is to propose a statistical downscaling model using regression-based technique for Peninsular Malaysia. To achieve this, the specified objectives were outlined as follows:

i) To determine the best predictors for downscaling models.

ii) To compare and evaluate the performance of the downscaling models.

iii) To generate future climate scenarios.

1.4 Scope of the study

In this research, 40 stations in Peninsular Malaysia with 30 years of historical rainfall data of a period of 1975 to 2004 were analyzed. 40 stations are chosen based on the length of the records and completeness of the data. The data is obtained from the Malaysian Meteorological Department (MetMalaysia) and Malaysian Drainage and Irrigation Department (DID). A complete data set is used in this study. The daily rainfall data from November-December-January-February were only considered in this study. This is due to the period of Northeast monsoon occurrence in Peninsular Malaysia. The rainfall is used as predictand in developing a model.

Predictors were the atmospheric variables which derived from National Centre for Environmental Prediction (NCEP) reanalysis data set The NCEP predictors were all downloaded from National Oceanic & Atmospheric Administration (NOAA) Earth System Research Laboratory (ESRL) physical sciences division website (www.esrl.noaa.gov). Sea level pressure (SLP), 500mb geopotential height (P500), 850mb geopotential height (P850), 500mb relative humidity (R500), 850mb relative humidity (R850), near surface relative humidity (RHUM), near surface specific humidity (SHUM) and mean temperature (TEMP) were extracted from the grid point output of the NCEP reanalysis which accounted for 20 grids from 0°N to 7.5°N and 100°E to 105°E. The different level of relative humidity (500mb, 850mb and near surface) indicated the pressure chart from sea level.

This study investigated that the predictor selection for downscaling model improved the performance of downscaling models used for Peninsular Malaysia. With the performance of the models, best downscaling model is selected to downscale General Circulation Model (GCM). The GCM used is the model of Max Plank Institute for Meteorology, Germany, ECHAM5/MPI OM with the scenarios of climate of the 20^{th} century experiments and SRES A2 experiments.

The scenarios of climate of the 20^{th} century experiments is used for simulating current climate and the scenarios of SRES A2 experiments is used for simulating the future climate. Both data are downloaded from World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset of Earth System Grid – Centre for Enabling Technologies (https://esgcet.llnl.gov:8443/index.jsp). In downscaling analysis, the Matlab programming is used for current and future climate simulation.

1.5 Significance of the study

This study investigates the predictor selection for downscaling model to improve the performance of downscaling models used for Peninsular Malaysia. Although there are 26 predictors in NCEP, and only 8 are accounted for the studies, selecting predictor is still carried out to find the most relevant to use for downscaling model. Statistical downscaling models using different methods are carried out in this research. With the performance of the models, best downscaling models can be selected. Scenarios of current and future climate can be assessed using the downscaling model. By having a high quality of downscaling model, meteorologist can wisely make decisions in future infrastructure and water management systems in Peninsular Malaysia.

1.6 Organization of thesis

This thesis comprises of six chapters that can be divided into two parts, which are statistical downscaling model building and scenarios development study. For chapter 2, a literature review of statistical downscaling model is listed. Chapter 3 provides a description of the data sources and study area. It also presents the methodology of statistical downscaling model. Chapter 4 provides the result and discussion for the performance of the proposed models. And lastly, Chapter 5 is the conclusion of the models.

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APPENDIX D

PUBLICATIONS LIST

Journal Publications

1. Kho, P. K., Fadhilah Y., Zalina, M. D. (2013). Verification of Forecast Rainfall Anomalies. *MATEMATIKA*. 29 (1b), 77-87.

Conference Proceedings

2. Kho, P. K., Fadhilah Y., Zalina, M. D. (2013). Exploration on Atmospheric and surface data. *National Science Postgraduate Conference 2011*. 15–17 November. Johor, Malaysia.

3. Kho, P. K., Fadhilah Y., Zalina, M. D. (2013). Verification of Forecast Rainfall Anomalies. *1st ISM International Statistical Conference 2012*. 4–6 September. Johor, Malaysia.

4. Kho, P. K., Fadhilah Y., Zalina, M. D. (2014) Multi-dimensional Reduction using Self-organizing Map. *The 21st National Symposium on Mathematical Sciences*. 6–8 November. 932-937. Penang, Malaysia. **(Indexed by Scopus)**