GEOGRAPHICALLY WEIGHTED REGRESSION MODEL FOR SPATIAL DOWNSCALING OF GLOBAL PRECIPITATION MEASUREMENTS DATA IN KELANTAN

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DEDICATION

This thesis is dedicated to

My husband, Mohd Hafizuddin bin Md Husseini

My mother, Noor Laila bt Shariff

My father, Ramlan bin Hj Ibrahim

My Siblings and My kids

You are all the source of my inspiration.

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ABSTRACT

Rainfall is one of the prominent parameters in the hydro-climatic process, it is typically measured by using gauge which is limited to station samples and inherent systematic error with the requirement for regular instrument calibration. To overcome such limitations, the Tropical Rainfall Measuring Mission (TRMM) and the Global Precipitation Measurement (GPM) which are remote sensing precipitation satellite missions, have been used at a regional scale to provide reliable precipitation estimates over large spatial extent within the spatial resolution of 0.25^{o} and 0.1^{o} respectively. However, it is difficult to spatially match with the point-based gauge data at an acceptable local scale and thus, gives a poor empirical relationship. Previously, spatial downscaling algorithms using simple statistical models were devised by spatially correlating them with normalized difference vegetation index (NDVI), and digital elevation model (DEM) data at the higher spatial resolution, but the outcomes were unsatisfactory due to goodness of fitting dependent and spatial non-stationary influence. As such the aim of this research was to apply the Geographically Weighted Regression (GWR) method which put forward local regression with spatial non-stationary modelling to downscale both satellite precipitation data by showing the cross-correlation between NDVI and DEM data at high spatial resolution. The objectives were to develop a local downscaling method using multi and single variables to estimate rainfall at 1km spatial resolutions by using GWR modelling based on non-linear regression method; to assess the impact of spatial variability on local downscaled rainfall algorithm in the different model considering the different spatial resolutions; and to evaluate the quality of downscaled rainfall data with rain gauge measurements in differentiating the light and heavy rainfall. GPM, TRMM, Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI, Shuttle Radar Topography Mission (SRTM) DEM and ground gauge data were applied over Kelantan area for three consecutive periods from October 2013 to December 2016. Polynomial Regression (PR) and GWR were employed to downscale annual and monthly satellite precipitation from 25km and 10km to 1km spatial resolutions. Ground gauge data were used to validate the accuracy of light and heavy rainfall at below and above 200 mm, respectively. The GWR model improved the precipitation accuracy obtained by GPM as compared to TRMM by about 40% due to better spatial resolution pixels. PR models were limited for higher spatial non-stationary exhibited by homogeneous vegetated areas at low elevation and heterogeneous elevation. GWR had the least impact of the spatial non-stationary with 30% reduction of Root Mean Square Error (RMSE) similarly obtained by PR. Light rainfall was evident along the coastal line and the heavy rainfall was concentrated in the vigorous vegetated areas around the Kelantan area. This study proves that the GWR downscaling approach is suitable for tropical rainfall types in Kelantan and cross-correlating it with other rainfall related geo-parameters such as vegetation index and elevation.

ABSTRAK

Kajian pemendakan adalah salah satu daripada parameter penting dalam proses hidro iklim dan biasanya diukur dengan menggunakan tolok ukur dan terhad pada sampel stesen dan kesalahan sistematik yang wujud dengan keperluan untuk penentukuran instrumen biasa. Untuk mengatasi had batasan tersebut, *Tropical Rainfall Measuring Mission* (TRMM) dan *Global Precipitation Measurement* (GPM), yang melakukan misi satelit pemendakan penderiaan jarak jauh, telah digunakan pada skala wilayah untuk memberikan anggaran hujan yang boleh dipercayai melebihi luas ruang dalam resolusi spatial masing-masing pada 0.25^{o} dan 0.1^{o}. Walau bagaimanapun, adalah sukar untuk menyesuaikan spatial dengan data tolok berasaskan titik pada skala tempatan yang dapat diterima dan dengan itu memberikan hubungan empirik yang tidak baik. Sebelum ini, algoritma penjejakan ruang spatial menggunakan model statistik sederhana dirancang dengan menghubungkannya secara spatial dengan *Indeks Normalized Difference Vegetation Index* (NDVI) dan *Digital Elevation Model* (DEM) pada resolusi spatial yang lebih tinggi, tetapi hasilnya tidak memuaskan kerana kebaikan sesuai bergantung dan tidak berpusat pada ruang. Oleh itu, tujuan kajian ini adalah untuk menerapkan kaedah *Geographically Weighted Regression* (GWR) yang mengemukakan regresi tempatan dengan pemodelan tidak berpaut ruang untuk mengecilkan saiz data curah hujan satelit dengan menunjukkan korelasi silang antara data NDVI dan DEM pada resolusi spatial tinggi. Objektifnya adalah untuk membangunkan kaedah penskalaan tempatan menggunakan pemboleh ubah pelbagai dan tunggal untuk menganggarkan hujan pada resolusi spatial 1km dengan menggunakan permodelan GWR berdasarkan kaedah regresi bukan linear; untuk menilai kesan kebolehubahan spatial pada algoritma hujan tempatan dalam model yang berbeza dengan mempertimbangkan resolusi ruang yang berbeza dan untuk menilai kualiti data hujan dalam skala yang kecil dengan pengukuran hujan untuk membezakan hujan renyai dan lebat. GPM, TRMM, *Spectroradiometer Imaging Moderate Imaging* (MODIS) NDVI, DEM *Shuttle Radar Topography Mission* (SRTM) dan data tolok darat digunakan di Lembangan Kelantan selama tiga tempoh pengukuran berturut-turut dari Oktober 2013 hingga Disember 2016. Regresi eksponen (ER) pelbagai linear dan GWR digunakan untuk pemendakan satelit tahunan dan bulanan dari resolusi jarak 25km dan 10km hingga 1km. Data tolok darat digunakan untuk mengesahkan ketepatan hujan renyai dan hujan lebat masing-masing di bawah dan di atas 200 mm. Model GWR meningkatkan ketepatan kiraan hujan yang diperoleh GPM dibandingkan dengan TRMM kira-kira 40% kerana piksel resolusi spatial yang lebih baik. Model ER terhad untuk spatial bukan pegun yang lebih tinggi dipamerkan oleh kawasan vegetatif homogen pada ketinggian rendah dan ketinggian heterogen. GWR mempunyai kesan paling kecil dari spatial bukan pegun dengan pengurangan 30% *Root Mean Square Error* (RMSE) yang serupa diperoleh oleh *Multi Linear Regression* (MLR). Hujan renyai adalah bukti jelas di sepanjang pesisir pantai dan hujan lebat tertumpu di kawasan hijau tebal yang bertiup di sekitar Lembangan Kelantan. Kajian ini membuktikan bahawa pendekatan pengecilan saiz GWR sesuai untuk jenis hujan tropika di Kelantan dan saling mengaitkannya dengan geo-parameter yang berkaitan dengan hujan seperti indeks tumbuhan dan ketinggian.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
GA	-	Genetic Algorithm
PSO	-	Particle Swarm Optimization
MTS	-	Mahalanobis Taguchi System
MD	-	Mahalanobis Distance
TM	-	Taguchi Method
UTM	-	Universiti Teknologi Malaysia
XML	-	Extensible Markup Language
ANN	-	Artificial Neural Network
GA	-	Genetic Algorithm
PSO	-	Particle Swarm Optimization

LIST OF SYMBOLS

δ	-	Minimal error
D, d	-	Diameter
F	-	Force
v	-	Velocity
p	-	Pressure
I	-	Moment of Inersia
r	-	Radius
Re	-	Reynold Number

CHAPTER 1

INTRODUCTION

1.1 Introduction

Precipitation is one of the products of the water cycle where condensation takes place in the atmosphere and returns to the earth surface through the clouds. Precipitation takes many forms (drizzle, rain, sleet, snow, ice pellets, graupel and hail) and these all become the most crucial parameters for hydrological studies. As time went by, several techniques were developed that served as surrogates for obtaining atmospheric data and information, which are accurate in both spatial and temporal characteristics and eventually led to access key information that relates to the hydrological basin and enabling the prediction of extreme weather events such as flash floods and drought (Arnaud et al., 2002; Sarr et al., 2015; Vischel and Lebel, 2007).

Rainfall is a primary source of water for agriculture and many other uses. There are three main characteristics of rainfall that are very important (its amount, frequency and intensity) and this is because the values of each vary from place to place, day to day, month to month and also year to year. A precise knowledge of these characteristics is essential in planning for the full utilization of the benefits of rainfall globally. This is done through the use of long-term measurements of daily rainfall, compiled over years, and getting from the measurements which are eventually used to predict trends of floods, droughts and climatic zones of potential evapotranspiration in many regions of the world. These kinds of measurements are the focus of the study in Malaysia using Kelantan as a case study after the assessment of the method of the measurement technique. The study area still applies the use of direct rainfall gauges and the aerial coverage is still poor as the gauge's locations were selectively distributed only at flat regions with large radius distances between each other. For regional-scale consideration, it is difficult to apply direct measurement techniques and obtain reliable information with rain-gauges, but easier when remote sensing and in-situ measurement are applied in integration. The in-situ is comprised of rain-gauges and Disdrometer. The outcomes are usually accompanied by biases that pose uncertainties for accurate environmental studies and analysis.

The use of remote sensing data gives rise to consistent data and also provides the spatial heterogeneity of the data distribution for the region under consideration. Since 1997, the Tropical Rainfall Mission (TRMM) has revealed knowledge and the use of space-borne precipitation radar information that gave rise to 0.25˚ x 0.25˚ resolution that covered the tropics from 50 ˚ N-S at 3 hour time intervals (Chen et al., 2013). This particular application revealed that the visible and infrared data obtained for the study was used to estimate the precipitation based on the information obtained from the observation of the cloud top properties and correlated these measurements with ground-based radar measurements. Apart from the use of Radar information, other multi-satellite data could also be put to use, but care must be exercised so that minimum biases and errors are minimised as it is from them that an estimate could be made to calculate the amount of rainfall using the global regression model. Nevertheless, tropical application considering hourly rainfall data is quite difficult as explained by (Suzana & Wardah, 2011).

In 2014, a newer model of the TRMM, Global Precipitation Measurement (GPM) sensor was launched and provided its data with a better resolution of 0.1 ˚ x 0.1 ˚ degree capacity at every 30 minutes spatial coverage. This feat improved monitoring, prediction of weather, climate and precipitation. It has both active and passive sensors which together operate in Ku/Ka-band dual-frequency which became very useful for application even at microphysical studies. The frequency of Ka-band (35GHz) can contribute by integrating and removing other attenuations found in precipitation clouds. It also can identify, with high sensitivity, weak raindrops and snow. The minimum detectable rainfall rate in the high sensitivity mode is approximately 0.2mm/h (Seto & Iguchi, 2015). This new sensor technology implies that it is possible to combine the in-situ data obtained by the direct method of measurement with that of the satellite remote sensing procedure to achieve reliable information on precipitation data (Sharifi et al., 2016a)

1.2 Background of Study

Rainfall is the precipitation in the form of water droplets of size between 0.5mm to 7 mm. it can be classified into 3 classes which are light rain, moderate rain and heavy rain. The estimation of rainfall is basically in mm or inch unit which is being measured as total depth of rainfall over an area in one day. The instruments for measuring rainfall include rain gauges, snow gauges and various types are manufactured according to the purpose at hand. There can be substantial variation in rainfall amounts depending on whether the gauge applied is the type used by National Weather Services and if the measurements are of the same location. Some errors are inherited when the exposure of the rain gauge is not obstructed by vegetation, not truly vertical or blown off by wind gusts. There are point, aerial precipitation measurements with Radar, and those undertaken using Satellite image Data. The point measurements are not always well distributed, while the radar category makes use of the backscatters of the power of the returns of echo notwithstanding whether the area is flat or mountainous. This power of the echo returns is used to calculate the reflectivity factor Z. The Z is applied in an equation called Z-R to acquire the relationships that enable the determination of the rainfall rate. In some sensor products, 1-hour radar precipitation estimates are provided for an area of responsibility approximately 4 x 4 km square grid resolution. It is not easy to compile consistent radar data for large regions such as that provided by satellite data.

Regional coverage of precipitation information is easier with satellite data because of the frequency in data archiving over a large area. Global and regional satellite sensing began with the TRMM (Chiu, 2002) with a spatial resolution of 0.25˚. However, with the advent of a new precipitation satellite mission called GPM, the accuracy of results has greatly increased to 0.1˚ every 30 minutes (Zhan et al., 2018). The new sensor can also measure light and heavy rainfall accurately at both local and regional coverage. And more recently, remote sensing and Geographical Information systems (GIS) have made it possible to have a new method of acquiring better analysis to estimate rainfall even in tropical environments (Jia et al., 2011;(C. Chen et al., 2015). The combination of satellite remote sensing and GIS technology has greatly enhanced the measurement accuracy of the precipitation (Boushaki et al., 2009; C. Chen et al., 2015), making it now possible to have a detailed characterization of the spatial distribution of the rainfall patterns and flood disaster prediction capacities. To incorporate precipitation information into the hydrological cycle, high-density rain gauge networks is a prerequisite to capture how heterogeneous are the components of hydrology. This study endeavours to downscale the aerial coverage to better accuracy of a 1x1km radius.

There is a model of climatic is related to downscaling. The models which widely been used is called General Circulation Model (GCM) and Regional Climatic Models (RCM). However, these two models cannot be used directly as a tool to measure and retrieve the climate variabilities such as rainfall measurements. To use them in this capacity will require the information to be broken down by what is called downscaling. There are several methods of undertaking downscaling processes, most of them are statistical and each differs one from another by the level of extreme events (Jia et al., 2011; Juneng et al., 2010). The downscaling data is very crucial as an input in the hydrological model and has been widely used in climate studies. The procedure of this downscaled technique is to attempt to solve the gap between the mismatch of the resolution. Various models have been developed to propose the relationship between atmospheric parameters with rainfall precipitation, especially Digital Elevation Model (DEM) and Normalised Difference Vegetation Index (NDVI) in statistical downscaling. (Jeong et al., 2012) conducted a downscaling study using a multiple regression approach with the help of the Principal Component Analysis (PCA) technique. To determine the predictor and predictand, spatial correlation or Pearson correlation method can be used to select the appropriate sensible and realistic model. Presently, downscaling is used in improving the grid precipitation when a higher resolution environment parameter is absent. This approach is being conducted in the study area to strengthen the relationship between rainfall and its variabilities with multi regression. This became necessary because previous assessment using TRMM products revealed poor correlation with gauge data due to poor detection of light rainfall, resulting generally in an underestimation of the total rainfall. As mentioned earlier, the higher spatial resolution rainfall data is essential for environmental studies, and it can be greatly improved by establishing the statistical model between precipitation and environmental factors (Jia et al., 2011).

There have been the previous study made by (Amirabadizadeh et al., 2016) which applied the use of the statistical downscaling procedure to bridge the difference between spatial on-grid and sub-grid box methods in Peninsular Malaysia. However, the statistics used were the multi-scale type that revealed the relationship taken from observation of environmental predictors that led to the production of the multi-scale rainfall field (Fowler et al., 2007). Downscaling is a good procedure to obtain enhanced predictions even for local-scale data from a global scale. Generally, downscale is either linear, exponential or polynomial models. To get the correlation between gauge observation and satellite-based information requires other additional parameters in higher resolution to downscale the precipitation. (F. Chen et al., 2014a; S. Xu et al., 2015) studies have used Vegetation indices and topography information are the variables that have been widely used as an additive to downscale the TRMM rainfall products. The relationship between the parameters as dependent variables and the rainfall rate as independent variables is being established using multiple linear regressions. A study by Immerzeel et al. (2009) extended the multiple regression to the polynomial and exponential relationship to find the best fit correlation between NDVI and rainfall for environmental applications. To this end, the use of satellite observation has proved to be the most practical tool with which suitable models are determined for the measurement of the impact of downscaling rainfall on high-resolution maps. This research study showed the different varieties of rainfall rates between different models used to downscale the rainfall estimation.

1.3 Problem Statement

Based on the background study, the issues can be highlighted as follows.

GPM is a new mission that provides a better spatial resolution of 0.10˚ x 0.10˚ compared to the previous TRMM of 0.25˚ x 0.25˚ (300 x 300km^2). To develop a location-based downscaling model that makes use of multi regression is different from using single and linear regression which could not provide the locality estimation accurately.

Several authors have applied downscaling methodology, which involved interpolation and aggregation procedures to increase the spatial resolution of satellite-based precipitation predictions (Cheema & Bastiaanssen, 2012; S.-T. Chen et al., 2010; Quiroz et al., 2011). Today, many sources of geoscience information are used as supporting parameters to retrieve the rainfall measurements in higher spatial resolution in the downscaling process. Some of the information is extracted from NDVI, EVI, temperature and elevation data. All these parameters said having positive correlates with rainfall and other climatic data. So far most studies have applied the use of NDVI as a proxy for downscaling precipitation while others used regression analysis with spatial model parameters (Z. Duan & Bastiaanssen, 2013; Fang et al., 2013; Park, 2013). Thus, this study is taken GWR as an additional tool of the linear regression method in combining two possible parameters as a proxy of different locations.

Kelantan, the study area, has a complex topography with spatial heterogeneity. This makes the rainfall pattern differ from one region to another and gives rise to heterogeneity spatial bias concerning the area and location covered which is required to be resolved to acquire accurate rainfall measurement with high resolution. Benefiting from the high spatiotemporal resolution and near-global coverage, satellite-based precipitation products are applied in many research fields. However, the applications of these products may be limited due to a lack of information on the uncertainties. it is crucial to quantify and document their error characteristics otherwise rainfall results will be either overestimated or understated.

Due to the measurements, the result will experience huge errors. To minimize those issues, the spatial downscaling with the potential model is chosen for this study.

Previous satellite data such as the TRMM and Precipitation Radar (PR) product were used for an improved resolution to 1km by the downscaling procedure which used exponential regression and quadratic polynomial regression as explained by (Z. Duan & Bastiaanssen, 2013; Immerzeel et al., 2009). On the other hand, Fang et al. (2013) applied the use of meteorological parameters in multiple linear regression to fit the regression model of downscaling. Based on all these studies, it became clear that the fundamentals of downscaling are based on the regression model and the auxiliary variables. However, the regression model between the proxies used were all based on the assumption of spatial stationarity in the relationship which is still under research (Foody, 2003). Many studies (Bordoy & Burlando, 2014; Immerzeel et al., 2009; Jia et al., 2011; Quiroz et al., 2011; Shi & Song, 2015) have used TRMM as the primary satellite data to downscale the rainfall to finer resolutions. Even though TRMM has operated for over 2 decades, it still has a limitation in detecting either very light or very heavy rainfall. It also could not measure light rainfall ranging (<250mm/month) (Friesen et al., 2017; Shi & Song, 2015; Zhan et al., 2018). Based on (Liu et al., 2018), stated annual precipitation derived from original TRMM products is overestimated as compared to observed precipitation during the 2001–2014 period. Overestimation and underestimation are more likely to occur in the relatively wet and relative dry regions, respectively after the data are calibrated with observed precipitation data. Estimating light rainfall is critical to the earth ecosystem due to the high occurrence rate. For heavy rainfall, TRMM product such as TMPA over detects heavy rainfall events. As stated in the (Prakash et al., 2016) study, he stated GPM IMERG shows promising results in the rainfall model especially in detecting light rainfall. Due to the problems mentions above, this study is designed to test how the GWR model can tackle the spatial stationary issue and was expected to give a better correlation between the rainfall and auxiliary variables. As was highlighted by NASA approaches, to acquire reliable information of light precipitation is by the use of GPM at both regional and local scales (Wei et al., 2018).

1.3.1 Research Questions

This research study will be able to answer the following research questions;

(a) How can a local downscaling method be developed that applies multi and single variables to estimate rainfall at the spatial resolution of 1 km ?

(b) How can the assessment of the impact of spatial variabilities of rainfall be made on a local rainfall parameter using downscaling?

(c) Which approach best evaluates the quality of downscaled rainfall products to differentiate light and heavy rainfall?

1.3.2 Research Objectives

This study aims to downscale the satellite-based rainfall (GPM) grid data to 1 km resolution using the appropriate statistical technique over the Kelantan state. The objectives of this study are:

(a) To develop a local downscaling method using multi and single variables to estimate rainfall at 1 km spatial resolutions by using linear regression method (GWR) modelling based and non-linear regression method.

(b) To assess the impact of spatial variability on local downscaled rainfall algorithm in the different sensors considering the different spatial resolutions from TRMM (25km) and GPM (10km).

(c) To evaluate the quality of downscaled rainfall data with rain gauge measurements in differentiating the light and heavy rainfall based on the residuals value.

1.4 Significance of the Study

Satellite-derived precipitation information has been used widely to achieve an accuracy of 25km spatial resolution. However, this resolution is not good enough for practical hydrological studies as well as for forecasting. The spatial and temporal reliable information of precipitation is crucial for accurate modelling for agriculture and floods. Accurate knowledge of the amount of annual and monthly precipitation with high reliability is crucial for mitigating strategies of natural hazards and disaster risk reduction. Furthermore, this study increases our understanding uses of rainfall for hydrology and water resource management especially for regions without sufficient ground rain gauges.

The model in retrieving the rainfall measurements derived parameters can be established as a tool for flood and weather forecasting modelling as it can provide critical information of a region where the gauge information is unavailable, especially in the mountainous and rural areas. The information of the accurate amount of heavy and light rainfall at high spatial resolution (1km) from this approach could be used to provide hazard warnings for areas that lie at risk. Warnings could be issued with greater accuracy and in a timelier manner to enhance environmental management and possibly save lives. Therefore, this study is very useful in analysing the relationship between the rainfall and proxy parameters chosen in downscaling modelling since rainfall precipitation is an essential part of the hydrological cycle, flood monitoring and also in disaster management study.

Due to rapid urbanization, which sometimes involves reclamation exercises of land from the sea and the issues of continuous rainfall, especially during the monsoon seasons, flood events may likely occur. This is why the addition of topographic elevation data used in this study is another variable that has the potential to help in improving the water tides management and building of embarkments for water volume study. This study is expected to be of great benefit to the public as well as decision-makers under the National Policy on the Environment and Disaster Management where they can derive useful information of the present and forecasting of the rainfall and flood event in the cities as well as the rural areas through the development of satellite rainfall indicator. From the study, future studies on the estimation of rainfall at very high resolution can be accurately estimated. Accurate forecasting of rainfall is always demanded by related agencies as it is one of the most important issues in hydrological research. Rainfall forecasting involves complex data patterns, either linear or non-linear.

1.5 Study Area

Kelantan state is located on the east coast of Malaysia covering a total area of 1500 km^2. This region receives a significant amount of rainfall throughout the year due to its geographical location. The measurements record is based on the direct gauge measurements distributed at 60 stations around the state. This data is controlled by the Department of Irrigation Drainage (DID). Kelantan experiences the North-East Monsoon, which usually hits the East coast around November – February. The monsoon comes with non-stop heavy rain and sometimes causes episodes of flooding events (Sabena, 2012). As a consequence of frequent precipitation, the region has a high percentage of vegetation cover, estimated to cover an area of about 862,196 hectares. The predominant land use is agriculture, paddy and mixed agriculture. The rainfall distribution in Malaysia is highly dependent on wind flow. The local climates are influenced by the mountain ranges throughout and climate changes at the highland, lowland and coastal regions. Temperature ranges between (23-32^{0}C) and precipitation range from 10-30 centimetres on monthly estimates. Figure 1.1 shows the study region with a distribution of rain gauge station overlay with the Digital Elevation Model (DEM) of Kelantan.

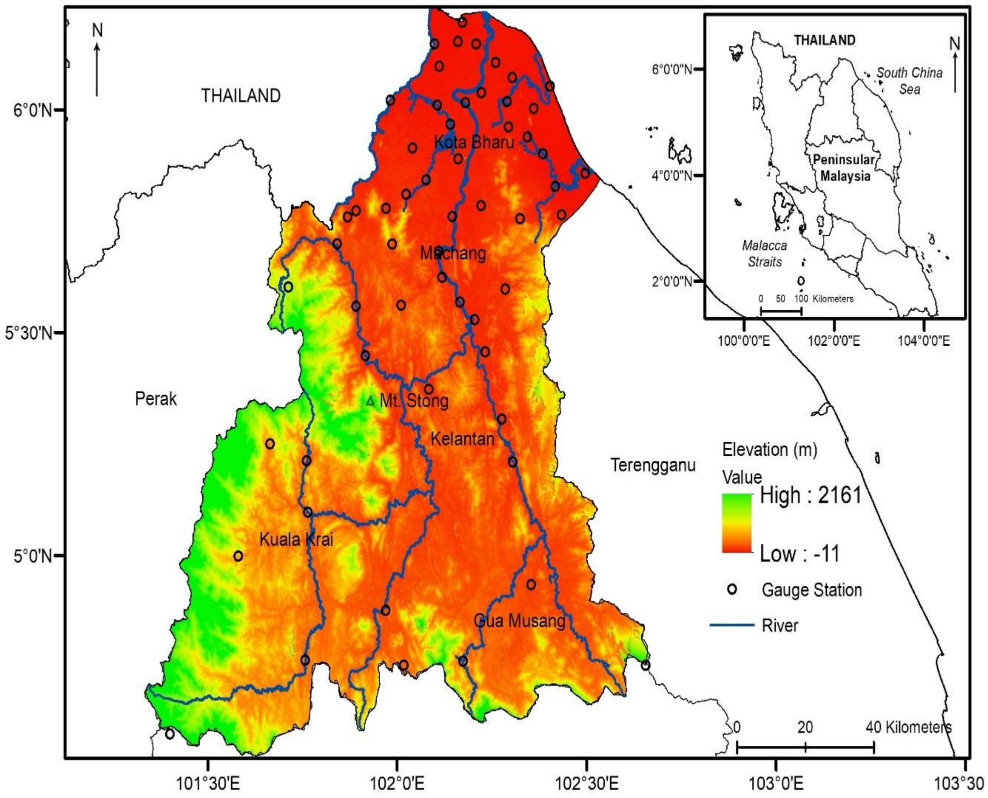

Figure 1.1 The study region and locations of gauge station

1.6 Scope of the Study

To achieve the objectives, of the study, the first part focuses on the retrieval of high spatial rainfall data using NDVI and DEM as the geospatial parameter for rainfall estimation. These two parameters are considered since limitation in getting another atmospheric variable in the study area such as humidity. This study also focuses on the calibration of downscaling model based on these two parameters NDVI and DEM.

NDVI is chosen as the parameters in downscaling technique based on the assumption that precipitation can be simulated by vegetation and topography proxies at various spatial scales. However, the non-stationarity of the relationship between precipitation and vegetation or topography has not been appropriately considered when low-resolution satellite precipitation datasets are downscaled using NDVI and DEM in previous studies. The NDVI data used in this study is derived from the atmospherically corrected reflectance in the red and near-infrared wavebands of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard the Terra satellite.

The DEM data used in this study was provided by the Shuttle Radar Topography Mission (SRTM) operated by the National Geospatial-Intelligence Agency (NGA) and the National Aeronautics and Space Administration (NASA). Considering the spatial scales of this study, we downloaded the DEM images with a spatial resolution of 90 m and then re-sampled them to 1 km by calculating the mean values of all pixels within each 1 km pixel.

The second part deals with the comparison and the improvement of the GPM approach when compared with the TRMM estimation. Satellite-derived data from TRMM and GPM were both used, although at different spatial resolutions. NASA webpage, which describes the GPM as a better alternative to TRMM, forms the inspiration to use GPM IMERG data as a new product that began to be used in 2016, dovetailing with the period of observation for this study which started in October 2016 during the wet monsoon season. TRMM data is being chosen based on the date and time of GPM data to meet the same temporal resolution to minimize the temporal variability of the satellite data itself.

The study has focused on the Kelantan state where rain gauge stations are sparsely distributed. Since the northern part of Kelantan having less coverage of rain gauge, thus the interpolation method of gauge measurement is limited and does not cover the particular part. Since Kelantan is having a flash flood in 2004 due to non-stop light rainfall and heavy rainfall has hit the Kelantan area thus Kelantan is chosen as the main study area for this research study.

1.7 Thesis Organization

To achieve the listed objectives of the study, Chapter 2 reviewed the literature that has a relationship with the niche of the study. It started with a brief description of rainfall and focusing on the rainfall as the type of precipitation. Then, this chapter also explained the existing methods that are used for estimating the amount of rainfall using satellite-data rainfall information. Further, this chapter introduces spatial downscaling procedures. Each of the objectives listed is addressed by adopting the research method has explained in Chapter 3. Chapter 4 presents the results of the operation of the methodology and Chapter 5 discusses and conclude the thesis with the recommendation as well.

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Ramlan,Emi. Reba,M.N, 2018, Statistical Downscaling Technique of Global Precipittion Measurement (GPM) Precipitation Using Satellite Derived Vegetation and Topographic Data. Asian Association of Remote Sensing (ACRS)

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