GEOGRAPHICAL WEIGHTED REGRESSION (GWR) RAINFALL SPATIAL DISTRIBUTION AND VARIABILITY IN MALAYSIA

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Civil Engineering

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"GEOGRAPHICAL WEIGHTED REGRESSION (GWR) RAINFALL SPATIAL DISTRIBUTION AND VARIABILITY IN MALAYSIA"** was prepared by **CHEW KIM SOON** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Civil Engineering at Universiti Tunku Abdul Rahman.

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ABSTRACT

The aims of this study are to compare the spatial interpolation methods and study the rainfall patterns in Peninsular Malaysia. Geographical Weighted Regression (GWR) and Multiscale Geographical Weighted Regression (MGWR) were used to analyse the monthly rainfall data. The GWR is an extension of the traditional linear regression model as it is using the spatial (x, y) coordinates to build up a relationship between location and other parameters. The MGWR is a further improvement of the model of GWR; in which it removes the constraint of all analysis and is modelled using different spatial scale with different bandwidth. Moreover, MGWR allows the range of data-borrowing to vary across the parameter surfaces so that the scale of the independent variable, and dependent variable will not be inconsistent across the analysis. The daily rainfall data for Peninsular Malaysia during 1988-2017 was acquired from the Department of Irrigation and Drainage (DID) for the analysis. The missing rainfall data was repaired in order to increase the estimation accuracy of both methods. The monthly rainfall data, number of wet days and maximum daily rainfall were extrapolated from the daily rainfall data. After that, the rainfall data was broken down into 6 sub-parts, with each part being of a length of 5 years. The root means square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) were used to evaluate the GWR and MGWR to study the accuracy for predicting the monthly rainfall. Besides, the rainfall stations were zoned into four regions such as northern region, east coast region, southern region and central region, in order to further study the accuracy of both methods in different regions. The results shown that the MGWR has a better performance compared to GWR in the estimation of rainfall data of Peninsular Malaysia as a whole, or as zoned into the four regions, as MGWR has higher R^2 and lower RMSE and MAE compared to GWR in all cases. During the peak of the Northeast Monsoon, which are November, December and January, the high average Number of Wet Days and Maximum Daily Rainfall contributed to high average Monthly Rainfall at the northeast region of Peninsular Malaysia. From May to September, the average Monthly Rainfall was high at the northern region of Peninsular Malaysia due to the contribution of high Number of Wet Days. The

rainfall was found only be concentrated at the northern region of Peninsular Malaysia during the Southwest Monsoon, due to most of the rainfall being block by the island of Sumatra, Indonesia. The average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall from January to December were also divided into 5-year periods. It was noticed that the major issue was the effect of increasing average Monthly Rainfall becoming significant in the month of December and January in the year 2013-2017, when comparing with sub-period of year 1988-1992, 1993-1997, 1998-2002, 2003-2007 and 2008-2012.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS / ABBREVIATIONS

AIDEW	Areal Inverse Distance and Elevation Weighting
AIDW	Areal Inverse Distance Weighting
CLR	Cluster-wise Linear Regression
DID	Department of Irrigation and Drainage
GWR	Geographical Weighted Regression
GWRE	Geographically Weighted Regression with Elevation
GWRS	Geographically Weighted Regression with Slope
IDEW	Inverse Distance and Elevation Weighting
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
MGWR	Multiscale Geographical Weighted Regression
MLR	Multiple Linear Regression
OK	Ordinary Kriging
OLS	Ordinary Least Square

d	Index of Agreement
MAE	Mean Absolute Error
NSE	Nash-Sutcliffe Efficiency
R^2	Coefficient of Determination
RMAE	Relative Mean Absolute Error
RMSE	Root Mean Square Error

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 General Introduction

Rainfall is the most significant element in the hydrological cycle and acts as the primary source of water to the earth's surface. The global climate's change is always one of the main reasons which cause the variation of rainfall over the land area. The intensity, amount, frequency and type of precipitation can be affected by climate change. Therefore, the prediction of rainfall should be carried out, taking into cognizance the impacts of climate change, in order to estimate the rainfall data so that the engineer can make preparation for the flood and drought precaution planning.

Spatial interpolation modelling is an important improvement in the hydrological engineering field as it will help to estimate the missing rainfall data which are a result of manual estimation errors, data retrieval management problems or faulty electronic rain gauge, or some other possible cause. There are several spatial interpolation modelling methods that have been used widely in estimating the missing or faulty rainfall data such as the multi-scale geographical weighted regression (MGWR), geographical weighted regression (GWR), inverse distance weighting (IDW) and the ordinary kriging (OK). The GWR model is able to carry out the estimation of spatial rainfall by integrating the geographical location, altitude and other factors, and shows the non-stationary relationship between rainfall and the factors. The MGWR is the extension of the GWR where it allows the spatial scale of the relationship between the response variable and predictor variables to be different. Other than that, the IDW is the deterministic interpolation method, which uses the principle of two points would have similar properties when they are getting closer. In contrast, the OK is the geostatistical interpolation method and able to provide the unbiased estimation of variables by spatially autocorrelating all the available data.

Several studies had been carried out by the past researchers to determine the performance of spatial interpolation method in Malaysia and other countries. The GWR model has the ability to calculate distances between a certain number of observing points and the investigated point, and use it as a weight (Wang, et al., 2017). However, the MGWR has a better performance compared to the GWR model because the characteristic of the MGWR allowed the scale to be varied instead of using the same spatial scale as this will improve the estimation become more accurately (Yang, et al., 2019). The OK model is able to produce a rainfall data which is more consistent with the natural rainfall compared to the IDW model because the IDW model only focuses on the distance between the estimated point and the observed point, but it does not take care of the spatial dependence rainfall pattern (Pellicone, et al., 2018).

Che Ros and Tosaka (2018) had carried out research in Kelantan, Malaysia using the IDW, Inverse Distance and Elevation Weighting Method (IDEW), Areal Inverse Distance Weighting Method (AIDW) and Areal Inverse Distance and Elevation Weighting Method (AIDEW). Their results have indicated that elevation is the main variable, and the watershed should be divided into the smaller segments to enhance the estimation accuracy of rainfall data in Kelantan. Narashid, et al. (2017) had also carried out research in Peninsular Malaysia to estimate the performance of the ordinary least square regression (OLS) and the GWR. Their results have indicated that the GWR model gave a superior performance that the OLS model because the OLS model only can demonstrate the relationship between the variables over a global scale. The earlier study had indicated that the performance of spatial interpolation method could be further studied in order to determine the best spatial interpolation model for use in Malaysia.

According to Chinnasamy and Ganapathy (2017), the Department of Irrigation and Drainage (DID) has indicated that Malaysia should be facing the problem of increasing flood and drought issues in 2020 and beyond, due in part to climate change impacts and to the increasing population and higher per capita water in urbanizing cities which has been causing more stress on water availability, respectively. However, rainfall is significantly related to floods and droughts. The spatial information enables the process to predict the missing rainfall in order to facilitate the potential locating of the water infrastructure project so that small dam and reservoir are able to build in the right place in order to store flood and save surface water for drought seasons, respectively. Therefore, the aim of this research is to figure out the most suitable spatial interpolation method to predict missing rainfall data in Malaysia.

1.2 Importance of the Study

Climate is one of the important components in the earth's weather system. The climate and weather are a result of the multilateral contribution from many parameters such as rainfall, atmospheric pressure, temperature and humidity etc. The climate change will bring significant effects to the long-term rainfall pattern, thus consequently affecting the availability of water. It will also cause calamities and consequential damages to the people, such as increasing the frequencies of floods and droughts occurrence. Both rainfall and temperature are the most significant fundamental physical parameters among those affecting climate. This is because the condition of environmental of a particular region is determined by these parameters and will affect human activities such as agriculture productivity and hydroelectricity generation.

Accurate and complete climatological data is important for the water resources system design and drainage system design. The improvement of technology such as automatic weather station has been introduced to the world in order to record the rainfall data in shorter time-scale measurement such as over a minute or hourly value. However, the traditional manual mode of measurements or electronic sensors may also inevitably lead to some faulty or missing data. The development of spatial interpolation methods is to fill in the gaps of missing data in order to get the rainfall data as accurate as possible, for future development.

Floods and droughts will cause heavy impacts on the population in terms of life inconveniences and property damages. The occurrences of floods and droughts are inevitable, tied to a significant relationship with the rainfall. Heavy rainfall will lead to the occurrence of flooding, whereas conversely, the low rainfall density will lead to the occurrence of drought. Hence, accurate rainfall records are important for future planning in order to prepare and mitigate the natural disasters resulting from climate change. However, the rainfall data over the complex terrain is difficult to record, and the rainfall pattern may vary in different regions. Therefore, it is difficult but nevertheless essential, to have complete and accurate rainfall data set for future planning for a particular region. The implementation of spatial interpolation model is helpful and important to estimate the rainfall data accurately for efficient and timely drainage systems planning and water resources planning.

1.3 Problem Statement

According to the Intergovernmental Panel on Climate Change (IPCC) (2012, cited in Chan et al., 2018), the regularity of occurrence of extreme climatic events such as storms, floods and droughts has increased worldwide in the recent decades. The properties, lives and livelihood will be threatened by climatic calamities in Malaysia as elsewhere, that are due to the natural phenomenon such as heavy seasonal rainfall, monsoon winds, river characteristic and human-related factors such as land-use change and rapid development. The floods have brought a significant loss of life and property damage, as indicated in the country's history. People have suffered huge damage to their properties, crops, and vehicles, along with indirect losses as a result of floods.

As a recent example, the Negeri Sembilan state has experienced heavy rainfall on 13 July 2020, which caused the breaking of a riverbank, and the drainage system has been overwhelmed with floodwaters. The flooding effect has affected three cities in Negeri Sembilan which is Port Dickson, Rembau and Seremban. 282 victims were evacuated to relief centres located in Seremban and Port Dickson. The Linggit River located at Sua Betong, Port Dickson had risen by 3 metres in a few hours, and it had reached a peak of 7.2 metres that has far exceeded the danger level of 5.8 metres (The Star, 2020). Elsewhere, similar situations are repeated.

There was another flooding event that had occurred in Malaysia at the end of November 2019, during the normal seasonal rainfall period. The significantly higher rainfall on 26 November 2019 had resulted in severe flooding in four states in Peninsular Malaysia, and there are the states of Terengganu, Kelantan, Pahang and Johor. This event had displaced approximately 15,000 families across Peninsular Malaysia. This rainfall event continued over the following weekend of 30 November 2019 and subsequently affected more districts. The number of evacuees in Kelantan has increased significantly from 4, 177 families to 12,087 families (IFRC, 2019).

It is noticed that the study on rainfall distribution patterns should be carried out in order to design mitigation procedures to manage the annual flooding events in Malaysia. The distribution of the rainfall may vary from time to time now even more so with having to consider and deal with the climate change phenomenon. Therefore, the rainfall distribution pattern should be frequently studied in order to track the rainfall trend in Malaysia more closely in the era of global climate change.

1.4 Aim and Objectives

This study aims to investigate the varying rainfall distribution patterns in Peninsular Malaysia for a reliable spatial representation of rainfall. The objectives of this study are:

i. To evaluate the estimation's accuracy of the spatial interpolation methods for rainfall interpolation in Peninsular Malaysia.
ii. To generate spatial distribution maps using spatial interpolation model and analyse the rainfall's spatial change in Peninsular Malaysia for corresponding periods.

1.5 Scope and Limitation of the Study

The scope of this study is to determine the spatial distribution of rainfall in Peninsular Malaysia during 1988-2017 historical period. The analysis of this study is to carry to evaluate the accuracy of specifically the GWR model and the MGWR model for completing the rainfall data sets for hydrologic use thereafter.

A denser network of rainfall stations is important in order to get accurate rainfall data in Peninsular Malaysia. However, the limited installation of rainfall stations in Peninsular Malaysia, especially in complex terrain, will be one of the limitations in this analysis. It must be acknowledged that setting up meteorological stations is a costly affair and the maintenance of such facilities poses even more problems both technical and logistically, therefore, the historical data recorded of that particular area will be interpolated in the analysis. The second limitation is the missing or faulty data recorded at the rainfall stations. Given the complexities, however, these data need to be corrected and completed in order to carry out the meaningful follow-up analyses. The missing of rainfall data may be caused by the natural disasters, equipment conditions over the years, the unfriendly environment where they are set up and of course uncalled for human and animal's activities and disturbances.

1.6 Contribution of the Study

The improvement of spatial interpolation methods is to enable better tracking of the rainfall pattern in Peninsular Malaysia. This has helped to benefit the potential collaborators such as the DID and hydrological engineering fraternity, to understand the rainfall trend in order to enhance the design of the drainage system and reservoir. In order to prevent flooding and drought occurrences in the urban areas, an understanding of the rainfall patterns can help to improve in the designing of water resources systems and drainage systems, thus contributing to mitigation works. In conclusion, a clearer and accurate rainfall pattern provided can help to benefit society by enhancing the drainage system and water supply technologically.

1.7 Outline of the Report

The rainfall characteristic and climate pattern in Peninsular Malaysia is shown in this report. It is important for the local researchers and authorities to take care of the importance of spatial rainfall distributions to prevent flooding and drought occurring in Peninsular Malaysia. There are two main methods that will be discussed in this report which are the GWR and the MGWR models, both slightly related. The performance of these two spatial interpolation methods will be evaluated to find out the better model suitable to predict the missing rainfall data in Peninsular Malaysia. Papers of past researchers about the rainfall interpolation method have been reviewed in this study to enhance the understanding and accuracy of the GWR and the MGWR methods. The data acquisition and procedure of conducting the analysis is shown in the methodology section, which will also describe the workflow of the analysis in order to make a comparison for both the GWR and MGWR models.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Rainfall data is important for decision making in many sectors, including in the engineering and agriculture sectors. Several spatial interpolation methods had been employed in order to estimate the missing rainfall data accurately. In this chapter, the GWR, MGWR, IDW, OK, Cluster-wise Linear Regression (CLR) and Multiple Linear Regression (MLR) methods used in the hydrological and meteorological sectors shall be reviewed. Different parameters and study areas shall be investigated for every method in order to ascertain their precision.

2.2 Geographical Weighted Regression (GWR)

The GWR method has been widely adopted for studying of georeferenced data since the introduction to geographical and spatial econometric literature by Brunsdon et al, and McMillen in 1996 (Pa¨ez, et al., 2011). According to Fotheringham (2001 cited in Tu and Xia, 2008), the GWR has extended the traditional framework of the standard regression which in this method locally estimation rather than globally estimation was allowed for. It helps to show the relationship of local parameters and to get some information of the potential cause of spatial pattern by having an examination of the local estimation of spatial pattern. Past researches were done in order to evaluate the performance of GWR, and this will be discussed below.

Kumari, et al. (2016) had carried out research at the Central Himalayas, India to compare the accuracy of the GWR, GWR with elevation (GWRE), GWR with slope (GWRS), GWR with terrain ruggedness index (GWRTRI) and the OLS. Annual rainfall, seasonal rainfall, elevation, slope and terrain ruggedness index (TRI) were chosen as variables for the research. Coefficient of determination, Wilmott’s index of agreement (d), mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE) were employed to evaluate the performance of these methods. The results have shown that the RMSE and MAE of the GWR were lower than those of the

OLS model, and the higher NSE and d value of the GWR compared to the OLS model has shown that the GWR has higher precision than the OLS model. The research also proved that using a slope as an input variable can help to provide a better result compared to that with elevation and TRI. Pearson's correlation coefficient, r also increased from 0.42 to 0.68 when the rainfall data was gathered into lowland and upland. This indicated that apportioning of the rainfall data at a complex terrain into a smaller segment can help to improve the linear relationship between the parameters.

Kumari, et al. (2017) also came out with another research at the Indian Himalayas of Uttarakhand region using the models of Ordinary Co-Kriging (OCK), OLS, GWR, GWR-Kriging (GWRK) and Stratified GWR-Residual Kriging (s-GWRK). The parameters used in this research were the annual rainfall and elevation. The methods above were evaluated using the same methods as in the previous research in 2016, which are the RMSE, MAE, NSE and d. The results showed that the s-GWRK model's performance was much better when compared with OCK, OLS, GWR and GWRK. The s-GWRK has shown higher d value and lower RMSE at both Ashburton and Bhutan. The NSE of the s-GWRK also showed an enhancement of 10% in comparison with the GWRK. The MAE of s-GWRK also has the lowest value among the other methods.

Lv and Zhou (2016) carried out research at the Qaidam Basin of China. The GWR and the raw-and-unsampled 3B42RT from the Tropical Rainfall Measuring Mission (TRMM) were evaluated by using daily rainfall, monthly rainfall and elevation as input data. These 2 methods were evaluated by using the root mean square error (RMSE), mean error (ME), MAE and relative mean absolute error (RMAE). The Lower value of RMSE, MAE and RMAE showed that the GWR has higher accuracy of estimation compared to the raw and resampled 3B42RT data for both daily rainfall and monthly rainfall. But however, the ME and RME were slightly higher compared to the 3B42RT model. The superiority of using the GWR was that the GWR was able to carry out the integration theoretically for geographical location, altitude and other factors related to spatial rainfall estimation in order to present the relationship of non-stationary spatial. The non-spatial relationship between other factors and rainfall also reflected in when using the GWR model. This made the GWR different from other traditional precipitation interpolation method as the GWR provide not only high accuracy estimation, but also provided a clear image of precipitation spatial distribution characteristics.

Georganos, et al. (2017) conducted a research using the normalized difference vegetation index (NVDI) and the seasonal rainfall in Sahel, Africa. In this research, the performance of the GWR and the OLS were compared by both the RMSE and coefficient of determination, R^2. The value of R^2 for the GWR model was between the range of 0.84 to 0.88, which was higher than the R^2 value of the OLS model, which had ranged between 0.60 to 0.70. The RMSE of GWR were 0.18 and 0.24 in 2002 and 2012 respectively, and were lower than the RMSE of OLS at 0.30 and 0.39 in 2002 and 2012 respectively. This had shown that the GWR has a better performance compared to the OLS. This was because GWR model can measure the variability within the classification of land cover, and take into account for the species configuration and dissemination and other factors such as soil type, human interruption of ecological communities and climate.

Another research carried out by Narashid, et al. (2017) in Peninsular Malaysia was comparing the GWR model and OLS model. The parameters used were the NVDI and annual rainfall. Performance of both methods was evaluated using the R^2 and Akaike Information Criterion (AIC). The results had shown that the value of AIC is lower, and the value of R^2 is higher for the GWR model compared to the OLS model. This explained the GWR model was able to explore the non-stationary spatial variable locally, whereas the OLS model only can determine the relationship of related variables at a global scale. The extremely low R^2 (0.01 in 2000 and 0.04 in 2011) demonstrated that the OLS model was not able to determine the spatial variation of rainfall accurately.

One of the researches carried out in China was by Wang, et al (2017) who had used the Kriging, IDW, Spline, Multiple Linear Regression (MLR) and GWR methods. The parameters used in this research were the NDVI, monthly near-surface air temperature (NSAT), daily near-surface air temperature (NSAT) and elevation. All of these methods were evaluated using the RMSE and R^2. The GWR has lower RMSE, and higher r^2 compared to the MLR and indicated that the GLR has a better performance in predicting the

NSAT in all the months at large scale, compared to the MLR. This was because the GWR model was able to calculate the distance between numbers of the observation points, and the distance was used as a weight. This has made a difference with the MLR as the MLR made an assumption on the relationship between the vulnerable variable and supplementary variable to be constant over space. The results also showed that the GWR has lower mean RMSE and higher mean R^2 compared to the Kriging, Spline and IDW. Overall, the GWR model had shown better performances compared to the MLR, Kriging, Spline and IDW in predicting NSAT.

In order to carry out the performance evaluation of GWR and OLS, Mallick, et al. (2018) also carried out another research at Aseer, Saudi Arabia using parameters of monthly rainfall data and elevation. R^2, AIC, RMSE and MAE were used to evaluate the accuracy of GWR and OLS. The results showed that R^2 of GWR was higher than OLS method for all four years. The range of R^2 for GWR was between 0.86 to 0.94, however, the range of R^2 for OLS was only between 0.22 to 0.35. The AIC value of GWR was also lower than OLS model. Moreover, the RMSE and MAE of GWR were smaller than OLS, which indicate that GWR model has higher accuracy compared to OLS. This was because the GWR model will take into account the local characteristics, but OLS model assumed constant relationship over an extensive area with high spatial heterogeneity and led to miscalculating of elevation with low value.

2.3 Multiscale Geographical Weighted Regression (MGWR)

The MGWR model is an upgraded version of the GWR as it allows the model to vary with different spatial scale. The GWR does not allow for the operation of a process over a local scale and another to contact over a regional scale. However, for example, the operation of the reaction of rainfall on vegetation density occur at a spatial scale, but the relationship between rainfall effect with other variables may occur at a different scale (Fotheringham, et al., 2017). Therefore, the introduction of the MGWR is important to study the relationship of real-life variables as the MGWR allow conditional relationships to operate at different scales among the response variable and predictor variable according to Yang (2004, cited in Fotheringham et al., 2017).

Fotheringham, et al. (2019) had carried out a research in China using the method of the OLS, OLS with spatially lagged dependent variable (OLSL), GWR, GWR with spatially lagged dependent variable (GWRL), MGWR, and the MGWR with spatially lagged dependent variable (MGWRL). The parameter used in this research was the air quality index (AQI), and the accuracy of the methods above were evaluated using the residual sum of squares (RSS), MAE, corrected AIC (AICc), and coefficient of determination, R^2. The result showed that MGWRL has higher R^2 and lower RSS, MAE and AICc compared to OLS, OLSL, GWR, GWRL and MGWR. This is because the MGWRL is a combination of MGWR and spatially lagged dependent variable. The characteristic of MGWR provides covariate-specific bandwidths in order to be improved instead of using the same bandwidth and applied to every relationship between the variables. The performance of the MGWR, GWR and OLS also improve by adding the spatial lag variables. However, the improvement of MGWRL is slightly higher compare to MGWR, and this indicates that MGWR had done better in taking into account the spatial dependency in the error term compared to the OLS and GWR.

Another research conducted by Liu, et al. (2019) at Wuhan, China used the MGWR, GWR and OLS. The variables used in this research were the land surface temperature (LST), fractional vegetation cover (FVC), albedo, water percentage (WP), building density (BD), building height (BH) and building volume density (BVD). Evaluation methods used were the R^2, AICc, and RSS in order to determine the estimation's accuracy of these models. The R^2 of the GWR model was higher than the OLS model, especially during winter as the R^2 increases from 0.5302 to 0.8681. The r^2 of the MGWR further outstrip the R^2 of the GWR despite the fact that the difference was not large during summer and transition seasons. The AICc and RSS also declined in the order of the models of the OLS, GWR and MGWR, showing an improvement in model fitting. This has shown the significance of scale in analysing the non-stationary spatial association between the LST and other indicators by applying MGWR as GWR only provide the same spatial scale and using the same bandwidth across the analysis.

Yang, et al. (2019) had also carried out a research at Wuhan, China by using the NDVI, normalized difference built-up index (NDBI), and albedo as the input data. The RMSE and R^2 were used to determine the accuracy of the MGWR with area-to-point kriging (MGWRK), GWR and DisTrad model. The MGWRK had provided higher R^2 and lower RMSE in comparison to the GWR and DisTrad. This was because the MGWR interpret spatial fact more specifically by allowing the scale to be different along with the analysis. The second reason was that applying area-to-point kriging (ATPK) allowed the MGWR to avoid the “boxy effect” faced by the DisTrad model due to the adding back directly, the coarse resolution residual.

2.4 Inverse Distance Weighting Interpolation (IDW)

The IDW method is a deterministic spatial interpolation model which had been implemented in GIS packages and used by geoscientists and geographers. It is referring to the concept of the attribute value of two points are related between each other, whereas their affinity is inversely proportional to the distance between their location (Lu and Wong, 2008). According to Chen and Liu (2012), the IDW was developed based on the Tobler’s first law from 1970 as it defined everything has a relationship with each other, but the shortest distance will have the greater influence compared to those over long distances. The following are some of the research that had been conducted to evaluate the performance of the various interpolation methods.

Moeletsi, et al. (2016) has conducted a research at Free State Province, South Africa using the model of the Inverse Distance Weighting (IDW). Daily rainfall data was employed in this research, and the IDW was evaluated by using the R^2, MAE and mean bias error (MBE). The results showed that the R^2 for the estimated rainfall versus the observed rainfall for every station had ranged from 0.63 to 0.877. The MAE for all the station’s rainfall values is lower than 1mm, and the MBE value was -0.08mm, and it is low and slightly bias. The high R^2, low MAE and low MBE indicated that the IDW estimated the rainfall data accurately, and it was recommended for estimating the missing data in the Free State Province of South Africa.

Hazra, et al. (2017) also conducted a research in order to determine the performance of the Kriging, Inverse Distance Weighted (IDW) and Spline using weekly average rainfall data as the input. The study area of this research was located at West Bengal, India. All of the methods were evaluated using the mean absolute deviation (MAD) and mean squared deviation (MSD). The results had shown that the IDW method had the lowest MSD and MAD among the three interpolation methods. This data reflected that the average weekly rainfall was mainly determined by the distance between the sources and the observation points. The Kriging and the IDW use distance as a weighting factor. Therefore, kriging and the IDW showed more significance to the nearest data points. The difference between the IDW and the Kriging is that the Kriging is simpler where no statistical models are used so that it is easy to define and therefore, easy to understand the results. Unlike the IDW, the Spline was able to estimate surface values above and below the maximum and minimum values of average weekly rainfall whereas the IDW does not produce values higher than the maximum values because the information of observations decreases with distance from known points.

Che Ros and Tosaka (2018) had performed a research at Kelantan, Malaysia using daily rainfall data. The methods used were the IDW, IDEW, AIDW and AIDEW. They evaluated the performances using the RMSE and NSE. The range of RMSE was found, ranging from 0.05 to 78.5. This large range indicated that the RMSE was inadequate to evaluate the better interpolation method in this case. The NSE proofed that the IDW method has the minimum mean value of NSE, nearly close to zero. However, other interpolation methods illustrated a high mean value of NSE, which was close to 1. This showed that the accuracy of rainfall prediction in Kelantan, Malaysia can be enhanced by using elevation as a variable and also the need to divide the watershed into smaller portions in the interpolation.

Giarno, et al. (2020) had carried out a research at the Sulawesi Island using the daily rainfall data as the variable. The RMSE and R^2 were employed to examine the performance of the IDW and kriging models in the prediction of daily rainfall. Independent location, the Kriging was better than the IDW method mainly in both rain and dry season due to the lower RMSE. However, the IDW method was performed better than kriging as the higher r^2 will be obtained by IDW. During the rainy season, interpolation carried out has shown that the IDW has better result compared to kriging. Contrary, the kriging is illustrated a better result than the IDW in the dry season. It was clearly shown that the rainfall intensity had an effect on the conduct of the interpolation method, as it may result in the IDW being better than the Kriging. This is because the IDW assumes the nearest location has the most influence. Therefore, during wet periods, the rainfall intensity is higher, which can provide more accurate result if using IDW.

Lam, et al. (2015) also carried out a research in order to evaluate the estimation accuracy of IDW using monthly rainfall data at the Jornada Basin. This method was evaluated using the MAE, RMSE, ME and R^2. The ME for IDW was -7.811mm and -3.768mm for 1992 and 1994 rainfall data, respectively. The RMSE for IDW was 55.69mm and 32.36mm for the 1992 and 1994 rainfall data, respectively. The R^2 for the IDW was 0.1141 and 0.6373 for 1992 and 1994 rainfall data respectively, within the study area boundary. The MAE for IDW was 31.84mm and 17.67mm for the 1992 and 1994 respective rainfall data within the study area boundary. The RMSE for IDW is 43.65mm and 21.36mm for 1992 and 1994 rainfall data within the borderline of the study area. The results from constraining the boundary of the study area for rainfall-interpolation showed that the interpolation error could be reduced from the corner effects and produce a more accurate result of the estimated values which were nearer to the measured values.

2.5 Ordinary Kriging (OK)

The Ordinary Kriging method conducts spatial analysis based on the principle of geostatistical analysis. According to Varouchakis, et al. (2018), the geo-statistic is defined as a set of spatial statistics methods anticipated at predicting the physical variable distributed in space by using existing measurement. The Kriging has an advantage due to its flexibility compared to other interpolation methods as weights are chosen by kriging based on their role of the function across space. According to Kitanidis (1997 cited in Gupta, et al., 2017), the mean value is also provided by kriging in order to evaluate the magnitude of estimation error.

Pellicone, et al. (2018) conducted a research on the performance's evaluation of the IDW, OK, Kriging with an external drift (KED), Ordinary cokriging (COK) and the Empirical Bayesian kriging (EBK). The study area of the research was located at Calabria, southern Italy, and monthly rainfall will be used as the input data. All of the methods were evaluated using the MAE and RSME. The results showed that the KED is the best interpolation method for rainfall estimation in the Calabria region as the KED had the lowest RMSE and MAE compared to the other methods. The cross-validation's results have shown a fair indication of the practicality of kriging in the rainfall data's spatial interpolation. The IDW provided undoubtedly different maps when in comparison with the COK, EBK and KED method as it does not consider the arrangement of rainfall data's spatial dependence. This is because of IDW only the distance between prediction and observed locations. Contrary, the spatial distribution produced by OK, KED, EBK and COK interpolators, shown that the result is more likely with natural precipitation. The KED is better because it includes the altitude and distance to the shoreline as secondary information.

Gupta, et al. (2017) had carried out a research at the hot arid region and north-west semi-arid region of India using daily rainfall, monthly rainfall, annual rainfall, latitude and longitude as input variables. The ME, mean standardized error (MSDE), root-mean-square standardized error (RMSSDE), mean standard error (MSE) and RMSE were used to evaluate the estimation's accuracy of COK, spherical OK (SOK), exponential OK (EOK), Gaussian OK (GOK) and EBK. EBK and EOK were found that they have a similar value of ME, MSDE, RMSSDE, MSE and RMSE as they have smaller ME, MSE, RMSSDE, MSE and RMSE compared to other methods. The EBK and EOK were then compared for their certainty in spatially interpolating the annual rainfall for the India Meteorological Department (IMD) and Climate Forecast System Reanalysis (CFSR) datasets separately, and it was found that EBK has smaller RMSE for CFSR and IMD. This showed that the EBK has a better performance compared to EOK.

Rata et, al. (2018) conducted a research at the Cheliff watershed, Algeria. The objective of this research was to determine the accuracy of OK and lognormal kriging (log_OK) using Pearson correlation coefficient, RMSE, mean relative percentage error (MRE), ME and Lin coefficient of concordance.

The results have shown that the ordinary kriging Log method was suitable because the RMSE (62.08mm) is lower compared to RMSE (62.34 mm) determined by ordinary kriging. Although the difference is not significant, it is shown that the estimation error was minimized by using logarithmic transformation. The MRE and ME of the log_OK are lower than the OK model. The Pearson correlation coefficient for the kriging method is higher in comparison with the OK method. Lin's coefficient of concordance also showed that the agreement had passed the guideline, which is less than 0.65. The results have clearly shown that the log_OK method has better performance than the ordinary kriging as log_OK method takes into account the significant high data in the spatial prediction.

The purpose of the research carried out by De Carvalho, et al. (2015) at Brazil was to determine the accuracy of the Spatio-temporal model, OK and OCK. The input variable used was the daily rainfall data. All of the methods were evaluated using the Skill Score (SS) and MSE. The estimation of the spatio-temporal model has shown a result of 24.41% superior to the estimation predicted by kriging (SS1), and it is 17.77% better than the estimation of cokriging as referring to SS2 for the first date at the first zone. The result showed the same for the second date at a similar area as the spatio-temporal model was 32.12% and 26.16% better than OK and COK, respectively. The MSE for the spatio-temporal model is lesser than MSE of OK and COK in all case. This has shown that the spatio-temporal model is always better than OK, and COK, and the result will not be affected by the year of location.

Varouvhakis, et al. (2018) carried out a research at Crete, Greece, using annual rainfall as the input data. This research used the MAE, RMSE and mean absolute relative error (MARE) to evaluate the estimation’s accuracy of regression kriging (RK) and ordinary kriging (OK). The results have shown that the RK had the highest interpolation accuracy comparing to OK. The MAE, MARE and RMSE of RK were 42mm, 0.15 and 54mm respectively. It was lower than the OK, where the MAE, MARE and RMSE of OK are 63mm, 0.26 and 77mm, respectively. This is because the RK used the ground surface altitude as ancillary data to provide higher accuracy results compared to the OK.

2.6 Other Methods

In this section, the CLR, MLR and Artificial Neural Network (ANN) will be discussed. According to Bagirov, et al. (2017), the CLR is a combo of clustering process and regression analysis in order to solve the optimal partition of data simultaneously within clusters. The ANN is a non-linear model which is able to capture the non-linear relationship between the variable in order to predict the future scenario, and it has been commonly employed to predict time-series phenomena along with hydrological variables. The MLR is a linear model which has been used wisely to forecast the hydrological variables (Hossain, et al, 2019). The accuracy and performance of these methods are discussed in the following sections.

Adnan, et al. (2018) had conducted a research at Pakistan to evaluate the MLR model and the Principal Component Regression (PCR) model, using the method of MAE, RMSE, correlation coefficient (r) and bias. Seasonal rainfall was employed as an input variable in this research. The result showed that the PCR has a smaller mean bias, MAE ad RMSE compared with the MLR. The correlation coefficients between observed and predicted value for the PCR method are higher than the MLR methods; both for training and verification components of the method. This has shown that the PCR method has higher performance than the MLR method. This is because the PCR method transformed the original correlated variable into a new uncorrelated variable and combined with the regression technique. This has helped to reduce the error as the huge number of predictors in the MLR method will result in a highly unstable regression coefficient.

Chen, et al. (2017) also carried out a research at Fuhu River, China to evaluate the performance of the MLR and the principal component regression with residual correction (PCRR), with an additional method of the IDW model. Daily rainfall, hourly rainfall, longitude, latitude, elevation, slope and aspect were used as input variables, and the models were evaluated using the MAE, RMSE and MRE. The result indicated that the PCRR scheme has smaller RMSE, MAE and MRE compared to the MLR and IDW. The superior of interpolation effect of the PCRR compared to the IDW and MLR is due to the addition of terrain variables and the multicollinearity between the independent variables were taken into consideration will provide a better estimation accuracy using PCRR in prediction. The performance of the MLR method was slightly worse than the IDW method.

The performance evaluation of the CLR, cluster wise regression method based on EM algorithm (CR-EM), MLR, support vector machines for regression (SVMreg) and ANN using RMSE, MAE, mean absolute scaled error (MASE) and coefficient of efficiency (CE) was the subject of the research of Bagirov et. al., (2017). This research was located at Victoria, Australia. The input variables were the evaporation (Evap), maximum temperature (TMax), minimum temperature (TMin), monthly rainfall data, solar radiation (Rad) and vapour pressure (VP). The results have shown that the CLR model with a full set of five input variables such as TMax, TMin, Evap, VP and Rad to estimate the excellent predictions. This is because the increasing amount of input variables help in enhancing the performance of the CLR method, but it does not improve performance of SVMreg model. By taking Station Dimboola as an example, the RMSE of CLR was lowest, which is 19.7, but the RMSE for CE-EM, MLR, SVMreg and ANN were 21.1, 21.2, 23.2 and 21.6 respectively. Therefore, it was concluded that the CLR model was adequate for monthly rainfall estimation, and it is better than the CR-EM, MLR, SVMreg and ANNs models in most study area used in this study.

Hossain et. al. (2019) has conducted a research at Western Australia to evaluate the performance of the MLR and ANN using Pearson correlation coefficients (R), RMSE, MAE and Willmott index of agreement (d). Seasonal rainfall was used as the variable in this research. The correlation coefficients of MLR models were ranging from 0.35 to 0.83, and the ANN model was shown a better result, which had resulted in higher correlation coefficients ranging from 0.76 to 0.90. The MAE and RMSE for ANN were smaller than those of the MLR and the 'd' value for ANN was higher than the MLR. This had shown that the ANN had better performances compared to the MLR. This is because MLR has a statistical limitation to merge with three months of climate indicator in a single model. The ANN training data set was used to determine the form of the input parameters. Since the developing of the model was using the training data set, the outcomes from the training data set were considered as assessment in this research, in order to make comparison with the MLR models.

The Generalized Estimating Equation (GEE) model was evaluated using R^2 and RMSE using monthly rainfall, TMax, relative humidity, TMin, sunshine hours and wind speed. The results of the research were given by Bahrami and Mahmoudi (2019). The study area was located at Fasa Plain, Iran. The GEE method, which is the derive mode of the MLR method taking into account the dependence between successive observations, was used for monthly rainfall modelling. The predicted value calculated by the GEE had illustrated the superiority of this model in the estimation, as the determination coefficient of more than 96% was achieved when comparing with the observed data. The RMSE of GEE also had a range of 3.42mm to 6.22mm.

2.7 Summary

There were several performance evaluations that had been conducted in the past by researchers with regards to models like GWR, MGWR, OK, and IDW, etc. The results had shown that the MGWR and the GWR gave better performances compared to the other models such as the OK, IDW and OLD. According to Chen, et al. (2012), the GWR has a better performance compared to OK, COK and IDW, especially at low sampling density. This is because the spatial interpolation model such as OK and IDW tend to produce blurry images compare to regression models like the GWR and MGWR, due to the limitation of estimating the sudden change of geographic features such as elevation and slope. Conversely, the GWR model was able to produce more accurate estimation and maintained the original shape of a geographic feature. The slope factor has played an important role as the input data into the GWR for rainfall prediction, and the complex terrain should be divided into smaller segments in order to improve the relationship between each parameter and increase the accuracy of the estimation (Kumari, et al., 2016). According to LV and Zhou (2016), the characteristic of the GWR had made it different from traditional interpolation methods, and this is because the GWR was able to provide clear relationships of precipitation, spatial distribution by interpolating theoretically for geographical location, altitude and other factors. In contrast, the traditional interpolation method, such as the MLR had made an assumption in which the relationship is constant over space between the dependent variable and explanatory variable. The MGWR is an upgrade version of the

GWR as it allowed the model to vary with different special scale compared to the GWR. According to Fotheringham, et al. (2019), the MGWR was able to provide covariate-specific bandwidths in order to be optimized in all variable rather than using the same bandwidth across the analysis which is same as the characteristic of GWR. By adding a spatially lag dependent variable did not result in significant difference for the MGWR, Although the results for the MGWR and MGWRL had only shown little improvement, it actually provides improvement for other methods such as the OLS and GWR. The Area-to-point kriging (ATPK) also help the MGWR to avoid the “boxy effect” due to adding back the coarse resolution residual which was faced by the DisTrad model as this will help to improve the accuracy of MGWR (Yang, et al., 2019).

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Workflow/ Flowchart

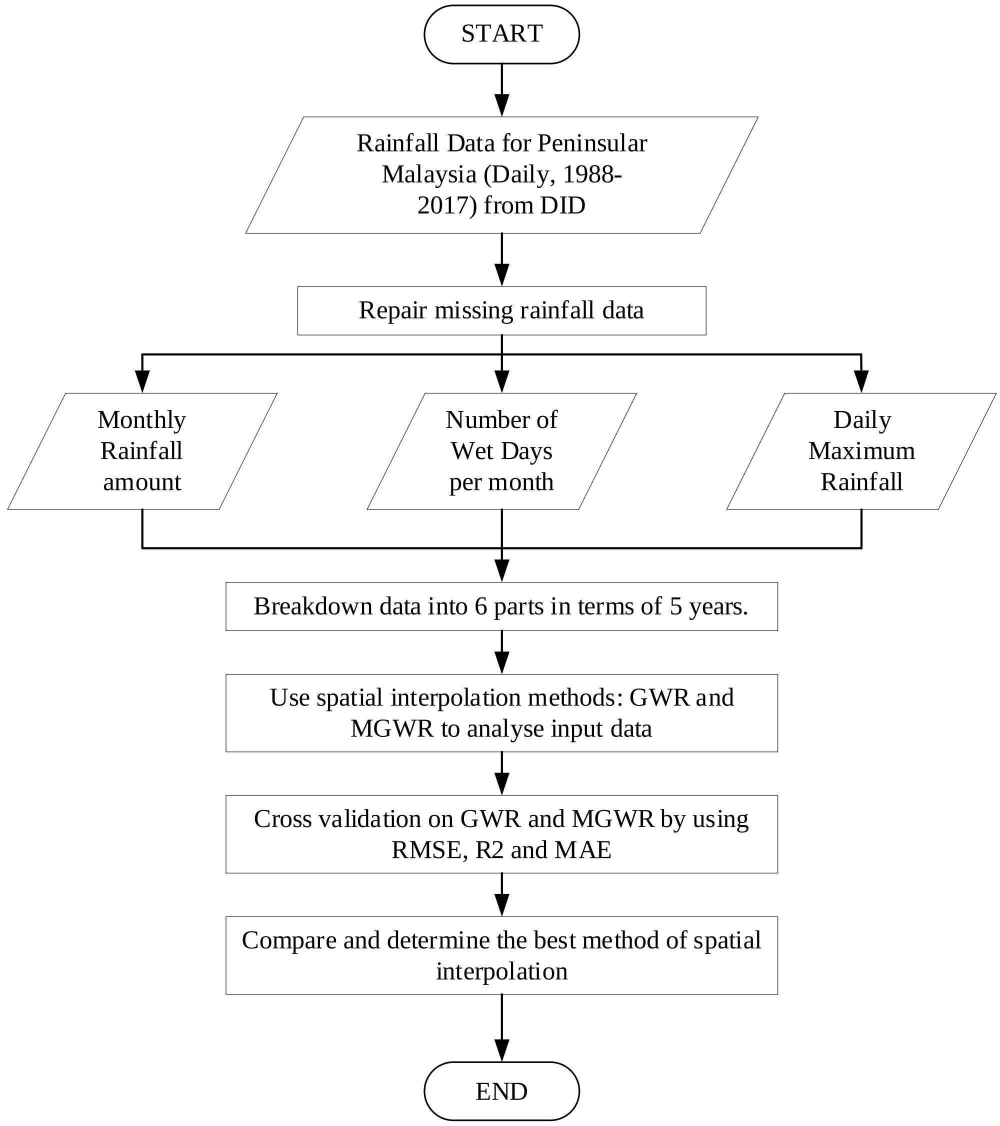


Figure 3.1: Flow Chart.

The daily rainfall data acquired is for the mapping of spatial rainfall distribution. The daily rainfall data for Peninsular Malaysia was provided by the DID. The missing daily rainfall data were filled in using the known data repairing methods in order to have full sets of data to improve the accuracy of the analysis. The parameters of Monthly rainfall amount, number of wet days and maximum daily rainfall were extrapolated from the daily rainfall data. After the missing rainfall data has been repaired, the rainfall data was broken down into 6 sub-parts each part being of a length of 5 years. The spatial interpolation methods, such as GWR and MGWR were used to analyse the rainfall data. The RMSE, R^2, and MAE were used to evaluate the accuracy of the GWR and MGWR models. The performance of GWR and MGWR for estimating the rainfall data in Peninsular Malaysia were compared and discussed in order to select the best interpolation model.

3.2 Mapping, Location of Study and Data Acquisition

Peninsular Malaysia is placed between 1˚ and 7˚ to the north and 99˚ to 105˚ to the east (Wong, et al., 2009). The area of Peninsular Malaysia is 131 587 km^2, and it consists of the floodplain, highland and shore zones. The weather of Peninsular Malaysia is humid and warm all year with the range of temperature between 21 ˚C to 32 ˚C, as distinctive for a humid tropical climate. There are two precipitation climate regime characteristics of rainfall in Peninsular Malaysia; which are the two rainy seasons related with the Northeast Monsoon from November to March and the Southwest Monsoon from May to September. April and October will be the transitional periods in which substantial rainfall will occur (Wong, et al., 2019).

The daily rainfall data for Peninsular Malaysia from 1988 to 2017 was provided by the DID. The daily rainfall data was collected for 244 rainfall stations located all over Peninsular Malaysia. The monthly rainfall data was computed by accumulating the daily rainfall data for that particular month. Another parameter, the number of wet days per month which is important for the analysis can be obtained from the daily rainfall data as well. The third parameter is the monthly Daily Maximum rainfall. Lastly, the 30 years rainfall data period was broken down into 6 sub-parts each with a 5 years period in order to carry out the temporal variation analysis.

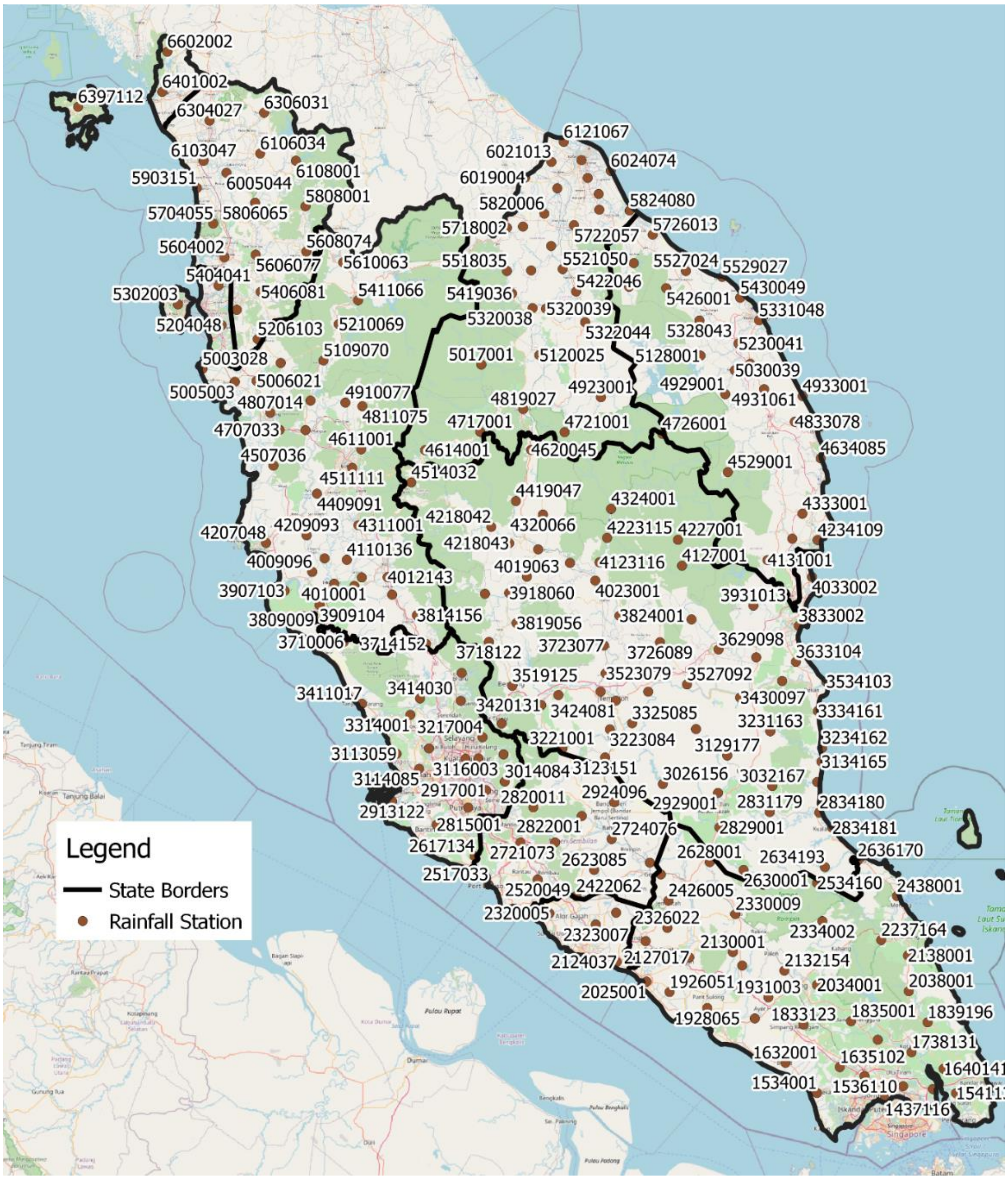


Figure 3.2: Distribution of Rainfall Stations in Peninsular Malaysia.

3.3 Geographical Weighted Regression (GWR)

The GWR is an extension of the traditional linear regression model as it is using the spatial (x, y) coordinates to build up a relationship between location and other parameters. The regression coefficients of the GWR were generated based on the sub-sampled data from the nearest neighboring data instead of globally information. The principle relationship of the GWR is shown below:

$$y_i = \beta_0(u_i, v_i) + \sum_{i=1}^{n} \beta_j\,(u_i, v_i)x_{ij} + \varepsilon_i, i = 1, 2 \ldots, m; j = 1,2, \ldots, n \qquad (3.1)$$

where y_i ; x_{i1} , x_{i2} , …, x_{ij} are the observation coefficients between the dependent variable y and independent variables x at different geographical locations (u_i, v_i). The u_i represents the longitude of the independent variable, v_i represent the latitude of the independent variable, and $\beta_j(u_i, v_i)$ represent the unknow parameters at the observation site located at (u_i, v_i). As the elevation was selected as the independent variable, the GWR model established referred to the error of precipitation background at the weather station and the measurements of actual precipitation.

The actual observation site, *i* and its adjacent observation sites were used to build a local regression model in order to solve the mathematical problem. The difference between these two points was reflected using the spatial distance decay weight matrix, w_{ij}. There are 2 kernel types of the GWR model, and which is the bi-square kernel function and the Gaussian. The Gaussian kernel weight decreases gradually from the centre of the kernel but will never reach zero, whereas the bi-square kernel function is using the clear-cut range where the weighting will not be zero. The weight matrix was derived using the bi-square function, which the equation is:

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2 when\ d_{ij} < b \qquad (3.2)$$

$$w_{ij} = 0 \qquad when\ d_{ij} < b \qquad (3.3)$$

where d_{ij} is Euclidean distance between jth point and neighboring observation, i and b is the kernel bandwidth. The Golden section search is also employed in order to determine the optimal bandwidth for the analysis.

The monthly rainfall data and elevation are used as an input variable in order to carry out the spatial interpolation using the GWR model. The mean value of the monthly rainfall will be generated by the GWR model. The number of wet days can be obtained by accumulating the frequency of rainfall events during the month. In addition, the maximum daily rainfall can be obtained by scrutinizing the daily rainfall data and selecting the maximum rainfall.

3.4 Multiscale Geographical Weighted Regression (MGWR)

The MGWR is a further improvement of the model of GWR; in which it removes the constraint of all analysis and is modelled using the same spatial scale with the same bandwidth. This enables the range of data-borrowing to vary across the parameter surfaces so that the scale of the independent variable, and dependent variable will not be inconsistent across the process. The equation of the GWR has been modified by MGWR and it becomes:

$$y_g = \beta_{bw0}(u_g, v_g) + \sum_{i=1}^{n} \beta_{bwi}(u_g, v_g) x_{ig} + \varepsilon_g \qquad (3.4)$$

where (u_g, v_g) represents the location g's coordinate. y_g and x_{ig} are the local predictions. β_{bw0} and β_{bwi} show that the estimation was based on bandwidth b_{w0} and b_{wi}, where m indicated that the number of independent variables involved in this analysis. The Bi-square kernel is also preferred in this analysis where the equation is shown below:

$$w_{ghi} = \left[1 - \left(\frac{d_{gh}}{b_{wi}}\right)^2\right]^2 \; when \; d_{gh} < b_{wi} \qquad (3.5)$$

$$w_{ghi} = 0 \qquad when \; d_{gh} > b_{wi} \qquad (3.6)$$

where w_{ghi} is the specific spatial weight of location g 's observation point with the neighboring observation point located at h. d_{gh} is the distance between the locations g and h, and b_{wi} is the relationship's kernel bandwidth between the dependent variable and independent variable.

The monthly rainfall data and elevation are used as an input variable in order to carry out the spatial interpolation using the MGWR model. The mean value of monthly rainfall will be generated by the MGWR model. The number of wet days can be obtained by accumulating the frequency of rainfall event during the month. In addition, the maximum daily rainfall can be obtained by going through the daily rainfall data and selecting the maximum rainfall.

3.5 MGWR 2.2 Software

The MGWR software was first released in October 2018, and the MGWR 2.2 is the latest version of the MGWR, and it was released in March 2020. The MGWR 2.2 is able to calibrate the GWR and the MGWR models. It is able to show the relationship between the dependent variable and the independent variable, which vary geographically.

There are two spatial kernel options available in the MGWR 2.2 and which are the adaptive bisquare kernel and the fixed gaussian spatial kernel. The adaptive bisquare kernel is to be selected in this spatial analysis for both the GWR and the MGWR models. The Golden Section search will be selected in order to find the optimal value of the bandwidth for both the GWR and MGWR models in order to improve the accuracy of the data.

3.6 Cross-validation

The cross-validation technique is employed in order to evaluate the accuracy of the GWR and the MGWR. It helps to check the unity between the input variable and the model by removing each data point at one time from the data set, and it is also utilizing the information from the surroundings in order to estimate the variable value at a different location. In particular, the methods used to evaluate the performance of GWR and MGWR in this paper are the RMSE, R^2, and MAE.

3.6.1 Root Mean Square Error (RMSE)

The RMSE is very commonly used in evaluating the accuracy of prediction errors for different models. The RMSE consists of 3 simple steps in order to carry out the accuracy of the model. First, the individual squared error was sum up. This means that larger error will lead to great influence on the total square error as RMSE take into account every error rather than its magnitude. Next, the total squared error is divided by *n*, which will get mean-square value (MSE). Lastly, the MSE value is the square root, and RMSE value will be obtained (Willmott & Matsura, 2005).

The equation of the RMSE is shown below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{3.7}$$

where $|e_i| = |y_i - \hat{y}_i|$, with actual value = y_i and predicted value = $\hat{y}_i$.

3.6.2 Mean Absolute Error (MAE)

The MAE measures the mean value for the magnitude of error in a set of predicted data without considering the direction of the value. The MAE is relatively simple when compared to the RMSE as is only done by summation of the magnitude of the error and then dividing the total error by n (Willmott & Matsura, 2005)

The equation of the MAE is written below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{3.8}$$

where $|e_i| = |y_i - \hat{y}_i|$, with actual value = y_i and predicted value = $\hat{y}_i$.

3.6.3 Coefficient of Determination, R^2

The R^2 is used to evaluate the performance of the GWR model and the MGWR model. It characterizes the distribution of variance explained by measured data's model. The strength of the model is indicated by the value of R^2 where the range of R^2 is between 0 to 1. The higher the R^2 value indicates that the model has a better estimation accuracy which has a better understanding of the variable responsible for the dependent variable's variation (Kumar, et al, 2016). The equation of R^2 is formulated as below:

$$R^2 = \left(\frac{\sum_{i=1}^{n} (Rr_i - \bar{R}r)(Rs_i - \bar{R}e)}{\sqrt{\sum_{i=1}^{n} (Rr_i - \bar{R}r)^2} \sqrt{\sum_{i=1}^{n} (Re_i - \bar{R}e)^2}} \right)^2 \qquad (3.9)$$

where R_r represents the rainfall data from a rain gauge, $\bar{R}_r$ represents the average value of R_r, R_e represents rainfall estimated using interpolation model, $\bar{R}_e$ represents the average value of R_e, n represents the total number of rain gauge and *i* represents the index number of station.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Comparisons of Methods

In this study, there are two spatial interpolation methods to estimate the spatial rainfall distribution in Peninsular Malaysia, which are the GWR and MGWR models. Both the GWR and MGWR models were evaluated using the MAE, RMSE and R^2 in order to determine their accuracy in estimating the Monthly Rainfall in Peninsular Malaysia. The RMSE able to present the standard deviation of the prediction errors. The higher the RMSE represent higher prediction error and lead to low accuracy in predicting rainfall. The MAE is able to show the total prediction error, which does not take into account of positive error and negative error. The lower the MAE represent that the higher the accuracy of the method in predicting the rainfall data. Moreover, the R^2 shows how close the estimated rainfall data are to the fitted regression line, and the higher the R^2 represent higher accuracy of the method. First, monthly rainfall data of the total of 244 rainfall stations was collected and run the software stimulation for the GWR and MGWR. The missing data are then repaired by using both methods and determine the accuracy of GWR and MGWR using RMSE, MAE and R^2. The Monthly Rainfall, Number of Wet Days and Daily Maximum Rainfall estimated using the best method will be further study by plotted into the maps through QGIS software.

The monthly rainfall data was first stimulated for both GWR and MGWR using the MGWR 2.2 software in order to generate beta, β and estimated standard error, ε as these two parameters will be useful in estimating the rainfall data. The independent variables use in the stimulation process are the elevation and monthly rainfall of previous three months. For example, during the stimulation for April 1988, the independent variable will be elevation and monthly rainfall data from nearby stations, inclusive of the rainfall data of previous three months which are January 1988, February 1988 and March 1988. After all the stimulation was completed, the rainfall data can be estimated and evaluated using the MAE, RMSE and R^2. The results of MAE, RMSE and R^2 is tabulated in Table 4.1.The rainfall data predicted by the best method will be used to plot the maps using QGIS software for further discussion.

Table 4.1: The MAE, RMSE and R^2 of GWR and MGWR.

Method	MAE	RMSE	R^2
GWR	76.7	112.8	0.5
MGWR	66.9	95.9	0.6

By referring to the results shown in Table 4.1, it is noticed that the MAE and RMSE of the MGWR were lower than the GWR, which means that the rainfall data estimated by MGWR have lower predicted error compared to GWR. The value of R^2 for MGWR is also higher than the GWR, which indicated that the predicted rainfall data of MGWR was closer to the fitted regression line. Overall, the MGWR method has better accuracy in estimating the rainfall data in Peninsular Malaysia compared to GWR. This is because the MGWR allowed different bandwidth for each station across the analysis, and this help that the bandwidth selected are optimum for every station. However, the GWR only allowed to select one fixed bandwidth which is optimum in general by accounting all the rainfall stations, and this lead to the reduction of accuracy in estimating the rainfall data.

Moreover, the performance measure results for 244 rainfall stations were divided into four regions by location, which are the northern region, east coast region, southern region and central region. This can help to determine the estimation accuracy at a different region of Peninsular Malaysia. The estimation accuracy for both GWR and MGWR was evaluated using RMSE, MAE and R^2. The results are tabulated in Figure 4.1, Figure 4.2 and Figure 4.3. Figure 4.1 and Figure 4.2 have shown that the RMSE and MAE of MGWR are lower than GWR during the estimation of rainfall data across four regions of Peninsular Malaysia. As shown in Figure 4.3, the R^2 value of MGWR in estimating the rainfall data in four regions of Peninsular Malaysia is also higher than GWR as shown in Figure 4.3. This can show that the MGWR has a better performance compared to GWR in the estimation of rainfall data of Peninsular Malaysia as a whole, or when split it into four regions.

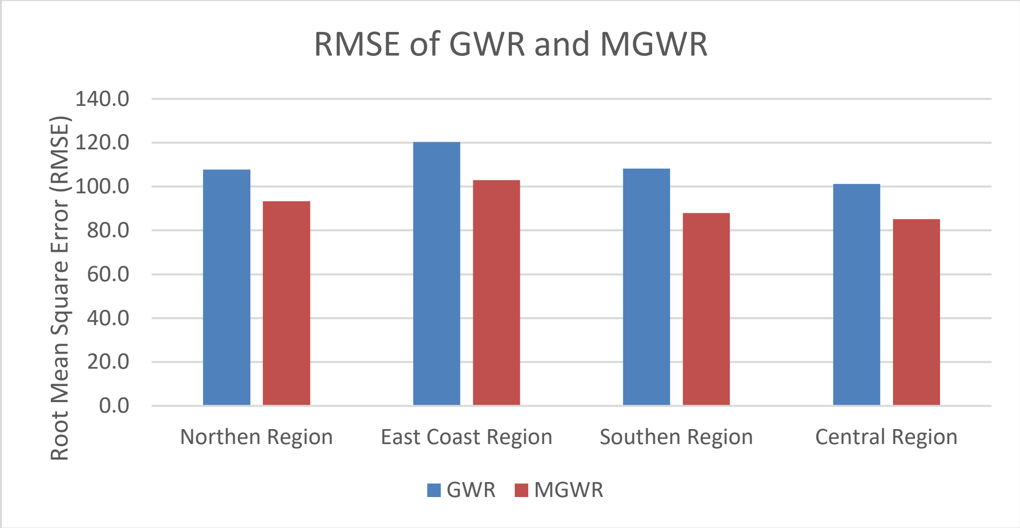


Figure 4.1: RMSE of GWR and MGWR at Different Regions.

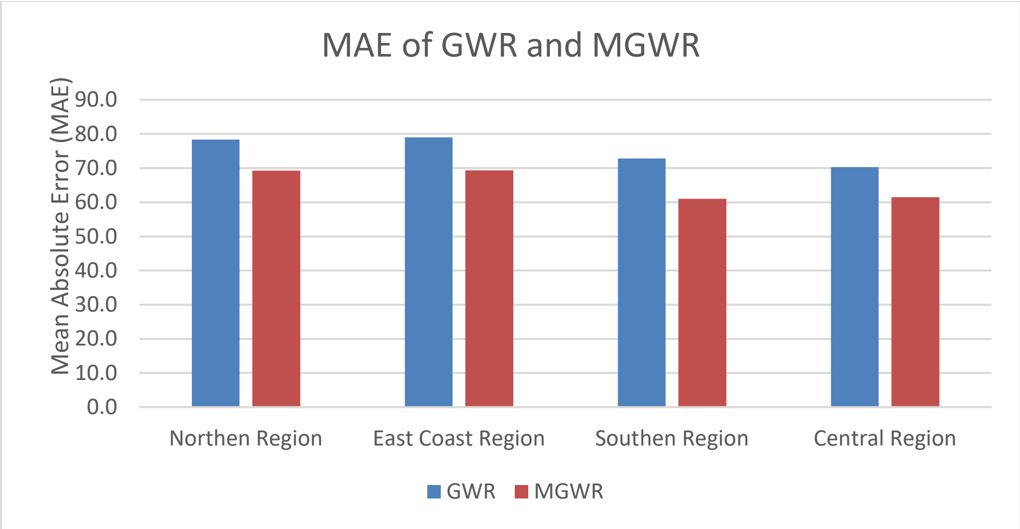


Figure 4.2: MAE of GWR and MGWR at Different Regions.

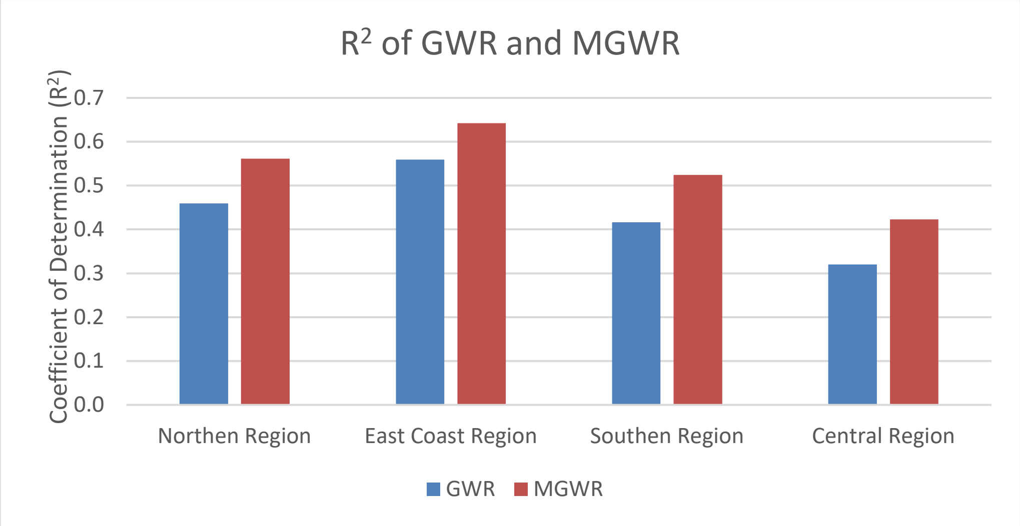


Figure 4.3: R^2 of GWR and MGWR at Different Regions.

It is noticed that the R^2 of the MGWR in the central region is only 0.3 and it is relatively low compared to other regions. This is because the land use of the central region consists of many categories such as forest, plantation forest, oil palm, rubber plantation, coconut plantation, paddy, mixed horticulture, urban and built-up, wetland forest and marshland, and bareland (Abdullah and Nakagoshi, 2006). The agriculture of the central region also consists of cocoa plantation, sugarcane plantation, tea, orchard and diversified crop (Abdullah and Nakogoshi, 2006). This has affected the estimation accuracy of the rainfall data in the central region as the estimation of rainfall data using GWR and MGWR does not take into consideration of the land use of the nearby station. Although the distance between the estimated rainfall station and nearby rainfall station is small; however, the land use between estimated station and nearby rainfall stations is different. Therefore, it could affect the estimation accuracy of the rainfall data as all the rainfall station has own characteristic at the particular land use, and this lead to different humidity, land surface temperature and rainfall.

4.2 Rainfall Map

The MGWR method has shown that it has better estimation accuracy compared to the GWR method. Therefore, the rainfall data estimated by MGWR will be plotted using QGIS software for further study. The Monthly Rainfall, Number of Wet Day and Maximum Daily Rainfall was plotted using QGIS software in order to study the rainfall pattern in Peninsular Malaysia. These three parameters can be present in the form of average, monthly and 5-year period. The rainfall maps plotted in Figure 4.4 were using the average value of Monthly Rainfall, Number of Wet Day and Maximum Daily Rainfall.

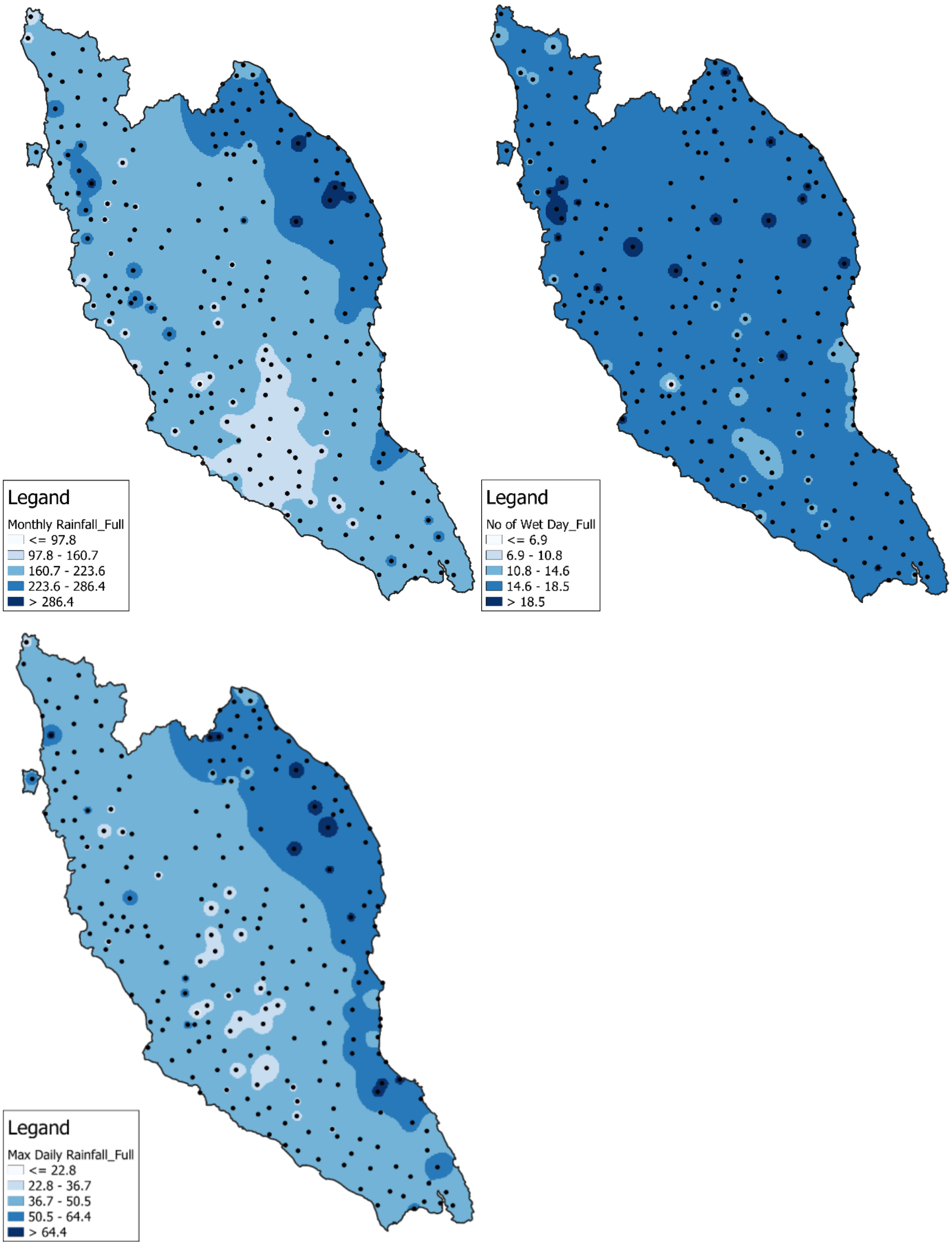


Figure 4.4: Average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall along 1988-2017.

Figure 4.4 shows that the Number of Wet Days was consistent across the whole Peninsular Malaysia for this 30 years period, ranged from 14.6 to 18.5 days. On average, the Maximum Daily Rainfall in the northeast region of Peninsular Malaysia is relatively higher compared to other regions. The Maximum Daily Rainfall and Monthly Rainfall at the northeast region are range from 50.5 to 64.4 mm and 223.6 to 286.4 mm, respectively. The high average Maximum Daily Rainfall at the northeast region contributed to the high average Monthly Rainfall at that particular area. The average Monthly Rainfall from January to December across these 30 years are plotted and shown in Figure 4.5.

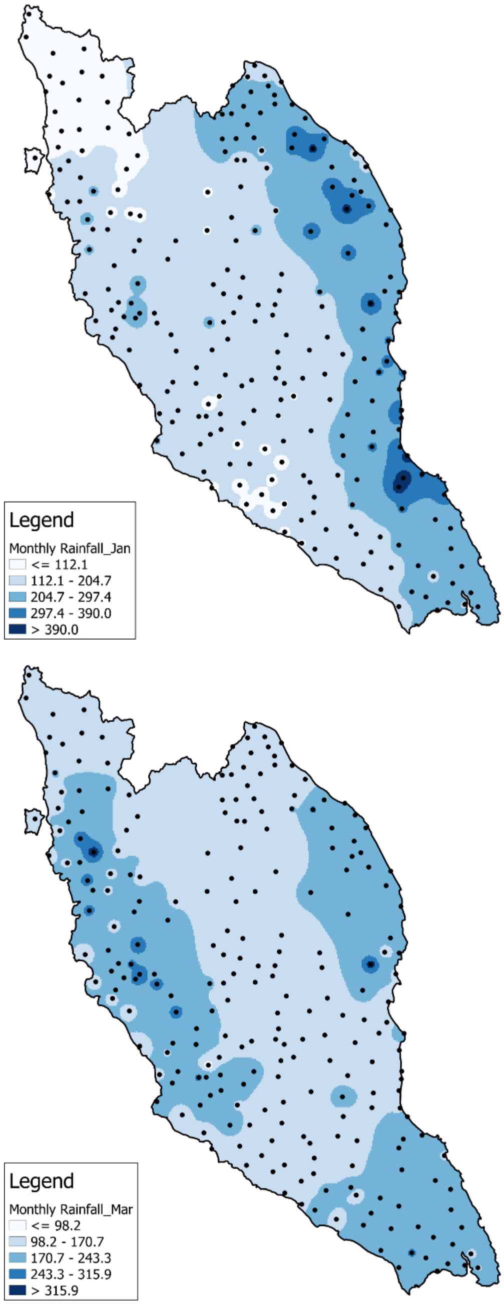


Figure 4.5: Average Monthly Rainfall from January to December along 1988-2017.

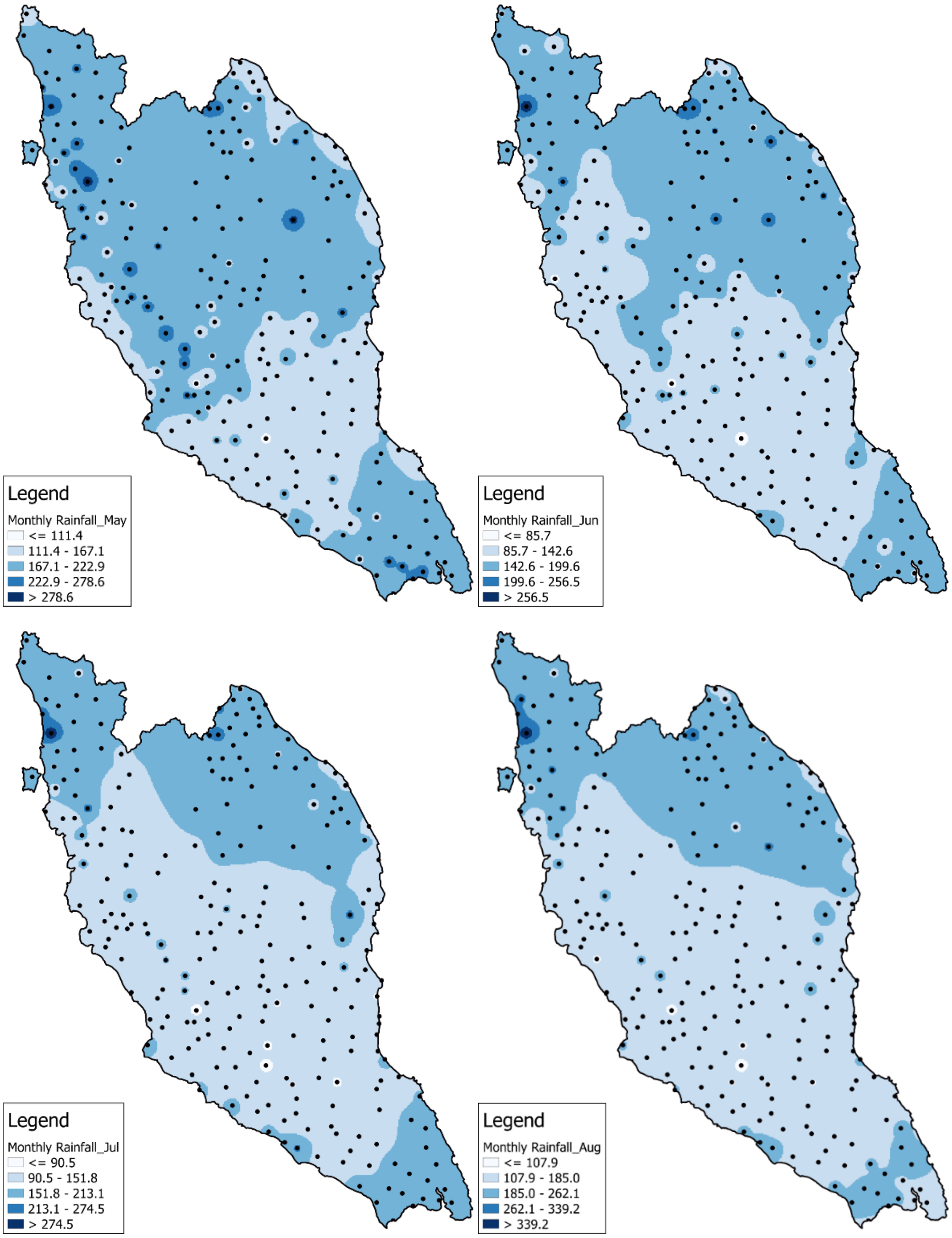


Figure 4.5: Average Monthly Rainfall from January to December along 1988-2017. (Cont’)

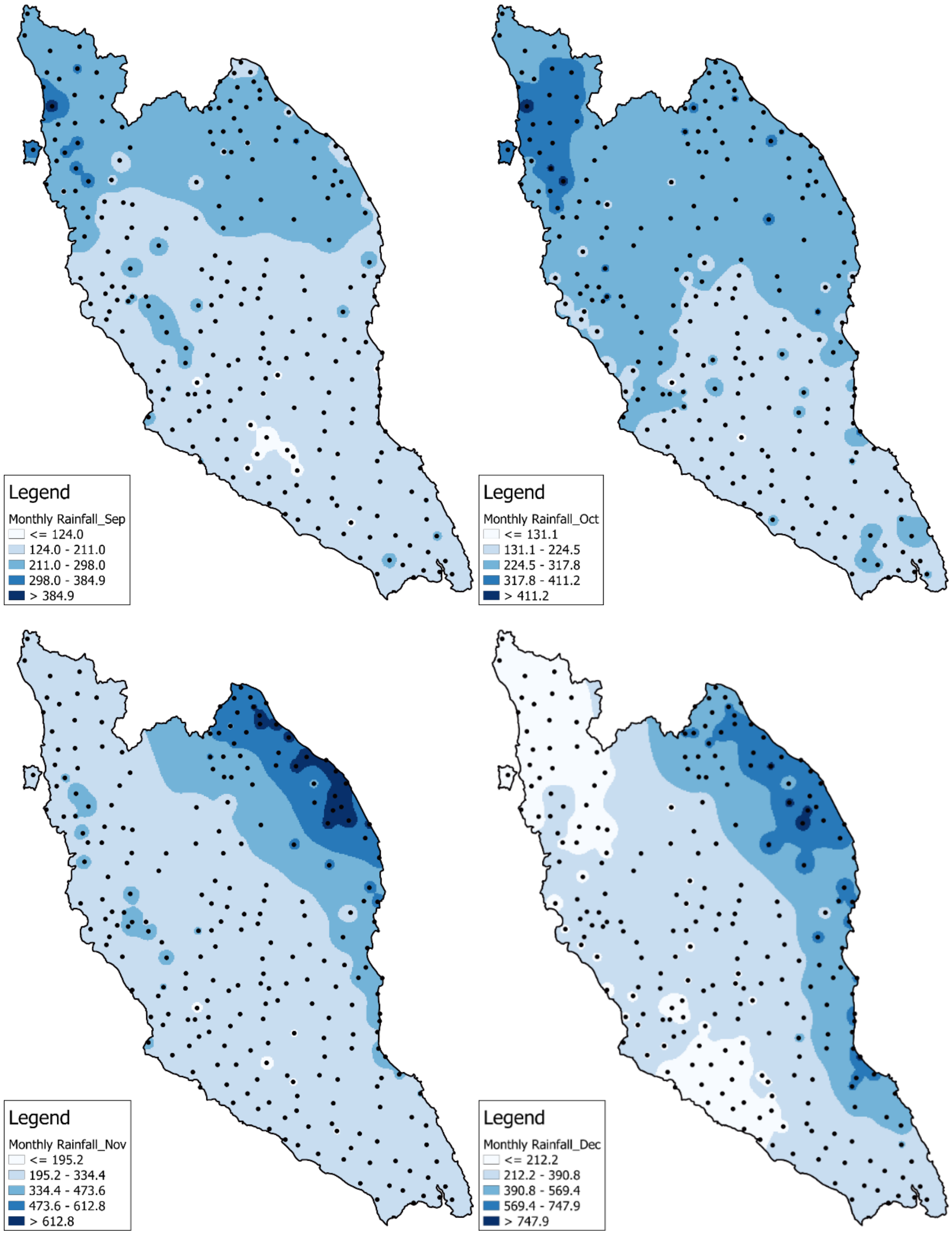


Figure 4.5: Average Monthly Rainfall from January to December along 1988-2017. (Cont')

By referring to Figure 4.5, the range of average Monthly Rainfall for November, December and January at the northeast region were 334.4 to 612.8 mm, 390.8 to 747.9 mm and 297.4 to 390.0 mm, respectively. It is noticed that the average Monthly Rainfall at the northeast region from November to January was relatively higher compared to other months. This is because Peninsular Malaysia in experiencing Northeast Monsoon from October to March, where November to January is experiencing the peak of Northeast

Monsoon. The average Monthly Rainfall for February and March at the northeast region was range from 118.6 to 215.2 mm and 170.7 to 243.3 mm, respectively and it is lower than other months of Northeast Monsoon. This is because February and March are experiencing the end of the Northeast Monsoon; therefore, the monthly rainfall at the northeast region will be reduced. However, the maps showed that the Northeast Monsoon is not fully blocked by Banjaran Titiwangsa. Thus, the monthly rainfall in the west part of Peninsular Malaysia will have delay raise from February (118.6 – 215.2 mm) to April (196.2 – 348.8 mm). The Peninsular Malaysia is experiencing the Southwest Monsoon from May to September. However, most of the rainfall is blocked by the island in Sumatra, Indonesia. Therefore, only part of the rainfall is able to reach the northern region of Peninsular Malaysia. This lead to the Monthly Rainfall at the northern region is higher than southern region from May to September, which the Monthly Rainfall from May to September at northern region and southern region was range from 142.6 to 384.9 mm and 124.0 to 278.6 mm, respectively. The rainfall pattern of October, which experience Northwast Monsoon does not show a significant effect as the Northeast Monsoon may begin during the middle or end of October. The average Number of Wet Days from January to December throughout these 30 years were plotted, as shown in Figure 4.6 and will be discussed below.

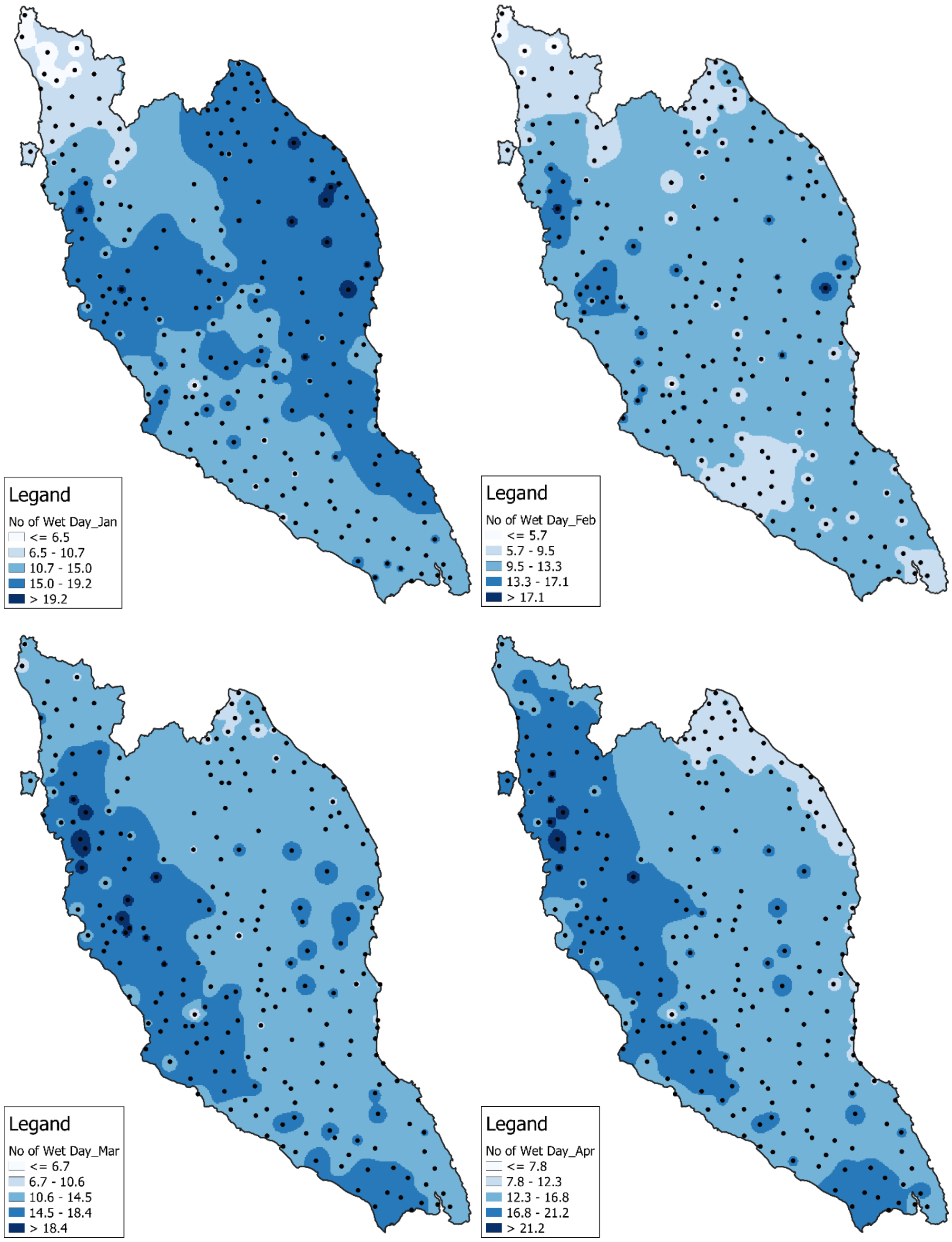


Figure 4.6: Average Number of Wet Day from January to December along 1988-2017.

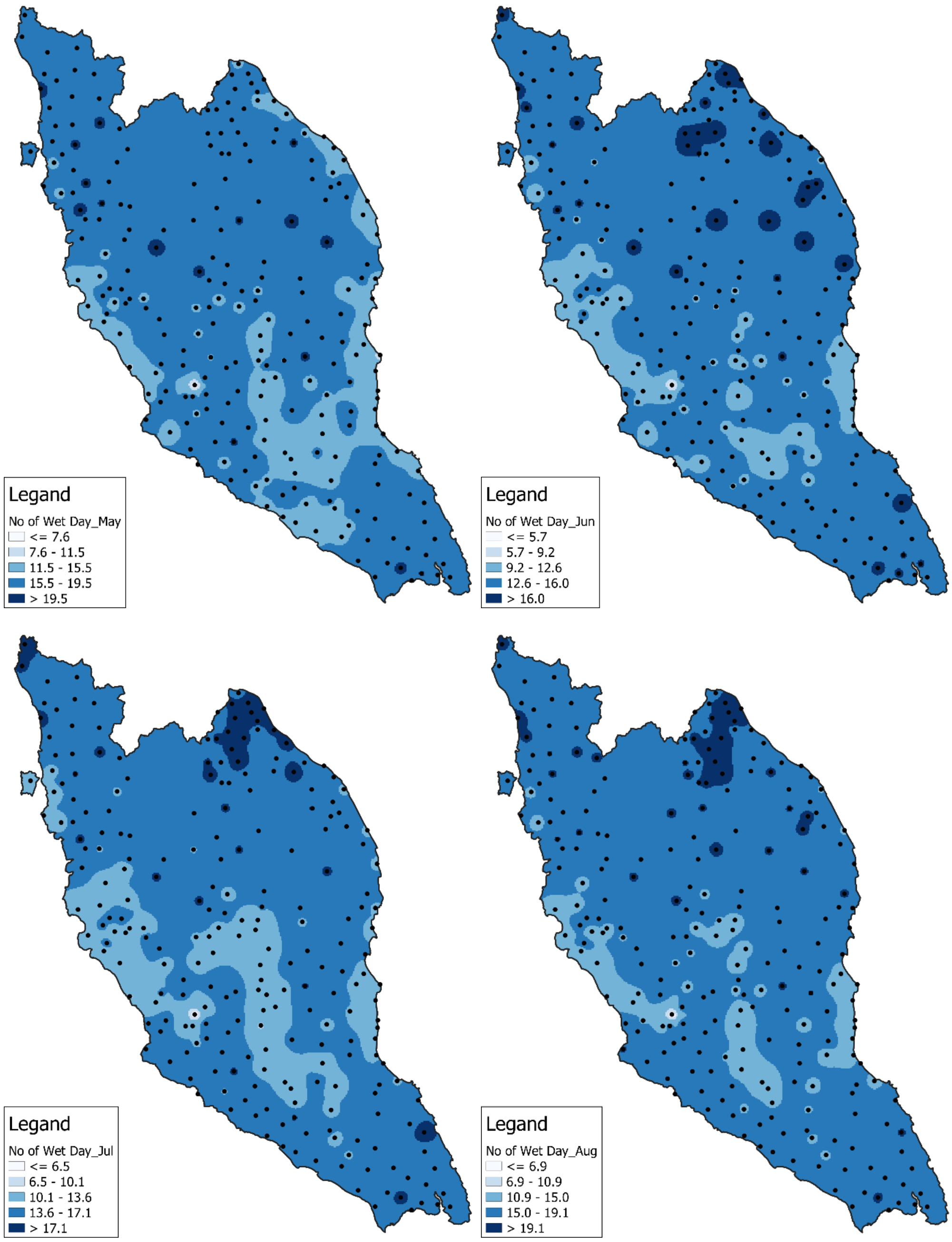


Figure 4.6: Average Number of Wet Day from January to December along 1988-2017. (Cont')

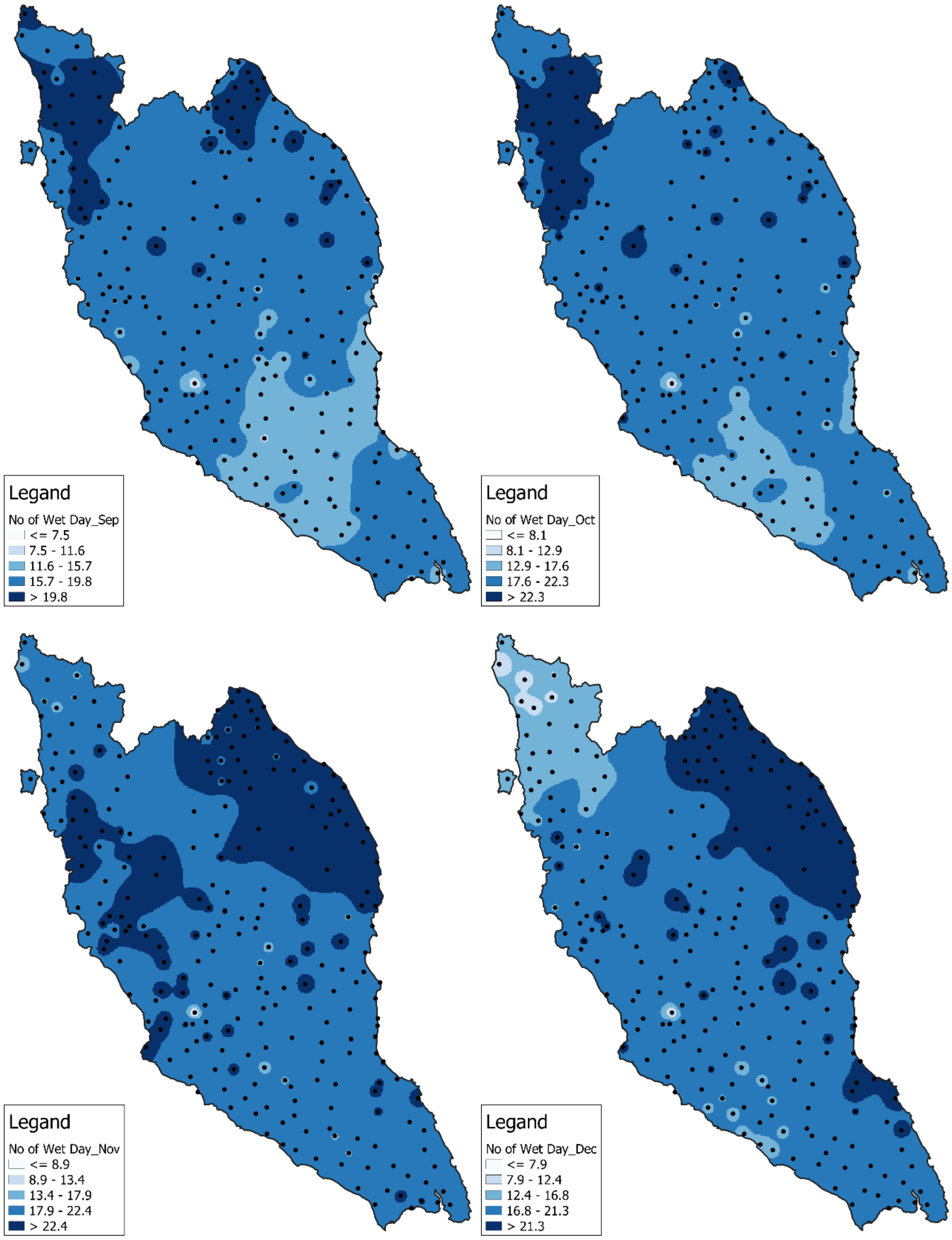


Figure 4.6: Average Number of Wet Day from January to December along 1988-2017. (Cont')

Figure 4.6 shows that the Northeast Monsoon effect has caused the Number of Wet Days from November to January to be higher at the northeast region compared to other regions as it is range from 15.0 to 22.4 days. The rainfall from the Northeast Monsoon blocked by the Banjaran Titiwangsa has reached the west part of Peninsular Malaysia in March and April, as shown in Figure 4.6. Therefore, the Number of Wet Days in the west region of Peninsular Malaysia for March and April increase to the range of 14.5 to 21.2

days. The maps of the Number of Wet Days from May to October have relatively similar rainfall pattern in which the Number of Wet Days is uniformly distributed across the Peninsular Malaysia. After that, the maps of average Max Daily Rainafall from January to December were plotted in Figure 4.7 and discussed below.

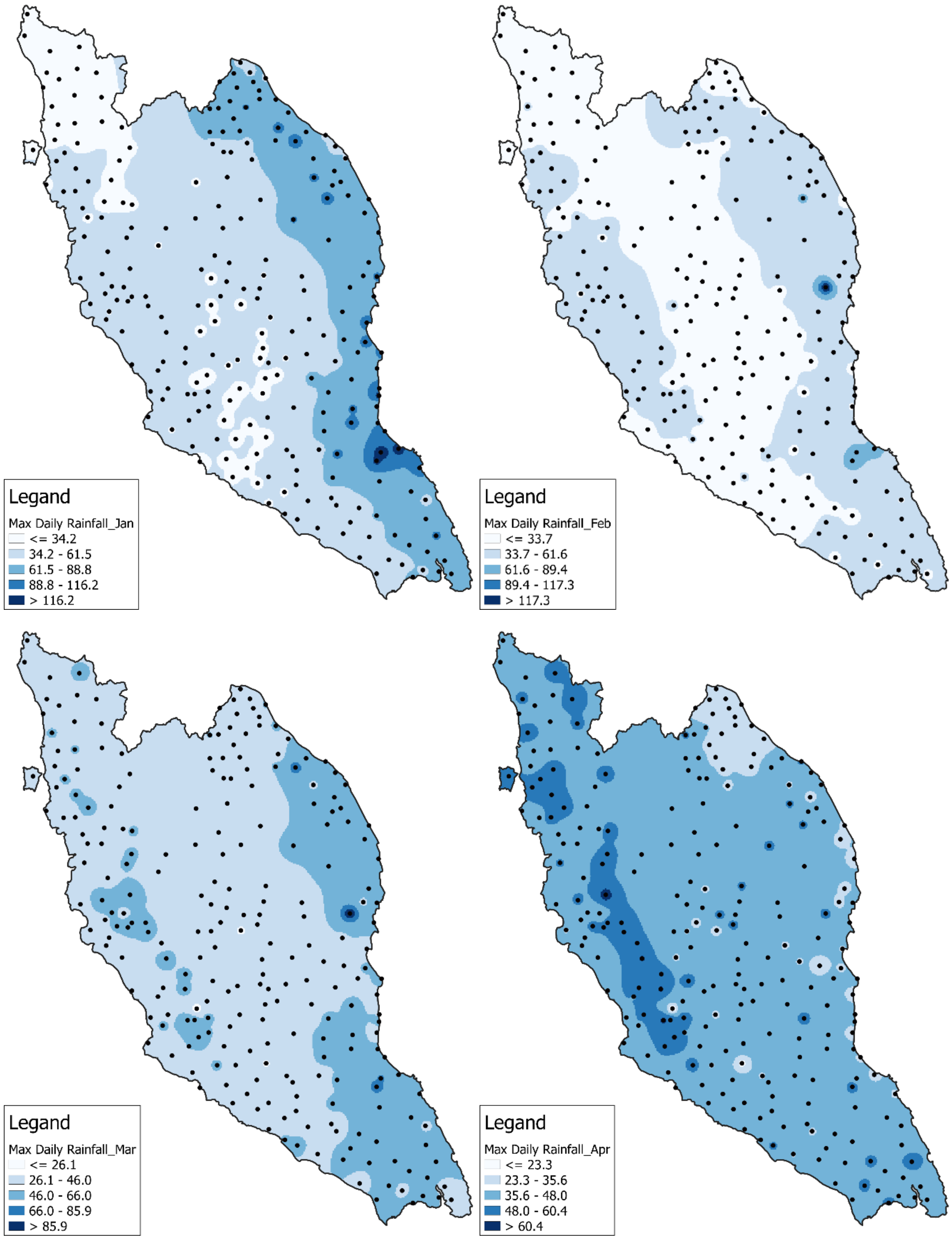


Figure 4.7: Average Maximum Daily Rainfall from January to December along 1988-2017.

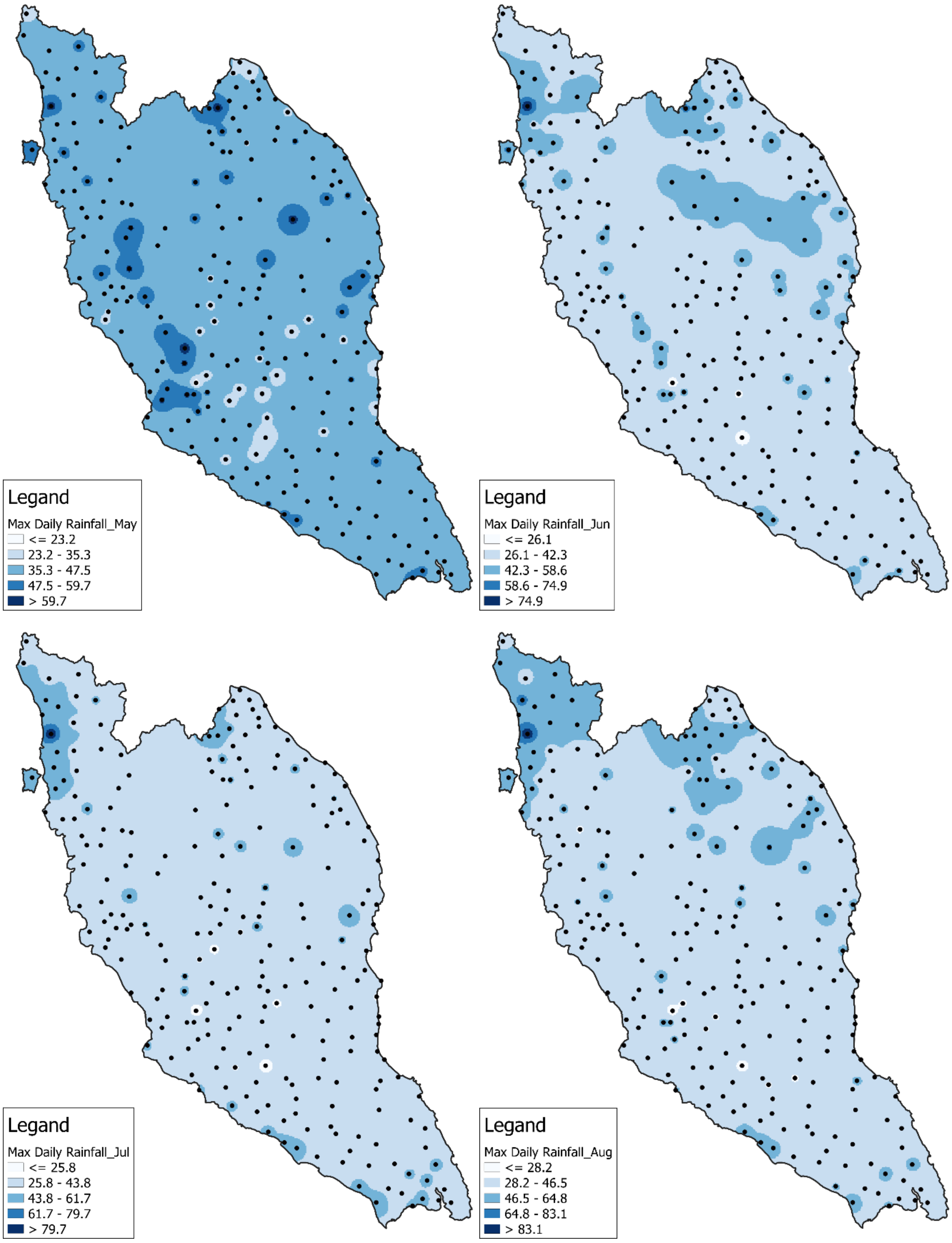


Figure 4.7: Average Maximum Daily Rainfall from January to December along 1988-2017. (Cont')

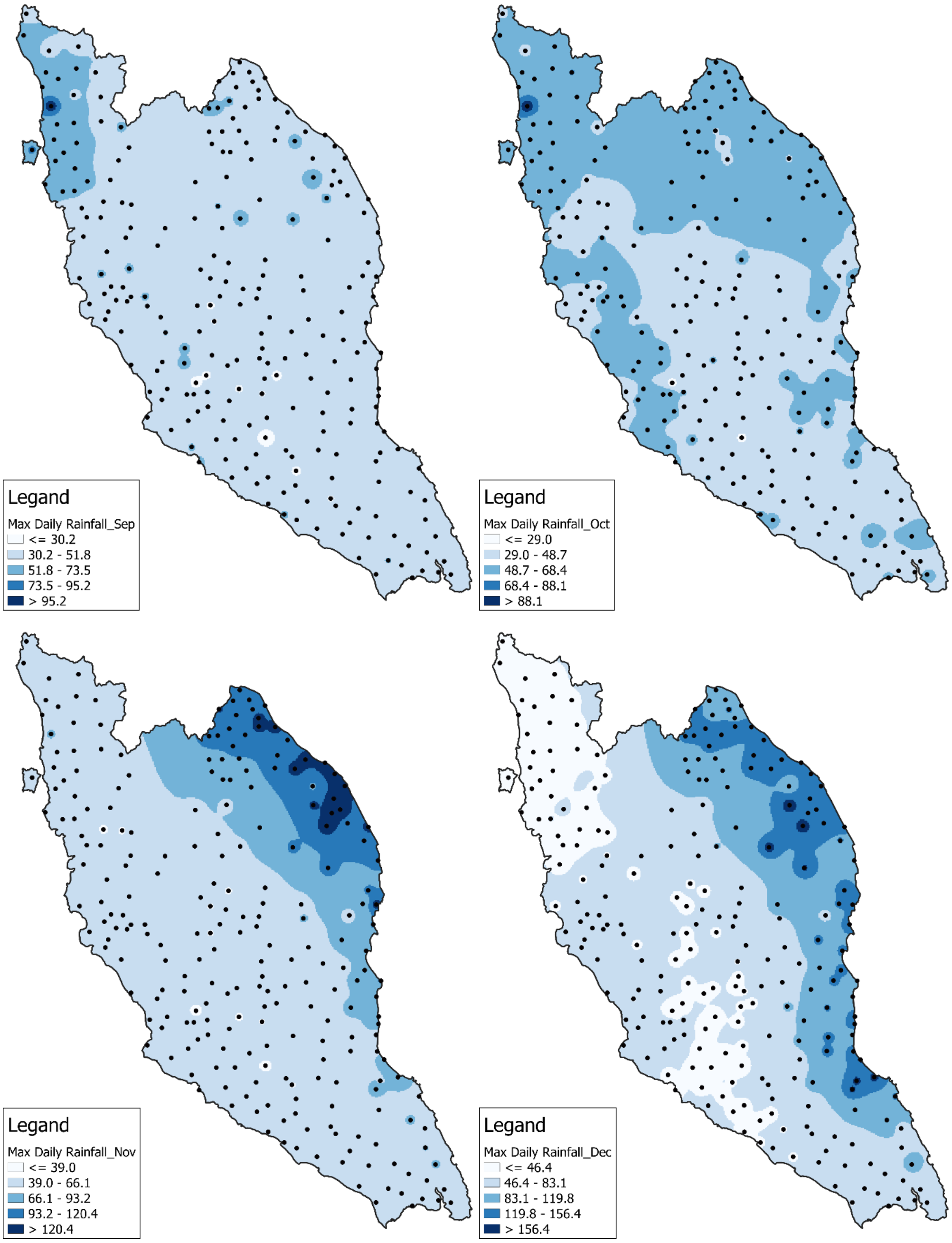


Figure 4.7: Average Maximum Daily Rainfall from January to December along 1988-2017. (Cont')

By referring to Figure 4.7, the maps from November to January show higher Maximum Daily Rainfall at the northeast region of Peninsular Malaysia as it range from 61.5 to 156.4 mm due to the effect of Northeast Monsoon. The Maximum Daily Rainfall starts to reduce from the northeast region and shift to the west part of Peninsular Malaysia from February to April, where the range of Maximum Daily Rainfall able to reach 60.4 mm on April. The range of Maximum Daily Rainfall from May to September across the whole Peninsular

Malaysia are from 23.2 to 95.2 mm and it was relatively the same rainfall pattern across Peninsular Malaysia; however, the value is low compared to other months. During October, the Northeast Monsoon has started, and the north part of Peninsular Malaysia show slightly higher Maximum Daily Rainfall (68.4 – 88.1 mm) at the north part of Peninsular Malaysia.

Referring to Figure 4.5, Figure 4.6 and Figure 4.7, the maps show that the average Monthly Rainfall (204.7 – 390.0 mm) for January in the east coast region of Peninsular Malaysia is higher due to the contribution of high Number of Wet Days (15.0 – 19.2 days) and Maximum Daily Rainfall (61.5 – 116.2 mm) in the east coast region in January. The Number of Wet Days (9.5 – 17.1 days) for February are consistent across the Peninsular Malaysia, as shown in Figure 4.5. However, the high Maximum Daily Rainfall (33.7 – 61.6 mm) in the east coast region and west part of Peinsular Malaysia have contributed to the high Monthly Rainfall (118.6 – 215.2 mm) at east coast region and west part of Peninsular Malaysia. Moreover, the average Monthly Rainfall (170.7 – 315.9 mm) for March was high in some regions of Peninsular Malaysia, which are east coast region, southern region and west part. The high Monthly Rainfall for March at the east coast region and southern region of Peninsular Malaysia was contributed by the high Maximum Daily Rainfall (46.3 – 66.0 days) in east coast region and southern region of Peninsular Malaysia. However, the high Monthly Rainfall for March at the west part of Peninsular Malaysia was due to the effect of the high Number of Wet Days (14.5 – 18.4 days) at the west part of Peninsular Malaysia. Figure 4.5, Figure 4.6 and Figure 4.7 also show that the high Number of Wet Days (16.8 – 21.2 days) and Maximum Daily Rainfall (48.0 – 60.4 days) has led to the high Monthly Rainfall (196.2 – 348.8 mm) at the northwest part of Peninsular Malaysia for the month April.

Besides, the average Monthly Rainfall (142.6 – 298.0 mm) at the northern region of Peninsular Malaysia from May to September is higher compared with other regions due to the contribution of the high Number of Wet Days (12.6 – 19.8 days) at northern region of Peninsular Malaysia. However, the Maximum Daily Rainfall (25.8 – 51.8 mm) from May to September was consistent across Peninsular Malaysia. As shown in Figure 4.5, Figure 4.6 and Figure 4.7, the average Monthly Rainfall (224.5 – 411.2 mm) for October at the northern region of Peninsular Malaysia is high due to the effects of high Maximum Daily Rainfall (48.7 – 68.7 days) at the northern region of Peninsular Malaysia, whereas the Number of Wet Days (17.6 – 22.3 days) for October was consistent across Penisular Malaysia. During the peak of Northeast Monsoon (November and December), the high Number of Wet Days (greater than 22.4 days) and Maximum Daily Rainfall (66.1 – 156.4 mm) in the northeast region contributed to the high Monthly Rainfall (334.4 – 747.9 mm) for November and December at the northeast region of Peninsular Malaysia.

Also, the Monthly Rainfall was further broken down into the 5-year periods in order to study the change of rainfall pattern over every five years. The Monthly Rainfall was piecemealed into six parts which are the year 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017, and the maps are shown in Figure 4.8.

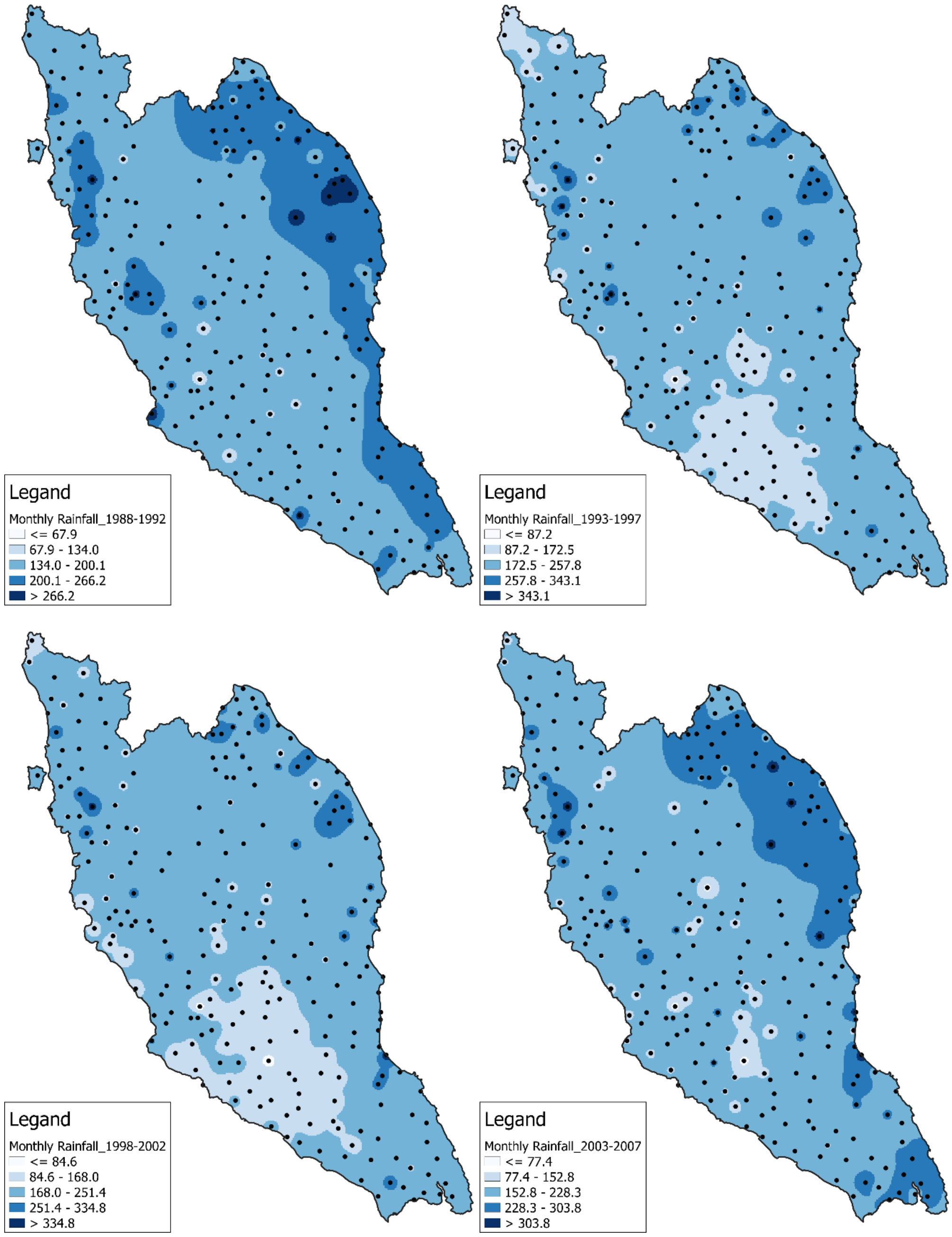


Figure 4.8: Monthly Rainfall Maps for 1988-1992, 1993-1997, 1998-2002 2003-2007, 2008-2012, 2013-2007.

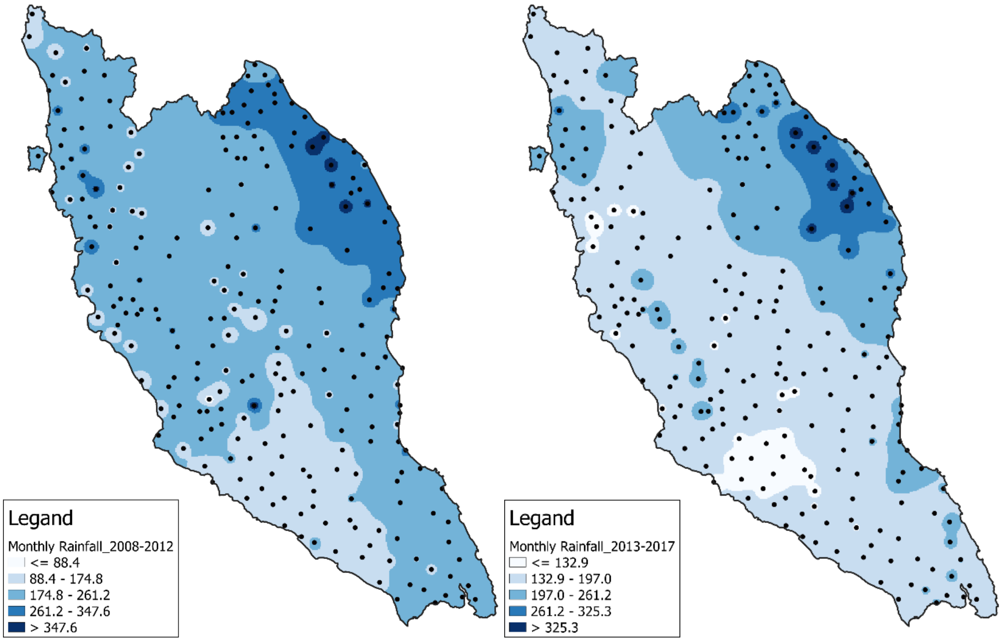


Figure 4.8: Monthly Rainfall Maps for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012, 2013-2007. (Cont')

As shown in Figure 4.8, all the maps for Monthly Rainfall has show a similar pattern in which the northeast region is relatively higher than other regions, especially the Monthly Rainfall at the northeast region able to reach the range of 261.2 to 347.6 mm during the year 2008-2012. The Monthly Rainfall map for 2013-2017 has obvious effect on the northeast region of Peninsular Malaysia. One major event caused by the high monthly rainfall at the East Coast region was the major flood that occurred in Kelantan during the year 2014. The Number of Wet Days for the year 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017 was plotted and shown in Figure 4.9.

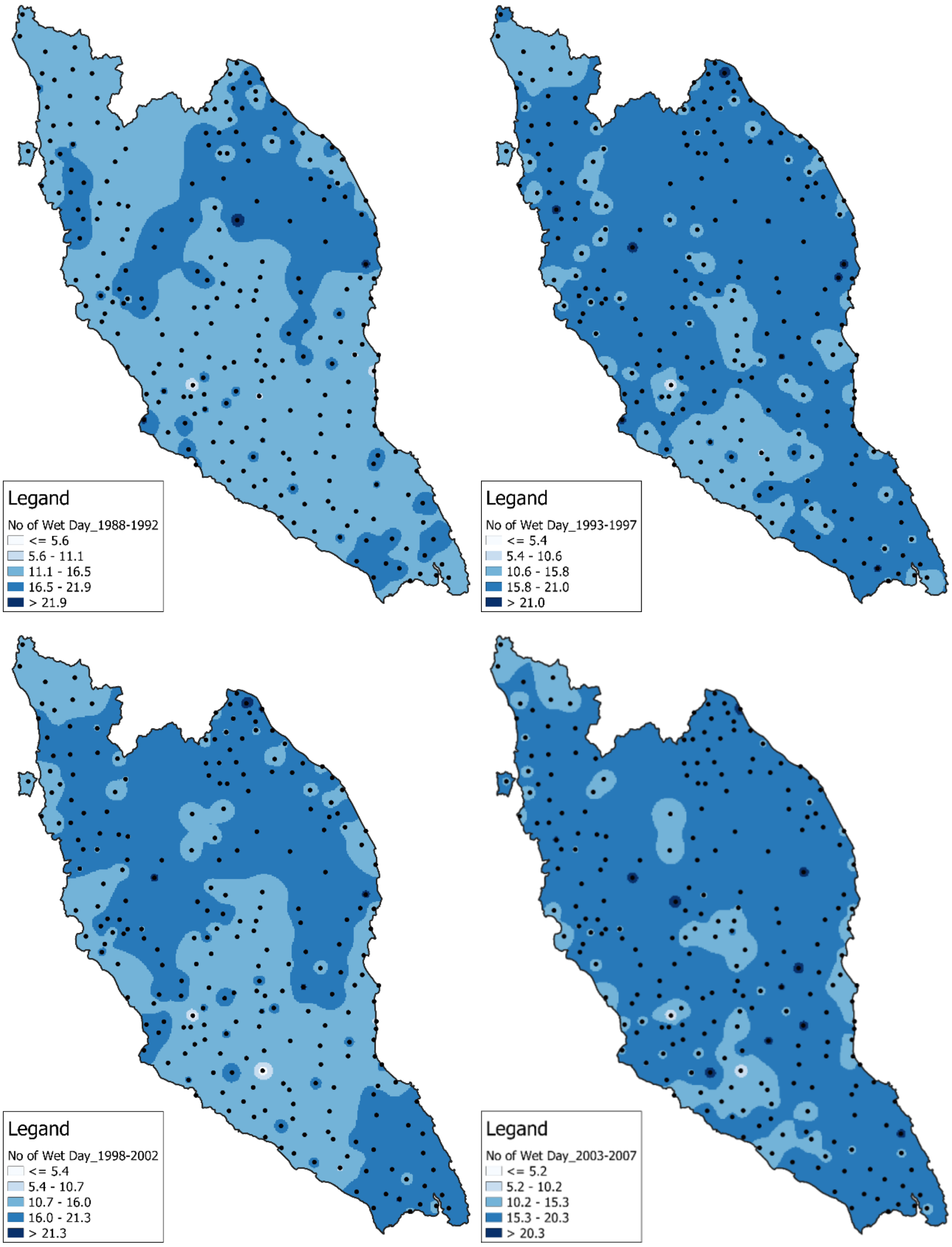


Figure 4.9: Average Number of Wet Days Maps for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

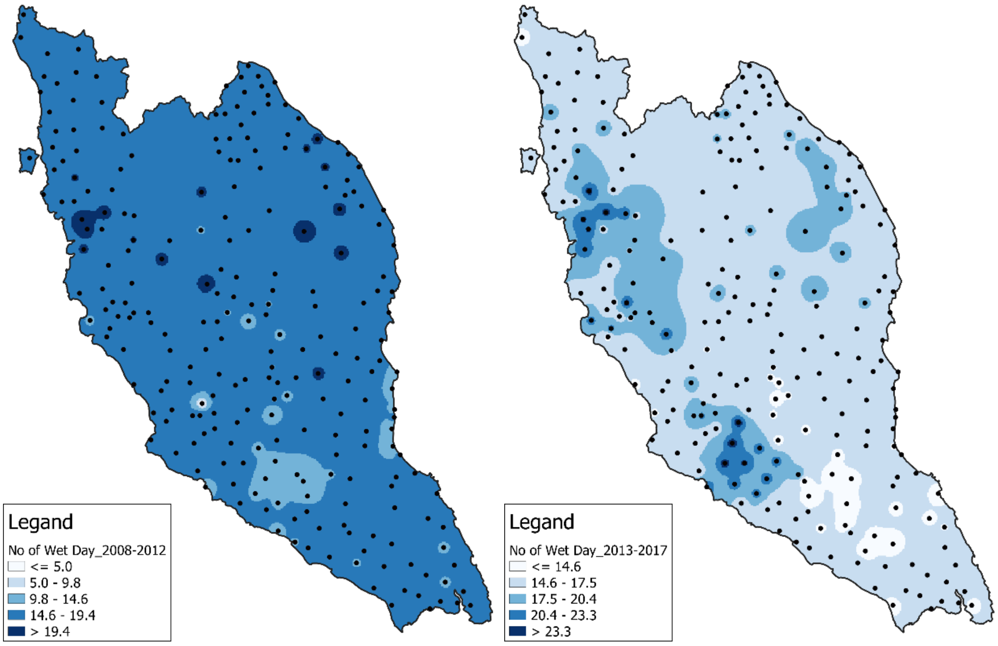


Figure 4.9: Average Number of Wet Days Maps for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

The maps shown in Figure 4.9 have provided the information that the Number of Wet Days in the year 2008-2012 was lower compared to other 5-years periods, which range from 9.8 to 19.4 days. Moreover, the Number of Wet Days in the year 1988-1992 was higher at the northeast region of Peninsular Malaysia, which have a range of 16.5 to 21.9 days. However, maps of the year 1993-1997, 1998-2002, 2003-2007 and 2013-2017 has shown a similar pattern and the range of Number of Wet Days are 14.6 to 21.0 days. The Maximum Daily Rainfall maps are shown in Figure 4.10 and discussed below.

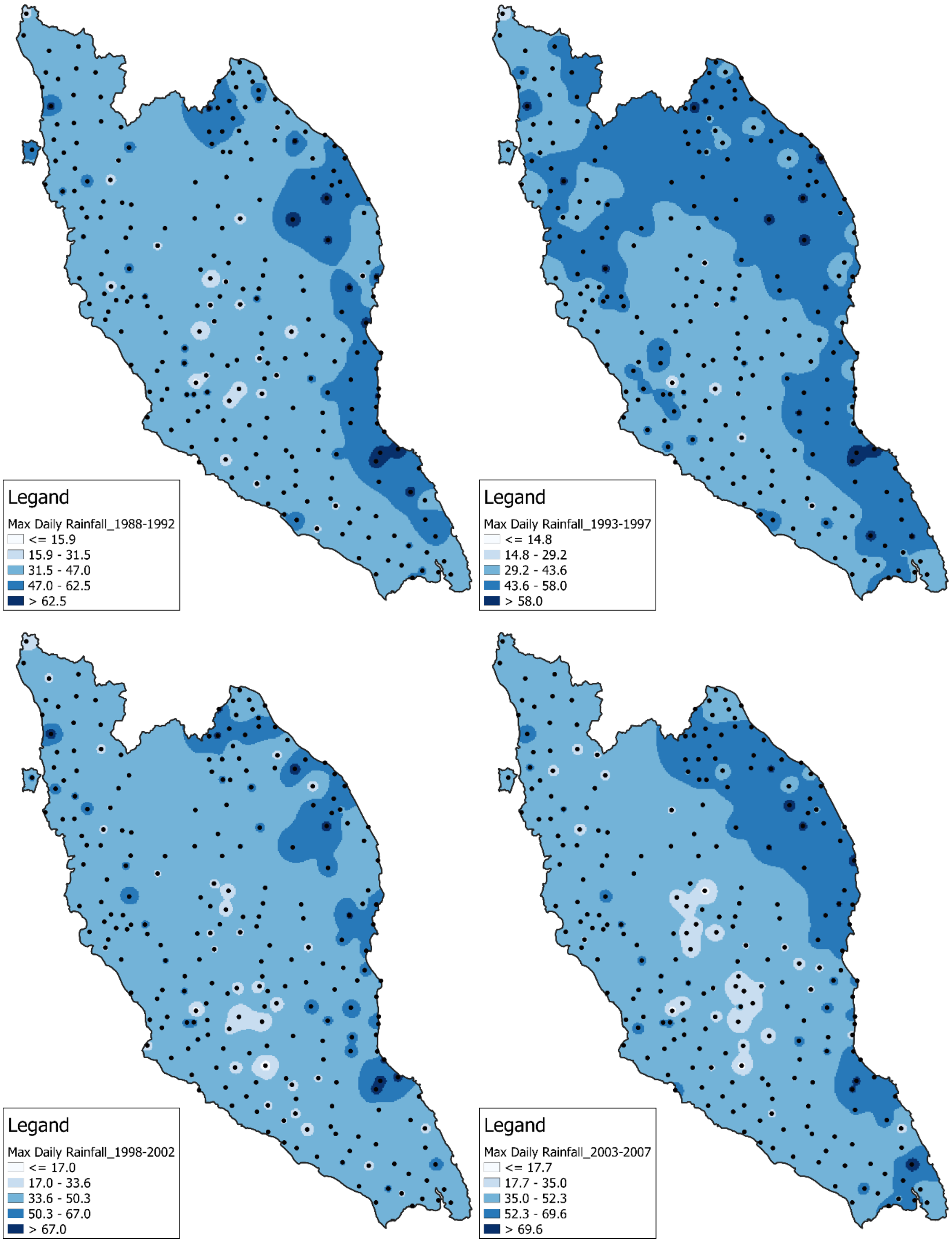


Figure 4.10: Average Maximum Daily Rainfall Maps for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

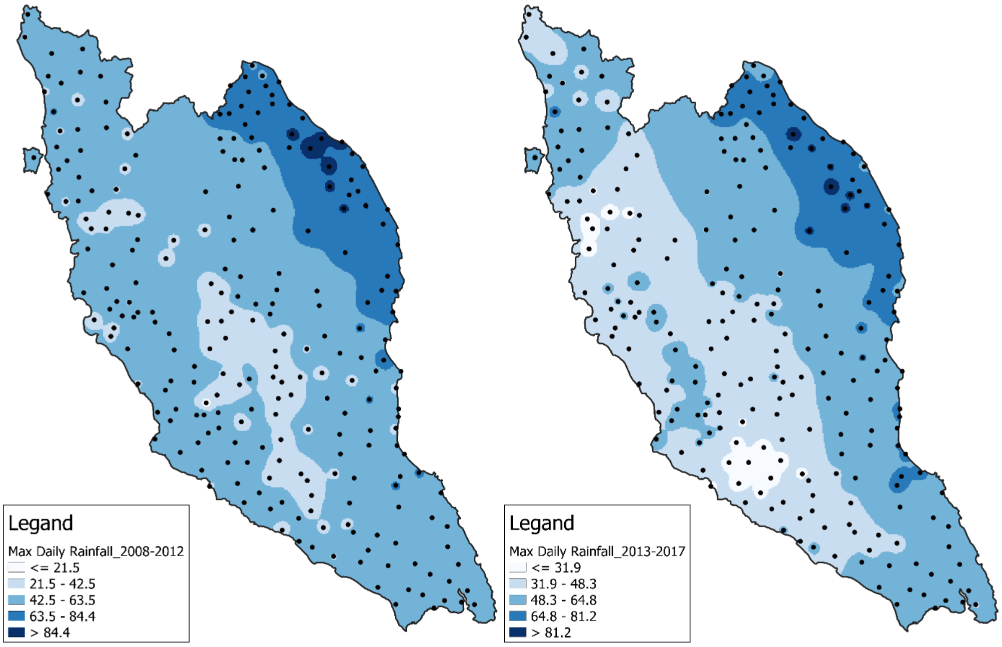


Figure 4.10: Average Maximum Daily Rainfall Maps for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

Figure 4.10 has shown that all the maps have the same rainfall pattern across Peninsular Malaysia. However, the Maximum Daily Rainfall is increasing significantly in the northeast region of Peninsular Malaysia, and it reached the highest value of 84.4 mm in year 2008-2012. By referring to Figure Figure 4.8, Figure 4.9 and Figure 4.10, the high Number of Wet Days (16.5 – 21.9 days) at the northeast region and high Maximum Daily Rainfall (47.0 - 62.5 mm) at the south east region contributed to high Monthly Rainfall (200.1 – 266.2 mm) at the east coast region of Peninsular Malaysia in year 1988-1992. It was noticed that the central region of Peninsular Malaysia was dry in year 1993-1997. This is because the low Maximum Daily Rainfall (29.2 – 43.6 mm) and low Number of Wet Days (10.6 - 15.8 days) at the central region of Peninsular Malaysia led to low Monthly Rainfall (87.2 – 172.5 mm) at central region. Moreover, the Maximum Daily Rainfall (33.6 - 67.0 mm) in year 1998-2002 was consistent across Peninsular Malaysia. However, the low Number of Wet Days (10.7 – 16.0 days) at the central region of Peninsular Malaysia in year 1998-2002 brought the effect of low Monthly Rainfall (84.6 – 168.0 mm) in central region of Peninsular Malaysia in year 1998-2002. For the year 2003-2007 and 2008-2012, the Monthly Rainfall (228.3 – 347.6 mm) is high at the northeast region of Peninsular Malaysia due to the high

Maximum Daily Rainfall (52.3 – 84.4 mm) at northeast region, whereas the Number of Wet Days (14.6 – 20.3 days) was consistent across the Peninsular Malaysia. Besides, the Number of Wet Days (17.5 - 23.3 days) in year 2013-2017 in the west part of Peninsular Malaysia was slightly higher compared to other region; however, it does not increase the Monthly Rainfall at the west part of Peninsular Malaysia. The Monthly Rainfall (197.0 – 325.3 mm) in northeast region of Peninsular Malaysia is higher than other region due to the contribution of high Maximum Daily Rainfall (64.8 – 81.2 days). Figure 4.11 to Figure 4.22 show the maps of average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall from January to December along year 1988-2017.

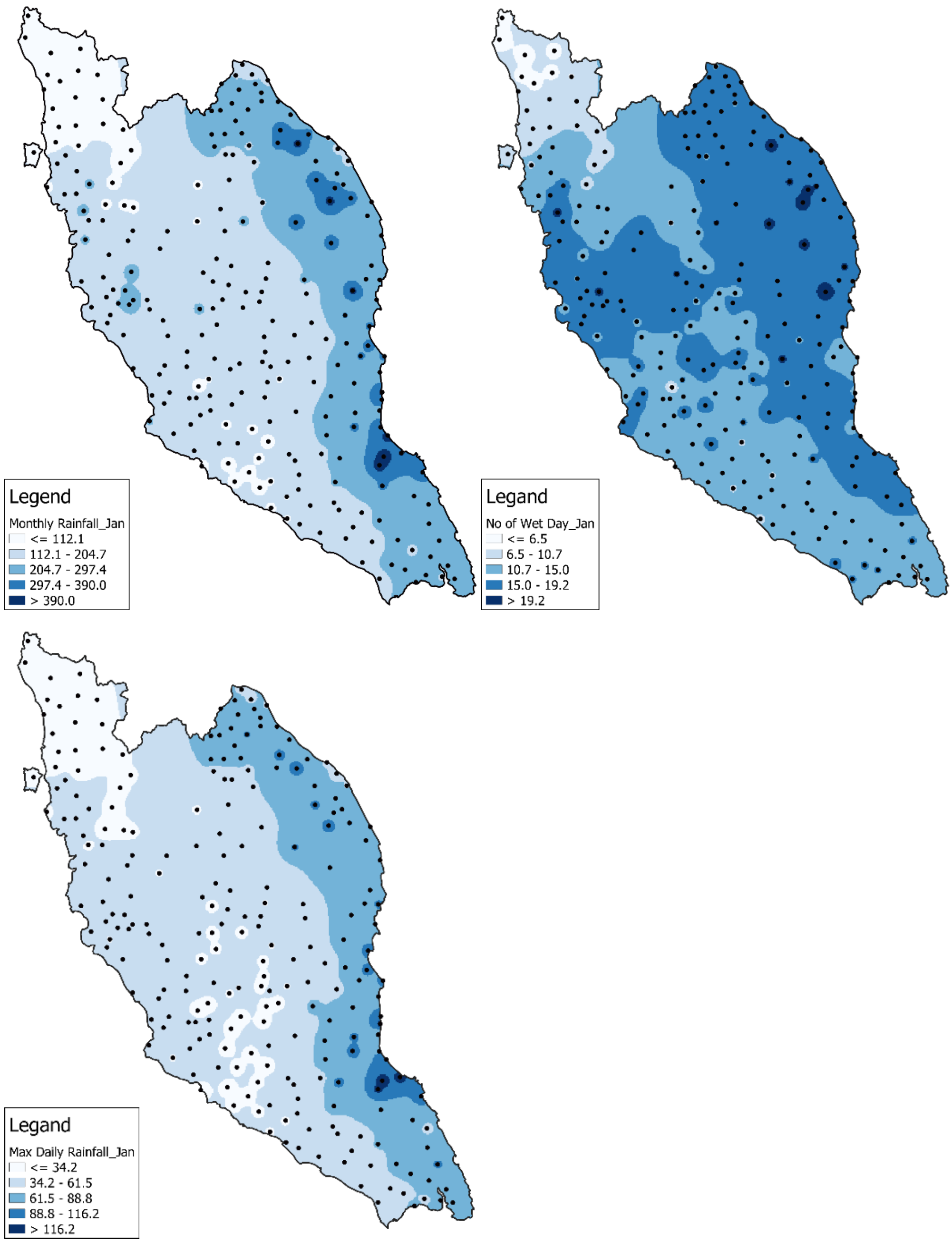


Figure 4.11: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of January along 1988-2017.

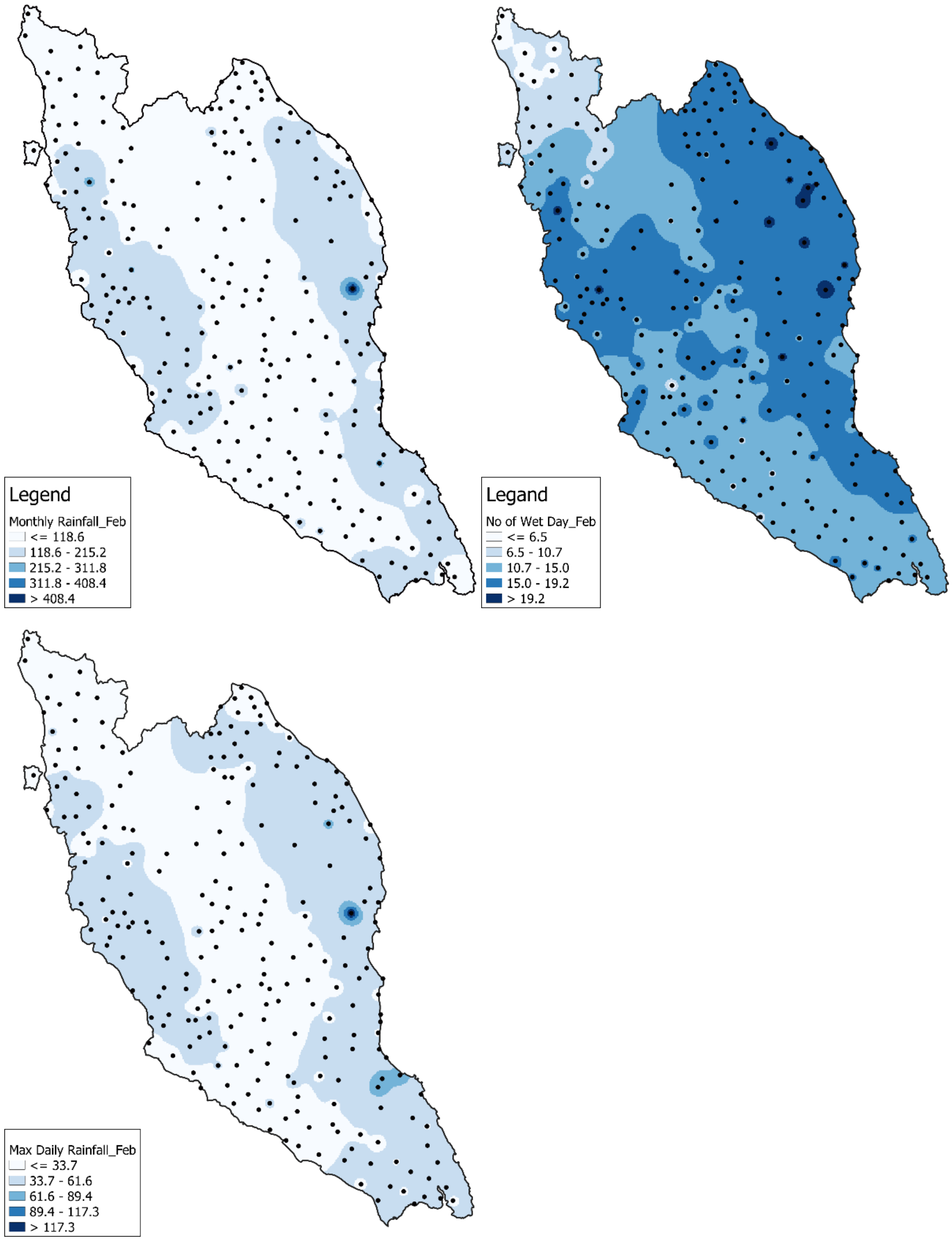


Figure 4.12: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of February along 1988-2017.

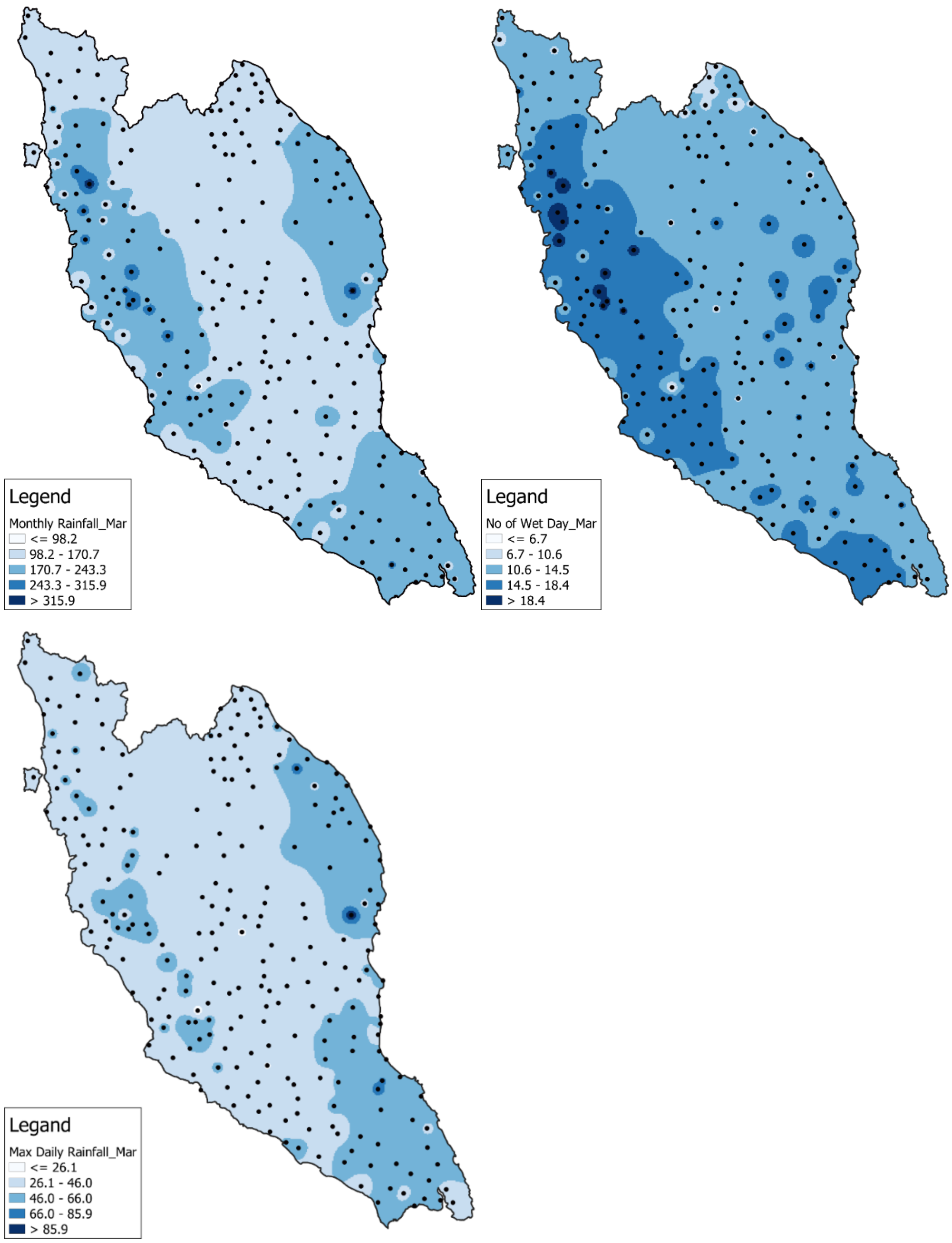


Figure 4.13: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of March along 1988-2017.

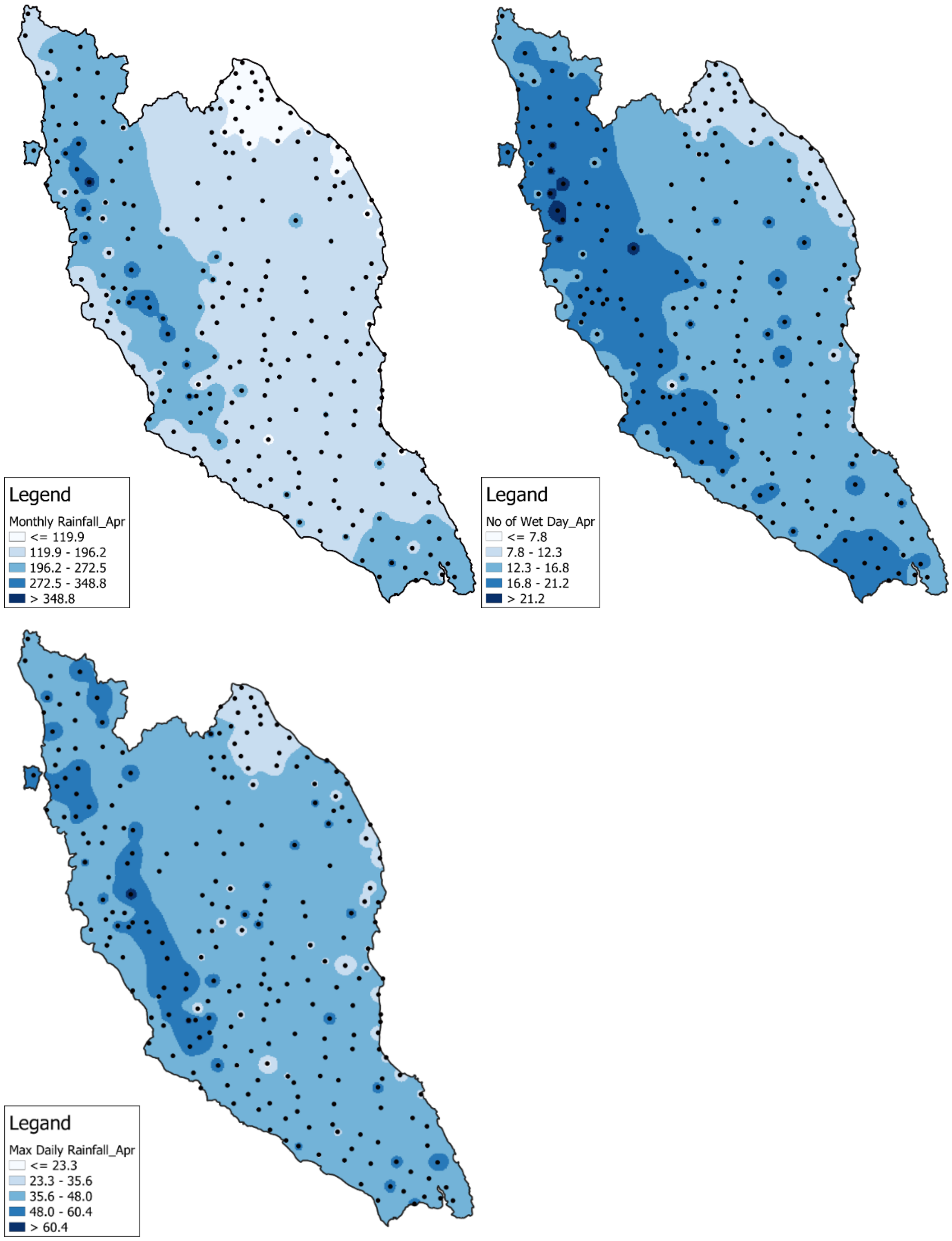


Figure 4.14: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of April along 1988-2017.

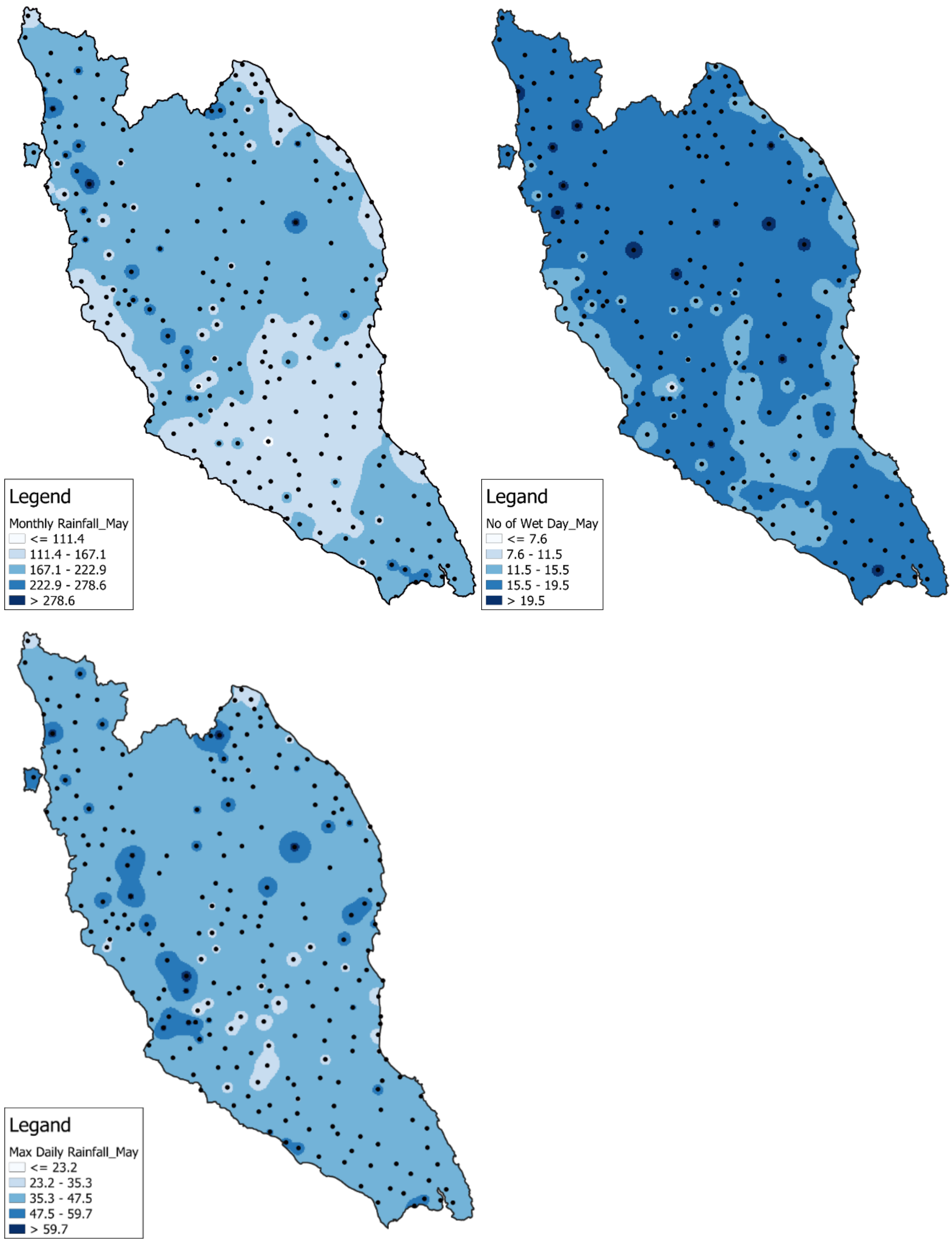


Figure 4.15: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of May along 1988-2017.

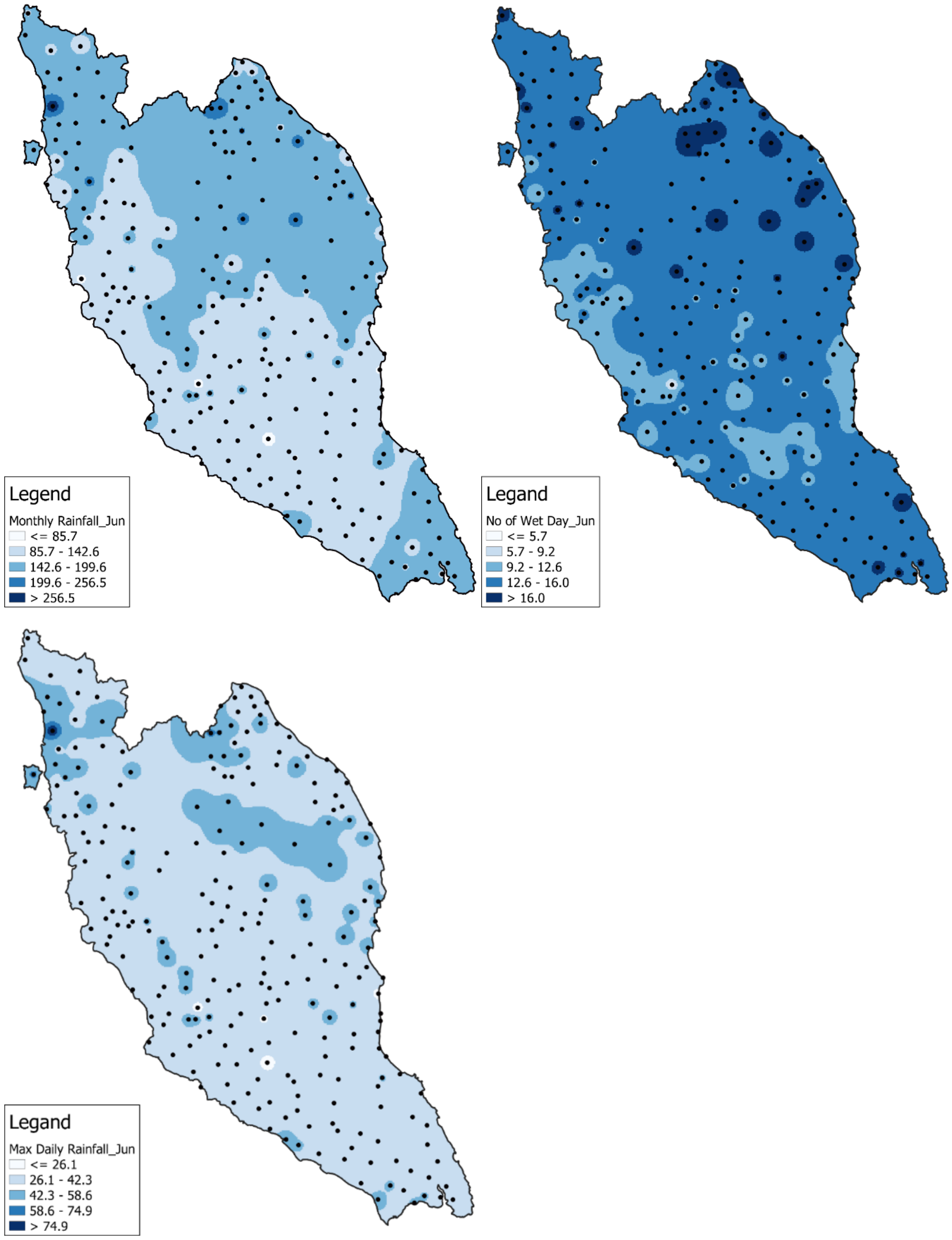


Figure 4.16: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of June along 1988-2017.

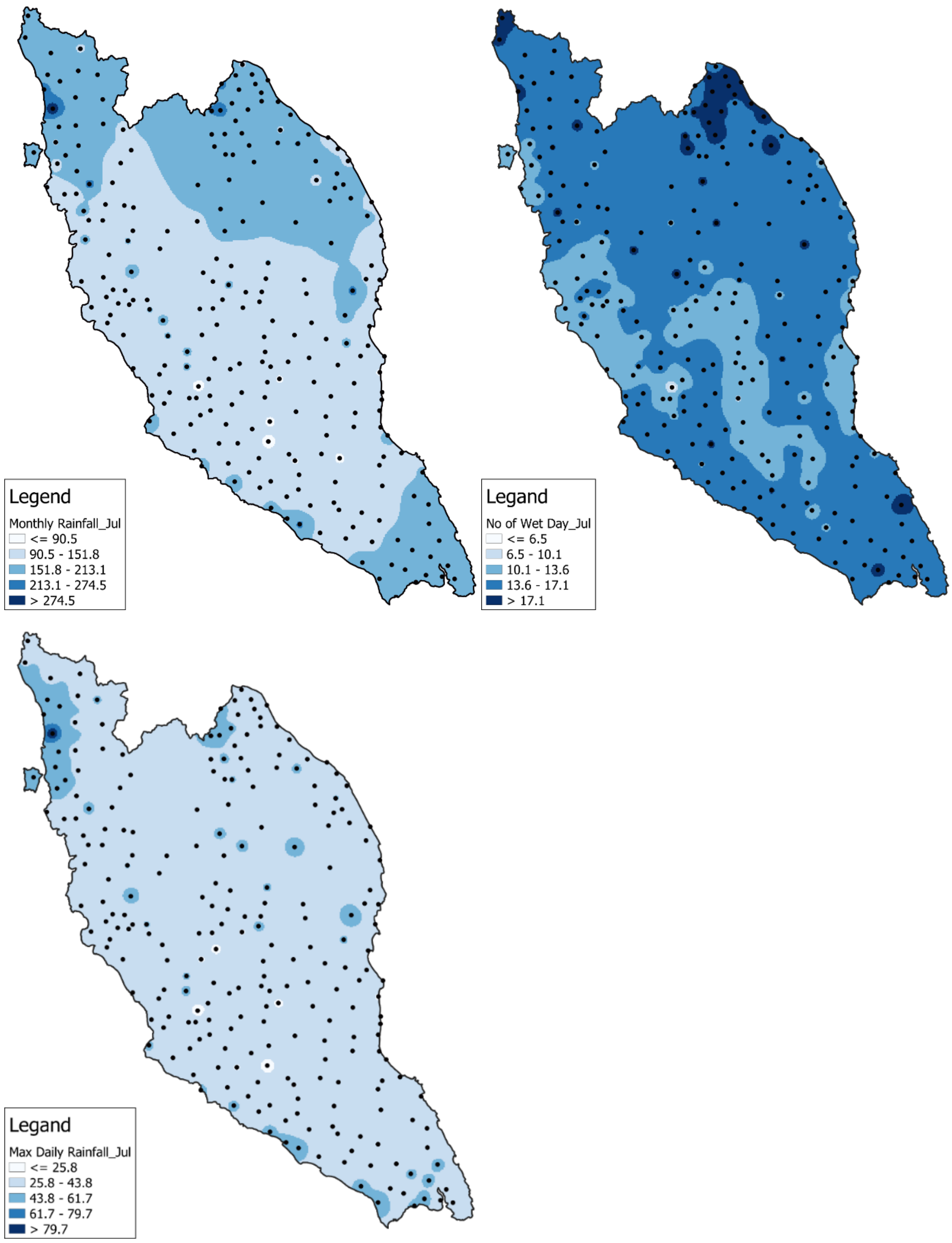


Figure 4.17: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of July along 1988-2017.

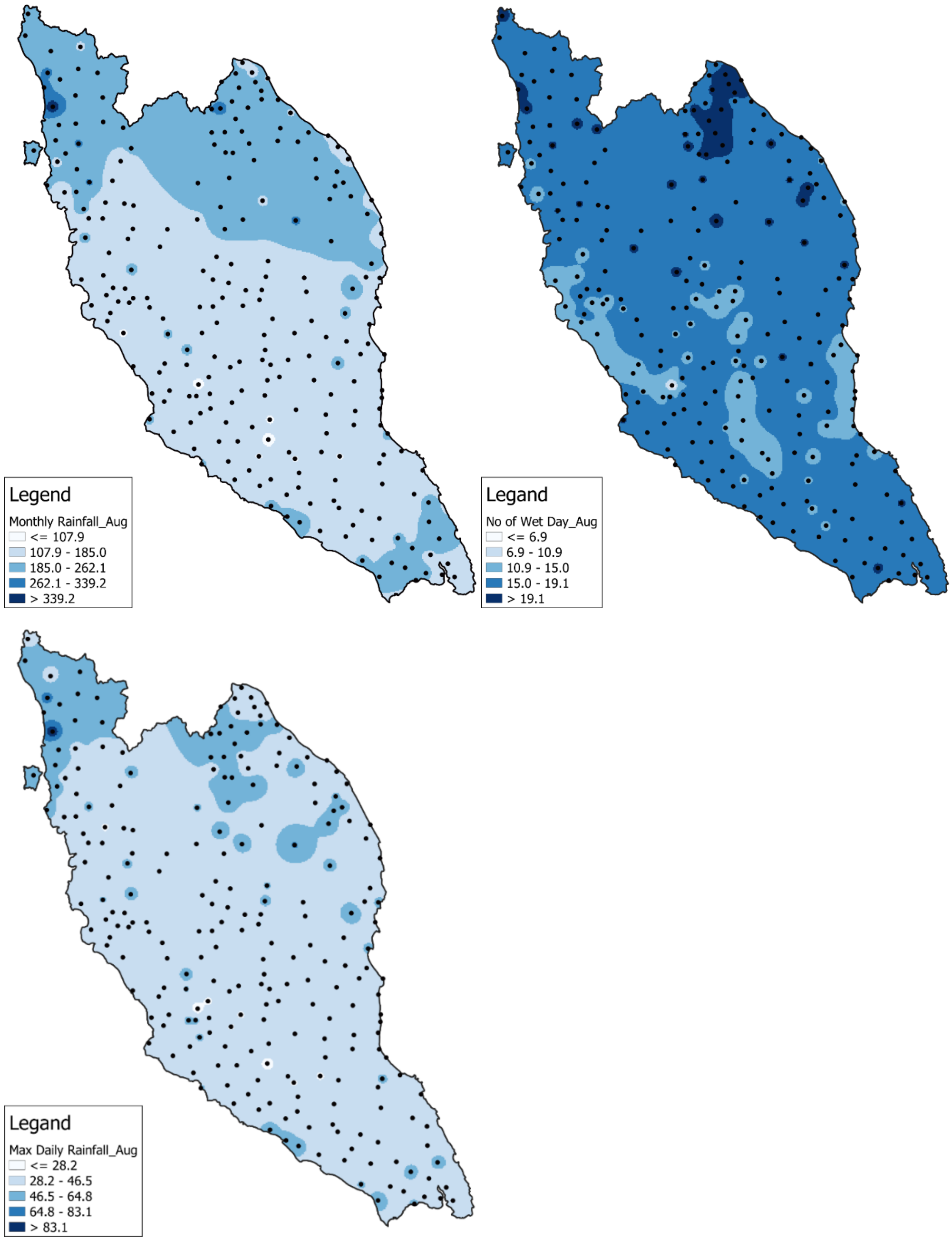


Figure 4.18: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of August along 1988-2017.

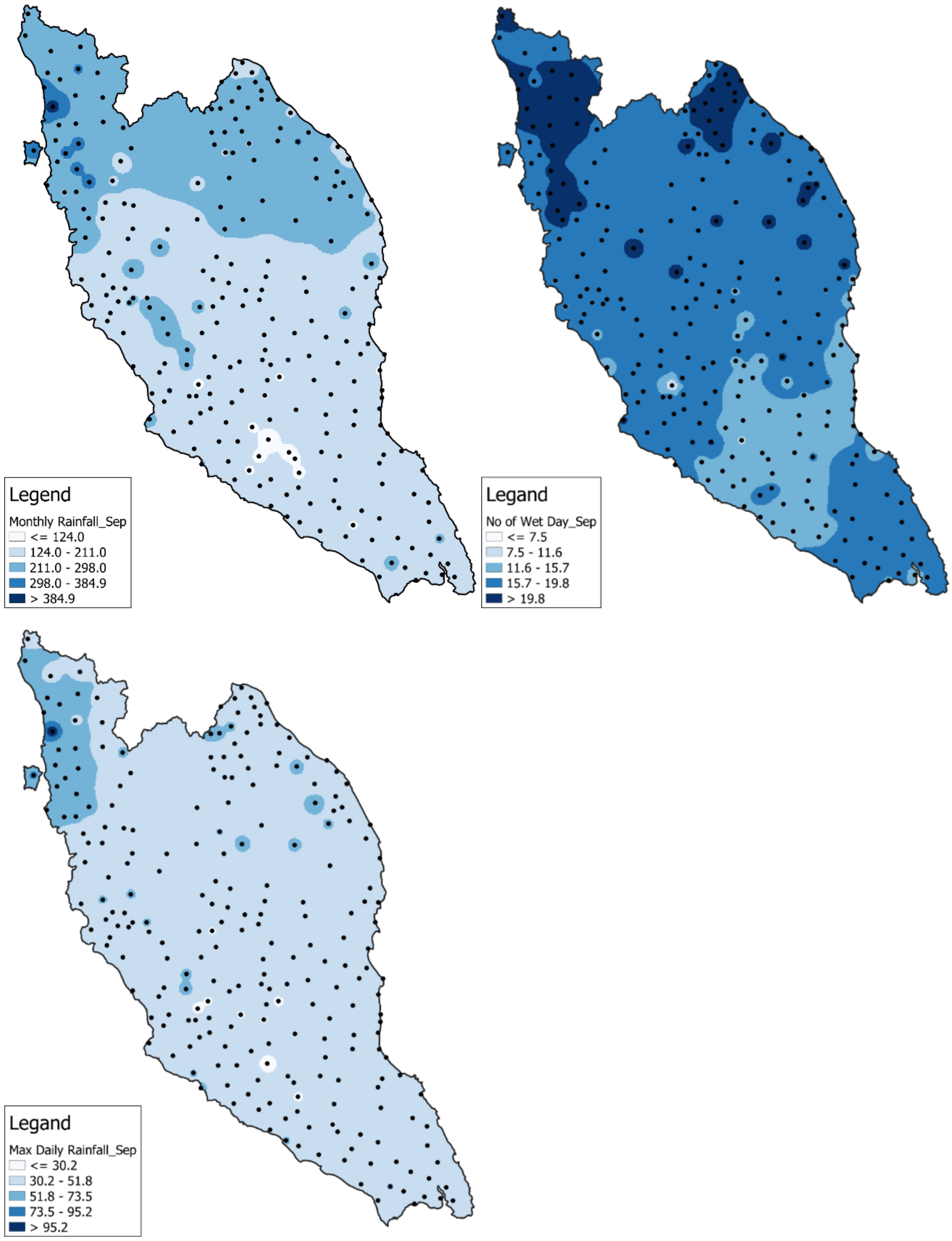


Figure 4.19: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of September along 1988-2017.

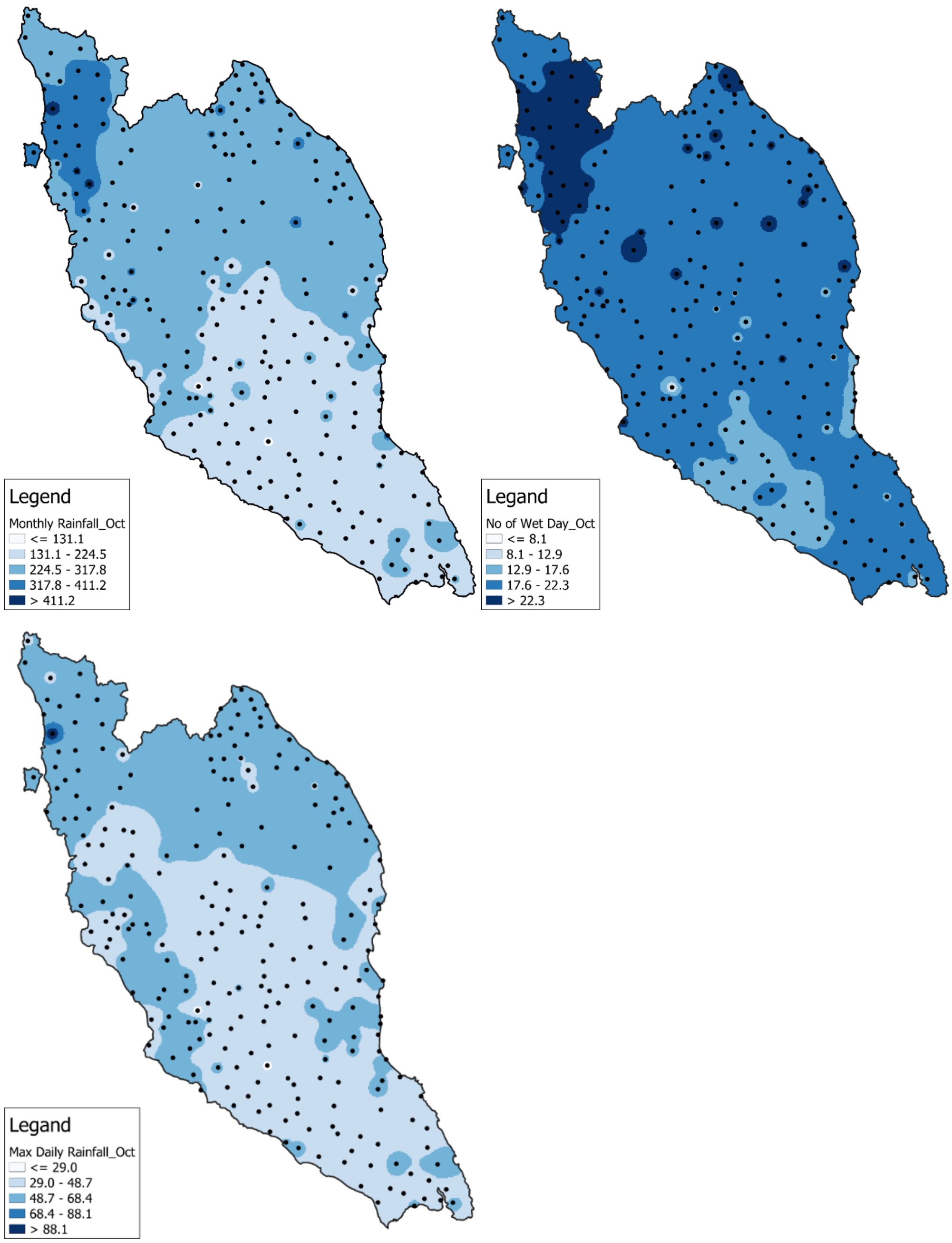


Figure 4.20: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of October along 1988-2017.

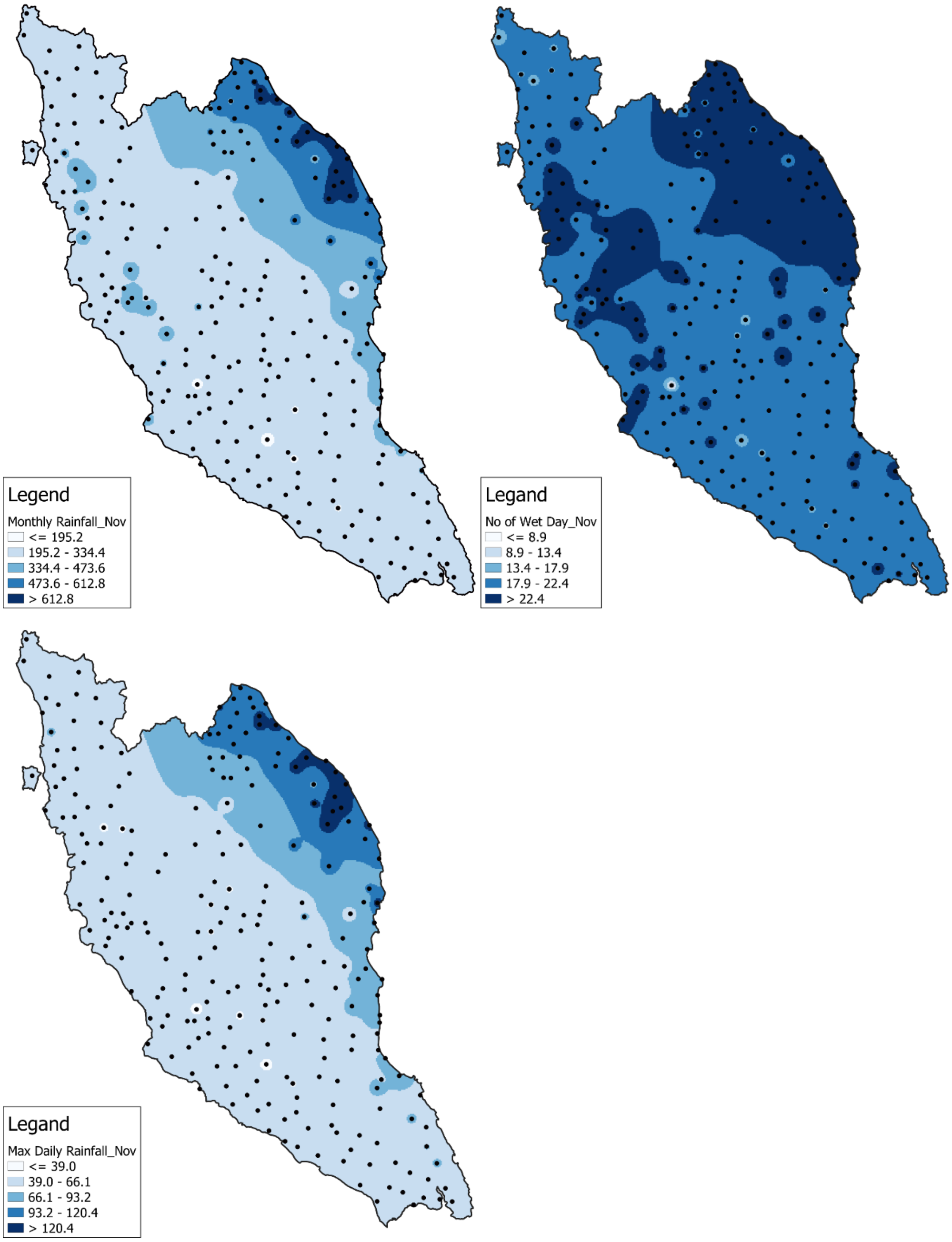


Figure 4.21: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of November along 1988-2017.

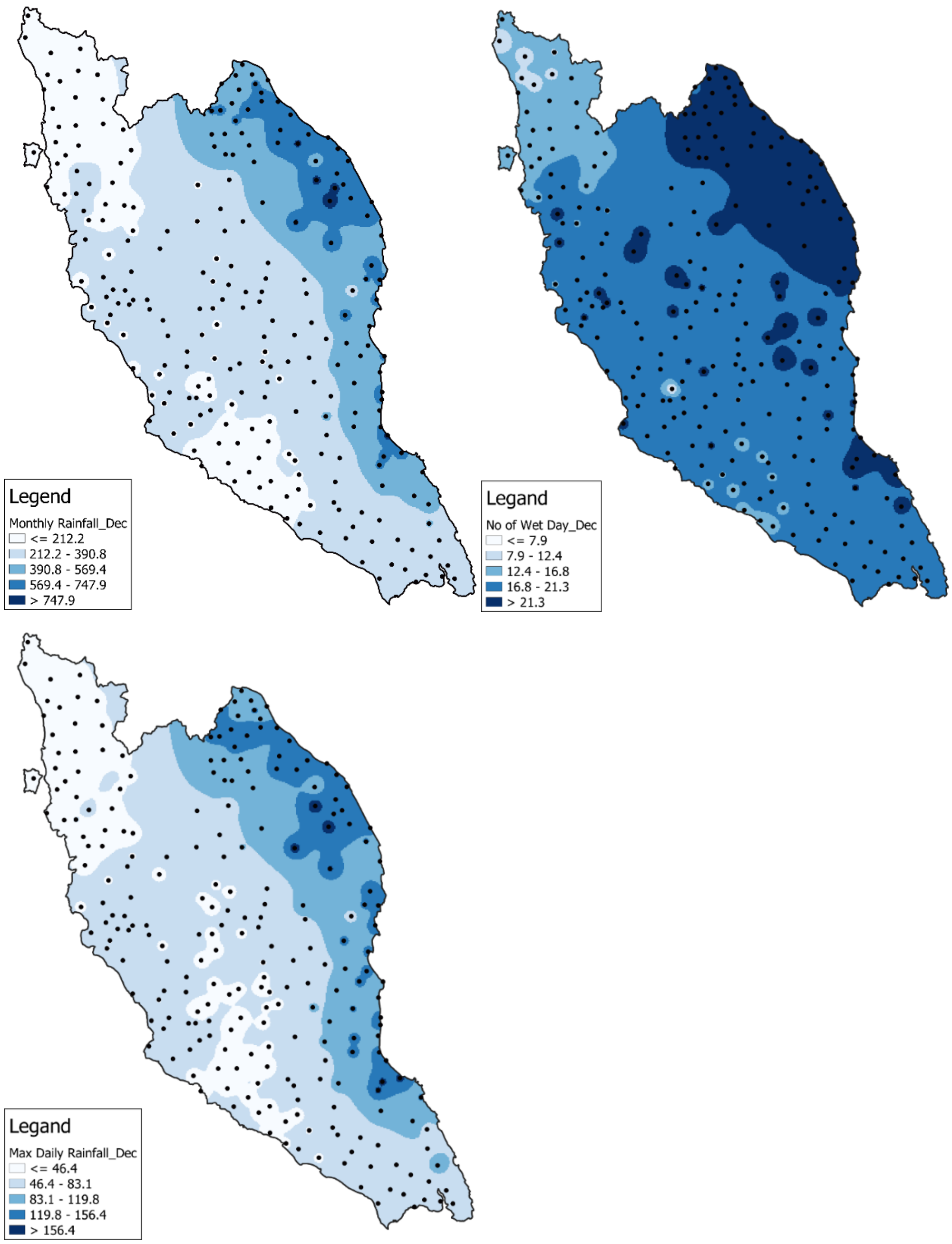


Figure 4.22: Maps of Average Monthly Rainfall, Number of Wets Days and Maximum Daily Rainfall of December along 1988-2017.

As shown in Figure 4.11, the average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall in the east coast region for January are higher than other regions. The high average Month Rainfall (204.7 – 390.0 mm) at the east coast due to the contribution of high average Number of Wet Day (15.0 – 19.2 days) and Maximum Daily Rainfall (61.5 – 88.8 mm). By referring to Figure 4.12, the average Number of Wet Days in the east coast region during February was consistent over the Peninsular Malaysia, which range from 5.7 to 13.3 days. However, the Maximum Daily Rainfall and Monthly Rainfall were higher at the west and east coast of Peninsular Malaysia, which have a range of 33.7 to 61.6 mm and 118.6 to 215.2 mm, respectively. At the end of Northeast Monsoon (March), the Number of Wet Days in the east coast (10.6 – 14.5 days) start to reduce, and the Number of Wet Days at the west part (14.5 - 18.4 days) of Peninsular Malaysia rises, as shown in Figure 4.13. The Maximum Daily Rainfall at the east coast area has a range of 46.6 to 66.0 mm, and also higher than other regions. These two effects lead to high Monthly Rainfall in March in the east coast and west part of Peninsular Malaysia, which the Monthly Rainfall in both east coast and west part of Peninsular Malaysia is 170.0 to 243.3 mm.

During the transition month (April) from Northeast Monsoon to Southwest Monsoon, Figure 10.14 shows that the west part of Peninsular Malaysia has higher Number of Wet Days (16.8 – 21.2 days) and Maximum Daily Rainfall (48.0 – 60.4 mm), which consequently lead to high Monthly Rainfall (196.2 – 348.8 mm) compare to other regions. This may occur due to the delay effect of Northeast Monsoon in which not all the rainfall was blocked by Banjaran Titiwangsa. As shown in Figure 4.14 to Figure 4.19, the Monthly Rainfall, Maximum Daily Rainfall and Number of Wet Days from May to September has shown a similar pattern. The Maximum Daily Rainfall is consistent across the whole Peninsular Malaysia, but the Number of Wet Day are mostly concentrated at the northern region and southern region. Therefore, the Monthly Rainfall from May to July is particularly higher in the northern region and southern region, as the range of Monthly Rainfall are from 142.6 to 278.6 mm. The Monthly Rainfall at the northern region of Peninsular Malaysia is higher compared to other regions as most of the rainfall from the Southwest Monsoon had been blocked by the island at Sumatra, Indonesia as the rainfall not able to reach the southwest region of Peninsular Malaysia.

The Northeast Monsoon starts in the month of October. Therefore, the Number of Wet Days (> 22.3 days)and Maximum Daily Rainfall (48.7 – 68.4 mm) is high in the northwest region, and this lead to the high Monthly Rainfall (317.8 – 411.2 mm) in the northwest region, as shown in Figure 4.20. The Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall for

November and December were plotted at Figure 4.21 and Figure 4.22, respectively. During the peak of Northeast Monsoon, November and December at the northeast region of Peninsular Malaysia has high Number of Wet Days which is greater than 22.4 days and greater than 21.3 days, respectively. The Maximum Daily Rainfall for November and December at the northeast region of Peninsular Malaysia was 66.1 to 120.4 mm and 83.1 to 156.4 mm, respectively. The high value of both Number of Wet Days and Maximum Daily Rainfall has lead to high Monthly Rainfall for November and December, which has range of 334.4 to 612.8 mm and 390.8 to 747.9 mm, respectively. Lastly, the Monthly Rainfall, Number of Wets Days, and Maximum Daily Rainfall for the 5-year periods are plotted monthly from January to December.

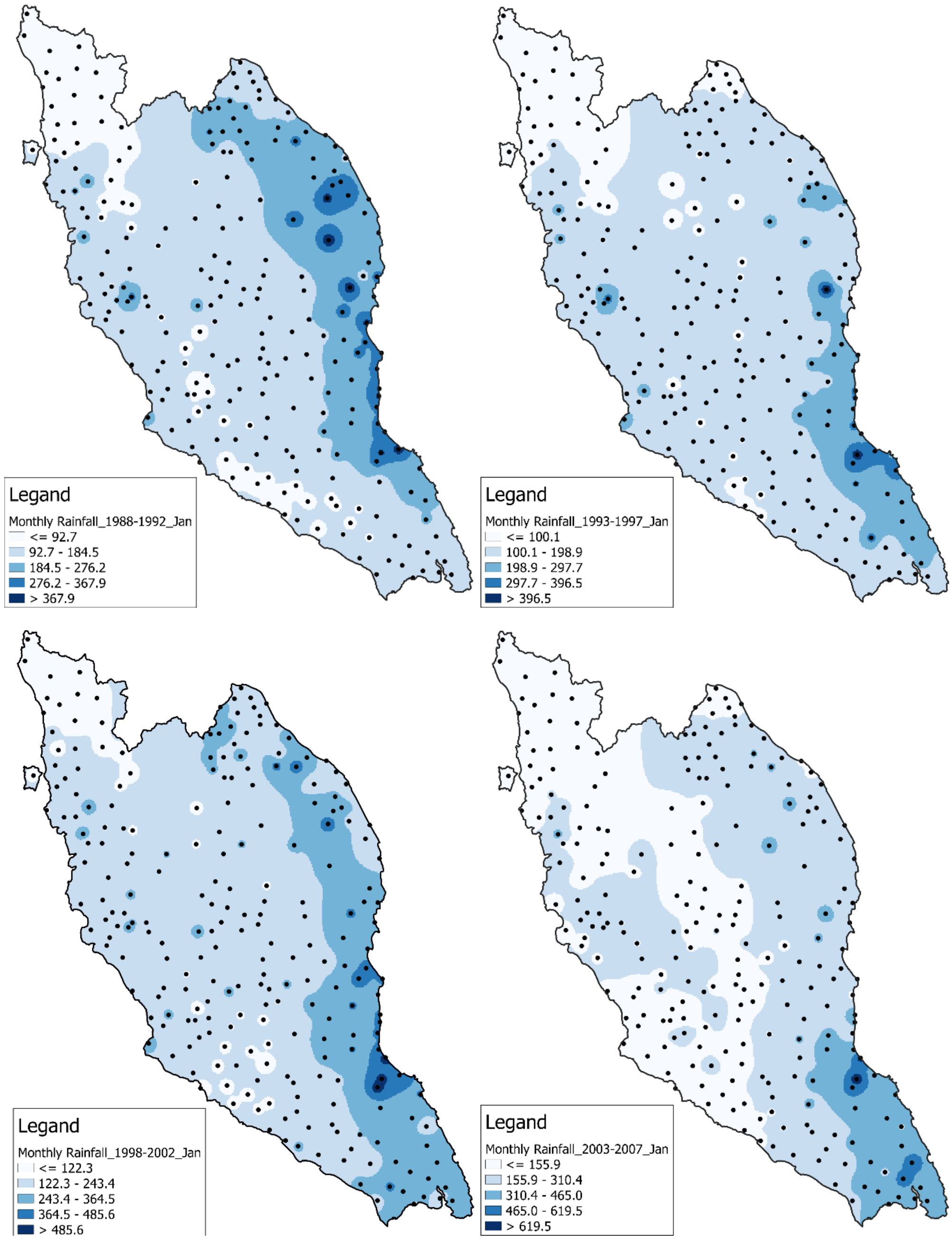


Figure 4.23: Average Monthly Rainfall Maps on January for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

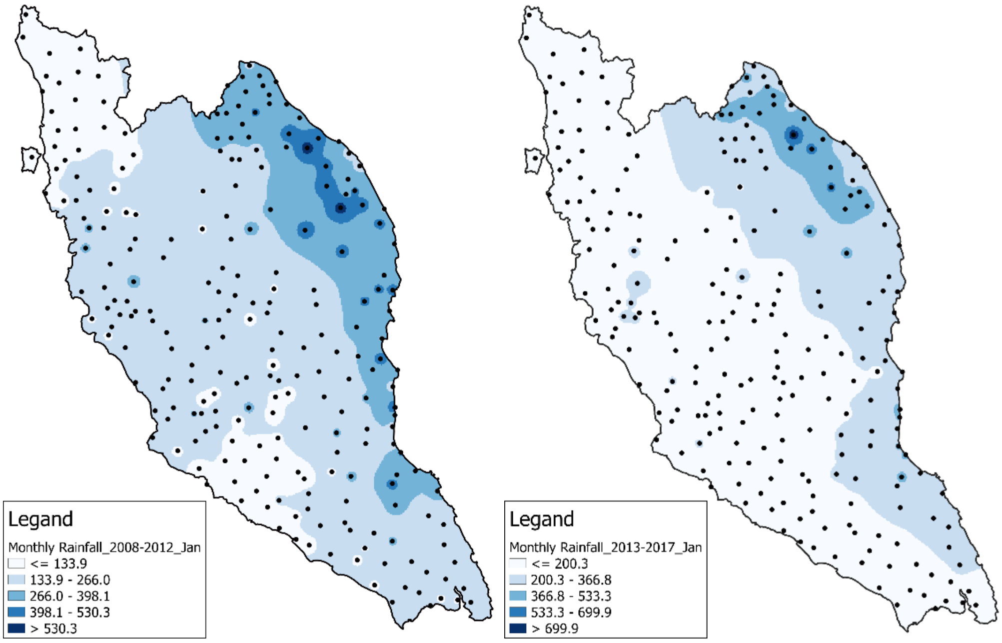


Figure 4.23: Average Monthly Rainfall Maps on January for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

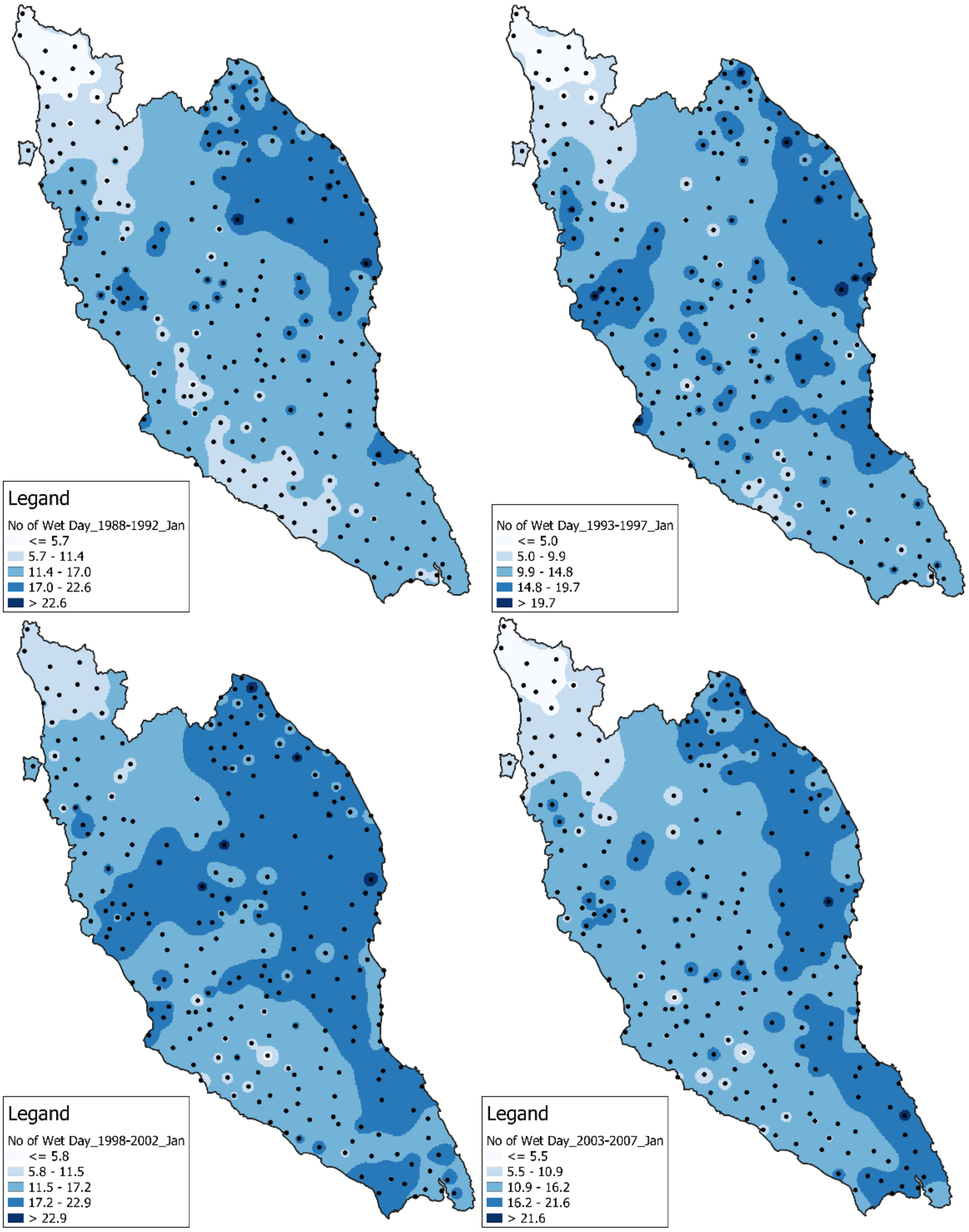


Figure 4.24: Average Number of Wet Days Maps on January for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

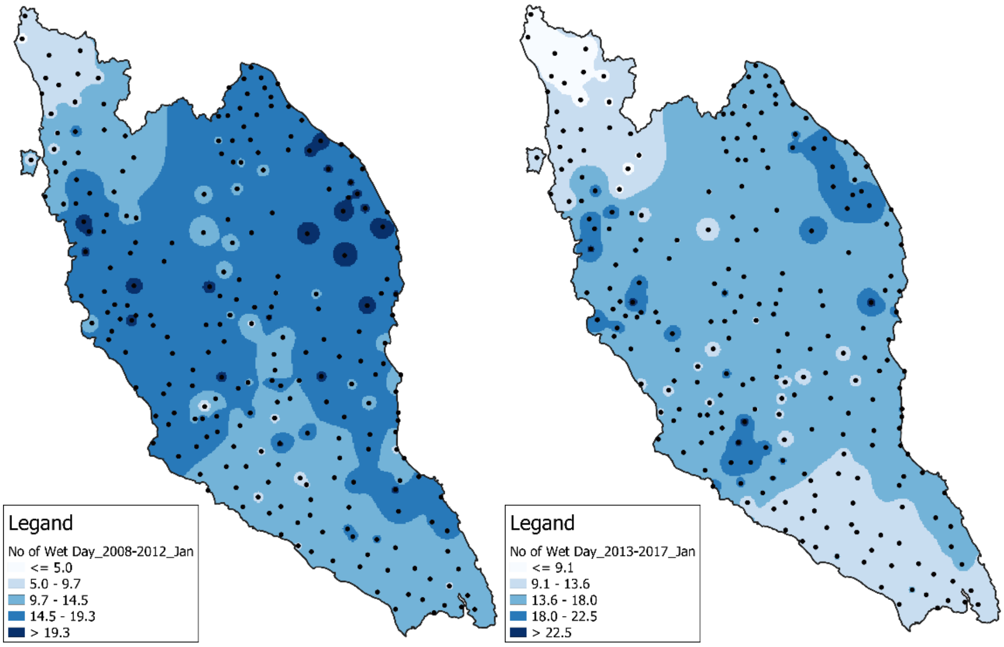


Figure 4.24: Average Number of Wet Days Maps on January for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

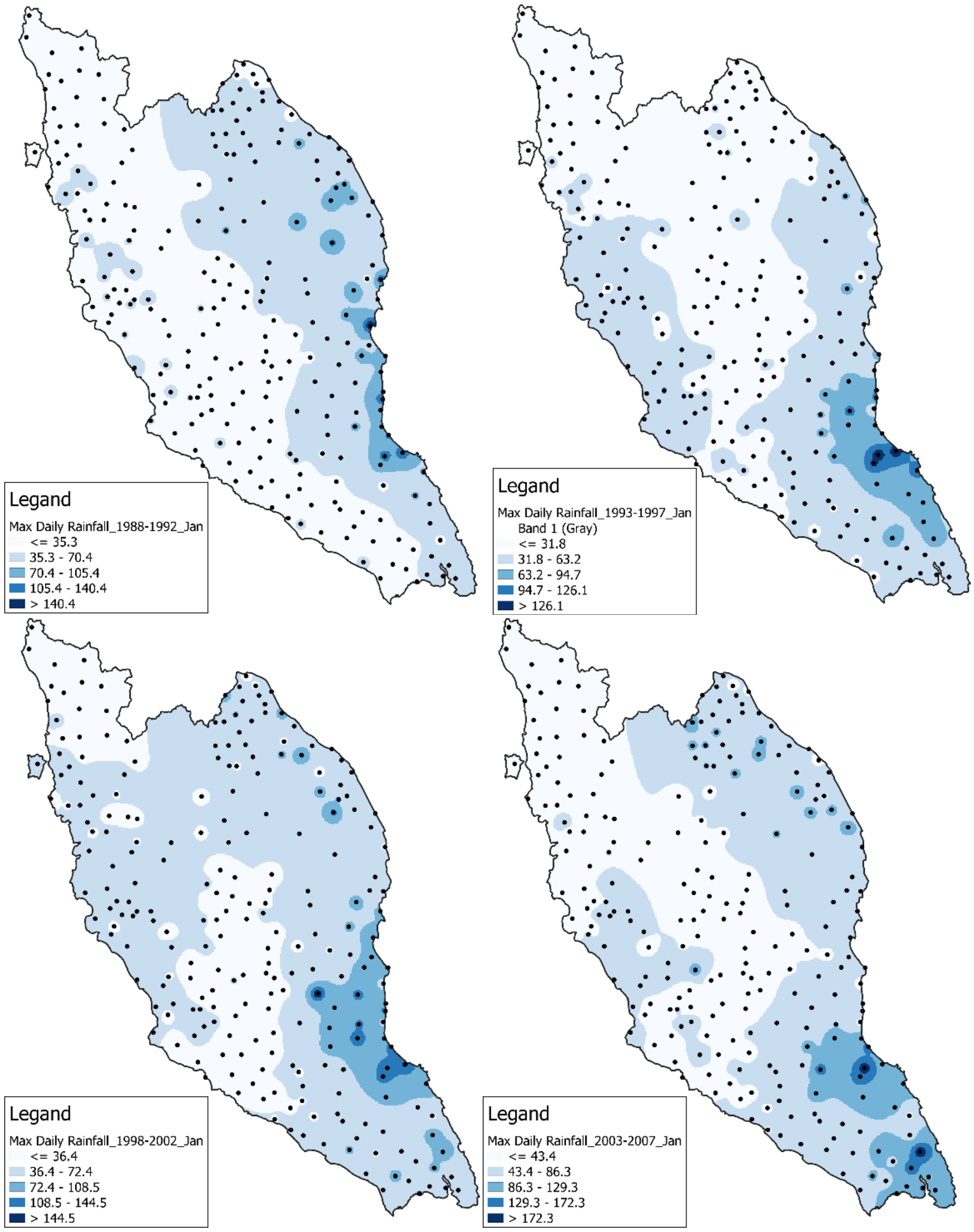
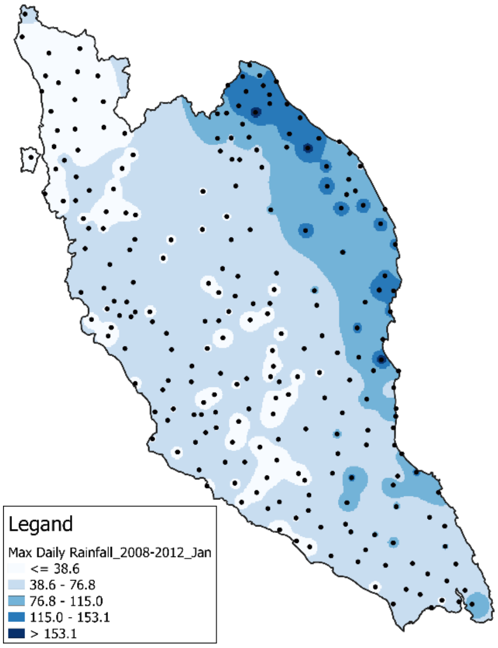


Figure 4.25: Average Maximum Daily Rainfall Maps on January for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



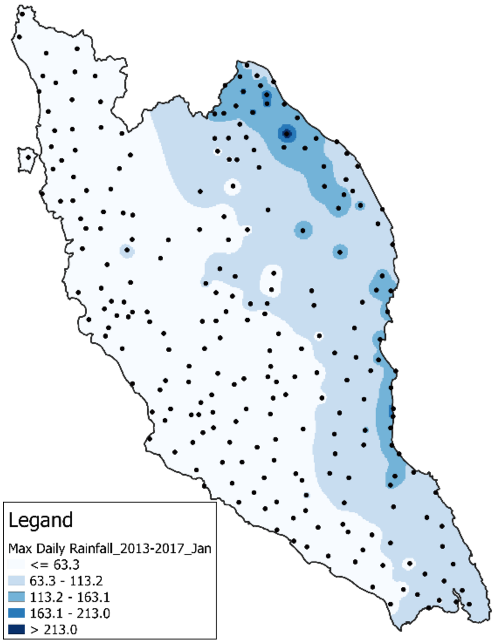


Figure 4.25: Average Maximum Daily Rainfall Maps on January for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

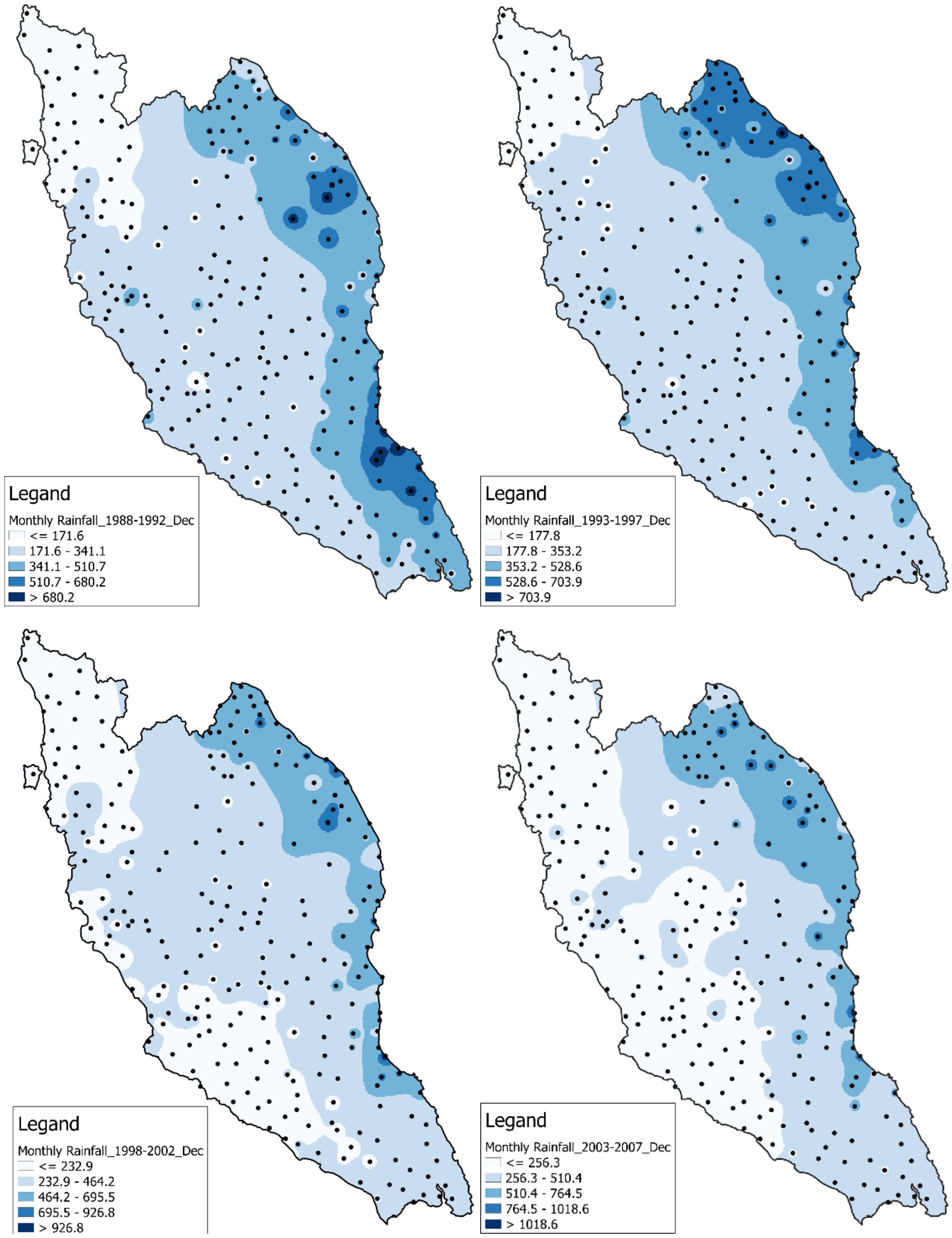


Figure 4.26: Average Monthly Rainfall Maps on December for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

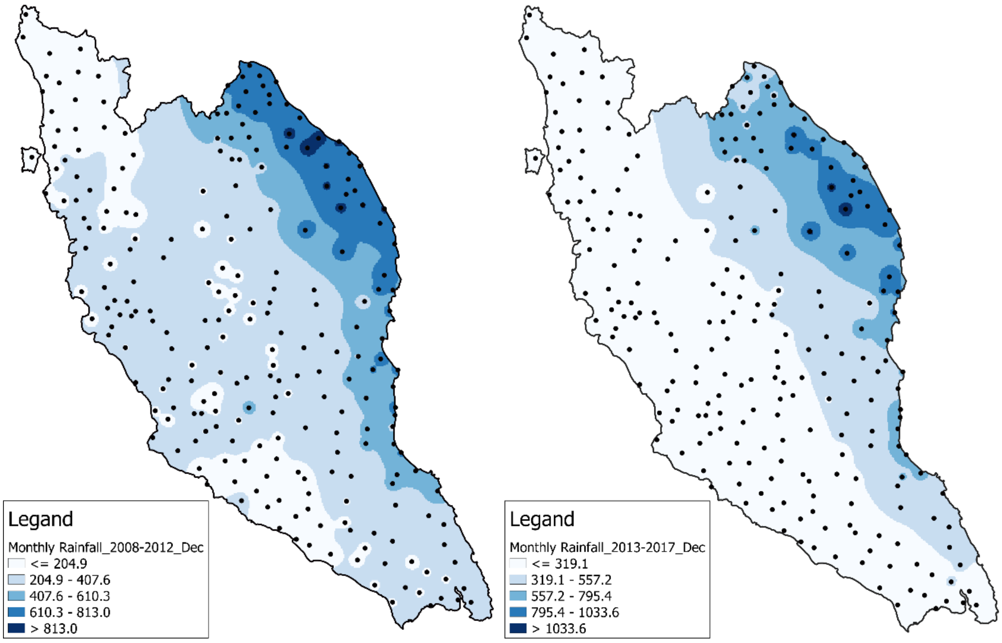


Figure 4.26: Average Monthly Rainfall Maps on December for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

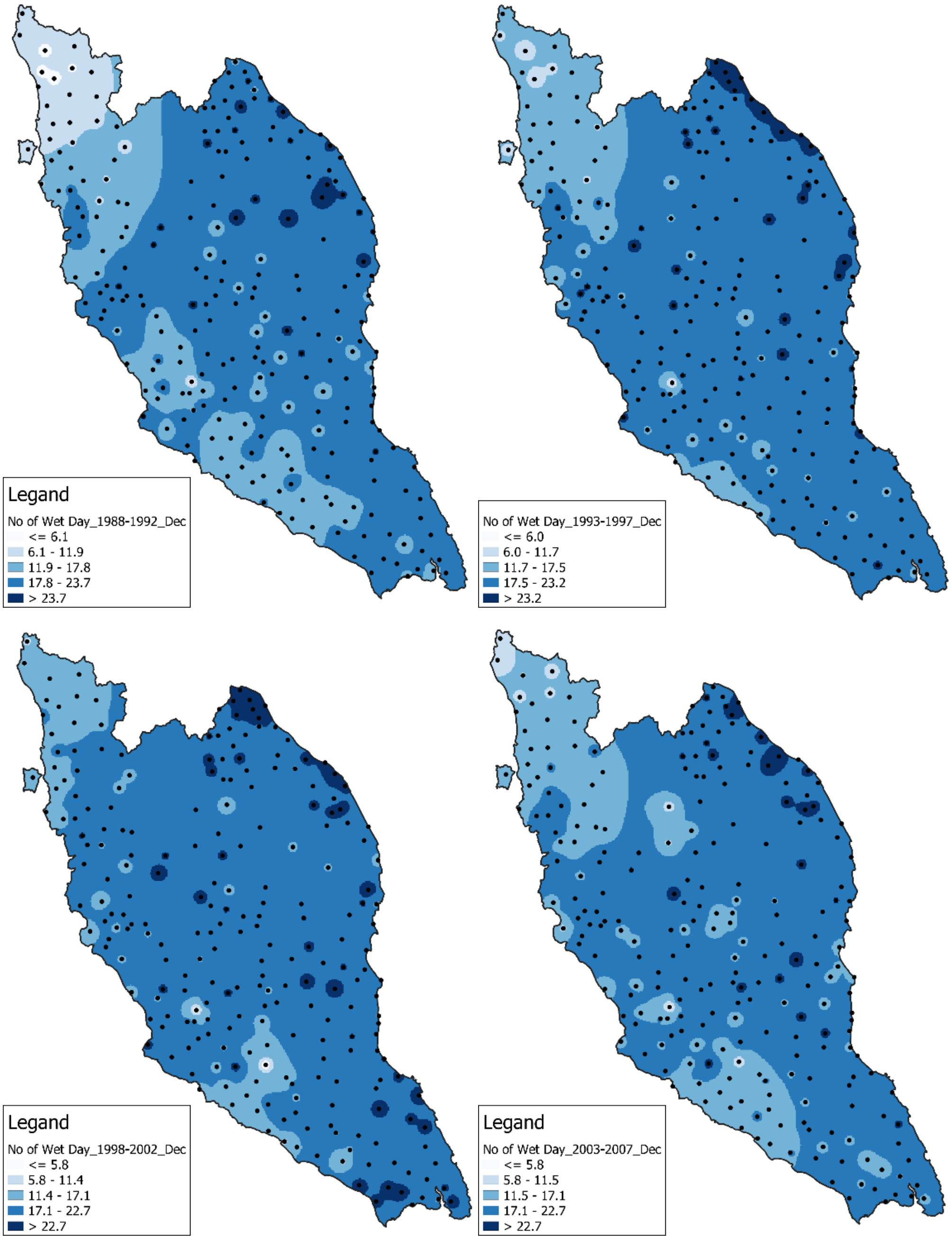


Figure 4.27: Average Number of Wet Days Maps on December for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

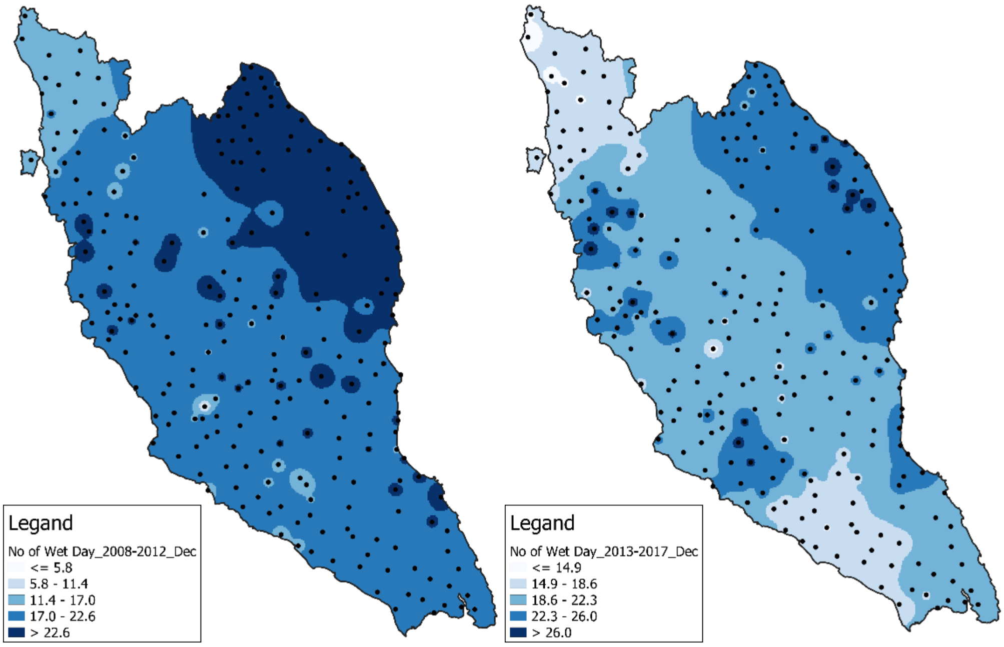


Figure 4.27: Average Number of Wet Days Maps on December for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

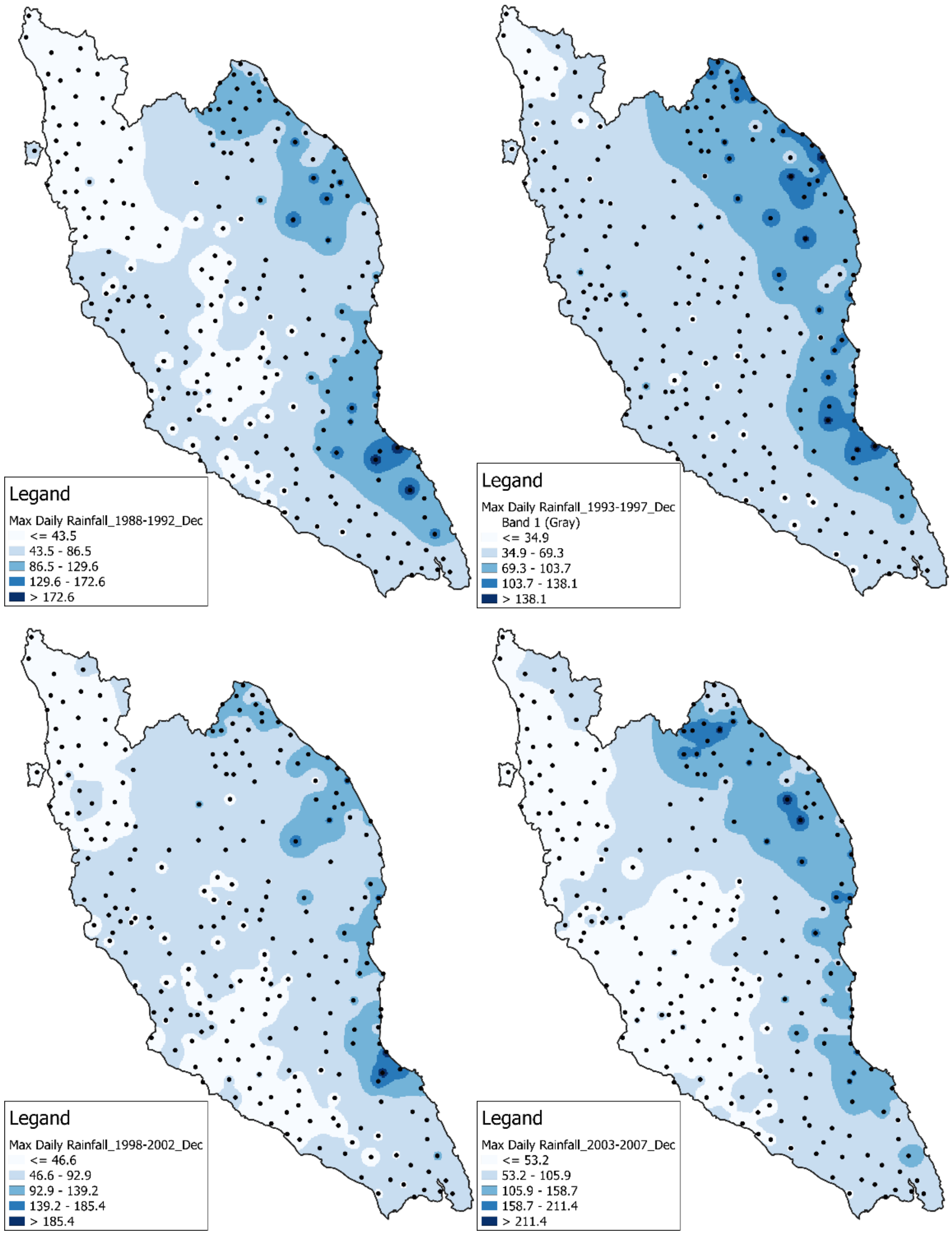


Figure 4.28: Average Maximum Daily Rainfall Maps on December for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

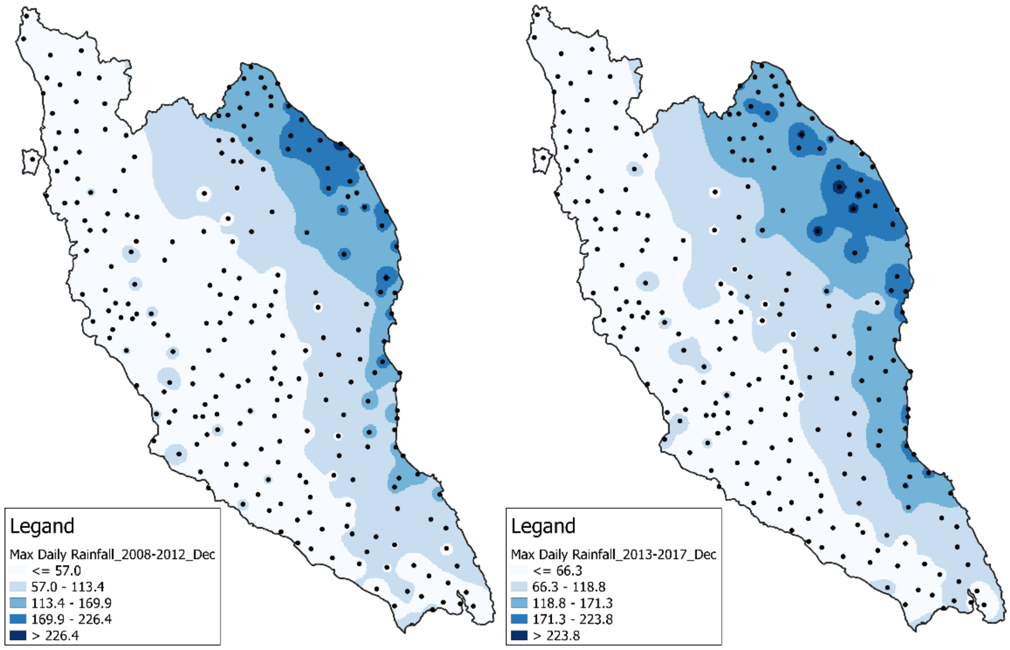


Figure 4.28: Average Maximum Daily Rainfall Maps on December for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

The average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall from January to December have been plotted for the 5-year periods. However, only the cases of January and December will be discussed in detail, and the maps for the months of February to November will be shown at the Appendix; due to the maps of average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall from February to November across these 30 years have shown insignificant change in the rainfall spatial distribution.

By referring to Figure 4.25, the maps showed that the Maximum Daily Rainfall for January in the sub-period of years 1988-1992, 1993-1997, 1998-2002 and 2003-2007 has similar pattern, which the rainfall covered mostly at the east coast region of Peninsular Malaysia and a small portion of west part of Peninsular Malaysia; however, the south east part of Peninsular Malaysia has slightly higher of Maximum Daily Rainfall for January in year 1988-2007, which has a range of 63.2 to 172.3 mm. The Maximum Daily Rainfall for January in the northeast region were higher than other regions in the sub-period of year 2008-2012 and 2013-2017, which was ranging from 63.3 mm to 213.0 mm. Moreover, the Number of Wet Days for January in sub-period of year 1988-1992 and 1993-1997 were slightly higher at the northeast region, which have a range of 14.8 to 22.6 days. The Number of Wet Days for January in sub-period of year 1998-2002 and 2003-2007 were higher at the northeast region, which have a range of 16.2 to 22.9 days, whereas the Number of Wet Days for January in year of 2008-2017 was consistent across Peninsular Malaysia which has a range of 13.6 to 19.3 days, but it was lower at the southern region and northwest part of Peninsular Malaysia, which has a range of 5.0 to 13.6 days. Besides, Figure 4.23 shows that the average Monthly Rainfall (184.5 – 367.9 mm) for January in the east coast region of Peninsular Malaysia in sub-period of year 1988-1992 was higher compared to other regions due to the contribution of high Maximum Daily Rainfall (70.4 – 140.4 mm). During the sub-period of year 1998-2002, the average Monthly Rainfall (243.4 – 485.6 mm) for January in the east coast also higher than other region; however, it was due to the effect of high Number of Wet Days. For the sub-period of year 1993-1997 and 2003-2007, the high Maximum Daily Rainfall (63.2 – 172.3 mm) has led to the effect of high Monthly Rainfall (198.9 – 619.5 mm) at the south east part of Peninsular Malaysia. The Monthly Rainfall (266.0 – 699.9 mm) for January in the year 2008-2017 was high at the northeast region of Peninsular due to the contribution of high Maximum Daily Rainfall (76.8 – 213.0 mm).

As shown in Figure 4.27, the Number of Wet Days for December in the sub-period of year 1988-1992, 1993-1997 and 2003-2007 was consistent across Peninsular Malaysia which has a range of 11.4 to 22.7 days, except for the northwest part of Peninsular Malaysia which has lower range of 5.8 to 11.9 days. The Number of Wet Days for December in the sub-period of year 1998-2002 was consistent across the whole Peninsular Malaysia which has a range of 17.1 – 22.7 days. However, the Number of Wet Days for December in year of 2008-2017 was higher at the northeast region compared to other regions which has a range of 22.3 to 26.0 days. By referring to the Figure 2.8, the Maximum Daily Rainfall for December have a similar pattern throughout these 30 years, in which the Maximum Daily Ranfall was high at the east coast of Peninsular Malaysia. As shown in Figure 4.26, the average Monthly Rainfall (341 – 703.9 mm) for December in the year 1988-1997 was higher than other regions due to the high Maximum Daily Rainfall (69.3 – 172.6 mm) at the east coast region. However, the average Monthly Rainfall (407.6 – 1033.6 mm) for December in year 1998-2017 was higher at the northeast part of Peninsular Malaysia due to the high Number of Wet Days (17.0 – 26.0 days) and Maximum Daily Rainfall (92.9 – 226.4 mm).

By referring to Figure 4.23 and Figure 4.26, the average Monthly Rainfall maps in northeast region of Peninsular Malaysia for January and December in the year 2013-2017, has increased significantly compared to other 5-years periods, which able to reach the maximum value of 699.9 mm and 1033.6 mm, respectively. The increase of Monthly Rainfall in January for year 2013-2017 was contributed by the increase of Maximum Daily Rainfall (163.1 – 213.0 mm), as shown in Figure 4.25. However, the increase of Monthly Rainfall in December for year 2013-2017 was due to the increase of the Number of Wet Days (118.1 – 223.8 mm), as shown in Figure 4.27.

4.3 Summary

The GWR and MGWR models were used to estimate the rainfall data across Peninsular Malaysia in this study and are themselves evaluated by using MAE, RMSE and R^2. By referring to Table 4.1, it is noticed that the MGWR has a better performance compared to the GWR on average for all stations, in terms of RMSE, MAE and R^2. The total of 244 rainfall stations was further sectored into four regions which are the northern region, east coast region, southern region and central region. As shown in Figure 4.1 to Figure 4.3, the MGWR has a higher R^2, and lower value of MAE and RMSE, for all four regions compared to the GWR. This indicated that the MGWR has higher estimation accuracy compared to the GWR.

On average, the results show that the Monthly Rainfall at the northeast region is higher than other regions in Peninsular Malaysia due to the high Maximum Daily Rainfall. The Northeast Monsoon starts in October and ends in March. Therefore, the average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall will be high during the peak months of the Northeast Monsoon, which are November, December and January, after being broken down for monthly aalysis. The high Monthly Rainfall for November to January along 1988-2017 was contributed by the high Maximum Daily Rainfall and Number of Wet Days. Other than that, the Southwest Monsoon which starts in May to September, but however, most of the rainfall will be blocked by the island of Sumatra, Indonesia. Therefore, only part of the rainfall will reach the northern region of Peninsular Malaysia during the months of May to September. The high Monthly Rainfall from May to September in the northern region of Peninsular Malaysia was high due to the high Number of Wet Days.

The average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall for all months were also divided into 5-years period and plotted using the QGIS software. It was clearly shown that the Monthly Rainfall in the central regions from year 1993 to year 2002 was dry compared to other regions. The low Monthly Rainfall at the central region in sub-period of year 1993-1997 was due to low Number of Wet Days and Maximum Daily Rainfall, whereas the low Monthly Rainfall at the central region in sub-period of year 1998-2002 was due to low Number of Wet Days. During sub-period of year 2003-2007 and 2008-2012, the high Monthly Rainfall in the northeast region was due to the high Maximum Daily Rainfall at the northeast region of Peninsular Malaysia. The high Maximum Daily Rainfall at the northeast region in sub-period of year 2013-2017 was contributed to high Monthly Rainfall at the northeast region.

Besides, the major issue that need paying attention was the effect of increasing average Monthly Rainfall becomes significant in the month of December and January in the year 2013-2017 when the Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall have being broken down into 5-years periods, and plotted using the QGIS software. The increase of Monthly Rainfall on January and December were due to the increase of Maximum Daily Rainfall and Number of Wet Days, respectively.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Two spatial interpolation methods were used to estimate the monthly rainfall in Peninsular which are the GWR model and the MGWR model. The GWR is an extension of the traditional linear regression model as it is using the spatial (x, y) coordinates to build up a relationship between location and other parameters. The MGWR is a further improvement of the model of GWR; however, it removes the constraint of all analysis and is modelled using different spatial scales with different bandwidths. Both methods were evaluated using the performance statistical parameters of MAE, RMSE and R^2 across Peninsular Malaysia. The MGWR method has smaller MAE and RMSE, and lower R^2 compared to the GWR method. The rainfall stations were also divided into four regions which are the northern region, east coast region, southern region, and central region, and the MGWR method was also shown to give higher R^2, and lower MAE and RMSE compared to the GWR in all four regions. All these results have shown that MGWR method has better performance in rainfall estimation across Peninsular Malaysia. However, the estimation accuracy of both the GWR and MGWR has lower accuracy at central region, as both methods have lower R^2 value compared to other regions. This is because the land use in central region consists of many categories including housing area, built-up and agriculture., and each land use has its own characteristic. However, both the GWR and MGWR models do not consider the land use nearby the rainfall station, and lead to low estimation accuracy.

The estimated rainfall data predicted by the MGWR model was used to plot maps using the QGIS software, since the MGWR has better performance than the GWR. The monthly averages of Monthly Rainfall of 1988-2017 will be higher at the northeast region due to the contributions of high Maximum Daily Rainfall at the northeast region; even though the Number of Wet Days were consistent across Peninsular Malaysia. During the Northeast Monsoon, the monthly averages of Monthly Rainfall for November to January were high at the northeast region due to the contributions of both the high Number of Wet Days and the Maximum Daily Rainfall. The average Number of Wet Days for February along these 30 years were consistent across Peninsular Malaysia; however, the high Monthly Rainfall for February in the east coast region and west part of Peninsular Malaysia along these 30 years was due to the effect of high Maximum Daily Rainfall. The Monthly Rainfall for April in year 1988-2017 was high at the northwest part of Peninsular Malaysia due to the delay effect of Northeast Monsoon as the rainfall not fully blocked by the Banjaran Titiwangsa. The monthly averages Monthly Rainfall at the northern region of Peninsular Malaysia were high during the Southwest Monsoon (May to September) due to the contribution of the high Number of Wet Days. The reason for the rainfall being concentrated at the northern regions of Peninsular Malaysia was that most of the rainfall was blocked by the island of Sumatra, Indonesia. The rainfall from the Southwest Monsoon was only able to reach northern regions of Peninsular Malaysia.

The average Monthly Rainfall, Number of Wet Days and Maximum Daily Rainfall were also plotted into five sub-periods with 5 years for each period. It was noticed that average Monthly Rainfall in the central region was low during sub-period of year 1993-1997 and 1998-2002. The low Monthly Rainfall in central region of Peninsular Malaysia during year 1993-1997 was due to the low Number of Wet Days and Maximum Daily Rainfall, whereas the low Monthly Rainfall in central region of Peninsular Malaysia during year 1998-2002 was due to the contribution of low Number of Wet Days. Lastly, the average Monthly Rainfall map of the northeast region of Peninsular Malaysia for January and December in the years 2013-2017 have increased significantly compared to other 5-years periods. The increase of Monthly Rainfall for January and December during year 2013-2017 were contributed by the increase of Maximum Daily Rainfall and Number of Wet Days, respectively.

5.2 Recommendations for future work

There are total of 244 rainfall stations involved in this study; however, there are still some missing rainfall data in this study. It is recommended that the rainfall stations should be repaired and frequently maintained for less or no missing data in any future study. The number of rainfall stations also need to be increased in the study so that the spatial interpolation method can cover more nearby rainfall stations during the analysis to increase the estimation accuracy.

Moreover, the spatial interpolation does not consider the land use of the nearby stations. This may lead to the low estimation accuracy as different land use may have different characteristic. Hence, it is recommended that the rainfall station should be separated by categories of land use which may help to improve the estimation performance.

Lastly, the rainfall spatial interpolation analysis can include more parameters such as moisture content, terrain ruggedness index (TRI), normalized difference vegetation index (NVDI), monthly near-surface air temperature (NSAT) and daily near-surface air temperature (NSAT). These parameters were used widely in other country to predict the rainfall using spatial interpolation method. This may help to reduce the estimation error during the analysis.

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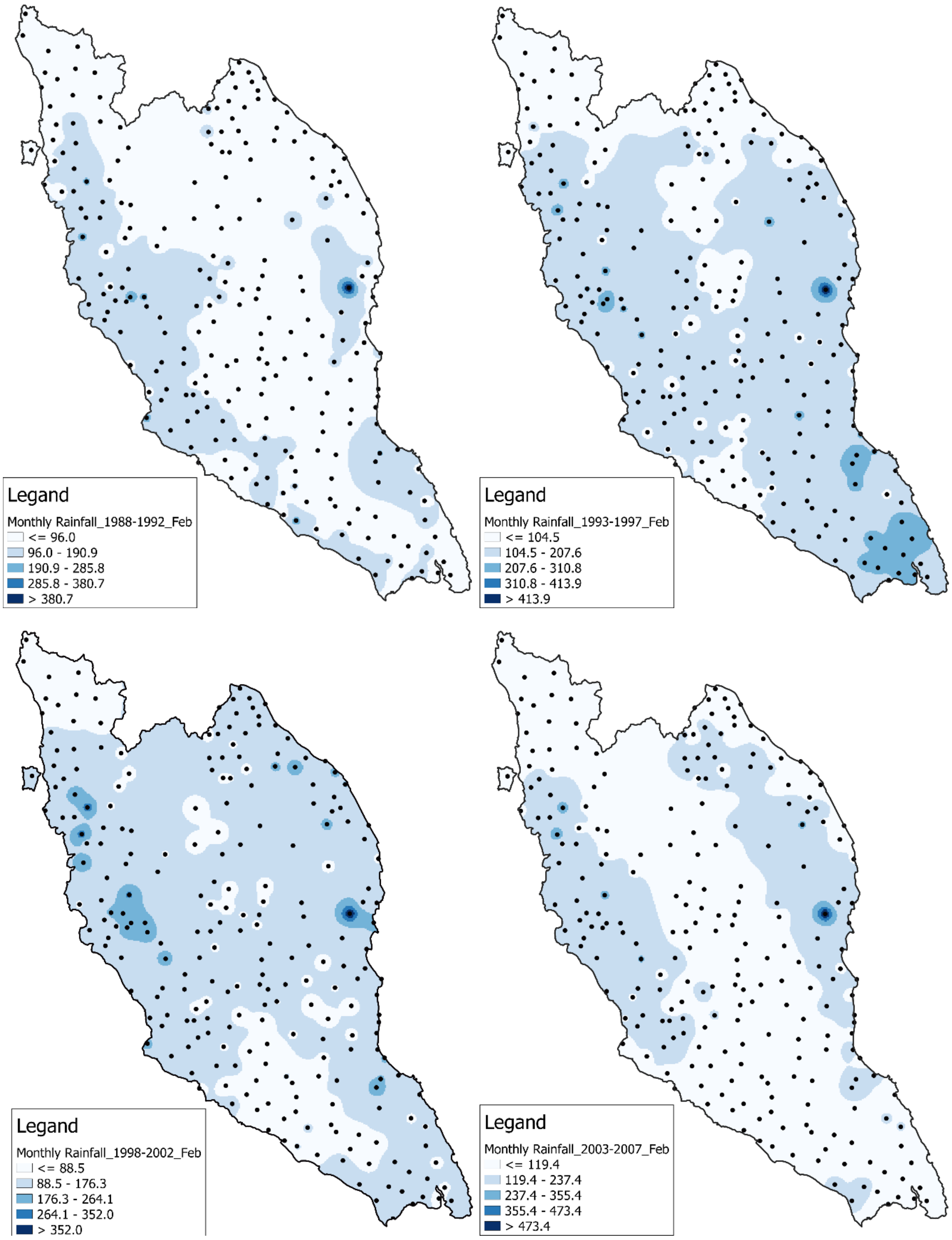
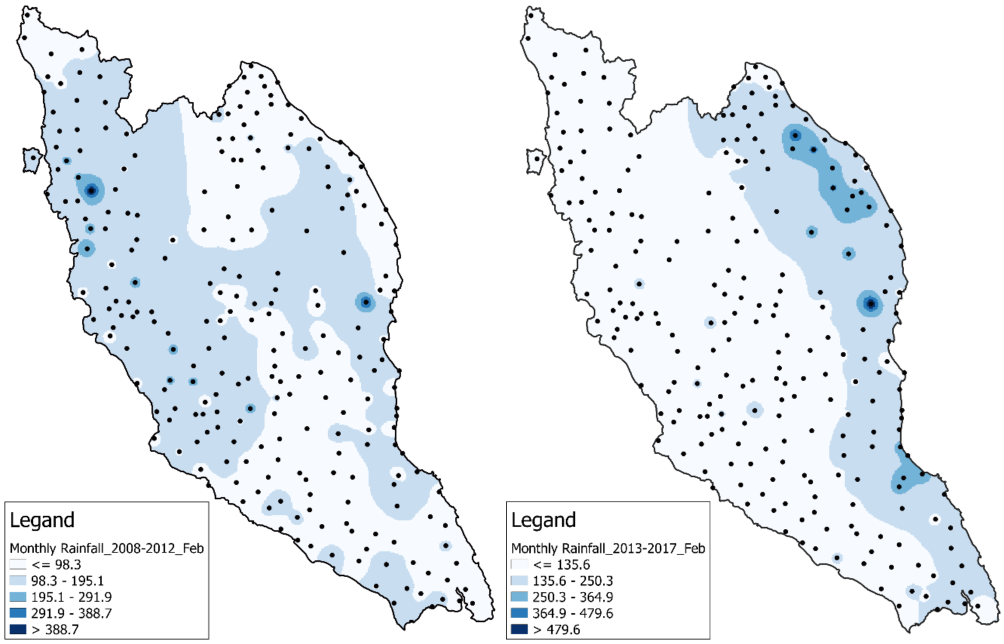
APPENDICES

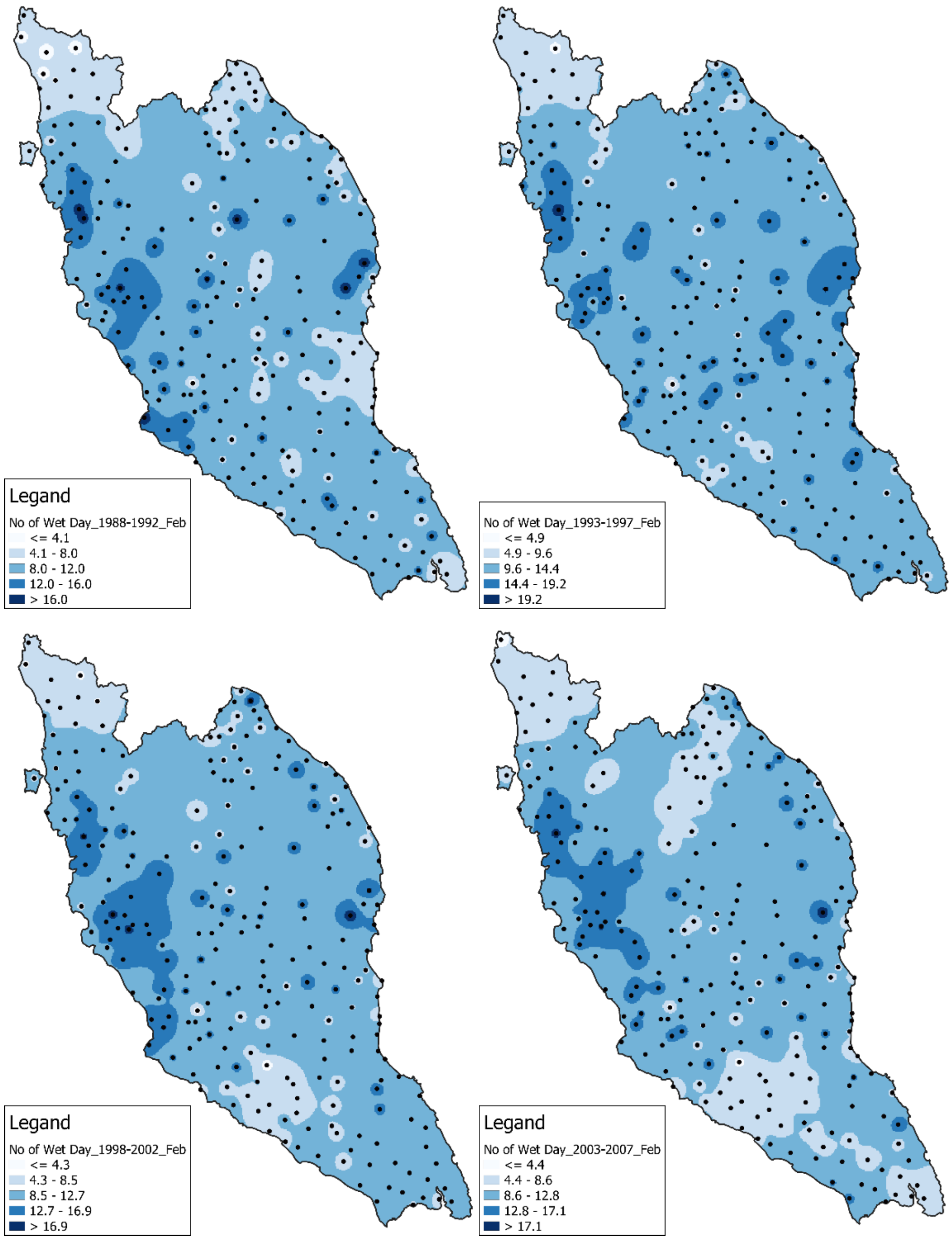
APPENDIX A: Maps



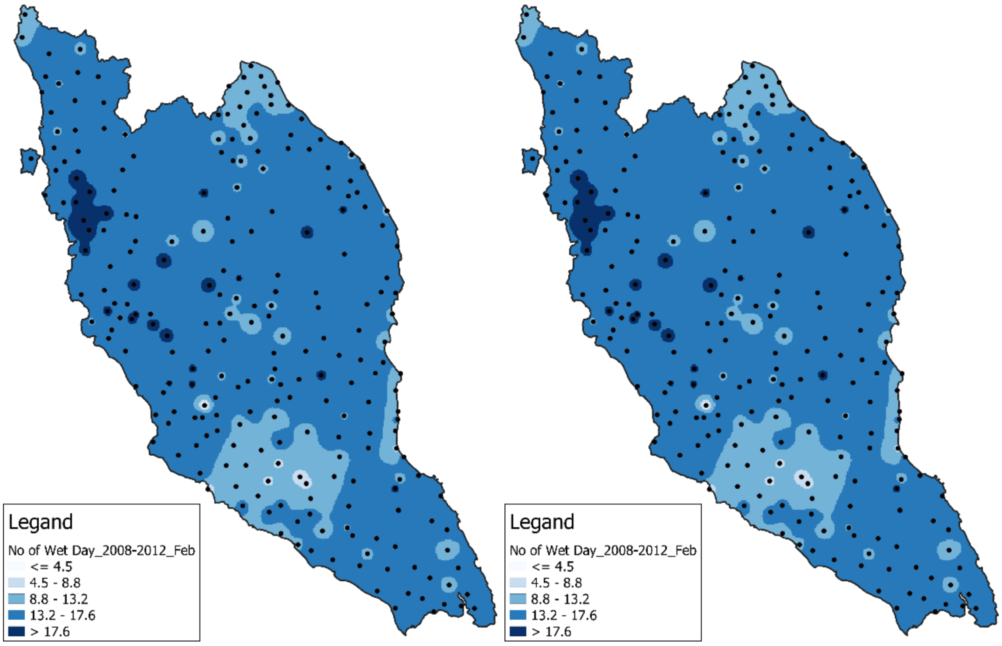
MapA- 1: Average Monthly Rainfall Maps on February for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



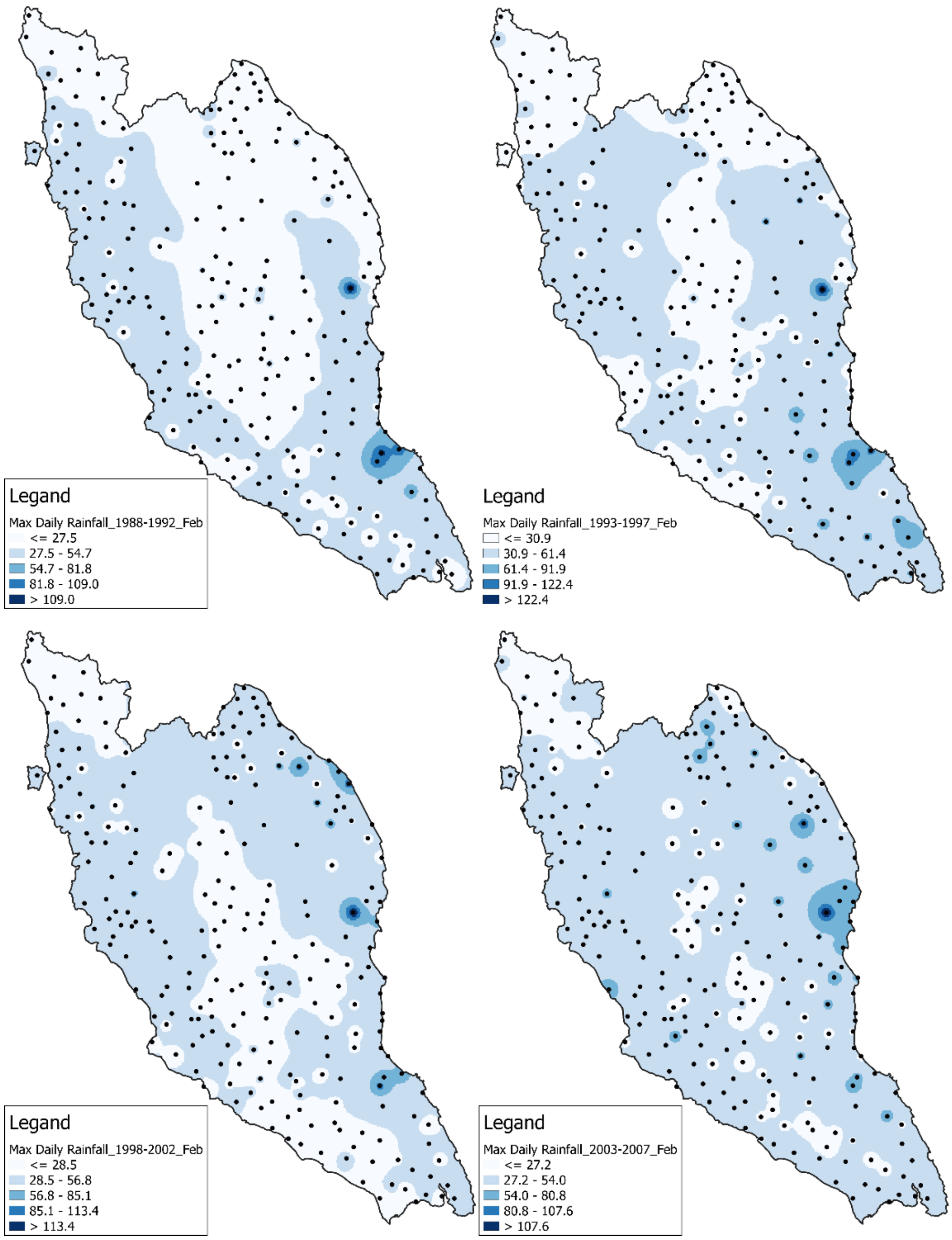
MapA- 1: Average Monthly Rainfall Maps on February for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



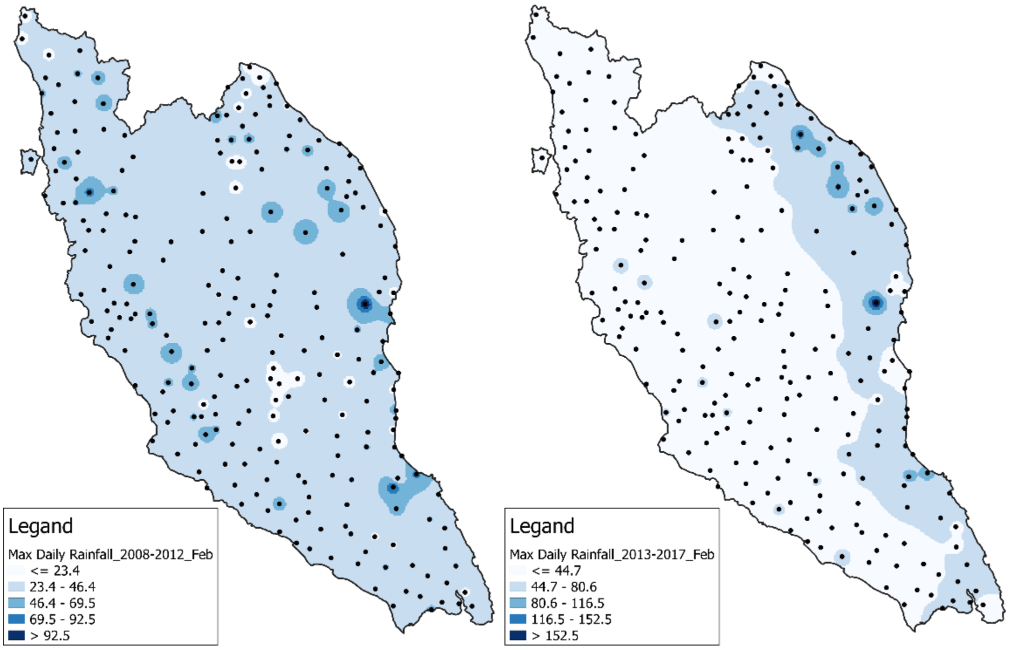
MapA- 2: Average Number of Wet Days Maps on February for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



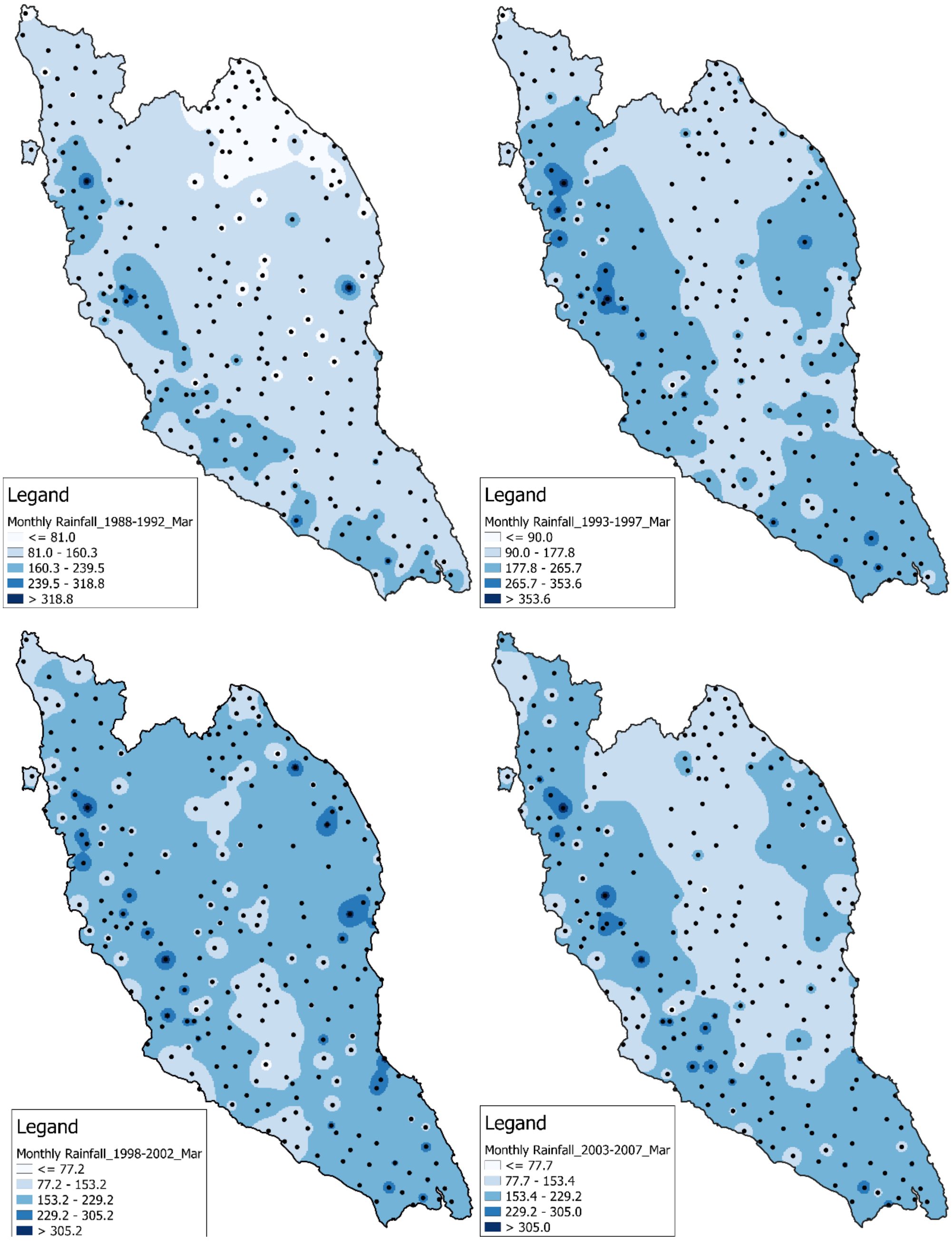
MapA- 2: Average Number of Wet Days Maps on February for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



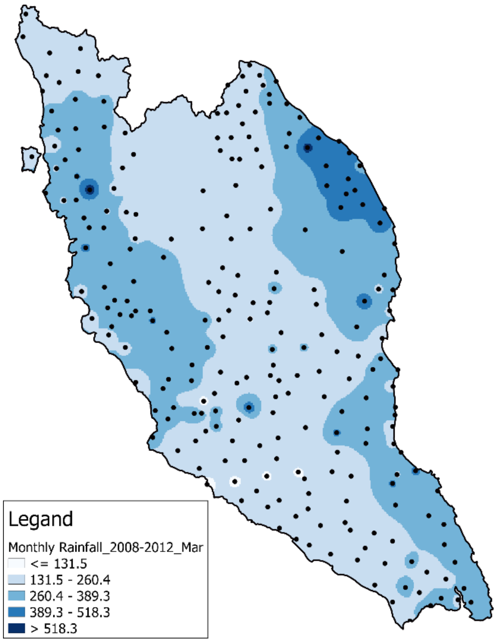
MapA- 3: Average Maximum Daily Rainfall Maps on February for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

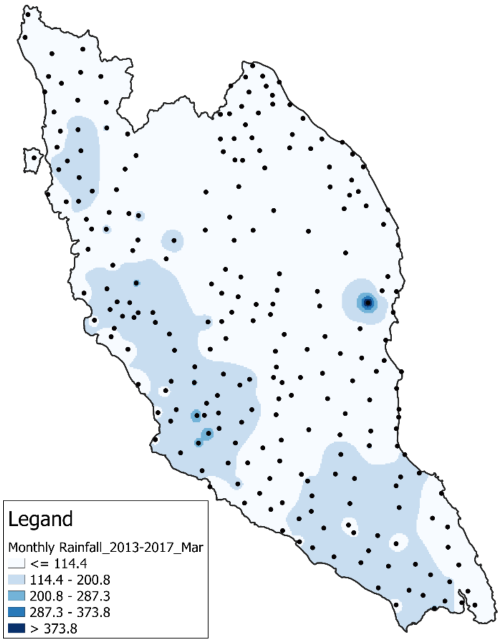


MapA- 3: Average Maximum Daily Rainfall Maps on February for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

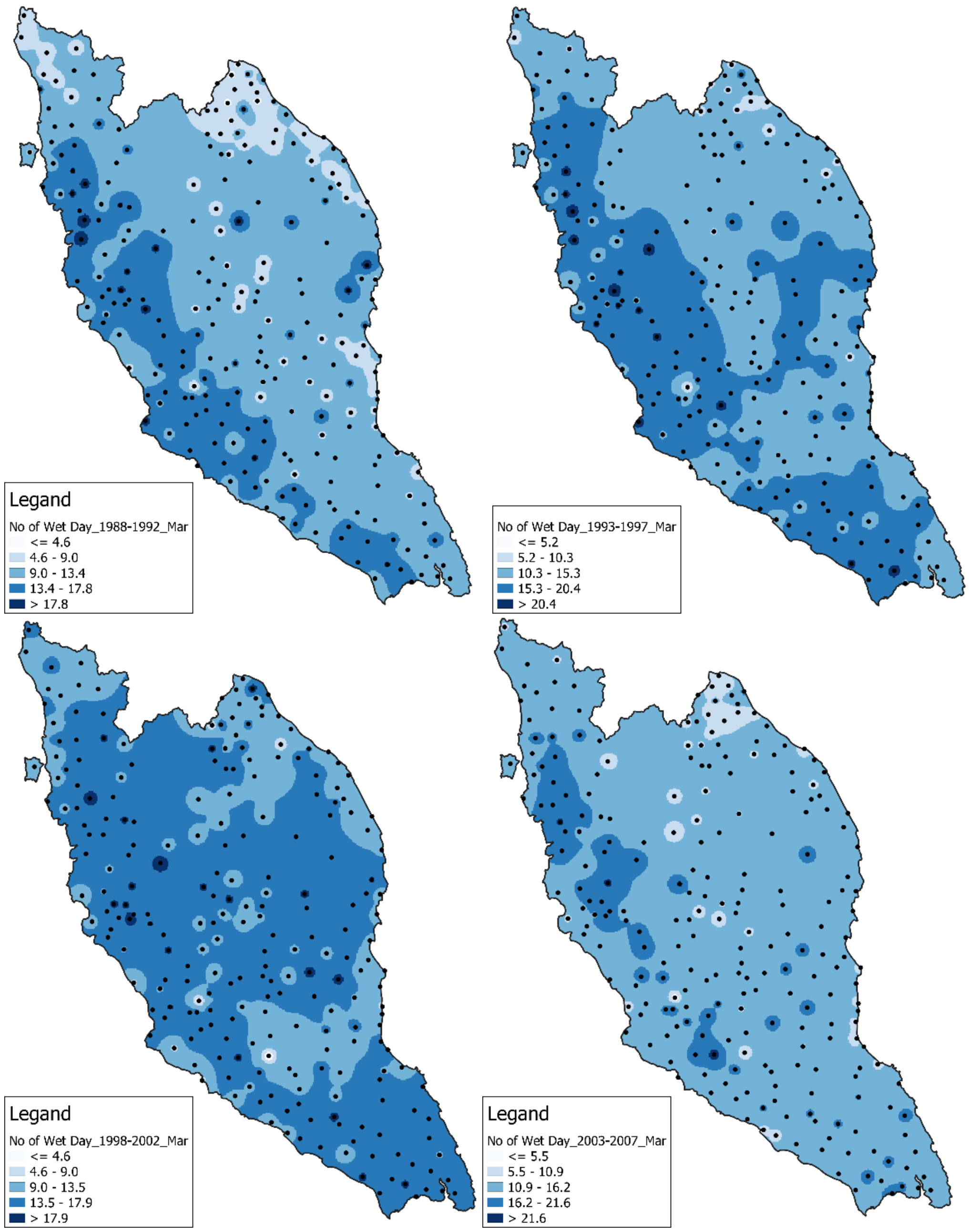


MapA- 4: Average Monthly Rainfall Maps on March for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

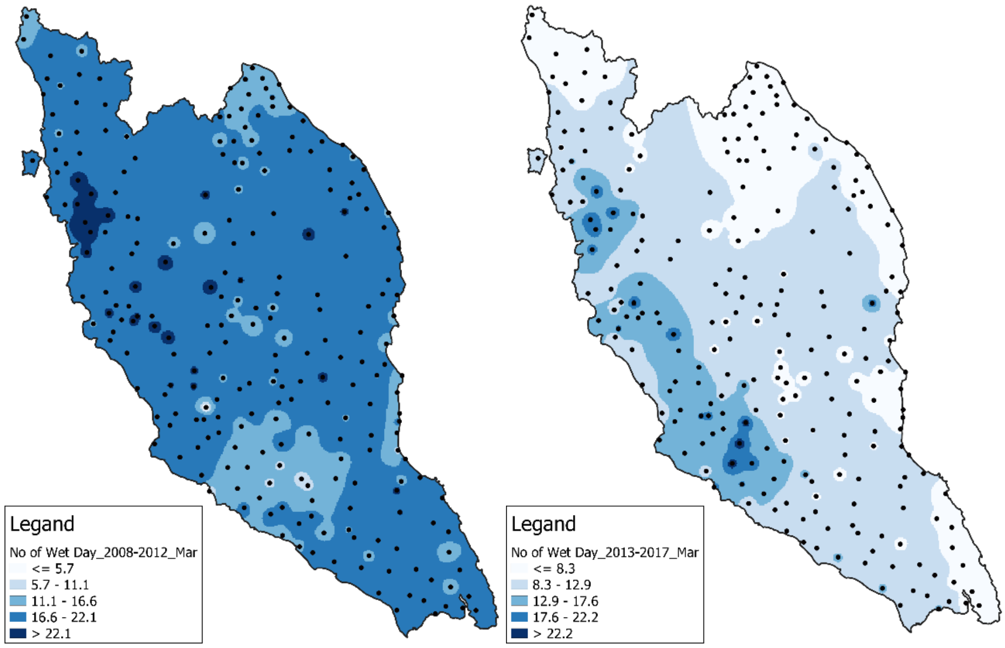




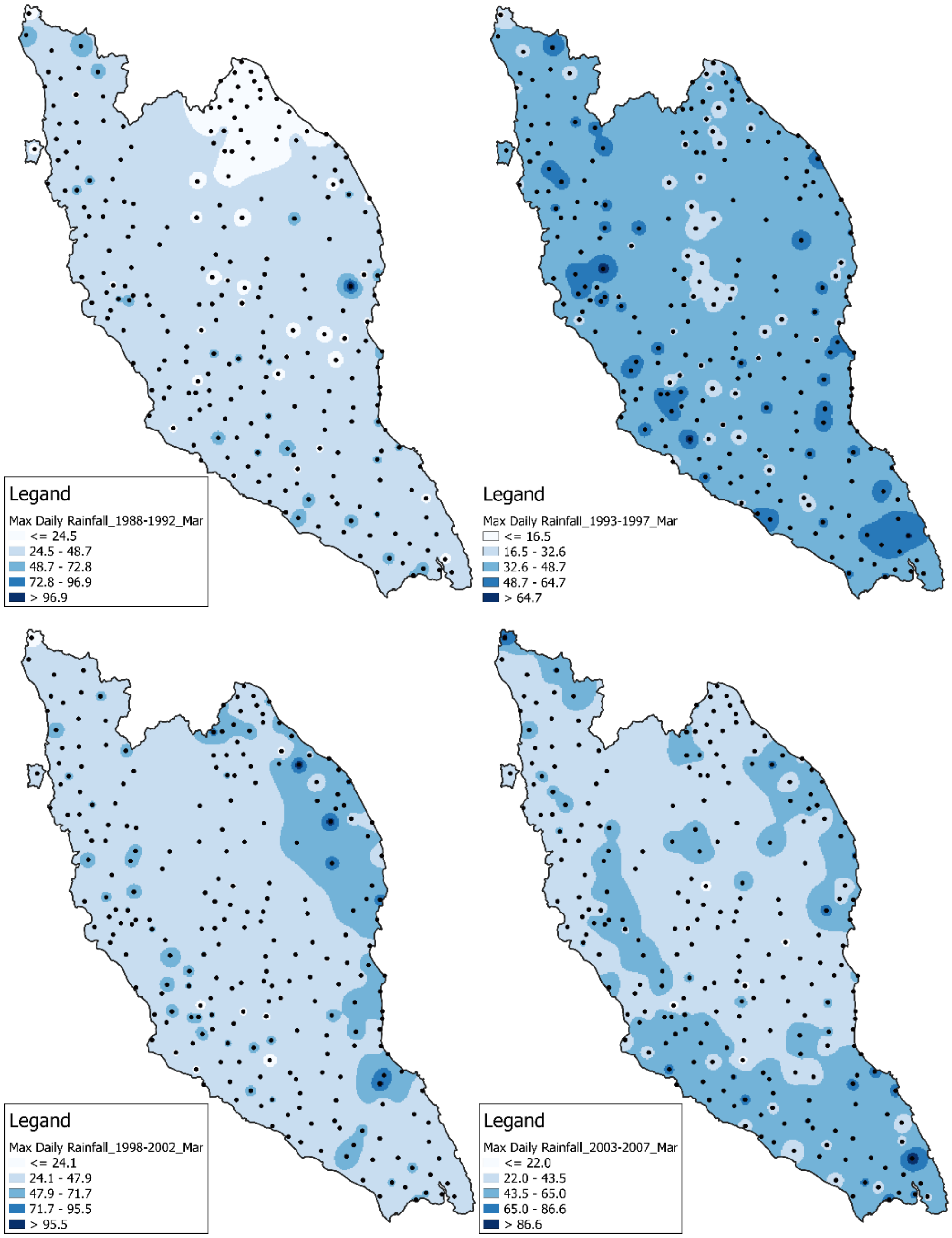
MapA- 4: Average Monthly Rainfall Maps on March for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



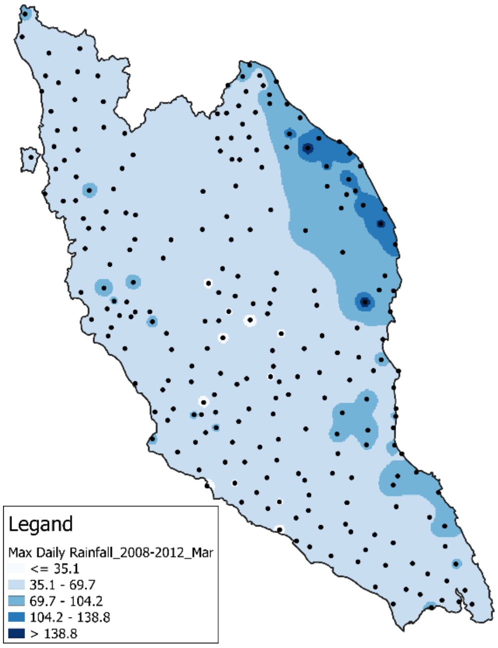
MapA- 5: Average Number of Wet Days Maps on March for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

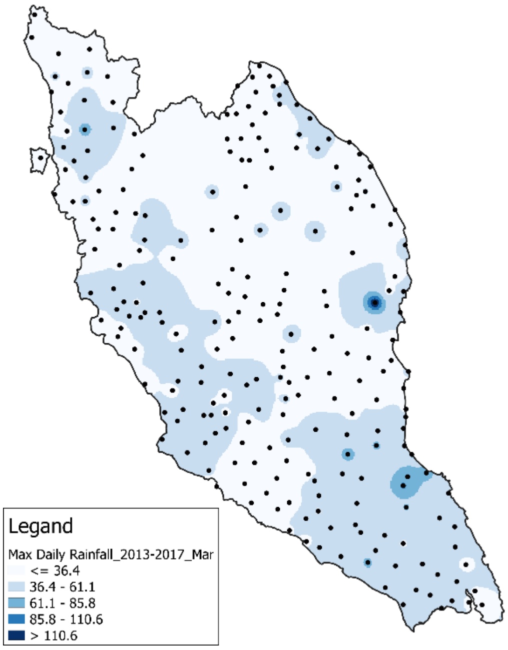


MapA- 5: Average Number of Wet Days Maps on March for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

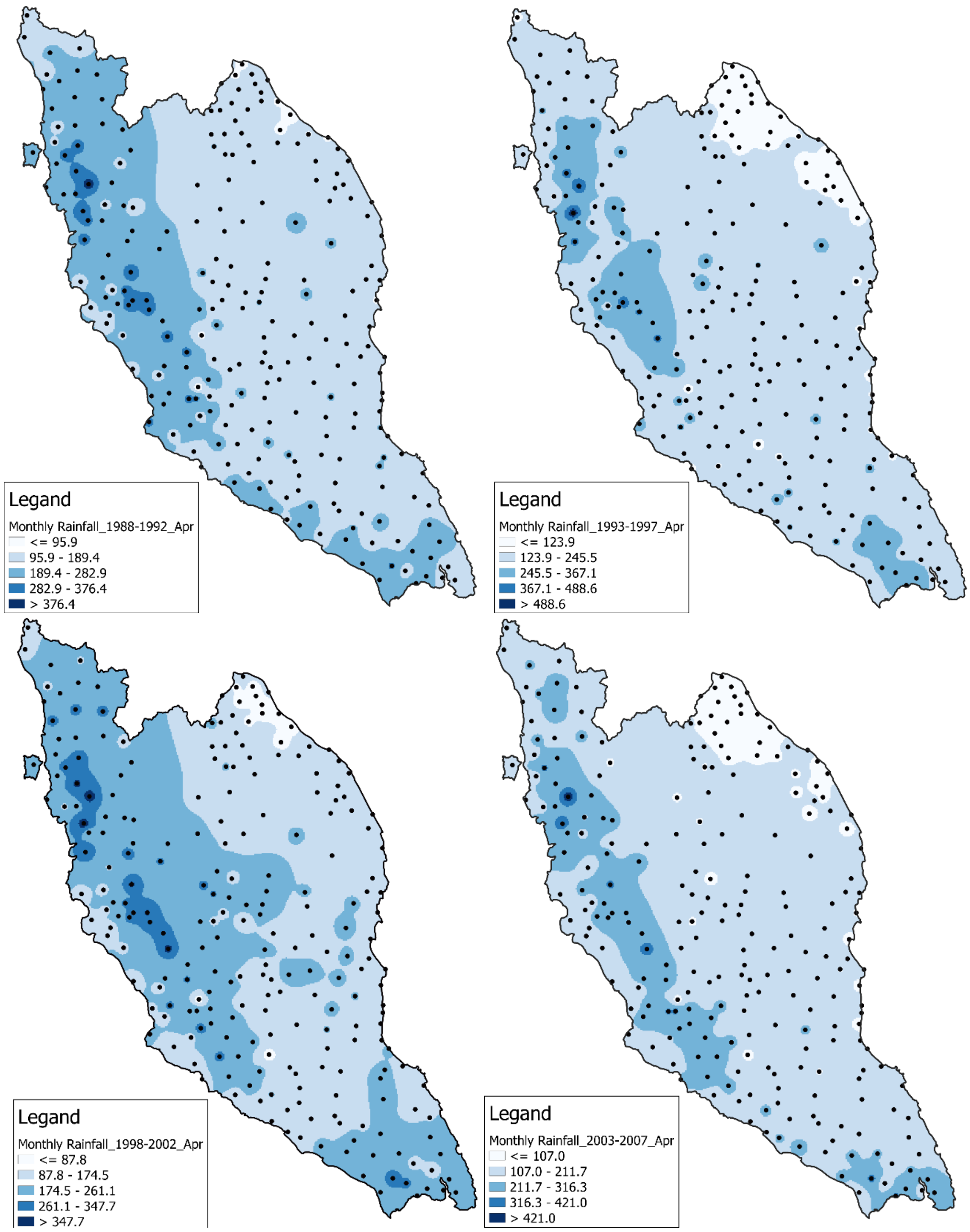


MapA- 6: Average Maximum Daily Rainfall Maps on March for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

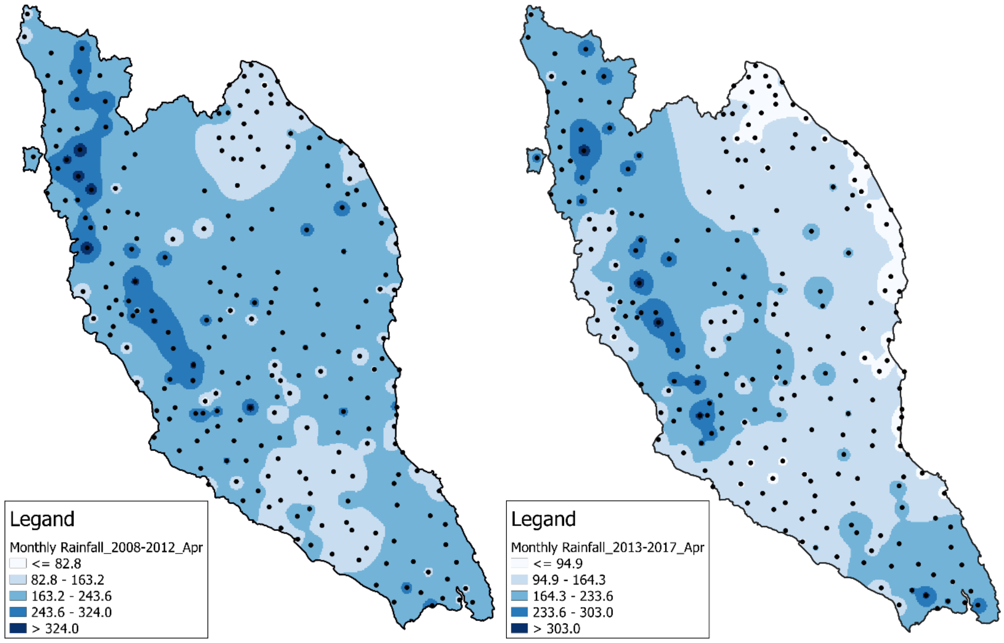




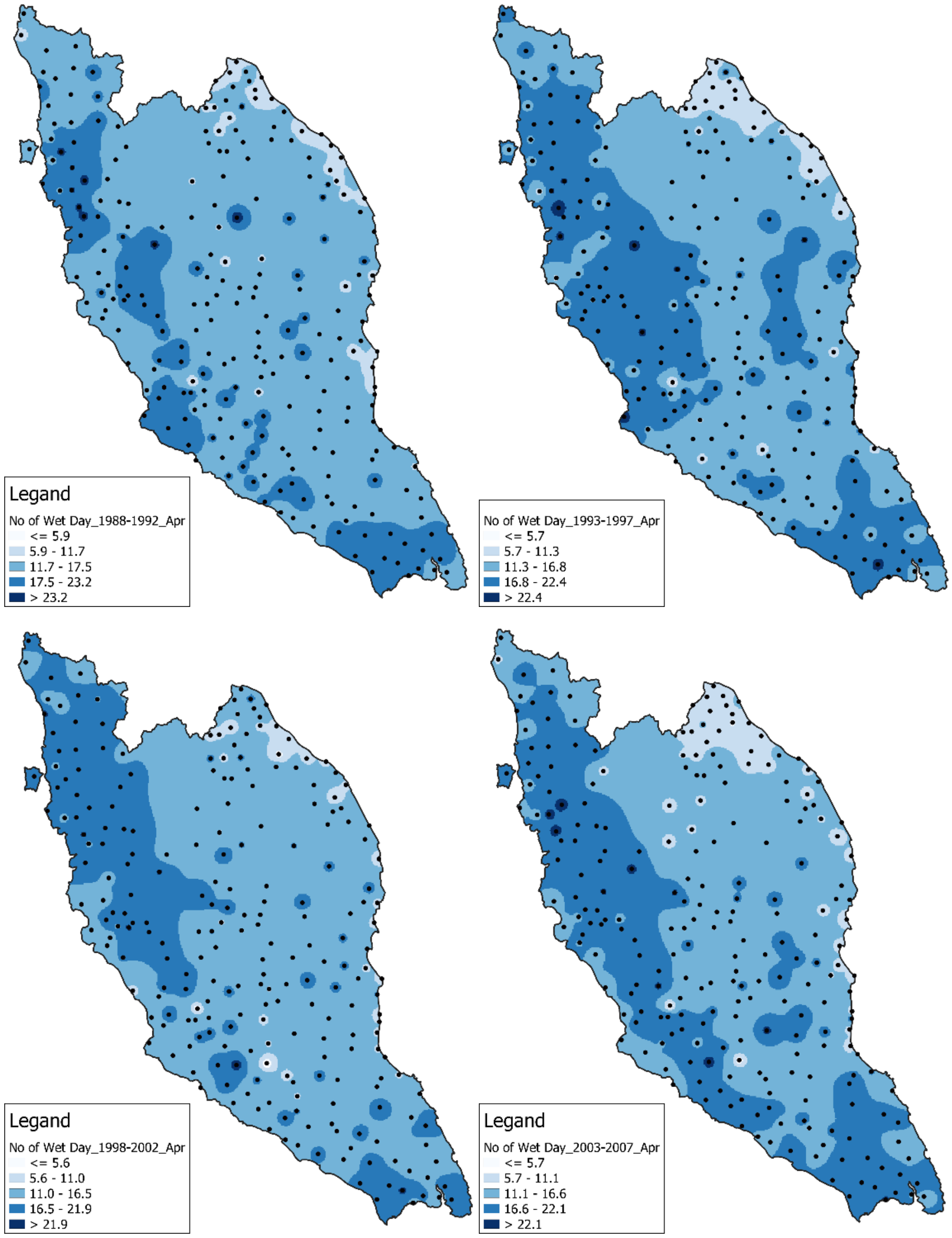
MapA- 6: Average Maximum Daily Rainfall Maps on March for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



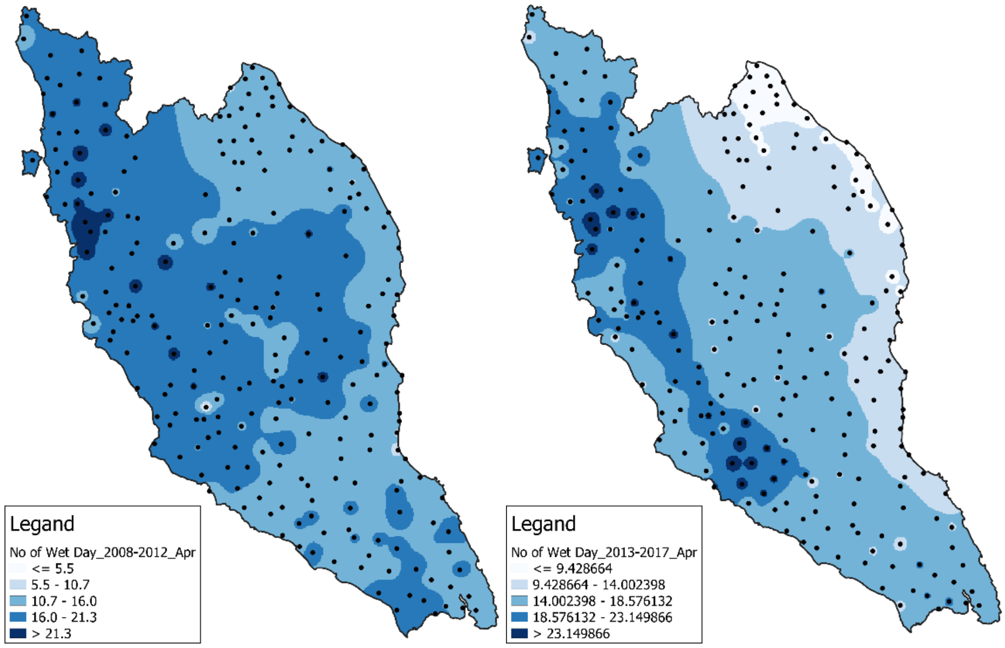
MapA -7: Average Monthly Rainfall Maps on April for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



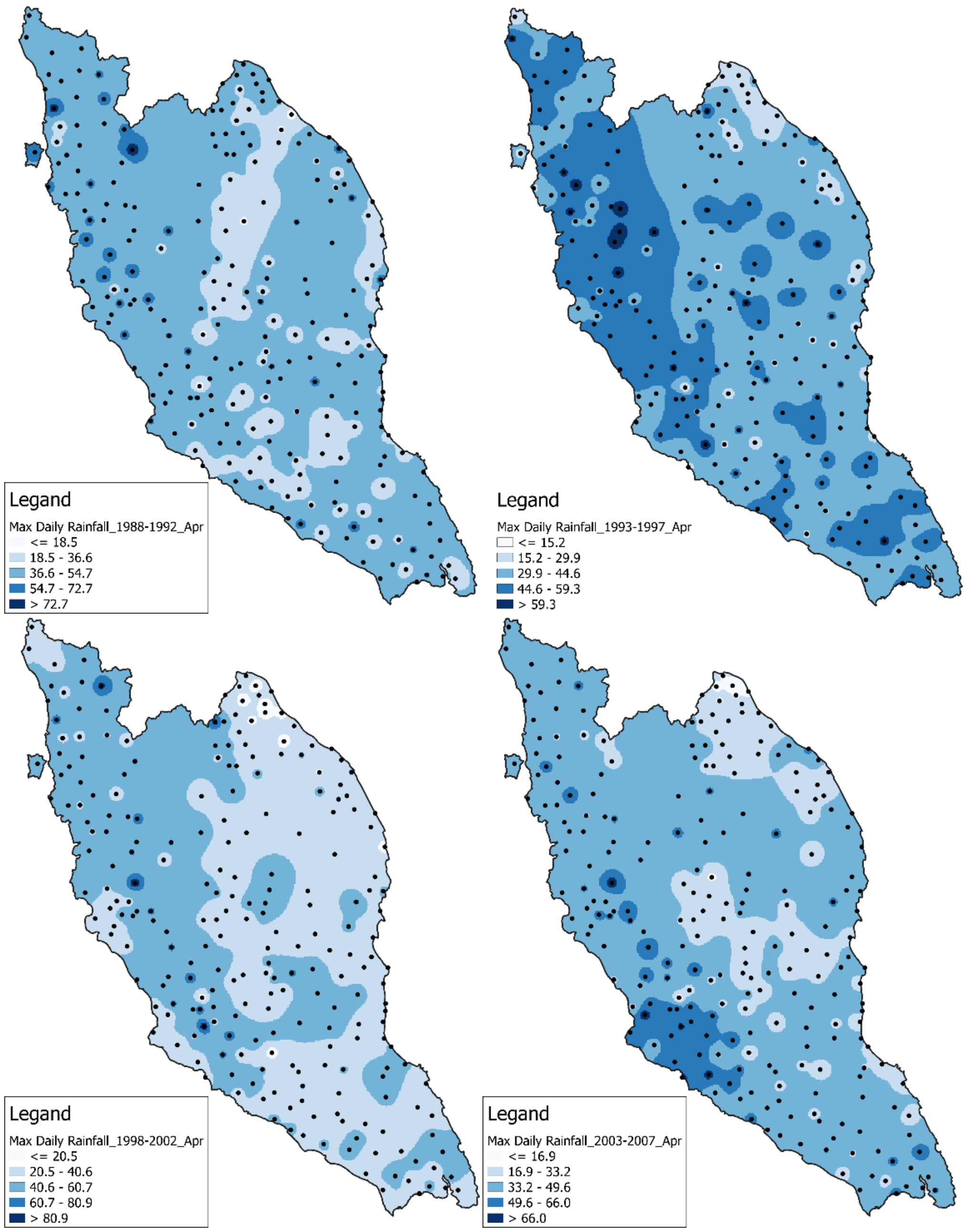
MapA -7: Average Monthly Rainfall Maps on April for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



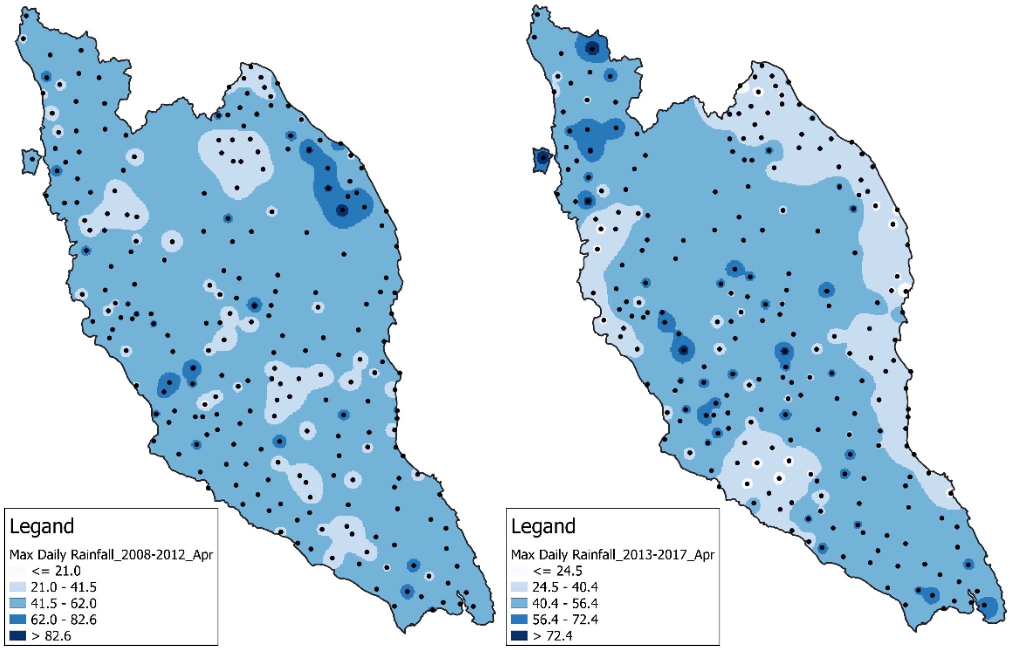
MapA- 8: Average Number of Wet Days Maps on April for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



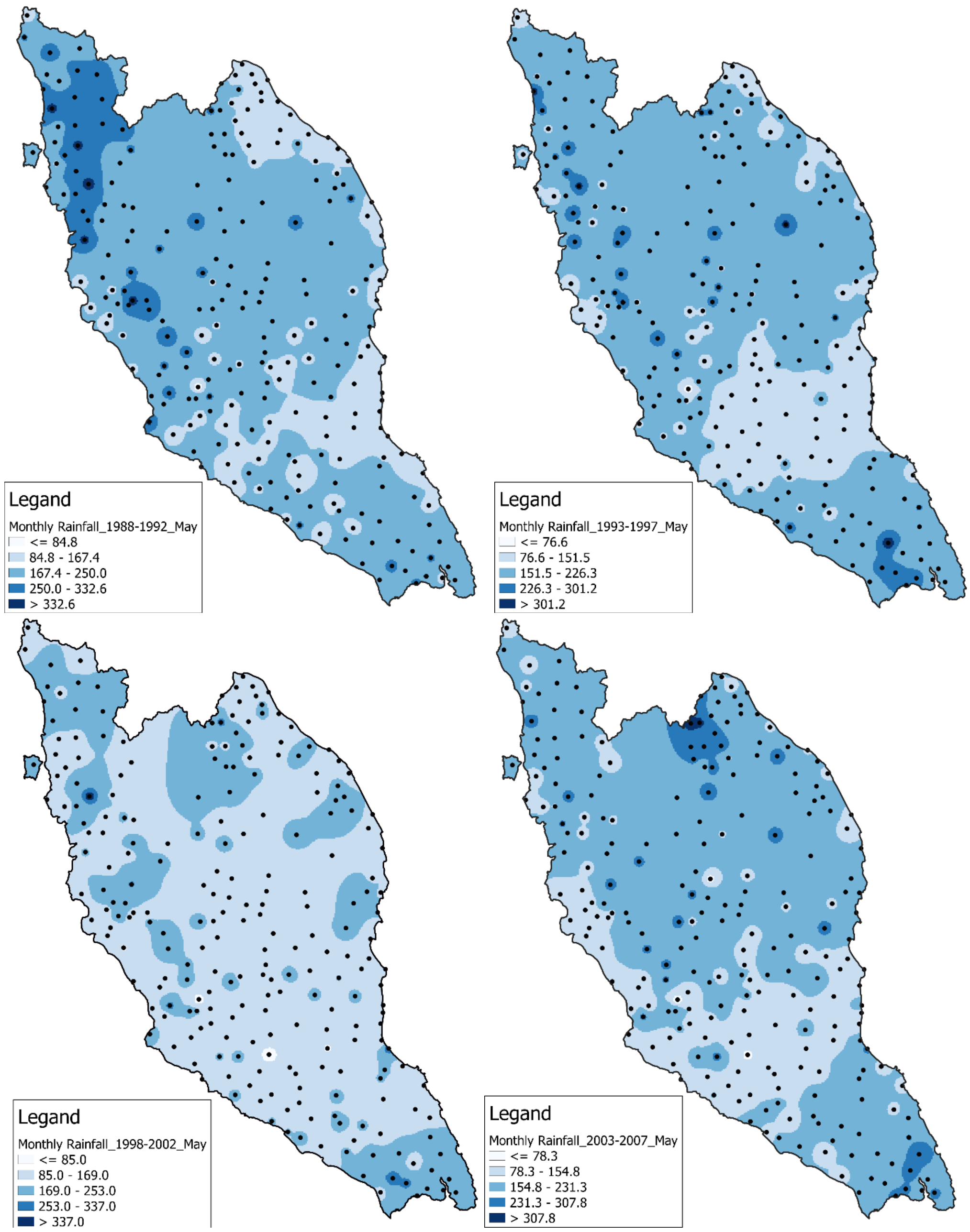
MapA- 8: Average Number of Wet Days Maps on April for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



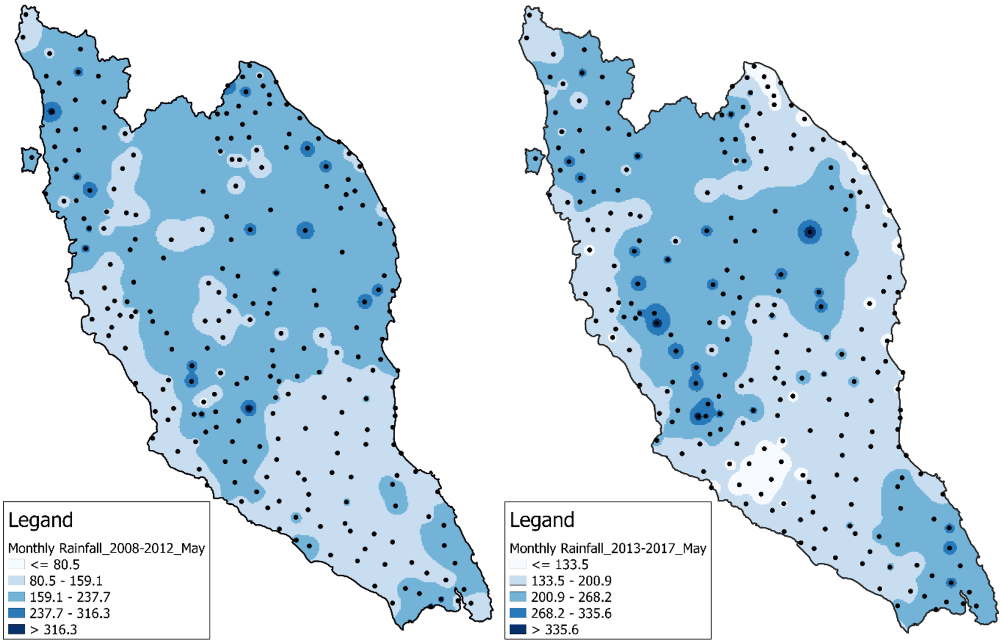
MapA- 9: Average Maximum Daily Rainfall Maps on April for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



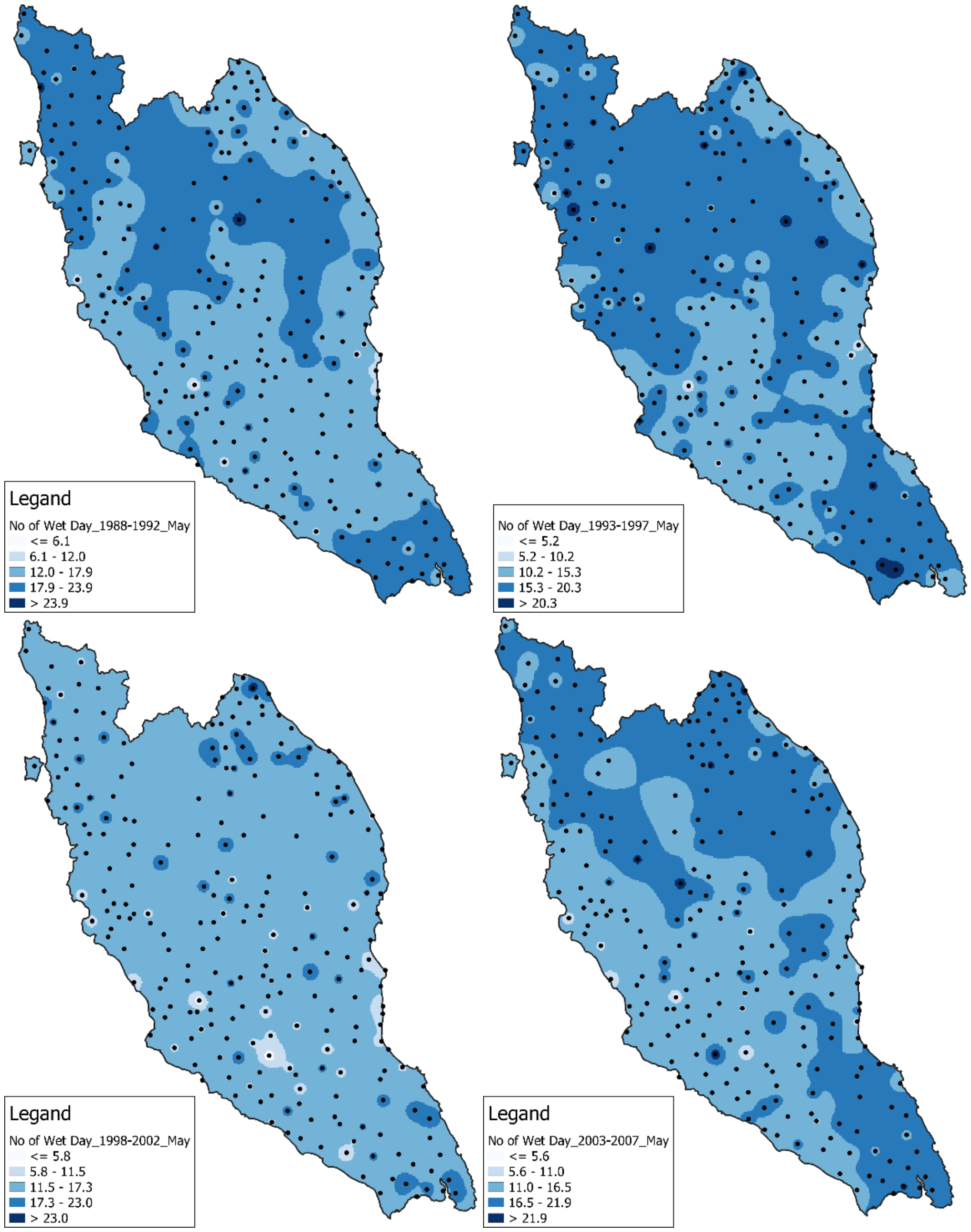
MapA- 9: Average Maximum Daily Rainfall Maps on April for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



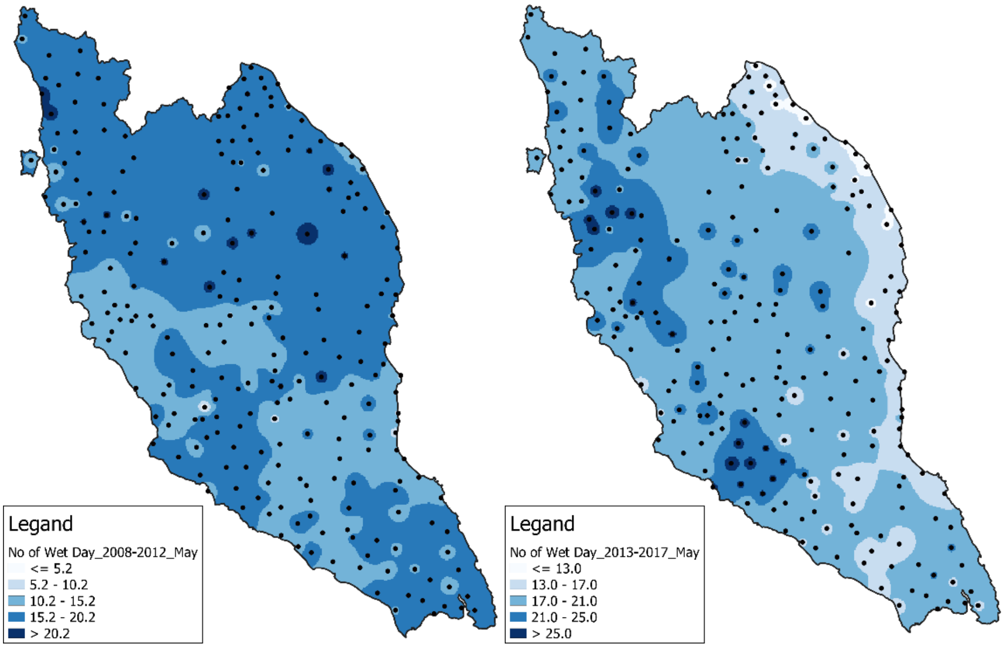
MapA- 10: Average Monthly Rainfall Maps on May for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



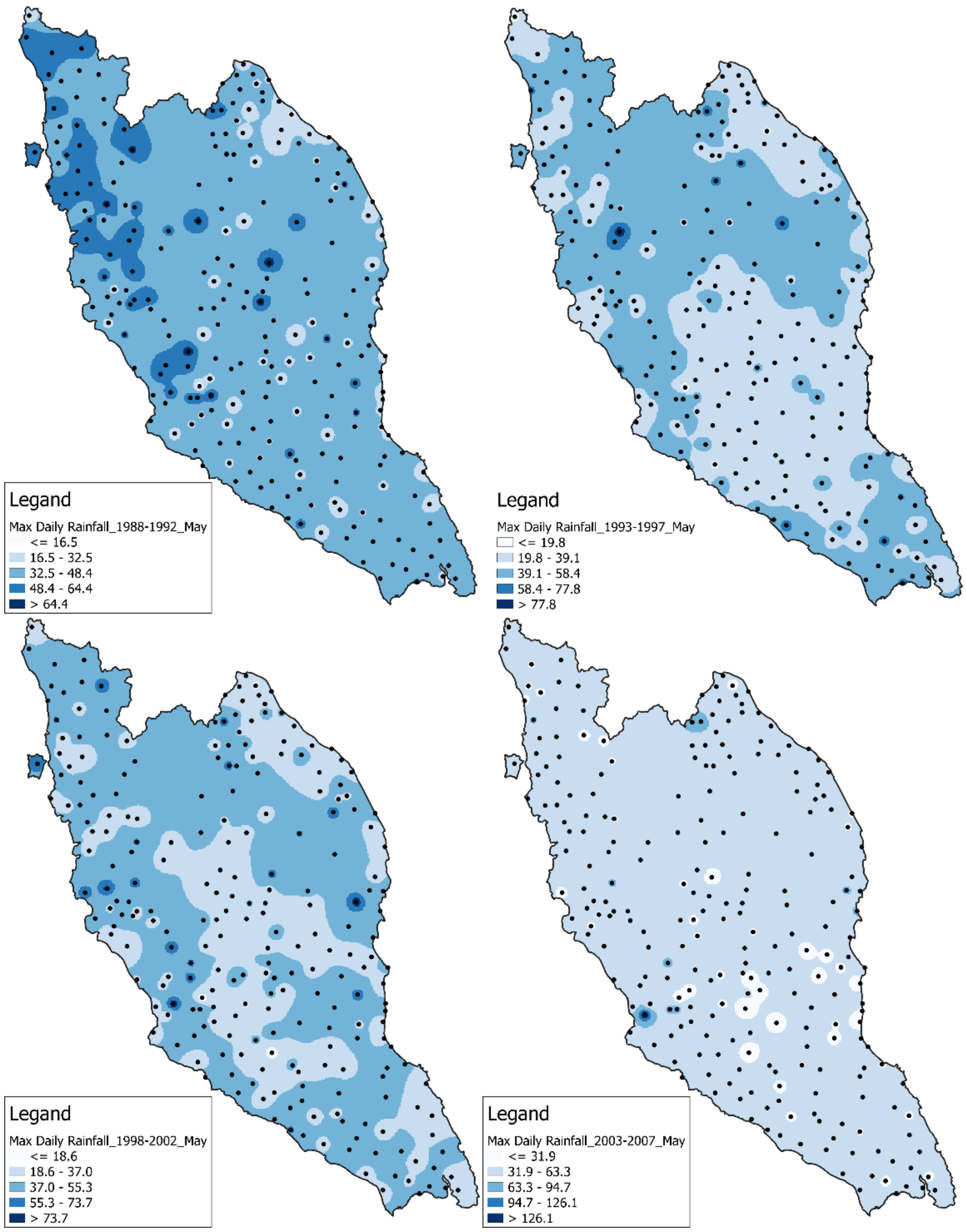
MapA- 10: Average Monthly Rainfall Maps on May for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



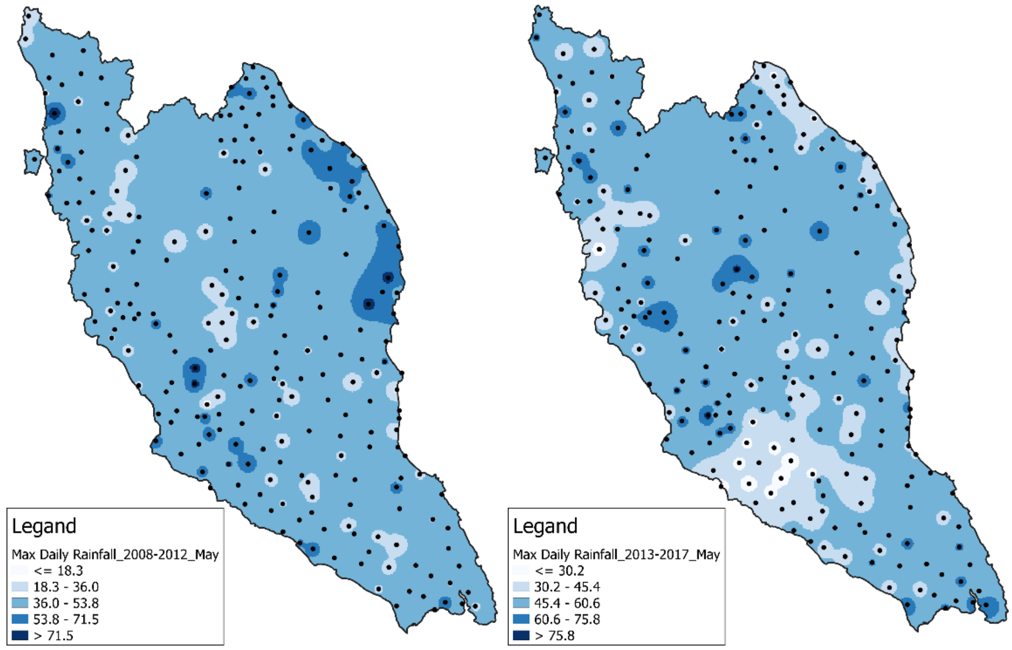
MapA- 11: Average Number of Wet Days Maps on May for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



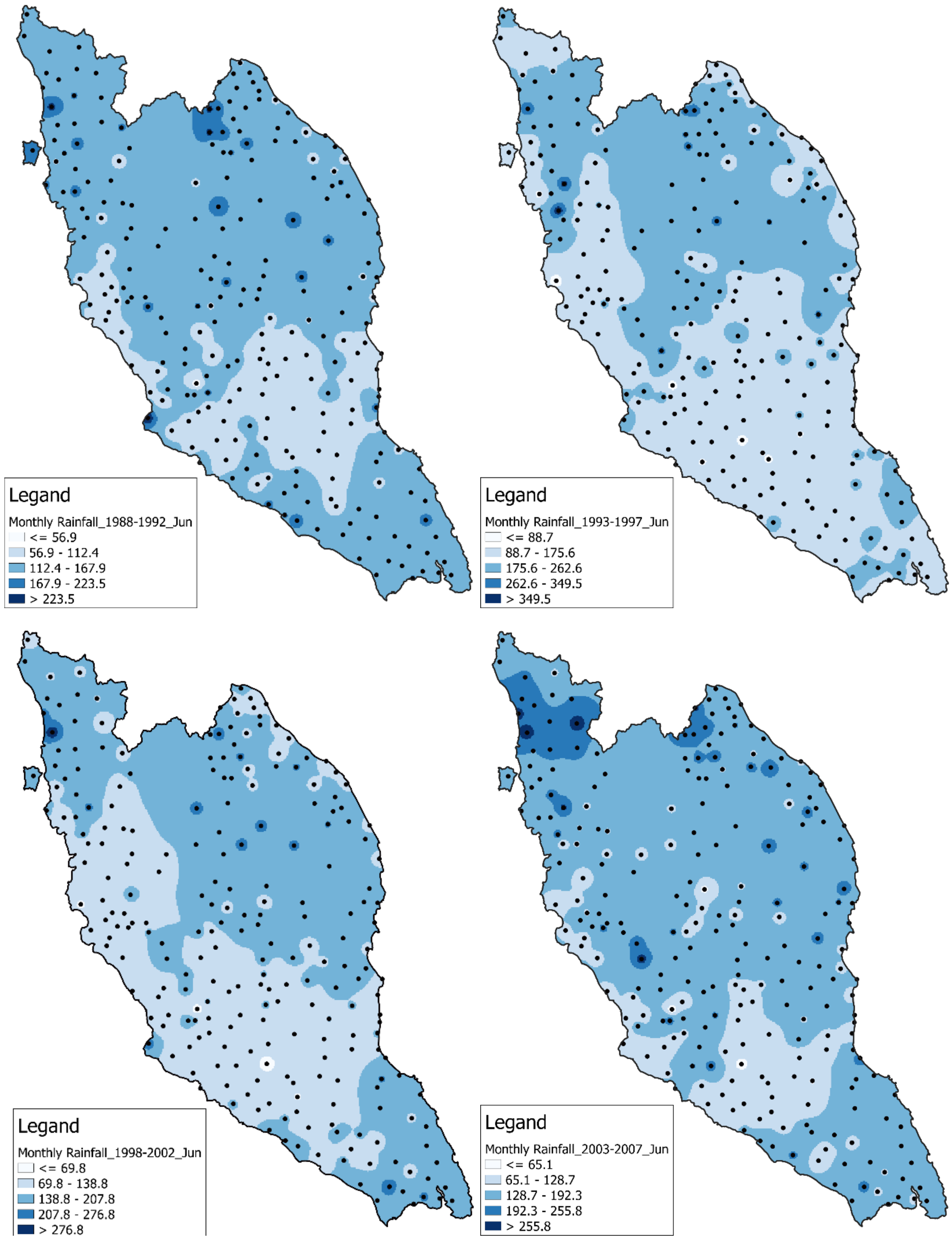
MapA- 11: Average Number of Wet Days Maps on May for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



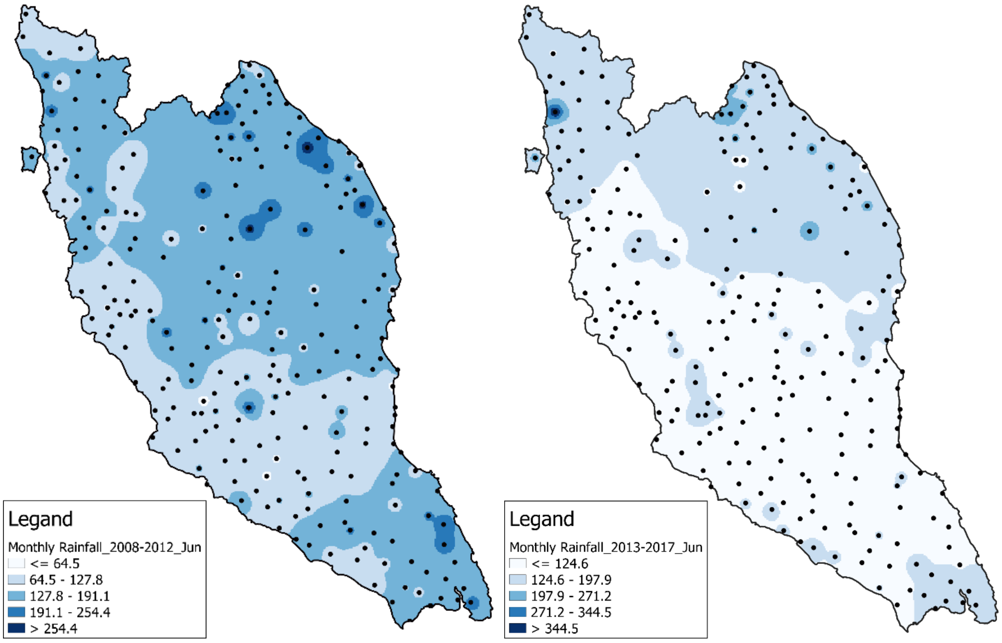
MapA -12: Average Maximum Daily Rainfall Maps on May for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



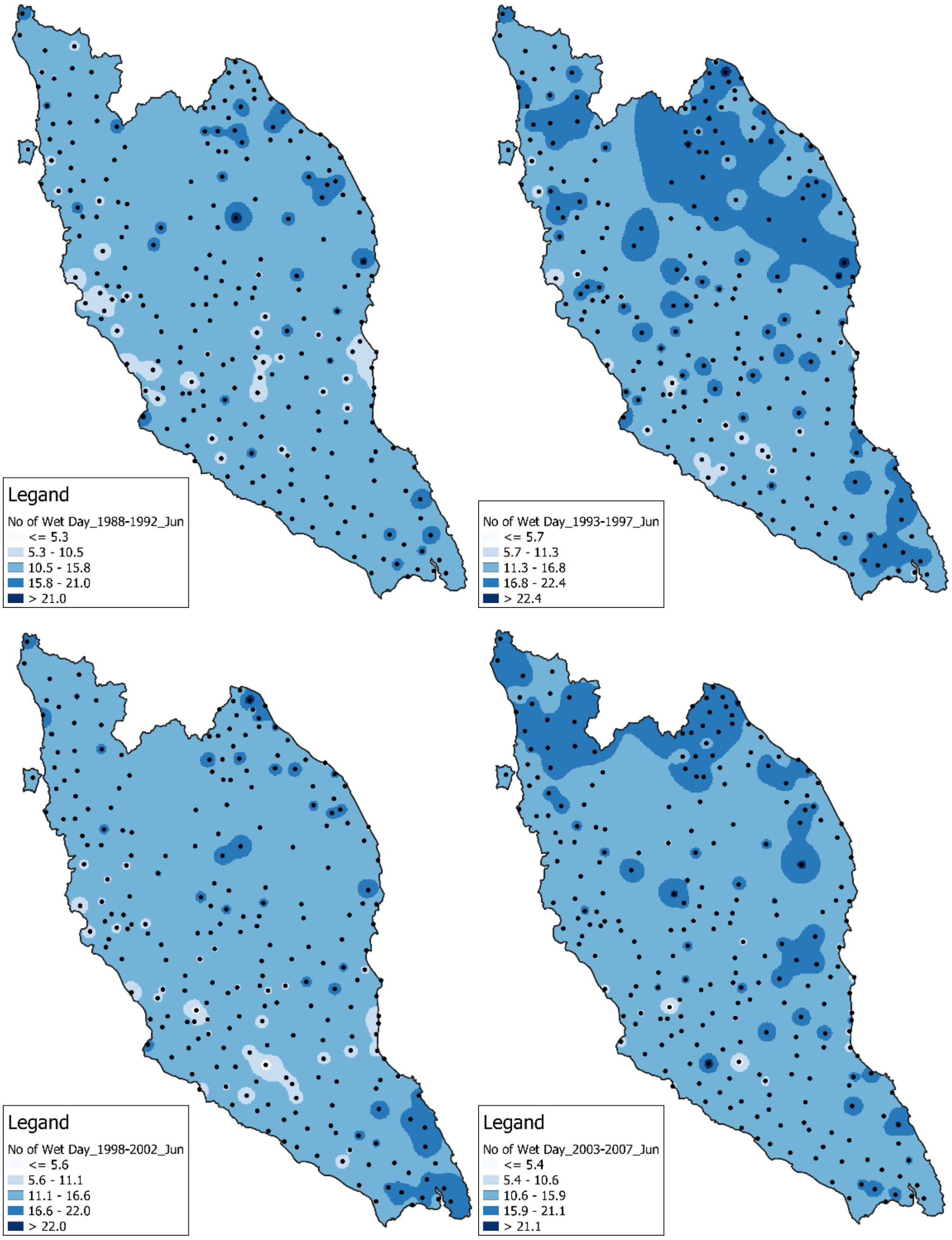
MapA -12: Average Maximum Daily Rainfall Maps on May for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



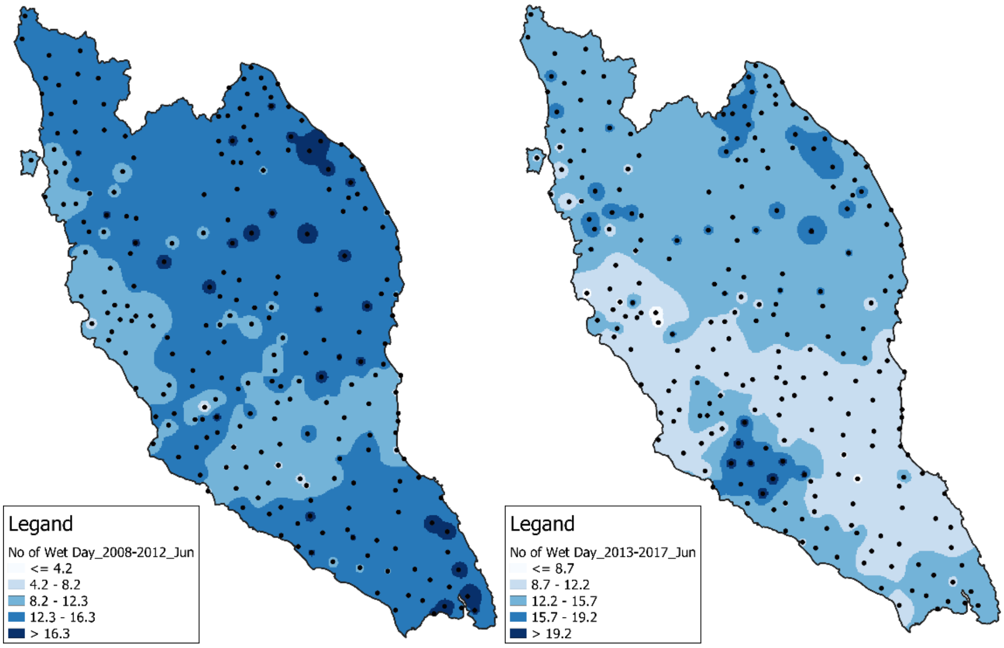
MapA- 13: Average Monthly Rainfall Maps on June for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



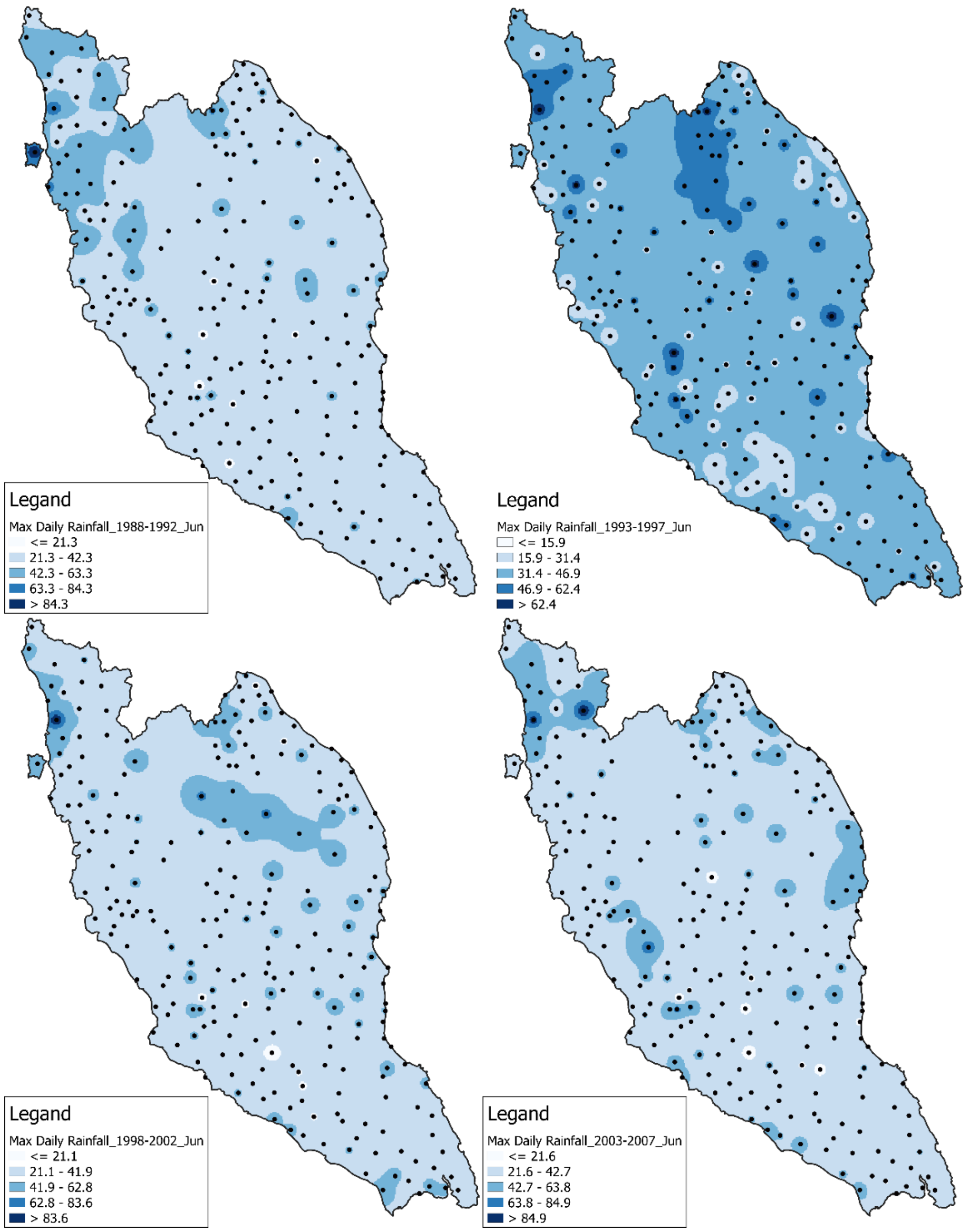
MapA- 13: Average Monthly Rainfall Maps on June for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



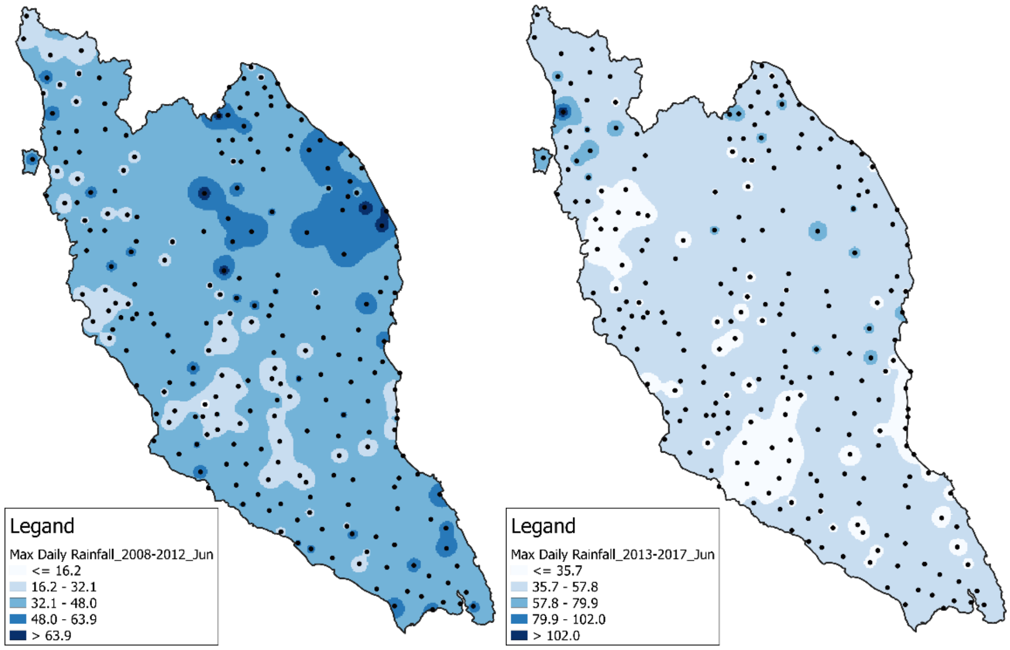
MapA- 14: Average Number of Wet Days Maps on June for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



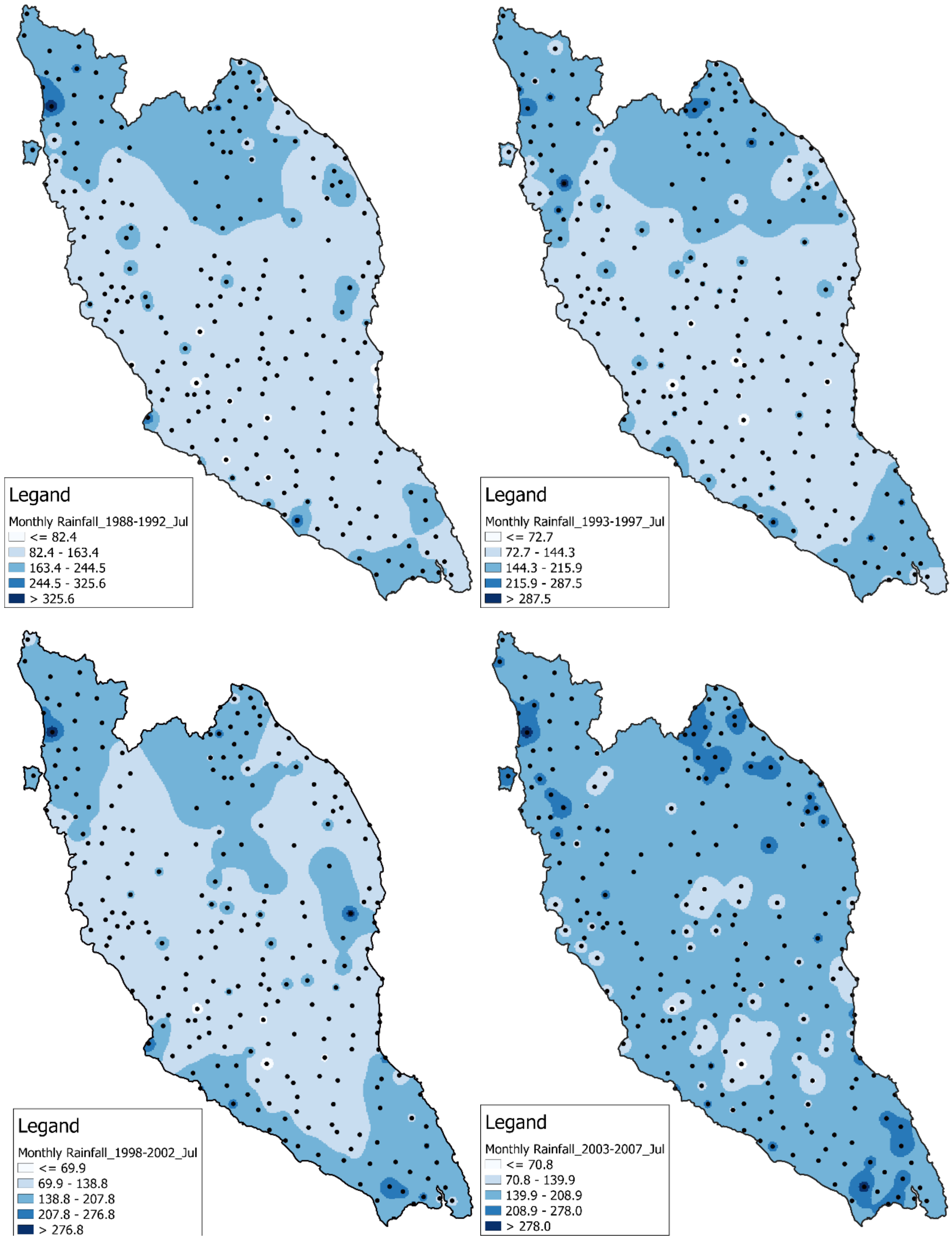
MapA- 14: Average Number of Wet Days Maps on June for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



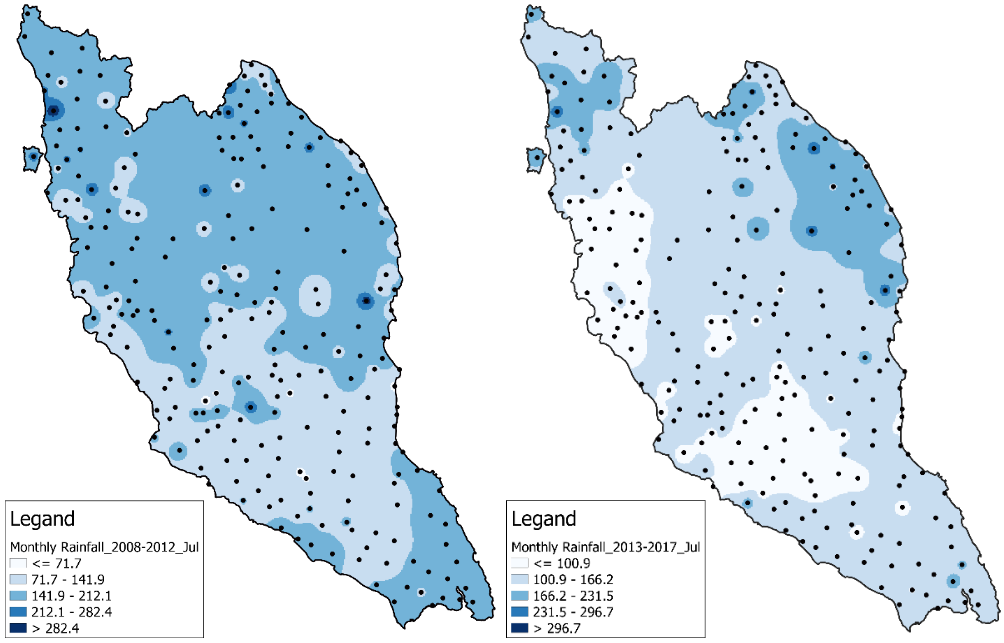
MapA- 15: Average Maximum Daily Rainfall Maps on June for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



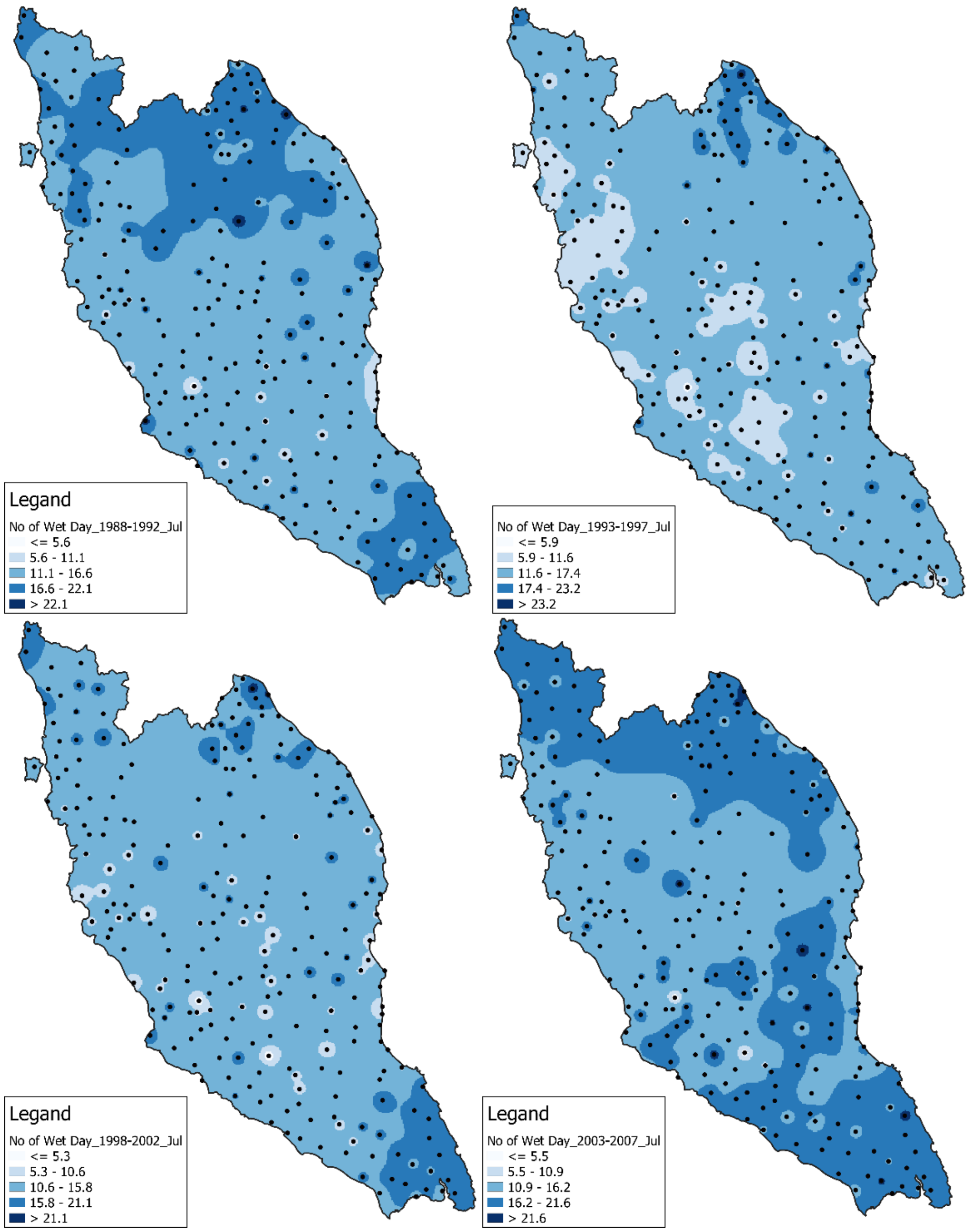
MapA- 15: Average Maximum Daily Rainfall Maps on June for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



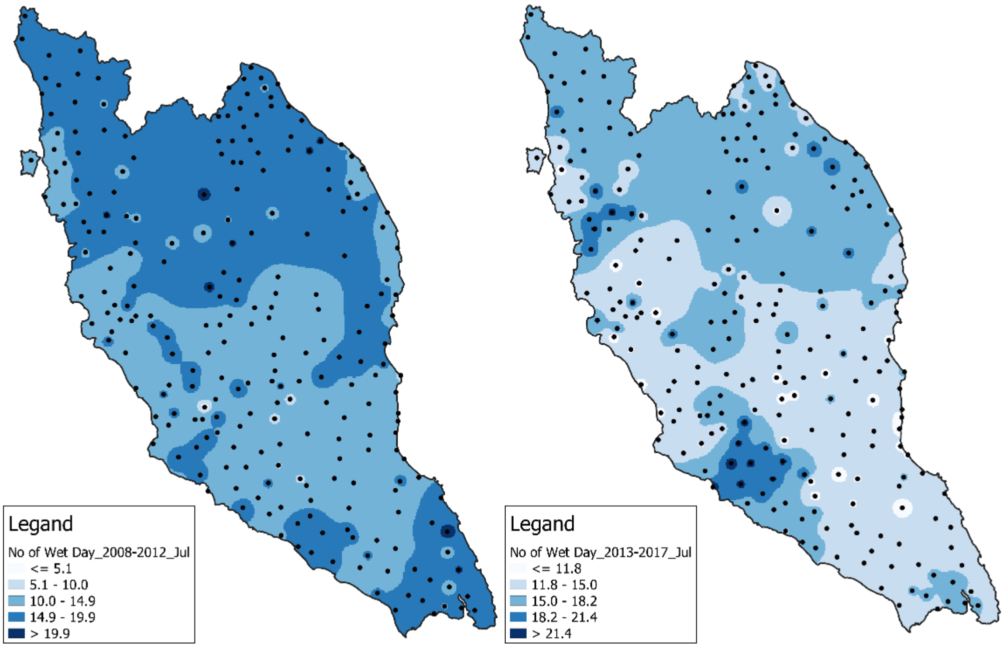
MapA- 16: Average Monthly Rainfall Maps on July for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



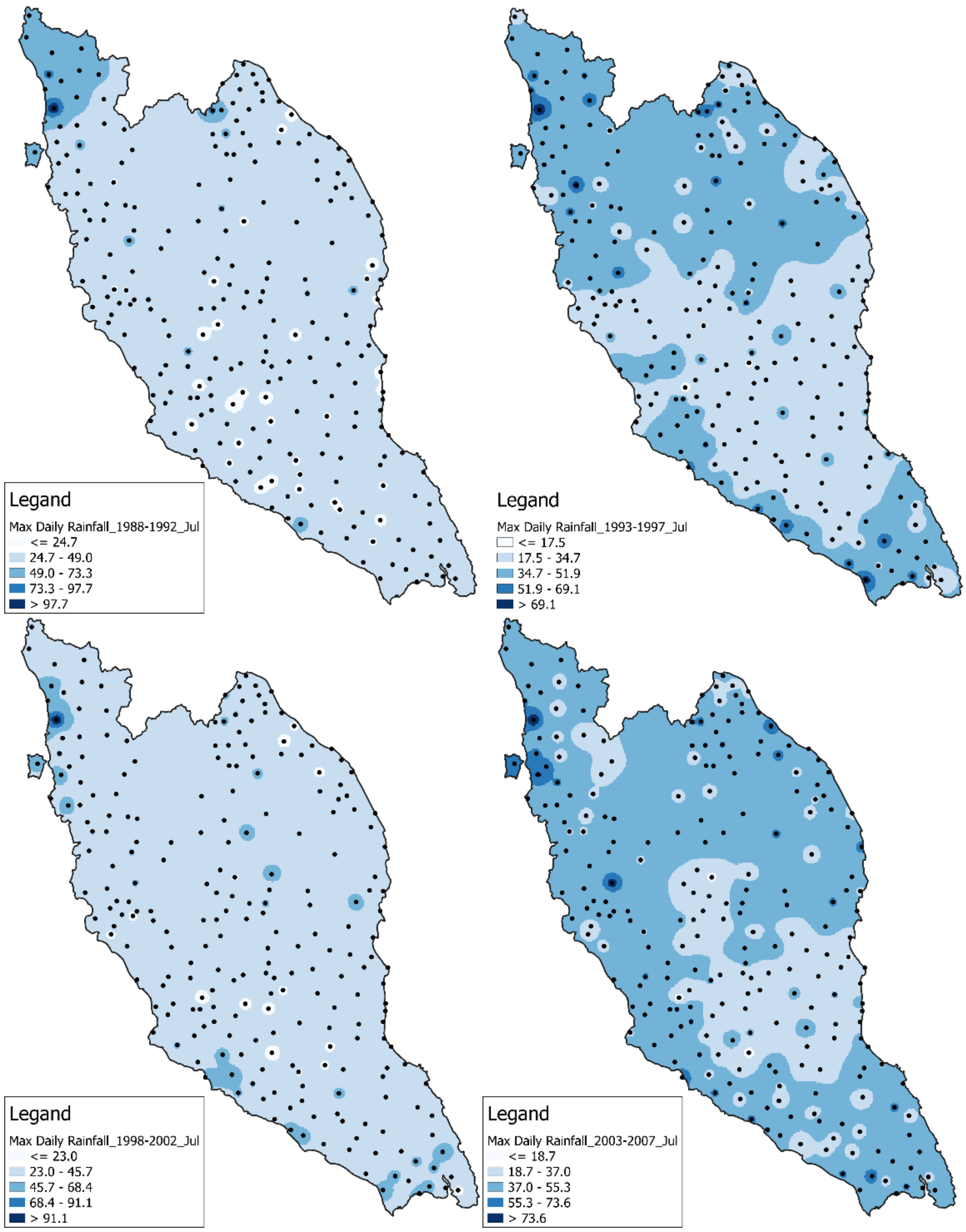
MapA- 16: Average Monthly Rainfall Maps on July for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont’)



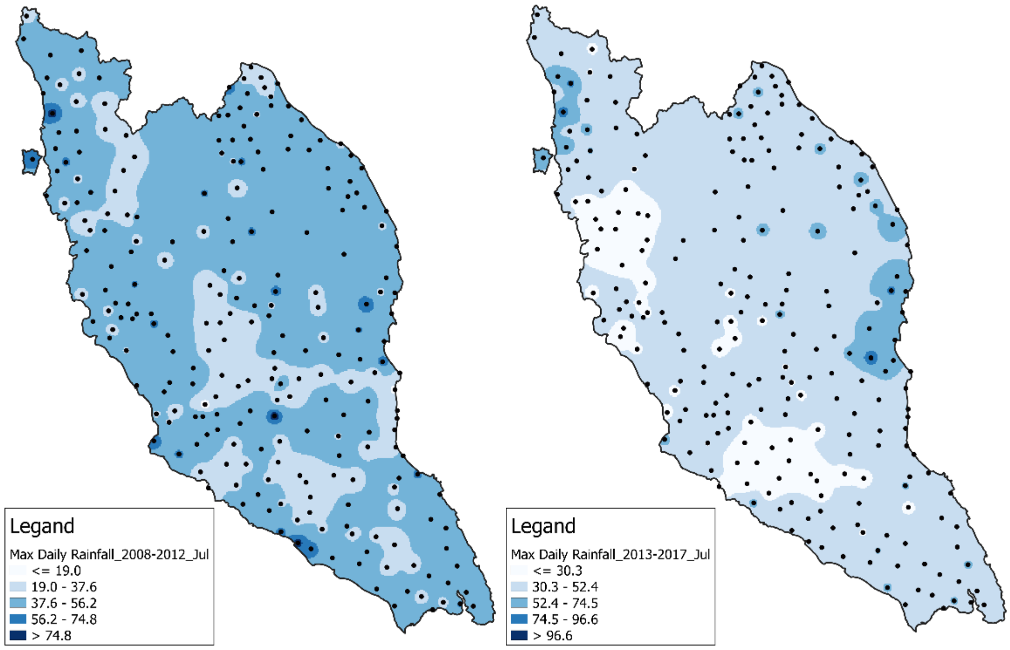
MapA- 17: Average Number of Wet Days Maps on July for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



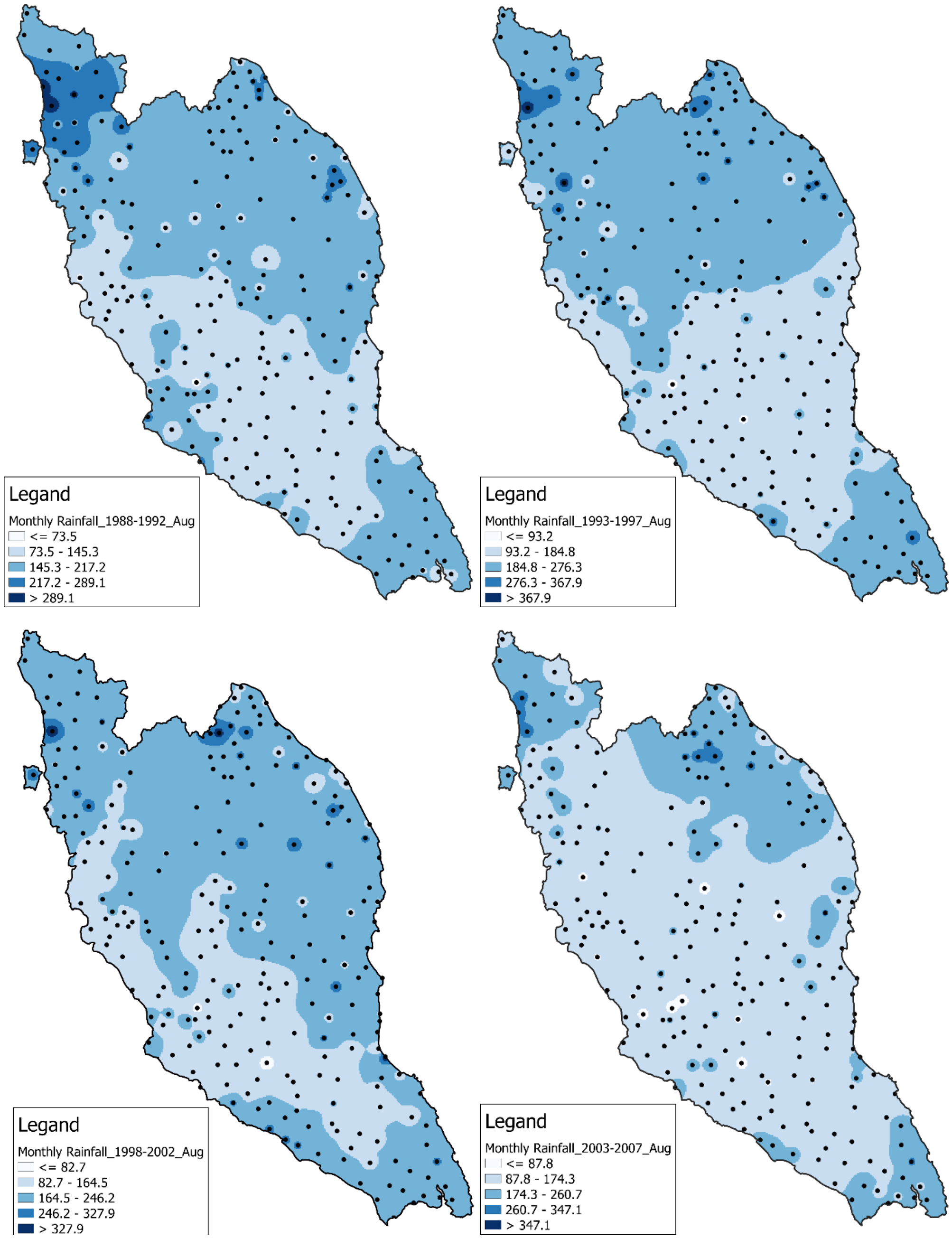
MapA- 17: Average Number of Wet Days Maps on July for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



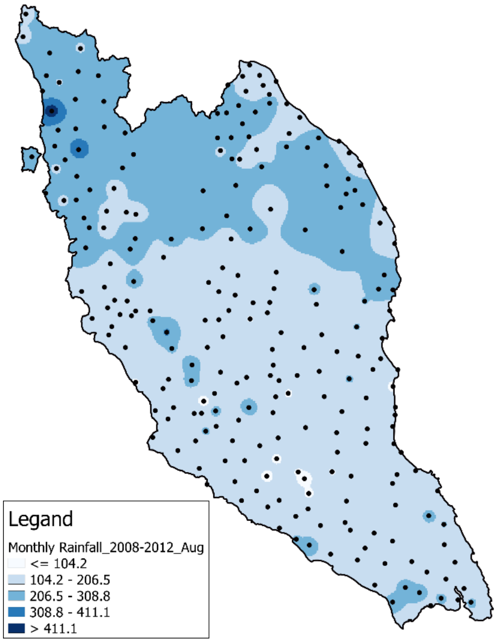
MapA- 18: Average Maximum Daily Rainfall Maps on July for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

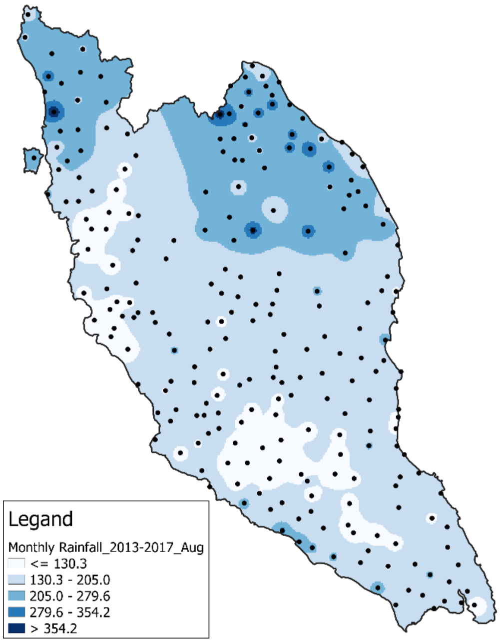


MapA- 18: Average Maximum Daily Rainfall Maps on July for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')

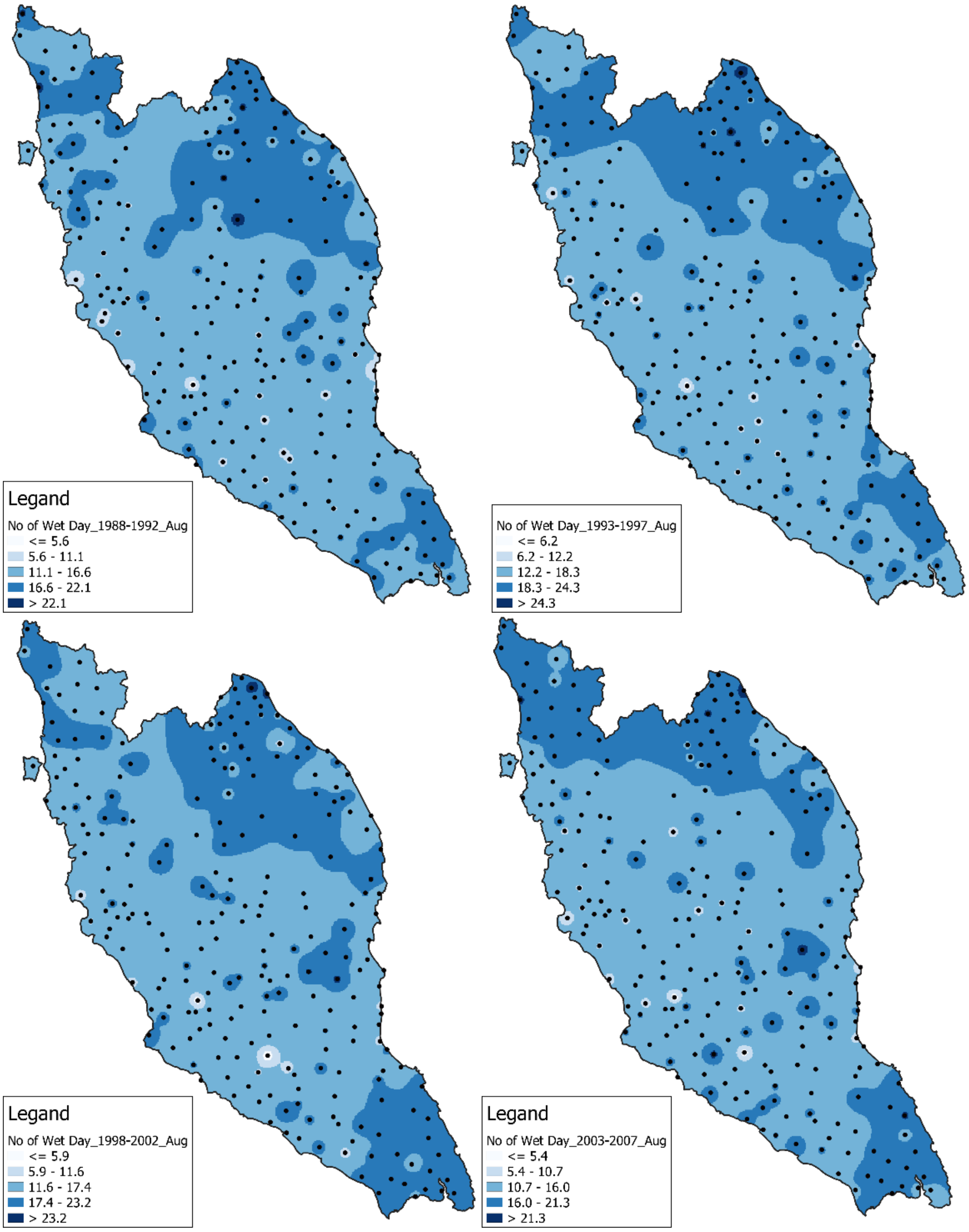


MapA- 19: Average Monthly Rainfall Maps on August for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.

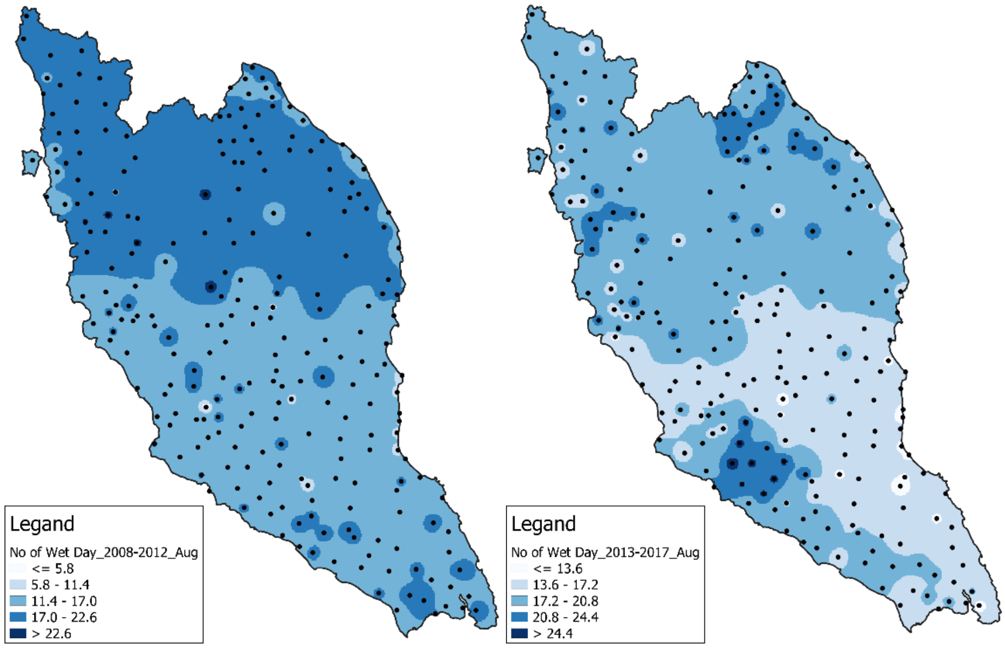




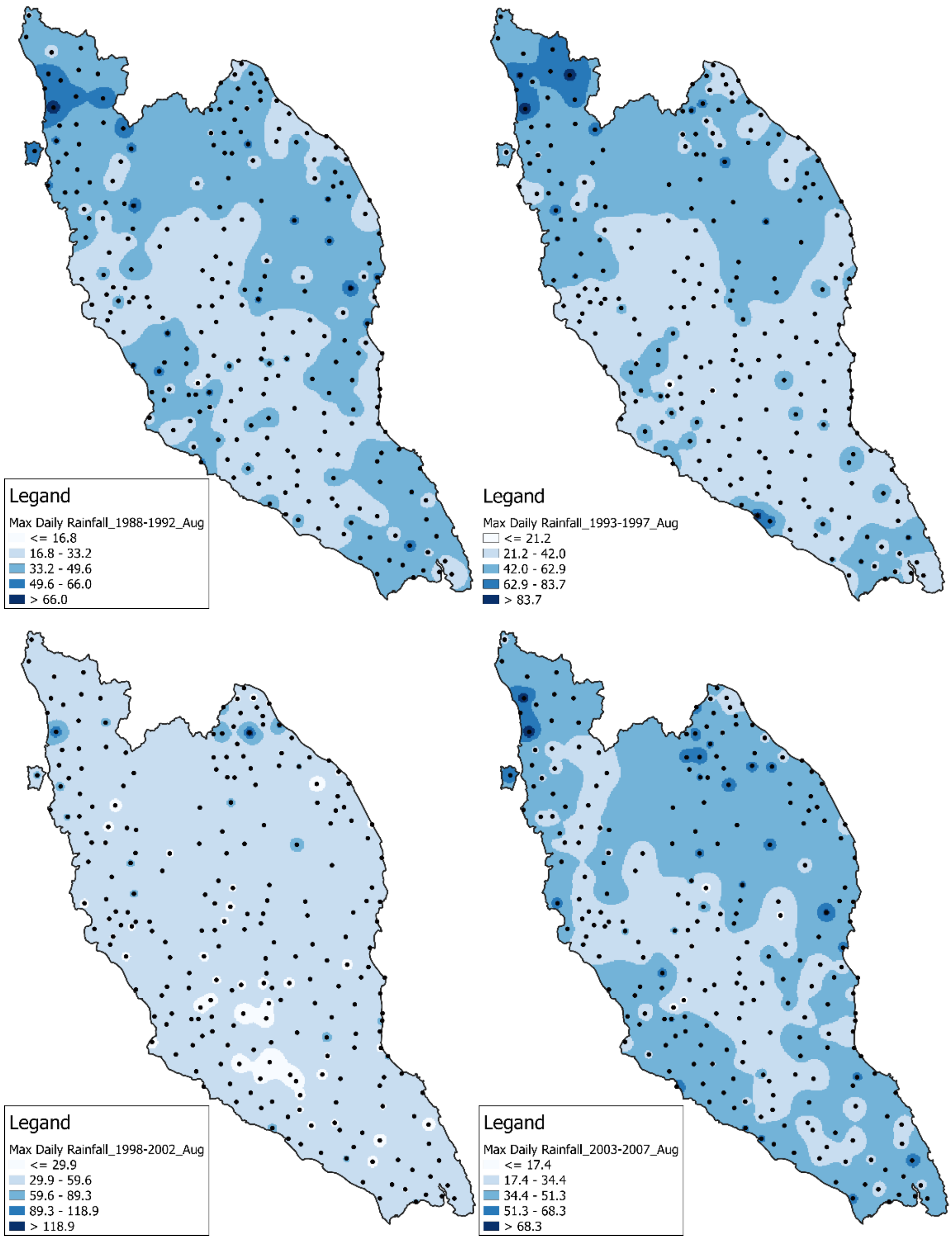
MapA- 19: Average Monthly Rainfall Maps on August for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



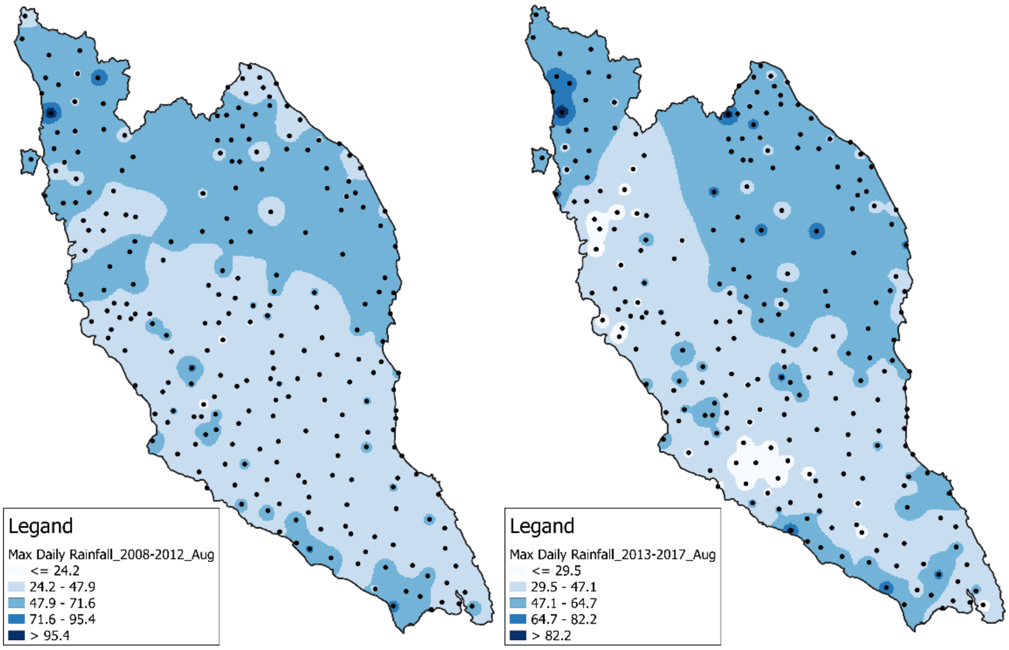
MapA- 20: Average Number of Wet Days Maps on August for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



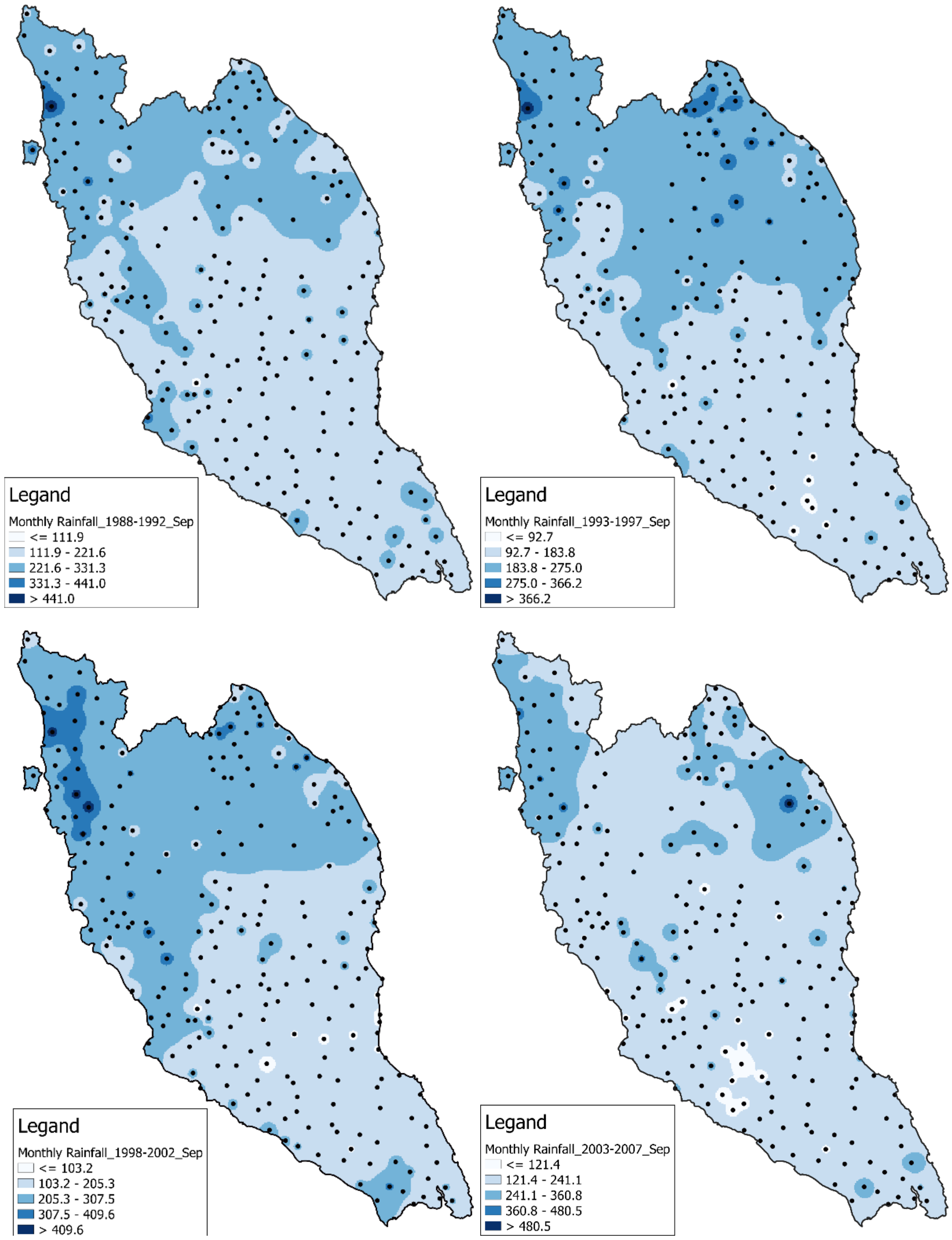
MapA- 20: Average Number of Wet Days Maps on August for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



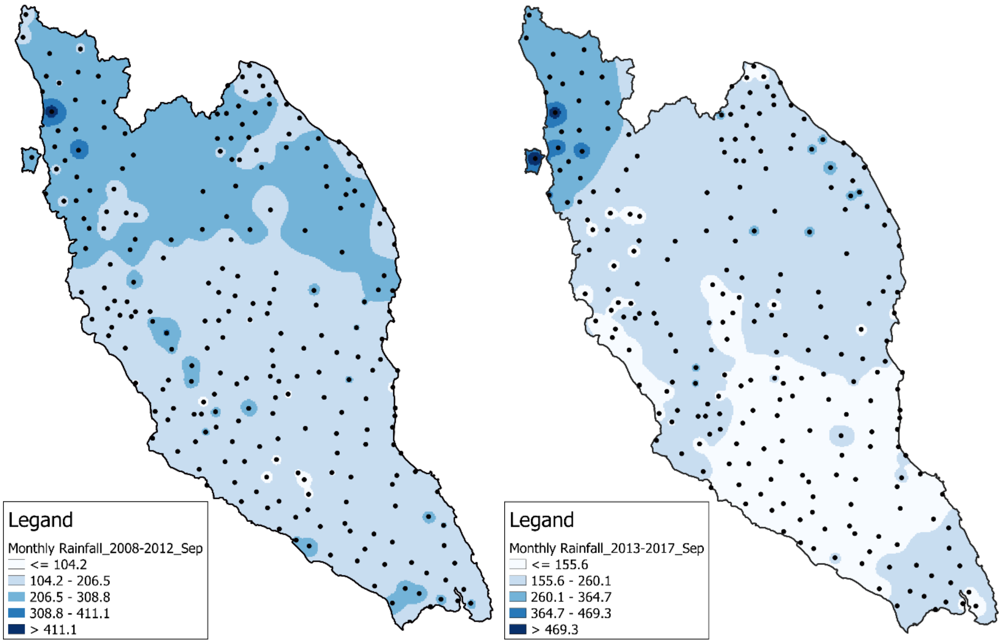
MapA- 21: Average Maximum Daily Rainfall Maps on August for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



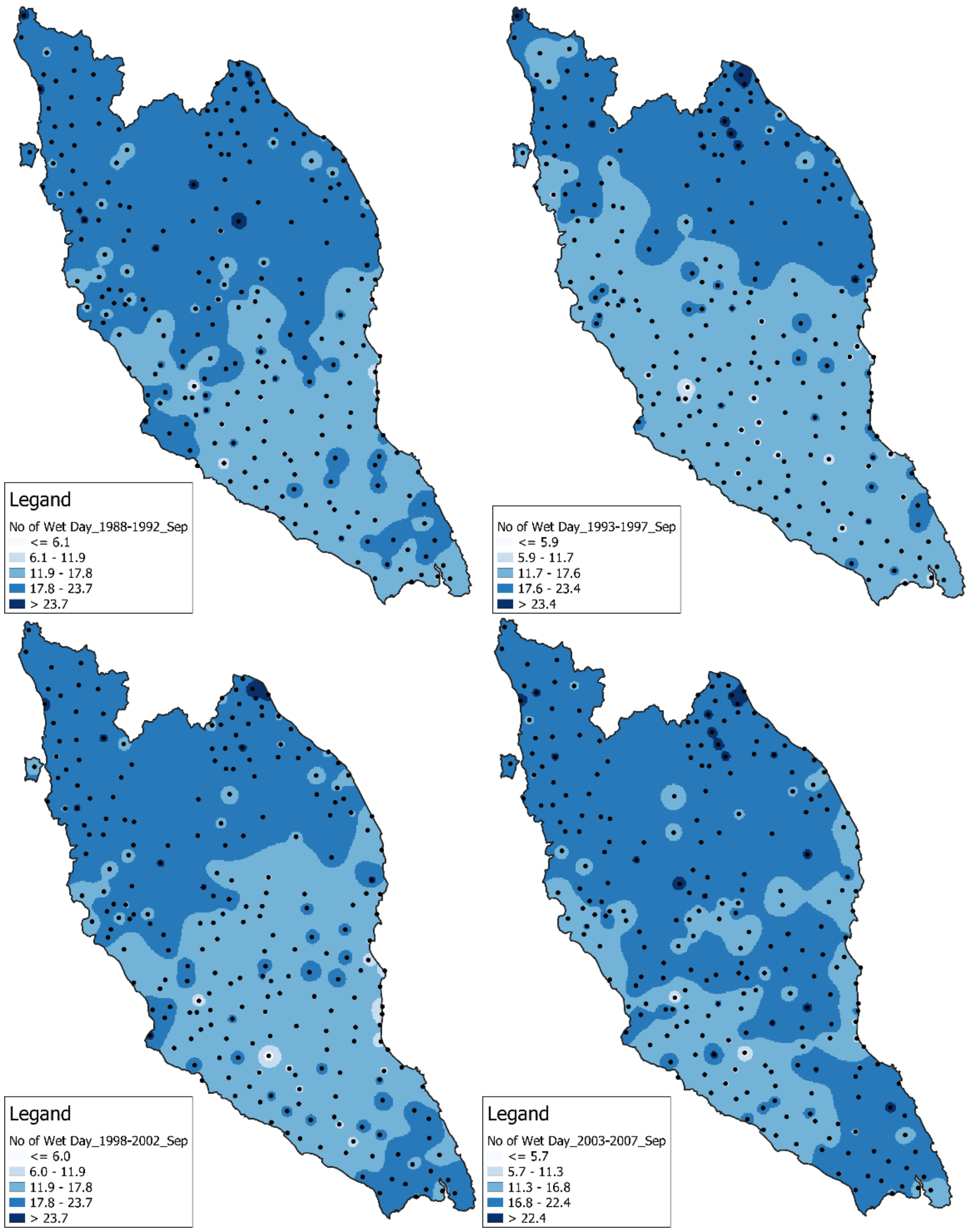
MapA- 21: Average Maximum Daily Rainfall Maps on August for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



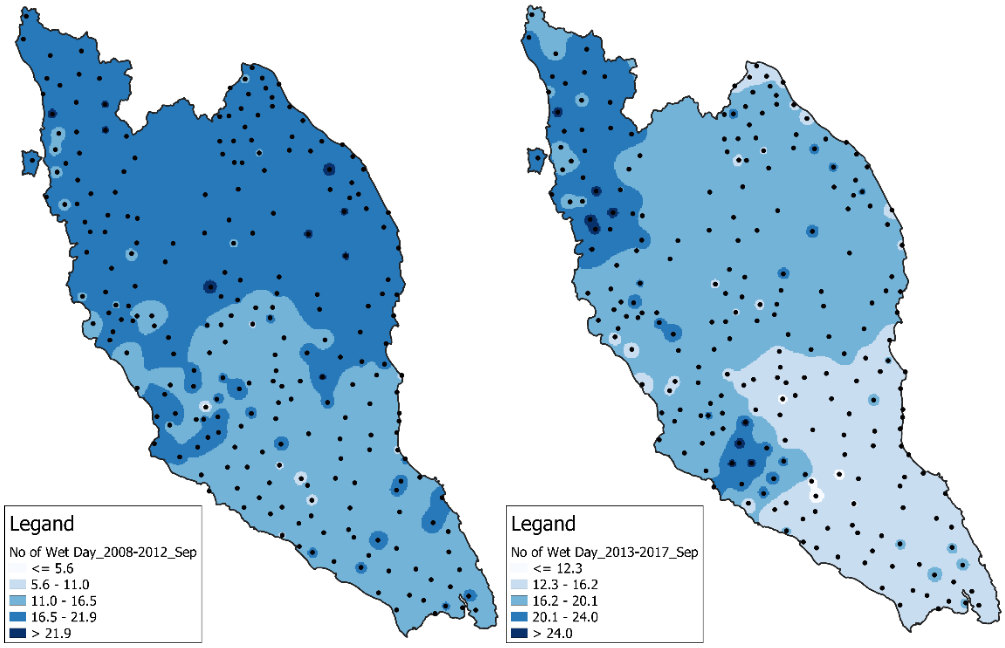
MapA- 22: Average Monthly Rainfall Maps on September for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



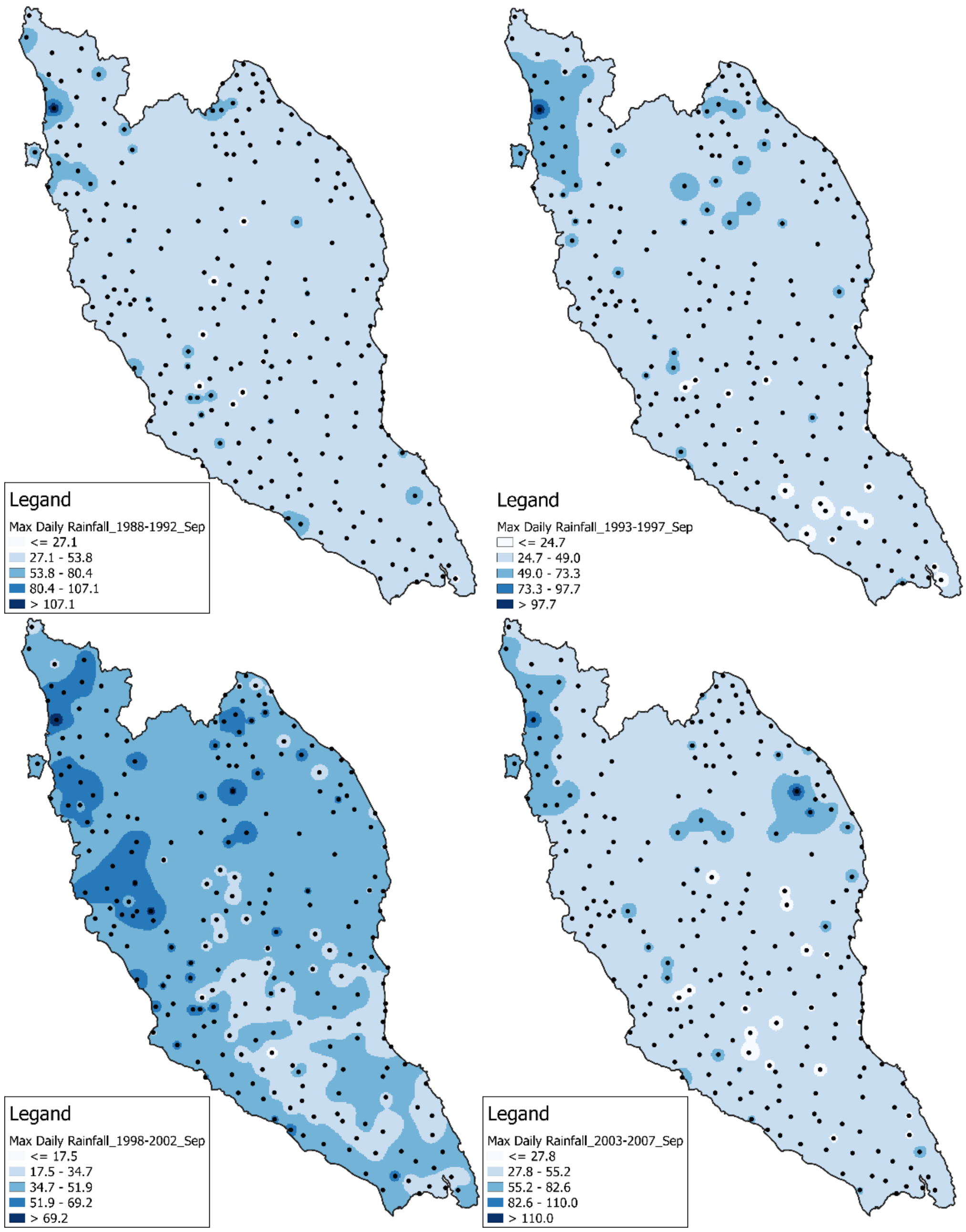
MapA- 22: Average Monthly Rainfall Maps on September for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



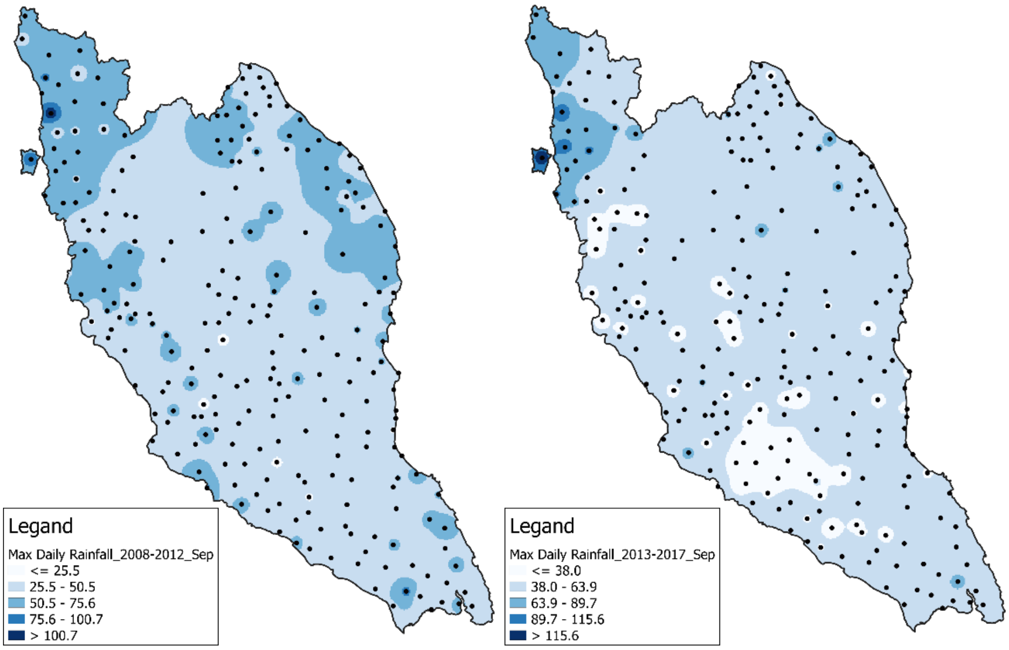
MapA- 23: Average Number of Wet Days Maps on September for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



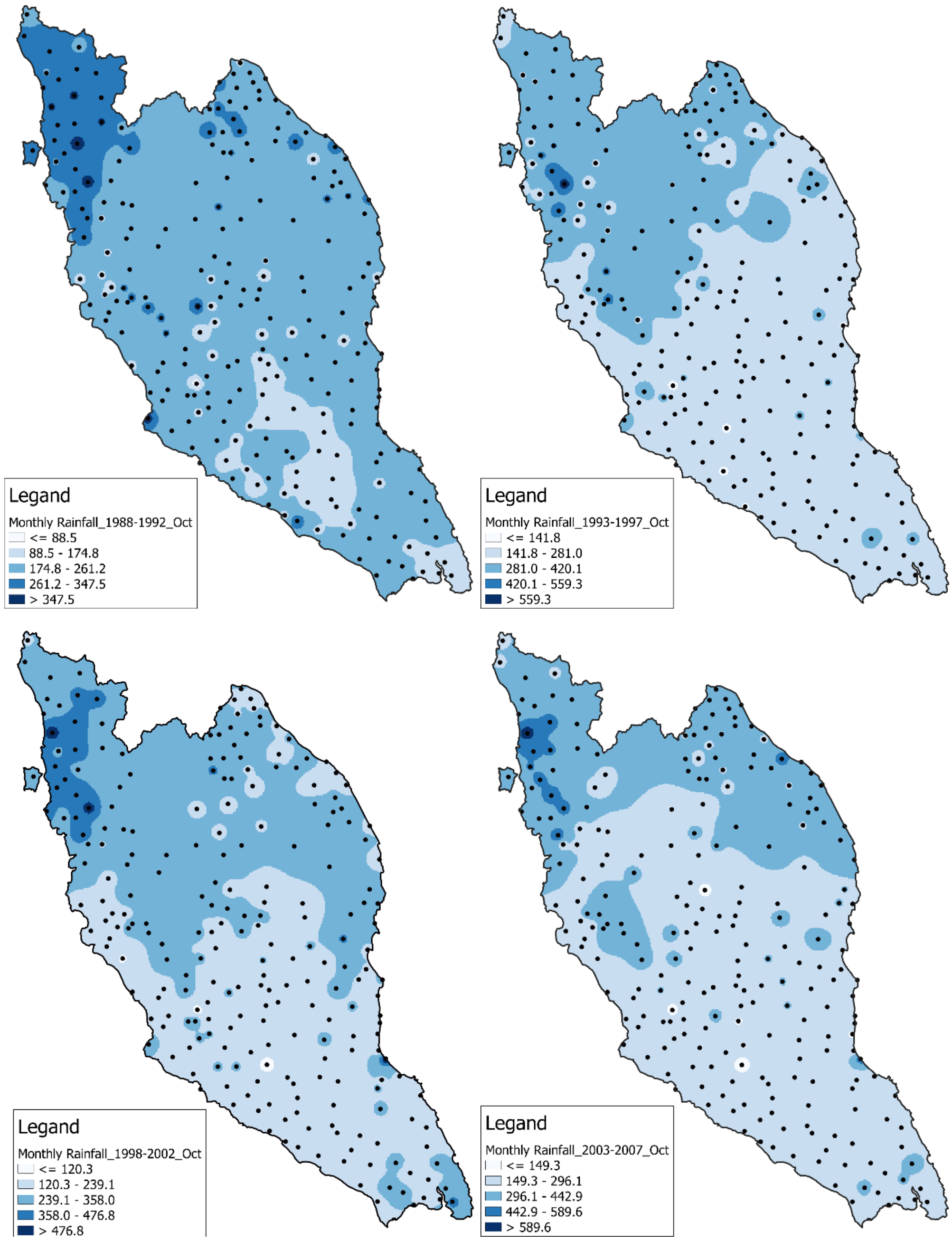
MapA- 23: Average Number of Wet Days Maps on September for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



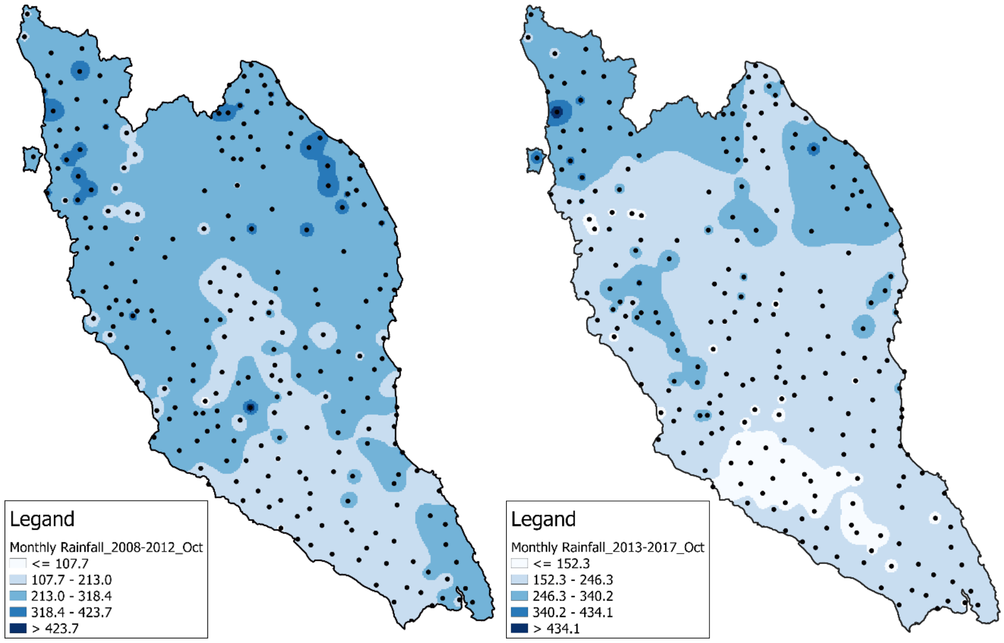
MapA- 24: Average Maximum Daily Rainfall Maps on September for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



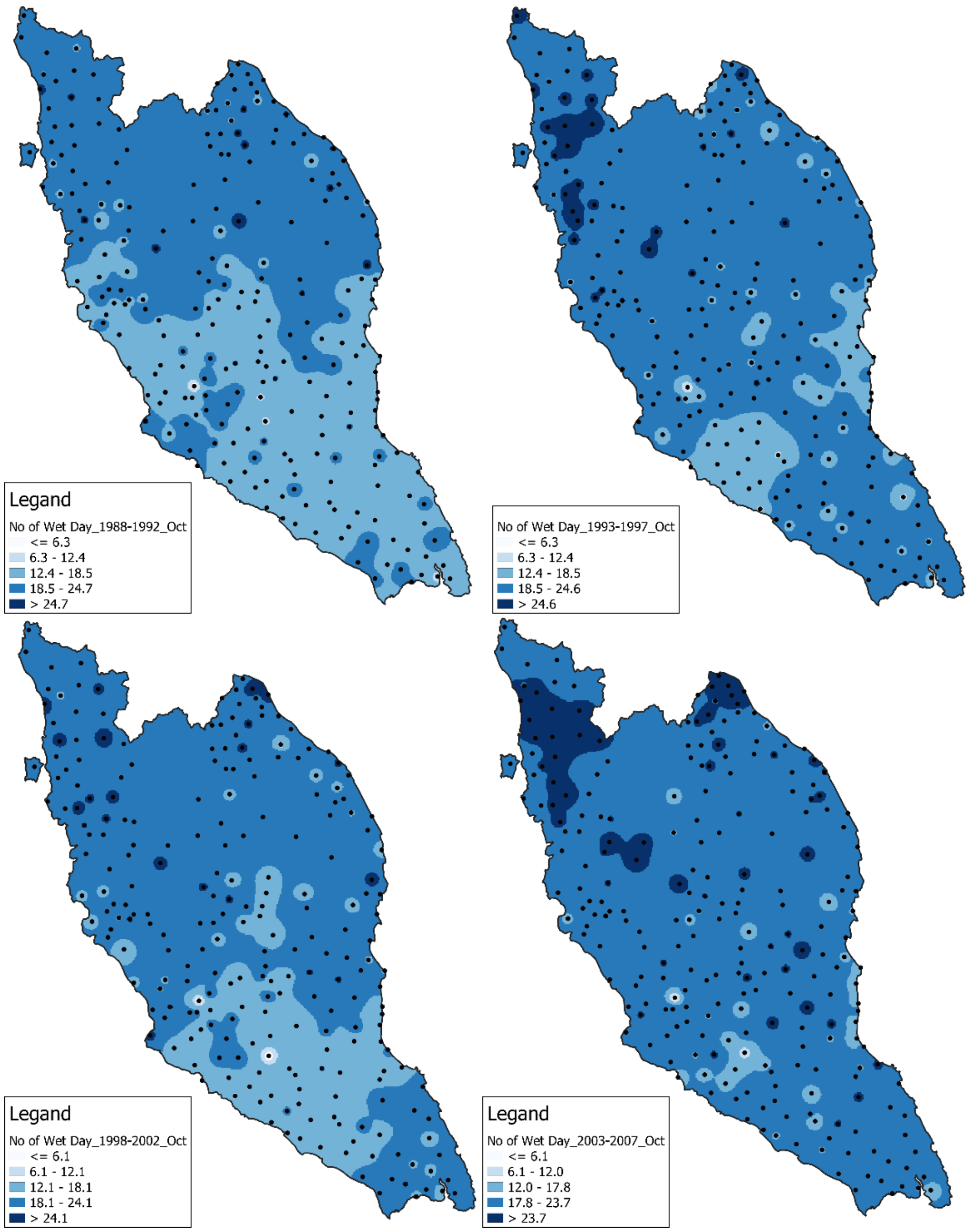
MapA- 24: Average Maximum Daily Rainfall Maps on September for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



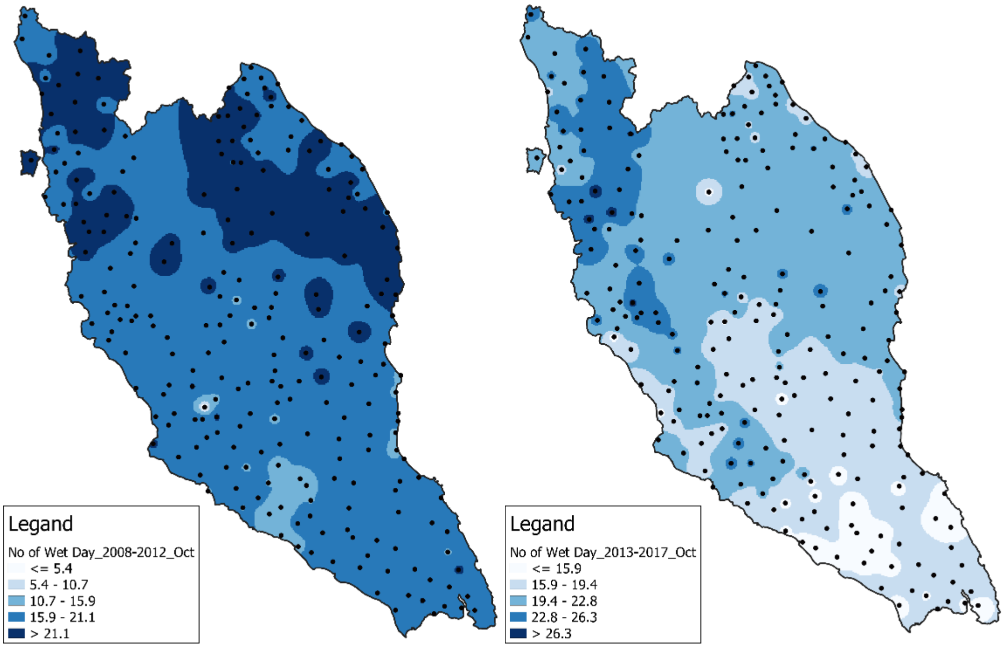
MapA- 25: Average Monthly Rainfall Maps on October for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



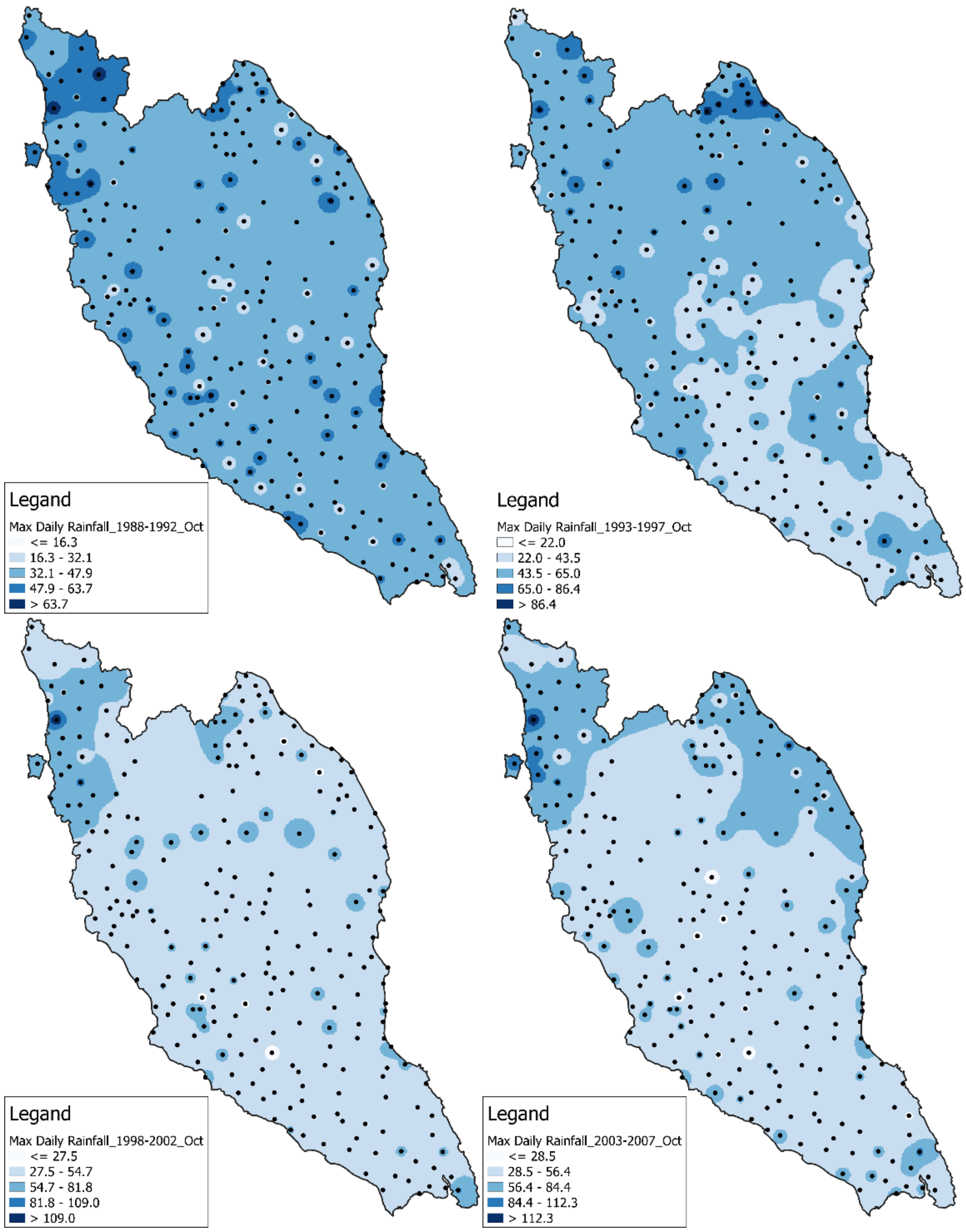
MapA- 25: Average Monthly Rainfall Maps on October for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



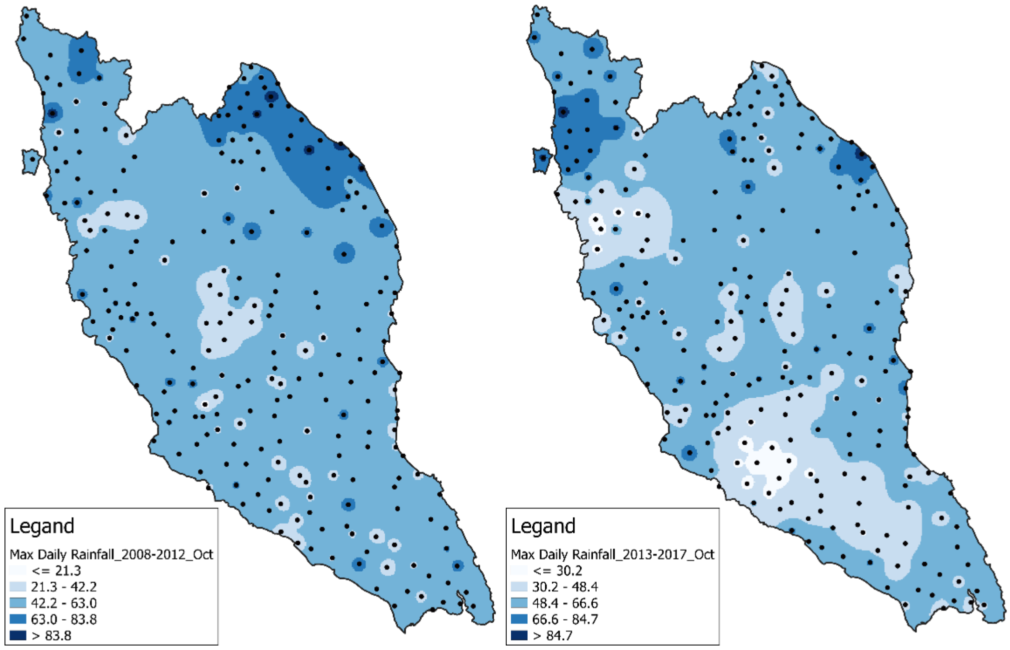
MapA- 26: Average Number of Wet Days Maps on October for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



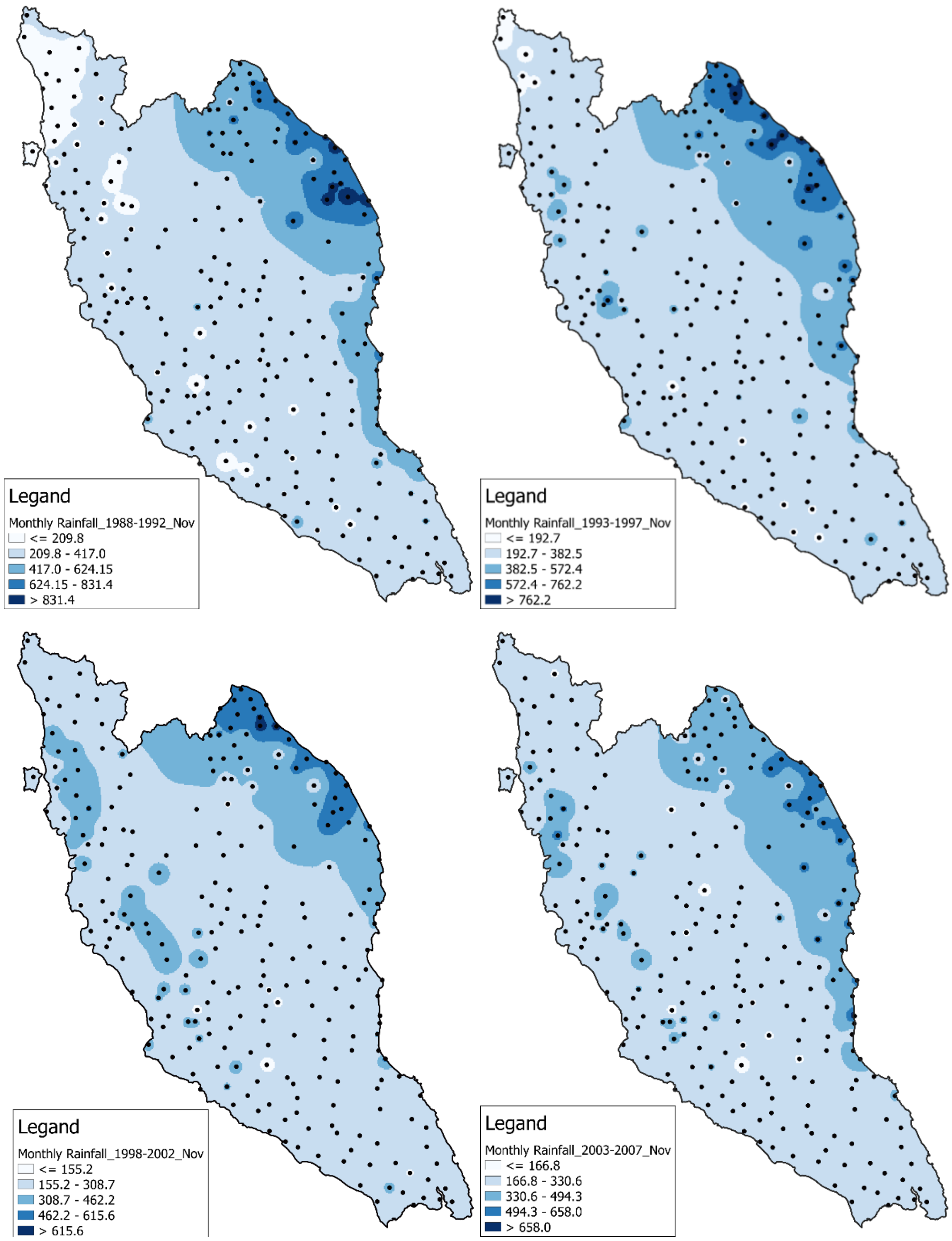
MapA- 26: Average Number of Wet Days Maps on October for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont’)



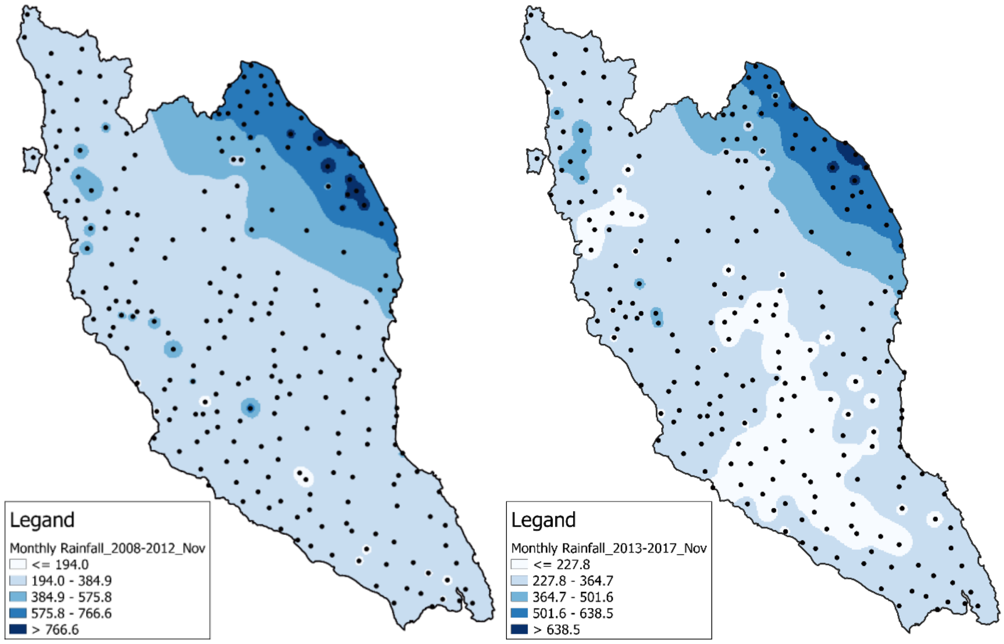
MapA- 27: Average Maximum Daily Rainfall Maps on October for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



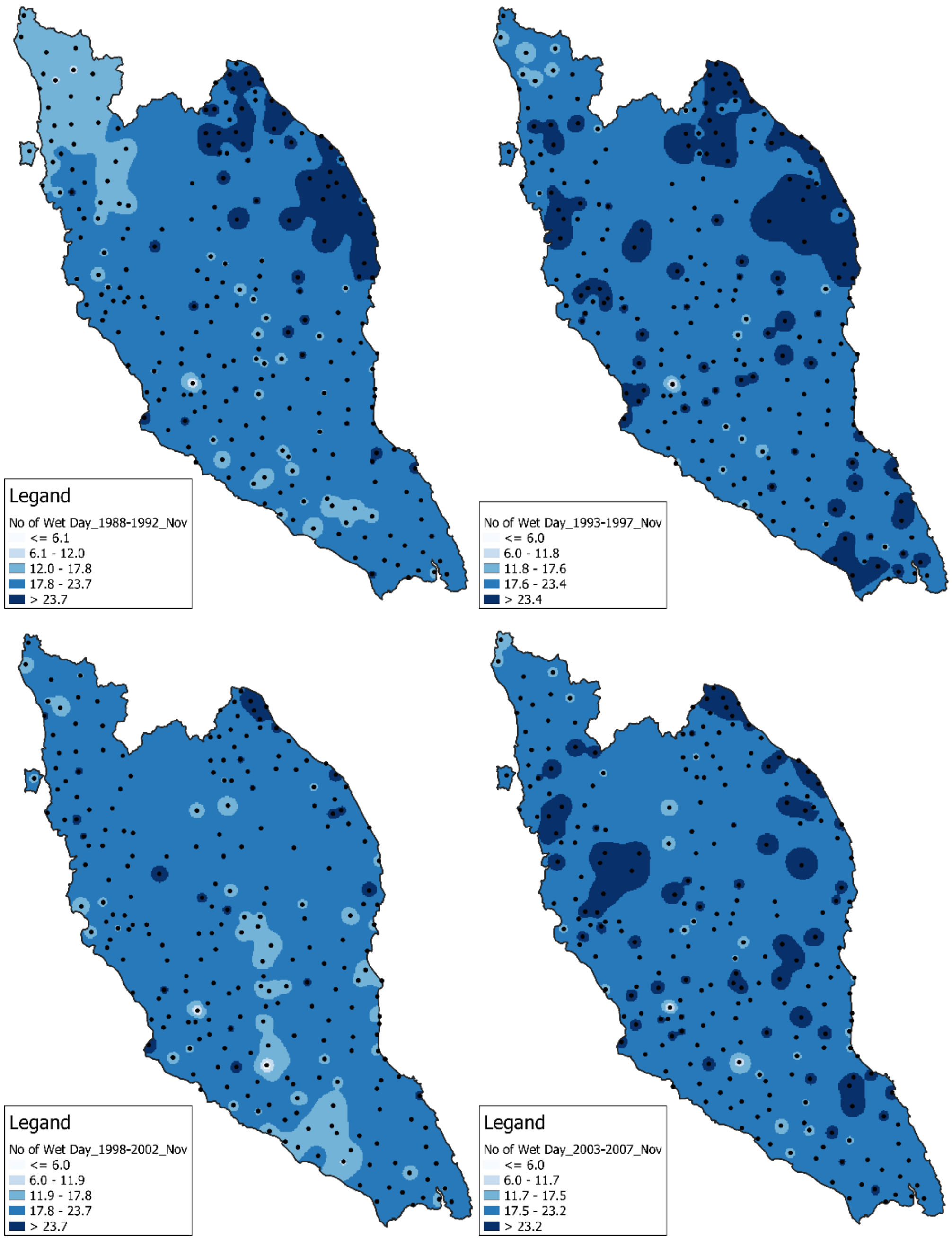
MapA- 27: Average Maximum Daily Rainfall Maps on October for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



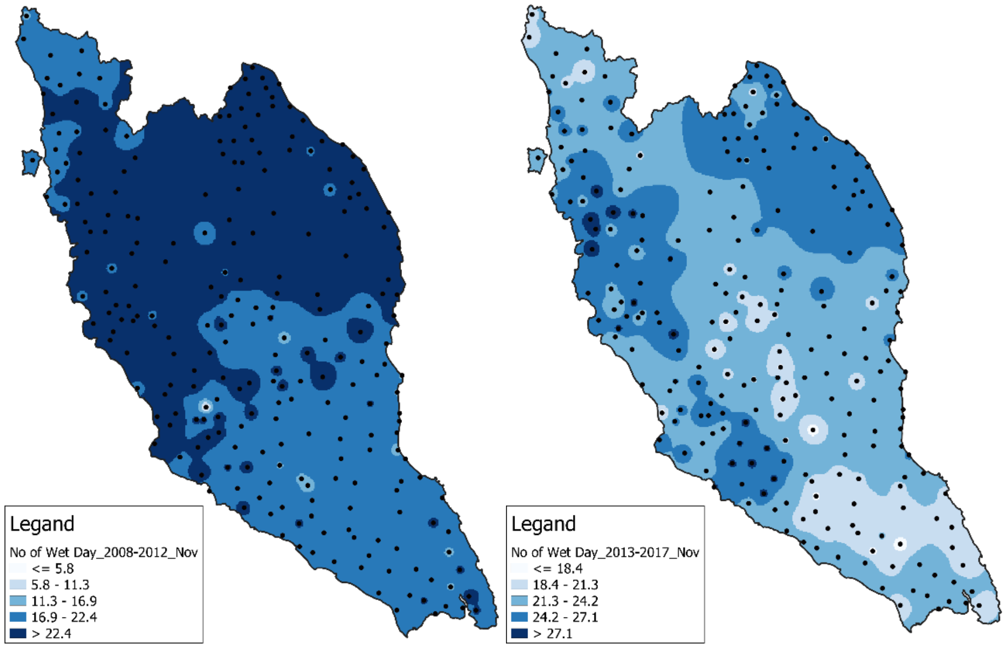
MapA- 28: Average Monthly Rainfall Maps on November for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



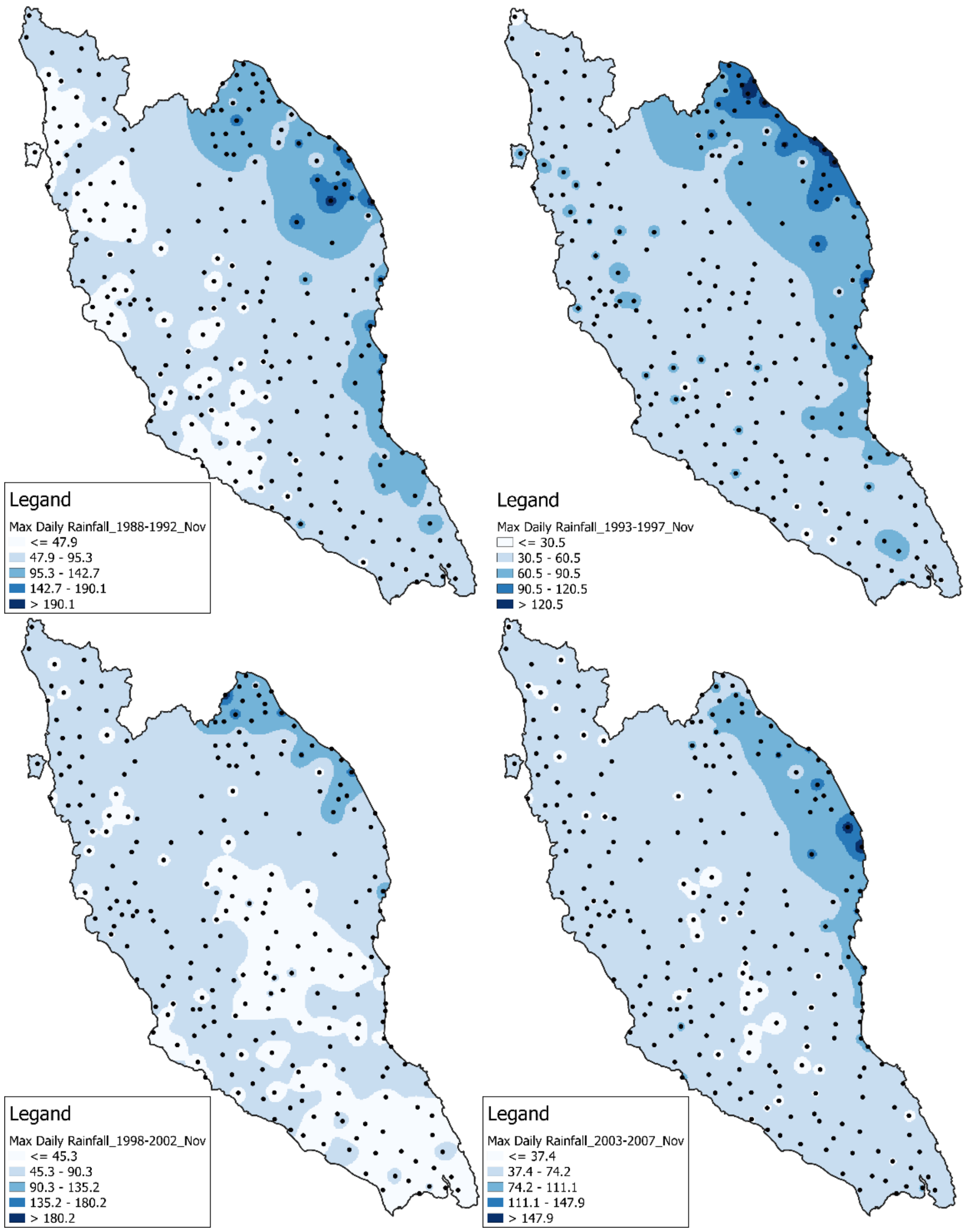
MapA- 28: Average Monthly Rainfall Maps on November for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont’)



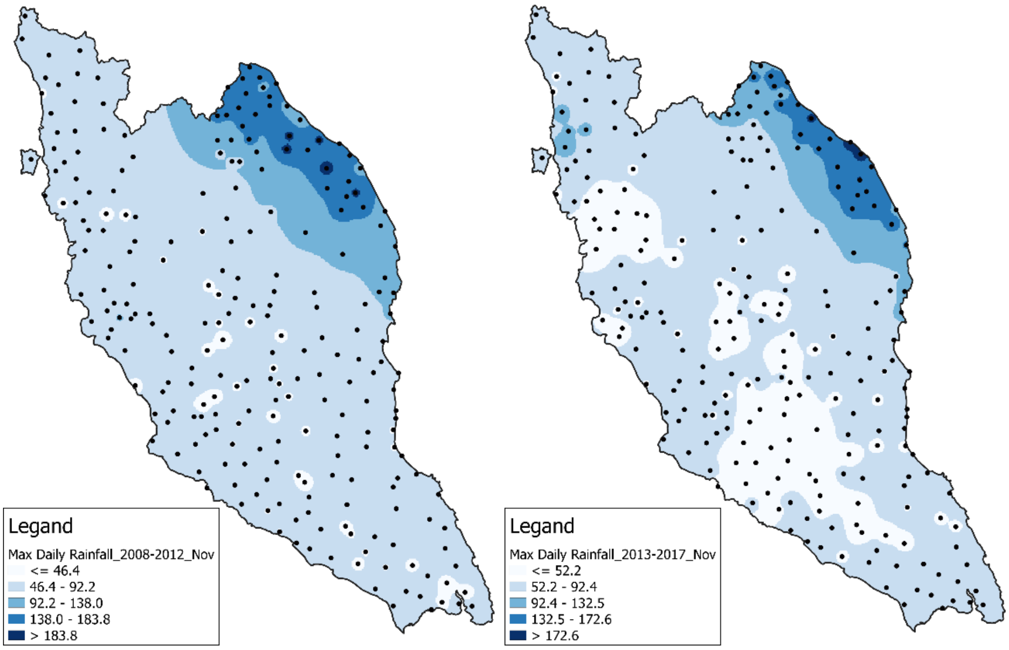
MapA- 29: Average Number of Wet Days Maps on November for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



MapA- 29: Average Number of Wet Days Maps on November for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')



MapA -30: Average Maximum Daily Rainfall Maps on November for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017.



MapA -30: Average Maximum Daily Rainfall Maps on November for 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012 and 2013-2017. (Cont')