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Research Article

Keywords: Rainfall Trends, General Circulation Model

Posted Date: July 13th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-673266/v1>

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Impacts of Climate Change on Rainfall Trends Under RCP Scenarios in Johor, Malaysia

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Abstract

Changes in the spatial and temporal rainfall pattern affected by the climate change need to be investigated as its significant characteristics are often used for managing water resources. In this study, the impacts of climate change on rainfall variability in Johor was investigated by using General Circulation Model (GCM) on the availability of daily simulation for three representative concentration pathways (RCP) scenarios, RCP2.6, RCP4.5 and RCP8.5 for interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$. In addition, the annual future rainfall trend for the first interval year of $\Delta 2030$ was also made. Daily rainfall series from eight (8) stations in Johor, Malaysia capturing 30 years period (1988-2017) with less than 10% missing data were chosen. The annual mean rainfall for RCP 2.6, 4.5 and 8.5 was predicted increase by 17.5%, 18.1% and 18.3%, respectively as compared to historical data. Moreover, the Mann-Kendall (*MK*) test was used to detect the trend and resulted in no trend for RCP2.6. Even so, RCP4.5 showed a significant upward trend in Muar and Kota Tinggi, and for RCP8.5, all regions were detected to have an upwards trend except for Pontian and Kluang. In general, the concentration of greenhouse gases from RCP8.5 gave the highest rainfall in future.

1 Introduction

It is now widely accepted that global climate change results in a rise within the frequency and intensity of climatic extremes, such as droughts and floods. More intense rainfall events had occurred all over the world and Malaysia has also received the impacts of the changes. In November 2019, the south region of Malaysia had an intense rainfall for almost a week that

led to flash flood and was one of the worst tragedies that have ever happened, especially in Johor as the number of flood victims rise rapidly (Shah *et al.*, 2019). The latter is the 2020/2021 flood, which suffers heavy rains for several days, hitting parts of Peninsular Malaysia. Prediction of rainfall events and climate changes in the future will lead to preparation before extreme events occur. Climate prediction models and statistical analysis are a great tool to estimate future rainfall data. Various types of climate prediction models can be found to predict any climate data such as rainfall, temperature, wind velocity and others from different studies (Hock & Holmgren, 2005; Gagnon *et al.*, 2005; Robinson & Catling, 2012; Bajracharya *et al.*, 2018). However, the General Circulation Model (GCM) has been used in many studies all over the world to predict future rainfall, temperature and other climate properties. GCMs is the infamously mathematically computer models that represent various global climate system of physical processes (Wilby *et al.*, 2002). GCM is a system of the many grid cells that represent horizontal and vertical areas on the Earth's surface which consider the potential level of greenhouse gases (GHGs). It computes water vapour and atmospheric cloud interactions, direct and indirect effects of aerosols on radiation and precipitation, changes in snow cover and sea ice, the storage of warmth in soils and oceans, surfaces fluxes of warmth and moisture, and large-scale transport of warmth and water by the atmosphere and oceans (Ghil & Robertson, 2000).

Canadian Earth System Model 2 (CanESM2) is one of the many center groups provide the GCMs data. Nevertheless, currently GCMs are depending on the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) which that is the modification from the AR4 series in terms of expected %CO₂ and the climate variables. Proportionately, CanESM2 is an appropriate centre group to provide the GCMs data as CanESM2 represents a part of the modelling community's contribution to the IPCC Fifth Assessment Report (AR5) (Scinocca *et al.*, 2008; IPCC, 2014). IPCC AR5 made a finding of a new set of scenarios that provide time-dependent projections of atmospheric greenhouse gas (GHG) concentrations. The new scenarios are called Representative Concentration Pathways (RCPs) which consists four types of pathways; RCP 8.5, RCP 6, RCP 4.5 and RCP 2.6. Each number for each RCPs represents their forcing (Wayne, 2013). The RCPs are the latest iteration of the scenario process and it is important for climate change research to use RCPs data to investigate the plausible trajectories of different aspects of the future.

A statistical process is required to create a bridge between GCM scale and native scale because the GCM scale is just too vast. In this case, the downscaling method was chosen to minimize the GCM scale to the local scale. A process termed downscaling has been developed

to formulate climate predictions at the local scale. Downscaling methods might be broadly classified into two categories, namely dynamical and statistical downscaling. Statistical is the most generally used compared to dynamical because it is often implemented easily in any region and cheap. In order to choose the suitable downscaling method, the desired spatial and temporal resolution of the climate information, resources and time constraints need to be considered (Wilby & Dawson, 2013).

Johor has been receiving increasing number of heavy rainfalls over the past years. According to the research made by Shafie (2009), a storm that blows from South East China Ocean and West Pacific Ocean cause heavy rainfall events that led to major floods in December 2006 and January 2007. Kota Tinggi district was hit badly from the storms that brought 287 mm and 338 mm of rain in four (4) days recorded in Bandar Kota Tinggi for the year 2006 and 2007, respectively. There has been evidence made by the scientific community at NASA by Buis (2020) that as global temperatures increase, extreme precipitation will very likely increase as well but these researches have yet to have any significant effects on climate change in future rainfall intensities at a specific area of Johor. Climate changes have affected rainfall intensities, especially in monsoon seasons which resulted in floods to occur without warning. Consequently, the rising temperature will lead to the unpredicted dry season. Thus, it is important to estimate future changes in rainfall for finding suitable measures to mitigate this natural disaster problem.

2 Study Methodology

2.1 Study Area and Rainfall Data

Johor is a state in Malaysia and located in the southern part of Peninsular Malaysia (1°48'N, 103°76'E). The total land area of Johor is 19,102 km² and divided into nine (9) districts. In general, Johor experiences a warm and humid tropical climate all year round, with an average annual rainfall of 2300 mm based from the average of annual rainfall from all eight (8) stations from Table 1. Rainfall is characterised by two rainy seasons associated with the Southwest Monsoon (SWM) (May to September) and the Northeast Monsoon (NEM) (October to March). NEM causes rainy season usually between mid-October and end of March on the eastern side of Peninsular Malaysia, while SWM is usually between May and October on the western part of peninsular and SWM season will affect Johor the most.

The eight (8) rainfall stations selected for this study area and their details are shown in Fig. 1 and Table 1. The rainfall stations were selected based on the percentage of missing data

to control the quality and accuracy of the result. Thirty years of monthly data were selected, and the amount of missing data calculated are 0.3 to 3.1%. It is important to have at least 30 years period of data to have a more accurate outcome for calibration and validation (Wilby *et al.*, 2002; Almazroui *et al.*, 2017; Hasan *et al.*, 2018). The lowest annual mean rainfall for 30 years period (1988-2017) was 1714.9 mm at Ladang Paya Lang. The highest was at Ladang Pekan Layang-layang, Kluang with 2603.6 mm for 30 years historical period.

2.2 Statistical Downscaling Model (SDSM)

GCMs are based on a large grid-scale (230 km - 600 km). Hence, statistical downscaling model (SDSM) will act as the bridge between regional/local scale and GCM scales (coarse scale). Therefore, SDSM was used to lessen the scale so that the outcome will be more accurate (5 km – 50 km). To show the possible changes in rainfall patterns of Johor due to climate change, observed daily rainfall data were used to downscale the future rainfall from 20 GCMs predictors of Coupled Model Intercomparison Project phase 5 (CMIP5) for 3 Representative Concentration Pathways (RCP) scenarios, namely RCP 2.6, RCP 4.5 and RCP 8.5. Fig. 2 shows the steps involved in the downscaling technique using SDSM. The predictand was the historical rainfall data of each selected rainfall station where quality control of the data was made to ensure no missing data in the file.

To control the accuracy in the simulation process, a total of 26 atmospheric agents (known as predictors) were screened to measure how strong the influence of these agents to the local climate formation. Two types of climate predictors at the grid box of 38X x 34Y were used on the statistical downscaling procedure. The first type was the National Centre of Environmental Prediction (NCEP) reanalysis data set for calibration and validation from 1988 until 2017. Secondly, the type was the GCMs predictors of CanESM2 for projection climate scenarios such as rainfall for interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$. Both NCEP and GCMs consists of the same types of climate predictor variables such as airflow variables, air temperature and others. Higher correlation value (R) shows a greater relation to the local climate. The selected predictors are significant variables in the climate equation using multiple regression.

After a quick check on selecting predictors by screen variables was made, the model was set into “Conditional process” for rainfall. Both steps of climate predictors selection and projection future rainfall need to go through the calibration step under the “Weather Generator” and “Scenario Generator” function, respectively. The output for Weather Generator was used

to find the standard error between the raw historical and historical data that has been generated with selected predictors. The chosen predictors for each station were used for prediction rainfall from the year of 2010 until 2099. However, in this study 2010 – 2039 were used for validation process while three (3) different time scales of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$ were used for prediction results. Future rainfall projected by all CMIP5 GCMs under three (3) RCPs were downscaled separately by SDSM at all eight (8) stations. The results of the rainfall prediction data were analysed for trend analysis to get the precise results of what will be climate change effects on towards rainfall trend in Johor in the future.

SDSM for rainfall occurrences on each day is shown in Eqn. (1) where t is time (days), W_t is the conditional possibility of rain occurrence on day t . $\hat{u}_t^{(j)}$ is the normalized predictor, w_{t-1} and α_{t-1} are the conditional probabilities of rain occurrence on day $t - 1$ and lag-1 day regression parameter, respectively based on the studied region and predictand. The estimated value of rainfall on each rainy day can be represented with a z score as in Eqn. (2).

$$W_t = \alpha_0 + \sum_j^n \alpha_{t-1} \hat{u}_t^{(j)} + \alpha_{t-1} w_{t-1} \quad (1)$$

$$Z_t = \beta_0 + \sum_j^n \beta_j \hat{u}_t^{(j)} + \beta_{t-1} + \varepsilon \quad (2)$$

Z_t is the z -score on day t , β_j is the calculated regression parameter, and β_{t-1} is the regression parameter and the z -score on day $t - 1$. Thus rainfall (y_t), can be written as in Eqn. (3), where Φ is the normal cumulative distribution function and F is the empirical function of y_t .

$$y_t = F^{-1}[\Phi(Z_t)] \quad (3)$$

2.3 Mann-Kendall (MK) Test for Trend Analysis Test

Mann-Kendall trend test is a non-parametric test used to identify a trend in a series which means it works for all distributions, even if there is a seasonal component in the series. However, the data should have no serial correlation. This test can be used to find trends for as few as four samples. Nonetheless, the test has high probability not to show a trend if the data points are too small because in *MK* test, the more data points, the more likely the test is going to show a real trend. The significance of the detected trends is often can be achieved at different

levels of significance (which is 0.05). It has been suggested by the World Meteorological Organisation (WMO) to determine the existence of statistically-significant trends in climate and hydrologic data time series. The *MK* test statistics and the sign function are calculated using Eqn. 4 – 7.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (4)$$

$$\text{sign}(x_j - x_i) \begin{cases} +1 & x_j > x_i \\ 0 & x_j = x_i \\ -1 & x_j < x_i \end{cases} \quad (5)$$

where n is the number of data, x is the data point at times i and j ($j > i$). The variance of S is as follows

$$\text{var}(S) = \left[n(n-1)(2n+5) - \sum_{i=1}^m t_i i(i-1)(2i+5) \right] / 18 \quad (6)$$

where t_i is the number of ties of extent i and m is the number of tied groups. For n larger than 10, the standard test statistic Z is computed as the *MK* test statistic as follows

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{VAR}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{VAR}(S)}} & \text{if } S < 0 \end{cases} \quad (7)$$

The presence of a statistically significant trend is evaluated using the Z value. Positive values of Z indicate increasing trends, while negative values show decreasing trends. To test for either increasing or decreasing monotonic trend (a two-tailed test) at α level of significance, H_0 should be rejected if $|Z| > Z_{1-\alpha}$, where $Z_{1-\alpha}$ is obtained from the standard normal cumulative distribution tables. For example, at the 5% significance level, the null hypothesis is rejected if $|Z| > 1.96$. A higher magnitude of Z value indicates that the trend is more statistically significant.

3 Results and Discussion

3.1 Projection of Future Rainfall using Canadian Earth System Model 2 (CanESM2)

The climate predictors were first screened by screen variables to screen all twenty-six (26) predictors in order to choose the best five (5) predictors. The results revealed that different atmospheric variables affect different local variables. Hence, the predictors variable varied across all eight (8) stations. The most effective parameters on rainfall in most stations were the surface specific humidity (ncepshum) and mean temperature (nceptemp) at 2 m, and this has been proven from the previous research made by Al-Mukhtar and Qasim (2019). These parameters are associated and highly correlated to rainfall occurrence because their synchronous variation is dependent on the saturated phase of water vapour in the air.

The significant predictors were used in the SDSM calibration and validation. The results of the projection of future rainfall were developed by the SDSM model for each site for the interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$ (hereinafter 1st, 2nd and 3rd periods, respectively) based on the RCP2.6, RCP4.5 and RCP8.5 scenarios generated from CanESM2. Therefore, the mean for every 30 years of each RCPs scenario was used as tabulated in Table 2. The highest average annual rainfall was predicted at Ladang Pekan Layang-layang, Kluang station of 3058.16 mm (RCP2.6), 3074.92 mm (RCP4.5) and 3079.52 mm (RCP8.5). While the lowest mean rainfall was predicted at Ladang Paya Lang, Segamat station of 1989.09 mm (RCP2.6), 1985.31 mm (RCP4.5) and 1960.80 mm (RCP8.5) was predicted to be captured. Different scenarios of GCMs predictors of CanESM2 gave different results as the concentration of emission radiation varies. Fig. 3 depicts the annual future change in rainfall for Ladang Getah Malaya, Ladang Pekang Layang-layang, Ladang Paya Lang, Ladang Telok Sengat, Ladang Temiang Renchong and Pintu Kawalan Sembrong and Stor JPS stations by three scenarios. Under all scenarios, the results dictated that more extreme localized event of heavy rainfall in the future as all scenarios resulted in increasing amount of rainfall. However, Kompleks Perumahan Pontian station, the average annual rainfall will likely negatively change for all RCPs. These showed that for this station area will have lesser rain annually in the future due to the effects from increase of emission radiation.

The mean projection rainfall was plotted to show the spatial distribution in Fig. 4. The spatial distribution of the changes in rainfall can help for better understanding of future rainfall variations in Johor but due to the limitations of rainfall stations considered, some of the areas might not be correctly incorporated from the spatial distribution analysis. In order to see the differences on the spatial distribution, 90 years period of projected future rainfall were used

but was divided into three (3) interval year for all the RCPs of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$. Based on the low emission scenario (RCP2.6), as shown in Fig. 4(a), the results showed an obvious change throughout every 30 years. Lesser rain was predicted to occur in the North-west region of Johor. While, heavy rain was predicted in the South-east region. For the climate model on the common emission scenarios (RCP4.5), the result of the spatial distribution is shown in Fig. 4(b). Projected rainfall resulted in a slightly different amount of rainfall in the future throughout the interval year for all the RCPs of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$. North-west region showed a small difference in the decreasing rainfall amount for the future. Fig. 4(c) shows the results of the plotted spatial distribution of RCP 8.5. Lesser rainfall was predicted to occur generally at all districts throughout the predicted years due to RCP 8.5 contributes the highest concentration in carbon dioxide release. Hence, more effects were predicted to happen when applying RCP 8.5 as carbon dioxide release is the major effect on climate change.

3.2 *Trend Analysis of Annual Projected Rainfall for all Stations*

The *MK* tests were used to identify trends in annual rainfall for interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$ and the results are summarised in Table 3. No trend found for all stations in Johor for RCP2.6. The answer for the no trend is mostly because of the characteristics of RCP2.6, which contain the lowest emission scenario to supply logical future scenario anthropogenic forcing spanning. For the RCP4.5 scenario, Ladang Getah Malaya, Ladang Telok Sengat and Ladang Temiang Renchong stations showed a significant increasing trend. Both stations located in Kota Tinggi; Ladang Getah Malaya and Ladang Telok Sengat stations resulted in positively increasing trend with the *Z* value of +2.13 and +2.62, respectively. Another positively increasing trend with the *Z* value of +2.08 was found at Ladang Temiang Renchong station in Muar. Kota Tinggi and Muar are two districts that always experience flood events as well as the contributions from the emission scenario. However, the remaining stations such Kompleks Perumahan Pontian, Ladang Paya Lang, Pintu Kawalan Sembrong, Ladang Pekan Layang-layang station and Stor JPS showed no trend because of their *Z* values were less than 1.96.

RCP8.5 scenario influenced the most trend for all station as all stations showed trends. Six (6) stations resulted in significant increasing trend while two (2) stations in Pontian (Kompleks Perumahan Pontian) and Kluang (Ladang Pekan Layang-layang) showed significant decreasing trends. Kota Tinggi stations; Ladang Getah Malaya and Ladang Telok Sengat showed a significantly positive increasing trend with the *Z* value of +3.5 and +3.37, respectively. North-west of Johor which included Ladang Paya Lang, Ladang Temiang

Renchong and Pintu Kawalan Sembrong stations showed a significantly positive trend. Stor JPS station in Johor Bahru also resulted in significantly positive trend with the Z value of +3.32. However, Kompleks Perumahan Pontian and Ladang Pekan Layang-layang stations resulted in significantly negative trend with the Z value of -2.27 and -2.8, respectively. This proved that RCP8.5 scenarios gave a significant impact on the rainfall trends in the future for interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$. Besides, the results also proved that with a future climate scenario that characterized by increasing greenhouse gas emission over time will lead into significantly positive trend for the majority of the stations. Fig. 5 illustrates the symbol of the trend at each station of all RCPs for a more precise explanation. The vulnerability to storms might further be aggravated if extreme rainfall episodes continue in the RCP8.5 future scenarios and may consequently result in inland and coastal flooding.

4 Conclusions

Long-term rainfall trend which considered the impact of climate changes under three (3) different RCPs were successfully generated using GCMs with the help from SDSM on downscaling the huge scale of GCMs data. In general, the SDSM model is a feasibility tool to downscale and project future rainfall corresponding to CanESM2 scenarios. During the calibration and validation, the model has a capability to capture the observed daily rainfall well. This research also predicted increasing rate of rainfall will be the lowest during the period of interval year of $\Delta 2030$ when the localized minimum downpour will be at the Kompleks Perumahan Pontian station area. Increased rainfall during interval year of $\Delta 2050$ and $\Delta 2080$ periods will make the rainfall more spatially distributed in the Batu Pahat and Pontian areas corresponding to the IPCC scenario. On the other hand, an extreme localized rainfall event may be more apparent in the Kota Tinggi, Kluang and Johor Bahru area in Johor. It is expected that the results obtained from this study will be helpful in impact assessment studies in the Johor region.

The changes in the trend of rainfall for interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$ were well examined using Mann-Kendall analysis. There were no significant upward or downward trend detected for RCP 2.6 for all eight (8) rainfall stations throughout the interval year of $\Delta 2030$, $\Delta 2050$ and $\Delta 2080$. Hence, low greenhouse gas concentration levels will not be affected on the rainfall trend in the future. However, with RCP4.5 which is a stabilization without overshooting radiative forcing target scenario resulted in an upward trend at Ladang Temiang Renchong Muar, Ladang Getah Malaya and Ladang Telok Sengat Kota Tinggi stations

throughout all the interval years. Moreover, RCP 8.5 proved that with increment of greenhouse gas emissions over time will lead to significant upward trend in the future of Johor for most of the stations area, except for Kompleks Perumahan Pontian and Ladang Pekan Layang-layang, Kluang area. Despite the significant upward trend for most of the stations from RCP 8.5, more research could be made to study on the impact of the trends in the region.

Acknowledgements

Authors would like to thank Ministry of Higher Education, Malaysia in funding the project through Fundamental Research Grant Scheme (FRGS) (Vote K335).

Author contribution

Siti Nazahiyah and ‘Aainaa Hatin, wrote the article, analysed the source data and prepared appropriate figures and; Nurul Nadrah contributed in writing and editing the manuscript.

Data availability Rainfall data are available on request.

Code availability Not applicable.

Declarations

Ethics approval and consent to participate The authors confirm that this article is an original research and has not been published previously in any journal.

Consent for publication The authors have agreed to submit this manuscript in its current form for publication in the journal.

Competing interests The authors declare no competing interests.

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Figures

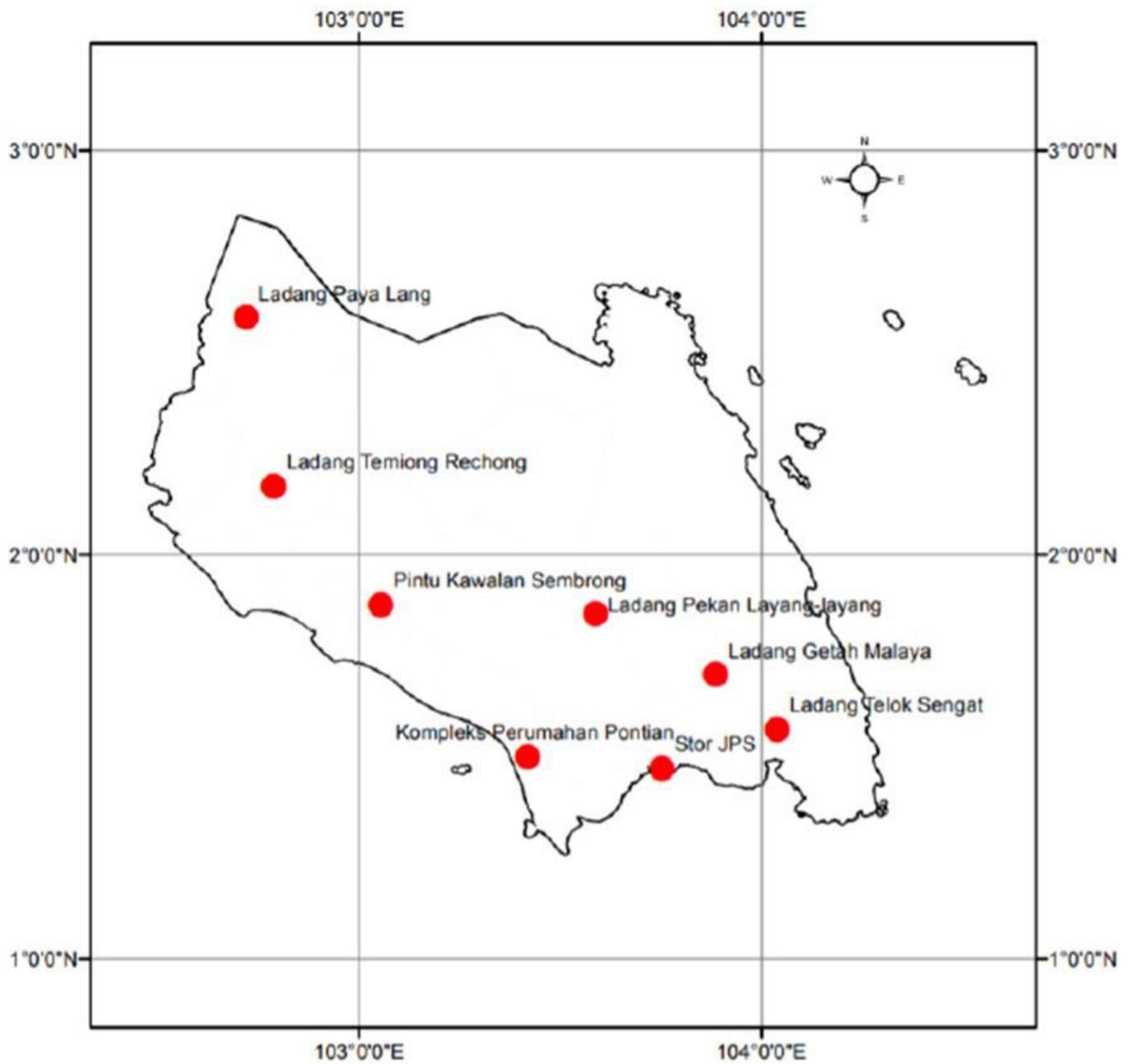


Figure 1

Rainfall stations selected for the study

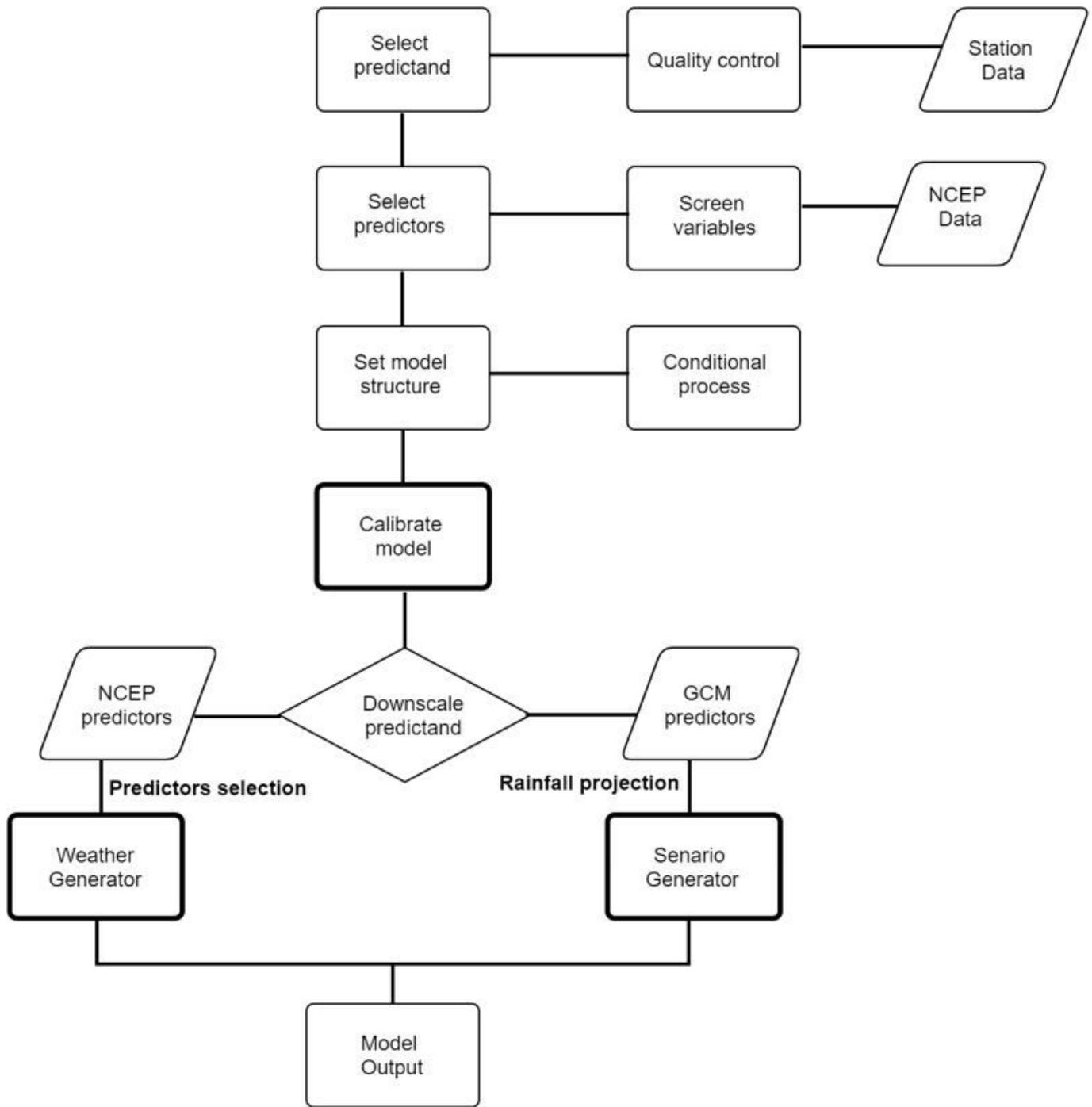
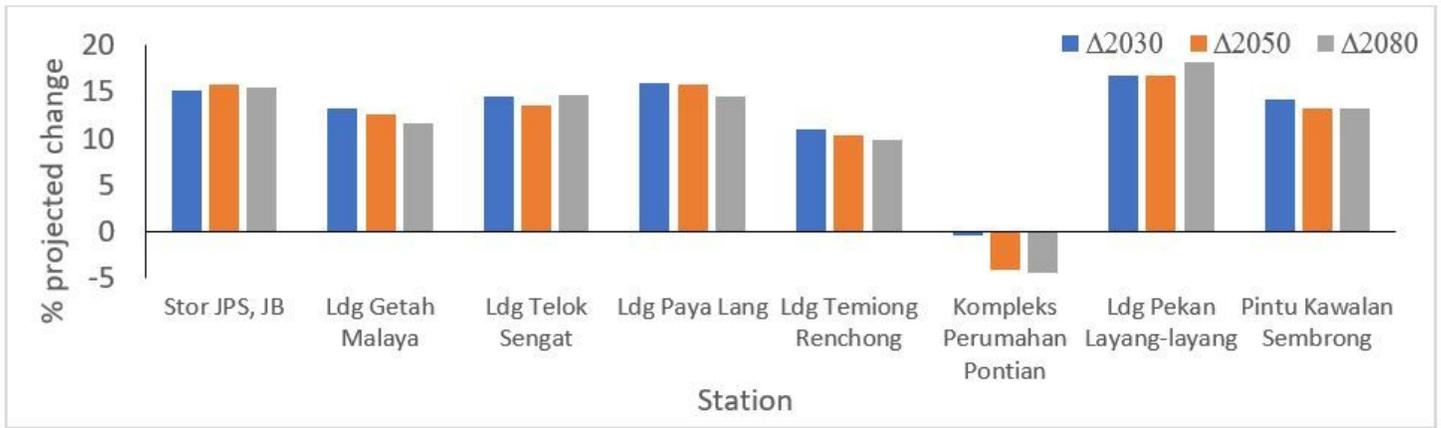
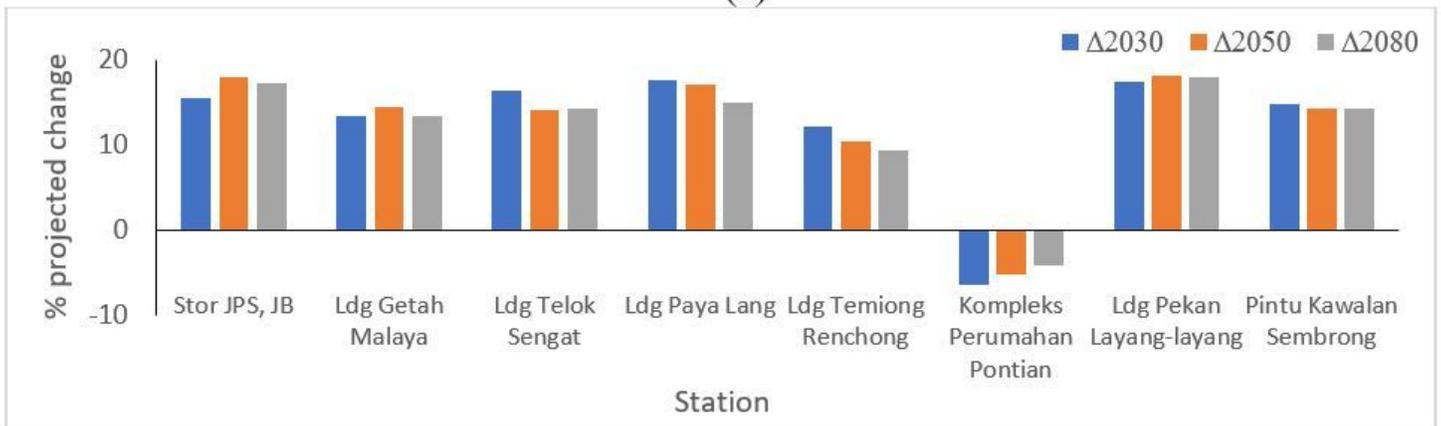


Figure 2

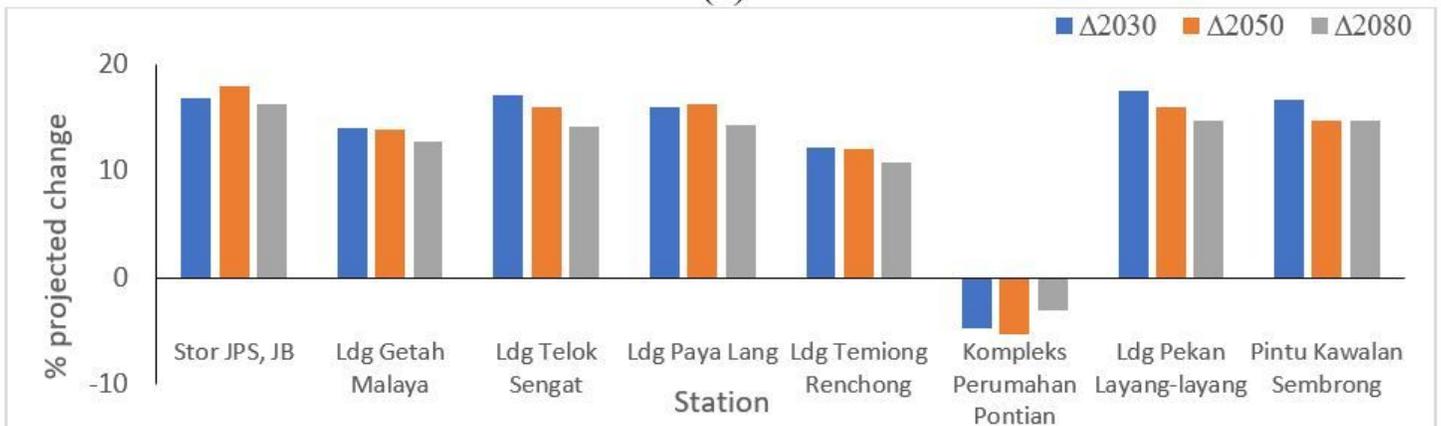
Climate simulation using SDSM



(a)



(b)



(c)

Figure 3

Percentage of projected change in average annual rainfall under (a) RCP2.6, (b) RCP4.5 and (c) RCP8.5 scenarios

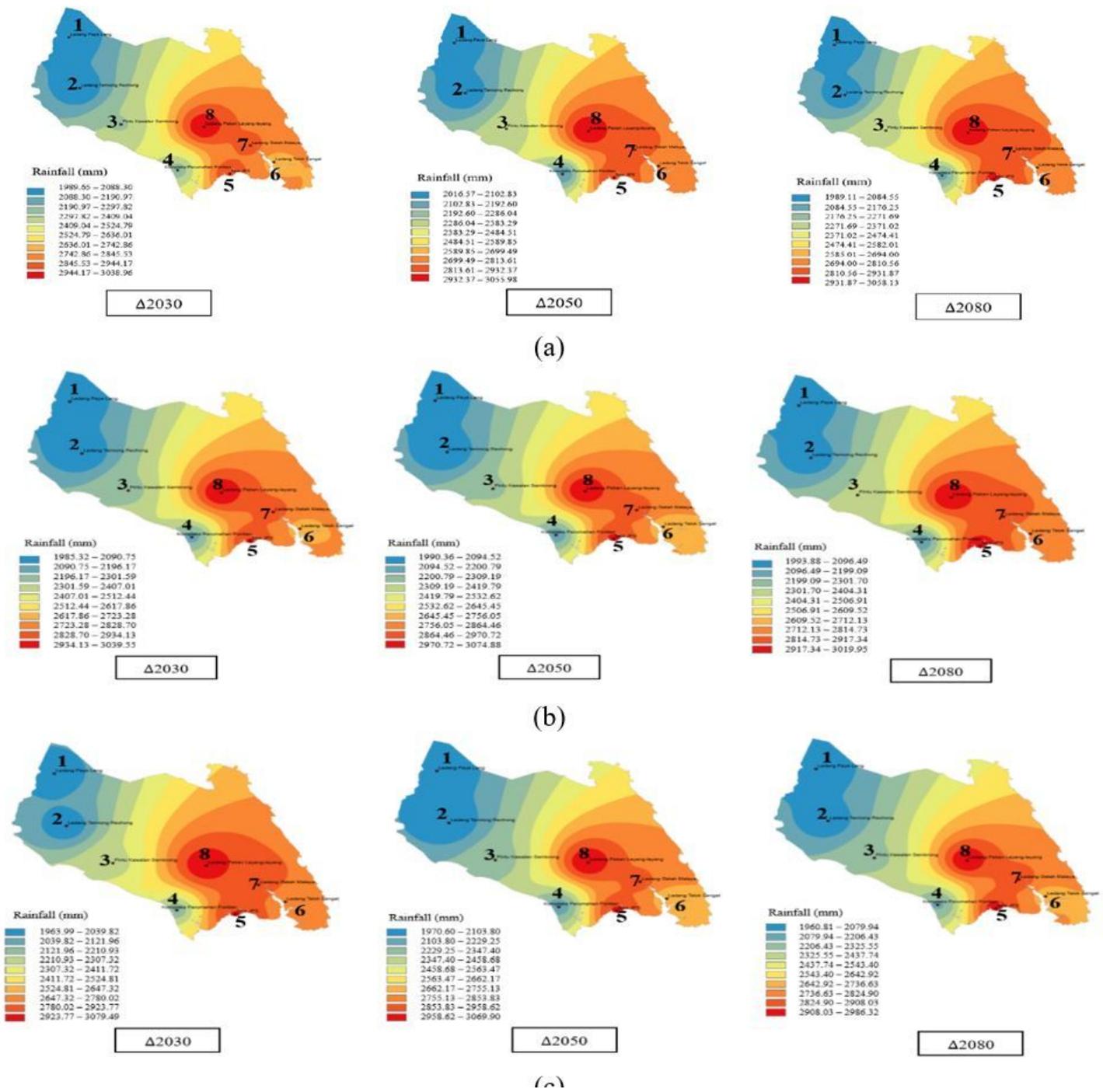


Figure 4

Spatial distribution of (a) RCP8.5, (b) RCP8.5, and (c) RCP8.5 for all period

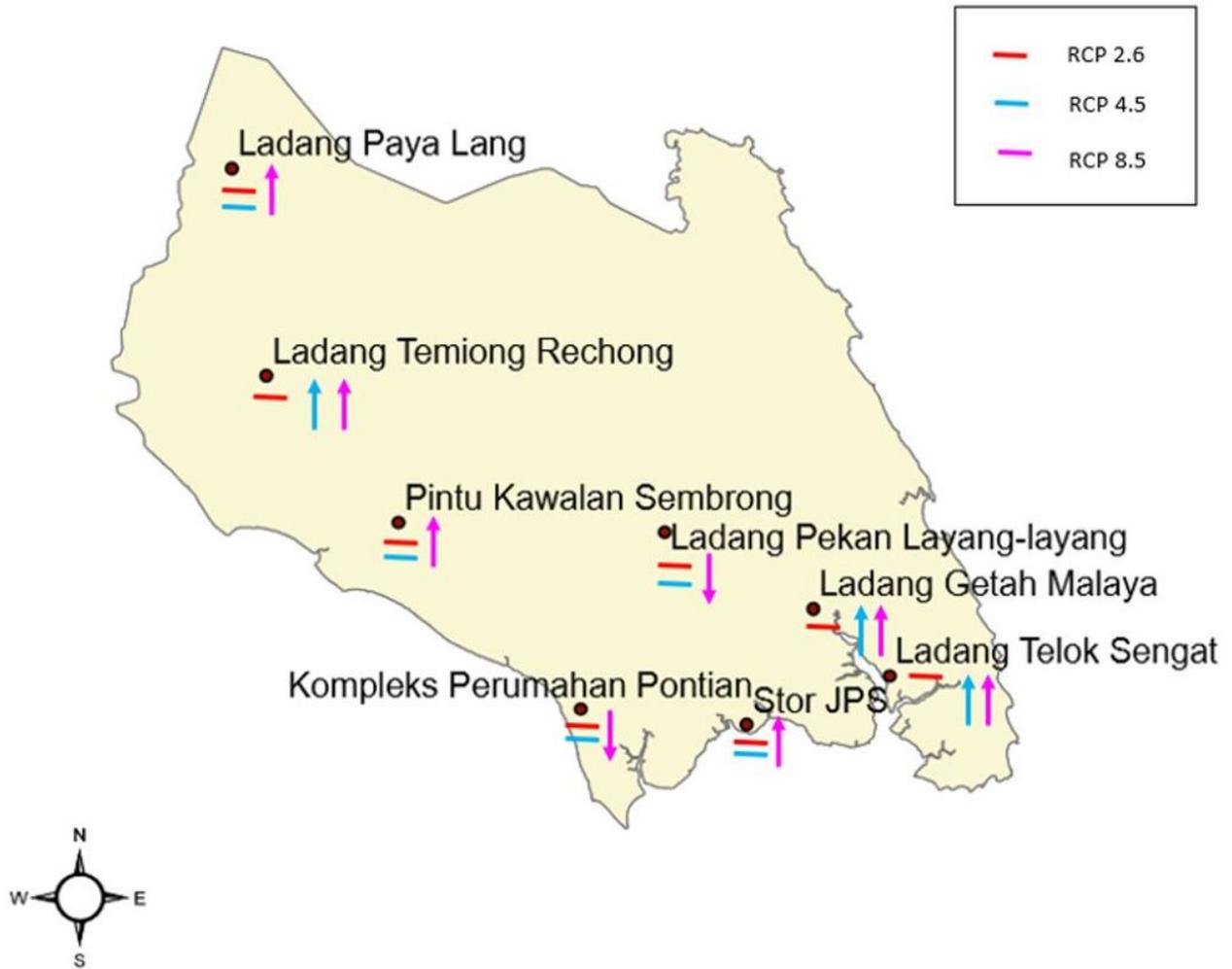


Figure 5

Trend analysis of annual rainfall for all stations