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Forecasting of Rainfall Using General Circulation Model - Statistical Modelling in Johor

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Abstract: Immaculate prediction of rainfall in a catchment is intrinsic for hydrologists to facilitate water resources management and flood risks assessment. Hence, the forecast rainfall and rainfall pattern, due to climate change needs to be investigated for guidance in managing water resources in Johor. In this paper, 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 Δ2030, Δ2050 and Δ2080. Daily rainfall data from eight (8) stations spreading all around Johor capturing 30 years period (1988-2017) were considered for the study. There is considerable variation of mean annual rainfall in different parts of Johor. As for example, the mean annual rainfall can be as low as 1714.9 mm at Ladang Paya Lang, Segamat station to as high as 2603.6 mm at Ladang Pekan Layang-layang, Kluang. Statistical Downscaling Model (SDSM) was used effectually to carry out predictor selection as well as future rainfall projection. The study noted that temperature (nceptemp), surface specific humidity (ncepshum) and near surface relative humidity (nceprhum) had the most significant influence in the local weather formations with R values ranged from 0.5 to 0.7. In addition, low standard error (SE) ranging from 3.82% to 11.64% was observed for all the stations considered in the study. The annual mean rainfall for RCP 2.6, 4.5 and 8.5 was predicted increase by of 17.5%, 18.1% and 18.3%, respectively as compared to historical data. Kluang was predicted to receive the highest amount of rainfall, and the lowest was in Segamat. The eastern part of Johor was expected to receive higher rainfall intensity and then disperse to the western part of Johor. It is expected that improved knowledge about predictions of future rainfall will expedite the mitigation strategies regarding climate change effect in Johor.

Keywords: Climate change, SDSM, spatial, temporal, rainfall

1. Introduction

Climate change has a detrimental effect on hydrological cycle, resulting impact on rainfall pattern and can lead to several extreme events [1]-[3]. This phenomenon is particularly evident during past decades as reported in Alsumaiei & Bailey [4]. According to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the

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globally averaged combined land and ocean surface data showed a warming of 0.85 over the year of 1880 to 2012 which proven that almost the entire globe has experienced surface warming [5]. The augmentation of global warming can impact the hydro-logical cycle, affecting water resources, public health, water energy exploitation and the ecosystem [6]. The IPCC [5] reported that significant trends observed in precipitation in many regions from 1900 to 2005. Precipitation was observed to be decreased in the Mediterranean coast, southern Africa and parts of southern Asia. The statement from IPCC has made some points and has been proven by many researchers [7]-[11]. Mohd [12] carried out a study on the trends, contributors and adaptations climate change in Malaysia and found an increased in annual temperature, occurrences of extreme events, rainfall showing variability and increased in mean sea level. These trends are worrying to be taken off especially to the future generations. Rainfall irregularities caused by climate change in Malaysia have been reportedly occurred almost three decades [13].

General Circulation Models (GCMs) is an advanced tool and numerical-based coupled models interpret global systems such as sea-ice, the oceans and atmosphere [6]. Although GCMs is a very helpful in terms of investigations and predictions on future climate changes, the outputs can be in a large grid scale (250 km – 600 km) [14]. Thus, the outputs cannot be used thoroughly to investigate hydrological impacts on a regional scale [15]. There are two approaches that can be applied to help in creating a bridge between regional/local scale and GCM scales which are dynamical and statistical downscaling [16]. In dynamical downscaling, a high-resolution numerical model or Regional Climate Model (RCM) with a resolution of 5-50 km is coupled with GCM [14]. Statistical downscaling is known for the simplicity and inexpensive of the model. It also offers approaches that have been commonly used and adopted by a wider community of scientists [17]-[19].

Mahmood and Babel [6] stated that statistical downscaling method was much simpler than dynamical downscaling method in terms of downscaled the outputs of GCM. However, statistical downscaling requires a long historical meteorological data such as rainfall or temperature data to construct an appropriate link with large-scale variables [20]. Akhter et al. [21] evaluated the capabilities of RCM (dynamical model) and statistical downscaling model (SDSM) (statistical model) in producing the current and future rainfall at a small urban catchment scale. Both methods projected an increase in magnitudes of future events however, RCM projections were lower compared to SDSM. In this study, statistical downscaling was used as this method produced empirical/statistical links among the large-scale and local-scale variables. SDSM methods are much faster and computationally inexpensive. Several studies have been carried out to downscale and project rainfall using SDSM [22]-[24]. In Brunei, Hasan et al. [24] carried out a study using SDSM and found increasing temperature and less rainfall occurrence in the future but with possibility of intense and drastic rainfall. Bessah et al. [22] predicted there will be increment in the length of dry season for the period of 2020-2048, and planning for alternative sources of water should be implemented. While Tukimat et al. [23] proved that integration of SDSM and Geographic Information System (GIS) had huge potential to generate the long-term rainfall pattern at ungauged station.

A study using SDSM to show the accuracy of long-term projected rainfall at ungauged station and resulted on SDSM was proven to give reliable long-term rainfall projection [25]. The overall picture of country rainfall distribution has become important for future water resources planning and management. However, a comprehensive study of future rainfall patterns is still very limited especially in Johor, Malaysia. Johor has been receiving increasing number of heavy rainfalls over the past years. According to the research made by Shafie [26] a storm blows from South East China Ocean and West Pacific Ocean cause heavy rainfall events that lead 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 [27] 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.

Therefore, this paper attempts to highlight on the effects of climate change on rainfall events by using SDSM. Some analyses were carried out including missing data, selection the most appropriate predictors, calibration, and validation of historical data with predictors that had been chosen. Consequently, the research on climate change in Malaysia mostly focused on the effects of climate change rather than on one parameter as in rainfall and its future trends.

2. Materials and Methods

2.1 Study Area

Johor is a state of Malaysia and located in the southern part of the Peninsular Malaysia (1°48’N, 103°76’E). The total land area of Johor is 19,102 km^2 and divided into nine (9) districts. Johor is one of the most economically developed states of Malaysia. In general, the Johor experiences a warm and humid tropical climate all year round, with average annual rainfall of 2600 mm. 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 which this season will affect Johor the most. Average daily rainfall in Johor ranged from 5 to 10 mm but during the monsoon season the amount of rainfall can reach up to 70 mm/day.

The eight (8) rainfall stations selected for this study and their details are illustrated 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. Mean method was applied to calculate the missing monthly rainfall data. In this study, 30 years of monthly data were selected, and the amount of missing data ranged from 0.3 to 3.1%. The study noted that there is considerable variation of mean annual rainfall in different parts of Johor. In particular, the mean rainfall for the study area can be as low as 1714.9 mm at Ladang Paya Lang, Segamat station to as high as 2603.6 mm at Ladang Pekan Layang-layang, Kluang.

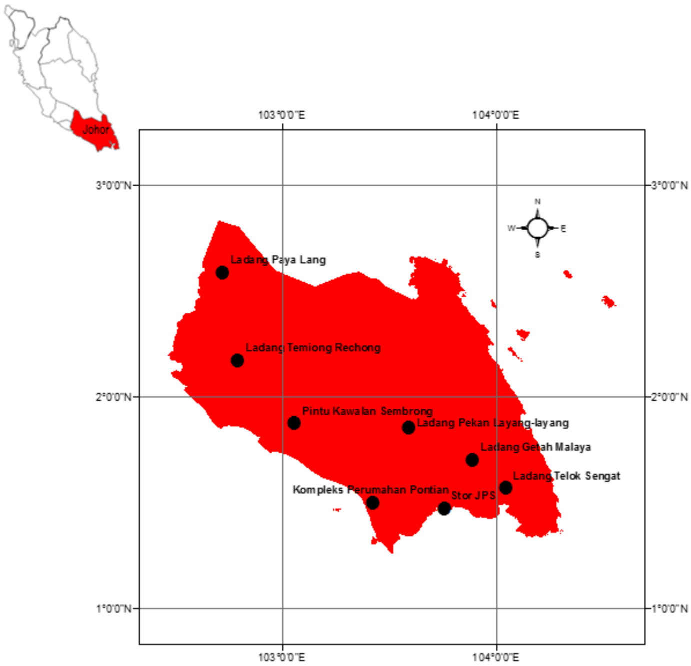


Fig. 1 - Location of eight (8) rainfall stations in Johor, Malaysia

Table 1 - List of rainfall stations in Johor

No.	Station Name	Location	Annual Mean Rainfall (mm)
Stn 1	Ladang Paya Lang	Segamat	1714.9
Stn 2	Ladang Temiang Renchong	Muar	1802.3
Stn 3	Pintu Kawalan Sembrong	Batu Pahat	2006.6
Stn 4	Kompleks Perumahan Pontian	Pontian	2260.6
Stn 5	Stor JPS	Johor Bahru	2537.7
Stn 6	Ladang Telok Sengat	Kota Tinggi	2372.2
Stn 7	Ladang Getah Malaya	Kota Tinggi	2543.3
Stn 8	Ladang Pekan Layang-layang	Kluang	2603.6

2.2 Statistical Downscaling

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 26 GCMs predictors of Coupled Model Intercomparison Project phase 5 (CMIP5).

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. After a quick check on selecting predictors by screen variables was made, the model was set into “Conditional process” for rainfall/precipitation. 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. However, Scenario Generator output is in daily data of 90 years period (2010 – 2099) of rainfall prediction where 2010 – 2017 will be used for validation process. Hence, analysis of the rainfall prediction data can be made. In order to retrieve the climate predictors, there are websites individually to download the climate predictors data both historical (NCEP/NCAR) and future (GCMs) observations. For historical observation (1948 to present), the data were downloaded from https://sdsm.org.uk/data.html. While for future observation, climate predictors were retrieved from http://climate-scenarios.canada.ca/?page=pred-canesm2.

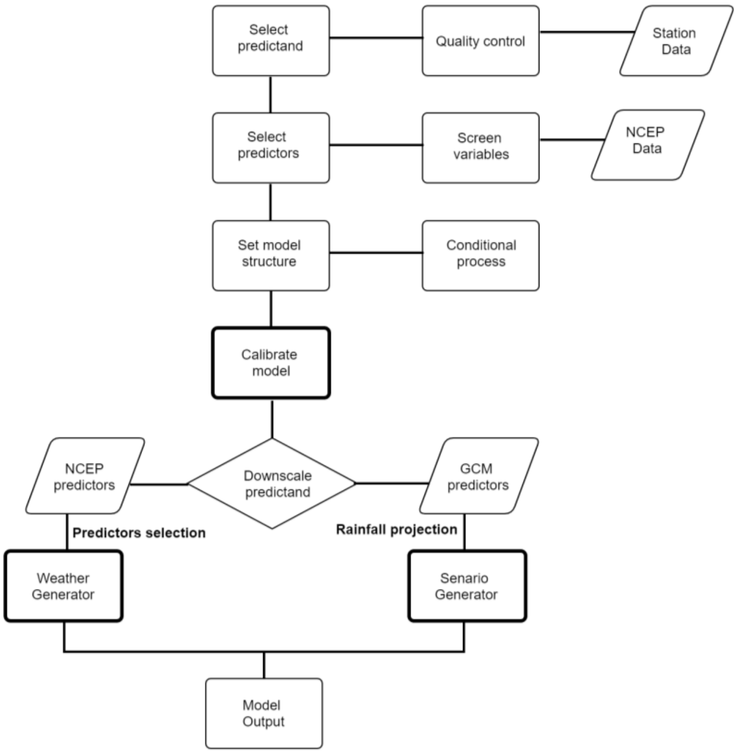


Fig. 2 - Climate simulation using SDSM

SDSM for rainfall occurrences on each day is shown in Eq. (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 $\propto_{t-1}$ are the conditional probabilities of rain occurrence on day $t-1$ and lag-1day 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 Eq. (2).

$$W_t = \propto_0 + \sum_{j}^{n} \propto_{t-1} \hat{u}_t^{(j)} + \propto_{t-1} w_{t-1} \tag{1}$$

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

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 Eq. (3), where $\emptyset$ is the normal cumulative distribution function and F is the empirical function of y_t.

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

2.3 Screening of Climate Predictors

The selections of climate predictors were one of the most important and crucial steps in this research and will affect the result of the rainfall projections. Studies made by Gebremeskel et al. [28] and Feyissa et al. [29] have applied more than five (5) GCMs-variables in their SDSM analysis for each stations or study area. These numbers of GCMs climate variable have been chosen in order to show real condition of climate change in future. Therefore, in this research, only five (5) of GCMs climate variables have been applied for each station between seven (7) of the variables such as mean sea level pressure (ncepmslp), surface specific humidity (ncepshum), near surface relative humidity (nceprhum), mean temperature at 2 m (nceptemp), relative humidity at 500hPa (ncepr500), relative humidity at 850hPa (ncepr850), 500hPa geopotential height (ncepp500) and 850hPa geopotential height (ncepp850). These results have a similar pattern with the patterns from Zulkarnain & Sobri [30], which used only four (4) of GCMs climate predictor.

The screening of predictors is the most crucial part of getting useful prediction data. In this study, coefficient of determination (R^2) and root mean square error (RMSE) were used to check the goodness of fit between the observed and modelled data. The correlation analysis was carried out to screen 26 predictor variables for predictand data. A correlation matrix and explained variance were the outputs of the monthly regression. Significance level test is used to define the significance of predictor-predictand correlations and to find the most correlated predictor-predictand variables, the significance level should be p<0.05 (5%). Specifically, the coefficient of determination (R^2) is used to determine the variability in observed data that the model could capture. R^2 was calculated using Eq. (4) where X_i is the observed data, X_{av} is the average observed data, Y_i is the modelled value and Y_{av} is the average modelled value.

$$R^2 = \frac{(\sum[X_i - X_{av}][Y_i - Y_{av}])^2}{\sum(X_i - X_{av})^2 \sum(Y_i - Y_{av})^2} \tag{4}$$

RMSE is an error-index type of model evaluation statistics (dimensional) and can be calculated using Eq. (5). The closer the value to zero, the better model performance [31].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}} \tag{5}$$

The standard error (SE) was calculated to ensure the predictors selected were the most suitable for that specific location in the validation step. SE of each station was calculated using Eq. (6) where ABS is the absolute number.

$$SE = ABS\left[\left(\frac{Validation - Observation}{Validation}\right) \times 100\right] \tag{6}$$

2.4 Scenario Generator on Projection of Future Rainfall

Prediction of rainfall can be proceeded after the selection of the predictors. For this step, SDSM was used in downscaling the coarse scale of GCM predictors. GCM predictors were retrieved from http://climate-scenarios.canada.ca/?page=pred-canesm2 and only selected predictors that has been validated from the predictor selection steps were used. Representative concentration pathways 2.6 (RCP 2.6) was chosen as the trajectories for carbon dioxide emissions for this study. For accuracy purposes and to see the differences of the changes throughout the years, 90 years data were divided into three (3) different time scales of Δ2030, Δ2050 and Δ2080. Scenario generator function in SDSM, displays the prediction rainfall result on a daily basis. Future rainfall projected by RCP 2.6, 4.5 and 8.5 were downscaled by SDSM at all eight (8) stations. The results of the rainfall prediction data were analysed to get the precise results of what will be climate change effects on towards rainfall trend in Johor in the future.

3. Results and Discussion

3.1 Selection of Predictors for Climate Simulation

The selection of predictors was based on the R analysis of monthly predictor-predictand relationship as shown in Table 2. The highest and the lowest correlation values that can be achieved by these relationships were 0.56 and 0.02, respectively, and showed better than other predictors-predictand relationships. Hence the predictors set were used to form the rainfall equations at each region for prediction future rainfall data analyses. In order to obtain a more realistic and unbiased data of future climate, validation was also applied to the two downscaled data sets using HadCM3 predictors.

The calibration process was made to evaluate SDSM performance concerning the observed rainfall data. Based on the available observed daily historical data, two data sets, 1988 – 2002 and 2003 – 2017 were used for the rainfall calibration to ensure the accuracy of the outputs. Predictors were also separated for 15 years each for the data sets. For rainfall modelling, the evaluation of the performance shows that observed and modelled data were close to each other. R is a measure of how well the predicted values from a forecast model fit with the real-life data with a perfect fit gives a coefficient of 1.0 [30]. The values of the RMSE and R^2 were ≤ 0.44 and ≤ 0.40, respectively across all stations during the calibration period, hence it shows a good agreement between the observed and simulated mean daily rainfall (Table 3).

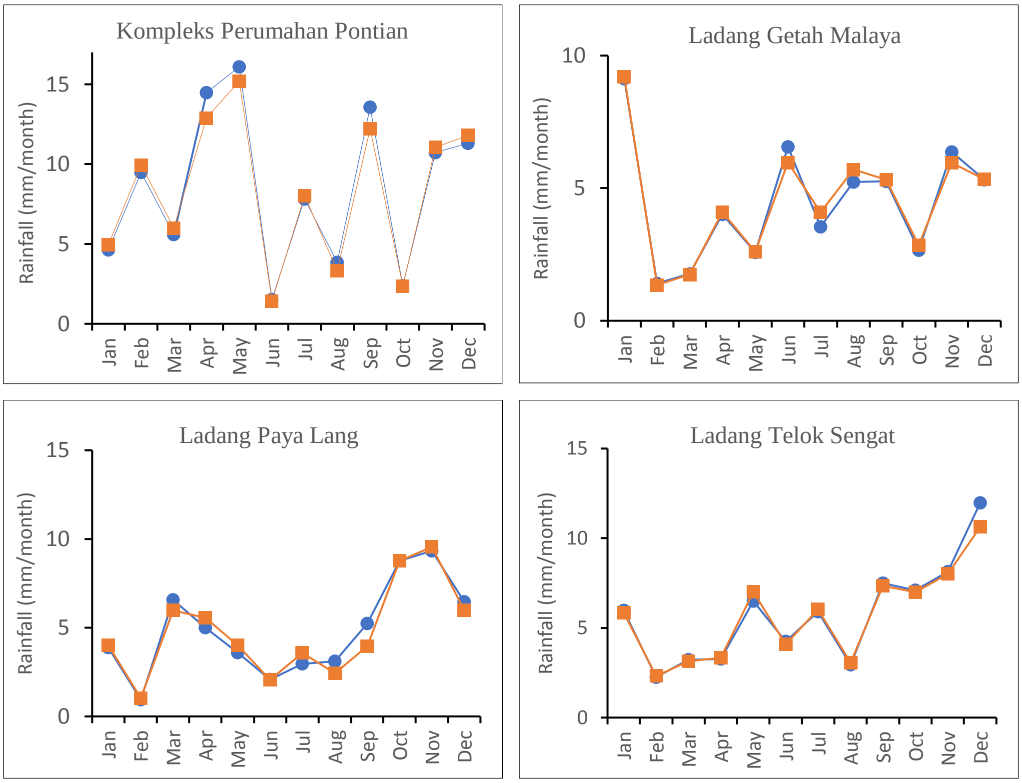
After the process of calibration between the climate predictors and historical rainfall, validation of the chosen climate predictors was carried out. Validation was conducted due to the uncertainty in the downscaling analysis. The uncertainty originating from the location can be physically consistent, whereas uncertainty from any other source can lead to incorrect results [32]. Validation result of each rainfall station from the performance of the downscaling method was evaluated by reproducing the mean and variability of the observed precipitation by comparing downscaled precipitation obtained from climate predictors of the year (1988 – 2017) with observed precipitation records (2010 – 2039). These predictors set for each station was used to form the rainfall equations at each region. The performance of these equations was evaluated during validation process as shown in Fig. 4 and it can be seen that all stations performed well with minimum errors (Table 3). The validation results were acceptable if the errors were less than 23% [21].

Table 2 - R analyses for monthly predictor-predictand relationship

Predictor	***Predictand***							
	Stn 1	**Stn 2**	**Stn 3**	**Stn 4**	**Stn 5**	**Stn 6**	**Stn 7**	**Stn 8**
temp	0.45	0.03	0.53	0.55	0.56	0.36	0.18	0.30
shum	0.11	0.09	0.05	0.31	0.54	0.28		0.17
rhum	0.08	0.07	0.06	0.50		0.53		
r850	0.51	0.07	0.27	0.08		0.43	0.14	
r500					0.51		0.35	0.51
p500				0.43			0.06	0.02
p850			0.55		0.56			0.49
mlsp	0.51	0.37			0.55	0.40	0.02	

Table 3 - Statistical performance of rainfall modelling during calibration

Station	**RMSE**	R^2
Stn 1	0.52	0.51
Stn 2	0.47	0.70
Stn 3	0.49	0.55
Stn 4	0.54	0.40
Stn 5	0.48	0.65
Stn 6	0.51	0.63
Stn 7	0.57	0.50
Stn 8	0.44	0.51



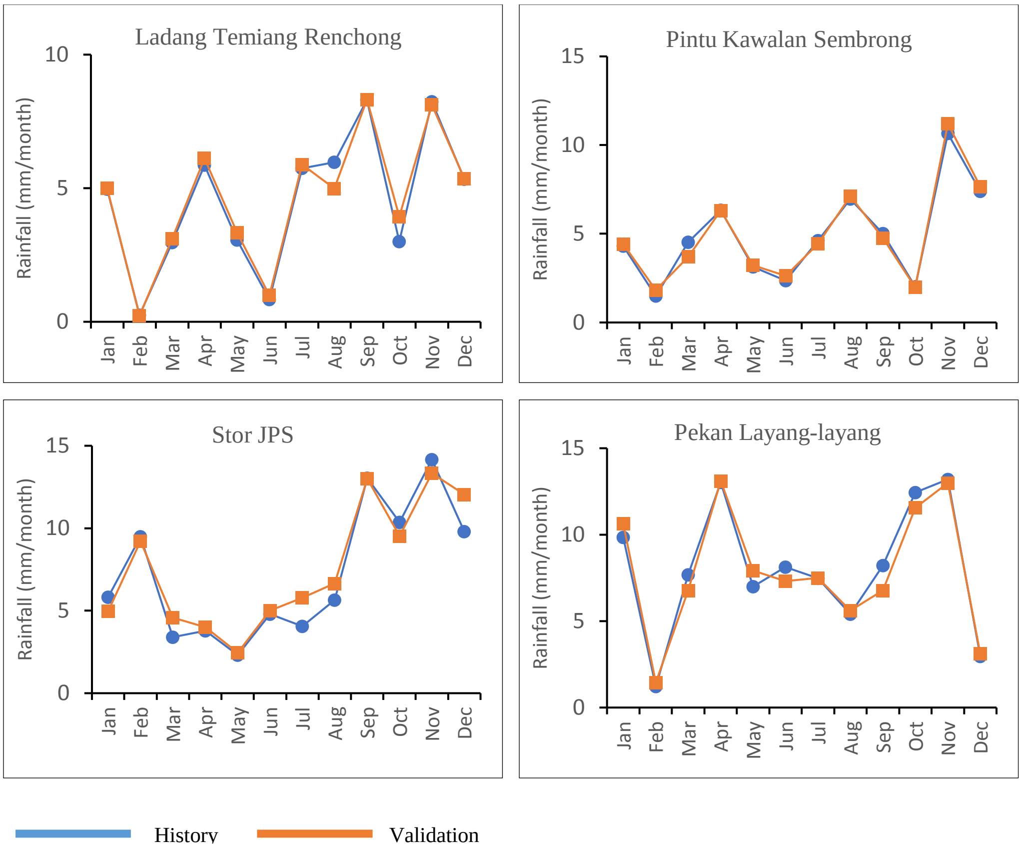


Fig. 3 - Performance of validated result compared to the historical data for all rainfall stations

Based on Table 4, the best simulated result was at Ladang Telok Sengat station which gave the lowest SE of 3.82%. Meanwhile, Stor JPS station showed the highest SE with 11.64% but the result was still acceptable. It can be seen that all stations obtained acceptable SE values (less than 23%) and proved that the predictors were well selected and gave huge influence to the local climate. Table 5 delineates all the predictors that were selected for all eight (8) stations in Johor. Most of the stations gave positive results on temperature (nceptemp), surface specific humidity (ncepshum) and near surface relative humidity (nceprhum). These predictors set for each station were used to form rainfall equations at each region.

Table 4 - Percentage (%) of SE for mean observed (historical) and modelled (validation) values

No.	Station Name	Mean (mm)		SE (%)
		Observed	Modelled	
1	Kompleks Perumahan Pontian	8.45	8.26	6.77
2	Ladang Getah Malaya	4.48	4.52	4.63
3	Ladang Paya Lang	4.82	4.73	10.78
4	Ladang Telok Sengat	5.74	5.64	3.82
5	Ladang Temiang Renchong	4.54	4.61	7.44
6	Pintu Kawalan sembrong	4.89	4.93	6.60
7	Stor JPS JB	7.22	7.54	11.64
8	Ladang Pekan Layang-Layang	8.05	7.89	8.22

Table 5 - Selected NCEP predictors for all stations

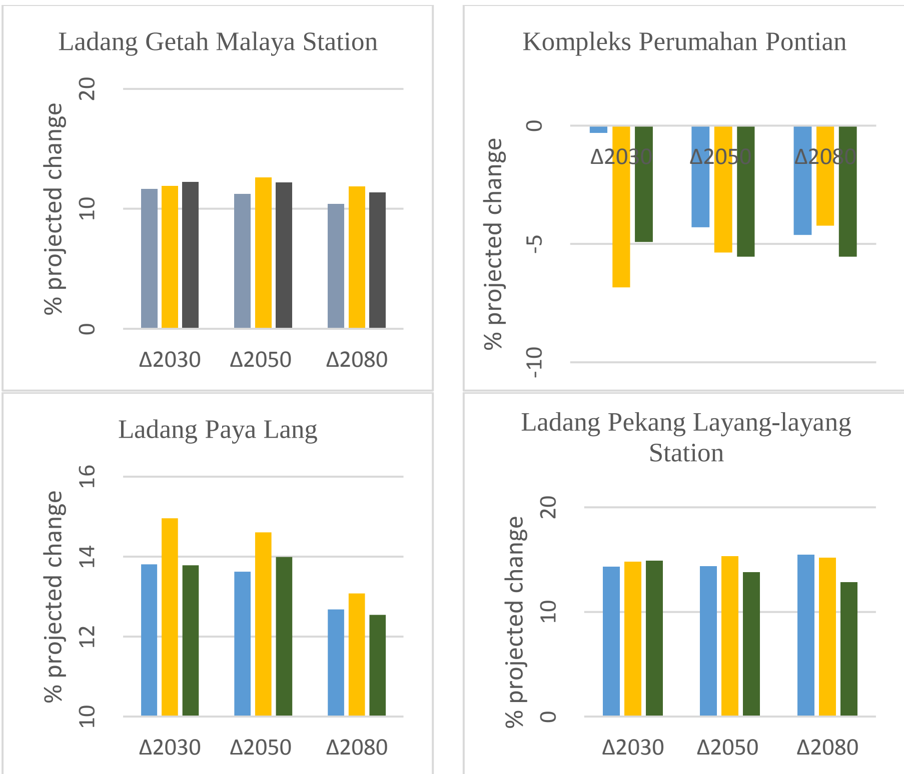
Predictors / Stations	ncep-mslp	ncep-shum	ncep-rhum	ncep-temp	ncep-r500	ncep-r850	ncep-p500	ncep-p850
1		□	□	□	□	□		
2	□	□		□			□	□
3	□	□		□	□		□	
4	□	□	□	□		□		
5	□	□		□	□			□
6		□	□	□		□		□
7	□	□	□	□		□		
8		□	□	□	□	□		

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

The results of the projection of future rainfall were developed by the SDSM model for each site for the interval year of Δ2030, Δ2050 and Δ2080 (hereinafter 1st, 2nd and 3rd periods, respectively) based on the RCP 2.6, RCP 4.5 and RCP 8.5 scenarios generated from CanESM2. Therefore, the mean for every 30 years of each RCPs scenario was used as tabulated in Table 6 (refer Appendix). Different scenarios of GCMs predictors of Canadian Earth System Model 2 (CanESM2) gave different results as the concentration of emission radiation varies.

Spatial distribution of observed historical rainfall data is plotted, as shown in Fig. 4. Generally, the differences between the highest projected and observed historical rainfall were increasing up to 17.5% (RCP 2.6), 18.1% (RCP 4.5) and 18.3% (RCP 8.5). The highest average annual rainfall was predicted at Station Ladang Pekan Layang-layang, Kluang region where 3058.16 mm (RCP 2.6), 3074.92 mm (RCP 4.5) and 3079.52 mm (RCP 8.5). While the lowest mean rainfall was predicted at Station Ladang Paya Lang, Segamat of 1989.09 mm (RCP 2.6), 1985.31 mm (RCP 4.5) and 1960.80 mm (RCP 8.5) was predicted to be captured.

The annual future change in rainfall for Ladang Getah Malaya station is depicted by three scenarios. As it can be noticed, the annual rainfall was projected positively change by + 11.6%, + 11.9%, + 12.2% for RCP 2.6, + 11.2%, + 12.6%, + 12.2% for RCP 4.5, and + 10.4%, + 11.8%, + 11.3% for RCP 8.5 during 1st, 2nd and 3rd periods, respectively with respect to the baseline period. The average annual rainfall was projected to increase in Ladang Pekang Layang-layang station by + 14.3%, + 14.8%, + 14.9% for RCP 2.6 and + 14.3%, + 15.3, + 13.8 for RCP 4.5, and + 15.5%, + 15.2%, + 12.8% for RCP 8.5 during 1st, 2nd and 3rd periods, respectively.



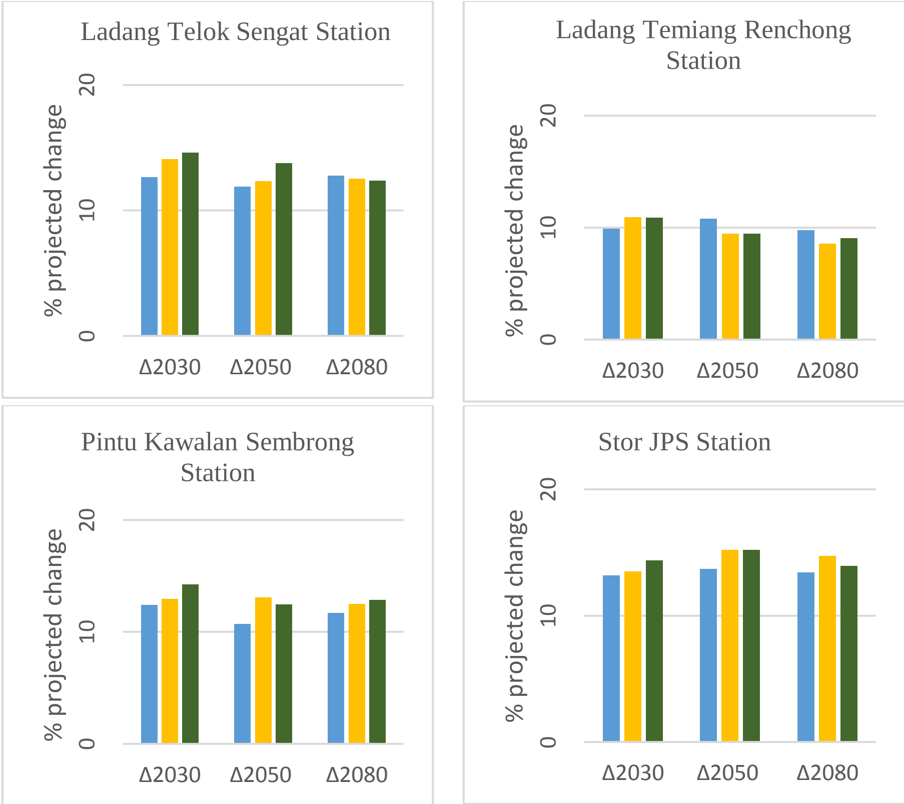


Fig. 4 - Percentage of projected change in average annual rainfall compared to average annual historical rainfall under RCP 2.6, RCP 4.5 and RCP 8.5 scenarios

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, referring to Kompleks Perumahan Pontian station, the average annual rainfall will likely negatively change by – 0.3%, - 6.8%, - 4.9% for RCP 2.6 and – 4.3%, - 5.4%, - 5.5% for RCP 4.5 and – 4.6%, - 4.2%, - 5.5% for RCP 8.5 during 1st, 2nd and 3rd periods, respectively with respect to the baseline period. These showed that for Kompleks Perumahan Pontian station area will have lesser rain annually in the future due to the effects from increase of emmision radiation. While in Ladang Paya Lang station, the average annual rainfall would be likely increase by + 13.8%, + 15.0%, + 13.8% by RCP 2.6 and + 13.6%, + 14.6%, + 14.0% by RCP 4.5 and + 12.7%, + 13.1%, + 12.5% by RCP 8.5. The increase of rainfall for each RCPs showed that ncepshum, nceprhum, nceptemp, ncepr500 and ncepr850 gave impacts towards the revolution.

The average annual rainfall for Ladang Telok Sengat station for 1st, 2nd and 3rd periods, respectively was projected to increase by + 12.7%, + 14.1%, + 14.6% by RCP 2.6 and + 11.9%, + 12.3%, +13.8% by RCP 4.5 and + 12.8%, + 12.5%, + 12.4% by RCP 8.5 as shown in Figure 4.4. The chosen climate variables; ncepshum, nceprhum, nceptemp, ncepr850 and ncepp850 proven to increase the amount of rainfall in future at Ladang Telok Sengat station area. Moreover, the projected change in the average annual rainfall for Ladang Temiang Renchong station was projected to change by +9.9%, + 10.9%, + 10.9% by RCP 2.6 and + 10.8%, + 9.4%, + 9.4% by RCP 4.5 and + 9.8%, + 8.5%, + 9.1% by RCP 8.5 throughout 1st, 2nd and 3rd periods, respectively caused by the changes of ncepmslp, ncepshum, nceptemp, ncepp500 and ncepp850.

Pintu Kawalan Sembrong showed that the rainfall projected to increase by + 12.4%, + 13.0% + 14.2% by RCP 2.6 and + 10.7%, + 13.1%, + 12.4 by RCP 4.5 and + 11.7%, + 12.5, + 12.8% by RCP 8.5 influenced by the changes of future climate variables of ncepmslp, ncepshum, nceptemp, ncepr500 and ncepp500. The average annual rainfall for Stor JPS station was projected to increase throughout the periods of 1st, 2nd and 3rd respectively by + 13.2%, +13.5%, + 14.4% by RCP 2.6 and + 13.7%, + 15.2%, + 15.2% and + 13.4%, + 14.7%, + 13.9% by RCP 8.5. All RCPs were influenced with the changes from ncepmslp, ncepshum, nceptemp, ncepr500 and ncepp850.The statistical downscaling model showed superior performance in modelling daily rainfall across eight (8) selected rainfall stations. For average annual rainfall for 1st, 2nd and 3rd periods, the results showed that the increase in annual rainfall is more remarkable throughout Johor (Batu Pahat, Muar, Kota Tinggi, Johor Bahru, Segamat and Kluang) except for Pontian. Kompleks Perumahan Pontian station is the only station that resulted in decreasing annual rainfall for each RCPs and period. This indicates the possibility of more extreme rainfall in Johor with the increase of mean rainfall at the majority of the stations area.

Spatial distribution of historical rainfall data is plotted as shown in Fig. 5. It is observed that the highest mean annual rainfall is 2603.56 mm in north-east Johor while in north Johor receives below 1714.95 mm. The mean projection rainfall was plotted in ArcGIS Software to show the spatial distribution. 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 the results at Mersing area 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 Δ2030, Δ2050 and Δ2080. Based on the low emission scenario (RCP 2.6), as shown in Fig. 6(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 (RCP 4.5), the result of the spatial distribution is shown in Fig. 6(b). Projected rainfall resulted in a slightly different amount of rainfall in the future throughout the interval year for all the RCPs of Δ2030, Δ2050 and Δ2080. North-west region showed a small difference in the decreasing rainfall amount for the future. Fig. 6(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.

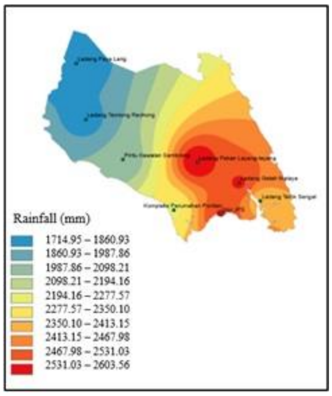
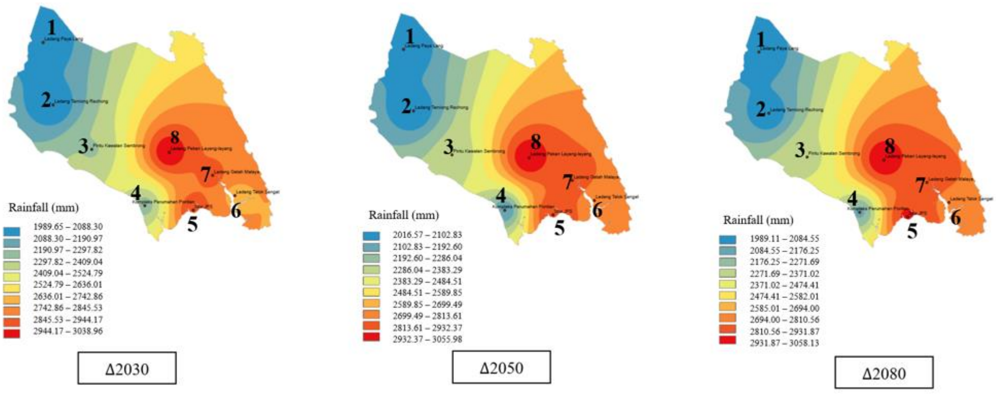
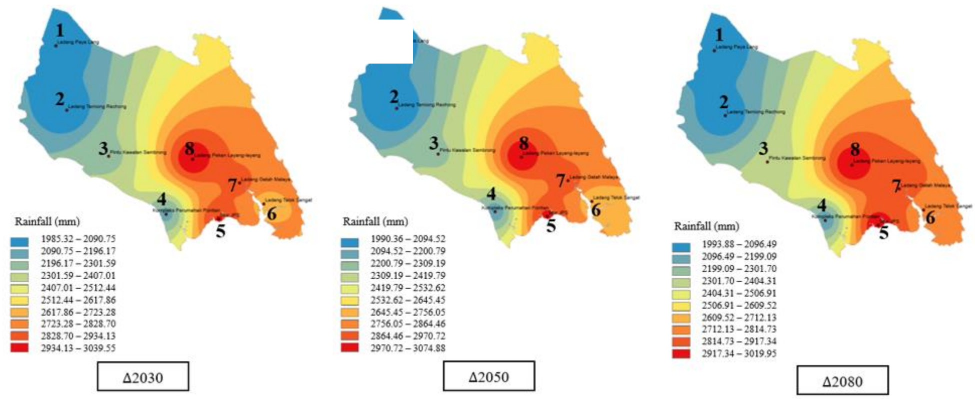


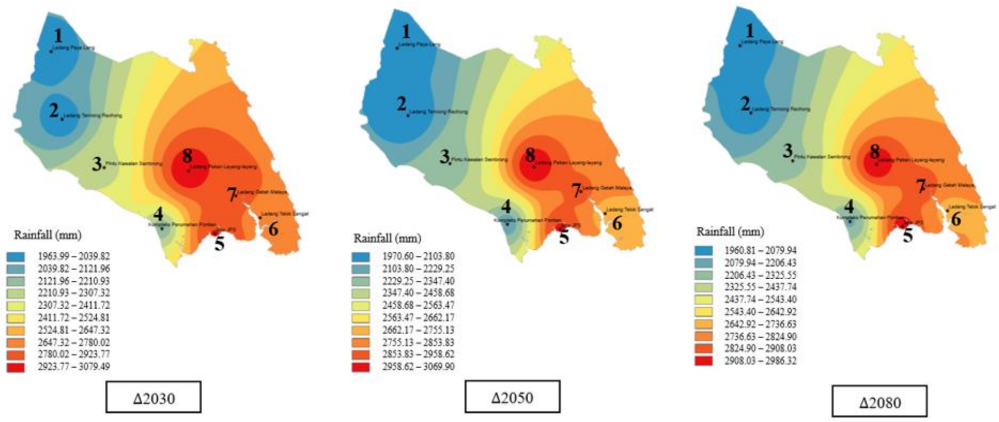
Fig. 5 - Spatial distribution of historical rainfall (1988-2017)



(a)



(b)



(c)

Fig. 6 - Spatial distribution of future rainfall for a) RCP 2.6 (b) RCP 4.5 and (c) RCP 8.5

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 the current study, SDSM was used effectually in downscaling rainfall data, when using predictors representing the observed current climate (NCEP predictors). Although, 26 predictors were correlated with each other before the calibration process. Number of predictors were narrowed down to five (5) at the end. After validation of the selected predictors and predictand (historical rainfall) were made, SE for each station was calculated. The SE did not exceed the acceptable limit which was 23% as the highest value was at JPS Johor Bahru station with 11.64% and the lowest standard value was 3.82% at Ladang Telok Sengat station.

During the calibration and validation, the model has a capability to capture the observed daily rainfall well, based on the performance indicators such as R^2 and SE. This research also predicted increasing rate of rainfall will be the lowest during the period of interval year of Δ2030 when the localized minimum downpour will be at the Kompleks Perumahan Pontian station area. Increased rainfall during interval year of Δ2050 and Δ2080 periods will make the rainfall more spatially distributed in the Batu Pahat and Pontian area 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. In general, the SDSM model is a feasibility tool to downscale and project future rainfall corresponding to CanESM2 scenarios. Future research will focus on the research regarding mitigation strategies to withstand frequent occurrence of extreme events in the future.

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Appendix

Table 6 - Mean future rainfall in Johor

No	Station Name	Δ2030 (mm)			Δ2050 (mm)			Δ2080 (mm)		
		RCP 2.6	RCP 4.5	RCP 8.5	RCP 2.6	RCP 4.5	RCP 8.5	RCP 2.6	RCP 4.5	RCP 8.5
1	Ladang Paya Lang	1989.64	1985.31	1963.98	2016.55	2008.32	1972.89	1989.09	1993.86	1960.80
2	Ladang Temiong Renchong	1999.87	1989.97	1981.75	2023.25	1990.33	1970.56	2022.83	2020.35	1997.16
3	Pintu Kawalan Sembrong	2290.83	2271.75	2271.75	2305.36	2292.49	2292.49	2340.01	2302.42	2302.42
4	Kompleks Perumahan Pontian	2253.06	2167.07	2160.43	2115.56	2145.18	2168.45	2154.13	2141.65	2189.89
5	Stor JPS, JB	2923.34	2940.09	2931.10	2933.67	2992.43	2975.08	2963.00	2991.74	2948.86
6	Ladang Telok Sengat	2716.11	2692.50	2719.28	2761.35	2706.35	2712.24	2777.62	2750.82	2707.43
7	Ladang Getah Malaya	2878.61	2864.50	2838.14	2886.38	2909.62	2884.73	2897.97	2895.88	2868.64
8	Ladang Pekan Layang-layang	3038.99	3039.58	3079.52	3056.02	3074.92	3069.93	3058.16	3019.98	2986.35