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Prediction of Future Temperature and Rainfall Characteristics Using Statistical Downscaling Model (SDSM) for Empangan Sg. Sembrong in Batu Pahat Catchment

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Abstract: Climate changes has become a major driver in the increasing of global temperature, changes in rainfall patterns and frequency, and distribution of weather events such as droughts, floods and heat waves [1]. This study aims to calibrate and validate temperature and rainfall simulation in Sembrong Dam Reservoir by using Statistical Downscaling Models (SDSM). Calibration conducted using temperature and rainfall data from 2010 to 2014, while validation process used data from 2015 to 2019. The outputs of National Center for Environment Prediction (NCEP) are used in calibration and validation process. The observed data and simulated NCEP results are compared to observe the correlation to the local predictand. Then, SDSM used to project future temperature and rainfall from 2020 to 2050. Projection of future temperature and rainfall conducted based on Representative Concentration Pathways (RCP) scenarios, which are RCP4.5 and RCP8.5. The comparison of results for RCP4.5 and RCP8.5 is conducted to observe how concentrations of greenhouse gases affect temperature and precipitation. The outcomes of this study can be used to provide planning on conservation of water to maintain the availability of water supply.

Keywords: Climates Change, Sembrong Dam, Statistical Downscaling Models

1. Introduction

Climate change has becomes one of the most serious environmental problems and a threats to the humankind. The climate change can be refer to the global phenomenon of climate transformation to the usual climate of the Earth, which mostly caused by human activities such as burning fossil fuels (coal, oil, natural gas) to produce electricity, power vehicles and deforestation for construction and farms [1]. Climate change has affect temperature and precipitation volumes that sometimes leads to extreme weather such as extreme precipitation event, droughts or dryness and extreme increase in sea level [2]. The climate change influences the pattern of weather as it become more intense in terms of total rainfall and cause increase of global temperature. Sembrong Dam reservoir is chosen to observe the changes of

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temperature and rainfall in the future. The main function of Sembrong Dam reservoir is is as flood mitigation [3]. Sembrong dam also provide clean water supply for about 240,000 people in district of Kluang and parts of Batu Pahat [4]. This dam reservoir covers approximately 130 km^2 of catchment area [3]. Two rivers flow into Batu Pahat River, which are Simpang Kanan River and Simpang Kiri River. Simpang Kiri River has length of 57 km from north near Simpang Kanan River, Chaah while starting from the junction of the Sembrong and Bekok River. Bekok River flows 55vkm to meet Sembrong and Simpang Kanan River [5].

Figure 1: The location of Sembrong Dam Reservoir

In this modern era, there are many climate models or software being created to allow prediction and projecting the future climate changes in terms of rainfall and temperature. General Circulation Models (GCM) are often used to predict future climates. However, the spatial resolution of GCMs grids are coarser and unable to resolve many important subgrid processes [6]. Thus, GCM perform poorly at smaller partial and temporal scales according to regional impact analyses. SDSM is required, as they are able to provide station-scale information that important in long term planning. The researcher used statistical downscaling to evaluate the maximum temperature changes under global warming in Iran [7]. SDSM is used on the output of CGCM3-T63 Model under existing scenarios (A2, A1B and B1) to predict maximum temperature changes in near future (2041-70) and far future (2071-99) [7]. Another study conducted in Limbang River Basin in Sarawak using SDSM to investigate the severity of rainfall under three RCPs, which are RCP2.6, RCP4.5 and RCP8.5 [8]. RCP2.6 recorded increment of 8.13 %, RCP4.5 recorded increase of 14.70 % and RCP8.5 show increase of 40.60 %. Thus, indicate the future rainfall constantly increase in all scenarios due to climate changes [8].

A study on future maximum and minimum temperature and precipitation has been conducted for 12 stations in Iraq under different scenarios [9]. The outcomes from the study show the increasing in temperatures and declining in precipitation in Iraq. The performance of SDSM is superior in modeling present data as the RMSE and R^2 value closer to 1 [9]. Another study in Essaouira Basin, Morocco also using SDSM model to project possible future climatic changes[10]. The future climate estimated from 2018 to 2050 based on the RCPs scenarios. The annual rainfall shows upward trends for RCP2.6 (12.50 %) and RCP8.5 (21.33 %), while RCP4.5 shows declining in annual rainfall (17.29 %). The annual temperature are expected to be increasing for all the RCPs scenarios[10]. The projections of future climate are linked with large uncertainties, which arise from future emissions, model uncertainties, and natural climate variability [11]. There is a research that used SDSM and Automated Statistical Downscalling (ASD) to analyze uncertainties for temperature and precipitation in Iran [12].

SDSM is described as a hybrid of the stochastic weather generator and regression based methods [13]. The large-scale predictors for meteorological projection employed by the SDSM model is referred to the NCEP reanalysis for calibration and validation processes and CanEMS2 for the long-term generation of future climates [14]. The study aims to use SDSM to calibrate for temperature and rainfall simulation, with data from 2010 to 2014, and validation process with data from 2015 to 2019. SDSM also used to project future temperature and rainfall from 2020 to 2050.

2. Materials and Methods

This study required the use of SDSM model in calibration and validation of present data. SDSM also used in order to project and simulate future climate changes based on Representative Concentration Pathways (RCP) from Global Climate Model data. The data required for the study are maximum temperature, minimum temperature and the rainfall in Sembrong Dam reservoir. Table 1 shows the location of rainfall and temperature stations.

Table 1: The data for rainfall and temperature stations

Station no. and name	Type of data	Location	
		Latitude	Longitude
1931003 Empangan Sg. Sembrong, Air Hitam, Johor	Rainfall	01°58'25"	103°10'45"
48670 Malaysian Meteorological Department Batu Pahat	Temperature	01°52'00"	102°59'00"

National Centers of Environment Prediction (NCEP) data, which covers period of year 1961 to 2005 was reanalyzed to calibrate and validate SDSM and to establish the relationship between predictor and predictand. Prediction for future climate is using two RCPs scenarios, which are RCP 4.5 and RCP8.5. Representative Concentration Pathways (RCPs) is a set of greenhouse gas concentration and emission pathways to support research on impacts of climate changes [15]. RCP4.5 is described as a scenario of long-term global emissions of greenhouse gases that stabilizes radiactive forcing at 4.5 W/m^2 which approximately 650 ppm CO_2-equilvalent) in year of 2100 [16]. While, RCP8.5 is refer to a high emissions of greenhouse gases, which increase considerably over time, leading radiative forcing of $8.5W/m^2$ [15].

2.1 Statistical Downscaling Model (SDSM)

The downscaling process is shown in Figure 2 and the bold box in the figure shows the main discrete process in the SDSM model. The SDSM 4.2 software reduces the task of statistically downscaling daily weather series into seven discrete steps as shown in Figure 2, which includes quality control and transformation, screening of predictor variables, model calibration, weather generation (using observed predictors), statistical analyses, graphing model output, scenario generation (using climate model predictors). The crucial task in calibration of model is the selection of predictors as it has huge impacts to the results [17]. The predictors chosen should have strong correlation and has sensible meaning for the predictand being downscaled [17].

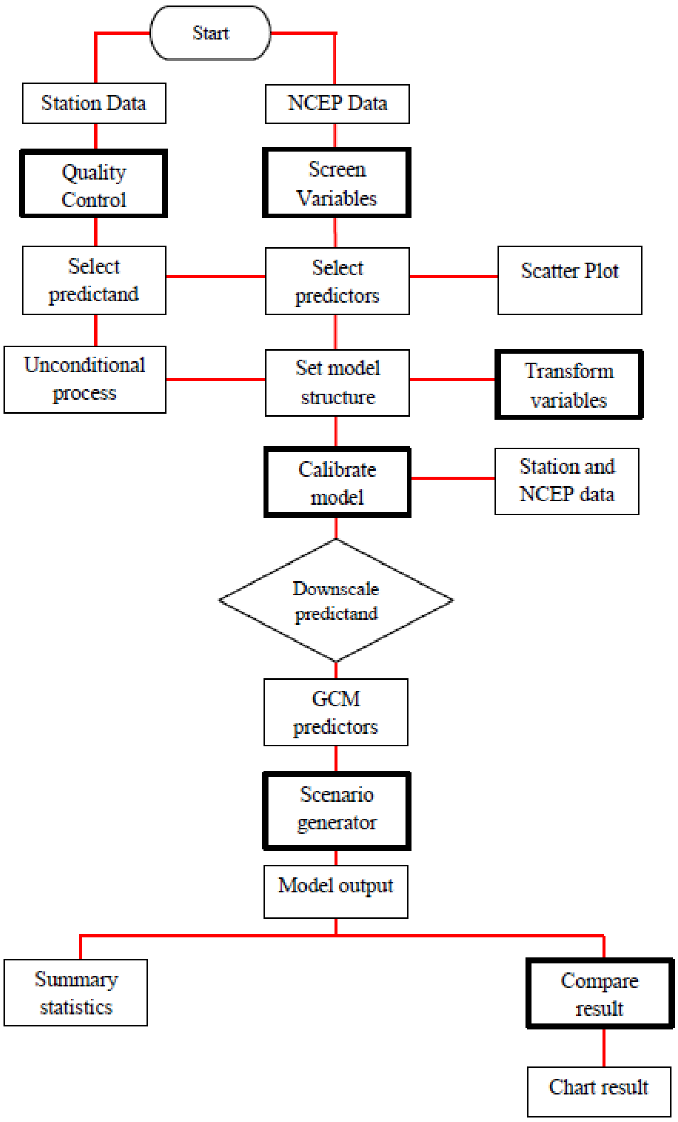

Figure 2: Schematic diagram of SDSM [13], [18]

2.2 SDSM Calibration and Validation Process

The National Centers of Environment Prediction (NCEP) data covers period of year 1961 to 2005 was reanalyzed at a scale of 2.5° (latitude) x 2.5° (longitude) to calibrate the statistical downscaling models and to establish the relationship between predictor and predictand. When the most suitable predictor are selected, multi-regression equations are applied, and the assumptions have to be made on the predicted variable. The outcome of the SDSM calibration process contains reports on the explained variance and standard error (SE) for each regression model [13], [18]. In this study, the temperature and rainfall were calibrated for the same period of 2010 to 2014. Then, temperature and rainfall were validated for the period of 2015 to 2019. The process involved comparing observed daily rainfall and temperature during the same period.

The final step in SDSM model is involved using the scenario generator in order to downscale the future GCM grid climate series projected from changed climate scenarios to local scale for each site. The statistical relationship is assumed to remains the same in the future. The data available from NCEP is used to downscale the future emission scenario for two periods, which are 2030s and 2050s. The outcomes from the SDSM model indicating the important variations in local climate response due to climate change.

2.3 Performance of SDSM Model

The performance of SDSM was measured by using the coefficient of determination (R2), coefficient of correlation (R), Root Mean Square Error (RMSE) and Model Absolute Error (MAE) [19]. These equations are used to measure the difference between values predicted by a model and the actual observation from the environment being modeled. All the coefficients are calculated based on the Equation 1 to 4, which are defined as below:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(obs - obsavg)(sim - simavg)}{\left(\sum_{i=1}^{n}(obs - obsavg)^2 \sum_{i=1}^{n}(sim - simavg)^2\right)^{0.5}}\right)^2 \qquad Eq.1$$

$$R = \frac{n\sum_{i=1}^{n}(obs)(sim) - \left(\sum_{i=1}^{n} obs\right)\left(\sum_{i=1}^{n}(sim)\right)}{\sqrt{\left(n\left(\sum_{i=1}^{n} obs^2\right) - \left(\sum_{i=1}^{n} obs\right)^2\right)\left(n\left(\sum_{i=1}^{n} sim^2\right) - \left(\sum_{i=1}^{n} sim\right)^2\right)}} \qquad Eq.2$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(obs - sim)^2}{n}} \qquad Eq.3$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(sim - obs) \qquad Eq.4$$

In which, obs=observed data value; pred=predicted data value; $\overline{(obs)}$ = mean observed data value and $\overline{(pred)}$ = predicted mean data.

The values of R^2 and R should be closer to 1. If the value less than 0, it show that the model has performed worse than the average observed value. The RMSE used to measures the average error between the observed and simulated output. The model performance is better when RMSE value is closer to zero [19].

3. Results and Discussion

3.1 Calibration and Validation for Temperature Simulation

The simulation of temperature data (predictand) refers to the meteorological station in Batu Pahat station. The recorded temperatures at Batu Pahat meteorological station are assumed to represent the temperature trend in study area. The temperature was calibrated from 2010 to 2014. After calibration process for temperature, the predictors-predictands relationship is determined through the calibration parameters. These parameters then tested during validation period from 2015 to 2019 [20].

The observed data and simulated NCEP results are compared to observe the performance of SDSM. The selected predictors were well correlated to the local predictand, thus produce a close simulated outcome to the observed temperature. However, calibration of minimum temperature is estimated to produce slightly lower temperature than observed record starting from January to July with the difference between 0.79 to 2.59 ºC. Meanwhile, the validation minimum temperature produces slightly lower temperature than observed record on January, June and August with difference of 0.78 to 1.74 ºC.

The performance of calibration and validation results presented in Table 2, consist of coefficient of determination (R^2), coefficient of correlation (R) and root mean square error (RMSE). Based on the results, the R^2 value gave better performance (during calibration and validation) with RMSE $\geq$ 0.50. The SDSM may performed better if the $R^2 \geq 0.30$. The statistical R during calibration and validation for minimum temperature are 0.46 and 0.38 respectively. Meanwhile, the statistical R-value during calibration and validation of maximum temperature are 0.40 and 0.42 respectively. The RMSE values in the whole analysis are ranging from 0.0 to 1.36. Higher correlation values were estimated in the calibrated and validated results for minimum and maximum temperature simulation closer to 1.0. It shows that the calibrated and validated values were in a good agreement with historical records.

Table 2: Performance of calibration and validation results of temperature using SDSM model

Evaluation	Minimum Temperature		Maximum Temperature	
Indices	Calibration	Validation	Calibration	Validation
R^2	0.23	0.16	0.16	0.18
R	0.46	0.38	0.40	0.42
RMSE	0.83	0.84	1.17	1.11

3.2 Calibration and Validation for Rainfall Simulation

The calibration and validation for rainfall conducted using NCEP variables for station at Sembrong Dam Batu Pahat. The calibration is conducted from 2014 to 2019 and validations from 2015 to 2019. The combinations of selected predictors are used to simulate the relationships with the local stations.

The performance of downscale rainfall simulated by SDSM at Sembrong Dam is tabulated in Table 3. The R-values for calibration and validation are 0.17 and 0.22 respectively. The result show that a strong positive linear correlation since the R-values are closer to 1. The result also shows that the daily rainfall series simulated from NCEP variable with mean of R^2 value less than 0.6 and R-value smaller than 1. Overall, the performance of SDSM is a good to the simulation of rainfall.

Table 3: Performance of calibration and validation results of mean rainfall using SDSM model

Evaluation Indices	Rainfall	
	Calibration	Validation
R^2	0.03	0.05
R	0.17	0.22
RMSE	0.46	0.47

3.3 Prediction of Future Temperature

The SDSM used to generate future maximum and minimum temperature from 2020 to 2050. The results present the average monthly temperature for each 10-year interval; which are the 2025 – 2035 (2030s), 2035 – 2045 (2040s) and 2045 – 2055 (2050s). Figure 3 and 4 shows simulated changes on future minimum temperature based on historical temperature for RCP4.5 RCP8.5 respectively. Overall, the minimum temperatures for both RCPs are consistent below 26.00 °C. For future minimum temperature, the higher temperature expected to occur in August, and October, while the lowest temperature expected to occur in January and February. RCP8.5 produces higher increment compare to RCP4.5. For example, in August of 2050, RCP4.5 shows increase of 1.34 °C while RCP8.5 shows increase of 1.54 °C.

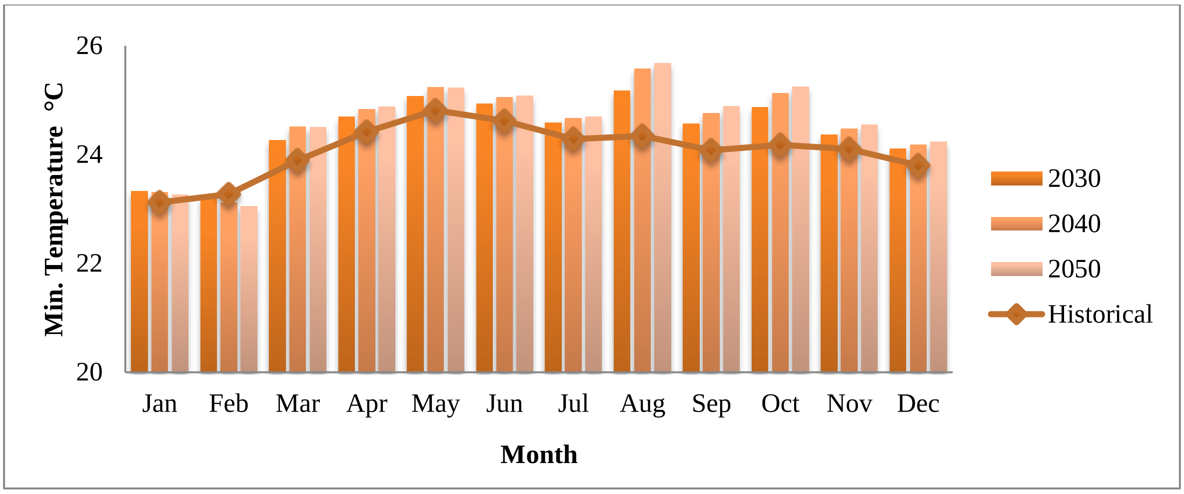

Figure 3: Projection of future minimum temperature trend using SDSM for RCP4.5

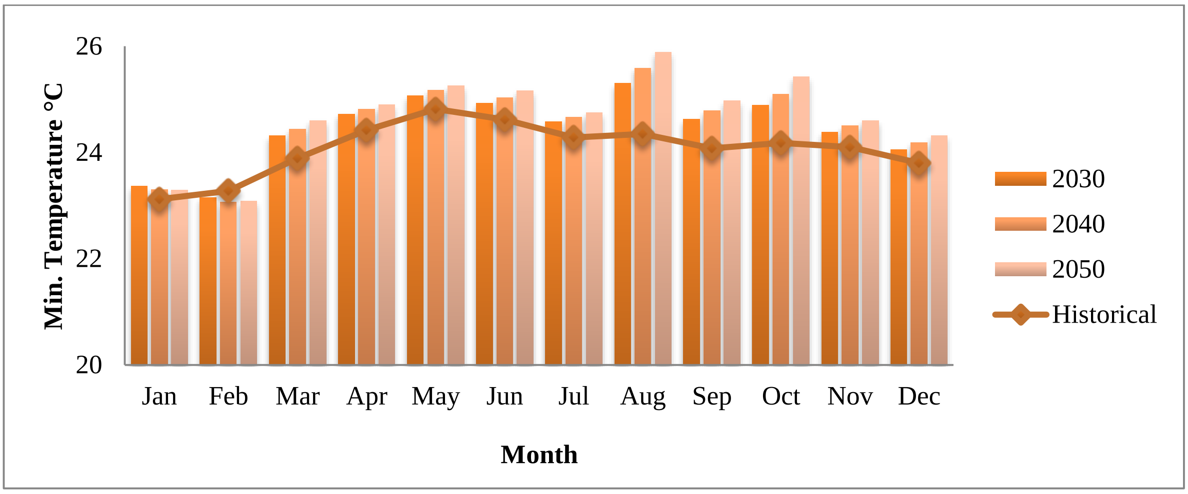

Figure 4: Projection of future minimum temperature trend using SDSM for RCP8.5

The maximum temperature for both RCP 4.5 and RCP8.5 are expected occur in February, where maximum temperature for RCP4.5 achieving 34.80 °C and RCP8.5 achieve 35.00 °C. The higher temperatures are predicted to occur in February, March, October and December due to the interchange of northeast monsoon to the south-west monsoon. The increment recorded in February for RCP8.5 is 2.01 °C while RCP4.5 recorded increase of 1.82 °C.The increment of maximum temperature for RCP8.5 is higher than RCP4.5 since RCP8.5 represents the worst scenario of greenhouse gases emission reaching 940 ppm by year of 2100. Even though the maximum temperature predicted are not extremely high, the precautions are highly recommended. The temperature above 35.00 °C causing high vulnerability of crops, which may affect the ripening stage and thus reducing production of rice [21]. This is because high temperature may increase the rate of which water is lost from soil [22]. In addition, the high temperature along with higher humidity, which caused by increased rainfall can increased the indoor pollutants [23].

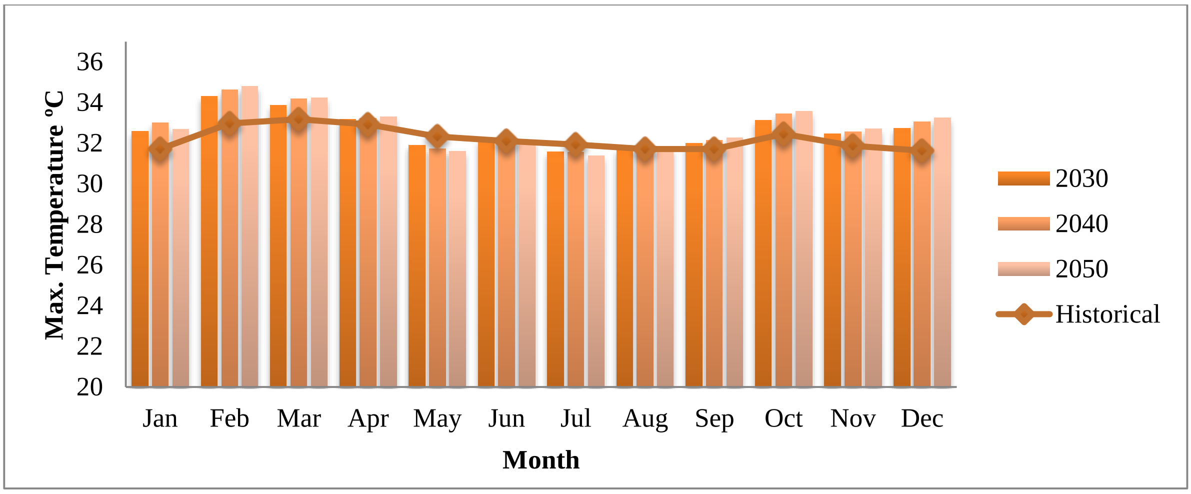

Figure 5: Projection of future maximum temperature trend using SDSM for RCP4.5

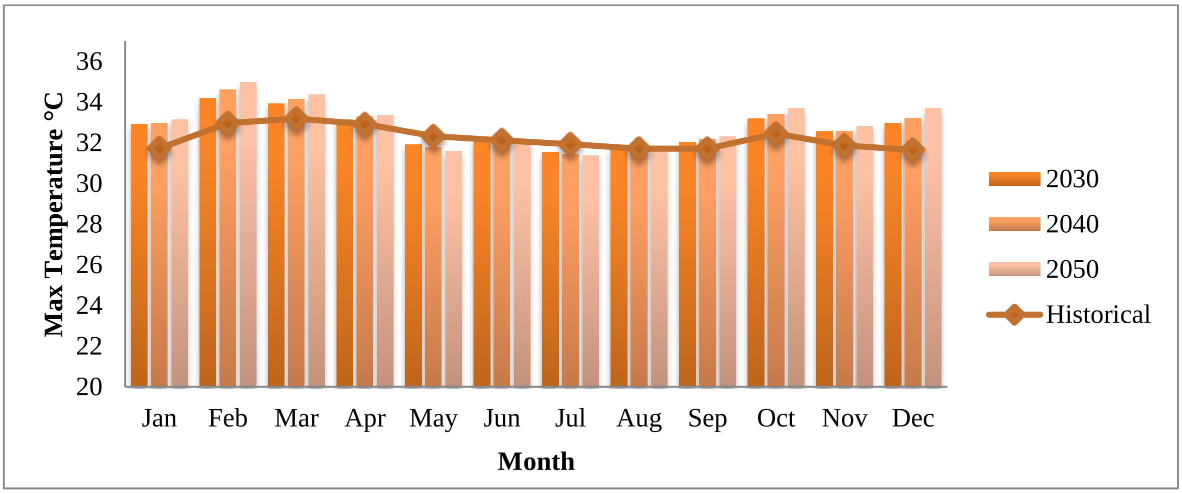

Figure 6: Projection of future maximum temperature trend using SDSM for RCP8.5

3.4 Prediction of Future Rainfall

Future monthly mean rainfalls for station of Sembrong Dam are compared between historical and future periods under scenarios of RCP4.5 and RCP8.5. The period are divide into three (3) decades, which are 2030s (2025-2035), 2040s (2035-2045) and 2050s (2045-2055). The mean rainfall predicted for all periods are compared to the historical data for mean rainfall.

The simulated changes based on historical rainfall for RCP4.5 are shown in Figure 7. From the graph, the mean of monthly rainfall for the future are mostly shows declining in monthly rainfall. The increment of future rainfall are only occurs in February, May and November. The highest mean rainfall is expected to occur in November, where the average rainfall for 2030s is 10.89 mm, 12.09 mm in 2040s and 12.83 mm in 2050s. Overall, the percentage of increment in mean rainfall was between 6.00 - 26.20 %. The lower mean rainfall estimated occur in January, June, July August and October, where all the mean rainfalls are below 2 mm.

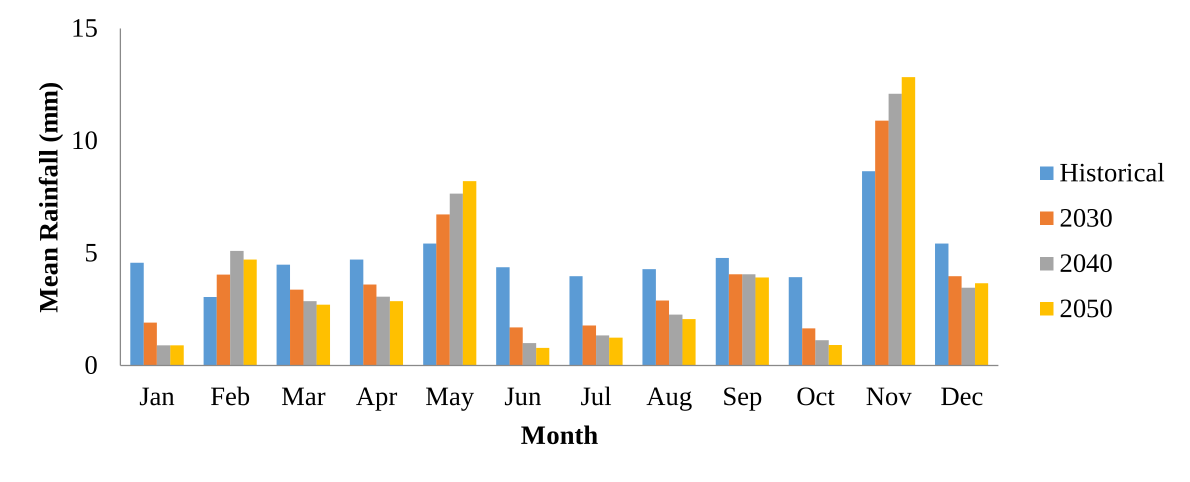

Figure 7: Future rainfall under scenario RCP4.5

Figure 8 shows simulated changes of rainfall for RCP 8.5. The highest mean rainfalls are predicted in November, which is 11.03 mm in 2030s, 12.26 mm in 2040s and 13.9 mm in 2050s. The percentage of increment in average of monthly rainfall was between 7.30 - 27.00 %. The lower mean rainfall estimated occur in January, June, July August and October, where all the mean rainfalls are below 2 mm.

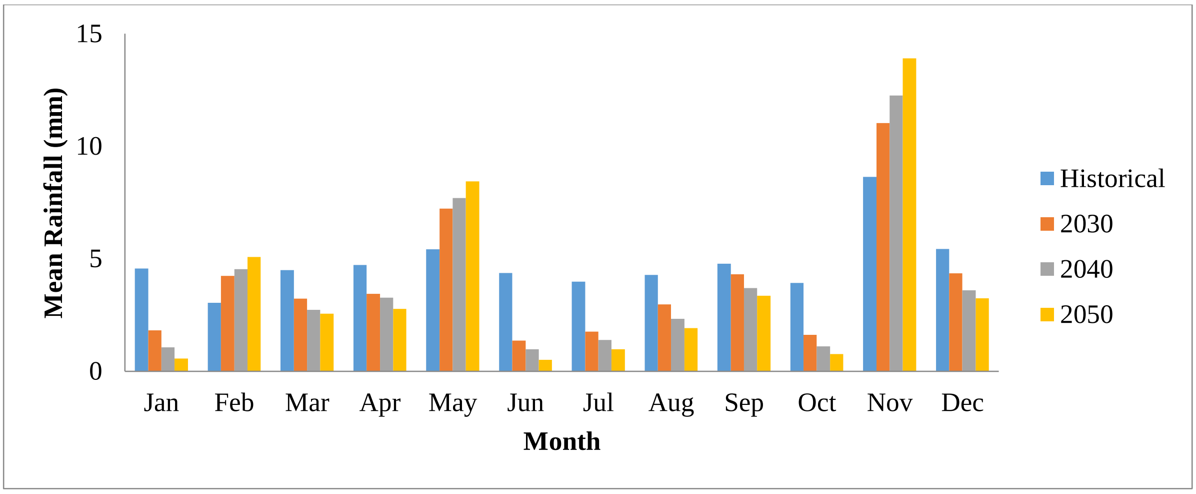

Figure 8: Future rainfall under scenario RCP8.5

4. Conclusion

The climate change gives huge impacts to the temperature and rainfall, thus affecting the quantity of water resources at Sembrong dam reservoir. The rainfall and temperature data collected were downscaled by using SDSM software. The downscale data was tested through calibration and validation process in order to measure the performance of statistical downscaling model (SDSM). From the results obtained, the coefficients of determination (R^2) are less than 0.30. This shows that the SDSM produces a better performance for both temperature and rainfall for this study. The SDSM models show the best performance if R^2 and R-value are closer to 1. The coefficient of correlation (R) is in moderate and the root mean square error (RMSE) can be acceptable as the values are more than 0.5 for temperature. Meanwhile, even though the RMSE values for rainfall are less than 0.5, the value can be accepted due to the small difference of RMSE and 0.5.

The projection of future rainfall, minimum temperature, and maximum temperature are presented in interval of year period of 2025 – 2035 (2030s), 2035 – 2045 (2040s) and 2045 – 2055 (2050s). The predicted future climate was conducted based on two RCPs scenarios, which are RCP4.5 and RCP8.5. The data projected by RCP8.5 produces the higher increment compared to RCP4.5. The outcomes show that RCP8.5 scenario produce higher changes for both rainfall and temperature compared to RCP4.5. This is because RCP 8.5 represents the worst scenario with continuing high emission of carbon dioxide (CO_2) up to 940 ppm by year of 2100 than RCP4.5 with medium emission of CO_2. This proves that the emission of carbon dioxide (CO_2) or greenhouse gases does affect the climates changes in terms of rainfall and temperature. The findings from the study helps policy makers in making planning to adapts with the impacts from climate changes. In addition, the result from the study helps in preparing strategies to conserve more water in the dam reservoir.

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