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DEVELOPMENT OF EMPIRICAL ELECTRICITY DEMAND EQUATION BASED ON CLIMATIC VARIABLES

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Abstract

Nowadays, the electricity demand (ED) is rising quickly in line with the rapid development. As a result, hydropower becomes a significant energy sources for generating sufficient electrical energy to cater the demand in the particular local areas. However, rising greenhouse gases (GHGs) concentration significantly increase carbon dioxide which traps more heat and eventually affects the reservoir's water availability for hydropower generation. Therefore, the objective of the study was to develop the empirical ED equation in relation to the climatic variables. It is very significant to estimate the future ED affected by the climate changes. This study employed the Statistical Downscaling Model (SDSM) for 3 types of representative concentration pathways scenarios (RCPs); RCP2.6 (lowest impact), RCP4.5 (middle impact), and RCP8.5 (highest impact) to analyse the pattern changes of climate variables in anticipating the future evaporation rates. Then, a multiple linear regression analysis was conducted to investigate the relationships between these climate variables and the equation for ED had been developed. From the analysis, the rainfall projection each year are set to decrease during the inter-monsoon and Southwest monsoon and begin to increase as the Northeast monsoon happens. The projection of maximum temperature under all the RCPs show a gradual increase and peaked from February to October from 4.5% to 6.5% each year. The projection of relative humidity was seen to decrease for all RCPs especially RCP4.5 that gradually decreased to 4.5% in 2070 to 2100 for November until January. Projection of evaporation for months September and November showed the biggest difference where the evaporation under all RCPs were expected to decrease to about 22% and 24%. Backward elimination found that the most significance variable were the minimum temperature, mean temperature, and evaporation with give the smallest p-value and highest correlation coefficient, r, which are subsequently incorporated as independent variables within the ED equation. Based on ED equation, there are some significant increase of the projected ED throughout the years of 2025-2100 especially in February, July and October.

Keywords: Climate changes, Climate variables, Electricity demand, Future demand, RCP.

1. Introduction

As the world evolved through the years, increasing demand for energy has been the concerns of many countries around the world particularly in regard to the challenge brought on by climate change. The need to sustain current available sources of energy is essential as the socio-economic development of the country. As a result, they are moving towards the consumption of renewable and environment friendly electrical energy generations. As the reports made by the International Energy Agency [1] states that about the burning of fossil fuel (which 81.1% from the total world primary energy) resulting to the greenhouse gases (GHGs) rises.

Aside from producing harmful impacts on the environment such as global warming, acid rain, air pollution, depletion of ozone layer, and emission of radioactive substances, excessive use of non-renewable energy such as fossil fuel will lead to scarcity of the energy resources in the future [2]. When the future electricity demand is increasing, the energy production from hydropower will also increase [3].

Securing its spot-on top as the largest renewable energy source of electricity among other sources and technologies, hydropower energy is expected to maintain about 3% rate of growth of annual electricity generation in 2022-2030 by 2050 [1].

Despite being the largest renewable source, hydropower generation had seen a decrease of about 0.4% of its production in 2021 due to large drought happening in most hydropower-rich countries such as China, Canada and Brazil. The report also mentioned that only one third of the required growth rate was achieved in the past five years. This indicates a need in more effort to increase the output and maintaining the current situation of existing hydropower plants.

Generally, hydropower system implements the use of potential energy of water to generate power without making changes on its composition, hence avoiding direct pollution on the environment. Amount of energy produced from each hydropower plant is made to cater the electricity demand for local area.

According to Tenaga National Berhad [4], the development of hydropower plant in Malaysia began in 1900 where the first hydropower station was constructed in Raub, Pahang. Since the establishment of the Central Electricity Board (CEB) in September 1949, development of power stations from various source of energy including fuel energy, steam power station as well as the hydropower stations has been growing rapidly.

According to the US Energy Information Administration (EIA), as of 2019, the primary energy source in Malaysia is from petroleum and other liquid at 37%, 36% of natural gases and 21% from coal. Renewable energy accounts for only 6% of the total consumption. Some initiative has been taken to increase awareness on reducing the use of non-renewable energy which has been increasing in demand while the sources keep decreasing.

Built in 1978, the hydropower station used as the main location of this study is one of Malaysia's biggest hydropower plant as of now. The power station is located on the largest natural lake in Malaysia, Lake Kenyir in Hulu Terengganu, Terengganu. This hydropower station is the largest in peninsular Malaysia while the current largest hydropower plant is the Bakun Dam in Sarawak.

The long-term emission of GHGs is expected to have strong impacts on climate change. Increasing concentration of GHGs significantly the carbon dioxide causing more heat to be trapped and eventually raising the global temperature. As the temperature rise, the evaporation rate on the surface of the water-in this case, reservoir surface-increase.

In the area of study, the weather is highly affected by the Monsoon seasons which hit the country in four seasons which are the Northeast Monsoon (November-March), the Southwest Monsoon (May-June), and two inter monsoon periods. Climate changes driven by GHGs result in a shift in monsoon patterns such as in the regions that previously received abundant rainfall now are experiencing less rainfall [5].

Due to the inconsistency of the surface temperature, the evaporation value could also vary [6]. Evaporation on the reservoir surface affected the water availability in the hydropower plant. With decreasing levels of water, the energy produced by the hydropower plant would also be reduced. In the long term, the effect of changes in evaporation can be tackled by analysing the future climate conditions in the area of study [7].

Therefore, the study aimed to develop the empirical ED equation in relation to the climatic variables. It is very significant to estimate the future electricity demand affected by the climate changes. To address this problem, the idea of net water balance was introduced where the amount of water entering the reservoir as precipitation was considered [8].

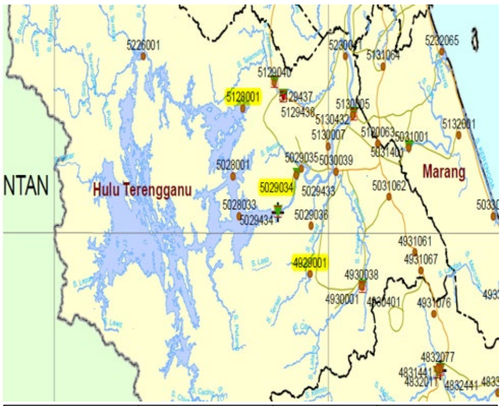
2. Study Area

Lakes in Malaysia are important as it provides multipurpose functions from being home to important ecosystem of biological species to hosting some of popular tourism and recreational site. Some of other main uses of lakes in Malaysia is to form as storage basins for water supply municipal and industrial area and reservoir for generation of hydropower electricity. Located in the world oldest tropical rain forest, Kenyir Lake in Terengganu is one of the popular destination for tourists in Malaysia [9].

With the Kenyir Lake as the reservoir, Sultan Mahmud Hydropower Station situated on the lake functions as the main hydropower station on the lake to provide electrical energy supply for the country. Figure 1 shows the location of Sultan Mahmud Power Station on Kenyir Lake, Terengganu. Built between the year 1978 until 1986, Sultan Mahmud Power Station or Kenyir dam is 40 km inland of Hulu Terengganu, Terengganu at approximate latitude 5º1’20” North and longitude 102º54’30” East.

Previously known as the largest dam in Malaysia before the opening of Bakun Dam in Sarawak, this 369 km^2 large reservoir made of rock fill clay core dam has gross storage volume at 13.6 billion m^3 and a catchment area of 2600 km^2. The reservoir received water from five major tributaries which are Sg. Terengganu as the main river, Sg. Cacing, Sg. Petang, Sg. Tembat and Sg. Petuang [10].

In this area, the average temperature is 27.8 ºC with the maximum temperature is below 35 ºC. The relative humidity is between 80% (dry season) to 88% (wet season) with the average annual rainfall is 3746 mm/year. The rate of evaporation within the range of 3.3 to 5.2 mm/month.



Station ID	Station Name	Latitude (N)	Longitude (E)
RF 4929001	Kg. Embong	04 57 10	102 58 00
RF 5029034	Kg. Dura	05 04 00	102 56 30
RF 5128001	Sg. Gawi	05 08 35	102 50 40
Temperature	Kuala Terengganu	05 23 00	103 06 00
Relative Humidity	Kuala Terengganu	05 23 00	103 06 00
Evaporation	Kuala Terengganu	05 23 00	103 06 00

Fig. 1. Sultan Mahmud power station Hydroelectric Dam, Terengganu.

3. Methods of the Study

Figure 2 shows the flow chart of the methodology. The main objective of this study was to develop the empirical ED equation based on climatic variables. The analysis in this study can be divided into two major phases. The 1st phase was spatial downscaling of daily rainfall data obtained from GCMs-CanesM2 for 3 types of scenarios of representative concentration pathways (RCPs) in term of RCP2.5, RCP4.5 and RCP8.5 with consideration of climate change impact.

In the process of downscaling the rainfall data, the statistical downscaling model (SDSM) was employed to formulate the future rainfall based on predictand-predictor relationship. The predictand refers to the local rainfall meanwhile predictor refers to the 26 of atmospheric characteristics as listed in Table 1. There were only 5 predictors were selected that having better correlation among predictand-predictor relationship based on correlation coefficient value. Then, the climate formulation was used to generate the long-term series of rainfall until year of 2099.

The 2nd phase was developing the empirical ED equation using linear regression equation. The historical data from 1989-2020 was analysed the level of association between climatic variables (relative humidity, temperature, and rainfall) with ED. It was very important to determine the type of association (+ve or -ve) and how strong that relationship in influencing the value of ED. Finally, the future ED was generated after combining the findings from 1st and 2nd phases.

3.1. Climate simulation using statistical downscaling model (SDSM)

Statistical downscaling (SD) is analogous to the Model Output Statistic (MOS) and perfect prog approach used for short range numerical weather prediction. The weather generator method is used in the model, which was created by Wilby and Dawson [11] to construct multiple realizations of a synthetic daily climate variables. The software determines the statistical association between the local climate (known as predictand) and the large-scale (known as predictor) using multiple regression approaches.

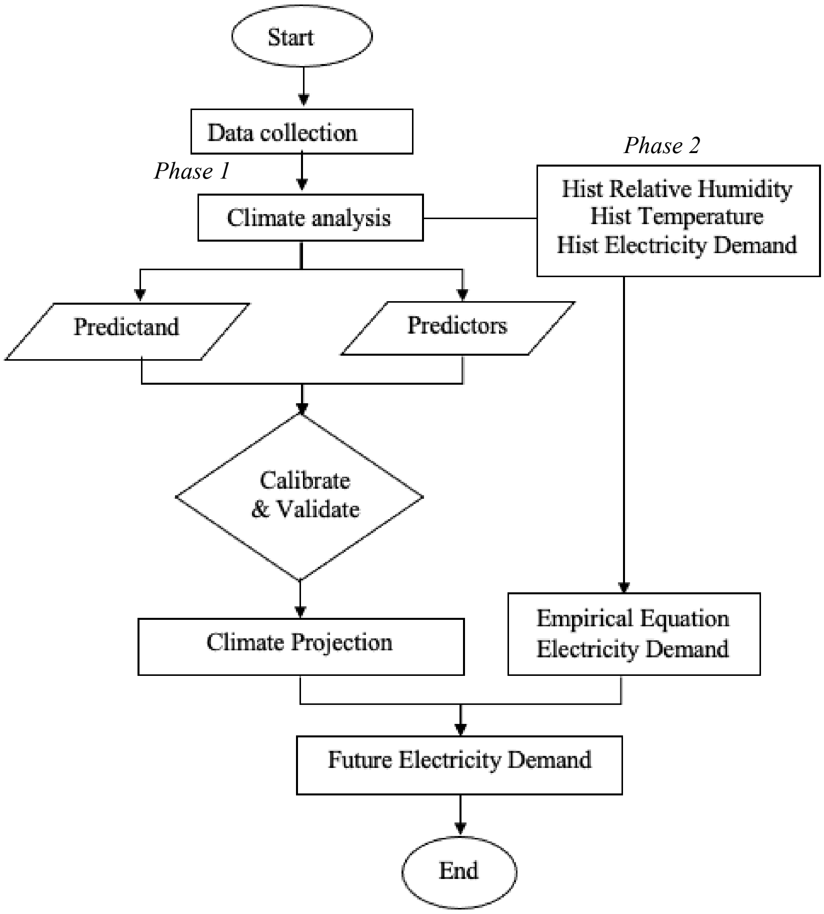


Fig. 2. Methods of the study.

It generates the daily scenarios at meteorological station including rainfall, maximum and minimum temperatures, and evaporation for the chosen location, along with using statistical parameters including variance and frequency of extremes. The SDSM was widely used to understand the changes pattern and trend of climate variables responding to the long-term dispersion of GHGs and aerosol emission into the atmospheric system [12]. The SDSM has several advantages such as rapid assessments of local climate change, low cost and less time consuming over dynamical downscaling method. A statistical downscaling model carries out as a decision support tool for the assessment of regional climate change impact using a statistical downscaling technique. As of today, the downscaling algorithm of SDSM has been applied widely among the researches of meteorological, hydrological and environmental assessments, as well as a range of geographical contexts in assessing the climate changes impact.

Table 1. List of NCEP predictors.

Predictor	Description	Predictor	Description
temp	Mean temperature at 2 m	**Predictor**	Description
mslp	Mean sea level pressure	**p1_zh**	Divergence at surface
p500	500 hPa geopotential height	**p5_f**	Geostrophic air flow velocity at 500 hPa
p850	850 hPa geopotential height	**p5_z**	Vorticity at 500 hPa
r500	Relative humidity at 500 hPa height	**p5_u**	Zonal velocity component at 500 hPa
r850	Relative humidity at 850 hPa height	**p5_v**	Meridional velocity component at 500 hPa
shum	Near surface specific humidity	**p5_th**	Wind direction at 500 hPa
prec	Total precipitation	**p5_zh**	Divergence at 500 hPa
p1_f	Geostrophic air flow velocity at surface	**p8_f**	Geostrophic air flow velocity at 850 hPa
p1_z	Vorticity at surface	**p8_z**	Vorticity at 850 hPa
p1_u	Zonal velocity component at surface	**p8_u**	Zonal velocity component at 850 hPa
p1_v	Meridional velocity component at surface	**p8_v**	Meridional velocity component at 850 hPa
p1_th	Wind direction at surface	**p8_th**	Wind direction at 850 hPa
temp	Mean temperature at 2 m	**p8_zh**	Divergence at 850 hPa

It consists of two significant steps there were validating daily rainfall occurrence based on historical data and estimating the daily rainfall considered estimated GHGs. In developing the predictor-predictand equations, the multi-linear regression approach had been considered and the accuracy of the equation had been monitored based on the validation performances. The rainfall (y) on day (t) can be determined using these Eqs. (1) and (2) as stated below:

$$y_t = F^{-1}[\varnothing Z_t] \tag{1}$$

$$Z_t = \beta_0 + \Sigma\beta_j\widehat{u_t} + \beta_{t-1} + \varepsilon \tag{2}$$

where F is the empirical function of y_t, $\varnothing$ is the normal cumulative distribution function, Z_t is the z-score on day t, β is the regression parameter, but is normalized predictor and ε is the variable parameter. For the rainfall analysis, the equation was transformed to the fourth root to take account for the skewed nature of the rainfall distribution.

3.2. Development of empirical ED equation using regression analysis

Regression analysis is a statistical method used to examine the relationship between one dependent variable and one or more independent variables [13]. In linear regression, the relationship between the dependent variable and independent variables is assumed to be linear. In this study, multiple linear regression was used to investigate the relationship between the variables, identify the significant variable and estimate the ED based on climate variables.

Multiple linear regression is a regression model with more than one independent variable. It involves the use of more than one independent variable to estimate or predict a dependent variable. A multiple linear regression model is used to describe linear relationships involving a dependent variable with more than one independent variables. The model is shown in Eq. (3):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (3)$$

where $\beta_{0,}\beta_{1,}\beta_{2,} \ldots \beta_{k,}$= unknown parameter (unitless), β_0= slope for population (unitless), ε= random error (unitless), *y*= dependent variable (GWh), $x_1, x_2 \ldots x_k$= climate variables.

In this study, the backward elimination regression analysis is used in selecting the significant variables. In the initial phase of backward elimination regression analysis, all the independent variables are included in the model. Next, the variable with the highest p-value or greater than 0.05 or 5% significance level will be removed. The, the process will continue until all the p-value for the variable is smaller than the significance level, 0.05. Analysis of variance (ANOVA) in multiple linear regression is used in analysing the relationship between the independent and dependent variables. The null hypothesis is all the independent is not related to the dependent variables. Failure to reject the null hypothesis indicates that there are no independent variables related to the dependent variables.

4. Results and Discussions

4.1. Climate projection analysis by SDSM

In SDSM, calibration and validation are essential processes to ensure the reliability and accuracy of the model's predictions. The purpose of calibration was to train the SDSM model using historical climate data while validation was to assess the performance and accuracy of the calibrated SDSM model. First, the actual historical data (Predictand) of each climate variables from 1989 to 2020 were divided into calibrated data (1989 to 2005) and the validated data (2006 to 2020). In the calibration process, the climate variables equation was built using a multiple regression equation in SDSM with the predictors as variables. Meanwhile in the validation process, the estimated climate variables were formed by identical climate variable model. Figs. 3 and 4 show the comparison of historical and simulated data for the calibrated and validated data for all the climate variables.

From the figures, the calibrated and validated rainfall, temperature, evaporation and relative humidity demonstrate almost the same pattern of the actual historical data. The combination of five selected predictors was successfully able to model the climate variables' relationships. Rainfall formation within this catchment were having strong correlation with the wind variables in term of divergence (*zh*), airflow strength (*f*) and vorticity (*z*). As supported by Luan et al. [14] and Sheng et al. [15], the changes in these potential variables can induce changes in rainfall intensity. However, the air temperature at 2 m (temp) has a greater impact on the formation of temperature and evaporation.

In rainfall simulation, there was significant error, notably in Dec with less than 20%. Meanwhile the calibrated gap at station Sg Gawi is almost every month. However, the formation of climate equation at this station is still acceptable since it was successfully to produce better simulated result during validation stage. Referring to the simulated results of temperature, evaporation and relative humidity, all variables were successfully to produce good simulation with very minimum error (< 4.0%).

Table 2 shows the statistical analyses for all climate variables during calibration and validation processes. The results were analysed using mean absolute error (MAE), root mean square error (RMSE), and correlation coefficient (r). When evaluating the SDSM model, smaller MAE values and higher *r* values were considered acceptable, indicating suitability for making projections.

The results show that all rainfall stations produced high values or *r* for both calibration and validation process indicates that all the predictors were strong correlated where the value is between 0.88 to 0.99 with Kg Dura station gave the smallest MAE for validation process compared to the other station. Meanwhile, the simulated temperature was successfully produced good association in the calibrated and validated results.

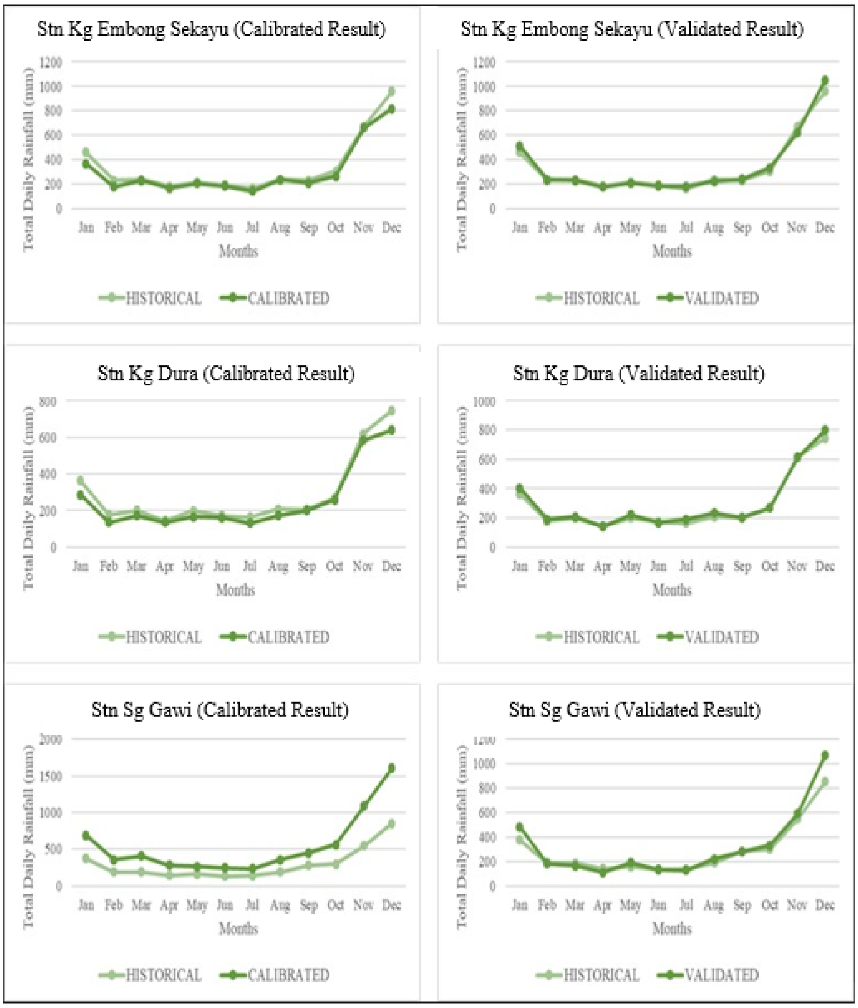


Fig. 3. Comparison of calibrated (1989-2005) and validated (2006-2020) rainfall with historical rainfall data.

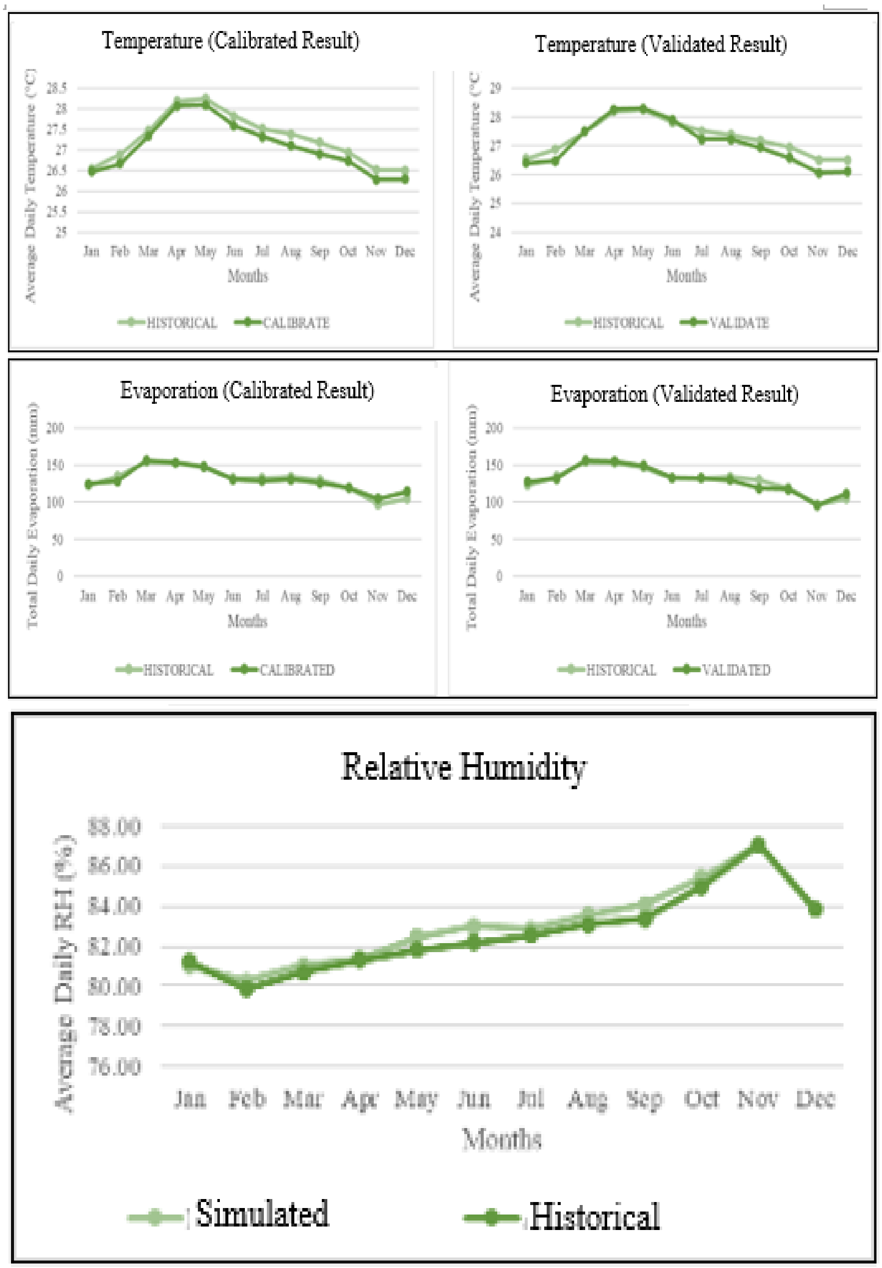


Fig. 4. Comparison of calibrated (1989-2005) and validated (2006-2020) temperature, evaporation and relative humidity with historical data.

All the *r* gives high value and the MAE together with RMSE is less than 4.0% of error. Consistent with the validated evaporation and relative humidity were also produced higher *r* which was close to 1.0 and small values of MAE and RMSE. These findings proved that the calibrated and validated results were related to the actual historical data for each climate variable, therefore is acceptable.

Projection of rainfall was done for all three stations which were Kg Embong Sekayu, Kg Dura and Sg Gawi under RCP 2.6, RCP 4.5 and RCP 8.5 for the three ranges of year 2025-2039 (Δ2030), 2040-2069 (Δ2055), and 2070-2100 (Δ2085). Figures 5-8 indicate the rainfall, temperature, relative humidity and evaporation changes in term of potential increment (+ve) or decrement (-ve) during the projected year, respectively.

Table 2. Performance of the calibrated and validated results.

Predictand	r		MAE (%)		RMSE (mm)	
	Calibrate	Validate	Calibrate	Validate	Calibrate	Validate
Rainfall						
Kg Embong Sekayu	0.91	0.92	13.98	13.69	2.20	1.84
Kg Dura	0.89	0.96	14.77	7.48	7.64	2.42
Sg Gawi	0.88	0.91	22.22	14.53	9.72	6.23
Temperature						
Tmean	0.99	0.99	0.20	0.23	0.04	0.01
Evaporation						
Kuala Terengganu	0.96	0.97	3.64	3.39	0.68	0.73
Relative Humidity						
	R	**MAE**	**RMSE**			
Kuala Terengganu	0.99	0.37	0.11			

At the first next 20 years, the average monthly rainfall for all stations is expected to rise except in July. However, during year 2040 onward, month of Sept and Oct were also expected to receive lesser rainfall compared to the previous year with -3.5 % (2040-2069) and -4.5 % (2070-2100). The biggest change was expected on Feb whereby the average rainfall intensity is keep increasing in every interval year. It is supported by all RCPs that showing consistent rise trend in different radiation level with RCP8.5 as the highest increment (< +20 %) at the end of century.

This finding also indicates that the area was potentially experiences heavier rainfall than the historical during North-East monsoon with Feb as the month of concentration.

Meanwhile the projected mean temperature shows an increment trend in temperature especially from Mar to June during South-West monsoon. The temperature will rise gradually by 4.3% (RCP8.5) on average by the end of the century. All RCPs agreed that the mean temperature will drop during the North-East monsoon (Oct to Feb) with RCP8.5 predicting the biggest drop, at -6.4%.

The projected rainfall pattern in this area is consistent with the changes in the mean temperature. Therefore, the climate changes cause the South-West monsoon brings hotter weather with less rainfall, whereas the North-East monsoon brings lower temperatures with more rainfall intensity.

The future relative humidity in this area is expecting to similar to the historical pattern with very small changes. The month of Nov and Feb are the highest (86%) and lowest (81%) relative humidity, respectively. RCP8.5 illustrates the biggest changes in relative humidity where at this stage, the GHGs dispersion at the highest level compared to other RCPs. The relative humidity is expected to rise in all months except Nov to Jan during North-East Monsoon. Even it is rainy season, but the decrement of relative humidity might because of the high wind speed [16, 17].

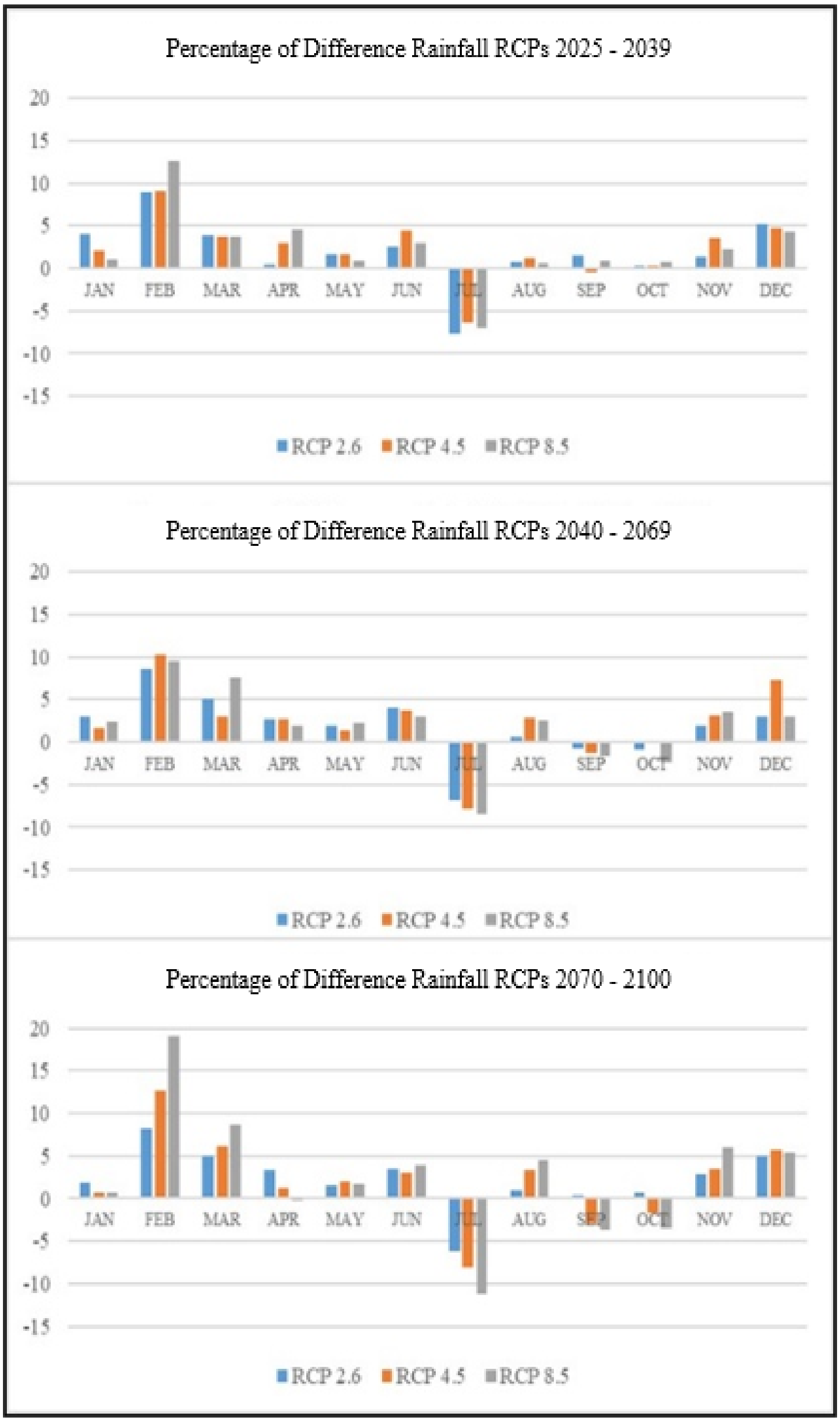


Fig. 5. Percentage difference (increment/decrement) of rainfall during projected year 2025-2100.

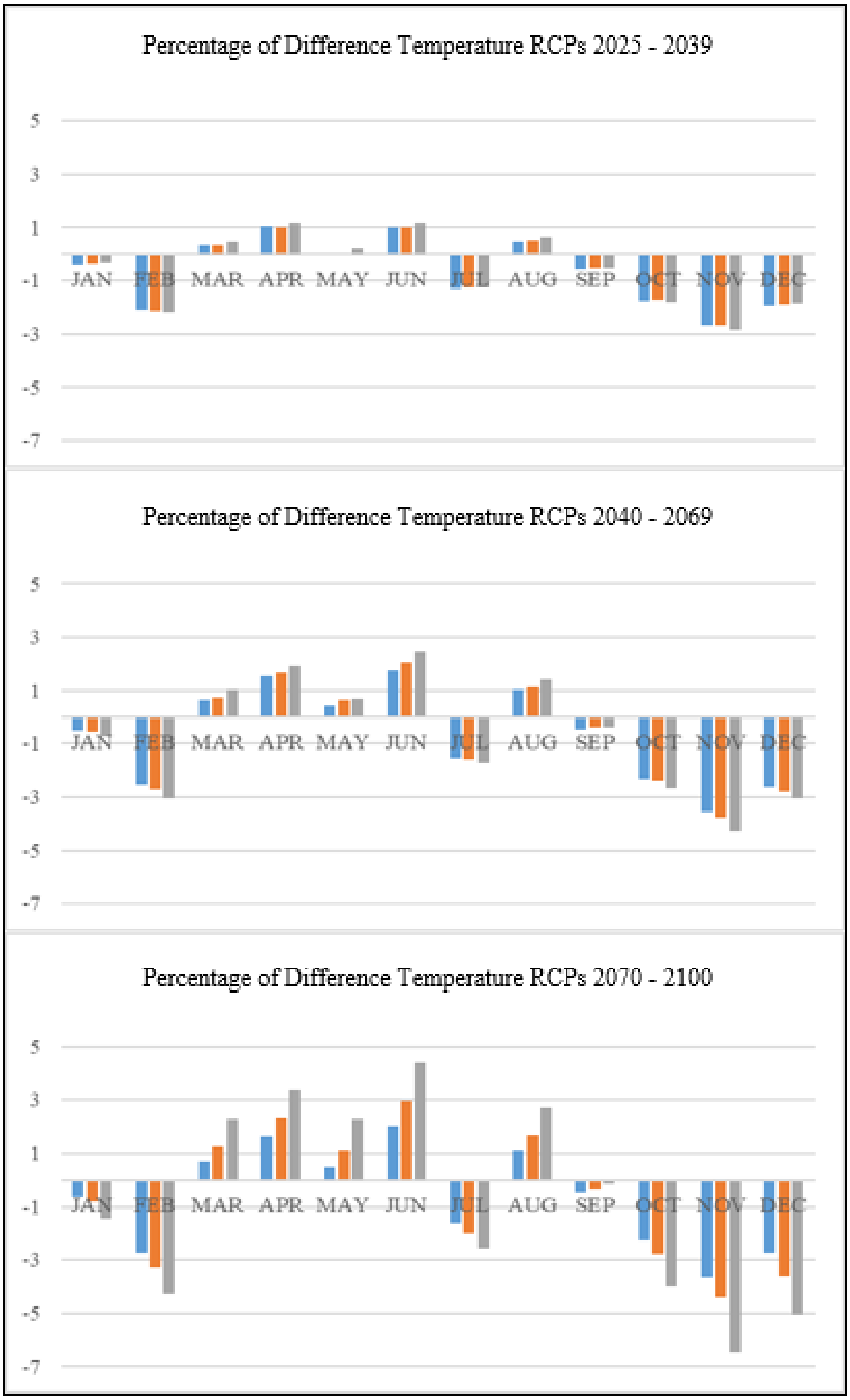


Fig. 6. Percentage difference (increment/decrement) of temperature during projected year 2025-2100.

Fig. 7. Percentage difference (increment/decrement) of relative humidity during projected year 2025-2100.

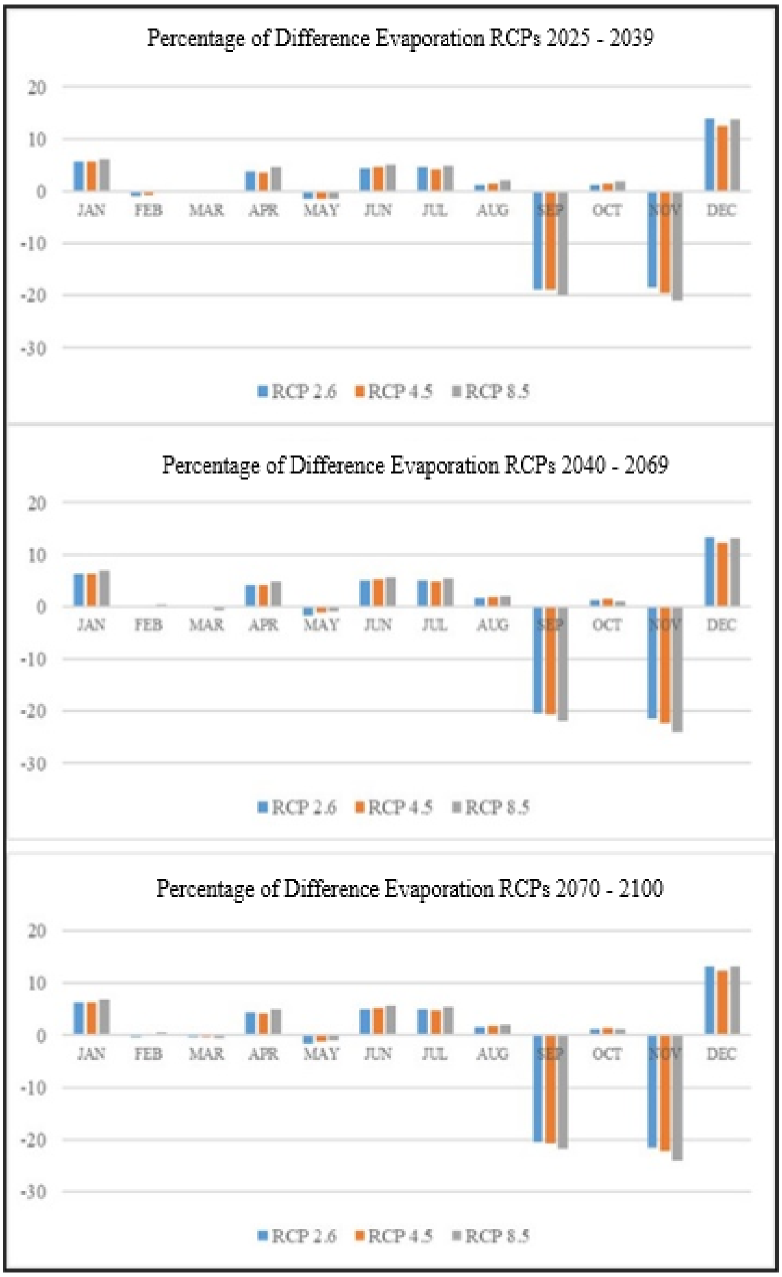


Fig. 8. Percentage difference (increment/decrement) of evaporation during projected year 2025-2100.

The future evaporation shows consistent changes pattern to other climate variables, the North-East Monsoon experiences the lowest evaporation, at 100 mm/month, while March has the maximum evaporation, at 150 mm/month. But due to the climate changes, the pattern of evaporation gradually shifts with April experiencing the highest evaporation in the future year. Month of Sept and Nov are predicted to experience a significant decrease in evaporation (< -24%) at the end of the century. It portrayed an important information on the reservoir evaporation where under each level of emission, the predicted evaporation for the next century changed accordingly.

4.2. Performances of an empirical ED equation

An ED is significantly depending on the different climate variables [18]. In this study, the different climate variables are rainfall, minimum temperature, maximum temperature, mean temperature, relative humidity and evaporation. These variables were analysed to investigate the effect to the electricity demand. First, Pearson correlation matrix was employed to investigate the relationship between all the variables. Then, a multiple linear regression model was applied to model the data using the significance variable and make prediction for the electricity demand.

In Pearson correlation, a correlation coefficient was computed within the range of -1 to +1, as an indicator of the strength of the relationship between distinct variables. A value of +1 denotes a strong positive correlation, while -1 indicates a strong negative correlation, and 0 signifies no correlation. In this study, the Pearson correlation was done using Microsoft Excel and the output is shown in Table 3. In this table, the *RF* refer to rainfall, *Tmin* is minimum temperature, *Tmax* is maximum temperature, *Tmean* is mean temperature, *RH* is relative humidity, *eva* is evaporation and *ED act* is actual electricity demand.

The table also depicts the Pearson correlation matrix, showing the connections between the climate variables through different correlation coefficients. Based on the matrix, there exist a positive and negative relationship between the variables indicated that there exists relationship between the variables. In addition, the strongest positive correlation is between mean temperature and maximum temperature which give the value of correlation is 0.9 while the negative strongest correlation is between evaporation and rainfall with the correlation value is -0.8. The weakest positive correlation is between evaporation and minimum temperature which the correlation value is 0.4 while the weakest negative correlation is between relative humidity and minimum temperature with the correlation value -0.18. Next, multiple linear regression analysis will be employed to determine the statistically significant variables while excluding those that are not statistically significant to the electricity demand.

Initially, the variables which are rainfall, minimum temperature, maximum temperature, mean temperature, relative humidity, and evaporation have been included in the regression model. Then, using “Data Analysis” in Microsoft Excel, regression analysis has been performed and associated coefficients have been investigated. Table 4 shows the backward elimination regression analysis.

Based on Table 4, first, rainfall variable was removed due to its high p-value of 0.56 in the first model. This led to the formation of second model with the remaining variables. Then, relative humidity was excluded because it had the highest p-value of 0.2087. In the third step, minimum temperature was eliminated due to its highest *p-value* of 0.1015. The resulting model after this step was considered the final model, as all p-values were found to be less than 0.05. The remaining variables, maximum temperature, mean temperature and evaporation is selected as the most significant factors influencing electricity demand.

Table 3. Pearson correlation output.

	RF	*Tmin*	*Tmax*	*Tmean*	*RH*	*eva*	*ED act*
RF	1						
Tmin	-0.243	1					
Tmax	-0.789	0.613	1				
Tmean	-0.726	0.794	0.934	1			
RH	0.558	-0.188	-0.242	-0.423	1		
eva	-0.816	0.455	0.707	0.817	-0.777	1	
P act	-0.379	-0.453	0.197	-0.068	-0.027	0.074	1

Table 4. Backward elimination regression analysis.

Model	**Model Summary**		***p-value* of the predictors**						
	r	*Adj R^2*	**Constant**	*RF*	*Tmin*	*Tmax*	*Tmean*	*RH*	*eva*
1	0.93	0.72	0.005	0.562	0.099	0.013	0.021	0.202	0.094
2	0.93	0.75	0.002	Removed	0.076	0.006	0.014	0.209	0.083
3	0.90	0.71	0.001	Removed	0.101	0.008	0.018	Removed	0.026
4	0.85	0.62	0.001	Removed	Removed	0.002	0.002	Removed	0.046

From the multiple linear regression analysis using the significant variables, value of correlation coefficient, *r* which equals to 0.85 indicates that there exists strong correlation between all the climate variables to the electricity demand. The coefficient of determination, adjusted R^2 is 0.62 indicates that 62% variation in ED can be explained by the climate variables. The p-value in ANOVA table equals to 0.0124, which is less than 5% significance level, we have to reject the null hypothesis that all the climate variables are not related to the electricity demand. Hence, at least one of the climate variables is related to the electricity demand. All the *p-values* for the predictors are less than 0.05 indicated that the predictor is significant. Finally, the ED equation is given in Eq. (4).

$$\hat{y} = 15407.99 + 357.15x_1 - 881.77x_2 + 8.32x_3 \tag{4}$$

where $\hat{y}$= monthly predicted electricity demand, x_1= monthly maximum temperature, x_2= monthly mean temperature, x_3= monthly evaporation.

The simulated ED was compared with the actual ED, as shown in Fig. 9. The plot illustrates a remarkably close correspondence between the simulated and actual electricity demand, affirming the capability of the selected climatic variables to accurately estimate ED.

Figure 10 shows the projected of ED based on average 3 rainfall stations under RCP 2.6, RCP 4.5 and RCP 8.5 for the three ranges of year 2025-2039 (Δ2030), 2040-2069 (Δ2055), and 2070-2100 (Δ2085). In general, there are some significant increase of the projected ED throughout the years in average +20% at the end of century. Consistent to the historical monthly electricity demand pattern, the highest and lowest ED are on Oct and Apr, respectively. However, the ED is anticipated to increase significantly each month as a result of climate change. In comparison to other RCPs, the RCP8.5 produces largest changes, demonstrating that it has the greatest influence on climate change. The projected increases in ED brought on by climate changes will increasing the water consumption for hydropower. The increased generation of power will result in a higher emission of GHGs that worsen the climate change.

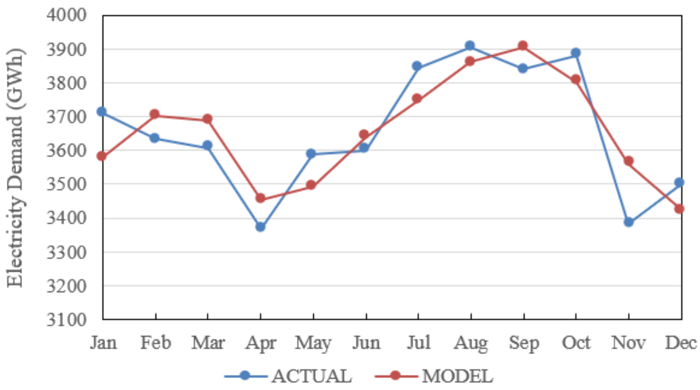


Fig. 9. Comparison of actual with the simulated of ED.

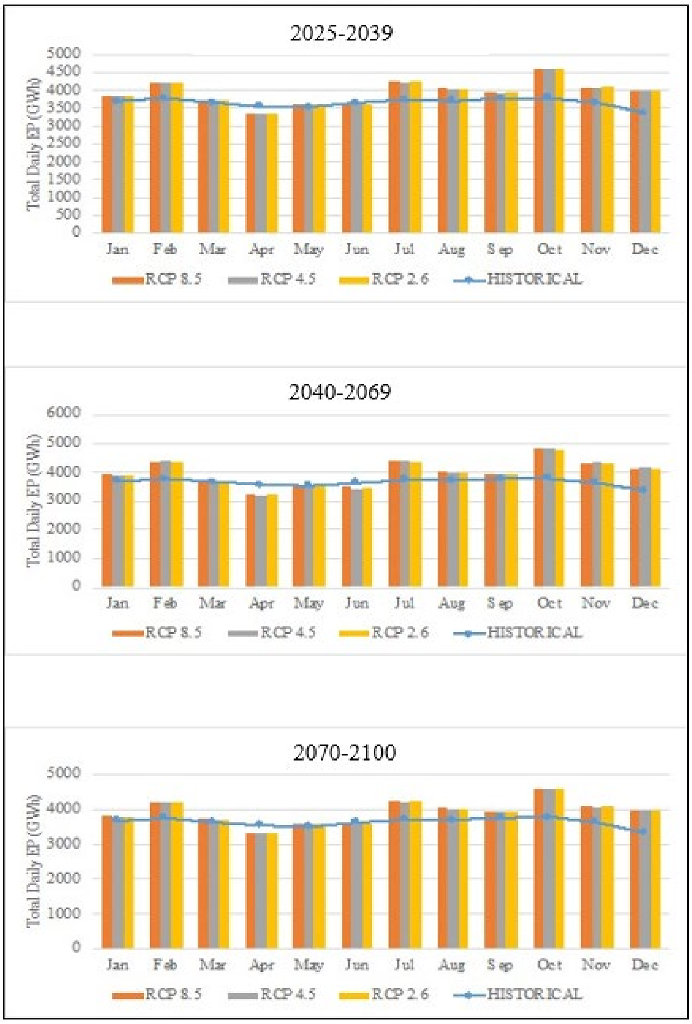


Fig. 10. Projection of average monthly ED from 2025 to 2100.

5. Conclusions

In order to estimate future climatic changes in the research region, the SDSM was used to analyse the changes patterns of hydrological components including rainfall, temperature, evaporation, RH, and rainfall from year 2025-2100. Until end of century, the projected rainfall was expected to decrease especially during inter-monsoon and southwest monsoon but increase during northeast monsoon (wet season). The projection of maximum temperature shows that all the RCPs gradually peaked from February to October (dry season) from 4.5 % to 6.5% each year. The projection of RH was seen to decrease for all RCPs especially RCP4.5 that gradually decreased to 4.5% in 2070 to 2100 for November until January.

Meanwhile for projected evaporation was parallel to the temperature pattern whereby the increment and decrement of potential evaporation occurred during dry and wet seasons, respectively. According to the backward elimination regression analysis, there were 3 climate variables in term of maximum temperature, mean temperature and evaporation were having good association with the EP because there were successfully to produce the smallest p-value and highest correlation coefficient. These results subsequently incorporated as independent variables within the ED projection equation.

The equation was used to investigate the future ED of the hydropower plant by inserting the projected climate variable values by the SDSM earlier under all RCPs. The results show that from 2025 to 2100 there are some significant increase of the projected energy production throughout the years in February, July and October. This is because of the amount of projected rainfall were predicted to increase during those months simultaneously increasing the amount of water in the reservoir. Besides, the evaporation during those months was projected and is set to decrease. With low rate of evaporation and high rainfall, the ED value increased likewise.

This study recommends improving the quality of hydrological climate data by using alternative methods to replace missing data from climate stations and by increasing the number of climate stations in the study area. Enhanced data quality would lead to significantly better results from climate analysis.

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Abbreviations

ED	Electricity Demand
GCMs	General Circulation Models
GHGs	Greenhouse gases
MAE	Mean Absolute Error
MOS	Model Output Statistics
RCPs	Representative Concentration Pathways
r	Correlation
RMSE	Root Mean Square Error
SD	Statistical Downscaling
SDSM	Statistical Downscaling Model

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Appendix A

Statistical Downscaling Model

A. 1. Introduction

A statistical downscaling model carries out as a decision support tool for the assessment of regional climate change impact using a statistical downscaling technique. Figure A-1 shows the steps of SDSM in predicting the future climate.

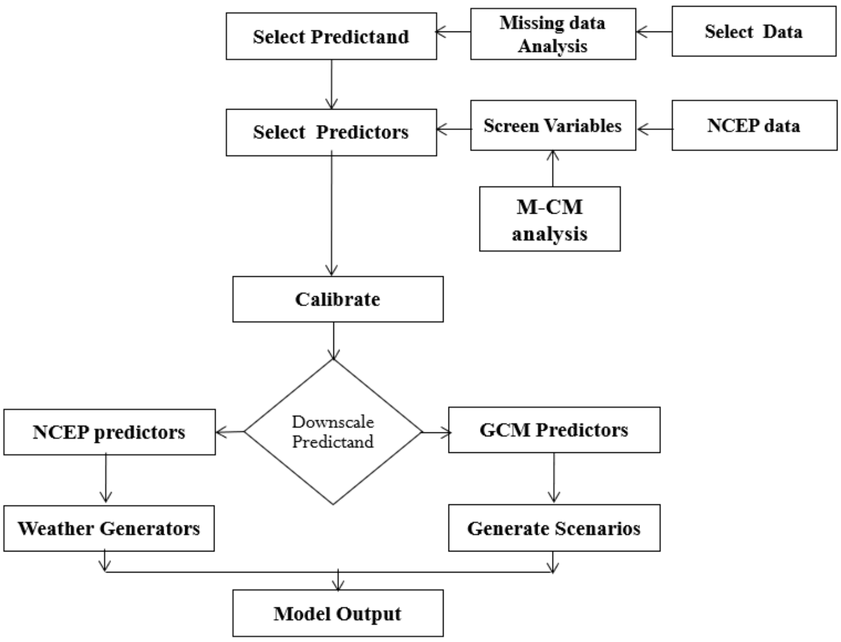

Fig. A-1. Flow chart of the SDSM modelling for climate projection.