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CLIMATE CHANGE IMPACTS ON HYDROPOWER GENERATION AT KENYIR LAKE

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Abstract

Climate change is triggered by human activities that produce greenhouse gas emissions and affect people in various ways. It is crucial to study the severity of rainfall in the certain potential areas that exposed to hydro-meteorological disasters in climatic trends transition. The objectives of the study are to evaluate the severity of rainfall trends and also to predict the fluctuations of hydropower generation in Kenyir Lake triggered by the variations of climatic factors under selected Representative Concentration Pathways, RCPs (RCP2.6, RCP4.5 and RCP8.5) suggested in the Intergovernmental Panel on Climate Change's (IPCC) fifth assessment report. The historical daily data of seven rainfall stations for 30 years' period (1988 - 2017) and global climate model data for RCP2.6, RCP4.5 and RCP8.5 also for 30 years' period (2041-2070) were used. The statistical downscaling model (SDSM) was used to analyse the data. The predicted rainfall data from 2041 to 2070 then compared with the base period rainfall (1988-2017). Kenyir Lake received highest amount of rainfall in November to January during north-east monsoon. The significance differences were recorded in November and December where abrupt fall of rainfall distribution predicted to happen for all RCPs. The results proved that the higher emissions level will give the more effect to the climate trend as previous researcher found that warming will remain beyond 2100 for all RCP scenarios except RCP2.6. The lowest generated value at Kenyir is in 1997 and the highest value is in 2017. The increment of NUG clearly happens in 10 years' interval where there was 78.67% of increment in 2007 compared to 1997. There is an increase that occurs although there are fluctuations every year. Increases in temperature because of climate change effects will increase the energy demand. Rising temperatures gives the varies patterns of demand because higher temperature will create higher cooling demand. Besides that, power generation can change accordingly by the decreasing stream flow and increasing water temperature. It shows that climate change tremendously affects the energy demand patterns and supply systems.

Keywords: Climate change, Hydropower, NUG, RCP, SDSM.

1. Introduction

Malaysian weather hot and humid all year long with high rainfall amount makes it rich in hydro potential. Electricity generation through hydropower in Malaysia was started early in July 1900 [1]. After crude oil, natural and coal, the fourth energy sources in Malaysia is hydropower [2]. The hydropower generated extents to about 1911 MW [3], covering industrial, domestic, and commercial uses.

Hydropower is one of the most effective technologies in power generation. It can be used to generate electricity or to power machinery or both at the identical time. It is the only renewable energy technology and most effective technologies in power generation that is presently commercially viable on a large scale. It is the least costly way of storing large amounts of electricity and can easily adjust the amount of electricity production based on the amount of demand. In 2016, 13% of total Malaysian power generation contributed by hydropower generation [4]. The population growth and rapid economic development in developing countries led to increased energy demand. Developing countries are suitable for the application of renewable energy systems due to high demand of sustainable energy [5]. According to Fan et al. [6], the increasing of power demand can stimulate hydropower generation.

One of the critical features that affects hydropower is rainfall [7]. With other factors remain unchanged, it is expected that hydropower generation increase if there is an increasing in rainfall. Hydropower daily operation relies on climate conditions and weather. So, it is very sensitive to climate fluctuation [8]. The geographical condition is the main issue in the increasing of development of the hydropower station in Malaysia [9]. Kaunda et al. [5] quote that hydropower supply potential is subtle to climate change because it depends on run-off water, which is rely on precipitation and temperature. The duration and levels of precipitation are affected due to global warming. Also, the increase in global temperature can cause water loss through evaporation.

Climate change is triggered by human activities that produce greenhouse gas emissions. Long-term precipitation changes are driven mainly by the increase of the surface temperature besides other factors. Recent research suggest that CO_2 increase has a significant direct impact on atmospheric circulation, and on tropical and global precipitation changes [10].

Representative concentration pathways, RCPs

The reason of the RCP been classified is to give informational data on potential expansion trails of climate changes' key forcing agents. The RCPs are significant in climate study. The main input in climate study to afford possible explanations of how the upcoming might change are socio-economic and emission scenarios. It also depends on series of variables including socio-economic variant, revolution of technology, energy and land use, greenhouse gases emissions and air pollutants. All of them are the input for climate model and as an origin for estimation of possible climate effects, find the alternatives to mitigate the effects and related costs. Climate modellers will refer the time series of upcoming of air pollutants, land-use change, greenhouse gases emissions and concentrations, from the RCPs to try different climate model trials and managed to produce another climate scenario [11]. The RCPs are entitled based on target level of radiative forcing for 2100. Main characteristics of every RCP listed in Table 1.

Table 1. Main characteristics of each RCP [11-13].

	RCP2.6	RCP4.5	RCP8.5
Description	Peak radiative forcing: ~3 W/m^2. A strict reduction scenario. It preserves global warming <2◦C above pre-industrial temperatures.	Stabilization without overshoot pathway: 4.5 W/m^2. A reduction scenario. A significant GHG mitigation policy is applied.	Rising radiative forcing pathway leading: 8.5 W/m^2. Very high GHG emissions. Scenarios without extra efforts to limit emissions.
Greenhouse gas (GHG) emissions	Very low	Medium-low mitigation. Very low baseline.	High baseline
CO_2-eq Concentration (ppm)	480–530 (~490 before 2100)	580–720 (~650 at stabilization after 2100)	>1000 (~1370 by 2100)
Agricultural area	Medium for pasture and cropland	Very low for both pasture and cropland	Medium for both pasture and cropland
Air pollution	Medium-Low	Medium	Medium-high

2. Materials and Methods

2.1. Study area

Kenyir dam is the largest hydroelectric dam in Peninsular Malaysia and second largest in Malaysia located in Terengganu. It is a multipurpose dam managed by electricity power provider. It was built mainly for hydroelectric generation besides providing water resource regulation benefits and flood mitigation. The lake was formed by impounding the Sg. Terengganu; 55 km upstream of Kuala Terengganu and 15 km west of Kuala Berang.

Kenyir dam produces 400 megawatts. The lake holds water up to 13.6 billion m^3 at full supply level (FSL) with catchment area is 2,600 km^2. Completed in 1986, the Kenyir dam is a rock fill clay-core dam with 155 m high. The appurtenant structures are power station building, a spillway and outlet structure. Figure 1 shows the study area location.

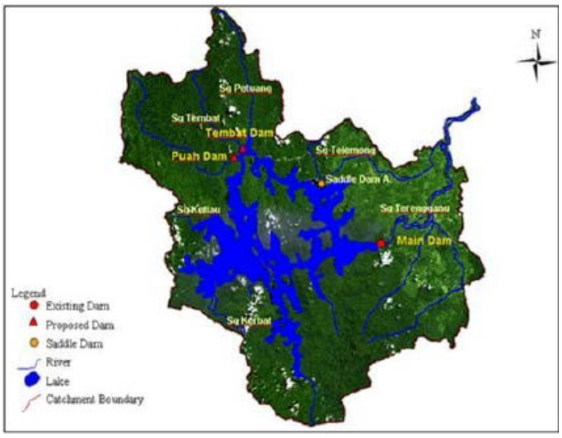


Fig. 1. Kenyir dam.

2.2. Data sources

Climate change is a long spell scale process. So, daily rainfall data from 1988 to 2017 (30 years) were used to study the fluctuation of hydropower generation forecasting. This is to make sure the better reflect on the effect of climate change in 30 years on the hydropower generation. The historical daily data of precipitation gathered from seven rainfall stations observed by electricity power provider. Besides that, Global Climate Model (GCM) data under RCPs of RCP2.6, RCP4.5 and RCP8.5 for the period of 2041-2070 were used to predict the rainfall for that particular year range.

2.3. Methodology

Rainfall downscaling process at the study area were conducted using SDSM version 4.2 [14], because it is a hybrid instrument to forecast the climate variations. SDSM was being vastly used to downscale different climatic parameters like precipitation and temperature to predict future variation in hydrological conditions [15, 16] and much more popular than dynamical downscaling techniques for deriving future climate scenarios [17]. According to Tavakol-Davani et al. [18], SDSM gives the local-scale information, and it is helpful in climate change studies. The value of coefficients of correlation (r) and coefficients of determination (R^2) will show the model performance during validation and calibration process.

$$r = \frac{[n\,(\sum xy) - (\sum x)(\sum y)]}{\sqrt{[n(\sum x^2) - (\sum x)^2][n(\sum y^2) - (\sum y)^2]}} \tag{1}$$

Mann-Kendall (MK) test chose to assess the trends of variables in the historical and simulated data. This is the best method to determine variations in hydrologic regimes [19]. The analysis of trend is conducted to study whether it is decreasing, increasing, or no data value. Important criteria of climate change and variability are precipitation, temperature, and discharge.

Kendall’s Tau rank correlation coefficient evaluate statistical relations according to the data ranks and suitable on independently allocated and numbered variables. The values of correlation coefficients are between -1 and +1. The increasing ranks of both variables indicates that the correlations between the variables is positive while negative correlation shows that as certain variable rank is increased, the rank of other variable will decrease.

The trend magnitude is determined by slope trend detection approaches [20]. Sen’s slope estimator was used to compute the actual gradient of time series data trends. A linear trend slope indicates the scale of the monotonic trend in hydrologic time series and can be calculated by using the following equation [21].

$$\beta \ = median\ \left(\frac{x_j - x_i}{j - i}\right) \tag{2}$$

where β is the median value of the slope values between x_i and x_j at the time steps i and j ($i < j$), respectively. Positive value of β specifies an increasing trend while negative value of β shows a trend is decreasing. The sign of β indicates the trend direction, while its value specifies the trend steepness. The benefit of this technique is that it lessens the missing values impact or the outliers on the slope compared to linear regression.

3. Results

3.1. Calibration and validation

30 years of daily rainfall data were separated into two sets: for the periods 1988-2002 and 2003-2017 for model calibration and validation. The performance of the

calibration and validation process were determined using statistical analysis. r value as in Eq. (1) noting the correlation between two variables. Basically, it is defined between -1 to +1. r value nearest to 1 in either direction will have higher R^2 (close to 1). The value of r and R^2 as in Table 2. For calibration process, the range of R^2 value is 0.81-0.89 while the lowest and highest R^2 value for validation process are 0.81 and 0.93, respectively. R^2 is a statistical measure of fit that indicates how much variation of a dependent variable is explained by the independent variable(s) in a regression model [22]. A high R-squared, between 85% and 100%, indicates the rainfall distribution are based on RCP for calibration and validation process. The results proved that there is correlation between the seven selected rainfall stations in terms of the rainfall distribution at Kenyir Lake. These differences were because of the assorted characteristics of rainfall [23].

Table 2. Results of r and R^2 for model calibration and validation.

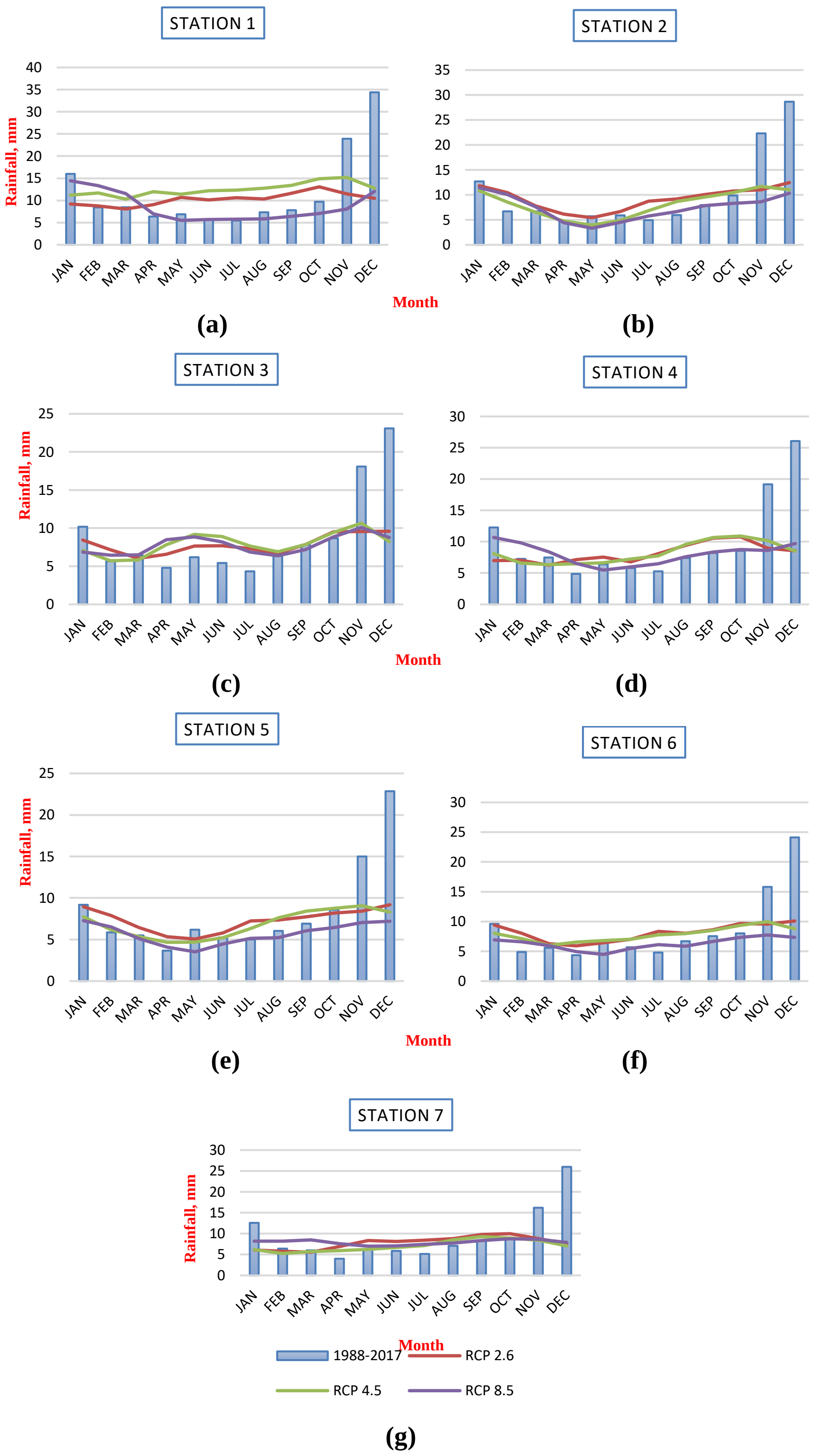
Station	Calibration		Validation	
	r	R^2	r	R^2
1	0.93	0.86	0.94	0.89
2	0.94	0.89	0.97	0.93
3	0.93	0.87	0.93	0.87
4	0.92	0.84	0.95	0.90
5	0.92	0.85	0.95	0.89
6	0.90	0.81	0.91	0.83
7	0.91	0.83	0.90	0.81

3.2. Differences of observed values and RCPs

The study investigated three different RCPs which are RCP2.6, RCP4.5 and RCP8.5 which modelled in the SDSM to observe the upcoming rainfall for the duration of 2041-2070 under several carbon emissions level. The period 1988-2017 is selected as a base period since many researchers found that this is adequate to evaluate the change in climate [24]. So, the comparison of the data is depending on these two durations which are 1988-2017 and 2041-2070. Figures 2(a)-(g) show the rainfall distribution between observed value (1988-2017) and all RCPs (2.6, 4.5 and 8.5).

Terengganu receives heavy rainfall during the north-east monsoon between November and January and the graphs portray that facts. The graphs for all seven stations show that Kenyir Lake received highest amount of rainfall in November to January. December received the highest amount of rainfall for all seven stations with station 1 recorded the highest daily rainfall (>30 mm) while the lowest amount daily rainfall is >20 mm at station 5. Outside monsoon seasons (February-October), the number of daily records varies from 5 mm to 10 mm where April and July received less rainfall amounts than others. These situations are in line with the statement in [25] where April through July are warmest months.

It has been projected that the difference in rainfall is slightly diverse for all RCPs from January to October. The significance differences were recorded in November and December where abrupt fall of rainfall distribution predicted to happen for all RCPs. The findings comply with Fifth Assessment Report (AR5) that changes in precipitation due to climate change scenarios will not be uniform [12]. From the chart, RCP8.5 showed the worst impact compared to RCP2.6 and RCP4.5. Most of the stations are predicted to get the minimum rainfall amount for RCP8.5.



(a) (b) (c) (d) (e) (f) (g)

Fig. 2. The rainfall distribution between observed value (1988-2017) and all RCPs (2.6, 4.5 and 8.5).

3.3. Mann-Kendall (MK) test

The MK test method is a non-parametric test normally conducted to study trends of hydro-meteorological time series data [26]. The trend analysis is implemented to inspect either the trend is increasing, decreasing, or no data value [20]. The summary statistics and MK trend test results for seven stations are listed in Table 3. The mean value for all stations is decreasing from observed data (1988-2017) and predicted data (RCP2.6, RCP4.5 and RCP8.5) where all stations have the lowest mean for RCP8.5 except for station 7. The lowest mean value for station 7 is 7.109 for RCP4.5. Mean value for observed data are 8.3-11.7 while the mean value for RCP8.5 are 5.6-8.5. The value range shows the clear differences between mean values for observed data compared to RCPs mean values. The standard deviation values also decreasing from observed data (1988-2017) and predicted data (RCP2.6, RCP4.5 and RCP8.5). A high value of standard deviation means that the numbers are more spread out. These results reflect the graphs in Figs. 2(a)-(g) where the values for observed data (1988-2017) are more spread out than predicted data (RCP2.6, RCP4.5 and RCP8.5).

Kendall's Tau rank correlation coefficient measure statistical relations by the data ranks and suitable on the separately allocated and are numbered variables. The correlation coefficients values are between -1 and +1 . When both variables rank are increasing, the correlation value is positive. Meanwhile, if the rank of one variable is decreased while the rank of the other is increased, the correlation value is negative. The highest positive value is 0.149 at Station 1 for RCP4.5 and the lowest is 0.013 at Station 7 for RCP2.6 while the negative values are -0.562 and -0.007. The highest and lowest negative values are at Station 6 for RCP8.5 and observed data (1988-2017). This output shows that the highest value Kendall's Tau rank correlation coefficient is -0.562 and proved that RCP 8.5 will give the most effect on the climate especially rainfall where the negative value correlation shows that as the rank of emission is increased, the rank of the rainfall is decreased and vice versa. According to Olaka et al. [27], the predictions for annual rainfall show a progressive to drop lower than the average of the base period at higher emission scenarios. Meanwhile both RCP2.6 and RCP4.5 shows that the ranks of both variables (emission and rainfall) are increasing because correlation between them are positive.

Table 3. Summary statistics and Mann Kendall trend test results of rainfall in Kenyir Lake.

Stn.	Data Description	Mean	Std. deviation	Kendall's tau	Sen's slope	p-value > 0.05, accept H_0 < 0.05, reject H_0	Hypothesis
1	1988-2017	11.704	11.807	0.034	0.009	0.386	accept H_0
	RCP 2.6	10.296	2.638	-0.109	-0.042	0.086	accept H_0
	RCP 4.5	12.518	2.770	0.149	0.069	**0.006**	reject H_0
	RCP 8.5	8.562	3.497	-0.230	-0.052	**< 0.0001**	reject H_0
2	1988-2017	10.183	9.973	0.076	0.034	0.050	accept H_0
	RCP 2.6	9.208	4.289	-0.043	-0.022	0.579	accept H_0
	RCP 4.5	8.154	4.157	-0.296	-0.127	**< 0.0001**	reject H_0

	RCP 8.5	7.399	3.797	-0.500	-0.222	**< 0.0001**	reject H_0
3	1988-2017	8.925	8.409	0.072	0.068	0.090	accept H_0
	RCP 2.6	7.848	2.552	0.016	0.017	0.819	accept H_0
	RCP 4.5	7.941	2.060	0.111	0.024	**0.020**	reject H_0
	RCP 8.5	7.795	1.849	0.020	0.007	0.712	accept H_0
4	1988-2017	9.899	9.543	0.144	0.092	**0.002**	reject H_0
	RCP 2.6	8.182	2.216	0.033	0.004	0.515	accept H_0
	RCP 4.5	8.251	2.305	0.025	0.006	0.513	accept H_0
	RCP 8.5	8.040	1.917	-0.159	-0.028	**0.000**	reject H_0
5	1988-2017	8.335	7.723	0.055	0.017	0.219	accept H_0
	RCP 2.6	7.300	2.678	-0.035	-0.021	0.655	accept H_0
	RCP 4.5	6.860	2.509	-0.223	-0.054	**0.000**	reject H_0
	RCP 8.5	5.673	3.118	-0.514	-0.232	**< 0.0001**	reject H_0
6	1988-2017	8.637	9.235	-0.007	-0.013	0.868	accept H_0
	RCP 2.6	8.112	2.550	-0.099	-0.023	0.140	accept H_0
	RCP 4.5	7.814	1.667	-0.167	-0.028	**0.002**	reject H_0
	RCP 8.5	6.271	2.839	-0.562	-0.230	**< 0.0001**	reject H_0
7	1988-2017	9.375	8.929	0.098	0.046	**0.035**	reject H_0
	RCP 2.6	7.858	1.726	0.013	0.003	0.760	accept H_0
	RCP 4.5	7.109	1.732	-0.029	-0.007	0.497	accept H_0
	RCP 8.5	7.948	0.994	-0.235	-0.034	**< 0.0001**	reject H_0

Sen's slope estimator is given by Eq. (2) was used to estimate the actual slope of time series data trends. The sign values of Sen's slope, β shows whether the trend is increasing (+) or decreasing (-). There are six increasing trends and one decreasing trend for observed data (1988-2017). The opposite situation recorded for RCP8.5 where there are six decreasing trends and only one increasing trend. For RCP2.6 and RCP4.5, there are three increasing trends and four decreasing trends. The results reflect that the emissions bring the great impact to climate trends or specifically rainfall that complies to Figs. 2(a)-(g). Zhang et al. [28] also agreed that under RCP 8.5, significant decreases recorded in precipitation. Aung et al. [29] said that RCP8.5 have steepest increasing trends at later period.

MK test tested the null hypothesis (H_0) of no trend, against the alternative hypothesis (H_a), weather there is a monotonic (increasing or decreasing) trend in the time series. The test interpretation as follow:

H_0: There is no trend in the series

H_a: There is a trend in the series

The last column in Table 3 shows the interpretation of the result from MK test. As stated in 7th column in Table 3, if the calculated *p*-value is larger than the significance level alpha=0.05, the null hypothesis H_0 is accepted while if the *p*-value is lower than 0.05, null hypothesis H_0 is rejected. For observed data (1988-2017), five stations recorded that there is no trend in the series while other two stations show the trend. MK test result for simulated data (2041-2070) indicates the pattern for RCP2.6, RCP4.5 and RCP8.5. None from seven stations show the trend for RCP2.6. There is abrupt transformation when five stations show the trend in the series for RCP4.5 and, RCP8.5 recorded that six stations show the trend while only one station have no trend. The findings proved that higher emissions level will give the more effect to the climate trend. According to IPCC [12], warming will remain beyond 2100 for all RCP scenarios except RCP2.6. In many areas, fluctuating precipitation are varying hydrological systems, affecting quantity and quality of water resources.

3.4. Net unit generated (NUG)

The values of net unit generated (NUG) at Kenyir are recorded by electricity power provider. The lowest generated value is in 1997 and the highest value is in 2017. It was 161.58% of increasing in 21 years. The increment of NUG clearly happens in 10 years' interval where there was 78.67% of increment in 2007 compared to 1997. There is an increase that occurs although there are fluctuations every year. Power generation could be severely regulated by the increasing of river water temperature and decreasing stream flow [30]. Climate change tremendously affects the energy demand patterns and supply systems. Rising temperatures gives the varies patterns of demand because higher temperature will create higher cooling demand and vice versa [31].

4. Conclusions

Kenyir Lake received highest amount of rainfall in November to January during north-east monsoon. December received the highest daily rainfall (>20 mm). Outside monsoon seasons (February-October), the number of daily records varies from 5 mm to 10 mm where April and July received less rainfall amounts. The variation in rainfall is predicted slightly different for all RCPs from January to October but the significance differences were recorded in November and December.

The mean and standard deviation values for all stations are decreasing from observed data (1988-2017) and predicted data (RCP2.6, RCP4.5 and RCP8.5). A high standard deviation means that the numbers are more spread out for observed data than predicted data.

The value of Kendall's Tau rank correlation coefficient proved that RCP 8.5 will give the most effect on the climate. Meanwhile positive correlation indicates that both variables' ranks (emission and rainfall) are increasing for RCP2.6 and RCP4.5. The Sen's slope estimator results reflect that the emissions bring the great impact to climate trends or specifically rainfall. For observed data (1988-2017), the *p*-value for five stations recorded that there is no trend in the series while other two stations show the trend. MK test result for simulated data (2041-2070) indicates the pattern for RCP2.6, RCP4.5 and RCP8.5. None from seven stations show the trend for RCP2.6. There is abrupt transformation when five stations show the trend in the series for RCP4.5 and, RCP8.5 recorded that six stations show the trend while only one station have no trend. These results proved that the higher emissions level will give the more effect to the climate trend.

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Nomenclatures

i	Time steps
j	Time steps
n	Sample size
r	Correlation
R^2	Coefficients of determination

Greek Symbols

β	Median value of the slope

Abbreviations

AR5	Fifth Assessment Report
GCM	Global Climate Model
GHG	Greenhouse Gas
IPCC	Intergovernmental Panel on Climate Change
ISE	Institute of Sustainable Energy
MK	Mann-Kendall
NUG	Net Unit Generated
RCP	Representative Concentration Pathways
SDSM	Statistical Downscaling Model

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