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Impact of Climate Change on Rainfall Trend in Southern of Johor, Malaysia

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Abstract: Climate change has a significant impact on shifting rainfall patterns in humid tropics; as a result, rainfall pattern changes are more noticeable in tropical regions like Malaysia. This study was carried out to forecast rainfall data for selected stations in southern Johor by using Statistical Downscaling Model (SDSM) and assess the trend of historical and future rainfall using a non-parametric test of Mann-Kendall Trend Test. The current study will concentrate on the implementation of a computational framework for downscaling climate data of two rainfall stations in southern of Johor. The data gathered was focused on the historical rainfall data (1988-2017) and projected future rainfall data for the next 30 years, spanning the years 2008 to 2037 and 2038 to 2067. The data were processed and analyzed annually for 30 years period of different time series using the non-parametric Mann-Kendall Trend Test method. Stor JPS Johor Bahru station showed a significant increasing trend for the historical data (1988-2017) and projected future data (2008-2037) and (2038-2067). While for Ldg. Lim Lim Bhd., Masai station, the historical data (1988-2017) showed no significance. However, both time series for projected future rainfall data presents a significant increasing trend.

Keywords: Climate Change, Precipitation, Johor, SDSM, Mann-Kendall Trend Test

1. Introduction

Climate change is occurring at a faster rate than it has ever happened in the history of our civilization, and it is mostly attributable to human activities. Global climate change has already had a wide range of effects in every part of the country, as well as in several industries that are expected to grow in the next decades [1]. In humid tropics, climate change has a significant impact on modifying rainfall patterns; as a result, rainfall pattern changes are more noticeable in tropical regions like Malaysia than temperature changes [2]. Furthermore, changes in rainfall patterns generate disturbances in rainfall frequency, intensity, and amplitude, as well as other climate variables, impacting the quantity and quality of water resources, are due to the impact of climate change on hydrological systems. As a

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result, in recent years, the topic of hydrologic data trend identification has sparked a lot of attention, especially when it comes to predicted changes in global climate. Many studies have revealed that changes in climate have a serious impact on rainfall patterns and river discharge around the world [3]. However, the majority of research concentrated on climate change's implications and did not include the study of historical and projected rainfall trends [4]. Climate change will have varying effects, with some areas enjoying higher rainfall and others enduring severe droughts. As a result, the irrigation water supply is unpredictable. During the severely hot season, the amount of water in the reservoirs for each location in Malaysia is decreasing day by day. This hot season affects people all across the world, not just Malaysians. As a result, this study analyzing projected rainfall trends and comparing them to historical data on rainfall trends could be a strategic plan to address water shortage challenges and irregular weather changes in the next years. Furthermore, the issue emphasizes that if people all over the world are not aware of changes in the climate, it will have a significant effect on the continuity of future generations' ability to live. However, choosing effective adaptation measures necessitates a thorough grasp of how global climate change will impact the local ecology.

The current study concentrated on the implementation of a computational framework for downscaling climate data at the regional size at southern Johor, Malaysia, to see how climate change affects the trend of rainfall over time. The method was implemented using the SDSM, which correlates large-scale climatic variables from the Global Circulation Models (GCM) with the local climate variables [5]. This connection was established using a statistical model that can be used to create future data for climate prediction. There are two stations located in Johor Bahru district, Johor, that will be used in this study to analyze the rainfall trend. The data gathered was focused on the next 60 years, spanning the years 2008 to 2067. Furthermore, the non-parametric Mann–Kendall approach had attracted attention in recent years for trend analyses since it does not require normally distributed datasets and had limited specificity to inhomogeneous time series breakdowns. The Mann–Kendall trend test had the advantage of being able to be run on any time scale. As a result, in this study, SDSM was used to collect the rate of precipitation data and evaluate them using the non-parametric test in order to analyze the outcome of changes in the climate on precipitation rates in Johor. The objectives of the research are to forecast rainfall data for selected stations in Johor using Statistical Downscaling Model (SDSM), and to assess the trend of historical and future rainfall using a non-parametric trend test.

Besides, the Man-Kendall test has been used to identify rainfall trends in a variety of situations, including monsoon rainfall in Kerala, India, daily and monthly rainfall concentration in southern Italy, and climate variability in Iran's desert and semi-arid environments, to name a few. To account for the seasonal impact, a non-parametric test was designed, then it was evaluated and refined [6]. The previous studies using Mann-Kendall Trend Test discussed the features and trends of monthly and annual rainfall in Johor Bahru and Kota Bharu. Daily rainfall readings at the stations were used during a period of 13 years, from 2004 to 2016. In Johor Bahru and Kota Bharu, respectively, the minimum and maximum total annual rainfall were 1708.0 mm and 3455.5 mm, and 1036.3 mm and 3037.0 mm. According to the Mann-Kendall test, the monthly and annual rainfall patterns at both sites are minor [7].

Climate change's impacts may be observed throughout the globe, and no state is safe from the effects of climate change. The increase in temperature, broad changes in precipitation patterns, an additional risk of drought, rising sea levels, and more frequent bad weather are all expected consequences [8]. Nowadays, changes in the climate affect the rainfalls' pattern. The impacts of these changes include the extreme occurrence of flooding and droughts. Flooding and droughts have become more common as a result of these changes. Indeed, predicting rainfall using a reliable and accurate method is essential for anticipating the effects.

1.1 Global Circulation Models (GCMs)

The Global Circulation Model (GCM) is a set of models for predicting climate change and studying climate variability. GCMs are numerically coupled models that can mimic the climate change phenomena, such as air circulation cells, intertropical convergence zones, and jet streams at the continental scale, as well as oceanic circulation features such as the conveyor belt and thermohaline circulation, reasonably well [9]. Dynamical and statistical downscaling, two methods for bridging the gap between regional and local scales and GCM scales. In dynamical downscaling, a high-resolution numerical model or Regional Climate Model (RCM) with a range of 5-50 km is connected with the GCM. Statistical downscaling is well-known for its ease of use and low cost. The approaches included were the ones that have been commonly used and embraced by a larger group of scientists [10]. A wide range of downscaling strategies are available for both dynamical and statistical downscaling, a rising number of model comparisons based on generic data sets and diagnostics have emerged. Each of these methodologies has its own advantages and disadvantages.

Statistical downscaling techniques have many advantages over dynamical downscaling methods. In cases where low–cost, fast assessments of localized climate change implications are required, statistical downscaling looks to be the more appealing option. The Aggregation of Plants in Soils RCM downscaling is the process of reducing the size of a computer program GCM SDS Model Grid for Climate Change using grid resolution GCM output, scale climate change scenarios for individual sites on daily timescales [11]. In past studies at Limbangan River Basin b using SDSM, shows that the comparison of these two-time spans, 1976-2005 and 2071-2100, is used to estimate future rainfall. The results reveal that due to climate change, the overall amount of rainfall in this Limbang region will increase from 2071 to 2100 in comparison to the baseline period [12].

2. Methodology

The state of Johor is located near the southern end of Peninsular Malaysia, having a total size of 19 984 km². Due to its position near the equator and marine exposure, the state has consistent year-round temperatures, pressure, high humidity, and plenty of rain. Hence to that, rainfall data were collected from a total of two sites positioned in the district of Johor Baharu, Johor (Table 1). Rainfall data for the next 60 years were compared.

Table 1: The selected rainfall stations in Johor

No.	Station ID	Station's Name	Coordinates	
			Longitude (E)	Latitude (N)
1.	1437116	Stor JPS, Johor Bahru	103 45 10	01 28 15
2.	1539136	Ldg. Lim Lim Bhg., Masai	103 59 30	01 31 15

2.1 Data Collection

There are a total of three sets of data, which are rainfall station data, NCEP data, and GCM data. Firstly, the historical data from the selected rainfall station is retrieved from the Department of Irrigation and Drainage (DID). The data collected from DID is available from the year 1967 until 2017 based on the station selected. In the SDSM, historical data is used for the quality control method before the calibration and validation are done. Next, the National Centre for Environment Prediction (NCEP) data that will be used for SDSM can be taken from their official website by specifying the coordinates for the area needed. The NCEP data was provided from the year 1964 to 2017. The NCEP data is used during the screening variables, where all 26 variables will be screened to make the best five predictors. Then, it is used in the calibration and validation of the historical rainfall data. Lastly, the GCM data was retrieved from the official website of the second-generation Canadian Earth System Model (CanESM2). The data period for future projection using GCM is from the year 2006 to 2100. There are three sets of Representative Concentration Pathway (RCP) scenarios, named RCP 2.6, RCP 4.5, and RCP 8.5.

2.2 Statistical Downscaling Model (SDSM)

SDSM is a tool for downscaling rainfall from global circulation models to the regional level. It includes both a stochastic technique and multiple linear regression (MLR). The first stage in SDSM is to establish a quantifiable link between predicted and predictor variables. The SDSM is further subdivided into three sub-models: yearly, seasonal, and monthly. A regression equation is driven by all of these models. However, the annual sub-model produces a single equation for the entire year, whereas the seasonal sub-model derives the equation independently for every season. The monthly sub-model, on the other hand, generates the equation for each month separately. Furthermore, depending on the type of parameter to be downscaled, the sub-models may be conditional or unconditional. For example, the conditional model is suitable for downscaling rainfall, while the unconditional model is appropriate for temperature downscaling [12].

Since the impact scales are too small for the climate model to resolve or the model contains errors, downscaling is justified when GCM (or RCM) simulations of variables used in effects modelling are impractical at the temporal and spatial scales of interest. Downscaling can also be used to create scenarios because the impact scales are too small for the climate model to resolve or because the model has errors. Downscaling can also be used to build scenarios for exotic variables that cannot be derived directly from GCMs and RCMs, such as urban heat island intensity. The host GCM, on the other hand, must have a track record of handling large-scale variables that are closely associated with local processes. In practice, the availability of archived observational and GCM data influences the downscaling technique chosen, as both are required to construct future climate forecasts. The SDSM software breaks down the statistical downscaling of the daily weather series into seven steps (Figure 1). In SDSM procedures, the data must be processed with the variables. There is a total of 26 variables that will be screened through screen variables.

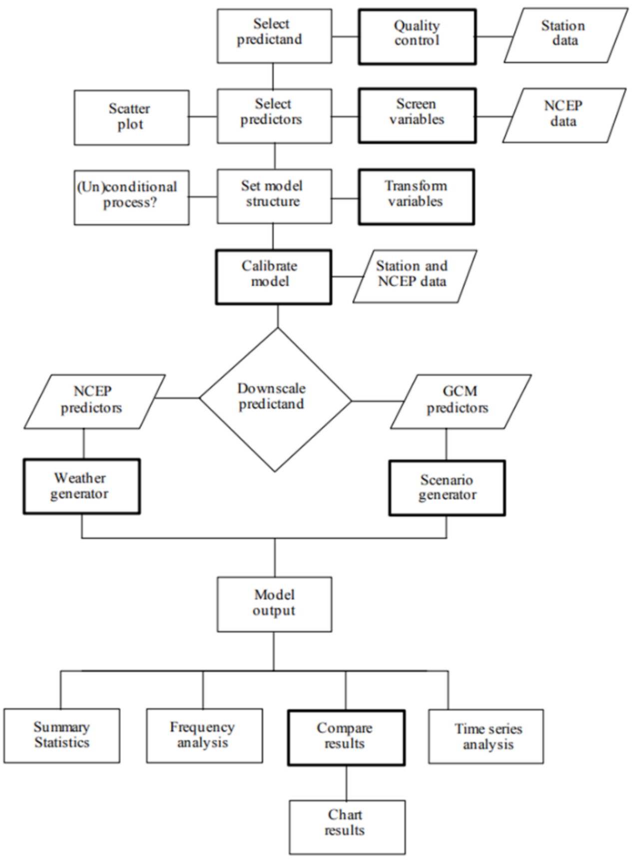

Figure 1: Steps in SDSM to process and generate data for historical and projected future rainfall data

2.3 Non-parametric Mann-Kendall Trend Test

The Mann-Kendall trend test is a non-parametric test for detecting a trend in a series. It works for all distributions, even those with a seasonal component. However, there should be no serial correlation in the data. If the data points are too tiny, the test is less likely to indicate a trend because, in the MK test, the greater the number of data points, the more likely the test will show an actual pattern. The significance of discovered patterns can frequently be accomplished at several levels of significance, which is 0.05. The World Meteorological Organization has proposed it as a method for identifying statistically significant patterns in time series of climatic and hydrologic data.

Using the formula below (Eq. 1), the Mann-Kendall test statistic (S) is calculated [13]:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \qquad (Eq. 1)$$

where,
x_i , x_j = values of i and j(j > i) in time series,
sgn ($x_j - x_i$) is the sign function.
n = number of data points.

$$sgn\left(x_j - x_i\right) = \begin{Bmatrix} +1, if\ x_j - x_i\ >\ 0 \\ 0, if\ x_j - x_i\ =\ 0 \\ -1, if\ x_j - x_i\ <\ 0 \end{Bmatrix} \qquad (Eq. 2)$$

If sample size n > 10, the mean and variance are given by.
μ (s) = 0

$$\sigma^2(s) = n(n-1)(2n+5) - \frac{\sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)}{18} \qquad (Eq. 3)$$

where,
t_i = number of ties of extent i,
m = number of tied groups.

A tied group is a collection of data with the same values. If the values of ties between the observations are missing, then

$$\sigma^2(s) = \frac{n(n-1)(2n+5)}{18} \qquad (Eq. 4)$$

The standard normal test statistic Zs is computed as:

$$Z_s = \begin{Bmatrix} \dfrac{s-1}{\sqrt{\sigma^2(S)}} & if\ \ s\ >\ 0 \\ 0 & if\ \ s =\ 0 \\ \dfrac{s+1}{\sqrt{\sigma^2(S)}} & if\ \ s\ <\ 0 \end{Bmatrix} \qquad (Eq. 5)$$

The increasing and declining trends are represented by positive and negative Zs values, respectively. The trend analysis was done at a 5% level of significance, and the null hypothesis of no trend was rejected at this level. If | Zs | is greater than 1.96.

3. Results and Discussion

The analysis and results of the data were obtained from the Statistical Downscaling Model (SDSM) software. This research used the non-parametric tests, the Mann-Kendall trend test method, to determine the trend of the historical and future rainfall data. The emission scenario of RCP 2.6 was selected to project the future rainfall data for two periods: RCP 2.6 (2008-2037) and RCP 2.6 (2038-2067).

3.1 Screening of Predictors

After completing all the processes, including retrieving missing data and obtaining climate data NCEP from the SDSM official website, the climate predictors were initially screened by screen variables in SDSM, with all twenty-six (26) predictors being checked to select the best five (5) predictors. The correlation, partial correlation (r), and p-values are all dependent on this stage will assist in accurately identifying the most effective predictors on predictands. Predictors having a high correlation with the predictand were chosen, and the calibration procedure was carried out. P values, as Wilby et al. point out, were a measure of statistical significance [11]. The predictor's and predictand's correlation strength is measured. A lower P-value ($P<0.05$) indicates a stronger relationship between variables. The annual rainfall data from two selected stations in Johor were generated to choose the highest correlation coefficient using five predictors presented in Table 2. The best-correlated predictor variables were chosen based on the p-value and partial r, with the super predictor (SP) being the first ranked predictor in each station. The ncepp_temp (mean temperature) was the super predictor for the Johor Bahru areas, while for area Masai, the super predictors were ncep_prec (precipitation, mm).

Table 2: The list of predictors for two selected rainfall stations in Johor

Rainfall Station	Predictors	Partial r	p-value
Stor JPS Johor Bahru	ncep_temp	-0.084	0.0000
	ncep_p500	0.048	0.0026
	ncep_mslp	-0.029	0.0799
	ncep_p850	0.016	0.3017
	ncep_shum	0.016	0.3094
Ldg. Lim Lim Bhd, Masai	ncep_prec	0.121	0.0000
	ncep_shum	-0.040	0.0415
	ncep_p500	-0.028	0.1491
	ncep_temp	-0.026	0.1771
	ncep_mslp	0.022	0.2606

3.2 Calibration and Validation of SDSM

The calibration procedure evaluated the SDSM software’s performance using observed rainfall data. Two data sets, 1988-2002 and 2003-2017 were used for rainfall calibration based on the available observed daily historical data to ensure the accuracy of the outputs. For each data set, predictors were separated by 15 years. For the calibration process, the observed daily historical data for 30 years (1988-2017) was used. The result of the root means square method (RMSE) from the process is tabulated in Table 3. it shows that both stations have an RMSE value that is close to zero. This means that the data of future rainfall data projection has high accuracy, as the predictors will be accurate if the RMSE value is smaller.

Table 3: Statistical comparison of observed data and modeled data for mean annual rainfall during calibration

Stations	NCEP (1988-2002)	NCEP_(2003-2017)
	RMSE	RMSE
Stor JPS Johor Bahru	0.006	0.007
Ldg. Lim Lim Bhd.	0.042	0.013

Validation of SDSM can be carried out under the weather generator tab. Its functionality is to verify the calibrated model and reconstruct predictands or fill in the missing data. The result from the validation can be compared between the observed, which is data obtained from the rainfall station and model data generated through the SDSM software and produce a line chart.

The observed data from Stor JPS Johor Bahru rainfall station was compared with the NCEP model data from the year 1988 until 2002 (Figure 2). It is noted that the closer the line chart of both data to each other, the smaller the value of RMSE. Therefore, there is a high possibility to show an accurate result made from the predictions. Figure 2 presents the line chart for the comparison of the observed data and modeled data for the year 2003 until 2017. The calculated RMSE was 0.007, which showed the result produced to have high accuracy.

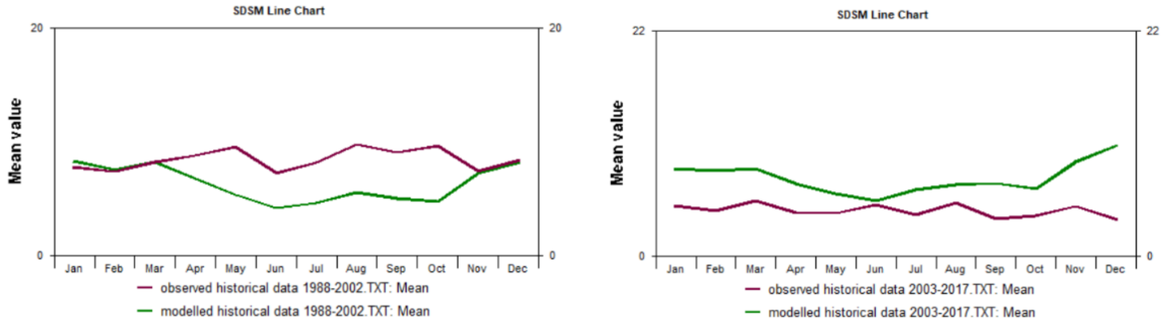

Figure 2: Comparison between observed and modeled data for Stor JPS Johor Bahru using NCEP (1988-2002) and NCEP (2003-2017)

As in Figure 3, the observed data from Ldg. Lim Lim Bhd., Masai rainfall station is compared with the NCEP model data from the year 1988 until 2002. For this station, there is a significant gap between both data. However, the difference between the two mean values is not that big. Hence, it still can provide an accurate result for rainfall trends as it has a small value of RMSE, which is 0.042. The line chart for the comparison of the observed data and modeled data for the year 2003 until 2017 shows a little difference between both data. In addition, the RMSE value shows the value of 0.013, which can support that there is a possibility for the result produced to have high accuracy.

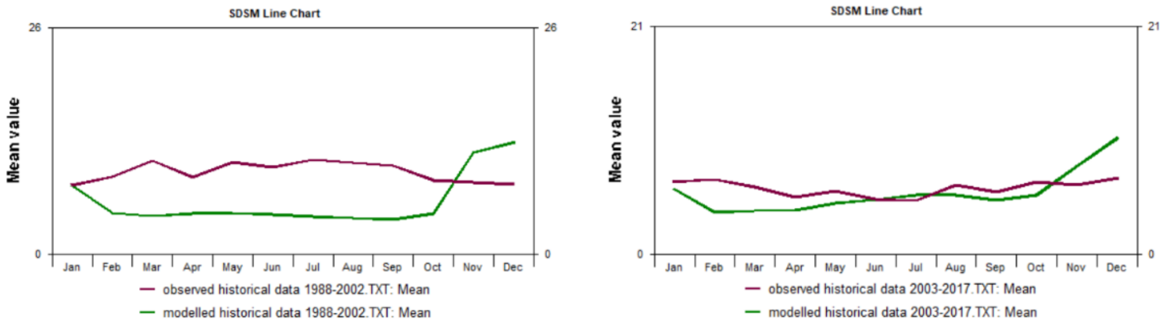

Figure 3: Comparison between observed data and modeled data Ldg. Lim Lim Bhd., Masai using NCEP (1988-2002) and NCEP (2003-2017)

3.3 Projection of Annual Rainfall Data

The projection of future rainfall data is made through scenario generators in SDSM software with GCM predictors. The GCM's future rainfall data outputs were projected 60 years ahead, commencing in 2008 and ending in 2067. Pollution scenarios (RCP 2.6) were used to forecast future rainfall, with a radiative forcing average of around 3 W/m² in 2050, declining to 2.6 W/m² by 2100. During future projection periods, two base periods, such as GCM (2008-2037) and GCM (2038-2067), were used to determine various emission scenarios for selected rainfall stations in Johor.

The data were processed in two periods of 30 years to produce more accurate results. The generated data came out in daily data, so the mean calculation for annual data is done and presented in the table. As indicated in Table 4, the summary statistics factors such as mean, maximum, and minimum data were tabulated among historical and projected rainfall data using RCP 2.6 for comparison.

Table 4: Statistic for the rainfall stations with historical and projected future rainfall data (mm/year)

No.	Station Name	Statistics	Historical Data (mm/year)	Projected future data RCP 2.6 (mm/year)	
			1988 - 2017	2008 - 2037	2038 - 2067
1	Stor JPS Johor Bahru at Johor	Mean	2556.20	2505.89	2480.72
		Maximum	3438.00	3439.56	3504.09
		Minimum	1651.23	1388.56	1639.11

2	Ldg. Lim Lim Bhd. at Masai, Johor	Mean	2134.06	2024.81	2043.43
		Maximum	2772.60	2629.60	2311.50
		Minimum	1256.28	1072.13	1744.26

For Stor JPS Johor Bahru rainfall station, the mean value for historical data (1988-2017) presents the highest data, which is 2556.20 mm per year compared to the projected future data using RCP 2.6. The mean value for both two periods for the projected future data using RCP 2.6 (2008-2037) and (2037-2067) were 2505.89 mm per year and 2480.72 mm per year, respectively. Next, the mean value for historical data (1988-2017) was 2134.06 mm per year. On the other hand, the mean values for projected future rainfall using RCP 2.6 for the period 2008 until 2037 was 2024.81 (mm/year), and the period 2038 until 2067 was 2043.43 (mm/year). It shows that the mean value of historical data is higher than the projected future rainfall data. From these results, both stations in Johor display a decrease in the volume of precipitations received at the areas. As the data processed used RCP 2.6, it proves that climate change has a major effect on precipitation amounts in both places.

3.4 Trend analysis for Historical and Future Annual Rainfall Data

The results of historical and future annual rainfall data were analyzed by using a non-parametric trend test. Mann-Kendall trend test analysis was conducted to analyze the trend of rainfall data generated from SDSM software. The data produced from SDSM were in the form of rainfall daily data for every 30 years it was processed. From daily data, the calculation and formula are used to find the mean or average annual rainfall for every year. The rainfall trend for each station was determined by using the time-series lot, Mann-Kendall Trend Test in XLSTAT software add-in in Microsoft Excel. Results obtained show a significant trend at a 95% confidence level for both stations. A trend line was also made to indicate the pattern. Before the trend test was considered significant, the p-values must be smaller than 0.05.

Table 5: Historical and projected future data trend analysis

Station	Period (Year)	p-value	Kendall's tau (Z)
Stor JPS Johor Bahru	Historical (1988-2017)	0.031	0.286 (↑)
	Future (2008-2037)	<0.0001	0.571 (↑)
	Future (2038-2067)	0.019	0.310 (↑)
Ldg. Lim Lim Bhd.	Historical (1988-2017)	0.159	-0.187 (-)
	Future (2008-2037)	<0.0001	0.576 (↑)
	Future (2038-2067)	0.004	0.379 (↑)

***significant increase trend ($Z \geq \pm 1.96$)(↑)**
***significant decrease trend ($Z \leq \pm 1.96$)(↓)**

In Figure 4, the analysis for Mann-Kendall Trend Test resulted a significant trend in the historical rainfall trend from 1988 to 2017 at Stor JPS Johor Bahru. The data shows a positive trend line with Kendall’s tau value of 0.286, and the p-value for this station is 0.031, which is lower than the significant level alpha equal to 0.05. This implies that there is a significant level of volume of the precipitation. In addition to that, Figure 5 shows the non-parametric trend analysis has resulted in positive patterns for projected future rainfall data on the same station for two different periods, 2008 to 2037 and 2038 to 2067. From Table 7, Kendall’s tau values were 0.571 for the first period and 0.310 for the later period. Both periods have computed p-values lower than 0.05, which were less than 0.0001 and 0.019, respectively.

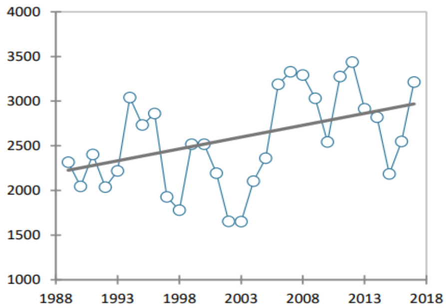

Figure 4: Mann-Kendall trend test analysis for historical data (1988-2017) at Stor JPS Johor Bahru rainfall station

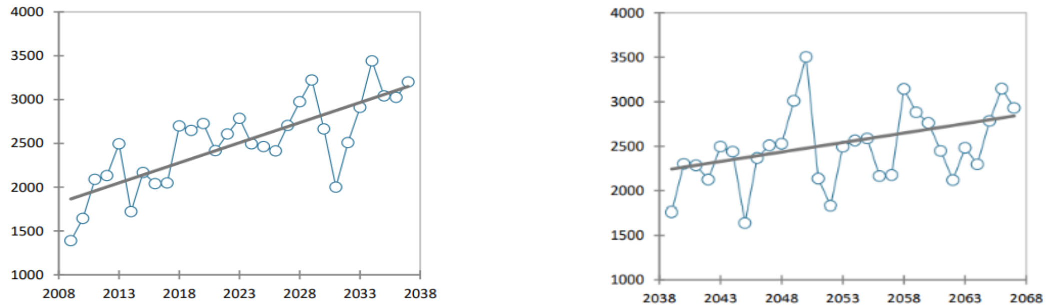

Figure 5: Mann-Kendall trend test analysis for projected future rainfall data using RCP 2.6 (2008-2037) and (2038-2067) at Stor JPS Johor Bahru rainfall station

As in Figure 6, the historical data analysis on Ldg. Lim Lim Bhd. station trend gave Kendall's tau value of -0.187. Therefore, the null hypothesis was accepted that there is no trend of precipitation from 1988 to 2017. The analysis on the projected rainfall for the year 2008-2037 and 2038-2067 have resulted in the trend of precipitation on the Ldg. Lim Lim Bhd. station (Figure 7). From Table 5, Kendall's tau values were 0.0.576 for the year 2008-2037 and 0.379 for the year 2038-2067. For both periods, the p-value that accumulated is smaller than significant level alpha equal to 0.05, which were less than 0.0001 and 0.004, respectively. This indicates that the volume of precipitation in the station's area has a significant trend.

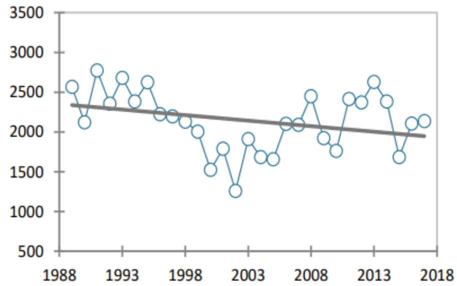

Figure 6: Mann-Kendall trend test analysis for historical data (1988-2017) at Ldg. Lim Lim, Masai rainfall station

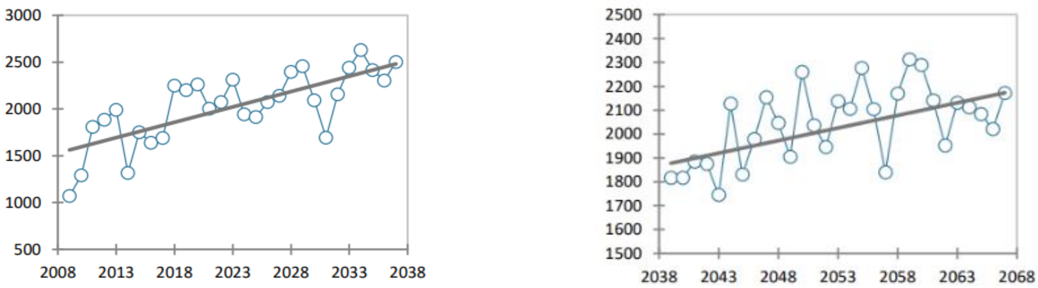

Figure 7: Mann-Kendall trend test analysis for projected future rainfall data using RCP 2.6 (2008-2037) and (2038-2067) at Ldg. Lim Lim, Masai rainfall station

4. Conclusion

In conclusion, this study objective to forecast rainfall data for selected stations in Johor using the Statistical Downscaling Model (SDSM) and to assess the trend of historical and future rainfall using a non-parametric trend test was achieved. The first objective was achieved when the projection of future rainfall data had successfully been generated by SDSM software. For this study, the emission scenario RCP 2.6 was used to look into the effects of climate change on precipitation that had successfully projected future rainfall that determined the annual rainfall changes in the selected areas. It concludes that SDSM able to generate the projected future rainfall for upcoming years with the effect of climate change variables provided from the SDSM and CanESM2. For the second objective, the trend of historical and future rainfall data was successfully assessed by using the non-parametric Mann-Kendall trend test method. The result of significant increases and decreases of the trend of time series was obtained for the historical data (1988-2017), future rainfall data using RCP 2.6 (2008-2037), and future rainfall data using RCP 2.6 (2038-2067). The first station had a significant trend for both historical and future rainfall data, while the second station showed a positive significant positive trend for future rainfall data only and no significant trend for historical data.

Therefore, the conclusions can be drawn from this study as the overall objectives have been achieved. The results from this study may be used to compare the data for further research at the selected station, especially at Ldg. Lim Lim Bhd., Masai, there are still not many rainfalls analysis found around the area. The forecasting of rainfall data through the SDSM method can include the factors of climate change by using the varieties emission scenarios to ensure the sustainability of resources and increase the awareness to minimize the activities prone to climate change. To adapt the future climate change and the lack of rain or drought, there are several recommendations for the community. The most important thing to do is create advanced planning to survive during dry years. From now, try to practice ourselves to minimize the water consumption for every household, starting by self-reminder to save water as much as possible while using the toilet. Next, legal authorities need to take firm action toward the illegal activities of deforestation that may destroy the natural groundwater recharged. This action may also lead to lower the risk for a landslide to happen at the hillside. Therefore, everyone needs to be more aware of the impact of climate change on the world, especially in terms of the rainfall trend, as water plays the biggest role in the continuity of lives.

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