Prediction of Future Climate Change for Rainfall in the Upper Kurau River Basin, Perak Using Statistical Downscaling Model (SDSM)

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Abstract Climate change is considered to be one of the biggest threats faced by nature and humanity today. The goal of this study is to predict future climate change for rainfall in the Upper Kurau Basin. In this research, the applicability of statistical downscaling model (SDSM) in downscaling rainfall in the Upper Kurau River basin, Perak, Malaysia was investigated. The investigation includes calibration of the SDSM model by using large-scale atmospheric variables encompassing the National Centers for Environmental Prediction (NCEP) reanalysis data. Rainfall data were derived for three 30-year time slices, 2020s, 2050s and 2080s, with A2 and B2 scenarios. A2 is considered among the “worst” case scenarios, projecting high emissions for the future. Unlikely, B2 projected a lower emission for the future and it is considered as “environmental” case scenarios. Results from simulation showed that during the calibration and validation stage, the SDSM model was well acceptable in regards to its performance in downscaling of daily and annual rainfalls. Under both scenarios A2 and B2, during the prediction period of 2010–2099, changes of annual mean rainfall in the Upper Kurau River basin would present a trend of increased rainfall in 2020s; insignificant changes in the 2050s; and a surplus of rainfall in the 2080s, as compared to the mean values of the base period. Annual mean rainfall would increase by about 33.7% under scenario A2 and increase by 27.9% under scenario B2 in the 2080s. Most of the areas of the Upper Kurau River Basin were dominated by increasing trend of rainfall and will become wetter in the future.

Keywords Climate Change, Malaysia, Rainfall, Statistical Downscaling Model

1. Introduction

Global warming will have a significant impact on local and regional precipitation and hydrological regimes, which in turn will affect ecological, social and economic systems of human, such as health of ecosystems and fish resource management, industrial and agricultural water supply, resident living water supply, water energy exploitation, human health, etc. These potential changes will affect some qualitative and quantitative estimation on the impact of climate change upon regional water resources [1]. The direct impact of climate change can be variation and changing pattern of water resources availability and hydrological extreme events such as floods and droughts, with many indirect effects on agriculture and water supply [2].

The Global Climate Models (GCMs) are the optimal tools to estimate future global climate changes resulting from the continuous increase of greenhouse gas concentration in the atmospheres [3]. There are currently two major popular downscaling approaches, namely statistical downscaling (SD) and dynamic downscaling (DD). “Statistical downscaling” adopts statistical relationships between the regional climates and carefully selected large-scale parameters [4]. Dynamical downscaling methods, on the other hand, are extremely computationally intensive and have data requirements which may not be easily available [5]. Compared to other downscaling methods, the statistical method is relatively feasible to be used as it provides station-scale climate

information from GCM-scale output [6]. Statistical method has comparable accuracy to that of dynamical downscaling [7,8,9]. Many studies have shown that this model is simple to handle and operate, and its large and superior capability makes it have been widely applied [10,11]. These studies indicated that there would be an increase in future rainfall simulation using SDSM model applications. Huang et al. (2011) showed that the annual mean precipitation in most parts of the Yangtze River basin would be dominated by an increasing trend under both scenarios A2 and B2. A2 is considered among the “worst” case scenarios, projecting high emissions for the future. Unlikely, B2 projected a lower emission for the future and it is considered as “environmental” case scenarios. Hassan et al. (2013) stated that the southern and central of Malaysia will face higher raining compared to the northern Malaysia under both scenarios of A2 and B2.

To date, downscaling algorithm of SDSM has been applied to a host of meteorological, hydrological and environmental assessments, as well as a range of geographical contexts, including the Europe, North America and Southeast Asia [12,13]. The objective of this study is to predict future climate change for rainfall in the Upper Kurau Basin in Perak using Statistical Downscaling Model (SDSM) for the year 2010 until 2099. The main reason for the selection of the Upper Kurau River basin in this research is because the Bukit Merah reservoir is located at the downstream of the basin which acts as the

main drainage for paddy fields and the source of drinking water. The study area used to experience extreme flood and drought that seriously affected the paddy cultivation (staple food), ecosystem and human health. Therefore, good knowledge of future rainfall scenarios in the Upper Kurau basin will be of great importance in better evaluating the risk of floods and droughts.

1.1. Study Area

The Upper Kurau River basin, Perak, as shown in Figure 1, lies between latitude 4° 51' (N) and 5° 10' (N), longitude 100° 38' (E) and 101° 01' (E). The catchment area is approximately 359.2 km², and is drained by the Kurau River and the Ara River. The rivers meet at Pondok Tanjung town, Kurau. The river originates partly in the Bintang Range and partly in the Main Range where the terrain in the upper reaches is steep and mountainous. Mid valleys of the river are characterized by low to undulating terrain, which gives way to broad and flat floodplains. Ground elevations at the river headwaters are moderately high.

From 1961 to 1990, the average annual rainfall was 215 mm. For the same period, the minimum temperature was around 23°C and the maximum temperature was 34°C. The relative humidity fluctuated between 54% and 98% and the wind speed was in the range of 0 to 12 knots during normal weather.

Figure 1. Upper Kurau River Sub-basin in Perak

2. Materials and methods

2.1. Statistical Downscaling Model (SDSM)

Statistical Downscaling Model (SDSM) is a decision support tool which facilitates the rapid development of multiple, low-cost, single-site scenarios of daily surface weather variables under current and future regional climate [14]. It also assesses the regional impacts of global warming by allowing the process of spatial scale reduction of data provided by large-scale GCMs. Statistical downscaling methods rely on empirical relationships between local-scale predictions and regional-scale predictors to downscale GCM scenarios. The SDSM 4.2 reduces the task of statistically downscaling daily weather series into five discrete processes (1) screening of predictor variables; (2) model calibration; (3) synthesis of observed

data; (4) generation of climate change scenarios; (5) diagnostic testing and statistical analyses. SDSM is well documented and has been successfully tested in numerous studies [15].

2.2. Data

The location of rainfall stations in the study area is shown in Figure 2. The observed daily rainfall data from 10 stations were used to predict rainfall change in Upper Kurau River basin as listed in Table 1. The missing data of one day or two days were replaced by the average precipitation values of the neighboring stations. If consecutive days had the missing data, the missing values were replaced with long term averages of the same days. The data was carefully checked and calibrated for avoiding unexpected errors (mainly by human errors).

Figure 2. The location of rainfall gauging stations in Perak

Table 1. Rainfall stations in Upper Kurau River Basin, Perak

No	Station Id	Station Name	Latitude (N)	Longitude (E)
1	4807016	Bkt. Larut, Taiping	04° 51' 45"	100° 47' 35"
2	4907017	Ldg. Windsor, Ulu Sepetang	04° 56' 35"	100° 43' 55"
3	4907019	Ldg. Norseman	04° 57' 55"	100° 45' 50"
4	4908013	Ibu Bekalan Sempeneh, Batu Kurau	04° 56' 05"	100° 49' 40"
5	4908018	Pusat Kesihatan Kecil, Batu Kurau	04° 58' 45"	100° 48' 15"
6	5006021	Kolam Air Bkt. Merah	05° 02' 00"	100° 39' 10"
7	5007020	Ldg. Pondoland, Pondok Tanjung	05° 00' 35"	100° 43' 50"
8	5007029	Ibu Bekalan Jelai	05° 01' 20"	100° 48' 00"
9	5107006	Ldg. Stoughton, Batu Kurau	05° 06' 25"	100° 46' 20"
10	5108005	Ibu Bekalan Ulu Ijok	05° 07' 20"	100° 48' 20"

(Sources: Department of Irrigation and Drainage, DID)

2.3. Selection of Predictors (Parameter)

Predictor variables are available from the Canadian Institution of website for model output. The predictor variables are supplied on a grid box by grid box basis. On entering the location of study area, as Figure 3, the correct grid box will be calculated and a zip file will be made available for downloading. When unzipping this file, there are three directories, which are NCEP_1961-2001, H3A2a_1961-2099, H3B2a_1961-2099. Table 2 listed 26 predictor variables from the NCEP reanalysis and HadCM3 simulation output that are used as potential inputs to the multiple linear regression model. In this study,

HadCM3 is used for predictors. HadCM3 was chosen because the model is widely used in many climate-change impact studies [16]. Furthermore, HadCM3 provides daily predictor variables, which can be used for the SDSM model. In addition, HadCM3 has the ability to simulate for a period of a thousand years, showing little drift in its surface climate. Its predictions for temperature change are average, and for the precipitation, the predictions' increases are below average [17]. The decision process to select suitable predictors is also complicated due to the fact that the explanatory power of individual predictor variables varies spatially and temporally [18].

Figure 3. Asia continent window with 2.5°latitude x 3.75°longitude grid size

Table 2. Large-scale atmospheric variables from the NCEP reanalysis and HadCM3 simulation output that are used as potential inputs to the multiple linear regression model

No	Predictor Variables	Predictor Description	No	Predictor Variables	Predictor Description
1	mslpas	mean sea level pressure	14	p5zhas	500 hpa divergence
2	p_fas	surface air flow strength	15	p8_fas	850 hpa airflow strength
3	p_uas	surface zonal velocity	16	p8_uas	850 hpa zonal velocity
4	p_vas	surface meridional velocity	17	p8_vas	850 hpa meridional velocity
5	p_zas	surface vorticity	18	p8_zas	850 hpa vorticity
6	p_thas	surface wind direction	19	p850as	850 hpa geopotential height
7	p_zhas	Surface divergence	20	p8thas	850 hpa wind direction
8	p5_fas	500 hpa airflow strength	21	p8zhas	850 hpa divergence
9	p5_uas	500 hpa zonal velocity	22	p500as	Relative humidity at 500 hpa
10	p5_vas	500 hpa meridional velocity	23	p850as	Relative humidity at 850 hpa
11	p5_zas	500 hpa vorticity	24	rhumas	Near surface relative humidity
12	p500as	500 hpa geopotential height	25	shumas	Surface specific humidity
13	p5thas	500 hpa wind direction	26	tempas	Mean temperature at 2 m

(Source: http://www.cccsn.ca/Help_and_Contact/Predictors_Help-e.html)

2.4. Calibration and Validation

The model was calibrated using output from NCEP reanalysis data which predictor variable(s) (parameter for climate models) have been screening for 30 years data and were divided into two period times, which were 15 years for rainfall calibration (1961 to 1975) and another 15 years for model rainfall validation (1976 to 1990). The choices of 1961-1990 and 1976-1999 as the calibration and validation periods were made based on the availability of the rainfall data. The selected parameters for all the stations are precipitation (prcp), surface specific humidity (Shum) and wind velocity at 500 hPa. The predictor prcp is the dominant predictor in all the station so it may be said that prcp is the super predictor for this area [19].

During the calibration process, some of the SDSM setup parameters for bias correction and variance inflation were adjusted to obtain a good statistical agreement between the observed and simulated climate variables. In general, the

correlation between the predictor variables and each predictor is not high in the case of daily precipitation. The steps to identify predictor variables that were used in this study being recommended by several researchers [20, 21] are all predictors that are chosen and the explained variance is run on a group of eight or ten of predictors at a time and of each group, high explained variance of predictor(s) is chosen. Then, partial correlation analysis is done for selected predictors based on correction of each predictor. There could be a predictor with a high explained variance, but it might be very highly correlated with another predictor. This means that it is difficult to tell that this predictor will add information to the process, and therefore, it will be dropped from the list. Finally, the scatter-plot is used to show the relationship between potential predictors. The predictor variables identified for downscaling rainfall used in this study were shown in Table 3 and 4 below.

Table 3. Summary of GCM predictor for the downscaling rainfall analysis

Station Name	Predictors
Bkt. Larut, Taiping	<i>ncepp_fas.dat, ncepp5_uas.dat, ncepp8_fas.dat and ncepshumas.dat</i>
Ldg. Windsor, Ulu Sepetang	<i>ncepp850as, ncepp8_uas and ncepshumas</i>
Ldg. Norseman	<i>ncepp5thas.dat, ncepshumas.dat</i>
Ibu Bekalan Sempeneh, Batu Kurau	<i>ncepp_thas.dat, ncepp850as.dat and ncepshumas.dat</i>
Pusat Kesihatan Kecil, Batu Kurau	<i>ncepp_fas, ncepp5_fas and ncepshumas</i>
Kolam Air Bkt. Merah	<i>ncepp_uas.dat, ncepshumas.dat</i>
Ldg. Pondoland, Pondok Tanjung	<i>ncepp_fas.dat, ncepshumas.dat</i>
Ibu Bekalan Jelai	<i>ncepp_fas.dat, ncepp_850as and ncepshumas</i>
Ldg. Stoughton, Batu Kurau	<i>ncepp5_uas.dat, ncepshumas.dat</i>
Ibu Bekalan Ulu Ijok	<i>ncepp_uas.dat, ncepshumas.dat</i>
Ldg. Norseman	<i>ncepp5thas.dat, ncepshumas.dat</i>

Table 4. Types of predictors

Variables	Descriptions
<i>temp</i>	Mean temperature at 2m
<i>mslp</i>	Mean sea level pressure
<i>p500</i>	500 hpa geopotential height
<i>p850</i>	850 hpa geopotential height
<i>rhum</i>	Near surface relative humidity
<i>r500</i>	Relative humidity at 500 hpa height
<i>r850</i>	Relative humidity at 850 hpa height
<i>shum</i>	Near surface specific humidity
<i>s500</i>	Specific humidity at 500 hpa height
<i>s850</i>	Specific humidity at 850 hpa height
<i>**_f</i>	Geostrophic air flow velocity
<i>**_z</i>	Vorticity
<i>**_u</i>	Zonal velocity component
<i>**_v</i>	Meridional velocity component
<i>**zh</i>	Divergence
<i>**thas</i>	Wind direction

** refers to different atmospheric levels: the surface (*p_*), 850 hPa height (*p8*), and 500 hPa height (*p5*).

Meanwhile, for the validation process, Weather Generator is used to produce synthetic current daily weather data based on inputs of the observed time series data and the multiple linear regression parameters produced. During this process, the input file is obtained from the calibration process and the predictor direction is three sets of atmospheric data, NCEP and HadCM3 Scenario A2 and B2. The output from Weather Generator is the synthesized artificial weather time series data which represent actual weather. 100 simulations of synthetic daily weather are performed. 100 simulations mean 100 numbers of assembly sizes of SDSM interface. The result of validation may be different from calibration model and each ensemble of validation due to the relative significance of the relative significance of the deterministic and stochastic components of the regression models.

Performance of SDSM model is measured using coefficient of determination (R^2) and Root Mean Square Error (RMSE). The Root Mean Square Error (RMSE) is frequently used to measure the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These coefficients are calculated according to the following equations:

$$R^2 = \left(\frac{\sum_{i=1}^n (Q_{(obs)i} - Q_{obsave}) (Q_{(sim)i} - Q_{simave})}{\left(\sum_{i=1}^n (Q_{(obs)i} - Q_{obsave})^2 \sum_{i=1}^n (Q_{(sim)i} - Q_{simave})^2 \right)^{0.5}} \right)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Q_{(obs)i} - Q_{(sim)i})^2}{n}} \quad (2)$$

Definition 1: In above equations 1 and 2, Q_{obs} is the observed value at time, Q_{sim} is the simulated value at time, n is the sum number of observations, and Q_{obsave} and Q_{simave} are the average of observed and predicted values, respectively.

2.5. Downscaling Precipitation under Future Emission Scenarios

The long term future climate is divided into 30-year period, 2010 to 2039 (2020s), 2040 to 2069 (2050s), and 2070 to 2099 (2080s). For this study, the model output of HadCM3 GCM was used for the A2 (medium-high) and B2 (medium-low) emission scenarios. 100 ensembles of synthetic daily time series are produced for HadCM3 A2 and B2, 139 years (1961 to 2099). The HadCM3A2 and B2 are the emission scenario from GCM output files. Details

about HadCM3A2 and B2 are listed in Table 5.

Table 5. Group of Special Report on Emissions Scenarios (SRES)

SRES Scenario	Description
A2	Lower trade flows, relatively slow capital stock turnover, and slower technological change. Self-reliance in terms of resources and less emphasis on economic, social, and cultural interactions between regions are characteristic for this future.
B2	Increased concern for environmental and social sustainability presents a particularly favorable climate for community initiative and social innovation, especially in view of the high educational levels.

3. Results and discussion

3.1. Calibration and Validation of SDSM

The downscale daily rainfall simulated by SDSM (using the NCEP variables) at Stations 5, 6, 7 and 8 as tabulated in Table 5, gives a higher value for R^2 compared to other stations during calibration with 0.24, 0.30, 0.20 and 0.23 respectively. For validation part, station 5 gives higher among all stations with value R^2 being 0.20. It can be seen that the SDSM model is unable to predict well for daily rainfall when $R^2 < 0.3$ during calibration and validation. Meanwhile Root Mean Square Error (RMSE) at Station 4 gives the highest RMSE value during calibration with 6.61mm/day and validation with 5.54mm/day. The result shows that the daily rainfall series simulated from NCEP with the mean R^2 values is less than 0.3, which is comparable with literature values [22]. This is because the amount of rainfall is stochastic processes, the downscaling of daily rainfall is always a difficult subject, and the stimulation results of daily rainfall in the most of similar researches were worse than those of monthly [23]. From the results obtained, it shows a higher value of RMSE and the small value of R^2 , which indicates poor performance in downscaled rainfall time series.

In general, the study showed that the SDSM model was poor in predicting on a daily rainfall between observed and simulated rainfall. The results were similar with other studies such as [24]. Hence, results from this study are considered fully justified according to early research works. Furthermore, daily rainfall is the most difficult variables for prediction and it is a condition process which involves an inter-connected with many factors/variables.

Table 5. The R^2 and RMSE between observed and simulated rainfall results for each station for the SDSM model

Station Name	Calibration	Validation	Calibration	Validation
	R^2		RMSE	
Bkt. Larut, Taiping (1)	0.01	0.11	4.27	4.56
Ldg. Windsor, Ulu Sepetang (2)	0.01	0.11	3.47	4.12
Ldg. Norseman (3)	0.08	0.07	2.94	3.12
Ibu Bekalan Sempeneh, Batu Kurau (4)	0.03	0.01	6.61	5.54
Pusat Kesihatan Kecil, Batu Kurau (5)	0.24	0.20	2.00	1.71
Kolam Air Bkt. Merah (6)	0.30	0.04	2.24	3.13
Ldg. Pondoland, Pondok Tanjung (7)	0.20	0.01	2.63	3.11
Ibu Bekalan Jelai (8)	0.23	0.15	3.27	3.87
Ldg. Stoughton, Batu Kurau (9)	0.01	0.07	2.49	2.15
Ibu Bekalan Ulu Ijok (10)	0.03	0.10	3.60	3.49

3.2. Downscaling for Future Emission

The period of 1961–1990 was taken as the base period as it was used in most impact studies worldwide, and the future period was divided into 2020s (2010–2039), 2050s (2040–2069), 2080s (2070–2099). Future annual mean rainfall for 10 stations rainfall was depicted in Figure 4 to show the pattern between current and future periods under scenario A2 and B2.

Figure 4. Future annual mean rainfall for 10 stations under scenarios A2 and B2

Patterns of change about future rainfall scenarios compared to the base period were then analysed at stations 5, 6, 7 and 8, which represented the Upper Kurau River Basin using H3A2 and H3B2 data. The selection of these

stations is according to the result of highest correlation R^2 among all the 10 stations. Taking the simulation results of SDSM in the modeling rainfall of current period (1961–1990) into account, the change of annual mean rainfall of Kurau River basin under scenarios A2 and B2 was discussed in this paper.

Figure 5 shows changes of annual mean rainfall for 10 stations in Upper Kurau River Basin. Stoughton (station 5) has shown the increase in future 2080, followed by station Norseman (station 3) and Sepetang (station 2). It is seen that under scenario A2, the changes of annual mean rainfall of future periods (2020s, 2050s and 2080s) for the whole Upper Kurau River Basin would be 13.87, 25.09 and 39.52% respectively. Under scenario B2, the changes of annual mean rainfall of future periods (2020s, 2050s and 2080s) in the Upper Kurau river basin would be 14.11, 22.41 and 32.38% respectively.

Figure 5. The changes of percentage annual mean rainfall (compared to base period) in 2020s, 2050s, and 2080s under scenarios A2 and B2.

The simulation results of future rainfall when compared to the base period, the annual mean rainfall of the Upper Kurau river basin of three future periods would show an increase of rainfall in the future. As for A2 scenario, in the 2020s, the change would present a situation of increase of 14%; as for the 2050s, the change increase of 25%; when it

comes to 2080s, the change would present a situation of increase being larger than 35%. Scenario B2 would also show an increase in future rainfall but lower than A2. Increment of annual rainfall showed that Upper Kurau River basin will receive an increase of rainfall in the future. Results obtained from this study are similar with Huang et al. (2011) and Hassan and Sobri (2012).

4. Conclusions

SDSM was applied in this study to predict future rainfall in Upper Kurau River Basin. The results obtained from calibration and validation of SDSM model show that the model was average in predicting the daily rainfall but successful in simulating annual rainfall. The discrepancies between observed and generated data could be driven from uncertainty of input data, errors in the forcing of GCM scenarios and incomplete representation of key processes for the downscaling model. Results for future rainfall indicate an increasing trend in all future time horizons for both A2 and B2 emission scenarios. It proves that the SDSM model is able to predict the future rainfall at the Upper Kurau River Basin. These results would provide important scientific base and practical information for water resources planning and management in the basin.

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REFERENCES

- [1] Huang J., Zhang J., Zhang Z., Xu C. Y., Wang B., Yao J., (2011). Estimation of future precipitation change in the Yangtze River basin by using statistical downscaling method, *Stoch Environ Res Risk Assess* (2011) 25:781–792 DOI 10.1007/s00477-010-0441-9
- [2] Fenta Mekonnen, D., & Disse, M. (2018). Analyzing the future climate change of Upper Blue Nile River basin using statistical downscaling techniques. *Hydrology and Earth System Sciences*, 22(4), 2391-2408.
- [3] Busuioc, A., Chen, D., Hellstrom, C. (2001) Performance of Statistical downscaling Models in GCM validation and regional climate change estimates: application for Swedish precipitation. *International Journal of Climatology*.
- [4] Wilby, R.L. & Dawson, C.W. (2004) Using SDSM Version 3.1 – A Decision Support Tool for the Assessment of Regional Climate Change Impacts. User Manual. 67pp
- [5] Harun, S., Hanapi, M. N., Shamsuddin, S., Mohd Amin, M. Z., and Ismail, N. A. (2008) Regional Climate Scenarios Using a Statistical Downscaling Approach. Technical Report, Universiti Teknologi Malaysia, Skudai. 1-91pp.
- [6] Wilby RL, Dawson CW, Barrow EM (2002) SDSM – A Decision Support Tool for The Assessment Of Regional Climate Change Impacts. *Env Mod Soft* 17: 147–159
- [7] Kidson JW, Thompson CS (1998) A comparison of statistical and model-based downscaling techniques for estimating local climate variations. *J Clim* 11: 735–753
- [8] Solman SA, Nuñez MN (1999) Local Estimates Of Global Climate Change: A Statistical Downscaling Approach. *Int J Climatology* 19: 835–861
- [9] Schoof JT, Pryor SC (2001) Downscaling temperature and precipitation: a comparison of regression-based methods and artificial neural networks. *Int J Climatology* 21: 773–790
- [10] Wilby RL, Wigley TML, Conway D, Jones PD, Hewitson BC, Main J, Wilks DS (1998) Statistical downscaling of general circulation model output: a comparison of methods. *Water Resource Research* 34(11):2995–3008
- [11] Wilby RL, Harris I (2006). A framework for Assessing Uncertainties in Climate Change Impacts: Low-Flow Scenarios. *Water Resource Research* 42:W02419. doi:10.1029/2005WR004065
- [12] Hassan, H., Aramaki, T., Hanaki, K., Matsuo, T., Wilby, R.L., (1998). Lake stratification and temperature profiles simulated using downscaled GCM output. *Journal of Water Science and Technology* 38, 217–226
- [13] Hay, L.E., Wilby, R.L., Leavesley, G.H., (2000). A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. *Journal of the American Water Resources Association* 36, 387–397
- [14] Wilby, R.L., Hay, L.E., Leavesley, G.H., (1999). A Comparison of Downscaled and Raw GCM output: Implications for Climate Change Scenarios in The San Juan River Basin, Colorado. *Journal of Hydrology* 225, 67–91.
- [15] Hassan, Z., Shamsudin, S. and Harun, S., (2013) Application of SDSM and LARS-WG for Simulating and Downscaling of Rainfall and Temperature. *Theor Appl Climatol* Volume 116, Issue 1-2, pp 243-257. doi: DOI 10.1007/s00704-013-0951-8
- [16] Simonovic. S.P (2010) A New Methodology for the Assessment of Climate Change Impacts on a Watershed Scale. *Current Science*, Vol. 98, No. 8, 25 April 2010
- [17] McCarthy, J., Canziani, O., Leary, N., Dokken, D., and White, K. (2001) *Climate Change 2001: Impacts, Adaptation, and Vulnerability*. Cambridge University Press, New York. 105-110pp
- [18] Hessami, M., Gachon, P., ourda, T. B. M. J., and St-Hilaire, A. (2007) Automated regression based statistical downscaling tool. *Environmental Modeling and Software*, Science Direct.
- [19] Tahir, T., Hashim, A. M., & Yusof, K. W. (2018, April). Statistical downscaling of rainfall under transitional climate in Limbang River Basin by using SDSM. In *IOP Conference Series: Earth and Environmental Science* (Vol. 140, No. 1, p. 012037). IOP Publishing.

- [20] Hassan, Z. and Harun, S., (2012) Application of Statistical Downscaling Model for Long Lead Rainfall prediction in Kurau River Catchment in Malaysia, *Malaysian Journal of Civil Engineering* 24(1):1-12 (2012)
- [21] Wilby, R. L., and Dawson, C. W. (2007) SDSM 4.2 — A Decision Support Tool For The Assessment Of Regional Climate Change Impacts, User Manual
- [22] Dibike, Y. B. and Coulibaly, P. (2005) Hydrologic impact of climate change in the Saguenay watershed: Comparison of downscaling methods and hydrologic models. *Journal of Hydrology*, 307(1-4): 145-163.
- [23] Khan MS, Coulibaly P, Dibike Y (2006) Uncertainty analysis of statistical downscaling methods. *J Hydrology* 319:357–382
- [24] Karamouz, M., Fallahi, M., Nazif, S., and Rahimi Farahani, M. (2009) Long lead rainfall prediction using Statistical Downscaling and Artificial Neural Network modeling. *Scientia Iranica*, 16(2): 165-172.