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Regional precipitation scenarios using a spatial statistical downscaling approach for Klang watershed, Malaysia.

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REGIONAL PRECIPITATION SCENARIOS USING A SPATIAL STATISTICAL DOWNSCALING APPROACH FOR KLANG WATERSHED, MALAYSIA

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ABSTRACT

Climate change is a consequence of changing in climate on environment over the worldwide. Multi rain gauge stations have been selected to make a spatial downscaling. SDSM uses a multi-regression method to link large scale climate variables as provided by Global Climate Models (GCMs) simulations with daily climatic data at local site using the SDSM. The aim of study is to assess the impact of climate changes on the future precipitation for three timeslices 2020's, 2050's and 2080's under A2 IPCC scenario. To estimate rainfall trend over Klang catchment it was attempted to establish a spatial rainfall analysis of the 10 selected rainfall stations using Geo-statistical function in GIS. The watershed seems to experience increased rainfall towards the end of the century. However, the analysis indicates that there will likely be a negative trend of mean precipitation in 2020s and with no difference in 2050s. The precipitation experiences a mean annual decrease amount by 7%, 0.6% and 0.9 % for A2 scenario in 2020s, 2050s respectively and an increase by 12.4% in 2080s. It can be concluded which days with heavy precipitation will occur more frequently causing a higher frequency of high river flow events.

Key Words : Climate change, Statistical downscaling model, HadCM3, SDSM, GIS

INTRODUCTION

Climate is one of the most important components in the physical environment and can reflect the statistical characterizations of the average weather over a period of time. Then any changes in the mean or the variability of its properties throughout the longtime can be defined as climate change. Intergovernmental Panel on Climate Change, IPCC,[1] defines climate change as a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods. Many investigations have been conducted to estimate the variability in precipitation considering the climate change impacts for demonstration of the probability of extreme precipitation in the future.[2-6] Malaysia situated in equatorial region which is considered as sensitive region by IPCC. It has been facing many flooding events which are originated by convectional storms causing intensive and localized rainfall. The watershed has been facing often flash floods rising out of an intense rainfall in a short time.

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AIMS AND OBJECTIVES

The study aims to demonstrate the rainfall pattern based on the climate change scenarios in the future. It has been attempted to evaluate spatially the impact of climate changes on the future precipitation for three time slices 2020's, 2050's and 2080's. The simulation of climate change model using A2 scenario as the worsen IPCC scenario was run to project the mean and maximum precipitation of in the Upper Klang watershed, Malaysia.

METHODOLOGY

Study area

Catchment description

Klang watershed locates on the west coast of Peninsular Malaysia. Klang is situated in Kuala Lumpur, Selangor province in Malaysia. The region experiences heavy precipitation due to located in an equatorial zone particularly during the Northeast and Southwest monsoon. The Northeast monsoon is strengthened by pressure surge from South China Sea. To estimate rainfall trend over Klang catchment it was attempted to establish a spatial rainfall analysis of the 10 selected rainfall stations using GIS system. The **Fig.1** shows the selected rainfall stations over the scope of study.

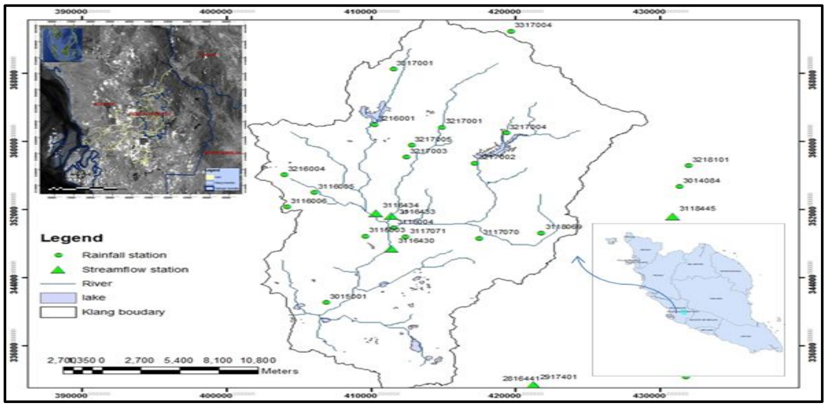

Fig. 1 : Location of the rainfall and river flow stations used in Klang watershed, Malaysia

Data used in SDSM

Predictand data

Predictand data includes rainfall gauge stations in Klang. A gap of data may affect on SDSM results and it is important to run statistical downscaling with a reliable results and minimum uncertainty. Then 10 rainfall stations were selected based on high quality with no gap or a minimum of daily time series which spatially distributed in the scope of the study covering the whole of watershed.

Large scale predictor NCEP/NCAR Re-analysis data

NCEP is a joint product with the National Center for Atmospheric Research (NCAR) involves all the gridded predictor variables to use in calibration and validation in SDSM. The horizontal grid resolution in NCEP atmospheric predictors is 2.5°, 2.5°. NCEP/NCAR provided a 40-year record of global analysis of atmospheric predictors. The 26 predictor variables are produced by state-of-art assimilation of all available observed weather data into a global climate forecasting model that produces interpolated grid output of many weather variables. The data can be obtained from *httt://www.cics.uvic.ca/ scenarios/index.cgi.*

HadCM3 model

Hadley Centre Third Generation (HadCM3) Model was used as the GCM model downscaling which is a couple oceanic - atmospheric general circulation model. Hadley Centre Coupled Model, HadCM3, is a coupled Atmosphere-Ocean General Circulation Model (AOGCM). It composed of the atmospheric model, HadAM3, and the ocean model, HadOM3. The model was developed for the whole of the world. The high quality of simulation of current climate using HadCM3 model, made it one of the most efficient and reliable model in climate change studies. It still ranks highly compared to other models in this respect.[7]

Statistical Down Scaling Model (SDSM)

Statistical Down-Scaling Model (SDSM) was developed by Wilby and Dawson[8] was used to construct climate change scenarios for the catchment of Klang in Malaysia. Downscaling is a technique of changing in climate data resolution of a coarse resolution into a fine resolution. SDSM as a statistical tool was adopted due to several advantages such as low cost and user friendly of using over dynamical methods. There are many studies which used of SDMS in climate change impact assessments.[9-11]
Regression method establishes a linear or non-linear regression between predictands and predictors. Therefore, this method is highly depends on the empirical statistical relationships was made. The main advantage of it is simplicity and less computationally demanding of running the regression statistical method. However it is limited to the locations where good regression results could be found.
Selection of predictor variables is the most important steps in the statistical downscaling

processes because it largely affects the character of the generated scenarios. The predictor variables were selected based on the criteria such as physically related to the predict and, produce the highest explained variance (r^2) and the lowest Standard Error (SE). Obviously, the high correlation values indicate a strong relationship of two data series (predictand and predictors) of all the twelve months. The correlation analysis is carried out to screen all the 26 predictor variables (NCEP Re-Analysis) for predictand data. A monthly regression of the relationship is constructed. A correlation matrix and explained variance are the outputs of the monthly regression. To find the most correlated predictor variables with the predictand the Significance Level of $p<0.05$ (5%) is defined to test the significance of predictor–predictand correlations. Then, the values of less than significance level indicate the high correlation of data.

Generally, Statistical downscaling implements a quantitative relationship between large scale atmospheric variable (predictors) and local surface variable (predictands). In its most general form the downscaling model is

$$R_t = F_{xt} \qquad F_{xt} \text{ for } T \leq t \tag{1}$$

Where, $\mathbf{R_t}$: the local scale predictand at single or multiple sites at time t, XT: the predictor data of large- scale atmospheric variables, and F: the techniques used to quantify the relationship between two disparate spatial scales.

The conditional method in precipitation downscaling consists of two steps: the first step is the probability of occurrence and the second is to estimate the amount of climatologic parameters. Probability of precipitation is modeled by

$$\omega_i = \alpha_o + \sum_{j=1}^{n} \alpha_j \mu_i^{\,j} \tag{2}$$

Where, ω_i is the conditional probability of precipitation occurrence on day i, μ^i are the normalized predictors. Wet/dry spell length are estimated stochastically by comparing ω_i with the output of a linear random-number generator, r_i, the precipitation occurs, ($\omega i \leq r_i$).

The predictand (precipitation) amount at the site on the large-scale atmospheric circulation is modeled by

$$Z_i = \beta_o + \sum_{j=1}^{n} \beta_j \mu_i^{\,j} + \varepsilon \tag{3}$$

Where Z_i is the z-score for day t, β_j are estimated regression coefficients for each month, and ε is a normally distributed stochastic error term, and

$$Z_t = \phi^{-1}[F(y_i)] \tag{4}$$

Where $\phi^{-1}$is the normal cumulative distribution function, $F(y_i)$ is the empirical distribution function of y_i, the daily precipitation amounts.

Spatial mapping of downscaled precipitation

The interpolation processes employed the Inverse Distance Weighting (IDW) method in GIS to estimate spatial mean of precipitation as the downscaled precipitation data of distributed rain gauges in Upper Klang and also long time series used. IDW, developed by U.S. National Weather Service in 1972, is based on the distance weighting. Many studies have been used this method for a long time precipitation.[12-14] The amount of rainfall at the non-sample location is then estimated by interpolation with IDW. The IDW formula is given below:

$$\mathbf{R_p} = \sum_{i=1}^{n} \left(\frac{\mathbf{d_i^{-\alpha}}}{\sum_{i=1}^{n} \mathbf{d_i^{-\alpha}}}\right) \mathbf{R_i} \tag{5}$$

Where, $R_p$is the unknown rainfall data (mm), R_i is the rainfall value at the known location (mm), di is the distance from each Rainfall Station to unknown site, n is the number of rainfall gauge station and α is the coefficient value which is assumed equal to 2.[15-18]

RESULTS AND DISCUSSION

To set up the statistical downscaling, the value of 0.3 mm/day was used as threshold value in precipitation data specifying the threshold value is useful to trace the rainy days in calibration and validation in SDSM. And also, bias correction to value of 1was selected to demonstrate that the process will be run without any bias correction. The bias correction is able to moderate for any tendency to over or underestimate the mean of conditional processes by the downscaling model **(Table 1)**.

Selection of predictors

A multiple linear regression equation is constructed via an optimization algorithm (dual simplex/ordinary least squares) between predictands and the predictors which are determined through the screening variables step. Screening variables in SDSM shows a linear regression between gridded predictors and predictands which is the most significant phase to the statistical downscaling method to choose appropriate downscaling predictor variables which largely affects on the generated scenarios. SDSM generates a correlation matrix and explained variance reveals the correlations between the predictand and predictors. The predictors are the high correlated with the predict and ($p<5\%$) are chosen for the future processes. The selected large scale predictors for all the local predictands are listed in **Table 2.** For precipitation, mean sea level pressure, 850 hPa Geopotential height, 500 hPa Geopotential height, Near surface relative humidity, Surface specific humidity and Mean temperature at 2m were chosen as the predictors provide a good correlation to the rainfall gauge stations.

Table 1 : The climatological stations used for the downscaling in Klang watershed, Malaysia

Id	Station name	Station no.	Longitude (degree)	Latitude (degree)	Period (year)
1	Taman maluri	3116005	101.65	3.2	1977-2001
2	Edinburgh	3116006	101.63	3.18	1977-2001
3	Pusat penyelidekan	3117070	101.75	3.15	1972-2001
4	Pemasokan ampang	3118069	101.79	3.16	1972-2001
5	Kg. Sg. Tua	3216001	101.69	3.27	1973-2001
6	Ibu bekalan km	3217001	101.73	3.27	1975-2001
7	Empangan genting klang	3217002	101.75	3.23	1975-2001
8	Ibu bekalan km	3217003	101.71	3.24	1975-2001
9	Kg.kuala sleh	3217004	101.77	3.26	1975-2001
10	Genting sempah	3317004	101.77	3.37	1975-2001

Table 2 : Large scale predictor variables selected for predicting daily precipitation

Predictands / Predictors	ncep-mslpas	ncep-mslpas	ncep-mslpas	ncep-mslpas	ncep-mslpas	ncep-mslpas
3116005	*	*				*
3116006	*	*		*		*
3117070	*	*	*	*	*	*
3118069	*	*	*	*	*	*
3217001	*	*	*	*	*	*
3216001	*	*	*	*	*	*
3217002	*		*	*	*	
3217003	*	*	*	*		
3217004		*		*	*	*
3317004	*		*	*	*	*

Model calibration and validation

SDSM presents two kinds of model calibration based on the nature of climate data which are categorized into conditional and unconditional processes. A conditional process is defined for the precipitation as a dependency on the regional scale predictors. There is an indirect link is assumed between them to predictors. Whereas an unconditional process can be established like the temperature data as a direct link to the predictors is assumed. Therefore, in conditional process some more local parameters of precipitation would estimate such as wet/dry-day occurrence. In order to run the calibration in SDSM, the NCEP-Re-analysis data set is used in compliance with the specified year period for each predictand **(Table 3)** to identify the empirical linear regression of the large scale predictors with the local sites. The historical data of predictands are split in two parts, which the first part is used for calibration and the remaining of the data is used for validation as an independent dataset. The best performance of the calibration results is determined based on higher correlation and lowest standard errors for every month.

Table 3 : The year period used for calibration and validation for downscaling in SDSM

Id	Station name	Station no.	Period (year)	Calibrated period (year)	Validated period (year)
1	Taman maluri	3116005	1977-2001	1977-1990	1991-2001
2	Edinburgh	3116006	1977-2001	1977-1990	1991-2001
3	Pusat penyelidekan	3117070	1972-2001	1972-1990	1991-2001
4	Pemasokan ampang	3118069	1972-2001	1972-1990	1991-2001
5	Kg. Sg. Tua	3216001	1973-2001	1973-1990	1991-2001
6	Ibu bekalan km	3217001	1975-2001	1975-1990	1991-2001
7	Empangan genting kelang	3217002	1975-2001	1975-1990	1991-2001
8	Ibu bekalan km	3217003	1975-2001	1975-1990	1991-2001
9	Kg.kuala sleh	3217004	1975-2001	1975-1990	1991-2001
10	Genting sempah	3317004	1975-2001	1975-1990	1991-2001

Table 3 shows the calibration and validation period lengths for the variety of predictands used in SDSM. The results reveal that the calibration can preserve the basic statistical properties and there in no significant varies of mean and variance of observed and calibrated precipitation. To evaluate the validation outputs the precipitation parameters as conditional variable, Dry spell and Wet spell length, of observed and validated were compa-red. The results illustrate that the model run is satisfactory validated and it can be seen that there is a remarkable skill of simulation data in compare with observed **(Table 4** and **Table 5)**.

Table 4 : R-Square of the calibration modelled for the downscaled rainfall,stations

Predictand variables	Mean (mm)	Maximum (mm)	Variance (mm)
3116006	0.966	0.689	0.802
3117070	0.884	0.121	0.907
3118069	0.968	0.236	0.992
3216001	0.99	0.12	0.993
3217001	0.998	0.114	0.918
3217002	0.996	0.78	0.914
3217003	0.96	0.232	0.814
3217004	0.92	0.632	0.853
3317004	0.99	0.99	0.892

Table 5 : Correlation of the validation modelled for the downscaled rainfall stations

Predictand	Mean	Maximum	Variance (mm:precipitation)	Dry Spell (day)	Wet Spell (day)
	mm: precipitation				
3116005	0.47	0.27	0.62	0.65	0.41
3116006	0.49	0.22	0.35	0.67	0.72
3117070	0.87	0.54	0.72	0.78	0.69
3118069	0.50	0.30	0.62	0.53	0.44
3216001	0.68	0.16	0.05	0.64	0.48
3217001	0.51	0.32	0.40	0.82	0.54
3217002	0.20	0.11	0.40	0.75	0.56
3217003	0.80	0.45	0.82	-	0.19
3217004	0.72	0.35	0.43	0.51	0.67
3317004	0.33	0.14	0.10	0.46	0.75

Spatial analysis of downscaled rainfall stations to generate an average and maximum precipitation for the entire Klang watershed, Malaysia

The scenario generator in SDSM produces ensembles of synthetic daily weather series for the current and future climate using NCEP re-analysis and GCM model. The simulation of HadCM3-GCM model using A2 scenario was run in SDSM to project the trend of future climate change variables in local scale. To evaluate the future climate change, the long time period of the projection (to 2100) is divided to three parts (2020's, 2050's and 2080's) to compare to the observed precipitation. Once all the precipitation data have been downscaled by SDSM, the spatial analysis needed to be conducted to achieve the average and maximum precipitation for the entire Klang watershed, Malaysia. It was accomplished using Geo-statistical function in GIS. SDSM generated different scenarios for the individual precipitation station projecting the possible climate in the future in three time slices (2020's, 2050's and 2080's). The interpolation produced the monthly map by assuming the current and future downscaled data. So there have been produced the monthly maps of the downscaled scenarios. This method is applies for 50's and 80's A2 scenario. GIS is able to estimate a mean value of each map as an average of all the point data values distributed over the whole of watershed. **Table 6** to **Table 8** show the monthly mean of Mean and maximum precipitation for the current and 2020's, 2050's and 2080's for as an average value of precipitation variables for whole the watershed, respectively.

Table 6 : Average monthly of precipitation in the observed and projected precipitation for all the rainfall stations covering Klang watershed

Mean precipitation(mm)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Observed	108.66	152.08	208.34	259.14	455.91	160.23	161.40	183.10	234.68	259.98	274.86	184.89
2020s	94.37	166.92	186.62	277.87	346.25	116.95	159.11	159.43	291.31	234.04	265.48	135.43
2050s	88.14	179.07	191.34	299.64	437.62	105.33	164.98	151.84	337.08	259.99	286.77	125.53
2080s	81.93	192.27	196.49	336.86	601.70	110.19	169.75	135.42	441.34	270.53	321.68	111.92

Table 7 : Maximum monthly of precipitation in the observed and projected precipitation for all the rainfall stations covering Klang watershed

Maximum precipitation(mm)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Observed	140.16	194.44	256.84	297.22	2011.36	181.51	184.68	199.41	252.28	285.58	329.55	218.27
2020s	149.54	217.06	203.69	369.45	739.82	202.96	192.52	192.16	357.16	344.46	336.62	152.81
2050s	156.31	235.59	222.16	418.52	770.36	264.06	206.84	198.07	457.80	398.04	395.86	156.51
2080s	162.29	301.72	234.76	469.58	893.68	395.48	224.97	211.77	678.35	520.59	471.84	166.13

Table 8 : Changes in precipitation variables in Klang Watershed relative to the observed data under A2 scenario

Precipitation variable	2020s	2050s	2080s	Observed	Change in 2020s	Change in 2050s	Change in 2080s
Mean precipitation (mm)	202.81	218.94	247.5	220.27	-16.13	-1.33	27.24
Max precipitation (mm)	288.19	323.34	394.3	202.17	-35.15	121.17	192.09

CONCLUSION

In this research, the data screening procedure was carried out to check the homogeneity, consistency and stationary of the raw data. The 10 rain gauge stations have been selected to make a spatial downscaling and in Klang area. Daily time series data was used to run the statistical downscaling in SDSM. SDSM uses a multi-regression method to link large scale climate variables (predictors) as provided by Global Climate Models (GCMs) simulations with daily climatic data at local site (predictands) using the popular Statistical Downscaling Model (SDSM). The spatial interpolation employed the Inverse Distance Weighting (IDW) method to estimate spatial mean of precipitation as the available data of distributed rain gages in Klang and also long time series used.

The fluctuated trend of each rainfall station modelled does not indicate a systematic increasing or decreasing trend. Finally the mean yearly of downscaled precipitation parameters were determined based on the relevant tables to indicate the mean of each precipitation variable by averaging of 12 months. The Table 8 shows the average changes in mean and maximum precipitation for the entire Klang Watershed for the future corresponding IPCC scenario.

The watershed seems to experience increased rainfall towards the end of the century. However, the analysis indicates that there will likely be a negative trend of mean precipitation in 2020s and with no difference in 2050s. The precipitation experiences a mean annual decrease amount by 7%, 0.6% and 0.9 % for A2 scenario in 2020s, 2050s respectively and an increase by 12.4% in 2080s. It can be concluded which days with heavy precipitation will occur more frequently causing a higher frequency of high river flow events.

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