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 40 51’ (N) and 50 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.
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 downsampling 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).
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                   | ncepp__fas.dat, ncepp5_uas.dat, ncepp8_fas.dat and ncepshumas.dat          |
| Ldg. Windsor, Ulu Sepetang             | ncepp850as, ncepp8_uas and ncepshumas                                      |
| Ldg. Norseman                          | ncepp5has.dat, ncepshumas.dat                                              |
| Ibu Bekalan Sempeneh, Batu Kurau      | ncepp_thas.dat, ncepp850as.dat and ncepshumas.dat                          |
| Pusat Kesihatan Kecil, Batu Kurau     | ncepp_fas, ncepp5_fas and ncepshumas                                       |
| Kolam Air Bkt. Merah                   | ncepp__uas.dat, ncepshumas.dat                                            |
| Ldg. Pondoland, Pondok Tanjung         | ncepp__ fas.dat, ncepshumas.dat                                            |
| Ldg. Norseman                          | ncepp5has.dat, ncepshumas.dat                                              |
| Ibu Bekalan Jelai                      | ncepp__fas.dat, ncepp8_uas and ncepshumas                                 |
| Ldg. Stoughton, Batu Kurau             | ncepp5_uas.dat, ncepshumas.dat                                            |
| Ibu Bekalan Ulu Ijok                  | ncepp__uas.dat, ncepshumas.dat                                            |
| Ldg. Norseman                          | ncepp5has.dat, ncepshumas.dat                                              |

Table 4. Types of predictors

| Variables | Descriptions                      |
|-----------|-----------------------------------|
| temp      | Mean temperature at 2m            |
| mslp      | Mean sea level pressure           |
| p500      | 500 hPa geopotential height       |
| p850      | 850 hPa geopotential height       |
| rhum      | Near surface relative humidity    |
| r500      | Relative humidity at 500 hPa height|
| r850      | Relative humidity at 850 hPa height|
| shum      | Near surface specific humidity    |
| s500      | Specific humidity at 500 hPa height|
| s850      | Specific humidity at 850 hPa height|
| **_f      | Geostrophic air flow velocity     |
| **_z      | Vorticity                         |
| **_u      | Zonal velocity component          |
| **_v      | Meridional velocity component     |
| **_th    | Divergence                        |
| **_thas   | 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:

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

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

**Definition 1:** In above equations 1 and 2, $Q_{\text{obs}}$ is the observed value at time, $Q_{\text{sim}}$ is the simulated value at time, $n$ is the sum number of observations, and $Q_{\text{ave}}$ 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.

| SRES Scenario | Description |
|---------------|-------------|
| A2            | Lower trade flows, relatively slow capital stock turnover, and slower technological change. |
| 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 simulation 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 |
|--------------------------------------|-------------|------------|-------------|------------|
| 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.

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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