Estimation of the Potential Trend Changes on the Streamflow with Climatic Responses Consideration

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Abstract. Uncontrolled rapid development will create the negative effects especially to the unstable climate variability. In Malaysia, the huge impact to this trend changes can be examined during North-East monsoon. The most of rivers in the Eastern parts of Malaysia are exposed to the drastic and unexpected water level (WL) rises. The objective of this study was to estimate the potential changes on streamflow at Sg Yap with climate change impact. Sg Yap is a part of Pahang River basin and recorded as the worst affected area of flooding in year 2017. Thus, the integration of climate model (SDSM) considered the representative concentration pathway (RCPs) and rainfall-runoff model (IHACRES) were implemented. According to the results, the selected predictors for climate simulation were successfully to have good association with the local rainfall and temperature stations. High correlation (>0.79) and least of percentage error (<21.51%) as proved the accuracy and reliability of the findings. In the long term projection, the temperature was expected to decrease in average 6%. Meanwhile the long term rainfall trend was slightly similar to the historical trend with small percentage of decrement in the annual rainfall as -8.1% (RCP2.6), -10.2% (RCP4.5), -10.8% (RCP8.5). Thus, the long term streamflow at this region is expected to decrease with 20.9%, 22.1%, and 27.9% by RCP2.6, RCP4.5 and RCP8.5, respectively. Therefore, the relationship between rainfall-runoff can be estimated in the ratio of 1:3 (RCP2.6), and 1:2 (RCP4.5 and RCP8.5).

1. Introduction
Escalation of the global temperature in responses to the alteration of the atmospheric composition will affect the long term hydrological patterns and water resources. This circumstance wills later leading to the necessity for an assessment of the climate change impacts. Malaysian Meteorological Department (MMD) reported plenty of disasters (drought, flood, storm, flash flood etc) occurred since year 1900s affected by the monsoons. There are South-West monsoon (SW) which bring drier condition occurred in the mid of the year and North-East (NE) monsoons which bring wetter condition occurred in the end of the year. According to the record, almost every year Malaysia was facing with the flood and drought but the condition become worse since year 1951 due to the climate changes impact. During NE, most of the rivers in the Eastern parts of Malaysia are exposed to the drastic water level (WL) rises. It is due to the formation of the cyclone vortices when the strong cold air convergence with the low atmospheric pressure which is resulting to the strong wind, high sea and heavy rainfall at the nearest area of South China Sea. As a result, the heavy rainfall happened in short spell which causes an extreme disaster at the nearest areas. In year 2014, the worst flood events were recorded in Eastern Malaysia including Kelantan, Terengganu, Pahang and Johor states. During that time, the convergence
between NE monsoon and full moon phenomenon which resulted to the high tides and heavy rainfall in the same time. This situation caused the excessive water receded very slow and inundated at nearest residential areas.

The downstream rivers became overflow caused by extreme heavy rainfall which came from the upstream. Referring to the MMD report in Dec 2014, the total monthly rainfall in December at these areas achieved >1200 mm, 60% higher than the average monthly rainfall during normal condition. The highest total rainfall amount was recorded at Kuantan station with 1806 mm/month. According to the Department of Irrigation and Drainage (DID) stated there were 4 main River surrounding Pahang state over the danger WL such as Sungai Tembeling with 75.35m (danger level: 68m), Sungai Yap with 54.93m (danger level: 52m), Sungai Kuantan at Pasir Kemudi with 8.79m (danger level: 8.2m) and Sungai Kuantan Bypass with 5.27m (danger level: 3.5m). It proved that the pattern of climate can be as a core factor in investigating the hydrological systems effects. Even the calamities were affected by the natural of cyclical monsoons, however it might be extremely affected by the climate change.

Changing trend in rainfall distribution and streamflow will create huge impact to the hydrological analysis. [1] proved the increment of potential annual rainfall and temperature causes the rises of the water stream at Johor River Basin. Meanwhile [2] proved the rises of rainfall and temperature trend at Muda Agriculture Scheme was expected to change the historical reservoir management policies where the supply/demand ratio reach to 1.009 optimized by Nondominated Sorting Genetic Algorithm (NSGA II). Therefore, the climate assessment becomes significant data input for many purposes such as for detecting climate change towards catchment response, design floods calculation, water resources management, flood forecasting, estimation of land use change impact, and stream flow prediction. It is an important tool to understand the changes impact in the climate pattern and trend affecting by the greenhouse gases and aerosol dispersion into the atmospheric system. The most popular model is a Statistical Downscaling Model (SDSM) because it has potential to generate the reliable results while having limited sources [3-5]. It uses multiple regression equation to build the statistical relationship between local climate (known as predictand) with the global atmospheric parameter (known as predictor). It is widely used in context of hydrological issue due to the climate scenarios because it provides station scale climate information from grid resolution GCM-scale output. To assess the long-term changes trend at upstream flow, Identification of unit Hydrograph and Component flow from Rainfall, Evaporation and Streamflow data (IHACRES) [6] has been applied. The model is classified as the hybrid metric-based model. In the recent year, IHACRES has been successfully used as a rainfall-runoff model because it has advantages over the physical and conceptual model, since it able to stimulate non-linearity in a system [7, 8]. IHACRES also effectively distinguish between relevant from irrelevant data characteristics. In addition, IHACRES is non-parametric techniques. The model does not require the assumptions of constraints.

2. Methodology
The methodology of the study (Figure 1) has been built to estimate the long-term changes of the streamflow pattern at Sg Yap with adapting the climate change impact. The study started with the statistical climate prediction, namely as SDSM model. The SDSM used to generate the current and future climate trend especially at upstream river catchment. The function of the SDSM was to analyse the long term pattern changes of local climates which affected by the transition of greenhouse emission in the atmosphere circulation during future years. Next, the results from the climate projection were used to simulate and generate the monthly streamflow using IHACRES model. The purpose was to estimate the stream water discharge along the river with considered the climate assessment. The rainfall and temperature be as significant data input to estimate the effective rainfall by non-linear loss module and then estimating inflow volume via linear hydrograph module.
2.1. Climate Assessment using Statistical Downscaling Model (SDSM)

The SDSM 4.2 [9] was widely implemented in the issues which related to the climate changes. The SDSM utilized a linear regression method in built the predictor-predictand relationship. It consists of two steps: 1) develop the predictor-predictand equation for validation process and 2) generating the daily weather with considered the level of GHGs and radiation forcing. The large-scale predictors were provided by two climate groups at the grid box of 28X x 33Y there were NCEP reanalysis (for validation processes) and GCMs (for the long-term generation). The GCMs depends on three RCPs which provided by GCM-CanESM2 (AR5) to produce potential future time series of weather scenarios. The RCPs was based on the level of radiation forcing start from low (RCP2.6), intermediate (RCP4.5) and high (RCP8.5) emissions.

Even the statistical downscaling has several limitations, however the SDSM model does not require high computational demand to view the simulation results but has ability to produce high quality of projection results. These advantages, as a whole, had made SDSM a reliable tool for climate downscaling and was selected as a downscaling tool to generate the future climate trend at the study site [4];[10];[11].

The predictor-predictand equations were developed using multi-linear regression approach for generation the long-term climates at the region. The rainfall \( (y) \) on day \( t \) can be determined by Eq. 1 and Eq. 2:

\[
y_t = F^{-1}[\varnothing Z_t]
\]

\[
Z_t = \beta_0 + \sum_{j=1}^{n} \beta_j \bar{u}_t + \beta_{t-1} + \epsilon
\]

Where \( F \) is the empirical function of \( y_t \), \( \varnothing \) is the normal cumulative distribution function, \( Z_t \) is the z-score on day \( t \), \( \beta \) is the regression parameter, \( \bar{u}_t \) is normalized predictor and \( \epsilon \) is the variable parameter. For the rainfall analysis, the equation was transformed to the fourth root to take account for the skewed nature of the rainfall distribution.
2.2. Streamflow Analysis

IHACRES was integrated to simulate and generate the runoff behavior under projected climatic changes. This model was recognized as a hybrid conceptual-metric by [12] to reduce the numbers of uncertainty parameters and was able to provide more specific internal processes. The historical temperature and rainfall records were used as the base for the measurement. These climatic data were characterized into the dynamical relationship to generate the water flow [13]. IHACRES model consisted of a simple structure and undemanding parameters which made it more preferable than others. It also allowed parametric efficiency and statistical rigor in presenting the dynamic response characteristics of the catchment area. Figure 2 explains the streamflow estimation approach. In the non-linear loss module, the rainfall volume was disintegrated at the first stage into two components consisted of quick flow where the rainfall had potential to be direct runoff and slow flow is identified as the remaining rainfall amount that is probably loss because of the evaporation or held in the soil storage. Afterward, the effective rainfall (\( k_u \)) was computed after considering the catchment soil moisture index (\( k_s \)) in ranges of \( 0< k_s <1 \). The catchment wetness index represented the proportion of rainfall that eventually became streamflow at the catchment area. A dynamic responses of the catchment control that may influence the wetness index, viz. catchment drying time constant, \( w \tau \); reference temperature, \( R \); monthly temperature, \( k_t \); proportion of the rainfall, \( C \); and temperature modulation factor, \( f \).

![Figure 2. Basic concept of runoff model by IHACRES (Source [13])](image)

Then, the linear module computed the streamflow by adding these two stores in parallel; the quick flow (\( x_k^{(q)} \)) and the slow flow (\( x_k^{(s)} \)) [14]. The streamflow (\( x_k \)) volume estimates in unit cumecs from the following equations:

\[
x_k = ax_{(k-1)} + bu_k
\]

(3)

\[
 u_k = r_k s_k
\]

(4)

\[
 s_k = C r_k + (1 - \frac{1}{\tau_w(t_k)}) s_{(k-1)}
\]

(5)

\[
 \tau_w(t_k) = \tau_w e^{0.062/(R-t_k)}
\]

(6)

where \( r_k \) refers to the observed rainfall (mm). \( a \) and \( b \) are the parameters of unit effective rainfall in a linear unit hydrograph module with \( b>0 \) and \( -1<a<0 \).

\[
b_0 = b_0^{(e)} + b_0^{(s)}
\]

(7)

(8)
2.3. Reliability of the Results using Statistical Analyses

There were 3 significant statistical analyses; mean absolute error (MAE), correlation coefficient (R), and Nash Sutchliffe Efficiency (NSE) have been used to evaluate the accuracy and reliability of the predictor-predictand equations as shown in Table 1 where X_{obs} refers to the ith month observed data, X_{est} is the ith month estimated data and n is the number of data. The function of MAE is to measure the accuracy of continuous variables through the average of errors between the two sets of data representing the whole disparity of two data sets. Meanwhile R and NSE were to evaluate the strength and efficiency of the predictand-predictor relationship between simulated and observed data.

| Name  | Equation |
|-------|----------|
| %MAE  | \[
\frac{1}{n} \left( \frac{\sum (X_{est} - X_{obs})}{X_{obs}} \right) \times 100
\] (11) |
| R     | \[
\frac{n(\sum X_{est}X_{obs})-(\sum X_{est})(\sum X_{obs})}{\sqrt{[n(\sum X_{est}^2)-(\sum X_{est})^2][n(\sum X_{obs}^2)-(\sum X_{obs})^2]}}
\] (12) |
| NSE   | \[
1 - \frac{\sum (X_{est} - X_{obs})^2}{\sum (X_{obs} - \bar{X}_{obs})^2}
\] (13) |

The focused area of this study was at Sg Yap, Pahang because the weather trend in Pahang was influenced by the wind direction and the monsoons. Pahang is the largest state in Peninsular Malaysia. It was located at Eastern of Malaysia and nearest to the equator. Meanwhile Temerloh (one of the districts in Pahang state) has been recognised as a centre of Peninsular Malaysia. Tropical monsoon at Pahang state brings with the series of uniform temperature between 21°C to 32°C throughout the year. The dry season occurred during months of January to April meanwhile months of May to December would be the wettest. The average annual rainfall at Pahang state is 2,540 mm with humidity of 84%. The location of rainfall and temperature stations as shown in Figure 3.
3. Results and Discussions

3.1. Climates Simulation and Projection
There were 5 predictors had been selected in producing the climate equation as shown in Table 2. It consists of meridional velocity (p_v), surface divergence (p_zh), relative (rhum) and specific humidity (shum), vorticity (p_z), geopotential height (p_500), and surface temperature (temp). These selected predictors were successfully to provide higher monthly R-value in the single predictand-predictor relationship.

| Predictand | p_v | p_zh | r500 | r850 | shum | p_z | p_500 | Temp |
|------------|-----|------|------|------|------|-----|-------|------|
| Rainfall Stn | /   | /    | /    | /    | /    | /   | /     | /    |
| Temp Stn   | /   | /    | /    | /    | /    | /   | /     | /    |

The performances of these selected predictors can be controlled during calibration and validation processes. Therefore, Figure 4 below shows the comparison of calibrated and validated results between simulated and historical of rainfall and temperature data at the region. There were 30years length records had been considered in each stations. According to the results, the simulated pattern of rainfall and temperature were successfully to produce similar pattern with the historical with very small monthly biases. The %MAE for both analyses were less than 20% with R values were greater than 0.79. Thus, the results were considered satisfactory for simulation and projection purposes. Meanwhile for the simulated temperature matched reasonably well with that of observed temperature of the station. This indicated that SDSM produced good performances in the simulation of temperature and rainfall in the study area. Then, the climate projection had been done using similar predictors trend however this time was produced by the GCMs. There were 3 scenarios involved including RCP2.6, RCP4.5 and RCP8.5. Thus, Figure 5 shows the projection of the rainfall and temperature trends at this region for all RCPs. Based on the results, all of the scenarios agreed that the rainfall trend at the region was expected to decrease at the end of century. Lesser rainfall occurred started from January to August during dry season.
But then, the rainfall was expected to become heavier started from Sept to Dec during wet season. Projected by RCP2.6, the percentage decrement of rainfall amount was in average -8.1% annually. Meanwhile by RCP4.5, the decreasing estimated to achieve -10.2% annually. By RCP8.5, the average rainfall intensity could be reduced -10.8% annually. Even the projected rainfall were produced similar trend with the historical however the rainfall intensities are expected to become lesser and greater during dry and wet seasons, respectively. The imbalance of the rainfall distribution might cause drought and flood in the critical months if having longer dry and wet lengths.

Figure 6 depicted the projection of monthly and annual mean temperature by all RCPs until end of century. The RCP2.6 and RCP4.5 agreed the temperature was predicted to slightly lower than the historical trend however inconsistent projected result produced by the RCP8.5. In the RCP2.6 scenario, the average mean temperature is predicted to decrease by -0.83% by 2020 to 2049, then by year 2050-2079 it is reduced with -0.76% and subsequently decline with -0.83% by year 2080-2099. Meanwhile based on the RCP4.5, the temperature was decreased with -0.26% in 2020 to 2049, -0.57% in 2050 to 2079 and -0.60% in 2080-2099. Among the RCPs, the highest mean temperature is predicted to occur in 2099 (27.19°C) under RCP8.5 and the lowest mean temperature is happened in 2070 (25.97°C) by RCP8.5. In contrast, the mean temperature projection by RCP8.5 shows larger warming trend in the end of projection period than other two RCPs. In the fifth phase, the temperature is expected to become lower -0.53% (2020-2049) compared to the historical data, but then slightly higher with +0.15% (2050-2079) and +0.64% (2080-2099). As primary of energy mix of RCP8.5 was dominated by fossil fuels, leading to the extraction of large amounts of unconventional hydrocarbon resources, the mean temperature projection was influencing negatively in 2020-2049 as the contribution of climate change in the study area was may more toward anthropogenic. However, it was subsequently responding positively after 2050s due to the pathways with increasing of high GHG emissions. The RCP8.5 was the assumption of its long-term grow of GHG emissions and high energy demand in absence of climate change policies. This
from the high population and relatively slow income growth with modest rates of technological changes and energy intensity improvements.

![Figure 5. Monthly and annual projected rainfall trend at Sg Yap in different scenarios](image1)

![Figure 6. Monthly and annual projected temperature trend at Sg Yap in different scenarios](image2)

### 3.2. Long Term Generation of Water Streamflow

Table 3 shows the list of important parameter values that were used in the IHACRES analysis. Meanwhile, Figure 7 indicates the association between historical and modelled streamflow for the
calibrated (Mar 2003 – August 2003) and validated (September 2003 – February 2004) results. In this analysis, the streamflow simulation was based on 1-year length records due to missing data. Based on the simulated result, the accuracy of modelled streamflow was good except on June, July, September and November 2003. The simulated result was slightly over/under estimated during that month.

Table 3. List of IHACRES Parameters

| List of IHACRES parameter | Value |
|---------------------------|-------|
| **Nonlinear model module** |       |
| Mass balance term (c)     | 0.087 |
| Drying rate at reference temperature (t<sub>w</sub>) | 90   |
| Temperature dependence of drying rate (f) | 0    |
| Reference temperature (t<sub>ref</sub>) | 20   |
| Moisture threshold for producing flow (l) | 0    |
| Power on soil moisture (p) | 1    |
| **Linear model module**   |       |
| Recession rate 1 (α<sup>(1)</sup>) | -0.9 |
| Peak recession 1 (β<sup>(1)</sup>) | 0.1  |
| Coefficient of correlation (R<sup>2</sup>) | 0.78 |
| %ARPE                     | 0.23  |
| %Error                    | 19.56 |

However, this analysis was considered successful and can be used for the further analysis because produced higher R<sup>2</sup> (0.78) with lesser %ARPE and %Error with 0.23 and 19.56%, respectively. Therefore, the equation of long term streamflow of Sg Yap can be built as stated in Eq. 11 below:

\[
x_k = -0.9 x_{k-1} + 0.1 r_k \left[ 0.087 r_k^2 + (1 - \frac{1}{90 t_k}) s_{k-1} \right]
\]

where \( x_k, r_k, t_k, s_k \) refer to the streamflow, rainfall (mm), temperature (celsius), and soil moisture index respectively.

Figure 8 depicted the changes pattern of monthly streamflow at the region. All RCPs were produced similar trend with the historical record but lower estimated streamflow volume. This trend was consistent to the rainfall trend where expected to reduce until end of century. Normally, the streamflow increasing start from September to December and then become lesser until August. The RCP8.5 is estimated to produce lower streamflow generation compared to other RCPs. By RCP2.6, the highest streamflow volume is predicted on December 2089 with 917.41 cumecs and the lowest volume was expected on July, 2095. However by RCP4.5, the highest volume is expected to occur on November 2020 with 933.45 cumecs and the lowest volume might occur on March 2039 by 0.32 cumecs. Meanwhile by RCP8.5, the highest volume is expected to happen in December 2036 with 1063.43 cumecs and the lowest is expected to happen in August 2039 with 1000.45 cumecs. These
results were generated solely based on the projected data for rainfall and temperature station of the study area which will enter the flows of the river.

![Figure 7](image_url) Comparison performances between historical with simulated in calibration and validation analyses

![Figure 8](image_url) Generated monthly streamflow until year 2100 by RCP2.6, RCP4.5 and RCP8.5

4. Conclusion
SDSM was successfully to produce good performances in the calibrated and validated in the temperature simulation however average performances in the rainfall simulation. Based on the temperature projected result, there were inconsistent results produced by RCPs. By RCP2.6 and RCP8.5, the temperature was expected to drop with -0.83% and -0.48% in every decade, respectively. However, the temperature was expected to increase with +0.64% at the end of century by RCP8.5. Consistent to the rainfall estimation where all RCPs agreed that the rainfall was predicted to decrease achieving -8.7% (RCP2.6), -10.8% (RCP4.5) and -10.9% (RCP8.5). These trends might affecting the long term streamflow volume at this region. The streamflow was expected to be lesser at the end of the century in the three scenarios. It is consistent with the future rainfall trends due to the climate change impact. Streamflow volume is expected to decrease in average 20.9% (RCP2.6), 22.1% (RCP4.5) and 27.9% (RCP8.5) annually until end of century. It is consistent with the future rainfall pattern where estimated to drop due to the climate change impact. Thus, the relationship between reducing of rainfall-runoff can be estimated in the ratio of 1:3 (RCP2.6) and 1:2 by RCP4.5 and RCP8.5. It is also proved that the RCP with higher radiation forcing will producing huge impact to the hydrological cycle compared to other RCPs with lower radiation forcing.

5. References
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