

Assessment of Impacts of Future Climate Change on Water Resources of the Hulu Langat Basin Using the Swat Model

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Received: 1 March 2017 / Accepted: 29 June 2017

Abstract

This study conducted to assess the impacts of climate changes on hydrological regime of Langat River Basin using the Soil and Water Assessment Tool (SWAT). The Statistical Downscaling Model (SDSM) applied as a practical tool to bridge the spatial difference between GCM grid-box scale and sub-grid box scale in the Langat River Basin as a tropical area. The calibrated and validated SDSM was applied to project the possible scenarios in two future periods (2030s and 2080s) of meteorological variables. The SDSM predicts increasing mean monthly precipitation and maximum temperature during the two future periods. The Sequential Uncertainty Fitting (SUFI-2) algorithm was used for sensitivity analysis and calibration of the SWAT model in simulating of observed average monthly streamflow. The observed data matched reasonably well with the simulated flows with respect to Nash-Sutcliffe coefficient, PBIAS, RSR, and R^2 with values of 0.62, 5.7, 0.61, 0.63 during calibration process (1997–2004) and 0.55, 3.5, 0.67, 0.56 during validation process (2005–2011), respectively. The projected results of monthly streamflow revealed that the average annual streamflow may increase about 71% and 108% in future mid-century and significantly for end century period, respectively along with increase in surface runoff.

Keywords: SDSM, CGCM3.1, SWAT model, SUFI-2, tropical area, Malaysia.

1. Introduction

Studies of climate change impacts on water resources have become an attractive topic since the late twentieth century. The main source of discussion in assessment studies is supported by the outputs from a Global Climate Model (GCM) under different emission scenarios. A GCM is a three-dimensional numerical model of a planetary, ocean and atmosphere that employs many principles of physics, mathematics and fluid

mechanics. Among the outputs of the GCMs, the temperature and precipitation data were frequently used as input data into hydrological models to simulate the impact of climate change in regional scale.

The output of GCMs in simulation of the climate system has coarse resolution that is not enough to match with sub grid scale features such as topography and landuse characteristics. To bridge this gap, downscaling is a commonly way to investigate the impact of climate change on

water resources at a regional scale. The basic assumption in downscaling is that the large-scale atmospheric system extremely influences the local scale system, but the inverse effects from regional scales to global scales are unimportant (H. Fowler, S. Blenkinsop, & C. Tebaldi, 2007; B. Hewitson & R. Crane, 1996; Maraun et al., 2010; Teutschbein, Wetterhall, & Seibert, 2011; R. Wilby et al., 2004; Xu, 1999).

The existing downscaling methods have two broad categories: namely dynamical downscaling and statistical downscaling which extensive discussion on these downscaling classes includes theories, application, and advantage and deficiency of them can be found in many previous research works (e.g.(H. J. Fowler, S. Blenkinsop, & C. Tebaldi, 2007; B. C. Hewitson & R. G. Crane, 1996; Teutschbein et al., 2011; R. L. Wilby et al., 2004; Xu, 1999).

The method of coupling GCMs and hydrological models is a regular way to study the climate change in watershed scale. The Soil and Water Assessment Tool (SWAT) model and GCM are widely used around the world. Narsimlu et al (2013) studied the future climate change impacts on the hydrology of Upper Sind River Basin using climate data from PRECIS and SWAT model. This study illustrated that the average annual streamflow could increase by 16.4 % for the 2021-2050 and a significant increase of 93.5 % by the 2071-2098. The results also showed that streamflow may increase severely in monsoon season, but will decrease in non-monsoon season due to the projected future climate change.

Stone and Hotchkiss (2001) investigated the impacts of climate change on Missouri River Basin water yield by coupling the CISRO GCM and SWAT model that was modified earlier. The SWAT model input data were generated by nesting the Reg CM into the CISRO GCM. There was a 10-20% reduction in water yield at the basin outlet during spring

and summer months and an increase in the rest of the year. In another study by Stone et al. (2003) an important shift in water yield of the Missouri River Basin was obtained when the SWAT model was executed by input data from the downscaled CISRO GCM projection only versus the nested RegCM-CISRO GCM approach.

The current study tries to fill the gap in future view of water resources in a dense population in Klang Valley area due to climate change by integrating the Statistical Downscaling Model (SDSM) and SWAT model in simulating the climate characteristics and hydrological regime of the Hulu Langat Basin.

2. Materials and Methods

Study area

The study area is the Langat River Basin, figure (1). which is one of the most urbanized catchments in Malaysia, located in southern parts of Klang Valley, in which the capital city of Kuala Lumpur is located. It supplies water to two third of water required for the state of Selangor for different water usage. This watershed experienced rapid development in urbanization, agriculture, and industrialization along with changes in temperature and precipitation in recent decades (Amirabadizadeh, Huang, & Lee, 2014). The total area of the Langat River Basin is approximately 2352 km². It lies between latitudes 2° 40' 15" to 3° 16' 15" N and longitudes 101° 17' 20" to 101° 55' 10" E. The northern part of the basin is a mountainous area; while its central and western parts consist of flat areas figure (2). The average annual values of precipitation as well as the maximum and minimum temperatures are 1994 mm, 32°C and 23°C, respectively. The highest recorded monthly rainfall is about 327 mm in November, and the lowest is 97.6 mm in June. Table 1) The climatic data used in this study were obtained from the Malaysian Meteorological

Department (MMD) and the Department of Irrigation and Drainage (DID). Daily precipitation and maximum and minimum temperatures data of ten stations within and outside the Langat watershed have records of lengths between 16 and 30 years. The geographic locations of these stations and river network of the study area are shown in

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The NCEP/NCAR reanalysis dataset and also large-scale predictors of the third generation of Coupled Global Climate Model (CGCM3.1) version T47 for baseline period

as well as Special Report on Emission Scenarios (SRES) A2 were used to develop the downscaling model and projection of daily precipitation and maximum and minimum temperatures for the two future periods. On the list of SRES scenarios, A2 is known as, among the most severe scenario, projecting high emissions in the future (Nakićenović et al., 2000). The closest grid cell for the study area in the NCEP/NCAR database has coordinates of 1.86°N and 101.25°E.

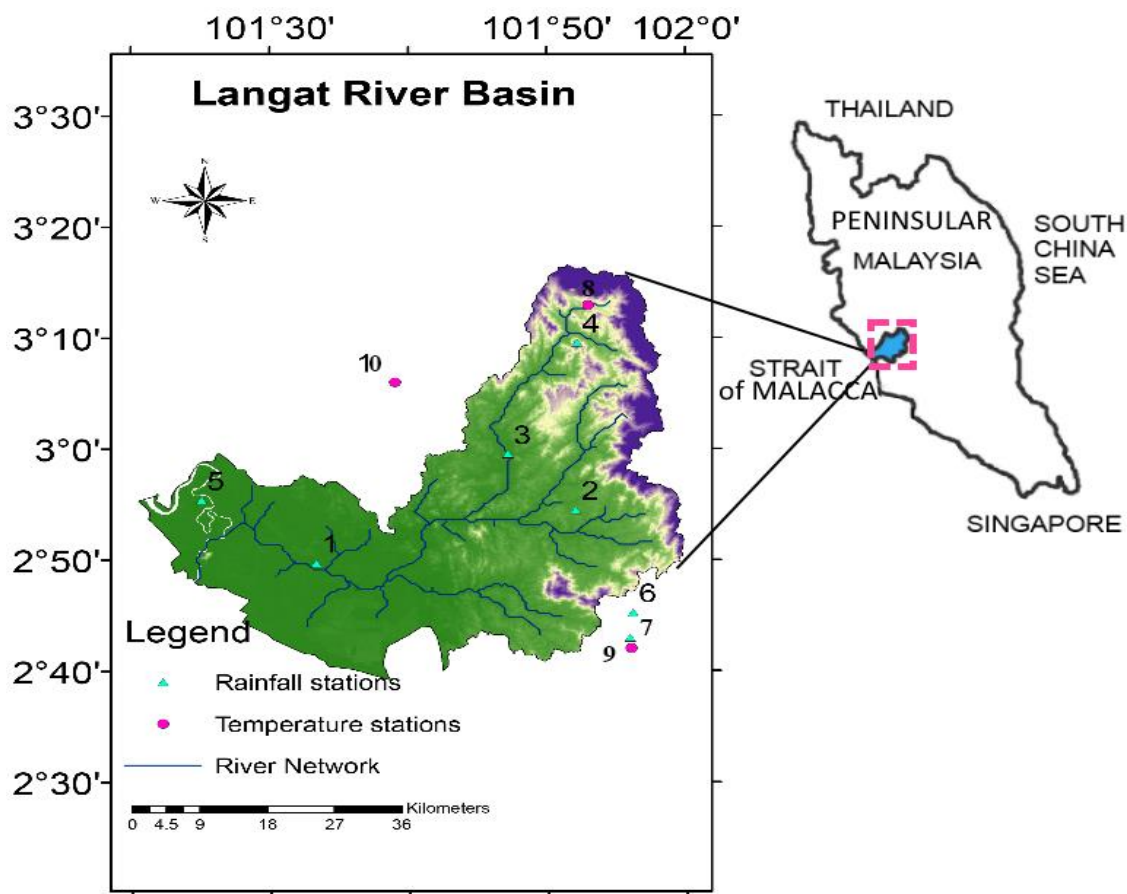


Fig. 1. Geographic location and spatial distribution of stations in the Langat River Basin from the Department of Irrigation and Drainage

Table 1. Geographic characteristics of stations for recorded precipitation and extreme temperature data

ID	Longitude(E)	Latitude (N)	Altitude (m)	Resolution	Period
1	101°32′	2°49′	3	Daily	1971-2001
2	101°52′	2°53′	36	Daily	1971-2001
3	101° 47′	2°59″	39	Daily	1976-2001
4	101°52′	3°10′	91	Daily	1971-2001
5	101°23′	2°55′	3	Daily	1974-2001
6	101°56′	2°45′	93	Daily	1971-2001
7	101° 56′	2° 43′	64.1	Daily	1974-2001
8	101° 53′	3° 13′	233.3	Daily	1985-2001
9	101° 56′ 37″	2° 42′ 33″	64.1	Daily	1971-2001
10	101° 39′	3° 6′	60.8	Daily	1974-2001

While the original predictor dataset of NCEP/NCAR contained 26 daily predictors (describing atmospheric circulation, thickness and moisture content at the surface, geopotential heights at 850 and 500 (hectopascal), the candidate predictors are just

eight predictors in Malaysia. The candidate lists of large-scale predictor variables from NCEP/NCAR and CGCM3.1 used in downscaling the climate variables are presented in Table 2).

Table 2. Summary of predictors of daily reanalysis from NCEP/NCAR Reanalysis

Code	Abb.*	Predictor	Code	Abb.*	Predictor
1	MSLP	Mean Sea level pressure	5	S500	500hPa specific humidity
2	P500	500 hPa Geopotential height	6	S850	850hPa specific humidity
3	P850	850 hPa Geopotential height	7	SHUM	Near surface specific humidity
4	PRCP	Accumulated precipitation	8	TEMP	Mean temperature at 2m

*Abbreviation

The results found in this research are expected to provide more insight into the availability of water for the citizen, and to provide local water management authorities with a planning tool.

Methodology

1- Downscaling Model Description and Setup

In this study, the SDSM was used in downscaling the local climatic variables on a daily scale (precipitation, maximum and

minimum temperatures) using the large-scale predictors of NCEP/NCAR Reanalysis data. Some primary process steps such as quality control and screening the predictors were done to create a common dataset for these statistical downscaling methods. In this study, the fourth root transformation has been done for precipitation, which is usually skewed climatic variable as preprocessing for application of the SDSM model (Chen, Brissette, & Leconte, 2011).

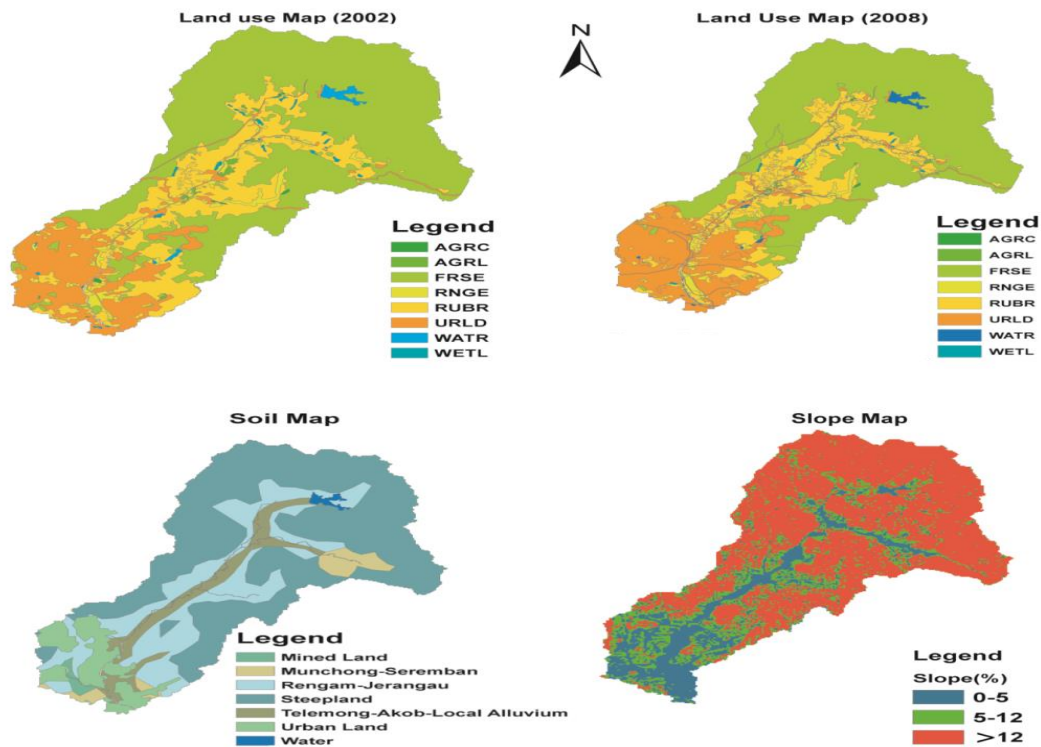


Fig. 2. Physiographic characteristics of the Hulu Langat Basin

1-1 Statistical Downscaling Model

The SDSM uses a hybrid of stochastic weather generator and multiple linear regression techniques in downscaling the climate variables. Wilby et al. (2002) described seven major steps for developing the best execution of the multiple linear regression equation for the downscaling process, including quality control and data transformation; screening of predictor variables; model calibration weather generation (using observed predictors); statistical analyses graphing model output and finally scenario generation (using climate model predictors). Unlike the simple multiple linear regression, the temperature and precipitation variables were modeled as unconditional and conditional processes, respectively. The bias correction and variance inflation factors were set to 12 and 1, respectively, in the calibration period as proposed by Hessami et al. (2008).

2- SWAT Model

The SWAT model is a long-term, continuous time, spatially distributed model which was developed by Arnold, Srinivasan, Muttiah, and Williams (1998) and widely used to simulate the response of watershed for climate change. In the SWAT model, a basin is divided into multiple subbasins, which are then further divided into one or more Hydrological Response Units (HRUs) according to topography, land use, and soil characteristics. The HRUs are created based on homogeneous spatial units characterized by similar geomorphological and hydrological properties (Flügel, 1995).

The water balance in the SWAT model in watershed scale is based on mass balance scheme concept:

$$SW_t = SW_0 + \int (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{pw}) \quad (1)$$

where, SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day i (mm), t is the time (day), R_{day} is the amount of precipitation on day i (mm), Q_{surf}

is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), W_{soil} is the amount of water entering the vadose zone from the soil profile, and Q_{rsw} is the amount of return flow on day i (mm) (Neitsch, Arnold, Kiniry, Williams, & Documentation, 2011).

3- SWAT Model Inputs

The SWAT model requires some spatial layer including Digital Elevation Model (DEM), landuse, soil, and weather data to simulate the hydrological cycle of a watershed. A 90m \times 90m DEM and stream network map was obtained from the Shuttle Radar Topography Mission (SRTM) (CGIAR, 2014) of USGS website to delineate the boundary and stream network of the watershed and analysis the characteristics of watershed. The landuse, soil, and slope layers which were used to compute the HRU of the watershed are shown in. Two landuse maps of 2002 and 2008 which were provided by the Department of Agriculture (DOA) were reclassified into eight categories and imported to the SWAT model for calibration and validation process, respectively (Li, Liu, Zhang, & Zheng, 2009). The locations of Water Treatment Plants (WTPs) and reservoir within the Hulu Langat Basin were digitized and added to the SWAT model as water usage and storage parameters. The weather generator files were constructed using 24 years of historical data from two weather stations: the Universiti Putra Malaysia Station (ID: 44302) and Petaling Jaya Station (ID: 48648) to generate wind speed, relative humidity, and solar radiation data in the SWAT model for further physical processes. The time series of precipitation as well as the maximum and minimum temperatures were constructed based on recorded data weather stations in the basin over the period 1975–2011. The sensitivity analysis and validation of SWAT model j and end century (2070-2099) was imported to the SWAT model to forecast the monthly stream

flow in the outlet of the basin.

4- SWAT Model Setup

The delineation of watershed that includes DEM setup, streamflow network definition, watershed outlet selection, reservoir digitization, and definition and calculation of subbasins parameters was done. The watershed delineation and HRU analysis of the Hulu Langat basin detected 47 subbasins and 363 HRUs based on landuse map, soil characteristics, and slope of the basin. In defining HRUs, 10 % threshold value has been considered for landuse, slope and soil area to ignore minor land uses, slope and soil types in each subbasin (Panhalkar, 2014).

According to the data obtained from the National Hydraulic Research Institute of Malaysia (NAHRIM) and Puncak Niaga Sdn Bhd (PNSB), the Langat reservoir was managed to provide at least 30% of the water requirement for downstream Water Treatment Plants (WTPs) from November to April. Furthermore, it releases 270×103 m³/day balancing capacity in the months from May to October.

There are five WTPs within the Hulu Langat Basin. The Sungai Lolo, Sungai Pangsoon, Sungai Langat, Sungai Serai, and Cheras Batu 11 WTPs along the Langat River produce 0.41, 1.82, 386.4, 0.9 and 27×103 m³/day of purified water, respectively (Juahir, 2009; Panhalkar, 2014). The created SWAT database was updated for water-use based on the water intake quantity by WTPs for respective subbasin.

Calibration and Validation of SWAT Model

The performance of SWAT models in simulating the observed mean monthly stream flow at the outlet of the Hulu Langat basin (Kajang station (ID: 2917401)) was examined using four known indices which were the Coefficient of Determination (R^2), Nash-Sutcliffe Efficiency (NSE), Percent BIAS (PBIAS) and RMSE-Observation Standard Deviation Ratio (RSR) as follows:

$$R^2 = \frac{(\sum_{i=1}^n (Q_i^{obs} - \bar{Q}_i^{obs})(Q_i^{sim} - \bar{Q}_i^{sim}))^2}{\sum_{i=1}^n (Q_i^{obs} - \bar{Q}_i^{obs})^2 (Q_i^{sim} - \bar{Q}_i^{sim})^2} \quad (2)$$

$$NSE = \left[1 - \frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2}{\sum_{i=1}^n (Q_i^{obs} - Q_{mean}^{obs})^2} \right] \quad (3)$$

$$PBIAS = \frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})}{\sum_{i=1}^n Q_i^{obs}} \times 100 \quad (4)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2}}{\sqrt{\sum_{i=1}^n (Q_i^{obs} - Q_{mean}^{obs})^2}} \quad (5)$$

where, \bar{Q}_i^{sim} and \bar{Q}_i^{obs} are the mean monthly simulated and observed discharge, Q_i^{obs} is observed discharge on the i th day, Q_i^{sim} is the simulated discharge in the i th month, n is the total number of months, and Q_{mean}^{obs} is the average observed streamflow in month in streamflow time series.

3. Results and Discussion

1- Selection of Predictors

The selection of predictors mainly ascertains the character of the downscaled climate scenario. A Cross Correlation Analysis (CCA) was carried out to find the optimum lags which correspond with maximum correlation between each pairs of predictands and the NCEP/NCAR predictors (Hashmi, Shamseldin, & Melville, 2011). While for many of the NCEP/NCAR predictors at stations, the CCA improved correlation between the large-scale predictors and local-scale predictand, few of the NCEP/NCAR predictors did not show any lag for improvement of the correlation. This lagged NCEP/NCAR predictors and also the local precipitation and maximum and minimum temperatures are then employed for screening the predictors as a process in calibration of the statistical downscaling model.

Table 3. Summary of selected predictors and respective predictands at different stations at the Langat River Basin

Stations	Predictand	Selected predictors	AIC	P-value	
1		P500, P500, P850, S850, SHUM, TEMP	51989.1	0.00*	
2		MSLP, P500, S500, S850, SHUM, TEMP	59494.1	0.00*	
3		MSLP, P500, S500, S850, SHUM, TEMP	52983.5	0.00*	
4		P500, S500, S850, SHUM, TEMP	60377.2	0.00*	
5	Precipitation	MSLP, P500, S500, S850, SHUM, TEMP	54613.7	0.00*	
6		P500, S500, S850, SHUM, TEMP	59707.4	0.00*	
7		P500, P850, S500, S850, SHUM, TEMP	55967.9	0.00*	
8		T _{Max}	MSLP, P500, P850, PRCP, S500, S850, SHUM, TEMP	4803.3	0.00*
		T _{Min}	MSLP, P500, P850, S500, S850, TEMP	-356.8	0.00*
9		T _{Max}	P500, P850, PRCP, S500, S850, TEMP	5835.6	0.00*
		T _{Min}	MSLP, P500, P850, PRCP, S850, SHUM	-3523.3	0.00*
10	T _{Max}	MSLP, P500, PRCP, S500, S850, TEMP	6980.7	0.00*	
	T _{Min}	MSLP, P500, PRCP, SHUM, TEMP	-3824.1	0.00*	

*Significant at the 95% confidence level

The stepwise regression with both directions (backward and forward) was adopted to screening the predictors and select the best combination of them by reaching the smallest Akaike Information Criterion (AIC) (Hessami et al., 2008; Tavakol- Davani, Nasseri, &Zahraie, 2013) (Table 3).

From the selected predictors, it was discovered that the local variables were controlled by non-atmospheric parameters. The selected predictors at all stations were used for calibration and validation of SDSM version 4.2.9 (Wilby et al., 2002). The observed historical dataset until the year 2001 was split into two equal parts for calibration and validation processes of the downscaling method.

2- Validation and Projection of Statistical Downscaling Model

The statistical downscaling approach was evaluated in simulating the predictand time series during the validation period (independent data set) at all stations in the

Langat River Basin. The results of SDSM model showed that this model is efficient at reproducing the inter-annual variability to reproduce the mean daily precipitation and daily maximum and minimum temperatures which conform to Sachindra, Huang, Barton, and Perera (2013). The result also illustrated less error values in downscaling the maximum and minimum temperatures than the precipitation parameter. Statistical characteristics of daily precipitation time series are important for future projection of downscaling models.

Table (4) illustrates statistical characteristics of downscaled precipitation including mean and standard deviation (SD) during the validation period at stations of the Langat River Basin. Finally, the SDSM was applied for generating future scenario (2030s and 2080s) of the rainfall as well as the maximum and minimum temperatures as regional climatic variables using the A2 emission scenario from CGCM3.1 T47 at all stations.

Table 4. Statistical properties of downscaled precipitation and temperatures for validation period at stations of the Langat River Basin

Station	Variable	Mean, SD		Station	Variable	Mean, SD	
		Obs	SDSM			Obs	SDSM
1	Precipitation	4.1, 10.4	6.4, 5.5	8	T _{Max}	31.8, 1.53	31.2, 0.93
2		4.9, 11.6	6.5, 5.7		T _{Min}	21.5, 0.611	21.7, 0.94
3		5.7, 12.8	8.1, 6.9	9	T _{Max}	31.8, 1.5	31.8, 0.74
4		5.5, 12.8	6.1, 5.5		T _{Min}	23.6, 0.77	23.0, 0.44
5		4.1, 11.1	6.2, 5.4	10	T _{Max}	32.7, 1.55	33.0, 0.86
6		5.3, 12.1	7.2, 5.9		T _{Min}	24.1, 0.98	23.6, 0.51
7		6.2, 13	8, 7.2				

Obs: Observation

SD: Standard Deviation

Analysis of projected time series of precipitation exhibited an increasing in the mean monthly rainfall at most of the stations in two future periods compared to current period. The average percentage rate of change of mean monthly precipitation in 2030s and 2080s predicted by the SDSM at different stations varies from 34 to 113% and 25 to 255%, respectively. The results of the SDSM

showed an increasing in the values of rainfall through the southwest monsoon rainfall by 2030s compared to the baseline period. The comparative results of monthly dry and wet spell lengths between the current period and downscaled daily precipitation in the 2030s and 2080s periods indicated increasing in wet spell and decreasing in the dry spell length figure (3).

The results of trend analysis using the Mann-Kendall and Theil-Sen's Slope method for annual rainfall in two future periods are shown in Table (5). It illustrates that there are significant increasing trends in two future periods. The rate of changes in significant trends for the 2080s period was higher than that in the 2030s. The projected annual rainfall for two future periods at station 2 and station 3 did not indicate any significant trend for two future periods at the 5% significance level. The analysis of generated precipitation

time series by these models indicated that the predicted trend which was generated for the 2030s, continues in the 2080s period too.

The map of percentage change for two monsoon seasons during two future periods was created using the IDW technique for the study area. As it can be seen, the flat area of the basin shows more change than the mountainous area in the future periods. In addition, the area close to cities illustrated higher percentage change than the area with forest land cover.

Table 5. The Mann-Kendall and Theil-Sen's Slope method trend test results for annual rainfall and maximum and minimum temperatures generated by the SDSM during the 2030s and 2080s periods

Station	Parameter	S-value		P-value		Theil-Sen's Slope	
		2030s	2080s	2030s	2080s	2030s	2080s
1	Precipitation	81	245	0.15	<0.001*	+11.4	+70
2		137	215	0.014*	<0.001*	+30.4	+37.9
3		-25	97	0.67	0.08	-3.5	+7.3
4		103	103	0.07	0.07	+14.7	+10.3
5		165	197	0.003*	<0.001*	+18.8	+66.7
6		225	269	0.001*	<0.001*	+50.3	+94.1
7		73	277	0.2	<0.001*	+11.9	+140.3
8	T _{Max}	57	55	0.31	0.34	+0.002	+0.002
	T _{Min}	311	361	<0.001*	<0.001*	+0.031	+0.038
9	T _{Max}	221	289	<0.001*	<0.001*	+0.01	+0.014
	T _{Min}	335	359	<0.001*	<0.001*	+0.02	+0.026
10	T _{Max}	269	273	<0.001*	<0.001*	+0.022	+0.028
	T _{Min}	343	347	<0.001*	<0.001*	+0.021	+0.03

*: Significant at the 95% confidence level

The downscaling results of maximum temperature indicated that most of the sites in this watershed will increase during two future periods. The rate of change was positive in the southwest monsoon months (May to August) and slight decline occurs in the northeast monsoon months (November to February). The SDSM predicted an increase

in monthly T_{Max} by 0.37°C and 1°C for 2030s and 2080s periods, respectively. The SDSM model tries to replicate the variance of maximum temperature in current period for the 2030s and 2080s periods as the variance inflation adjustment in the calibration process of SDSM forced the model to follow the observed data (Wilby et al., 2002).

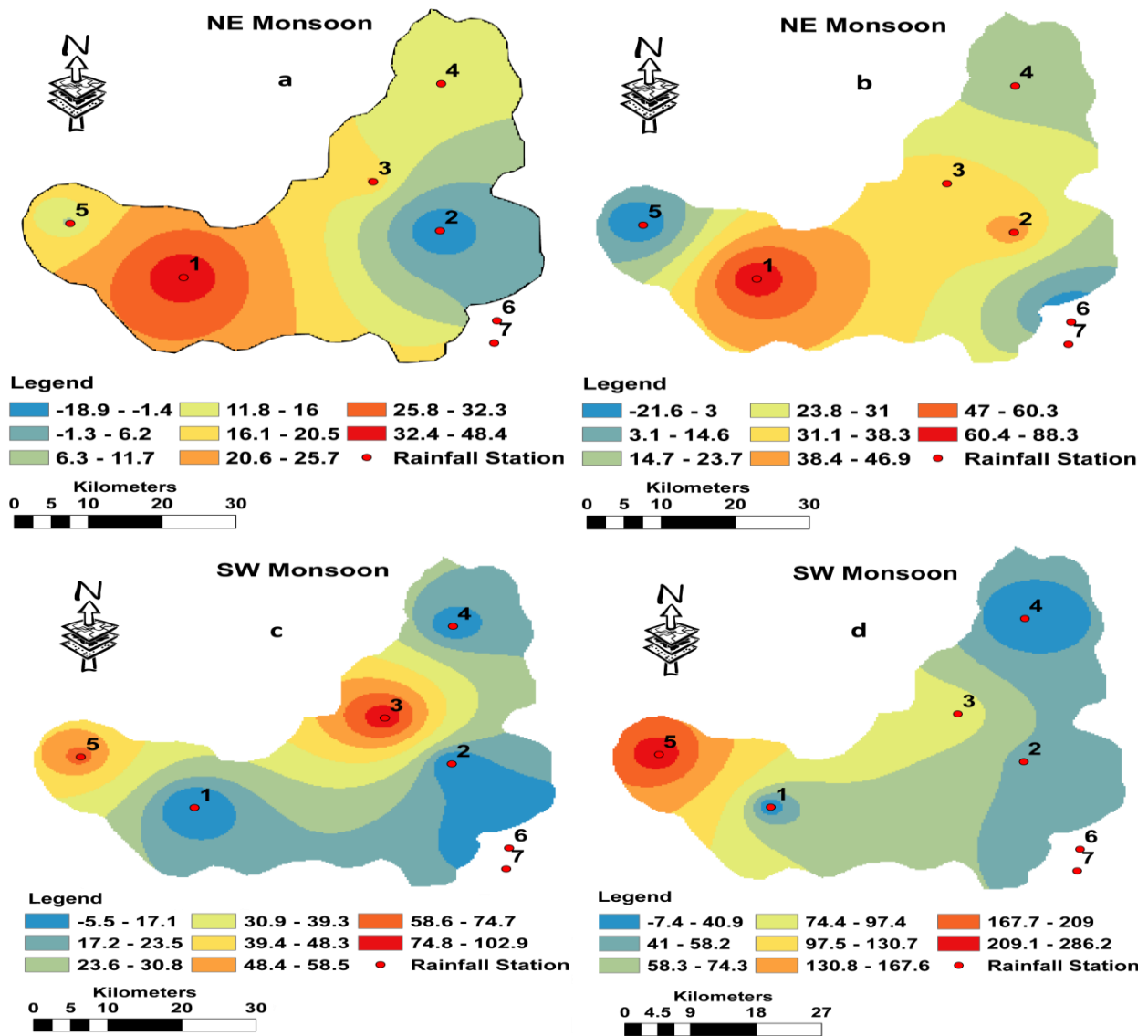


Fig. 3. Percentage change of mean monthly precipitation during two monsoons season in 2030s (a, c) and 2080s (b, d) periods predicted by SDSM

The results of trend analysis indicated that, while there were significant trend in predicted annual TMax at Station 9 and Station 10, the trend test did not detect any significant trend for two future periods at the 95% confidence level. The rate of change in significant trends obtained by Theil-Sen's test in 2080s period was greater than that during the 2030s.

The SDSM model expects decrease in the mean values of TMin for the southwest monsoon months by the 2030s and 2080s periods. The generated downscaling time series under the A2 emission scenario showed the highest rate of percentage change by the 2030s and 2080s at station 8, which is located

in a mountainous area in comparison with stations in flat areas.

Analysis of downscaled minimum temperature at stations of this basin explored more variability in generated minimum temperature than the maximum temperature time series. The downscaling results of TMin by the SDSM predicted mean increasing of 0.83°C and 2.2°C in the basin by the 2030 and 2080s period, respectively compared to baseline period. The results also showed the mean variance of TMin by 1.0°C in projected time series generated by the SDSM for the 2080s period. The Mann-Kendall test analysis detected an increasing trend in annual TMin

generated by the SDSM for two future periods at all stations of the Langat River Basin. The Theil-Sen's Slope method obtained higher increasing rates in annual TMin for the 2080s than 2030s period. The difference of change slopes in 2030s and 2080s in predicted annual rainfall was greater than that for annual maximum and minimum temperatures (Table 5).

3- SWAT Calibration and Validation

The SWAT simulation was conducted using 7-year warm-up in monthly time scale for the period of 1990 to 2011. The calibration and uncertainty analysis of the SWAT model was conducted in monthly scale by comparing simulated and observed monthly streamflow at the Kajang station at outlet of the Subbasin no 47 during 1997-2004. In this way, The SUFI-2 (Sequential Uncertainty Fitting Ver. 2) algorithm, under the SWAT calibration and uncertainty procedure (SWAT-CUP V5.1.6) interface, was applied for the calibration,

uncertainty analysis, and validation of the SWAT model (Abbaspour, Johnson, & Van Genuchten, 2004). The results of global sensitivity analysis indicated that the ALPHA_BNK and REVAPMN parameters were the most and least sensitive parameters respectively, in streamflow simulation. These parameters control the bank storage for baseflow and groundwater respectively (Neitsch et al., 2011). In addition, CH_K2, SOL_K(..), and CN2 showed considerable sensitivity in streamflow simulation (Table 6). More description of these parameters and their application can be found in Neitsch et al. (2011). This finding conforms to results from previous studies conducted in the Langat watershed (Ayub, Hin, & Aziz, 2009; Memarian et al., 2014). The uncertainty analysis demonstrated that 76% of observed discharge was bracketed by the 95PPU in the SUFI-2 algorithm. This value of uncertainty indicates a desirable certainty in streamflow simulation (Narsimlu et al., 2013).

Table 6. Results of sensitivity analysis of parameters used for simulation of streamflow in outlet of the Hulu Langat Basin

Parameter	rank	Description	Range value	Fitted value	process
v__ALPHA_BNK.rte	1	Baseflow alpha factor for bank storage (day)	0-1	0.0004	Channel
v__CH_K2.rte	2	Effective hydraulic conductivity in main channel alluvium (mm/hr.)	0-127	39.9	Channel
r__SOL_K(..).sol	3	Soil saturated hydraulic conductivity (mm/hr.)	0-2000	1409.8	Soil
r__CN2.mgt	4	Initial SCS runoff curve number for moisture condition II	35-98	(1+(-0.0398))	Runoff
v__EPCO.bsn	5	Plant uptake compensation factor	0.01-1	0.85	Soil
v__GW_REVAP.gw	6	Groundwater "revap" coefficient	0.02-0.2	0.14	Groundwater
r__REVAPMN.gw	7	Threshold depth of water in shallow aquifer for "revap"(mm)	0-500	241.8	Groundwater

Table 7. The results of four evaluation metrics during the calibration and validation of water discharge in monthly time scale

Period	Years	NSE	PBIAS (%)	RSR	R ²
Calibration	1997-2004	0.62	5.7	0.61	0.63
Validation	2005-2011	0.55	3.5	0.67	0.56

The performance of the SWAT model in simulating the observed streamflow for calibration and validation periods was evaluated using four indices including NSE, PBIAS, RSR, and R² as described already. The NSE was set as goal function and NSE=0.5 was defined as the threshold of accepted simulation by the SUFI-2 (Gassman, Reyes, Green, & Arnold, 2007; Moriasi et al., 2007). The performance results for calibration and validation periods are shown in Table 7). While, the evaluation results showed better performance in all evaluation parameters for calibration in comparison with validation period, the model showed reasonable results in both of periods figure (4). Considering the values of PBIAS during the calibration and validation periods indicated underestimation in simulating the overall values of observed discharge.

The projected monthly streamflow during three periods include baseline, mid-century (2030s), and end century (2080s) is presented in. As shown, the projected monthly streamflow time series are illustrated to be

increase during two future periods related to the baseline period under A2 emission scenario. The rates of increase in monthly discharge were 71% and 108% for the 2030s and 2080s relative to the baseline period, respectively. The patterns of change in the mean and Coefficient of Variation (CV) in monthly streamflow for different month are shown in. The CV statistics of predicted monthly streamflow indicated decrease in values in two future stages related to baseline. However, a lower CV in future stream flows in mid and end century referred to the lower occurrence frequency of extreme high intensity events such as flood and drought due to climate change. In spite of increasing of rainfall in two future periods, the mean rainfall in the months of May, June, November, and December will decrease in future periods. The months of May and June belong to southwest monsoon and other two months are related to northeast monsoon season. Therefore, decreasing of rainfall may change the pattern of precipitation in these two seasons.

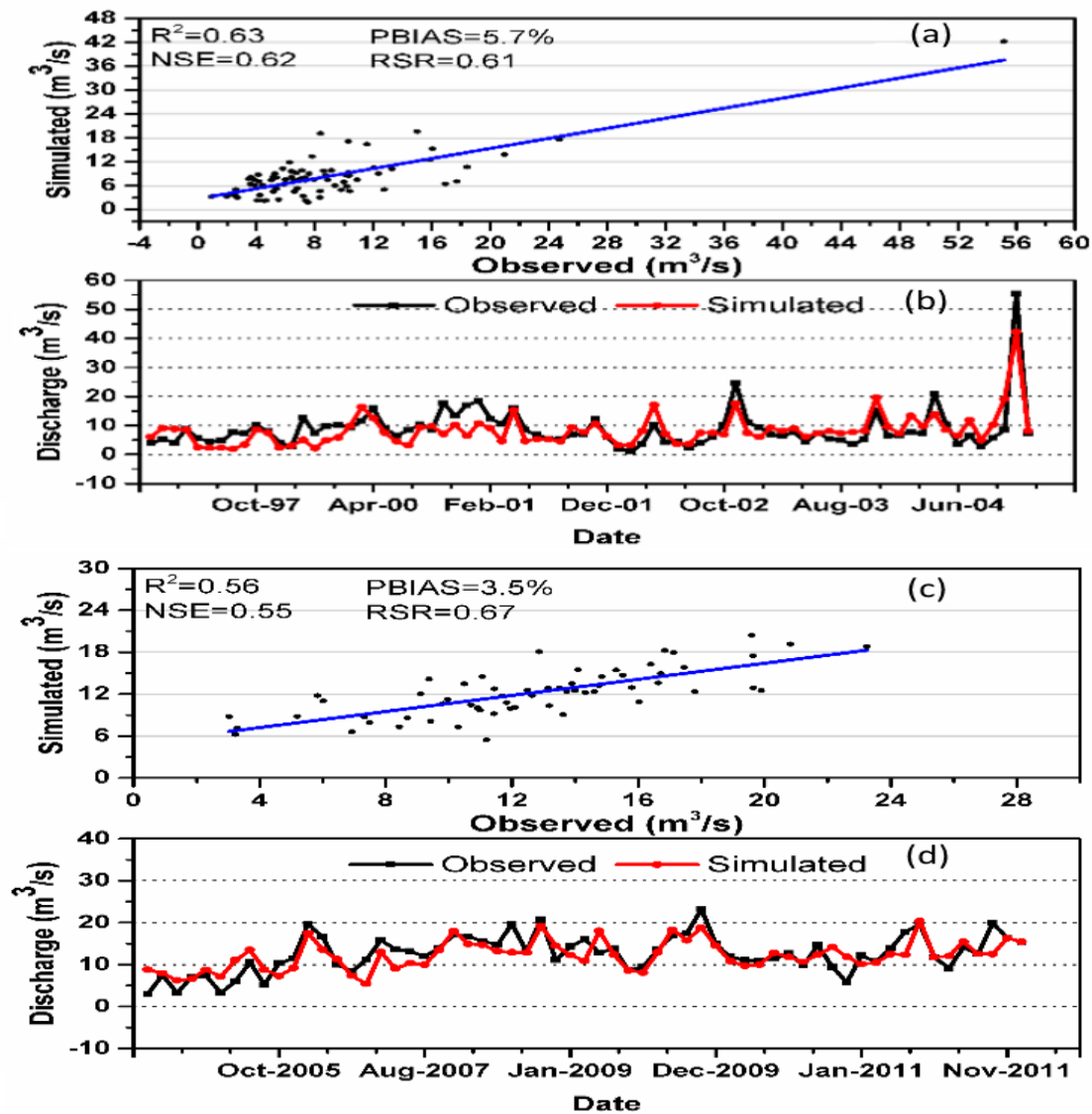


Fig. 4. Observed monthly discharge and the best estimates during (a,b) calibration and (c,d) validation period at outlet of the basin using the SWAT model

4- Projected Streamflow Change

The results of the SWAT simulation for average annual water cycle components for the Hulu Langat catchment are shown in Table (8). This table also illustrates other results that refer to the impact of likely future climate change on the hydrologic response of the watershed. The results for the mid-century period in comparison with the baseline period indicate an increase in annual precipitation of 41.5 %, and the future annual average streamflow will increase by 71 % (Table 8). However, in this period, the streamflow contribution of surface runoff will increase by

313% and baseflow will increase by 78.4 %. According to Table 8), for an increase in annual precipitation of 59.2 % (baseline–end century), the future annual average streamflow and surface runoff would increase by 108 % and 441.8%, respectively. This rate of increase of surface runoff among other hydrological component during two future stages may be due to rising of mean daily precipitation along with low infiltration rate of soil layers. The rate of increase of baseflow discharge in mid-century and end century relative to baseline period was approximately identical figure (5, 6).

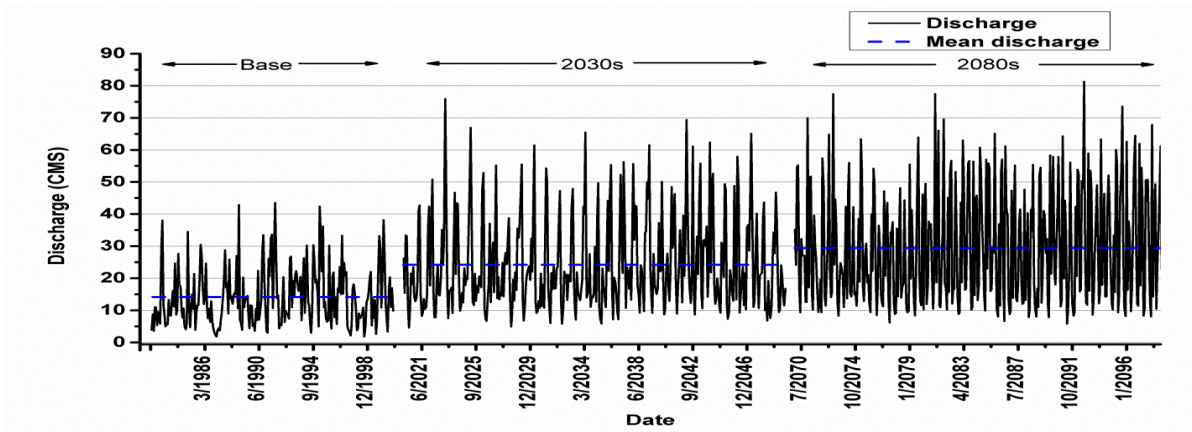


Fig. 5. Predicted discharge due to climate change in two future and baseline periods

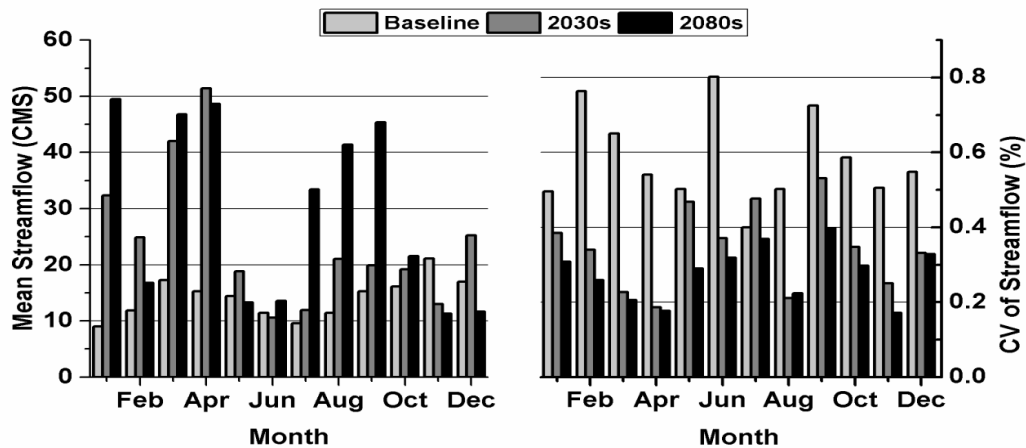


Fig. 6. Mean and CV (Coefficient of Variation) of monthly streamflow in different months simulate by the SWAT model

Table 8. The values of hydrologic cycle components simulated by the SWAT model for three periods

Period	P	ET	SR	RF	BF	Discharge (m ³ /s)
baseline	2056.5	782.6	83.4	81.0	7.9	14.2
2030s	2910.7	859.7	344.6	140.0	14.1	24.2
2080s	3273.7	854.5	451.9	186.2	13.8	29.4
Relative Change (%)						
BL- midcentury	+42	+9.9	+313.2	+73	+78	+71
BL- endcentury	+59	+9.2	+441.8	+129	+75	+108

P: Mean Stage Precipitation (mm) ET: Evapotranspiration (mm) BL: Baseline
 SR: Surface Runoff (mm) RF: Return Flow (mm) BF: Baseflow (m³/s)

5- Conclusion

This study examined the climate change effects on hydrological response of a tropical watershed, in Malaysia using the SWAT model. The performance of a multiple linear regression, called SDSM was evaluated in simulating baseline as well as two future periods (2020-2049, 2070-2099) of daily precipitation, maximum and minimum temperatures under the A2emission scenario

using CGCM3.1. The downscaling model was calibrated and validated using large-scale predictors NCEP/NCAR reanalysis data and regional climate variables (precipitation, maximum and minimum temperatures). The results of the SDSM showed a rising change in rainfall through the southwest monsoon season in the mid-century compared to the baseline period. The downscaling models indicated that most of the sites in the river

basin experience increasing for TMax during the two future periods. But, the rate of change was more during the southwest monsoon months (May to August) and slightly less during the northeast monsoon (November to February). Therefore, warmer weather conditions in two future periods were predicted by the downscaling model (SDSM). The SWAT model was calibrated and validated by SUFI-2 algorithm for observed monthly streamflow during 1997-2004 and 2005-2011 periods, respectively. The acceptance values of evaluation indices during validation indicate a reasonable calibrating process. The projected values of monthly streamflow revealed that the average annual streamflow may increase about 71% and 108% in future mid-century period and significantly for end century period, respectively along with the increase in surface runoff.

Acknowledgments

The authors would like to thank the Department of Irrigation and Drainage (DID) and the Malaysian Meteorological Department (MMD), both under the Ministry of Natural Resources and Environment Malaysia (NRE), for providing data and technical support. The authors would also like to sincerely thank the Ministry of Science, Technology and Innovation (MOSTI) for the financial support provided for the project.

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