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Performance of HEC-HMS and ArcSWAT Models for Assessing Climate Change Impacts on Streamflow at Bernam River Basin in Malaysia

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ABSTRACT

Hydrological models are reliable tools that have been extensively used for hydrological studies. However, the complexity of some of these models has been a major setback, which affects their performance. This study compared Hydrologic Engineering Corps Hydrologic Modeling System (HEC-HMS) with most widely applied Soil Water Assessment Tool (ArcSWAT) model and used to assess impacts of climate change on streamflow at Bernam Basin, Malaysia for 2010-2039, 2040-2069 and 2070-2099 to the baseline period (1976-2005) using an ensemble of ten GCMs under three RCP scenarios (RCPs 4.5, 6.0 and 8.5). The models performed satisfactorily. However, HEC-HMS performed better compared to ArcSWAT with 0.74, 0.71, 4.21 and 0.37; and 0.71, 0.69, 5.32 and 0.31 for R^2, NSE, PBIAS and RSR, respectively, during the calibration and validation periods. Future periods suggest a decreasing pattern in streamflow, with a higher percentage (−5.94%) expected for the RCP 8.5 scenario in the late century (2080s) during dry season period. In the wet season, streamflow decreases in all future periods except for RCP4.5 where it is expected to increase (0.36%). Therefore, the Basin may likely experience tremendous pressure in the late century due to low streamflow, particularly in dry season months.

Keywords: ArcSWAT, climate change, flow regime, HEC-HMS, hydrological model

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INTRODUCTION

Climate change brings a severe impact on water resources, which affects many watersheds. Changes in rainfall and temperature patterns threaten phases of hydrological cycle, disturb the ecosystem, affect agricultural production and increase the vulnerability (Schlenker et al., 2007). Conversely, ground-water level shows significant variability due to climate change with drastic decline as reported by Sivarajan et al. (2019). As pressure on the world's freshwater resources increases, many river basins will face both increasing freshwater scarcity and increasing pollution. Therefore, adaptation strategies under the new realities of climate change are one of the most important challenges in the 21st century for global water and food security. Due to spatial and temporal variations in climate, water availability in different water catchments in the world has been affected and there are occurance of flooding in many áreas. For example, severe flooding has frequently affected Malaysia, especially during the boreal winter moonsoon (Hamzah et al., 2019; Ibadullah et al., 2019). Therefore, it is imperative for the country to have a reliable and skilful early warning system of both weather and flood events. The general circulation models (GCMs) are currently the most reliable tools for assessing the changes in climate. However, regional hydrological changes can only be predicted by using hydrological models to simulate hydrological impacts of climate change at basin scales, using downscaling techniques (Jiang et al., 2007).

It is quite hard to manually quantify and regulate streamflow at different sections of a channel in a large irrigation scheme, resulting in inadequate delivery between wáter supply and irrigation demand. Hydrological models are essential tools that facilitate the streamflow monitoring for adequate water allocation for industrial, domestic and agricultural purposes, particularly when projecting the impacts of variability in climate. However, some models are more reliable particularly when handling ungauged stations or stations with poor input data, which is a common situation in most of the watersheds. Abdulkareem et al. (2018), highlighted details of hydrological models used in Malaysia, about 65% of the studies applied semi-distributed and distributed hydrological models. Out of these 65% of the modelling studies, 60% applied HEC-HMS model due to its least input parameters followed by ArcSWAT model (20%) and MIKE-SHE (9%).

The Bernam River Basin is the primary source of irrigation supply for the Tanjung Karang Rice Irrigation Scheme, which is the fourth largest in Malaysia. The hydrological processes of this river basin under climate change are paramount to the planning and management of the irrigation scheme's potential water requirements. Water shortage is an annual issue for the scheme. An imbalance between water supply from the upstream and the water demand at the intake of the scheme is often experienced (DID, 2018).

Among the hydrological models, the use of ArcSWAT in streamflow simulation and forecast for present and projected climate scenarios has been extensive (Ajayi, 2017; Alansi et al., 2009; Dlamini et al., 2017; Dlamini et al., 2016; Lai & Arniza, 2011). However, the difficulty in data preparation into ArcSWAT format and the high number of parameters required to run the model are some of its major weakness (Abbaspour et al., 2007a), particularly for ungagged stations, where data is scarce . MIKE-SHE has an advantage in terms of seamless integration of all the important processes of the hydrological cycle (Refsgaard et al., 1995). However, it requires extensive model data and physical parameter that may not be available all the time, which make the model setup difficult. Amin et al. (2017) applied the Watershed Environmental Hydrology (WEHY) model to assess future climate change impact on hydrologic processes of watershed. The model requires detailed topographic information and simulations are conducted on model computational units. HEC-HMS is an open-source hydrological modeling software for simulating precipitation-runoff processes of watershed systems (Ghorbani et al., 2016; Kabiri, 2014; Mohammed et al., 2011; Razi et al., 2010; Yusop et al., 2007). Among the advantages of the model over other hydrological models is the various options in methods selection, to compute different hydrological responses for watershed development. Previous studies have extensively applied HEC-HMS model to examine the impacts of future climate projections on water resources (Chu & Steinman, 2009; Kabiri et al., 2015). Hydrological modeling studies (Alansi et al., 2009; Dlamini et al., 2017) were carried out in the study area using different model. Thus, the need to evaluate HEC-HMS and ArcSWAT models as different hydrological models perform best in certain hydrological catchments. Therefore, this study assesed the performance of these models for climate change impacts assessment on streamflow in Bernam River Basin Malaysia.

MATERIALS AND METHODS

Study Area

The Bernam River Basin is an agro-hydrological watershed situated at the boundary between the States of Perak and Selangor, Malaysia (Figure 1). The mean elevation is about 950 m above sea level. The climate of the area is a humid tropic that is largely characterized by the two predominant rainfall seasons, dry season (January–June) and the wet season (July–December) (Deni et al., 2010). The average annual rainfall in the region is about 2,000 mm, and its distribution is mostly between the months of October–January and only to a limited extent over April–May. The distribution of rainfall is unpredictable between the months of January–August. The mean maximum and minimum temperatures are 31.5°C and 22.3°C, respectively.

Downscaling of GCMs Variables

Adoption of multi-models is essential and recommended for impact studies and adaptation strategies (Ghosh & Mujumdar, 2007; New & Hulme, 2000), because single GCM does not

Figure 1. Typical view of Upper Bernam River Basin (UBRB), Malaysia

actually provide useful information in assessing the climate change impacts. Therefore, ten global climate projections were acquired from Program for Climate Model Diagnosis and Inter-comparison (PCMDI). A baseline period (1976-2005) was adopted and three future periods of 30-year time segments were defined as the 2020s (2010-2039), 2050s (2040-2069) and 2080s (2070-2099) for the ten GCMs under three Representative Concentration Pathways (RCPs) scenarios (RCP 4.5, RCP 6.0, and RCP 8.5). The spatial resolution from the output of GCMs cannot give a good climate change scenario to a target watershed because GCMs operate on a large spatial scale. Therefore, downscaling is required to represent the impact of climate change on a catchment área. A Climate-smart Decision Support System (CSDSS) for downscaling hydro-meteorological variables, which was developed by Rowshon et al. (2019), was used to downscale the extracted GCMs outputs. The CSDSS was built in MATLAB environment using First-order Markov Chain Model and "Delta change factor" statistical downscaling method. In the First-order Markov

Chain Model, the occurence of rainfall is characterized by two transition probabilities; the probability of a wet day preceded by a dry day $P_{(dw)}$ and the probability of a wet day preceded by wet day $P_{(ww)}$, as given in Equations 1 and 2. The two transition probabilities were estimated from the observed rainfall series and were constant for a given month but differ from one month to the other.

$$P_{dw} = P\{wet\ on\ day\ (t) \mid dry\ on\ day\ (t-1)\} \qquad [1]$$

$$P_{ww} = P\{wet\ on\ day\ (t) \mid wet\ on\ day\ (t-1)\} \qquad [2]$$

In order to simulate the occurrence of rainfall, $P_s(t)$, on day t, a random number, U_t was generated using MATLAB program and compared with the critical transition probability, P_c, depending on the preceding day's $(t-1)$ rainfall (Equation 3).

$$P_c = \begin{cases} P_{dw}\ \ if\ P_s(t-1) = d \\ P_{ww}\ if\ P_s(t-1) = w \end{cases} \qquad [3]$$

Where, w = wet day and d = dry day. A wet day is simulated when the random number is less than the critical probability, otherwise it is simulated as a dry day (Equation 4).

$$P_s(t) = \begin{cases} w\ if\ U_t \le P_c \\ d\ if\ U_t > P_c \end{cases} \qquad [4]$$

The variation in the amount of rainfall on wet days is defined using a probability density function, which best describes the amount of rainfall. The gamma distribution (Equation 5), which is the most popular distribution widely used in rainfall studies (Dlamini et al., 2015) was adopted in this study. The gamma distribution is fitted to all days modeled as wet days and a threshold value of 1 mm was considered for Malaysia due to the high humidity condition (Deni et al., 2010; Zin et al., 2010).

$$f(x) = \frac{\left(x/\beta\right)^{\alpha-1} exp\left(-x/\beta\right)}{\beta\Gamma(\alpha)}; \alpha, \beta > 0; x > 0 \qquad [5]$$

Where, α is a shape parameter, β is a scale parameter, and $\Gamma(\alpha)$ represents the gamma function. The maximum likelihood estimators were used to estimate the gamma parameters (Haan, 1977).

Rainfall generator models are evaluated on the basis of how well they preserve the statistical properties of the original data. Daily observed rainfall datasets for 30 years (1976-2005) were used to calculate representative parameters for model evaluation. The data was provided in the model to compute area specific parameters from the generated daily series by running the model 100 times. This was done so that the statistical properties of the synthetic data would be close to the distribution of the original dataset. A number of statistical properties of the synthetic data describing rainfall occurrence, quantity and distribution (including monthly mean rainfall, standard deviation, rainy days, wet/dry spells and annual maximum rainfall) was calculated. Deteils procedure of the probability distribution and statistical properties could be found in other study (Dlamini et al., 2015).

In the "Delta change factor" method, the mean values of GCM simulated baseline and future climates were estimated using Equations 6 and 7:

$$\overline{GCM_b} = \sum_{i=1}^{Nb} GCM_{bi}/N_b \qquad [6]$$

$$\overline{GCM_f} = \sum_{i=1}^{Nf} GCM_{fi}/N_f \qquad [7]$$

Where, $\overline{GCM_b}$ and $\overline{GCM_f}$, GCM_b and GCM_f are the mean values and values from GCM baseline and GCM future climate scenario, respectively. N_b and N_f are the total number of values in the downscaling for baseline and future periods, respectively.

Subsequently, monthly additive (CF_{add}) and multiplicative Change Factor (CF_{mul}) changes between the baseline and future periods in the equivalent climate variable of interest are calculated for the GCM grid box using Equations 8 and 9. Relative change factors are used in the case of rainfall (ΔP), derived from the ratio of projected-to-baseline averages, while absolute change factors are used for temperature, solar radiation, relative humidity and wind speed (ΔV), by subtracting the GCMs averages representing baseline from the future.

$$CF_{Rain} = \left(\bar{P}_{GCM,fut,m} \big/ \bar{P}_{GCM,base,m} \right) \qquad [8]$$

$$CF_{var} = \left(\bar{V}_{GCM,fut,m} - \bar{V}_{GCM,base,m} \right) \qquad [9]$$

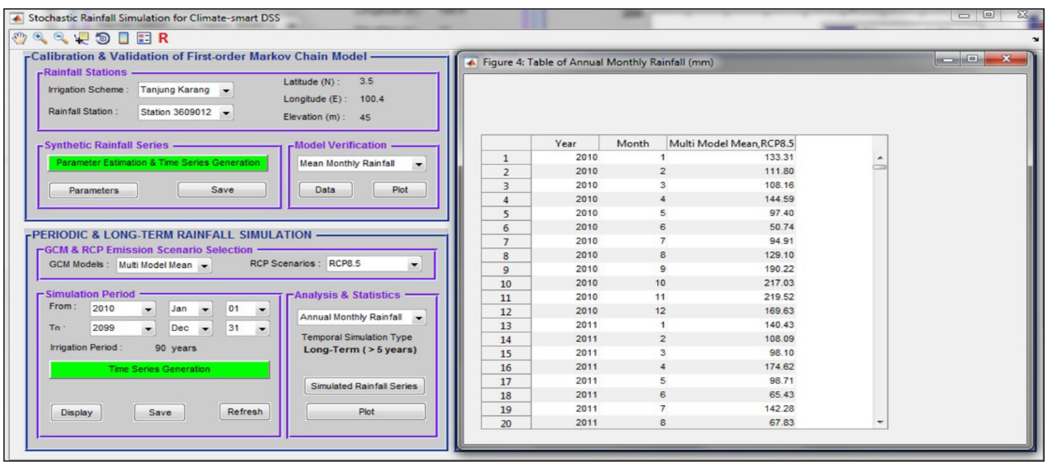
Finally, local scaled future climate values were obtained by applying the Change Factors using Equations 10 and 11. This involves superimposing the change factors suggested by the GCM-scenario combinations to the daily baseline time series to give perturbed climate series.

$$P_{adj,fut,d} = P_{obs,d} \times CF_{Rain} \qquad [10]$$

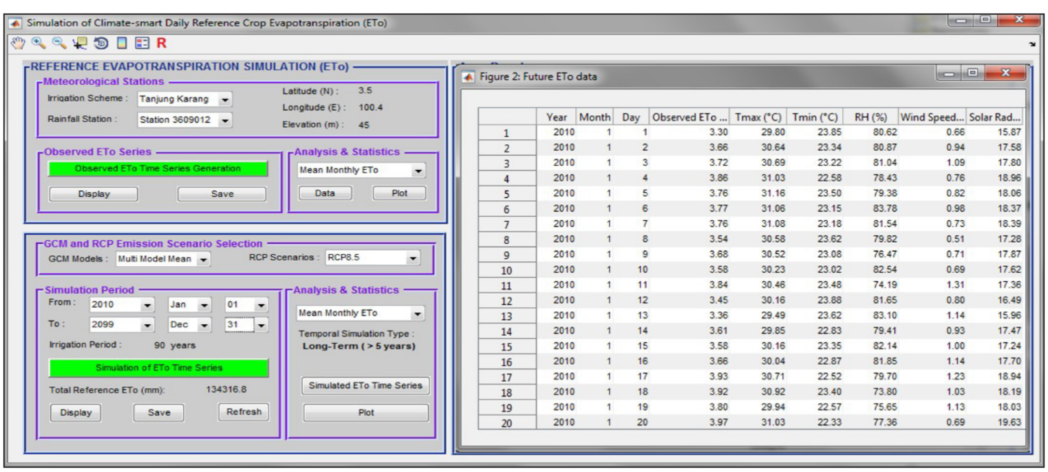
$$V_{fut,d} = V_{obs,d} + CF_{var} \qquad [11]$$

Where, P and V are the rainfall and climate variables, respectively, the subscrip; *adj,fut,d* denotes the downscaled future daily variable; *obs,d* denotes daily observations; CF denotes calculated additive and multiplicative change factors for rainfall and climate variables; *GCM,fut,m* and *GCM,base,m* are the average monthly values of GCM output and baseline periods, respectively.

A simulation dialog window appears after clicking on a specific command button from the CSDSS main dialog window to generate daily sequences of hydro-meteorological variables as shown in Figure 2. The program was validated using the observed and simulated monthly average values for the baseline period. The outputs can be generated as daily time series and long-term monthly time scale, and can be viewed from the "*Analysis and Statistics*" button as tables and graphs.



(a)



(b)

Figure 2. Windows for downscaling daily climatic variables time-series (2010-2099): (a) Daily rainfall generation; and (b) Daily temperature, relative humidity, wind speed and solar radiation

Hydrological Modeling for Bernam River Basin

Two hydrological models HEC-HMS and ArcSWAT were adopted in this study based on their availability and accuracy. The models require two types of data for hydrological simulation, the spatial and hydro-climatic data. The spatial data include digital elevation model (DEM), soil and land use maps of the área. The DEM was downloaded from DIVA-GIS website while soil and land use maps were obtained from the Department of Agriculture (DOA) Malaysia. A gridded daily climate dataset including rainfall, minimum and maximum temperature, relative humidity, wind speed and solar radiation for 1976-2005 was obtained from the Water Resources and Hydrology Division, Department of Irrigation and Drainage (DID) Malaysia. The gridded data, covering the entire Peninsular Malaysia was developed by Wong et al. (2011), at a spatial resolution of 5 km based on Angular Distance Weighting (ADW) procedure. Further detail procedure of the data processing and development can be found in Wong et al. (2009) and Wong et al. (2011). Daily discharge records (m^3/s) of the Bernam watershed were taken at gauging station known as SKC. The systematic approach for the study is depicted in Figure 3.

HEC-HMS Setup for the Bernam River

The sub-basin element in HEC-HMS model conceptually represents interactions of infiltration, surface runoff and subsurface processes. Priestly-Taylor method was used to compute the potential evapotranspiration, ET (mm/day) as mostly used in continuous simulation using HEC-HMS (Meenu et al., 2013). The model is expressed as in Equation 12:

$$ET = \frac{\Delta}{\lambda \Delta + \gamma}(R_n - G) \quad [12]$$

Where, $\alpha = 1.26$, λ is latent heat of evaporation (MJ/kg), R_n is net radiation at crop surface (MJ m^{-2} day^{-1}), G is soil heat flux density (MJ m^{-2} day^{-1}), Δ is slope vapour pressure curve (kPa $°C^{-1}$), γ is Psychrometric constant (kPa $°C^{-1}$).

The Deficit and Constant Loss (DCL) method was used to compute the runoff-volume (loss). It uses one layer to account for continuous changes in moisture and requires only four parameters namely initial deficit, maximum deficit, constant rate and percentage of impervious área. The method is simple, requires lesser-input parameters and is yet to be applied for climate change study in Malaysia. The DCL parameters were obtained from the land use and soil grids of the area using HEC-GeoHMS, a GIS extension of HEC-HMS. The DCL method was combined with simple canopy and surface methods. The canopy method accounts for precipitation intercepted by plants from one storm to another, which subsequently evaporates and the water extracted by the plants through the process of transpiration. The surface method on the other hand accounts for the maximum amount of water that held on the soil before surface runoff begins.

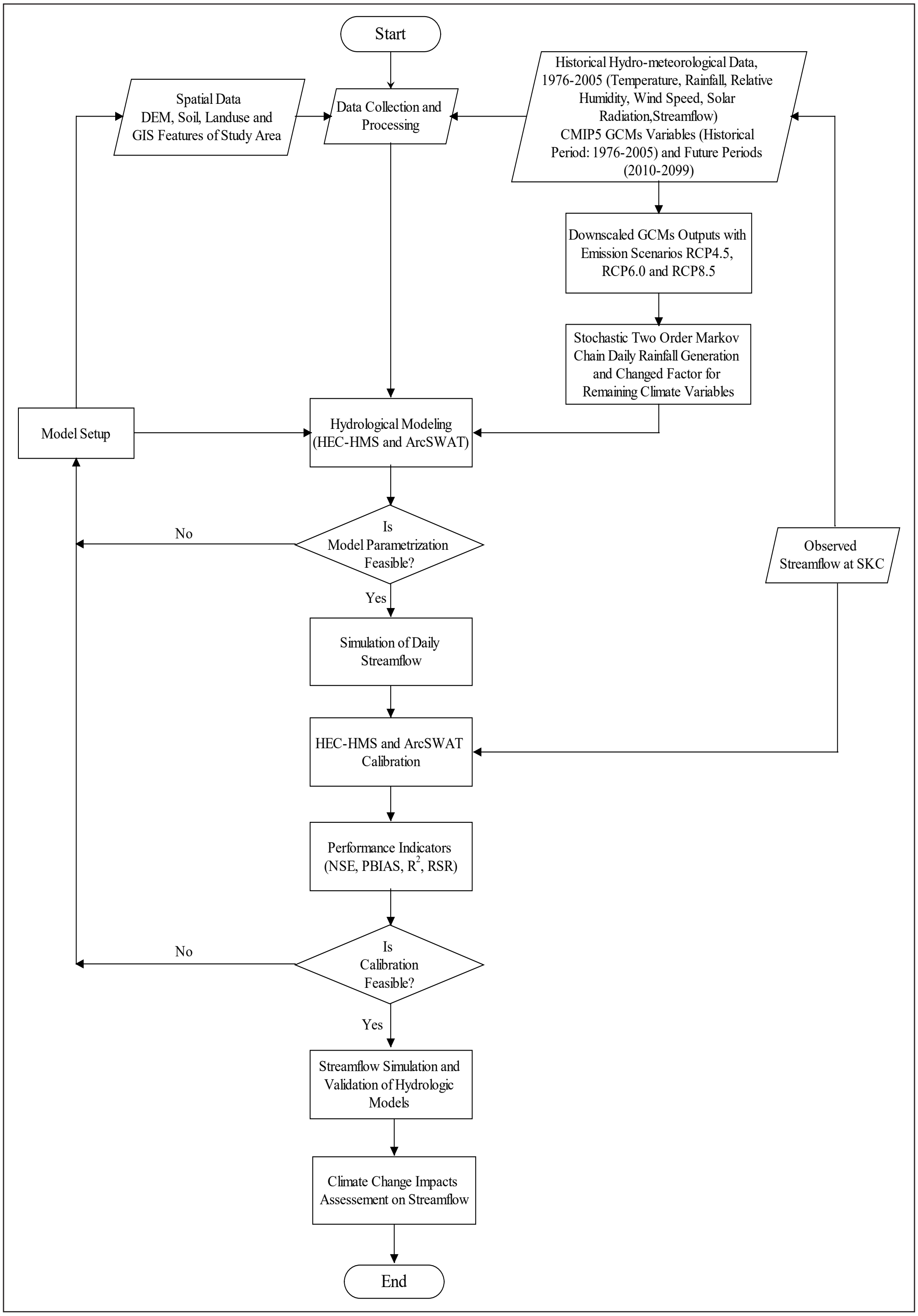


Figure 3. Framework for the projection of hydrologic response under climate change.

Soil Conservation Service Unit hydrograph (SCS-UH) method was used for the transformation of precipitation excess into point runoff. The unit hydrogrph (UH) diischarge, U_t is given as a ratio to the UH peak discharge, U_p, for any time t, a fraction of T_p, the time to UH peak (Equation 13 & 14).

$$U_p = C\frac{A}{T_p} \quad [13]$$

$$T_p = \frac{\Delta t}{2} + t_{lag} \quad [14]$$

Where, A is the watershed area, C is the conversión constant (2.08), Δt is duration of excess precipitation and t_{lag} is the basin lag.

The baseflow in each sub-basin was modeled using constant monthly-varying method. In this method, the program represents baseflow as a constant flow but may vary monthly. The monthly flows were approximated from the long-term series of monthly-observed flow data and were added to the direct runoff, computed from rainfall for each time step of the simulation. The channel flow was computed using Muskingum routing method. The method consists of two parameters; the travel time through the reach, K and a weighing factor, X. The parameters K and X were estimated using the channel geometry. The travel time, K (hr) was computed using Equation 15 (Griffin, 1994):

$$K= \frac{L}{3600Vw} \quad [15]$$

Where, L is the reach length (m), and V_w is the flood wave velocity (m/s).

ArcSWAT Setup for the Bernam River

The ArcSWAT model requires spatial and climatic data. A similar spatial and gridded data set used for HEC-HMS was input to the model. To setup the model, climate data was prepared into ArcSWAT format using Microsoft excel and uploaded to the weather generator (WGEN) user in ArcSWAT mother folder. A look-up table for rainfall was created using the locations of the rainfall stations in the área. The DEM was uploaded to ArcSWAT interface to créate stream network and delineated the catchment boundary. Land use and soil data was processed and reclassified within ArcGIS with the aid of notepad ++ to fit the classes that are compatible to the ArcSWAT land use and soil database, respectively. Subsequently, a land use look-up table was created and attached to the ArcSWAT database to serve as a link between the land cover data of the basin and that of ArcSWAT database. ArcSWAT mother folder consists of soil user covering USA. Therefore, a soil look-up table was created and attached to the ArcSWAT database to serve as a link between the soil data of the basin and that of ArcSWAT database. Other properties of the soil like soil depth, texture, etc., for the ArcSWAT database were obtained from other sources (Lai, 2001; Wong, 1970). The delineated catchment was sub-divided into sub-basins and hydrologic response units (HRUs), which contain combinations of land use and soil attributes. Finally, the model was evaluated using the discharge data.

Calibration and Validation of Hydrological Models

Monthly streamflow records of 30 years (1976-2006) were used for evaluating the performance of the HEC-HMS and ArcSWAT models. Out of the 30 years records, 18 years (1981-1998) was used for the calibration while 8 years (1999-2006) used for the validation with 5 years warm-up period in each. In both calibration and validation periods, the monthly observed and simulated discharges from the models were compared. Manual and automatic calibration techniques was applied to optimize HEC-HMS parameters. ArcSWAT Calibration and Uncertainty Procedures (SWAT-CUP) software developed by Abbaspour et al. (2007b) was used to perform calibration, validation and sensitivity analysis of ArcSWAT model. Four statistical criteria were employed to evaluate the hydrological goodness of fit; Coefficient of determination (R^2), Nash-sutcliffe Efficiency (NSE), Percent Bias (PBIAS) and Root mean square error-standard deviation ratio (RSR), by comparing the observed streamflow with the models simulated values. NSE is the ratio of the mean square error between observed and simulated values to the variance of the observed data. NSE value 1 indicates the perfect prediction of model. The PBIAS measures the average tendency of the simulated results to be higher or lower than the observed data. Simulated value is over-estimated when the value is negative and under-estimated when it is positive. RSR varies from optimal value of zero, which indicates zero root mean square error (RMSE) or residual variability and therefore accurate model simulation, to a large positive value. The smaller the value of RSR, the greater the ability of the model to simulate the hydrological characteristics of a basin and viceversa (Equation 16, 17, 18 & 19).

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(P_i^{obs} - P_i^{mean}\right)\left(P_i^{sim} - P_i^{mean}\right)}{\left[\sum_{i=1}^{n}\left(P_i^{obs} - P_i^{mean}\right)^2 \sum_{i=1}^{n}\left(P_i^{obs} - P_i^{sim}\right)^2\right]^{0.5}} \right)^2 \qquad [16]$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_{O_i} - Q_{S_i}\right)^2}{\sum_{i=1}^{n}\left(Q_{O_i} - \bar{Q}_O\right)^2} \qquad [17]$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Q_{oi} - Q_{si}\right)}{\sum_{i=1}^{n} Q_{oi}} \times 100\% \qquad [18]$$

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}(Q_{obs} - Q_{sim})^2}}{\sqrt{\sum_{i=1}^{n}(Q_{obs} - \overline{Q_{obs}})^2}} \qquad [19]$$

Where, *Qo,i, Qs,i* are the *i* th observed and simulated discharges respectively; $\overline{Qo}$ = mean observed discharge; P_i^{obs} and P_i^{sim} are observed and simulated flows, respectively; P^{mean} is the mean of observed flow; *n* is the total number of reference data points.

Simulation of Future Impacts of Climate Change

To project the future flow regime in the Bernam basin, the downscaled GCMs outputs for the baseline (1976-2005) and future (2010-2099) periods, which include rainfall, temperature, solar radiation, relatve hummidity and wind speed were used as input to the validated HEC-HMS model (Figure 3). Flow simulation was performed for each RCP scenario for 30-year time segments centered on the three future periods. For long-term analysis, data was prepared in accordance with the 'period change' approach by defining future periods as (i) 2020s (2010-2039), (ii) 2050s (2040-2069) and (iii) 2080s (2070-2099), to analyze change from a defined baseline period.

Flow Regime

Three streamflow classes were assessed and studied how they were influenced with the change in climate at the Basin as presented in Table 1. The classes studied for streamflow are high-flow disturbances, low-flow disturbances and flow variability. There are three variables for the high-flow disturbance streamflow: a high-flow disturbance (Q1.67), a duration of flood (FLDDUR), and a seven-day maximum-flow (7QMAX). The high-flow disturbance calculation was based on the most dominant channel forming flow (known as bankfull).

Low-flow disturbance streamflow indicators comprise of baseflow index (BFI), for a baseflow variable change measurement and a minimum 7-day (7QMIN) variable. Flow variability streamflow indicators include temporal shifts in peak flows (TSQPEAK) and coefficient of variation (DAYCV).

RESULTS AND DISCUSSION

Downscaling of GCMs Variables

The stochastic rainfall model was validated using the observed station rainfall in the study catchment prior to application for future simulation. The model demonstrated good performance in the simulation of different rainfall statistics. Estimated transition probabilities and gamma parameters (Figure 4) derived from the observed period (1976-2005) indicated that during the dry season (January to June), the probability of not receiving

Table 1
Streamflow regime variables for climate changes impacts assessment

Variable Name	Symbol	Definition	Streamflow Classification
High-Flow disturbance	Q1.67	Flow of magnitude exceeding return interval of 1.67 years based on a log-normal distribution	High-Flow disturbance
Duration of flood	FLDDUR	The average number of days of flow equal to or exceeding Q1.67 per year	
7-day maximum flow	7QMAX	The average annual maxima of 7 day means of daily mean streamflow	
Base flow index	BFI	The ratio of the smallest annual daily flow to the mean daily flow multiplied by 100 over a water year	Low-flow disturbance
7-day minimum flow	7QMIN	The average annual minima of 7 day means of daily mean streamflow	
Coefficient of variation	DAYCV	The ratio of the standard deviation of daily flows to the average of daily flows multiplied by 100 during a water year	Flow variability
Temporal shifts in peak flows	TSQPEAK	Shifts of peak flows in timing and magnitude	

rains was high if there was no rain the previous day, and the chance of receiving rains when it was raining the previous day increased during the wet season (July to December). The estimated values of α ranged from 0.83 to 0.96 and 0.73 to 1.11, respectively during the dry and wet seasons. Whilst β ranged from 13.09 to 19.93 and 14.27 to 20.60 for the same seasons. The simulated mean monthly rainfall matched quite well with the observed rainfall with R^2 value of 0.98. In addition, the simulation results closely resembled the actual rainfall pattern of the área, where most of the rain fell during the wet season while lower rainfall occured during the dry season. In Figure 4, P00 is the probability of not receiving rains if there was no rain in the previous day; P01 is the probability of not receiving rains if there was rain the previous day; P11 is the probability of receiving rains when it was raining the previous day; and P10 is the probability of receiving rains when it was not raining the previous day.

Temperature (maximum and minimum) and rainfall are among the key climatic variables that bring about the change in climate of an area. They have greatest effect on the estimation of irrigation wáter demand (Goodarzi & Eslamian, 2018). The future temperature increases due to climate change effects as presented in Table 2. The mean máximum temperature was predicted to increase under RCPs 4.5, 6.0 and 8.5 by an average of 1.18^{o}C, 1.14^{o}C and 1.97^{o}C, respectively compared to the baseline period. The largest increment (3.25 ^{o}C) was noticed from the most severe scenario (RCP8.5) in the late century (2080s). Similarly, the projected minimum temperature increased by 1.27^{o}C, 1.21^{o}C and 2.08 ^{o}C for the same future periods. The rate of change in the minimum temperature was slightly higher than the maximum temperature. This result inferred that in the future, the

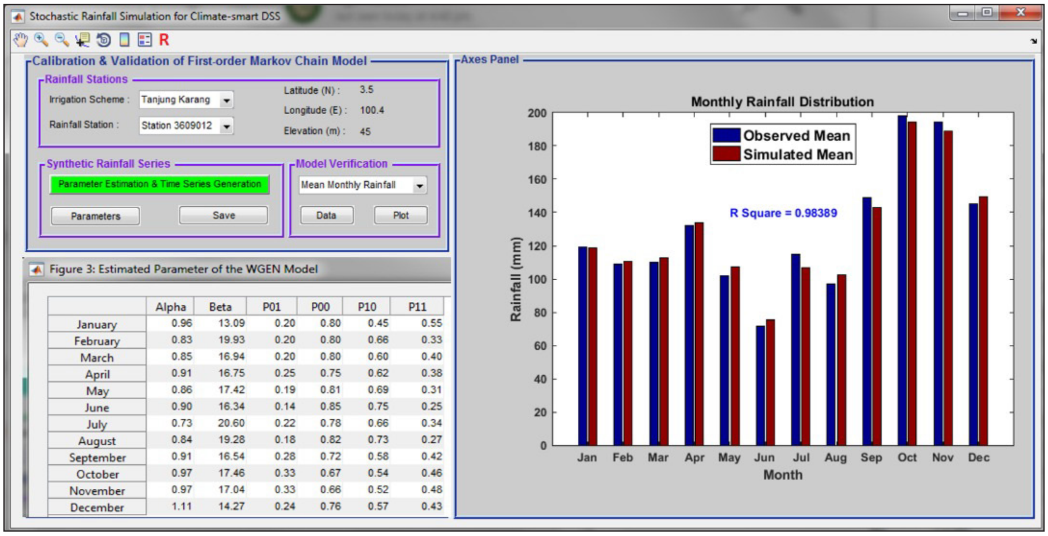


Figure 4. Validation of First-order Markov Chain model for rainfall generation

basin is anticipated to be warmer, especially during the dry season months. Mean surface temperature was also projected to increase in previous studies (Meinshausen et al., 2011; Tangang et al., 2012).

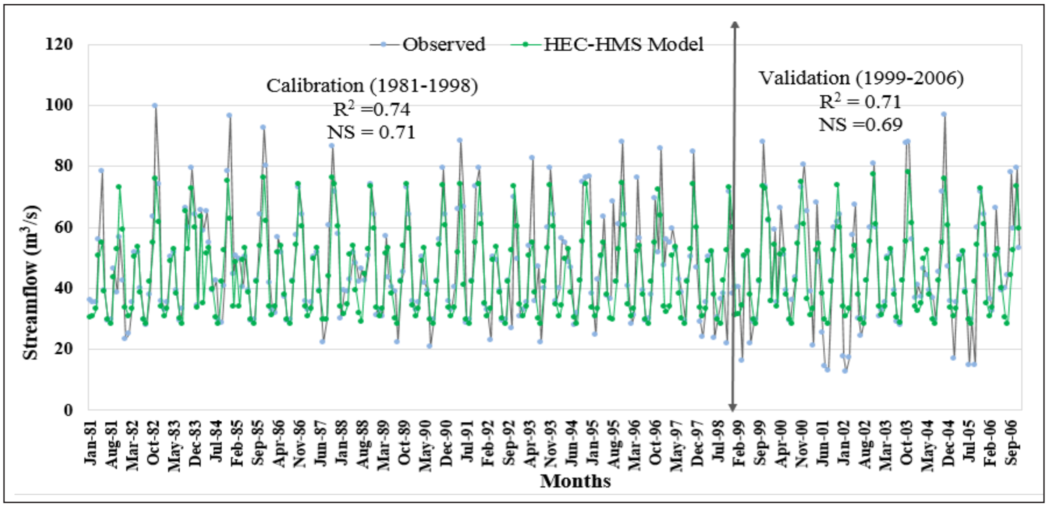
In the other hand, rainfall may slightly increase in the wet season (July to December) and decrease in the dry season (January to June) during the future period. The wet season average changes are projected to be 1.0%, 0.8% and 2.4% under RCPs 4.5, 6.0 and 8.5 scenarios, respectively with a range of 0.2% for RCPs 4.5 and 6.0 in the 2050s to 2.7% for the RCP8.5 in the 2080s. Whereas, the average changes for the dry season are -2.4%, -3.2% and -3.7% under RCPs 4.5, 6.0 and 8.5 scenarios, respectively.

Table 2
Projected changes in temperature under multi-model projections based on RCP scenarios

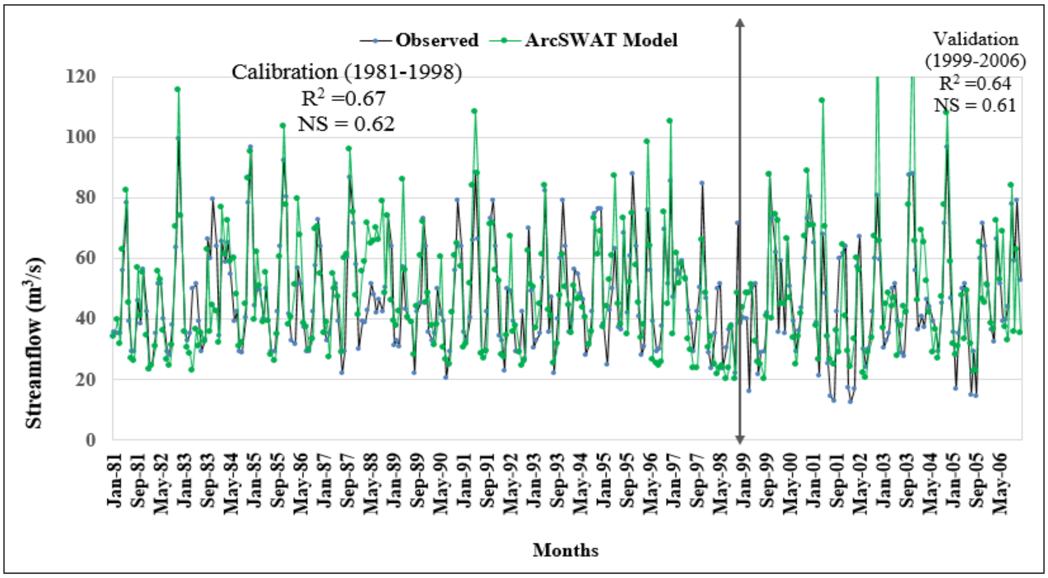
Period	Changes in temperature under RCPs		
	RCP4.5	RCP6.0	RCP8.5
Maximum temperature (°C)			
2020s	0.68	0.52	0.82
2050s	1.29	1.06	1.85
2080s	1.57	1.85	3.25
Average	1.18	1.14	1.97
Minimum temperature (°C)			
2020s	0.71	0.62	0.92
2050s	1.36	1.16	1.95
2080s	1.75	1.85	3.36
Average	1.27	1.21	2.08

Hydrological Modeling

The performance of HEC-HMS and ArcSWAT models was assesed using monthly average discharge data. The models performed satisfactorily both during calibration and validation periods as the values are greater than 0.5 (Moriasi et al., 2007) as shown in Figure 5. However, HEC-HMS performs better in the watershed compared to ArcSWAT model with 0.74, 0.71, 4.21 and 0.37; and 0.71, 0.69, 5.32 and 0.31 for R^2, NSE, PBIAS and RSR, respectively, during the calibration and validation periods and ArcSWAT model is 0.67,



(a)



(b)

Figure 5. Simulated and observed monthly discharge for Bernam river basin: (a) HEC-HMS model; and (b) ArcSWAT model

0.62, -5.4 and 0.64; and 0.64, 0.61, -4.2 and 0.65 for the same model efficiency. This might be associated with complexity in ArcSWAT input parameters, which rendered calibration difficult. Similar trend was obtained by Dlamini et al. (2017) when ArcSWAT model failed to simulate high peak discharges in some months in the same basin.

The average percentage of impervious area computed using the DCL method for the delineated sub-basins was 3.83%, which indicates that the portion where all contributing precipitation runs off, with no infiltration, evaporation or other volume losses in Bernam basin is small, likely due to the type of forest in the area. Initial deficit, maximum deficit and constant rate, which signify the properties of soil in the área were found to be among the sensitive parameters in HEC-HMS. The sensitivity analysis was conducted by varying one parameter at a time from -50% to 50% with increments of 10%, keeping all other parameters constant. The soil layer within the sub-basins would require average of 39.4mm (initial déficit) to saturate to maximum storage and can hold about 49.5mm (máximum déficit). The infiltration rate when the soil layer is saturated (constan trate) was estimated to be 49mm/hr.

A consistent under-prediction of peak flows with much higher values and over-prediction of flows with much lesser value was noticed in HEC-HMS and *vice-versa* for the ArcSWAT model during the evaluation. Meenu et al. (2013) reported a similar trend when HEC-HMS failed to simulate peak flows. HEC-HMS also failed to reproduce peak flows in late winter and early spring runoff (Gyawali & Watkins, 2012). The observed discharge data in the study area is associated with large variations in some of the years, with a difference up to about 70m^3/s in some similar months across the years, which is possible for the models to either under-estimate or over-estimate such discharge values, in trying to fit well with the observed v alues. Similarly, Dlamini et al. (2017) noticed challenge using ArcSWAT model and concluded that the problem was attributed to the poor quality of the data in the watershed. However, HEC-HMS has to be applied with caution in the area especially for flood analysis.

Impacts of Climate Change on Future Streamflow

Sequence to the results from the models evaluation, HEC-HMS model was applied to predict the climate change impacts in the basin. The changes in major rice farming (dry and wet) season results are assessed. The changes were the differences relative to the baseline period (1976-2005) for the three 30-year defined future period (2020s, 2050s and 2080s). The changes in future streamflow at Bernam river basin was more pronounced during the dry season period as presented in Table 3. This is expected because warmer temperature during the dry season usually increases the rate of evapotranspiration more compared to wet season period, which consequently affects the future streamflow. The average changes under RCP 4.5, RCP 6.0 and RCP 8.5 are −0.40%, −1.68% and −5.71%, respectively, during the dry season. In general, the future periods indicate a decreasing streamflow trend in this season, with a higher percentage (−5.94 %) predicted in the late century (2080s) under the RCP 8.5 scenario. Similarly, in the wet season, streamflow decreases in all future periods except for RCP4.5 where is expected to increase (0.36%). The average changes under RCP6.0 and 8.5 are −0.67% and −3.83%, respectively. Though the changes in streamflow is not much, the basin might suffer water pressure, particularly during the dry season period. A study by Dlamini et al. (2017) in the same watershed using ArcSWAT model reported future streamflow to decrease in the dry season months and increase in some months during the wet season. Also, Alansi et al. (2009) used ArcSWAT model to forcast streamflow due to landuse changes in the same catchemet. The flow depths decreased during low flow months. Similar decrease in annual streamflow was observed by Chien et al. (2013). Arnell and Reynard (1996) also reported a decrease in annual streamflow in the wettest scenarios and decline in the driest scenarios. The highest changes in streamflow during the wet season was -8.97% under worst-case scenario (RCP8.5) in 2020s period.

The streamflow projections in this study were based on predicted changes in hydro-climatic parameters. However, other factors like human activities, particularly related to land transformations might also have impacts on the hydrologic cycle in the area. Therefore, it is recommended to integrate projected land use changes in future hydrologic modeling studies in the área.

Table 3
Projected changes in streamflow under multi-model projections based on RCP scenarios

Period	Changes (%) in streamflow		
	RCP 4.5	RCP 6.0	RCP 8.5
Dry Season			
2020s	-0.40	-1.70	-5.66
2050s	-0.63	-1.90	-5.54
2080s	-0.18	-1.44	-5.94
Average	-0.40	-1.68	-5.71
Wet Season			
2020s	0.19	-0.84	-3.92
2050s	0.59	-0.47	-3.67
2080s	0.31	-0.71	-3.90
Average	0.36	-0.67	-3.83

Flow Regime

The assessment of climate-induced shifts in high flow disturbances indicated that all parameters that assess high flow disturbances (Q1.67, FLD-DUR and 7QMAX) showed a decrease in the future irrespective of the emission scenario (Table 4). The Q1.67 in the baseline period showed a decrease of about 5% to 6% during the future period under the

RCPs scenarios. Flood duration (FLD-DUR) decreased from 6 days during the baseline period to an average of less than one day in all the future periods under the three emission scenarios. Although the pattern of change in 7QMAX with years is not clear, however, for the three emission scenarios, results indicate that the average of the seven maximum runoffs in the future will shift by 6% on average. Though the changes in streamflow is not much, the basin might suffer water pressure, particularly during the dry season period.

Table 4
Projected annual flow regimes under multi-model projections based on RCP scenarios

High Flow Disturbance									
	Q1.67 (%)			FLDDR (HR)			7QMAX (%)		
Scenarios	2020s	2050s	2080s	2020s	2050s	2080s	2020s	2050s	2080s
RCP 4.5	-5.71	-5.69	-5.72	10.24	14.36	14.24	-6.05	-6.08	-6.51
RCP 6.0	-5.15	-5.57	-6.00	10.36	14.24	14.48	-5.80	-6.23	-6.51
RCP 8.5	-5.90	-6.29	-6.32	12.48	14.24	13.36	-5.73	-6.51	-7.06
Low Flow Disturbance									
	BFI (%)			7QMIN (m^3/s)					
Scenarios	2020s	2050s	2080s	2020s	2050s	2080s			
RCP 4.5	64.14	64.00	64.00	28.33	28.33	28.67			
RCP 6.0	64.10	64.01	64.30	28.33	28.30	28.30			
RCP 8.5	64.20	64.10	64.81	28.30	28.30	28.31			
Flow Variability									
	DAYCV (%)			TSQPEAK (%)					
Scenarios	2020s	2050s	2080s	2020s	2050s	2080s			
RCP 4.5	31.17	32.70	32.70	-0.24	-0.65	0.41			
RCP 6.0	32.20	32.71	32.00	-1.99	-2.36	-0.71			
RCP 8.5	32.60	32.70	31.00	-2.65	-2.72	-4.94			

Climate-induced shifts in low-flow disturbances were also assessed. The findings showed that the indicators quantifying low-flow disturbances (BFI and 7QMIN) had minor changes in the future for all emission scenarios. Historical and future streamflow data indicate that the 7QMIN and median of BFI at the study area is 28 m^3/s and 64%, respectively. This implies that the flow in the Bernam River Basin is stable and not susceptible to drying.

The DAYCV defines total flow variability without taking into account the temporal sequence flow variation. Baseline and future data indicate that the DAYCV median at the study catchment is about 33%, suggesting a small rate of streamflow change. The future peak flows were not temporally shifted from the baseline period for all the future periods irrespective of the RCP scenario. Conversely, the magnitude of the future monthly peak flows has decreased from baseline peak flow with a range of 0.24% to 4.94%, through the three future periods under the RCP scenarios. These results inferred that Bernam basin may not face an increase in the frequency of floods but the magnitude of future peak flows might slightly decrease.

CONCLUSION

Hydrologic processes in the Bernam watershed were simulated by employing two hydrological models, namely ArcSWAT and HEC-HMS. The statistical results of the evaluation during both calibration and validation show that the models performed satisfactorily. HEC-HMS model (with DCL method), with less input data is easy to calibrate and therefore gives better statistical values compared to ArcSWAT model. A consistent under-prediction of peak flows with much higher values was noticed in HEC-HMS model, which was also reported by other studies. Therefore, HEC-HMS has to be applied with caution in the study area especially for flood analysis. Temperature is projected to increase in future periods with higher rate during the dry season period. This inferred that in the future, the basin is anticipated to be warmer, especially during the dry season months. In the other hand, rainfall may slightly increase in the wet season (July to December) and decrease in the dry season (January to June) during the future period. Future periods indicate a decreasing streamflow trend in dry season, with a higher percentage (−5.94 %) predicted in the late century (2080s) under the RCP 8.5 scenario. In the wet season, streamflow decreases in all future periods except for RCP4.5 where is expected to increase. Though the changes in streamflow is not much, the basin might suffer water pressure, particularly during the dry season period.

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REFERENCES

Abbaspour, K. C., Vejdani, M., Haghighat, S., & Yang, J. (2007a, December 10-13). SWAT-CUP calibration and uncertainty programs for SWAT. In *MODSIM 2007 International Congress on Modelling and Simulation, Modelling and Simulation Society of Australia and New Zealand* (pp. 1596-1602). Canberra, Australia.

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., & Srinivasan, R. (2007b). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology, 333*(2-4), 413-430.

Abdulkareem, J., Pradhan, B., Sulaiman, W., & Jamil, N. (2018). Review of studies on hydrological modelling in Malaysia. *Modeling Earth Systems and Environment*, *4*(4), 1577-1605.

Ajayi, J. O. (2017). *Modelling the impact of climate change on hydrology and water resources in the Niger-South Sub-catchment of the Niger River Basin, Nigeria.* (PhD Thesis), Universiti Putra Malaysia, Malaysia.

Alansi, A., Amin, M., Abdul Halim, G., Shafri, H., & Aimrun, W. (2009). Validation of SWAT model for stream flow simulation and forecasting in Upper Bernam humid tropical river basin, Malaysia. *Hydrology and Earth System Sciences Discussions, 6*(6), 7581-7609.

Amin, M., Shaaban, A., Ercan, A., Ishida, K., Kavvas, M., Chen, Z., & Jang, S. (2017). Future climate change impact assessment of watershed scale hydrologic processes in Peninsular Malaysia by a regional climate model coupled with a physically-based hydrology modelo. *Science of the Total Environment, 575*, 12-22.

Arnell, N., & Reynard, N. (1996). The effects of climate change due to global warming on river flows in Great Britain. *Journal of Hydrology, 183*(3-4), 397-424.

Chien, H., Yeh, P. J. F., & Knouft, J. H. (2013). Modeling the potential impacts of climate change on streamflow in agricultural watersheds of the Midwestern United States. *Journal of Hydrology, 491*, 73-88.

Chu, X., & Steinman, A. (2009). Event and continuous hydrologic modeling with HEC-HMS. *Journal of Irrigation and Drainage Engineering, 135*(1), 119-124.

Deni, S. M., Suhaila, J., Zin, W. Z. W., & Jemain, A. A. (2010). Spatial trends of dry spells over Peninsular Malaysia during monsoon seasons. *Theoretical and Applied Climatology, 99*(3-4), 357-371.

Dlamini, N., Rowshon, M., Saha, U., Lai, S., Fikri, A. Z., & Zubaidi, J. (2015). Simulation of future daily rainfall scenario using stochastic rainfall generator for a rice-growing irrigation scheme in Malaysia. *Asian Journal of Applied Sciences, 3*(05), 492-506.

Dlamini, N. S., Kamal, M. R., Soom, M. A. B. M., Mohd, M. S. F. b., Abdullah, A. F. B., & Hin, L. S. (2017). Modeling Potential Impacts of Climate Change on Streamflow Using Projections of the 5th Assessment Report for the Bernam River Basin, Malaysia. *Water, 9*(3), 1-23.

Dlamini, N. S., Rowshon, M. K., Fikhri, A., Lai, S. H., & Mohd, M. S. F. (2016, August 23). Modelling the streamflow of a river basin using enhanced hydro-meteorological data in Malaysia. In *III International Conference on Agricultural and Food Engineering 1152* (pp. 291-298). Kuala Lumpur, Malaysia.

Ghorbani, K., Wayayok, A., & Abdullah, A. F. (2016). Simulation of flood risk area in kelantan watershed, Malaysia using numerical model. *Jurnal Teknologi, 78*(1-2), 51-57.

Ghosh, S., & Mujumdar, P. (2007). Nonparametric methods for modeling GCM and scenario uncertainty in drought assessment. *Water Resources Research, 43*(7), 1-19.

Goodarzi, M., & Eslamian, S. (2018). Performance evaluation of linear and nonlinear models for the estimation of reference evapotranspiration. *International Journal of Hydrology Science and Technology, 8*(1), 1-15.

Griffin, R. H. (1994). Department of the army EM 1110-2-1417. *Analysis, 5*(6), 5-5.

Gyawali, R., & Watkins, D. W. (2012). Continuous hydrologic modeling of snow-affected watersheds in the Great Lakes basin using HEC-HMS. *Journal of Hydrologic Engineering, 18*(1), 29-39.

Haan, C. T. (1977). *Statistical methods in hydrology.* Ames, Iowa: The Iowa State University Press.

Hamzah, F. M., Yusoff, S. H. M., & Jaafar, O. (2019). L-moment-based frequency analysis of high-flow at Sungai Langat, Kajang, Selangor, Malaysia. *Sains Malaysiana, 48*(7), 1357-1366.

Ibadullah, W. M. W., Tangang, F., Juneng, L., & Jamaluddin, A. F. (2019). Practical predictability of the 17 December 2014 heavy rainfall event over East Coast of Peninsular Malaysia using WRF model. *Sains Malaysiana, 48*(11), 2297-2306.

Jiang, T., Chen, Y. D., Xu, C.Y., Chen, X., Chen, X., & Singh, V. P. (2007). Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China. *Journal of Hydrology, 336*(3-4), 316-333.

Kabiri, R. (2014). Simulation of runoff using modified SCS-CN method using GIS system, case study: Klang watershed in Malaysia. *Research Journal of Environmental Sciences, 8*(4), 178-192.

Kabiri, R., Bai, V. R., & Chan, A. (2015). Assessment of hydrologic impacts of climate change on the runoff trend in Klang Watershed, Malaysia. *Environmental Earth Sciences, 73*(1), 27-37.

Lai, S. H. (2001). *Application of swat hydrological model with GIS interface to Upper Bernam River Basin* (Doctoral dissertation). Universiti Putra Malaysia, Malaysia.

Lai, S. H., & Arniza, F. (2011). Application of SWAT hydrological model to upper Bernam River Basin (UBRB), Malaysia. *IUP Journal of Environmental Sciences, 5*(2), 7-19.

Meenu, R., Rehana, S., & Mujumdar, P. (2013). Assessment of hydrologic impacts of climate change in Tunga–Bhadra river basin, India with HEC-HMS and SDSM. *Hydrological Processes, 27*(11), 1572-1589.

Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M., Lamarque, J. F., … & Riahi, K. (2011). The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change, 109*(1-2), 213-241.

Mohammed, T. A., Said, S., Bardaie, M. Z., & Basri, S. N. (2011). Numerical simulation of flood levels for tropical rivers. *IOP Conference Series: Materials Science and Engineering, 17*, 1-10.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE, 50*(3), 885-900.

DID. (2018). *National water balance management system (NAWABS) for Sungai Bernam Basin*. The Ministry of National Resources and Environment, Malaysia (NRE), The Government of Malaysia: Department of Irrigation and Drainage.

New, M., & Hulme, M. (2000). Representing uncertainty in climate change scenarios: A Monte-Carlo approach. *Integrated Asessment, 1*(3), 203-213.

Razi, M. A. M., Ariffin, J., Tahir, W., & Arish, N. A. M. (2010). Flood estimation studies using hydrologic system (HEC-HMS) for Johor River, Malaysia. *Journal of Applied Sciences, 10*(11), 930-939.

Refsgaard, J., Storm, B., & Mike, S. (1995). *Computer models of watershed hydrology*. Colorado, USA: Water Resources Publication.

Rowshon, M., Dlamini, N., Mojid, M., Adib, M., Amin, M., & Lai, S. (2019). Modeling climate-smart decision support system (CSDSS) for analyzing water demand of a large-scale rice irrigation scheme. *Agricultural Water Management, 216*, 138-152.

Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2007). Water availability, degree days, and the potential impact of climate change on irrigated agriculture in California. *Climatic Change, 81*(1), 19-38.

Sivarajan, N. A., Mishra, A. K., & Rafiq, M. (2019). Examining climate change impact on the variability of ground water level: A case study of Ahmednagar district, India. *Journal of Earth System Science, 128*(5), 122-128.

Tangang, F. T., Juneng, L., Salimun, E., Sei, K., & Halimatun, M. (2012). Climate change and variability over Malaysia: Gaps in science and research information. *Sains Malaysiana, 41*(11), 1355-1366.

Wong, C., Venneker, R., Jamil, A., & Uhlenbrook, S. (2011). Development of a gridded daily hydrometeorological data set for Peninsular Malaysia. *Hydrological Processes, 25*(7), 1009-1020.

Wong, C., Venneker, R., Uhlenbrook, S., Jamil, A., & Zhou, Y. (2009). Variability of rainfall in Peninsular Malaysia. *Hydrology and Earth System Sciences Discussions, 6*(4), 5471-5503.

Wong, I. F. T. (1970). *Reconnaissance soil survey of Selangor*. Kuala Lumpur, Malaysia: Ministry of Agriculture and Lands.

Yusop, Z., Chan, C. H., & Katimon, A. (2007). Runoff characteristics and application of HEC-HMS for modeling stormflow hydrograph in oil palm catchment. *Water Science Technology, 56*(8), 41-48.

Zin, W. Z. W., Jamaludin, S., Deni, S. M., & Jemain, A. A. (2010). Recent changes in extreme rainfall events in Peninsular Malaysia: 1971-2005. *Theoretical and Applied Climatology, 99*(3-4), 303-314.