Journal of Engineering and Applied Sciences 15 (5): 1228-1236, 2020
ISSN: 1816-949X

Impact of Potential Evapotranspiration Method on Sensitivity and Uncertainty in Streamflow Analysis for Kelantan River Basin

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Abstract: Range of sensitive parameter value associated with uncertainty should be performed in the calibration and validation process to establish more accurate watershed hydrological models. Evapotranspiration is one of the most dominant in a hydrological cycle other than surface runoff and subsurface processes. This research aims at an in-depth understanding of the SWAT-CUP ability on analyzing the impact of Potential Evapotranspiration (PET) methods on sensitive parameter and uncertainty streamflow simulations of the Kelantan river basin. The hydrological model was developed using the SWAT with three option of PET methods: Penman-Monteith (P-M), Priestley-Taylor (P-T) and Hargreaves (HG). The SWAT-CUP with SUFI-2 optimization algorithm and Nash-Sutcliffe as objective function were used to evaluate the model simulation compared to the streamflow discharge from years 1985-2000 for calibration and 2001-2016 for validation periods. The best value of NSE, R2 and PBIAS, indicated no significant difference and the model achieved very good performance during calibration and good performance during validation. The 95PPU plot and statistics value, p-factor yielded acceptable outcomes during calibration by bracketing of the observed streamflow data with 82, 74 and 75% for HG, P-T and P-M, respectively. However, the p-factor was achieved only 46, 40 and 44%, respectively during the validation period. The calibration strength of the r-factor was reached with HG (0.75, 0.67), P-T (0.92, 0.84) and P-M (0.88, 0.81) during calibration and validation. The uncertainty analysis showed that P-T is better performer during both the calibration and validation. Overall the SWAT Model was considered can give good performance with the built-in PET methods options.

Key words: SWAT-CUP, SUFI-2, potential evapotranspiration, uncertainty, sensitive parameter, streamflow

INTRODUCTION

Evaluation of a hydrological model performance through parameters sensitivity test and model uncertainty analysis is a critical measure to verify the model strength. Regular model evaluation by using the basic statistic of the determination coefficient (R2), Nash-Sutcliffe Efficiency (NSE) and Percent Bias (PBIAS) was insufficient to assess the fit and model correlation. In addition, the 95PPU analysis by the value of p-factor and r-factor should be considered to have the degree of uncertainty and sensitivity of the optimized parameter values for a site-specific. NSE, R2, PBIAS, p-factor and r-factor will enhance the calibration and validation process to have a good model. A well-calibrated model will able to describe and simulate the hydrological processes for any forecast situations in more precise and sufficient accurate as of the real situation (Kannan *et al*., 2019; Querner and Zanen, 2013).

Nowadays, the Soil and Water Assessment Tool (SWAT) has been proven to be a useful hydrological model for the watershed assessment of water quantity and quality (Qi *et al*., 2009; Querner and Zanen, 2013; Thavhana *et al*., 2018), sediment and nutrient transport (Dakhlalla and Parajuli, 2018; Megersa *et al*., 2019), future effect of land management (Ayivi and Jha, 2018; Zhang *et al*., 2017), potential climate change impacts (Bekele *et al*., 2019; Zhao *et al*., 2019) and valuation ecological problems (Sun *et al*., 2017; Vigiak *et al*., 2018). The SWAT is integrated with Arc-GIS as an extension to have semi-distributed and continuous long-term simulation model which reflects various of physical processes included portioning into sub-watersheds, hydrologic cycle (precipitation, evaporation and transpiration, potential evapotranspiration, infiltration, lateral flow, percolation, recharge to aquifer, return flow, surface runoff), pesticides and nutrient cycle (nitrogen and phosphorus) and erosion and sedimentation (Neitsch *et al*., 2011).

The SWAT Model has incorporated more than 250 parameters with a set of pre-defined parameter

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value cover soils properties, surface runoff, infiltration, percolation, evaporation and evapotranspiration. Range of sensitive parameter value associated with uncertainty should be performed in the calibration and validation process to establish more accurate watershed hydrological models. Evapotranspiration is one of the most dominant in a hydrological cycle other than surface runoff and subsurface processes. Potential Evapotranspiration (PET) is referring to the possible highest volume of evaporation water and transpiration from the vegetated surface under standard soil moisture and vegetation conditions with unlimited water supply due to the prevailing meteorological conditions. The PET in a watershed ecosystem directly influences the hydrological cycle and energy balance which can disturb the dynamics of soil content storage, groundwater physical properties and streamflow discharge (Dinpashoh *et al*., 2019).

The SWAT Model offer with four calculations methods available within SWAT for PET calculation: Penman-Monteith (P-M), Priestley-Taylor (P-T), Hargreaves (HG) and the user defines (Neitsch *et al*., 2011). However, the available built-in methods estimate varying values due to their development process consider for a specific climatic region with a different perspective, assumptions and input data requirements (Alemayehu *et al*., 2015). The data requirements for PET calculation is varying for each selected methods. The Penman-Monteith method involves information of daily solar radiation, minimum and maximum air temperature, relative humidity and wind speed. The Priestley-Taylor method is an empirical approach of P-M where only needs radiation of solar, temperature of air and relative humidity. Relative humidity is required for vapor pressure calculation in P-M and P-T methods. While the Hargreaves method depending only on the mean, maximum and minimum of air temperature. This method is desirable in the case missing data either the wind speed, solar radiation or relative humidity (Efthimiou *et al*., 2013).

MATERIALS AND METHODS

Study area: The SWAT Model was applied to the Kelantan river basin at the Guillemard Bridge discharge station, covering an area of 12,600 km^2 with the lowest elevation of 1.1 m and the highest elevation of 2,159.9 m (Fig. 1a). The total stretches length is 514 km included the main tributaries of Lebir river, Galas river and Pergau river with the longest path is 273 km from the most upstream. The station is located to the Northwards of Kelantan river about 65 km to the river mouth. The area received annual average rainfall is about 2,500 mm. Fig. 1b shows the Guillemard Bridge Watershed (GBW) land use which was predominated by forest at the upstream and midstream, occupying approximately 76%, agriculture activity (rubber, oil palm, coconut, etc.) was 23% in the middle and downstream of the catchment. There was <1% development used for residential, commercial and industrial.

SWAT Model setup: Guillemard Bridge Watershed hydrological model was established using the SWAT Model (Neitsch *et al*., 2011). The applications integrate the watershed spatial data (Digital Elevation Model (DEM), soil and land used) with daily climatic variables data (precipitation (mm), evaporation (mm), air temperature (°C), relative humidity, wind speed and solar radiation) for the modeling. Historical rainfall data from years 1980-2016 in daily time-series format were derived from 16 stations within the GBW. While the daily observed streamflow discharge from 1985-2016 at Guillemard Bridge station (Fig. 1) was divided to years 1985-2000, for calibration and 2001-2016 for validation. The DEM 5 m resolution of Interferometric Synthetic Aperture Radar (IFSAR) was used for topography elevation data and classification map was used to represent the land use data for the year 2010.

The DEM integrated with soil and land use, slope classes options (0-15, 15-24, 24-35, 35-49 and >49%) and threshold values of 10% for soil, 20% for land used and slope were discretized by ArcGIS to smaller spatial sub-units (Her *et al*., 2015; Megersa *et al*., 2019; Yacoub and Foguet, 2012). Based on these spatial pieces of information, 29 sub-watersheds was created with 224 Hydrological Response Units (HRU). The HRUsre main the homogeneous and contains combinations of soil properties, land used type, slope features and land management in the watershed. The elevation at the outlet of the sub-basin 2 (Guillemard Bridge station) represents the reference low points in the mainstream. Surface water originating from the sub-watersheds eventually accumulate at low points to represents as a tributary stream in each sub-watersheds and leaves to join into the mainstream ofthe Kelantan river (Chunn *et al*., 2019).

Model calibration and sensitivity analysis: We recently conducted the parameters sensitivity analysis, calibration, validation and uncertainty analysis of SWAT Models by using the SWAT Calibration and Uncertainty Programs (SWAT-CUP) (Abbaspour, 2015). We had chosen the SUFI-2 option with objective function NSE 0.5 and selected parameters for the model sensitivity analysis. The parameters which being considered to have influential on streamflow discharge based on knowledge of a catchment and those suggested in the reference literatures (Ayivi and Jha, 2018; Bekele *et al*., 2019; Ligaray *et al*., 2015; Maharjan *et al*., 2013; Narsimlu *et al*., 2015; Tan *et al*., 2014; Thavhana *et al*., 2018).

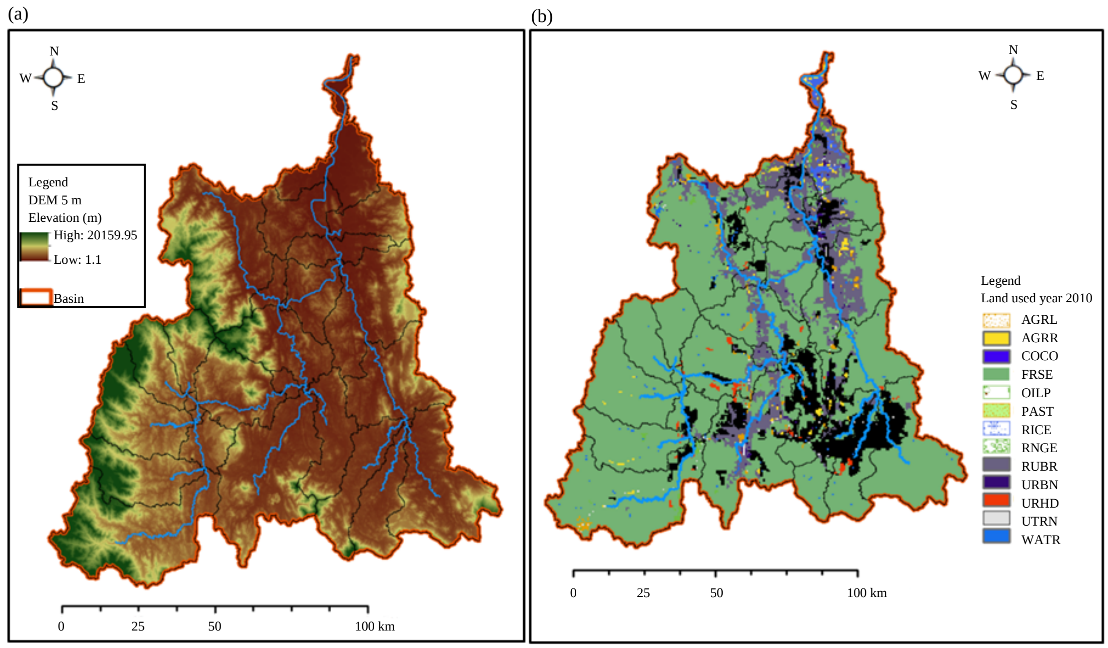

Fig. 1(a-b): (a) Topographical view of DEM 5 m with the network of main and tributaries rivers in the Guillemard Bridge watershed and (b) Guillemard Bridge sub-basin and land use for the year 2010

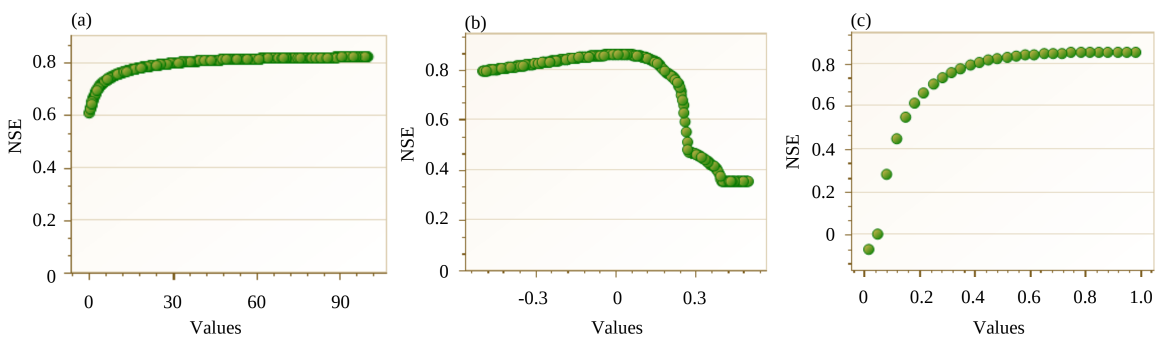

Fig. 2(a-c): Results of local analysis dotty plot with the objective function of NSE for the streamflow most sensitive parameters (a) 1: CANMX.hru, (b) 1: CN2.mgt and (c) 1: ALPHA_BNK.rte

At the early stage, local sensitivity analysis for 29 parameters was performed to identify the governing flow factors through the SWAT-CUP output of the dotty plot (Narsimlu *et al*., 2015). The local sensitivity analysis or one-factor-at-a-time demonstrates the sensitiveness of model performance with the change of a variable input value when other parameters are kept constant as drown in Fig. 2 and 3 (Khalid *et al*., 2016). Then, the significance of the parameter sensitivity and ranking among the selected parameter were identified for the three PET SWAT Models based on global sensitivity analysis (Abbaspour, 2015).

The calibration procedure starts by providing a large range based on default parameters value as the initial parameter range. The calibration algorithms run with varied iteratively values and narrows down the range until the best parameter range is obtained with an optimal agreement between observation and simulation (Samadi *et al*., 2017). In each iteration, the SUFI-2 algorithm performs Latin Hypercube sampling for user-defined parameter ranges and creates multiple parameter set samples.

The SWAT-CUP was run with the 22 selected sensitive parameters for a few iterations during calibration until the defined objective function was satisfied and each iteration was set for 500 simulation runs. Later, the values range for each parameter were updated and each new ranges were smaller than the initial range. The parameter

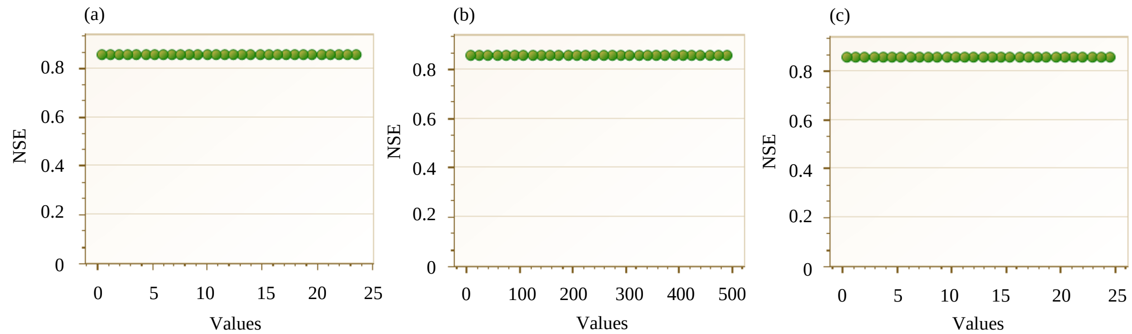

Fig. 3(a-c): The dotty plot for streamflow insensitive parameters (a) 1: SURLAG.bsn, (b) 1: REVAPMN.gw and (c) 1: GWHT.gw

Table 1: The statistical evaluation criteria for monthly streamflow models performance

Statistical criteria	Very good	Good	Satisfactory	Unsatisfactory
R^2	$R^2>0.85$	$0.75<R^2\leq 0.85$	$0.60<R^2\leq 0.75$	$R^2\leq 0.6$
NSE	NSE>0.80	0.70<NSE≤0.80	0.50<NSE≤0.70	NSE≤0.50
PBIAS	PBIAS<±5	±5≤PBIAS<±10	±10≤PBIAS<±15	PBIAS≥±15
p-factor	p-factor>0.70		p-factor≤0.70	
r-factor	r-factor<1.5		1.5≤r-factor	

ranges get thinner through the iterations until the best performing parameter range is obtained. Afterward, the ranges of the parameters with the better performance results were used for the validation process.

Model performance evaluation: The SWAT-CUP compares the best simulation from the SUFI-2 with the observed discharge and computes the statistical measures. In this study, the model performance was evaluated based on the Nash-Sutcliffe coefficient (NSE), coefficient of determination (R^2) and Percent BIAS (PBIAS). Furthermore, the 95PPU indicator of p-factor and r-factor was used to measure the degree of the model uncertainties. The p-factor is the percentage of the observations data are bracketed within the 95PPU and denoted by an ideal value of 100% where all the quantifies uncertainties were in the shaded region of the simulation results by the parameter range. The degree of uncertainty, r-factor is the average distance between the 95PPU and the standard deviation of the observed variables (Abbaspour, 2015). The evaluations of the model performance were based on recommended by the works of literature as shown in Table 1 (Abbaspour *et al*., 2015; Paul and Negahban-Azar, 2018).

RESULTS AND DISCUSSION

Streamflow sensitivity parameter: The local analysis has confirmed that the 22 out of 29 parameters were found are sensitive and considered to be appropriate for Guillemard Bridge Watershed Model for all the three PET methods. SUFI-2 uses a multiple regression and the significant parameters that highly influences on the streamflow simulations represent by p-value and t-stat. The parameters with the smallest p-values close to zero (<0.05) indicate to be meaningful and have a high level of significance to the model and larger in absolute t-stat values are more significance sensitive (Samadi *et al*., 2017). Table 2 illustrates the rank of the 22 sensitive parameters selected and their optimize value obtained in the calibration process using SWAT-CUP. The p-value and t-stat were fluctuating from 0.00-0.97 and -13.19 to 4.51 (P-T), 0.00-0.91 and -12.49 to 3.41 (P-M) and 0.00 to 0.88 and -20.97 to 25.82 (HG), respectively. The GWQMN (mm H_2O) is a parameter that related to the sub-base water flowing from the shallow aquifer to the river at the certain range of aquifer depth only was sensitive while use P-M method.

CANMX (mm H_2O) is one of the sensitive land cover features of a basin that should be calibrated independently and the values fed-in at each HRUs before further calibration with other sensitive parameters. The CANMX is related to the amount of precipitation that can be trapped in the form of droplets on the canopy and affect the evapotranspiration. The parameters values vary from 0.25-75 depending on the selection of PET estimation methods (Table 2). The lowest values were optimized by models that use the HG method and the fitted values by P-T method was five. On the other hand, the highest value was fitted by the model with P-M method as well as the finding by Alemayehu *et al*. (2015) where the higher values are obtained for models that apply P-M method.

The sensitive parameters rank for the watershed generally varies with the difference PET estimation methods and divided to significant sensitive for the first

Table 2: The 21 sensitive parameters, ranking and optimized value selected for the SWAT model streamflow calibration process using different PET method

PET methods/	Prestley (P-T)				Penman-Monteith (P-M)				Hargreaves (HG)			
Parameters name	t-stat	p-values	Ranks	Opt. values	t-stat	p-values	Ranks	Opt. values	t-stat	p-values	Ranks	Opt. values
v_CANMX.hru				5.00				75.00				0.250
r_CN2.mgt	-12.85	0.000	1	0.091	-11.44	0.000	1	0.069	25.82	0.000	1	-0.032
r_SOL_Z(..).sol	4.45	0.000	2	2.63	3.55	0.000	2	3.16	6.16	0.000	5	1.07
v_LAT_TTIME.hru	-3.56	0.000	3	46.31	-2.60	0.010	3	66.42	-20.97	0.000	2	30.90
v_GW_DELAY.gw	-3.20	0.002	4	47.93	-2.24	0.031	5	6.62	-3.55	0.000	6	21.85
v_CH_K2.rte	2.39	0.017	5	440.83	2.41	0.016	4	234.1	-3.30	0.001	7	123.92
r_SOL_K(..).sol	-2.30	0.022	6	4.47	-1.58	0.115	8	33.46	-0.153	0.879	20	51.78
v_EPCO.hru	-1.68	0.093	7	0.740	-1.71	0.088	6	0.710	-0.990	0.323	13	0.921
v_ALPHA_BNK.rte	1.48	0.141	8	0.669	1.59	0.112	7	0.829	7.19	0.000	4	0.742
v_SURLAG.bsn	1.46	0.146	9	15.74	1.35	0.178	9	23.34	0.983	0.326	14	13.53
v_ALPHA_BF.gw	-1.27	0.206	10	0.823	-1.13	0.260	11	0.399	-0.197	0.844	19	0.560
r_SOL_BD(..).sol	-1.15	0.251	11	0.414	-1.22	0.223	10	0.610	0.684	0.494	17	-0.048
v_CH_K1.sub	-0.911	0.363	12	189.52	-0.105	0.917	21	221.39	-8.89	0.000	3	3.83
v_GW_REVAP.gw	-0.882	0.378	13	0.139	-0.302	0.763	19	0.135	0.691	0.490	16	0.1287
v_DEEPST.gw	-0.807	0.420	14	45.276	-0.734	0.463	14	46.513	-1.63	0.104	12	39.030
v_RCHRG_DP.gw	-0.742	0.458	15	0.362	-0.328	0.743	18	0.431	-0.75	0.451	15	0.715
r_CH_N2.rte	0.664	0.507	16	14.46	0.511	0.610	16	20.47	1.77	0.078	9	9.67
v_SHALLST.gw	0.116	0.908	17	15.645	-0.876	0.381	13	8.909	1.74	0.082	10	11.721
r_SOL_AWC(..).sol	-0.092	0.927	18	1.87	-0.215	0.830	20	1.56	-0.317	0.751	18	2.80
r_OV_N.hru	0.082	0.935	19	1.70	0.522	0.602	15	0.9117	-1.74	0.083	11	0.887
v_ESCO.hru	-0.046	0.963	20	0.904	-0.890	0.376	12	0.7083	2.62	0.009	8	0.910
v_GWQMN.gw	Insensitive				-0.105	0.917	17	4.615	Insensitive			

'v' and 'r' were the type of change applied to the existing parameter value:'v' means the original value was replaced by a value from the range, 'r' means the original value was multiplied by the adjustment factor (1+given value within the range) Descriptions for each parameter can refer to the source (Arnold et al., 2012).

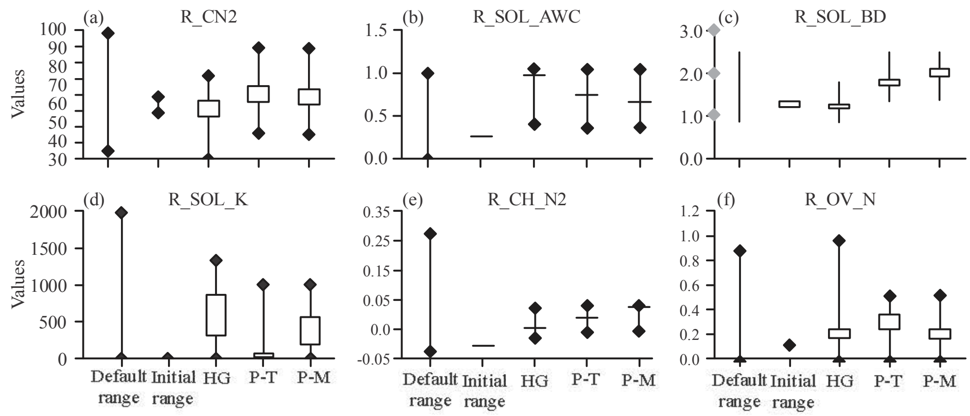

Fig. 4(a-f): The final ranges and optimize value with 'r' adjustment for the sensitive streamflow parameters (a) CN2.mgt, (b) SOL_K.sol, (c) SOL_AWC.sol, (d) SOL_BD.sol, (e) OV_N.hru and (f) CH_N2.rte

ten and others considered insignificant sensitive. These results suggest that the most significance sensitive parameters were kept the same ranks due to the same climate and topography data. Almost of the parameters mainly have direct effect to the sub-surface water generation of lateral and return flow (ALPHA_BF, GW_REVAP, DEEPST, RCHRG_DP, SHALLST, LAT_TIME, SOL_Z, SOL_AWC, SOL_K and SOL_BD), to the channel flow (ALPHA_BNK, CH_K2, CH_N2 and CH_K1) and to the surface runoff (CN2, CANMX, EPCO, ESCO, SURLAG and OV_N). Among those, there was agreed that the CN2 (SCS runoff curve number), the SOL_Z (depth of bottom layer to soil surface) and LAT_TIME (Lateral Flow travel Time) were most sensitive for the PET methods. Whereas the CH_K1 (hydraulic conductivity in tributary channel alluvium) only showed significant sensitive with HG and it was in the third-ranking. The base flow alpha (ALPHA_BF) is the parameters related to baseflow recession coefficient factor that sensitive for P-T and P-M (Fig. 4).

The GW_DELAY (time for water in the soil to become recharge), ALPHA_BNK (baseflow alpha factor for bank storage) and the geomorphology input of CH_K2 (hydraulic conductivity in main channel alluvium) were ranked in the top significant sensitive parameters. It was also shown that the soil input parameters, SOL_AWC (water capacity of soil layer) and SOL_BD (moist bulk density) show insignificant to the three PET methods, while the SOL_K (saturated hydraulic conductivity) was insensitive for HG. While the RCHRG_DP (fraction of deep aquifer percolation), GW_REVAP (coefficient of movement shallow aquifer water to root zone), SHALLST (initial water level of shallow aquifer) and DEEPST (initial water level of deep aquifer) was assessed as insignificant groundwater parameter. In addition, the OV_N (Manning's coefficient of surface roughness) for surface flow estimation was more sensitive of the geomorphology HRUs characteristics with HG and no significant with P-T and P-M.

Uncertainty and calibration performance: The SWAT-CUP automatically calculate the performance statistic comparing observed data with the best simulation. The performance obtained by SUFI-2 was based on the best value optimized for each parameter of the iteration and defined a new value range for each selected parameters in each simulation band. The best model performance was evaluated by using the R2, NSE and PBIAS values while p-factor and r-factor results through relative measurements and simulations coverage, were used to show the model prediction uncertainty.

Figure 5 shows the observed and simulation flow hydrographs from the year 1985-2016 with the statistical criteria for HG, P-T and P-M methods. The results of R2, NSE and PBIAS values showed that a very good calibration and good performance during validation period over the entire catchment between observed and simulated streamflow at the watershed outlet by using the three PET methods. The comparison exposed that among the three PET method, the HG performed better in term of R2 and NSE. It was found for the HG methods, achieved NSE value of 0.85 and 0.77 in the calibration and validation periods, respectively. Moriasi *et al.* (2015) recommended the model with NSE more than 0.80 considers excellent and the values between 0.7-0.80 were good for monthly response output (Table 1). While for P-T and P-M prediction, the model NSE are 0.74 and 0.78 for calibration and 0.74 and 0.73 for validation, respectively.

The p-factor of 82, 74 and 78% at the 95% prediction uncertainty level in the calibration at monthly time-step while using HG, P-T and P-M, respectively shows the high percentage of observed data bracketed by the 95PPU. Furthermore, the r-factor values of uncertainties degree found for the best simulation to be 0.75, 0.92 and 0.90 were <1.5 as recommended by Abbaspour *et al.* (2015). However, the p-factor calculated with SUFI-2 yielded unsatisfactory outcomes in the validation period where the value obtained <0.5 where

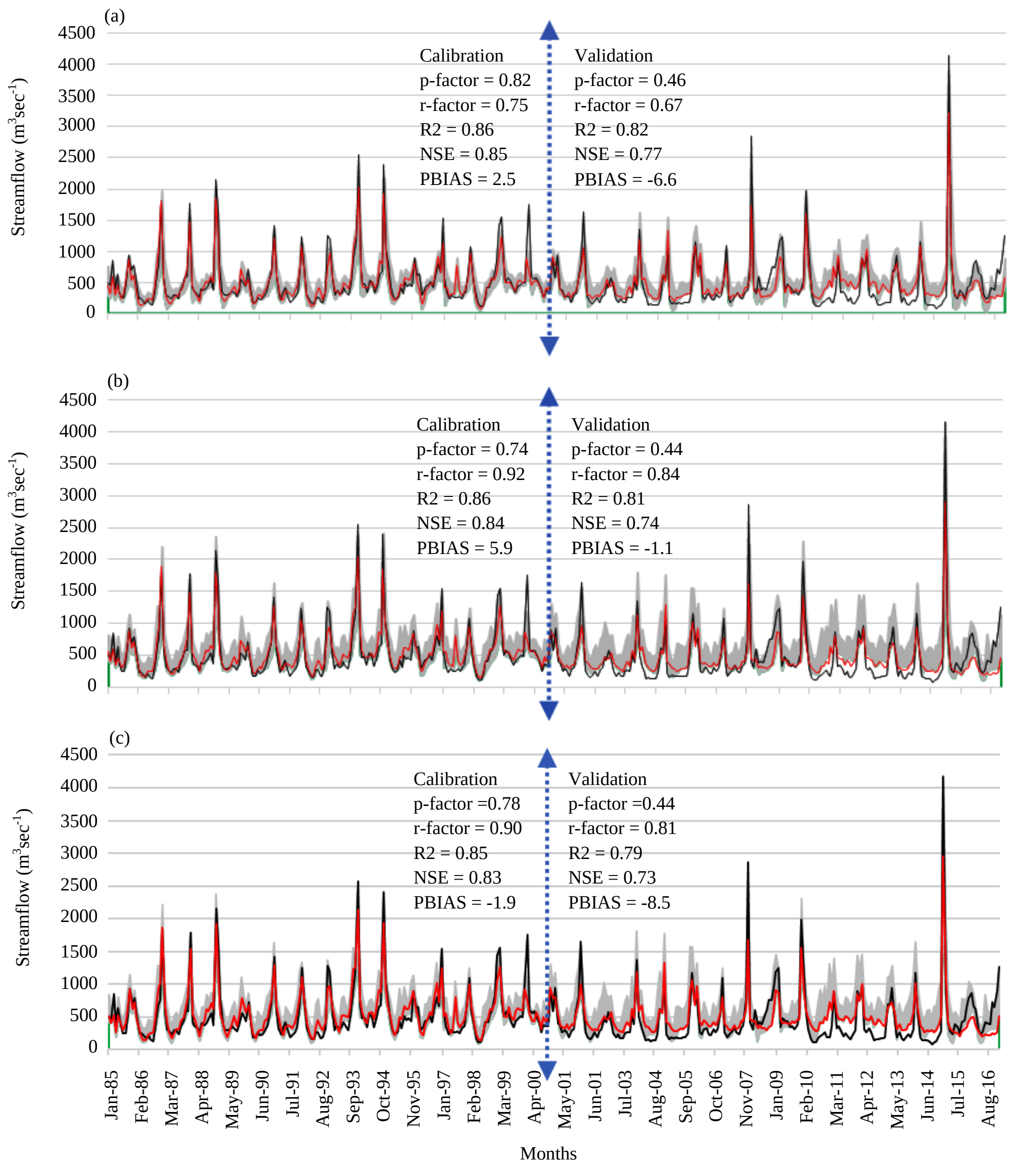

Fig. 5(a-c): The best model performance with 95PPU SWAT-CUP illustrations of the three PET methods for monthly output calibration (1985-2001) and validation (2001-2016) periods at the Guillemard Bridge station

the scholars proposed acceptable value more than 0.7. Figure 5 shows clearly the observed flows were bracketed within the 95PPU band below than 50% during calibration compared more than 70% in the calibration period. Figures also show the low of observed baseflow in the years 2010-2014 and the simulation far away to reach the peak as observed, especially in December, 2007 and 2014. These could happen influenced by information uncertainty and inconsistency in weather data or geography. There are also recorded big flood in whole Kelantan catchment in year 2014 that have possibility altered physically the surface of landscape and soil properties. The SWAT-CUP used various parameter with their vary ranges in calibration can affect the overall streamflow simulation including the base and peak flow (Lee *et al*., 2018).

CONCLUSION

The model performance for the flow simulation at the Guillemard Bridge station has proven the effectiveness of the SWAT Model and representing practical sensitive parameters by automatically calibration using SWAT-CUP. The SWAT-CUP with SUFI-2 algorithm was successfully identified as the most significant sensitive parameters for the three PET methods and considered to be applicable for Guillemard Bridge Watershed. The parameters included for surface runoff, lateral flow, channel and soil properties to be updated in the SWAT Model. The sensitivity analysis discovered the sensitive parameter ranking varies with different PET estimation method. However, the most significance sensitive parameters (CN2, SOL_Z and LAT_TIME) kept the same ranks due to the same climate and topography data.

Conclusions that could be resulting from this study: the significant of the parameter sensitivity analysis, which are considered to have an influence on streamflow were show different ranking for different PET methods in the Guillemard Bridge Watershed. However, the results obtained show a good agreement between the three PET methods, the streamflow simulations is most influenced by the parameters such as CN2, SOL_Z, LAT_TIME, GW_DELAY and CH_K2. SOL_K show more sensitive while using P-T and P-M and less sensitive in HG method. In contra, ESCO more sensitive with HG than the P-M and P-T methods.

The results have confirmed among the sensitive parameters, the GWQMN was only sensitive while P-M method was selected in the SWAT Model. The SUFI-2 results show that HG method has larger uncertainties than the P-M and P-T for streamflow simulation. The uncertainty for HG, P-T and P-M were 25, 8 and 10% during calibration while during calibration were 33, 16 and 19%, respectively. HG has high uncertainty because the PET calculation depends only onair temperature data. Therefore, HG option should be less preferable unless there are incomplete the solar radiation, relative humidity or wind speed data.

Although, the NSE, R2, PBIAS, p-factor and r-factor results value of HG, P-T and P-M were relatively small, the SWAT Model with option P-T method was considered more accurately reflected the smaller PBIAS and higher r-factor than HG and P-M methods.

Overall, the performance and uncertainty result for each PET methods, the SWAT Model with P-T methods performed a better Rainfall-runoff Model for the Kelantan river basin. The sensitivity findings should make an important contribution to the field of data collections and verifications for the hydrological modeling by demonstrating the significant and insignificant input parameters. In future, the performance of the SWAT Model could be enhanced by multiple gauge calibration and the computed ET should also be validated at each sub-basin because it is one of the main water balance components of a basin catchment.

ACKNOWLEDGEMENTS

The researcher are thankful for the scholarship and the financial support from the Public Service Department Malaysia. The researcher appreciates those people and agencies that assisted in accessing research data and information. The researchers would like to acknowledge the Universiti Tenaga Nasional (UNITEN) grant, BOLD2025 with reference number 10436494/B/2019136.

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