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OPTIMIZATION OF SPATIAL INPUT PARAMETER IN DISTRIBUTED HYDROLOGICAL MODEL

Khalid K.[1], Ali M. F.[2], Rahman N. F. A.[2], Mispan M. R.[3], Rasid M. Z. A.[3], Haron S. H.[4] and Mohd M. S. F.[5]

[1]Faculty of Civil Engineering, Universiti Teknologi MARA Pahang, Jengka, Pahang, Malaysia

[2]Faculty of Civil Engineering, Universiti Teknologi MARA, Shah Alam, Malaysia

[3]Strategic Resource Research Centre, MARDI, Serdang, Malaysia

[4]Faculty of Science and Technology, Universiti Kebangsaan Malaysia, Bangi, Malaysia

[5]Water Resources and Climate Change Research Centre, NAHRIM, Seri Kembangan, Malaysia

E-Mail: khairikh@pahang.uitm.edu.my

ABSTRACT

Hydrologic models are particularly useful tools in enabling the modeler to investigate many practical and significant issues that arise during planning, design, operation, and management of water resources systems. Distributed models should pass through a careful calibration procedure before they are utilized as the process of decision-making aids in the planning and administration of water resources. Although manual approaches are still repeatedly used for calibration, they are tedious, time-consuming and have the need of experienced personnel. This paper describes a semi-automatic approach for calibrating long term daily streamflow periods estimated by the Soil and Water Assessment Tool (SWAT) hydrological model. Optimization of three different sets of spatial input parameters were tested using SUFI-2 algorithms by firstly focusing on the sets of the groundwater inputs parameter. The second set is for the soil input parameters and the final set consists of 21 SWAT input parameters that reflect sensitivity on the streamflow simulation. For Langat river basin, the Rchrg-dp.gw, GW_Delay.gw and CN2.mgt were found to be most sensitive input parameters. SOL_AWC.sol was established to be the most sensitive to soil input parameter and followed by SOL_BD.sol and SOL_K.sol. On the final sets, it was shown that the three input parameters of OV_N.hru, SL_SUBBSN.hru, and HRU_SLP.hru were included as sensitive parameters in addition to the previous parameters. The next step should be conducting a long-term continuous hydrological modeling into SWAT 2012 model with all the selected sensitive SWAT input parameters in order to finalize the objective functions for the watershed.

Keywords: hydrological modelling, daily streamflow, SWAT input parameter, SUFI-2 algorithms.

INTRODUCTION

Distributed watershed models are progressively being used to support decisions on many water resources management such as in the design and operation of the hydraulic structures, water supply, irrigation, flood control, and many mores engineering practices (McCuen, 1998) and (Shaw *et al*., 2010). It is essential for these models to pass a careful calibration and uncertainty analysis before it can be utilized in management strategies. The calibration of watershed models, however, is a challenging task because of input, model structure, parameter, and output uncertainty. Sources of model input uncertainty are frequently related spatially interpolated measurements of model input or rainfall intensity, temperature, and initial groundwater levels. The uncertainties in distributed models may also arise due to the errors in the data used for parameter calibration including the spatial input parameter. Most of the hydrologic models utilize these geospatial data including topography map, land used and soil map with properties in describing the physical variability of the watershed. The soil properties are strongly affected by three forces, such as hydraulic conductivity, diffusivity, and water holding capacity. The hydraulic conductivity is of critical importance to the infiltration rate since it expresses how easily water flows through soil and is a measure of the soil's resistance to flow. Water holding capacity is the amount of water that can be held due to the pore size distribution, texture, structure, the percentage of organic matter, chemical composition and current water content.

SWAT is a continuous-time, spatially distributed simulator developed to assist water resource managers in predicting impacts of land management practices on water, sediment and agricultural chemical yields (ASCE, 1999). SWAT has been successfully used by researchers around the world for distributed hydrologic modeling and management of water resources in watersheds with various climate and terrain characteristics. A comprehensive review of SWAT model applications, calibrations and validations are given by (Gassman *et al*., 2007), (Arnold *et al*., 2012). SWAT has many parameters to be calibrated on the streamflow, sediment and for other environmental purposes. The twelve most frequent input parameters used in the calibration process of surface runoff and baseflow has been reported in previous 64 selected SWAT watershed studies (Arnold *et al*., 2012). In the other study for calibrating streamflow alone, SWAT needs to consider about 26 related input parameters (Shi *et al*., 2013). This paper will report an optimization study of a SWAT model input parameter on the tropical river basin. In this study, 21 number of SWAT input parameters were being assessed, and the parameters were selected from various

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references (Arnold *et al*., 2012), (Murty *et al*., 2013), (White and Chaubey 2005). These parameters have been set up in three different sets in order to assess the critical input parameter related to groundwater, soil input properties and all the sensitive parameters related to the streamflow. SWAT-CUP is a SWAT Calibration Uncertainties Program, which is developed to analyze the prediction uncertainty of SWAT model calibration and validation results. The SWAT-CUP is able to integrate various calibration/uncertainty analysis procedures for SWAT in one user interface. It is a public domain program that links Sequential Uncertainty Fitting ver.2 (SUFI-2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov Chain Monte Carlo (MCMC) procedures to SWAT.

In SUFI-2, the degree to which all uncertainties are accounted for is quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). Another measure quantifying the strength of a calibration/uncertainty analysis is the R factor, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2, hence seeks to bracket most of the measured data with the smallest possible uncertainty band. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling, disallowing 5% of the very bad simulations. Theoretically, the value of the P factor ranges between 0 and 100% while that of R-factor ranges between 0 and infinity. A P-factor of 1 and R-factor of zero is a simulation that exactly corresponds to the measured data. The further goodness of fit can be quantified by the Coefficient of the determination (R^2) or Nash-Sutcliff (NSI) coefficient between the observations and the final "best" simulation. In this study, SWAT model performance evaluation is measured by the value of R^2.

STUDY AREA

Langat River basin, a tropical river watershed in Malaysia is chosen for the study in accessing the critical input parameters of the SWAT model. The basin occupies the south and south-eastern parts of Selangor, as well as a small portion of Negeri Sembilan and Wilayah Persekutuan, Malaysia. Several studies have been conducted on the basin in relation to water resources and hydrological behavior of the basin. The basin became the first watershed in the country initiated towards the implementation of Integrated River Basin Management (IRBM) (Mokhtar *et al*., 2004). Many studies were carried out on the hydrological processes of the basin including a historic water discharges study by (Hai *et al.*, 2011), (Ali *et al*., 2014a), (Rahman *et al*., 2014); and the impact of land used change on discharge and direct runoff (Hafizan *et al*., 2010), (Amini *et al*., 2009), (Khalid et al., 2015). Another study was found during the gathering of literature, utilizing groundwater input including ALPHA_BF.gw (Baseflow alpha factor), GW_DELAY.gw (Groundwater delay), GW_QMN.gw (Threshold depth of water in the shallow aquifer required for return flow to occur) and RCHRG_DP.gw (Deep aquifer percolation fraction) in two years calibration period of SWAT model (Ali *et al*., 2014b).

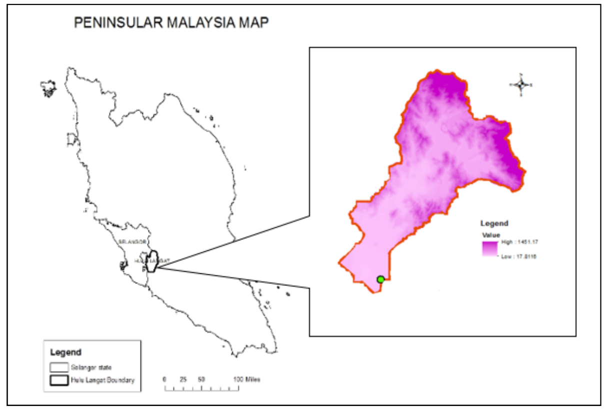

Figure-1. Location of Langat River basin showing the delineation of the watershed.

Model setup and simulation

The major geospatial input data includes Digital Elevation Model (DEM), soil data, land use and stream network layers. SWAT requires daily meteorological data that can either be read from a measured data set or be generated by a weather generator model. The weather variables used in this study are daily precipitation, minimum, and maximum air temperature for the period 1976 to 2010. A weather generator developed by (Schuol and Abbaspour, 2007) was used to fill the gaps due to missing data. Daily river discharge values for Kajang streamflow station were obtained from the Department of Irrigation and Drainage (DID) Malaysia. The model setup involved five steps: (1) data preparation; (2) sub-basin discretization: (3) Hydrologic Response Unit (HRU) definition; (4) parameter sensitivity analysis; (5) calibration and uncertainty. The sub-basin discretization only focused on the 331.36km^2 upper part of the Langat River basin as in Figure-1. The watershed was divided into 17 sub-basins and 142 numbers of HRUs after completing the first three processes in the model setup.

In SWAT model, input parameters can be either manually adjusted in the SWAT model or can be accessed in the SWAT-CUP. SWAT-CUP is a semi-automatic approach to a computer program for calibration of SWAT models, and the programs link SUFI-2 algorithms to SWAT. It enables sensitivity analysis, calibration, validation, and uncertainty analysis of SWAT models (Abbaspour *et al*., 2004), (Abbaspour, 2012). Optimization of three different sets of spatial input parameters were tested, in order of, firstly focusing on the sets of groundwater inputs parameter, secondly for the soil input

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parameters and finally for the set consisting of 21 SWAT input parameters (Table-1) which reflect sensitivity on the streamflow simulation. After setting up the model, the default simulation of streamflow was conducted in the Langat River basin for the calibration period and, after that, compared with the observed streamflow. About 17 years (1976 to 1992) of daily rainfall data was utilized in the calibration periods with the first four years used for the model warm-up.

Table-1. Selected input parameter of SWAT model.

No.	Input parameter	Description of parameter	Min and max range
1	CN2.mgt	SCS runoff curve number	35 - 98
2	SURLAG.bsn	Surface runoff lag time (days)	0.05 - 24
3	OV_N.hru	Manning's "n" value for overland flow	0.01 - 30
4	SL_SUBBSN.hru	Average slope length (m)	10-150
5	HRU_SLP.hru	Average slope steepness (fraction)	0-1
6	EPCO.bsn	Soil evaporation compensation factor	0 - 1
7	ESCO.bsn	Plant uptake compensation factor	0 - 1
8	CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/hr)	0.025 to 250
9	ALPHA_BF.gw	Baseflow alpha factor (days)	0 - 1
10	GW_REVAP.gw	Groundwater "revap" coefficient	0.02 -0.2
11	GW_DELAY.gw	Groundwater delay (days)	0 - 500
12	GW_QMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0 - 5000
13	REVAP_MN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	0 - 500
14	RCHARG_DP.gw	Deep aquifer percolation fraction	0 - 1
15	SOL_AWC.sol	Available water capacity of the soil layer (mm H2O /mm soil)	0 - 1
16	SOL_BD.sol	Moist bulk density (g/cm^3 @ Mg/m^3)	0.9 to 2.5
17	SOL_Z.sol	Depth from soil surface to bottom of layer (mm)	0 to 3500
18	SOL_K.sol	Saturated hydraulic conductivity(mm/hour)	0 to 2000
19	SOL_CBN.sol	Organic carbon content	0.5 to 10
20	SOL_ALB.sol	Moist soil albedo (fraction)	0 to 0.25
21	USLE_K.sol	USLE equation soil erodibility (K) factor	0 to 0.65

RESULTS AND OPTIMIZATION ANALYSIS

After the default simulation in the SWAT 2012 had been completed, the simulated streamflow output at Kajang streamflow station with the watershed spatial input was then transferred to SWAT-CUP for optimization processes. The model was run for 1000 times simulation. A graph of monthly streamflow hydrograph optimization output in Figure-2 shows the agreement between observed and simulated streamflow. A value of the coefficient of determination, R^2 of 0.75 as in Figure-3 was gained from a simulation, and the value can be considered as good achievement of the calibration processes in a hydrological model. But, it is also shown by the hydrograph that the model does not effectively simulate the monthly peaks discharge of the streamflow station. It is clearly observed that the simulated output in June, 1984; July, 1985 and May, 1991 were lesser than the observed streamflow.

In SUFI-2, the assessment of the sensitive parameters is measured using the t-stat values where the values are more sensitive for a larger in absolute t-stat values. P-values are used to determine the significance of the sensitivity where the parameter becomes significance if the P-values is close to zero. Tables 2(a), (b) and (c) show the output of these optimization processes of the selected spatial input parameters in the watershed and the sensitivity of the input parameters were ranked based on

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these two objective functions. The results confirmed Rchrg_dp.gw, CN2.mgt, and GW_Delay.gw were assessed as a main critical input parameter for Langat river basin. Rchrg_dp.gw and GW_Delay.gw were ranked 1 and 3, respectively in the first assessment of the groundwater input parameters and ranked 4 and 10, respectively in the evaluation of 21 input parameters. In the optimization of the soil input parameters, simulation output shows the SOL-AWC.sol, SOL_BD.sol, and SOL_K.sol were measured as critical input parameters. The output in the assessment of 21 input parameters also confirmed that parameter SOL-AWC.sol and SOL_BD.sol are more critical compared to SOL_K.sol in the continuous hydrological model.

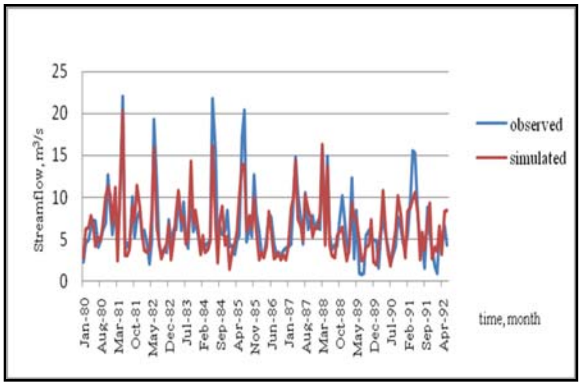

Figure-2. SWAT 13 years streamflow simulation output.

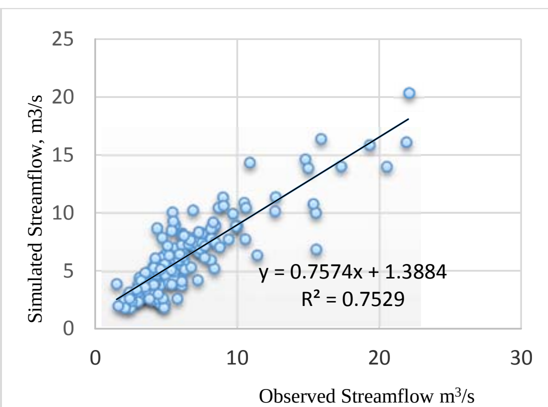

Figure-3. Coefficient of determination, R^2.

Table-2(a). Summary of global sensitivity analysis on the 21 input parameter.

No.	SWAT input parameter	21 input parameter		
		P-value	t-stat	Ranking
1	SOL_BD.sol	0.000	-35.321	1
2	SOL_AWC.sol	0.000	15.082	2
3	OV_N.hru	0.000	13.713	3
4	Rchrg_dp.gw	0.000	11.947	4
5	SL_SUBBSN.hru	0.000	10.837	5
6	HRU_SLP.hru	0.000	-8.406	6
7	SOL_K.sol	0.000	-7.268	7
8	CN2.mgt	0.001	-3.475	8
9	SOL_Z.sol	0.038	2.076	9
10	GW-Delay.gw	0.076	-1.774	10
11	SOL_Cbn.sol	0.118	1.565	11
12	GWQMN.gw	0.156	1.421	12
13	EPCO.bsn	0.216	1.238	13
14	ESCO.bsn	0.219	1.229	14
15	SOL-Alb.sol	0.226	-1.21	15
16	SURLAG.bsn	0.455	0.747	16
17	CH_K2.rte	0.540	-0.612	17
18	GW_Revap.gw	0.615	0.502	18
19	REVAPMN.gw	0.681	0.411	19
20	USLE_K.sol	0.758	0.308	20
21	Alpha_BF.gw	0.890	-0.138	21

Table-2(b). Summary of global sensitivity analysis on the groundwater input parameter.

No.	SWAT input parameter	Groundwater input parameter		
		P-value	t-stat	Ranking
1	SOL_BD.sol	NT*	NT	
2	SOL_AWC.sol	NT	NT	
3	OV_N.hru	NT	NT	
4	Rchrg_dp.gw	0.000	66.698	1
5	SL_SUBBSN.hru	NT	NT	
6	HRU_SLP.hru	NT	NT	
7	SOL_K.sol	NT	NT	
8	CN2.mgt	0.000	-29.819	2
9	SOL_Z.sol	NT	NT	
10	GW-Delay.gw	0.000	-4.965	3

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11	SOL_Cbn.sol	NT	NT	
12	GWQMN.gw	0.496	-0.682	5
13	EPCO.bsn	NT	NT	
14	ESCO.bsn	NT	NT	
15	SOL-Alb.sol	NT	NT	
16	SURLAG.bsn	0.758	-0.278	8
17	CH_K2.rte	NT	NT	
18	GW_Revap.gw	0.547	0.602	6
19	REVAPMN.gw	0.350	0.936	4
20	USLE_K.sol	NT	NT	
21	Alpha_BF.gw	0.661	-0.438	7

*NT – Not tested

Table-2(c). Summary of global sensitivity analysis on the soil input parameter.

No.	SWAT input parameter	Soil input parameter		
		P-value	t-stat	Ranking
1	SOL_BD.sol	0.000	-4.148	2
2	SOL_AWC.sol	0.000	14.395	1
3	OV_N.hru	NT*	NT	
4	Rchrg_dp.gw	0.076	1.777	7
5	SL_SUBBSN.hru	NT	NT	
6	HRU_SLP.hru	NT	NT	
7	SOL_K.sol	0.006	2.776	3
8	CN2.mgt	0.022	-2.286	5
9	SOL_Z.sol	0.013	2.494	4
10	GW-Delay.gw	0.485	0.698	10
11	SOL_Cbn.sol	0.309	-1.018	8
12	GWQMN.gw	NT	NT	
13	EPCO.bsn	NT	NT	
14	ESCO.bsn	NT	NT	
15	SOL-Alb.sol	0.481	0.705	9
16	SURLAG.bsn	NT	NT	
17	CH_K2.rte	NT	NT	
18	GW_Revap.gw	NT	NT	
19	REVAPMN.gw	NT	NT	
20	USLE_K.sol	0.037	2.089	6
21	Alpha_BF.gw	0.625	-0.489	11

*NT - Not tested

CONCLUSIONS

A stream flow of the upper part of the Langat River basin was successfully modeled by the version of Soil and Water Assessment Tool (SWAT), ArcSWAT 2012.10_1.12 embedded in ArcGIS 10.1. The SCS runoff curve number (CN2.mgt), groundwater delay (GW-Delay.gw), deep aquifer percolation fraction (Rchrg_dp.gw), available water capacity of the soil layer (SOL_AWC.sol) and moist bulk density (SOL_BD.sol) were found to be the most sensitive input parameters in the watershed. The optimization of the spatial input parameters in the model is recommended to have further fine adjustment by conducting a short time series of simulation processes. The next step should be conducting long-term continuous hydrological model into SWAT 2012 model with all the selected sensitive SWAT input parameters in order to finalize the objective functions for the watershed model. A data-driven method approach for the prediction of streamflow using monthly time series data is also recommended for improving the calibration processes of the SWAT model. The integration will improve the accuracy of simulation and prediction of the dynamic behavior of a streamflow over any time interval.

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