https://doi.org/10.33271/nvngu/2025-6/168

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CALIBRATION AND VALIDATION OF THE SWAT MODEL FOR UPPER BERNAM RIVER BASIN IN MALAYSIA

Purpose. The calibration and validation of the Soil and Water Assessment Tool (SWAT) model are essential to ensure its accuracy in simulating hydrological processes for effective decision-making. This study focuses on the Upper Bernam River Basin (UBRB) in Malaysia, where the SWAT model was calibrated and validated using observed streamflow data from 1985 to 2022.

Methodology. Calibration and validation were performed in three categories: category 1 (10-year calibration, 5-year validation), category 2 (15-year calibration, 10-year validation), and category 3 (20-year calibration, 10-year validation).

Findings. Statistical indices for category 1 indicated a satisfactory model performance, with calibration results showing a p-factor of 0.82, r-factor of 0.88, R^2 of 0.72, NSE of 0.70, PBIAS of –1.1 %, and KGE of 0.85. Validation results indicated a p-factor of 0.80, r-factor of 1.04, R^2 of 0.75, NSE of 0.65, PBIAS of –6.6 %, and KGE of 0.79. Moreover, the results from category 1 showed better performance over the other categories indicating that simulation length does not usually improve data quality or model performance. The 15-year model setup for category 1 was subjected to water balance evaluation and the result shows that the simulated inflow (precipitation) and outflow (water yield + ET) differences for 1991–2005 and 2006–2020 were 9.8 and 11.5 %, respectively.

Originality. This study uniquely applies long-term observed streamflow data and multi-scenario calibration-validation to improve SWAT model reliability for simulating hydrology in the Upper Bernam River Basin.

Practical values. This study demonstrates the SWAT model's reliability in predicting agro-hydrological processes and provides insights into sustainable agricultural water management in UBRB.

Keywords: *SWAT model, calibration, validation, Upper Bernam River Basin (UBRB), streamflow, agricultural water management*

Introduction. Hydrological modelling plays a pivotal role in understanding water resource dynamics, enabling informed decision-making for sustainable management and planning. This results in effective water resource management, which is a cornerstone of sustainable development, particularly in regions that heavily depend on agriculture. In tropical river basins like the Upper Bernam River Basin (UBRB) in Malaysia, agricultural water management is critical due to the increasing demand for irrigation and the looming impacts of climate variability [1]. The UBRB is one such critical area, as it provides water resources essential for agricultural activities within the Selangor Integrated Agricultural Development Area (IADA) [2]. This region, like many others, faces increasing challenges from climate change, land-use transformation, and population growth, all of which place immense pressure on available water resources [3]. These issues necessitate the adoption of reliable hydrological models to simulate and predict water balance components accurately [4].

Hydrological models such as the Soil and Water Assessment Tool (SWAT) are widely used due to their ability to simulate the impacts of land use, climate change, and management practices on water resources in large, complex watersheds [5]. The SWAT model's ability to integrate diverse datasets, including land use, soil, and climate data, makes it a powerful tool for decision-makers. However, the accuracy and reliability of the SWAT model depend heavily on its calibration and validation processes, which are critical for minimizing uncertainties and ensuring realistic predictions [6].

Previous studies, such as [7], have explored the application of the SWAT model in the UBRB. However, these studies often relied on simulated climate data, introducing uncertainties in the model outputs. Moreover, the calibration and validation periods in prior research were not comprehensive enough to capture the full variability of hydrological processes in the study area. This study addresses these gaps by utilizing observed climate and streamflow data spanning 37 years (1985–2022), offering a robust basis for model calibration and validation.

The UBRB serves as a critical water source for irrigated agriculture, particularly rice cultivation, which is a staple food crop in Malaysia. As water demand continues to grow, understanding the hydrological dynamics of the basin becomes increasingly important. This study aims to calibrate and validate the SWAT model for the UBRB under three distinct scenarios and assess their performance; evaluate the water balance components,

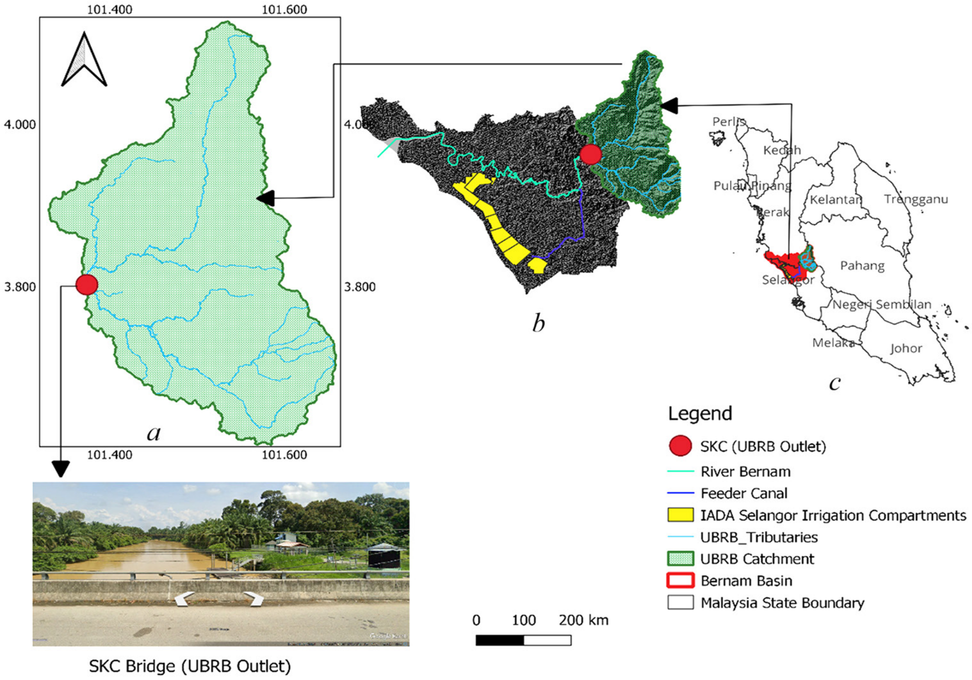


Fig. 1. Study area

including inflow and outflow dynamics for the selected category, and provide insights into the applicability of the SWAT model in guiding sustainable water and agricultural planning in the UBRB. By providing reliable simulations of water balance components, this research offers valuable insights to support sustainable water resource management and agricultural planning in the face of changing environmental conditions.

Materials and methods. *Study area*. Figs. 1 and 2 describe the study location (Upper Bernam River Basin (UBRB)), which covers about 108,000 ha, arising from the mountainous areas of the main range bordering Pahang and flowing 200 km to the Melaka straits. It forms the border between the states of Selangor and Perak, with approximately 65 % of the basin in Perak [8]. The UBRB serves as the main source of irrigation water for the Integrated Agricultural Development Area (IADA) in Selangor. The IADA Selangor is in the Northwest of Malaysia, which is about 98 km north of Kuala Lumpur (The main capital of Malaysia). The Bernam and Tengi rivers are the sole irrigation water sources for the irrigation scheme [7]. Fig. 1, *a* presents the UBRB catchment, whilst Fig. 1, *b* shows the location of the Integrated Agricultural Development Area (IADA) Selangor and UBRB in Bernam Basin, and Fig. 1, *c* is the location of the Bernam Basin in Malaysia.

The Malaysia Meteorological Department (MMD) recorded an average dry season temperature of 28 to 35 °C (January to June). The humidity is over 75 % year-round [7, 9]. Malaysia is situated north of the equator in Southeast Asia, which has an equatorial, hot, and humid climate with 21–32 °C daily temperatures [10]. Annual rainfall in Peninsular Malaysia is 2,500 mm [11]. The rainfall is determined by the Northeast monsoon (November to February) and Southwest monsoon (May to August), with peaks from October to December and February to May. The inter-monsoon seasons, March to April and September to October are labelled dry seasons with low rainfalls. The northeast monsoon's heavy rainfall causes high air humidity in the main season and low humidity in the off-season [9]. Thus, the UBRB catchment serves as the main source of irrigation water to IADA Selangor which operates from January to June as the off-season, and July to December as the main season. The off-season is defined by low rainfall and the main season with heavy rainfall. The basin supports irrigation for rice and other crops under the Selangor IADA scheme.

SWAT and SWAT-CUP Programs. The SWAT model is a semi-distributed, process-based hydrological model designed to simulate water, sediment, and nutrient dynamics in large watersheds [5]. The model was configured using input data, including land use, soil type, and observed meteorological data. The evaluation of the SWAT model has become imperative due to its intended application in simulating the present and future agro-

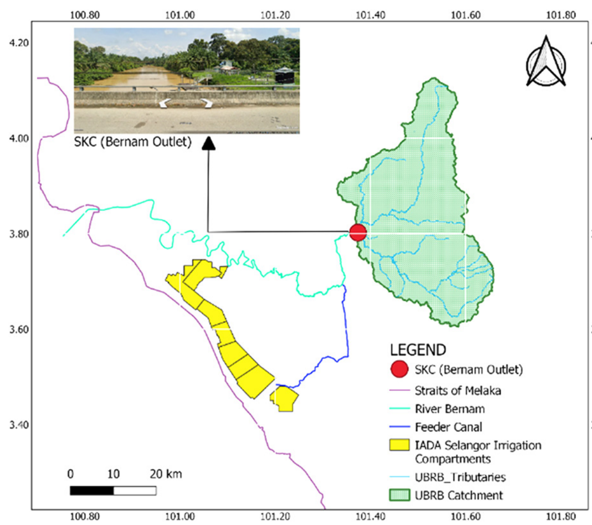


Fig. 2. UBRB and IADA Selangor irrigation compartment

hydrological processes of the UBRB with complex topography and the downstream of the basin for agricultural productivity in Malaysia. The SWAT model was evaluated to determine its capabilities of simulating the climate change impacts on the agro-hydrological processes of UBRB.

The SWAT model is compatible with a variety of computer programs. This study used the QSWAT3_9 version 1.5.10 model with an interface in QGIS 3.28.13 Firenze [12]. In addition, SWAT Editor software [13] was used for model computations. The SWAT model is a deterministic model developed by the US Department of Agriculture [14]; it maps physical, chemical, and biological processes using mathematical equations. The model was developed to predict the impact of basin-scale management methods on water and agricultural chemical yields [14]. However, for the calibration and validation of the SWAT model, the SWAT Calibration and Uncertainty Programs (SWATCUP-premium) version (Abbaspour, 2015) was used to calibrate the SWAT model to the natural environment of the research area. The program evaluates the SWAT model's calibration, validation, sensitivity, and uncertainty [15]. The SUFI-2 method was used since it works well for small catchments [16].

SWAT model data and setup. A comprehensive collection of geospatial data from multiple sources was used to evaluate the SWAT model's capabilities to simulate climate change effects on UBRB's agro-hydrological processes: Digital elevation models (DEMs) were downloaded from the Shuttle Radar Topography Mission (SRTM) website (30-Meter SRTM Tile Downloader) and processed in QGIS (Fig. 3, *a*). The DEM used in the catchment area have a 30-meter spatial resolution.

The area's digital soil map was downloaded from the FAO Map Catalogue's Digital Soil Map of the World (DSMW) in ESRI shapefile format and processed using QGIS software (Fig. 3, *b*). The study area's land-use land cover map was obtained from the ESRI website (Global Land Cover; Sentinel-2 10-Meter Land Use/Land Cover, 2022) and processed using QGIS (Fig. 3, *c*). The Malaysian Department of Irrigation and Drainage (DID) provided the observed streamflow data from 1985–2022, and meteorological data, including precipitation, maximum and minimum temperature, relative humidity, and wind data for this research. This study considered climate simulations for the historical periods of 1985 to 2022.

During the SWAT run, the "Edit Inputs and Run SWAT Model" window was filled with meteorological data for executing the SWAT model. The data included daily precipitation sums (mm), daily minimum and maximum air temperature (°C), average daily wind speed (m/s), daily mean relative humidity expressed as a percentage (%), and daily sums of total solar radiation (MJ/m^2). The flowchart presented in Fig. 4 was followed by running the SWAT model.

The SWAT model mimics the land phase of the hydrological cycle using the water balance

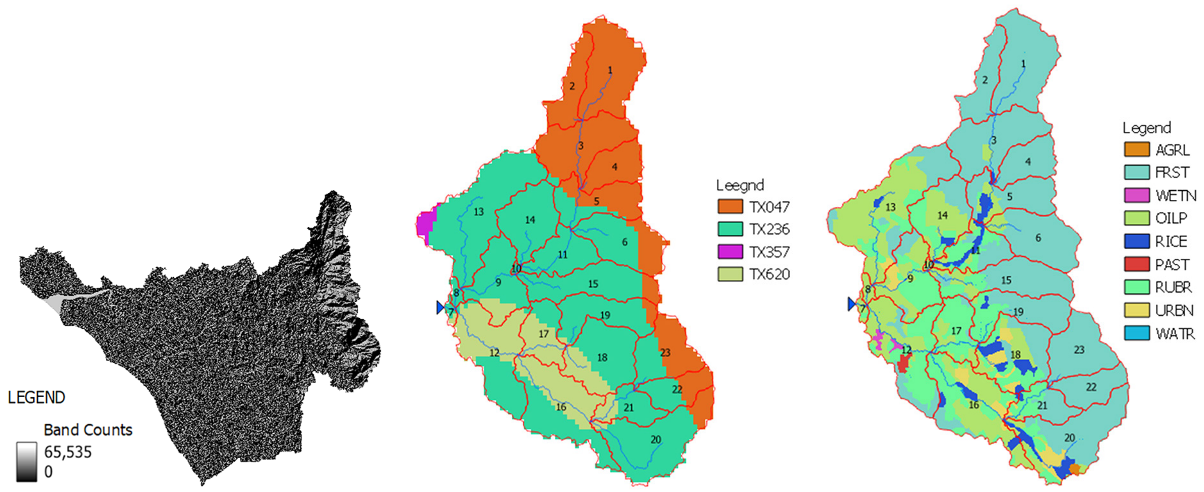
$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}),$$

where SW_t is the soil's final water content; SW_0 is its initial water content, t is time in days; R_{day} is daily precipitation; Q_{surf} is daily surface runoff; E_a is daily evapotranspiration (ET); W_{seep} is daily percolation; Q_{gw} is daily return flow, (all units are in mm).

Calibration and Validation of the SWAT-CUP. The SWATCUP premium program was used in calibrating the SWAT model to match reality better [17]. SWAT-CUP helps in the challenging calibration of the parameters included in SWAT model to meet an objective function. This doesn´t necessarily mean that it will be a better match to reality. The study employed three calibration-validation scenarios:

- Category 1 (10-year calibration, 5 years validation);
- Category 2 (15-year calibration, 10 years validation);
- Category 3 (20-year calibration, 10 years validation).

Average monthly streamflow was utilized for calibration as follows: category 1 (1991–2000, 2001–2010, 2011–2020), category 2 (1991–2005), and category 3 (1991–2010). According to [14], longer simulation du-



a *b* *c*

Fig. 3. SWAT model's spatial data input for the Upper Bernam River Basin:
a – DEM; b – soil map; c – land use map

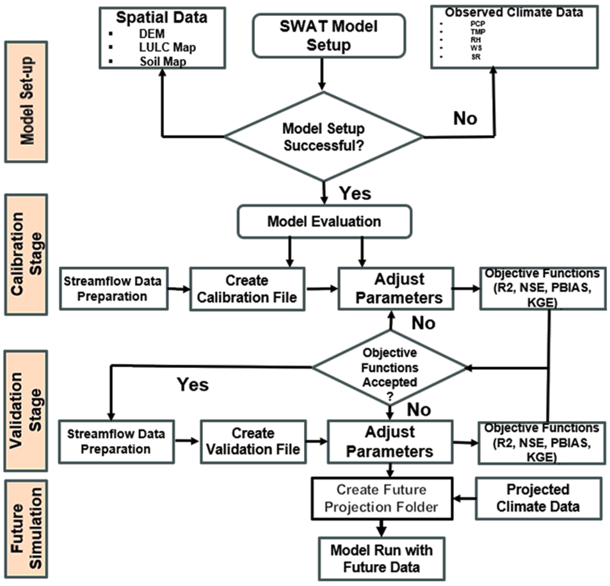


Fig. 4. Model run flowchart

rations and pre-processing times do not usually improve data quality or performance, nor do higher-resolution data while other researches have contrary report [18]. However, this study tends to investigate which of these durations or categories will provide an acceptable result.

After a suitable calibration, the model was validated using monthly average streamflow at the outlet of the basin (Jambatan Kuala Slim (SKC)) as follows: category 1 (2001–2005, 2011–2015, 2021–2022), category 2 (2006–2015), and category 3 (2011–2020). The accuracy requirements of calibration and validation were examined for the best-fit parameter ranges [19].

Calibration was performed using the SUFI-2 algorithm in SWAT-CUP, with statistical indices (p-factor, r-factor, NSE (Equation 1), PBias (Equation 2), Kling-Gupta Efficiency (KGE: Equation 3), and coefficient of determination (R^2: Equation 4)) used to evaluate the model performance.

$$NSE = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m.i} - \bar{Q}_m)^2}, \quad (1)$$

where Q is a variable (discharge); m and s stand for measured and simulated, respectively, and the bar stands for average.

$$PBIAS = 100 \cdot \frac{\sum_{i=1}^{n} ((Q_m - Q_s)) \sum_{i=1}^{n} i}{\sum_{i=1}^{n} Q_{m.i}}, \quad (2)$$

where Q is a variable (discharge); m and s are measured and simulated, respectively.

$$KGE = 1 - \sqrt{((r-1)^2 + (a-1)^2 + (\beta - 1)^2)}, \quad (3)$$

where $\alpha = \frac{\sigma_s}{\sigma_m}$; $\beta = \frac{\mu_s}{\mu_m}$; r is the coefficient of linear regression between simulated and measured variables; μ_s and μ_m are means of simulated and measured data and σ_s and σ_m are the standard deviations of simulated and observed data.

$$R^2 = \frac{\left[\sum_i (Q_{m,i} - \bar{Q}_m)(Q_{s,j} - \bar{Q}_s)\right]^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2 \sum_i (Q_{s,j} - \bar{Q}_s)^2}, \quad (4)$$

where Q is a variable (discharge); m and s stand for measured and simulated; i is the i^{th} measured or simulated data.

Parameter Sensitivity Analysis. Table 1 presents SWAT parameters for sensitivity analysis. Before calibration and validation, an experiment was undertaken to understand how the SWAT model responds and analyses the sensitivity and uncertainty of factors affecting streamflow in the UBRB at the SKC gauge station. Based on the catchment's hydrology, 26 parameters were selected, and a global sensitivity analysis was carried out.

In the calibration process, two approaches are applied for parameter adjustment in SWAT. Parameters marked with r (relative) are modified by applying the fitted value in a relative manner, i.e., the fitted value is added to 1 and then multiplied by the existing parameter value in SWATEdit. Parameters marked with v (replace) are adjusted by direct substitution, meaning the given value in SWATEdit replaces the existing parameter value.

Reducing calibration runs and parameter fittings to avoid overparameterization is crucial because excessive calibration runs or settings might cause unrealistic catchment conditions or model sensitivity to specific input data; on this basis, an experiment was done, and Table 2 shows the results. During the calibration and validation, we applied the v (replace) method to HRU_SLP and SUB_ELEV parameters at the sub-basin level to capture average slope and elevation variations while preserving spatial heterogeneity, ensuring accurate hydrological simulations in the Upper Bernam River Basin.

The 26 parameters were simulated 500 times throughout a 21-year (1985–2005) data period, including a 6-year warm-up, 10-year calibration, and 5-year validation phase. A global sensitivity analysis following the simulation showed 10 parameter sensitives. Table 2 shows the remaining sets of runs at 100, 200, 300, 400, and 500 with default data from a project backup of the TextInOut folder. The 300 default simulations performed better, so further calibrations and validations were set to start from 300 simulations. After 300 simulations, 400-, 500-, 600-, and 700 iterations were run, and the model performed best at 600 simulations, as shown in Table 2. This was the optimal iteration for subsequent calibrations and validations. This technique helps the researcher understand the catchment's behaviour with the starting parameters, save time, and determine the best SWATCUP program iteration level for the modelled basin.

Results and discussion. Table 3 presents the land use distribution in the UBRB, while the following parameters were extracted from the model set-up such as 23 subbasins, 1,396 HRUs, and 227 channels. Over 50 and 20 % of the land use in the basin is occupied by forest and oil palm plantations respectively and over 18 % is rubber plantation, while the remaining percentage are rice, urban, non-forested wetlands, pasture, wetlands, and agricultural land. Due to diverse land use and soil types, the SWAT model divides sub-basins into numerous hydrological response units (HRUs) to increase simulation accuracy with identical land use, management, and soil characteristics [20].

Table 1

SWAT parameters for sensitivity analysis and calibration

S/N	Parameter code	Parameter description	Object type	Range	t-Stat	P-Value	Method
1	CN2	SCS runoff curve number	mgt	–0.2–0.2	–23.4601	0	r
2	ESCO	Soil evaporation compensation factor	hru	0–1	–12.3956	0	v
3	ALPHA_BNK	Baseflow alpha factor for bank storage	rte	0–1	–8.2881	0	v
4	CANMX	Maximum canopy storage	hru	0–100	5.7818	0	v
5	HRU_SLP	Average slope steepness	hru	0–0.7	–4.6095	0	v
6	SUB_ELEV	Elevation of subbasin	sub	0–6,000	4.3778	0	v
7	GWQMN	Minimum water depth in the shallow aquifer needed for return flow to happen (mm)	gw	0–10,000	3.1901	0.0015	v
8	CH_N2	Manning's "n" value for the main channel	rte	–0.01–0.3	3.1237	0.0019	v
9	RCHRG_DP	Deep aquifer percolation fraction	gw	0–1	2.9187	0.0037	r
10	CH_K2	Effective hydraulic conductivity in main channel alluvium	rte	–0.01–1,000	2.6109	0.0093	v
11	SOL_K	Saturated hydraulic conductivity	sol	0–2,000	–1.5428	0.1235	r
12	SOL_BD	Moist bulk density	sol	0.9–2.5	1.5034	0.1334	r
13	SLSUBBSN	Average slope length	hru	10–150	–1.3440	0.1796	r
14	CNOP	SCS runoff curve number for moisture condition	mgt	0–100	1.3038	0.1929	r
15	GW_DELAY	Groundwater delay (days)	gw	0–500	–1.2816	0.2006	v
16	EVLAI	Leaf area index threshold for zero evaporation from the water surface	bsn	0–10	1.1153	0.2653	r
17	ALPHA_BF	Baseflow alpha factor (days)	gw	0–1	–1.0837	0.2790	v
18	GW_REVAP	Groundwater "revap" coefficient	gw	0.02–0.2	1.0390	0.2994	v
19	DEEPST	Initial water depth in the deep aquifer measured in millimetres	gw	0–10,000	0.9622	0.3364	r
20	SURLAG	Surface runoff lag time	bsn	0.05–24	0.6097	0.5424	v
21	EPCO	Factor of compensation for plant absorption	hru	0–1	0.3762	0.7069	r
22	REVAPMN	Minimum water depth in the shallow aquifer required for "revap" to take place (mm)	gw	0–1,000	0.3566	0.7215	r
23	SOL_AWC	Capacity of available water within the soil stratum	sol	0–1	0.2299	0.8182	r
24	FFCB	Initial soil water storage is represented as a proportion of the water content at field capacity	bsn	0-1	0.1816	0.8559	r
25	OV_N	The "*n*" value of Manning for overland flow	hru	0.01–4.0	0.1462	0.8838	r
26	GW_SPYLD	Shallow aquifer's specific yield (m^3/m^3)	gw	0–0.4	0.0597	0.9524	r

Table 2

SWATCUP experiments on the Bernam watershed

SET1	Variable	p-factor	r-factor	R^2	NS	PBIAS	KGE	STATUS	No. of parameters
Sensitivity Analysis =500	FLOW_OUT_7	0.84	2.02	0.69	0.61	–12.3	0.79	Initial par	26
Iter1=100	FLOW_OUT_7	0.78	1.77	0.68	0.62	–5.8	0.81	Initial Sensitive Par	10
Iter1=200	FLOW_OUT_7	0.83	1.91	0.64	0.54	–14	0.76	Initial Sensitive Par	10
Iter1=300	FLOW_OUT_7	0.85	1.85	0.71	0.68	–2.3	0.84	Initial Sensitive Par	10
Iter1=400	FLOW_OUT_7	0.82	1.89	0.68	0.65	–0.9	0.83	Initial Sensitive Par	10
Iter1=500	FLOW_OUT_7	0.82	1.85	0.7	0.64	–6.8	0.82	Initial Sensitive Par	10
Iter1=300	FLOW_OUT_7	0.85	1.85	0.71	0.68	–2.3	0.84	Initial Sensitive Par	10
Iter1_1=400	FLOW_OUT_7	0.91	2.17	0.7	0.68	–3	0.83	New Par of Iter1	10
Iter1_2=500	FLOW_OUT_7	0.91	1.69	0.72	0.69	2.8	0.84	New Par of Iter1_1	10
Iter1_3=600	FLOW_OUT_7	0.82	0.88	0.72	0.7	–1.1	0.85	New Par of Iter1_2	10
Iter1_4=700	FLOW_OUT_7	0.68	0.63	0.72	0.7	–0.9	0.85	New Par of Iter1_3	10

According to Table 1, only 10 parameters were sensitive in the basin discharge simulation. Table 4 lists the most sensitive parameters and their best-fit values. The table also shows whether parameters are replaced ('*v*') or proportionately changed ('*r*').

The parameters were modified according to the SWAT handbook [21] and other relevant literature [22, 23] suggested range. The sensitive parameter must have a p-value below 0.05 ($tStat > p < 0.05$) and below the matching t-Stat, as indicated by [22, 23]. The parameter

Table 3

Land use distribution

SWAT Code	Land use description	Area, ha	Area, %
agrl	Agricultural land	86.69	0.08
frst	Forest	58,324.74	54.15
oilp	Oil Palm	22,427.59	20.82
past	Pasture	260.76	0.24
rice	Rice	3,268.83	3.03
rubr	Rubber	20,232.12	18.78
urbn	Urban	2,662.24	2.47
wetn	Wetlands_non-forested	276.35	0.26
wetw	Wetlands_wet	173.42	0.16
Total		107,712.74	100

is increasingly sensitive as the absolute t-statistic increases. Table 4 shows the best-fit values used in validation and future simulations without change. The sensitive parameters, ranked in order of descending sensitivity, are SCS runoff curve number (CN2), Soil Evaporation compensation factor (ESCO), Baseflow alpha factor for bank storage (ALPHA_BNK), Maximum canopy storage (CANMX), Average slope steepness (HRU_SLP), Elevation of subbasin (SUB_ELEV), Minimum water depth in the shallow aquifer needed for return flow to happen (mm), (GWQMN), Manning's "n" value for the main channel (CH_N2), Deep aquifer percolation fraction (RCHRG_DP), and Effective hydraulic conductivity in main channel alluvium (CH_K2) on flow in the UBRB. Nonetheless, other parameters on the basin streamflow were insensitive, as shown in Table 2.

SWAT calibration and validation. Fig. 5 presents the uncalibrated runoff model with a Nash-Sutcliffe Efficiency (NSE) of –0.33 and a Pearson correlation value of 72 %. Though it overestimates discharge, the model shows a 72 % linear connection between simulated and observed flow. Before calibration, the model overestimated the runoff.

The model was calibrated using four iterations by adjusting parameter ranges. Each iteration had 300–600 model simulations with diverse parameters (new parameters from previous iterations) given by SWATCUP. Simulations were run in 300, 400, 500, and 600 simulations. The model performed satisfactorily at 600 simulation runs during the experiment. The calibration and validation summary results, which cover January 1, 1985, to December 31, 2022, with a 6-year warm-up time, are presented in Table 5. The calibration and validation periods were split into 3 categories: Category 1 (10-year calibration- and 5-year validation period: 1991–2000: 2001–2005; 2001–2010: 2011–2015; and 2011–2020: 2021–2022); category 2 (15-year calibration- and 10-year validation period: 1991–2005: 2006–2015); and category 3 (20-year calibration- and 10-year validation period: 1991–2010: 2011–2020). These categories were subjected to 2 sets of parameter settings; thus: Set 1 (26 parameters chosen based on catchment hydrology and trimmed down to 10 after a comprehensive global sensitivity analysis) and Set 2 (9 parameters previously adopted by [7, 9] in the same catchment) were applied to these categories.

Table 5 shows that the 1991–2000 and 2001–2005 calibration and validation periods, which fall in category 1, yielded acceptable model performance. Table 6 shows iterations and performance indicators from Table 5. The experiment showed that indicator performance deteriorated after the fourth iteration. Thus, calibration was terminated. The P-factor, r-factor, R^2, NSE, PBIAS, and KGE indicators demonstrated satisfactory values.

Table 6 presents the iterations and performance indicator values for the calibrated and validated model output. The p-factor (0.82), r-factor (0.88), R^2 (0.72), NSE (0.7), PBIAS (-1.1), and KGE (0.85) are the statistical indices extract of model performance during the calibration, whilst for validation period has a p-factor (0.8), r-factor (1.04), R^2 (0.75), NSE (0.65), PBIAS (–6.6), and KGE (0.79).

In line with Abbaspour [22], the p-factor (≥ 0.7) and r-factor (≤ 1.5) assess the model calibration, with around 70 % of observed data within the 95 % PPU band (Fig. 6). The results of the calibration met Moriasi, Gitau [24] criteria (NSE > 0.65; $R^2 > 0.5$; |PBIAS| ≤ 25 %), showing a satisfactory model performance and effective simulation during calibration and validation periods.

Table 4

SWAT-sensitive parameters and their "best fit"-values

S/N	Parameter code	Parameter description	Object type	Range	"Best fit"-Values	t-Stat	P-Value	Method
1	CN2	SCS runoff curve number	mgt	–0.2–0.2	0.082182	–23.4601	0	r
2	ESCO	Soil evaporation compensation factor	hru	0–1	0.149648	–12.3956	0	v
3	ALPHA_BNK	Baseflow alpha factor for bank storage	rte	0–1	0.18104	–8.28811	0	v
4	CANMX	Maximum canopy storage	hru	0–100	31.875715	5.781076	1.3E-08	v
5	HRU_SLP	Average slope steepness	hru	0–0.7	0.645705	–4.60945	5.2E-06	v
6	SUB_ELEV	Elevation of subbasin	sub	0–6,000	5,643.671387	4.377764	1.48E-05	v
7	GWQMN	Minimum water depth in the shallow aquifer needed for return flow to happen (mm)	gw	0–10,000	9,160.946289	3.190084	0.001517	v
8	CH_N2	Manning's "n" value for the main channel	rte	–0.01–0.3	–0.073626	3.12361	0.001896	v
9	RCHRG_DP	Deep aquifer percolation fraction	gw	0–1	0.236758	2.918687	0.003683	r
10	CH_K2	Effective hydraulic conductivity in main channel alluvium	rte	–0.01–1,000	753.380676	2.61088	0.009318	v

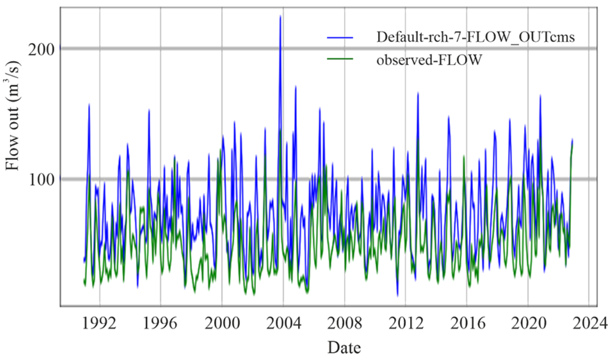


Fig. 5. Comparison between observed and simulated discharge at SKC gauge station, UBRB, for the calibration period 1991 to 2022

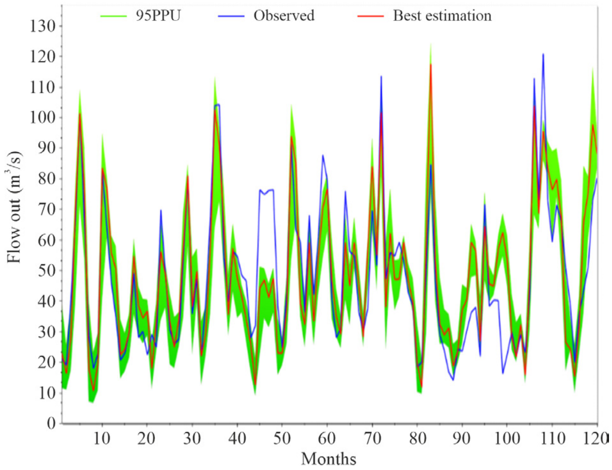


Fig. 6. The 95 ppu plot of all variables for the calibrated model

Moreso, Abbaspour [22] states that the p-factor and r-factor are statistical parameters determining calibration performance or goodness of fit in each iteration. The p-factor indicates model accuracy and ranges from 0 to 1. It represents the percentage of observed data inside the 95PPU range. The model error is 1 minus p-factor. Model uncertainty, represented by the r-factor, is the mean thickness of the 95 % prediction uncertainty divided by the observed data standard deviation. It may range from 0 to substantial value. A favourable r-factor value is about 1, the observation's standard deviation. Two parameters fully describe the calibrated model's performance. A calibrated model better captures obser-

Table 5

Calibration and validation summary (Variable - FLOW_OUT_7)

Period	Set	Settings	p-factor	r-factor	R^2	NS	PBIAS	KGE	STATUS
Cal-1991-2000	SET1	Iter1_3=600	0.82	0.88	0.72	0.7	–1.1	0.85	New Par of Iter1_2
Val-2001-2005	SET1	VAL2001-2005	0.8	1.04	0.75	0.65	–6.6	0.79	New Par of Iter1_2
Cal-1991-2000	SET2	Iter1_3=600	0.68	1.17	0.73	0.73	–2.7	0.77	New Par of Iter1_2
Val-2001-2005	SET2	VAL2001-2005	0.45	1.14	0.73	0.62	–19.4	0.76	New Par of Iter1_2
Cal-2001-2010	SET1	Iter1_3=600	0.78	1.3	0.62	0.6	–1.9	0.78	New Par of Iter1_2
Val-2011-2015	SET1	VAL2011-2015	0.75	1.29	0.78	0.66	14.7	0.81	New Par of Iter1_2
Cal-2001-2010	SET2	Iter1_3=600	0.6	0.81	0.63	0.63	1.4	0.69	New Par of Iter1_2
Val-2011-2015	SET2	VAL2011-2015	0.68	0.7	0.73	0.72	2.6	0.71	New Par of Iter1_2
Cal-2011-2020	SET1	Iter1_3=600	0.75	1.06	0.53	0.52	–0.4	0.68	New Par of Iter1_2
Val-2021-2022	SET1	VAL2021-2022	0.63	1.1	0.69	0.61	9.3	0.78	New Par of Iter1_2
Cal-2011-2020	SET2	Iter1_3=600	0.58	0.46	0.62	0.62	0.9	0.69	New Par of Iter1_2
Val-2021-2022	SET2	VAL2021-2022	0.63	0.58	0.7	0.68	2.3	0.67	New Par of Iter1_2
Cal-1991-2005	SET1	Iter1_3=600	0.52	0.68	0.69	0.61	–10.1	0.8	New Par of Iter1_2
Val-2006-2015	SET1	VAL2006-2015	0.71	0.79	0.61	0.49	10.4	0.76	New Par of Iter1_2
Cal-1991-2005	SET2	Iter1_3=600	0.63	1	0.71	0.69	–7	0.79	New Par of Iter1_2
Val-2006-2015	SET2	VAL2006-2015	0.83	1.1	0.67	0.67	1.4	0.74	New Par of Iter1_2
Cal-1991-2010	SET1	Iter1_3=600	0.82	1.24	0.64	0.58	–3	0.79	New Par of Iter1_2
Val-2011-2020	SET1	VAL2011-2020	0.77	1.24	0.58	0.47	8.5	0.74	New Par of Iter1_2
Cal-1991-2010	SET2	Iter1_3=600	0.6	0.8	0.65	0.65	–1.7	0.71	New Par of Iter1_2
Val-2011-2020	SET2	VAL2011-2020	0.71	0.76	0.63	0.63	–0.9	0.73	New Par of Iter1_2

Table 6

Model performance indicators

	Calibration				Validation
Parameter	Iter 1 (300 simulations)	Iter 2 (400 simulations)	Iter 3 (500 simulations)	Iter 4 (600 simulations)	Val (600 simulations)
p-factor	0.85	0.91	0.91	0.82	0.8
r-factor	1.85	2.17	1.69	0.88	1.04
R^2	0.71	0.70	0.72	0.72	0.75
NSE	0.68	0.68	0.69	0.70	0.65
PBIAS	–2.3	–3.0	2.8	–1.1	–6.6
KGE	0.84	0.83	0.84	0.85	0.79

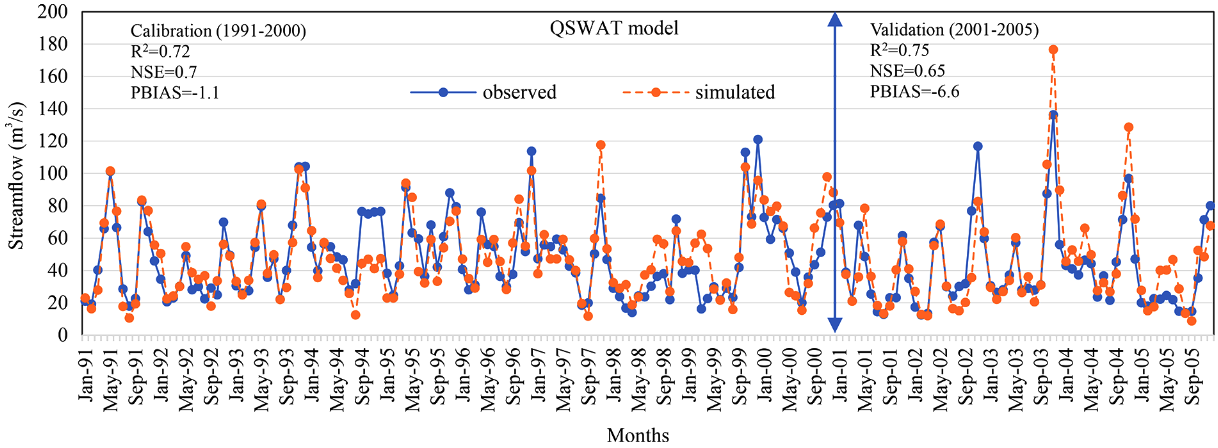
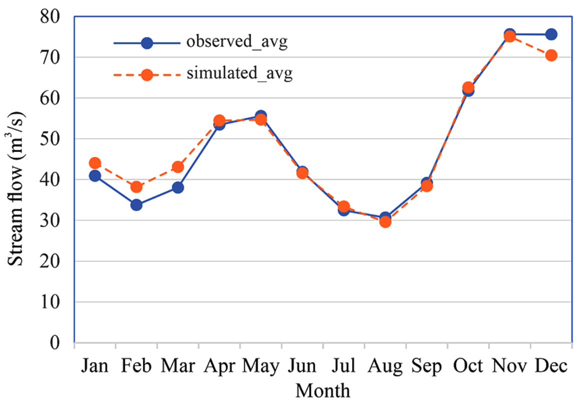


Fig. 7. SWAT model monthly streamflow for simulated and observed

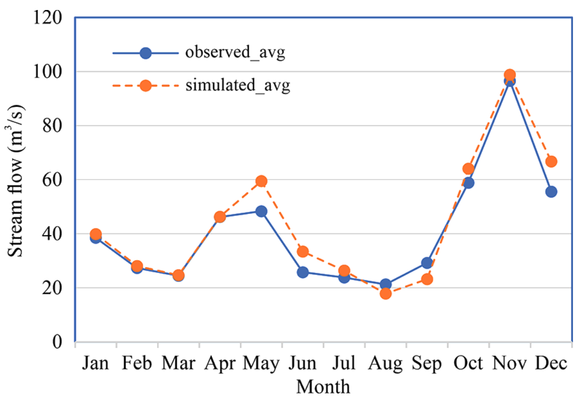
vations when the p-factor is closer to 1, and the r-factor is closer to 0.

Fig. 7 shows the calibration and validation streamflow plot, showing a close correlation between simulated and observed flows. Overall, the calibration (PBIAS = –1.1) and validation (PBIAS = –6.6) periods overestimated flow by less than 10 %, within the tolerance level.

Figs. 8, *a*, *b* shows UBRB streamflow at the SKC gauge station during calibration and validation periods. The SKC gauge station data points were reduced from 120 to 12 for calibration and 60 to 12 for validation using Microsoft Excel to show how the model predicted streamflow.



a



b

Fig. 8. UBRB streamflow at the SKC gauge station during calibration and validation:

a – average monthly observed and simulated streamflow for SWAT model (calibration period 1991–2000); b – average monthly observed and simulated streamflow for SWAT model (validation period 2001–2005)

Fig. 8, *a* shows the monthly average streamflow. The graph indicates a close match and steady pattern between the observed and simulated streamflow during calibration, especially from April to November. In December, the model predicted less flow than in January to March. Fig. 8, *b* indicates a significant connection between observed and simulated streamflow during validation, especially from January to April and July to November. The model overestimated May–June and December flow. In this investigation, the SWAT model performed well with values beyond 0.5, as suggested by [24] and [23].

Simulation of UBRB using the SWAT Model. Fig. 9 represents the monthly water balance parameters of UBRB at two distinct periods.

The result of the SWAT simulation after adjusting the model parameters with calibrated best-fit values indicated that the inflow (rainfall) and the outflow (water yield + ET) are 2,873.36 and 2,592.78 mm, respectively. This shows a difference of 9.8 % for 1991–2005, while 2,921.98 and 2,586.07 mm for the inflow and outflow, during the 2006–2020 period with a difference of 11.5 %. The overall result, with a difference of 10.6 % between the inflow and outflow within the simulation period of 1985 to 2020 with a 6-year warm-up period, has shown that the SWAT model can project future UBRB simulations.

Discussion. The calibration and validation of the SWAT model for the UBRB streamflow model has been carried out achieving a satisfactory model performance according to [22]. However, based on criteria (NSE > 0.65; R^2 > 0.5; |PBIAS| ≤ 25 %) from [24], the statistical indices of model performance during the calibration and validation period met with the recommended criteria, indicating a satisfactory model performance and effective simulation during calibration and validation. Despite the complex topography and diverse land cover, the model achieved high performance metrics, which were superior to those reported in similar studies by [7] by 17 % (R^2 = 0.62) and higher than the R^2 (0.64) value obtained and [9] by 15 % in the catchment, and this possibly as a result of observed historical data used as compared to the simulated historical data used in their studies, this implies that the use of observed data in this study reduces uncertainty compared to simulations,

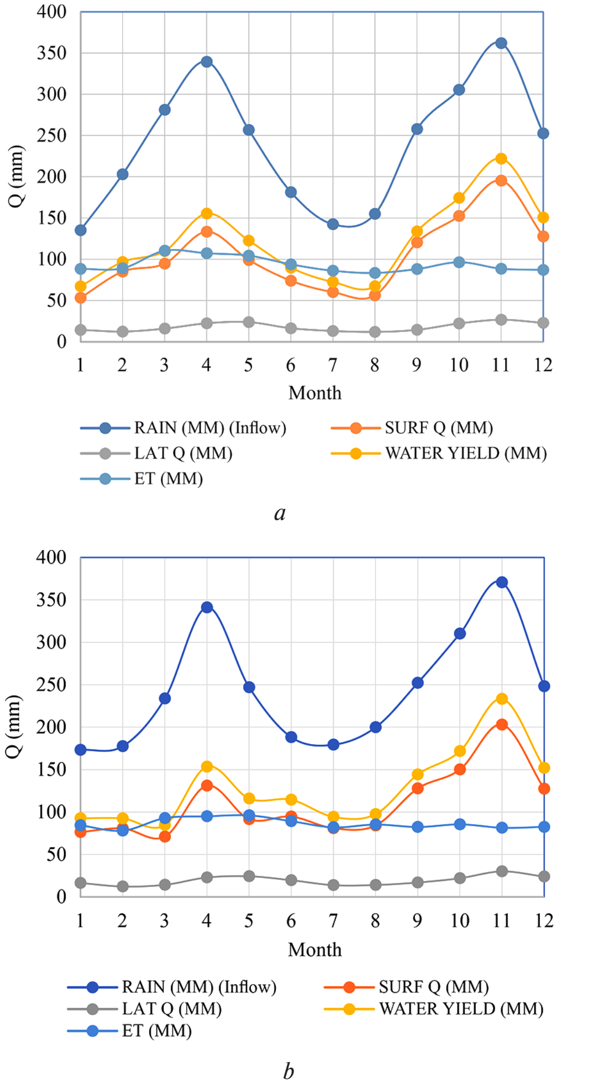


Fig. 9. SWAT simulation output: average monthly basin streamflow:

a – for the periods 1991–2005 (calibration); b – 2006–2021 (validation)

based on modelled climate data [7, 9]. The results indicate that the SWAT model is reliable for simulating hydrological processes in the UBRB. The PBIAS value of –1.1 simulates streamflow with a closer agreement to the observed data than [7 and 9], which are –9.4 and –5.4, respectively. This shows that a shorter calibration and validation period may increase model performance, though it could also depend on the watershed. This result highlights an improvement in the calibration and validation of the SWAT model for reliable simulation of hydrological processes for the UBRB.

It is worth noting that in the same catchment, [9] used a subset of parameters presented in Table 2 which includes: CH_N2, GW_DELAY, ALPHA_BF, CH_K2, CN2, GW_REVAP, ESCO, SOL_BD, GWQMN. During the sensitivity analysis in this study, only 5 parameters (CH_N2, CH_K2, CN2, ESCO, and GWQMN) were sensitive. However, both sensitivity analyses found that CH_N2, CH_K2, and CN2 were sensitive, but GW_DELAY, ALPHA_BF, GW_REVAP, and SOL_BD were not. This study partially agrees with the findings of [25], who reported a similar catchment (Langat River Basin, Malaysia) to have ALPHA_BF and GW_REVAP non-sensitive during sensitivity analysis. In their study, 10 out of 21 parameters in Langat River Basin, Malaysia, were non-sensitive, whilst 10 out of 26 parameters were sensitive in our study. It is important to note that sensitive parameters vary by land use and watershed. Thus, sensitive parameters in specific catchments may not be sensitive to others.

The ESCO and GWQMN are also found sensitive but, non-sensitive in [9] report. However, the resolutions of DEM, soil map data, land use–land cover changes, and category 1 [26, 27] considered may have influenced the variation observed as compared to the previous studies and in return, affected the soil evaporation and the minimum water level in the subsurface aquifer needed for return flow to transpire, affecting catchment streamflow. Moreover, category 1 resulting in superiority over the other categories indicates that longer simulation durations do not usually improve data quality or model performance. Nevertheless, our findings partially agree with [7, 9], which found a similar pattern of sensitivity in the same catchment.

Meanwhile, CN2, ESCO, ALPHA_BNK, CANMX, HRU_SLP, SUB_ELEV, GWQMN, CH_N2, RCHRG_DP, and CH_K2 were found to be more significant in streamflow modelling of the Bernam catchment than in previous studies of the same catchment, this implies that future research should focus on these parameters for the same catchment modelling.

A simulation of streamflow was carried out and compared to the observed data. During the calibration period, the streamflow was underestimated in November for most years, from 1991 to 1997 and from March 1994 to March 1995. The model accurately predicted peak discharge but overpredicted certain months. The Complexity of the UBRB basin, with several manmade ponds for flood controls and other activities, may create excess and deficit simulations. Nevertheless, the SWAT model can underestimate or overestimate discharge levels to fit observations [26]. Despite this limitation, the SWAT model remains a valuable tool for long-term agro-hydrological process prediction. The model accurately replicated monthly discharge data throughout validation, except for the overestimations of July 2002–November 2002 and November–December 2005.

Recent research has indicated mixed results pertaining to SWAT model performance during calibration and validation, some reported strong performance in both phases, whilst other studies observed a decline in the performance of the model during validation [28]; however, this study demonstrated that the statistical indices are similar during both phases. During the validation period from October 2004 to January 2005, which falls within the Malaysian Northeast monsoon period (November–February) [29], and from April 2005 to July 2005, which falls within the Malaysian Southwest monsoon period (May–August), the streamflow was consistently overestimated. The model replicated months with high peak discharges, unlike [7, 9], who used ArcSWAT to predict streamflow in the same basin. To assess the SWAT model's reliability in simulating historical and future projections, the Kling-Gupta efficiency (KGE) [30] was used, comprehensively evaluating the model's capacity to replicate the observed flow regime while considering timing, volume, and variability. The KGE shows that the SWAT model could sufficiently simulate the streamflow in the UBRB basin. The SWAT model's ability to simulate the water balance in the UBRB was demonstrated through the close agreement between simulated and observed data, with an overall inflow-outflow difference of 10.6 %. These findings align with similar studies in other basins, where the SWAT model has been successfully used to assess water resources [21]. The inflow and outflow simulations for two distinct periods (1991–2005 and 2006–2020) revealed consistent performance, with differences of 9.8 and 11.5 %, respectively. This consistency underscores the robustness of the calibrated parameters.

The model's performance can be attributed to the use of observed historical data and detailed parameterization during sensitivity analysis. As noted by [24], such approaches are critical for improving model reliability. The variations in inflow and outflow observed during peak rainfall months may be due to the complex topography and the presence of human interventions, such as ponds for flood control, which can affect the basin's hydrology. These challenges have been similarly reported by [5], emphasizing the importance of including local watershed dynamics in modelling efforts.

Conclusions. This study successfully calibrated and validated the SWAT model for the Upper Bernam River Basin (UBRB), achieving satisfactory model performance. The results demonstrate the reliability and robustness of the SWAT model in simulating hydrological processes in the UBRB despite the basin's complex topography, diverse land cover, and human interventions. The following conclusions are drawn:

1. The calibrated and validated results of the SWAT model for the UBRB met the criteria recommended by (NSE > 0.65; R^2 > 0.5; |PBIAS| ≤ 25 %), demonstrating satisfactory model performance. The model achieved superior performance metrics compared to similar studies, attributed to the use of category 1 and observed historical data, which reduced uncertainty and improved simulation reliability. Moreso, the category 1 resulting superior over the other categories indicates that longer simulation durations do not usually improve data quality or model performance.

2. The SWAT model effectively simulated the streamflow in the UBRB, capturing monthly discharge trends and peak discharges. However, some discrepancies were observed, such as underestimation during specific months and overestimation during monsoon periods. These variations are influenced by the basin's complexity and human-made structures, such as ponds for flood control. Despite these challenges, the model demonstrated strong reliability in replicating the observed flow regime, with high performance metrics, including Kling-Gupta Efficiency (KGE).

3. The SWAT model demonstrated robust performance in simulating the water balance of the UBRB, with an inflow-outflow difference of 10.6 %. The consistency of water balance simulations across two distinct periods (1991–2005 and 2006–2020) underscores the robustness of the calibrated parameters. The model's ability to capture the impact of topographic and human interventions highlights its utility for assessing water resources and hydrological processes in the basin.

4. These findings underscore the value of the SWAT model for long-term simulations and resource management in the UBRB and similar river basins.

Acknowledgments. *The authors acknowledge the financial support of Nigeria's Petroleum Technology Development Fund (PTDF). Also, the financial support of the Putra Grant under University Putra Malaysia (Grant No. 9769000) is gratefully acknowledged, and we appreciate the Department of Irrigation and Drainage (DID) and the Malaysian Meteorological Department (MMD) for providing the daily meteorological data for this study. Additionally, the authors acknowledge the support of the Soil and Water Engineering Research Group, Faculty of Engineering, University Putra Malaysia.*

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Калібрування й валідація моделі SWAT для верхньої частини басейну річки Бернам у Малайзії

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Мета. Калібрування й валідація моделі оцінки стану ґрунтів і водних ресурсів (SWAT) є необхідними для забезпечення її точності при моделюванні гідрологічних процесів і підтримки ефективного прийняття рішень. Це дослідження зосереджене на вивченні верхньої частини басейну річки Бернам (Upper Bernam River Basin, UBRB) у Малайзії, де модель SWAT була відкалібрована й валідована на основі спостережених даних про стік річки за період з 1985 по 2022 рік.

Методика. Калібрування й валідацію проведено у трьох категоріях: категорія 1 (10 років калібрування, 5 років валідації), категорія 2 (15 років калібрування, 10 років валідації) та категорія 3 (20 років калібрування, 10 років валідації).

Результати. Статистичні показники для категорії 1 свідчать про задовільну роботу моделі: результати калібрування показали p-factor 0,82, r-factor 0,88, R^2 = 0,72, NSE = 0,70, PBIAS = –1,1 % та KGE = 0,85. Результати валідації засвідчили p-factor 0,80, r-factor 1,04, R^2 = 0,75, NSE = 0,65, PBIAS = –6,6 % та KGE = 0,79. Крім того, результати для категорії 1 продемонстрували кращу продуктивність порівняно з іншими категоріями, що вказує на те, що збільшення тривалості симуляції не завжди покращує якість даних або ефективність моделі. Модель категорії 1 із 15-річним періодом була також перевірена за водним балансом: різниця між змодельованими вхідними (опади) й вихідними потоками (водний стік + ET) для періодів 1991–2005 та 2006–2020 років становила відповідно 9,8 і 11,5 %.

Наукова новизна. У цьому дослідженні вперше використані дані довгострокового спостереження за стоком річок і багатосценарне калібрування-валідацію для підвищення надійності моделі SWAT у моделюванні гідрологічних процесів у верхній частині басейну річки Бернам.

Практична значимість. Дослідження демонструє надійність моделі SWAT у прогнозуванні агрогідрологічних процесів і надає цінну інформацію для сталого управління водними ресурсами в басейні річки Бернам.

Ключові слова: *модель SWAT, калібрування, валідація, річка Бернам, стік, управління водними ресурсами*

The manuscript was submitted 24.09.25.