Article

Not peer-reviewed version

Calibration and Validation of the SWAT Model for Upper Bernam River Basin in Malaysia

Muazu Dantala Zakari * , Md Kamal Rowshon * , Norulhuda Binti Mohamed Ramli , Balqis Mohamed Rehan , Mohd Syazwan Faisal Bin Mohd , Franklin Aondoaver Kondum

Posted Date: 12 December 2024

doi: 10.20944/preprints202412.1043.v1

Keywords: SWAT model; Calibration and Validation; Streamflow; Projections; Agro-hydrological; Upper Bernam River Basin

Article

Calibration and Validation of the SWAT Model for Upper Bernam River Basin in Malaysia

Muazu Dantala Zakari [1,2,*], Md. Kamal Rowshon [1,*], Norulhuda binti Mohamed Ramli [1], Balqis Mohamed Rehan [3], Mohd Syazwan Faisal Bin Mohd [4] and Franklin Aondoaver Kondum [1]

1 Biological and Agricultural Engineering Department, Faculty of Engineering, Universiti Putra Malaysia
2 Agricultural and Environmental Engineering Department, Faculty of Engineering, Bayero University, Kano-Nigeria
3 Civil Engineering Department, Faculty of Engineering, Universiti Putra Malaysia
4 River Basin Research Centre, National Water Research Institute of Malaysia
* Correspondence: mdzakari.age@buk.edu.ng (M.D.Z.); rowshon@upm.edu.my (M.K.R.); Tel.: +2348034315364 (M.D.Z.); +60 12-662 7589 (M.K.R.)

Abstract: Enhancing sustainable agricultural practices and water resources management calls for this study, which focuses on calibrating and validating the SWAT model using data from CMIP6. The SWAT model was validated using Bernam streamflow data from 1985-2022, divided into three categories: category 1 (10 years calibration- and 5 years validation), category 2 (15 years calibration- and 10 years validation), and category 3. The SWAT model performed "GOOD" in the Bernam watershed, as indicated by statistical analysis during calibration and validation phases, utilizing statistical indices. The results for the p-factor, r-factor, R2, NSE, PBIAS, and KGE were 0.82, 0.88, 0.72, 0.70, -1.1%, and 0.85 during the calibration period and 0.8, 1.04, 0.75, 0.65, -6.6%, and 0.79 during the validation period. The result of the simulation after adjusting the SWAT model parameters with calibrated best-fit values indicated that the inflow (rainfall) and the outflow (water yield + ET) are 2,873.36mm and 2,592.78mm respectively, with difference of 9.8% for the period of 1991-2005 while 2,921.98 mm and 2,586.07 mm for the inflow and outflow, during 2006-2020 period with difference of 11.5%. The SWAT model effectively predicts agro-hydrological processes, aiding decision-makers in UBRB's agricultural water management and guiding sustainable agriculture through advanced climate projections.

Keywords: SWAT model; calibration and validation; streamflow; projections; agro-hydrological; Upper Bernam River Basin

1. Introduction

Water, the second most essential natural resource after air, has dominated the world agenda for decades [1–3]. Most of the earth's surface is water. Still, only a small portion is usable, making this resource extremely limited and vulnerable to climate change, rising demand for food, feed, and energy, and water scarcity and drought [1,3–6]. Agriculture uses 70% of global freshwater, while other sectors use the rest [3]. As agriculture competes with different sectors of the economy, extensive water use for agriculture and irrigation is likely [1,7,8].

Climate change and population development will continue to increase water demand for various activities. The Columbia University Climate School's Urban Climate Change Research Network (UCCRN) report predicts that by 2050, 685 million people in over 570 cities will face a least 10% drop in freshwater availability owing to climate change [9]. Climate change affects our environment and community health. That's why the Sustainable Development Goals (SDGs) require the United Nations (UN) to take drastic steps to fight food security and sustainable agriculture, a sustainable human environment, and climate change and its impacts. Individuals, groups, private, public, and academic institutions were to help transform the world for sustainable development. By

2050, agricultural food demands were expected to rise by 60% [6,10]. These demonstrate the importance of irrigation water management for agriculture's well-being, especially in developing nations where agriculture drives economic growth [6]. Due to rising temperatures and diminishing precipitation in many regions, irrigation water management and conservation are crucial.

On this basis, irrigation water consumption should be efficient. Irrigation involves artificially applying water to crops to make up for low/erratic rainfall. Due to insufficient/erratic rain and rainfall pattern changes, effective and efficient water resources management is needed. To attain this management aim, the projection of future agro-hydrological processes of the irrigation supply basin is necessary, and this can be achieved by adopting the Soil and Water Analysis Tool (SWAT) model evaluation of the respective basins. The SWAT model exhibits uncertainty, which can be significantly minimized by calibration and validation [11–13]. The Integrated Agricultural Development Area (IADA), Selangor, is one of Malaysia's largest Rice Irrigation Schemes, and the significant irrigation supply comes from the Upper Bernam River Basin (UBRB).

The UBRB is a critical source of irrigation water for IADA agricultural activity, and the water resources are essential for sustaining crop production and supporting the local economy. However, the basin is increasingly vulnerable to the impacts of climate change, including changed precipitation patterns and extreme weather events. ArcSWAT was used to project future UBRB basin hydrological processes using CMIP5 for the existing hydrological models [14,15]. However, the ArcSWAT was not comprehensively calibrated and validated, including the use of the most recent Coupled-Model-Intercomparison-Project Phase 6 (CMIP6) data for the basin, leading to uncertainties in projecting future agro-hydrological processes and water availability for agricultural productivity. Given the global importance of accurate climate projections, there is a pressing need to refine regional or local agro-hydrological models using advanced climate datasets such as those from CMIP6. This study addresses these gaps by calibrating and validating the SWAT model for the UBRB in the tropical river basin, providing reliable projections of agro-hydrological processes under future climate scenarios. The outcomes will assist policymakers and stakeholders in devising effective strategies to mitigate climate risks and ensure sustainable water resources management, thereby enhancing the resilience of the agricultural industry.

2. Materials and Methods

2.1. Study Area

Figure 1 describes the study location, the IADA in Selangor, Northwest Malaysia, 98 km north of Kuala Lumpur. The Bernam and Tengi rivers are this scheme's sole irrigation water sources. The Southwest and Northeast monsoons dominate the humid tropical regions. The Northeast monsoon from October to December brings 70% of rainfall. In contrast, February to March and June to August during the Southwest monsoon season are dry. The dry or off-season (January–June) and main-season (July–December) irrigated rice plan is employed. The project region gets more than 1500 mm of rainfall annually, generally between October and January, with October having the most and June the least (data for 1971–2020).

The MMD recorded an average dry season temperature of 28°C to 35°C (January to June). The humidity is over 75% year-round [14–22]. Malaysia is situated north of the equator in Southeast Asia, which has an equatorial, hot, and humid climate with 21–32oC daily temperatures [23]. Annual rainfall in Peninsular Malaysia is 2500 mm [24]. The off-season (March–July) and main-season (August–February) are when major rice-growing regions cultivate rice.

The northeast monsoon's heavy rainfall causes high air humidity in the main-season and low humidity in the off-season [18–20]. These granaries generated 74% of Malaysia's rice in 2016. However, climate, cultivation areas, and agricultural techniques impact granary productivity per hectare [25].

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 12 December 2024 doi:10.20944/preprints202412.1043.v1

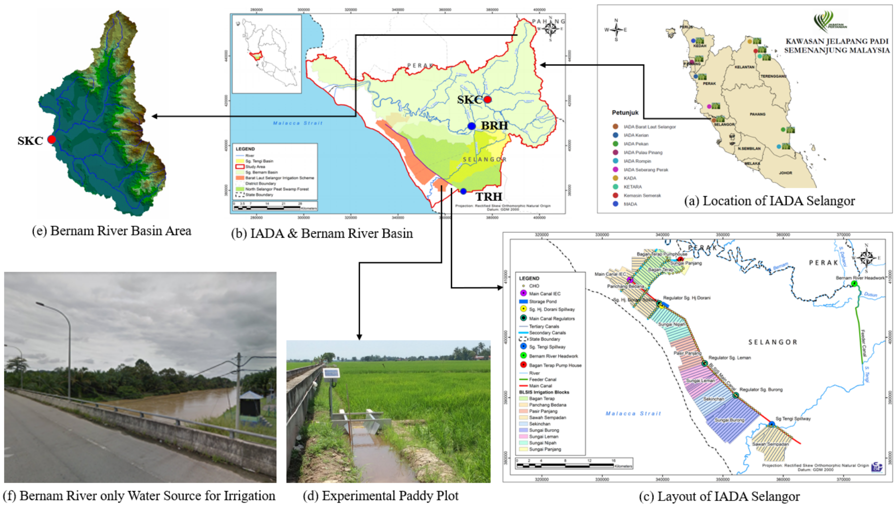


Figure 1. IADA Selangor study area. **Source:** M.K. Rowshon.

2.2. SWAT and SWAT-CUP

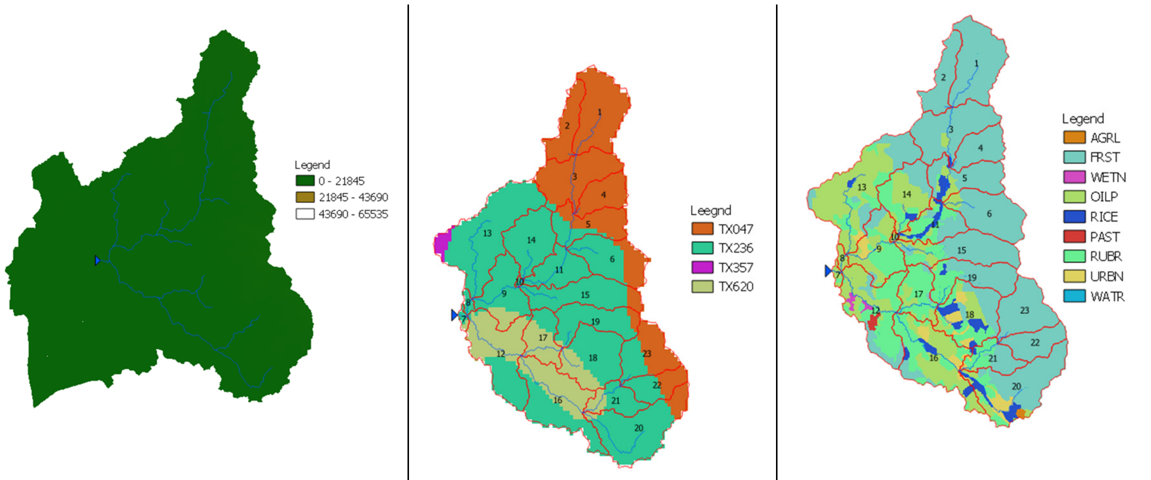
The evaluation of the SWAT model has become imperative due to its intended application in simulating the agro-hydrological processes of the UBRB and the downstream of the basin for agricultural productivity in Malaysia. The SWAT model was evaluated to ascertain the capabilities of simulating the climate change impacts on the agro-hydrological processes of UBRB [23–25], which supplies water to the IADA Selangor Rice Irrigation Scheme. As a result, analyzing the SWAT model before carrying out the projection was critical to understanding how the model works and establishing the ability and reliability of the model for future predictions.

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 [26]. In addition, SWAT Editor software [27] was used for model computations. The SWAT model is a deterministic model developed by the US Department of Agriculture [28–30]; 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 [28,30–32].

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 SWATCUP program was used to calibrate the SWAT model. The program evaluates the SWAT model's calibration, validation, Sensitivity, and uncertainty [11,12,28]. The SUFI-2 method was used since it works well for small catchments [11,28,33,34].

2.3. SWAT Model Data and Setup

A comprehensive collection of geographical data from multiple sources was used to evaluate the SWAT model's capabilities to predict climate change's effects on UBRB's agro-hydrological processes: Digital elevation models (DEMs) were downloaded from the Shuttle Radar Topography Mission (SRTM) website and processed in QGIS (Figure 2(a)). The DEMs used in the catchment area have a 30-meter spatial resolution.



a. DEM for the Upper Bernam River Basin

b. Soil spatial data for UBRB

c. Land use spatial data for UBRB

Figure 2. SWAT Model's Spatial data for the Upper Bernam River Basin.

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 (Figure 2(b)). The study area's land use and land cover map were obtained from the ESRI website (Global Land Cover; Sentinel-2: 10m land use/land cover; 2022) and processed using QGIS (Figure 2(c)). The Malaysian Department of Irrigation and Drainage (DID), Water Resources and Hydrology Division provided meteorological data for this research, and this study considered climate simulations for the historical periods of 1985 to 2022.

The "Edit Inputs and Run SWAT Model" window was filled with meteorological data necessary 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/m2]. The SWAT input meteorological data were obtained from the Division of Water Resources and Hydrology, Department of Irrigation and Drainage (DID), Malaysia. After delineating and developing the UBRB model using SWAT, the model gave 107,712.74 ha of UBRB size, 23 subbasins, 1,396 HRUs, and 227 channels. 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 [35,36]. SWAT mimics the land phase of the hydrological cycle using the water balance equation (1):

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

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 and Q_{gw} is daily return flow; all units are in mm. Figure 3 depicts the hydrological cycle process of the SWAT model output for UBRB from 1985 to 2005 with a 6-year warm-up period inclusive.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 12 December 2024 doi:10.20944/preprints202412.1043.v1

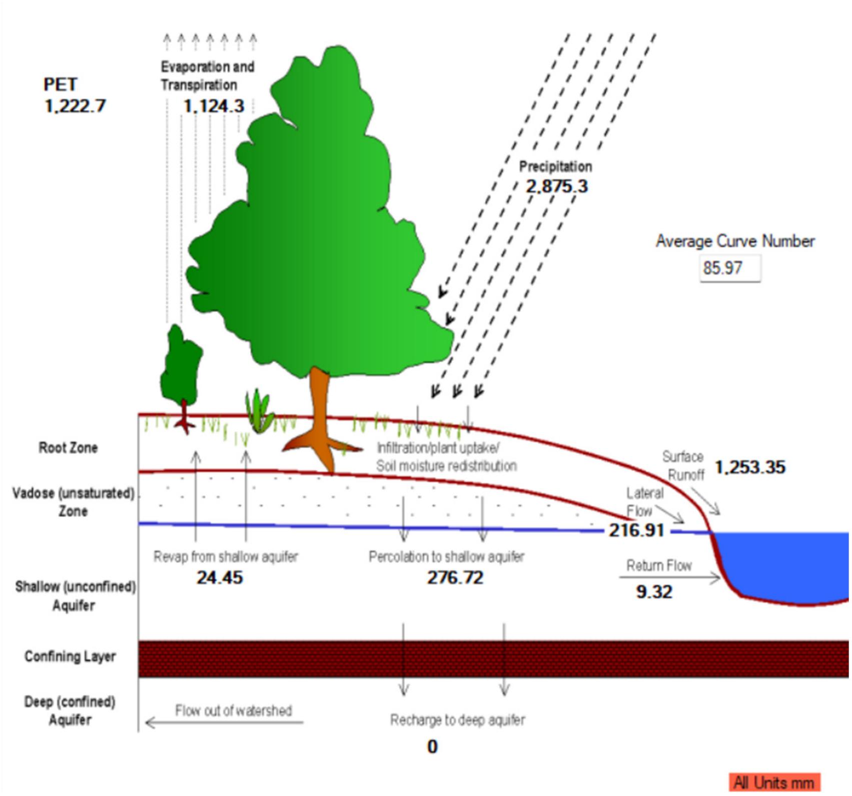


Figure 3. The hydrological cycle process of the SWAT model output for UBRB (1991-2005).

2.4. Calibration and Validation of the SWAT-CUP

The SWATCUP premium program calibrated the SWAT model to match reality better [28,30,37–39]. This helped overcome GCM and SWAT output uncertainties and inadequacies in the hydrological process modeling. Average monthly flow velocities surrounding the study area's inlet were utilized for 1991-2000, 2001-2010, 2011-2020, 1991-2005, and 1991-2010. Longer simulation durations and pre-processing times do not usually improve data quality or performance, nor do higher-resolution data [30].

This study used data from Malaysia's Water Resources and Hydrology Division's Department of Irrigation and Drainage (DID). After a suitable calibration, the model was validated using monthly average flow velocities [m3/s] near the research area's mouth (Jambatan Kuala Slim (SKC)) for 2001–2005, 2011–2015, 2021–2022, 2006–2015, and 2011–2020. The accuracy requirements of calibration and validation were examined for the best-fit parameter ranges [11,28,40–45]. Calibrating the model employed the p-factor, r-factor, NSE, PBias, Kling-Gupta Efficiency (KGE), and coefficient of determination (R2) for evaluating the model performance.

3. Results

3.1. Parameter Sensitivity Analysis

Before calibration and validation, an experiment was undertaken to understand how the SWAT model responds and analyzes 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. Table 1 lists these 26 parameters.

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.

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	0-2000	-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	0-10000	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	0-1000	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

doi:10.20944/preprints202412.1043.v1

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 (m3/m3)	gw	0-0.4	0.0597	0.9524	r

Table 2. SWATCUP experiments on the Bernam watershed.

SET1	Variable	p-factor	r-factor	R2	NS	bR2	MSE	SSQR	PBIAS	KGE	RSR	MNS	VOL _FR	Mean _sim	Mean _obs	StdDev _sim	StdDev _obs	STATUS	No. of Par
Sensitivity Analysis=500	**FLOW_OUT_7**	**0.84**	**2.02**	**0.69**	**0.61**	**0.5749**	**2.40E+02**	**5.60E+01**	**-12.3**	**0.79**	**0.62**	**0.42**	**0.89**	**51.59**	**45.94**	**24.75**	**24.85**	**Initial Par**	26
Iter1=100	FLOW_OUT_7	0.78	1.77	0.68	0.62	0.5911	2.20E+02	2.20E+01	-5.8	0.81	0.62	0.41	0.95	51.03	48.24	25.03	23.81	Initial Sensitive Par	10
Iter1=200	FLOW_OUT_7	0.83	1.91	0.64	0.54	0.5149	2.80E+02	7.20E+01	-14	0.76	0.68	0.33	0.88	52.35	45.94	24.71	24.85	Initial Sensitive Par	10
Iter1=300	**FLOW_OUT_7**	**0.85**	**1.85**	**0.71**	**0.68**	**0.5955**	**1.80E+02**	**1.10E+01**	**-2.3**	**0.84**	**0.56**	**0.49**	**0.98**	**49.35**	**48.24**	**23.74**	**23.81**	**Initial Sensitive Par**	**10**
Iter1=400	FLOW_OUT_7	0.82	1.89	0.68	0.65	0.5749	2.00E+02	1.20E+01	-0.9	0.83	0.59	0.44	0.99	48.66	48.24	24.22	23.81	Initial Sensitive Par	10
Iter1=500	FLOW_OUT_7	0.82	1.85	0.7	0.64	0.6005	2.00E+02	2.50E+01	-6.8	0.82	0.6	0.44	0.94	51.5	48.24	24.45	23.81	Initial Sensitive Par	10
Iter1=300	FLOW_OUT_7	0.85	1.85	0.71	0.68	0.5955	1.80E+02	1.10E+01	-2.3	0.84	0.56	0.49	0.98	49.35	48.24	23.74	23.81	Initial Sensitive Par	10
Iter1_1=400	FLOW_OUT_7	0.91	2.17	0.7	0.68	0.5592	1.80E+02	1.40E+01	-3	0.83	0.56	0.48	0.97	49.66	48.24	22.69	23.81	New Par of Iter1	10
Iter1_2=500	FLOW_OUT_7	0.91	1.69	0.72	0.69	0.6095	1.80E+02	9.00E+00	2.8	0.84	0.56	0.49	1.03	46.87	48.24	23.86	23.81	New Par of Iter1_1	10
Iter1_3=600	**FLOW_OUT_7**	**0.82**	**0.88**	**0.72**	**0.7**	**0.6147**	**1.70E+02**	**8.30E+00**	**-1.1**	**0.85**	**0.55**	**0.5**	**0.99**	**48.79**	**48.24**	**23.85**	**23.81**	**New Par of Iter1_2**	**10**
Iter1_4=700	FLOW_OUT_7	0.68	0.63	0.72	0.7	0.6081	1.70E+02	9.20E+00	-0.9	0.85	0.55	0.5	0.99	48.67	48.24	23.64	23.81	New Par of Iter1_3	10

doi:10.20944/preprints202412.1043.v1

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 behavior with the starting parameters, save time, and determine the best SWATCUP program iteration level for the modeled basin. According to Table 1, only 10 parameters were sensitive in the basin discharge simulation. Table 3 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 [46] and other relevant literature [42,47–49] 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 [37,49]. The parameter is increasingly sensitive as the absolute t-statistic increases. Table 3 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 1. It is worth noting that in the same catchment, Alansi, Amin [50], and Ismail [17] used a subset of Table 1 parameters: CH_N2, GW_DELAY, ALPHA_BF, CH_K2, CN2, GW_REVAP, ESCO, SOL_BD, GWQMN. This study's sensitivity analysis shows that only 5 factors (CH_N2, CH_K2, CN2, ESCO, and GWQMN) are sensitive. Both tests found that CH_N2, CH_K2, and CN2 were sensitive, but GW_DELAY, ALPHA_BF, GW_REVAP, and SOL_BD were not. In Malaysia's Langat River Basin, ALPHA_BF and GW_REVAP are non-sensitive, partly supporting Khalid, Ali [51]. This study found that the ESCO and GWQMN are sensitive. However, Ismail [17] found those parameters non-sensitive. ESCO was also one of the most sensitive parameters in the watershed, as studied by Alansi, Amin [50]. DEM, soil map data, and land use–land cover changes considered in this research may affect soil evaporation and the minimum water level in the subsurface aquifer needed for return flow to transpire, affecting catchment streamflow.

However, this study partially agrees with Dlamini, Kamal [14], Ismail [17], Alansi, Amin [50], which found a similar pattern of sensitivity in the same catchment. Only 10 of 16 parameters studied by Thebe [52] in Poland of Czech Republic were sensitive. In central Poland, Smarzyńska and Miatkowski [32] explored 26 parameters and identified 10 sensitive ones, similar to our study. In Tanzania, Mollel, Mulungu [49] found that 14 of 20 parameters in their "Assessment of climate change impacts on hydrological processes in the Usangu catchment of Tanzania under CMIP6 scenarios" were sensitive, and about 43% of these parameters were also sensitive in this study.

Moreover, 10 of 21 parameters studied by Khalid, Ali [51] in Langat River Basin, Malaysia, were non-sensitive. Please note that sensitive parameters vary by land use and watershed. Thus, sensitive parameters in specific catchments may not be sensitive in others. However, hydrologic conditions differ greatly between catchments. 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 modeling of the Bernam catchment than in previous studies of the same catchment, as shown in the calibration and validation discussion section.

Table 3. 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	5643.671387	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	9160.946289	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

r_ denotes relative; the fitted value is added by 1 and then multiplied by the given value existing parameter in the SWATEdit. v_ denotes replace; a given value in the SWATEdit will replace the existing parameter.

doi:10.20944/preprints202412.1043.v1

3.2. SWAT Calibration and Validation

Figure 4 shows that the uncalibrated runoff model has 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 runoff, which accounted for all catchment water volume.

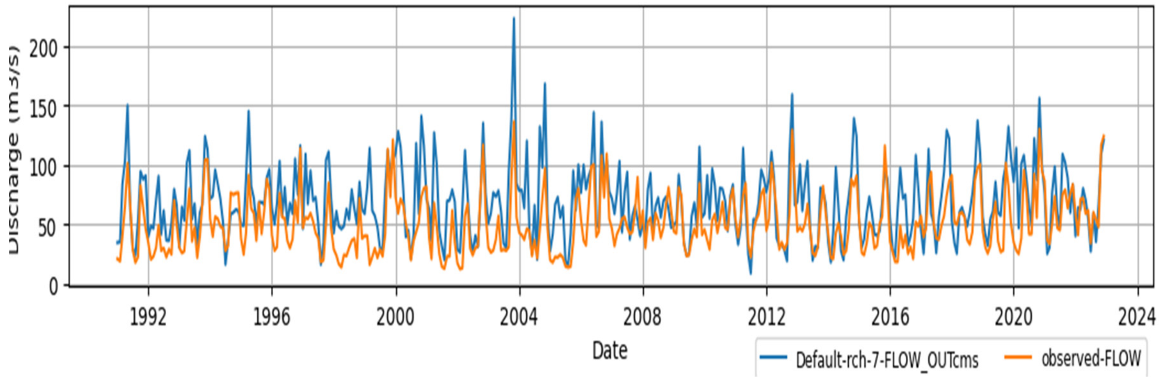


Figure 4. Comparison between observed and simulated discharge at SKC gauge station, UBRB, for the calibration period 1991 to 2022.

The model was calibrated at 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 4. The calibration and validation periods were split into 3 categories: Category 1 (10 years calibration- and 5-year validation period: 1991-2000: 2001-2005; 2001-2010: 2011-2015; and 2011-2020: 2021-2022); category 2 (15 years calibration- and 10-year validation period: 1991-2005: 2006-2015); and category 3 (20 years 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 Dlamini, Kamal [14], Ismail [17], Alansi, Amin [50] in the same catchment) were applied to these categories.

Table 4 shows that the 1991-2000 and 2001-2005 calibration and validation periods yielded acceptable model performance. Table 5 shows iterations and performance indicators from Table 4. The experiment showed that indicator performance deteriorated after the fourth iteration. Thus, calibration was terminated. The P-factor, r-factor, R2, NSE, PBIAS, and KGE indicators demonstrated satisfactory values.

Table 4. Calibration and validation summary.

Period	Set	Settings	Variable	p-factor	r-factor	R2	NS	bR2	MSE	SSQR	PBIAS	KGE	RSR	MNS	VOL_FR	Mean_sim	Mean_obs	StdDev_sim	StdDev_obs	STATUS
Cal-1991-2000	SET1	Iter1_3=600	FLOW_OUT_7	0.82	0.88	0.72	0.7	0.6147	1.70E+02	8.30E+00	-1.1	0.85	0.55	0.5	0.99	48.79	48.24	23.85	23.81	New Par of Iter1_2
Val-2001-2005	SET1	VAL2001-2005	FLOW_OUT_7	0.8	1.04	0.75	0.65	0.7376	2.40E+02	3.90E+01	-6.6	0.79	0.59	0.46	0.94	44.08	48.24	30.05	23.81	New Par of Iter1_2
Cal-1991-2000	SET2	Iter1_3=600	FLOW_OUT_7	0.68	1.17	0.73	0.73	0.5127	1.50E+02	2.80E+01	-2.7	0.77	0.52	0.52	0.97	49.53	48.24	19.44	23.81	New Par of Iter1_2
Val-2001-2005	SET2	VAL2001-2005	FLOW_OUT_7	0.45	1.14	0.73	0.62	0.6039	2.60E+02	8.40E+01	-19.4	0.76	0.61	0.35	0.84	49.37	41.33	25.36	26.22	New Par of Iter1_2
Cal-2001-2010	SET1	Iter1_3=600	FLOW_OUT_7	0.78	1.3	0.62	0.6	0.4583	2.30E+02	2.30E+01	-1.9	0.78	0.63	0.37	0.98	48.83	47.93	22.6	24.21	New Par of Iter1_2
Val-2011-2015	SET1	VAL2011-2015	FLOW_OUT_7	0.75	1.29	0.78	0.66	0.6701	2.00E+02	7.30E+01	14.7	0.81	0.58	0.42	1.17	45.19	52.99	23.61	24.04	New Par of Iter1_2
Cal-2001-2010	SET2	Iter1_3=600	FLOW_OUT_7	0.6	0.81	0.63	0.63	0.383	2.20E+02	4.90E+01	1.4	0.69	0.61	0.41	1.01	47.27	47.93	18.54	24.21	New Par of Iter1_2
Val-2011-2015	SET2	VAL2011-2015	FLOW_OUT_7	0.68	0.7	0.73	0.72	0.4655	1.60E+02	4.80E+01	2.6	0.71	0.53	0.47	1.03	51.63	52.99	17.94	24.04	New Par of Iter1_2
Cal-2011-2020	SET1	Iter1_3=600	FLOW_OUT_7	0.75	1.06	0.53	0.52	0.3234	3.00E+02	3.30E+01	-0.4	0.68	0.69	0.33	1	53.53	53.29	20.69	24.83	New Par of Iter1_2
Val-2021-2022	SET1	VAL2021-2022	FLOW_OUT_7	0.63	1.1	0.69	0.61	0.5131	2.00E+02	9.00E+01	9.3	0.78	0.62	0.34	1.1	58.66	64.65	20.29	22.6	New Par of Iter1_2
Cal-2011-2020	SET2	Iter1_3=600	FLOW_OUT_7	0.58	0.46	0.62	0.62	0.3771	2.30E+02	4.20E+01	0.9	0.69	0.61	0.42	1.01	52.83	53.29	19.04	24.83	New Par of Iter1_2
Val-2021-2022	SET2	VAL2021-2022	FLOW_OUT_7	0.63	0.58	0.7	0.68	0.4195	1.60E+02	7.00E+01	2.3	0.67	0.57	0.4	1.02	63.16	64.65	16.22	22.6	New Par of Iter1_2

Cal-1991-2005	SET1	Iter1_3=600	FLOW_OUT_7	0.52	0.68	0.69	0.61	0.586	2.40E+02	5.10E+01	-10.1	0.8	0.62	0.41	0.91	50.57	45.94	25.52	24.85	New Par of Iter1_2
Val-2006-2015	SET1	VAL2006-2015	FLOW_OUT_7	0.71	0.79	0.61	0.49	0.4841	2.50E+02	4.50E+01	10.4	0.76	0.72	0.27	1.12	48.17	53.76	22.52	22.1	New Par of Iter1_2
Cal-1991-2005	SET2	Iter1_3=600	FLOW_OUT_7	0.63	1	0.71	0.69	0.5284	1.90E+02	3.60E+01	-7	0.79	0.55	0.48	0.93	49.13	45.94	21.88	24.85	New Par of Iter1_2
Val-2006-2015	SET2	VAL2006-2015	FLOW_OUT_7	0.83	1.1	0.67	0.67	0.4477	1.60E+02	2.80E+01	1.4	0.74	0.57	0.42	1.01	52.99	53.76	17.98	22.1	New Par of Iter1_2
Cal-1991-2010	SET1	Iter1_3=600	FLOW_OUT_7	0.82	1.24	0.64	0.58	0.5265	2.40E+02	2.60E+01	-3	0.79	0.65	0.4	0.97	49.53	48.08	24.83	24.01	New Par of Iter1_2
Val-2011-2020	SET1	VAL2011-2020	FLOW_OUT_7	0.77	1.24	0.58	0.47	0.4713	3.30E+02	4.10E+01	8.5	0.74	0.73	0.3	1.09	48.74	53.29	26.17	24.83	New Par of Iter1_2
Cal-1991-2010	SET2	Iter1_3=600	FLOW_OUT_7	0.6	0.8	0.65	0.65	0.4166	2.00E+02	3.90E+01	-1.7	0.71	0.59	0.44	0.98	48.88	48.08	18.96	24.01	New Par of Iter1_2
Val-2011-2020	SET2	VAL2011-2020	FLOW_OUT_7	0.71	0.76	0.63	0.63	0.4125	2.30E+02	2.80E+01	-0.9	0.73	0.61	0.42	0.99	53.75	53.29	20.61	24.83	New Par of Iter1_2

doi:10.20944/preprints202412.1043.v1

 doi:10.20944/preprints202412.1043.v1

Table 5. Overview of model performance indicators for the Iterations performed.

	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**

During calibration, the p-factor (0.82), r-factor (0.88), R2 (0.72), NSE (0.7), PBIAS (-1.1), and KGE (0.85) are statistical extracts of model performance. During validation, extracts of model performance are p-factor (0.8), r-factor (1.04), R2 (0.75), NSE (0.65), PBIAS (-6.6), and KGE (0.79). Abbaspour [42] 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 (Figure 5). 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 favorable 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 observations when the p-factor is closer to 1, and the r-factor is closer to 0.

According to Abbaspour [42], around 70% of river discharge data should fall within the 95PPU range (p-factor ≥ 0.7, r-factor ≤ 1.5). This study's calibrated model estimated UBRB streamflow data well with p-factor (0.82), r-factor (0.88), and 95ppu (Figure 4.4). The Porijogi catchment of Estonia by Kmoch, Moges [30] has a p-factor of 0.27-0.86 and an r-factor of 0.1-1.75, which closely agrees with some of these findings. Mollel, Mulungu [49] presented a Tanzanian study with a p-factor of 0.58) and an r-factor of 0.55. The r-factor is better than this study's, while the p-factor is better than the Tanzania study's. However, this study's different catchments and pre-calibration tests caused the p-factor and r-factor discrepancies.

The calibration period produced R2 (0.72), NSE (0.7), PBIAS (-1.1), and KGE (0.85). The model's suitability was evaluated using Moriasi, Arnold [13], Moriasi, Gitau [53] statistical criteria: NSE > 0.65 (Very good: 0.75 < NSE < 1.00), good: 0.65 < NSE < 0.75, satisfactory: 0.5 < NSE < 0.65, or unsatisfactory: NSE < 0.50), $R^2 > 0.5$, and |PBIAS| ≤ 25%. The calibration and validation findings showed a successful simulation with good to satisfactory and efficient model performance.

In this study, the PBIAS value of -1.1 simulates streamflow and is closer to observed data than Dlamini, Kamal [14], and Ismail [17], which are -9.4 and -5.4, respectively. It shows that a shorter usage period may increase model performance. It could also depend on the watershed. Figure 6 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. During calibration, flow 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. The model can underestimate or overestimate discharge levels to fit observations.

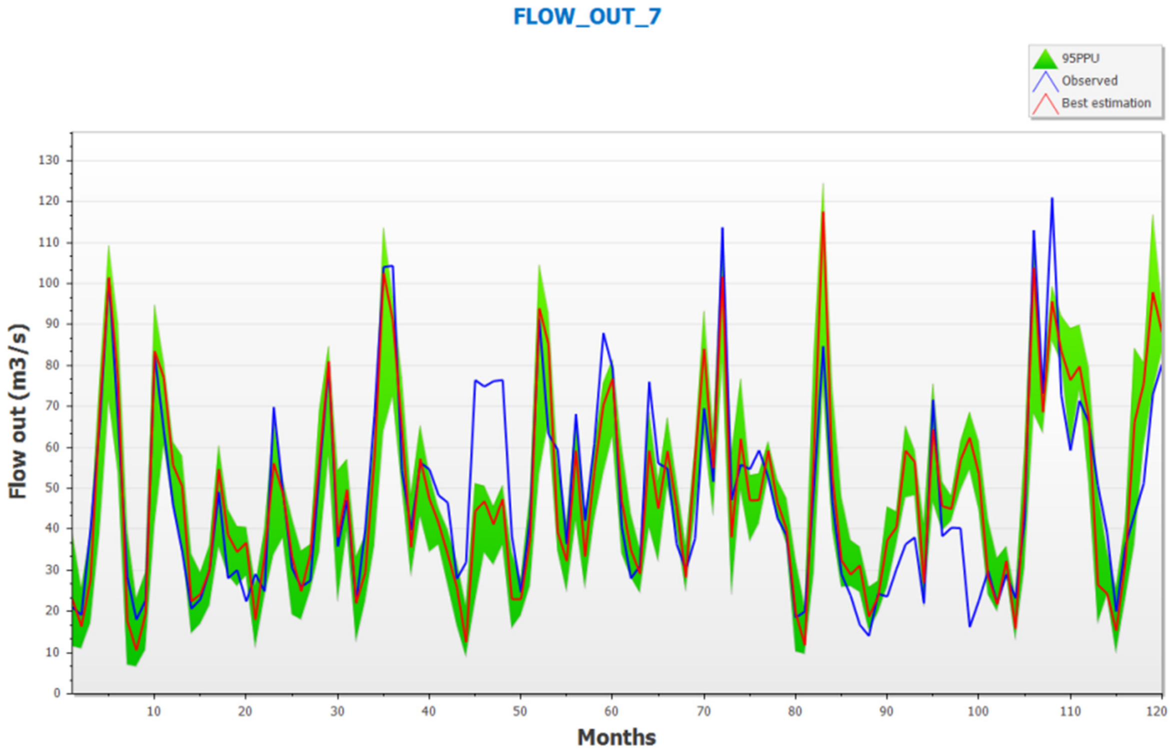


Figure 5. The 95ppu plot of all variables for the calibrated model.

The model accurately replicated monthly discharge data throughout validation, except for the overestimations of July 2002–November 2002 and November–December 2005. Validation findings for R2 (0.75), NSE (0.65), PBIAS (-6.6), and KGE (0.79) align with calibration trends. As stated by Moriasi, Arnold [13], Mollel, Mulungu [49], Moriasi, Gitau [53], the simulation was successful with values beyond 0.5. This study's R2 value is 17% higher than Dlamini, Kamal [14]'s 0.62 and 15% higher than Ismail [17]'s 0.64. Recent research has indicated that model assessment statistical results are poorer during validation than calibration; 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 of November–February every year [54], and from April 2005 to July 2005, which falls within the Malaysian Southwest monsoon period of May-August every year, the flow was consistently overestimated. The Northeast monsoon has shifted backward by one month (October to January instead of November to February), and the Southwest monsoon has also shifted backward by a month (April to July instead of May to August). This shift could be attributed to climate change, so farmers in this region, especially those who depend on rainfall agriculture, should plan their farming season early. Nevertheless, the SWAT model replicated Malaysia's seasonal cycle, proving it is reliable for simulation and projections.

The model replicated months with high peak discharges, unlike Dlamini, Kamal [14] and Ismail [17], 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) [43,44] was used, comprehensively evaluating the model's capacity to replicate the observed flow regime while considering timing, volume, and variability. The KGE was 0.85 and 0.79 for calibration and validation periods, respectively, indicating that the SWAT model could sufficiently simulate the streamflow in the UBRB basin.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 12 December 2024 doi:10.20944/preprints202412.1043.v1

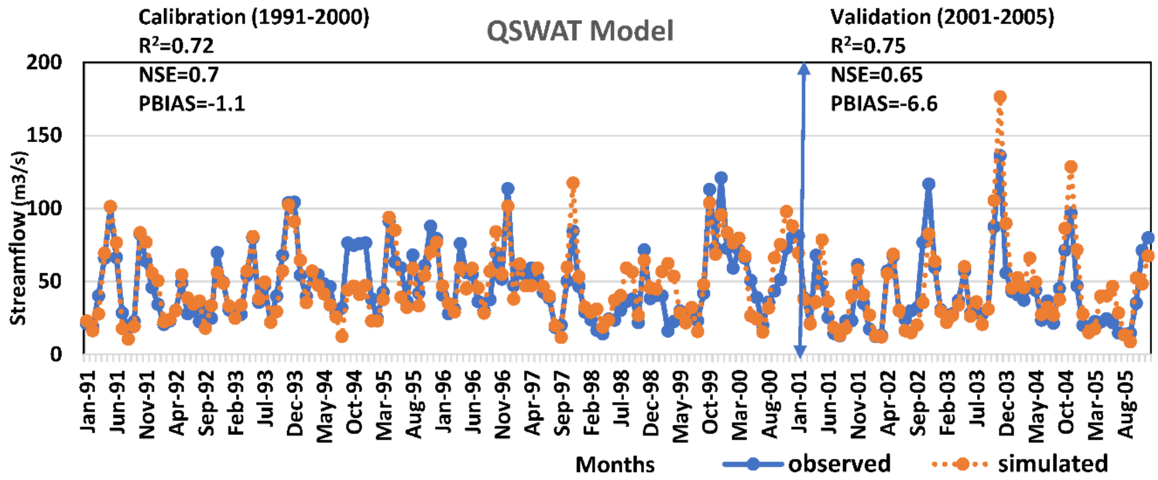
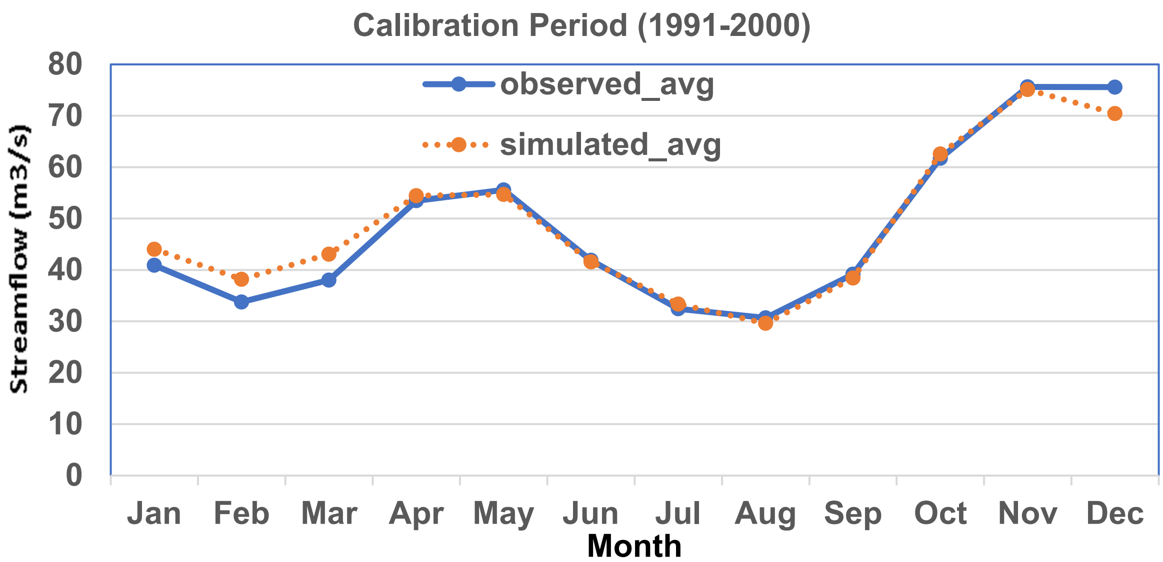


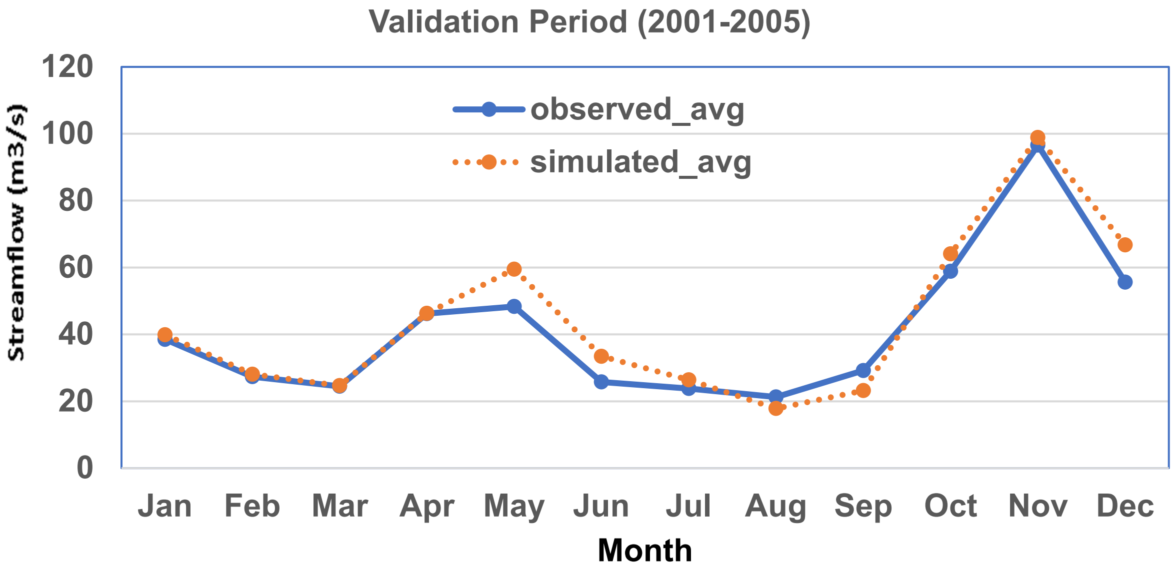
Figure 6. SWAT Model Monthly Streamflow for Simulated and Observed.

Figure 7 (a and b) shows UBRB streamflow at the SKC gauge station during calibration and validation. 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. Figure 4.6a shows the monthly average streamflow. The graph indicates a close match and steady pattern between observed and simulated streamflow during calibration, especially from April to November. In December, the model predicted less flow than in January to March. Figure 4.6b 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 Moriasi, Arnold [13], Mollel, Mulungu [49], Moriasi, Gitau [53].



(a) Average Monthly Observed and Simulated Streamflow for SWAT Model (Calibration period)

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 12 December 2024 doi:10.20944/preprints202412.1043.v1

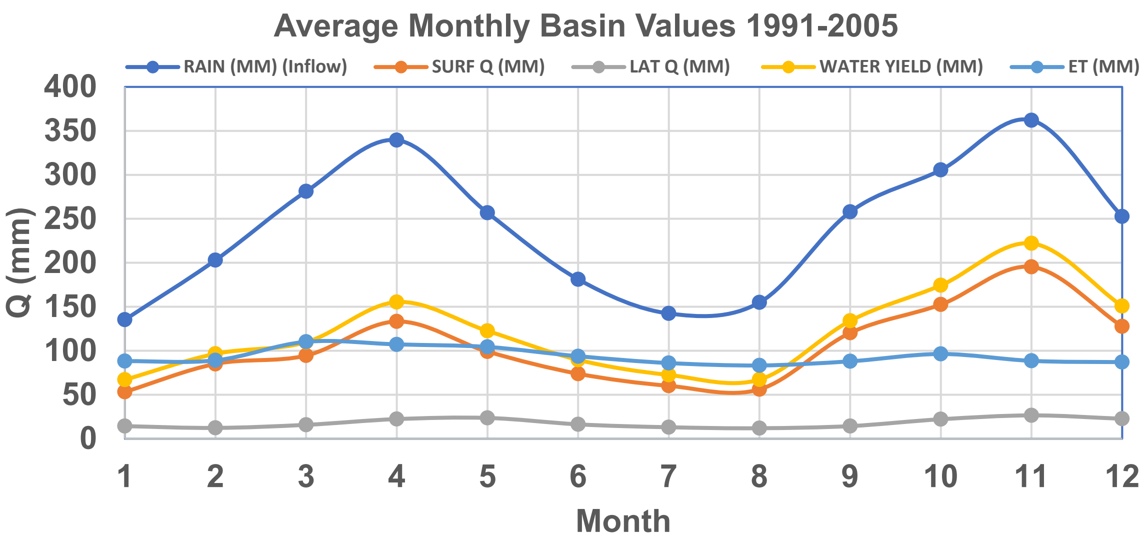


(b) Average Monthly Observed and Simulated Streamflow for SWAT Model (Validation period)

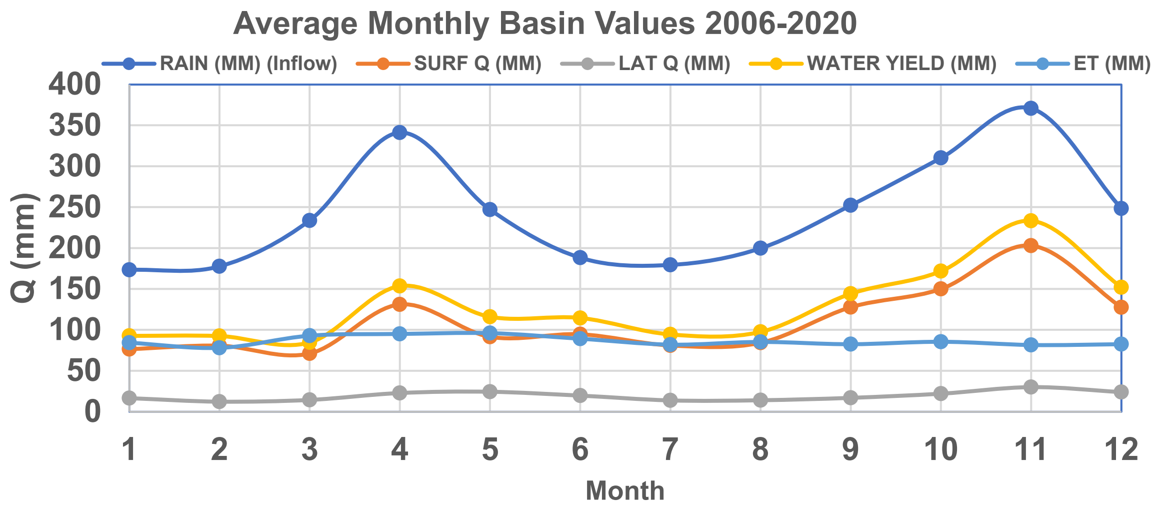
Figure 7. UBRB streamflow at the SKC gauge station during calibration and validation.

3.3. Simulation of UBRB Using the SWAT Model

The result of the SWAT simulation after adjusting the model parameters with calibrated best-fit values is presented in Figure 8. The results indicated that the inflow (rainfall) and the outflow (water yield + ET) are 2,873.36mm and 2,592.78mm, respectively. This shows a difference of 9.8% for 1991-2005, while 2,921.98 mm 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.



(a)1991-2005



(b) 2006-2020

Figure 6. SWAT Simulation Output (Average Monthly Basin Values for 1991-2005 and 2006-2021).

4. Discussion

The sensitivity analysis identified CN2, ESCO, ALPHA_BNK, CANMX, HRU_SLP, SUB_ELEV, GWQMN, CH_N2, RCHRG_DP, and CH_K2 as key parameters influencing streamflow in the UBRB. The results showed partial alignment with previous studies, with some parameters such as CH_N2, CH_K2, and CN2 consistently sensitive, while others: GW_DELAY and ALPHA_BF were non-sensitive here but sensitive elsewhere. Variations in sensitivity were attributed to differences in land use, soil properties, and hydrological conditions, emphasizing the need for context-specific modeling and calibration.

The SWAT model's calibration and validation (1985-2022 with a 6-year warm-up) used three periods (10/5, 15/10, and 20/10 years) and two parameter sets: Set 1 (26 refined to 10) and Set 2 (9 from prior studies). The model achieved strong performance: p-factor (0.82, 0.8), r-factor (0.88, 1.04), R2 (0.72, 0.75), NSE (0.7, 0.65), KGE (0.85, 0.79), and |PBIAS| (-1.1, -6.6). The model accurately captured UBRB streamflow with 95% prediction uncertainty (95PPU). Seasonal flow patterns were well-replicated despite monsoon period overestimations, indicating reliability for historical and future projections. Climate change-driven monsoon shifts underscore the need for adaptive agricultural planning. Performance exceeded key benchmarks (NSE > 0.65, |PBIAS| ≤ 25%).

5. Conclusions

Calibration and Validation of the SWAT model at UBRB for Agro-Hydrological Process Projections in Malaysia was successfully carried out using the QGIS environment. A multifaceted approach was employed, and the calibration and validation were divided into three categories. Category 1, with 10-year calibration and 5-year validation data, has shown that the 1991-2000 and 2001-2005 calibration and validation periods yielded the best model performance. The result analysis demonstrated that the Northeast monsoon shifted backward by one month (October to January instead of November to February), and the Southwest monsoon shifted backward by a month (April to July instead of May to August). This shift could be caused by climate change, and thus, farmers in this region, especially those who depend on rainfall agriculture, should plan their farming season early. The overall result of the simulation showed a difference of 10.6% between the inflow and outflow between the simulation period of 1985 to 2020 with a 6-year warm-up period, implying that the SWAT model can project future UBRB simulations. Nevertheless, this study demonstrates the SWAT model's capability to predict agro-hydrological processes of Malaysia's seasonal cycle, proving it is reliable for simulation and projections and providing a valuable tool for decision-makers in the UBRB to optimize agricultural water resource management.

Author Contributions: Conceptualization, Md. Kamal Rowshon and Muazu Dantala Zakari; methodology, Md. Kamal Rowshon and Muazu Dantala Zakari; software, Muazu Dantala Zakari and Franklin Aondoaver Kondum; validation, Md. Kamal Rowshon, Muazu Dantala Zakari, Mohd Syazwan Faisal Bin Mohd, and Franklin Aondoaver Kondum; formal analysis, Md. Kamal Rowshon and Muazu Dantala Zakari; investigation, Muazu Dantala Zakari; resources, Md. Kamal Rowshon and Muazu Dantala Zakari; data curation, Md. Kamal Rowshon; writing—original draft preparation, Muazu Dantala Zakari; writing—review and editing, Md. Kamal Rowshon and Muazu Dantala Zakari; visualization, Md. Kamal Rowshon and Muazu Dantala Zakari; supervision, Md. Kamal Rowshon, Norulhuda binti Mohamed Ramli, Balqis Mohamed Rehan, and Mohd Syazwan Faisal Bin Mohd; project administration, Md. Kamal Rowshon, Norulhuda binti Mohamed Ramli, Balqis Mohamed Rehan, and Mohd Syazwan Faisal Bin Mohd; funding acquisition, Muazu Dantala Zakari. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Petroleum Technology Development Fund (PTDF), the Federal Republic of Nigeria and the APC was funded by PTDF.

Data Availability Statement: The original data used in this study are available in Shuttle Radar Topography Mission (SRTM) website, FAO Map Catalogue's Digital Soil Map of the World (DSMW) in ESRI, ESRI website (Global Land Cover; Sentinel-2: 10m land use/land cover; 2022), and the Malaysian Department of Irrigation and Drainage (DID), Water Resources and Hydrology Division for meteorological and hydrologic data.

Acknowledgments: The authors acknowledge the financial support of Nigeria's Petroleum Technology Development Fund (PTDF) for funding this research and also appreciate the Drainage and Irrigation Department and the Malaysian Meteorological Department for providing the daily meteorological data for this study. Also, the authors acknowledge the support of the Soil and Water Engineering Research Group, Faculty of Engineering, University Putra Malaysia.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Mancosu, N., et al., *Water scarcity and future challenges for food production.* Water, 2015. **7**(3): p. 975-992.
2. Porkka, M., et al., *Causes and trends of water scarcity in food production.* Environmental research letters, 2016. **11**(1): p. 015001.
3. Roy, R., *An introduction to water quality analysis.* ESSENCE Int. J. Env. Rehab. Conserv, 2019. **9**(1): p. 94-100.
4. Cisneros, B.J., et al., *Freshwater resources. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects.* Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 2015: p. 229-269.
5. Gheewala, S., et al., *Water stress index and its implication for agricultural land-use policy in Thailand.* International journal of environmental science and technology, 2018. **15**: p. 833-846.
6. Li, M., et al., *Efficient irrigation water allocation and its impact on agricultural sustainability and water scarcity under uncertainty.* Journal of Hydrology, 2020. **586**: p. 124888.
7. COAG, *Agriculture and Water Scarcity: a Programmatic Approach to Water Use Efficiency and Agricultural Productivity Comparing notes on institutions and policies.* International Water Management Institute 2007.
8. Khan, T.H., *Water scarcity and its impact on agriculture.* 2014.
9. UCCRN, *The Future We Don't Want: How Climate Change Could Impact the World's Greatest Cities*. 2018, UCCRN-C40Cities New York, NY, USA.
10. Day, F., *Energy-smart food for people and climate.* FAO, Rome, 2011.
11. Abbaspour, K., M. Vejdani, and S. Haghighat, *SWAT-CUP calibration and uncertainty programs for SWAT. Modsim 2007: International Congress on Modelling and Simulation: Land.* Water and Environmental Management: Integrated Systems for Sustainability, Christchurch, New Zealand, 2007.
12. Abbaspour, K.C., *SWAT calibration and uncertainty programs.* A user manual, 2015. **103**: p. 17-66.
13. Moriasi, D.N., et al., *Model evaluation guidelines for systematic quantification of accuracy in watershed simulations.* Transactions of the ASABE, 2007. **50**(3): p. 885-900.
14. Dlamini, N.S., et al., *Modeling potential impacts of climate change on streamflow using projections of the 5th assessment report for the Bernam River Basin, Malaysia.* Water, 2017. **9**(3): p. 226.

15. Ismail, H., et al., *HYDROLOGICAL MODELLING FOR EVALUATING CLIMATE CHANGE IMPACTS ON STREAMFLOW REGIME IN THE BERNAM RIVER BASIN MALAYSIA.* FUDMA JOURNAL OF SCIENCES, 2021. **5**(3): p. 219-230.
16. Dlamini, N.S., *Decision Support System for Water Allocation in Rice Irrigation Scheme under Climate Change Scenarios*. 2017, Universiti Putra Malaysia Seri Kembangan, Malaysia.
17. Ismail, H., *Climate-smart agro-hydrological model for the assessment of future adaptive water allocation for Tanjong Karang rice irrigation scheme*. 2020, Universiti Putra Malaysia.: UNIVERSITI PUTRA MALAYSIA INSTITUTIONAL REPOSITORY.
18. Ismail, H., et al., *Modeling Future Streamflow for Adaptive Water Allocation under Climate Change for the Tanjung Karang Rice Irrigation Scheme Malaysia.* Applied Sciences, 2020. **10**(14): p. 4885.
19. Ismail, H., et al., *Climate-smart agro-hydrological model for a large scale rice irrigation scheme in Malaysia.* Applied Sciences, 2020. **10**(11): p. 3906.
20. Ismail, H., et al. *Assessment of climate change impact on future streamflow at Bernam river basin Malaysia*. in *IOP Conference Series: Earth and Environmental Science*. 2020. IOP Publishing.
21. Rowshon, M., M. Amin, and A. Shariff, *GIS user-interface based irrigation delivery performance assessment: a case study for Tanjung Karang rice irrigation scheme in Malaysia.* Irrigation and drainage systems, 2011. **25**: p. 97-120.
22. Rowshon, M., et al., *Improving irrigation water delivery performance of a large-scale rice irrigation scheme.* Journal of Irrigation and Drainage Engineering, 2014. **140**(8): p. 04014027.
23. Saadati, Z., N. Pirmoradian, and M. Rezaei, *Calibration and evaluation of aqua crop model in rice growth simulation under different irrigation managements.* 2011.
24. Rowshon, M.K., et al., *Modeling climate-smart decision support system (CSDSS) for analyzing water demand of a large-scale rice irrigation scheme.* Agricultural water management, 2019. **216**: p. 138-152.
25. Tan, B.Y., et al., *Impact of Climate Change on Rice Yield in Malaysia: A Panel Data Analy sis.* Agriculture, 2021. **11**(6): p. 569-569.
26. Dile, Y.T., et al., *Introducing a new open source GIS user interface for the SWAT model.* Environmental modelling & software, 2016. **85**: p. 129-138.
27. Winchell, M.F., et al., *Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region.* Hydrological Sciences Journal, 2015. **60**(5): p. 844-862.
28. Badora, D., et al., *Modelling the hydrology of an upland catchment of Bystra River in 2050 climate using RCP 4.5 and RCP 8.5 emission scenario forecasts.* Agriculture, 2022. **12**(3): p. 403.
29. Douglas-Mankin, K., R. Srinivasan, and J. Arnold, *Soil and Water Assessment Tool (SWAT) model: Current developments and applications.* Transactions of the ASABE, 2010. **53**(5): p. 1423-1431.
30. Kmoch, A., et al., *The Effect of Spatial Input Data Quality on the Performance of the SWAT Model.* Water, 2022. **14**(13): p. 1988.
31. Arnold, J.G., et al., *Large area hydrologic modeling and assessment part I: model development 1.* JAWRA Journal of the American Water Resources Association, 1998. **34**(1): p. 73-89.
32. Smarzyńska, K. and Z. Miatkowski, *Calibration and validation of SWAT model for estimating water balance and nitrogen losses in a small agricultural watershed in central Poland.* Journal of Water and Land Development, 2016. **29**(1): p. 31-47.
33. Bilondi, M.P. and K.C. Abbaspour, *Application of three different calibration-uncertainty analysis methods in a semi-distributed rainfall-runoff model application.* Middle-East Journal of Scientific Research, 2013. **15**.
34. Yang, W., et al., *Distribution-based scaling to improve usability of regional climate model projections for hydrological climate change impacts studies.* Hydrology Research, 2010. **41**(3-4): p. 211-229.
35. Shawul, A.A., T. Alamirew, and M. Dinka, *Calibration and validation of SWAT model and estimation of water balance components of Shaya mountainous watershed, Southeastern Ethiopia.* Hydrology and Earth System Sciences Discussions, 2013. **10**(11): p. 13955-13978.
36. Janjić, J. and L. Tadić, *Fields of Application of SWAT Hydrological Model—A Review.* Earth, 2023. **4**(2): p. 331-344.
37. Abbaspour, K.C., et al., *A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model.* Journal of hydrology, 2015. **524**: p. 733-752.
38. Abbaspour, K.C., S.A. Vaghefi, and R. Srinivasan, *A guideline for successful calibration and uncertainty analysis for soil and water assessment: a review of papers from the 2016 international SWAT conference.* Water, 2017. **10**(1): p. 6.

doi:10.20944/preprints202412.1043.v1

39. Arnold, J.G., et al., *SWAT: Model use, calibration, and validation.* Transactions of the ASABE, 2012. **55**(4): p. 1491-1508.
40. Abbaspour, K., *SWAT-CUP Tutorial (2): Introduction to SWAT-CUP program.* Parameter Estimator (SPE), 2020.
41. Abbaspour, K.C., *User manual for SWATCUP-2019/SWATCUP-Premium/SWATplusCUP Calibration and Uncertainty Analysis Programs*. 2022, 2w2e Consulting GmbH Publication: Duebendorf, Switzerland.
42. Abbaspour, K.C., *The fallacy in the use of the "best-fit" solution in hydrologic modeling.* Science of the total environment, 2022. **802**: p. 149713.
43. Chilkoti, V., T. Bolisetti, and R. Balachandar, *Multi-objective autocalibration of SWAT model for improved low flow performance for a small snowfed catchment.* Hydrological Sciences Journal, 2018. **63**(10): p. 1482-1501.
44. Gupta, H.V., et al., *Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling.* Journal of hydrology, 2009. **377**(1-2): p. 80-91.
45. Houshmand Kouchi, D., et al., *Sensitivity of calibrated parameters and water resource estimates on different objective functions and optimization algorithms.* Water, 2017. **9**(6): p. 384.
46. Neitsch, S.L., et al., *Soil and water assessment tool theoretical documentation version 2009*. 2011, Texas Water Resources Institute.
47. Koch, M. and N. Cherie. *SWAT-modeling of the impact of future climate change on the hydrology and the water resources in the upper blue Nile river basin, Ethiopia*. in *Proceedings of the 6th international conference on water resources and environment research, ICWRER*. 2013.
48. Memarian, H., et al., *SWAT-based hydrological modelling of tropical land-use scenarios.* Hydrological sciences journal, 2014. **59**(10): p. 1808-1829.
49. Mollel, G.R., et al., *Assessment of climate change impacts on hydrological processes in the Usangu catchment of Tanzania under CMIP6 scenarios.* Journal of Water and Climate Change, 2023. **14**(11): p. 4162-4182.
50. Alansi, A., et al., *Validation of SWAT model for stream flow simulation and forecasting in Upper Bernam humid tropical river basin, Malaysia.* Hydrology and Earth System Sciences Discussions, 2009. **6**(6): p. 7581-7609.
51. Khalid, K., et al., *Optimization of spatial input parameter in distributed hydrological model.* ARPN J Eng Appl Sci, 2015. **10**(15): p. 6628-6633.
52. Thebe, T., *SWAT Runoff Modeling and Salinity Estimation in the Odra River Catchment*, in *Department of Physical Geography*. 2023, Stockholms Universitet: Poland, Czech Republic. p. 69.
53. Moriasi, D.N., et al., *Hydrologic and water quality models: Performance measures and evaluation criteria.* Transactions of the ASABE, 2015. **58**(6): p. 1763-1785.
54. Suhaila, J., et al., *Trends in peninsular Malaysia rainfall data during the southwest monsoon and northeast monsoon seasons: 1975–2004.* Sains Malaysiana, 2010. **39**(4): p. 533-542.