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Evaluation of the Agricultural Best Management Practices (ABMPs) and Their Effect on Discharge Reduction of Shiroro Dam Site using SWAT Model

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Abstract

Best Management Practices (BMPs) have proven to be effective in reducing erosion, sediment yield, and nutrient loss. However, there is little information on their effects on annual inflow. This study used the SWAT model to delineate the Shiroro Dam, divide it into 18 subbasins and 35 hydrological response units, and further modifies the curve number and support practice factor to represent terrace, contour, and strip cropping on the agricultural land. The research calibrated and validated the inflow data from 2011 to 2021. Sequential Uncertainty Fitting (SUFI2) algorithm was used to perform calibration and validation. Whereas the objective function used was Nash-Sutcliffe efficiency (NSE). Other performance indices identified included the coefficient of determination (R²), P-factor, r-factor, and Percent Bias (PBIAS). The results show that the NSE values ranged from 0.58 to 0.65 in the validation stage. It implies that the models are satisfactory. In addition, the sensitivity analysis revealed that saturated hydraulic conductivity (SOL_K) was highly sensitive to inflow under terrace, contour, and strip cropping, with the highest t-statistic, implying that SOL_K influences the simulated inflow in the catchment. The percentage reductions in inflow under terrace, contour, and strip cropping were 23%, 8%, and 1.3%, respectively. It implies that terrace and contour implementations would reduce annual inflow to the Shiroro Dam and serve as appropriate conservation practices in the study area.

Keywords: *Discharge, Agricultural Best Management Practices, ArcSWAT, SWAT model, SUFI2, Shiroro Dam site.*

1.0 Introduction

Traditional agricultural practices, compact soil layers, slow water infiltration, and increase runoff generation. In addition, overflow discharge, water erosion, nutrient loss, sediment yield, and water infiltration are part of the identified problems militating against Agricultural Best Management Practices. These menaces affect downstream discharge [1, 2, 3, 4]. This excess discharge is dependent on the wrong agricultural practices and rainfall, leading to excess surface runoff, eroded sediments, and dam sedimentation [1, 2, 3, 4]. The surface water and eroded sediments from the River Kaduna and other rivers causes unstable reservoir discharge due to dam sedimentation, which causes water scarcity for irrigation in dry season. Therefore, there is an urgent need to introduce and implement BMPs, which would reduce unnecessary flow from agricultural land in the study area, as there are no BMPs currently implemented in the Shiroro dam.

Best management practices (BMPs) are agricultural and structural measures designed in the field to reduce streamflow, sediment yield, and runoff. Moreover, these practices contribute to the baseflow of surface flow (7.8%) and groundwater (48.2%), respectively [3], but their quantitative impact on discharge remains poorly understood for many African watersheds [1, 2, 3, 5]. This is especially relevant for the Shiroro Dam (watershed) in Nigeria, where rapid agricultural practices are changing discharge, yet simulation of BMP scenarios and their hydrological effects has not been conducted.

Physical-based models such as SWAT are widely used to predict how BMPs affect streamflow and sediment at the watershed scale. These models have also helped identify critical erosion zones in India and Morocco and found that combining structural and agricultural BMPs can reduce surface runoff by 4–22% and sediment yield by 70–80%, while boosting baseflow and groundwater recharge [1, 3, 5]. Furthermore, a study in India found that structural BMPs (66–70%) are more effective than agricultural BMPs (2–7%) in reducing eroded sediment at the watershed scale. In Brazil and Ethiopia, SWAT simulations suggest that structural BMPs can reduce sediment erosion by up to 40%, indicating their potential to lower surface runoff and reservoir sedimentation in large dams [6, 2]. However, there is little review on the effect of conservation practices on annual reservoir discharge at Shiroro Dam. SWAT has also been used in data-scarce or ungauged catchments. Hybrid SWAT–BiLSTM strategies have improved streamflow simulation at daily resolution and enabled evaluation of multiple BMP scenarios, including mulch, vegetative filter strips, and fertiliser management, resulting in significant reductions in nitrogen and phosphorus loads [17]. At the same time, few studies indicate that BMPs such as check-dam, tail water pond, Vegetative Filter Strips (VFS), nutrient management, conservation tillage, contour farming, bench

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terrace, Cover Crops (CC), a combination of VFS and CC, conservation tillage, contour farming, consistently reduce sediment and nutrient erosion [8, 1, 9, 5]. However, the effects of contour, terracing, and strip cropping on streamflow are poorly understood.

Despite extensive global efforts, three gaps remain important to the Shiroro Dam catchment. First, there is a clear geographic gap: BMP–hydrology modelling has been applied to large hydropower reservoirs worldwide, with the most detailed SWAT-based BMP assessments in Asia, North Africa, Europe, and the United States of America [10, 1, 6, 2, 3, 5]. Second, existing studies tend to prioritise sediment and nutrient reduction [4, 1, 6, 2, 10, 3, 5]. However, there is little review on the effects of conservation practices on annual discharge to quantify discharge reduction. Third, evidence remains limited on which individual BMPs—such as contour farming, strip cropping, and terraces — are appropriate for discharge reduction [1, 2, 3].

Computing how probable BMP scenarios would alter the extent, timing, and variability of discharge to Shiroro Dam is essential for implementing BMPs around the farmland to protect and secure the hydropower production, storage reliability, and downstream environmental flow; for guiding cost effective targeting of BMPs to critical source areas, following evidence that spatially optimized BMP placement substantially increases watershed scale benefits relative to untargeted implementation [1, 11, 12]; and for providing empirical evidence for Stakeholder in water sector on the efficacy of nature based and BMPs interventions that can complement structural reservoir operations for climate risk adaptation [1, 6, 2, 5]. The objectives of this research were as follows: (i) to predict the discharge of Shiroro dam using SWAT model, and (ii) to evaluate agricultural BMPs and their effect on discharge reduction of Shiroro dam.

2.0 Materials and Methods/Methodology

2.1 Description of the Study Area

The Shiroro Dam in North Central Nigeria is one of the primary hydroelectric storage facilities. The facility has an initial installed capacity of 600 MW, a surface area of about 320 km2, a total storage capacity of 7 billion m3 of water [13], and a crest length of 700 m [14]. It is located at latitudes 9° 46 '35" and 10° 08' 36" N and longitudes 6° 50' 51" and 6° 53' 14" E (Figure 1). Approximately 70% of the discharge into the Shiroro reservoir comes from the River Kaduna, while the remaining 30% originates from the rivers Dinya, Guni, Sarkin-Pawa, Erena, and Muyi [15]. The study area experiences wet and dry seasons, with rainfall occurring from May to October, and temperatures ranging from 27°C to 35°C [16]. The population of Shiroro Local Government Area, where the dam is situated, was 235,665. Most residents engage in subsistence farming, fishing, hunting, trading, and weaving [15, 16]. Its vegetation is predominantly savannah, with sparse woodlands consisting mainly of trees, along with shrubs and grasses [16], and the primary soil type is luvisols [16]. Moreover, the terrain is characterised mainly by gentle slopes [16].

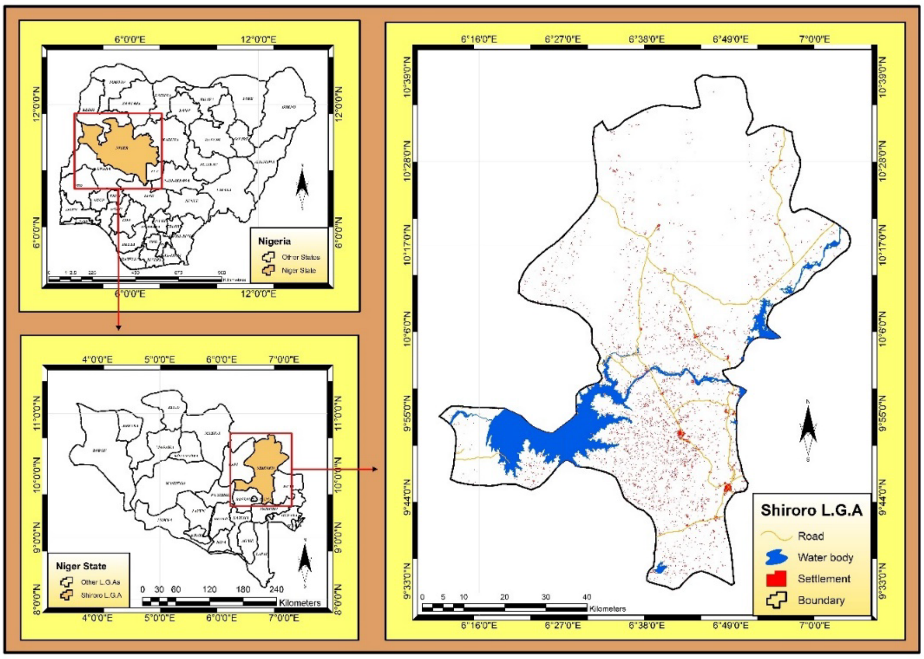

Figure 1: Locational map of Shiroro Dam

2.1 Theory of SWAT model

The SWAT model is a physically-based model developed to predict the impact of BMPs on eroded sediment, nutrients, and streamflow [17, 18, 19] by dividing the watershed into subbasins and hydrologic response units

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according to the land use, soils, and slope steepness. This model used water-balance equations to determine the available water in the channel of each subbasin [17, 18, 19], with channel routing to account for water movement through the dam.

2.1 Theory of SWAT model

DEM provides data on the terrain (slope) and elevation of the study area, which affects runoff and water infiltration. In this study, a 30 m DEM resolution was downloaded from http://srtm.csi.cgiar.org.

The land use map categorises the Earth's surface into various land-use types. Global land use has a higher resolution, which enhances model performance because it affects the curve numbers used in runoff calculation. The land-use map was downloaded from https://www.usgs.gov. This data was used to produce the land use map (Appendix I).

The global soil map provides data on soil textural classes, depth, and hydraulic conductivity, which influence water movement and retention. It was derived from the harmonised digital soil map of the world, developed by the Food and Agriculture Organisation, and downloaded from http://www.fao.org. It was used to produce soil map (Appendix II).

The climatic and hydrological data used were also collected from the Shiroro dam and the Solcast API. The data covers from 2011 to 2021.

2.3 Watershed delineation and hydrological response units

The boundary of Shiroro Dam was delineated using the polygon tool from Google Earth. Afterwards, the boundary was clipped to the digital elevation model using a standard procedure. The flow direction and accumulation (area: 5,904 ha) were extracted from the DEM, which includes water (5,759.88 ha) and agricultural land (144.4786 ha). The dam outlet was selected and defined before the model's sub-basin parameters were calculated. The delineated area was divided into 18 subbasins and 35 Hydrologic Response Units (HRUs). HRUs were generated using the multiple HRU option based on land use, soil type, and slope classes, with thresholds of 20% for land use, 10% for soil, and 20% for slope. The slopes of the delineated area were categorised into three: 0-10 % (4780.4266 ha), 10-20% (975.7604 ha), and above 20% (148.178 ha). The land-use and soil maps for the delineated area reflect the watershed's processes. Meteorological data were prepared for the years 2011-2021. The model input data was used to run the Soil Water Assessment Tool (SWAT), and the model was run for eleven (11) years as shown in Figure 2.

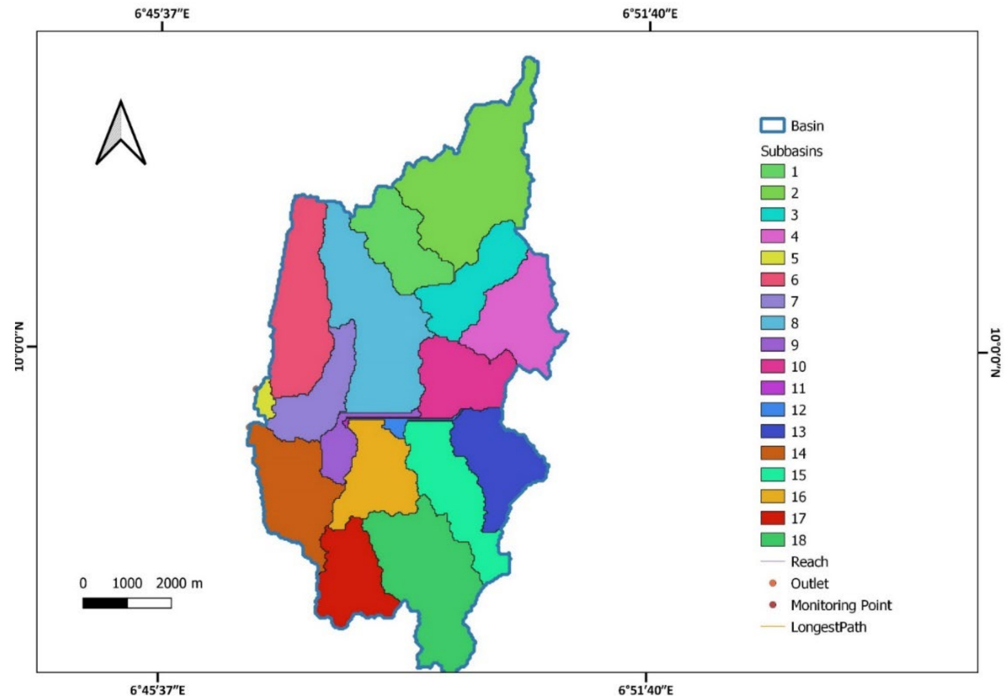

Figure 2: Delineation of Shiroro Watershed

2.4 Selection of SWAT Input Parameters

Table 1 presents the selected SWAT input parameters. The parameters were selected based on these literature reviews of related studies on streamflow prediction [15, 30]. The study employed the Latin hypercube method to calibrate discharge by varying the SCS runoff curve number for moisture condition and the USLE equation support practice factor in ArcSWAT.

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Table 1: Selected SWAT input parameters

S/N	SWAT Parameters	Description of the parameters	Minimum value	Maximum value
1	r__CN2.mgt	SCS runoff curve number for moisture condition	-0.2	0.2
2	v_ALPHA_BF.gw	Alpha factor	0	1
3	v__GW_DELAY.gw	Groundwater delay	30	450
4	v__GWQMN.gw	Threshold water depth aquifer	0	2
5	r__GW_REVA P.gw	Groundwater "revamp" coefficient	0	10
6	v__ESCO.hru	Soil evaporation compensation factor	0	1
7	r__CH_N2.rte	Manning's 'n' value	0	3
8	r__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium	5	130
9	r__SOL_K().sol	Saturated hydraulic conductivity	-0.8	0.8
10	r__SOL_BD().sol	Moist bulk density	-0.5	0.6
11	r__SOL_AWC().sol	Soil water storage capacity	-0.2	4

2.5 Best Management Practices (BMPs)

BMP scenario modelling was conducted using the SWAT model to evaluate discharge reduction in the Shiroro catchment. This study focused on common farming practices and integrated them into the SWAT model, such as terracing, contouring, and strip cropping. The control practice is termed "no BMP." These BMPs have been shown to reduce surface runoff by increasing infiltration, reducing water erosion, and lowering the amount of eroded sediment [4]. However, their application was absent around the Shiroro dam site, where crops are cultivated. The BMP scenario modelling mainly involved adjusting the curve number (CN2) and USLE Support Practice Factor (P) based on a related study [22], but did not consider slope in the study area. Table 2 displays the modifications made to SWAT input parameters in ArcSWAT to represent three BMPs. The SCS runoff curve number (CN2) and the USLE support practice factor (P) were modified along with the slope of study area (Table 2). Following these adjustments, the model for each practice was saved in the SWAT TxtinOut. These models were then used to calibrate and validate contouring, strip cropping, terracing, and the control practice (no BMP). This approach better reflects current local farming practices. This method enhances the ability of the model to simulate hydrological responses more accurately in ABMP scenarios. Incorporating the SCS runoff curve number (CN2) and the USLE support practice factor (P) addresses a key gap identified in previous studies, where reliant on default parameters compromised model reliability for conservation planning.

Table 2: Modification of SWAT Input Parameters

S/N	BMPs	SWAT Input Parameters	Original Value	Modified value	Slope (%)
1	Terrace	SCS runoff curve number (CN2) USLE equation support practice factor (P)	91 1	71 0.10	0-10
2	Contour	SCS runoff curve number (CN2) USLE equation support practice factor (P)	91 1	75 0.5	3-5
3	Strip cropping	SCS runoff curve number (CN2) USLE equation support practice factor (P)	91 1	75 0.38	3-5
4	No BMP	SCS runoff curve number (CN2)	91 1		3-5

S/N	BMPs	SWAT Input Parameters	Original Value	Modified value	Slope (%)
		USLE equation support practice factor (P)			

Furthermore, a potential reduction in monthly discharge was calculated as:

$$Reduction, \% = \frac{y_1 - y_2}{y_1} \times 100 \quad (1)$$

where y_1 and y_2 represents the mean model outputs before and after the implementation of BMPs.

2.6 Model optimisation, calibration, validation and uncertainty analysis

Sensitivity analysis evaluates the effect of selected parameters on monthly discharge, concentrating on 11 parameters. The study used the Sequential Uncertainty Fitting algorithm (SUFI-2), which applies optimisation within a Bayesian framework to calibrate and validate discharge [17, 18, 19, 20, 21, 22, 23, 24]. SUFI-2 helps to identify the most sensitive parameters affecting discharge, which vary with watershed characteristics and data input. The maximum, minimum and fitted values were shown in Table 1.

SUFI-2 algorithm was used to calibrate the discharge. Calibration involves comparing simulated discharge with observed data from January 2011 to December 2018 and optimise model parameters. The objective function used in this study was Nash-Sutcliffe efficiency (NSE), which measures how well the predicted values match observations during calibration. Moreover, the validation involves comparing the discharge with observed discharge which covers between January 2019 and December 2021, while keeping the eleven fitted SWAT input parameters constant. The calibration framework combines sensitivity analysis and optimisation algorithms to identify sensitive parameters and improve the accuracy of discharge simulations in watersheds.

Moreover, SUFI-2 algorithm was employed to analyse uncertainty in hydrological modelling due to its robustness in the SWAT model. The parameter used to analyse the uncertainty include p and r factors and percent bias. The p-factor ranges from 0 to 1, quantifying the proportion of recorded discharge data within the simulation Uncertainty 95% (95PPU) band. Any value of p above 0.7 or 0.75 is okay. Moreover, R-factor also measures the fraction of the mean 95% simulation Uncertainty width and the standard deviation of the observed discharge data, and the appropriate value of r is less than 1.5 [7, 15]. Furthermore, the Percent Bias (PBIAS) also quantifies the mean tendency of the predicted discharge comparative to the recorded discharge. The PBIAS with zero value means the best fit. The PBIAS with a low value means better prediction. Its high value above 25% means overestimation, while negative means underestimation [7, 30, 17, 23].

2.7 Model Performance Indices

The objective function employed to compare the predicted and observed discharge was Nash-Sutcliffe Efficiency (NSE). Other indices identified were coefficient of determination (R^2) and Percent Bias (PBIAS). These indices were computed as follows:

$$\text{Nash} - \text{Sutcliffe efficiency (NSE)} = 1 - \frac{\sum_{=i}^{n}(O_i - P_i)^2}{\sum_{=i}^{n}(O_i - O_{avr})^2} \quad (2)$$

$$\text{Coefficient of determination } (R^2) = \left[\frac{\sum_{=i}^{n}(O_i - O_{avr})(P_i - P_{avr})}{\sum_{=i}^{n}(O_i - O_{avr})^2 \sum_{=i}^{n}(P_i - P_{avr})^2}\right]^2 \quad (3)$$

$$\text{Percent bias (PBIAS)} = \left[\frac{\sum_{=i}^{n}(O_i - P_i) \times 100}{\sum_{=i}^{n}(O_i)}\right] \quad (4)$$

Where,

$O_i = i^{th}\, observed\ value,$

$O_{avr} = average\ observed\ value\ of\ the\ entire\ study\ period,$

$P_i = i^{th}\, simulated\ value,$

$P_{avr} = average\ of\ simulated\ value.$

3.0 Results and Discussion

Table 3 presents monthly descriptive statistics for discharge from 2011 to 2021. In the study area, the wet season is divided into three phases: onset, peak, and decline. The wet season begins in early April. June had an average discharge of 273.1 m3/s, with a standard deviation of 101.92 m3/s. This streamflow increased sharply in August to 1007.98 m3/s, with a high standard deviation of 210.52, which is 3 times the average discharge in June. This streamflow surge was caused by rainfall and runoff. In addition, September had the highest average monthly streamflow of 1451.95 m3/s, which is 5 times that of June, with a standard deviation of 461.58 m3/s. The discharge had a range value of 1339.77, indicating flood-prone periods. The streamflow (discharge) decreased from 1451.95 m3/s in September to 633.26 m3/s in October, indicating a 56% decrease. This finding is consistent

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with related work [25], which found that September had the highest discharge of 2,900 m3/s. During high-flow seasons, when rainfall strongly influences streamflow, consistent with the peak discharge period identified in this research [26, 27]. The conspicuous low-flow season from November to April, with reduced streamflow, aligns with global observations of seasonal low-flow during the dry season [27].

Table 3: Descriptive statistics of discharge between 2011 and 2021

Month	Mean (m^3/s)	Std. Deviation	Minimum (m^3/s)	Maximum (m^3/s)
Jan	50.53	15.55	27.29	76.29
Feb	29.66	11.06	14.32	49.83
Mar	24.13	18.76	1.48	55.26
Apr	20.30	8.66	7.43	33.00
May	97.15	45.65	13.55	168.71
Jun	273.31	101.92	130.6	434.50
Jul	614.05	215.96	330.1	906.97
Aug	1007.98	210.52	745.39	1304.58
Sep	1451.95	461.58	1027.17	2366.93
Oct	633.26	301.42	288.71	1382.26
Nov	134.43	63.83	78.30	316.13
Dec	73.54	19.71	39.65	113.84

3.2 Watershed delineation and Hydrological response unit of Shiroro dam

The watershed covers a total area of 5,904.37 ha (Figure 2). It is divided into 18 subbasins and ranges from 0.03% (2 ha in Subbasin 11) to 12.72% (751 ha in Subbasin 2). Water bodies dominate the landscape, making up 97.55% of the watershed area. Agricultural land is mainly concentrated in subbasins 5 (41%), 7 (23%), 12 (21%), and 13 (21%). The watershed features different slopes; for instance, subbasin 13 has steep slopes (>20%) over more than 45% of its area. Other slopes vary from flat to moderate (0-10%). The primary land use in the watershed is agriculture (51.24%), followed by water (45.14%), forest (3.54%), and residential land (0.07%). The main soil type is ferric luvisol (80.30%), with lithosol constituting the remaining 19.70%. It also supports diverse land-cover and hydrological responses across the watershed [28, 29].

3.3 Sensitivity analysis of discharge of Shiroro dam site

The results of the discharge sensitivity analysis are shown in Appendix III. The saturated hydraulic conductivity (SOL_K) indicated a t-statistic of 3.3832, followed by the moist bulk density (SOL_BD), with a value of -2.4011, along the ridge on the slope. These indicate the most sensitive parameters. Other SWAT parameters had lower t-statistic values, implying less sensitivity, supported by p-values greater than α (0.05) (Appendix III). For contouring, the SCS runoff curve number (CN2), SOL_K, and available water capacity of soil (SOL_AWC) had t-statistic values of 7.3229, 7.1192, and -3.3189, respectively, indicating high sensitivity. In strip cropping, SOL_K and CN2 were highly sensitive, with t-values of 16.9486 and 94.5994, respectively. The terracing scenario revealed SOL_K, CN2, and SOL_BD as the most sensitive parameters, with t-statistics of 101.0555, 18.7268, and 9.2299, respectively. Overall, higher t-statistics combined with p-values less than 0.05 indicate greater parameter sensitivity to streamflow [30, 31, 32].

Soil saturated hydraulic conductivity (SOL_K) consistently emerges as the most sensitive parameter in streamflow modelling because it directly controls water infiltration into the soil. It also affects runoff generation and groundwater recharge. SOL_K determines how quickly water moves through soil pores and influences runoff and subsurface flow components, which are vital to streamflow dynamics [33, 34, 35]. Few SWAT-based studies have identified SOL_K as a key driver of hydrological responses across various watersheds, including mountainous, loess-plateau, and agricultural regions. These studies reaffirm its fundamental role in managing water movement [33, 36, 37]. SOL_K was ranked as the most sensitive parameter impacting discharge at both daily and monthly resolutions, alongside CN2 and baseflow factors in China [33, 36]. Furthermore, its significance is connected to soil moisture content and soil water storage capacity, which influence runoff generation [34, 37]. Therefore, selecting soil saturated hydraulic conductivity, soil moisture content, and soil water storage capacity during the calibration and validation of the SWAT model enhances flow prediction.

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3.4 SWAT model calibration, validation and uncertainty analysis

The predicted discharge had NSE and R^2 values of 0.52 and 0.53, respectively, for the model without BMP. Other parameters include p-factor, r-factor, and PBIAS, with values of 0.13, 0.10, and -4.50 during calibration (Figure 6). Similar results were observed during validation. The monthly simulated discharge matched the observed data, with NSE and R^2 values of 0.58 and 0.63, respectively. Furthermore, the P-factor, R-factor, and PBIAS were 0.28, 0.42, and 20.50 during validation (Figure 6). These findings are consistent with related studies [38, 39, 40]. The results indicate that the values of p and r factors were acceptable.

In contouring, the NSE and R^2 values ranged between 0.58 and 0.64, and 0.58 and 0.65, respectively in the calibration and validation (Figure 7). Their corresponding value for PBIAS varied between -2.8 and –8.1, while p and r factors ranged from 0.07 and 0.31, 0.02 to 0.48, respectively. It means that NSE values were satisfactory during calibration and validation. Moreover, it means that the PBIAS values were underestimated. The results of uncertainty analysis indicated that the p and r factors were okay. These findings align with existing and related studies [38, 39, 40].

In strip cropping, the NSE and R^2 values ranged between 0.58 and 0.65, and 0.58 and 0.65, respectively in the calibration and validation (Figure 8). Their corresponding value for PBIAS varied between -2.7 and – 0.81, while p and r factors ranged from 0.13 and 0.28, 0.19 to 0.39, respectively, implying that the NSE values were satisfactory during calibration and validation. Moreover, it means that the PBIAS values were okay in the validation stage. The results of uncertainty analysis indicated that the p and r factors were okay. These findings agree with existing and related studies [38, 39, 40].

Finally, the simulated discharge (terrace) is satisfactory, with NSE, R^2, R-factor, r-factor, and PBIAS values of 0.58, 0.58, 0.09, 0.07, and -3.20 (Figure 9). Similar results were obtained during validation, with NSE, R^2, P-factor, R-factor, and PBIAS values of 0.58, 0.65, 0.22, 0.05, and 23.30, respectively (Figure 9). These discoveries agree with related studies [38, 39, 40]. Furthermore, research conducted in India watershed discovered that the values of NSE were 0.74 and 0.69 during calibration and validation. The corresponding values for P-factors ranged from 0.7 to 0.8 [38]. In addition, a study conducted in Australian catchment discovered that an NSE greater than 0.5 is appropriate [41].

Comparisons also show that strip cropping and contour practices yielded superior model performance relative to terraces, consistent with other research emphasising the influence of land management on the accuracy of hydrological response simulations [42, 43, 44]. Some studies note underestimation issues during validation phases similar to those observed in our results for terraces but confirm SWAT's capability to simulate discharge well when properly calibrated. The use of multiple objective functions and optimisation algorithms like SUFI-2 enhances parameter estimation reliability, uncertainty quantification, and supports the robustness of the results [40, 42, 45]. The calibration, validation, and uncertainty analysis results demonstrate acceptable model performance, consistent with established SWAT modelling studies globally, confirming the suitability of the applied methods for simulating streamflow under various best management practices, with quantified uncertainties [38, 39, 40, 42]. Strip cropping and contour practices appear particularly robust in predictive accuracy compared to terraces based on these performance indices.

3.5 Prediction of discharge of Shiroro dam

3.5.1 Calibration

In the Shiroro dam sub-basins, the monthly predicted discharge had mean values of 356 m^3/s and 350.11 m^3/s, respectively, for the model without BMP and contouring (Appendices IV and V), with maximum values of 356 m^3/s and 1,698 m^3/s, respectively. The average values for predicted discharge were 349.92 m^3/s and 351.44 m^3/s, respectively, for strip cropping and terracing (Appendices VI and VII), with maximum values of 1703 m^3/s and 1709 m^3/s for strip cropping and terracing, respectively. The upper limit of the 95PPU band during the discharge event was estimated at 1,698 m3/s, which was 1.2 times lower than the observed peak discharge, implying underestimation. These findings align with previous studies reporting discrepancies between simulated and observed peak sediment concentrations [4]. However, the study did not capture discharge. The variation may be due to factors such as climate change.

3.5.2 Validation

The average monthly predicted discharge values were 338 m^3/s and 459.5 m^3/s, respectively, for the model without BMP and contouring (Appendices IV and V), with maximum values of 1151 m^3/s and 1486 m^3/s. Furthermore, the mean discharge values were 419 m^3/s and 325 m^3/s for strip cropping and terracing, respectively (Appendices VI and VII). Their corresponding highest flow values were 1396 m^3/s and 1034 m^3/s, respectively. The upper limit of the 95PPU band during the discharge event was estimated at 1396 m3/s, which was less than the observed peak discharge, implying SWAT model could not capture the peak discharge but mean discharge well. There may be a need to use other models such as artificial intelligence to improve the peak flow and reduce flood risk management.

3.6 Evaluation of the BMPs and their effects on discharge reduction of Shiroro dam using SWAT model

Table 4 presents descriptive statistics for the simulated discharge reduction of Shiroro dam under BMPs (2019-2021). The results indicate that contouring, strip cropping, and terracing affect streamflow. Contouring had a mean simulated discharge of 459.50 m^3/s and reduced simulated discharge by 8%, while terracing had a stronger effect, reducing discharge by 23%. Strip cropping had a smaller impact, decreasing streamflow by only 1.3%. While no terrace increased discharge by 20%. These findings are consistent with other studies reporting that terracing (bench terraces) can reduce runoff by approximately 19% [46] and that contouring practices can reduce overland flow by more than 18% [47]. It implies that terraces and contour farming will reduce discharge and sediment yield. The application of terracing and contouring is an effective conservation practice for reducing discharge. The research contributes to the body of knowledge by evaluating ABMPs and their effects on discharge reduction of Shiroro dam using SWAT model, altering the flow regime relevant to hydropower and sediment reduction, and potentially mitigating reservoir siltation [1, 6, 2, 3, 5]. Moreover, the application of optimal conservation practices would increase water infiltration and reduce both surface runoff and discharge.

Table 4: Descriptive statistics for simulated discharge under BMPs practice during validation (2019-2021)

S/N	Variables (BMPs)	Mean	Maximum	Minimum
1	Contouring	459.50	1486.00	13.00
2	Strip cropping	419.44	1396.00	11.00
3	No BMP	338.00	1151.00	24.00
4	Terracing	325.94	1034.00	13.00

Limitations of the study

This research is limited to BMPs modelling, which captures the average discharge but does not capture peak discharge. There is a need to combine SWAT model with artificial intelligence to improve the peak discharge, which is critical part of flood risk management. In addition, there is an urgent need to conduct field measurements of soil saturated hydraulic conductivity (SOL_K) and other sensitive parameters in future to predict the discharge using SWAT model and artificial intelligence and recalibrate the model to better capture the extremes discharge at Shiroro dam.

4.0 Conclusion

The study evaluated BMPs and their effect on discharge reduction of Shiroro dam using SWAT model. This research revealed that the predicted and observed discharge values are in good agreement for contouring, strip cropping, and terracing. The findings suggest that the models for contouring, strip cropping, and terracing are satisfactory. The sensitivity analysis also revealed that soil saturated hydraulic conductivity was ranked as the most sensitive parameters that changes the discharge across the BMP practice. Compared with discharge predictions across the BMP practice at Shiroro Dam, the contour model is more reliable, as its performance indices exceeded 0.60 during validation. However, its PBIAS indicates underestimation (-8.10). The percentage reduction of annual discharge by terracing 23% followed by contouring (8%), and strip cropping (1.3%). In contrast, without BMP, simulated streamflow increases by 20%. These findings imply that application of terrace and strip cropping on the agricultural land of Shiroro Dam would reduce excess discharge and thereby reduce flooding at the dam outlet. It also means that terracing and contouring were appropriate conservation practices for growing crops around the dam and produced higher percentage reductions in discharge. As a result, terracing and contouring are recommended as the best management practices to reduce excess discharge into Shiroro Dam. Field measurement of soil saturated hydraulic conductivity (SOL_K) and other sensitive parameters are required in future to predict discharge using SWAT model and artificial intelligence.

CRediT authorship contribution statement

Ibrahim Abayomi Kuti: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Software, Validation, Visualization, Investigation and Writing - review & editing. **Sunday Emmanuel Ogunmola**: Visualization, Investigation and Writing. **Peter Aderemi Adeoye**: review & editing.

Conflicts of Interest

The authors affirm that they have no conflict of interest.

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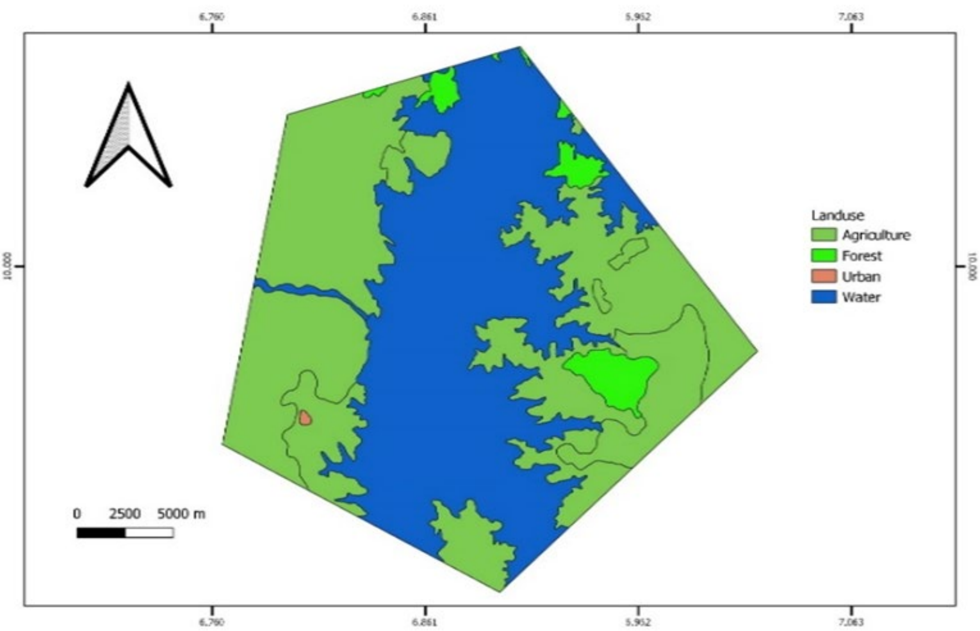
Appendix I: Land-use



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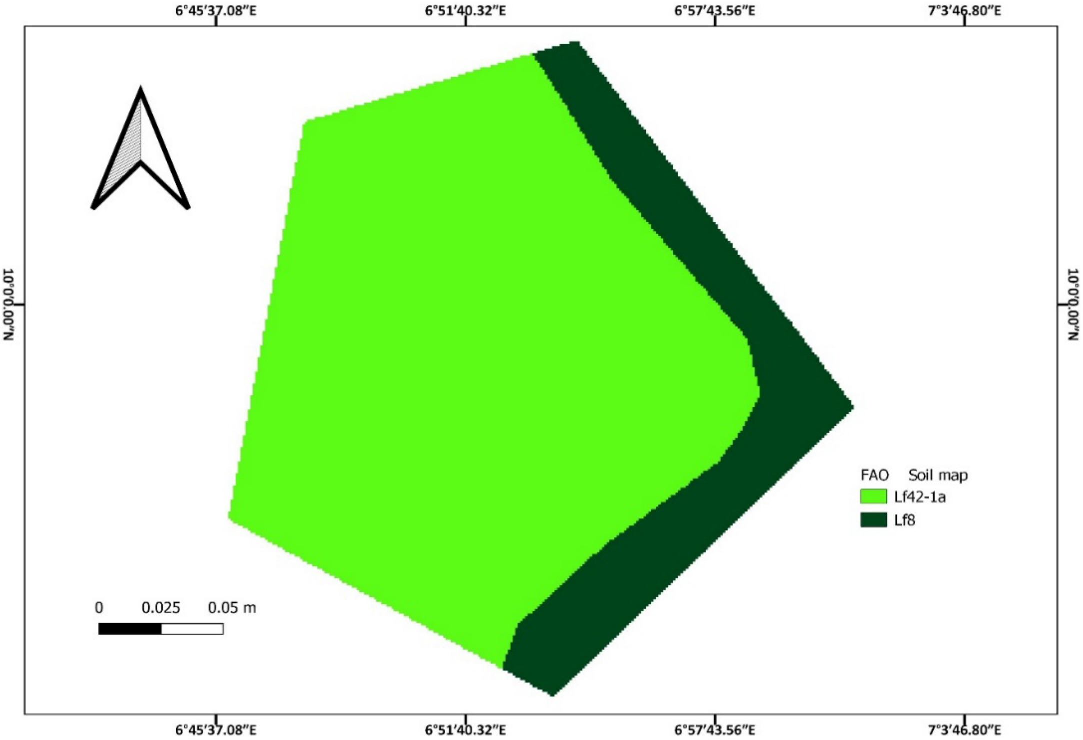
Appendix II: soil map



Appendix III: Sensitivity analysis of discharge during validation (a) no BMP, (b) Contouring, (c) Strip Cropping, and (d) Terracing

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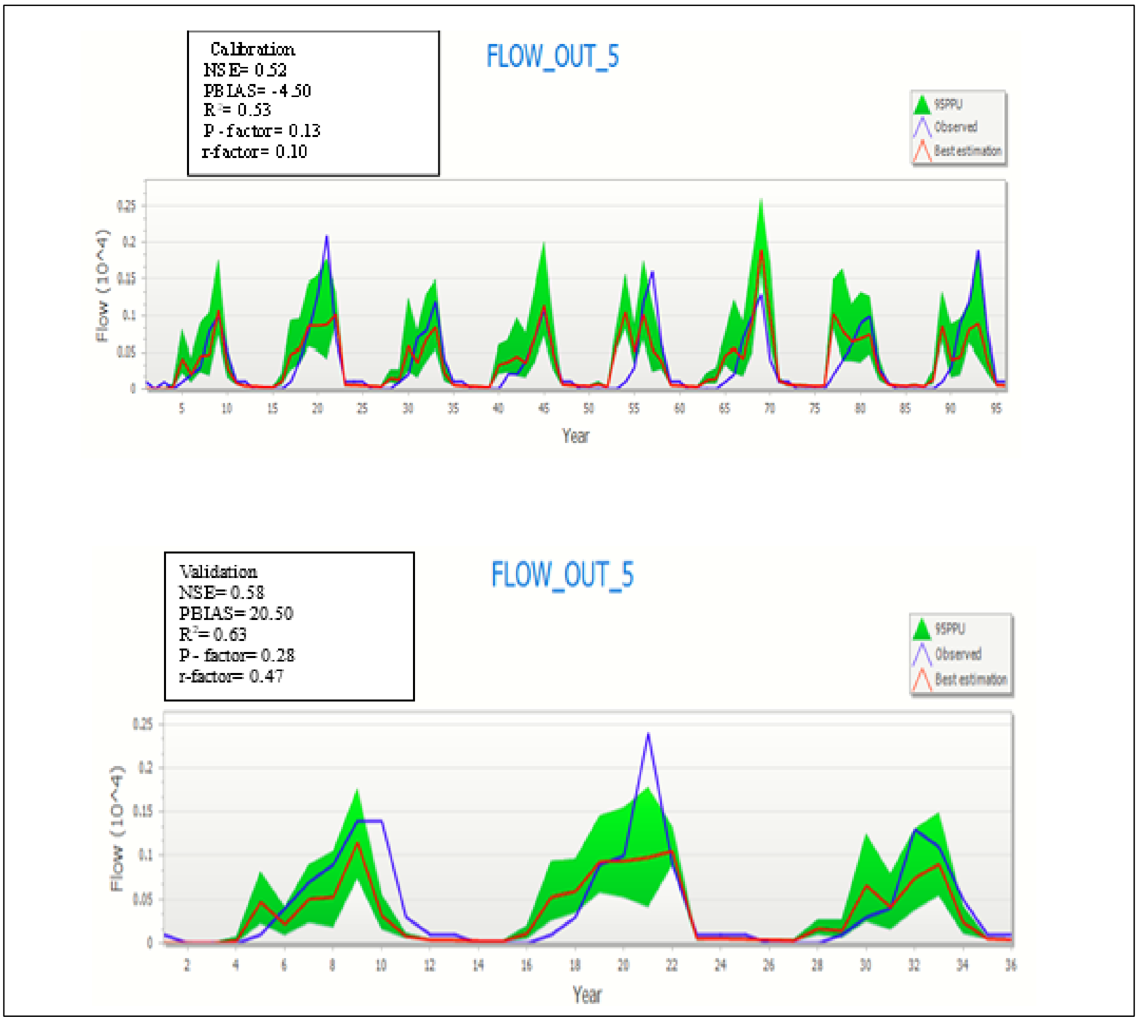
Appendix IV: Monthly Observed Vs SWAT Simulated discharge for calibration in no BMP



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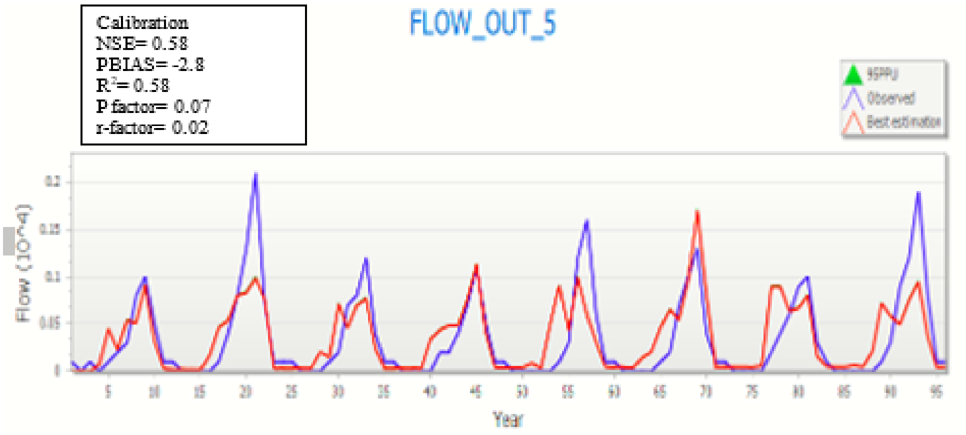
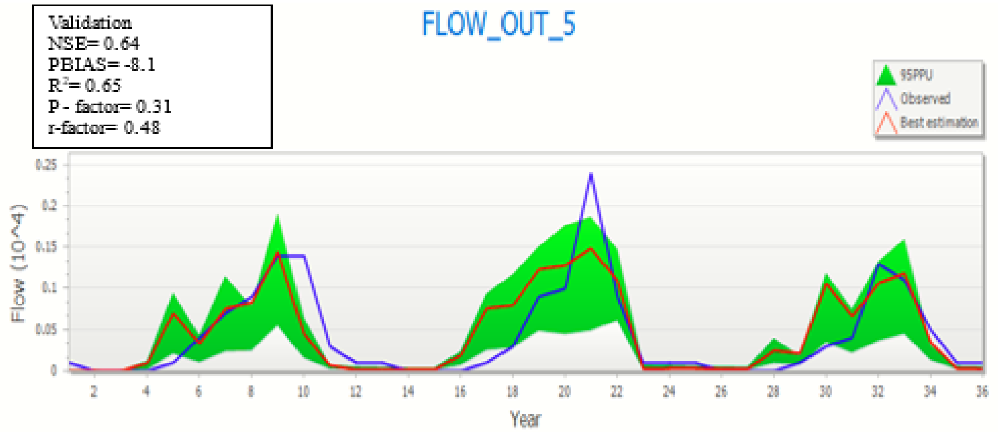
Appendix V: A Monthly Observed Vs SWAT Simulated discharge for calibration and Validation in a contouring





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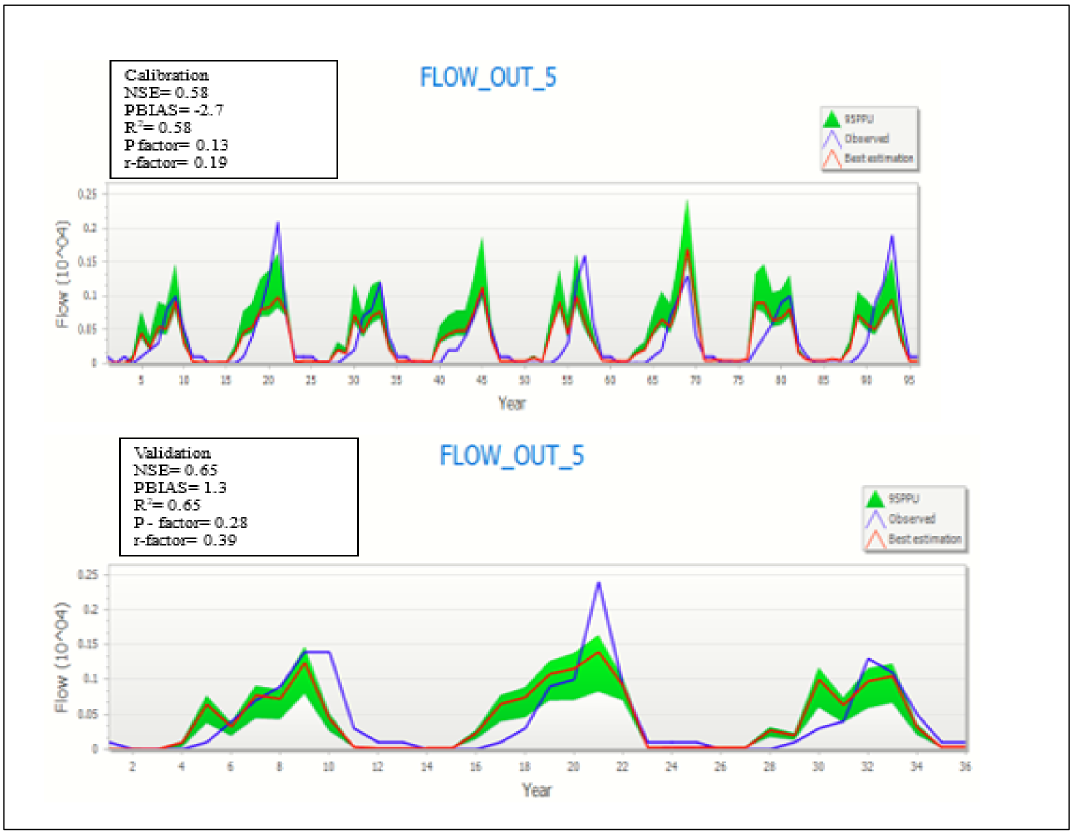
Appendix VI: A Monthly Observed Vs SWAT Simulated discharge for calibration and Validation in a Strip Cropping



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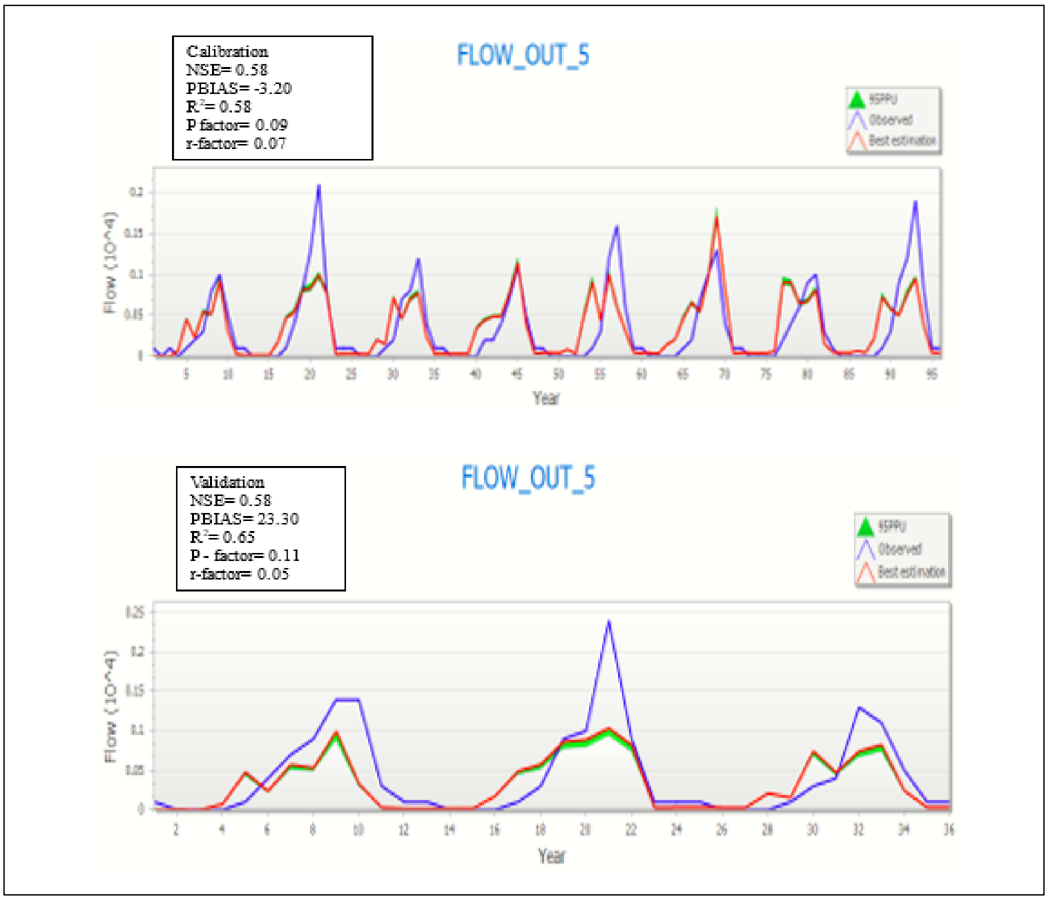
Appendix VI: A Monthly Observed Vs SWAT Simulated discharge for calibration and Validation in a terracing



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