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UNCERTAINTY ANALYSIS AND CALIBRATION OF SWAT MODEL FOR ESTIMATING IMPACTS OF CONSERVATION METHODS ON STREAMFLOW AND SEDIMENT YIELD IN THIKA RIVER CATCHMENT, KENYA

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ABSTRACT

Despite their imperative role in water resources management, distributed hydrological models like SWAT require calibration that can be challenging due to uncertainties of parameters involved. Prior to modelling of hydrological processes, these parameters and their uncertainty range need to be identified. The objective of this study was to conduct uncertainty analysis of hydrological processes and to calibrate the Soil and Water Assessment Tool (SWAT) for stream flow and sediment yield modelling in Thika River catchment. Sequential Uncertainty Fitting program (SUFI-2) was used to conduct sensitivity and uncertainty analysis. Stream flow was calibrated and validated between the years 1998 to 2013 for gauging stations 4CB05 and 4CB04. Manual sediments calibration was achieved by constraining the MUSLE parameters using the bathymetric survey data. Two uncertainty indices, p and r factor, were obtained as 0.72 and 0.65, 0.65 and 0.45 during calibration and validation, respectively. Statistical performance indicators showed a good match between the observed and simulated values which indicated that the model was well calibrated for simulation of stream flow and sediments yield in the catchment.

Contribution/Originality: This study contributes in the existing literature on the estimation of base scenarios using sequential uncertainty fitting algorithm. The study outlines the analysis of parameter uncertainties and calibration for estimating impacts of conservation methods on stream flow and sediment yield.

1. INTRODUCTION

Thika River catchment is the major source of surface water that contributes 90% of water consumed in Nairobi city and surrounding areas. Recently, catchment degradation through unsustainable farming methods and the influence of climate change has posed a great threat to the existing water resources. Increased conversion of previously uncultivated lands to small holder farms has been attributed to high soil erosion rates and subsequent deterioration of water quality and sedimentation of reservoirs [1]. Management of water resources and soil conservation are needed to effectively plan for the sustainability of the catchment. Soil and water conservation however involve understanding the complex hydrological processes both at the surface and subsurface level [2].

Agricultural best management practices influence biophysical processes that affects ecosystem services directly and thus provides a framework for planning and decision making on management of water resources.

Previous studies conducted in the catchment highlighted the importance of soil and water conservation measures and the magnitude of ecosystem services restored when such measures are implemented [3]. While implementation and management of conservation methods can reduce soil erosion and improve water quality, their effectiveness at the catchment level needs to be evaluated.

Hydrological distributed models have been used to evaluate the impacts of soil and water conservation measures on ecosystem services including water provision, nutrient retention and sediment yield [4-8]. These models therefore could be used by policy makers and researchers to model water resources and soil quality degradation by assessing the suitability of conservation methods or streamflow trends in a given catchment [9]. Faramarzi, et al. [10] used a hydrological model to simulate blue and green water resources availability in Iran. Phomcha, et al. [11] used SWAT to determine the impacts of soil conservation practices in an agricultural watershed. Abbaspour [12] used a modelling approach to assess the hydrology and water quality in Thur catchment, Switzerland.

From the review of preceding literature, it is explicit that understanding biophysical processes in the catchment is important for simulating ecosystem services like provision of water quantity and quality. The accuracy of the model to simulate catchment processes is assessed through uncertainty analysis of parameters and a precise calibration process [13]. A number of methods and algorithms have been developed for uncertainty analysis and calibration of models. They include but not limited to Generalized Likelihood and Uncertainty Estimation (GLUE), Sequential Uncertainty Fitting (SUFI-2), Particle Swarm Optimization (PSO) and Parameter Solution (ParaSol). Some of these methods are integrated with the SWAT model to establish parameters affecting hydrological processes and their respective uncertainties.

SWAT model has been used in other studies to analyze parameters influencing hydrological processes and their uncertainties [9]; [14]. For example in Wenjing river catchment, Wu and Chen [15] assessed the uncertainty estimates using SUFI-2, GLUE and ParaSol. They reported that SUFI-2 method produced better simulated results than any of the other methods. Research conducted by Uniyal, et al. [16] reported that SUFI-2 algorithm is promising in uncertainty analysis of parameters and recommended further studies in other catchments with varying agro-climatic conditions to assess their applicability. In Thika river catchment, uncertainty analysis of parameters governing hydrological processes and that are critical in modelling ecosystem services in the region has not been conducted. The objective of this study was to apply the sequential uncertainty fitting algorithm coupled with SWAT model to analyze parameter uncertainties and to calibrate the SWAT model for evaluating the impacts of conservation methods on streamflow and sediment yield. The study also aims at providing scientific locus based on the analysis of the catchment's parameters uncertainty for water experts and policy makers to promote management of resources through soil and water conservation.

2. MATERIALS AND METHODS

2.1. Study Area

Thika River catchment is located in central Kenya and is the main source of water for Nairobi and surrounding areas. It covers an average area of 839 km^2 and is situated between longitude 36.60° and 37.60° E and latitude 0.58° and 1.17° S (Figure. 1). The catchment has two main rivers, Thika and Chania, that has a confluence at gauging station 4CB04 that was selected as the outlet of the catchment. The region receives bimodal rainfall pattern with high peaks in March to May and short rains from October to December. The rainfall varies from 800 mm in low altitudes to 2200 mm in high altitudes areas of the catchment [17]. At the outlet of the catchment, temperatures are high (25° to 30° C) compared to high altitude areas (18° to 20° C) [18]. Elevation in the catchment varies from 1449 m at catchment outlet to 3861 m above mean sea level at the headwaters.

The upper Tana Land use map (2009) obtained from International Soil Reference and Information Center-Green Water Credit (ISRIC-GWC) was used as the base map to classify the land use types in the catchment. Small holder rainfed agriculture is the major land use and due to increase in population, previously uncultivated lands have been converted to agricultural lands A strip of forest cover is found in the upper parts of the catchment that separates the agricultural lands and helps in maintaining water quality and quantity [1] (Figure. 2). The major crops grown in the catchment include coffee, tea, corn and horticultural crops.

The catchment has more than 10 soil types that support different land uses as shown in Figure. 3. Dominant soil types include Umbric Andosols, Humic and Rhodic Nitisols that are found in the middle and lower reaches of the catchment where agriculture is the main land use.

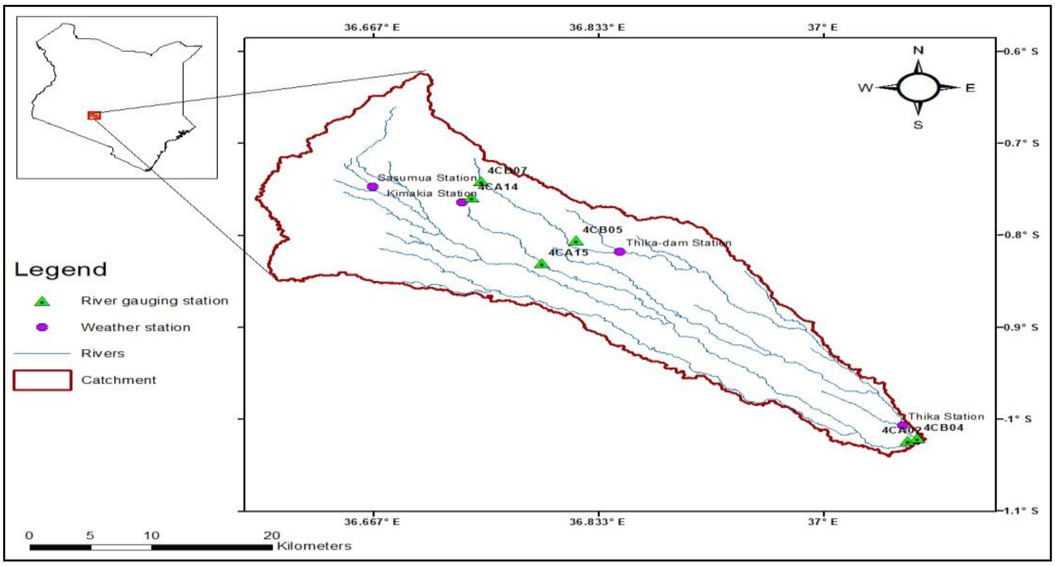

Figure-1. Location of Thika river catchment.

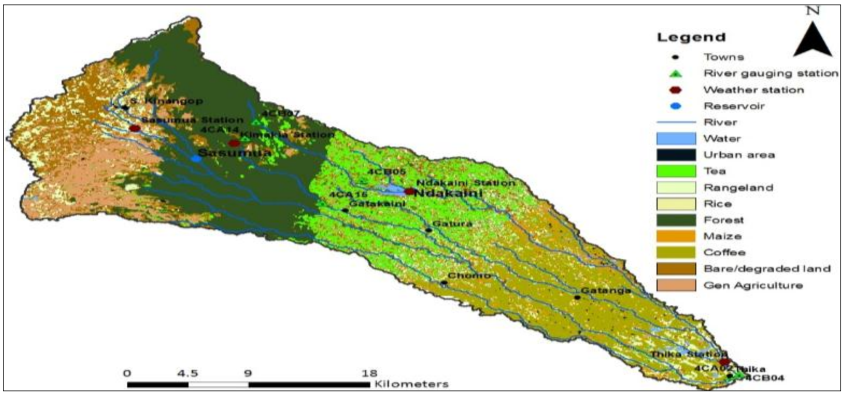

Figure-2. Land-use/cover in Thika river catchment.

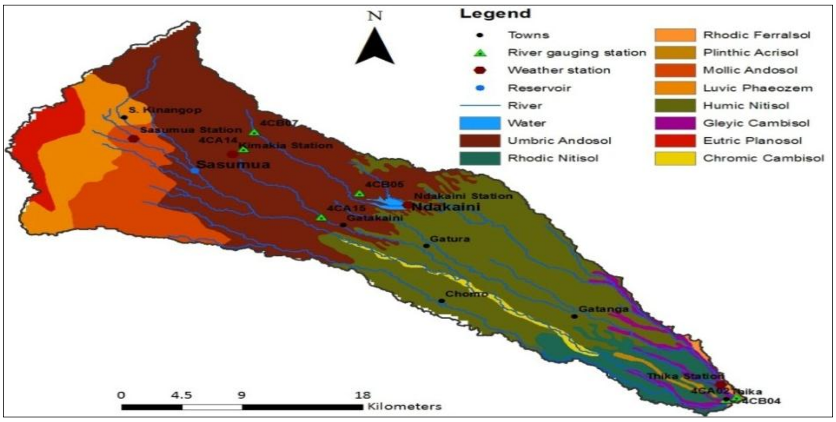

Figure-3. Soil types in Thika river catchment.

2.2. SWAT and SWAT-CUP Description

SWAT is a process based distributed hydrological model that operates on a daily time step to simulate ecosystem services. Hydrology in the catchment is divided into land and routing phase [19]. The routing phase models water and sediments movement through a river or channel. The land phase models the amount of water, sediments, pesticides and nutrients that enter the main channel in every sub-catchment. This phase is described in equation (1) where SW_t is the final soil water content (mm), SW_o is the initial water content in day i (mm), R is the amount of precipitation in day i (mm), Q_s is the amount of surface runoff in day i (mm), E_a is the amount of evaporation in day i (mm), W_{seep} is the amount of water entering the vandose zone in day i (mm) and Q_{qw} is the amount of return flow in day i (mm) [20].

$$SW_t = SW_0 + \sum_{i=1}^{t} (R - Qs - E_a - W_{seep} - Q_{gw}) \quad (1)$$

SWAT-CUP is a software that incoprorates the automatic calibration, validation and uncertainty analysis in SWAT model. All SWAT parameters can be included during the calibration process including management, catchment and weather generator parameters. SWAT-CUP includes a multi-site, semi automated inverse modelling routine SUFI-2 for calibration and uncertaintiy analaysis [10]. In SUFI-2, uncertain parameters accounts for all sources on uncertainties including climate data, model parameters and observed data. Propagation of the uncertainties in the parameters leads to uncertainties in the model output which is expressed as 95% probability distributions [21]. Propagation of uncertainties is conducted using Latin hypercube sampling expressed as 95% prediction uncertainty (95PPU). Measures quantifying the strength of a calibration or uncertainty analysis include the r-factor which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. Calibration and prediction uncertainty is judged on the basis of the closeness of the p-factor to 100% (i.e., all observations bracketed within the prediction uncertainty) and the r-factor to 1. The r-factor is determined using equation (2).

$$r - \text{factor} = \frac{p - \text{factor}}{\sigma_{obs}} \quad (2)$$

Five iterarions were used in SUFI-2 program where in each iteration, parameters ranges get closer to the region of the parameter space which provided better results in the previous iteration. As the parameter range becomes smaller, the 95PPU envelope get smaller implying that the objective function gets better in the subsequent iterations.

2.3. Data Acqusition and Model Set-Up

Daily streamflow data for River Gauging Station (RGS) 4CB05 and 4CB04 from 1998 to 2013 were used. The data was checked for consistency and gap filling was achieved through linear interpolation and correlation with records from neighboring stations. Climatic data including daily precipitation, minimum and maximum temperature, relative humidity and wind speed were collected from the Kenya Meteorological Department and Thika Dam station for the period between 1998 to 2013. A digital elevation model (30m resolution), soils and land use maps were uploaded to the SWAT interface after analysis in ArcGIS 10.2 software. The land use and soils obtained satisfactory overlap of more than 98% [22]. Climatic data were then uploaded to the model. The SCS curve number was used to compute the surface runoff while flow routing through the stream used the Muskingum routing method. FAO Penman Monteith formula was used to compute evapotranspiration rate in the catchment.

2.4. Uncertainty Analysis, Calibration and Validation

The sequential uncertainty fitting program was used to evaluate parameters sensitivity and uncertainty in simulating surface runoff. Latin hypercube sampling was used to conduct multiple regression system by setting the objective function as Nash Sutcliffe efficiency (NS). The threshold of the objective function (in this case 0.5 for NS) was used in determining the respective parameter sensitivities. Objective functions such as Root Mean Square Error (RMSE), coefficient of determination (R^2), NS and Chi-square have been used in many studies [23]. After one run of the Latin hypercube sampling, the initial uncertainty ranges were assigned to the respective parameters. Large parameters uncertainties were initially assumed so as to ensure that more observed data would be captured within the 95% Prediction Uncertainty band (95 PPU) [12]. The parameters ranges were then adjusted after every program run until the 95 PPU band bracketed most of the observed data. Data of low quality, for instance having many outliers, may have less than 0.5 of the data bracketed within 95 PPU [21]. To provide for the measure and significance of parameter sensitivity, t-test and p-values were used, respectively.

Streamflow data for the first two years (1998-2000) were used as model warm-up period for RGS 4CB05. The remaining data were split into two where those between 2000 to 2005 were used for calibration and the other (2006-2013) used for validation. To check whether the model correctly simulated the observed data spatially, graphical method was used to compare the observed and simulated values. for gauging station 4CB04 between the years 1998-2008. Begou, et al. [24] applied a similar methodology during streamflow calibration for Bani catchment in Mali. In absence of adequate continuous data for automatic calibration and validation of sediments using SUFI-2 program, bathymetric survey data collected in the catchment were used to manually calibrate and validate the model. This was achieved by adjusting the most sensitive MUSLE parameters to match the observed values in the catchment.

Statistical performance indicators e.g. NS, Percent Bias (PBIAS), ratio of RMSE to the standard deviation of measured data (RSR) and R^2 were used to check to the capability of the model to simulate the observed data. The most sensitive parameters and their respective uncertainty ranges were observed and recorded. After calibration and validation, the fitted values were used to run the model thus creating the base scenario for simulation of conservation methods, streamflow change in varying land uses and impacts of climate change on hydrological processes among others.

3. RESULTS AND DISCUSSION

3.1. Parameters Sensitivity and Uncertainty Analysis

Global sensitivity analysis in streamflow prediction was achieved after 500 simulations in SUFI-2 and the results are presented in Table 1. These are parameters that influence the overall hydrological processes in the catchment and that need to be taken into consideration during model calibration and validation. The most sensitive parameter was found to be the available soil water content (SOL-AWC) due to the high absolute t-stat value. According to Abbaspour [21] the bigger the absolute value of the t-stat in global sensitivity analysis, the more sensitive the parameter is. The null hypothesis that a parameter is not sensitive is either accepted or rejected based on the p-values. Low p-values in Table 1 therefore indicate that the respective parameter is sensitive to changes in streamflow. A study conducted to evaluate the impact of objective functions in SWAT calibration found that NS was adequate in addressing calibration and validation of the model [25]. The results of the uncertainty analysis were achieved by setting the objective function as NS.

After the sensitivity analysis, results for the streamflow calibration exercise were obtained after the fifth iteration. Parameters uncertainty ranges within which the calibration was conducted are presented in table 2. A model cannot be considered validly calibrated if the parameters uncertainty ranges are not indicated [21]. The parameter qualifier “r” refers to the relative change of the specified parameter where the fitted value is added to one and the multiplied by the initial SWAT value of the parameter. The qualifier “v” means that the initial SWAT parameter value is to be directly replaced by the fitted value. Once all the parameters have been entered in SWAT, the model is considered calibrated.

Table-1. Parameter sensitivity analysis for streamflow simulation.

Parameter	Description	t-stat	P-value
SOL_AWC.sol	Available water capacity of the soil layer	-10.214	0.000
GW_REVAP.gw	Groundwater revap coefficient	-3.303	0.001
CH_N2.rte	Manning's "n" value for the main channel	2.890	0.004
GW_DELAY.gw	Groundwater delay (days)	2.329	0.020
CN2.mgt	SCS runoff curve number factor	-1.804	0.072
CH_COV2.rte	Channel cover factor	1.694	0.091
ALPHA_BF.gw	Baseflow alpha factor (days)	-1.507	0.132
USLE_P.mgt	Support practice factor	0.577	0.564
EPCO.mgt	Plant uptake compensation factor	0.460	0.646
SURLAG.bsn	Surface runoff lag time	0.270	0.787
GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	-0.255	0.799
SLSOIL.hru	Slope length for lateral subsurface flow	0.125	0.900

Table-2. Parameters qualifiers and uncertainty range.

Parameter Name	Qualifier	Fitted value	Min_value	Max_value
GW_DELAY	v	49.08	44.65	61.49
GWQMN	v	480.06	467.98	624.83
GW_REVAP	r	0.007	-0.14	0.42
SURLAG	v	15.49	6.96	16.18
CH_COV2	v	0.100	0.03	0.15
CH_N2	v	0.66	0.29	0.66
CN2	r	0.39	0.16	0.54
SOL_AWC	r	-0.18	-0.95	-0.09
ALPHA_BF	v	0.01	-0.10	0.11

The p and r factors were found to be 0.72 and 0.65 during calibration process, respectively. According to Abbaspour [21] a p-factor greater than 0.70 and r-factor less than 1.5 are considered satisfactory for stream flow calibration. Therefore, the results of stream flow calibration in terms of p and r factor were acceptable. The percentage of data bracketed within the 95PPU during calibration was 72% which indicated a good performance of the model. The p-factor indicates the degree to which all uncertainties are accounted for in the model calibration and validation [13]. During the validation of the model, p and r factors were observed to be 0.65 and 0.45, respectively. This implied that 65% of the observed data during the validation period were captured within the 95% prediction uncertainty hence the model results are good. The low amount of data incorporated within the 95PPU band during validation could be attributed to the uncertainty in the input data such as rainfall or the wide data gaps in the validation period. Rostamian [26] reported that low r-factor values indicate the goodness of the model during calibration or validation. Therefore, the r-factor in this study portrayed better results during the validation process. An r-factor of 0 and p-factor of 1 represents a simulation that directly corresponds to the observed data [13].

3.2. Statistical Performance Indicators

Table 3 shows the statistical performance of the model during calibration and validation of the SWAT model. These results were considered good for stream flow prediction based on the recommendations of Moriasi, et al. [27]. According to the authors, if the NSE value is between 0.65 to 0.75, RSR between 0.5 to 0.6 and PBIAS value between ± 15 to 25, the model is considered good in simulating stream flow.

Table-3. Statistical performance indicators in calibration and validation.

Performance indicator	Calibration	Validation
NS	0.71	0.78
R^2	0.69	0.75
PBIAS	10.3	7.2
RSR	0.58	0.52

The model closely matched low flows but underestimated peak flows during calibration and validation (Figure. 4 and Figure. 5). Similar observation has also been observed in other studies using SWAT-CUP model Meaurio, et al. [14]; Rostamian [26]. Tolson and Shoemaker [28] reported that SWAT model does not accurately predict the high flows events thus leading to either underestimation or overestimation.

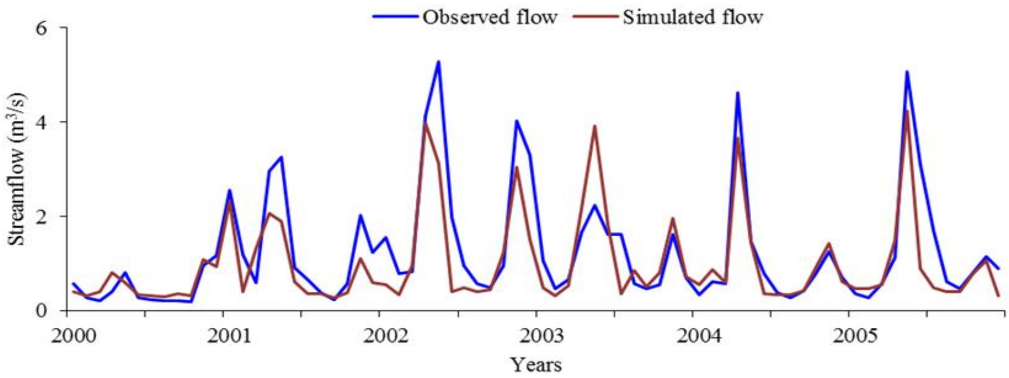

Figure-4. Monthly streamflow calibration results for RGS 4CB05.

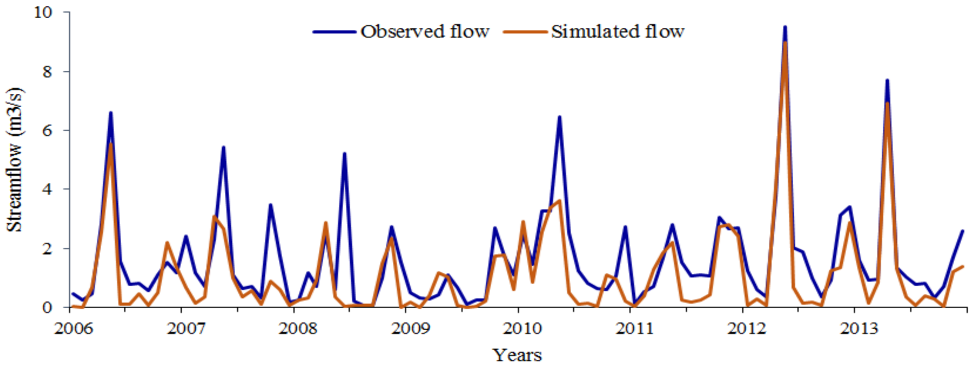

Figure-5. Monthly streamflow validation results for RGS 4CB05.

The model was checked for spatial accuracy in predicting streamflow by comparing the observed data at RGS 4CB04 without changing the calibration parameters and the results are shown in Figure. 6.

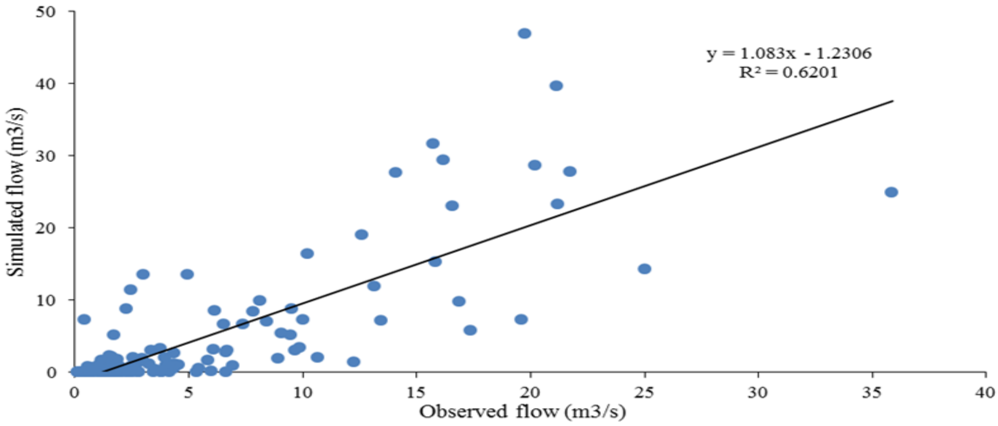

Figure-6. Plot of observed and simulated streamflow at gauging station 4CB04.

An R^2 of 0.62 was obtained which implies that the model was able to simulate streamflow correctly both spatially and temporally. Begou, et al. [24] recommended the use of observed data in RGS not considered in calibration processes in order to make simulations more representative and realistic and also ensure reliable performance of the hydrological processes within the catchment. According to the authors, the use of a different location for validation takes into account the heterogeneity of land use, climate, soils and terrain. The value of R^2 greater than 0.5 implies that the results of streamflow simulations are within acceptable ranges at different locations in the catchment [29].

3.3. Calibration and Validation of Sediments

In order to simulate changes in sediment yield as a result of implementing conservation measures or impact assessment of agricultural management practices, calibration of the model for sediments is required. Results of the sensitivity analysis indicated that the channel re-entrained exponent (SPEXP), channel re-entrained linear parameter (SPCON), channel erodibility factor (CH_COV1), channel cover factor (CH_COV2), support practice factor (USLE-P) and the curve number (CN) were sensitive to sediment. Abbaspour [12] reported similar results in a parameter sensitivity analysis for sediments using SWAT model in Thur watershed, Switzerland. The calibrated parameters and their uncertainty range are presented in Table-4.

Table-4. Calibrated parameters for sediments in Thika river catchment.

Parameter Name	Qualifier*	Fitted value	Min_value	Max_value
CH_COV1	v	0.29	0.1	0.3
SPEXP	v	1.35	1.0	1.60
SPCON	v	0.005	0.001	0.005
CH_COV2	v	0.3	0.1	0.3
CN	v	45-88	36	98
USLE-P	v	0.90-1	0.80	1

The mean annual sediment outflow from the catchment was compared with the simulated sediment yield. Results indicated that the simulated annual sediment yield from the entire catchment is 21.68 t/ha. These results matched the observed annual sediment yield of 21.45 t/ha at the outlet of the catchment from the bathymetric survey conducted in 2011 [30]. Therefore, the model accurately simulated the sediments yield at the catchment outlet.

The model was validated for sediments at Sasumua and Ndakaini dam which are located upstream of the Thika and Chania river confluence. It was found that the average annual sediments yield in Sasumua and Ndakaini dam was 0.55 and 0.48 t/ha. From the bathymetric survey data, the two reservoirs were found to have approximately annual sedimentation rate of 0 Mt/ha [30]. The results indicate although the model slightly over predicted the sediment at the two reservoirs, the variation of the sediment yield across the catchment was captured. The results were therefore considered accurate given the uncertainty in input data which may include the effect of land use change and reservoirs sediment trapping efficiency.

Further validation was conducted for Sasumua dam sub-catchment where the total annual yield was observed as 11.0 t/ha. These results compared well with those of Mwangi, et al. [31]who observed an annual sediments yield of 10.3 t/ha at the outlet of the sub-catchment. The results of the calibration and validation of sediments showed that the model simulations were satisfactory in terms of simulating sediments across the catchment.

Upon identifying the uncertainty of parameters and successfully calibrating and validating the model, a base scenario (Figure. 7) is thus created for any further modelling of streamflow, climate change, impacts of land use change or assessment of soil and water conservation methods prior to their implementation in the catchment. The base scenario provides a platform for policy makers and water managers to monitor and evaluate trends in the catchment management. Impacts of project activities could also be assessed using these results as the reference point.

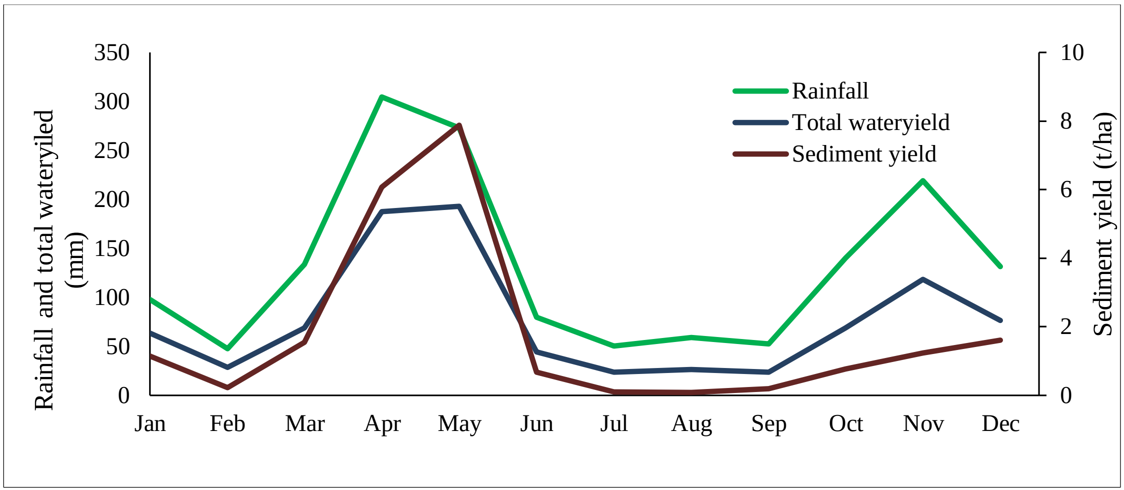

Figure-7. Average monthly sediment and water yield in Thika river catchment.

4. CONCLUSION

The current study observed that SUFI-2 can effectively be coupled with SWAT model to conduct uncertainty analysis, calibration and validation of streamflow. We also observed that in areas with inadequate sediments data for continuous calibration using SUFI-2, manual calibration can be conducted using existing data in the catchment. In Thika River catchment, the most sensitive parameters for streamflow were GW_DELAY, GWQMN, GW_REVAP and SURLAG. Sediments calibration was typically influenced by CH-COV1, SPEXP, SPCON and CH_COV2. Statistical indices indicated that SWAT model provided good results for the prediction of streamflow in the catchment.

The results of the current study show that SUFI-2 is adequate for calibration and identifying the underlying uncertainties in hydrological processes. It can be concluded that SWAT model is an appropriate tool for application in simulating ecosystem processes in catchments with inadequate observed data. The calibrated model could be used to conduct further studies on impact of climate and land use change on ecosystem services e.g. water provision and sediments regulation. The outcome of this study would be used in soil and water conservation, analysis and mitigation of hydrological extremes. Continuous collection of sediment and nutrients data should be prioritized in the catchment. This will not only improve plausibility of results but will also facilitate other research like modelling of nutrients yield in the catchment.

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