ER Environmental Review Journal

Volume 9 No. 4, 2024.
ISSN:1118-7190

Research Article

Simulation of River Flow using Soil and Water Assessment Tool (SWAT) Model in Imo River Basin

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Abstract

This study aims to simulate river flow using the Soil and Water Assessment Tool (SWAT) model for the Imo River Basin. Climate data, including daily rainfall, temperature, and others, were obtained from the Global Climate Forecast System Reanalysis weather database. The digital elevation model of the basin was obtained from the United States Geological Survey, the soil map from the Food and Agriculture Organisation Harmonized World Soil Database, and the monthly discharge data for the Imo River was obtained from the Imo River Basin Development Authority. These data were used to develop the SWAT model for the basin. The SWAT model for the Imo River Basin was calibrated and validated. The outcome of the model validation yielded a better response than calibration, given the performance indices producing NSE, PBIAS, and coefficient of determination values of 0.98, 4.35, and 0.87, respectively. The results showed that the calibration and validation for river flow performed very well for the Imo Basin. In most cases, the river discharge simulations followed the observed discharge data trend in the Imo basin. This suggests the SWAT model can reasonably simulate monthly river discharge for gauged and ungauged river basins through model parameter transfer. The outcome of this study will enhance the understanding of hydrological response parameters, especially in poorly instrumented regions with spatially similar physiographic attributes as the study area.

Keywords: SWAT, Simulation, Calibration, Validation, River flow, Imo River.

Article History: Received: November 18, 2024 Accepted: December 12 2024 Published:

1. Introduction

The global climate has remarkably changed from a system influenced by natural factors to one mostly driven by anthropogenic activities (Brönnimann, *et al.,* 2007). Thus, global warming-induced climate change has moved from speculation to general acceptance (Stefouli *et al.,* 2011). This realization has led to questions about the relative effects of shifts in climate conditions on natural ecosystems (Nzoiwu, 2015). Odjugo (2010) opined that global warming and associated rainfall variability will create water stress, especially in parts of Africa. Two primary hydro-meteorological variables affecting the river basin ecosystem are precipitation and air temperature (Magnuson *et al.,* 1997). Changes in air temperature and precipitation directly affect river systems' physical and hydrological characteristics. Freshwater ecosystems play an essential role in the regional water cycle and reflect watershed water balance in arid regions (Ma *et al.,* 2011; Wu *et al.,* 2014). Rivers and lakes are crucial links in the earth's hydrological cycle, and studies have noted that such predicted climatic changes can alter the hydrological and other physical features of these natural ecosystems (Magnuson *et al.,* 1997). Hydrological systems are highly susceptible to climate change (Arnell *et al.,* 1996). It can influence many aspects of river and stream ecosystems such as

hydrological flows into and out of basins, net basin water supply, and water levels of rivers. Over time, freshwater ecosystems, including rivers and lakes (e.g., Lake Chad) have varied in volume and extent due to climatic variability (Lozan *et al.*, 2001; Chindo and Nyelong, 2004).

Ayoade (1975) stressed that an accurate assessment of an area's water resources requires knowledge of rainfall magnitude, spatial and temporal distribution, as well as the nature and extent of water losses. Numerous studies (e.g., Bardossy, 2007; Pomeroy et al., 2007; Ghosh and Misra, 2010; Hrachowitz et al., 2013) have successfully shown that the assessment of river basin water resources with limited data could be addressed through hydrological modeling. A well-planned river basin manifests a stable ecosystem where energy and mass input and output are in quasi-equilibrium. Nearly all the basins in southeast Nigeria are ungauged. This makes water resources planning and management a difficult enterprise. The erosion-caused devastation in the Otamiri river basin on the Awka – Orlu upland around the Agulu-Nanka-Oko areas of Anambra State is a kind that arises from an unplanned basin. The Imo River basin has even more problems due to its size and importance in the Southeast region of Nigeria. The inadequacy of discharge data in most basins of Southeastern Nigeria complicates the assessment of climate-related impacts on the hydrological conditions of these watersheds. Studies (e.g., Bárdossy, 2007) have recorded successes in devising ways to manage these environmental problems in regions through hydrological modeling. The International Association of Hydrological Sciences (IAHS) has advocated improving these hydrological models to predict ungauged basins (Hrachowitz et al., 2013).

Recent advancements in remote sensing technologies have revolutionised hydrological response prediction, particularly in soil moisture sensing (Vereecken et al., 2008; Parajka et al., 2009). Troch et al. (2003) cited in Hrachowitz et al. (2013), succinctly articulated that despite reductions in ground-based observations due to funding cuts, hydrology will no longer be constrained by insufficient climate data owing to the enhanced availability and quality of remote sensing data. Furthermore, emerging opportunities for data assimilation will improve predictions in river basins. The SWAT model is one of the most widely applied hydrological models. SWAT is a watershed-modelling tool that simulates the effects of various land management and climatic scenarios on the hydrologic response of watersheds (Arnold et al., 1998).

2. Materials and Methods

2.1. Study Area

The Imo River basin is in southeastern Nigeria, and cuts across parts of Imo State, Abia State, and Rivers State. It is located within latitude $4^0\,52^1 30^{11}$ N and 6^0N and longitude $7^0\ 5^1$ E and $7^0\ 30^1$E (Figure 1). The Basin experiences both the topical monsoon (Am) and tropical rainforest (Af) climate based on Koppen's climatic classification (Uzor-Tott and Oyegun, 2020), with an average of 8 months of rainy season and 4 months of dry season. Rainfall often occurs between March and October, with a two-week break in August**.** Rainfall intensities frequently exceed 50mm/h with short interval intensities over 100 mm/h (Chiemelu *et al.*, 2019). The annual rainfall ranges from 1500mm to over 2500mm. The Imo River Basin is underlain by Upper Cretaceous sedimentary formations (Uma, 1989), such as the non-hardened sediments of the Benin and Ogwashi-Asaba formations (Ijeh and Onu, 2013).

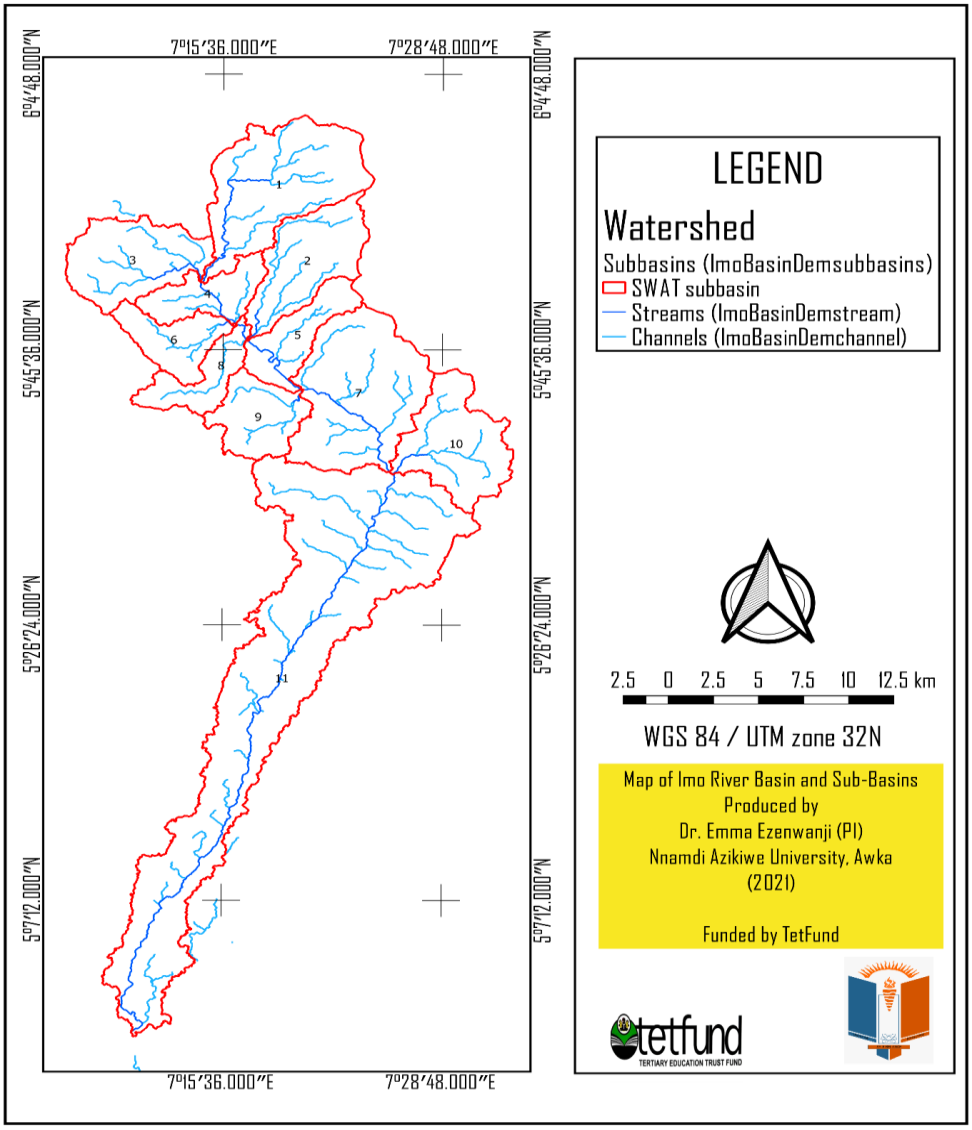


Figure 1. Imo River Basin

2.2. Methodology

2.2.1. SWAT Model Setup

The Soil and Water Assessment Tool (SWAT2012) QGIS interface (QSWAT) was used to estimate Imo River Basin streamflow. SWAT is a process-based hydrological model that simulates the hydrologic response of watersheds to land management and climatic scenarios (Arnold *et al.*, 1998). It predicts the basin water balance components, sediments, and nutrient contamination (Singh and Saravanan, 2020). The SWAT model divided the watershed into subbasins to represent spatial heterogeneity. The subbasins are divided into hydrologic response units (HRUs) based on soil types, land use, and slope. For every HRU, the soil water content, surface runoff, crop growth, management practice, and sediment yield are weighted and averaged to the subbasin level. The model requires several parameters (specified at the watershed, sub-basin, and HRU levels) to simulate hydrologic processes. These include weather, soil, groundwater, channel, plant water use, plant growth, soil chemistry, sub-basin, and HRU characterization

data. For this study, the SWAT model discretized the Imo River basin into 11 subbasins (see Figure 1) with 76 channels. It further split the basin into 3240 HRUs, however, the basic parameters are land usage, soil, topography, and climate. The model sets default values for the other parameters and entering known or measured values of these parameters improves watershed representation and the overall model accuracy (Gitau and Chaubey, 2010). Runoff was predicted separately for each HRU and routed at the subbasin level to obtain total runoff figures (Neitsch *et al.*, 2011; Roth *et al.*, 2016).

2.2.1. Input data

Climate, discharge, and soil data. The study data were obtained from both primary and secondary sources. Table 1 summarizes the data type, source, and spatial resolution. The basic climatic data needs, including minimum and maximum air temperature, daily rainfall, relative humidity, solar radiation, and windspeed were downloaded from https://globalweather.tamu.edu. The Imo River discharge data was obtained from the Imo River Basin Development Authority. The soil data for the study area was sourced from FAO harmonized world soil database v.12.

DEM. The United States Geological Survey 30m x 30m Digital Elevation Model (DEM) was used to set up the SWAT model. Subbasin partitioning and stream networks were computed automatically through the QSWAT interface, with the outlet feature classes manually configured to include the subbasin 1 channel of the Mamu River catchment as a calibration feature at the top of the watershed (see Figure 1).

Land use. Land use data was obtained from fieldwork by the research team. This information is critical for training the Landsat images obtained for the Mamu River Basin. Bands 2, 3, 4, and 5 were adopted. A false colour composite operation was performed using IDRISI software. The False Colour Composite was classified using the Maximum Likelihood Classification Technique. A supervised classification was performed by creating a training sample, which identified six land use types and cover classes based on the curve's spectral signature. The land use data was subsequently adapted for use in the SWAT model.

Table 1. Data type and sources.

Data Type	Description	Sources	Resolution
Digital Elevation Model	SRTM DEM	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm-1	30m x 30m
Land use	Landsat 8 Operational Land Imager	https://earthexplorer.usgs.gov/	30m x 30m
Soil map	FAO harmonized world soil database v.1.2	https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/	1:1, 000, 000
Meteorological data		https://globalweather.tamu.edu	

2.3. Model evaluation

The QSWAT model was run on a monthly time step over 37 years (1985 – 2021) with a 5-year warm-up period. The performance of the SWAT model was determined following the approach adopted by Baker and Miller (2013) by using Nash-Sutcliffe efficiency (NSE) and percent bias (PBIAS). The theoretical range of NSE is from -∞ to 1, with an optimal value of NSE = 1.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{n}(Q_{obs} - Q_{mean\ obs})^2}$$

$$PBIAS = \frac{\sum(Q_{obs} - Q_{sim})}{\sum Q_{obs}} \times 100$$

where Q_{obs}, Q_{sim} and $Q_{mean\ obs}$ represent the observed, simulated, and mean data.

This study applied model performance ratings, established by Moriasi *et al.* (2007), as shown in the table for runoff prediction. Vincent et al. (n.d.) opined that a model is deemed calibrated if there is significant NSE or PBIAS between the simulated and observed data for both calibration and validation datasets.

3. Results and Discussion

The SWAT model discretized the Imo River basin into 11 subbasins (see Figure 2) each characterised by 76 channels and 3240 hydrological response units (HRUs). The basin has a total area of 197,006 hectares, of which 31.96% is floodplain and 68.04% is upslope.

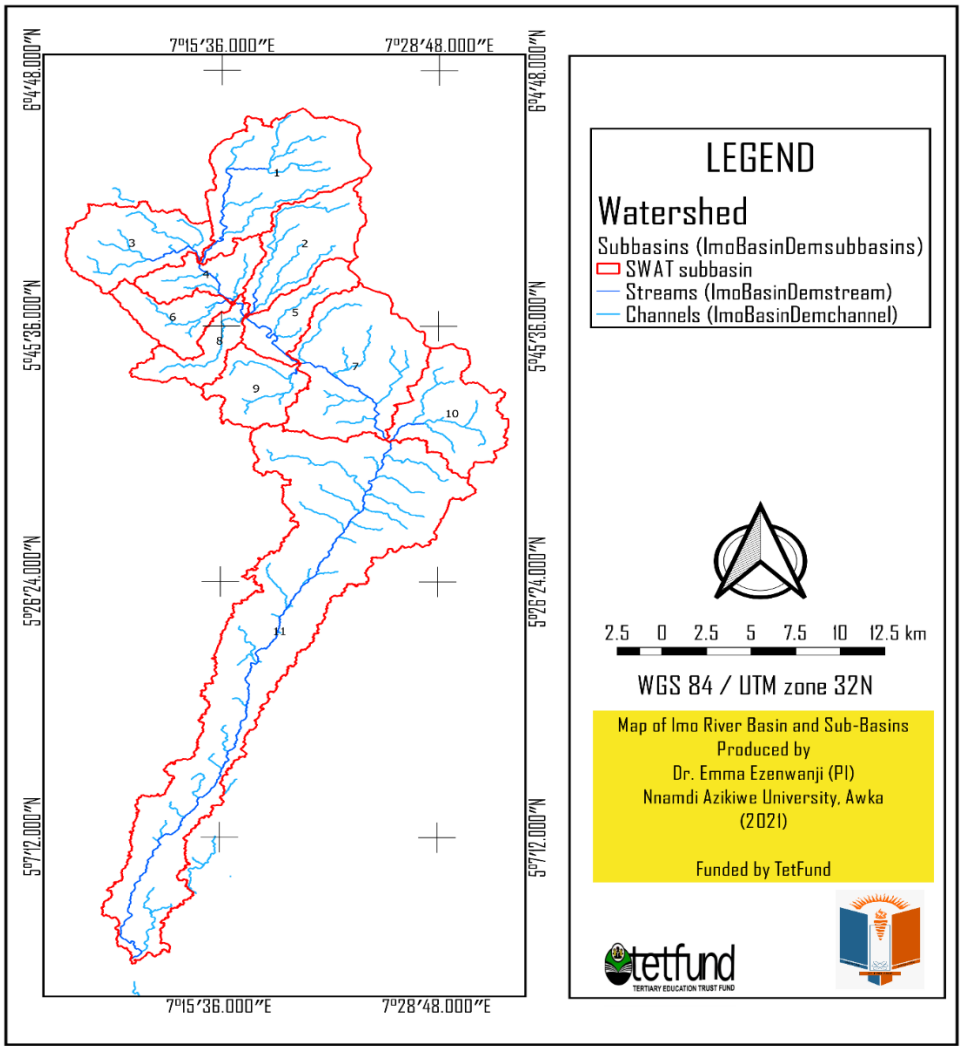


Figure 2. 11 sub-basins of Imo River Basin

Figure 3 illustrates the SWAT model's productivity, focusing on runoff and evapotranspiration (Gasirabo et al., 2023). More than 48% of total precipitation is lost through evapotranspiration and runoff. The land use classes found within the Imo River basin consist of six types: sparse vegetation (RNGE), farmlands (AGRL), bare soils or grasslands (PAST), drainage channels (WATR), built-up (URBN), and forested areas (FRST). Figure 4 illustrates the land use map. As shown in Table 2, the built-up environment and drainage channels each constitute less than 1% of the total land area. Bare soil or grasslands occupy only 0.6% of the total land area of the basin.

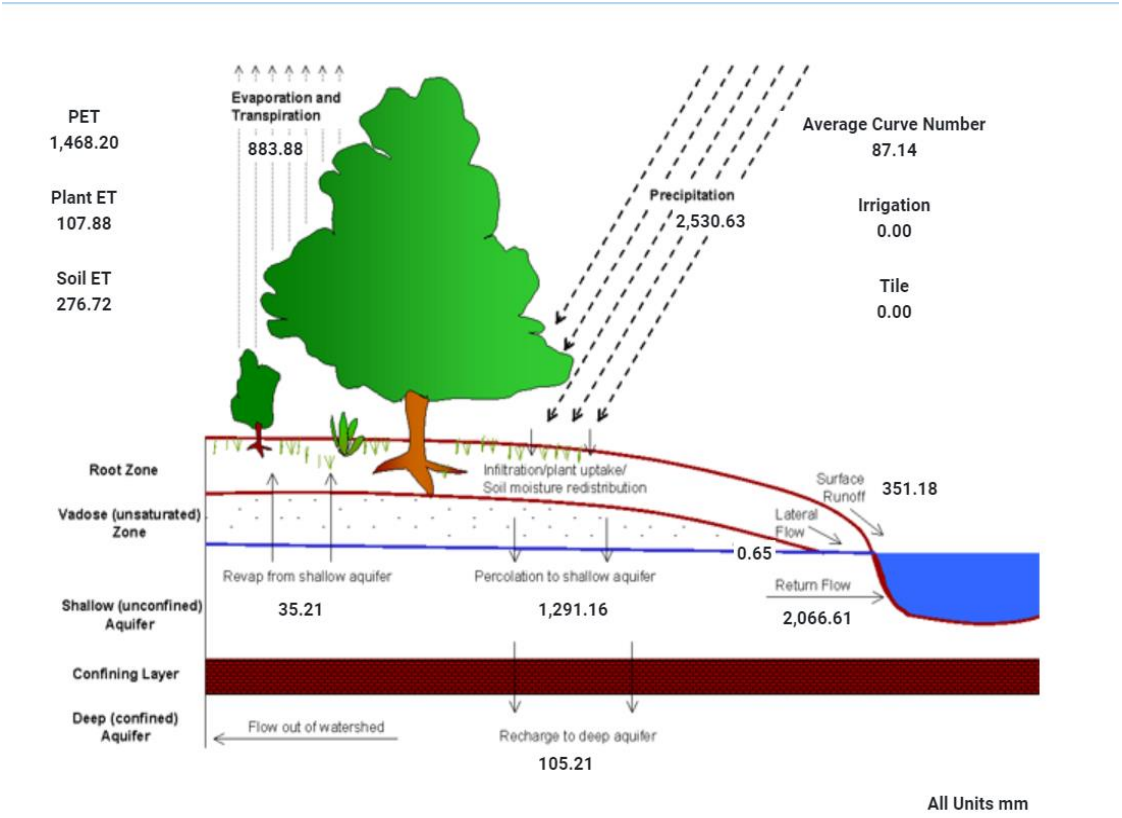


Figure 3. A pictorial depiction of SWAT output for Imo River Basin

Table 2. Land use and land cover classes in the Imo River Basin.

LULC Type	Area (Ha)	Percentage
Sparse vegetation (rnge)	135,975.24	69.0%
Farmlands (Agrl)	21,248.42	10.8%
Bare soil (past)	1,191.35	0.6%
Drainage channels (wetw)	1,778.00	0.9%
Built-up (Urbn)	1,590.62	0.8%
Forest (Frst)	35,222.80	17.9%
Total	**197,006.43**	**100%**

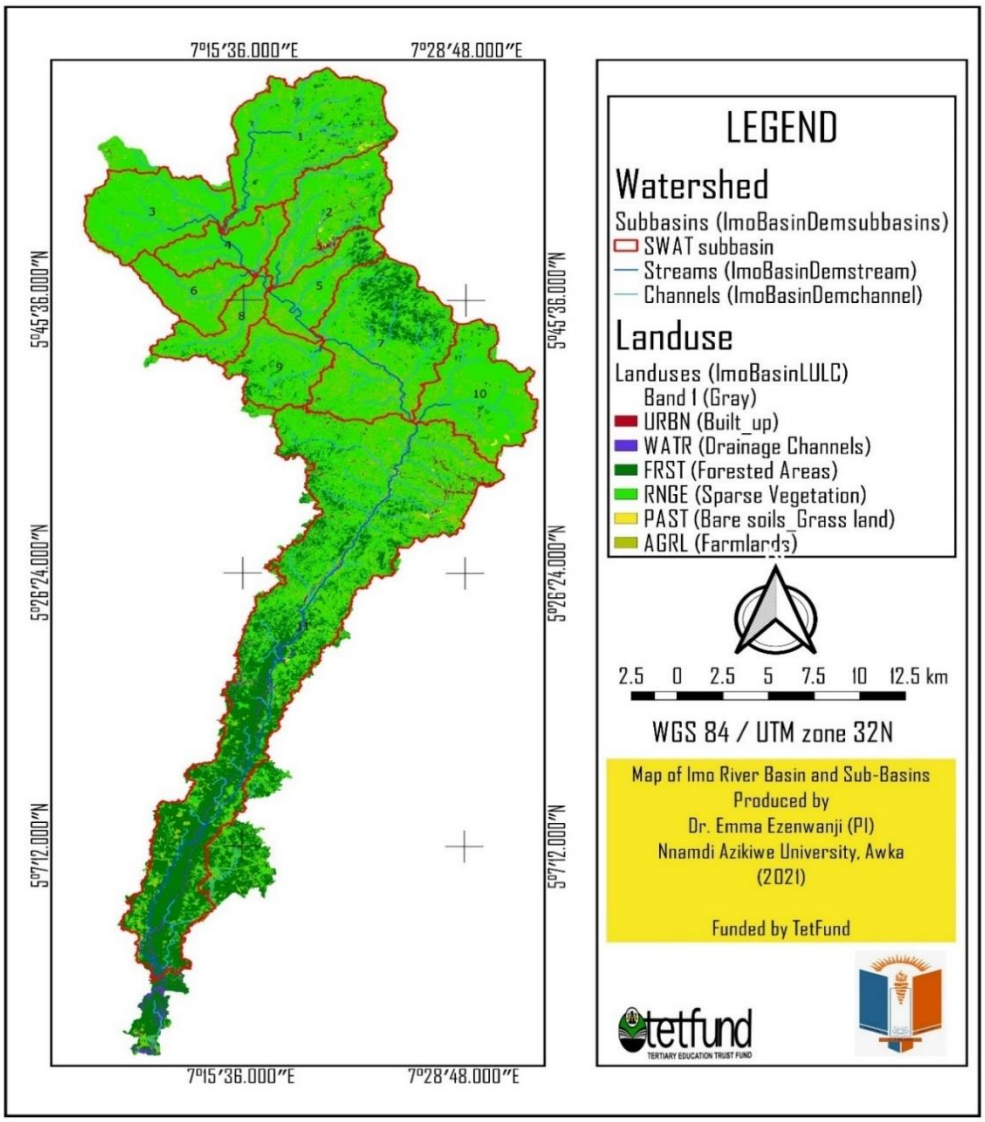


Figure 4. Land use and land cover classes

For the vegetation class, the sparse vegetation type dominated the landscape of the basin up to about 69.02% of the total land area. The forest land use maintained 17.88% of the total land area while farmlands (AGRL) occupy 10.79% of the basin's total land area. Forested lands dominate the southern part of the basin towards the outlet. Figure 5 shows the basin's soil characteristics while Table 3 shows the area coverage of each soil type. Satellite imagery analysis of the basin reveals that loamy soil and various variants of sandy-loamy soil primarily dominate the basin, while the SWAT model assigned codes to each soil type. Table 3 shows that the sandy-loamy soil variant coded Nd21-1a-1560 has the highest area coverage within the basin and is located at the central part of the basin covering an area of about 54,471.87ha of land area.

Table 3. Soil classes in the Imo River Basin.

Soil	Area (Ha)	Percent of watershed
Nd5-1a-1567	32148.49	16.32
Jd3-2a-677	34000.17	17.26
Nd15-1a-1552	53337.71	27.07
Nd21-1a-1560	54471.87	27.65
Fx8-1a-1190	23048.2	11.70
Total	**197,006.43**	**100%**

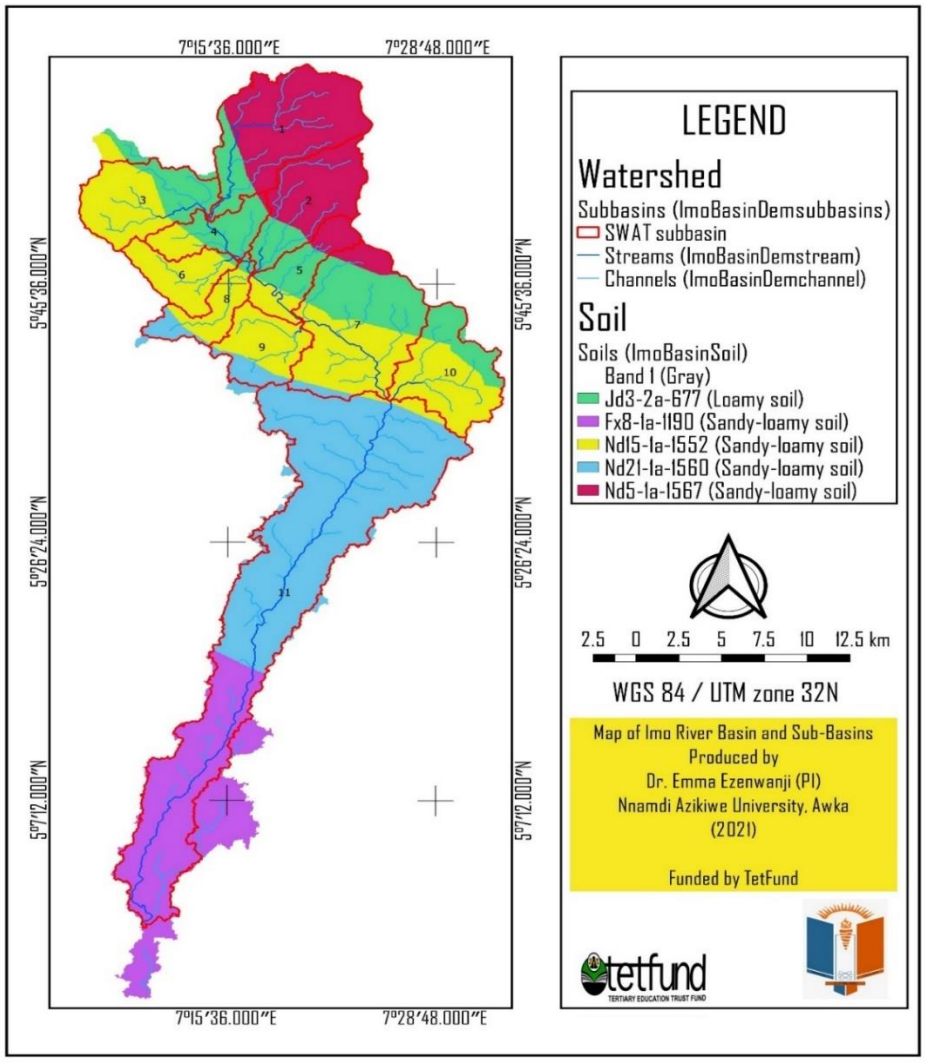


Figure 5. Soil characteristics of Imo Basin

The second largest soil type is a variant of sandy-loamy soil coded "Nd15-1a-1552", covering about 53,337.71 ha of the basin's land area. Next is the loamy soil type (Jd3-2a-677) occupying an area of 34,000.17 ha. In the southern part of the basin, characterised by forested land use, the predominant soil type is sandy-loamy, coded Fx8-1a-1190, occupying an area of 23,048.2 ha. The soil type in the upper-

most part of the basin is another variant of sandy-loamy soil coded Nd5-1a-1567 with an area of 32,148.49ha.

The digital elevation model (DEM) of the basin depicts the elevation of the entire basin above sea level, as shown in Figure 6. The elevation ranges from the lowest of 61m to the highest of over 170m above sea level. The river flows north-south, with first-order streams dominating the basin's highland areas.

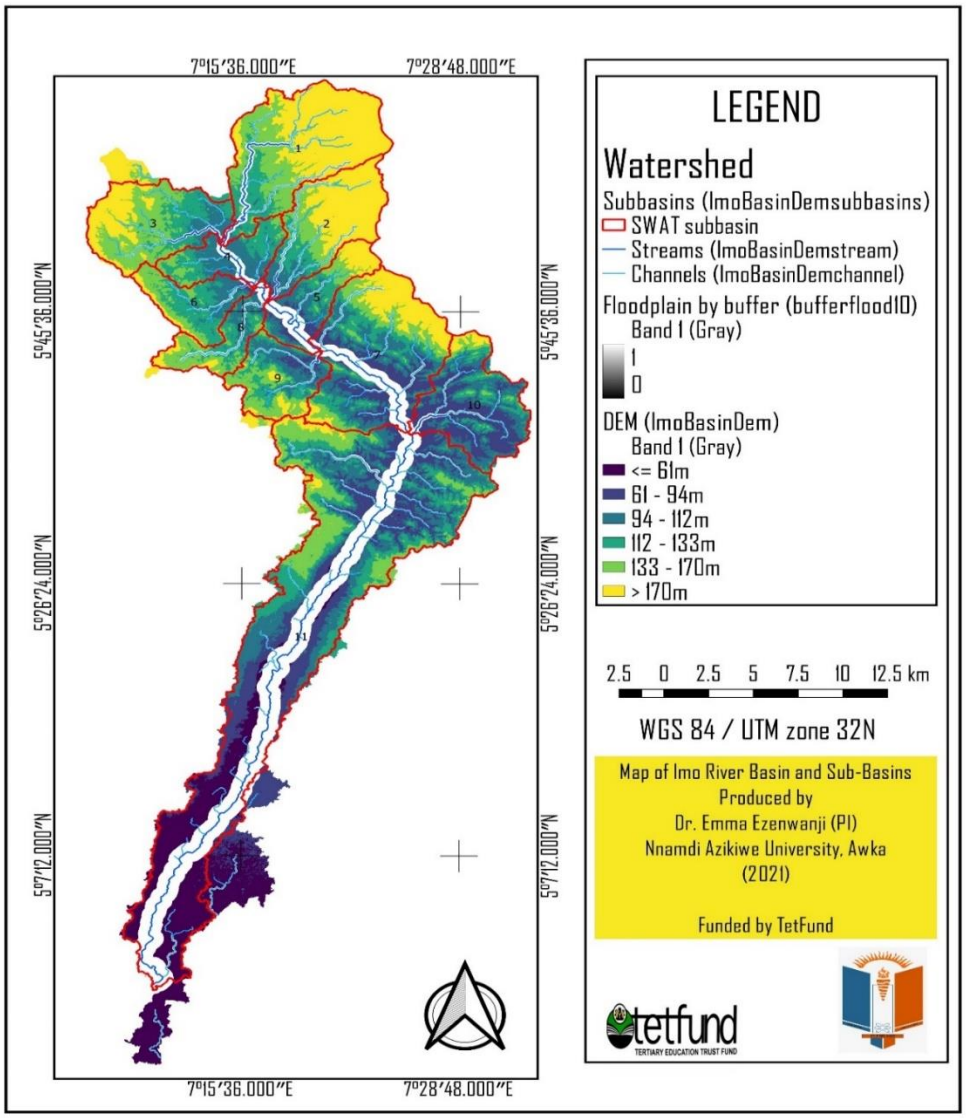


Figure 6. DEM of Imo River Basin

3.1. Sensitivity Analysis

Sensitivity analysis is a vital step in understanding model performance and is necessary before calibration and validation of the model. A total of 15 SWAT parameters were selected to test the runoff responses. The parameters chosen for sensitivity analysis were those that affect the hydrology of the basin outlet, as shown in Table 4.

Table 4. 15 selected parameters for sensitivity analysis and calibration.

Parameter	Definition	Rank
CN2	Curve number	1
REVAP_CO	Groundwater "revap" coefficient	2
AWC	Available water capacity of soil layer	3
ESCO	Soil evaporation compensation factor	4
CHN	Manning's "n" value for the tributary channels	5
REVAP_MN	Threshold depth of water in shallow aquifer for "revap" to occur	6
CANMX	Maximum canopy storage	7
SLOPE	Average slope	8
ALPHA	Baseflow alpha factor	9
USLE_P	USLE equation support practice	10
OVN	Manning's "n" value for overland flow	11
USLEC_LTE	Min value of USLE C factor applicable to land cover/plant	12
USLEK_LTE	USLE soil erodibility factor	13
USLELS_LTE	USLE topographic factor	14
CHEROD	Channel erodibility factor	15

3.2. Calibration and validation

The SWAT model was manually calibrated monthly following recommendations from Baker and Miller (2013), Ezenne *et al.* (2017), Vincent *et al.* (n.d.), and Singh and Saravanan (2020) in SWAT-Cup using SUFI-2, with 200 iterations. Iteratively modifying the sensitive parameters yielded values close to the observed monthly Imo River basin flow rates. Table 5 shows parameter calibration results.

Table 5. Fitted parameter ranges for 15 selected parameters for calibration.

S/N	Parameter	Definition	Fitted parameter range
1	CN2	Curve number	35 – 95
2	revap_co	Groundwater "revap" coefficient	0.02 – 0.2
3	revap_mn	Threshold depth of water in shallow aquifer for "revap" to occur	0 – 500
4	alpha	Baseflow alpha factor	0 – 1
5	Esco	Soil evaporation compensation factor	0.01 – 1
6	Canmx	Maximum canopy storage	7.5 – 92.5
7	Awc	Available water capacity of soil layer	0.85 – 1
8	usle_p	USLE equation support practice	-1.5 – -0.5
9	slope	Average slope	-0.5 – 15
10	uslec_lte	Min value of USLE C factor applicable to land cover/plant	0.001 – 0.29
11	uslek_lte	USLE soil erodibility factor	-0.34 – 0.2
12	uslels_lte	USLE topographic factor	0.1 – 0.9

13	cherod	Channel erodibility factor	-0.5 – 0.6
14	Ovn	Manning's "n" value for overland flow	0.01 – 15
15	chn	Manning's "n" value for the tributary channels	-0.01 – 0.29

The calibration performance of river flows in the Imo River basin was evaluated using Nash-Sutcliffe Efficiency (NSE) and PBIAS. The theoretical range of NSE is from -∞ to 1, with an optimal value of NSE = 1 (see Table 5). Values between 0.0 and 1.0 are generally viewed as an acceptable performance level, whereas values below 0.0 indicate that the mean observed value is a better predictor than the simulated value, indicating unacceptable performance (Moriasi et al., 2007; de Salis *et al.*, 2019). PBIAS measures over-and-underestimation (Politi, Cutler, and Rowan, 2012) or the average tendency of simulated data to exceed or fall short of the observed values (Ma, Wu, Liu and Abuduwaili, 2014). The optimal value of PBIAS is 0.0 with lower values indicating accurate model simulation.

Table 6. Performance Rating for Recommended Statistics (adapted from Moriasi et al., 2007).

Performance rating	**NSE**	**PBIAS**
Very good	0.75<NSE≤1.00	PBIAS<±10
Good	0.65<NSE≤0.75	±10>PBIAS<±15
Satisfactory	0.50<NSE≤0.65	±15>PBIAS<±25
Unsatisfactory	NSE≤0.50	PBIAS≥±25

The performance statistics showed that the model performed better during validation than calibration. The NSE statistics yielded a value of 0.66 during calibration. The PBIAS statistics yielded a value of 13.4, showing a satisfactory rating. Given the general performance rating, the calibration carried out is good. The observed and simulated hydrographs for comparison are displayed in Figure 7. The hydrograph's results show that measured and simulated river flow exhibits a similar trend. This implies that the river flow in the Imo River basin is satisfactorily represented for each year. The variations in seasonal incidences were well captured, with minor over-predictions in 2002, 2015, 2016, and 2019. The model was validated with monthly observed data from the Imo River Basin outlet for 2021. The river flow validation for the Imo River Basin yielded an NSE coefficient of 0.98 and a PBIAS value of 4.35. A lower PBIAS value during the validation period indicates fewer overestimations occurred during the validation period. The validation results indicate a good outcome based on the performance rating, surpassing the calibration values.

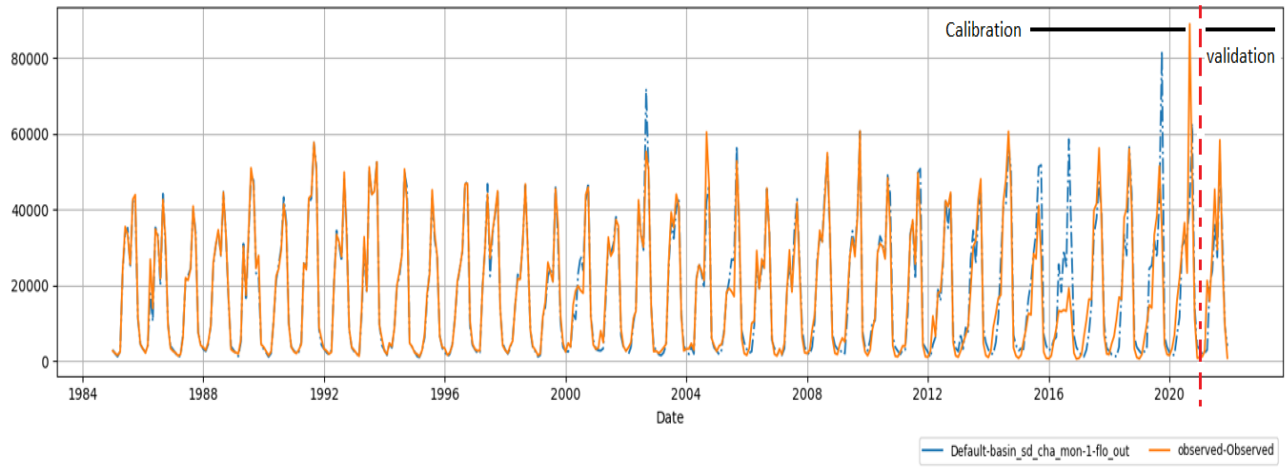


Figure 7. Calibration and validation graphics in Imo River Basin

However, the results of the observed and simulated river flows of the Imo River basin were correlated as shown in Figures 8 and 9. Correlation coefficients of 0.71 and 0.93 were obtained for the calibration and validation periods, respectively, along with R2 values of 0.50 and 0.87 for the same periods. This reveals a strong correlation between observed and simulated river flow data.

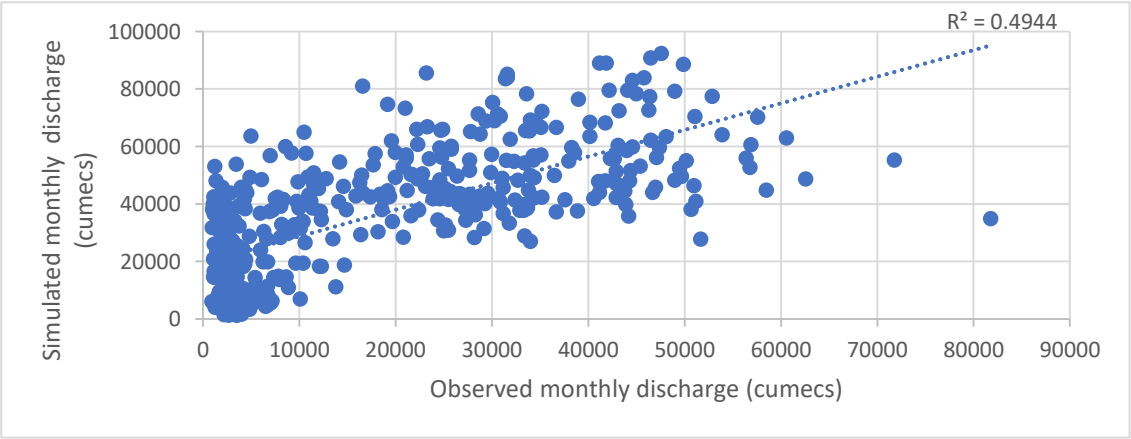


Figure 8. Observed river flow vs simulated river flow dot plot for calibration

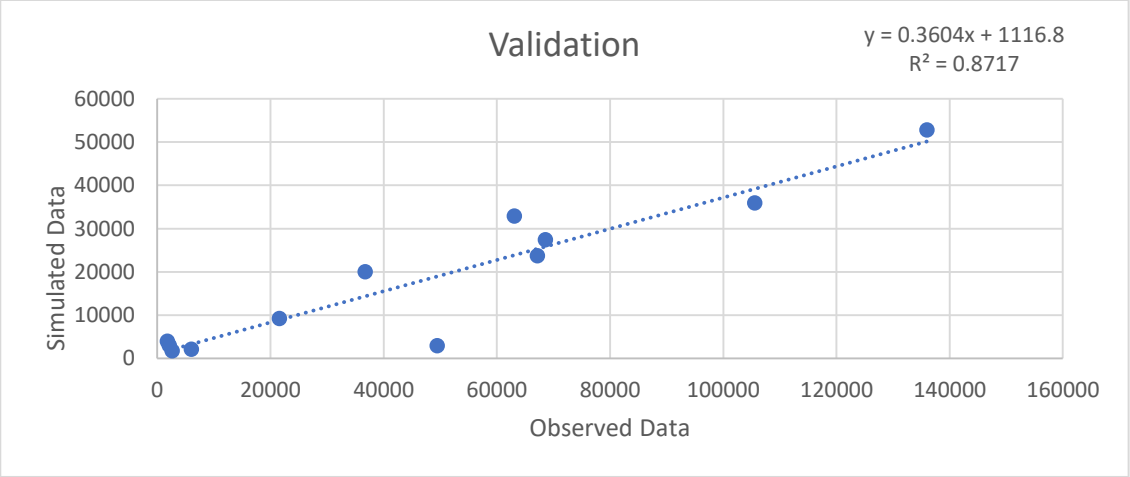


Figure 9. Observed river flow vs simulated river flow dot plot for validation

4. Conclusion

This study aimed to simulate river flow in the Imo River Basin using the SWAT Model to calibrate and validate model parameters for application in ungauged river basins in the region to simulate discharge. The performance of the SWAT model was evaluated. The result showed that the SWAT model had a strong performance, and the calibrated parameters showed excellent concordance for modelling flow in ungauged basins. The model produced satisfactory results for monthly and annual river discharge. The calibration and validation results produced a good performance as evaluated by the NSE and PBIAS performance indices. The SWAT model could predict the basin's discharge amounts and flow variability, optimising parameter ranges to produce better results. The calibrated SWAT model parameters can be used to model river discharges in ungauged basins by leveraging spatial proximity and similarity to the physiographic attributes of the Imo River Basin. This outcome would solve one of the hydrological challenges of understanding the river flow condition of most ungauged river basins scattered across southeastern Nigeria due to inadequate discharge data. This is critical for water resources management and assessment of climate-related impacts on the hydrological conditions of these watersheds.

Acknowledgement

The authors appreciate the Tertiary Education Trust Fund for the National Research Fund (TETFund-NRF) grant awarded to the authors. This grant has greatly improved our understanding of process-based hydrological models. We are grateful to the Department of Surveying and Geoinformatics, University of Nigeria for the South SDE Acoustic Echo Sounder used in this work.

Funding: This research work was sponsored by the TETFund-NRF Grant.
Declaration of Competing Interest. The authors declare no known conflict of interest that could have influenced the outcome of this research paper.

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