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Modeling of Water Availability for Food System Transformation in Upper Offin Sub-basin and Mankran Micro-Watershed of Ghana: A Baseline Study

A Research Report

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ACRONYMS AND ABBREVIATIONS

ASL	Above Sea Level
CFSR	Climate Forecast System Reanalysis
CHIRPS	Climate Hazard Group Infrared Precipitation with Station
DEM	Digital Elevation Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	Atmospheric Reanalysis for Global Climate (Fifth Generation)
ESA	European Space Agency
FAO	Food and Agricultural Organization of the United Nations
GIS	Geographic Information System
HRU	Hydrologic Response Unit
ISRIC	International Soil Reference and Information Centre
km^2	Square Kilometer
m^3/s	Cubic Meter Per Second
MM	Millimeters
OA	Orthic Acrisols
PBIAS	Percent Bias
SWAT	Soil and Water Assessment Tool
SWAT-CUP	Soil and Water Assessment Tool Calibration and Uncertainty Program
t/ha	Ton Per Hectare
USGS	United States Geographical Survey
USLE	Universal Soil Loss Equation

SUMMARY

The increasing population and changes in the climate in Africa demand a more sustainable approach to water usage for improved food and water security in the region. One of the key users of water, agriculture serves as the primary livelihood in Ghana, with a growing focus on cocoa production. To effectively implement sustainable water management strategies, it becomes imperative to conduct hydrological studies, including water balance components and water quality at sub-national and watershed scales. This would assist decision-makers in the proper planning and interventions for agriculture. This study aims to quantify and evaluate the hydrological response of the Upper Offin sub-basin and Mankran micro-watershed under baseline conditions. Upper Offin was selected because of its competing land uses of cocoa and mining, and Mankran was targeted as the CGIAR regional integrated initiative for Transforming Agrifood Systems in West and Sectral Africa (TAFS-WCA) is co-designing a landscape management plan for the area. The Soil and Water Assessment Tool (SWAT) model was first calibrated and validated at the Adimbera gauging station (Upper Offin sub-basin) using observed streamflow data from 2001 to 2011, considering Mankran as one of the SWAT sub-basins. After several iterations of the selected seven parameters that include mainly channel and groundwater flow, the SWAT model reproduced the observed flow with reasonable performance. The sensitivity analysis depicted that channel and groundwater parameters were markedly the most sensitive in the region. Evapotranspiration accounts for the largest share of the water cycle, with a mean annual rainfall of 72% and 74% for the Upper Offin and Mankran watersheds, respectively. The mean annual surface runoff and percolation were below 5% for both watersheds. Also, the mean annual percolation for Upper Offin and Mankran were 15% and 17% of the rainfall and the mean annual sediment yield was 0.68 t/ha and 0.37 t/ha, respectively. The SWAT model successfully captured the hydrological responses in the study areas, providing a reliable quantification of surface runoff, percolation, and sediment yield under baseline conditions. Utilizing SWAT in this context was essential for assessing the potential impact of future supplementary irrigation interventions, evaluating the effectiveness of water management strategies, and monitoring changes in hydrological processes over both spatial and temporal scales.

1. INTRODUCTION

Africa faces complex challenges at the crossroads of population growth and climate change, immersing pressure on food security across the continent (Giller 2020; Shankar 2018). With the fastest-growing populations globally, the demand for food in Africa is escalating rapidly (Walker 2016). Simultaneously, the region is grappling with the adverse effects of climate change, including prolonged droughts, erratic rainfall, and increased temperatures (Adaawen et al. 2019; Fagariba et al. 2018). These environmental shifts pose significant threats to agricultural productivity (Sultan and Gaetani 2016). Subsistence farming, a vital source of livelihood for many in Africa, is particularly vulnerable to these changes (Serdeczny et al. 2017). The combination of population growth and climate-related disruptions creates a delicate balance that, if not addressed strategically, could lead to widespread food shortages, malnutrition, and economic instability.

Agriculture in Ghana stands as a cornerstone of the nation's economy and livelihoods, encompassing a diverse range of crops and practices. Cocoa cultivation, a vital cash crop, plays a pivotal role in shaping agricultural landscapes (Nunoo et al. 2015). Ghana has emerged as one of the leading contributors to the world's cocoa market, known for its rich and flavorful cocoa (Voora et al. 2019). Smallholder farmers, often the backbone of this sector, relied on age-old techniques passed down through generations that relied on rainfed systems (Munthali and Murayama 2013; Nyssen et al. 2023). However, the rainfed agricultural system is grappling with the adverse effects caused by climate variability (Asante et al. 2021; Asante and Amuakwa-Mensah 2014) and population growth (Asante et al. 2022). In response to these challenges and the changing climate, a need arises for supplemental irrigation by cocoa farmers in Ghana (Akpoti et al. 2023; Tilahun et al. 2023).

To effectively implement an adaptation strategy and ensure sustainable water management with a focus on environmental conservation, it is crucial to conduct quantitative baseline studies on the hydrological balance at the watershed scale. (Atullley et al. 2022; Kotir et al. 2016). This baseline study will serve as a foundation for investigating various scenarios, such as cocoa supplementary irrigation, enabling an in-depth examination of the impacts on the spatiotemporal availability of water in a targeted landscape.

There have been water resource assessment studies conducted on both continental, such as Africa, and national scales, specifically in Ghana, exploring the potential of surface and groundwater for farmer-led irrigation (Gebrezgabher et al. 2021; Xie et al. 2014). Additionally, within the same geographical area of focus, studies by Awotwi et al. (2019) utilized the Soil and Water Assessment Tool (SWAT) modeling to examine the repercussions of land use changes in the Pra River Basin. Furthermore, the impact of mining on hydrological components and sediment yield in the Pra Basin was investigated by Awotwi et al. (2021) using SWAT, while another study by Awotwi et al. (2017) centered on assessing the influence of climate and anthropogenic activities on water balance components. Despite these studies, there is a notable gap in research regarding the potential of water resources for cocoa supplemental irrigation and its corresponding impact on water resources. A recent investigation in the cocoa region by Akpoti et al. (2023) identified the groundwater potential for cocoa, yet this study relied heavily on GIS and remote sensing techniques, lacking a quantitative assessment of water supplies.

To understand how supplemental irrigation could affect the spatio-temporal availability of water resources, spatio-temporal modeling at the watershed scale and basin scale is needed in the cocoa-producing area. This would help to examine the potential for expansion of cocoa smallholder agriculture in the region from catchment water yield and recharge. The objective of the study is, therefore, to evaluate the hydrological and sediment yield responses of the Upper Offin and Mankran watersheds under baseline conditions using SWAT. This study aimed to quantify the hydrologic water balance components (evapotranspiration, surface runoff, percolation, groundwater flow, and sub-surface flow) and the sediment yield under the current conditions. The output would serve as a baseline for further research and scenario analysis that leads to improved water management and agricultural productivity on a larger scale.

2. MATERIALS AND METHODS

2.1. Study Area Description

This study was conducted in the Upper Offin sub-basin and Mankran micro-watersheds of Ghana (Figure 1). The livelihood of the region is heavily dependent on agriculture, engaging approximately 70% of households in the sector (Asiedu-Darko 2014). On the other hand, mining contributes 40% of the nation's gross foreign exchange, equivalent to 5.7% of its GDP (Mensah et al. 2015). Based on a 30 m Digital Elevation Model (DEM), the elevation of the Upper Offin sub-basin ranges from 157 m to 777 m, with a mean elevation of 274 m above sea level (masl). Whereas the elevation of the Mankran watershed ranges from 186 m to 536 m, with a mean elevation of 284.5 masl. The topography of the two watersheds shows that most of the landscapes are above 8% slope for both the Upper Offin and Mankran watersheds.

The Upper Offin and Mankran watersheds cover an area of 3,068.5 km^2 and 127 km^2, respectively. Based on Climate Hazard Group Infrared Precipitation with Station (CHIRPS) rainfall data (Funk et al. 2015), the mean annual rainfall in these areas ranges from 1,019 mm to 1,751 mm. In terms of temperature, the areas experience maximum and minimum daily temperatures ranging from 23 ℃to 39 ℃and 13℃to 27 ℃, respectively, using data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Atmospheric Reanalysis for Global Climate (ERA5).

Based on the landcover classification for 2020 by the European Space Agency (ESA) (Zanaga et al. 2022), the Upper Offin sub-basin is predominantly covered by forest (66%), followed by shrub (15.8%) and grassland (8.2%). Similarly, the Mankran watershed's dominant land use is forest (74.8%), followed by shrub (15%) and grassland (5.6%). According to the soil classification by the Food and Agricultural Organization (FAO) (Sanchez et al. 2009), Orthic Acrisols constitute the dominant soils in both watersheds, accounting for 94% and 99.5% of the Upper Offin and Mankran watersheds, respectively. These soils are moderately well-drained, feature a sandy clay loam texture, and are categorized under the hydrologic soil group class C.

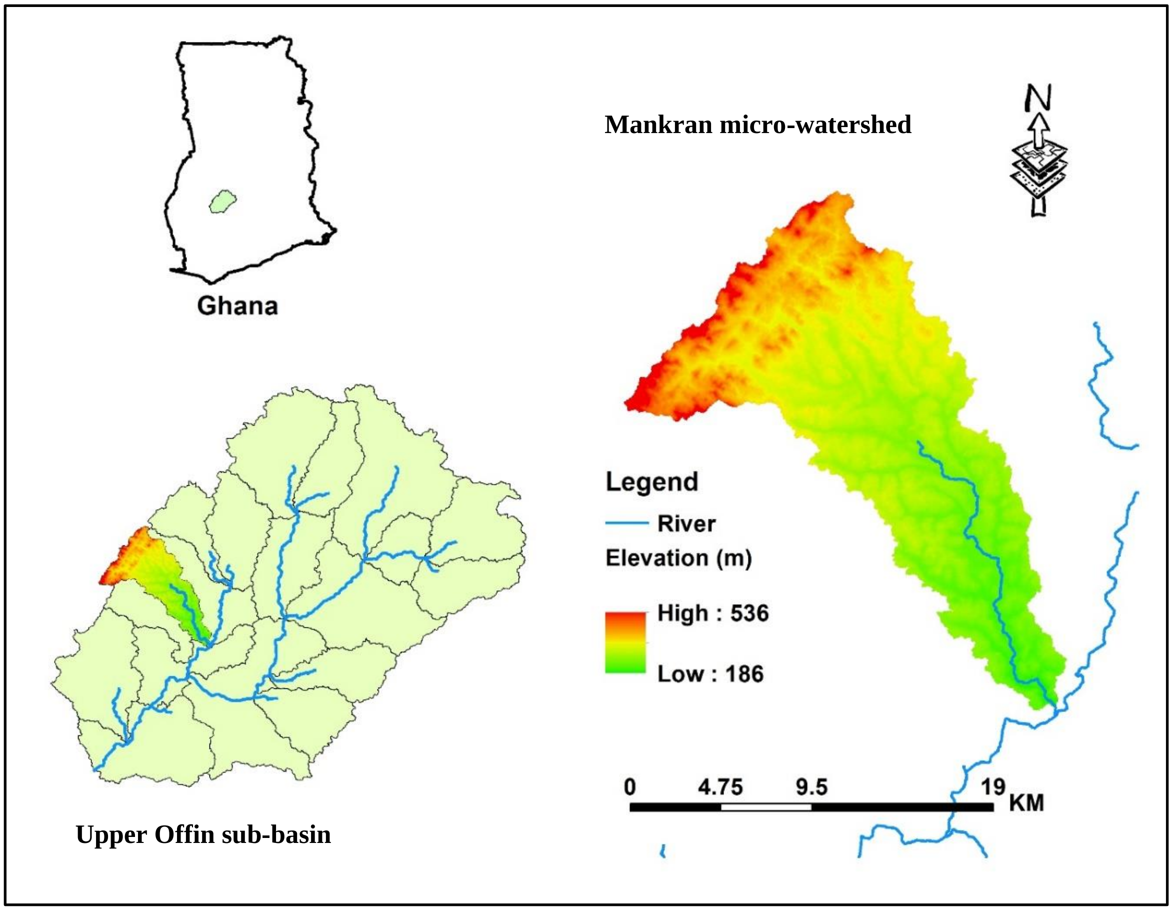


Figure 1. Location of Upper Offin sub-basin and Mankran micro-watershed in Ghana. (Source: Authors construct)

2.2. Data and sources

SWAT hydrological modeling relies on a wide range of temporal and spatial data to understand and simulate various components of the hydrological cycle (Arnold and Fohrer 2005; Taffese and Zemadim 2013). Spatial data inputs include the Digital Elevation Model (DEM), soil characteristics, and land use or cover information. The time series data inputs are the weather data, including precipitation, maximum and minimum air temperature, relative humidity, wind speed, and solar radiation. To calibrate and validate the model, it requires additional data such as stream flow records, groundwater level measurements, evapotranspiration, or combinations of these data. Recent hydrological studies also leverage remote sensing data, including satellite imagery and reanalyzed rainfall and temperature, to enhance model accuracy for sustainable water resource management (Abate et al. 2023; Mebrie et al. 2023). In this study, observed streamflow records at Adimbera station in Upper Offin were used for SWAT model calibration and validation. Table 1 presents the data types and their sources used to set up the SWAT model and calibrate and validate it for hydrology.

Table 1. Data types and their sources used for exploitable water assessment

Data	Source	Resolution (m)
Land use	European Space Agency, ESA, land covers 2020	10
Soil characteristics	Food and Agriculture Organization (FAO) through the World Soil Information, ISRIC	250
Digital Elevation Model (DEM)	United States Geographical Survey (USGS), 2000	30
Cocoa farmland cover	Abu et al. (2021)	10
Rainfall (mm)	Climate Hazard Group Infrared Precipitation with Station (CHIRPS)	5,000
Temperature (^{O}K)	European Centre for Medium-Range Weather Forecasts (ECMWF) and Atmospheric Reanalysis for Global Climate (ERA5)	25,000
Relative humidity, solar radiation, wind speed	Climate Forecast System Reanalysis (CFSR)	55,000
Streamflow Data	Ghana Hydrological Authority	Point data

The study utilized the Climate Hazard Group Infrared Precipitation with Station (CHIRPS) rainfall and the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF)-Atmospheric Reanalysis for Global Climate (ERA5) temperature datasets due to the inaccessibility of ground meteorological station records. CHIRPS integrates satellite infrared data with ground-based rain gauge observations, combining the strengths of both sources to provide long-term rainfall data with a high spatial resolution of 5 km (Cepeda Arias and Cañon Barriga 2022; Gao et al. 2018). On the other hand, ERA5 assimilates a vast amount of observation data, including satellite measurements and weather station data, into the model to produce reliable temperature estimates. ERA5 also offers long-term temperature estimates with a reasonable spatial resolution (25 km).

Both CHIRPS rainfall and ERA5 temperature have undergone extensive validation against independent observation data and have shown promising results in various regions worldwide (Dinku et al. 2018; Gleixner et al. 2020), including West Africa (Gbode et al. 2023; Sacré Regis M et al. 2020). In addition, the Climate Forecast System Reanalysis (CFSR) datasets were used as weather generators in SWAT to simulate additional weather variables such as wind speed, relative humidity, and solar radiation. The CFSR dataset has undergone extensive validation against ground-based observation, showing reasonable performance (Dile and Srinivasan 2014). It is worth noting that no reanalysis product is perfect, and indeed, limitations and uncertainties do exist (Condom et al. 2020; Thejll and Gleisner 2015).

2.3. Methodology for the modeling

The hydrological modeling methodology (Figure 2) began with the preparation of input datasets (i.e., weather, DEM, soil, and land use) formatted according to the SWAT requirement. Using 30 m DEM and the river outlet location, the watershed was delineated, and drainage patterns and associated topographic characteristics were generated. Land use and soil data were resampled to 30 m resolution and integrated with topographic characteristics (slope) to create hydrologic response units (HRUs). Weather data, including rainfall, temperature, wind speed, relative humidity, and solar radiation, were supplied into the model to set up a SWAT hydrologic model. The model was then employed to simulate various water balance hydrological components and compare them with observed stream flow data and literature values.

The Soil and Water Assessment Tool – Calibration and Uncertainty Procedure (SWAT-CUP) was used to calibrate and validate the hydrologic model using monthly observed streamflow data from 2001 to 2011 and literature values on evapotranspiration, runoff, and water yield ratios. Model performance evaluation criteria were applied to assess the model’s ability to simulate hydrological processes effectively. Following the successful reproduction of the hydrologic balance, the model was utilized to characterize the study areas in terms of water resources and sediment yield.

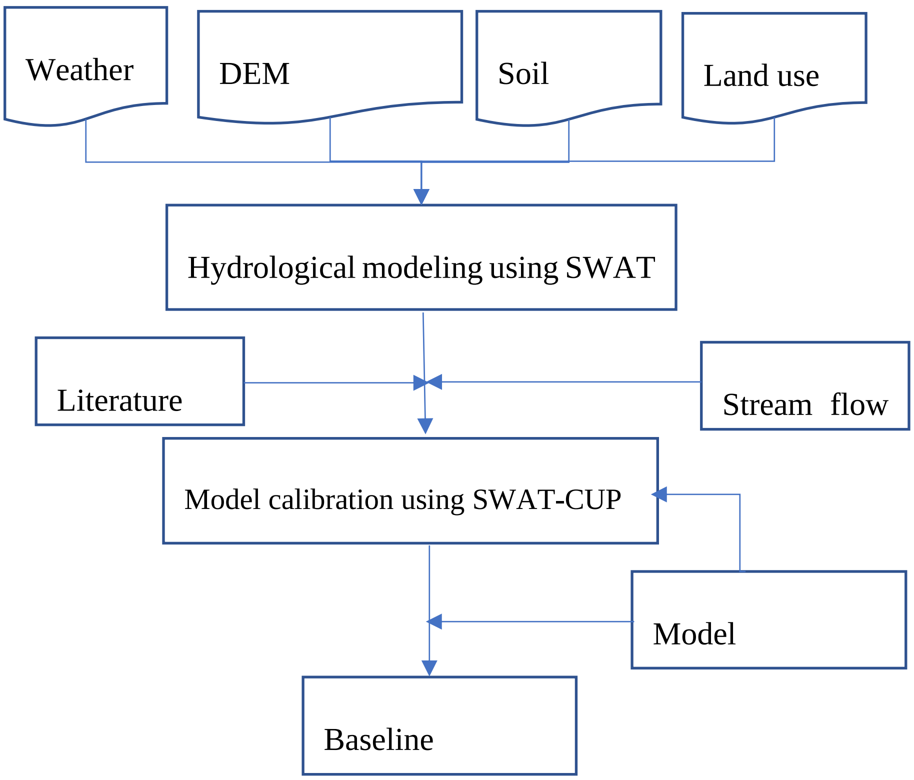


Figure 2. Methodology of hydrological modeling using SWAT to characterize baseline hydrology of Upper Offin and Mankran watersheds. (Source: Authors construct)

2.4. Description of the SWAT hydrology model

The Soil and Water Assessment Tool (SWAT) was used in this study to conduct baseline catchment characterization for the Upper Offin and Mankran watersheds. In SWAT, a watershed is divided into sub-basins based on topography, and then each sub-basin is conceptually divided into hydrologic response units, or HRUs (Worqlul et al. 2018). The HRUs have a unique combination of land use, soil, and slope. The Upper Offin sub-basin was delineated based on a flow gauging station located at Adiembra by considering Mankran as one of the sub-basins. The watershed was delineated with a default threshold value of (74 km^2), resulting in 20 sub-basins, including Mankran. Marginal land uses, soils, and slope threshold percentages below 5%, 10%, and 20% were considered, respectively. The analysis resulted in 147 and 8 HRUs for the Upper

Offin sub-basin and Mankran sub-watershed, respectively. The SWAT model simulates the soil water content, surface runoff, evapotranspiration, sediment yield, plant growth, and the impacts of management practices at the HRU level, and then aggregates at the sub-basin level (Neitsch et al. 2011). The general water balance equation used in SWAT is shown in Equation (1). A detailed description of the model conceptual framework and simulation strategies (Arnold et al. 2012; Arnold et al. 1998) can be found in the equation:

$$SW_t = SW_{t-1} + \sum_1^t (P_i - Q_{surf,i} - ET_i - Q_{loss,i} - Q_{gw,i} \tag{1}$$

Where SW_{t-1}, P_i, $Q_{surf,i}$, ET_i, $Q_{loss,i}$, and $Q_{gw,i}$ are soil water contents above the wilting point at the end of day t, the amount of precipitation on day i, the daily amount of surface runoff, evapotranspiration, percolation into the deep aquifer, and lateral sub-surface flow, respectively. All components are estimated in units of mm.

2.5. Model calibration and validation

Worqlul et al. (2018) identified 16 calibration parameters and their spaces (Table 2) for the SWAT model based on literature and expert opinion. These parameters were adopted for automated calibration in this study. The calibration parameters were constructed based on 'v_' and 'r_' meaning replacement and a relative change to the initial parameter value, respectively. A global sensitivity analysis was applied to identify parameters that significantly influence the streamflow. In the global sensitivity analysis, all parameters are allowed to change at the same time, followed by the estimation of the standard regression coefficient (Worqlul et al. 2018). The t-stat and p-value were used to evaluate the significance of the relative sensitivity. A p-value close to zero and a relatively small absolute value of t-stat represent higher significance (Nazari-Sharabian et al. 2020).

Table 2. Calibration parameters for the SWAT model, their descriptions, and parameter space used in SWAT-CUP automated calibration and sensitivity analysis

Parameter	Name	Parameter space
SCS runoff curve number	r_CN2.mgt	±0.35

Parameter	Name	Parameter space
Soil evaporation compensation factor	v_ESCO.hru	0.01 – 1.0
Average slope length	r_SLSUBBSN.hru	±0.5
Manning's "n" value for overland flow	v_OV_N.hru	0.01 – 0.3
Surface runoff lag time	v_SURLAG.bsn	0.0001 – 1.0
Depth to impervious layer for modeling perched water tables	v_DEP_IMP.hru	0.0 – 6000
Baseflow alpha factor (days)	v_ALPHA_BF.gw	0.0 – 1.0
Threshold depth of water in shallow aquifer required for return flow to occur (mm)	v_GWQMN.gw	0.0 – 5000
Groundwater "revap" coefficient	v_GW_REVAP.gw	0.02 – 0.2
Manning's "n" value for the main channel	v_CH_N2.rte	0.01 – 0.3
Average slope of main channel	r_CH_S2.rte	±0.5
Available water capacity of the soil layer	r_SOL_AWC().sol	±0.25
Depth from soil surface to bottom of layer	r_SOL_Z().sol	±0.25
Saturated hydraulic conductivity	r_SOL_K().sol	±0.25
Average slope of tributary channels	r_CH_S1.sub	±0.5
Manning's "n" value for the tributary channels	v_CH_N1.sub	0.001 – 0.3

Source: Worqlul et al. (2018)

The Soil and Water Assessment Tool Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour et al. 2015) with the Sequential Uncertainty Fitting Version 2 (SUFI-2) (Abbaspour et al. 2015) optimization algorithm was used to calibrate SWAT model parameters and perform sensitivity analysis. The SUFI-2 optimization algorithm is a robust and widely used method for hydrological model calibration that helps refine model parameters and improve the accuracy of simulated hydrological processes (Tang et al. 2021). A total of 2,800 parameter sets were sampled to identify a set of parameters that provides the maximum Nash-Sutcliff Efficiency (NSE). Five hundred iterations were performed, and the best set of parameters were used for the next 500 iterations. This procedure was repeated five times or more for the last 300 iterations.

2.6. Model performance evaluation criteria

The simulation period was divided into three phases: warm-up (1998–2000), calibration (2001–2008), and validation (2009–2011). The performance of calibrated SWAT model flow and predicted flow during the validation period was evaluated using commonly used multiple statistics such as R-squared (R^2), percent bias (PBIAS), and Nash-Sutcliff Efficiency (NSE) (Worqlul et al. 2018). The PBIAS, Equation (2), varies from negative infinity to positive infinity; however, the model performs best when the value is zero. The R-squared, Equation (3), varies from zero to one, where a value of one represents a perfect correlation and the reverse refers to no correlation. The NSE, Equation (4), value varies from negative infinity to one, where a value of one represents a perfect model simulation of the observed flow. A negative NSE value refers to the average of the observed time series being better than the model predictions.

$$PBIAS = \left(\frac{\sum_{i=1}^{n} Q_{obs(i)} - \sum_{i=1}^{n} Q_{sim(i)}}{\sum_{i=1}^{n} Q_{obs(i)}}\right) * 100 \tag{2}$$

$$R^2 = \left(\frac{n\sum Q_{obs(i)}Q_{sim(i)} - (\sum Q_{obs(i)})(\sum Q_{sim(i)})}{\sqrt{[n(\sum Q_{obs(i)})^2 - (\sum Q_{obs(i)}{}^2][n(\sum Q_{sim(i)}{}^2) - (\sum Q_{sim(i)}{}^2]}}\right)^2 \tag{3}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{sim(1)} - Q_{obs(i)})^2}{\sum_{i=1}^{n}(Q_{obs(1)} - \bar{Q}_{obs(i)})^2} \tag{4}$$

2.7. Hydrology of Upper Offin and Mankran watersheds

After calibrating the model parameters, the model simulation was extended to 2019, based on the temperature data limit. The hydrology of the Upper Offin sub-basin and Mankran sub-basin was analyzed at the outlet of the two catchments. The hydrological responses of the two catchments were quantified under the current biophysical conditions. The parameters include evapotranspiration, catchment water yield, surface runoff, percolation, groundwater flow, and sediment yield.

3. RESULTS AND DISCUSSION

3.1. Model parameter sensitivity analysis

The result of sensitivity analysis for the Upper Offin sub-basin (Table 3) revealed that the t-value (absolute) ranged from 8.73 (most sensitive) to 0.21 (least sensitive), and the p-value ranged from zero (most sensitive) to 0.91 (least sensitive). The parameters identified as most sensitive, listed in order of sensitivity, were CH_N1, CH_S1, CN2, GWQMN, GW_REVAP, OV_N, and Sol_Z. Using the seven sensitive parameters would be sufficient for obtaining reasonable streamflow estimates using the SWAT model in the Upper Offin sub-basin with the inclusion of other parameters and would not significantly affect overall model performance. In general, streamflow sensitivity was observed for sub-basin, management, and groundwater parameters. A study by Osei et al. (2019) on the Owabi catchment, employing the SWAT model, identified 14 sensitive parameters, 11 of which were the same as our findings. Similarly, studies by Awotwi et al. (2019, 2021) in the Pra River Basin used 14 sensitive parameters of SWAT, eight of which aligned with these study results. However, these SWAT studies did not present the relative sensitivity of the selected parameters.

Table 3. Parameter sensitivity analysis result for Upper Offin sub-basin

Parameter	t-stat	p-value	Rank
v_CH_N1.sub	8.73	0.000	1

Parameter	t-stat	p-value	Rank
r_CH_S1.sub	-8.51	0.000	2
r_CN2.mgt	-7.52	0.000	3
v_GWQMN.gw	-6.77	0.000	4
v_GW_REVAP.gw	-6.06	0.000	5
v_OV_N.hru	4.33	0.000	6
r_SOL_Z().sol	-3.88	0.000	7
v_ALPHA_BF.gw	1.90	0.058	8
r_CH_S2.rte	-1.73	0.085	9
v_CH_N2.rte	-1.38	0.168	10
r_SLSUBBSN.hru	-1.06	0.288	11
r_SOL_K().sol	-1.06	0.289	12
v_ESCO.hru	0.57	0.571	13
r_SOL_AWC().sol	-0.35	0.727	14
v_DEP_IMP.hru	-0.25	0.804	15
v_SURLAG.bsn	-0.21	0.838	16

3.2. Model calibration and validation

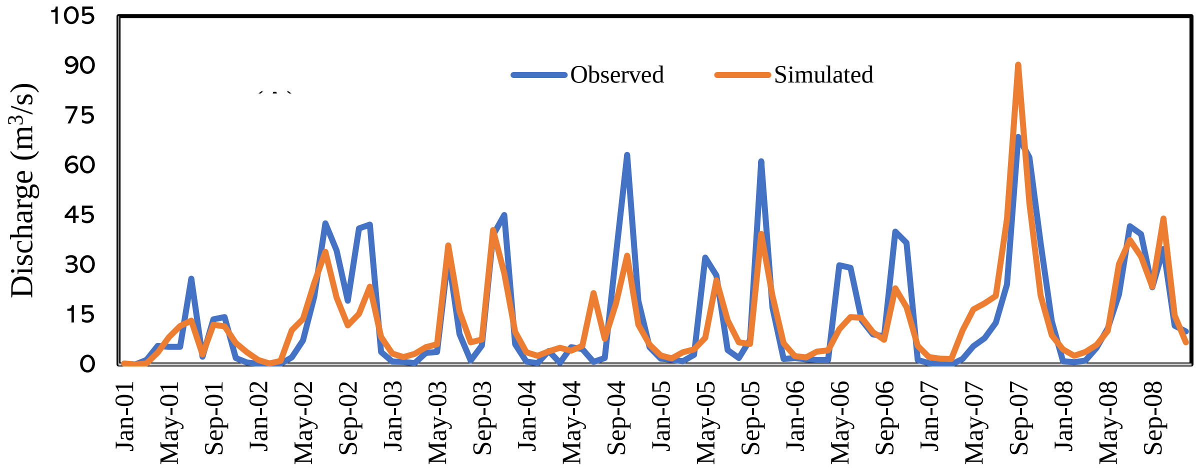
The calibration and uncertainty analysis of the SWAT model was carried out using SWAT-CUP, considering all parameters utilized in the sensitivity analysis (Table 4). Parameters denoted with 'v_' and 'r_' signify replacement and a relative change to the initial parameter value, respectively. Adjusting these parameters based on fitted values would yield a model with reasonable performance suitable for additional hydrologic characterization in the region.

Table 4. Parameter calibraton results for Upper Offin sub-basin

Parameter	Fitted value	Actual value
v_CH_N1.sub	0.39	0.39
r_CH_S1.sub	-0.62	0.003
r_CN2.mgt	-0.07	69.50
v_GWQMN.gw	3740.99	3740.99
v_GW_REVAP.gw	0.05	0.05
v_OV_N.hru	0.32	0.32
r_SOL_Z().sol	-0.08	*
v_ALPHA_BF.gw	0.91	0.91
r_CH_S2.rte	-0.17	0.002
v_CH_N2.rte	0.43	0.43
r_SLSUBBSN.hru	-0.02	46.50
r_SOL_K().sol	0.17	*
v_ESCO.hru	0.67	0.67
r_SOL_AWC().sol	-0.16	*
v_DEP_IMP.hru	5984.19	5984.19
v_SURLAG.bsn	0.02	0.02

Note: *refers to value varies per soil depth.

The model successfully replicated the observed flow pattern (Figure 3A) throughout the calibration period, achieving a "good" model performance rating (R^2 of 0.70, NSE of 0.70, and PBIAS of 3.9) based on Moriasi et al. (2007). However, challenges were encountered in capturing peak flows. Instances of underestimation were noted for the years preceding 2007, while overestimation occurred for the years 2007 and 2008 (Figure 3A). The overall model prediction indicated a slight underestimation of the observed flow (Figure 3B). From 2001 to 2008, the mean monthly observed discharge was 14.0 m^3/s, whereas the simulated flow recorded 13.3 m^3/s.



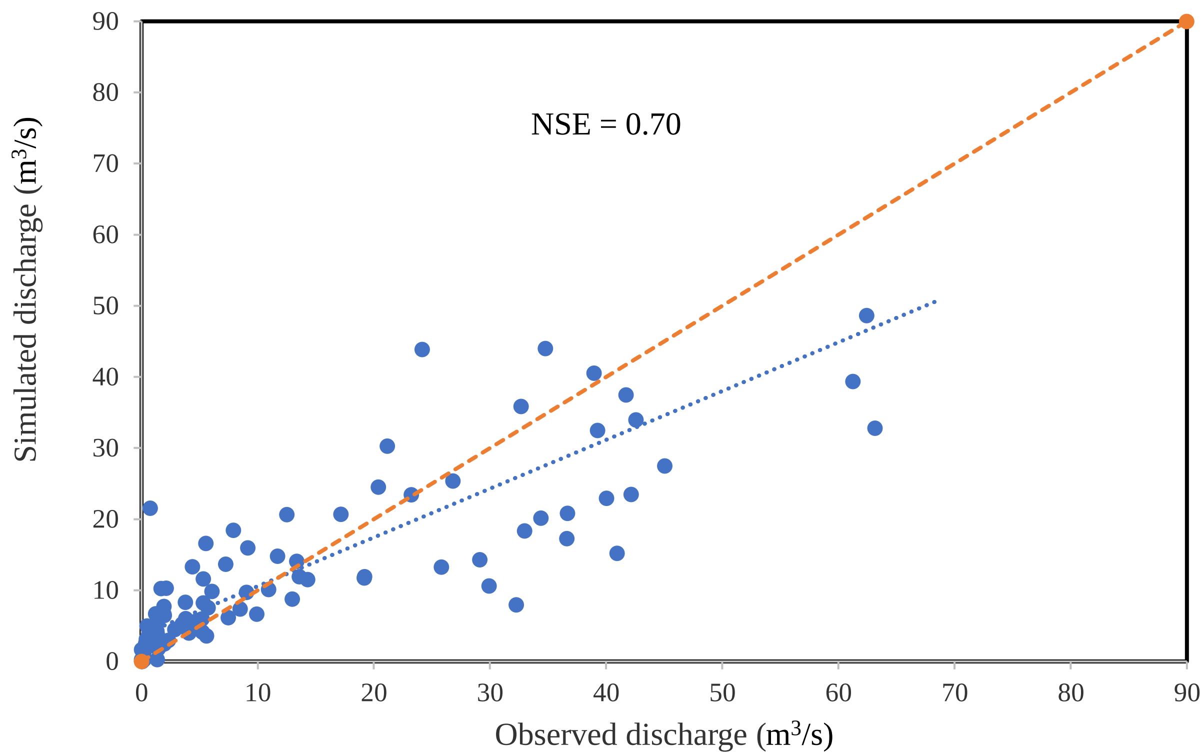
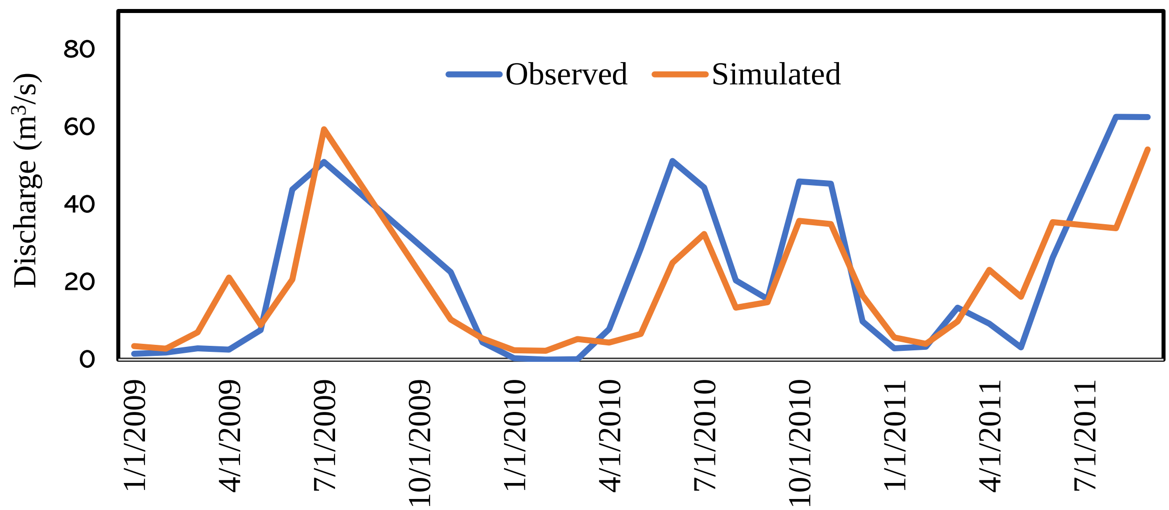


Figure 3. Monthly comparison of observed and simulated stream flow with a hydrograph (A) and scatter plot (B) representation during the calibration period (2001 to 2008). (Source: Authors construct)

Moreover, the model demonstrates reasonable performance in reproducing streamflow during validation (i.e., R^2 of 0.68, NSE of 0.66, and PBIAS of 12.8). However, challenges arise in accurately capturing the hydrograph during the validation period (Figure 4A). This discrepancy may stem from data quality concerns related to observed streamflow, a prevailing issue in the region (Bekoe, 2005). Notably, the model tends to underestimate the observed streamflow (Figures 4A and 4B). Over the period from 2009 to 2011, the mean monthly observed flow was 20.4 m^3/s, while the simulated flow registered at 17.8 m^3/s.



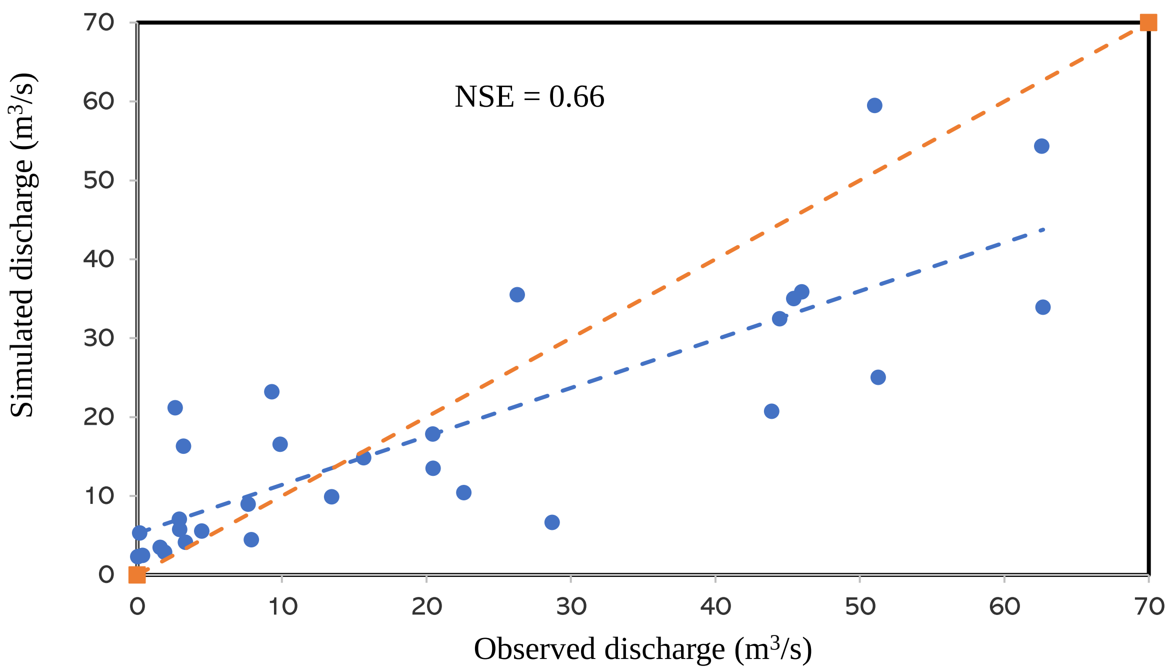


Figure 4. Monthly comparison of observed and simulated stream flow with a hydrograph (A) and scatter plot (B) representation during the validation period (2009 to 2011). (Source: Authors construct)

3.3. Hydrologic responses of the study areas

Hydrological responses of the Upper Offin (Figure 5A) and Mankran (Figure 5B) watersheds were analyzed for the period from 2001 to 2019, considering temperature data limitations. The mean annual precipitation was 1,333 mm, with evapotranspiration accounting for 72% of rainfall (957 mm) in the Upper Offin sub-basin and 74% of rainfall (987 mm) in the Mankran watershed. Surface runoff, on average, comprised less than 5% of rainfall for both watersheds (64 mm or 4.8% of rainfall for the Upper Offin sub-basin and 59 mm or 4.4% of rainfall for the Mankran watershed). Modest mean annual percolation was observed in both watersheds (285 mm or 21% of rainfall for the Upper Offin sub-basin and 255 mm or 19% of rainfall for the Mankran watershed). Sub-surface flow accounted for approximately 3% of rainfall, corresponding to 40 mm for the Upper Offin sub-basin and 44 mm for the Mankran watershed.

Researchers employing the SWAT model have provided diverse estimates for water balance components. Osei et al. (2019) reported that 55% and 16% of the rainfall in the Owabi catchment constituted evapotranspiration and percolation, respectively. Conversely, Acheampong (2021) identified that evapotranspiration accounted for 60% of the rainfall in the Pra River Basin. In the Pra Basin in 2016, Awotwi et al. (2019) estimated that approximately 80% of the rainfall was transformed into evapotranspiration. The evapotranspiration estimates in our study (ranging from 72% to 74% of the rainfall) fall within the range reported in the existing literature.

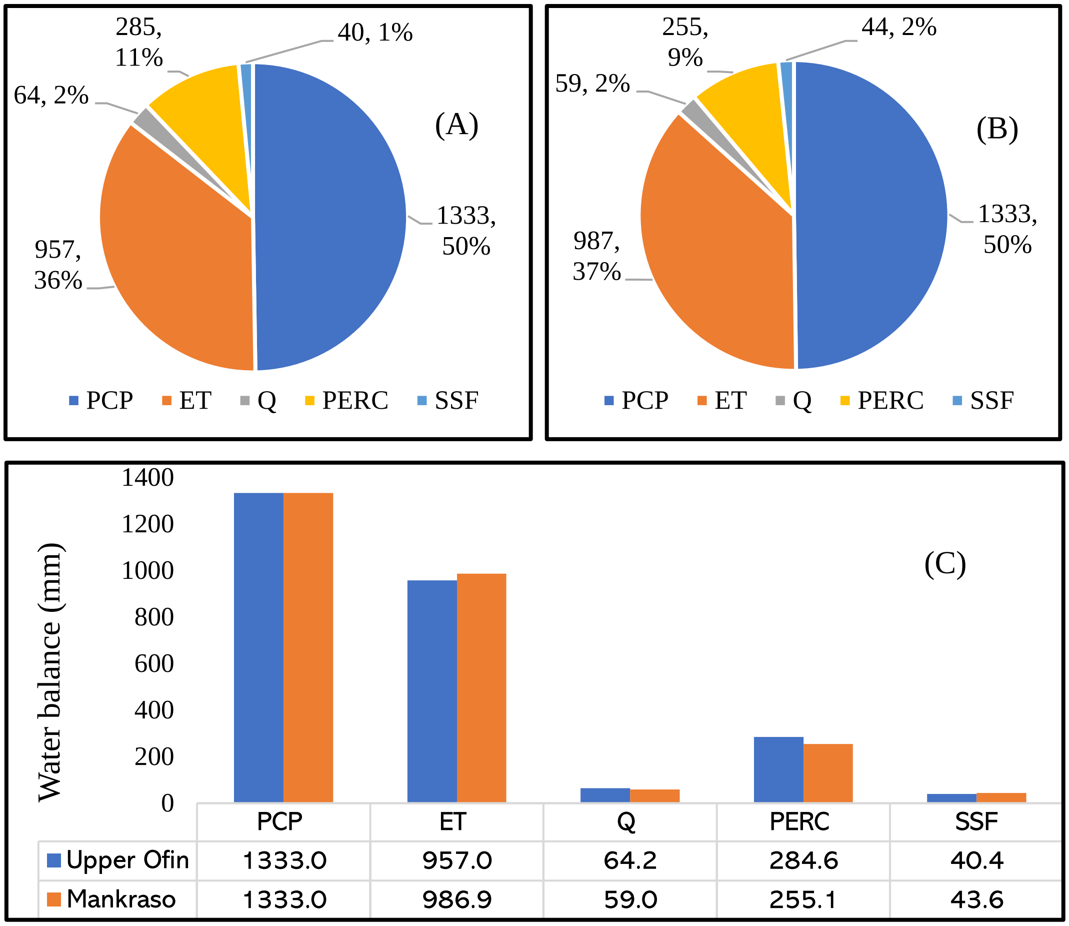


Figure 5. Hydrologic responses of Upper Offin (A), Mankran (B), and comparison of the two watersheds (C). (Source: Authors construct)
Note: PCP, ET, Q, PERC, and SSF were precipitation, evapotranspiration, surface runoff, percolation, and sub-surface flow, respectively. All units are in mm.

The trend in water balance components (ET, PERC, and SSF) for both the Upper Offin (Figure 6A) and Mankran (Figure 6B) watersheds indicates a decrease from 2008 to 2018, with a slight increase observed in 2019. The fluctuations in water balance closely align with the rainfall pattern, except for surface runoff in certain years (e.g., 2006–2010). Notably, percolation consistently surpasses surface runoff in both watersheds.

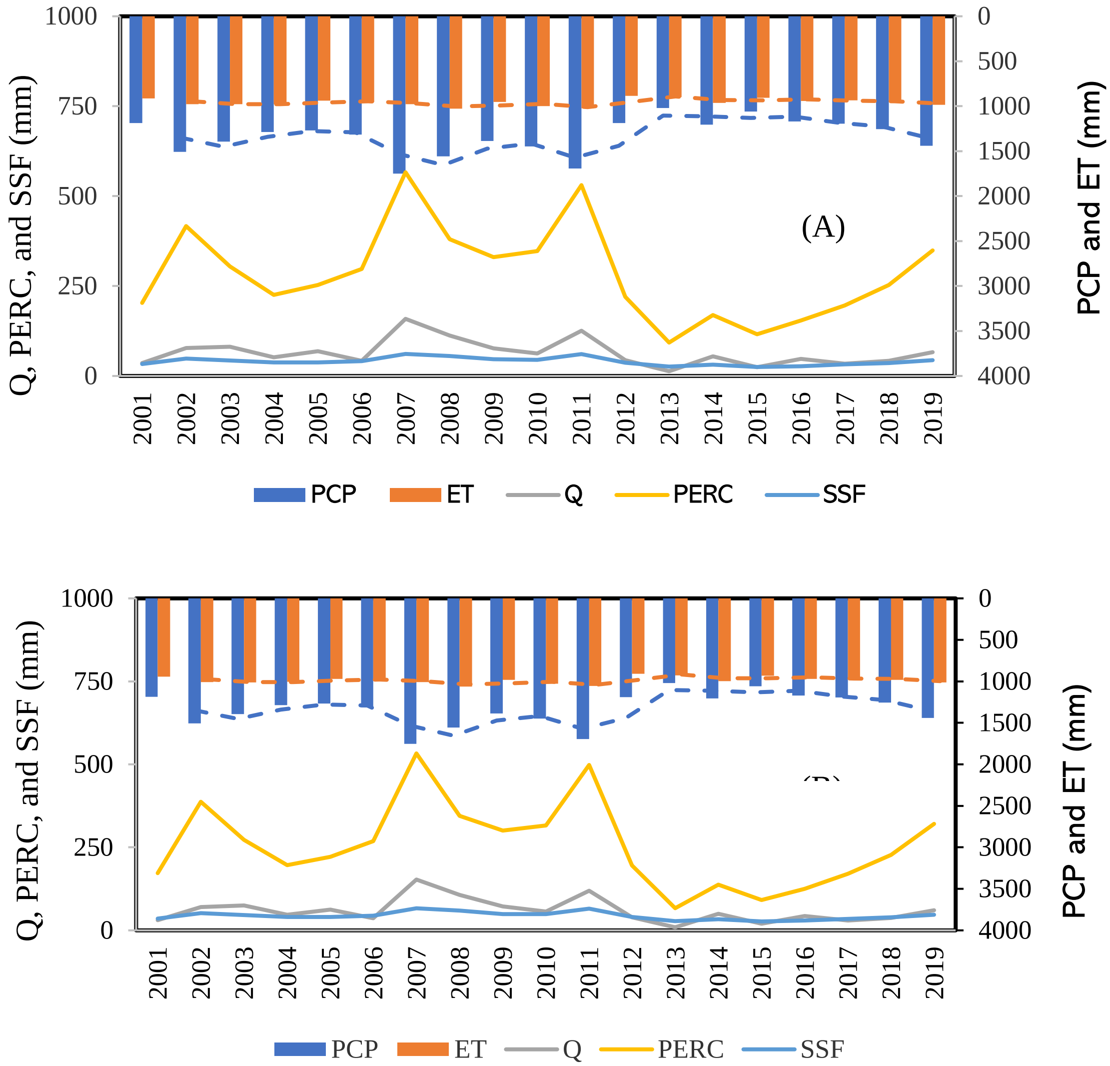


Figure 6. Temporal dynamics (2001 to 2019) of water balance components for Upper Offin (A) and Mankran watersheds. (Source: Authors construct)

Note: PCP, ET, Q, PERC, and SSF were precipitation, evapotranspiration, surface runoff, percolation, and sub-surface flow, respectively. All units are in mm.

The temporal patterns of sediment yield from 2001 to 2019 in both the Upper Offin and Mankran watersheds exhibit a similar trend (Figure 8), closely following the dynamics of rainfall. Notably, the Upper Offin sub-basin showed a higher sediment yield rate compared to the Mankran watershed. The peak sediment yield occurred in 2007 (1.97 t/ha for the Upper Offin and 1.37 t/ha for the Mankran watershed), aligning with the highest recorded rainfall of 1,751.3 mm. Subsequently, sediment yield from both watersheds declined from 2008 to 2018, with a slight increase observed in 2019. The mean annual sediment yield was 0.69 t/ha and 0.37 t/ha per year for the Upper Offin and Mankran watersheds, respectively.

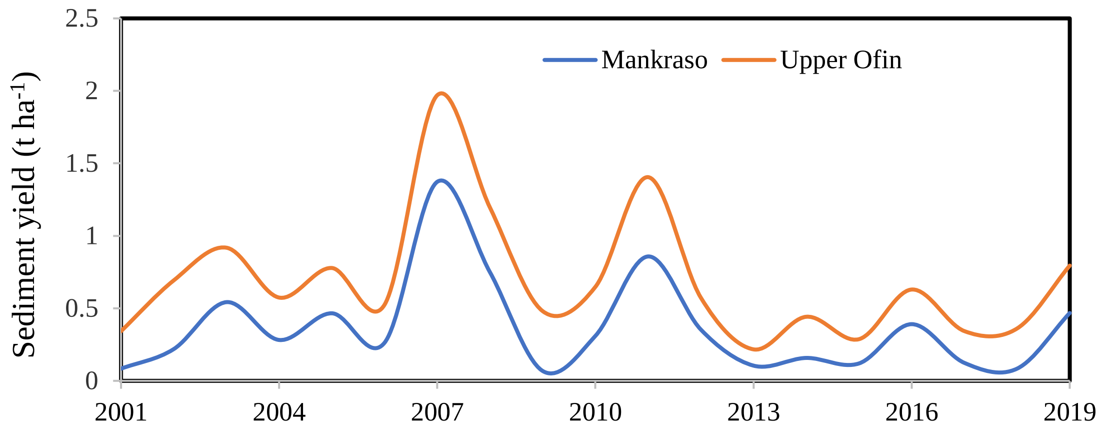


Figure 7. Temporal dynamics of sediment yield (2001 to 2019) for Upper Offin and Mankran watershed. (Source: Authors construct)

The region has seen varied estimates of sediment yield, providing a range of values. For instance, Kusimi et al. (2015) applied the Universal Soil Loss Equation (USLE) to estimate sediment yield for the Pra Basin, reporting values ranging from zero to 390.5 t/ha per year with a mean value of 0.08 t/ha per year. Similarly, Boakye et al. (2020) employed the USLE method in the same basin, yielding a mean value of 2.7 t/ha per year. Akrasi and Ansa-Asare (2008) estimated a mean sediment yield of 0.51 t/ha per year for the Pra River Basin. Furthermore, according to Boakye et al. (2022), sediment yield ranges from 0.1 t/ha per year to 1.4 t/ha per year for the Pra River basin and 0.25 t/ha per year for the Upper Offin sub-basin at the Adiembra gauging station. Though sediment yield estimates are variable, the estimate in our study was within the range of literature values and similar to the Boakye et al. (2022) estimates.

3.4. Spatial hydrological responses (baseline)

The spatial hydrological responses within the catchments are primarily influenced by the spatial datasets (Figure 8) and the spatial variability of climatic data. In the Upper Offin sub-basin, forest cover dominates the land at 42%, followed by cocoa plantations at 31% and shrubs at 11%. Similarly, the Mankran watershed exhibits a land cover dominated by forest (47%) and cocoa (33%), with shrubs comprising 13%. Both the Upper Offin and Mankran watersheds are predominantly characterized by Orthic Acrisols (OAc), accounting for 94% and 99% of the catchments, respectively.

Furthermore, the topography of the Upper Offin landscape indicates that a significant portion has a slope above 8% (constituting 45% of the watershed), followed by slopes ranging from 2% to 8% covering 40% of the watershed. Similarly, the majority of the Mankran watershed landscape features slopes above 8% (50% of the watershed), with slopes from 2% to 8% covering 35% of the area.

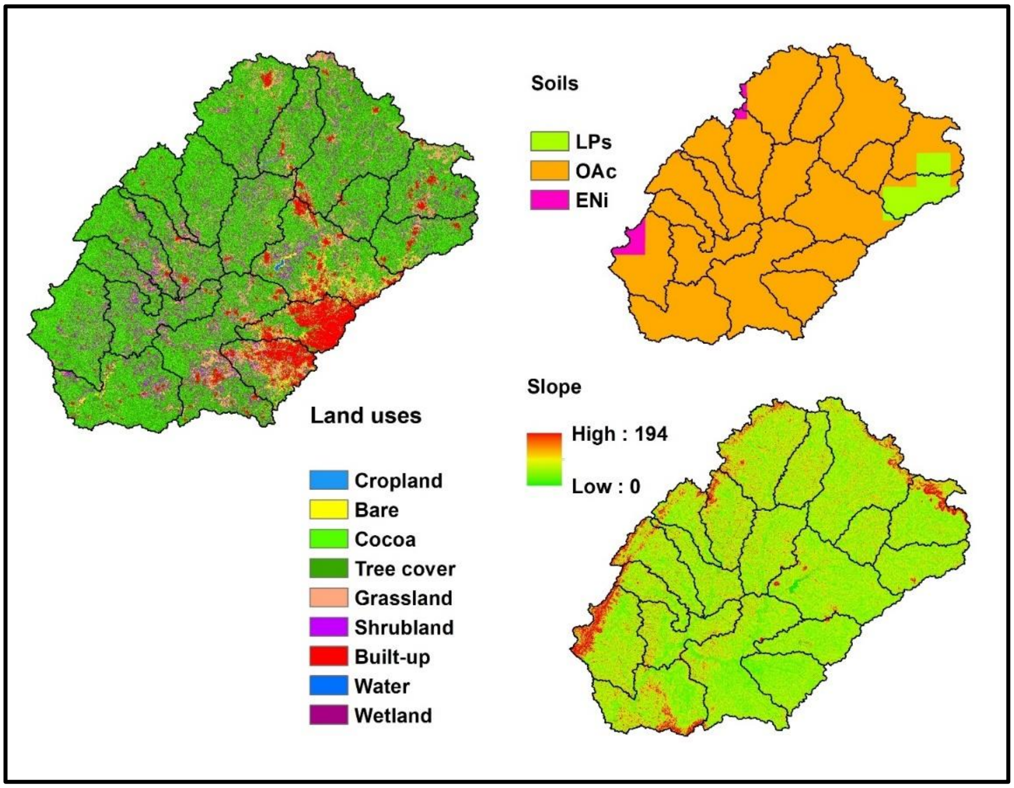


Figure 8. Land cover, soils, and landscape slopes of Upper Offin sub-basin. (Source: Authors construct)

The spatial hydrological response of the Upper Offin watershed under the baseline scenario was assessed through the examination of various variables, encompassing surface runoff, evapotranspiration, percolation, water yield, groundwater flow, sub-surface flow, soil water, and sediment yield (Figures 9 and 10). Annual evapotranspiration and surface runoff exhibited ranges of 499 mm to 988 mm and 15 mm to 119 mm, respectively. In contrast, percolation and water yield within the watershed spanned from 211 mm to 796 mm and 145 mm to 711 mm, respectively.

The Upper Offin sub-basin is characterized by elevated evapotranspiration and percolation, while the contribution of surface runoff to the overall water cycle is relatively modest. Areas with high runoff and low percolation (Figure 9) are linked to dominant built-up and bare land cover classes, coupled with generally mild landscape slopes (Figure 8). Additionally, soil water and groundwater flow exhibited ranges of 13 mm to 59 mm and 17 mm to 633 mm, respectively, while sub-surface flow varied from 22 mm to 62 mm. Meanwhile, sediment yield in the watershed ranged from 0.2 t/ha to 13.4 t/ha, with higher sediment yield associated with increased surface runoff (Figure 10).

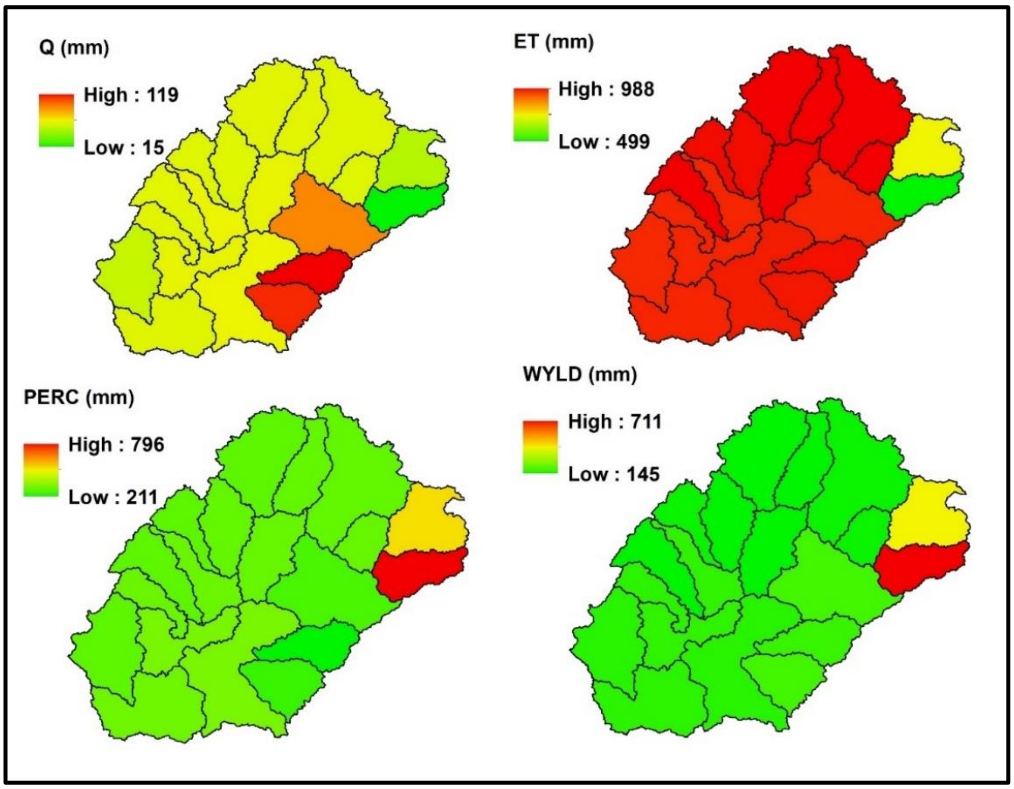


Figure 9. Spatial hydrological responses of Upper Offin sub-basin for surface runoff, evapotranspiration, percolation, and water yield
Note: Q, ET, PERC, and WYLD are surface runoff, evapotranspiration, percolation, and water yield, respectively. **(Source: Authors construct)**

The land use map clearly indicates that the southeastern part of the Upper Offin sub-basin is predominantly characterized by built-up areas (depicted in red) and bare lands (depicted in yellow). This area includes Kumasi, the second-largest town in the nation. The catchments in the built-up-dominated regions exhibit heightened runoff (Q) and sediment yield (SYLD) in three sub-basins (Figure 9), as highlighted by the red colors.

Conversely, areas dominated by tree cover land use classes and Leptosols (LPs), classified as hydrologic group B (Figure 10), demonstrate elevated percolation, water yield (Figure 9), groundwater flow, sub-surface flow, and soil water (Figure 10) upstream of the watershed in two sub-basins. In contrast, evapotranspiration was relatively low in these same sub-basins.

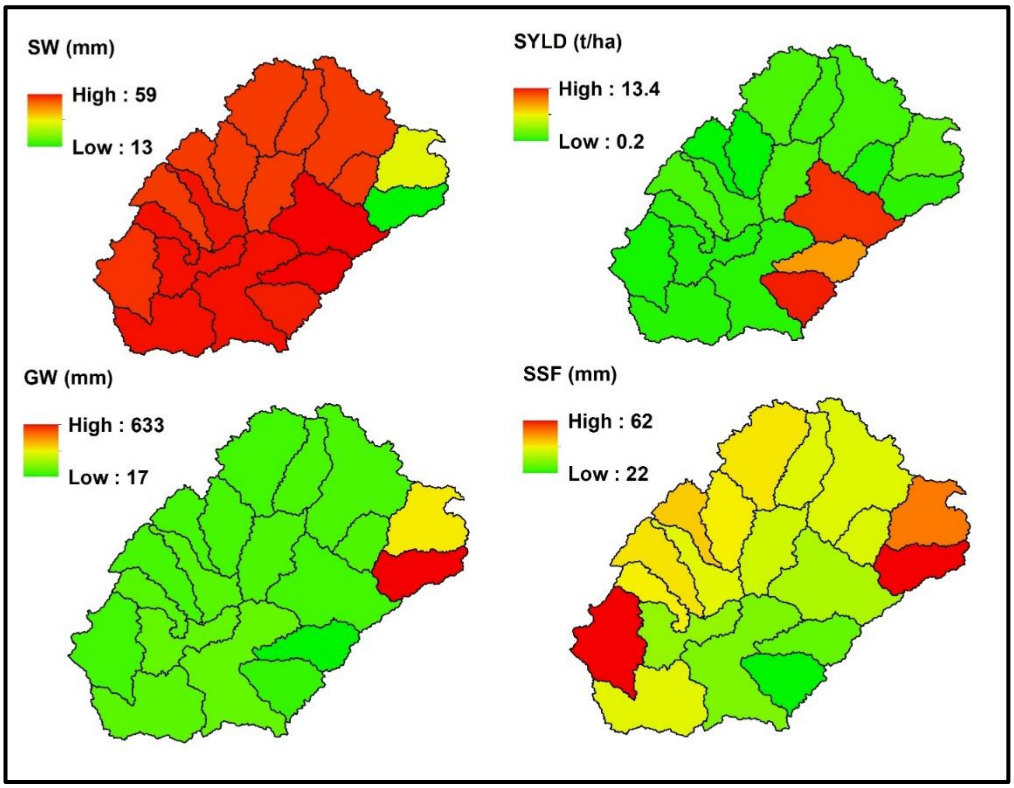


Figure 10. Spatial hydrological responses of Upper Offin sub-basin Spatial hydrological responses of Upper Offin sub-basin for soil water, groundwater flow, sub-surface flow, and sediment yield

Note: SW, GWQ, SSF, and SYLD are soil water, groundwater flow, sub-surface flow, and sediment yield, respectively. **(Source: Authors construct)**

4. CONCLUSIONS

The primary objective of this study was to evaluate the hydrological response of the Upper Offin and Mankran watersheds under baseline conditions. Initial calibration and validation of the Soil and Water Assessment Tool (SWAT) model were performed at the Adimbera gauging station in the Upper Offin sub-basin, with Mankran considered as one of the SWAT sub-basins. After 3,200 iterations involving 16 selected parameters, the model demonstrated reasonable performance in reproducing observed flow patterns. Among the parameters, CH_N1, CH_S1, CN2, GWQMN, GW_REVAP, OV_N, and Sol_Z were identified as the most sensitive in the region, with their relative order of sensitivity determined.

The findings revealed that 72% (957 mm) and 74% (987 mm) of the annual rainfall were transformed into evapotranspiration for the Upper Offin and Mankran watersheds, respectively. Surface runoff remained below 5% for both watersheds, while percolation accounted for approximately 17% and 15% for the Upper Offin and Mankran watersheds, respectively. The mean annual sub-surface flow was below 4% of rainfall for both watersheds. This indicates that evapotranspiration and percolation were the dominant hydrological components in the watersheds. The mean annual sediment yield was approximately 0.69 t/ha and 0.37 t/ha per year for the Upper Offin and Mankran watersheds, respectively.

A notable trend observed was a decreasing pattern in all water balance components and sediment yields from 2008 to 2018, with a slight increment in 2019, aligning with the rainfall pattern. The results highlight a substantial proportion of percolation in the region, suggesting a potential for irrigated agriculture. Moreover, the SWAT model was able to capture the hydrological responses of the study areas, demonstrating its potential to evaluate the impact of any developmental intervention in the landscape.

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