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Water Resources Modeling in Data-Scarce Watersheds: Contribution of the SWAT Model and the SUFI2 Algorithm to the Study of the Thiokoye River Basin

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Abstract

Effective management of water resources in West African basins is increasingly hindered by sparse hydrometeorological datasets, high interannual rainfall variability, and nonlinear feedbacks among climate, land use, and hydrological processes. To address these constraints, this study implemented the Soil and Water Assessment Tool (SWAT) in conjunction with the SUFI-2 (Sequential Uncertainty Fitting v2) algorithm in the Thiokoye River Basin—an understudied sub-catchment of the Gambia River situated at the interface of Southern Sudanian and Guinean climatic zones. The model was calibrated (1979-1992) and validated (1998-2002) using multiple performance metrics (NSE, R^2, KGE, PBIAS) and uncertainty indicators (p-factor, r-factor). Calibration yielded excellent results (NSE = 0.98, R^2 = 0.98, p-factor = 0.90), with similarly robust validation scores (NSE = 0.82, R^2 = 0.83, KGE = 0.81, PBIAS = −13.2%). Hydrological simulations showed strong seasonal partitioning, with blue water fluxes—surface runoff, percolation, and water yield—constrained to the May-October wet season, representing only 22% of annual rainfall. Conversely, green water availability remained low year-round (mean ET/PET = 0.19), suggesting persistent vegetative water stress. Sediment modeling indicated acute erosion risk, with over 96% of annual soil loss (15.5 t/ha) occurring during peak rainfall periods. Sensitivity analysis revealed CN2, ALPHA_BF, GW_DELAY, and CH_K2 as dominant controls on runoff and groundwater dynamics. These results underscore the utility of the SWAT-SUFI-2 framework for simulating hydrological and sediment processes in data-limited tropical basins and informing targeted strategies for watershed management and climate resilience.

Keywords

Blue Water, Green Water, SWAT, SUFI2, Thiokoye River Basin, Water Resources

1. Introduction

Access to effective water resource management relies on a deep understanding of hydrological processes, particularly in watersheds where hydrometeorological data are scarce. In many West African watersheds, the high spatiotemporal variability of precipitation, coupled with a lack of reliable measurement stations and continuous hydrological monitoring, complicates flow estimation and water resource planning (Bodian et al., 2011; Descroix et al., 2015, 2018; Faye & Mendy, 2018; Thiaw, 2020, 2023; Mendy et al., 2025). This situation is exacerbated by climate change, which leads to increased irregularity of precipitation and a higher frequency of extreme events, such as droughts and flash floods. These phenomena directly impact water availability and challenge local populations' adaptation strategies (Descroix et al., 2009; Descroix & Amogu, 2012; Descroix et al., 2015; Thiaw, 2017; Bodian et al., 2018; Thiaw et al., 2021).

In this context, the Thiokoye watershed, a tributary of the Gambia River illustrates these challenges well. It is characterized by strong spatial and temporal heterogeneity of precipitation, influenced by both climatic and anthropogenic factors (Thiaw, 2025). Land use and the evolution of agricultural practices also play a key role in the basin's hydrological dynamics by altering flow regimes and exacerbating erosion and sedimentation risks. However, the lack of sufficient hydrological data constitutes a major constraint, limiting the ability to analyze hydrological trends and complicating the implementation of sustainable water resource management strategies (Bodian et al., 2011; Thiaw et al., 2021; Thiaw, 2023). It is therefore essential to use modeling tools to compensate for this data deficit and improve the understanding of hydrological processes at the local scale.

Given these constraints, distributed hydrological models are valuable tools for modeling water flows and assessing the impacts of climate and land-use changes. Among these models, the Soil and Water Assessment Tool (SWAT) is one of the most widely used worldwide (Arnold et al., 1998; Arnold & Fohrer, 2005; Schuol et al., 2008; Neitsch et al., 2011; Bachmann, 2015; Givati et al., 2016; Omer et al., 2017; Faty et al., 2019). It simulates hydrological processes, water balances, and water quality in various contexts, including watersheds with data deficits (Gassman et al., 2007; Alejandra et al., 2008). Its semi-distributed approach divides the watershed into homogeneous units called Hydrologic Response Units (HRUs), allowing for a better representation of interactions between land use, soils, and climate.

However, despite its robustness, applying SWAT in watersheds with limited hydrometric data requires rigorous calibration and uncertainty quantification to ensure reliable simulations (Schuol & Abbaspour, 2007; Mulungu et Munishi 2007; Arnold et al., 2012). Errors related to input data, model parameters, and approximations of hydrological processes can compromise the accuracy of predictions. Therefore, advanced optimization and uncertainty analysis methodologies must be adopted to improve the model's performance.

The SUFI-2 (Sequential Uncertainty Fitting ver.2) algorithm, integrated into the SWAT-CUP software, is a particularly effective approach for calibrating and quantifying uncertainties associated with hydrological simulations (Abbaspour et al., 2007; Manoj, 2009; Abbaspour, 2012). This algorithm follows an iterative approach that gradually adjusts model parameters by minimizing discrepancies between simulations and observations while accounting for uncertainties inherent in input data and modeled processes (White & Chaubey, 2005; Rouholahnejad et al., 2014).

The advantage of SUFI-2 lies in its ability to reduce modeling errors by integrating a range of parameter values rather than a single value, quantifying uncertainties by defining confidence intervals for hydrological simulations, and optimizing model calibration by identifying the most influential parameters and iteratively adjusting their values. This approach is particularly suited to data-scarce watersheds, such as Thiokoye, where direct measurements of flows and precipitation are limited or imprecise. Through SUFI-2, it is possible to improve SWAT performance by adjusting its parameters to local conditions and incorporating uncertainties associated with hydrological estimates (Abbaspour et al., 2004; Ali et al., 2014). In this context, the present study seeks to evaluate the applicability and robustness of the SWAT–SUFI-2 modeling framework for hydrological simulation in the Thiokoye watershed. The specific objectives are threefold: 1) to calibrate and validate the SWAT model under data-scarce conditions; 2) to perform a sensitivity analysis to identify the most influential parameters affecting streamflow and water balance simulations; and 3) to quantify the uncertainties associated with model outputs through an integrated approach that combines calibration with uncertainty analysis.

2. Materials and Methods

2.1. Presentation of the Study Area

The Thiokoye River basin, located between latitudes 12˚10' and 12˚35' North and longitudes 12˚15' and 12˚40' West, covers an area of 973 km^2 with a perimeter of 182 km, resulting in a compactness coefficient of 1.63. This transboundary basin spans 973 km^2 across Senegal (563 km^2) and Guinea Conakry (410 km^2) (**Figure 1**). It originates at the confluence of two streams, Sembaou-Mandé and Guilère, which flow from the Mali highlands in Guinea, where altitudes reach approximately 1120 m. From this confluence, the Thiokoye River flows 9.8 km to the Senegal-Guinea border, covering an area of 291 km^2, and continues for another 7.5 km before successively receiving waters from the Yoro Nguéda (Mali Highlands) and Thianahé (Ségou Highlands) (Thiaw, 2025).

After 17.3 km, the river changes course northwestward, where it is joined by the Dandé, then slightly northeastward to receive the Gounoung. At 25.8 km from its source, it successively receives the Koumafelé and Batimba on its left bank, as well as the Ndébou on its right bank, all originating from the Ndébou and Dandé hills, which reach elevations of about 300 m. After the confluence with these tributaries, the Thiokoye flows 19.6 km to the monitoring station at Thiokoye-Bridge, covering a total area of 973 km^2 (**Figure 1**). The basin's altitudes range from 1120 m in the south (Mali Highlands) to 68 m in the north (Thiokoye-Bridge), directing water flows along a south-north axis (Thiaw, 2025).

The Thiokoye Basin has a tropical climate influenced by both Guinean and Sudanian domains, structured by the Egyptian-Libyan and Saint Helena anticyclones, as well as intertropical low pressures, which generate two distinct seasons: the rainy season and the dry season. Two main airflows alternately affect the study area:

- The Harmattan, a continental wind driven by the Egyptian-Libyan anticyclone, dominates the climate during the dry season.
- The monsoon flow, generated by the Saint Helena anticyclone during the rainy season, promotes rainfall formation by shifting the meteorological equator northward across the Thiokoye basin.

The basin's altitude and geomorphology contribute to high precipitation variability and shape the hydrographic network, thereby regulating surface and groundwater flows.

Beyond its hydrological and climatic characteristics, the Thiokoye Basin is a vital socioeconomic area for local communities in Senegal and Guinea Conakry. The study area is predominantly inhabited by rural communities whose economies rely primarily on agriculture and livestock farming. Agriculture, the main economic activity, consists of staple crops such as millet, sorghum, and maize, along with cash crops like peanuts and cotton. These crops, supported by the expansion of cultivated lands in lowland areas, enhance water and soil use efficiency, boosting production despite climatic challenges (ISRA, 2008).

Livestock farming is also a fundamental component of the local production system, integrating agro-pastoral practices that rely on available natural resources. However, pastoralists face increasing competition for land due to recurrent droughts and soil degradation, exacerbated by demographic growth and rising agricultural demands (DAPS, 2004). This growing pressure on resources heightens community vulnerability to climatic fluctuations and poses additional challenges to food security (ISRA, 2008; Thiaw, 2025).

Furthermore, basic infrastructure in the basin remains insufficient, directly affecting the quality of life and resilience of local populations to climatic hazards. Limited transportation networks, healthcare facilities, and potable water supply systems hinder rural communities' access to essential services (ISRA, 2008; Thiaw, 2025). This situation increases the inhabitants' dependence on natural resources, making sustainable water and land management crucial in the current context of climate change.

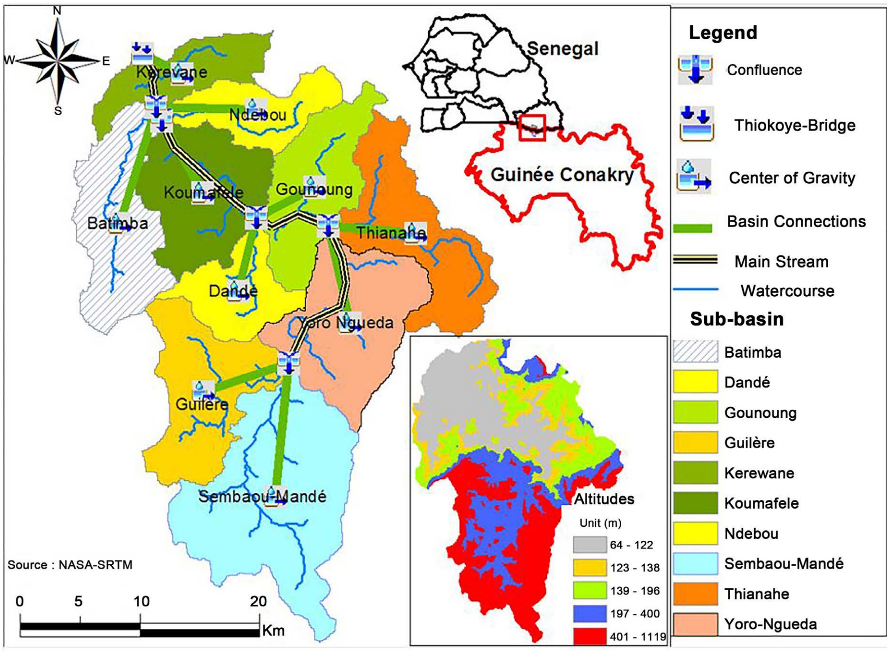

Figure 1. Geographical location of the Thiokoye River basin.

2.2. Data and Methods

2.2.1. Topography

Topography is a key component in hydrological modeling with SWAT, as it directly influences water flow and sediment transport processes within a watershed. It helps define the terrain configuration, flow direction and slope, as well as the segmentation of the watershed into Hydrologic Response Units (HRUs), which play a crucial role in the dynamics of water fluxes and erosion processes.

In this study, the topographic data used come from NASA's Shuttle Radar Topography Mission (SRTM), a satellite mapping program that provides digital elevation models (DEMs) with a 30-meter resolution (Cf. **Figure 1**). These data are accessible through the United States Geological Survey (USGS) platform via the Earth Explorer website (earthexplorer.usgs.gov). They allow the extraction of several key parameters for modeling, such as elevation, slopes, slope orientation, and the watershed's hydrographic network.

The topographic analysis of the Thiokoye watershed helps identify flow concentration zones, steep-slope areas where erosion is more intense, and potential water storage areas such as floodplains and depressions. Proper characterization of these elements is essential for improving the accuracy of hydrological simulations and optimizing water resource management in a context of climate variability and land-use changes.

2.2.2. Hydro-Climatic Data

Climatic data is essential for calibrating the SWAT model, as it directly influences hydrological processes such as evapotranspiration, runoff, and infiltration. This data includes precipitation, temperature, wind speed, relative humidity, and solar radiation and is sourced from the SWAT database accessible via *global-*

weather.tamu.edu. This source provides complete time series on a global scale for simulating hydrological dynamics. However, climatological observations from this database only began in 1979, thereby limiting the usable period for modeling.

The observed streamflow data comes from Senegal's Directorate for Water Resources Management and Planning (DGPRE) and is crucial for analyzing the hydrological behavior of the Thiokoye River, as well as for calibrating and validating SWAT. The reliability of streamflow records is key to ensuring the accuracy of simulations.

Data analysis reveals gaps in the annual average streamflow measurements at the Thiokoye station. Years with complete records (0% missing data) are predominant, particularly between 1970-1980 and 1998-2001. Minor gaps (1% - 5% missing data) appear in 1983 and 2001, while moderate gaps (6% - 15%) affect years such as 1984 and 1986, introducing uncertainty in trend evaluation. Major gaps (>30%) are observed in the early 1970s and around 1991-1992, making hydrological analysis more challenging. The Thiokoye River was not subject to hydrometric monitoring during the period 1993-1997 (**Figure 2**). To ensure robust model calibration, only the periods 1979-1992 and 1998-2002, which offer more complete data coverage, were selected. However, the presence of gaps in observed streamflow data, due to equipment failures or logistical constraints, remains a challenge for the reliability of the model's hydrological projections.

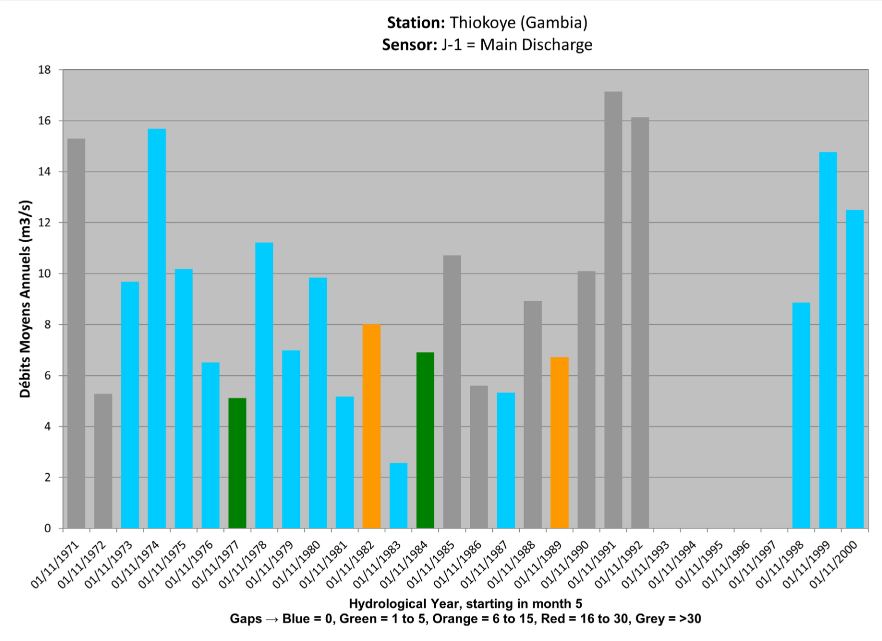

Figure 2. Gaps in the observed streamflow data of the Thiokoye River.

2.2.3. Soil and Land Use

Land use and land cover (LULC) as well as soil characteristics are fundamental input data in hydrological modeling with the SWAT (Soil and Water Assessment Tool) model. These inputs influence critical components of the hydrological cycle, such as surface runoff, evapotranspiration, infiltration, groundwater recharge, and sediment transport (Arnold et al., 1998; Neitsch et al., 2011). Their spatial distribution and physical characteristics directly affect model performance and the accuracy of simulation outputs.

In the Thiokoye watershed, LULC data were derived from high-resolution satellite imagery archived on Google Earth and dated January 1st, 2021. This specific date was selected to represent recent land surface conditions that align with the hydrological baseline period used in the model. The images were processed using ArcGIS software, combining photo-interpretation with supervised classification based on the maximum likelihood method, which is one of the most robust statistical classifiers in remote sensing (Jensen, 2005). This method allowed for the precise identification of seven dominant land use classes: Forest - Evergreen (FRSE), Water (WATR), Forest - Deciduous (FRSD), Barren (BARR), Wetlands - Non-Forested (WETN), Forest - Evergreen (Other) (FRSEO), and Agricultural - Generic (AGRL) (**Figure 3**).

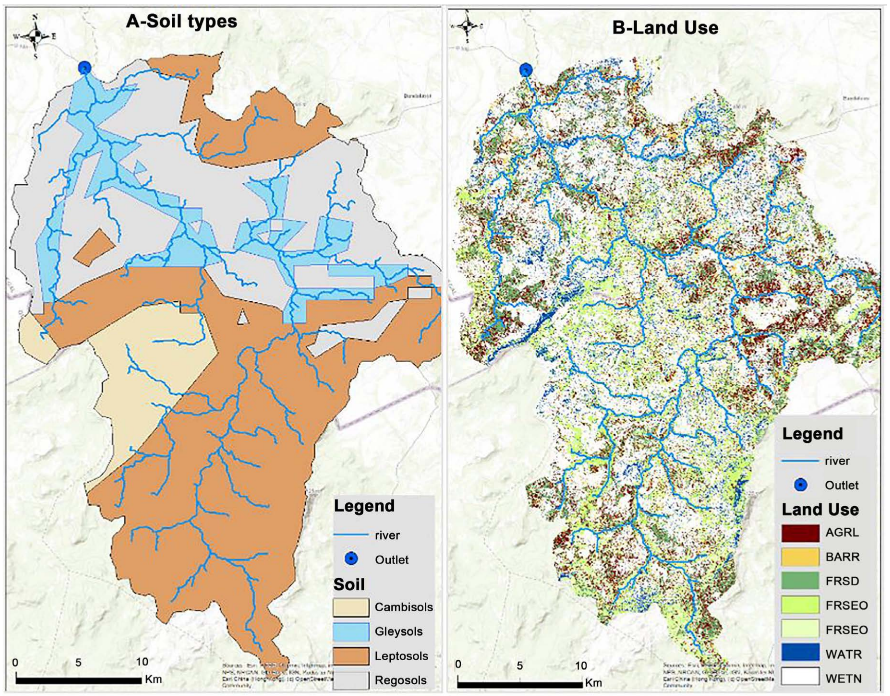

Figure 3. Thiokoye river basin: Soil classes (A) and Land Use (B) maps.

As indicated in **Table 1** and **Figure 3**, Wetlands-Non-Forested is the most extensive land use category, covering 47.71% of the watershed. The significant presence of wetlands suggests zones with permanent or seasonal water saturation, which may strongly influence the basin's hydrological dynamics. Forested and agricultural areas also represent key land cover classes, each playing a distinct role in evapotranspiration and runoff modulation.

The integration of accurate LULC data in SWAT is essential, as land use patterns govern the partitioning of rainfall into various hydrological components.

Several studies have demonstrated that incorrect or generalized land use inputs can lead to substantial errors in runoff and sediment yield estimations (Githui et al., 2009; Jha et al., 2004). Moreover, land cover changes over time can significantly alter hydrological responses, underlining the importance of using up-to-date and context-specific LULC datasets in model calibration and scenario analysis (Faramarzi et al., 2009; Thiaw et al., 2021).

Table 1. Characteristics of land cover in the watershed of Thiokoye River.

Type	Code (SWAT)	Area (km^2)	% of Total Area
Forest - Evergreen	FRSE	69.97	7.18%
Water	WATR	58.16	5.97%
Forest - Deciduous	FRSD	111.12	11.43%
Barren	BARR	32.32	3.32%
Wetlands - Non-Forested	WETN	464.09	47.71%
Forest - Evergreen (Other)	FRSEO	130.18	13.38%
Agricultural - Generic	AGRL	107.49	11.01%
Total Land Use		973.00	100%

In parallel, soil data were obtained from the FAO soil database (https://faostat.fao.org), a widely used global source for standardized pedological information. Four major soil types were identified across the Thiokoye watershed: Cambisols, Gleysols, Leptosols, and Regosols (**Table 2** and **Figure 3**). **Table 2** shows that Leptosols dominate the basin (50.07%), followed by Regosols (29.28%). Leptosols are typically shallow and stony, often leading to rapid runoff and low water retention, while Regosols are poorly developed and may be highly susceptible to erosion. These characteristics are crucial in SWAT modeling, as they affect the curve number (CN), soil water capacity, and the potential for sediment transport. The importance of soil data in SWAT simulations has been highlighted in numerous studies (Gassman et al., 2007; Abbaspour et al., 2007; Jothiprakash & Ch, 2024; Faty et al., 2019), where it is shown that spatial variation in soil texture, depth, and hydrological properties strongly influences both surface and subsurface flow processes. Accurate soil parameterization is thus critical for realistic water balance modeling, especially in regions with heterogeneous soil landscapes such as the Thiokoye basin. The integration of detailed and locally relevant LULC and soil data significantly enhances the reliability of SWAT simulations. This approach not only improves model calibration and validation but also ensures better scenario analysis for land management and climate adaptation strategies. As such, the use of high-resolution imagery and standardized soil datasets represents a methodological best practice for hydrological modeling in data-scarce environments.

2.2.4. Description of SWAT Model

The Soil and Water Assessment Tool (SWAT) is a semi-distributed hydrological

Table 2. Characteristics of the soil in the watershed of Thiokoye River.

Type	Area (km²)	% of Total Area
Cambisols	84.94	8.71%
Gleysols	116.14	11.94%
Leptosols	486.96	50.07%
Regosols	284.96	29.28%
Total Soil Types	973.00	100%

model developed by the Agricultural Research Service (ARS) of the United States Department of Agriculture (USDA) in the 1990s (Arnold et al., 1998). It is designed to evaluate the effects of land management practices and environmental changes on hydrology, water quality, and soil erosion at the watershed scale. SWAT is widely applied in water resource management, sediment and nutrient modeling, and assessing the impacts of climate change on watersheds (Arnold & Fohrer, 2005; Schuol et al., 2008; Neitsch et al., 2011; Bachmann, 2015; Givati et al., 2016; Omer et al., 2017; Jothiprakash & Ch, 2017; Faty et al., 2019).

The model divides a watershed into sub-basins, which are further subdivided into Hydrologic Response Units (HRUs) based on land use, soil type, and slope. This structure enables the model to capture spatial heterogeneity in hydrological processes without imposing excessive computational complexity (Arnold et al., 2012).

SWAT operates using the general water balance equation Arnold et al., (1998):

$$S_t = S_{t-1} + P - Q_s - ET - PERC - Q_g \tag{1}$$

where S_t is soil water storage at time (t) (mm), P represents precipitation (mm), Q_s is surface runoff (mm), ET is evapotranspiration (mm), PERC is percolation to groundwater (mm), and Q_g is groundwater flow (mm).

The model simulates the water cycle by integrating various hydrological processes, including precipitation interception, soil infiltration—calculated using the SCS-CN (Soil Conservation Service Curve Number) method (USDA-SCS, 1972)—evapotranspiration estimated through approaches such as Penman-Monteith, Hargreaves, and Priestley-Taylor, surface runoff influenced by soil conditions and topography, and groundwater flow modeled using a reservoir approach. The Penman-Monteith method was chosen for this study due to its ability to incorporate a broader range of physical parameters, including daily maximum and minimum temperature, wind speed, humidity, and solar radiation, providing a more accurate evapotranspiration estimation compared to empirical methods.

Soil loss estimation in the Thiokoye River Basin was performed using the Modified Universal Soil Loss Equation (MUSLE), which is integrated into the soil erosion module of the SWAT model (Williams, 1975; Arnold et al., 1998; Neitsch et al., 2011). This module simulates daily sediment yield at the level of Hydrological Response Units (HRUs) based on hydrometeorological conditions. Unlike the classical USLE, MUSLE replaces the rainfall energy factor with a term that incorporates surface runoff volume, peak runoff rate, and HRU area, making it more suitable for daily time-step modeling.

The erosion module also includes several key factors influencing soil loss, namely the soil erodibility factor (K), the cover management factor (C), the support practice factor (P), the topographic factor (LS), and the coarse fragment factor (CFRG). These parameters were derived from spatial datasets, including the digital elevation model (DEM), soil maps, and land use/land cover data, and were integrated into SWAT through georeferenced database layers covering the basin.

Soil loss is estimated using the following equation (Neitsch et al., 2011):

$$Sed = 11.8 \times \left(Qsurf \times qpeak \times A\right)^{0.56} \times K \times C \times P \times LS \times CFRG \tag{2}$$

where *Sed* is the daily sediment yield (tons/day), *Qsurf* is the surface runoff volume (mm), *qpeak* is the peak runoff rate (m^3/s), *A* is the HRU area (ha), and *K*, *C*, *P*, *LS*, and *CFRG* represent the respective erosion factors as defined in the SWAT theoretical documentation (Arnold et al., 1998).

2.2.5. Sensitivity Analysis

Sensitivity analysis is a crucial step in the calibration of hydrological models, as it helps identify the parameters that most significantly influence model outputs. In this study, the SWAT-CUP (SWAT Calibration and Uncertainty Procedures) tool was used, specifically the SUFI-2 algorithm developed by Abbaspour et al., (2004, 2007). This algorithm enables calibration, validation, and uncertainty analysis of SWAT model simulations.

The SUFI-2 approach is based on generating multiple sets of randomly sampled parameters within predefined ranges, followed by a statistical evaluation of model performance. With each iteration, SUFI-2 adjusts the parameter ranges to reduce uncertainty and improve simulation quality. Two key indicators are used to evaluate the uncertainty of the results: the p-factor and the r-factor. The p-factor represents the proportion of observed data that falls within the 95% prediction uncertainty band of the model simulations. It ranges from 0 to 1, with a value of 1 indicating that all observed data are within the prediction interval. A high p-factor thus reflects a good representation of observed variability. The r-factor measures the average thickness of the prediction uncertainty band, normalized by the standard deviation of the observed data. A lower r-factor value indicates reduced uncertainty in the simulations. In practice, a good calibration is typically achieved with a p-factor greater than 0.7 and an r-factor less than 1.5 (Abbaspour, 2015). Therefore, sensitivity analysis using SUFI-2 not only identifies the most influential parameters but also helps optimize their calibration while quantifying the uncertainty associated with the hydrological simulations of the SWAT model.

2.2.6. Performance Evaluation of the Model

Model performance evaluation is a crucial step in hydrological modeling, as it provides insight into how accurately the model represents real-world hydrological processes. A combination of statistical indicators is commonly used to assess the agreement between observed and simulated data, each offering distinct perspectives on model behavior. In this study, four widely recognized performance metrics were applied: the Nash-Sutcliffe Efficiency (NSE), the Coefficient of Determination (R^2), the Kling-Gupta Efficiency (KGE), and Percent Bias (PBIAS) (**Table 3**). These metrics help quantify the predictive power of the model, the degree of correlation, variability, and potential systematic errors in the simulations. Their definitions, optimal values, and references are summarized in the following table:

Table 3. Performance evaluation indicators for hydrological model calibration.

Indicator	Description	Optimal Value	Reference
Nash-Sutcliffe Efficiency (NSE)	Measures how well the simulated data matches the observed data. Values range from −∞ to 1. A value of 1 indicates perfect agreement, while 0 means the model is as accurate as the mean of observed data.	1	Nash & Sutcliffe (1970)
Coefficient of Determination (R^2)	Indicates the proportion of the variance in the observed data that is predictable from the simulated data. It ranges from 0 to 1. A higher value indicates better model performance.	1	Legates & McCabe (1999)
Kling-Gupta Efficiency (KGE)	Combines correlation, bias, and variability in a single metric. It improves on NSE by addressing some of its limitations. KGE ranges from −∞ to 1, with 1 indicating perfect simulation.	1	Gupta et al. (2009)
Percent Bias (PBIAS)	Indicates the average tendency of simulated data to be larger or smaller than observed values. A PBIAS of 0 indicates perfect agreement. Positive values indicate underestimation, and negative values indicate overestimation.	0	Moriasi et al. (2007)

2.2.7. Calibration of the Model

As part of the present study, the calibration of the SWAT hydrological model required the identification and adjustment of the most influential parameters affecting the simulated processes, including runoff, infiltration, evapotranspiration, and sediment transport. These parameters, which are closely related to soil characteristics, land use, and local climatic conditions, were calibrated using the SWAT-CUP tool with the SUFI-2 algorithm. **Table 4** presents a selection of the main parameters calibrated in this study, along with their description, unit, range of variation, and influence on the model simulations:

Table 4. Main hydrological parameters of the SWAT model.

Parameter	Description	Unit	Typical Range	Main Influence
CN2	SCS Curve Number for hydrologic soil group II	-	35 - 98	Surface runoff
SOL_AWC	Soil available water capacity	mm/mm	0.05 - 0.30	Soil water storage
SOL_K	Saturated hydraulic conductivity of the soil	mm/h	0.5 - 200	Infiltration, percolation
SOL_BD	Soil bulk density	g/cm^3	1.1 - 1.9	Soil water storage capacity and water movement

Continued

ALPHA_BF	Baseflow recession coefficient	day^{-1}	0.01 - 1.0	Baseflow
GW_DELAY	Delay time between recharge and groundwater flow to the stream	days	0 - 500	Delayed baseflow
GWQMN	Minimum threshold of shallow aquifer for return flow to occur	mm	0 - 5000	Groundwater contribution to streamflow
GW_REVAP	Groundwater "revap" coefficient	-	0.02 - 0.2	Groundwater–soil interaction
REVAPMN	Threshold water content in the soil for revap to occur	mm	0 - 500	Soil–groundwater interaction
ESCO	Soil evaporation compensation factor	-	0 - 1	Potential evapotranspiration
EPCO	Plant uptake compensation factor	-	0 - 1	Plant transpiration
CH_N2	Manning's roughness coefficient for the main channel	-	0.01 - 0.3	Water velocity in the channel
CH_K2	Effective hydraulic conductivity of the riverbed	mm/h	0 - 150	Streamflow
ALPHA_BNK	Baseflow recession coefficient from stream bank storage	day^{-1}	0 - 1	Lateral baseflow
SHALLST	Initial depth of water in shallow aquifer	mm	0 - 5000	Initial groundwater storage conditions
RCHRG_DP	Deep aquifer percolation fraction	-	0 - 1	Deep aquifer recharge
FFCB	Initial fresh organic carbon fraction	-	0 - 1	Carbon cycling, soil fertility
SLSUBBSN	Average slope length of subbasins	m	10 - 200	Sediment transport
OV_N	Manning's roughness coefficient for overland flow	-	0.01 - 0.3	Surface runoff
SURLAG	Surface runoff lag time	days	0 - 24	Surface runoff response

3. Results

3.1. Sensitivity Analysis of SWAT Model Parameters

The sensitivity analysis of the SWAT model parameters using the SUFI-2 algorithm highlighted the most influential variables in simulating the hydrological behavior of the Thiokoye watershed. Among the 20 parameters analyzed, several showed significant sensitivity in both the calibration and validation phases, indicating their major role in the hydrological processes of the basin (**Table 5**).

Notably, CN2 (Curve Number) emerged as one of the most sensitive parameters, with a 2.56% variation between calibration (78) and validation (80). As a proxy for surface runoff potential, CN2 is directly influenced by land cover and soil type, both of which are shaped by human activities and natural vegetation dynamics. Given the geological structure of the basin, where the Precambrian basement rocks limit deep infiltration, a higher CN2 value reflects a tendency for rapid runoff over relatively impermeable surfaces.

SOL_AWC (Available Water Capacity) and SOL_K (Saturated Hydraulic Conductivity), key soil parameters controlling water retention and percolation, showed moderate sensitivity (−3.3% and +4%, respectively) (**Table 5**). The slight variations observed reflect the influence of spatial heterogeneity in the weathered layers overlying the bedrock. The low permeability of the underlying crystalline rocks limits vertical percolation, accentuating the role of surface and near-surface processes.

ALPHA_BF (Baseflow Recession Constant) and GWQMN (Threshold Depth of Water in the Shallow Aquifer) also demonstrated high sensitivity, with differences of +8.3% and +6.3%, respectively (**Table 5**). These parameters regulate groundwater contributions to streamflow, particularly critical in a fractured aquifer system such as that of Thiokoye, where baseflow is highly dependent on rainfall infiltration through weathered and fractured bedrock zones. The fractured nature of the Precambrian formations creates discontinuous and shallow aquifers, making baseflow highly variable and sensitive to climatic and geological factors.

Furthermore, GW_REVAP and RCHRG_DP, which govern water movement between the soil, shallow aquifer, and deep aquifer, showed notable variations (+12.5% and +11.1%, respectively) (**Table 5**). This highlights the importance of vertical exchanges in the system and the role of deep percolation despite geological constraints. These fluxes are likely limited to zones where faults or fractures enhance permeability locally.

Parameters related to evapotranspiration and plant water use (ESCO and EPCO) showed minor variations (<3%), indicating stable vegetation and soil evaporation patterns between calibration and validation. Similarly, channel parameters (CH_N2, CH_K2) and overland flow resistance (OV_N) exhibited minimal to moderate variation, suggesting consistent hydrodynamic behavior of the main drainage paths. The parameters SHALLST (initial shallow aquifer storage) and SURLAG (surface runoff lag time) displayed moderate sensitivity, underlining the influence of initial groundwater storage and delayed runoff response in the simulation. In a region with low groundwater storage capacity, this supports the need to capture dynamic changes in shallow aquifer behavior during seasonal rainfall events.

Overall, the sensitivity analysis reflects a watershed with dominant surface processes, influenced by impermeable geological structures, thin and fractured weathering profiles, and spatially variable soil properties. The most sensitive parameters were associated with runoff generation (CN2, SOL_K), subsurface flow processes (ALPHA_BF, GWQMN, GW_REVAP), and infiltration dynamics, confirming the critical role of the basin's Precambrian basement geology in shaping hydrological responses.

3.2. Performance Analysis of the SWAT Model

3.2.1. Calibration Phase

The calibration phase of the SWAT model, conducted over the period 1979-1992, made it possible to assess the model's ability to accurately reproduce observed streamflows based on adjusted hydrological parameters. The results obtained demonstrate excellent model performance, indicating a remarkable agreement between simulated and observed flows.

Table 5. Calibrated and validated parameter values of the SWAT model for the Thiokoye watershed using the SUFI-2 algorithm.

Parameter	Unit	Calibrated Value (1979-1992)	Validation Value (1998-2002)	Difference (%)
CN2	-	78	80	+2.56%
SOL_AWC	mm/mm	0.15	0.145	−3.3%
SOL_K	mm/h	12.5	13.0	+4%
SOL_BD	g/cm^3	1.45	1.47	+1.4%
ALPHA_BF	Day^{-1}	0.12	0.13	+8.3%
GW_DELAY	days	120	115	−4.2%
GWQMN	mm	800	850	+6.3%
GW_REVAP	-	0.08	0.09	+12.5%
REVAPMN	mm	350	340	−2.9%
ESCO	-	0.85	0.83	−2.4%
EPCO	-	0.95	0.94	−1.1%
CH_N2	-	0.045	0.045	0%
CH_K2	mm/h	5.2	5.0	−3.8%
ALPHA_BNK	day^{-1}	0.05	0.048	−4%
SHALLST	mm	200	220	+10%
RCHRG_DP	-	0.18	0.20	+11.1%
FFCB	-	0.45	0.43	−4.4%
SLSUBBSN	m	95	95	0%
OV_N	-	0.14	0.15	+7.1%
SURLAG	days	4.5	4.7	+4.4%

The Nash-Sutcliffe Efficiency (NS) coefficient, which evaluates the predictive accuracy of the model, reached 0.98—very close to the ideal value of 1—indicating an almost perfect agreement between simulated and observed data (Figure 4). Similarly, the coefficient of determination (R^2) also achieved a value of 0.98, confirming the strong correlation and underscoring the model's ability to capture the temporal variability of flows (Figure 5). The Kling-Gupta Efficiency (KGE), which integrates correlation, bias, and variability into a single performance metric, recorded a high score of 0.95, suggesting that the model effectively reproduces both the dynamics and statistical characteristics (mean and variability) of streamflows. Regarding uncertainty, the p-factor shows that 90% of observed data fall within the 95% prediction uncertainty interval, reflecting strong reliability of the simulations, while the r-factor, with a value of 0.27, indicates a narrow prediction band relative to the observed standard deviation, pointing to high precision (Figure 4 and Table 6). The relative bias (PBIAS) of 1.5% reflects a slight overestimation of simulated flows, which remains well within acceptable thresholds for hydrological modeling. Statistically, the mean simulated discharge (8.22 m^3/s) closely matches the observed mean (8.35 m^3/s), and the standard deviation of the simulations

(11.80 m³/s) aligns well with that of the observed values (12.41 m³/s), further validating the model's capacity to reproduce interannual and seasonal flow variability (**Table 6**). Overall, these results demonstrate that, following proper calibration, the SWAT model offers a robust and accurate representation of the hydrological regime of the Thiokoye River Basin.

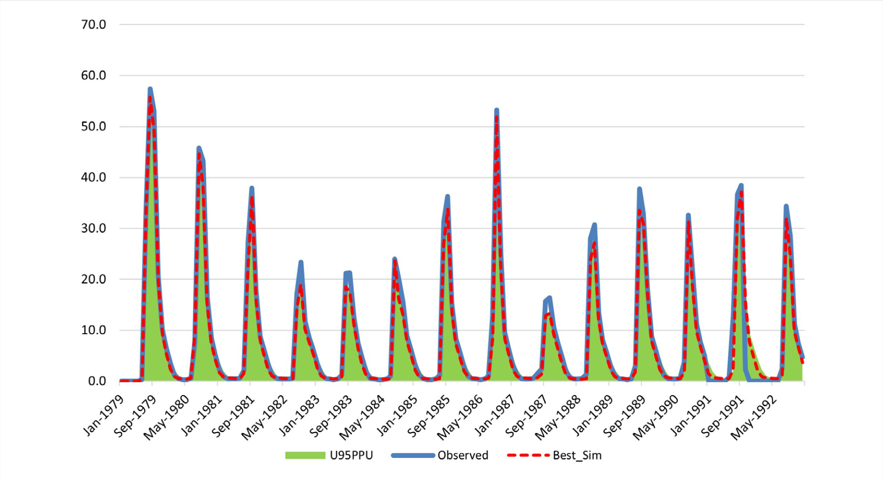

Figure 4. Simulated and observed hydrographs during the calibration period (1979-1992).

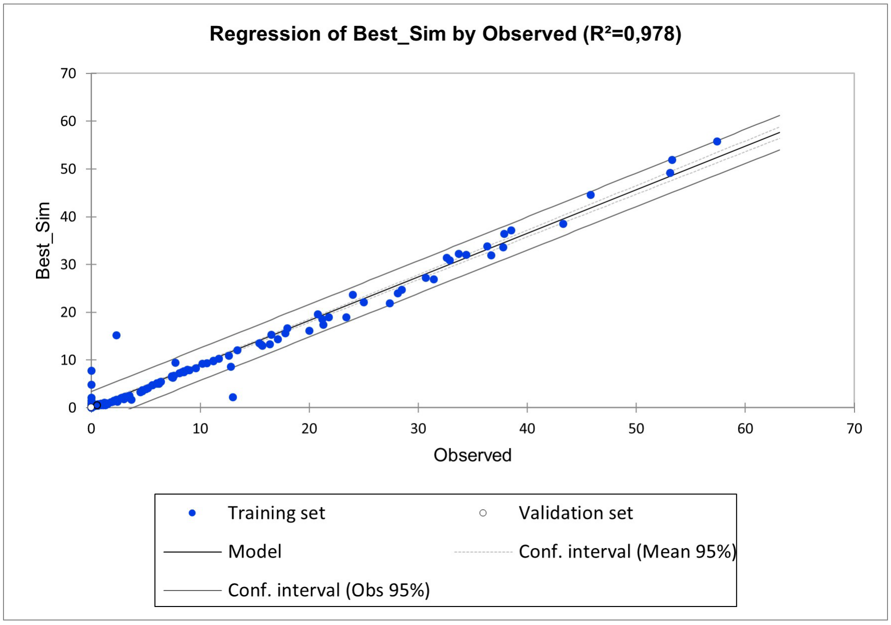

Figure 5. Regression of #imulated by observed discharges under the calibration period 1979-1992.

3.2.2. Validation Phase

During the validation phase (1998-2002) of the SWAT model applied to the Thiokoye river basin, the overall performance remains satisfactory, although slightly lower than that achieved during the calibration phase. Statistical indicators show a Nash-Sutcliffe Efficiency (NS) of 0.82 and a coefficient of determination (R^2) of

0.83, indicating a good correlation between simulated and observed streamflows, as well as a reasonable ability of the model to reproduce hydrological dynamics over this independent period. The Kling-Gupta Efficiency (KGE), with a value of 0.81, reinforces this assessment by jointly accounting for bias, variability, and correlation (Figure 6 & Figure 7).

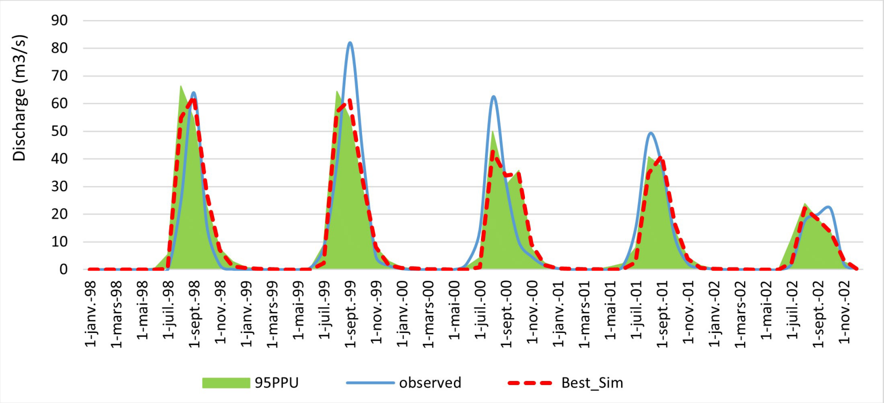

Figure 6. Simulated and observed hydrographs during the calibration period (1998-2002).

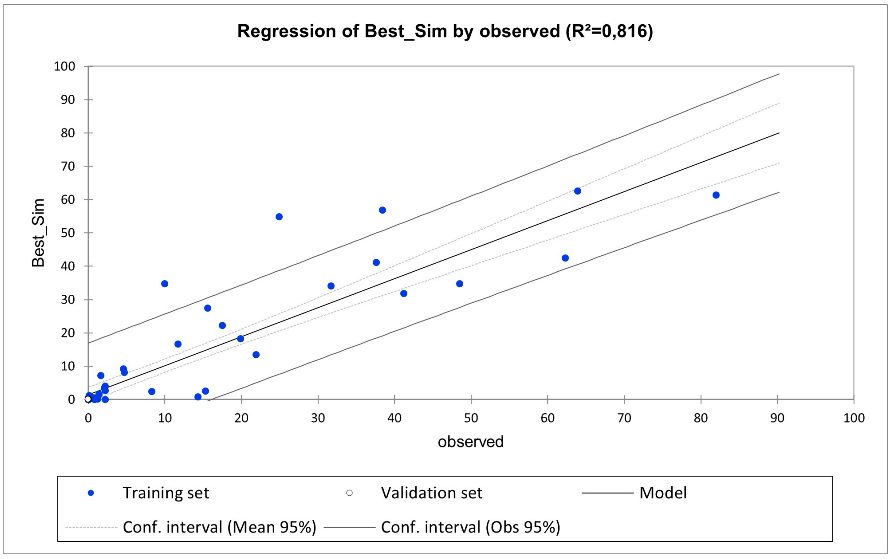

Figure 7. Regression of simulated by observed discharges under validation phase (1998-2002).

However, the analysis of uncertainty indicators shows an acceptable level of performance, though with room for improvement. The p-factor, which measures the proportion of observed data encompassed within the 95% confidence interval, reaches 0.65, indicating that approximately two-thirds of the observed values fall within the model's uncertainty bounds. The r-factor, representing the average width of the uncertainty band relative to the standard deviation of observed data, is 0.85—suggesting a moderately wide uncertainty range that remains within acceptable limits (Table 6).

This combination of a relatively high p-factor and a moderate r-factor suggests that the uncertainty bounds are generally well calibrated to capture the variability in observed flows, thereby enhancing confidence in the model outputs during the validation period. Nonetheless, these values still reflect some limitations in uncertainty representation, likely linked to external factors rather than internal model structure. Furthermore, the bias analysis, as revealed by the PBIAS indicator, shows a tendency to overestimate simulated flows, with a value of −13.2%. This is also reflected in the difference between the mean simulated discharge (11.16 m^3/s) and the mean observed discharge (9.86 m^3/s) (**Table 6**), confirming the presence of a systematic overprediction during the validation period.

Table 6. Model performance and uncertainty metrics during calibration and validation periods.

Indicator	Calibration (1979-1992)	Validation (1998-2002)
Nash-Sutcliffe Efficiency (NS)	0.98	0.82
Coefficient of Determination (R^2)	0.98	0.83
Kling-Gupta Efficiency (KGE)	0.95	0.81
PBIAS (%)	1.5	-13.2
p-factor	0.90	0.65
r-factor	0.27	0.85
Simulated Mean Flow (m^3/s)	8.22	11.16
Observed Mean Flow (m^3/s)	8.35	9.86

The performance evaluation of the SWAT model across both the calibration (1979-1992) and validation (1998-2002) phases highlights the model's capacity to simulate streamflow dynamics within the Thiokoye river basin with a high degree of accuracy and reliability. During the calibration period, statistical indicators (NS, R^2, KGE) reached near-optimal values, demonstrating excellent agreement between observed and simulated flows. The high p-factor (0.90) and low r-factor (0.27) further reflect a well-calibrated model with narrow and informative uncertainty bounds, reinforcing confidence in its predictive capabilities.

Although performance metrics slightly declined during the validation phase, the model continued to demonstrate robust results. With NS and R^2 values above 0.80 and a KGE of 0.81, the simulation remains statistically sound. The p-factor of 0.65 and r-factor of 0.85 indicate a broader uncertainty range but still within acceptable limits for hydrological modeling. These figures suggest that while some of the observed variability was not fully captured—likely due to gaps and inconsistencies in observed data—the model maintained a credible performance.

The presence of a moderate bias during validation (PBIAS = −13.2%) highlights a tendency toward overestimation, which should be interpreted in light of data limitations during the post-calibration period. Nonetheless, the proximity of simulated and observed mean flows across both phases confirms the model's ability to replicate long-term hydrological patterns.

3.3. Assessment of Water Reserves and Sediment Yield

3.3.1. Blue Water

Blue water refers to water that is mobilizable for human activities, whether originating from surface runoff, shallow groundwater, or percolation into aquifers. In this study, it is assessed through three variables derived from the SWAT model: surface runoff (SURQ), percolation (PERC), and water yield (WYLD), the latter representing the portion of water that effectively reaches the river network.

The monthly analysis of these components (**Table 7**) highlights a pronounced seasonality in blue water availability, concentrated primarily between June and October, which corresponds to the rainy season in the Thiokoye basin. August alone accounts for nearly 49% of the total annual WYLD, followed by September (26.4%) and July (19.1%). Conversely, the dry season months (November to May) show negligible or zero values, indicating an almost complete absence of mobilizable flows.

Table 7. Monthly variation of blue water components (SURQ, PERC, WYLD) and relative contribution to water yield (WYLD) in the Thiokoye basin.

Month	SURQ (mm)	PERC (mm)	WYLD (mm)	Contribution (%)
June	1.2	12.1	1.2	0.5%
July	46.2	92.4	46.3	19.1%
August	118.5	151.3	118.7	48.9%
September	63.9	77.4	64.1	26.4%
October	11.8	17.3	11.9	4.9%
Other months	~0	Low	~0	<1%
Total	241.6	358.7	242.7	100%

Total blue water represents 22% of the annual precipitation (1118 mm) in the Thiokoye River Basin, a proportion that, while moderate, is typical of watersheds underlain by low-permeability crystalline bedrock where deep infiltration is restricted and surface runoff accumulates rapidly during intense rainfall events (Descroix et al., 2009). The peak in both runoff and percolation observed in August reflects a temporary exceedance of the soil's water holding capacity, resulting in accelerated water transfer to the drainage network—a behavior consistent with observations by Abbaspour et al. (2007) in the Swiss Alps, where blue water availability closely tracks soil saturation under heavy rainfall. However, in the semi-humid context of West Africa, this period of availability is far more limited and abrupt, heightening the vulnerability of ecosystems and agricultural systems to interannual rainfall variability (Omer et al., 2017). Notably, the significant contribution of percolation (PERC), which alone accounts for over 30% of annual rainfall, suggests some potential for shallow aquifer recharge despite the restrictive bedrock; this localized infiltration may be facilitated by fracture zones or deeper weathered layers. As noted by Schuol and Abbaspour (2007), achieving realistic simulations of percolation in tropical basins requires fine-tuned calibration of soil hydraulic properties and subsurface transmissivity. The pronounced seasonality of blue water availability raises concerns regarding the basin's ability to support water supply systems throughout the year, particularly during the prolonged dry season, as nearly all blue water is concentrated within the July–September window. This underscores the importance of developing temporary water storage infrastructure—such as ponds, small dams, and retention basins—and implementing flow regulation strategies to distribute water more evenly across the year. Ultimately, incorporating these dynamics into an Integrated Water Resources Management (IWRM) framework is essential to better prepare for the anticipated impacts of climate change, which is expected to intensify extreme events while shortening the rainy season (Gupta et al., 2009; Rouhani & Abbaspour, 2009).

3.3.2. Green Water

Green water refers to the portion of water that infiltrates and is stored in the root zone of the soil, available for evapotranspiration and directly used by vegetation. It constitutes a key component of the hydrological cycle in tropical agro-ecological systems, particularly for rainfed agriculture. In the SWAT model, green water is estimated through two main variables: soil water content (SW) and actual evapotranspiration (ET). These components respectively quantify the water stock and the flux of green water consumed by plants.

The monthly analysis of the Thiokoye basin data reveals a strong seasonal variability of green water, closely linked to rainfall. Soil moisture (SW) begins to rise in June and reaches its maximum in August (162.6 mm), in direct correlation with peak precipitation (369 mm). Actual evapotranspiration (ET), representing the effective water consumption by vegetation, follows a similar trend, peaking in August at 87.9 mm (**Table 8**).

Table 8. Monthly dynamics of green water in the Thiokoye basin.

Month	SW (mm)	ET (mm)	PET (mm)	P (mm)	ET/PET
January	70.3	10.0	242.5	0.0	0.04
February	61.3	8.2	232.7	0.0	0.04
March	8.8	5.6	276.3	0.1	0.02
April	3.1	7.7	289.8	2.0	0.03
May	14.5	24.9	264.0	37.1	0.09
June	68.5	60.0	203.4	127.4	0.29
July	150.0	84.6	154.7	305.8	0.55
August	162.6	87.9	130.3	369.0	0.67

Continued

September	148.5	86.6	146.3	215.2	0.59
October	118.4	61.0	166.6	60.0	0.37
November	96.9	19.9	182.0	1.4	0.11
December	83.4	11.3	230.4	0.0	0.05
Total	—	468.0	2518.9	1118.0	~0.19

The average annual ET/PET ratio is 0.19, reflecting a significant water deficit for plants throughout most of the year. This imbalance indicates that, even when the energy required to evaporate water (PET) is high, the actual availability of water in the soil is often insufficient to meet the demands of crops. This situation is particularly acute between November and May, during which ET remains very low despite a high climatic demand. A similar pattern is described by Sivapalan et al., (2003), who note that tropical catchments with low soil water retention capacity exhibit ET regimes that are highly dependent on rainfall. In contrast, between July and September, the simultaneous increase in ET and SW reflects an optimal window for crop growth. However, this favorable hydrological window is short, which imposes significant limitations for long-cycle or perennial crops.

Soil water content is heavily influenced by the pedological characteristics of the basin (sandy-clay soils over crystalline basement), which have limited retention capacity. The relatively low values observed during the dry season (3.1mm in April) highlight the importance of strategies such as vegetation cover management, mulching to reduce evaporation, or infiltration enhancement through techniques like micro-catchments or contour farming. The results obtained corroborate the findings of Faramarzi et al., (2009), who showed that in Tropical watersheds, the portion of green water consumed by plants can be optimized through simple but effective land management practices. These also underscore the potential for improving water productivity through agricultural practices adapted to climatic and edaphic conditions.

3.3.3. Sediment Yield

Soil loss, expressed in tons per hectare (t/ha) through the Sediment Yield (YLD) variable in the SWAT model, serves as a critical indicator of water erosion in tropical watersheds, as it encapsulates the processes of soil particle detachment, transport, and deposition driven by surface runoff, with direct dependence on rainfall, runoff (SURQ), vegetation cover, and soil characteristics. In the Thiokoye River Basin, erosion exhibits both seasonal and episodic patterns, occurring almost exclusively during the rainy season; of the estimated 15.5 t/ha of annual soil loss, over 96% takes place between July and September, with a peak in August (**Table 9**). This peak month, which records the highest precipitation (369 mm) and surface runoff (118.5 mm), also shows the highest sediment yield (7.9 t/ha), representing more than 50% of the total annual soil loss, thus revealing a strong correlation between rainfall, runoff, and erosion—a pattern consistent with

Gassman et al. (2007), who highlight the sensitivity of sediment yield modeling in SWAT to both rainfall intensity and landscape features. From November to May, soil loss is negligible, indicating minimal hydrological activity; however, this dormant period leaves the soil highly vulnerable to the first heavy rains, a phenomenon also noted by Descroix et al. (2009) in the Sahel, where initial rainfall events are responsible for significant degradation. The basin's underlying crystalline bedrock, coupled with sparse vegetation at the onset of the rainy season, facilitates the rapid detachment of soil particles, while moderate slopes and the absence of erosion control structures further exacerbate sediment transport into the river network.

Table 9. Monthly sediment yield in relation to precipitation and surface runoff in the Thiokoye basin.

Month	Sediment YLD (t/ha)	Precipitation (mm)	SURQ (mm)
July	2.2	305.8	46.2
August	7.9	369.0	118.5
September	4.6	215.2	63.9
October	0.8	60.0	11.8
Other months	0.0	Low to none	~0
Total	15.5	1118.0	241.6

4. Discussion

The findings of this study clearly demonstrate the robust performance and reliability of the SWAT model when coupled with the SUFI-2 algorithm for simulating the hydrological functioning of the Thiokoye watershed. This basin, strategically located at the climatic transition between the Southern Sudanian and Guinean domains, presents a unique hydrological setting marked by pronounced variability in rainfall patterns and ecological conditions. This dual climatic influence amplifies the complexity of hydrological responses, making Thiokoye a representative case for testing advanced modeling frameworks in data-scarce, climatically sensitive environments.

During the calibration period (1979-1992), the model exhibited excellent predictive capacity, with very high statistical performance indicators (Nash-Sutcliffe Efficiency = 0.98, Coefficient of Determination R^2 = 0.98, and Kling-Gupta Efficiency = 0.95). These scores suggest an almost perfect agreement between simulated and observed discharges, a level of performance rarely achieved in semi-humid tropical basins with limited monitoring infrastructure. These results corroborate the conclusions of Abbaspour et al., (2007), who validated the effectiveness of SUFI-2 in improving model calibration through its ability to manage parameter uncertainty and variability across spatial scales.

Nevertheless, the validation phase (1998-2002) showed a slight but expected decrease in performance (NSE = 0.82, R^2 = 0.83, KGE = 0.81). This decline remains within acceptable thresholds for hydrological simulations and can be explained by multiple factors. Interannual variability in rainfall, potential changes in land use, and the inconsistencies often associated with hydrometeorological data quality during the post-calibration period likely influenced these results (Van Griensven et al., 2006; Bachmann, 2015; Givati et al., 2016; Omer et al., 2017; Faty et al., 2019). Moreover, the contrast in uncertainty metrics—p-factor dropping from 0.90 to 0.65 and r-factor increasing from 0.27 to 0.85—illustrates a broader spread and reduced confidence in the model outputs during validation. This is consistent with Rouhani and Abbaspour (2009), who highlighted the essential role of reliable, high-resolution input data in constraining uncertainty, especially in regions where observational networks are sparse.

The sensitivity analysis conducted as part of this modeling effort highlighted the predominant role of several parameters in shaping the hydrological regime of the basin. Among these, CN2 (Curve Number), ALPHA_BF (baseflow recession), GWQMN (threshold depth of groundwater), GW_REVAP (groundwater evaporation coefficient), and RCHRG_DP (deep percolation fraction) emerged as the most influential. These parameters directly control surface runoff generation, groundwater recharge, and baseflow contributions—processes that are critical in fractured rock terrains where water storage and movement are highly localized. The prominence of CN2 confirms the strong influence of land cover and soil hydrodynamic properties on runoff generation, a result that echoes the findings of Gassman et al., (2007), Alejandra et al., (2008), and Faty et al. (2019).

The blue water component of the hydrological cycle, estimated through SURQ (surface runoff), PERC (percolation), and WYLD (water yield), showed a marked seasonal concentration. More than 95% of the annual WYLD was generated during the core rainy season (July to September), with a striking peak in August alone, which accounted for nearly 49% of total output. Despite a relatively high annual precipitation of 1118 mm, only about 22% contributed to mobilizable blue water, underlining the predominance of rapid runoff and the limited vertical infiltration capacity of the crystalline basement. These observations are aligned with previous studies in similar hydrogeological settings, notably those by Descroix et al., (2009), who showed that surface flows in such regions are closely tied to saturation thresholds and storm event intensities. The temporal clustering of blue water availability underscores the critical need for infrastructure capable of buffering this seasonality—such as retention basins, ponds, or small dams—which could support dry season irrigation and drinking water supply.

Green water, representing soil-stored water available for evapotranspiration, displayed similar temporal dynamics. The maximum soil water content and evapotranspiration rates occurred during August, coinciding with peak rainfall and vegetation growth potential. However, the mean annual ET/PET ratio of only 0.19 indicates significant hydric stress for plants over extended periods of the year, particularly from November to May. This imbalance between atmospheric water demand and actual evapotranspiration reflects the basin's shallow soil depth and low water retention capacity, common in tropical regions with sandy or sandy-clay textures. Similar conclusions were drawn by Sivapalan et al. (2003) and Faramarzi et al. (2009), who emphasized the importance of water-saving agronomic practices—such as mulching, contour ridging, and cover cropping—in enhancing the efficiency of green water use and reducing plant stress during critical growth stages.

The study also revealed concerning trends in sediment yield, which was almost exclusively concentrated in the rainy season, with August alone accounting for more than 50% of the annual total (15.5 t/ha). This direct relationship between rainfall intensity, surface runoff, and erosion is well documented in the literature (Gassman et al., 2007; Descroix et al., 2009; Thiaw & Dacosta, 2018). The absence of soil loss during the dry months reflects the low hydrological activity but should not mask the system's vulnerability to initial rainfall events—where bare soils and minimal vegetation coverage accelerate detachment and sediment export. Without erosion control measures such as stone bunds, reforestation, and agroforestry systems, these losses threaten soil fertility, water quality, and the operational life span of hydraulic infrastructure.

The spatial granularity provided by SWAT through the delineation of Hydrologic Response Units (HRUs) offers a powerful lens to target management interventions. In heterogeneous landscapes like Thiokoye, this feature allows for site-specific recommendations—from identifying recharge zones for groundwater preservation to flagging erosion-prone areas requiring rehabilitation. As climate change projections for West Africa suggest shorter, more intense rainy seasons coupled with rising temperatures, the ability to anticipate hydrological behavior across space and time becomes increasingly vital. Scenario analyses using RCP-based regional climate models, when integrated into this modeling framework, can thus inform proactive and evidence-based resource planning.

Essentially, the application of the SWAT–SUFI-2 approach in the Thiokoye basin has yielded valuable insights into the interactions among climate, geology, land use, and hydrological processes. While model limitations related to data availability and structural simplifications must be acknowledged, the results provide a strong foundation for integrated water and land management. These insights can be scaled or transferred—with caution—to similar watersheds across the Sahel and beyond. As development pressures intensify and climatic uncertainty grows, tools like SWAT become indispensable for local governments, planners, and communities striving to build resilient and sustainable water systems.

5. Conclusion

The hydrological modeling conducted in the Thiokoye River Basin using the Soil and Water Assessment Tool (SWAT) in combination with the Sequential Uncertainty Fitting algorithm (SUFI-2) has substantially enhanced our understanding of water dynamics in a bioclimatic transition zone between the Southern Sudanian and Guinean domains, an area characterized by alternating dry and wet seasons and underlain by low-permeability crystalline formations that complicate water resource assessment in data-scarce contexts. Despite these challenges, the applied approach has demonstrated robustness and adaptability, with the model achieving exceptional performance during calibration (NSE and $R^2 = 0.98$), highlighting the effectiveness of the SWAT-SUFI-2 coupling in capturing streamflow variability under complex conditions. While a slight decrease in performance was observed during validation, it remained within acceptable limits, reaffirming the need for continuous data collection and periodic recalibration in the face of environmental and climatic changes. Sensitivity and uncertainty analyses further revealed the dominant influence of parameters controlling runoff, baseflow, and infiltration, which are highly dependent on land cover and soil characteristics, confirming that effective calibration must account for both climatic variability and geophysical heterogeneity. The study also emphasized the pivotal role of seasonality in hydrological dynamics, with blue and green water availability—encompassing surface runoff, percolation, soil moisture, and actual evapotranspiration—exhibiting marked temporal and spatial fluctuations that demand adaptive water management strategies. Sediment yield assessments highlighted the basin's susceptibility to erosion during peak rainfall months, underscoring the urgency of implementing erosion control measures and promoting sustainable land use. The spatial discretization of the SWAT model through Hydrological Response Units (HRUs) provided valuable insights for local planning, enabling the identification of water loss and soil degradation hotspots and supporting targeted interventions such as artificial recharge zones, reforestation, and climate-resilient agricultural practices. These outputs are directly applicable to the formulation of Local Integrated Water Resources Management Plans (PL-GIRE), which must balance institutional goals with community-level priorities. This research not only establishes a foundation for developing future scenarios aimed at enhancing the basin's climate resilience but also offers a replicable methodology for other West African watersheds. Future enhancements could include integrating high-resolution satellite data for real-time land use and vegetation monitoring, coupling SWAT with groundwater models to refine water balance assessments, and incorporating outputs from regional climate models to simulate long-term climate change impacts. Ultimately, the systemic insights into water availability, land degradation, and climate variability generated by this study provide a powerful decision-support tool for integrated, participatory, and evidence-based watershed management—an approach that is essential for safeguarding natural resources and enhancing the resilience of rural communities amid growing environmental pressures.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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