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Research Article

Simulation of Water Balance Components Using the SWAT Model in the Birr Watershed, Upper Blue Nile Basin

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Abstract

To manage water resources sustainably, understanding their quantity in spatial and temporal contexts is essential. Simulating Water Balance Components (WBCs) plays a crucial role. This study uses the Soil and Water Assessment Tool (SWAT) model to analyze water balance in the Birr Watershed of the Upper Blue Nile Basin, enhancing management strategies. By examining precipitation, evapotranspiration, surface runoff, and groundwater flow, the research provides insights into water availability and environmental impact. A comprehensive understanding of the water balance is crucial; however, past studies often overlooked long-term hydrological responses to climate and land use changes. To address this, the study uses datasets from 1990 to 2005, calibrating the model against streamflow records with the SUFI-2 algorithm, achieving high accuracy with NSE and R^2 values over 0.68. Findings indicate annual precipitation increased by 28.1%, from 457 mm in 1992 to 580 mm in 2006, then dropped to 264.88 mm in 2020, still 38% above initial levels, indicating significant climatic changes. Surface runoff surged by 55.7%, and groundwater flow grew by 42.7%, suggesting enhanced water availability but also potential risks for flooding and erosion. Evapotranspiration decreased slightly by 1.9%, likely due to varying climate factors. These hydrological changes affect agricultural productivity and ecosystem health, though uncertainties persist due to data constraints and insufficient integration of climate change assessments. Policymakers should implement integrated watershed management, promote sustainable land use, develop flood risk strategies, and strengthen hydrological data systems. Adaptive management strategies and cross-sector collaboration are essential for addressing climate change impacts and ensuring sustainable water resources for the basin's ecosystems. This study offers critical insights for effective policies aimed at sustainable hydrological management in vulnerable river basins.

Keywords

Birr Watershed, Water Balance Components, SWAT, Blue Nile Basin

1. Introduction

Water balance is a key concept in hydrology, reflecting the equilibrium between water inflow and outflow [1]. According to the conservation of mass principle, the water balance equation asserts that the total water entering a system equals the total water exiting it [2]. Comprehending the water balance within a watershed is essential for understanding water movement through the system [2]. The primary components of this balance comprise precipitation, evapotranspiration, lateral flow, surface runoff, groundwater flow, and soil potential evapotranspiration [3]. Precipitation indicates the

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volume of water that enters the watershed, while evapotranspiration includes water loss due to evaporation, transpiration, and evaporation from soils and water surfaces [4].

Maintaining water balance is crucial for effective water resource management and addressing global challenges like water scarcity, flooding, and the impacts of climate change [5]. Monitoring and modeling water balance play a vital role in water resource planning, flood forecasting, agricultural management, and ecosystem conservation [6]. To ensure successful governance and the sustainable use of water resources, focus has been placed on water balance concepts and elements of hydrologic science [7]. The significance of hydrological models in examining the effects of land-use changes and climate variability on water balance has been highlighted [8]. Accurate flow simulations can enhance watershed research [9].

Geochemical weathering processes and bedrock minerals play a key role in determining water quality and quantity [10]. Factors like human activities, population expansion, infrastructure growth, and climate change can affect the water balance. To address these impacts, it’s essential to implement conservation efforts, adopt sustainable agricultural practices, and enhance infrastructure [11].

The Soil and Water Assessment Tool (SWAT) is a detailed, semi-distributed, continuous-time hydrology model designed to assess how land management practices affect water, sediment, and agricultural chemical yields in complex watersheds [12]. SWAT is commonly used to analyze hydrological processes [13]. It forecasts runoff, non-point source pollution, and various intricate hydrological phenomena amid changing environmental conditions [14]. The model divides watersheds into sub-watersheds and hydrologic response units (HRUs). It evaluates the effects of land management on water resources, quality, and agricultural output [15]. Additionally, it accounts for landscape variability and complex interactions within river basins or watersheds [16]. However, the SWAT model has some drawbacks, such as the uncertainty of model parameters arising from numerous input variables and its limited ability to represent spatial and temporal variability in hydrological processes at more detailed scales [17]. Moreover, SWAT requires substantial data for accurate results, which may be unavailable in some areas.

The Soil and Water Assessment Tool (SWAT) has been widely used in various studies to simulate water resource management scenarios across different regions. In the Samalqan watershed, a 13-year SWAT model was established to simulate streamflow and inform water management strategies [18]. Additionally, in Nepal's Karnali River basin, both the SWAT and SRM models were utilized to simulate hydrological processes, revealing 12% snowmelt runoff and 25% evapotranspiration. In central India's upper Sabarmati basin, the SWAT model was used to assess the water balance, identifying a declining trend in precipitation and surface runoff [19]. Research on alpine lakes in the Tibetan Plateau highlighted their contribution to the water cycle and ecosystem maintenance, especially with the increase in precipitation and glacier melting [20]. Furthermore, a study estimated the SWAT model's effectiveness in analyzing watershed hydrology and streamflow variability in North Carolina, noting that land use changes increased surface runoff by 13.9% and water yield by 8.32% [21]. Ultimately, the SWAT model was employed to simulate various water balance components, including surface runoff, lateral flow, percolation, evapotranspiration, and soil water to aid in the sustainable management of water resources in Tamil Nadu, India [22].

The objective of this study was to develop a SWAT-based model that simulated the components of the water balance in developing countries. Its primary purpose was to enhance water resource management through analyzing the components of the water balance, addressing their uncertainties, and calibrating and validating the ARC SWAT. Modeling using the SWAT CUP SUFI-2 algorithm will assist stakeholders in identifying specific problem areas and implementing necessary intervention measures related to water risks. The watersheds in Birr face similar challenges, such as changes in land use, varied topography, fluctuating climate conditions, a dense population, and ecosystem degradation. The success or failure of the model will depend on its integration into local management strategies. The study identified deficiencies in the SWAT model, including inadequate integration with climate change, poor-quality data, and the complexity of hydrological analysis.

2. Materials and Methods

2.1. Study Area Description

The Birr River watershed is part of the Upper Blue Nile Basin and is situated in the South Gojjam sub-basin, located between 11°20′0″N and 11°0′0″N, and 37°0′0″E and 37°40′0″E, as shown in Figure 1. This watershed belongs to the South Gojjam sub-basin, one of the 16 sub-basins within the Abbay Basin. The study area covers 978 km ² with topography ranging from 1775 meters to 3519 meters above mean sea level. The predominant soil types are eutric nitisols and chromic luvisols. It experiences annual rainfall ranging from 994.75 mm to 2453.24 mm, with the majority occurring in July and August, while the dry season lasts from November to April. On average, the maximum and minimum annual temperatures are 29.5 ℃ and 11.2 ℃, respectively.

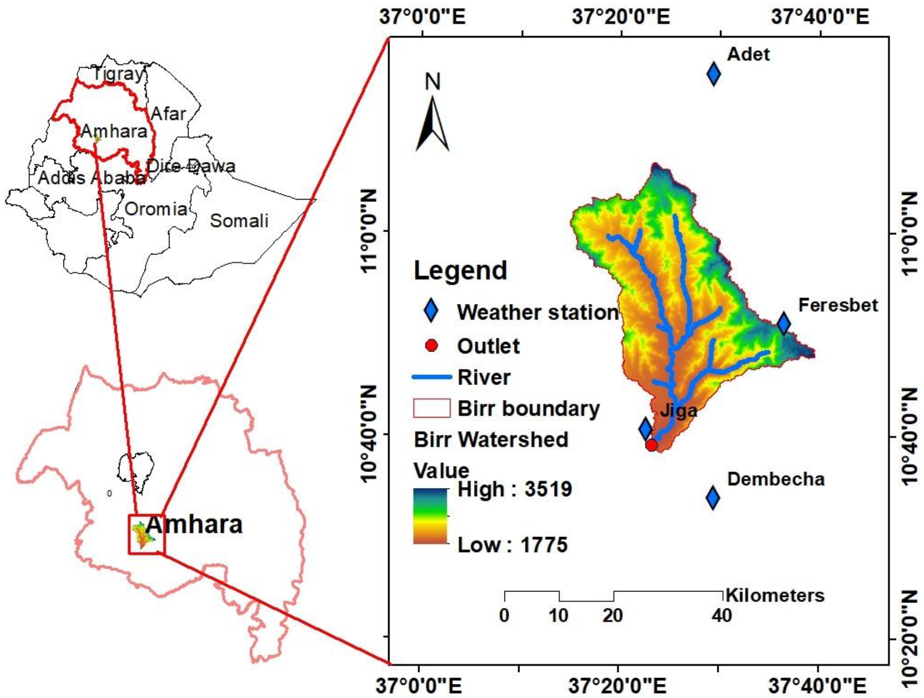

Figure 1. Location map of the study area.

2.2. Model Input Data

2.2.1. Digital Elevation Model (DEM)

The slope, elevation, and stream network of the Birr watershed were derived from DEM data. The DEM data used has a resolution of 12.5 m and was downloaded from https://asf alaska. edu/. Elevation varies from 1775 to 3519 meters above sea level and is projected to UTM Zone 37 North using the D_WGS_1984 datum with ArcGIS 10.4.1. The DEM data underwent preprocessing within the SWAT model to accurately delineate the watershed and perform the necessary topographic calculations. In the Arc SWAT 2012 model, calculated parameters for each sub-basin included the developed stream network as well as inlet and outlet points.

2.2.2. Slope Map

The slope map is regarded as one of the critical parameters of the SWAT HRU because it is the primary factor governing runoff generation, erosion, infiltration, and soil moisture dynamics. In this context, the study area was categorized into five slope classes: 0-5 degrees (8.53%), 5-10 degrees (16.63%), 10-15 degrees (12.39%), 15-20 degrees (10.86%), and 20-9999 degrees (51.59%). Flat or gently sloping areas are more suited for agricultural activities and development, while moderate slopes influence hydrological processes and require greater attention for soil and water conservation practices. Steeper slopes, such as 15-20 degrees, present significant challenges in water management and thus necessitate more intensive soil conservation measures.

2.2.3. Land Use/Land Cover Data

Land Use/Land Cover (LULC) data refers to information about the usage and coverage of land in a specific region or area, primarily collected through remote sensing technologies that utilize satellite images or aerial photographs [16]. The study area is characterized by low forest coverage, which accounts for only 2.71% of the total. A minimal portion, 0.22%, is classified as brush land. A significant share, 22%, consists of grassland. Cultivated land dominates land use, covering 73% of the study area. Wetlands represent a very small proportion at 0.11%. Residential areas make up 1.96%. The Land SAT image was derived from satellite imagery and classified into various land use/land cover categories. Satellite data with a 30-meter resolution was obtained from the USGS website (www.earthexplorer.usgs.gov).

2.2.4. Soil Data

Soil data, or maps, contain information on the characteristics, properties, and distribution of soil within a specific area. Soil properties include texture, organic matter content, pH levels, nutrient content, cation exchange capacity, and moisture-holding capacity. The analysis utilizes soil map data from the World FAO Soil Map DSMW Database, a comprehensive global dataset of soils.

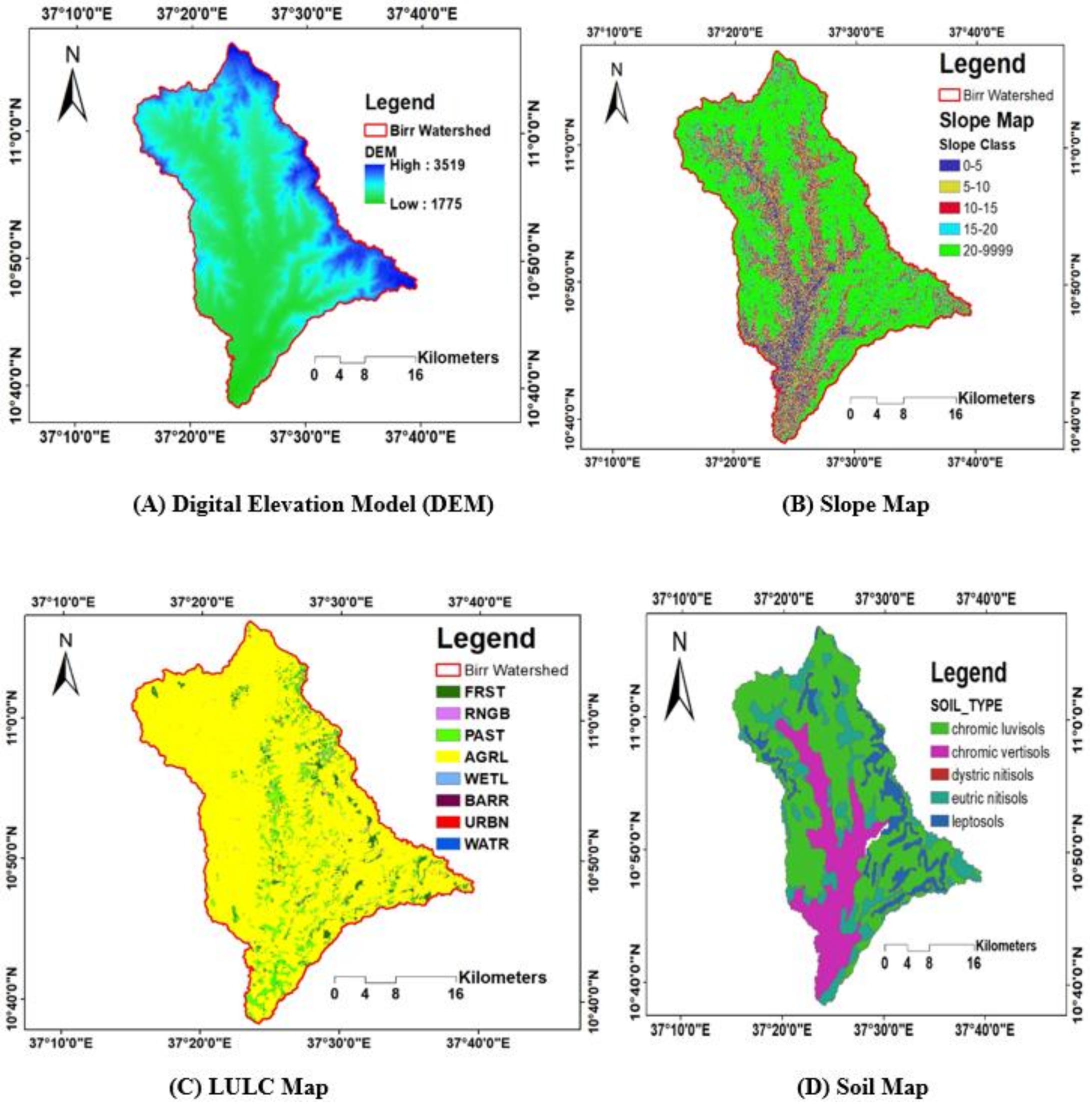

Figure 2. *Input spatial data.*

2.3. Hydrological Data

Streamflow Data. This data indicates the flow rate of water in rivers or streams and is, therefore, important for calibrating and validating the SWAT model. During the calibration process, streamflow data assists in adjusting model parameters to align the simulated flow with the observed flow. This is followed by validation, which involves comparing the simulated streamflow to independent observed data over several distinct periods. The Birr streamflow was measured at the Lay Birr station, and the data from 1990 to 2005 were obtained from the Ministry of Water and Energy. This station has been utilized for the calibration and validation of the hydrological model SWAT.

2.4. Weather Data

Weather data is one of the main inputs for the Soil and Water Assessment Tool (SWAT) model, as it shows the climatic conditions of the given watershed. The hydrological component of SWAT, including evapotranspiration, surface runoff, infiltration, and groundwater recharge, largely depends on the weather. Precipitation data quantifies rainfall intensity and volume within a watershed, influencing surface runoff and soil infiltration. Temperature readings help estimate evapotranspiration rates, which are crucial for understanding the water balance in ecosystems. Solar radiation data aids in determining evaporation and plant transpiration rates. Wind speed measurements were used to assess wind-driven evaporation and its effect on moisture distribution. Humidity levels assist in estimating potential evapotranspiration and simulating the water balance across different periods in a basin. Daily precipitation, wind speed, solar radiation, humidity, and minimum and maximum temperatures from 1990 to 2020 were retrieved from four representative meteorological stations: Adet, Jiga, Feresbet, and Dembecha, from the National Meteorological Agency.

2.5. SWAT Model Setup

The Soil and Water Assessment Tool (SWAT) model is designed to simulate hydrological processes within a watershed. This process includes defining the stream area, acquiring data inputs, and utilizing elevation models, land use/land cover, soil, historical weather, and streamflow data. Subsequently, preprocessing was performed to fill sinkholes, delineate river courses, and define catchment areas. Setting up this model involves data preparation, watershed delineation, weather documentation, defining HRUs, SWAT simulation, sensitivity analysis, calibration, and validation. The collected DEM was projected in UTM 37N. A projected 12.5 m × 12.5 m DEM is used for further delineating watersheds. HRUs were defined using multiple HRU classes with 10% land use, 5% soil, and 5% slope discretization. The SWAT simulation was conducted using HRUs and weather data as inputs. The SWAT simulation analyzed changes in surface flow, lateral flow, and groundwater flow, which were computed for catchment hydrology.

$$Swt = Swo + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \tag{1}$$

SW_t, *and* SW_O is the final and initial soil water content (mm) respectively, t is the time (days), R_{day} is daily precipitation i (mm), is surface runoff on day i (mm), E_a is evapotranspiration on day i (mm), W_{seep} water entering the vadose zone from the soil profile on day i (mm), and Q_{gw} return flow on day i (mm).

2.5.1. Weather Generator

Generator (WGN) is a hydrological modeling methodology that transforms historical weather data into a synthetic time series of meteorological variables, including minimum and maximum temperature, precipitation, humidity, wind speed, and solar radiation. The basic methodology includes data collection, data pretreatment, statistical analysis, model development, parameter estimation, weather generation, validation, and the integration of generated weather into hydrological models. The WGEN maker 4.1 Excel macro program was downloaded from the SWAT website, installed, and used to develop the SWAT weather generator database for preparing weather data input for the SWAT model. This Excel macro utility calculates the statistics of weather stations required by users to create weather station files for SWAT. It can utilize either a measured data set or data generated by the weather generator model WGEN. The measured data for precipitation and minimum and maximum temperatures, solar radiation, relative humidity, and wind speed were prepared daily to generate weather station statistics. The Dew02. exe program calculates dew point temperature using daily minimum and maximum temperature data.

2.5.2. HRU Analysis

HRUs are a significant consideration in the conceptualization of SWAT and represent spatial heterogeneity, facilitating simulations based on differences in land use, soil type, and slope. The sub-watersheds were further divided according to land use, land cover, soil, and slope percentage into HRUs. Land use and soil data were uploaded into the interface, with a corresponding code prepared for each. The land use, soil, and slope datasets were imported, integrating the available databases in SWAT 2012, which provided estimates of modeling parameters for each HRU and sub-basin. HRUs were defined using multiple HRU classes of 10% land use, 5% soil, and 5% discretization of slope. Multiple HRU thresholds were utilized for HRU analysis.

2.6. Water Balance Components

2.6.1. Surface Runoff

In the hydrological cycle, SWAT considers land surface runoff while calculating flood discharges and infiltration. It includes factors that influence these processes, such as land use type, landscape features, soil, and management practices. However, the curve number defines the catchment-area potential for runoff, whereas other physical models simulate changes in soil wetness based on system processes. The general formula for calculating surface runoff using the Curve Number method is as follows:

$$Q_{surf} = \frac{\left[\left(R_{day} - 0.2s\right)\right]^2}{\left(R_{day} + 0.8s\right)} \tag{2}$$

Q_{surf} stands for the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm), and *and S* is the retention parameter (mm). The equation determines the retention parameter.

$$S = 25.4\left[\left(\frac{1000}{CN}\right) - 10\right] \tag{3}$$

CN, this value depends on the soil water conditions, permeability, and land uses, and is estimated for the various land uses shown in SWAT.

2.6.2. Evapotranspiration (ET)

Evapotranspiration (ET) is the loss of water from the soil and plants to the atmosphere through the process of transpiration. The SWAT hydrology modeling programs estimate the monthly plant water intake over a year, based on vegetation coverage, climate, and soil type, according to occupation type. This process helps estimate hydrometric balance, analyze irrigated water needs, and assess environmental impact.

2.6.3. Water Yield

Water yield represents the total volume of water exiting a watershed, influenced by factors such as precipitation, evapotranspiration, soil characteristics, land cover, topography, and land-use practices. All these elements were simulated in SWAT to provide insight into the water balance and hydrologic response to changes in land use, climate variability, and water management practices. The general formula for water yield (WY) can be summarized as follows:

$$WY = P + SW_{i-1} - ET - R - G \tag{4}$$

Where (WY) and (P) are the water yield (in mm or m^3/ha) for a given time step, and the precipitation (in mm) over the time step, respectively. ($SW_{\_i-1}$) is the initial soil water content at the beginning of the time step (in mm), (ET) is the actual evapotranspiration (in mm) over the time step, (R) is the surface runoff (in mm) over the time step, and (G) is the percolation (or deep drainage, in mm) below the root zone over the time step.

2.6.4. Lateral Flow

Lateral flow is a process of great importance in hydrology and watershed modeling, responsible for the horizontal movement of water through soil, which has effects on general water availability, nutrient transport, and entire watershed dynamics. The lateral flow formula in SWAT can be expressed as

$$Lateral\ flow = \frac{Area \times Lat\_Time}{Drainage\ Area} \tag{5}$$

Where: Lateral Flow: Volume of water moving laterally through the soil profile (mm or m^3) Area: Area of the HRU contributing to lateral flow (m^2). LAT_TTIME: Lateral flow travel time (days). Drainage Area: Total drainage area of the HRU (m^2).

2.6.5. PET

PET is a key indicator of water evaporation and transpiration, encompassing factors like temperature, humidity, wind speed, and vegetation characteristics. It plays a critical role in hydrological studies and water resource management by estimating the quantity of water required by vegetation and maintaining a balance of water. The Penman-Monteith formula is commonly used in climate modeling to estimate water budgets. The Penman-Monteith formula was used for this study. The Penman-Monteith equation for calculating PET is as follows:

$$PET = \frac{0.408 \times \Delta \times (R_n - G) + \gamma \times \frac{900}{T + 273} \times U_2 \times (e_s - e_a)}{\Delta + \gamma \times (1 + 0.34 \times U_2)} \tag{6}$$

Where PET and δ are potential evapotranspiration (mm/day) and the slope of the saturation vapor pressure curve (kpa/ ℃), respectively. R_n is net radiation at the crop surface (mj/m^2/day), g is soil heat flux density (mj/m^2/day), γ is psychometric constant (kpa/ ℃), t is air temperature at 2 meters height (℃), U_2 is wind speed at 2 meters height (m/s), e_s is saturation vapor pressure (kpa), and e_a is actual vapor pressure (kpa).

2.6.6. Groundwater Flow (Shallow Aquifer)

The SWAT model is designed to study groundwater flow in shallow aquifers, which are typically unconfined water bodies that contribute to stream return flow. The SWAT model accounts for return flow, interactions with surface water, recharging and discharging, water balance, and land use effects. In this way, it simulates the interaction between surface water and groundwater, the contributions of groundwater to streamflow, and the overall water balance. The general equation of groundwater flow used for shallow aquifers by the SWAT model can be represented as

$$Q = K \times A \times \frac{dh}{dl} \tag{7}$$

Where Q, Groundwater flow rate (m^3/s), K Hydraulic conductivity of the aquifer (m/s), A Cross-sectional area of flow (m^2), dh/dl Hydraulic gradient (m/m).

2.7. Sensitivity and Uncertainty Analysis

The SWAT-CUP approach refers to the methodology used to calculate sensitivity for parameters in water quality models, emphasizing the identification of sensitive parameters based on their role in model calibration and validation. The sensitivity of a parameter is quantified using t-stat and p-value, with higher absolute values indicating greater sensitivity. Global sensitivity analysis assesses how parameter sensitivities change with variations in other parameter values. Model calibration seeks to minimize prediction uncertainty by parameterizing to local conditions, enhancing the likelihood of reliable results. Uncertainty analysis involves propagating uncertainties in model inputs. The most commonly used program for calibration and uncertainty analysis is SUFI-2, which has been applied in several studies [23, 24]. This is why SUFI-2 is used to calibrate the SWAT model, as it accommodates many parameters related to water balance modeling. Additionally, SUFI-2 is an efficient approach for a high number of iterations and for adjusting parameter ranges [23]. For these reasons, calibration and uncertainty analysis were conducted using SUFI-2 algorithms. A sensitivity analysis was performed using 10 years of recorded river flow to identify the most sensitive parameters.

$$\bar{r} = \frac{1}{n}\sum_{ti}^{n}\left(y_{ti,97.5\%}^{m} - y_{ti,2.5\%}^{m}\right) \tag{8}$$

$$r - factor = \frac{p - factor}{\delta_{Obs}} \tag{9}$$

Where $y_{ti,97.5\%}^{m} - y_{ti,2.5\%}^{m}$ Represent the upper and lower boundaries of the 95 PPU and δ_{Obs} Is the standard deviation of the measured data.

2.8. Model Calibration and Validation

SWAT is a watershed modeling tool for simulating hydrological responses within watersheds. It is calibrated and validated to improve model performance and accuracy. Calibration aims to align model behavior with actual observations, enhancing the interpretation of observed data. Model validation was conducted using calibrated parameters on independent datasets by comparing predictions with the observed data. The flow simulation, which utilized the identified sensitive parameters for the period from 1990 to 2000, was calibrated. The same was validated for the period from 2001 to 2005.

2.9. Model Performance Analysis

SWAT CUP stands for Soil and Water Assessment Tools Calibration Uncertainty Program and serves as a tool for validating the simulated output of the SWAT model against observed data. After calibration, a validation procedure was conducted to assess the performance of the calibrated parameters using an independent data set. This process includes gathering empirical observations, assessing fit, conducting vulnerability diagnostics, testing parameter reliability, detecting system errors, evaluating model accuracy, and potentially repeating estimates if necessary. In hydrological modeling, as in the SWAT model, performance evaluation is crucial to estimating the accuracy and reliability of simulated results [25]. Various criteria are employed to evaluate the performance of a hydrological model, including SWAT, in replicating observed data and capturing the dynamics of watershed processes. Common criteria for model performance include.

The coefficient of Determination R^2 gives the proportion of variance of observed data explained by the model. The higher the R^2, the more appropriate the fitted model is to the data.

$$R^2 = \frac{\sum_{i=1}^{n}\left(Q_i^{sim} - Q_{mean}^{sim}\right)\left[\left(Q_i^{obs} - Q_{mean}^{obs}\right)\right]^2}{\left[\sum_{i=1}^{n}\left(Q_i^{sim} - Q_{mean}^{sim}\right)\right]^2\left[\sum_{i=1}^{n}\left(Q_i^{obs} - Q_{mean}^{obs}\right)\right]^2} \tag{10}$$

Where Qi^{Obs} and Qi^{sim} are the observed and the simulated stream flows, respectively; $Qmean^{Obs}$ is the mean of the observed data; $Qmeansim$ is the mean of the simulated data. The R^2 value ranges between 0 to 1, where higher values indicate less error variance, with values larger than 0.5 often considered acceptable [26].

Nash-Sutcliffe Efficiency Perhaps the most commonly used statistic relates the simulated values to the observed values to the mean of the observed data; the values range from negative infinity to 1, where 1 represents a perfect match between simulated and observed data.

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_{mean}^{Obs}\right)^2} \tag{11}$$

The *RSR* represents an error index normalizing the root mean square error by using the standard deviation of the observations. The RSR indications are between 0.0 and 1, and for better model performance, it has a lower value. When RSR = 0 yields a perfect fit of the model simulation to the observed data, large positive RSR values will describe a poor fit in the model performance.

$$RSR = \frac{RMSE}{STDEV_{Obs}} = \frac{\sqrt{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_i^{sim}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_{mean}^{Obs}\right)^2}} \tag{12}$$

Percent Bias: It gives a global idea regarding whether, on average, the model under-predicts or over-predicts the measured data. "A PBIAS close to zero denotes a balanced performance of the model. Among them, one of the most used techniques is the SUFI-2 algorithm. This automated system calibrates and validates the hydrological parameters with sensitivity analysis, uncertainty analysis, and parameterization.

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_i^{sim}\right)}{\sum_{i=1}^{n}\left(Q_i^{obs}\right)} \times 100 \tag{13}$$

Table 1. Model performance criteria.

Performance rating	NSE	RSR	PBIAS
Unsatisfactory	NSE≤0.5	RSR≥0.7	PBIAS≥±25
Satisfactory	0.5≤NSE≤0.65	0.6<RSR≤0.7	±15≤PBIAS<±25
Good	0.65≤NSE≤0.75	0.5<RSR≤0.6	±10≤PBIAS<±15
Very good	0.75≤NSE≤1	0.5<RSR≤0	PBIAS< ±10

Source from [26].

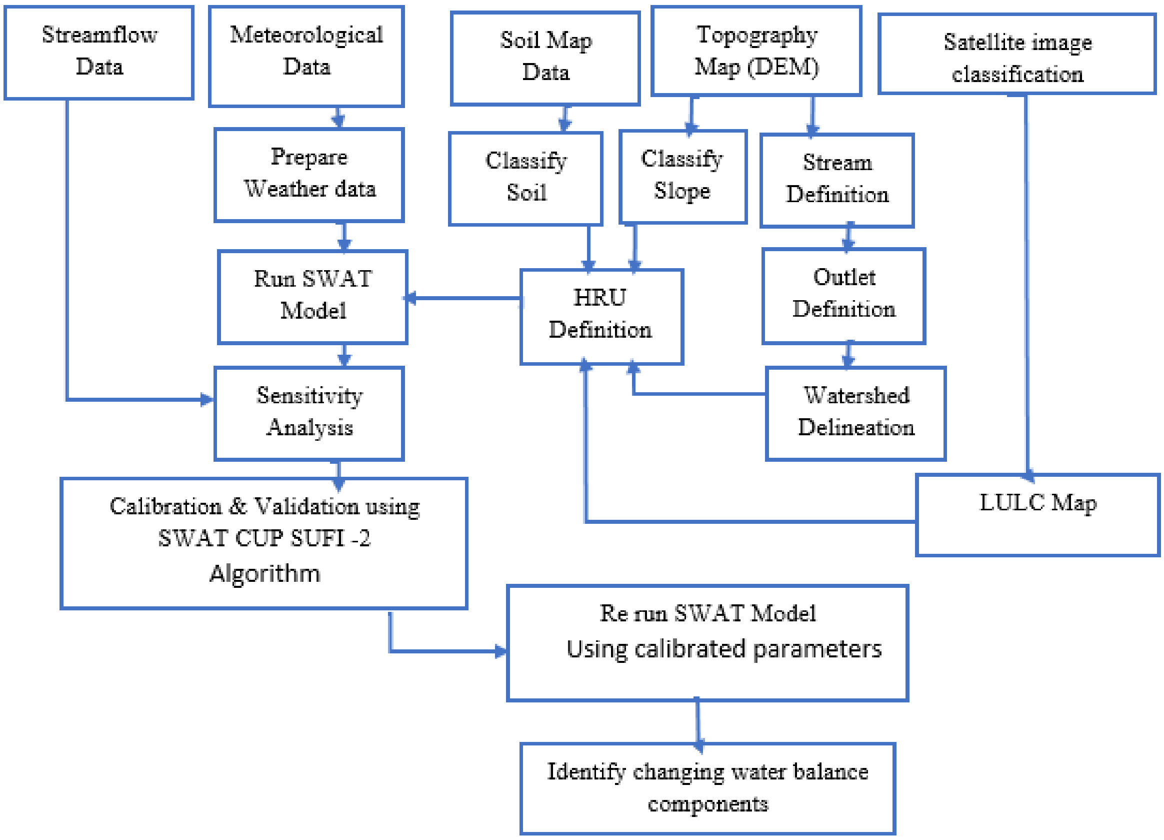

Figure 3. The general framework of the study.

3. Results and Discussion

3.1. Stream Flow Sensitive Parameters

The sensitivity parameters for stream simulation in SWAT were ranked based on their p-values and t-statistics. The larger the absolute value of the t-statistic, and the closer the p-value is to zero, the more sensitive the parameter. In the present research, thirteen SWAT parameters were calibrated based on sensitivity. Among these thirteen parameters, six were identified as the most sensitive and were ranked accordingly. The most sensitive parameters for stream flow identified in this study are CN2, CH_K2, Rte, and GWQMN. GW, ESCO. hru, SOL_AWC (.). sol., and GW_DELAY (Table 2). A smaller CN2 value indicates greater infiltration capacity or reduced runoff potential; this may suggest the presence of more permeable soils or greater vegetation cover. A small alpha factor for base flow may indicate a slow recession from groundwater to streamflow, likely due to deep water tables and low hydraulic conductivity in the aquifer.

The time delay in GW corresponds to the number of days required for water to reach the shallow aquifer. Low values of ALPHA_BF and longer GW_DELAY suggest that this is likely a deep, slow-responding groundwater system, probably due to low-permeability aquifer materials or a deep water table. The significant depth of water in a shallow aquifer is necessary for return flow, indicating deep water table conditions. SURLAG. bsn governs the time lag of surface runoff, which represents medium time lags from the formation of surface runoff to when the water ultimately reaches the streamflow, likely related to landscape characteristics.

The watershed model is calibrated to reduce runoff, slow groundwater response, and increase soil water storage compared to the default settings. The "n" value within the model relates to overland flow and controls the flow rate. Lower "n" values represent smooth surfaces with less resistance to overland flow. A low soil evaporation parameter limits the amount of water available for the root zone, while the evaporative compensation factor adjusts the rate of water evaporation. It has been observed that the calibrated ESCO value is lower, which could be due to a deeper root zone, greater water retention, or a cool climate. The calibrated ESCO value is low according to the correspondent, indicating that there will be a higher moisture transfer from deeper layers to the top surface.

The moderate steepness of the watershed influences surface runoff generation and flow paths. Available water capacity impacts the water volume stored within the soil layer, which, in the case of watershed soils, is relatively low. GW_REVAP facilitates some flow from the shallow aquifer into the root zone based on the depth to the water table and the soil's hydraulic properties. The average length of slope within sub-basins affects the volume and timing of surface runoff, while the effective hydraulic conductivity of channel alluvium governs discharge through the channel.

Table 2. *Calibrated parameters for stream flow.*

Parameter Name	Description	t-stat	p-value	Rank	Fitted Value	Range
R__CN_2.mgt	SCS runoff curve number	-34.24	0.00	1	-0.21985	35 - 98
V__CH_K2.rte	Effective hydraulic conductivity of the main channel (mm/hr)	4.28	0.00	2	2.130000	-0.02-500
V__GWQMN.gw	Shallow aquifer required for return flow (mm)	-1.38	0.00	3	175.000000	0-5000
V__ESCO.hru	Soil evaporation compensation factor	-1.26	0.00	4	0.479219	0-1
R__SOL_AWC (..).sol	Soil available water capacity (water/mm soil)	0.8	0.00	5	0.270000	0-1
V__GW_DELAY.gw	Groundwater delay	2.58	0.01	6	50.000000	0-500
V__REVAPMN.gw	aquifer for revap or percolation to the deep aquifer (mm)	-0.73	0.46	7	70.000000	0-500
R__SLSUBBSN.hru	Average slope length	-0.7	0.48	8	0.035900	10-150
V__SURLAG.bsn	Surface runoff lag time	-0.69	0.5	9	6.000000	0.05- 24
V__ALPHA_BF.gw	Base flow recession constant (days)	-0.3	0.78	10	0.000070	0-1
R__OV_N.hru	Manning's "n" value for overland flow	-0.23	0.8	11	0.020319	0.01- 30
V__HRU_SLP.hru	Average slope steepness	0.2	0.81	12	0.600000	0-1
V__GW_REVAP.gw	Groundwater “revap” coefficient	-0.12	0.9	13	0.010000	0.02- 0.2

3.2. Model Calibration and Validation

The stream flow simulated by the ARC SWAT model was calibrated and validated. The results indicate a good agreement between the measured and simulated monthly flows, with some underestimation of the peak flow values (Figure 4). Model efficiency was checked using statistical values, all of which suggest that the model predicts well, indicating that SWAT can be adopted for hydrological simulation in the study area (Table 3). The calibration process employed SWAT_CUP and consisted of 500 simulations, selecting the best parameters. Data from 1990 to 2005 was chosen for SWAT modeling because it is available, continuous, and best represents the long-term hydrological regime. This recent period is therefore most suitable as it effectively simulates hydrological processes, despite the limited recorded data in developing countries. It was also considered representative of the long-term hydrological conditions concerning climatic variability, land use changes, and water management practices in the Birr River basin. Goodness measures were utilized to assess the calibration and validation of model performance. The calibration and validation of the SWAT model for the Birr watershed are highly dependent on data quality and completeness. The years 1990 to 2005 were selected due to better data availability and reliability. The results of the SWAT model demonstrated that the observed and simulated stream flows are in good agreement (Figure 4). Different studies have also reported similar findings in the Abbay River basin [24], in the Andassa watershed, and [27] in the Dedissa sub-basin.

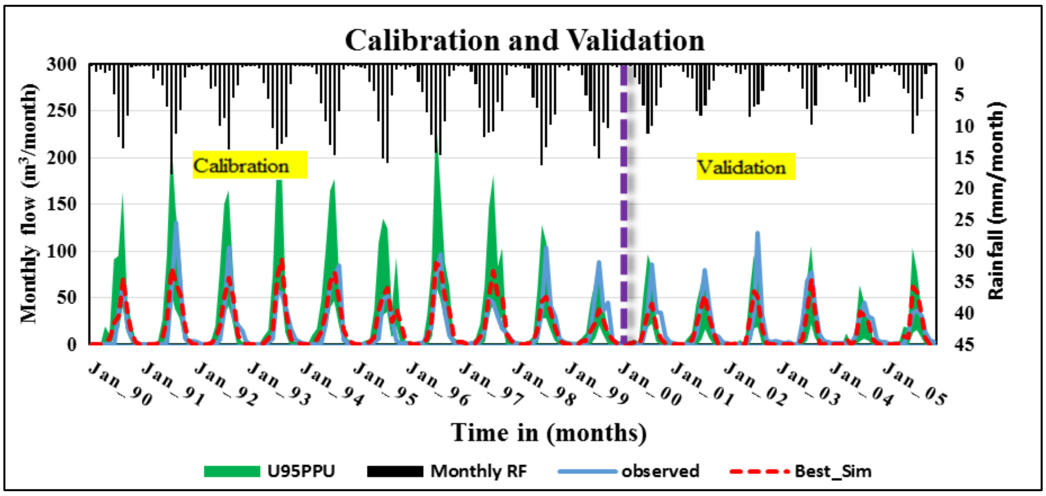

Figure 4. Monthly calibration and validation for the Birr River watershed.

Table 3. Model performance of calibration and validation for stream flow.

Calibration (1990-2000)	Validation (2001-2005)
R^2 0.72	0.7
NSE 0.72	0.68
PBIAS 2.7	18.9

In this regard, the SWAT model was tested to determine its ability to capture streamflow dynamics in the study area. During the calibration period from 1990 to 2000, it achieved an R^2 of 0.72, indicating that it explained 72% of the variability in observed streamflow data. The Nash-Sutcliffe Efficiency value was 0.72, which is considered good, suggesting that the model could simulate streamflow dynamics better than the mean of the observed data. A PBIAS value of 2.7% indicated a slight tendency for the simulated streamflow to differ from the observed values. It also performed well during validation, with an R^2 of 0.70, NSE of 0.68, and a PBIAS of 18.9%. These results indicate good performance for the SWAT model in supporting water resource management and decision-making for the study area. A slight degradation observed during the validation period may be attributed to variations in watershed characteristics or climate conditions. Therefore, the SWAT model is considered a reliable tool for supporting water resource management and decision-making in the study area. The model's performance during the calibration period was superior to that during the validation period.

3.3. Simulation of Water Balance Components

Table 4. Monthly water balance components.

Month	Rain (mm)	SURF Q (mm)	LATQ (mm)	Water yield (mm)	ET (mm)	PET (mm)
Jan	8.27	0.57	1.79	50.07	5.19	99.82

Month	Rain (mm)	SURF Q (mm)	LATQ (mm)	Water yield (mm)	ET (mm)	PET (mm)
Feb	10.12	0.06	0.92	32.67	8.44	105.48
Mar	30.87	0.36	0.84	27.94	35.88	133.53
Apr	65.74	1.40	1.13	22.80	65.11	137.42
May	143.30	9.10	2.58	30.95	86.24	137.49
Jun	234.77	21.53	5.45	57.82	94.90	121.10
Jul	410.32	70.23	11.92	155.28	82.01	118.56
Aug	383.50	56.16	17.49	206.20	61.89	121.17
Sept	205.27	20.00	16.09	185.34	44.97	119.62
Oct	90.07	8.62	11.38	150.10	24.20	113.78
Nov	26.67	0.56	6.32	99.69	12.70	97.87
Dec	11.16	0.30	3.43	71.06	6.64	94.66

Table 4 shows data on rainfall, surface runoff, lateral flow, total water yield, evapotranspiration, and potential evapotranspiration analyzed on a monthly basis. The series shows a seasonal trend, peaking in summer and recording the lowest values in winter. Surface runoff and lateral subsurface flow are high during summer months but low during dry periods. Summer experiences the highest water yield, reaching a maximum in August, while winter shows the lowest values. Evapotranspiration (ET) fluctuates at levels lower than potential evapotranspiration (PET), indicating a consistent moisture deficit. This information is crucial in making decisions about water management practices for irrigation, crop selection, and conservation. A comprehensive water management strategy that considers all seasons' precipitation, surface runoff, subsurface flow, and evapotranspiration can help guide the allocation and use of water for agricultural, domestic, industrial, and environmental sustainability and efficiency.

An implication of ET often being less than or equal to PET is that actual evapotranspiration tends to be governed by the availability of soil moisture rather than atmospheric demand. In the summer, PET surpasses ET to a lesser extent, suggesting that vegetation and soil can meet a larger share of atmospheric evaporative demand. This disparity is particularly evident during the winter months, from December to February, indicating that vegetation and soil struggle to keep up with higher atmospheric evaporative demands. The ET/PET ratio serves as an indicator of water stress in the region, with winter values ranging from 0.05 to 0.15 and summer values between 0.55 and 0.8. Low ratios signify water stress, whereas high ratios indicate no stress, thereby promoting diverse ecosystems. Several factors drive the complex changes in ET and PET, including climate variables such as temperature, humidity, wind speed, and solar radiation, all of which can significantly affect both ET and PET. Additionally, ET relies on the soil's capacity to retain moisture; more ample soil leads to higher ET rates, whereas drought diminishes them. The type and density of vegetation also play a significant role in influencing ET. Changes in land use, such as urban development, deforestation, and agricultural practices, can modify surface characteristics, impacting ET and PET. Variations in atmospheric pressure can affect the vapor pressure deficit, a key driver of evaporation rates. Seasonal changes cause fluctuations in ET and PET, underscoring the role of temperature, precipitation, and plant growth. Understanding these factors is essential for assessing water availability for evapotranspiration, where the ET/PET ratio can guide water management strategies by highlighting moisture shortages during drier winter months, assisting in irrigation planning and effective resource management. Furthermore, these insights help identify ecosystem needs and resilience under water stress.

Numerous studies have analyzed the ET/PET ratio; for instance, a 2023 study in Equatorial Africa found annual PET averages at 110 mm, with annual ET at 70 mm, yielding a ratio of 0.64. The highest ET values tend to occur in autumn. Climate factors significantly impact ET dynamics more than wind speed and precipitation [28]. Research shows that with climate change, ET/PET ratios can change drastically; as temperatures rise, potential evapotranspiration increases while actual evapotranspiration typically remains constrained by water limits, leading to lower ratios in drought-prone areas [29]. Another study [30] indicates that a sustainable agriculture ET/PET ratio should optimally be around 40%, though this varies by climatic zone. Striking a balance between actual and potential evapotranspiration is crucial for agricultural water use. In contrast, the ET/PET ratio connects to crop yield and irrigation effectiveness, varying across diverse climates and agroecosystem services. Enhanced water management, informed by the ET/PET ratio, can boost crop productivity and support healthy vegetation [30, 31].

3.4. Estimation of the Water Balance Components for Selected Years

Using annual estimates over 20 years, the water balance for the Birr River watershed was computed from 1992 to 2020.

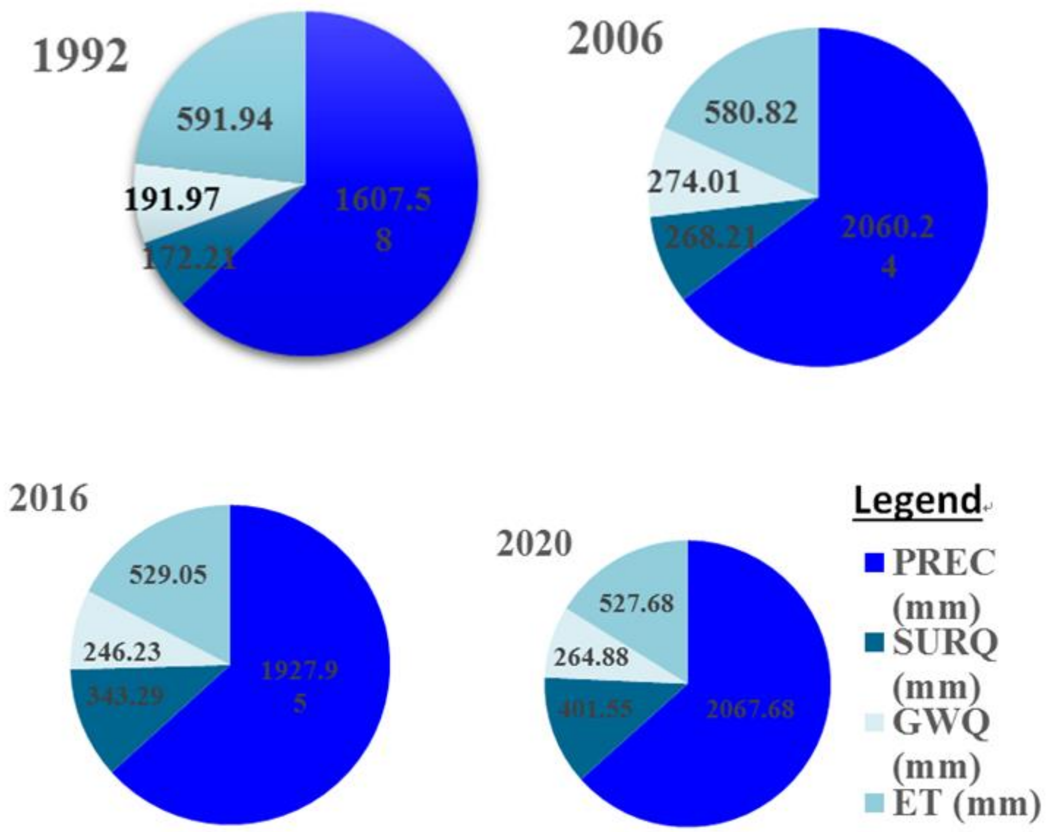

Figure 5. *Predicted water balance components for some selected years in the studied watershed.*

The pie chart displays values for four hydrological variables- PREC, ET, SURQ, and GWQ on an annual basis for the years 1992, 2006, 2016, and 2020, representing the beginning, middle, and end of the simulation period, respectively. From 1992 to 2006, precipitation increased from 1607. 58 mm to 2060.24 mm, a rise of 28. 1%. More rainfall may occur due to regional or global climatic changes, which could involve increased frequency and intensity of precipitation, shifting weather systems, or other factors. Evapotranspiration decreased from 591.94 mm in 1992 to 580.82 mm in 2006, a decline of 1.9%. In 2020, it further dropped to 527.68 mm, representing a reduction of 10.8%. Evapotranspiration fluxes are affected by changes in vegetation cover, land use, water use efficiency, and climatic conditions such as reduced vegetation, urbanization, improved irrigation techniques, crop selection, and varying weather. Surface runoff rose from 172.21 mm in 1992 to 268.21 mm in 2006, marking an increase of 55.7%. By 2020, this figure significantly increased to 401.55 mm, reflecting a total increase of 133.3%. The process of urbanization, along with changes in land use and water management, which includes the development of drainage systems and a decrease in green infrastructure, contributes to heightened surface runoff. Groundwater flow increased from 191.97 mm in 1992 to 274. 01 mm in 2006, indicating a rise of 42.7%. By 2020, it had decreased to 264.88 mm but remained 38% higher compared to the 1992 level. The increase in groundwater flow from 1992 to 2020 is attributed to higher precipitation levels, altered recharge rates, and groundwater management practices that evolve over time. Understanding how these trends develop is crucial for implementing effective strategies in water management and adapting to environmental changes. Long-term uncertainty in hydrological modeling offers valuable insights for decision-making regarding water resource management. This includes uncertainties related to model parameters, the quality of input data, climate change projections, land use dynamics, complexities in hydrological processes, and validation against observations, stakeholder engagement, scenario planning, and recommendations for future research. The SWAT model depends on various parameters, is sensitive to simulation outcomes, and uncertainty in parameter estimates results in inconsistencies in long-term predictions. The reliability of long-term predictions heavily relies on the accuracy of input data concerning land cover, climate, and soil.

4. Conclusion

This research models the water balance components of the Birr Watershed in the Upper Blue Nile Basin using the SWAT model to evaluate hydrological budgets for effective water resource management. Calibration, validation, and uncertainty analyses used SUFI-2 algorithms with data from MOWIE Ethiopia. The calibration period (1990–2000) and validation period (2001–2005) for the upper Birr station showed commendable results, with R^2 and NSE values reaching 0.72. Sensitive parameters identified included CN2, CH _ K 2. Rte, GWQMN.GW, ESCO.hru, SOL _ AWC (sol.), and GW _ DELAY. The analysis revealed notable seasonal and interannual fluctuations: precipitation rose by 28.1% from 1992 to 2006, while evapotranspiration reduced by 1.9%. Surface runoff increased significantly by 133.3%, and groundwater flow jumped from 191.97 mm in 1992 to 274.01 mm in 2006. These patterns underscore the impacts of climatic variability, alterations in land use, and water management on the hydrology of the Birr watershed. The findings stress the necessity for integrated water management strategies that consider both seasonal and long-term shifts, which affect flood risks, agricultural output, water availability, ecosystem services, and biodiversity. Shifts in surface runoff and precipitation can lead to infrastructure damage, decreased crop yields, soil degradation, and heightened competition for limited water resources. Furthermore, changing climatic and hydrological dynamics can disrupt habitats and ecosystem services. This study offers vital insights for stakeholders to formulate effective water management, agricultural planning, and conservation strategies. The SWAT model supports informed decisions for sustainable resource utilization. Nonetheless, challenges exist, such as data availability, model resolution, temporal and spatial scales, and neglecting climate change and human activity factors, all of which heighten simulation uncertainty. Future investigations should emphasize long-term monitoring, integrated modeling, and localized studies to tackle these concerns, including evaluations of socio-economic impacts, ecosystem services, and adaptive management approaches for the Birr watershed and analogous hydrological systems.

Abbreviations

PET	Potential Evapotranspiration
ET	Evapotranspiration
PREC	Precipitation
SURQ	Surface Run off
LULC	Land Use Land Cover
MOWIE	Ministry of Water, Irrigation, and Energy

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Author Contributions

Mamaru Mequanent Bitew is the sole author. The author read and approved the final manuscript.

Data Availability Statement

All relevant data are included in the paper, and any supplementary information, if required, can be provided upon reasonable request.

Conflicts of Interest

The author declares no conflicts of interest.

References

[1] S. Keesstra, G. Mol, J. de L. JanOkx, C. Molenaar, M. de Cleen, and S. Visser, "Soil-related sustainable development goals: Four concepts to make land degradation neutrality and restoration work," *Land*, vol. 7, no. 4, 2018, https://doi.org/10.3390/land7040133

[2] H. Mohajerani, D. A. Zema, M. E. Lucas-Borja, and M. Casper, "Understanding the water balance and its estimation methods," *Precip. Earth Surf. Responses Process.*, pp. 193–221, 2021, https://doi.org/10.1016/B978-0-12-822699-5.00019-7

[3] M. Idrissou *et al.*, "Modeling the Impact of Climate and Land Use/Land Cover Change on Water Availability in an Inland Valley Catchment in Burkina Faso," *Hydrology*, vol. 9, no. 1, 2022, https://doi.org/10.3390/hydrology9010012

[4] Q. Zheng, L. Hao, X. Huang, L. Sun, and G. Sun, "Effects of Urbanization on Watershed Evapotranspiration and Its Components in Southern China," *Water*, vol. 12, no. 3, 2020, https://doi.org/10.3390/w12030645

[5] D. Yang, Y. Yang, and J. Xia, "Hydrological cycle and water resources in a changing world: A review," *Geogr. Sustain.*, vol. 2, no. 2, pp. 115–122, 2021, https://doi.org/10.1016/j.geosus.2021.05.003

[6] V. Prasad, A. Yousuf, and N. Sharma, "Hydrological modeling for watershed management," *J. Nat. Resour. Conserv. Manag.*, vol. Vol. 1, pp. 29–34, 2020, https://doi.org/10.51396/ANRCM.1.1.2020.29-34

[7] R. Liu, Z. Li, X. Xin, D. Liu, J. Zhang, and Z. Yang, "Water balance computation and water quality improvement evaluation for Yanghe Basin in a semiarid area of North China using coupled MIKE SHE/MIKE 11 modeling," *Water Supply*, vol. 22, no. 1, pp. 1062–1074, 2022, https://doi.org/10.2166/ws.2021.214

[8] K. O. Babaremu, "A Review of Current Understanding and Implications for Watershed and Water," no. March 2024, https://doi.org/10.5281/zenodo.10049652

[9] S. Chen, J. Huang, and J.-C. Huang, "Improving daily streamflow simulations for data-scarce watersheds using the coupled SWAT-LSTM approach," *J. Hydrol.*, vol. 622, p. 129734, 2023, https://doi.org/10.1016/j.jhydrol.2023.129734

[10] Arifullah *et al.*, "Quality Assessment of Groundwater Based on Geochemical Modelling and Water Quality Index (WQI)," *Water*, vol. 14, no. 23, 2022, https://doi.org/10.3390/w14233888

[11] R. Çakmakçı, M. A. Salık, and S. Çakmakçı, "Assessment and Principles of Environmentally Sustainable Food and Agriculture Systems," *Agriculture*, vol. 13, no. 5, 2023, https://doi.org/10.3390/agriculture13051073

[12] Y. Wang, R. Jiang, J. Xie, Y. Zhao, D. Yan, and S. Yang, "Soil and Water Assessment Tool (SWAT) Model: A Systemic Review," *J. Coast. Res.*, vol. 93, p. 22, 2019, https://doi.org/10.2112/SI93-004.1

[13] J. Janjić and L. Tadić, "Fields of Application of SWAT Hydrological Model-A Review," *Earth*, vol. 4, no. 2, pp. 331–344, 2023, https://doi.org/10.3390/earth4020018

[14] S. S. J. Sadiqi, W.-H. Nam, K.-J. Lim, and E. Hong, "Investigating Nonpoint Source and Pollutant Reduction Effects under Future Climate Scenarios: A SWAT-Based Study in a Highland Agricultural Watershed in Korea," *Water*, vol. 16, no. 1, 2024, https://doi.org/10.3390/w16010179

[15] S. Aloui, A. Mazzoni, A. Elomri, J. Aouissi, A. Boufekane, and A. Zghibi, "A review of Soil and Water Assessment Tool (SWAT) studies of Mediterranean catchments: Applications, feasibility, and future directions," *J. Environ. Manage.*, vol. 326, p. 116799, 2023, https://doi.org/10.1016/j.jenvman.2022.116799

[16] M. Bitew and H. Kebede, "Effect of land use land cover change on stream flow in Azuari watershed of the Upper Blue Nile Basin, Ethiopia," *Sustain. Water Resour. Manag.*, vol. 10, 2024, https://doi.org/10.1007/s40899-024-01084-5

[17] F. Mikayilov, E. Rouholahnejad Freund, S. Ashraf Vaghefi, R. Srinivasan, H. Yang, and B. Klöve, "A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model," *J. Hydrol.*, vol. 524, 2015, https://doi.org/10.1016/j.jhydrol.2015.03.027

[18] S. Nasiri, H. Ansari, and A. N. Ziaei, "Simulation of water balance equation components using SWAT model in Samalqan Watershed (Iran)," *Arab. J. Geosci.*, vol. 13, no. 11, p. 421, 2020, https://doi.org/10.1007/s12517-020-05366-y

[19] A. Gupta, S. K. Himanshu, S. Gupta, and R. Singh, "Evaluation of the SWAT Model for Analysing the Water Balance Components for the Upper Sabarmati Basin," in *Advances in Water Resources Engineering and Management*, R. AlKhaddar, R. K. Singh, S. Dutta, and M. Kumari, Eds., Singapore: Springer Singapore, 2020, pp. 141–151.

[20] M. Adnan, S. Kang, G. Zhang, M. Saifullah, M. N. Anjum, and A. F. Ali, "Nam Co Lake Using SWAT Model," *Water*, vol. 11, no. 1383, pp. 1–23, 2019.

[21] F. Ayivi and M. K. Jha, "Author's Accepted Manuscript," *Int. Soil Water Conserv. Res.*, 2018, https://doi.org/10.1016/j.iswcr.2018.03.007

[22] D. Pandi, S. Kothandaraman, and M. Kuppusamy, "Simulation of Water Balance Components Using SWAT Model at Sub Catchment Level," *Sustainability*, vol. 15, no. 2, 2023, https://doi.org/10.3390/su15021438

[23] M. Belihu, S. Tekleab, B. Abate, and W. Bewket, "Hydrologic response to land use land cover change in the Upper Gidabo Watershed, Rift Valley Lakes Basin, Ethiopia," *HydroResearch*, vol. 3, pp. 85–94, 2020, https://doi.org/10.1016/j.hydres.2020.07.001

[24] T. Gashaw, T. Tulu, M. Argaw, and A. W. Worqlul, "Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia," *Sci. Total Environ.*, vol. 619–620, pp. 1394–1408, 2018, https://doi.org/10.1016/j.scitotenv.2017.11.191

[25] O. T. Leta, A. I. El-Kadi, H. Dulai, and K. A. Ghazal, "Assessment of SWAT model performance in simulating daily streamflow under rainfall data scarcity in Pacific island watersheds," *Water (Switzerland)*, vol. 10, no. 11, pp. 1–31, 2018, https://doi.org/10.3390/w10111533

[26] D. N. Moriasi, J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith, "Model evaluation guidelines for systematic quantification of accuracy in watershed simulations," *Trans. ASABE*, vol. 50, no. 3, pp. 885–900, 2007.

[27] M. Jemberie and B. Gebremariam, "Evaluation of Land Use Land Cover Change on Stream Flow: a Case Study of Dedessa Sub Basin, Abay Basin, South Western Ethiopia," *Int. J. Innov. Eng. Res. Technol. [Ijiert]*, vol. 3, no. 8, pp. 44–60, 2016.

[28] I K. Nooni *et al.*, "Temporal and Spatial Variations of Potential and Actual Evapotranspiration and the Driving Mechanism over Equatorial Africa Using Satellite and Reanalysis-Based Observation," *Remote Sens.*, vol. 15, no. 12, 2023, https://doi.org/10.3390/rs15123201

[29] U. Okkan, O. Fistikoglu, Z. B. Ersoy, and A. T. Noori, "Analyzing the uncertainty of potential evapotranspiration models in drought projections derived for a semi-arid watershed," *Theor. Appl. Climatol.*, vol. 155, no. 3, pp. 2329–2346, 2024, https://doi.org/10.1007/s00704-023-04817-2

[30] S. Sun *et al.*, "A global 5km monthly potential evapotranspiration dataset (1982-2015) estimated by the Shuttleworth-Wallace model," *Earth Syst. Sci. Data*, vol. 15, no. 11, pp. 4849–4876, 2023, https://doi.org/10.5194/essd-15-4849-2023

[31] M. Qiu, T. Van de Voorde, T. Li, C. Yuan, and G. Yin, "Spatiotemporal variation of agroecosystem service trade-offs and its driving factors across different climate zones," *Ecol. Indic.*, vol. 130, p. 108154, 2021, https://doi.org/10.1016/j.ecolind.2021.108154