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Analysis of Hydrological Characteristics of Blue Nile Basin, Nashe Watershed

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Abstract: Hydrological modeling is a technique for understanding hydrologic characteristics and estimation of the water balance of watersheds for integrated water resources development and management. The Soil and Water Assessment Tool (SWAT) model was used for modeling the hydrological behavior of the Nashe watershed in the north-western part of Ethiopia. The spatial data, daily climate, and stream flow were the required input data for the model. The observed monthly stream flow data at the outlet and selected sub-watersheds in the catchment were used to calibrate and validate the model. The model performance was assessed between the simulated and observed streamflow by using sequential uncertainty fitting-2 (SUFI-2), generalized likelihood uncertainty estimation, parameter solution (Parasol) and particle swarm optimization. The sensitivity of 18 parameters was tested, and the most sensitive parameters were identified. The model performance was evaluated using p and r- factor, coefficient of determination, Nash Sutcliffe coefficient efficiency, percent bias during uncertainty analysis, calibration and validation. Therefore, based on the set of proposed evaluation criteria, the SUFI-2 algorithm has been able to provide slightly more reasonable outcomes and Parasol is the worst compared to the other algorithms. An analysis of monthly and seasonal water balance has been also accomplished for the Nashe catchment. The water balance parameters were distinct for the three seasonal periods in the catchment. The seasonal water budget analysis reveals that the watershed receives around 19%, 69%, and 12% of rainfall through the short rain, long rain and dry seasons, respectively. The received precipitation was lost due to evapotranspiration by 29%, 34% and 37% for each season respectively. The surface runoff contributes to the catchment by 5%, 86% and 9% of the water yield.

Keywords: GLUE; parasol; PSO; SUFI-2; SWAT-CUP; uncertainty analysis; water balance

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1. Introduction

Water is the critical and valuable natural resource for sustaining life, development, and environment in order to achieve the long-term economic and social growth. Development and management of integrated water resources are important infrastructure for sustainable development even nowadays the management is a difficult task due to internal and external influences [1]. The development of water management and hydrological models are used to recognize all the measured and physical data of hydrologic behavior. The problems of water resources managing and understanding involve complex processes and relations at the interface [2]. Watershed characterization with regard to geographic disparities in hydrological response complements modeling, as one of the challenges of hydrological modeling is the difficulty in parameterizing differences in watershed characteristics.

The influence of catchment hydrology developments on watershed management depends on significant factors since it offers a basis for the development of land issues for developing and securing water resources [3,4]. The most significant characteristic in water development programs is understanding catchment and its hydrological developments to advance appropriate models for the watershed. For watershed hydrology, many models were developed [5] but the main constraint was the availability of temporal and spatial data impeding the implementation of these models especially in developing countries. The spatial distribution of weather stations is poor, with least coverage over rural areas, many non-functioning stations, inhomogeneous and missing data, and in some cases inefficient quality control systems in Africa [6]. The water resources availability is crucial for all countries especially for the areas facing the risk of drought, desertification, land use changes, and high population growth. Assessment of catchment is a precondition to understand the key processes of the hydrology.

The response of a watershed in terms of its state variables and characteristics is the main challenge of hydrological modeling. Water resources management has become more vital and complicated because of conflicting demands by various stakeholders, rapid population growth, industrialization, hydropower development, irrigation, urbanization and land degradation [7]. The water balance study in such a challenge provides an understanding of the hydrologic characteristics of the watershed and used to identify changes in the main hydrological processes [3]. Hydrological models are mathematical representations of real-world hydrological processes that can be used to simulate the water balance as well as plan and manage water resources. It is an essential constituent of water resources as well as simulating the effects of watershed processes. They were developed to monitor the water resources management strategies formulation by understanding the space and time variation distributions of water resources.

Water resources assessments, prediction of uncertainty analysis, calibration, and validation have been conducted with the hydrological models [8,9]. The purpose of using hydrological modeling is used to deliver the information for management of water resources in sustainable manner for hydrological analysis. The hydrological response of watershed characterization is decisive on the capacity to manage water scarcity in areas like Blue Nile River Basin and specifically around the study area. The interactions between various hydrological processes and drivers from external sources such as land use, rainfall, soil types, and temperature variability are used to investigate the behavior of catchments. The Soil and Water Assessment Tool (SWAT) model has a capacity to simulate hydrological processes with reasonable accuracy at comparatively bigger watersheds.

The poor results reported in SWAT studies might be partially ascribed to insufficient spatial coverage of rainfall inputs, because of an inadequate number of rain gauges in the simulated watershed or coarse sub watershed configurations that failed to capture the spatial detail of available rainfall data [10]. For Finchaa watershed, reference [11] studied the performance of the SWAT model utilizing the SUFI-2 algorithm SWAT-CUP for calibration and validation, and found satisfactory results. The performance of the model depends on graphical and statistical analysis to simulate various hydrological processes and to explore the model capability [3].

The performance of the SWAT based on the four algorithms was not ascertained for the study watershed. The authors compared four methods, the SUFI2, GLUE, Parasol, and PSO in SWAT-CUP algorithms, and found that SUFI2 performs best. Therefore, this study may serve as a benchmark for any studies in the country. The research was aimed to assess the SWAT model performance through sensitivity analysis, calibration, and validation and associated uncertainty analysis using SWAT-CUP algorithms that help to understand the catchment behavior before they are used for further scenario analysis. It was also aimed to apply a semi-distributed physically-based hydrological model to assess the hydrological characteristics of the Nashe catchment.

2. Materials and Methods

2.1. Description of the Study Watershed

The Nashe catchment is located in Oromia regional state, Ethiopia at about 300 km north-west of Addis Ababa. Geographically, the watershed is located at 9°35′ N and 9° 52′ N latitude, and 37°00′ E and 37°20′ E longitude (Figure 1). The watershed is a part of the Finchaa-Amerti-Nashe Project which is the sub-basin of Upper Blue Nile River Basin covering 94,578 ha. The Nashe river valley starts on the highland plateau with valley elevation above 2200 m and the surrounding ridges extend to over 2500 m. The elevation of the catchment varies from 1600 m in the lower plateau under the escarpment to hills and ridges of the highland climbing to over 2500 m. The average annual rainfall of the Nashe catchment varies from 1200 mm to 1600 mm, and June to September is the main rainy season of the watershed.

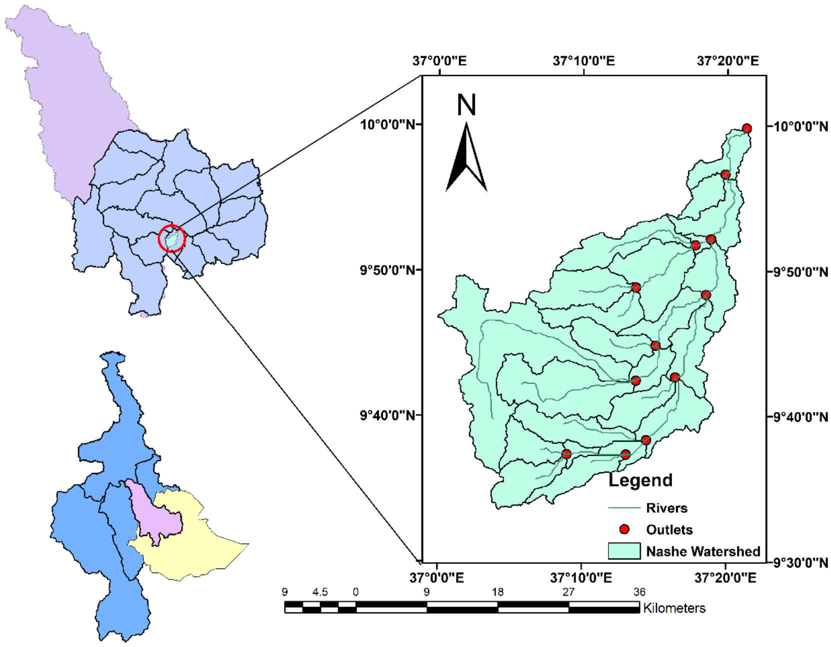

Figure 1. Location map of the study area.

2.2. Model Selection

In many regions of the world, the SWAT hydrological model has been successfully utilized at various times for long-term continuous simulations of flow in various catchments having different hydrologic, climatic conditions [12]. The SWAT is capable of simulating hydrological processes based on time and space variations to understand the processes of LULC change impact influences [3]. The ability of the SWAT model has been confirmed by many previous studies in the analysis of hydrological characteristics in different areas [13,14]. For assessment of water resources at a wide range of scales under different conditions, it has proven to be an effective tool across the globe [15].

The SWAT model can simulate hydrological processes from data-scarce and complicated catchments with acceptable capacity of the model and simulates the major hydrologic components as realistically as possible [16]. The SWAT model has been more efficient than the other models [4,17]. The model is utilized for hydrological simulations in particular watersheds and it is a capable model for investigation of the watershed. It may also be further extended to other similar watersheds across the country [11].

2.3. Soil and Water Assessment Tool (SWAT) Model Description

The SWAT is a semi-distributed hydrological model which depends on the daily time step and uses available spatio-temporal data to analyze hydrological parameters.

The SWAT model interface of ArcGIS was used to assess the small and large catchments by discretizing them based on the principle of dividing the watershed into sub-basins and HRUs that consists of homogenous soil, slope, and land use [16]. The hydrological parameter modeling in SWAT was undertaken at two separate partitions. Land phase and routing phase which control the quantity and movement of water, sediments, nutrients and organic chemicals to the channel in individual sub-basins and to the catchment outlet through the network of channels, respectively [18]. The water balance equation is used to determine hydrologic cycle for the land phase as simulated by SWAT [19]:

$$\mathrm{SWt} = \mathrm{SWo} + \sum_{i=1}^{n} (\mathrm{Rday} - \mathrm{QSurf} - \mathrm{Ea} - \mathrm{Wseep} - \mathrm{Qgw}) \quad (1)$$

where: SWt is the final soil water content (mm), SWo is the initial water content (mm), Rday is the amount of precipitation on day i (mm), Qsurf is the amount of surface runoff on day i (mm), Ea is the amount of evapotranspiration on day i (mm), Wseep is the amount of water entering the vadose zone from the soil profile on day i (mm) and Qgw is the amount of return flow on day i (mm), i and n is the initial and final day respectively.

Surface run-off was calculated using the modified SCS-CN. The runoff in SWAT using SCS-CN method is determined by using the following equation:

$$\mathrm{Qsurf} = \frac{(\mathrm{Rday} - 0.2\mathrm{S})^2}{(\mathrm{Rday} + 0.8\mathrm{S})},\ \mathrm{R} > 0.2\mathrm{S} \quad (2)$$

where: Qsurf: runoff accumulated, Rday: rainfall depth for the day, and S: retention parameter. The runoff will occur when $\mathrm{R} > 0.2\mathrm{S}$. The parameter of retention is:

$$\mathrm{S} = 25.4 * \left(\frac{100}{\mathrm{CN}} - 10\right) \quad (3)$$

The peak runoff based on modified rational method [20] is given by:

$$q_{\mathrm{peak}} = \frac{\mathrm{C.I.A}}{3.6} \quad (4)$$

q_{peak}: is the rate of peak runoff (m^3/s), C: coefficient of runoff, i: is the rainfall intensity (mm/h), A: sub-basin area (km^2) and 3.6 is utilized for unit conversion.

The Penman–Monteith method is use to determine evapotranspiration using all climatic variables:

$$\mathrm{ET} = \frac{0.408\Delta(\mathrm{Rn} - \mathrm{G}) + \gamma \frac{900}{\mathrm{T}+273} \mathrm{U2}(\mathrm{es} - \mathrm{ea})}{\Delta + \gamma(1 + 0.34\mathrm{U2})} \quad (5)$$

where ET—evapotranspiration (mm/day), Rn—net radiation (MJ/m^2day), G—soil heat flux density (MJ/m^2day), T—mean daily air temperature at 2 m height (°C), U2—wind speed at 2 m height (m/s), es—saturation vapor pressure (KPa), ea—actual vapor pressure (KPa), es-ea—the deficit of saturation vapor pressure (KPa), Δ—slope vapor pressure curve (KPa°C), #x3b3;—psychometrics constant (KPa°C).

For flow routing, the SWAT model uses the Manning's equation to estimate the velocity and amount of flow. The storage routing depends on the equation of continuity:

$$\Delta\mathrm{S} = \mathrm{Sin} - \mathrm{Sout} \quad (6)$$

where: ΔS—change in volume of storage, Sin—volume inflow, and Sout—volume outflow.

The base flow is the volume of stream flow originating from ground water and it is assumed that 50% of the water percolates down to the shallow ground water.

2.4. SWAT-CUP (Soil and Water Assessment Tool-Calibration and Uncertainty Programs)

The SWAT-CUP was developed to conduct sensitivity, uncertainty, calibration and validation and is an interface of ArcSWAT [15]. It can integrate various calibration/uncertainty analysis to provide a link between a calibration input/output and the model. Additionally, it is a program that links five algorithms: SUFI-2 [21], GLUE [22], Parasol [23], PSO [24] and MCMC [25].

2.4.1. SUFI-2

The SUFI-2 is the uncertainty analysis program that considers all uncertainty sources of model and the measured data uncertainties [21]. It was developed to offer the widest uncertainty parameter intervals among the other algorithms used for uncertainty analysis, calibration, and validation. Through Latin hyper cube sampling, SUFI-2 does a combined optimization and uncertainty analysis using global search methods with appropriate parameters.

2.4.2. GLUE

The GLUE also accounts for all sources of uncertainty since the likelihood measure reflects all sources of uncertainty [22]. For implementation GLUE is easy, so that it is widely used for the determination of uncertainties [26]. According to [27], the advantages of GLUE are: it is conceptually simple and does not require any limiting error assumptions, the model discontinuity is less vulnerable, and the magnitude of uncertainty are more likely reflected by uncertainty bounds.

2.4.3. PARASOL

The Parasol [23] is an optimization and statistical uncertainty for the assessment of parameters by using a modified shuffled complex to minimize a single function. In this algorithm, the uncertainty assessment is only the model parameter uncertainty [28].

2.4.4. PSO

The PSO [24] has a population of candidate solutions that solves a problem called particles. Its population-based stochastic optimization efficiency is based on the choice of PSO components. The firstly achieved value is the best solution, called individual optimal value (pbest). The second result achieved using any particle in the population is the best solution which is pursued by the particle swarm optimizer (gbest).

2.5. Data Collection and Analysis

The digital elevation model, weather, soil, LULC, and streamflow data were the most critical input data for development of the model and simulation of the hydrological components. SWAT is a data-intensive model that processes and generates output based on specific information about the catchment.

2.5.1. Digital Elevation Model (DEM)

The DEM is the input data to delineate the watershed into several sub-basins and is used to calculate parameters of sub-basins used to describe characteristics of the stream network. The DEM in the geographic coordinate system with 30 m spatial resolution has been utilized in this study (Figure 2a).

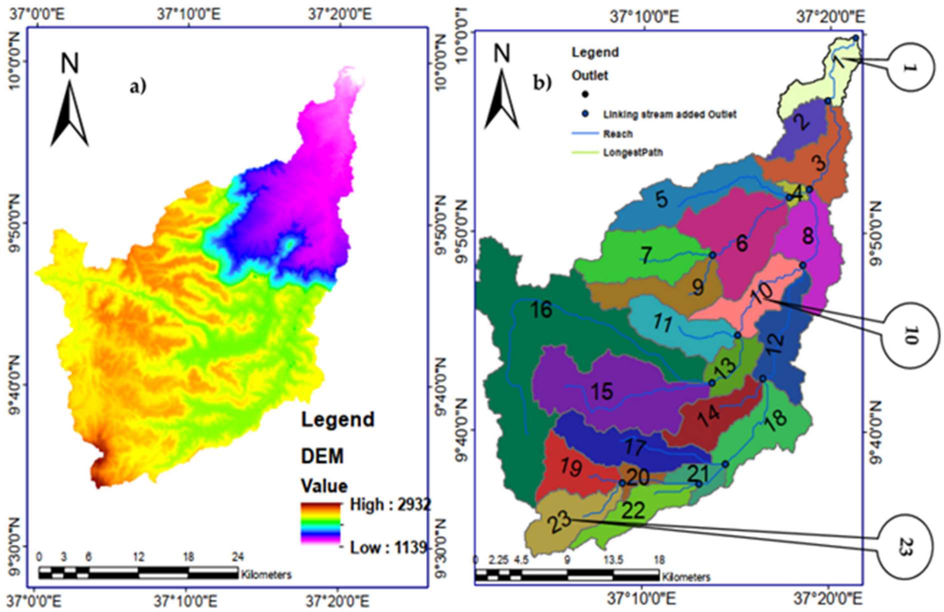

Figure 2. The digital elevation model (**a**) and sub-basin representation of the study area (**b**).

2.5.2. Soil Data

Soil is also one of the SWAT inputs and the soil database describes the surface and sub-surface of the watershed. The soil properties play an important role in hydrological modeling [29]. All information of the soil is associated to describe the physical and chemical properties. Eutric cambisols, haplic alisols, haplic arenosols, Rhodic nitosols, chromic luvisols, eutric vertisols, water, eutric leptosols, dystric vertisols are the soil types of the study area (Figure 3a). The dominant soil types of the study is haplic alisols and rhodic nitosols, respectively.

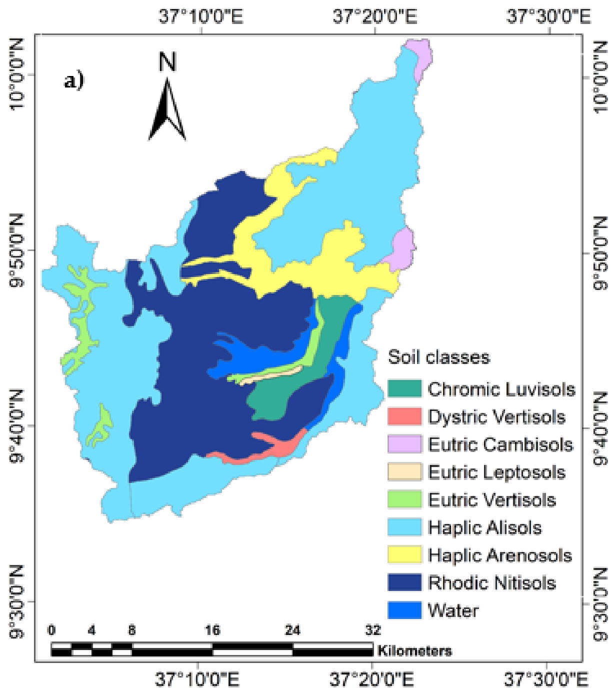

Figure 3. *Cont.*

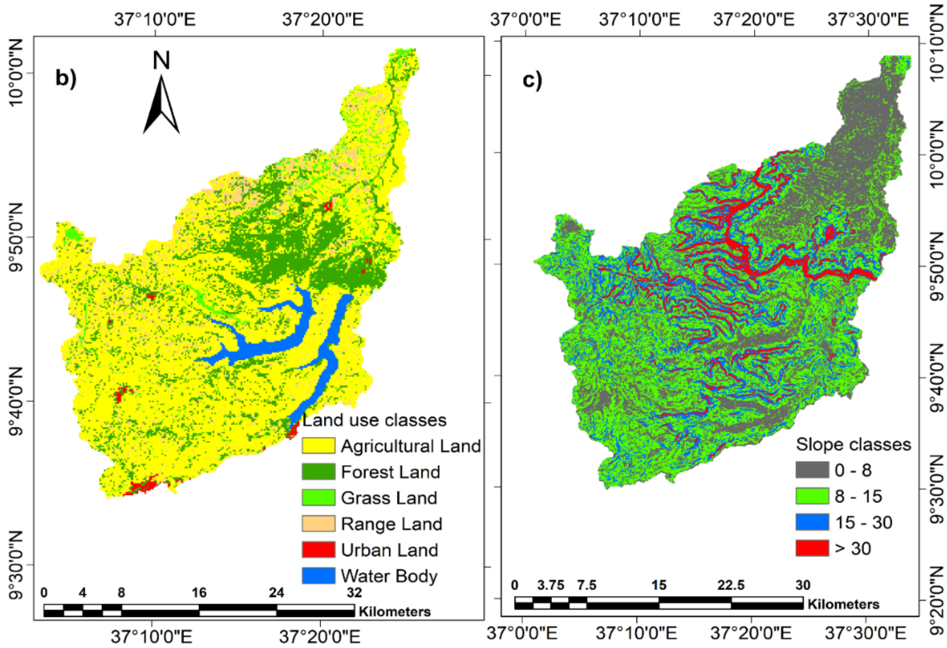

Figure 3. Map of the major (**a**) soil types, (**b**) land use land change (LULC) and (**c**) slope of Nashe watershed.

2.5.3. Land Use Land Change (LULC) and Slope Data

The LULC data are the most significant factor influencing different processes in the hydrological characteristics of the catchment [30]. The land use/land cover map of 30 m spatial resolution for the year 2018 was used for the Nashe watershed. The characteristics that can be affected might be surface runoff, erosion, groundwater system, and evapotranspiration. The LULC classification map shows the spatial extent of different LULC categories of the study watershed (Figure 3b) and its areal coverage is shown in Table 1. The topographic parameters of the study watershed, such as terrain slope, channel slope or reach length was also derived from the DEM. (Figure 3c) and Table 2 shows the spatial and areal extent slope classification of Nashe watershed respectively.

Table 1. Land use land cover types of the study area with their aerial coverage.

LULC Types	Area	
	Ha	Watershed (%)
Forest Land	16,139.47	17.06
Grass Land	7260.56	7.68
Rangeland	9423.44	9.96
Agricultural Land	57,823.41	61.14
Built-up area	785.17	0.83
Water body	3146.00	3.33
Total	94,578.00	100

Table 2. The classes of slope for the Nashe catchment.

Slope (%)	Area	
	Ha	Watershed (%)
0–8	28,683.68	30.33
8–15	23,225.51	24.56
15–30	28,660.19	30.30
>30	14,008.67	14.81
Total	94,578.05	100.00

2.5.4. Weather Data

The daily weather data required for the model are temperature (maximum and minimum), rainfall, solar radiation, wind speed, and relative humidity to simulate hydrological processes. The selected meteorological station was dependent on the presence of the data and representative of the total study area. Similarly, the selection of neighboring stations was based on horizontal distance (geographic distance) and correlation coefficient between stations. The necessary weather data were obtained for five stations (Alibo, Finchaa, Homi, Nashe, and Shambu) within and around the watershed. It is necessary to dedicate careful screening and quality checks for all data before use. The missing values were filled by Xlstat of selected stations before using for analysis. Additionally, the consistency of the data was also checked by a double mass curve and found to be consistent.

The statistical data required to generate representative daily climatic data for the watershed are contained in the weather generator input file [31]. The weather generator parameters were assessed for rainfall parameters and temperature. To cross-check the parameters calculated the SWAT weather database was also used. Accurate rainfall data are critical for accurate representation of temporal and spatial uncertainties of simulated watershed-scale hydrology and water quality from models. In the numerical simulation precipitation is a critical input of the hydrological responses in a watershed. A precise reproduction of the spatiotemporal variability of precipitation is crucial to accurately simulate hydrological processes. The SWAT model distributes the meteorological data to the sub-basins using the data from a single station or cell data that are closest to the centroid of each sub-basin [32].

2.5.5. Hydrological Data

Hydrological datasets are crucial for calibration and validation of the Nashe watershed. SWAT simulates streamflow at watershed scale [3,14]. SWAT does not utilize observed streamflow data values in calculations but they are utilized to compare the simulated and observed values in calibration and validation periods. The streamflow of the watershed recorded for 1985–2008 has been used for calibration and validation of the model including warm-up period. Arnold et al. [16] recommended the period of calibration and validation containing both dry and wet periods to guarantee that they reflected the range of conditions under which the model was predictable to operate. It is important to accentuate that the hydrological model does not know the initial circumstances of simulation, conditions that can exert great impacts on the simulated process, and therefore needs a warm-up period [33,34].

2.5.6. Model Set Up

The required input data were prepared as per the guidelines and in the form used for the model. After the data preparation, then the model setup was performed. The steps that were followed to set up the model were: data preparation (arrangement), watershed delineation, hydrologic response unit definition, write up weather, simulation of SWAT, analysis of sensitivity, calibration, validation, and uncertainty analysis. To build sub-basins and HRUs, the DEM, land use, soil, and slope datasets were combined, imported, overlaid, and linked with the SWAT databases. HRU definition was carried out in this work employing various HRU classes of 5% land use threshold, 10% soil, and 10% slope. The soil, land use/land cover and slope of the study area are indicated above in Figure 3a–c respectively.

2.6. Sensitivity Analysis

To identify the significant model characteristics, testing the model and improving the model sensitivity analysis are valuable. The process uses the most sensitive parameters to reduce the number of parameters that will be used in the calibration. The sensitivity analysis can be either local or global [21]. The global sensitivity analysis performs the single parameter while the values of the other related parameters are also changing [16]. The t-stat and *p*-values are used to evaluate the sensitivity of a single parameter in global sensitivity analysis. The smaller the p-value and the larger t-stat provides a measure and significance of the sensitivity. The system of one at a time or local sensitivity analysis allows only changing a single input parameter and keeping the other value constant. In this method, since the parameter value depends on each related parameter, the correct values of the other parameters are never known.

Eighteen flow parameters (CN2.mgt-SCS runoff curve number, GW_DELAY.gw-Ground water delay (days), ALPHA_BNK.rte—Base flow alpha factor for bank storage, CH_K2.rte—Effective hydraulic conductivity in main channel (mm/hr.), EPCO.hru—Plant uptake compensation factor, SOL_K.sol—Saturated hydraulic conductivity (mm/h), GWQMN.gw—Threshold depth of water in shallow aquifer required for return flow (mm), CH_N2.rte—Manning's roughness coefficient for main channel, REVAPMN.gw—Threshold water in the shallow aquifer for revap to occur (mm), SOL_AWC.sol—Soil available water capacity (mm H_2O/mm soil), GW_REVAP.gw—Ground water 'revap' coefficient, OV_N.hru—Manning's "n" value for overland flow, ALPHA_BF.gw—Base flow alpha factor (days), RCHRG_DP.gw—Deep aquifer percolation fraction, SURLAG.bsn—Surface runoff lag time (days), SLSUBBSN.hru—Average slope length (m), ESCO.hru—Soil evaporation compensation factor, SOL_BD.sol—Moist bulk density) were tested for the simulation of the streamflow. The sensitivity assessment is used to rank and identify the most sensitive parameters that have a significant impact on specific model output [35].

2.7. Model Calibration and Validation

Calibration is used to determine the appropriate parameter in modeling and a method that is used to compare the observed and simulated streamflow through parameter evaluation. Model calibration is necessary for preliminary testing of the model and observed data. The two types of calibration are automatic and manual where the automatic calibration is powerful, fast, less subjective, and labor-saving and reduces the uncertainty that often characterizes manual calibration. Manual calibration is time-consuming, very subjective and it is hard to acquire global optimality whereas the automatic calibration offers many advantages over the manual approach [16].

The process of validation is to analyze the efficiency of the calibrated parameters. For this watershed, the sensitivity, uncertainty, model calibration, and validation were analyzed using streamflow data by utilizing the four algorithms of SWAT-CUP: SUFI-2, GLUE, ParaSol, and PSO. These methods have been selected because they are widely used for parameter uncertainty analysis. The streamflow data from the period of 1987–1999 used for calibration and 2000–2008 for validation. The calibration and also validation of the watershed was performed at three selected sub-basins (upstream, downstream, and at the middle) since it represents the other sub-basins. The years from 1985–1986 were used to initialize the model.

The time period for calibration and validation years was determined by the length of the observed data record. When the observed record is not sufficient for an equal split, the length of the data may be different in such a way that the calibration period is sufficiently long. After the validation phases, if the model achieves a satisfactory performance, it becomes possible to perform model simulations according to different scenarios [36].

Inadequate model calibration measurement uncertainty in streamflow data and short streamflow records can also result in weak SWAT hydrologic predictions [37]. Most of the SWAT studies contain both calibration and validation, while others performed only calibration due to a lack of observed data [38]. The streamflow data play a critical role for calibration and validation processes. Therefore, the parameters of the SWAT model are calibrated by historical data and are assumed to have extrapolative ability even under future LULC scenarios. Similarly, the calibration of hydrological models is subject to the type of rainfall data source [16].

2.8. Uncertainty Analysis

The source of uncertainty always affects the hydrological models that play significant character in water resources management. Uncertainties in hydrological modeling are from three sources: data input uncertainties, model structure and model parameters [39]. The p-factor and r-factor are the suggested evaluation parameters [21]. The percentage of the measured data covered by 95PPU is the p-factor. The determination of 95PPU was conducted at 97.5% and 2.5% of the variable gained by LH sampling. The r-factor specifies the average thickness of 95PPU of the data measured. The value of r-factor and p-factor values are commonly used to confirm the accuracy of uncertainty assessment and model calibration [40]. A continuous series of data covering different weather conditions can effectively reduce the uncertainty of model parameter estimation [41].

2.9. Efficiency of Model

The efficiency of the hydrological model should be investigated on the degree of precision and consistency. To test the performance of the model, the NSE (Nash-Sutcliffe Efficiency), R^2 (coefficient of determination), and PBIAS (Percent Bias) coefficient are recommended [42]. The R^2 designates the strength of the observed and simulated relations and the value ranges from 0 to 1. The NSE is the degree of fitness of plots and varies from negative infinity to 1.0, whereas 1.0 indicates better agreement between the flow streams. The percent bias is a measure of tendency of the simulated data. A positive and negative value of bias percent indicates a model toward underestimation and overestimation respectively. The flow parameters were tested and the influential sensitive parameters were selected and used for further analysis based on the performance measurements of stream flow simulation (Table 3).

$$R^2 = \frac{\left[\sum_{i=1}^{n}(qsi - \bar{q}s)(qoi - \bar{q}o)\right]^2}{\sum_{i=1}^{n}(qsi - \bar{q}s)^2 \sum_{i=1}^{n}(qoi - \bar{q}o)^2} \tag{7}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(qoi - qsi)^2}{\sum_{i=1}^{n}(qoi - \bar{q}o)^2} \tag{8}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(qoi - qsi) * 100}{\sum_{i=1}^{n}(qoi)} \tag{9}$$

where; qsi: simulated streamflow in m^3/s, qoi: observed streamflow in m^3/s, $\bar{q}s$: mean simulated value, $\bar{q}o$: value of mean of the observed.

Table 3. Measurements of performance for streamflow simulation.

Rates of Performance	NSE	PBIAS	R^2
Unsatisfactory	$NSE \le 0.5$	$PBIAS \ge \pm 25$	$R^2 < 0.50$
Satisfactory	$0.5 < NSE \le 0.65$	$\pm 15 \le PBIAS < \pm 25$	$0.50 < R^2 < 0.70$
Good	$0.65 < NSE \le 0.75$	$\pm 10 \le PBIAS < \pm 15$	$0.70 < R^2 < 0.80$
Very good	$0.75 < NSE \le 1$	$PBIAS < \pm 10$	>0.80

3. Results and Discussion

3.1. Sensitivity Analysis

The sensitivity analysis was performed using SWAT-CUP algorithms by utilizing the watershed's observed flow data. The analysis of sensitivity was carried out at three selected sub-basins in the watershed hydrological flow parameters for stream flow. The result of the sensitivity analysis varies based on the methods used and their corresponding sub-basins. The sensitive parameters depending on t-stat conducted by utilizing the SWAT-CUP algorithms are depicted in Figure 4.

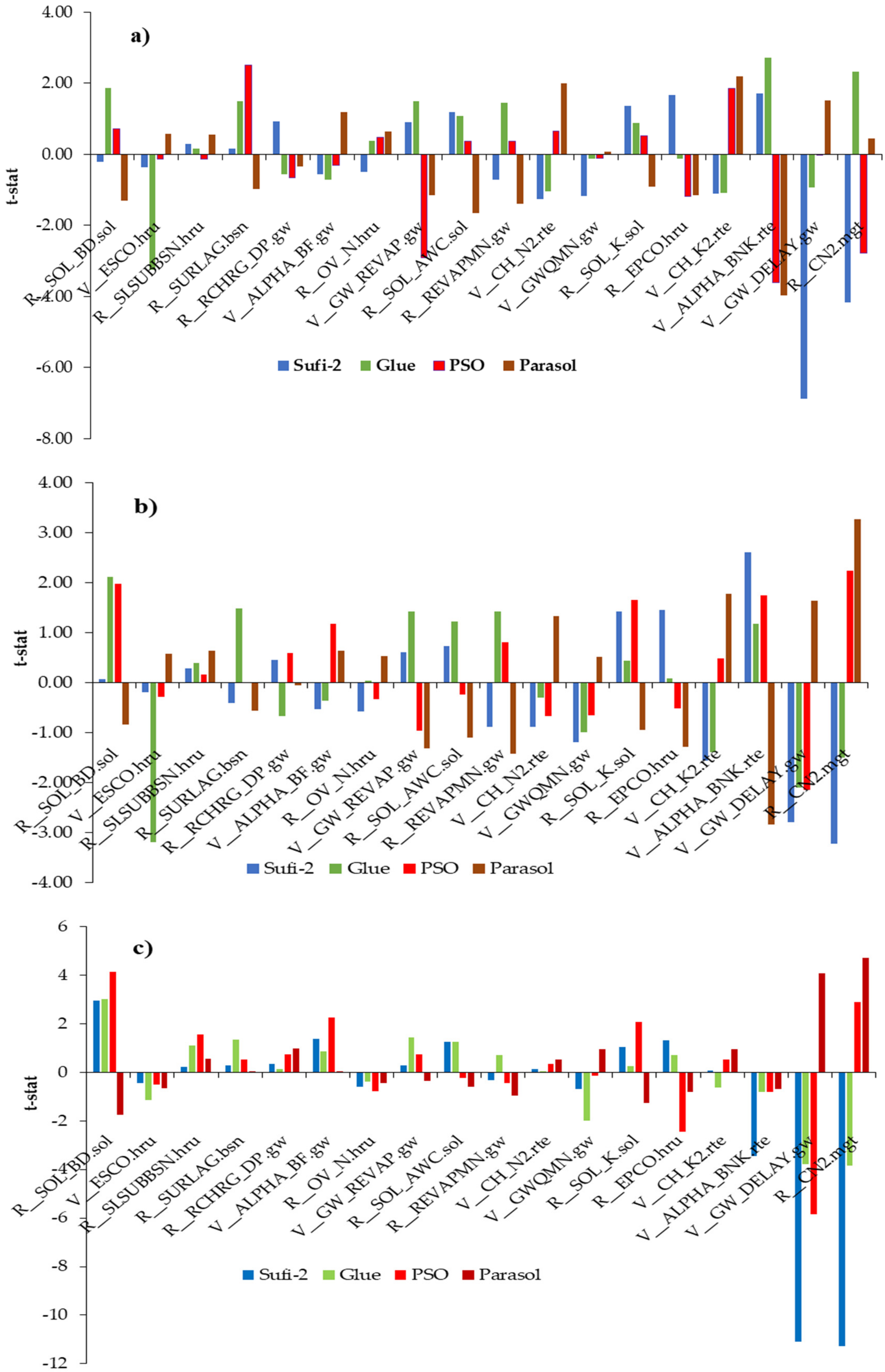

Figure 4. Sensitivity analysis of t-stat by SUFI-2, Glue, Parasol and PSO for selected sub-watersheds (**a**) 1, (**b**) 10 and (**c**) 23.

3.2. Model Calibration

It is required to determine the calibration after determining the sensitive parameters on streamflow simulation at the outlet of the watershed. In the Nashe watershed, the model was calibrated using the sensitive parameters in the selected upstream, middle, and downstream sub-basins utilizing SUFI-2, GLUE, Parasol and PSO algorithms. The observed and simulated streamflow were compared using flow data of 1987–1999 and the results showed a good agreement. The objective functions show that the result is in an acceptable range based on the monthly flows at selected stations (Table 4). In the first two years (1985–1986) flow data were initially reserved as the start-up period to mitigate unknown initial conditions. A considerable number of studies have shown that the data series selected for model calibration and validation should be representative of the various phenomena experienced by the catchment [43,44].

Table 4. Evaluation performance results of streamflow calibration and validation.

Objective Function	Methods	Calibration	Validation
R^2	Sufi-2	0.88	0.85
	Glue	0.87	0.85
	Parasol	0.87	0.84
	PSO	0.88	0.87
NSE	Sufi-2	0.78	0.80
	Glue	0.80	0.71
	Parasol	0.82	0.72
	PSO	0.73	0.77
PBIAS	Sufi-2	−2.70	1.60
	Glue	−8.70	5.70
	Parasol	10.00	8.00
	PSO	15.00	13.30
P-factor	Sufi-2	0.69	0.64
	Glue	0.37	0.26
	Parasol	0.22	0.15
	PSO	0.51	0.47
r-factor	Sufi-2	1.10	1.00
	Glue	0.86	0.78
	Parasol	0.37	0.40
	PSO	0.69	0.76

3.3. Model Validation

The validation was carried out to assess the model's efficiency using the calibrated components to simulate the watershed's hydrological parameters. Validation was also conducted using monthly flow data for 2000–2008. According to the performance evaluation requirements, good agreement between the simulations and observations was also shown in the validation. The observed and simulated streamflow were plotted to compare the correlation of stream flows of the watershed during calibration and validation period as shown in Figures 5–8 using different SWAT algorithms. The statistical values of objective functions were depicted at Table 4. Therefore, depending on the results, it is reasonable that the model is applicable specifically for Nashe catchment and the Blue Nile Basin in general.

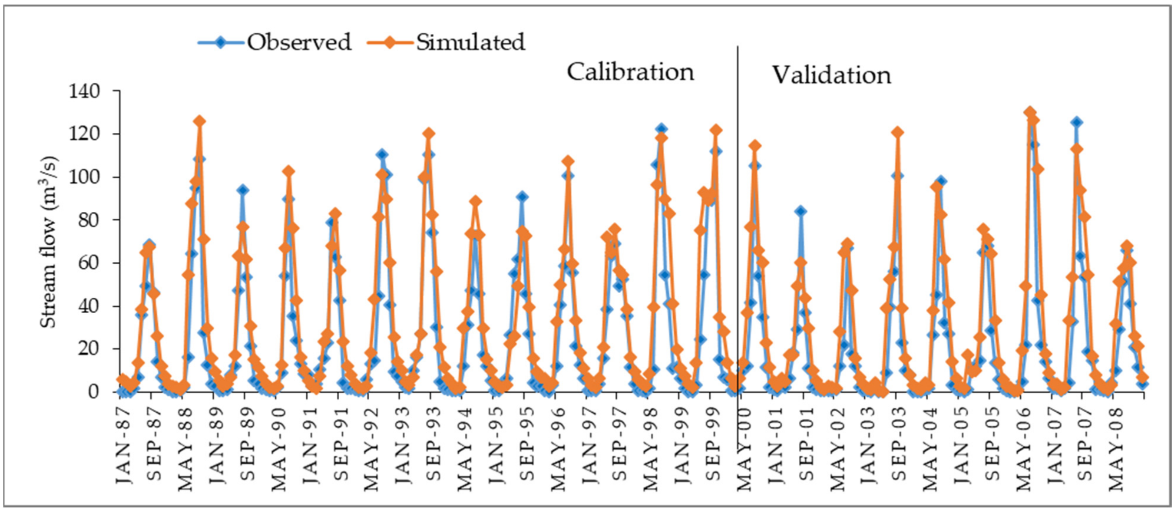

Figure 5. Monthly simulated and observed streamflow for calibration and validation using SUFI-2.

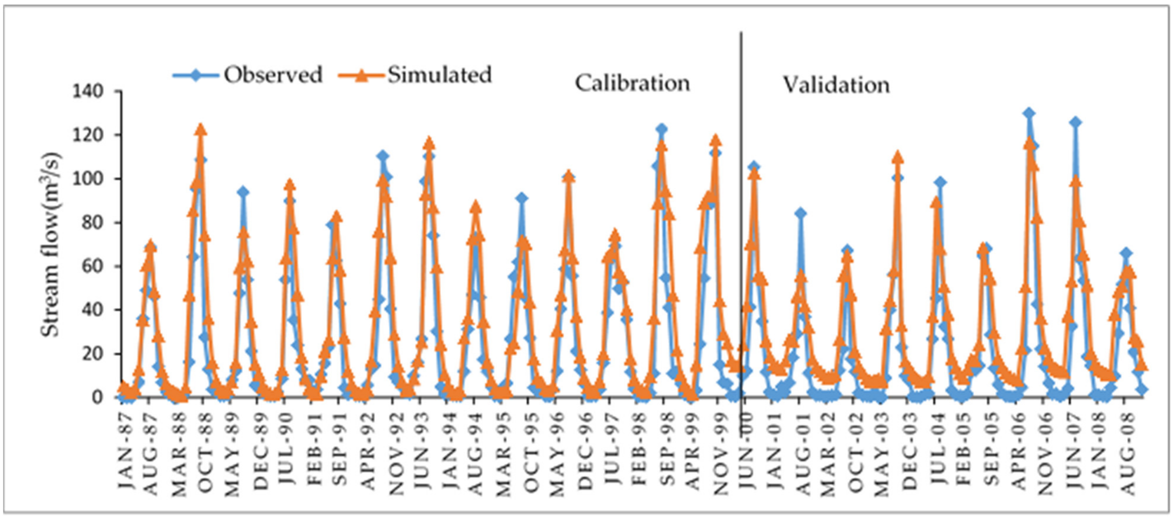

Figure 6. Monthly simulated and observed streamflow for calibration and validation using GLUE.

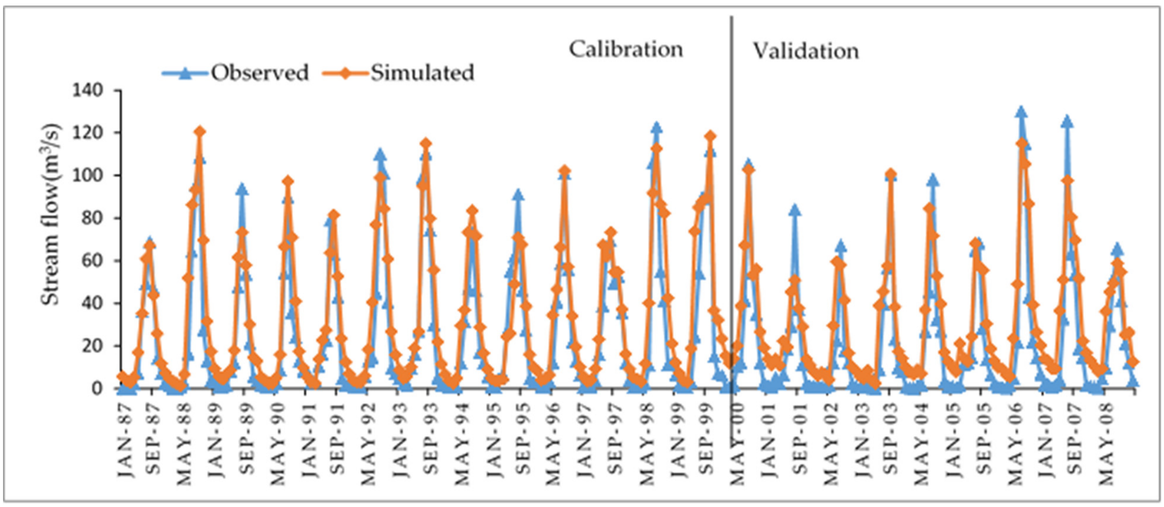

Figure 7. Monthly observed and simulated stream flow using Parasol.

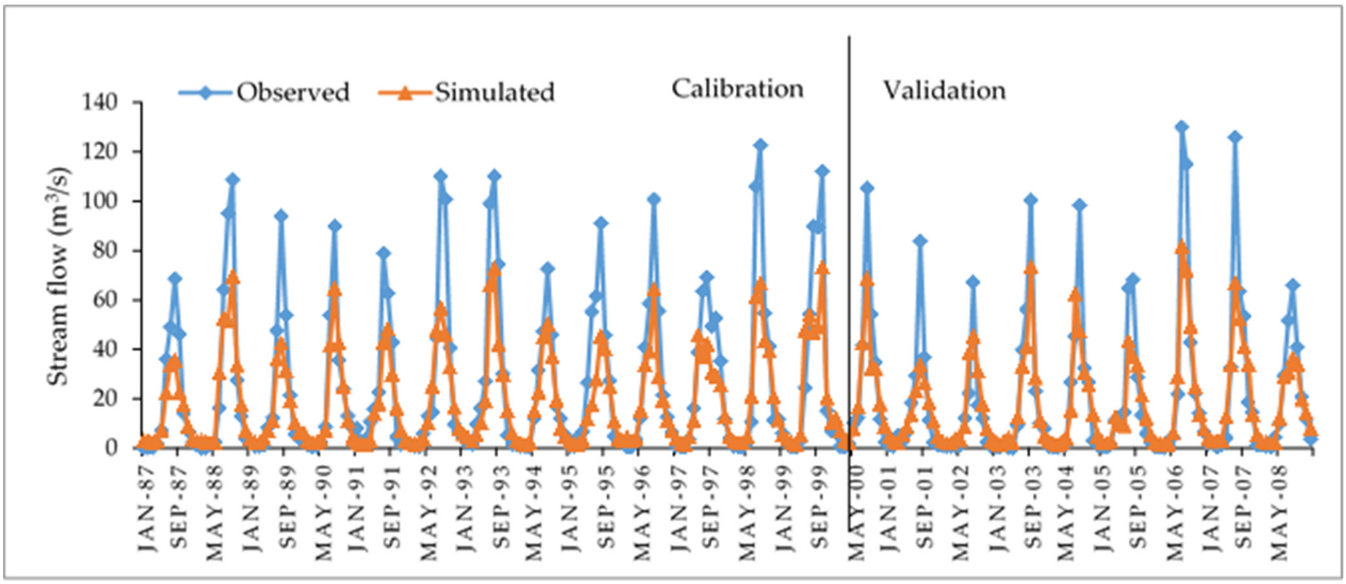

Figure 8. Monthly observed and simulated stream flow using PSO.

3.4. Uncertainty Analysis

The model's uncertainty covers a considerable portion of the measured data that contains model uncertainties (95PPU). The selected parameters in the model and the results of the uncertainty analysis by 95PPU was shown in Table 4. The minimum results of r-factor and p-factor shows ((0.29, 0.29), (0.37, 0.40), (0.29, 0.34)) and ((0.07, 0.11), (0.22, 0.15), (0.17, 0.47)) during calibration and validation for sub-basins 1, 10, 23 respectively using the Parasol algorithm and it can be observed that the uncertainty region is very narrow for this algorithm.

Comparing Parasol with SUFI-2, GLUE, and PSO, the p-factor and r-factors are small at all stations whereas SUFI-2 and PSO are the most accurate methods. From the result it was observed that Parasol failed relatively compared to the other methods to catch the reasonable prediction uncertainty [28]. This might be due to the fact that the Parasol method does not consider all uncertainties [45]. The uncertainty parameter in SUFI-2, GLUE, and PSO account for all uncertainty sources. According to [45], SUFI-2 provides the best assessment of uncertainty estimation from other methods. Therefore, comparing the performance of the algorithms throughout the evaluation criteria for uncertainty analysis, the SUFI-2 method has been capable of providing more reasonable results of R^2 and NSE and accurately capturing the optimal parameter set based on the p- and r-factors.

3.5. Hydrological Water Balance of the Watershed

The determination of water balance is one of the most essential variables addressed when determining whether the model is suitable for any particular application in the watershed. The SWAT model was used effectively for assessing the relevant components of water balance of the catchment. The investigation of water balance components was computed at the outlet of the watershed by using the SUFI-2 algorithm since it is slightly better than the other algorithms. Precipitation, surface runoff, lateral flow, base flow and evapotranspiration are the most essential components of the water balance of the watershed [9,46]. A water balance equation is used to quantify the major hydrological processes. This study investigated the model findings by establishing season-based water balance to explain the watershed behavior for the wet season, short rain season and dry season. For seasonal analysis, seasons in Ethiopia were classified into three seasons in the year based on the rainfall magnitudes.

The short rain season occurs between February and May, followed by the wet season between June to September. The other season is the dry season between October to January and which can be characterized generally over the majority of the country. The results show that the watershed receives around 19%, 69%, and 12% of precipitation during the short, long and dry seasons respectively. The received precipitation was lost due to evapotranspiration by 29%, 34% and 37% for each season, respectively. The surface runoff contributes to the catchment by 5%, 86% and 9% during the respective seasons. The catchment contribute high surface runoff on the northwestern and downstream of the watershed (Figure 9). The sub-basins that contribute high ground water were mostly upstream of the catchment. The monthly and annual water balance of the Nashe watershed were shown generally in Figures 10 and 11 respectively. The summary of the average monthly spatial distribution of water balance components of the watershed is presented in Figure 9.

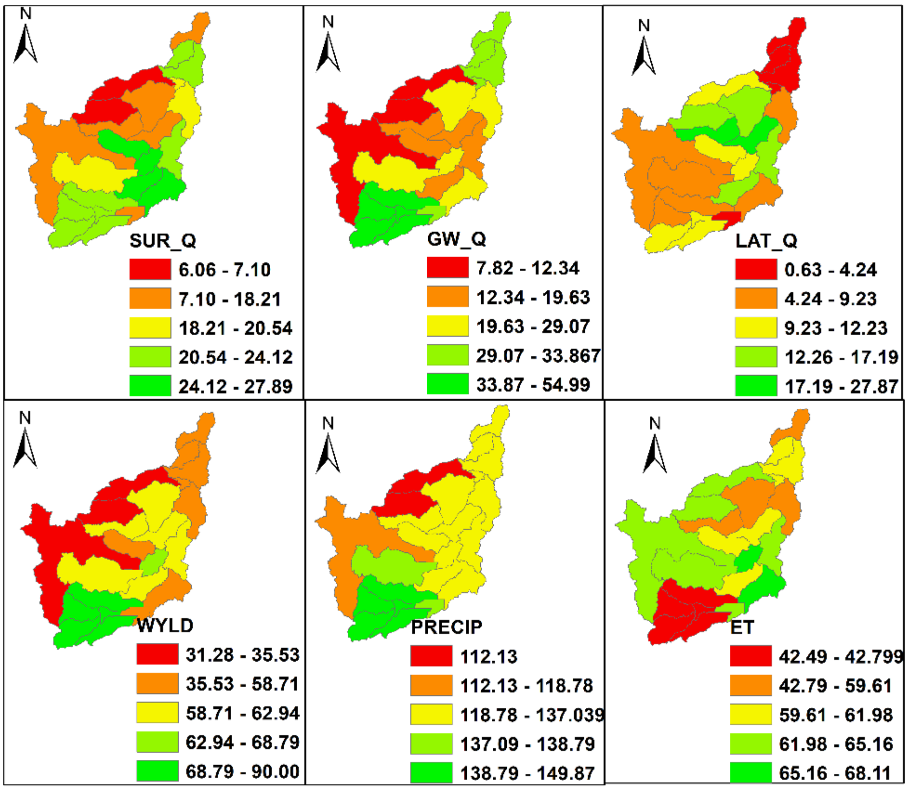

Figure 9. Spatial distribution of hydrologic components of the Nashe watershed.

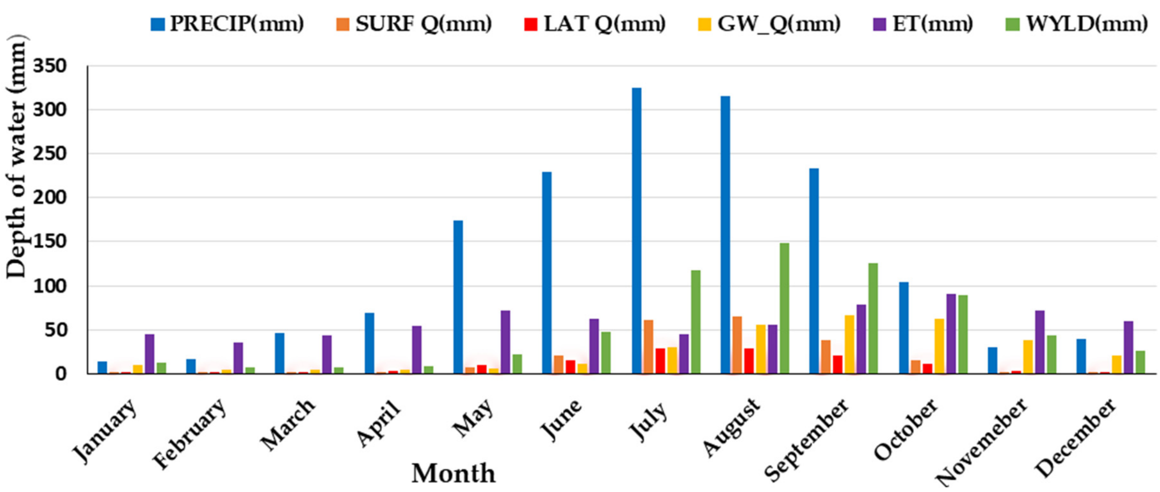

Figure 10. Monthly average water balance of the study area.

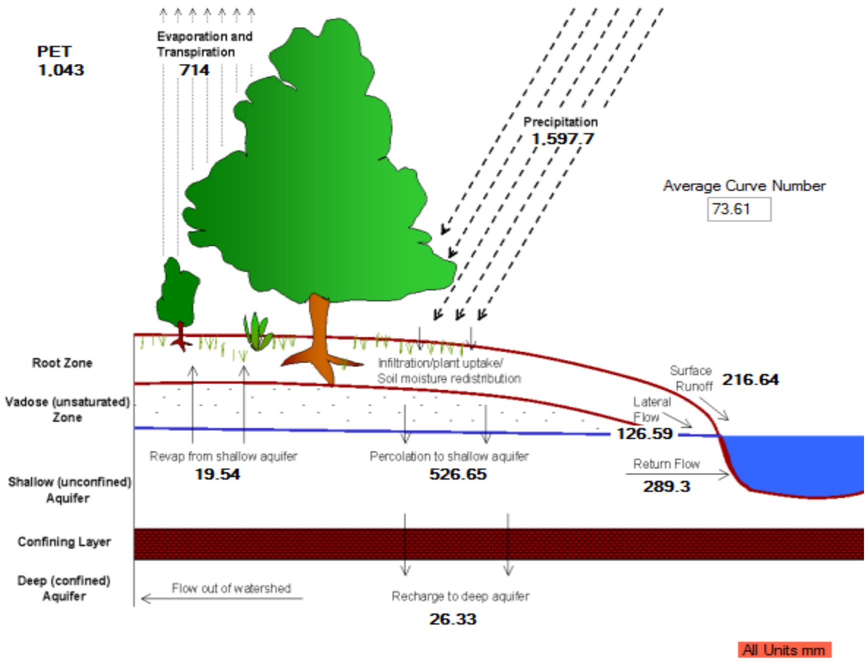

Figure 11. Pictorial representation of Soil and Water Assessment Tool (SWAT) output.

4. Conclusions

Hydrological modeling is a good way to understand water resources management systems in order to plan and develop integrated representations of real-world hydrological features that can be used to simulate water balances. The semi-distributed hydrological SWAT model was successfully performed for exploring hydrological characteristics of the Nashe watershed. The Nashe catchment was divided into 23 sub-watersheds that were further classified into 393 HRUs based on the integration that consists of homogenous soil, slope, land use, and management characteristics. The hydrological features of the Nashe watershed were successfully determined utilizing the four SWAT-CUP uncertainty algorithms. To evaluate the efficiency and capabilities in assessing uncertainty parameters, the SUFI-2, Parasol, GLUE, and PSO were used. Calibration, validation and uncertainty analysis were performed using the four algorithms that have been used for monthly streamflow measurements for the periods of (1987–1999) and (2000–2008) respectively. The spatial and temporal accuracy of precipitation data are crucial for the reliable simulation of hydrological processes.

The efficiency of the algorithms was compared using different objective functions. The comparison revealed that SUFI-2 performed slightly better than the other algorithms. The model was also used to quantify the water balance components of the watershed. The components of water balance such as surface runoff, precipitation, lateral flow, groundwater flow, and evapotranspiration were simulated based on the water balance equation.

The watershed characteristics for the wet season, short rainy season and dry season was assessed by defining seasonal water balance. The analyses were undertaken for the whole Nashe watershed at the outlet. The study found that the SWAT model can give accurate estimates of the various water balance components and can be utilized for further investigation for assessment of LULC, streamflow, soil erosion analysis as well as their management scenarios.

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