Research Article

Parameter Uncertainty Analysis for Streamflow Simulation Using SWAT Model in Nashe Watershed, Blue Nile River Basin, Ethiopia

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The hydrological model is an important tool in water resource management, allocation, and prediction. However, the hydrological models are subject to the uncertainty resulting from different sources of errors involved in the large number of parameters. The hydrological models in the management of water resources play a very significant role in quantifying uncertainty. Therefore, uncertainty analysis implementation is essential to advance confidence in modeling before performing the hydrological simulation. The purpose of the study was to assess the uncertainty parameters for the streamflow using the Soil and Water Assessment Tool (SWAT) hydrological model integrated sequential uncertainty fitting (SUFI-2) algorithm to Nashe watershed located in the Northwestern, Upper Blue Nile River Basin. The required input data for this study were digital elevation model, land use, soil map and data, meteorological data (precipitation, minimum and maximum temperature, wind speed, solar radiation, and relative humidity), and streamflow data. The calibration and validation model was computed to simulate the observed streamflow data from 1985 to 2008 including two years of warm-up periods. Model calibration, validation, and analysis of parameter uncertainty were conducted for both daily and monthly observed streamflows at the gauging stations through SUFI-2, which is one of the algorithms of the SWAT-Calibration and Uncertainty Program (SWAT_CUP). The results show that CN_2, GW_DELAY, ALPHA_BNK, CH_N2, and SOL_AWC were the most sensitive parameter for the monthly period and had a great impact on the streamflow simulation. Modeling results indicated that the method provides better results for the monthly time period than the daily time period for both calibration and validation. The result indicated that R^2 and NSE were 0.89 and 0.85 and 0.82 and 0.79, respectively, monthly and daily during the calibration. The validation likewise demonstrated a good performance with R^2 and NSE results of 0.88 and 0.78 and 0.85 and 0.76, respectively, for monthly and daily time periods. The results of this study provide a scientific reference based on uncertainty analysis to decision-makers to improve the decision support process in river basin management.

1. Introduction

Hydrological models were developed and utilized for mathematical representations of hydrological processes to improve the understanding of the impact of natural and anthropogenic disturbances on hydrological characteristics and forecast water resource changes, thereby assisting in water resource management decisions [1–3]. Hydrological models often contain many parameters that cannot be measured directly because they are costly, time-consuming, and sometimes difficult to achieve practically. They are extensively used since they can estimate flow and help to better understand the impact of natural disturbances on watershed systems. The uncertainty of model input occurs because of inherent randomness in natural processes, limitations in measurement, and lack of data [4]. As distributed watershed models are increasingly being used to support decisions on alternative management strategies, it is very important to apply hydrological models in practical water resource investigations. This necessitates proper calibration

and uncertainty analysis [5]. Due to various influencing factors (e.g., climate, land use, and other anthropogenic disturbances), watershed systems are complicated, and accurate hydrological process prediction is essential for watershed management [6].

The uncertainty issues in hydrological modeling have been paid much attention since their great effects on prediction and further decision-making in hydrological parameters [7]. The sources of uncertainties in hydrological modeling are related to three possible sources: data input, such as the meteorological data, which can change the hydrological modeling procedure and simulation results directly; a model structure that is mainly caused by the assumptions and simplification of the model; and model parameters [8]. Furthermore, parameter optimization is the most significant method in the hydrological simulation since the development of the hydrological model involves a huge number of parameters, each of which is particularly critical for the simulation results [4]. Parameter uncertainty is the most common but relatively easy to control through appropriate calibrations [9]. These parameters are usually difficult to measure directly, and they are generally derived from the empirical estimation and literature reference, which may introduce uncertainties into the modeling system [10]. The uncertainty analysis and sensitivity analysis are essential processes to reduce the uncertainties imposed by the variations of model parameters and structures [11, 12].

For the assessment of model behavior and to identify critical model components, sensitivity analysis is a useful tool. As a result, understanding the impact of each parameter on simulation outcomes during hydrological simulation requires model parameter sensitivity analysis. [13]. It has been demonstrated that parameter uncertainty is unavoidable in hydrological modeling and the corresponding assessment should be carried out prior to model prediction in the decision-making process. There are many uncertainties involved while working with hydrological models that arise due to large spatial variability and a multitude of input parameters [2, 4, 14]. The number of parameters required in the calibration process can be reduced and simulation efficiency improved by selecting parameters based on parameter sensitivity determined through sensitivity analysis. The uncertainty may cause overestimation or underestimation. Overestimation of uncertainty may lead to wasted time and money, as well as improper watershed management design, whereas underestimation of uncertainty may result in little impact on unexpected losses [15].

Therefore, uncertainty analysis is necessary and critical to ensure the success of hydrological modeling [16]. Similarly, the study of streamflow modeling and its uncertainty in the basin is critical for settling water resource disputes and managing water resources among the countries along the river basin [17]. The distributed and semi-distributed hydrological models have been widely used for streamflow modeling. The semi-distributed hydrological model, Soil and Water Assessment Tool (SWAT) combined with the SWAT-CUP (SWAT-Calibration and Uncertainty Program), links GLUE (generalized likelihood uncertainty estimation), ParaSol (parameter solution), SUFI-2 (sequential uncertainty fitting), MCMC (Markov chain Monte Carlo), and PSO (particle swarm optimization) procedures to SWAT.

Recent studies show that SWAT is now globally recognized for modeling large and small watersheds and has been regarded as an interdisciplinary endeavor [2, 18–21]. The hydrological model (SWAT) performs sensitivity analysis, calibration, validation, and uncertainty analysis. In this study, the Soil and Water Assessment Tool-Calibration and Uncertainty Program (SWAT-CUP) was combined with the SUFI-2 method to quantify the uncertainty of hydrological parameters to provide a necessary reference for hydrological modeling and to check the calibration and validation of the hydrological model at the study area [4]. Several researchers compared calibration and uncertainty analysis methods for the SWAT model including the generalized likelihood uncertainty estimation (GLUE) [22], sequential uncertainty fitting (SUFI-2) [23], parameter solution (ParaSol), and Markov chain Monte Carlo (MCMC). SUFI-2 is a semi-automated approach that makes the calibration process most widely used to carry out sensitivity analysis, uncertainty analysis, calibration, and validation of hydrological parameters on both daily and monthly time periods.

SUFI-2 is the more frequent method used for calibration and uncertainty analysis and is also a convenient method to use [24, 25]. The other advantage is a large number of parameters, and measured data from many gauging stations can be simulated simultaneously using SUFI-2. The SUFI-2 method has been widely applied to analyze parameter sensitivity and identify critical sources of uncertainty in modeling watersheds [4, 5, 26, 27]. This approach to comprehensive sensitivity analysis has the advantage of being relatively quick in comparison with similar procedures, and as a result, rather than an absolute measure of sensitivity, however, rather obtains a ranked order of the parameters. Additionally, this study may serve as a benchmark for any studies in the country. However, comparing uncertainty analysis methodologies in hydrological modeling presents a number of challenges. Similarly, the difficulty of constructing the likelihood function, the high number of simulations required to produce a fair approximation to the posterior, and the numerical implementation's inability to cover multimodal distributions are all drawbacks of this technique.

As far as the author's understanding, this is the first study concentrating on parameter uncertainty analysis for streamflow simulation using the SWAT model in the Nashe watershed of the Blue Nile River Basin in Ethiopia. Only a few articles comparing alternative uncertainty analysis methodologies are available, and they are limited to applications of simple hydrological models. As a result, this study presents a novel technique for quantifying the uncertainty of hydrological parameters, providing a necessary reference for hydrological modeling and checking the calibration and validation of the hydrological model in the study area by combining the Soil and Water Assessment Tool-Calibration and Uncertainty Program (SWAT-CUP) with the SUFI-2 (sequential uncertainty fitting) method. This research sheds light on how to choose an uncertainty analysis method in the

modeling field, with a focus on the hydrological modeling community. The drawback of this method is that it is semi-automated and requires the interaction of the modeler for checking a set of suggested parameters. Hence, the objectives of this study were (1) to evaluate the feasibility of the SWAT model for simulating streamflow over the Nashe station; (2) to analyze the uncertainty of the parameters using the SWAT model using the SUFI-2 method.

2. Materials and Methods

2.1. Study Area Description. The Nashe watershed is located in Oromia regional state, Ethiopia, at about 300 km northwest of Addis Ababa. The watershed is a subbasin of the Blue Nile River Basin covering an area of 945.78 km^2, and administratively, the area belongs to Abay Chomen Woreda and Horo Woreda. The watershed is found geographically between the longitudes 37°00′E and 37°20′E and 9°35′N and 9°52′N latitudes. The watershed varies in elevation from 1600 m in the lower plateau under the escarpment to hills and ridges of the highland climbing to over 2500 m. The catchment plateau has a mountainous landscape with steep mountain ranges, volcanic cones, and deep canyons intermingled. The annual average rainfall of the Nashe watershed ranges from 1200 mm to 1600 m with June, July, August, and September being the main rainy season of the catchment. The catchment's observed average temperature was 22°C. Figure 1 depicts the thorough study area location.

The Nashe River has a sharp drop of about 600 m at the Nashe cliff, forming a fall and torrents. The watershed has a subtropical climate with distinct wet and dry seasons. The Nashe watershed is the principal tributary and is mainly used for hydropower generation for the country. The watershed area is classified as having intensive irrigable fields downstream, huge water potential sites upstream, and a high head of hydropower potential [28]. Agriculture is the watershed's most important financial activity and the primary source of income for the local population. The average monthly rainfall and temperature features of the stations in the study watershed are depicted in Figure 2.

2.2. The Hydrological Model Description. The semi-distributed hydrological model SWAT is a physically based continuous, spatially distributed simulation developed to assist water resource managers in predicting the impacts of land management practices on water, sediment, and agricultural chemical yields [29]. SWAT is a hydrological model in which the watershed can be used to analyze small or large catchments by discretizing them into subbasins [14]. Each subbasin contains the main channel and many hydrological response units (HRUs), which consist of homogeneous land use, soil type, slope characteristics, and management practices. SWAT provides two methods for estimating surface runoff: the modified Soil Conservation Service Curve Number method for each HRU and the Green and Ampt infiltration method [30]. The Muskingum method was used to evaluate channel routing. The water balance was modeled for four different storage volumes for each HRU: snow, soil

profile, shallow aquifer, and deep aquifer. There are three methods to estimate potential evapotranspiration incorporated into the SWAT model: Hargreaves method [31], Priestley–Taylor method [32], and Penman–Monteith method [33].

For total streamflow, the groundwater flow contribution is simulated by generating shallow aquifer storage. From the bottom of the root zone, the percolation is considered a recharge to the shallow aquifer. The hydrological SWAT model simulates eight major components: hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and agricultural management [34]. Daily precipitation, runoff, evapotranspiration, percolation, and return flow from subsurface and groundwater movement are all used to compute the daily water balance in each HRU. The hydrological processes are divided into two phases: the land/soil phase and the channel/flood plain phase. The land/soil phase of the hydrological cycle is modeled in SWAT based on the water balance equation. The hydrological cycle for the land phase as simulated by SWAT depends on the water balance equation [35].

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

(1)

where SWt is the final soil water content (mm), SWo is the initial water content (mm), R day 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), Qgw is the amount of return flow on day i (mm), and t is the time (days).

2.3. SWAT-CUP. The SWAT-CUP was developed to perform calibration, validation, sensitivity analysis, and uncertainty analysis procedures for the SWAT model by different optimization techniques, together with the simulation [10]. The model is a public domain program that links a variety of techniques in one single platform: the sequential uncertainty fitting ver. 2 (SUFI-2) [26, 30], the generalized likelihood uncertainty estimation (GLUE) [22], parameter solution (ParaSol) [14], particle swarm optimization (PSO) [36], and Markov chain Monte Carlo (MCMC) [37] algorithms to SWAT model [4, 30].

2.4. SUFI-2 Algorithm. The SUFI-2 program was used for performing sensitivity analysis, calibration, validation, and uncertainty analysis. All sources of parameter uncertainties in SUFI-2 are considered that accounts such as uncertainty in driving variables, parameters, conceptual model, and measured data. SUFI-2 executes a combined optimization and uncertainty analysis using a global method and deals with plenty of parameters through Latin hypercube sampling [30, 38]. SUFI-2 is capable of analyzing a large number of parameters and measured data from many gauging stations simultaneously. It also requires the smallest number of
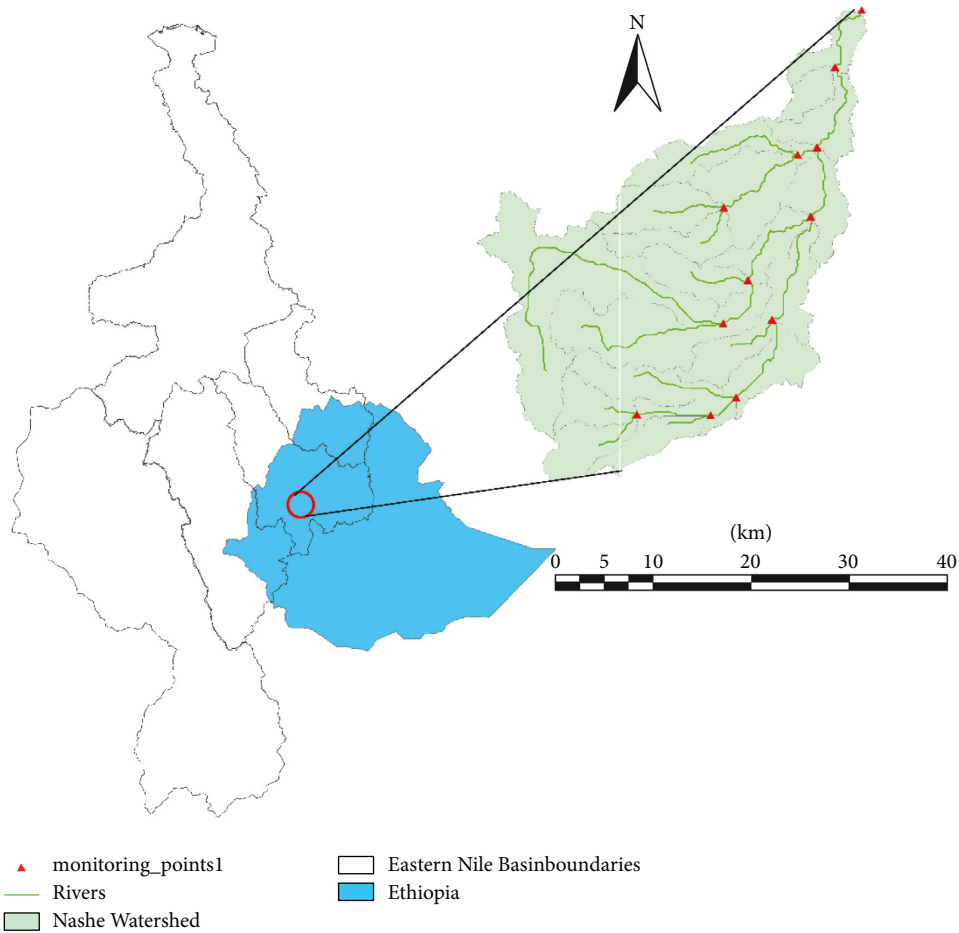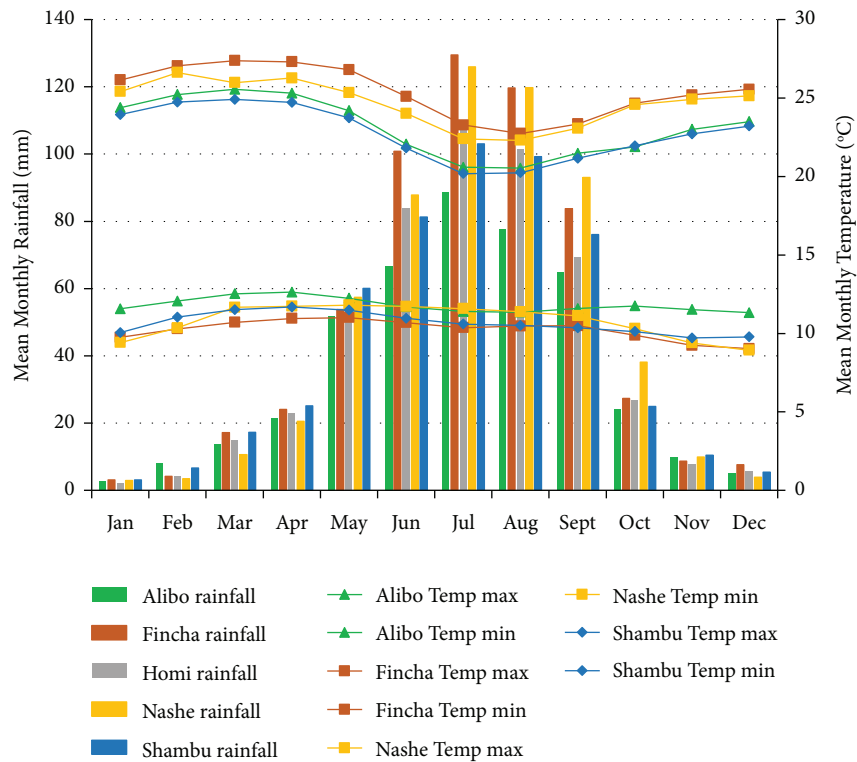
FIGURE 1: Location of the study area.

FIGURE 2: Monthly average rainfall and temperature features of the stations in the Nashe watershed.

model runs to achieve good calibration and uncertainty results.

The degree to which all uncertainties are accounted for is quantified in terms of the 95% prediction uncertainty (95PPU) band disallowing 5% of the very bad simulations. The 95PPU obtained through Latin hypercube sampling is calculated at the lower value of 2.5% and upper value of 97.5% levels of the cumulative distribution of an output variable. The strength of a calibration and uncertainty analysis is quantified as the p-factor and r-factor. The p-factor is the percentage of measured data bracketed by the 95PPU, while the r-factor is the average thickness of the 95PPU band divided by the measured data's standard deviation. The values for the p-factor and i-factor range between 0 and 100% and between 0 and infinity, respectively.

The value of the p-factor equal to 1 (100%) shows all observations covered by the prediction uncertainty and that of the r-factor is close to zero indicating that the simulated results exactly match the observed values [26]. The parameter ranges are larger than the optimal parameter ranges when the r-factor is high. A large p-factor can certainly be obtained at the expense of a larger r-factor. For the first iteration, the SUFI-2 technique assumes a substantial parameter uncertainty (physically meaningful range), ensuring that the observed data fall into the 95PPU, and then gradually reduces the uncertainty while monitoring the p-factor and r-factor for the next several rounds. Further goodness of fit can be quantified by the R^2 and Nash–Sutcliffe model efficiency (NSE) between the observations and the best simulation. The major procedures of SUFI-2 are shown as follows [5, 26, 30, 38].

(i) The objective function and reasonable parameter ranges [bj, min, and bj, max] are predefined. The final parameter ranges are always conditioned on the form of the objective function since the different formulations may lead to different results. There are a number of ways to formulate an objective function, and the Nash–Sutcliffe (NSE) and coefficient of determination (R^2) are two of the most popular objective functions.

(ii) Latin hypercube sampling is carried out in the hypercube [bj, min, and bj, max] leading to n parameter combinations, where n is the number of required simulation iterations. SWAT simulations employ the sampled parameter sets as parameter inputs.

(iii) The objective function is used to determine the 95PPU for simulated surface runoff. The assessed uncertainty measures are calculated using the percentage P of observed data bracketed by the 95PPU band, as well as the average distance d between the upper and lower 95PPU (the degree of uncertainty):

$$\bar{d} = \frac{1}{k} \sum_{i=1}^{k} (qu - ql)i, \qquad (2)$$

where i is iterate, k is the number of observed data points for variable q, qu and ql are the upper (97.5th) and lower (2.5th) percentiles of the cumulative distribution of every simulated point, and $\bar{d}$ is calculated by the r-factor:

$$R - \text{factor} = \frac{\bar{d}x}{\sigma x}, \qquad (3)$$

where σx is the observed variable's standard deviation x. A value less than one is a desirable measure for the r-factor. The 95PPU band is used to calculate the percentage P of observed data:

$$P - \text{factor} = \frac{\text{nqin}^*}{N} 100, \qquad (4)$$

where the total number of observed values is N, while the number of observed data bracketed by the 95PPU is nqin. For the next iteration, a reasonable combination of distinct factors should be identified for the necessary parameter ranges.

After each iteration, parameter ranges have been updated and defined (Appaspour, 2011); further sampling rounds are required to update parameter ranges (if the criteria are not fulfilled), which are calculated as follows:

$$b'j, \min(\text{new}) = bj, \text{lower} - \text{Max}\left[\frac{(bj, \text{lower} - bj, \min)}{2}, \frac{(bj, \max - bj, \text{upper})}{2}\right], \qquad (5)$$

$$b'j, \max(\text{new}) = bj, \text{upper} + \text{Max}\left[\frac{(bj, \text{lower} - bj, \min)}{2}, \frac{(bj, \max - bj, \text{upper})}{2}\right], \qquad (6)$$

where b' represents the new range following one more iteration. To be noticed, it is possible to produce inappropriate ranges for some parameters because equations (4) and (5) can only ensure that the updated parameter ranges are always centered on the best estimates. As a result, manual adjustment is essential to avoid using potentially inaccurate values based on previous practical parameter information.

2.5. Input Data Description and Model Setup.

The required important data for the model can be categorized into spatial data, hydrological data, and meteorological data [39]. The spatially distributed data needed for the ArcSWAT interface include the digital elevation model (DEM), soil data, and land use data. The spatial data were all collected from the Ethiopian Ministry of Water, Irrigation, and Energy. The observed daily streamflow data for a period of 1985–2008 at

the Nashe gauging station was also collected from the Ethiopian Ministry of Water, Irrigation, and Energy. The other input data for the SWAT were the daily maximum and minimum temperature, relative humidity, solar radiation, wind speed, and precipitation data collected at Alibo, Finchaa, Homi, Jermet, Nashe, and Shambu meteorological stations from 1985–2019 were used. The detailed required input data for the study are indicated in Table 1. Generally, the model setup consists of four steps: (1) data preparation, (2) subbasin discretization, (3) HRU definition, and (4) calibration and uncertainty analysis.

The Soil and Water Assessment Tool (ArcSWAT) coupled with ArcGIS was used for watershed delineation and other purposes, resulting in 23 subbasins and 339 HRUs after overlaying the soil data, land use data, and slope of the study watershed (Figure 3, Tables 2–4). SUFI-2 uncertainty analysis used in this study was embedded into a platform. The SWAT-CUP interface allows users to perform SWAT uncertainty analysis with a variety of methodological options [40]. Figure 4 shows the detailed procedure as a flowchart.

2.6. Sensitivity Analysis, Calibration, and Validation.

The sensitivity analysis is used to identify and rank the most responsive hydrological parameters that have a significant impact on the specific model output. Model calibration is the process of modifying input model parameters to ensure that simulations match data within the prescribed ranges, reducing forecast uncertainty, whereas validation is the process of confirming the calibrated parameters by evaluating them with an independent set of data without making any additional changes to the model parameters [29]. The sensitivity analysis was made using a built-in SWAT sensitivity analysis tool that uses the Latin Hypercube One-factor-At-a-Time (LH-OAT) [26, 41].

Twenty-one sensitive parameters were selected for sensitivity analysis; among them, ten most sensitive parameters were identified for model calibration and validation processes. The selected 21 parameters related to streamflow are depicted in Table 5. The model calibration was conducted using SWAT-CUP combined with the SUFI-2 method after the most sensitive parameters were identified [42]. The model validation is to establish whether the calibrated model has the ability to predict streamflow compared with the observed streamflow. The streamflow used in this study was divided into two periods for model calibration and validation. A warm-up period was also considered because it is recommended to initialize and then obtain reasonable starting values for model variables. The period from 1985 to 1986 was used for warm-up, the period from 1987 to 1999 for calibration, and the final nine years (from 2000 to 2008) for validation.

2.7. Evaluation of Model Performance.

The model performance evaluation was carried out to determine the consistency of simulated data compared with measured data during the calibration and validation periods [43]. The performance of the model was evaluated using statistical and graphical indicators for the objective function of the fitting effect and accuracy between the simulated and observed values of the model [44]. The SUFI-2 method is found to be the most efficient in terms of computational effort to reach a satisfactory simulation and analysis of all uncertainties in the study. The uncertainty in parameterization is quantified for behavioral parameters identified during the model calibration and validation. The p-factor and r-factor were also computed to further assess the calibration and validation results in terms of uncertainty in the model results. The calibration and validation were carried out using different objective functions. The Nash–Sutcliffe efficiency coefficient (NSE), which is the most widely used criterion for assessing the performance of the hydrological models, was selected as the objective function in this study. The other model performance statistics including percent bias (PBIAS), the coefficient of determination (R^2), the root-mean-square error (RMSE), and others were also calculated to evaluate the performance of the hydrological models.

R^2 is calculated by the following equation:

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

NSE can be calculated as follows with the same variables defined as follows:

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

The PBIAS is calculated by the following equation:

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

The RSR is calculated as follows:

$$RSR = \frac{RMSE}{STDEVob} = \frac{\sqrt{\sum_{i=1}^{n}(qoi - qsi)\hat{2}}}{\sqrt{\sum_{i=1}^{n}(qoi - qsi)\hat{2}}}. \tag{10}$$

The bR^2 is calculated by the following equation:

$$bR^2 = \text{Maximize: } \Phi = \begin{cases} |b|R^2 \text{if} |b| \le 1, \\ |b|^{-1}R^2 \text{if} |b| \ x > 1. \end{cases} \tag{11}$$

The Kling–Gupta efficiency (KGE) can be determined using the following equation:

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}. \tag{12}$$

$\alpha = \sigma s/\sigma o$, and $\beta = \mu s/\mu o$, and r is the linear regression coefficient between the simulated and measured variables.

The root-mean-square error is calculated using the following equation:

$$RMSE = \frac{1}{n} \cdot \sum_{i=1}^{n}(qsi - qoi)^2, \tag{13}$$

where qsi is simulated streamflow in m^3/s, qoi is observed streamflow in m^3/s, $\overline{q}s$ is mean of the simulated value, and $\overline{q}o$

TABLE 1: Input data description used in the SWAT model.

| Data types	Research data	Resolution/period	Sources
Spatial data	Digital elevation model (DEM)	30 m	The shuttle radar topographic mapping obtained from the Ministry of Water, Irrigation, and Energy, Ethiopia
	Land use land cover	30 m	Ministry of Water, Irrigation, and Energy (MoWIE), Ethiopia
	Soil	1 : 50,000	Ministry of Water, Irrigation, and Energy (MoWIE), Ethiopia
Meteorological data	Daily observed weather data	1985–2019	National Meteorological Agency, Ethiopia
Hydrological data	Daily streamflow	1985–2008	Ministry of Water, Irrigation, and Energy MoWIE), Ethiopia
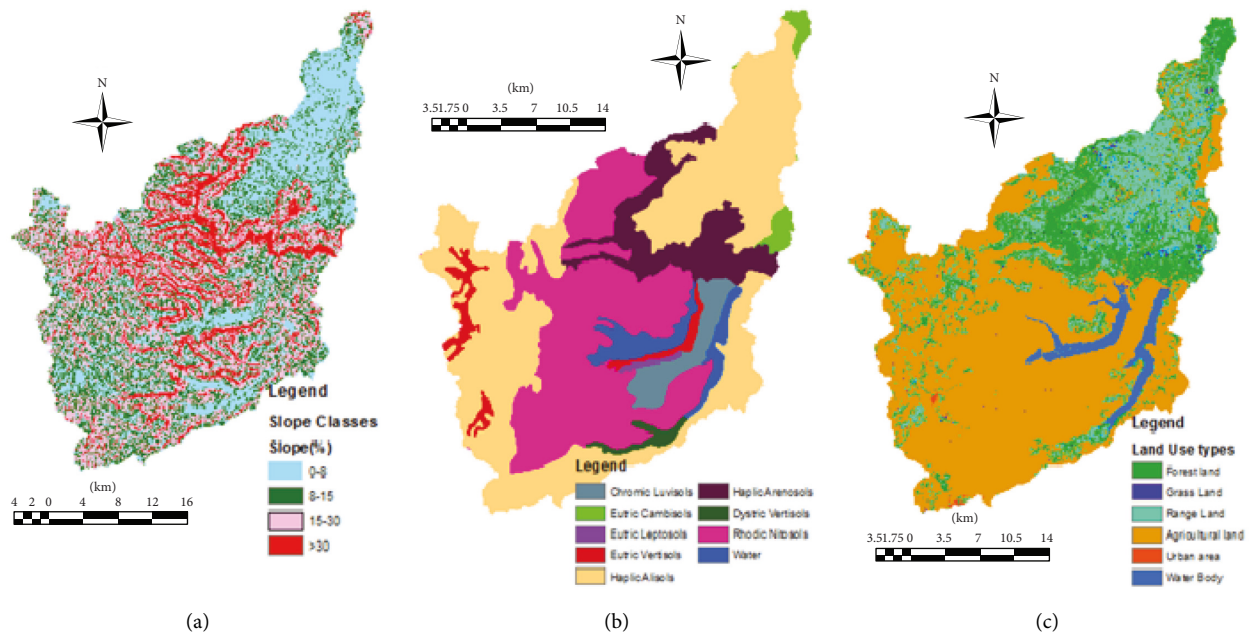
FIGURE 3: SWAT model inputs. (a) Topography, (b) land use, and (c) soil type.

TABLE 2: Soil types of the study area with their aerial coverage.

Soil types	Area Ha	Area % in the watershed
Eutric cambisols	1522.045	1.61
Haplic alisols	43248.87	45.73
Haplic arenosols	9249.55	9.78
Rhodic nitisols	29221.76	30.89
Chromic luvisols	3606.813	3.81
Eutric vertisols	2742.341	2.9
Water	3677.375	3.89
Eutric leptosols	318.9469	0.34
Dystric vertisols	989.9943	1.05
Total	94577.7	100

TABLE 3: Land use types of the study area with their aerial coverage.

Land use land cover types	Area Ha	Area % in the watershed
Forest land	15567.94	16.46
Grassland	642.5034	0.68
Rangeland	17212.14	18.2
Agricultural land	57847.74	61.16
Built-up area	165.4127	0.18
Waterbody	3141.955	3.32
Total	94577.7	100

is mean of the observed value. R^2 is the coefficient of determination, and b is the slope of the regression line between the measured and simulated variables. αs and αo are the standard deviation of the simulated and observed values. μo and μs are the mean of the observed and simulated values, respectively.

TABLE 4: Slope classes of the Nashe watershed.

Slope range (%)	Area Ha	Area % in the watershed
0–8	28683.59	30.33
15/Aug	23225.42	24.56
15–30	28660.1	30.3
>30	14008.58	14.81
Total	94577.7	100

TABLE 5: Selected sensitive parameters of Nashe Watershed.

| No.	Parameter	Description	Classification
1	r__CN2.mgt	SCS runoff curve number	Surface runoff
2	v__GW_DELAY.gw	Groundwater delay from soil to channels (days)	Groundwater
3	v__ALPHA_BNK.rte	Base flow alpha factor for bank storage	Channel
4	v__CH_K2.rte	Effective hydraulic conductivity in the main channel (mm/hr.)	Channel
5	r__EPCO.hru	Plant uptake compensation factor	Evapotranspiration
6	r__SOL_K.sol	Saturated hydraulic conductivity (mm/hour)	Soil
7	v__GWQMN.gw	Threshold depth of water in shallow aquifer required for return flow (mm)	Groundwater
8	v__CH_N2.rte	Manning's roughness coefficient for the main channel	Channel
9	r__REVAPMN.gw	Threshold water in the shallow aquifer for revap to occur (mm)	Groundwater
10	r__SOL_AWC.sol	Soil available water capacity (mm $H_2$0/mm soil)	Soil
11	v__GW_REVAP.gw	Groundwater "revap" coefficient	Groundwater
12	r__OV_N.hru	Manning's "n" value for overland flow	Overland flow
13	v__ALPHA_BF.gw	Base flow alpha factor (days	Groundwater
14	r__RCHRG_DP.gw	Deep aquifer percolation fraction	Groundwater
15	r__SURLAG.bsn	Surface runoff lag time (days)	Surface runoff
16	r__SLSUBBSN.hru	Average slope length (m)	Landform
17	v__ESCO.hru	Soil evaporation compensation factor	Evapotranspiration
18	r__SOL_BD.sol	Moist bulk density	Soil
19	r__SOL_Z.sol	Depth from the soil surface to bottom of the layer	Soil
20	r_SOL_ALB.sol	Moist soil albedo	Soil
21	r_TLAPS.sub	Temperature lapse rate (°C/Km)	Temperature
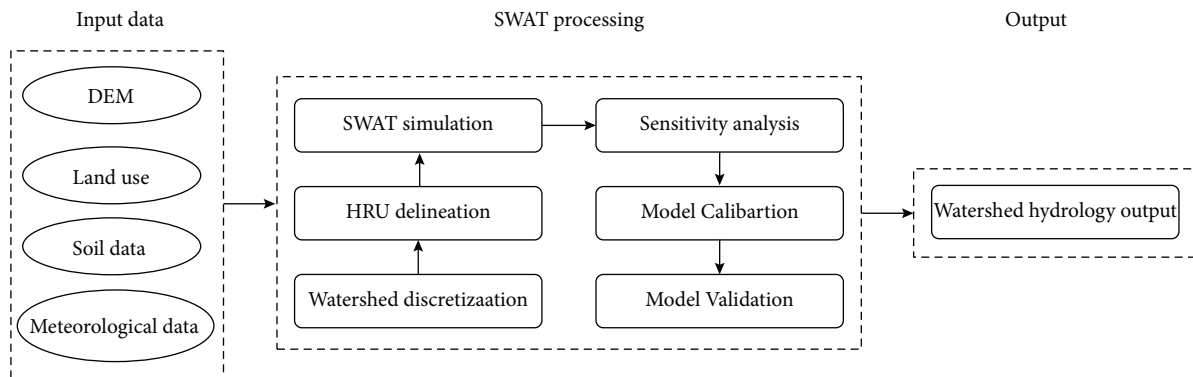
FIGURE 4: General framework methodology of the model.

3. Results and Discussion

3.1. Sensitivity Analysis. Sensitivity analysis for streamflow simulation has been performed using SWAT-CUP algorithm SUFI-2 optimization techniques. The SUFI-2 sampling is a Latin hypercube sampling method that is used to reduce the sampling size. Therefore, the SUFI-2 sampling method is considered as easy to implement [9, 45]. The sensitivity analysis was performed to identify important parameters in the Nashe watershed. The Latin Hypercube Sampling One-at-A-Time (LH-OAT) in the SUFI-2 method was applied for all twenty-one selected sensitive parameters. The parameters having a significant effect and the most influential parameters on streamflow simulation were selected.

The daily and monthly ten most sensitive parameters were selected and used for model calibration and validation as shown in Tables 6 and 7, respectively. The other remaining parameters have no significant effect on streamflow

simulations and are not considered for calibration and validation. Mengistu and Sorteberg [46] determined that the curve number depends on a number of factors, including soil types, soil textures, soil permeability, and land use features, and identified the CN2 as the most sensitive parameter in the Eastern Nile River Basin in addition to SOL-AWC, ESCO, and SOL-K.

The considered most sensitive parameters include surface water, groundwater, and soil properties, which indicates the results that show that the most sensitive parameters are those representing the surface runoff, groundwater, and soil properties that affect streamflow simulation. A *t*-test (high absolute values suggest more sensitivity) and *p* values (values close to zero suggest a high level of significance) were used to measure the sensitivity and significance of each parameter, respectively. The daily and monthly most sensitive parameters ranked according to their *t*-stat and *p* value are summarized in Tables 6 and 7 and Figures 5 and 6, respectively.

TABLE 6: Monthly most sensitive parameters of the watershed.

S. No	Parameter name	t-Stat	p Value	rank
1	r__SOL_K.sol	1.16	0.25	10
2	v__GWQMN.gw	−1.26	0.21	9
3	r__REVAPMN.gw	1.31	0.19	8
4	r__EPCO.hru	−1.36	0.17	7
5	v__CH_K2.rte	1.39	0.17	6
6	r__SOL_AWC.sol	−1.74	0.03	5
7	v__CH_N2.rte	2.13	0.01	4
8	v__ALPHA_BNK.rte	−2.35	0	3
9	v__GW_DELAY.gw	−2.65	0	2
10	r__CN2.mgt	5.03	0	1

TABLE 7: Daily most sensitive parameters of the watershed.

S. No.	Parameter name	t-stat	p Value	Rank
1	v__CH_K2.rte	0.66	0.63	10
2	v__ALPHA_BF.gw	0.7	0.61	9
3	r__SOL_AWC.sol	−0.77	0.58	8
4	v__GWQMN.gw	−0.91	0.43	7
5	r__REVAPMN.gw	0.95	0.22	6
6	r__SOL_K.sol	−1.02	0.1	5
7	v__GW_DELAY.gw	−1.03	0.03	4
8	v__CH_N2.rte	1.2	0.01	3
9	V__ALPHA_BNK.rte	−1.52	0	2
10	r__CN2.mgt	−2.03	0	1
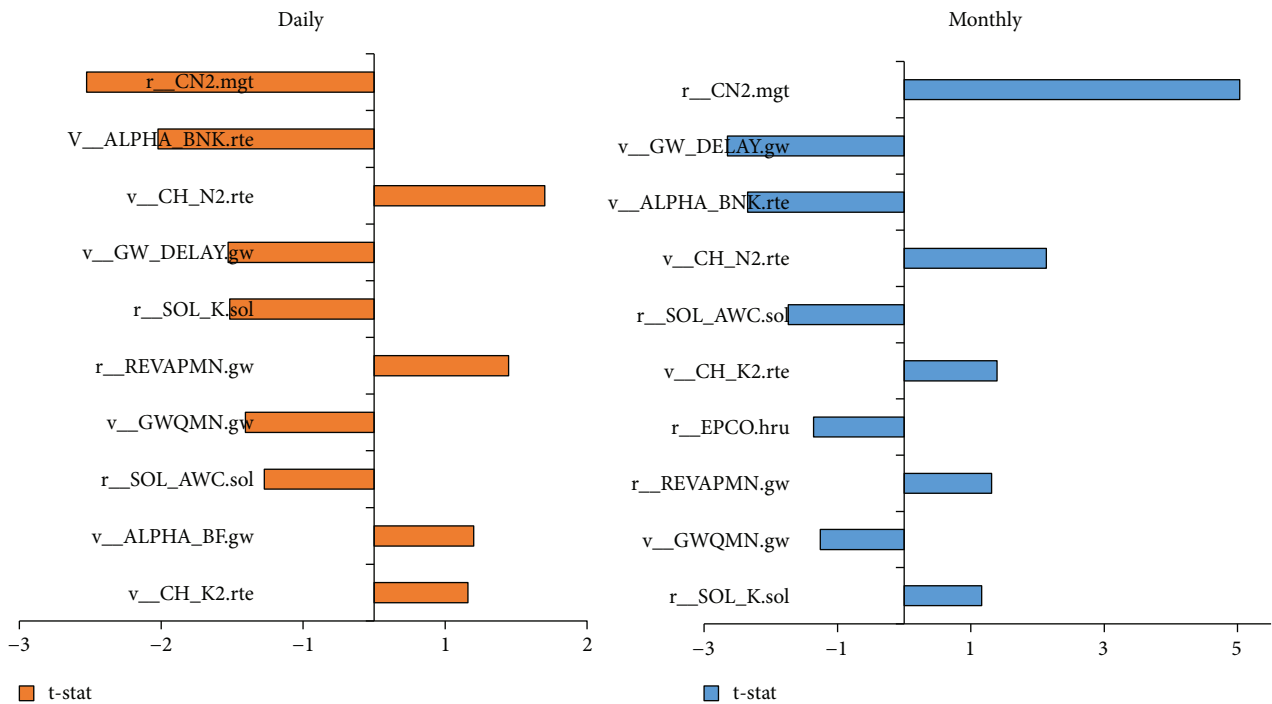
FIGURE 5: t-Stat of the daily and monthly most sensitive parameters using the SUFI-2 algorithm.

The fitted value with the highest sensitivity was used to calibrate and validate the model. The dotty plots are used to estimate the relative sensitivity of each parameter by observing the impact on an objective function. The dotty plot (Figures 7 and 8) is the plot of parameters versus objective function indicating the distribution of the sampling points, which explain the parameter sensitivity for daily and monthly time periods. In the dotty plots, if the points are scattered at random, the sensitivity is low for the parameter, and if the points do follow a trend, the sensitivity is higher.
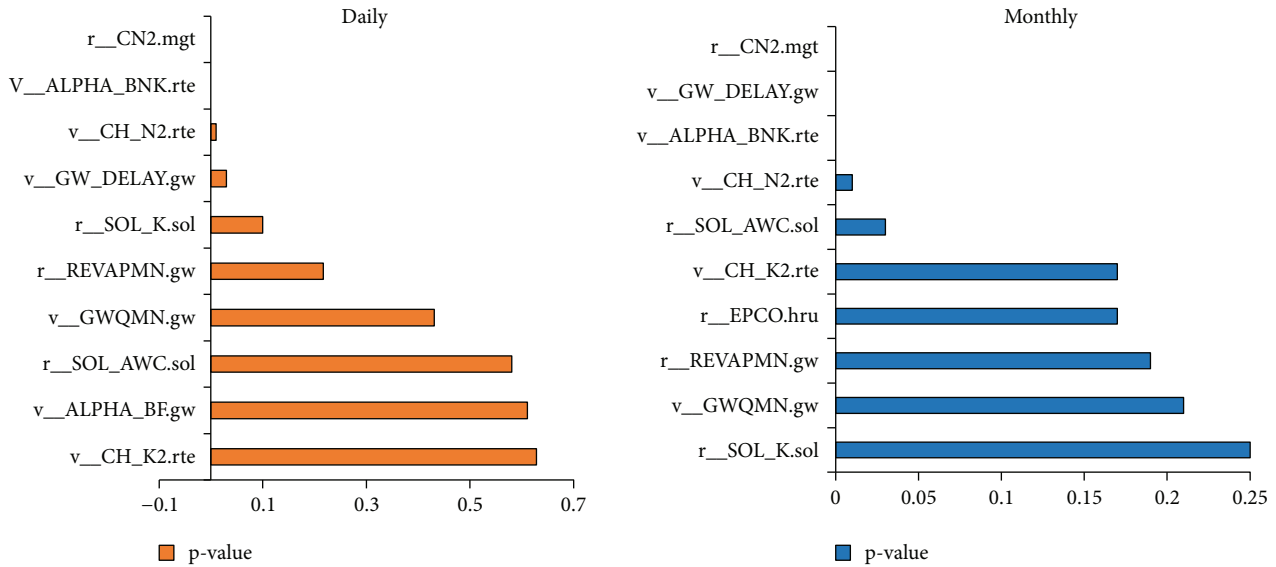
FIGURE 6: *t*-Stat of the daily and monthly most sensitive parameters using the SUFI-2 algorithm.

These were attained in the final iteration of the SUFI-2 algorithm after 1000 iterations.

3.2. Model Calibration and Validation. The calibration is the adjustment of model parameters until the model output matches the best result with the observed data within the recommended ranges to optimize the model output. Validation is the process of determining the degree to which a model or simulation accurately represents the observed set of data from the point of view of the model's intended uses. The calibration and validation were conducted using the SUFI-2 algorithm using the monthly and daily streamflow data at the gauging station of the watershed using ten of the most selected influential model parameters.

The recorded daily streamflow data during the years 1985–2008 were collected, and the monthly and daily streamflow data for thirteen years from 1987 to 1999 were used for calibration and nine years from 2000 to 2008 for validation. The years 1985–1986 were skipped for model warm-up. The comparison of the observed and simulated with their 95PPU plot for daily and monthly streamflows was graphically plotted for the Nashe watershed as presented in Figures 9 and 10 during the calibration and validation period, respectively. The main purpose of the scatter plots is to show the distribution of sampling points and parameter sensitivity and the scatter plots as shown in Figures 11–14 for calibration and validation for both daily and monthly time periods. The calibration and validation period's scatter plot shows good collinearity between observed and simulated flows and almost matches the value predicted by the model. It is generally agreed upon that the ineffective parameter ranges may be the primary cause of the large number of dots produced below the threshold values and that the values of

NSE are approaching their optimal levels once all parameter ranges have been updated.

The monthly scatter plots created for calibration and validation distribution parameter values in most of the parameters show under predictions mostly (>98 m³/s, 80 m³/s) and over predictions (<80 m³/s, 80 m³/s), respectively. The scatter plots of the observed and simulated streamflows illustrate that the model has underestimated the streamflow. Nine model efficiency measures were considered, R^2, NSE, RSR, PBIAS, bR^2, MSE, KGE, *p*-factor, and *r*-factor were calculated for calibration and validation periods, and the results attained were acceptable. During the monthly and daily streamflow calibration and validation periods, the values of NSE were 0.82 and 079 and 0.85 and 0.76, while that of R^2 were 0.89 and 0.85 and 0.88 and 0.78, respectively. Comparing the daily and monthly streamflow results, the daily results had larger uncertainty and lower values of objective functions because of high computational efficiency and low-performance efficiency. Figures 9(b) and 10(b) make it abundantly evident that the 95PPU achieved by the SUFI-2 approach was considerably higher than those obtained by the other three methods over the calibration and validation, demonstrating that SUFI-2 had a considerable advantage in the uncertainty analysis of streamflow simulation.

The statistical results obtained, and the graphical results, indicate that the model performance at monthly time steps of the Nashe watershed is satisfactory. Thus, it can be observed that SUFI-2 is capable of reasonably capturing observed streamflow during both calibration and validation periods, but it slightly overestimates peak values in the years 1989, 1991, 1995, 2001, and 2006, which could be due to the large uncertainty involved in the computation of recession by the SWAT model for monthly streamflow.
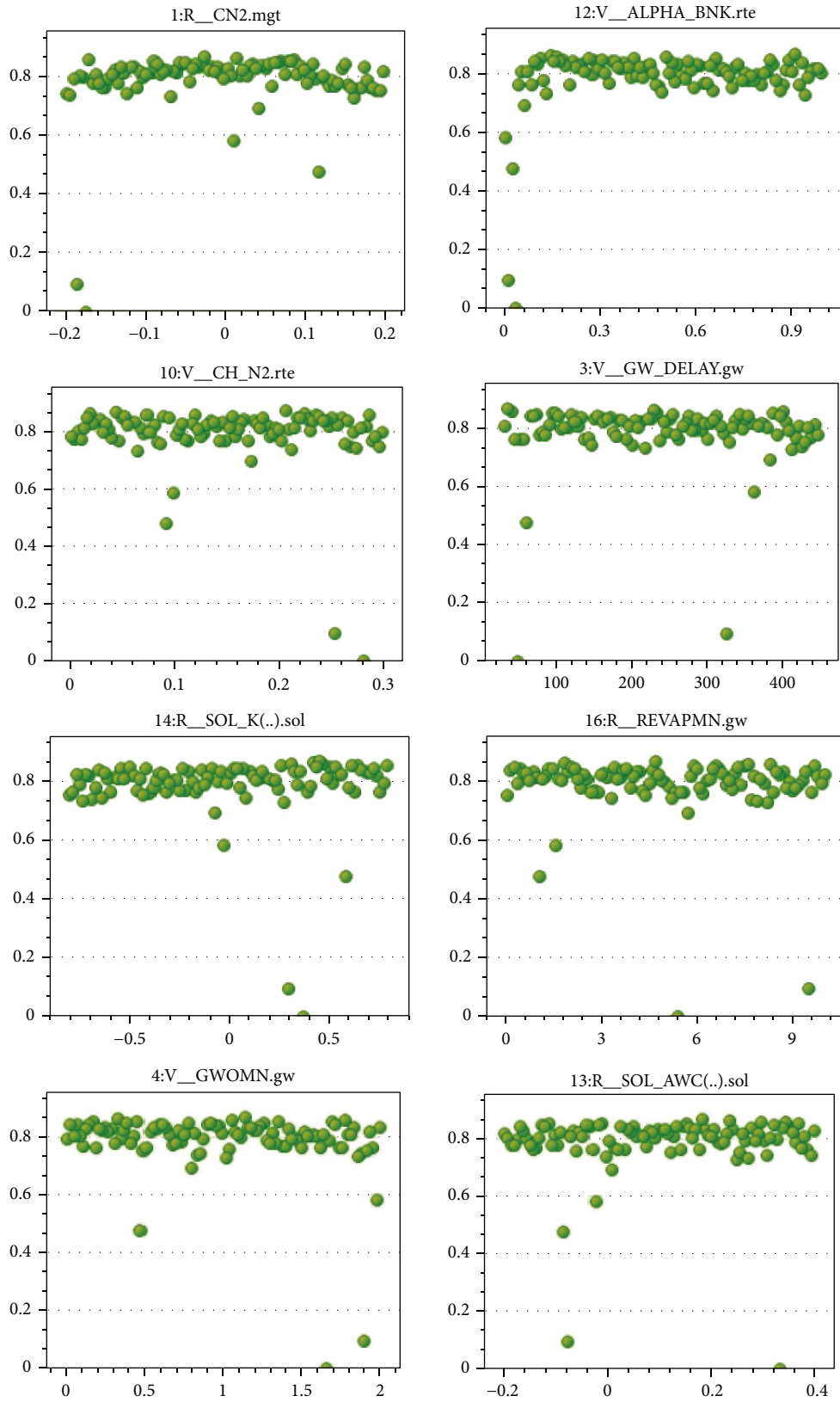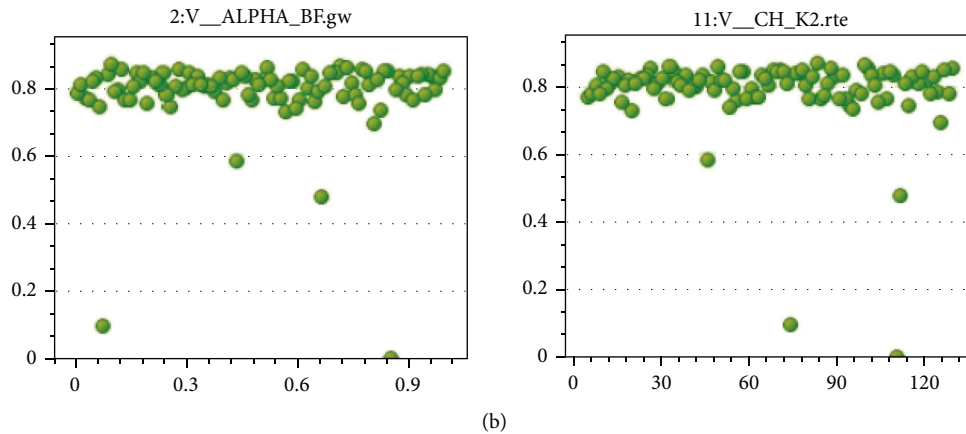
(a)

Figure 7: Continued.

(b)

FIGURE 7: Daily dotty plots of the most sensitive parameters of the Nashe watershed.

3.3. Uncertainty Analysis. Simulating streamflow is a challenging process due to the numerous uncertainties that exist in the form of input parameter inaccuracies, unaccounted processes by the model, and processes occurring in the catchment that are unknown to the modeler [47]. The SWAT model runs on a large number of parameters to account for uncertainties, and a large number of parameters further complicate the processes of the model's parameterization. However, this does not reduce the importance of parameterization in model calibration and validation [26]. SUFI-2 was utilized for parametric uncertainty analysis and is capable of capturing the model's behavior; for this reason, results obtained in the study demonstrate acceptable model performance in the streamflow simulation in the Nashe watershed. The model's uncertainty may be caused by soil erosion, which is not taken into account and changes the soil's structure, infiltration capacity, and other attributes.

The degree of measurement and results of uncertainty analysis during the calibration and validation periods were assessed by *p*-factor and *r*-factor. The model uncertainty analysis was evaluated using the *p*-factor and *r*-factor with the objective functions to minimize the width of the uncertainty band and encloses as many observations as possible. The uncertainty analysis was implemented firstly in the calibration period and then passed to the validation period. In the modeling of the daily streamflows, some of the observations fall outside of the corresponding 95PPU. As for the SUFI-2 algorithm, considering the uncertainties of hydrological models and other aspects in the process of optimizing streamflow simulation parameters, the range of parameters generated by the method was large. The simulated data that fall outside are a reflection of model structural error and possible inconsistencies in the data that are not being properly reflected in parameter sampling. The 95PPU and dotty plots for each parameter were used to compute the overall uncertainty in the output. The uncertainty of the

output variables was expressed as the 95% probability distributions calculated at 2.5% and 97.5% of the cumulative distribution resulting from the propagation of the parameter uncertainty, which is referred to as the 95% prediction uncertainty (95PPU).

The shaded region (95PPU) in the figures shows all uncertainties in the model from different sources because it covers a large amount of measured data. The result of the monthly streamflow (Figures 10 and 12) shows that 84% and 82% of the observed data were covered by the 95PPU, and the average thickness (r-factor) shows 1.10 and 1.00 for calibration and validation, respectively. The simulated and observed uncertainties were captured by 95PPU and located between the upper (97.5% PP) and lower (2.5% PPU) uncertainty ranges except at some peak and low streamflow. During the calibration and validation, the p-factor and r-factor with the other obtained objective functions were generally depicted in Table 8. Most of the measured values of the streamflow were in the range of 95PPU for both daily and monthly time periods (Figures 9 and 10). The overall performance evaluation criteria indicate that the monthly data performed better than the daily data, which shows that more observations fell into the 95PPU bands of the simulated outputs. The lack of an adequate number of observation stations affects the model output. Due to the heterogeneity of the catchments, a number of meteorological observation stations are required to represent the spatial variation in the hydrometeorological characteristics in the area. Furthermore, the high-resolution remote sensing soil moisture and evapotranspiration data can be used to calibrate the other primary hydrological components of the water cycle in a follow-up study, minimizing the simulation's uncertainty. In this study, the input data of the model are the main limitation for the application of the model. These elements also contribute to the inefficiency of using increasingly complicated and precise models [48–50].
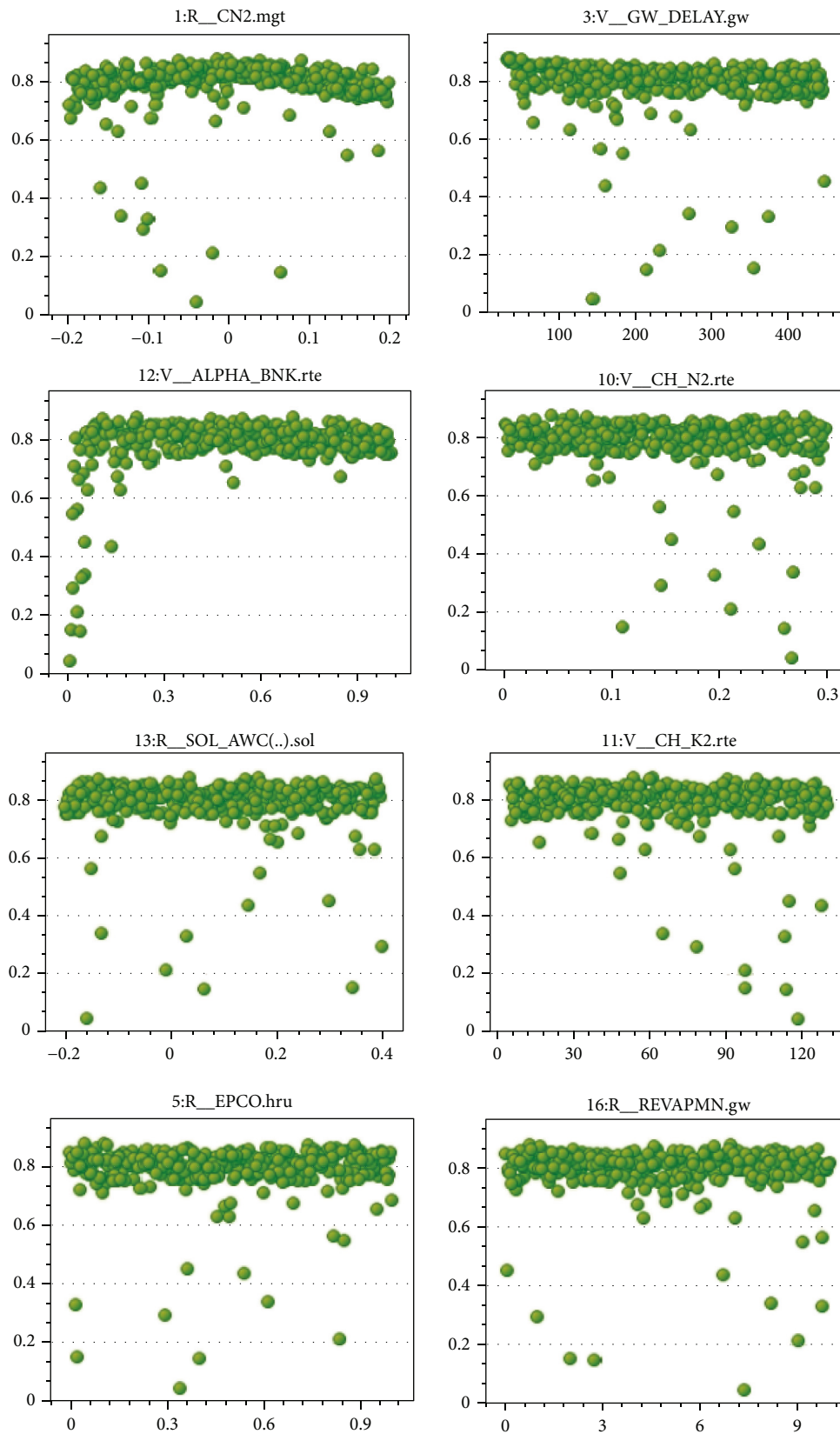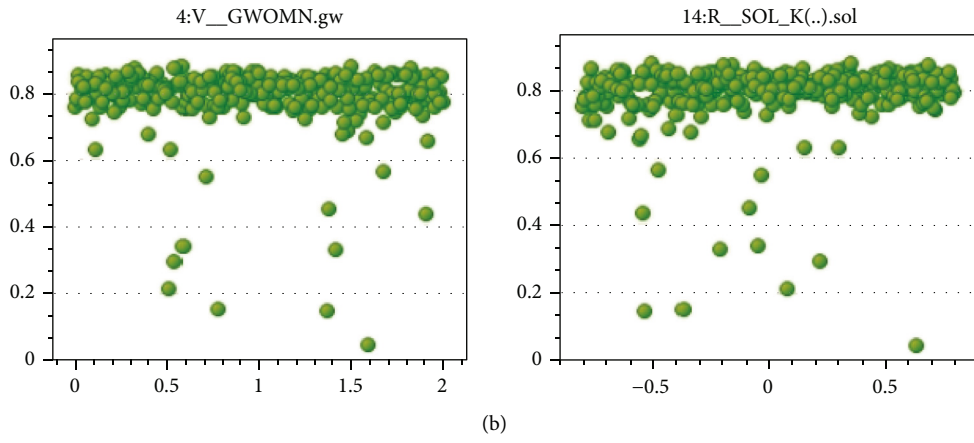
(a)

Figure 8: Continued.

(b)

FIGURE 8: Monthly dotty plots of the most sensitive parameters of the Nashe watershed.
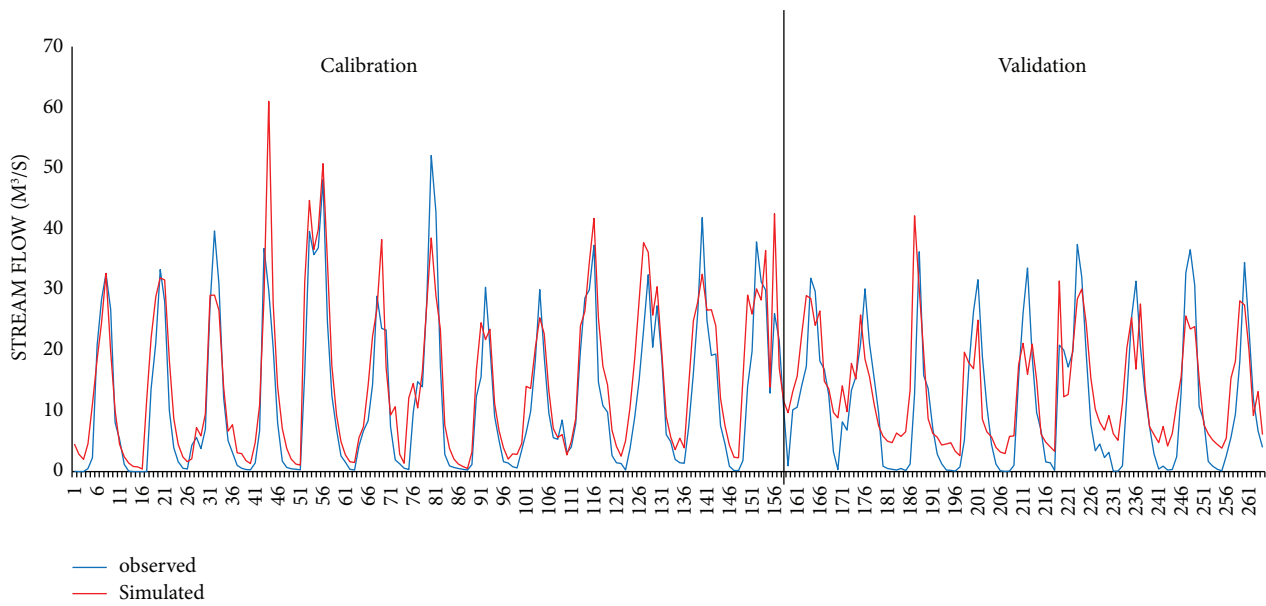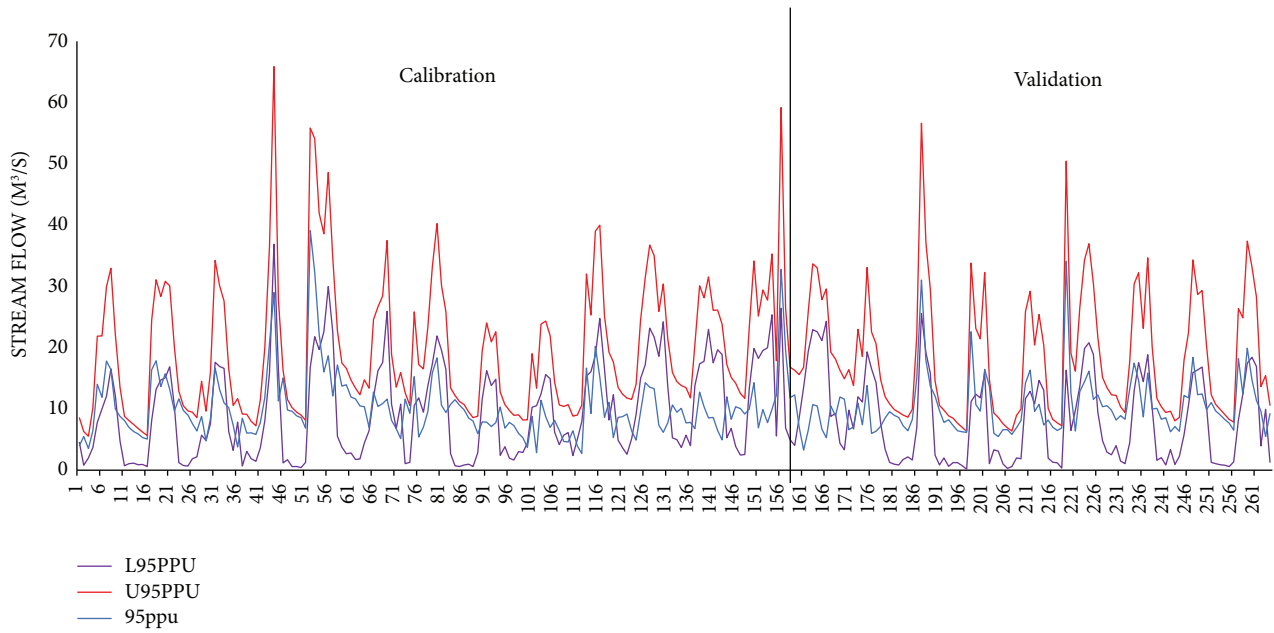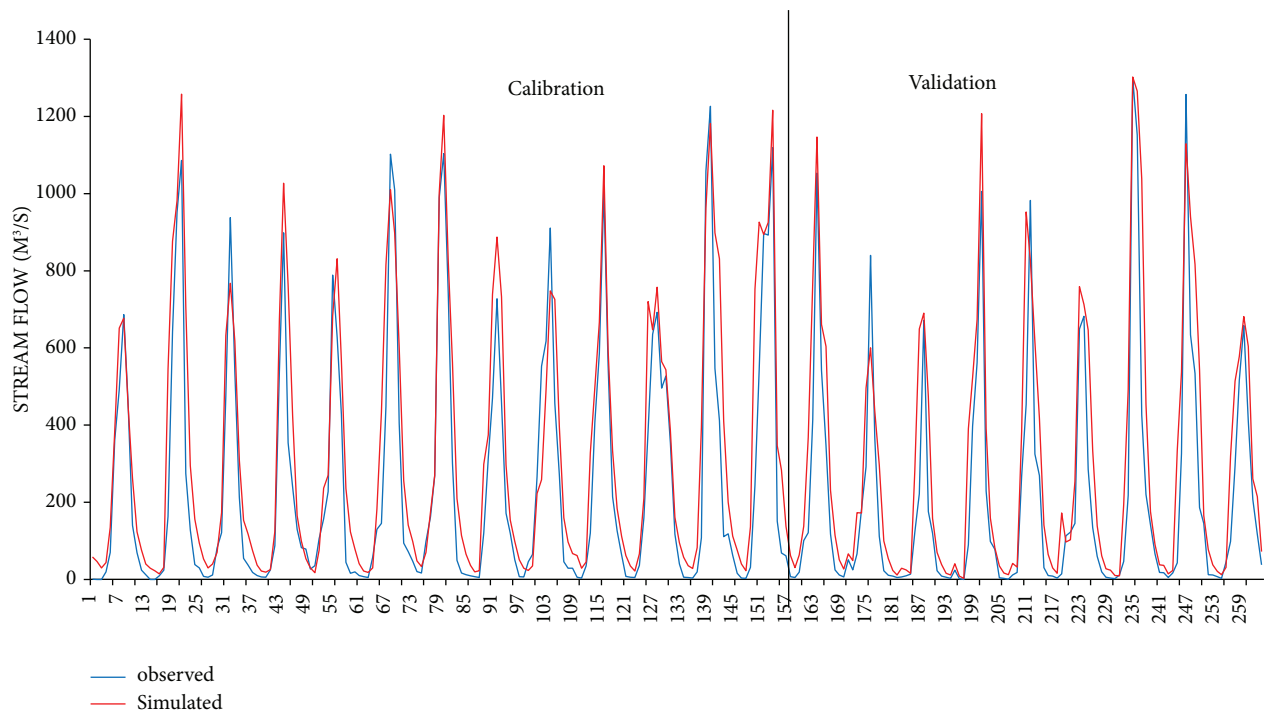

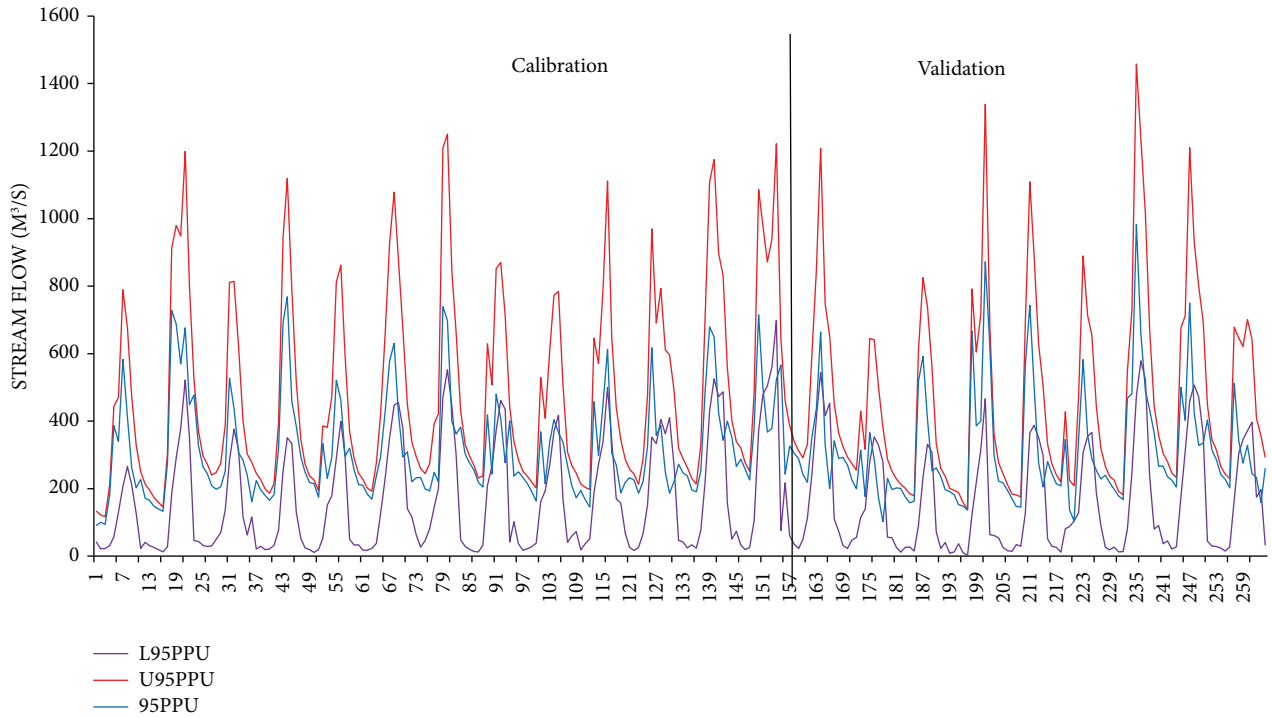(a)

FIGURE 9: Continued.

(b)

Figure 9: Daily streamflow of the Nashe watershed in calibration and validation periods. (a) Observed and simulated. (b) 95PPU plot.

(a)

Figure 10: Continued.

(b)

Figure 10: Monthly streamflow of the Nashe watershed in calibration and validation periods. (a) Observed and simulated. (b) 95PPU plot.
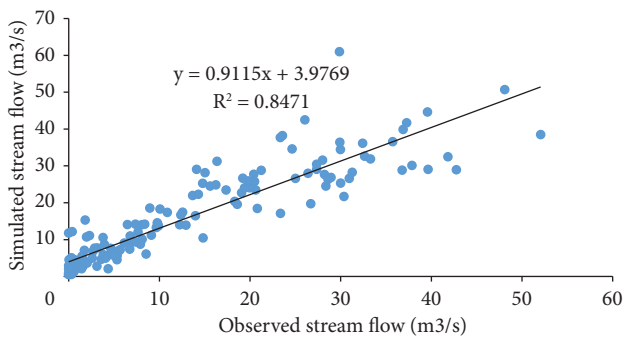

Figure 11: Scatter plots of observed and simulated daily streamflow for the Nashe watershed during the calibration period.
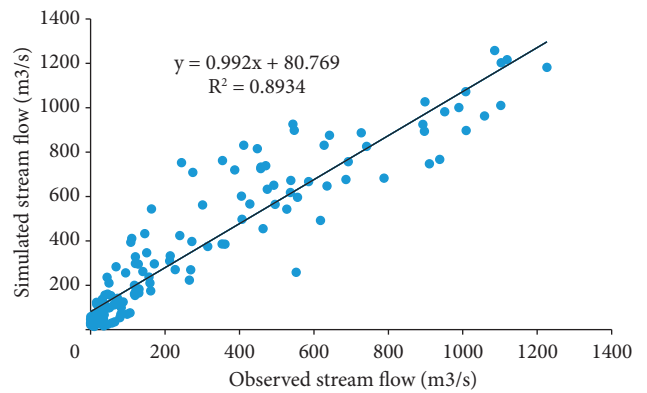

Figure 13: Scatter plots of observed and simulated monthly streamflow for the Nashe watershed during the calibration period.
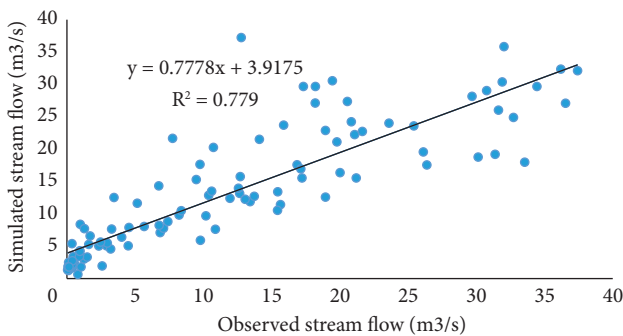

Figure 12: Scatter plots of observed and simulated daily streamflow for the Nashe watershed during the validation period.
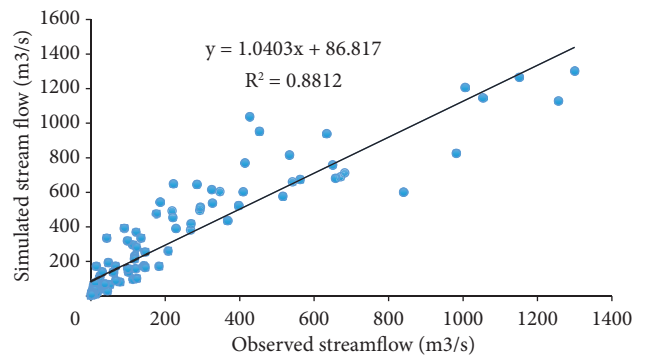

Figure 14: Scatter plots of observed and simulated monthly streamflow for the Nashe watershed during the validation period.

Table 8: Model evaluation performance of the streamflow calibration and validation results on monthly basis.

Objective functions	Monthly		Daily	
	Calibration	Validation	Calibration	Validation
R2	0.89	0.88	0.85	0.78
NSE	0.82	0.85	0.79	0.76
bR2	0.87	0.83	0.77	0.62
PBIAS	5.7	8.6	8.4	2.3
MSE	200	250	37	31
KGE	0.78	0.55	0.79	0.79
RSR	0.46	0.56	0.53	0.55
p-factor	0.84	0.82	0.7	0.79
r-factor	1.1	1	0.82	0.97

4. Conclusions

In hydrological modeling, uncertainties have a significant impact on prediction and subsequent decision-making. The uncertainty, and its measurement, is a difficult task in SWAT model predictions, and it is dependent on the uncertainty technique employed. The SUFI-2 algorithm of SWAT-CUP was utilized to analyze the sensitivity analysis, uncertainty analysis, calibration, and validation of the model for the Nashe watershed. The sequential uncertainty fitting 2 was implemented to investigate the uncertainty of the model, accounting for errors due to model structure, input data, and model parameters. The results reveal that CN2, followed by GW_DELAY, ALPHA_BNK, CH_N2, and SOL-AWC, is the most sensitive and has a significant impact on streamflow based on the monthly time period. The hydrological model was successfully calibrated and validated from 1987–1999 and 2000–2008, respectively, for daily and monthly time periods. The governing surface runoff generation processes in the selected subbasin of sensitive parameters were identified. There are 23 subbasins and 339 hydrological response units (HRUs) in the basin that were delineated using the model's data. The most significant sensitive parameters were selected and used for model calibration and validation. The model performance evaluation indicators in all calibration and validation techniques were mostly above the minimum threshold value. The research results indicated that the NSE of the monthly and daily streamflow simulation in the Nashe watershed was 0.82 and 0.79 and 0.85 and 0.76, respectively, and R^2 was 0.89 and 0.85 and 0.88 and 0.78, respectively, for daily and monthly. The result indicated that the model had good applicability in both time periods in the study area. The uncertainty analysis of the model indicated that the observed streamflow values covered more than 70% for both daily and monthly flows within the 95% prediction uncertainty (95PPU) band after calibration and validation. In general, the SWAT model is a valuable tool that generates good simulation results for daily and monthly time steps, which could be used to model water resource management and hydrological processes in a watershed. However, model performance is better during the monthly time-series calibration and validation phase, resulting in good objective functions. The SWAT-CUP is useful in forecasting flow and quantifying underlying uncertainties and related assumptions in the field of water resources, according to the findings of this study. It is recommended that the calibrated model be used in further climate change and land use/land cover effect assessments on water resources. Similarly, it is suggested in future studies, to use more uncertainty techniques in model calibration, sensitivity, and uncertainty analysis.

Data Availability

The data used in this study can be available from the authors on reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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