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Research Article

Modeling and Assessing Surface Water Potential Using Combined SWAT Model and Spatial Proximity Regionalization Technique for Ungauged Subwatershed of Jewuha Watershed, Awash Basin, Ethiopia

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Surface water potential is the availability of water on the surface of the Earth. It is a finite renewable resource, of which the quantity and quality are both space- and time-dependent. Careful estimation of the surface water potential of a river basin is very essential for the future development of any kind of water-related project in countries like Ethiopia. The surface water potential of the ungauged subwatershed of Jewuha watershed was estimated using the hydrological model of Soil and Water Assessment Tool (SWAT) and simple regionalization techniques. The study used different data inputs collected from various sources and field observations. The performance of the hydrological model was analyzed using performance checker parameters. After calibrating and simulating using observed flow, the model showed it was very well to simulate the hydrology of the watershed with a coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), and percent of bias (PBIAS) of 0.74, 0.73, and 0.80 for calibration and 0.71, 0.70, and 7.90 for validation, respectively, in Jewuha watershed. From the total watershed area of 680 km^2, 163.68 million m^3 of runoff was generated by the model annually. In conclusion, the watershed has high surface water potential, and the rivers in the subwatershed also have enough surface water that may be used for agricultural development.

1. Introduction

Surface water potential is the availability of water on the surface of the Earth. It is a finite renewable resource, of which the quantity and quality are both space- and time-dependent. Lakes and rivers, which have served as the major sources of water throughout human history, constitute less than 0.3% of nearly 3% of the Earth's freshwater [1]. However, the availability of freshwater in many regions is likely to decrease due to population growth, industrialization, land use, and climate change; unfortunately, demand for water increases across the world. Therefore, the careful estimation of the surface water potential of a river basin is very essential for the future development of any kind of water-related project in countries like Ethiopia.

Stream flow time series measurements are needed for assessing and characterizing the hydrologic behavior of river basins within modeling frameworks. However, in most catchments in Ethiopia, particularly in Jewuha watershed, the rivers are ungauged. Most watersheds have no hydrological data for hydrologic applications, thus tools for prediction in the ungauged watershed are indubitably required [2]. Also, accurate information on stream flow is the basis for the planning and designing of water resources schemes such as irrigation project development, water supply, hydropower, flood forecasting, and control and then to have a sustainable ecosystem. For better managing and assessing the associated risks and impacts, river water resources need a more detailed study. However, still, nothing is done to assess the water potential of the subwatershed in the area.

To tackle such problems, regionalization of gauged data hydrological parameters to an area of data scarce region is necessary. In the previous studies, the prediction of flow for the ungauged subwatersheds was done using hydrological model simulation. But distributed hydrological models are spatially complex and deal with large numbers of unknown parameters, thus parameterization techniques have to be applied. But the major problems when using distributed hydrological models are the nontransferability of model parameters through spatial resolution and the transferability of parameters across scale and space [3]. Several studies have shown that shifting model parameters across calibration scales generates a bias in the simulation of water fluxes and states. Similarly, variations occur when parameters are transferred across locations [4–6]. However, the hydrological model combined with other spatial regionalization techniques relatively makes it accurate and reliable to transfer the model parameters for gauged to ungauged watersheds.

Hydrologic models represent the most effective and viable means of predicting water availability and distribution systems under an array of demand loading and operating conditions. To assess the long-term dynamics of the hydrologic response to an environmental change, deterministic process-based models are used to assess the water potentials of the area [7]. Today, there are different hydrological models from simple to complex features available to simulate the hydrological process at the basin and watershed levels to assess the surface water potential such as physical models, conceptual models, and empirical models. Most of these hydrological models are applied in Ethiopia to simulate sediment yield and surface runoff at watershed and basin scale [8–11], but none of this estimate the water potential of the area in ungauged subwatersheds. Regionalization is the process of transferring hydrological information (parameters) of a model such as SWAT from a gauged watershed to an ungauged watershed to predict the stream flow for the ungauged station. There are different regionalization techniques existed such as spatial proximity (Kriging, Inverse Distance Weighted (IDW)), physical similarity approach, and regression-based approach. Regionalization is important for understanding the hydrological characteristics and analysis of sustainable water resource management of ungauged watersheds [12]. The physical similarity is expressed based on the similarity of catchment attributes such as catchment size, information on topography, land use, geology, elevation, soil characteristics, and climate variables. The physical similarity regionalization technique states that a catchment with similar attributes has similar hydrological characteristics [12]. From the different regionalization techniques, spatial proximity methods are mostly applicable [12, 13]. Herein, spatial proximity with inverse distance weighting (IDW) was applied to take the SWAT calibrated model parameters of the gauged watershed to the ungauged watershed.

The spatial proximity regionalization technique is based on the spatial distance between catchment centroids that are interpolated as a function of the geographic location. It can be done with inverse distance weighting, kriging, or regional pooling for a model. The spatial proximity regionalization approach has been used by many researchers [12, 13]. According to Oudin et al. [12], the spatial proximity regionalization technique is better for small watersheds that have gauged stations that are not densely located in the watershed. Also, the result reveals that when two catchments are closer, they have similar hydrological process. Van Liew and Mittelstet Aaron [14] compare the three regionalization approaches, namely, regional averaging, spatial proximity (nearest neighbor), and donor techniques to regionalize parameters in the Soil and Water Assessment Tool (SWAT) on eleven watersheds located in the dissected plains and rolling hill landforms in the eastern portion of the State of Nebraska, USA. From the three regionalization methods, the regional average gave better results than the other two; however, all three approaches were considered unsatisfactory in the study area. Roth et al. [3] studied model parameter transfers for stream flow and sediment loss prediction with SWAT in a tropical watershed. Minchet watershed is a highland of Ethiopia. The result shows that calibration and validation of the flow performed very well for the subcatchment and for the entire catchment using model parameter transfer. Therefore, for this study, spatial proximity with the inverse distance weighting method was used to transfer the model parameter from the gauged to the ungauged subwatersheds to estimate the surface water potential.

Therefore, the objective of this study was to assess surface water potential using the combined SWAT model and spatial proximity regionalization technique for the ungauged subwatershed of Jewuha watershed, Middle Awash basin, Ethiopia.

2. Materials and Methods

2.1. Study Area. The names of the rivers are given based on the town's name near the rivers. Jewuha, Robi, and Ataye rivers originated from the Guassa mountain and joined the Awash river basin. During its flow from the mountain to the Awash river, different perennial and semiperennial (effluent) tributaries are joined in Jewuha river such as Sewur river and Lomi Wonz. Jewuha watershed is positioned with geographic coordinates between 39°44′55″ to 40°10′4″E and 10°00′3″ to 10°21′10″N with an elevation range from 1109 to 3383 m above sea level with an area of 680 km^2 (Figure 1).

The distribution of the rainfall in the area is a bimodal rainfall type that has a short rainy season that occurs between March and April and a long rainy season that occurs between June and August, with a dry season from December to February. The rainfall in the area varies from 218 and

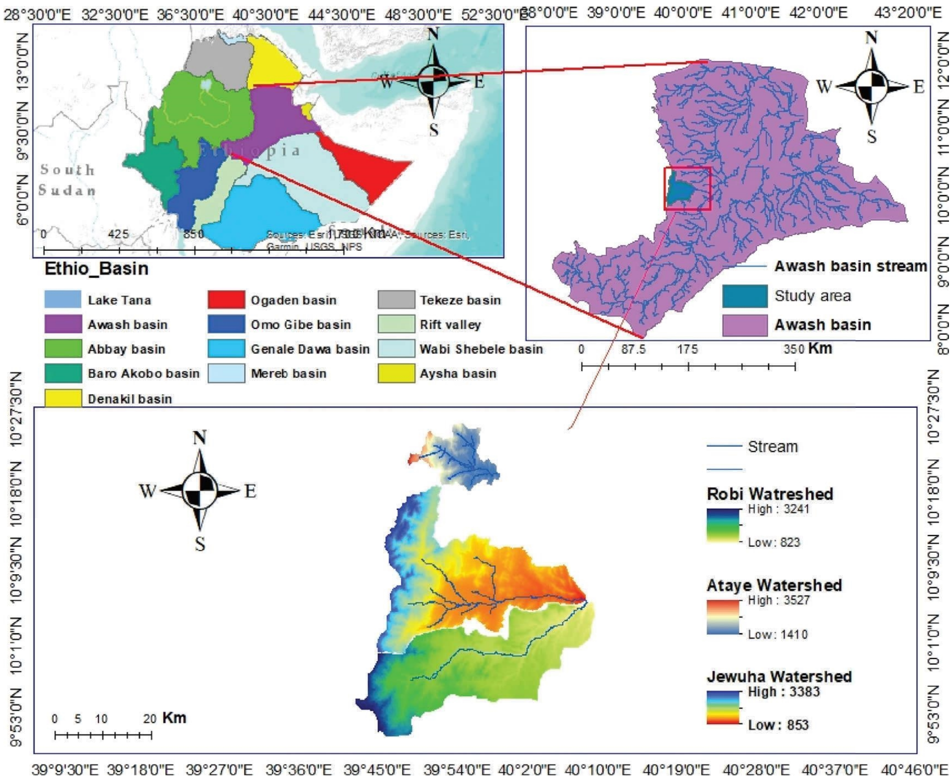

Figure 1: Location of the study area.

259 mm; however, in the rainy season, the value changes between 1200 mm and 1500 mm in the highland, but it reduces to 600 mm to 900 mm in the lowland areas (Table 1).

The other factor which characterizes the watershed is the temperature which is critical to the water balance. In the study area watershed, the temperature highly influences evapotranspiration and recharge. Unlike evapotranspiration, recharge is low when the temperature is high. The average value of 12.57°C has been recorded in the summer season and 20.6°C has been recorded in winter (dry season). However, the total average value of temperature in the watershed is 20°C.

Different land cover types have been found in the study area in terms of areal coverage; the important land cover units are trees, shrubs, grassland, cropland, vegetation aquatic or regularly flooded, bare areas, and built-up areas. The agricultural/cropland is the principal land use of the watershed distributed throughout the study area. Table 1 shows the general watershed characteristics of the given watershed.

Table 1: Watershed characteristics.

Characteristics	Watershed		
	Jewuha	Ataye	Robi
Size (km^2)	680	240	290
Annual precipitation (mm)	1051	1428	972
Annual mean temperature (°C)	20	22	25
Forest (%)	12.2	10	13
Urban (%)	0.17	0.2	0.25
Agriculture (%)	46.3	35.2	38.1
Surb land (%)	24.61	20	22.2
Average slope (%)	0.16	0.21	0.13
Mean elevation (m)	2246	2431	2150

2.2. Materials and Data Type

2.2.1. Meteorological Data and Quality Analysis. Meteorological and hydrological data were collected with their respected organizations such as Ethiopia National Meteorological Agency and the Minister of Water and Energy, respectively. The meteorological data includes daily data of precipitation, maximum and minimum temperature, relative humidity, wind speed, and solar radiation/sunshine hour, and they were collected from the National Meteorological Agency of Ethiopia (NMAE) from 1988 to 2017 for Ataye, Jewuha, Effeson and Shewa Robit gauge stations. Also, the daily stream flow data of Jewuha, Ataye, and Robi river gauging stations were collected (Figure 2).

The quality of the climate data was checked using Alexanderson's Homogeneity test. Meteorological data series has great importance for the study and analysis of climatological and hydrology. Nevertheless, meteorological time series data are suffering from different factors which it makes inhomogeneous. Therefore, homogeneity analysis of this time series data is necessary to identify a change in the statistical properties of the data which is caused by either natural or man-made factors. This includes change in land use and relocation of the observation station. Among the different statistical homogeneity test, Standard Normal

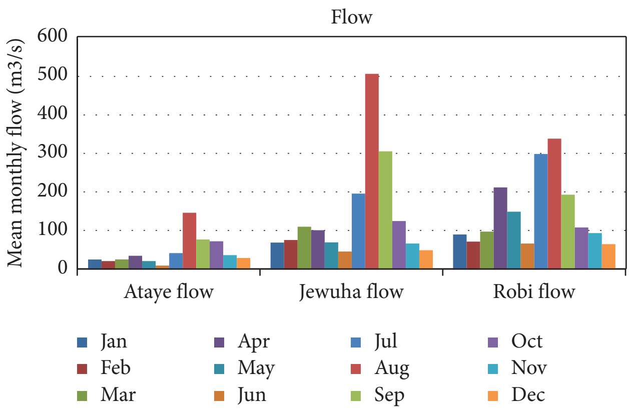

FIGURE 2: Mean monthly stream flow.

Homogeneity Test (SNHT) was used [15]. SNHT is usually applied to a series of ratios that compare the observations with an average. SNHT test describes a statistic $T(k)$ to compare the mean of the first k years of the record with that of the last k-n years as follows:

$$T(k) = k\overline{z}_1^2 + 9n - k\overline{z}_2^2, \quad k = 1, \ldots .n,$$
$$\overline{z}_1^2 = \frac{1}{k}\frac{\sum_{i=1}^{k}(y_i - \overline{y})}{S}, \qquad (1)$$
$$\overline{z}_2^2 = \frac{1}{n-k}\frac{\sum_{i=k+1}^{k}(y_i - \overline{y})}{S}.$$

If a break is located at the year K, then $T(k)$ reaches a maximum near the year $k = K$. The test statics T_0 is defined as

$$T_0 = \max(T(k)) \cdots \text{for } 1 \le k < n. \qquad (2)$$

In this study, the homogeneity was computed by SNHT in excel using the XLSTAT statistical software. As the computed p-value is greater than the significance level alpha = 0.05, the null hypothesis H_0 was accepted and the precipitation data set is homogeneous. If the mean of the first k value is the same with the mean of the k-n value then the data is homogenous. When the data is not homogeneous by removing the data value, it makes the data non-homogeneous and fills it by considering that the data is missed. As shown in Table 2, the p-value is greater than the significance level alpha; therefore, all the stations are homogeneous.

Figure 3 reveals the result of Alexanderson's homogeneity test for precipitation, in which mu is mean value of precipitation in the given station. Herein, data means the value of the annual PCP (Precipitation) of station. As shown in the graph, the straight line does intersect the annual precipitation data in one line. This expresses that the precipitation data are homogeneous for the given stations (Figure 3).

2.2.2. DEM, LULC, and Soil Data. The spatial data which are necessary for the input of the SWAT model including a soil map, digital elevation model, and land use/land cover were obtained from different sources. The Digital Elevation Model (DEM) was obtained from https://earthexplorer.usgs.gov website and soil map were extracted from the https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/. However, land use land cover data were obtained from Water and Land Resource Center office, Addis Ababa, Ethiopia.

TABLE 2: Alexanderson's SNHT for homogeneity of yearly rainfall.

Station name	Mean value	p-value	Alpha
Shewa Robit	972	0.097	0.05
Jewuha	1051	0.797	0.05
Ataye	1428	0.818	0.05
Effeson	1106	0.137	0.05

2.3. SWAT Model. The soil and water assessment tool (SWAT) is a well-known hydrological modeling tool that has been applied in various hydrologic and environmental simulations [7, 16, 17]. Mainly, SWAT is applied for water resource and stream flow assessment, to know the effect of a watershed, the effect of land use management on agriculture and water quality, and the climate change effect on the hydrology of a watershed [18]. The model estimates relevant hydrologic components such as evapotranspiration, surface runoff and peak rate of runoff, groundwater flow, and sediment yield for each HRUs unit. The water balance equation in the SWAT model is used to simulate the hydrologic cycle (equation).

$$SW_t = SW_o + \sum_{i=1}^{n}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right), \qquad (3)$$

where SW_t is the final water content (mm), SW_o is the initial soil water content on the day i (mm), t is time in day, R_{day} is precipitation amount on specific days i (mm), Q_{surf} is the runoff amount on specific day i (mm), E_a is evapotranspiration amount on day i (mm H_2O), W_{seep} is the amount of water percolated into the vadose zones on a day i (mm), day i (mm H_2O), and Q_{gw} is the return amount of flow on a day i (mm).

The routing phase defines the movement of water, sediment, etc. into the outlet through the channel network. Flow is routed through the channel using the variable storage routing method or the Muskingum method (equation (4)). In the variable storage routing method, storage routing is based on the continuity equation for a given reach segment.

$$\Delta V_t - V_o = \Delta v_s, \qquad (4)$$

where V_i = volume of inflow during the time step (in m^3); V_o = volume of outflow during the time step (in m^3); ΔV_s = change in volume of storage during the time step (in m^3).

The SWAT model consists of several primary components, including surface runoff estimated using different methods. The most commonly used method for estimating surface runoff in SWAT models is the modified SCS-CN2 [19] with daily time step or Green-Ampt Mein–Larson infiltration equation [20] with hourly or subdaily time steps.

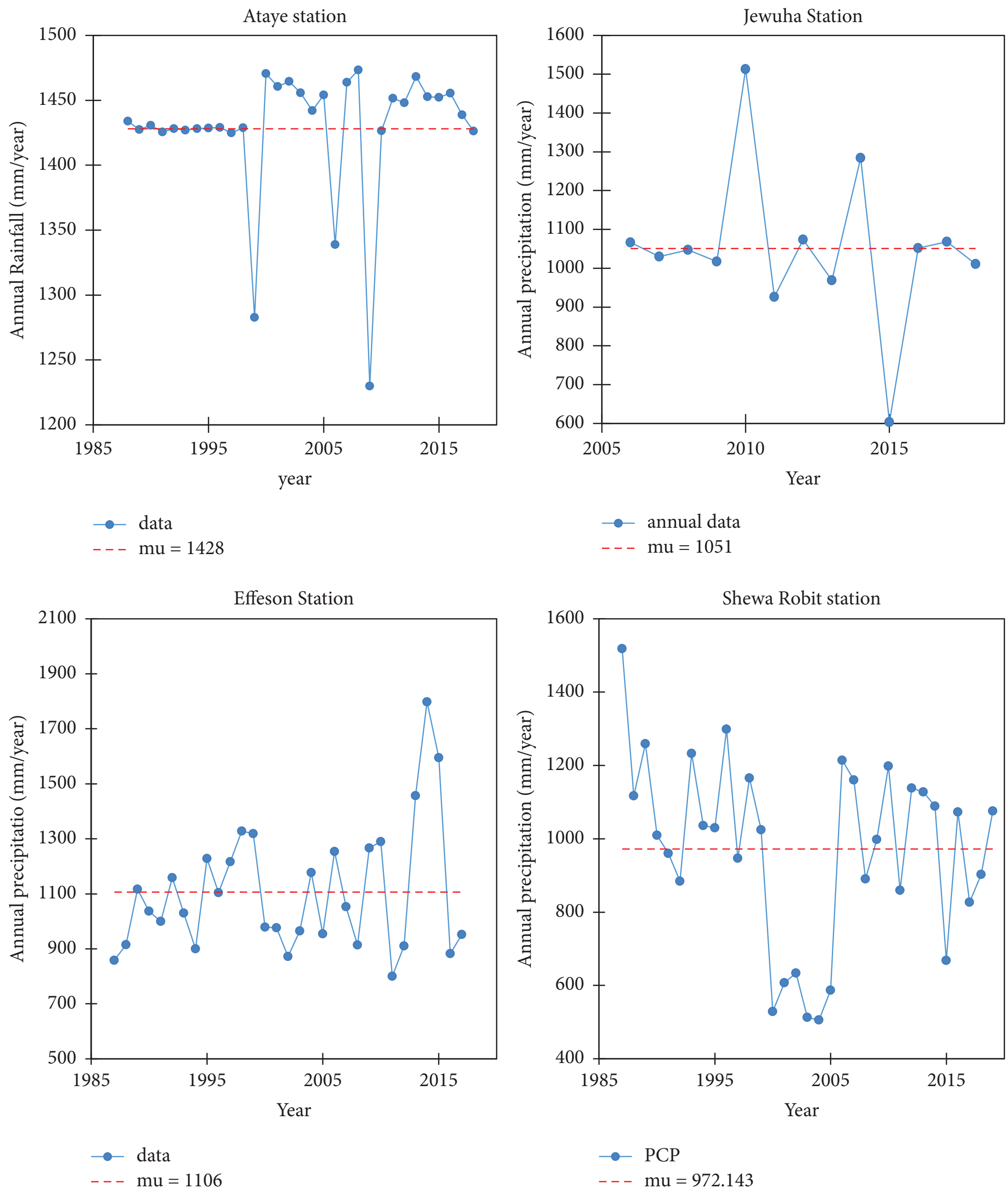

Figure 3: Result of Alexanderson's homogeneity test for precipitation.

The SCS curve number method is low data-intensive than the Green-Ampt method. Therefore, the SCS curve number method (equation (5)) was used to estimate the surface runoff volume in this study.

$$Q_{\text{surf}} = \frac{\left(R_{\text{day}} - I_a\right)^2}{\left(R_{\text{day}} - I_a + S\right)}, \tag{5}$$

where Q_{surf} is the depth of runoff in (mm), R_{day} is effective precipitation in (mm), I_a is the initial abstraction which includes surface storage, interception, and infiltration before runoff (mm), and S is the retention parameter (mm). The retention parameter changes spatially due to changes in soil, land use, management, and slope and temporally due to changes in soil water content. The retention parameter is defined as

$$S = 25.4\left(\frac{100}{\text{CN}} - 100\right), \tag{6}$$

where CN is the curve number for the day as a function of soil permeability, land use, and antecedent moisture content. The initial abstraction, I_a, is commonly approximated as $0.2S$, and equation (5) becomes.

$$Q_{\text{surf}} = \frac{\left(R_{\text{day}} - 0.2S\right)^2}{\left(R_{\text{day}} + 0.8S\right)}. \tag{7}$$

Table 3: Definition of SWAT land use and soil code for Jewuha watershed.

Value	LULC type	SWAT code	% of area coverage	Soil code	% of area coverage
1	Forest-mixed	FRST	12.2	Be9-3c-26	45.51
2	Wood land (forest deciduous)	FRSD	8.17	Re47-2c-239	5.4
3	Shrub land/brush	RNGB	24.61	Vp14-3a-286	49.09
4	Agriculture land	AGRL	46.3		
5	Grass land	RNGE	2.1		
6	Bare land	BARR	6.35		
7	Wet land	WETN	0.1		
8	Settlement- low density	URLD	0.17		

Runoff begins when P is greater than $0.5S$. Thus, the potential retention parameter depends on the slope of the watershed, soil, and land use practices [6]. The potential maximum retention of S is related to the dimensionless parameter CN using equation (6).

2.3.1. Model Input. As shown in Figure 2.3, the SWAT model is a data-intensive model which requires DEM (Digital Elevation Model), soil map, and land use/land cover (LULC) with their attributes tables (Table 2) in shape file and .txt format, climate, and hydrological data (river discharge) [21].

2.3.2. SWAT Model Setup

(1) Hydrological Response Unit (HRU). In SWAT, a watershed is divided into multiple subbasins, which are then further subdivided into HRUs that consist of homogeneous land use, management, topographical, and soil characteristics. Hydrological response units are a parcel of land that has homogeneous land characteristics. HRU consists of two parts, i.e., land use land cover, soil, slope classification, and HRU definition. After watershed delineation, the study area was discretized based on land use, soil, and slope, then overlaid to produce multiple HRUs. The definition of the watershed was given 10% for soil, 5% for LULC, and 15% for slope. This classification was depending on the objective of the study and was obtained from the literature [22]. Definition of SWAT land use and soil code for Jewuha watershed is described in the table below (Table 3).

The Digital Elevation Model was used in combination with soil and land use data for the definition of hydrological response units. The hydrological response unit is the smallest unit of land in the watershed with homogeneous physical characteristics.

(2) Sensitivity Analysis. Quantifying model sensitivity to parameter changes is an important step in understanding model performance and a crucial undertaking before model calibration; therefore, it addresses whether the appropriate quantity and quality of data can be obtained to provide realistic model outputs given the parameter sensitivity. In SUFI-2, to perform the sensitivity analysis, it includes two types, namely, one-at-a-time (OAT) and global sensitivity analysis. In the OAT technique, the response of the output is identified by changing only one parameter at a time [23]. But this technique needs to know the interval of the parameters and it results in eccentricity from the nominal parameter value. In global sensitivity analysis, all the parameter values are perturbed simultaneously and it makes it easier to identify the interaction between the parameters.

(3) Model Calibration. The prediction of the uncertainty of SWAT model calibration and validation results was analyzed by the SWAT calibration uncertainties program known as SWAT-CUP [23]. Among different algorithms, SUFI-2 was used for the calibration of the SWAT model. To show the intimate relationship between the simulation result, expressed as 95PPU, and the observation expressed as a single signal (with some error associated with it), two statistics values are used [16]. These are the p-factor and r-factor, which gave a good measure of the strength of the calibration results. The p-factor is the percentage of measured data bracketed by the 95PPU band, and the r-factor is a measure of the thickness of the 95PPU (equation (8)). The value of the p-factor and R-factor is between 0, 1, and 0 up to infinity, respectively. A p-factor of 1 and R-factor of 0 indicates that the simulations are exactly corresponding to the observed data [23].

$$\overline{r}\text{factor} = \frac{(1/n)\sum_{t=1}^{n}\left(Q_t^{s,97.5\%} - Q_t^{s,2.5\%}\right)}{\sigma_{\text{obs}}}, \tag{8}$$

where $Q_{ti}^{s,97.5\%}$ and $Q_{ti}^{s,2.5\%}$ are the upper and lower boundary of the 95PPU at time t and simulation i, respectively, nj is the number of data points, and $\sigma_{\text{obs}j}$ is the standard deviation of the jth observed variable. Generally, the structure of the SWAT model is shown in the (Figure 4) in a short and precised manner.

(4) Model Performance Evaluation. SWAT model performance was evaluated using statistical variables (Table 4). According to reference [24], the statistical tests that are used to evaluate the SWAT model include root mean square error (RMSE), nonparametric tests, t-test, objective functions, autocorrelation, and cross-correlation. For this study, Nash–Sutcliffe efficiency (NSE) (equation (9)), percent bias (PBIAS) (equation (10)), and coefficient of determination (R^2) (equation (12)) that is recommended by [25] are used (Table 4).

$$\text{NSE} = 1 - \left[\frac{\sum_{i=1}^{N}\left(O_i - P_i\right)^2}{\sum_{i=1}^{N}\left(O_i - \overline{O}_i\right)^2}\right], \tag{9}$$

$$\text{PBIAS} = \left[\frac{\sum_{i=1}^{N}\left(O_i - P_i\right)x100}{\sum_{i=1}^{N}O_i}\right], \tag{10}$$

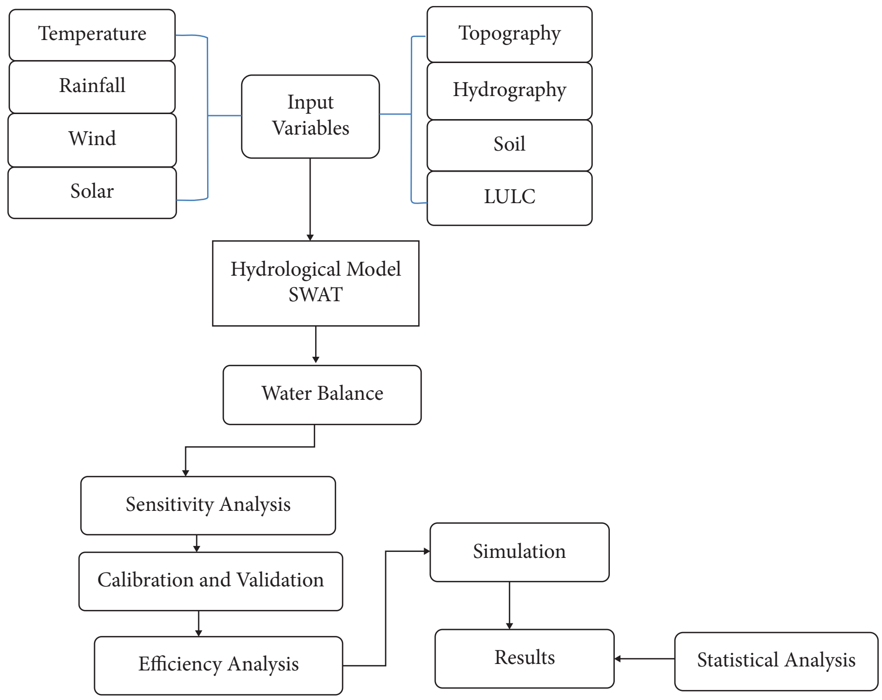

Figure 4: SWAT model flow structure.

Table 4: General performance ratings of simulated discharge.

Performance rating	NSE	PBIAS	R^2
Very good	0.75 < NSE < 1	PBIAS < ±10%	$0.75 < R^2 < 1$
Good	0.65 < NSE < 0.75	±10% < PBIAS < ±15%	$0.65 < R^2 < 0.75$
Satisfactory	0.5 < NSE < 0.65	±15% < PBIAS < ±25%	$0.5 < R^2 < 0.65$
Unsatisfactory	NSE < 0.5	PBIAS > ±25%	$R^2 < 0.5$

$$R^2 = \left[\frac{\sum_{i=1}^{N} (O_i - \overline{O})(P_i - \overline{p})}{\sqrt{\sum_{i=1}^{N} \left(O_i - \overline{O}^2\right)} \sqrt{\sum_{i=1}^{N} (P_i - \mathrm{P})^2}} \right]^2, \tag{11}$$

where P_i = simulated flow, O_i = observed flow, $\overline{O}_i$ = the mean of observed data, $\overline{P}$ is predicted flow, and the remaining variable is stated above and N is the total number of observations.

2.4. Prediction of Flow for the Ungauged Sub-Watersheds. The parameter regionalization is to transfer the calibrated parameters from gauged to ungauged catchments based on geographical proximity, functional similarity, and regression with catchment characteristics. Geographical proximity with inverse distance weighting was used for parameter regionalization for the ungauged watershed (equation (12)).

IDW was used to estimate the weight of the ungauged subwatershed of Jewuha watershed (equation (13)). The distance between the two watersheds was determined using GIS. The gauged watersheds of Ataye, Robi, and Jewuha are used to estimate the ungauged part of the Jewuha watershed. This regionalization technique was verified using leave-one-out cross-validation, in which a single gauged site is considered ungauged, and the transferred parameters to that site are entered through the SWAT model, and then the simulated flow was validated using SWAT-CUP with the observed flow. The general formula for spatial proximity with the IDW method to regionalize the calibrated parameters of the gauged watershed is

$$Z_{\mathrm{ug}} = \sum_{i=1}^{n} W_i Z_i, \tag{12}$$

where Z_{ug} is the estimated model parameter at the ungauged watershed; n is the total number of observed points (gauges); Z_i is the calibrated parameter value at gauged watershed; W_i is the weight contributing to the interpolation

$$W_i = \frac{\left(1/d_1^2\right)}{\sum_{i=1}^{n} \left(1/d_1^2\right)}, \tag{13}$$

where d_i is the distance between the centroids of gauged and ungauged subwatershed

3. Results and Discussion

3.1. SWAT Model Sensitivity Analysis. The sensitivity of each parameter was selected based on the absolute value of p-value and t-value. The lower the p-value and the higher the t-value, the more sensitive the parameter. The result of

Table 5: Sensitive parameters.

Parameter name	Fitted value	Min_value	Max_value	t-stat	p value	Rank
R_CN2.mgt	−0.0735	−0.3	0.2	−16.5807512	0	1
R_SOL_K.sol	−0.7226	−0.9	−0.7	1.82861450	0.0680751	2
V_GW_DELAY.gw	141.33300	43	150	1.20256725	0.2297342	3
R_OV_N.hru	1.4713	0.8	1.5	1.1415040	0.2542270	4
R_SOL_AWC.sol	0.7475	0.1	0.8	−1.07160796	0.2844324	5
V_GW_REVAP.gw	0.1933	0.1	0.2	−0.82199461	0.4114863	6
R_SOL_Z.sol	2.4949	2.2	2.5	0.73047918	0.4654522	7
V_RCHRG_DP.gw	0.00673	0	1	0.67145492	0.5022524	8
V_GWQMN.gw	4539.5	4500	5000	−0.6579447	0.5108877	9
R_SLSUBBSN.hru	0.2226	0.1	0.3	0.58538000	0.5585661	10
R_EPCO.hru	−0.0818	−0.1	0.1	−0.53285232	0.5943813	11
R_ESCO.hru	−0.0298	−0.1	0.1	−0.51351192	0.6078285	12
V_ALPHA_BF.gw	0.1414	0	0.2	−0.42358385	0.6720582	13
R_HRU_SLP.hru	−0.6435	−0.9	−0.4	0.3507220	0.7259501	14
V_REVAPMN.gw	81.5	50	150	−0.33305690	0.7392361	15

the global sensitivity procedure shows that about fifteen parameters (Table 5) were found to be sensitive under the category of high to low sensitivity. On the global setting procedures, 1000 numbers of iterations were selected in gaining the most sensitive input parameters. The SWAT-CUP parallel processing technology fastened the simulation processes by allowing two parallels simulation processing at one time. SWAT-CUP parallel processing currently allows SUFI-2 to perform faster using parallel computing technology [26].

Some model parameters (Table 5) of the catchment were assessed for their sensitivity during the calibration process. Curve number (R_CN2), saturated hydraulic conductivity (R_SOL_K), ground water delay (days) (V_GW_DELAY), Manning's "*n*" values for overland flow (R_OV_N), and available water capacity of the soil layer (R_SOL_AWC) are the top five sensitive parameters. A similar study studied by Khalid et al. [27] sensitivity analysis in the watershed model using the SUFI-2 algorithm, in Langat River Basin, uses the absolute value of p-value and t-value to indicate the sensitivity of the parameter. The study shows that CN2.mgt, GW_Delay.gw, SLOPE.hru, SOL_AWC.sol, and SOL_K.sol are the most sensitive parameters, which is almost similar to this study. This similarity may have happened due to land use land cover and ground water similarity of the watershed because the two watersheds have similarity in watershed management and ground model parameters. Another researchers conducted by Setegn et al. [22] studied hydrological modeling on lake Tana basin watershed. Ethiopia tests the performance and feasibility of the SWAT model for prediction of stream flow. During sensitivity analysis, ESCO, CN2, ALPHA_BF (days), REVAPMN.gw (mm H_2O) (days), SOL_AWC (mm of H_2O), GW_REVAP, CH_K (mm/hr), and GWQMN.gw (mm H_2O) are the most sensitive parameters which is similar to our study due to its physical similarity of the watershed except ESCO and ALPHA_BF due to the fact that the SWAT model performs well to simulate the ground water in lake Tana basin watershed than in middle Awash sub-basin, and also, the study considers the impact of sub-basin discretization which resulted in a better representation of the hydrological processes and produced streamflow yield which had a better model efficiency in comparison to those who are not considered in basin discretization.

The increase in R_SOL_AWC.sol indicates that it reduces the surface runoff and base flow and then it reduces the water yield of the watershed. Also, decrease in R_CN2.mgt shows that the surface water reduces the watershed during simulation (Table 5). V_RCHRG_DP.gw low value (close to 0) that is obtained (Table 5) indicates the watershed, where rivers are predominantly are not recharged by aquifers. In Table 5, the prefix R indicates the existing parameter is replaced by (one plus the given value multiplied by the existing value), and V indicates that the existing value is simply replaced by the given value.

3.2. Model Calibration and Validation. Using the river discharge data obtained from the Minister of Water, Irrigation and Energy (MoWIE), the SWAT model was calibrated at a monthly time scale from 1990 to 1997 and validated from 1998 to 2003. SWAT model is considered calibrated upon propagation of parameter uncertainties of the 95% prediction uncertainties (95PPU) between the 2.5th and 97.5th percentiles covers more than X% of the measured data (i.e., 100–X) % of the data is treated as outliers. Also, the average distance between 2.5th and 97.5th prediction percentiles is less than the standard deviation of the measured data (Figure 5).

Here, PCP is the mean annual precipitation in the watershed, and L95PPU and U95PPU are lower and upper 95% prediction uncertainties, respectively.

3.3. Model Performance Evaluation. The performance of the model was evaluated using a time series plot of observed and simulated value and the statistical measures such as R^2, NSE, and PBIAS. The statistical analysis of the watershed showed good agreements between observed and simulated monthly flow (Figure 6). The p-factor is a good measure of the strength of calibration results. P-factor is the percentage of

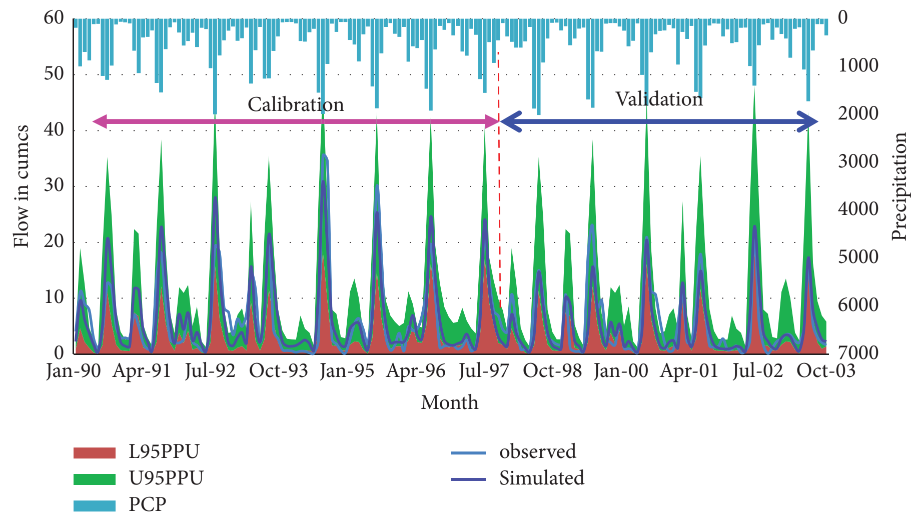

Figure 5: Model calibration and validation.

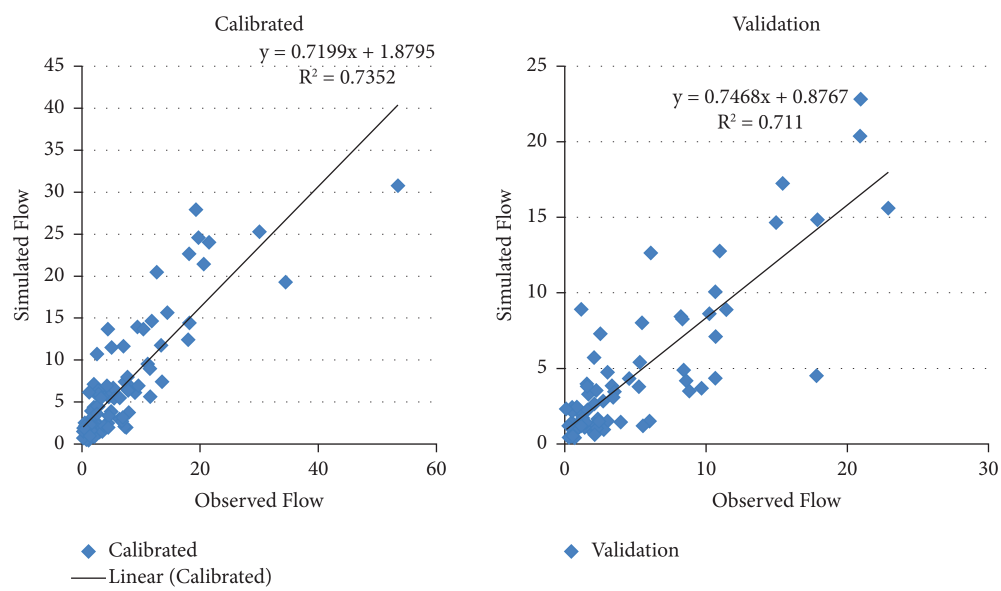

Figure 6: Scatter plot of model calibration and validation.

measured data bracketed by the 95PPU band, and its value is ranged between 0 and 1. When its value ranges between 0.7 and 1, the percentage of uncertainty is very good; thus, as shown in the (Table 6), p-factor was 0.83, 0.75, and 0.8 for Robi, Jewuha, and Ataye rivers. This value shows that the 95PPU band is within acceptable ranges in the watershed. Similar study reported by Daba [28] in the upper wash sub-basin shows that the SWAT model had a very good agreement between the simulated and observed data with NSE = 0.8 and $R^2 = 0.85$. When comparing the result of this study with the previous paper conducted by Daba [28], the performance of the model is less because in the middle of the Awash basin, there are more small-scale hydraulic structures which affect the observed flow data which are unable to obtain the data to enter the SWAT model. However, both calibration and validation results fulfilled the requirements suggested by [25, 29] for $R^2 > 0.6$ and NSE > 0.5.

3.4. Surface Water Potential of the Watershed. The result shows that (Table 7), in the study area, the surface water runoff of the watershed is 240.71 mm (12%), rainfall is 1100.56 mm, and 453.28 mm (23%) of potential evapotranspiration. From the total watershed area of 680 km^2, 163.68 million m^3 annual runoff was generated. As shown in Table 7, the highest rainfall and surface runoff are recorded in August. A similar study in lake Tana basin studied by Setegn et al. [22] hydrological modeling in the lake Tana shows that the model performs very good to model the surface water compared to the ground water in the wet season.

Table 6: Model performance.

Objective function	Calibration			Validation		
	Jewuha	Ataye	Robi	Jewuha	Ataye	Robi
R^2	0.74	0.76	0.82	0.72	0.75	0.73
NSE	0.73	0.74	0.81	0.7	0.7	0.71
PBIAS	−0.8	−3	9.1	7.9	−5	13
p-factor	0.75	0.82	0.83	0.74	0.75	0.88

Table 7: Average monthly water balance values of the watershed.

Month	Rain (mm)	SURF Q (mm)	LAT Q (mm)	Water yield (mm)	ET (mm)	PET (mm)
January	36.22	7.67	6.24	30.55	6.63	32.85
February	50.79	11.16	9.1	35.12	8.56	32.45
March	88.23	17.04	14.21	51.92	19.53	40.1
April	95.09	18.43	17.4	63.92	28.35	41.19
May	62.25	11.43	9.46	51.16	35.41	48.99
June	31.31	1.76	3.91	25.94	28.19	40.21
July	200.43	39.7	31.28	89.7	23.45	32.30
August	314.23	93.86	53.63	205.74	23.09	32.51
September	123.34	24.5	28.96	140.13	21.11	38.11
October	39.13	5.42	9.72	87.64	11.44	41.9
November	32.92	5.72	5.63	54.1	7.98	39.07
December	26.62	4.02	5.96	36.47	6.56	33.6

SURF Q is the surface runoff, LAT Q is the later flow in the watershed, ET is evapotranspiration, and PET is potential evapotranspiration.

Table 8: Weight estimated in the ungauged subwatershed.

Gauged watershed	Subwatershed	Distance	Weight
Jewuha	Gida	5505	0.82
Jewuha	Lomi	12369	0.17
Jewuha	Gundifit	5693	0.83
Robi	Ashmaq	16191	0.29
Robi	Samet	10417	0.71

Based on the previous result, we can discuss that the model can better predict the surface runoff than the groundwater due to lateral flow contribution to stream flow during April and May and from July to September season. The reason may be the soil and land use data quality and estimation of the curve number at dry moisture condition. Since the SCS curve number is a function of the soil's permeability, land use and antecedent soil water that condition the estimation of curve number at dry moisture condition (wilting point) might not be efficient in that watershed.

3.5. Weight Estimated to Transfer the Model Parameter. The model parameter which is obtained during the calibration was transferred to the ungauged subwatershed by multiplying the weight of the two watersheds. The weight was estimated by finding the centroid of the Euclidean distance between the donor watershed and the ungauged sub watersheds. Herein, only Jewuha and Robi gauged station (Table 8) was used to transfer the model parameters. However, Ataye gauged station was very far apart from the ungauged subwatershed relative to Jewuha and Robi; due to this, it was only used for the validation of spatial proximity regionalization technique.

3.6. Parameter Regionalization Using Spatial Proximity Technique. The flow from the gauged watershed to the ungauged watershed was estimated through parameter regionalization using the spatial proximity (SP) technique by Inverse Distance Weighting (IDW). For verification of the regionalization technique in the watershed, the statistical parameters of the objective function are good, and this shows that applying the spatial proximity technique to transfer the model parameters to the ungauged subwatershed to estimate was acceptable. A similar study by Gitau and Indrajeet [30] evaluated the use of regionalization as a means of obtaining SWAT model parameters for use in ungauged watersheds. The study evaluated two regionalization methods, namely, global average and regression-based estimates in terms of their predictive

Table 9: Transferred subwatersheds parameter.

Parameter name	Gida subwatershed	Lomi subwatershed	Gundifit subwatershed	Ashmaq subwatershed	Samet subwatershed
R__CN2	−0.04	−0.01	−0.05	0.05	−0.01
V__ALPHA_BF	0.13	0.11	0.13	0.09	0.12
R__ESCO	−0.05	−0.07	−0.05	−0.11	−0.07
R__EPCO	−0.05	−0.03	−0.06	0.02	−0.03
V__GW_DELAY	133.40	125.96	135.38	113.07	127.45
R__SOL_AWC	0.50	0.26	0.56	−0.15	0.31
R__OV_N	1.14	0.84	1.23	0.30	0.90
V__RCHRG_DP	0.02	0.03	0.02	0.05	0.03
R__SLSUBBSN	0.13	0.04	0.15	−0.12	0.06
V__GWQMN	4599.98	4656.68	4584.86	4754.96	4645.34
R__HRU_SLP	−0.61	−0.59	−0.62	−0.54	−0.59
V__GW_REVAP	0.18	0.17	0.18	0.15	0.17
R__SOL_Z	2.48	2.46	2.48	2.44	2.47
R__SOL_K	−0.71	−0.70	−0.71	−0.68	−0.70
R__SURLAG	8.35	6.95	8.72	4.52	7.23
V__REVAPMN	73.57	66.13	75.55	53.24	67.62

Table 10: Available surface water potential in the river from the selected locations.

Sub watershed	Coordinate location		Water availability (Mm^3)
	Long	Lat	
Gida	10.142	39.850	1.06
Lomi	10.136	39.881	8.4
Gundifit	10.093	39.912	2.34
Ashmaq	10.092	39.873	0.34
Samet	10.053	39.850	0.78

abilities using measured data from three different watersheds. The model performance which is obtained was comparable as with the observed flow during calibration.

The parameters which are estimated in (Table 9) are entered into the SWAT model and simulated to estimate the available surface water potential at the outlet of each subwatersheds in Jewuha watershed (Table 10).

4. Conclusion

To estimate the surface water potential, the SWAT model was calibrated and validated by the observed flow. During the calibration and validation of the model in the watershed, the model was performing well in all watersheds to simulate the hydrology of the watershed with R^2 0.74, 0.76, and 0.82, NSE 0.73, 0.74, and 0.81, and PBIAS −0.8, −3, and 9.1 for Jewuha, Ataye, and Robi watersheds, respectively. The model in Jewuha and Ataye overestimates and underestimates in the Robi watershed. However, a comparable measure has been taken to counterbalance these problems during a calibration process. Spatial proximity regionalization combined with the SWAT model was used to estimate the surface water potential of the ungauged subwatershed in the Jewuha watershed. The regionalized model parameters were obtained using data from the watershed situated in the vicinity of the watershed. These parameters were tested on three gauged watersheds in Jewuha, Ataye, and Robi, validating using leave-one out cross-validation techniques. Overall, the model performed well when these parameters were used on the test watersheds, thus, we are confident that the parameters would give satisfactory results when used in Jewuha ungauged subwatersheds. Also, surface water potential obtained in the ungauged subwatershed is sufficient to develop any hydraulic structures for the sake of obtaining agricultural productivity in the area or for water supply.

Data Availability

The digital elevation model (DEM) that supports the findings of this study is available at https://earthexplorer.usgs.gov and soil data are obtained from FAO website. The remaining data can be obtained from the corresponding author upon reasonable request.

Disclosure

The submitted work is original and has not been published elsewhere in any form or language (partially or in full).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Habtamu Hailu developed the study's conception and design; Manamno Beza performed the analytic calculations and performed the model simulations. Material preparation, data collection, and analysis were performed by Gezahegn Teferi. All the authors contributed to the final version of the manuscript and read and approved the final manuscript.

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