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SIMULATION OF RAINFALL-RUNOFF PROCESS USING SWAT MODEL IN BOUHAMDANE WATERSHED, ALGERIA

Abstract: The current research examines the runoff response in the Bouhamdane watershed in Algeria using the soil and water assessment tool (SWAT). The SWAT model is applied for the Bouhamane watershed, which includes three sub-watersheds and 45 Hydraulic Response Units (HRUs). To assess the ability and effectiveness of the model, one-gauge station in the basin (sabat) was chosen. Monthly discharge flow data are sourced from Algeria's National Water Resources Agency (NWRA). The soil and water assessment tool calibration uncertainty programs (SWAT-CUPs) with the sequential uncertainty fitting (SUFI 2) algorithm were used to calibrate and validate the model. The model was run from 1985 to 2004, with a calibration period between 1985 and 1994 and a validation period between 1995 and 2005. The model's runoff simulation efficiency has been improved by adjusting watershed input parameters. The SWAT model's performance was assessed statistically (coefficient of determination [R2], Nash-Sutcliffe Efficiency Coefficient [NSE], and Percent BIAS [PBIAS]). The monthly calibration R2, NSE, and PBIAS were 0.89, 0.68, and 43, respectively, and the monthly validation R2, NSE, and PBIAS were 0.78, 0.76, and 10.4, respectively. These results support that the SWAT model is an effective tool for simulating the surface runoff of the Bouhamdane watershed.

Key words: Bouhamdane watershed, SWAT, sensitivity, surface runoff

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Introduction

Estimation of surface runoff through the use of rainfall and flow modeling has an important role in planning and developing mechanisms that contribute to the management of water resources and even maintain them (Ghumman et al., 2017). The occurrence of an imbalance of these resources leads to natural disasters such as floods in the case of high precipitation and droughts in the event of a decrease in precipitation. These phenomena definitely result in the loss of achieving sustainable development (Mokhtari et al., 2023).

Hydrological modeling is important and essential for the management of water resources. However. there is a challenge in hydrologic models, where the overestimation of the flow results in the risk of floods, and the underestimation of its assessment leads to the loss of natural resources (Jimeno-Sáez et al., 2018). The type of hydrological model is chosen according to the purpose of the study and the type of available data. The scarcity of these data, which is usually considered as input to the simulation, may lead to a loss of credibility in the simulation outputs. Despite resorting to remote sensing techniques to cover the lack of this data, the simulation outputs still lack credibility in light of the lack of data. This problem was faced by many researchers in different parts of the world, especially in developing countries (El Alfy, 2016; Adane et al., 2021; Belayneh et al., 2020; Chadalawada et al., 2020; Ghumman et al., 2017; Kirchner, 2009; Kratzert et al., 2018; Nourani et al., 2009; Wu & Chau, 2011).

Hydrological models may describe the complicated surface hydrological cycle process, making them useful tools for investigating hydrological phenomena and processes (Pang et al., 2020) Hydrological models that are widely utilized include SWMM (Storm Water Management Model) (Del Giudice & Padulano, 2016), SLURP (Semi-Land Use Runoff Program), HSPF (Hydrological Simulation Program FORTRAN) (Xie et al., 2019), TOPMODEL (topography based hydrological model) (Azizian & Shokoohi, 2015), Xinanjiang model (Alazzy et al., 2015), WEPP (Watershed Erosion Prediction Project) (Saghafian et al., 2015), MIKE-SHE (MIKE-System Hydrologic European) (Rujner et al., 2018), and SWAT (Soil and Water Assessment Tool) (Arnold et al., 1998). One of these models, which has been widely used in different regions of the world, differing in terms of hydrological and climatic conditions is the SWAT model.

SWAT is a conceptual semi-distributed model that uses a huge quantity of geographical and temporal data and input parameters to estimate streamflow time series (Karki, 2020). SWAT has the ability to simulate many processes in the hydrology field like surface runoff, water quality, soil erosion, pollution loading, and nutrient and pesticide loading (Panhalkar, 2014). These characteristics made SWAT popular in its use on a large scale in the world, not to mention that many researchers have proven its ability and credibility in achieving the desired goals, which are generally related to the management of hydrological processes, whether in terms of treatment such as pollution, or in terms of protection such as floods and soil erosion. Some researchers who have proven the efficacy of SWAT in solving some problems related to the field of hydrology (Jakada & Chen, 2020; LV et al., 2020; Mahtsente et al., 2017; Ruan et al., 2017; Tasdighi et al., 2018; Tomy & Sumam, 2016; Troin et al., 2012a; Zhou et al., 2019).

Study area

The Bouhamdane watershed is located on Algeria's eastern coast. It is situated between the latitudes of 36° 07' 24" N and 36° 30' 04" N and the longitudes of 6° 47' 37" E and 7° 19' 05" E. It has a 1093 km² area and a 160 km perimeter with elevation ranging from 244 to 1289 meters (Fig. 1). Because of the periodic flooding it has experienced in recent decades, it is regarded as one of the most important watersheds in the Seybous River Basin. The Bouhamdane watershed is characterized by a sub-humid climate with average rainfall ranging from 450 to 650 mm from north to south, and annual average air temperature is 18.1 C° (10 C° in January and 27.8 C° in August) (ANRH 2008). Figure 2 shows a generally decreasing interannual distribution of precipitation in the study area over the period 1990-2012.

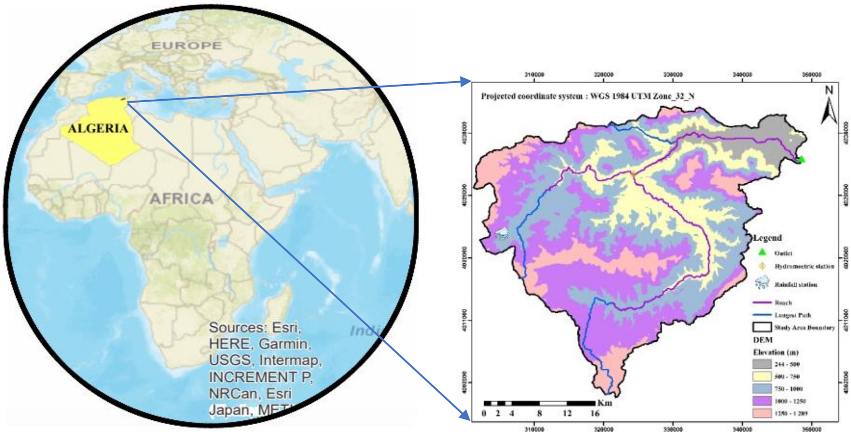

Fig. 1. Geographical location of the Bouhamdane Watershed

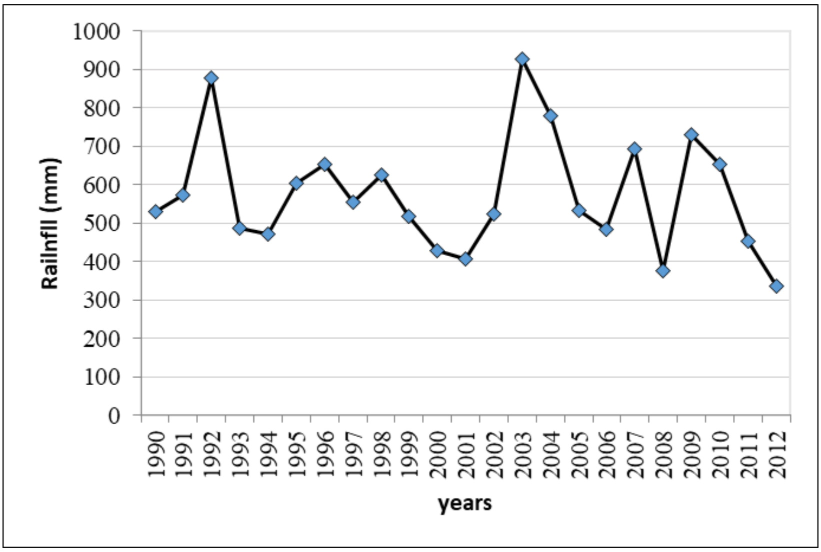

Fig. 2. Total intra-annual rainfall in Bouhamdane Watershed

Materials and methods

Data collection and analysis

Digital Elevation Model (DEM)

Digital elevation models (DEM) are used in hydrological modeling to extract the geomorphological and topographic parameters of the study catchment, some of which will be used as inputs to the simulation program. A DEM known as Shuttle Radar Topography Mission (SRTM) (Fig. 3) with a resolution of 30 meters was downloaded from the NASA site https://earthexplorer.usgs.gov/ for our study. The clarity of the digital elevation model is determined by the type of satellite and the time period in which the data were captured, as well as the algorithms used during the extraction of the satellite data (Abdelkebir et al., 2021). The GIS program processed and analyzed this satellite data to extract the previously mentioned parameters.

Land Use-Land Cover (LULC) map and Soil map

The LULC map for our study area was created using ESA Sentinel-2 imagery with a resolution of 10 meters and is a composite of land use/land cover predictions for nine classes for each year from 2017 to 2021. In our case we extracted six classifications as follows: trees, crops, built area, bare ground, rangeland, and water body. Google Earth Pro was used to verify the validity of the extracted map and correct what could be corrected in order to increase the value and credibility of the extracted map. The LULC of the Bouhamdane watershed is shown in Figure 1, while the coding of the latter and the area of each classification of the total area are shown in Table 1.

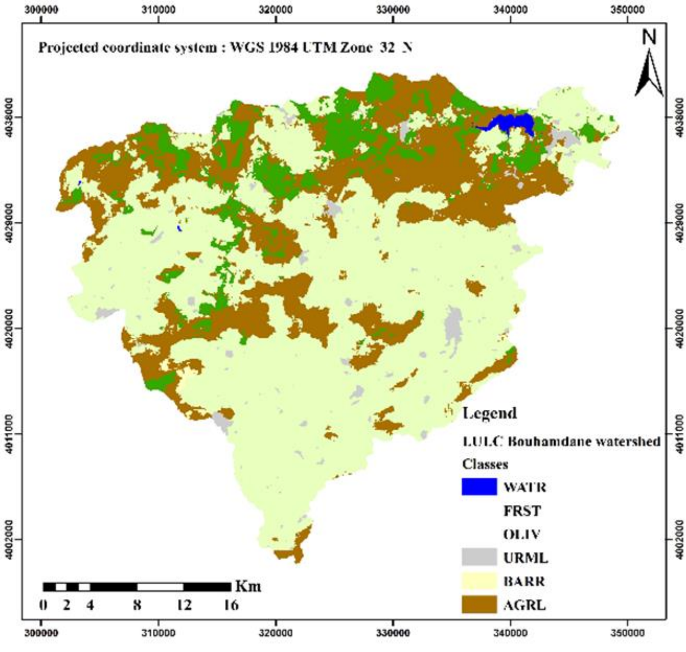

Fig. 3. LULC of the Bouhamdane watershed

Tab. 1. LULC distributions of the Bouhamdane watershed

LULC classification	Coding	Partial area (km²)	Percentage of Total area (%)	Total area (km²)
Water Body	WATR	4.81	0.44	1093
Forest-Mixed	FRST	99.14	9.07	
Olives	OLIV	670.77	61.37	
Urban Residential-Med/Low Density	URML	26.67	2.44	
Barren	BARR	4.59	0.42	
Agricultural Land-Generic	AGRL	285.93	26.16	

The World Food Organization (FAO) also provided a soil map, which can be found at https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/, that revealed the watershed under study is made up of two types of soil: loam and clay loam (Fig. 3). Curve Number must be calculated by combining the land use map and the soil map, an important parameter in the concerned model's rainfall-to-runoff transfer function (CN). The (CN) is highlighted, as well as other parameters such as lag-time, impermeability, and initial abstraction because it has an immediate impact on simulation output (flow and volume). Table 2 shows the coding and type of soil used in the SWAT model database.

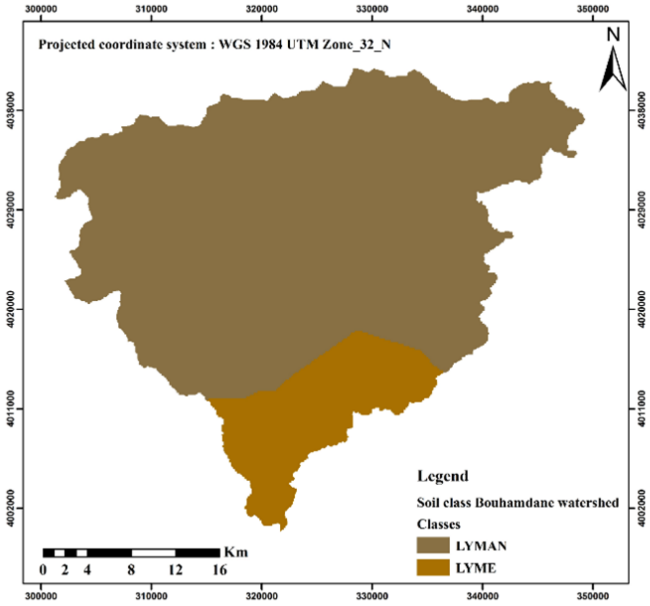

Fig. 4. Soil map of the Bouhamdane watershed

Tab. 2. Soil distributions of the Bouhamdane watershed

Soil classification	Coding	Partial area (km²)	Percentage of Total area (%)	Total area (km²)
Clay Loam	Lyme	155.64	14.24	1093
Loam	Lyman	936.37	85.67	

Weather data

Rainfall data were obtained from the station known as Ben Badiss, which is located at (6°49'49"E; 36°20'11"N) with an altitude of 807 meters and at a distance of 18 km from the flow measurement station, while other climatic data, i.e. wind. solar radiation, minimum and maximum temperatures, and relative humidity because it was not possible to obtain it. A Remote sensing (Rs) approach was used to collect it via the following link provided by the official website of the SWAT model https://swat.tamu.edu/data/cfsr for a period of 21 years with monthly time step, and meteorological data were collected and used to configure the ArcSWAT weather module.

Streamflow data

The flow monitoring station known as Sebbat is located at (7°22'6"E; 36°5'9"N) with an altitude of 518 meters and at a distance of 23 km from the outfall of the study area. Despite the fact that the station has been in operation since 1973, the actual recording of flow data began in 1985 and continued until 2005, which is what we focused on in our research.

Model development

SWAT is a semi-physical, semi-distributed model. SWAT considers the heterogeneity of a watershed by dividing it into sub-watersheds based on the river network and topography; sub-watersheds are then divided into hydrologic response units (HRUs), which classifies land areas based on their soil, land cover, and slope combinations. SWAT uses water balance to simulate the hydrologic cycle. Climate variables such as daily precipitation and maximum and minimum air temperature influence this. (Jimeno-Sáez et al., 2018) described the water balance equation used:

$$\text{SWt}=\text{SWinit}+\sum_{i=1}^{i}(R_{day}\,(\text{i})-Q_{surf}\,(\text{i})-E_{a}\,(\text{i})-E_{seep}\,(\text{i})-Q_{gw}\,(\text{i})) \quad (1)$$

Where: SWt is the final soil water content (mm). SWinit is the initial soil water content (mm). t is the time in days. Rday(i) is the precipitation on day i (mm). Qsurf(i) is the surface runoff (mm). Ea(i) is the evapotranspiration (mm). Wseep(i) is the percolation (mm) and Ggw(i) is the amount of baseflow (mm).

The SWAT estimates surface runoff using the soil conservation system (SCS, now NRCS) and the Green and Ampt infiltration methods (Kebede, 2019). The surface runoff is calculated using the SCS method. which is an empirical method. The SCS method is primarily determined by land use/land cover and soil hydrological groups:

$$\text{Qsur}=\frac{(R_{day}-0.2S)^2}{R+0.8S} \quad (2)$$

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

Model Setup and Data Sets

In the Bouhamdane watershed, the SWAT model requires physically based inputs such as hydro-meteorological data, topography, soil properties, and land-use/land-cover. For the simulation of the SWAT model, data on monthly precipitation (mm), maximum and minimum temperatures (C), relative humidity, solar radiation, and wind speed were collected from 1985 to 2005.

DEMs with a mesh size of 30 m were used to determine watershed and sub-watershed boundaries. Soil maps were used to characterize each soil type based on information such as soil texture, hydraulic conductivity, and available water content, among other things. One of the most important factors governing runoff, evapotranspiration, sediment deposition, and soil erosion is land cover (Sime et al., 2020).

SWAT divided watersheds into HRUs using a combination of these three data sets (DEM, soil maps, and land cover maps) and five slope categories 0-2%, 2-5%, and 5-15%. Finally, the study region was divided into three sub-watersheds and 45 HRUs.

Model Sensitivity analysis

Sensitivity analysis investigates how changes in parameter values affect the overall change in the model's output. This can be accomplished through simple sensitivity analysis, in which only one parameter is changed, or through more complex arrangements that investigate the relationships between multiple parameters. As a result, a sensitivity analysis for the SWAT model was performed on the entire data set (1985 -2005). The model was then calibrated using the most sensitive parameters.

Using sensitivity analysis, we were able to identify the most influential parameters in governing streamflow. This allowed us to calculate the rate of change in model output as a function of model parameter changes. The SUFI-2 algorithm was used to automatically perform sensitivity analysis and SWAT model parameterization in SWAT-CUP (Atkinson et al., 2010). Using sensitivity analysis, we were able to identify the most influential parameters in governing streamflow. This allowed us to calculate the rate of change in model output as a function of model parameter changes. The parameters were calibrated using observed daily discharge; the process involves adjusting them so that the daily simulations match the observations as closely as possible.

Model Performance

To determine the dependability of simulation outputs such as water yield, the model's performance must be evaluated. This is accomplished in two ways. First, the simulated and observed discharges are visually compared. Second, statistical parameters such as the Nash coefficient (NHSE), NSE (Nash-Sutcliffe efficiency), R2 (coefficient of determination), and percent bias (PBIAS) are calculated. This procedure runs concurrently with the procedure for investigating the most sensitive parameters in the simulation output. The latter, namely NSE, R2 and PBIAS, are three of the most commonly used performance indicators for hydrological models:

$$\text{NSE}=1-\frac{\sum_{i=1}^{N}(Q_{i.Sim}-Q_{i.Obs})^2}{\sum_{i=1}^{N}(Q_{i.Obs}-\bar{Q}_{Obs})^2} \quad (4)$$

$$\text{R}^2=\frac{\sum_{i=1}^{N}(Q_{i.Obs}-\bar{Q}_{Obs})(Q_{i.Sim}-\bar{Q}_{Sim})}{\sqrt{\sum_{i=1}^{N}(Q_{i.Obs}-\bar{Q}_{Obs})^2(Q_{i.Sim}-\bar{Q}_{Sim})^2}} \quad (5)$$

$$\text{PIBAS}=\frac{\sum_{i=1}^{n}(Q_{i.Obs}-Q_{i.Sim}).100}{\sum_{1=1}^{n}Q_{i.Obs}} \quad (6)$$

Where:

Qi.Obs is the observed flow;
Qi.Sim is the simulated flow at time t = I;

Q̄.Obs is the average observed discharge;
N is the number of observations;

NSE measures how well the observed versus simulated data plot fits the 1:1 line and is recommended because it is widely used and provides detailed information on reported values [51]. The degree of collinearity between simulated and measured data is described by R2. PBIAS measures the average tendency of simulated data to be larger or smaller than observed data and can clearly indicate poor model performance. The best performance for NSE and R2 is 1, while the best performance for PBIAS is 0. To judge the performance of the model used in our research, the values recorded in Table 3 must be respected.

Tab. 3. Model assessment criterion (Karki 2020)

Performance Rating	NSE	PBIAS (%)
Very good	$NSE \geq 0.7$	$\lvert PBIAS \rvert \leq 25$
Good	$0.5 \leq NSE < 0.7$	$25 < \lvert PBIAS \rvert \leq 50$
Satisfactory	$0.3 \leq NSE < 0.5$	$50 < \lvert PBIAS \rvert \leq 70$
Unsatisfactory	$NSE < 0.3$	$\lvert PBIAS \rvert > 70$

Result and discussion

Sensitivity analysis

The sensitivity analysis phase is considered essential before starting the calibration and validation procedures; the calibrated parameters and ranges for Bouhamdane watershed are shown in Table 4. To compensate for the excess runoff flow, the CN2 parameter range was reduced. The ALPHA BF parameter was increased to account for the low groundwater baseflow, while the GW DELAY.gw parameter was decreased. Groundwater delay time (in days) has been reduced. As a result, these calibrated ranges were discovered to be the best for simulating observed runoff.

Tab. 4. Calibration and validation parameters for discharge flow

Parameter_Name	Fitted_Value	Min_value	Max_value
1:R__CN2.mgt	-0.17	-0.20	0.20
2:V__ALPHA_BF.gw	0.09	0.00	1.00
3:V__GW_DELAY.gw	425.50	30.00	450.00

Discharge flow calibration

Model calibration is used to reduce model output uncertainty. The streamflow was calibrated using a monthly average. Ten years of measured streamflow data (1985-1994) were used. Three sensitive parameters were chosen for model calibration and validation based on the sensitivity analysis. Table 3 shows the values and intervals of the fixed parameters after manual and automatic calibration. During model calibration, R2, NSE, and PBIAS values of 0.89, 0.68, and 43, respectively, were obtained, indicating excellent model performance. The monthly average calibrated discharge flow is depicted in Figure 5.

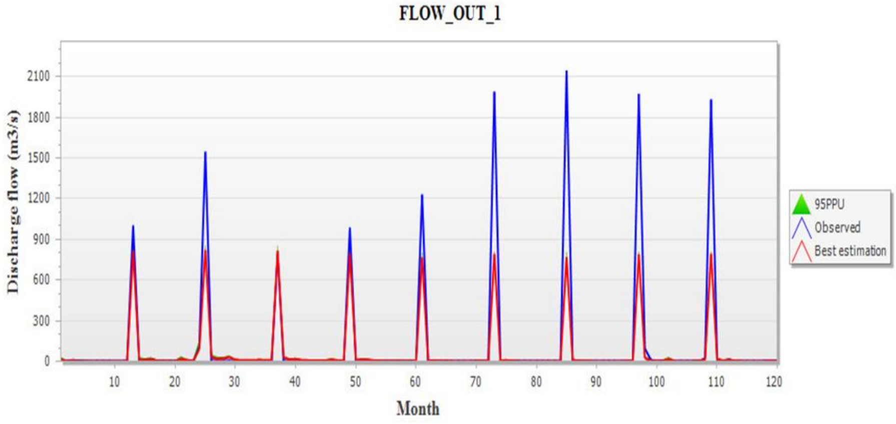

Fig. 5. Calibration of monthly average discharge flow

Discharge flow validation

Validation follows the same steps as calibration in terms of procedure, and no changes to the model were made during validation. The model was validated using discharge flow data from 1995 to 2005. The discharge validation yielded R2, NSE, and PBIAS values of 0.78, 0.76, and 10.4%, indicating an excellent relationship between the observed and simulated discharge flow. Figure 6 depicts the validation of monthly average discharge flow.

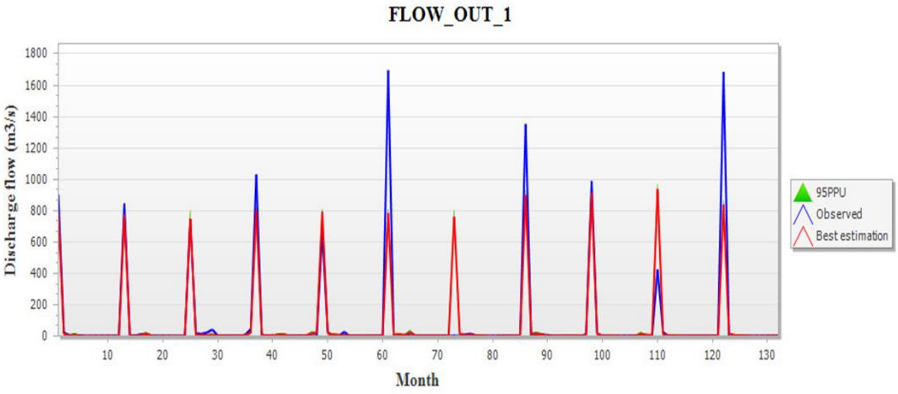

Fig. 6. Validation of monthly average discharge flow

Calibration and validation statistics

After the visual comparison between the observed flow discharge data and simulated discharge flow data at the calibration and validation phase, the statistical parameters, i.e., R2, NSE, and PBIAS were calculated, which depend mainly on the comparison between the simulation data and observation data outputs of our study. In our study, we dealt with flow discharge as a basic output. The three statistical parameters were evaluated by relying on the data of Table 3. The values obtained in Table 5 show that the performance of the model is better and more effective in the validation phase extending from 1995 to

2005 than it was in the calibration phase extending from 1985 to 1994, where the values of R2, NSE, and PBIAS were 0.89, 0.68, and 43%, respectively and in the validation phase were 0.78, 0.76, and 10.4%.

Tab. 5. Calibration and validation parameter statistics

Statistical parameter	R	NSE	PBIAS (%)
Calibration phase 1985_1994	0.89	0.68	43
Validation phase 1985_1994	0.78	0.76	10.4

The results obtained demonstrate the ability and effectiveness of the model to achieve the desired goals. Although comparison with previous studies on watersheds in different parts of the world showed similar trends, the study by Jain et al. (2010) found that the coefficients of determination (R2) for daily and monthly runoff during calibration and validation were 0.53 and 0.90, respectively. 0.33 and 0.62 for the period, and Dessu and Melesse (2012) found the results of calibration and validation (Nash-Sutcliff efficiency, coefficient of determination) to be (0. 68, 0.69) and (0.43, 0.44). (Troin et al., 2012) The calibration yields similar Nash - Sutcliffe efficiencies (NSE) on the monthly time scale for the two periods 1973 to 2004 (wet NSE = 0.86; dry NSE = 0.90) . (Fu et al., 2014) tested SWAT-CS using the Harp Lake watershed dataset. Over 30 years, the best Nash - Sutcliffe efficiency (NSE) results for daily flow calibration, daily flow verification, and SWE were 0.60, 0.65, and 0.87, respectively. Yaduvanshi et al. (2018) analyzed the runoff response during extreme rainfall events in the Subarnarekha river basin, India. The Nash-Sutcliffe efficiency (NSE) was 0.68 during daily scale calibration and 0.62 during validation. Zakizadeh et al. (2020) evaluated the performance of two differently structured SWAT and ANN models in simulating rainfall runoff in an urban watershed. The results of this study show that the performance of the artificial neural network is suitable for predicting the maximum and minimum flow values (R 2 = 0.75, NSE = 0.74), while the performance of the SWAT model is also suitable and very good for one performance in the management study (R 2 = 0.66, NSE = 0.65); they say that it is better to use the SWAT model when studying flow trends. Zorratipour et al. (2021) showed that the Nash - Sutcliffe calibration (2006 to 2012) and validation (2013) values between simulated and observed values are 0.71 and 0.74, respectively. Jaberzadeh et al. (2022), used coefficient of determination (R 2) and Nash - Sutcliffe efficiency (NSE) to simulate watershed flow. R2; NSE and NSE of the SWAT model are 0.75 and 0.78 (calibration) and 0.59 and 0.72 (validation), respectively. Aqnouy et al. (2023) showed that the Swat model performed well in two periods (2004-2008) and (2009-2011); (NSE = 0.76 at calibration) and improved at validation (NSE = 0.84), respectively. Based on the results of this study, SWAT can be reliably used to investigate runoff-related problems in watersheds similar to Bouhamdane.

Conclusions and recommendations

Runoff simulation is critical for managing water resources in humid and sub-humid regions. The SWAT physical model was used to simulate the monthly discharge flow in the Bouhamdane watershed, one of the most important parts of the Seybous Basin, Algeria. The study area is characterized by a semi-humid climate covering an area of 1093 km^2, perimeter of 160 km, average slope of 25 %, and average precipitation ranging from 450 mm to 650 mm. The watershed of Bouhamdane is divided into three sub-watersheds, each with its own climate data and channel characteristics. After that, 45 hydrological response units (HRUs) are defined for each of these sub-watersheds, which are areas with similar land use, soil, and slope characteristics. The model's performance is rated as good for the calibration phase (1985-1994), with R2, NSE, and PBIAS values of 0.89, 0.68, and 43%, respectively, and very good for the validation phase (1995-2005), with R2, NSE, and PBIAS values of 0.78, 0.76, and 10.4%, respectively. This procedure was carried out at the Sabat hydrometric station level. Although the SWAT model achieved acceptable performance in both phases, this performance was at the level of the monthly flow. Therefore, as an important step, we recommend decision makers develop strategies and new approaches to cover the river basins with more climate monitoring stations. Because of this last deficiency, the use of the SWAT model is limited in Algeria in particular and in underdeveloped countries in general. SWAT can be a valuable tool for integrated basin management in terms of water flow and availability, particularly in agriculturally dominated basins. This will increase the potential for irrigation and better agricultural management practices, improving people's socioeconomic lives both directly and indirectly.

Conflicts of Interest: The authors declare no conflict of interest.

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