RESEARCH ARTICLE

Sensitivity analysis of a GIS-based model: A case study of a large semi-arid catchment

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Abstract Water resource and hydrologic modeling studies are intrinsically related to spatial processes of hydrologic cycle. Due to generally sparse data, and high rainfall variability, the accurate prediction of water availability in complex semi-arid catchment depends to a great extent on how well spatial input data describe realistically the relevant characteristics. The Geographic Information System (GIS) provides the framework within which spatially distributed data are collected and used to prepare model input files. Despite significant recent developments in distributed hydrologic modeling, the over-parameterization is usually a critical issue that can complicate calibration process. Sensitivity analysis methods reducing the number of parameters to be adjusted during calibration are important for simplifying the use of these models. The objective of this paper is to perform a sensitivity analysis for flow in a semi-arid catchment (1,491 km2), located in northwestern of Tunisia, using the Soil and Water Assessment Tool (SWAT) model. The simulation results revealed that among eight selected parameters, curve number (CN2), soil evaporation compensation factor (ESCO), soil available water capacity (SOL_AWC) and threshold depth of water in the shallow aquifer required for return flow (GWQMN) were found to be the most sensitive parameters. Calibration of hydrology, facilitated by the sensitivity analysis, was performed for the period 2001 through 2003. Results of calibration showed that the model accurately predict runoff and performed well with a monthly Nash Sutcliffe efficiency (NSE) of 0,78, a coefficient of determination (R^2) of 0,85 and a percent of bias (PBIAS) equal to −13,22 %.

Keywords GIS-based hydrological model · Sensitivity analysis · Runoff calibration · SWAT

Introduction

Located in northern Africa along the Mediterranean Sea, Tunisia is a country dominated by a semi-arid climate. In this region, hydrological processes are largely variable both in time and space due to the high variability of rainfall regime characterized with long dry periods followed by heavy bursts of intensive rainfall. To the utmost extent, climate condition, particularly rainfall is the key factor to determine runoff characteristics (Liu 2004). However, in past decades, hydrological processes have also dramatically changed due to human activities, such as, soil and water conservation works, dams buildings and land use changes. The Sarrath river catchment (1,491 km²), located in the north-west of Tunisia and subject for a future dam, is a typical Mediterranean semi-arid basin exposed to a high variability of rainfall, annual means for the period 1985–2008 varies between 195 mm and 610 mm.

Over the past two decades, hydrologic models have benefited from significant advances that improved the understanding and the interpretation of complicated hydrologic systems. Since limited hydrological information is available in semi arid watersheds, adequate hydrological assessment tools should be flexible to deal with poor quantity and quality input data (Pilgrim et al. 1988). One approach to assisting sustainable water resource development and management within river basins is the use of mathematical modeling of watershed hydrology (Singh and Woolhiser 2002). In recent

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years, GIS has made an enormous contribution in the field of water resources engineering and has shown to be a very useful tool for manipulation, processing, visualization and analysis of spatially referenced information (Westervelt 2002), therefore, the integration between GIS and watershed models became a necessity.

A growing number of semi-distributed and distributed hydrological models coupled with Geographic Information Systems were developed in the last years such as AGNPS (Agricultural None Point Source model) (Young et al. 1989), WEPP (Water Erosion Prediction Project) (Laflen et al. 1991), HSPF (Hydrologic Simulation Program in FORTRAN website) (Bicknell et al. 1997), SWAT (Soil and Water Assessment Tool) (Arnold et al. 1998), SWIM (Soil and Water Integrated Model) (Krysanova et al. 2000) and J2000 (Krause 2002), many of these models were applied for runoff, water quality and soil loss modeling (Morgan 2001; Santhi et al. 2006; Abbaspour et al. 2007). Among the foregoing models, the SWAT model was chosen for this study, because it has gained international recognition as is evidenced by a large number of applications and has shown the success of hydrologic simulation with scarce data, and because it is especially applicable for large complex watersheds (Neitsch et al. 2002). However, SWAT model presented also some limitations inherent in distributed hydrological models, as its sensitivity to the DEM resolution (Chaplot 2005; Chaubey et al. 2005; Lin et al. 2010), to subbasin size (Jha et al. 2004; Arabi et al. 2006; Mosbahi et al. 2009; Gong et al. 2010), to spatial distribution of rainfall (Chaplot et al. 2005; Cho et al. 2009; Gao et al. 2012) and to input parameters (Spruill et al. 2000; Francos et al. 2003; Van Griensven et al. 2006; Chahinian et al. 2011; Fiseha et al. 2013; Sellami et al. 2013; Aouissi et al. 2014).

Since, we are working on a complex semi-arid catchment and the SWAT model includes a large number of input parameters describing the different hydrological conditions across the basin, sensitivity analysis was conducted for this case of study on model input parameters that cannot be easily optimized. Sensitivity analysis methods are needed for reducing parameters to be adjusted during calibration and are important for simplifying the use of model (Van Griensven et al. 2002). These methods identify parameters that do or do not have a significant influence on model simulations of real world observations for specific catchments (Van Griensven et al. 2006). Classification of the existing methods refers to the way that the parameters are treated (Saltelli et al. 2000), numerous sensitivity analyses have been reported in the SWAT literature, which provide valuable insights regarding which input parameters have the greatest impact on SWAT output (Gassman et al. 2007):

Spruill et al. (2000) performed a manual sensitivity analysis of 15 SWAT input parameters for a 5.5 km^2 watershed in Kentucky, USA. The approach adopted by Francos et al. (2003) in the Ouse watershed (3.5 km^2) in the U.K, consists

of two-step sensitivity analysis: (1) "Morris" screening procedure that is based on the one factor at a time (OAT) design, and (2) the use of a Fourier amplitude sensitivity test (FAST) method.

Van Griensven et al. (2006) used the Latin hypercube (LH) OAT sampling method for determining the most sensitive parameters for the Upper North Bosque River catchment (932 km2) in Texas and the Sandusky River catchment (3,240 km^2) in Ohio. The sensitivity analysis was assessed for the total amount of water, sediments, nitrogen and phosphorus.

Chahinian et al. (2011) have calibrated 14 SWAT model parameters for modeling flow and nutrient emission processes. They found that 12 sensitive parameters are directly and indirectly related to flow simulation.

Fiseha et al. 2013 have identified 18 parameters for flow prediction in The Upper Tiber River Basin, located in central Italy (4,145 km^2). They used for sensitivity analysis, the manual approach and Latin hypercube (LH) OAT approach. On the basis of their relative indexes, only the top ten most sensitive parameters were considered for further use in the model calibration and validation processes.

Sellami et al. (2013) have tested the SWAT model to simulate the flow for two small Mediterranean catchments (the Vène and the Pallas) in southern France. The sensitivity analysis was conducted using the LH-OAT method, 10 sensitive SWAT parameters are identified for each of the Pallas and the Vène catchment. The identified sensitive parameters are the same for both cases but they differ in their rank.

In Tunisia, Aouissi et al. (2014) have applied the SWAT model in Joumine basin (418 km^2) for stream discharge predictions. They have selected 17 sensitive parameters, the 7 most sensitive were used for the hydrological calibration process.

In this study, the SWAT model was applied in the Sarrath catchment to assess flow. The model was calibrated using the observed flow at the outlet of the basin for the period (2001/2002–2003/2004). The objective of this paper is to perform a sensitivity analysis of hydrological input data taking into account limited data availability in such context.

Materials and methods

A GIS-based hydrological model

SWAT is a GIS-linked basin scale model capable of simulating, over long periods, the impact of land management practices on water, sediment, and agricultural chemical loads in large complex watersheds with varying soils, land use, and management conditions. It is a physically based model supported by the United States Department of Agriculture-Agricultural Research Service (USDA-ARS)

(Arnold et al. 1998); it operates on daily time-steps to produce daily, monthly and annual results. The SWAT model is embedded within Geographic Information System (GIS) that allows the discretization of watershed into sub-watersheds which streams are routed. The sub-watershed is further subdivided into Hydrological Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics.

The model requires a number of basin specific input data encompassing different components like, weather, hydrology, soil temperature, plant growth, nutrients, pesticides, and land management. The hydrological component of SWAT is based on the following water balance equation (Eq. (1)):

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - Q_{suf} - ET - W_{seep} - Q_{gw} \right)_i \qquad (1)$$

Where:

SW_t	the final soil water content (mm)
SW_0	the initial soil water content on day I (mm)
T	the time (days)
R_{day}	the precipitation on day i (mm)
Q_{surf}	the surface runoff on day i (mm)
ET	the evapotranspiration on day i (mm)
W_{seep}	the amount of water entering the vadose zone from the soil profile on day i (soil interflow) (mm)
Q_{gw}	the amount of return flow on day i (mm).

Soil water processes include infiltration, runoff, evaporation, plant uptake, lateral flow, and percolation to lower layers, the details of which can be found in SWAT theoretical document (Neitsch et al. 2002). Thus, Surface runoff is estimated using the SCS curve number equation (USDA-SCS 1972):

$$Q = \frac{(R - 0,2S)^2}{R + 0,8S} \ , \ R > 0,2S$$
$$Q = 0.0 \ , \ R \leq 0, 2S \qquad (2)$$

Where Q is the daily surface runoff (millimeters), R is the daily rainfall (millimeters) and S is a retention parameter. The retention parameter S, varies among watersheds because soils, land use, management, and slope all vary, and with time because of changes in soil water content. The parameter S is related to CN by the SCS equation:

$$S = 254 \left(\frac{100}{CN} \right) - 1 \qquad (3)$$

The peak runoff rate is the maximum runoff rate that occurs with a given rainfall event. SWAT calculates the peak runoff rate with a modified rational method (Neitsch et al. 2005):

$$q_{peak} = \frac{Qsurf \times \alpha \times Area}{3.6 \times t_c} \qquad (4)$$

Where q_{peak} is the peak runoff rate (m3/s), Q_{surf} is the surface runoff (mm), Area is the HRU area (km^2), t_{conc} is the time of concentration (h), and α is the fraction of daily rainfall that occurs during the time of concentration.

Estimation of percolation is conducted by using a storage routing technique combined with a crack flow model (Arnold et al. 1995). This is based on the assumption that percolation occurs when the field capacity of the soil is exceeded and if the layer below is unsaturated. The model assumes that the potential evapotranspiration can be estimated in SWAT using three options: Priestley-Taylor, Penman-Monteith, and Hargreaves methods. In this study, the Hargreaves equation (Hargreaves and Samani 1985) based on daily temperatures was used. The flow routing in the river channels is computed using the variable storage coefficient method (Williams and Berndt 1977). Soil erosion and sediment caused by rainfall and runoff are estimated with the Modified Universal Soil Loss Equation (MUSLE) for each sub-catchment (Williams and Berndt 1977).

Location of the Sarrath Catchment

The Sarrath river basin is a part of the large Tunisian Medjerda catchment (24,000 km2), the principal watercourse and water supply for more than half of the Tunisian population (Bouraoui et al. 2005). This transboundary catchment is located in Northwestern of Tunisia (Fig. 1); its river originates in the semi-arid Atlas Mountains of eastern Algeria and drains an area of 1,491 km^2. Topography is ranging from moderately alluvial valleys along the major channels to important hilly uplands where elevation ranges from 573 to 1,350 m.

The area under study lies in sub-humid to semi-arid climate with hot summers and mild winters, It is characterized with an extreme variability in annual and inter-annual rainfall. The rainy season extends from September to May with intense precipitations in September, October, and February. The mean annual rainfall for the period 2001–2008 is 409 mm, average temperature ranges from 4 to 28 °C. July is the hottest month with maximum monthly temperatures values between 19 and 28 °C. The coldest month is usually January with maximum monthly temperatures between 4 and 10 °C. Most of the catchment area is poorly covered with vegetation with the exception of some degraded forests and dense brushes on hilly areas. Major land covers in the catchment are corn representing 31 % of the total area, range brushes (27 %) and forest (18 %). The major soil types found in the Sarrath

Fig. 1 Location of the sarrath
river catchment
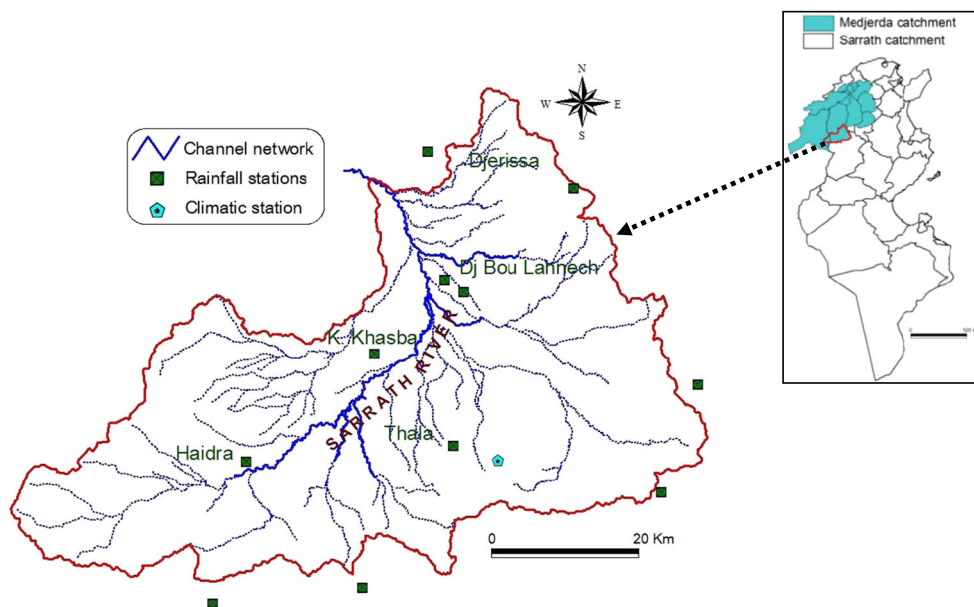
river catchment include calcareous brown soils (32 %), complex soils (30 %) and undeveloped soils (29 %).

Data generation

GIS data layers

The SWAT model interface uses ArcGIS as the platform for inputting spatial data sets. The interface required a number of data layers including a Digital Elevation Model (DEM), a soil map and a land use map.

Digital Elevation Model is frequently a crucial source of information for GIS hydrological modeling. The DEM is used to define sub-catchment boundaries and a stream network. The SWAT model interface has an ArcGIS script that automates the process to define sub-catchment boundaries, stream network and slope factors. The DEM of the Sarrath catchment, presented in Fig. 2, was generated using contours lines created for the purpose of this study from national topographic maps with a scale of 1:50,000. The cell resolution with an interval of 50 m was used to generate the derived physical characteristics of the catchment.

Landuse map is a critical input for SWAT model. Land use/land cover map was obtained from the Soil and Water Conservation Agency using remote sensing data of Landsat Thematic Mapper images (Fig. 3). This database covers only the Tunisian part of the basin. The Algerian part of the basin was completed based on maps at the scale of 1/100,000 and validated with Google maps.

Soil plays an important role in modeling various hydrological processes; soil layer was produced from soil maps

(Fig. 4). Soil properties like texture, hydraulic conductivity, bulk density and available water content were obtained from Soil Database created by the Soil and Agriculture Land Authority and completed for the transboundary part from geologic maps at the scale of 1/100,000.

Weather data

SWAT requires daily meteorological data that could either be read from a measured data set or be generated by the weather generator of model. A hydro-meteorological observation network was set up within and around the Sarrath catchment. Daily precipitation time series were gathered from eleven rain gauge stations for the period 2001–2008 from the National Water Authority. Daily maximum and minimum temperatures were collected for the same period, for Thala weather station, from the National Meteorological Institute. The river
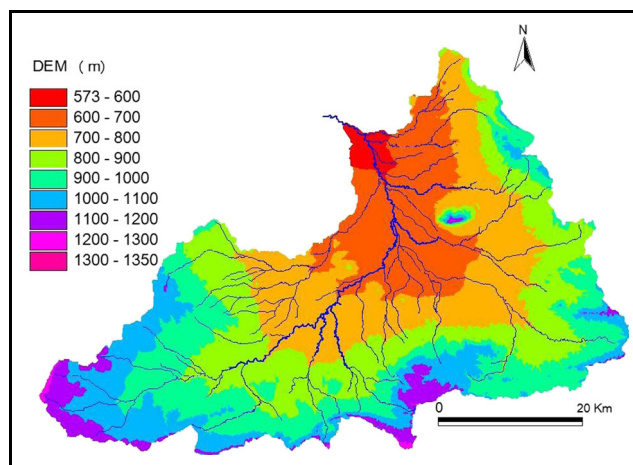

Fig. 2 Digital elevation model (dem) of the sarrath catchment
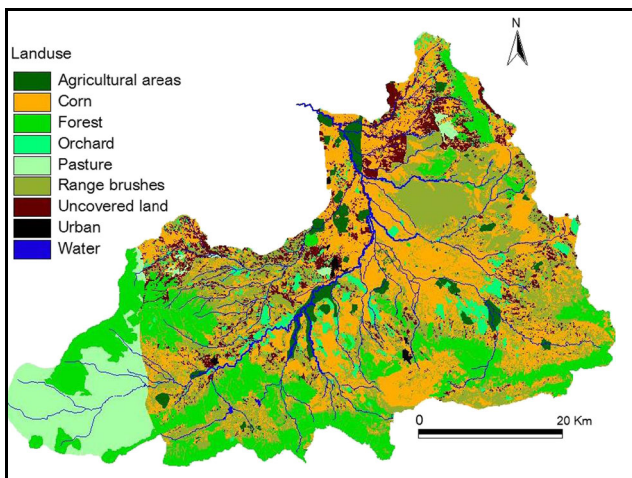
Fig. 3 Landuse map of the sarrath catchment

discharges of the Sarrath catchment outlet were obtained from the National Water Authority. They were used for comparing observed and simulated values in calibration and validation periods.

Model setup

The ArcSWAT interface was used to delineate a catchment into sub-catchments based on a DEM, with a resolution of 50 m, and drainage network. This tool uses and expands ArcGIS Spatial Analyst function to perform watershed delineation (Neitsch et al. 2002).

In the present study, ArcSWAT calculated 27 sub-catchments as shown in Fig. 5. Based on the formation of unique combinations of slope, land use and soil type, the sub-catchments were further divided into 273 HRUs.

Subdividing the areas into hydrologic response units enables the model to reflect the evapotranspiration and other hydrologic conditions for different land cover and soils. One
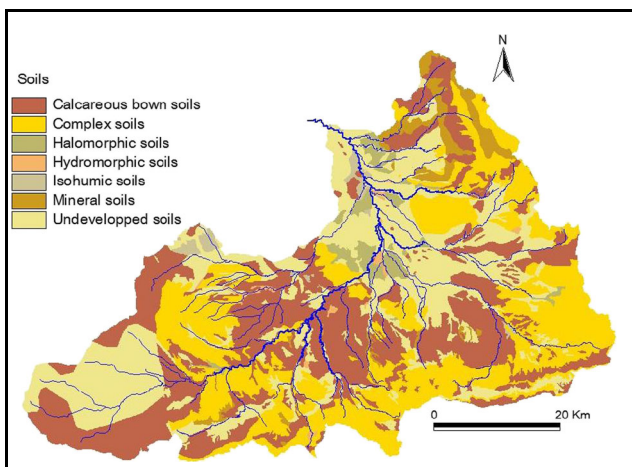

Fig. 4 Soil map of the sarrath catchment

of the main sets of input for simulating the hydrological processes in SWAT is climate data, the ArcSWAT interface prepared precipitation and weather data in a suitable format. At this stage the model is ready to run and simulation to proceed. Output loads were calculated separately from each HRU and routed to obtain the total runoff for the catchment; this increases accuracy and gives a much better of the water balance.

Model performance

The statistical indicators used for evaluating model performance are, the Nash-Sutcliffe Efficiency (NSE); Coefficient of Determination (R^2) and the percent bias (PBIAS) (Table 1).

Nash-Sutcliffe coefficient measures the efficiency of the model by relating the goodness-of-fit of the model to the variance of the measured data. Perfect agreement between predicted and observed data results in NSE=1.

The R^2 coefficient describes the proportion of the total variance in the measured data that can be explained by the model. Lastly, the PBIAS is a measurement of the tendency of a simulated value to be smaller or larger than its observed counterpart (Moriasi et al. 2007).

Results

Sensitivity analysis

Given that all SWAT input parameters do not have the same weight on model outputs, sensitivity analysis prior to the calibration process, is the investigation of the relationship between model inputs and outputs, it aims to determine the parameters whose variation leads to significant changes in model results and on which more attention should be paid during calibration (Francos et al. 2003; Schuol and Abbaspour 2007). It speeds up the optimization process by concentrating on finding the optimum values for a limited number of parameters that govern the model.

Sensitivity analysis was carried out for flow on a monthly basis, over 8 years (2000/2001 to 2007/2008). The first year was used as a warm-up period for the model. The provision of the warming up period is to initialize unknown variables such as moisture content.

In this research, since we are working on a complex semi-arid catchment, with empirical parameters, the sensitivity analysis was carried out by changing manually one parameter at a time. Several model runs were executed for each input parameter with a range of values, keeping simulation options and other parameters values constant.

Fig. 5 sub-catchments delineation in the study area
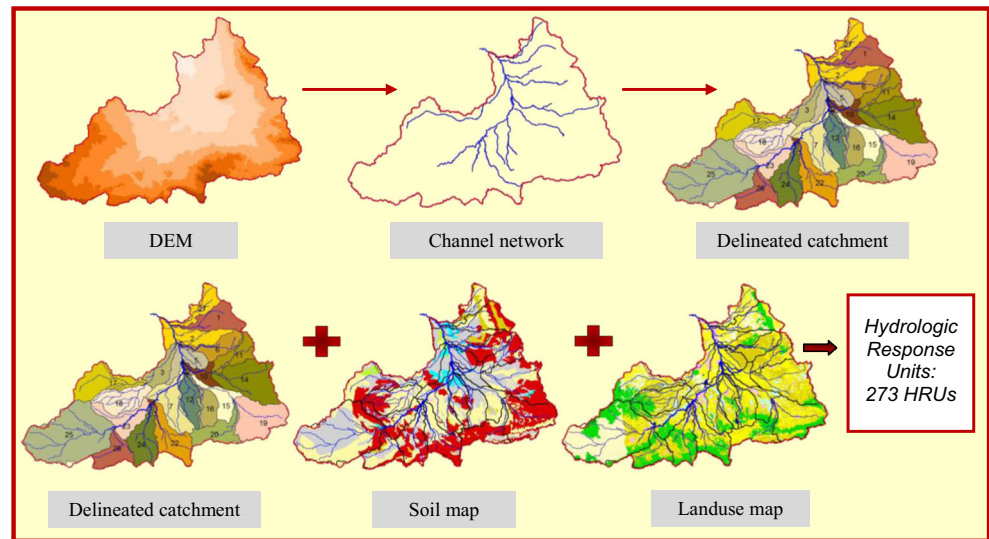
Manipulation of the sensitive parameters values was assessed within the allowable range (Table 2).

A total of eight model input parameters were selected for sensitivity analysis based on extensive literature review on potential sensitive parameters of the SWAT model and the model documentation (Neitsch et al. 2005; White and Chaubey 2005; Cibin et al. 2010). These parameters were classified according to the processes that they constrain: three parameters are related to surface runoff (CN2, ESCO and Sol_AWC), and five parameters are involved in base flow (ALFA_BF, GW_QMN, GW_REVAP, REVAPMN, GW_DELAY). Table 2 lists the model parameters along with their initial values and acceptable ranges. Parameter that induces the highest model output change is the most sensitive.

Table 1 Statistical indicators for evaluating model performance

Name	Formula
Nash-Sutcliffe Efficiency	$NSE = 1 - \dfrac{\sum\limits_{i=1}^{n} (O_i - S_i)^2}{\sum\limits_{i=1}^{n} (o_i - \overline{o})^2}$
Coefficient of Determination	$R^2 = \left[\dfrac{\sum (O_i - \overline{O}) \cdot (S_i - \overline{S})}{\sqrt{\sum\limits_{i=1}^{n} (o_i - \overline{o})^2} \cdot \sqrt{\sum\limits_{i=1}^{n} (s_i - \overline{S})^2}} \right]^2$
Percent bias	$PBIAS = \dfrac{\sum\limits_{i=1}^{n} (O_i - S_i) \cdot 100}{\sum\limits_{i=1}^{n} O_i}$

O_i observed flow (m³/s), S_i simulated flow (m³/s), O mean observed flow

CN2 parameter

The Curve Number (CN2), is an empirical parameter used for approximating the amount of direct runoff for the moisture condition, it varies with each HRU. Since, it depends on soil properties and on land cover type, this parameter is always open to question (Hawkins et al. 2009). Given the critical role of vegetation to minimize runoff, Curve Number was varied for each land cover type, a low value indicates high infiltration potential and consequently low runoff. In this study, three CN values were distributed among the sub-watersheds by the SWAT model.

The sensitivity analysis of flow to CN2, shows that the best efficiency is reached on reducing CN2 by 9 % for forests and range brushes, 5 % for corn and 3 % for pasture. On the whole, we can say that the decrease in CN2, reduced the overestimated runoff and improved the The Nash–Sutcliffe model efficiency coefficient (NSE) from 0.62- 0.69.

SOL_AWC parameter

SOL_AWC is the ability of the soil to retain water, it is a determining factor in the calculation of the field capacity of soil parameter, its value varies between 0 and 1. This parameter depends on the soil type, thus, soil water saturation, and hence the related processes of evaporation and percolation, are strongly influenced by this factor. In the sensitivity analysis of the hydrological component of the SWAT model, SOL_AWC was varied in a range from −25 to 25 % for all types of soils. It was found that the best NSE is reached when this parameter is increased by 15 % (Fig. 6).

Table 2 Selected parameters for sensitivity analysis and their range of perturbation

Parameter	Process	Initial value	Range	Optimal value
CN2	Surface runoff	–	35–98	–
ESCO	Surface runoff	0.55 (–)	0–1	0.88 (–)
SOL_AWC	Surface runoff	0.12 (mm/mm)	0–1	0.14 (mm/mm)
GWQMN	Base flow	500 (mm)	0–5,000	900 (mm)
ALPHA_BF	Base flow	0.048 (days)	0–1	0.062 (days)
GW_REVAP	Base flow	0.02 (–)	0.02–0.2	0.032 (–)
REVAPMN NNN	Base flow	1 (mm)	0–500	1.5 (mm)
GWD_ELAY	Base flow	31 (days)	0–500	46 (days)

ESCO parameter

ESCO is the soil evaporation compensation factor, its value represents the depth distribution of soil evaporation and varies between 0 and 1. Raising the ESCO value decreases the soil depth to which SWAT can satisfy potential soil evaporative demand (Neitsch et al. 2002), thus decreasing soil evaporation and evapotranspiration.

The sensitivity of SWAT runoff to the variation of this parameter is shown in the graph of Fig. 6. There is a significant trend towards greater efficiency by increasing the value of the compensation factor up to 60 % (Fig. 6). When exceeding 60 %, the efficiency decreases as it is shown by the NSE coefficient. Higher ESCO value, causes less evaporation at a given soil depth within the model and consequently results in higher flow values.

ALPHA_BF parameter

ALPHA_BF is the base flow alpha factor; this parameter affects the amount of base flow simulated in SWAT model. Its value varies from 0.1-0.3 days for a slow response and from 0.9-1 day for a quick response. The sensitivity of flow to this factor is illustrated in the graph of Fig. 7.

The assessment of sensitivity analysis for ALPHA_BF is done by varying this parameter from −50 to 50 % of its initial value. It is noted that the increase of this parameter has

positively influenced the NSE coefficient. The efficiency becomes stable with an increase of 30 % and thereafter.

GWQMN parameter

GWQMN is the threshold depth of water in the shallow aquifer required for return flow. Groundwater can flow only, into the stream reach, when depth of water in the aquifer is equal to or greater than this threshold. GWQMN varies from 0 to 5,000 mm, changing this parameter has a strong effect on model output, for this reason SWAT model was run with many iterations of changing values of GWQMN. The graph of Fig. 7 shows the variation of this parameter with NSE coefficient. It is found that increasing GWQMN, significantly improves NSE coefficient up to 80 % (the best value). When exceeds this value, there is a decrease in efficiency.

GW_REVAP parameter

GW_REVAP is the groundwater revaporation coefficient which controls the rate of transfer of water from the shallow aquifer to the root zone. It ranges between 0.02 and 0.2. The closer it is to 0, the more upward movement of water from superficial aquifer is reduced. The graph in Fig. 8 gives the variation of this parameter depending on the NSE coefficient. GW_REVAP showed some degree of sensitivity to the simulated number of flow days for the catchment. The change in this parameter does not greatly impact the NSE coefficient as

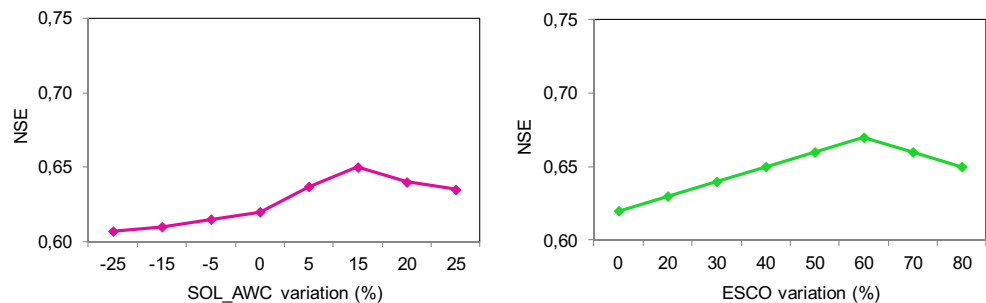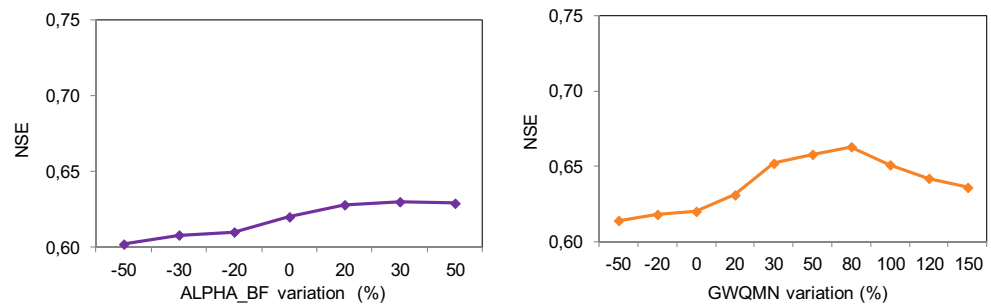**Fig. 6** Runoff sensitivity to SOL_AWC and ESCO parameters

Fig. 7 Runoff sensitivity to
ALPHA_BF and GWQMN
parameters

it ranges between 0.63 and 0.62 when varying GW_REVAP
from −30 % to 100 %.

REVAPMN parameter

REVAPMN is the minimum depth of water in shallow
aquifer for re-evaporation to occur. Under this threshold,
movement of water from the shallow aquifer to the unsat-
urated zone is not allowed. This parameter varies between
0.5 and 500 mm. Fig. 8 showed that varying REVAMN
values didn't significantly affect the NSE coefficient.
Hence, it does not impact the simulated flow significantly
as the groundwater flow is not important in this basin.

GW_DELAY parameter

GW_DELAY is the groundwater delay time (days), its
value is comprised between 0 and 500 days. The variation
of NSE coefficient as a function of variability in this
model input parameter is shown in Fig. 9. It is noted that
different values of GW_DELAY used in this study do not
have significant effects on the NSE coefficients. This
parameter, showed a low sensitivity under the base-case
condition in this study, it is found that it is slightly sensi-
tive in a fairly narrow range of values between 35 and
50 days. The best efficiency is obtained for an increase of
GW_DELAY with 50 % which corresponds to a value of
46 days.

Among the eight parameters used in this sensitivity analy-
sis, CN2, ESCO, SOL_AWC and GWQMN were the most
sensitive parameters in this case study.

This result supports those found by other studies
confirming that these three parameters are the crucial sensitive
parameters for the water balance (White and Chaubey 2005).
Gassman et al. (2007) summarized the results of the SWAT
sensitivity analysis and reported that CN2 is the primary
influence on the amount of runoff generated from a hydrologic
response unit, and hence a relatively greater sensitivity index
can be expected for most of the watersheds. Other researchers
have reported that flow was also found to be sensitive to
ESCO and SOL_AWC parameters in catchment with higher
evapotranspiration as well as semi-arid catchments, due to
greater mean air temperature and solar radiation (Fadil et al.
2011; Bilondi et al. 2013). It should be noted that both of these
parameters affect simulation of evapotranspiration processes
in SWAT model.

The parameters ALPHA-BF and GW-REVAP affecting the
groundwater flow were the next most sensitive parameters in
this case study. The two parameters having relatively minor
impact on Nash Sutcliffe Efficiency are REVAPMN and
GW_DELAY, thus, these input parameters were not consid-
ered in calibration process.

The results obtained from the sensitivity analysis give
a clear understanding of the relationship between SWAT
input parameters and different outputs of hydrological

Fig. 8 Runoff sensitivity to
GW_REVAP and REVAPMN
parameters
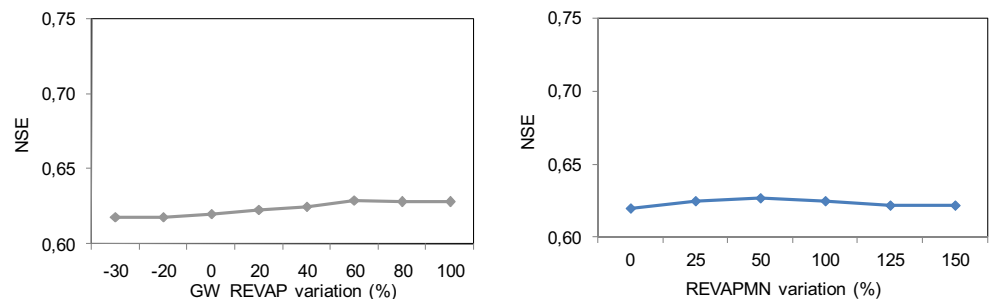
processes under arid catchment conditions. The relationship of changes in the values of the investigated input parameters to Nash Sutcliffe Efficiency (NSE) is depicted in Fig. 10.

Model calibration

Facilitated by the sensitivity analysis, the calibration process was performed, it focused on the adjustment of model sensitive input parameters. In this process, model parameters varied until recorded flow patterns are accurately simulated. For this study, since we are working on a complex catchment, and given that empirical parameters in SWAT model are not directly measurable at the scale of application, the manual calibration was applied, it forces the user to better understand the model and the important processes in the catchment (Arnold et al. 2012).

The SWAT model was calibrated using monthly data of discharge observed at the outlet of the Sarrath catchment for 2 years period (2001/2002–2002/2003). Based on their influence on Nash Sutcliffe Efficiency, the most sensitive parameters that can be calibrated are CN2, ESCO, SOL_AWC, GWQMN, ALPHA-BF AND GW-REVAP. The two other parameters (REVAPMN and GW_DELAY) were not taken into consideration in the process of calibration since their variation induced a minor impact on hydrologic response predictions (Fig. 10).

Running SWAT model with the specified optimal values reduced uncertainty and greatly improved the agreement between measured and simulated monthly flow. The time series plot of observed and simulated monthly runoff for calibration period are showed in Fig. 11.

In general, it can be observed that the model overestimated major peaks of runoff, despite the optimization of parameters. However, the overall flow trend is well simulated by the model and there is a good correlation between simulated and observed flow which is indicted by an R^2 of 0.8, as shown in linear graph (Fig. 12).

A better model efficiency is also obtained with the two other goodness-of-fit measures, NSE and PBIAS, that are within good ranges, respectively, 0.78 and −13.22 %. This negative value of PBIAS indicates model overestimation bias (Gupta et al. 1999).

Model validation

After the calibration, the accuracy of the model was determined during the validation process. SWAT was validated by using a different time-period flow data, from September 2003 to August 2008. The final value of all calibrated parameters that showed optimal model efficiency was used for model validation without their further modification.
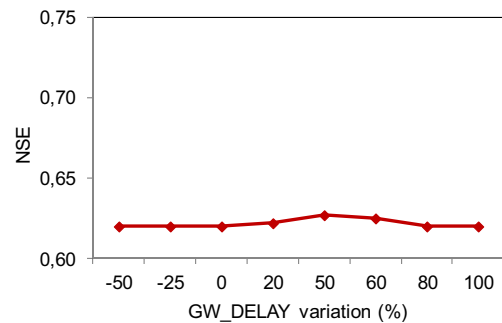

Fig. 9 Runoff sensitivity to GW_DELAY parameter

Figure 13 shows the time-series plot of simulated and measured monthly discharge for validation period, it appears that observed and the simulated flows matched well, despite the overestimation of some peaks that occurred in high rainfall events (October and December 2003). The measured and simulated average monthly flow volumes for the validation period were 20.3 and 21.5 mm, respectively.

Overall, the validation performance is expected to be less than the calibration performance (Moriasi et al. 2007). In this study, in spite of the improvement of coefficient of determination ($R^2=0.90$), (Fig. 14), the obtained validation results presented comparable results to that obtained for the calibration phase, with a NSE and PBIAS equal to 0.75 and −16.5 %, respectively.

Discussions

Like many other models, SWAT is based on conceptual representation of physical processes that govern the flow of water through the catchment. Model input parameters are of two types: physical parameters, measurable from the catchment and empirical parameters that are not directly measurable at the scale of application and need to be calibrated to optimize
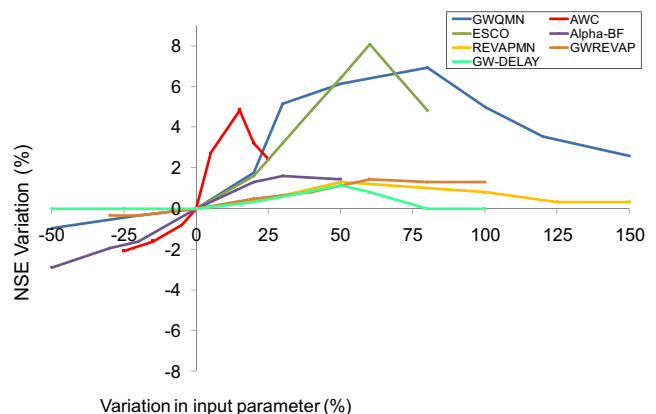

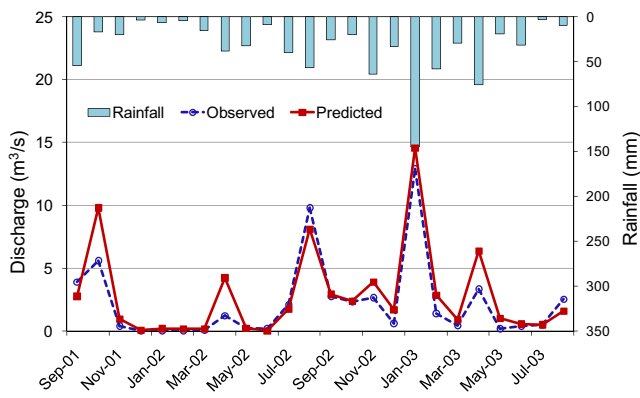**Fig. 10** Variation of NSE in response to the variation of model input parameters

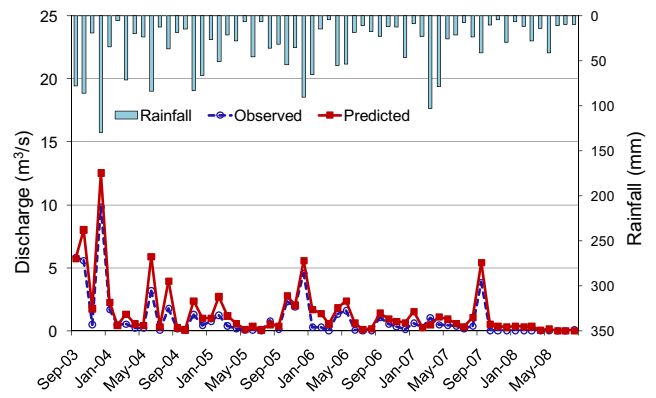Fig. 11 Observed and predicted mean monthly runoff for calibration period

Fig. 13 Observed and predicted mean monthly flow for validation period

the simulated monthly discharge at the catchment's outlet. The implementation of the sensitivity analysis procedure before calibration is very important step for simplifying the use of the model, since it reduces the number of parameters to be adjusted.

In this study, sensitivity analysis was performed for the period 2000/2001–2007/2008, on eight SWAT model parameters that may have a potential to influence the flow in the Sarrath catchment, northwestern Tunisia. The sensitive parameters were evaluated using different model simulations; the variation of each parameter was reported depending on the NSE coefficient. The ranges of variation are based on the SWAT manual (Neitsch et al. 2005).

Results of sensitivity analysis showed that the largest influence on the hydrologic modelling was induced by surface runoff. This process, expressed by the runoff curve number (CN2), the soil evaporation compensation factor (ESCO) and the soil available water capacity (SOL_AWC), is the most sensitive process in this catchment.

Changes in CN2 and ESCO parameters values can improve NSE by approximately 11 % and 7 % respectively, whereas changes in SOL_AWC Values can influence annual NSE by

approximately 5 % (Fig. 10). Thus, CN2 and ESCO are more critical in maximizing model efficiency during model calibration than is SOL_AWC.

The default value for CN2 parameter was determined in SWAT and assigned to each HRU, depending on the soils type and land-use cover information. The parameter CN2 is the primary influence on the amount of runoff generated from a hydrologic response unit, thus, decreasing the CN2 values increases the soil infiltration capability and, therefore, decreases the resulting simulated surface runoff. The CN2 parameter is the primary control on the abstraction of runoff from precipitation and has been reported to be a significant driver of model output by many researchers (Francos et al. 2003; White and Chaubey 2005; Holvoet et al. 2005; van Griensven et al. 2006).

Gassman et al. (2007) summarized the results of the SWAT calibration and reported that CN2 was an important parameter affecting hydrologic simulations in all of the model applications.

The ESCO parameter adjusts the depth distribution for evaporation from the soil, it is a calibration parameter and not a property that can be directly measured. This parameter
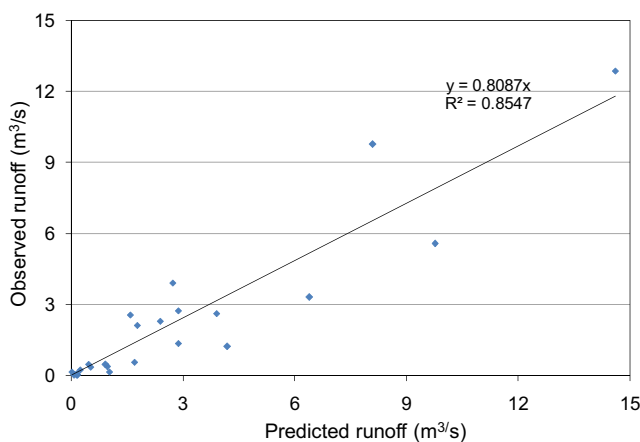

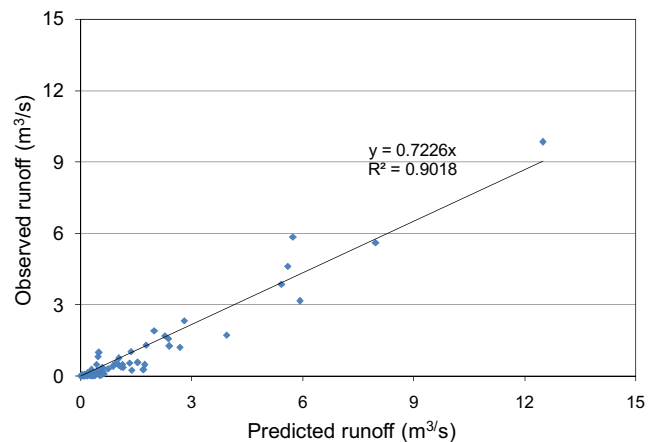Fig. 12 Correlation between predicted and observed runoff for calibration period

Fig. 14 Correlation between predicted and observed runoff for validation period

which directly influences the evapotranspiration losses from the watershed was found to have a higher impact on flow, due greater mean air temperature and solar radiation in semi-arid catchment. Other researchers have also reported ESCO to be a sensitive parameter for SWAT model (White and Chaubey 2005; van Griensven et al. 2006; Fadil et al. 2011; Bilondi et al. 2013; Aouissi et al. 2014).

Less sensitivity of the model is shown for the soil available water capacity (SOL_AWC) parameter. Higher values of SOL_AWC means higher soil water capacity, causing less water available for surface runoff and percolation.

The most sensitive groundwater parameter is threshold water level in shallow aquifer for base flow (GWQMN), it affected greatly the base flow process and hence the total water yield. This parameter turned out to be the most influential factors for lowering the base flow and improving the simulation of water discharge, the changes of GWQMN parameter values improve NSE by approximately 8 % (Fig. 10). The base flow alpha factor (ALPHA_BF), is the next sensitive groundwater parameter, followed by groundwater revaporation coefficient GW_REVAP, these two parameters do not have a great influence when each one is treated only, but when they are adjusted together they allow an improvement of hydrologic response predictions in the watershed. Other groundwater model parameters (REVAPMN and GW_DELAY REVAP) were not significant in either watershed implying that these parameters may not play a critical role in calibrating the SWAT.

While sensitivity analysis is a routine process, it is imperative for successful calibration and application of the model. Calibration is performed manually and consists of changing values of the six most sensitive input parameters to produce simulated values that are within a certain range of the measured data.

Both calibration and validation graphs showed good similarity between observed and predicted flow, with most observed runoff events being replicated by SWAT. The statistic evaluators computed in this study for calibration and validation period showed a good correlation between the monthly observed and simulated river discharge with R^2 of 0.80, NSE of 0.78 and PBIAS of −13.22 for the calibration period. The validation period revealed good values for R^2 (0.90), but less accurate values for NSE (0.75) and PBIAS (−16.5). According to Moriasi et al. (2007) this model performance for both calibration and validation periods is evaluated as good to very good performance rating. The values of PBIAS indicate that the model had slightly overestimated the discharge during calibration and validation period.

Further, these results are in agreement with those reported in other case studies, which have shown successful applications of SWAT for flow predictions in Tunisia. Bouraoui et al. (2005) found NSE coefficients ranging between 0.53 and 0.84 depending to the gauging stations in the Medjerda catchment.

It was also successfully applied in the watershed of Wadi Oum Zessar, southeast of Tunisia, by Ouessar et al. (2006), with a Nash coefficient of 0.83 for calibration period.

The performance of SWAT model in this case study can be enhanced furthermore using more accurate input data especially for the soil that were estimated with global data. The integration of some other climatic data such as solar radiation, humidity and wind can also improve the accuracy of the evapotranspiration estimation and therefore the other water balance components. More accurate daily rainfall data can also improve results of simulation.

Therefore, better calibration is possible if seasonally dependent parameters could be adjusted throughout the year. For example, since we are working in a semi-arid catchment, different values for the ESCO parameter during winter and summer would permit more realistic simulations of water evaporation during both seasons and thereby increase model efficiency.

Conclusion

In the present study, SWAT a distributed hydrological model having an interface with ArcGIS software was assessed for predicting the flows of Sarrath river basin in northwestern Tunisia. This was meant to determine whether SWAT is a suitable alternative for modeling semi-arid catchment with scarce data, and therefore could be applicable for water resources assessments. The main objective of this study was to analyze the sensitivity of hydrologic component to input parameters. After preparing all GIS data layers and database required by ArcSWAT, the model was setup and run at a monthly time step.

Analysis of the influence of the most sensitive parameters on NSE for the hydrologic response indicated that surface runoff has the major impact with three sensitive parameters: CN2, ESCO and SOL_AWC. The groundwater flow is in next sensitive, from most to least, GWQMN, ALPHA_BF, GW_REVAP, REVAPMN and GW_DELAY REVAP.

The sensitivity analysis provides good insight into the model input parameters especially in the case of highly parameterized models, such as the SWAT model. Based on the assessment of investigated parameters to which the model is most sensitive, SWAT was calibrated and validated for flow at the watershed outlet. The calibration process used measured data for 2 years period (2001/2002–2002/2003) and yielded a good correlation (R^2=0.80 and NSE=0.78) between measured and simulated flow. Model validation was performed for the period 2003/2004–2007/2008 and generated an R^2 value of 0.9 and NSE=0,75. Based on these coefficients, model performance evaluation was reasonably good for predicting flow in this semi-arid catchment with limited data availability.

This study indicates that the SWAT model can be an effective tool for accurately simulating the hydrology of Sarrath river basin. Accurate flow simulations are required to accurately predict sediment loads and chemical concentrations.

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