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Modelling the monthly hydrological balance using Soil and Water Assessment Tool (SWAT) model: A case study of the Wadi Mina upstream watershed

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Abstract: Modelling the hydrological balance in semi-arid zones is essential for effective water resource management, encompassing both surface water and groundwater. This study aims to model the monthly hydrological water cycle in the Wadi Mina upstream watershed (northwest Algeria) by applying the Soil and Water Assessment Tool (SWAT) hydrological model. SWAT modelling integrates spatial data such as the Digital Elevation Model (DEM), land use, soil types and various meteorological parameters including precipitation, maximum and minimum temperatures, relative humidity, solar radiation and wind speed. The SWAT model was calibrated and validated using data from January 2012 to December 2014, with a calibration period from January 2012 to August 2013 and a validation period from September 2013 to December 2014. Sensitivity and parameter calibration were conducted using the SWAT-SA program, and model performance evaluation relied on comparing the observed discharge at the outlet of the basin with model-simulated discharge, assessed through statistical coefficients including Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2) and Percent Bias (PBAIS). Calibration results indicated favourable objective function values (NSE=0.79, R^2=0.93, PBAIS= −8.53%), although a slight decrease was observed during validation (NSE=0.69, R^2=0.86, and PBAIS= −11.41%). The application of the SWAT model to the Wadi Mina upstream watershed highlighted its utility in simulating the spatial distribution of different components of the hydrological balance in this basin. The SWAT model revealed that approximately 71% of the precipitation in the basin evaporates, while only 29% contributes to surface runoff or infiltration into the soil.

Keywords: SWAT model; Performance; Parameters; Runoff; Groundwater; Wadi

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Introduction

Water stands as the most critical natural resource on our planet, irreplaceable and non-renewable (Wang et al. 2016). However, its availability in terms of both quantity and quality faces significant threats, particularly in underdeveloped countries (Sintondji et al. 2008). The challenges arise from rapid population growth, expanding urbanization, and economic development, all of which impact water availability (Liu et al. 2023). Additionally the effects of climate change have become evident through aggressive hydrometeorological phenomena, including erratic precipitation patterns (Llasat et al. 2009; Mishra and Singh, 2010), placing substantial strain on water resources (Vairavamoorthy et al. 2008).

Algeria, especially its west regions, is experiencing a gradual depletion of surface and groundwater resources (Meddi and Hubert, 2003). This decline can be attributed to diminishing precipitation coupled with significant temperature rises since 1980s (Khaldi, 2005). Such climatic aggressiveness has led to a notable increase in evaporation within the country. Remini (2005) revealed that between 1992 and 2002, evaporation accounted for half of the water volume consumed by

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irrigation, drinking water supply and industry. Consequently, this heightened evaporation rate renders surface water storage less effective, necessitating a reliance on groundwater resources (Gyamf et al. 2017).

In this context, evaluating the various components of the hydrological water balance at the watershed scale becomes imperative for effective water resource management (Vittecoq et al. 2010). Such evaluations play a crucial role in meeting water demands (Robins and Fergusson, 2014) and in making planning decisions aimed at preventing the over-exploitation of water resources. However, quantifying these hydrological components in our country poses significant challenges due to data scarcity, encompassing both hydrological and hydrogeological data (Bouaïchi et al. 2006). In addition, traditional methods make their measurements arduous (Ang, 2018). Therefore, modeling the hydrological behavior of watersheds allows for the simulation of various hydrological cycle processes at the watershed scale, with the obtained results aiding in the effective management of water resources (Graf and Jawgiel, 2018; Taleb et al. 2019). Such models are frequently applied to estimate surface runoff, groundwater percolation, and storage in lakes and dams, considering all meteorological, hydrological and geological factors (Hassen, 2016; Ang, 2018).

In recent years, numerous models have been developed for hydrological modeling at the watershed scale. These models can be classified according to their description of hydrological processes (empirical, conceptual and physical basis), spatial representation (global, semi-distributed or distributed), and temporal discretization (event-based and continuous). Among the models proven effective for assessing the hydrological balance in watersheds is the SWAT model, which is a semi-distributed, physically based model (Arnold, 1998). Originally designed to predict water quantity and quality at the watershed level under various meteorological and spatial conditions and at different time scales (daily, monthly and yearly), SWAT can also aid in planning and decision-making processes aimed at environment protection and ensuring water availability for future uses (Silva et al. 2015; Fatichi et al. 2016). SWAT has been utilized in numerous projects worldwide (Sophocleous and Perkins, 2000; Tripathi et al. 2003; Hao, 2004; Laurent, 2007; Xiang et al. 2022), and has been applied in several watersheds in Algeria (Zettam et al. 2017; Hallouz, 2018; Otmane et al. 2019; Mami et al. 2021).

The successful application of the SWAT model requires various input data, including the Digital Elevation Model (DEM), land use, soil types and weather data (Ndomba et al. 2008; Shivhare et al. 2018). It also needs multiple parameters describing different hydrological cycle processes. The precise values of these parameters depend on sensitivity analysis and calibration (Duan, 1992), which are typically conducted using programs such as SWAT-CUP, R-SWAT and SWAT-SA. In our study, we utilized the SWAT-SA platform due to its simplicity, allowing for calibration and sensitivity analysis of model parameters using iterative methods, such as the Fourier Amplitude Sensitivity Test (FAST) (Cukier et al. 1973), Morris screening (Morris, 1991), Sobol analysis (Sobol, 1993) and Extended Fourier Amplitude Sensitivity Test (EFAST) (Saltelli et al. 2000; Saltelli et al. 2004).

In this work, the SWAT model was applied to water balance modeling in the Wadi Mina upstream basin. Situated in the semi-arid region of northwest Algeria, this basin experiences irregular precipitation and heterogeneous soil surfaces, posing challenges for water resources assessment (Meddi and Hubert, 2003). The primary objective of this study was to evaluate the SWAT model's capability to simulate the monthly hydrological balance in the Wadi Mina upstream basin, aiming to predict the water potential of Wadi and facilitate water management, particularly groundwater resources.

1 Study area

The Wadi Mina upstream basin is located in the northwest of Algeria (Fig. 1), spanning between longitudes 0°31′51.6′′E and 1°55′55.56′′E, and latitudes 35°52′31.44′′N and 34°31′10.2′′N. It is a constituent part of the largest watershed in northern Algeria, the Wadi Cheliff watershed. Encompassing an area of 1,173 km^2, the Wadi Mina upstream basin holds significance within the regional context.

Geographically, the study basin is bounded by the Tiaret Mountains to the east, the Mascara massif to the west and the Beni Chougrane to the north and Chott Ech-Chergui Mountains to the south. This basin plays a pivotal role in the hydrological system of the northwest region of Algeria, discharging its water into Bakhada dam, a substantial reservoir located in the northwestern part of the country. Altitudes within the basin range from 1,267 m upstream to 247 m at the outlet. The slopes of the catchment vary from gentle to moderate in the upstream area and become steeper in the

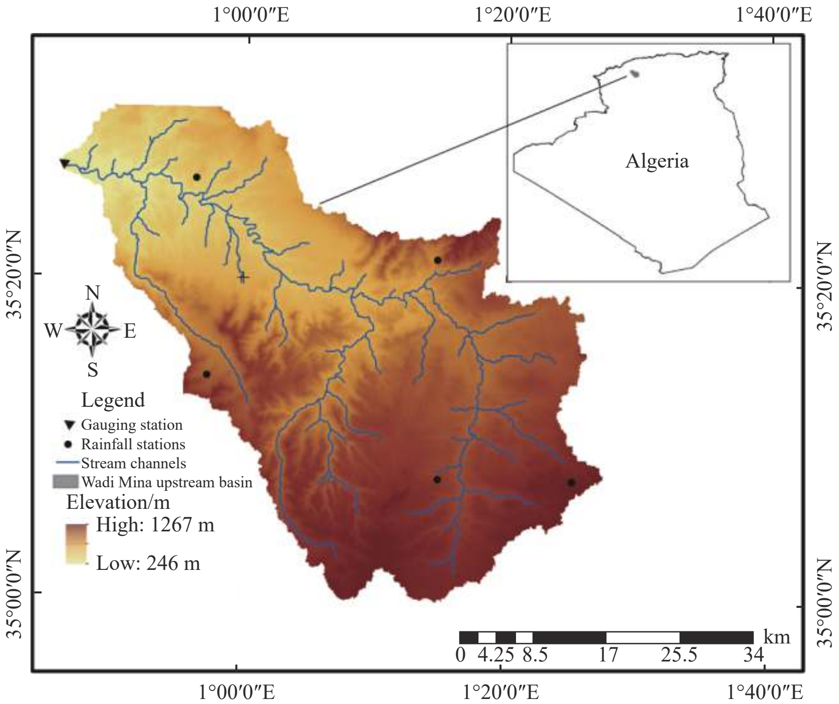

Fig. 1 Position map and DEM of the Wadi Mina upstream Basin

center and downstream sections.

The climate of the study area is semi-arid, characterized by cold winters and hot summers. January registers as the coldest month in the basin, with temperature averaging 7°C, while July marks the hottest month, with temperatures reaching around 39°C.

The mean annual rainfall in the study basin is approximately 370 mm/a (2000–2014). Precipitation distribution in the basin is irregular throughout the months, with the rainiest period occurring from October to April and the driest period spanning from May to September. During these drier months, rainfall often exceeds the mean monthly value (Fig. 2). Indeed, the precipitation levels in the basin begin to rise from September to February, gradually declining until July. The monthly variation of runoff (Fig. 2) in the Wadi Mina upstream demonstrates the direct correlation between precipitation and the flow of Wadi, with its mean monthly runoff averaging approximately 1.9 m^3/s. The surge in flow during October is attributed to intense rainfall events, which occasionally lead to devastating floods. Rapid and heavy rainfall in Algeria serves as the primary factor behind these exceptional flood occurrences (Kerdoud, 2006).

This watershed experiences spatial and temporal variability in rainfall and runoff (Hallouz,

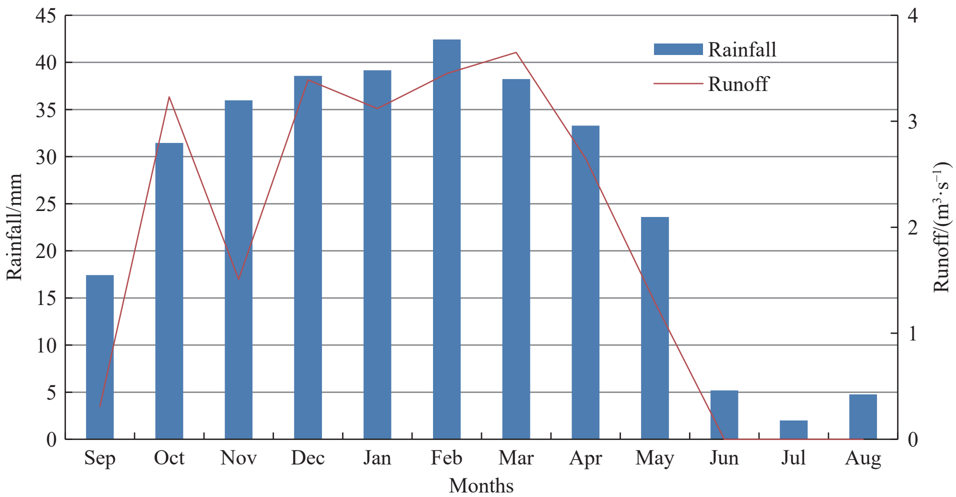

Fig. 2 Average monthly variation of rainfall and runoff in the Wadi Mina upstream

2013). Previous studies have consistently indicated that the climate of the majority of the basin in northwest Algeria is semi-arid, characterized by highly irregular rainfall patterns at different times (Bouguerra, 2016; Mami, 2020). The rainfall deficit in northwest Algeria reached 36%, leading to a significant reduction in runoff (Ghenim, 2013). In this region, decreased rainfall directly corresponds to decreased flow in the Wadi (Hallouz et al. 2018).

The study of relative humidity is crucial for understanding the hydrological balance of a watershed. In the study basin, relative humidity ranges from 78% in December and August to 62% in March (Fig. 3). Analysis of the relationship between relative humidity and rainfall (Fig. 3) during the same period (2000–2014) reveals two distinct periods: One humid between November and April, characterized by abundant rainfall but low humidity, and a second period from May to October.

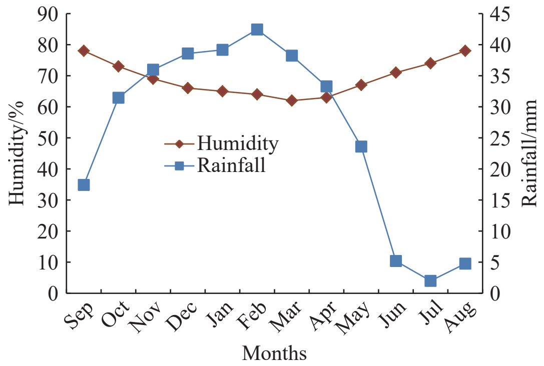

Fig. 3 Average monthly variation of rainfall and humidity in the Wadi Mina upstream basin

The land use map (Fig. 4) illustrates the distribution of land cover within the basin as follows: Crops cover 54.25% of the surface, flooded vegetation occupies 31.39%, forest/shrubs account for 7.74%, while built-up areas and water collectively cover 0.18%.

The soil in the Wadi Mina upstream basin comprises three main types, as depicted in Fig. 5. According to the FAO classification, the first class (BK14-2c) and the second class (BK2-2ab) are dominated by Calcic Cambisols, covering 17.46% and 36.31% of basin surface, respectively. The remaining 46.24% consists of the soil type (XK12-2a), dominated by Calcic Xerosols.

2 Methods

2.1 SWAT model description

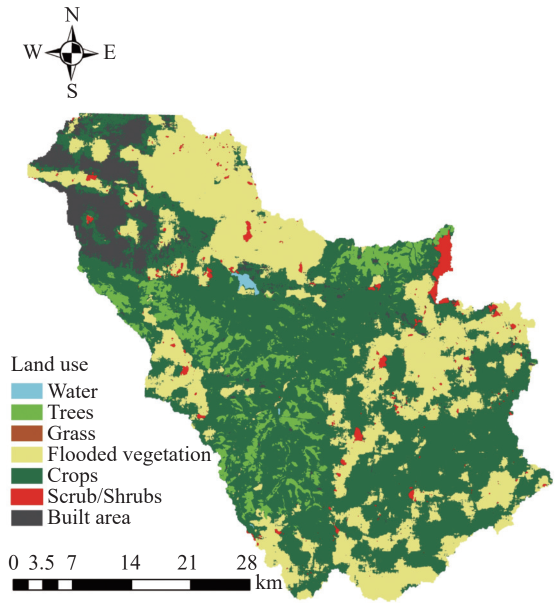

Fig. 4 Land use map of the Wadi Mina upstream

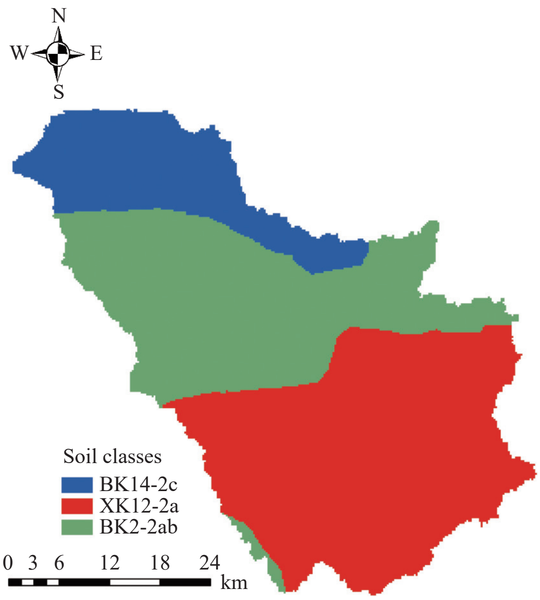

Fig. 5 Soil map of the Wadi Mina upstream

Soil and Water Assessment Tool (SWAT) is a hydrological model specifically designed for watershed-scale hydrological modeling, applicable to areas ranging from a few hundred to several thousand square kilometers (Zettam et al. 2017). Originally developed by researchers from the Department of Agriculture and laboratories at the University of TEXAS in the United States (Arnold, 1998), SWAT is a semi-distributed physically based model. Its semi-distributed character means that certain model parameters are spatially linked, while others remain global. The physical basis of the model allows for the utilization of complex equations to replicate the processes occurring within the watershed (Arnold, 2012). Being a continuous-time model, SWAT is capable of simulating events over extended periods (Payraudeau, 2002).

The hydrological modeling approach using the SWAT model involves dividing the watershed into several sub-basins, further subdivided into Hydrologic Response Units (HRUs). HRUs represent homogeneous areas in terms of land use, soil type and topography. This subdivision enables the study of variations in evapotranspiration and other hydrological conditions across different land covers, soils and slopes (Setegn et al. 2008).

In this study, the studied basin was divided into 23 sub-basins and 2,387 HRUs (Fig. 6). SWAT simulates various hydrological processes along a watershed using the following hydrological balance equations:

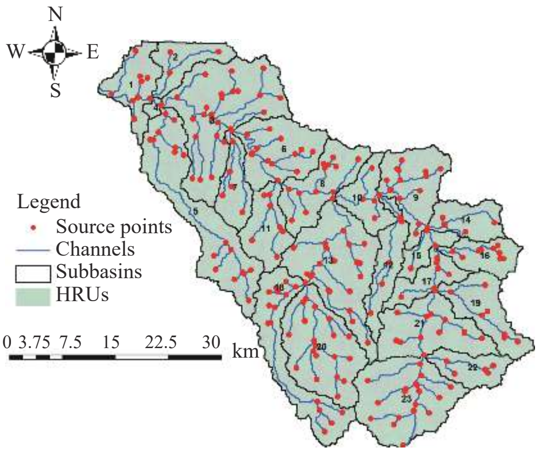

Fig. 6 Subdivision of sub-basins and HRUs in the Wadi Mina upstream basin

$$SW_t = SW_0 + \sum_{i=1}^{n} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad (1)$$

Where: SW_t: Final soil water content available for plants(mm); SW_0: Initial soil water content at the time 0 (mm); R_{day}: Precipitation on day i (mm); Q_{surf}: Surface runoff (mm) ; E_a: Evapotranspiration (mm) ; W_{seep}: Water percolation (mm); Q_{gw}: Runoff during low flow (mm); n: Duration in days.

In the SWAT model, the amount of surface runoff is calculated by the flowing formula:

$$Q_{surf} = \frac{P_e^2}{P_e + S} \quad (2)$$

Where: S (mm) is the retention parameter; P_e (mm) is net rainfall.

The value of S depends on the Curve Number (CN):

$$S = 245\left(\frac{1000}{CN - 1}\right) \quad (3)$$

Where: CN is the Curve Number, which varies from 35 to 98 according to soil permeability, antecedent soil conditions and land use.

Potential evapotranspiration is estimated through three equations integrated into the SWAT model, namely: Penman-Monteith, Priestley-Taylor and Hargreaves. In this study, the Hargreaves method was chosen due to its widespread application (Mosbahi et al. 2015; Zettam et al. 2017; Mami, 2020). Aouissi (2016) demonstrated that this method is most suitable for semi-arid basins in North Africa.

The equation by Hargreaves and Samani (1985) is expressed as follows:

$$ET_{HS} = 0.0023 \times 0.408 R_a \times (T_{mean} + 17.8) \times TD^{0.5} \quad (4)$$

Where: ET_{HS}: Evapotranspiration according to Hargreaves and Samani (mm/d);

R_a: Extraterrestrial solar radiation (mm/d);

$TD = (T_{max} - T_{min})$: Difference between the maximum and minimum air temperature (°C);

T_{mean}: Average temperatures.

Aquifer recharge was calculated using the exponential decay function proposed by Venetis (1969):

$$W_{rchrg,i} = \left\{ W_{seep} \cdot \left(1 - exp\left[\frac{-1}{\delta_{gw}}\right]\right) + W_{rchrg,i-1} \cdot exp\left[\frac{-1}{\delta_{gw}}\right] \right\} \quad (5)$$

Where: $W_{rchrg,i}$ (mm) is the amount of recharge entering the aquifers on day i; δ_{gw} (days) is the delay time or drainage time of the overlying geological formations; W_{seep} (mm) is the total amount of water exiting the bottom of the soil profile on day i and; $W_{rchrg,i-1}$ (mm) is the amount of recharge entering the aquifers on day i-1.

2.2 SWAT model inputs

The data required to execute the SWAT model include topographic, land use, soil types and weather data. These data are collected from various sources and databases (Table 1).

2.3 SWAT simulation steps

The steps of hydrological simulation using the SWAT model are summarized in the following diagram (Fig. 7):

2.4 Sensitivity analysis

Sensitivity analysis serves to understand the behavior of the modeled system and evaluates the

Table 1 Input data for the SWAT model

Data	Sources	Description
Digital Elevation Model (DEM)	USGS website (https://earthexplorer.usgs.gov/) in Shuttle Radar Topography Mission(SRTM)	30 m×30 m resolution
Land use map	https://www.arcgis.com/apps/instant/media/index.html?appid=fc92d38533d440078f17678ebc20e8e2	Land use classification (1/400,000 scale)
Soil map	FAO–UNESCO Soil Map of the Word (https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/en/)	Soil classification and physical properties (1/300,000 scale)
Weather data	Hydro-meteorological database of the National Water Resources Agency (ANRH) and National Metrology Office (ONM)	Daily data of precipitation, temperatures (max and min), humidity, solar radiation and wind speed for the period 2012 to 2014
Hydrometric data	National Water Resources Agency	Monthly flows observed during the period 2012 to 2014

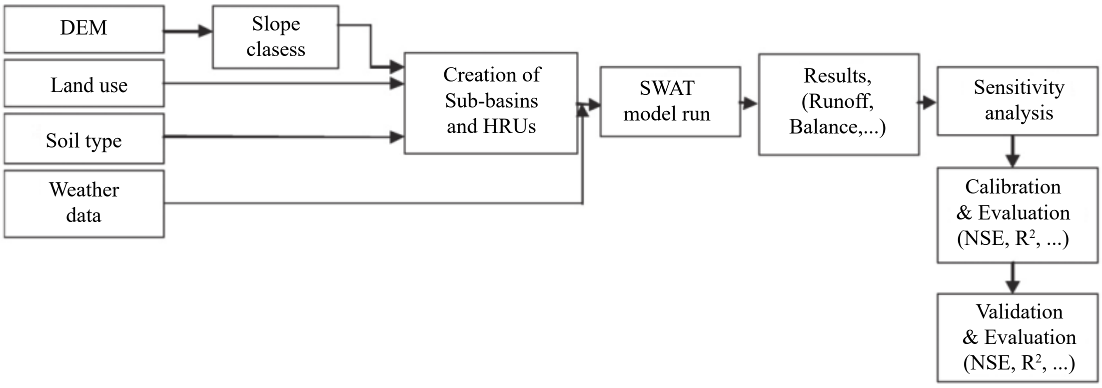

Fig. 7 Simulation steps using the SWAT model

model's applicability. It enables the estimation of how much the model output varies in response to the changes in model inputs and helps identify influential parameters (Ang, 2018).

SWAT is a highly parameterized model (Sane et al. 2020), with parameters numbering up to 30. These parameters describe various processes such as runoff, hydrological balance and sediment transport across the watershed. In this context, numerous programs (e.g. SWAT-CUP, R-SWAT and SWAT-SA) have been developed to perform sensitivity analysis and calibration of SWAT model parameters. In this study, the SWAT-SA code was employed for sensitivity analysis and calibration of the SWAT model. The SWAT-SA platform was developed by Koo et al. (2020) and programmed in R language.

The SWAT-SA code determines the most sensitive parameters using iterative methods, including both local and global sensitivity analysis (Saltelli et al. 2004). Local sensitivity analysis methods include GLUE and Simplex, while global analysis methods encompass Fourier Amplitude Sensitivity Test (FAST) (Cukier et al. 1973), Morris screening (Morris, 1991), Sobol analysis (Sobol, 1993) and Extended Fourier Amplitude Sensitivity Test (EFAST) (Saltelli et al. 2000). Many studies have demonstrated that global sensitivity analysis methods are most suitable for multi-parameter hydrological models (Cibin et al. 2010; Liu et al. 2022). In this case, the Morris screening method for sensitivity analysis and the calibration of the model parameters were selected due to its relatively fast calculation time. Overall, 22 parameters were selected for sensitivity analysis to assess the influence of each parameter on the model results (Table 2).

2.5 SWAT calibration and validation

SWAT calibration involves adjusting the values of the most sensitive parameters and comparing the predicted outputs to the measured data until the chosen objective functions are optimized (James and Burges, 1982). Subsequently, validation entails running the model with parameter values that lead to good performance during the calibration phase. During validation, the model's outputs are evaluated by comparing its predictions to observed data that were not used for calibration (Arnold, 2012).

In this study, the SWAT model was calibrated using monthly flow data observed at the outlet of the Wadi Mina upstream basin. This calibration period spans from January 2012 to August 2013, while validation encompasses the period from

Table 2 Parameters chosen for modeling the different hydrological processes by SWAT

Parameters	Description	Hydrological processes	Min	Max
CN2	Initial SCS runoff curve number for humidity conditions	Runoff	35	98
SURLAG	Surface runoff lag time		0.05	24
ESCO	Soil evaporation compensation factor	Potential and effective Evapotranspiration	0	1
EPCO	Plant uptake compensation factor		0	1
CANMX	Maximum storage of plant cover (mm H_2O)		0	100
SOL_AWC	Available water capacity of the soil layer (mm H_2O/mm soil)	Soil water	0	1
SOL_K	Saturated hydraulic conductivity of the soil layer (mm/h)		0	2,000
SOL_BD	Moist bulk density ((Mg/m^3 or g/cm^3)			
GW_REVAP	Groundwater evapotranspiration coefficient	Groundwater/Baseflow	0.02	0.2
GW_DELAY	Groundwater delaytime (days)		0	500
REVAPMN	Threshold depth of water in the shallow aquifer for evapotranspiration or percolation to the deep aquifer to occur (mm H_2O)		0	500
GWQMN	Threshold depth of water in the shallow aquifer for return flow to occur (mm H_2O)		0	5,000
ALPHA_BF	Base flow alpha factor (days)		0	1
RCHRG_DP	Deep aquifer percolation fraction			
CH_K2	Effective hydraulic conductivity inmain channel alluvium (mm/h)	Conveying water in canals	−0.01	500
CH_N2	Manning's "n" value for the mainchannel		−0.01	0.3
ALPHA_BNK	Base flow alpha factor for bank storage (days)		0	1
SLSUBBSN	Average slope length	Concentration time	10	150
OV_N	Manning's "n" value for overland flow		0.01	30
CH_N1	Manning's "n" value for tributary channels		0.01	30
CH_K1	Effective hydraulic conductivity in alluvium of tributary channels (mm/h)	Transmission losses due to surface runoff	0	300
HRU_SLP	Average slope steepness (m/m)	Lateral flow	0	1

September 2013 to December 2014. The monthly modeling scale is commonly employed for water resources development and management (Pandi et al. 2023). Schuol et al. (2008) simulated the hydrology of the entire African continent with SWAT at sub-basin spatial resolution and at monthly time intervals.

To evaluate the model's performance, objective functions such as the Nash-Sutcliffe coefficient (*NSE*) (Nash and Sutcliffe, 1970), coefficient of determination (R^2) and percent bias (*PBIAS*) were utilized.

1. *NSE* represents the accuracy of the model simulation (Marcelo et al. 2009) and is defined as follows :

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{oi} - Q_{si})^2}{\sum_{i=1}^{n}\left(Q_{oi} - \bar{Q}_{oi}\right)^2} \tag{6}$$

Where:

Q_{oi} and Q_{si}: Observed and simulated discharges, respectively;

$\bar{Q}_{oi}$: Average of observed discharges;

n: Number of total observed and simulated discharges.

2. R^2 gives an indication of the correlation quality between the observed and simulated values (Arnold, 2012) :

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(Q_{oi} - \bar{Q}_{oi}\right)\left(Q_{si} - \bar{Q}_{si}\right)}{\sum_{i=1}^{n}\left(Q_{oi} - \bar{Q}_{oi}\right) \times \sum_{i=1}^{n}\left(Q_{si} - \bar{Q}_{si}\right)}\right]^2 \tag{7}$$

$\bar{Q}_{si}$: Average of simulated discharges.

3. *PBIAS* specifies the average tendency of simulated data to be higher or lower than observed data,with the ideal value for *PBIAS* being zero (0) (Gupta, 1999). A positive *PBIAS* percentage indicates that the model underestimates its prediction, and vice versa (Moriasi, 2007). PBIAS is described by the following equation:

$$PBIAS = 100 \times \frac{\sum_{i=1}^{n}(Q_{oi} - Q_{si})}{\sum_{i=1}^{n} Q_{oi}} \tag{8}$$

The different performance levels of the model can be assessed based on the value ranges of the three coefficients (*NSE*, R^2 and *PBIAS*), as shown in Table 3.

Table 3 Recommended values of the three objective functions used to evaluate the performance of SWAT model

Objective functions	**NSE**	**R^2**	**PBAIS/%**
Insufficient	NSE ≤ 0.5	R^2≤0.5	PBAIS ≥ ±25
Satisfying	0.5<NSE ≤0.65	0.5 <R^2≤ 0.7	±15≤PBAIS< ±25
Good	0.65 <NSE≤0.75	0.7<R^2≤ 0.8	±10 ≤PBAIS< ±15
Very good	0.75 <NSE≤1	R^2> 0.8	PBAIS< ±10

3 Results and discussion

3.1 Model performance and uncertainty

The calibration result of the SWAT model for simulating monthly flow in the Wadi Mina upstream demonstrate a high level of performance. This is evident from the values of the *NSE*, R^2 and *PIBAS,* which are 0.79, 0.93 and −8.53%, respectively. A slight decrease in the values of the statistical coefficients (*NSE*=0.69, R^2=0.86 and *PIBAS*= −11.41%) was observed during the validation phase of the SWAT model. Consequently, the model performs well in validation.

The graphical comparison between observed and simulated monthly runoff in the Wadi Mina upstream during both the calibration and validation period reveals a strong similarity between the two hydrographs, as depicted in Fig. 8.

In this study, it is observed that the SWAT model tends to overestimate certain runoff peaks, particularly during heavy precipitation events (Mosbahi et al. 2015).

To assess the simulation quality and prediction uncertainty of the SWAT model, several metrics such as the 95PPU (95 Percent Prediction Uncertainty) band, p-factor and r-factor are utilized. The 95PPU band, calculated using the latin hypercube sampling method, quantifies uncertainties with a probability range between 2.5% and 97.5% (Abbaspour et al. 2007). The p-factor represents the percentage of observed data falling within the prediction uncertainty of 95% (95PPU) (Zhao et al. 2018), while the r-factor indicates the average thickness of the 95 PPU band divided by the standard deviation of the observed data (Setegn et al. 2008). A higher p-factor signifiesthat more observations fall within the 95PPU limit (Poméon et al. 2018; Zhao et al. 2018). Theoretically, p-factor = 1 and r-factor = 0 indicate perfect agreement between simulated and observed data (Abbaspour et al. 2007).

As depicted in Fig. 8, the 95 PPU uncertainty band is relatively wide, but does not cover the calculated runoff exceeding 3 m^3/s. During calibration, the p-factor and r-factor values are 0.35 and 1.95, respectively. However, during validation, the p-factor increases significantly (p-factor = 0.56), while the r-factor value (r-factor = 1.76) remains of the same order of magnitude. It is evident that the p-factor values are too low during calibration and average during validation. Conversely, the r-factor values are higher for both periods, indicating that the SWAT model struggles to replicate high runoff. Setegn et al. (2008) attributed the large uncertainty in simulated flow to input data such as precipitation and temperature, as well as the potential for errors in soil type and corresponding soil properties in the area. The degree of uncertainty in

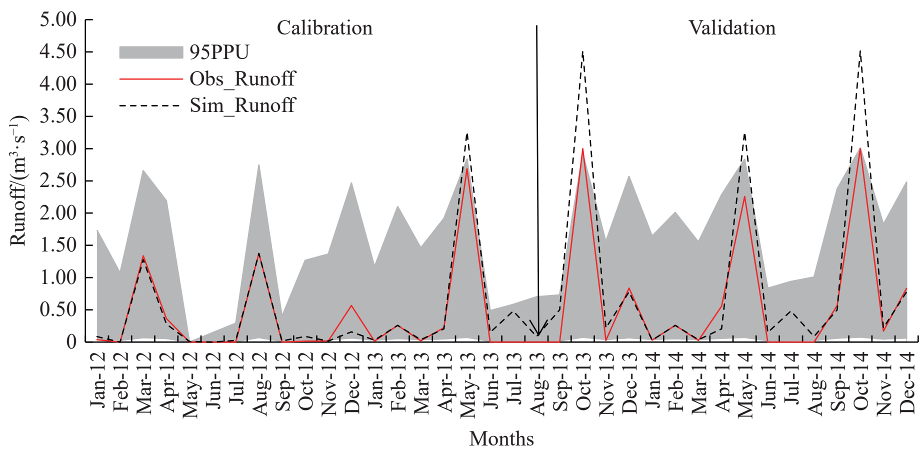

Fig. 8 Comparison between observed and simulated monthly discharge for the calibration (01/2012 to 08/2013) and validation (09/2013 to 12/2014) periods

the SWAT model is also linked to model structure, boundary conditions, and input parameters due to heterogeneity and data resolution (Pandi et al. 2023).

3.2 Parameter sensitivity

Parameters sensitivity is assessed using the t-stat and p-value coefficients. The t-stat provides a measurement of the sensitivity of the considered parameter, with a larger absolute value indicating higher sensitivity. Meanwhile, the p-value indicates the importance of the parameter's sensitivity, where a p-value close to zero suggests greater importance for the parameter. It is worth noting that the minimum value of p-value is typically 0.05 (Whittaker et al. 2010). In this study, sensitivity analysis identified 16 parameters as the most sensitive, as presented in Table 4.

The parameters identified through the sensitivity analysis closely resemble those found in other studies using hydrological modeling with the SWAT model (e.g. Lenhart, 2002; Tang et al. 2012, Premanand et al. 2018; Taleb et al. 2019; Xiang et al. 2022).

These 16 parameters predominantly govern key components of the hydrological balance, including evapotranspiration, groundwater flow and surface runoff. *ESCO* is a soil evaporation compensation factor (Setegn et al. 2008), regulates the soil's evaporation demand (Cibin et al. 2010). A lower *ESCO* value signifies more water loss from the lower ground levels to meet the evaporation demands (Marhaento et al. 2017). The obtained *ESCO* value (0.43) for the Wadi Mina upstream basin suggests moderate soil saturation, indicating a balanced level of soil moisture. The *CANMX* parameter regulates the storage capacity of forest cover for rainfall interception (Santos et al. 2020). Higher *CANMAX* values indicate greater canopy capacity (Marhaento et al. 2017). In this study, the *CANMAX* value of 78 (on a scale from 0 to 100) signifies a substantial influence of vegetation cover on evapotranspiration.

The *SOL_AWC* parameter defines the available water capacity of the topsoil (Santos et al. 2020). A lower parameter value results in increased groundwater percolation and a delay in flow reaching the stream (Santos et al. 2020). In our study, the *SOL_AWC* value of 0.09 is close to the upper limit of the recommended range (0-1). This indicates reduced groundwater percolation and rapid flow reaching the Wadi. This type of flow is referred to as Hortonian flow or Infiltration Excess Overland Flow, which is typical in Mediterranean basins (Albergel et al. 2003).

The *ALPHA_BF* parameter, representing the base flow recession coefficient, serves as a direct indicator of the response of groundwater flow to recharge variations (Cibin et al. 2010). A higher *ALPHA_BF* value indicates rapid base flow recession, suggesting less water retention in the aquifer (Zhao et al. 2018). In this study, the moderate value of *ALPHA_BF* (0.4), within the range of 0 to 1, suggests a moderate level of water retention in the shallow aquifer due to drainage of water

Table 4 Ranking of the most sensitive parameters

Parameters	Sensitivity rank	Value obtained	t-stat	p-value
CH_K2	1	166.66	19.52	8.49E-56
SOL_BD	2	1.97	12.14	5.23E-28
REVAPMN	3	300	10.88	1.51E-23
OV_N	4	10.01	−9.76	8.35E-20
CH_K1	5	100	−9.70	1.34E-19
CH_N2	6	0.09	−6.84	4.19E-11
SOL_AWC	7	0.67	−4.95	1.19E-06
RCHRG_DP	8	0.33	4.92	1.36E-06
SURLAG	9	8.03	4.48	1.03E-05
CANMX	10	78	−4.38	1.57E-05
SLSUBBSN	11	58.97	−3.34	9.39E-04
ESCO	12	0.43	2.84	4.70E-03
GW_DELAY	13	333.33	−2.52	1.20E-02
ALPHA_BNK	14	0.6	−2.34	1.97E-02
GW_REVAP	15	0.08	−2.27	2.37E-02
ALPHA_BF	16	0.4	2.04	4.14E-02

towards the Wadi. The *GW_DELAY* parameter determines the time interval between water exiting the soil layers and entering the shallow aquifer. A higher *GW_DELAY* value allows for greater evaporation from the unsaturated zone (Marhaento et al. 2017). In this study, the relatively high value of *GW_DELAY* (333 days) indicates significant water loss from the soil layers through evaporation, prolonging the recharge time of the aquifer. *GW_REVAP* parameter controls water movement in the capillary fringe, transferring water upwards between the unsaturated and the saturated zones to meet evaporation demand. A larger *GW_REVAP* value results in a higher water transfer from the shallow aquifer to the unsaturated zone (Marhaento et al. 2017). With a low *GW_REVAP* value of 0.08, obtained in this study, within the range of 0.02 to 0.2, evaporation in the shallow aquifer appears relatively low. Regarding, the *RCHRG_DP* parameter, which adjusts the overall water balance (Santos et al. 2020), the obtained value of 0.33 indicates that 33% of the infiltrated water is lost to a deep aquifer. The *SURLAG* parameter regulates the proportion of runoff that reaches the outlet of the watershed on a daily basis, and its value correlates positively with stream flow (Cibin et al. 2010). In the case of the Wadi Mina upstream basin, the *SURLAG* value of 8.03 is relatively low, ranging from 0.05 to 24. This suggests that the basin generates less flow at the outlet due to the strong evaporation and infiltration of water infiltration into the groundwater.

3.3 Spatial distribution of rainfall

Furthermore, the SWAT model enables the visualization of the spatial distribution of specific components of the watershed's hydrological balance. The spatial distribution map of monthly rainfall (Fig. 9) shows spatial heterogeneity in precipitation across the Wadi Mina upstream basin. The southern part experiences the highest rainfall (55–60 mm), while the northern region receives comparatively less precipitation (35–40 mm). Furthermore, the western area receives more rain (50–55 mm) than the eastern part (45–50 mm).

The spatial heterogeneity of precipitation in the Wadi Mina upstream basin may be attributed to the contrast in altitudes within the basin, where higher areas receive more rainfall compared to lower areas. Meddi and Hubert (2003) revealed that in the Tafna basin, located in the northwest of Algeria, mountainous regions receive abundant rainfall, while the plain areas receive less. This spatial variability in rainfall across the basin can be naturally explained by differences in altitude gradients

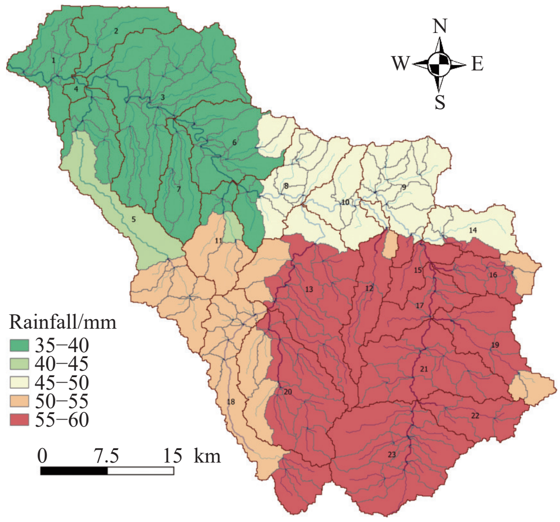

Fig. 9 Spatial distribution of monthly rainfall in the Wadi Mina upstream

(Bakreti, 2013). Habibi (2013) demonstrated in his study of the Chott Chergui watershed, situated in the high plateaus of western Algeria, that there is a significant spatial irregularity in precipitation due to the topography of the Atlas chain and the direction of prevailing westerly winds. Therefore, the spatial distribution of precipitation is most often associated with topographical factors such as altitude and distance from the sea (Shen and Anagnostou, 2017).

3.4 Spatial distribution of evapotranspiration

Regarding evapotranspiration (Fig. 10), a noticeable similarity between its spatial distribution and that of precipitation were observed. Evapotranspiration magnitudes gradually decrease from upstream (39–41 mm) towards the downstream of the Wadi Mina upstream basin (22–28 mm). Studies by Ertürk (2014), Bucak (2017) and Grusson (2018) have attributed this decrease in evapotranspiration to a reduction in the water level in the soil caused by decreased precipitation and higher temperature.

3.5 Spatial distribution of surface runoff

Regarding the spatial distribution of monthly surface runoff (Fig. 11), heterogeneity across the watershed was observed. Surface runoff is closely tied to the spatial pattern of precipitation. In the southern part of the basin, three classes of surface runoff were distinguished: 13–20 mm, 20–26 mm and 26–33 mm, whereas the norther part of the

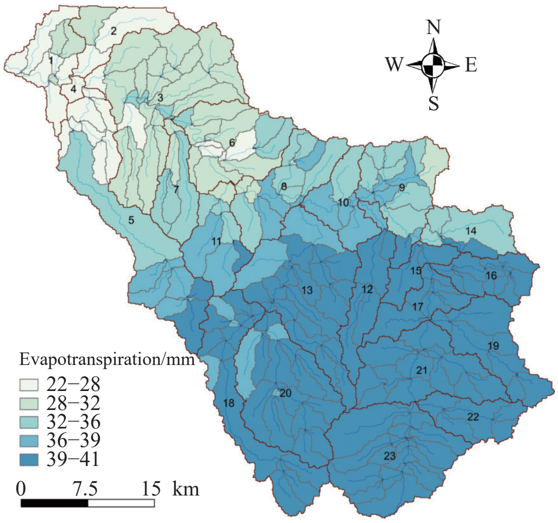

Fig. 10 Spatial distribution of monthly evapotranspiration in the Wadi Mina upstream

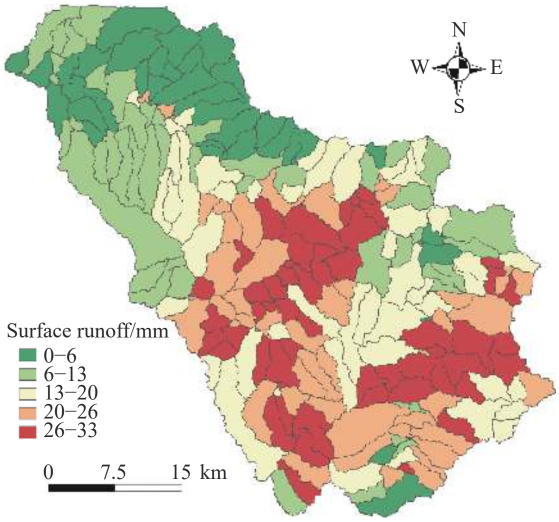

Fig. 11 Spatial distribution of monthly runoff in the Wadi Mina upstream

basin is dominated by two classes: 0–6 mm and 6–13 mm. Vegetation cover, soil type, and slope steepness are significant factors influencing surface runoff (El Kateb, 2013). The irregularity of precipitation, diversity of soil types and steep slopes are the primary factors disrupting the distribution of water within the watershed (Benslimane, 2014).

3.6 Spatial distribution of aquifer recharge

The spatial distribution of the monthly recharge of shallow aquifers across the Wadi Mina upstream basin indicates a correlation with the spatial pattern precipitation. Five classes of aquifer recharge are observed in this basin (Fig. 12), with higher recharge occurring upstream and in the central areas, while lower recharge is observed downstream.

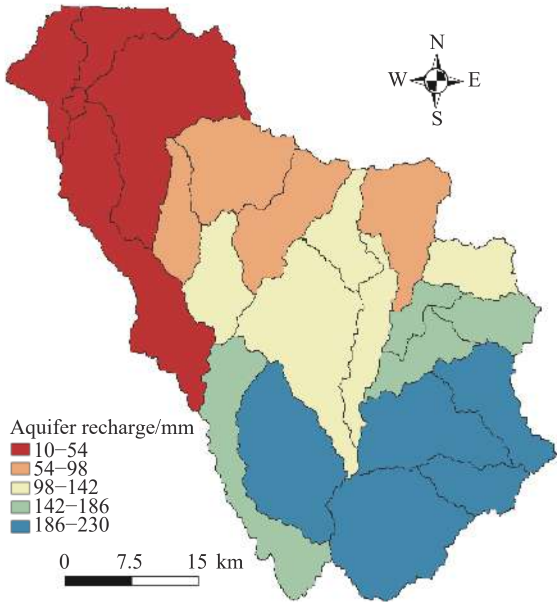

Fig. 12 Spatial distribution of monthly aquifer recharge in the Wadi Mina upstream

It's noteworthy that despite the upper areas of the basin having less permeable soil (clayey marl) compared to the lower areas, the aquifer recharge remains high. This is probably due to lateral flows in the downstream zones, leading to water loss from the shallow aquifer towards the Wadi. This observation aligns with the explanation provided in section 3.2. The magnitude of recharge depends on terrain slope overall (Chen et al. 2021) and the hydraulic properties of geological formations in the vadose zone (unsaturated zone) and the water table (Neitsch et al. 2009). Groundwater recharge in the basin results from vertical processes such as infiltration, percolation, evapotranspiration, and reevaporation, as well as lateral or fluvial exchange flows between groundwater and surface water (Krause and Bronstert, 2007). Moreover, the influence of time-space and water bearing medium can lead to variable groundwater recharge (Cheng and Dong, 2015).

3.7 Water Balance analysis

Furthermore, the SWAT model is capable of simulating various types of surface flow as well as the soil profile in the Wadi Mina upstream basin (Fig. 13). These flows are categorized into surface runoff, lateral flow, return flow and outflow from watershed. In the study basin, only 29% of the rainfall that falls into the basin contributes to runoff or infiltration into aquifers. This distribu-

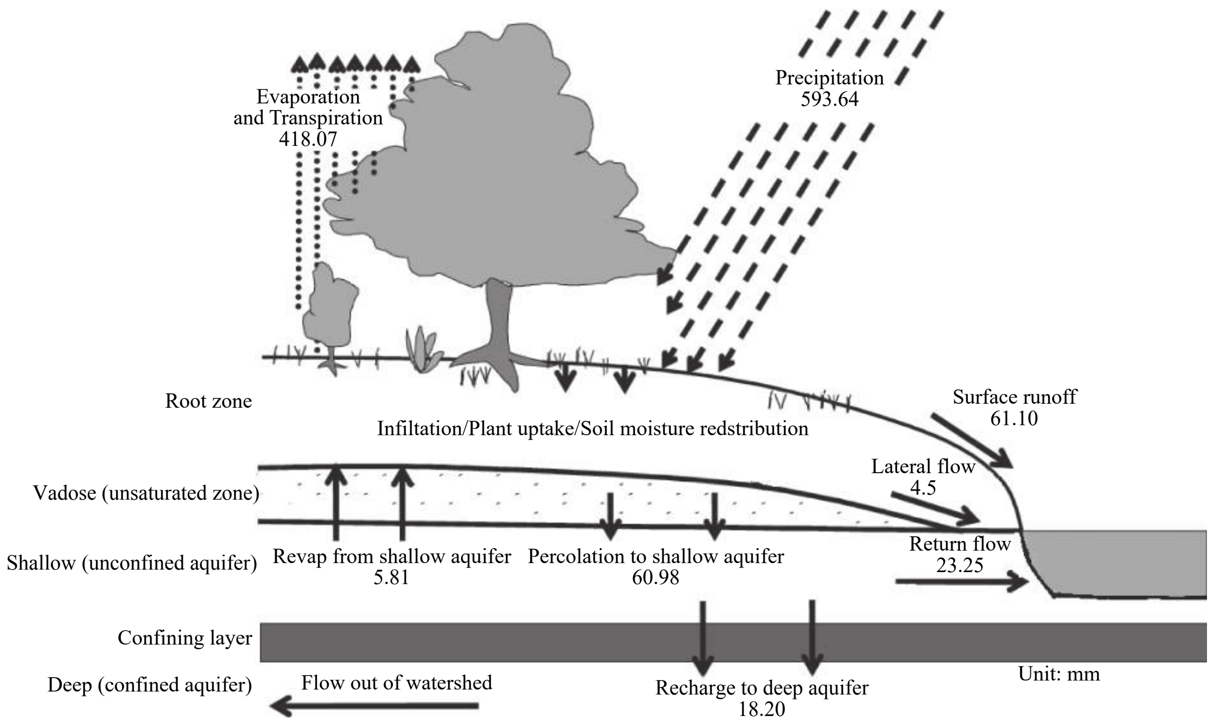

Fig. 13 Schematization of the annual hydrological balance in the Wadi Mina upstream basin

tion is as follows: 10.30% accounts for surface runoff, 1% of infiltrated water contributes to the flow of the Wadi Mina upstream as lateral flow, and 4% represents drainage from the aquifer towards the Wadi. The remainder (10.27%) percolates into shallow aquifer, and 3.06% infiltrates towards the deep aquifer.

The disparity in the distribution of the hydrological balance components in Algerian basins was also observed by Otmane et al. (2019). Their study of the Wadi Mekerra basin (northwest Algeria) using the SWAT model revealed that approximately 72% of precipitation in the basin returns to the atmosphere through evapotranspiration, with only 6% generating flow into the Wadi. This finding indicates that the majority of Wadis in Algeria exhibit temporary flow patterns.

Additionally, it can be inferred that groundwater recharge in the Wadi Mina upstream basin is significantly influenced by lateral flows, leading to low recharge of both shallow and deep aquifers. This highlights the importance of cautious groundwater exploitation to prevent over-exploitation. Surface water and groundwater interconnect and exchange based on various hydraulic properties and geological formations of the vadose (unsaturated zone) and groundwater zones (Sophocleous, 2002). Furthermore, changes in land use/land cover can impact other components of the water balance such as evapotranspiration, soil water content and groundwater recharge (Marhaento, 2017).

4 Conclusions

The application of the SWAT model for modeling the hydrological balance on a monthly scale in the upstream basin of Wadi Mina demonstrated performances ranging from very good to good in both calibration and validation phases. However, analysis of SWAT model uncertainty using the 95 PPU band (95% forecast uncertainty), p-factor and r-factor revealed some uncertainty in reproducing runoff greater than 3 m^3/s. In general, the model tends to overestimate flow rates during heavy precipitation events. Scientists accounted for SWAT mode uncertainty related to the heterogeneity and resolution of input data, such as precipitation and temperature, as well as the soil type and corresponding soil properties. These factors affect the model structure, boundary conditions and input parameters.

Sensitivity analysis of the SWAT model using the SWAT-SA code identified 16 sensitive parameters. These parameters affect surface runoff, groundwater recharge, evapotranspiration and water-soil interactions. Soil saturation in the basin is moderate, leading to reduced groundwater percolation and rapid surface flow. These factors characterize the Hortonian type flow (Infiltration Excess Overland Flow), which generally characterizes Mediterranean basins. Vegetation cover significantly influences evapotranspiration, with a significant amount of water lost through soil evaporation and prolonging aquifer recharge. Furthermore, drainage from the shallow aquifer towards the Wadi moderates water retention, impacting the deep aquifer recharge, where only 33% of the infiltrated water flows into a deep aquifer.

Spatial distribution analysis of hydrological balance components in the Wadi Mina basin revealed spatial heterogeneity in precipitation influenced by altitude gradient and topography. This variability extends to evaportanspiration, surface runoff and aquifer recharge. Furthermore, this study showed that evaportranspiration significantly influences the basin's hydrological balance, characteristic of semi-arid climates where Wadi flow is temporary. Groundwater recharge is strongly influenced by lateral flow, resulting in low recharge of both shallow and deep aquifers, emphasizing the need for cautious groundwater exploitation to prevent overexploitation.

In conclusion, the SWAT model serves as a highly adaptable hydrological modeling tool for various applications, including monthly-scale hydrological balance modelling in semi-arid basins. It can support rational groundwater exploitation to prevent depletion.

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