EVALUATING SWAT MODEL'S APPLICATION FOR ESTIMATING STREAMFLOW IN THE CIDACOS RIVER WATERSHED IN NAVARRE, SPAIN

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RESUMEN. Se utilizó el modelo SWAT para simular el caudal del río Cidacos en Navarra. El SWAT podría ayudar a predecir los futuros impactos hidrológicos debidos a los cambios en el uso del suelo agrícola, como la transformación de la agricultura de secano a la de regadío. La idoneidad del modelo se evaluó mediante la parametrización, la sensibilidad, la incertidumbre, la calibración, la validación y la evaluación de su rendimiento mediante indicadores estadísticos. Los caudales fueron calibrados y validados entre los años 2000-2010 y 2011-2020 respectivamente en la estación de aforo de Olite. Las incertidumbres en el modelo se analizaron mediante los factores p y r que resultaron satisfactorios durante la calibración y la validación. Los índices estadísticos de rendimiento proporcionaron una buena coincidencia entre los valores observados y los simulados, lo que indicó que el modelo SWAT era muy satisfactorio para la simulación del flujo de la corriente en la cuenca.

ABSTRACT. The Soil Water Assessment Tool (SWAT) model was used to simulate streamflow in the Cidacos River in Navarra. SWAT could help in predicting future hydrological impacts due to agricultural land use changes such as transformation from rainfed to irrigated agriculture. The model's suitability was assessed by carrying out parametrization, sensitivity and uncertainty analysis, calibration, validation, and assessing its performance using statistical indicators. Streamflow in the watershed was calibrated and validated between the years 2000-2010 and 2011-2020 respectively at the Olite gauging station. Uncertainties in the model were analyzed using the p-factor and r-factor which satisfactory results for both calibration and validation periods. Statistical performance indices provided a good match between the observed and simulated values which indicated that the SWAT model was very satisfactory for simulation of stream flow in the watershed.

1.- Introduction

Agriculture is one of the most important sectors of any regional or national economies in the world. It is the main source of livelihood as well as the backbone of most nations' economic systems globally with up to more than 60 percent of the population directly dependent on it as a means of living (FAO, 2017). However, the intensification of agriculture creates a lot of pressures on the available water resources and the environment. Agriculture is the highest global freshwater consumer accounting for more than 90 percent of the world water resources withdrawals (Siebert et al., 2010). Irrigation forms the bulk of agricultural water demand with over 70 percent consumption (Zeng and Cai, 2014). Despite its immense benefits to the society and economy, agricultural activities have the potential to cause substantial damage to the environment especially affecting the water quality through non-point source pollution from sedimentation (Chahor et al., 2014; Giménez et al., 2012; Merchán et al., 2018), the application of pesticides (Muñoz-Carpena et al., 2018), fertilizers and agrochemicals such as nitrate contamination from agricultural fertilizer application which is a threat to human health and the environment (Sutton et al., 2011). The intensity of erosion processes is usually much higher in agricultural environments than for other soil uses (Almagro et al., 2016; Boardman and Poesen, 2006).

Globally, the area under irrigation farming has almost doubled within the 50 years period from 1965 up to 2015 having increased from 170 Mha to 333 Mha (FAO and IWMI, 2018). In Europe, the irrigable area increased by 13 percent for the 10 years period from 2003 to 2013, and in Spain the increase was around 11 percent in the 10 years period between 2007-2017 (MAPA, 2021). Irrigation which covers only 14 percent of the surface area contributes to over 50 percent to Spain's final agricultural production which is on average six times more than rainfed areas (MAPA, 2021). In Navarre, irrigated area has increased by over 25 percent (110,000 ha) for the period between 2000 and 2015 with pressurized irrigation being implemented in those lands (DDRMAAL, 2021). Previous studies have shown that the transition from rainfed to irrigated agriculture affects water quality by increasing its salinity (Duncan et al., 2008; Pulido-Bosch et al., 2018) and nitrate concentration (Muñoz-Carpena et al., 2002), among other environmental problems such as overexploitation of aquifers or pollution with pesticides (Muñoz-Carpena et al., 2018). Washing out the salt from the soil profile is a requirement of irrigated agriculture (Letey et al., 2011), as salinity reduces the availability of water for plants. Nitrate pollution as a result of eutrophication threatens the quality of water for human consumption as well as the environment (Merchán et al., 2020).

This study builds on the previous research conducted by

Merchán et al. (2020) which analyzed the effects of irrigation implementation on salinity and nitrate concentration in the Cidacos River Watershed in Navarre, Spain. The main objective of this study was to evaluate the SWAT model's capability to simulate streamflow in the Cidacos River Watershed in Navarra in order to predict future hydrological and agricultural land use changes such as transformation from rainfed to irrigated agriculture. This was done through conducting sensitivity analysis, calibration, and validation of the SWAT model, as well as assessing its performance using statistical indicators such as Nash-Sutcliffe, RMSE, R2 and PBIAS.

2.- Materials and Methods

2.1. Study Area

The Cidacos River is a tributary of the Aragón River, which is one of the tributaries of the Ebro River. It is located within latitudes 42˚ 69' and 42˚ 34' North and longitudes 1˚ 72' and 1˚ 47' West which is approximately 15 km south from the city of Pamplona, the capital of the "Floral" Community of Navarre in Spain (Fig. 1). The river is formed in the town of Mendívil by the confluence of the Arlusia stream and the Mairaga stream. It spans a length of approximately 44 km that runs through Valdorba and the foothills of Tafalla-Olite to the mouth around Traibuenas where it flows into the Aragón River. The Cidacos River drains a watershed of 477 km^2 that mostly follows the north-south direction with an approximate width of 15 km in its widest section. The headwater of the watershed is somewhat mountainous with high altitudes of slightly over 1000 m above sea level at the North of the watershed, but then crosses down to slightly uneven to low terrain of approximately 300 m above sea level at the river's mouth in Traibuenas where it joins with the Aragón River. The climate of the watershed is mild Mediterranean, with cold winters and high levels of summer aridity that varies spatially from North to South. The watershed receives annual precipitations ranging from 800 mm to 400 mm, characterized by a strong inter-annual irregularity and the most rainfalls in the months of April and May (Merchán et al., 2020).

The predominant land use/land cover (LULC) in the study area is agriculture covering more than half (53 percent) of the watershed. The watershed is characterized with rainfed agriculture in the upper reaches until around Olite town whereas the lower reaches mostly practice pressurized irrigated agriculture. The "Canal of Navarre" supplies irrigation water from a reservoir located outside the watershed in the North of Navarre. Other major land uses in the study area include forests covering a quarter of the watershed (25 percent), pasture and bushlands at 17 percent, and the rest of the area including urban, residential areas, built-up land, bare land, and water bodies covering the remaining 5 percent. All the land uses in the watershed are as shown in Fig 2b.

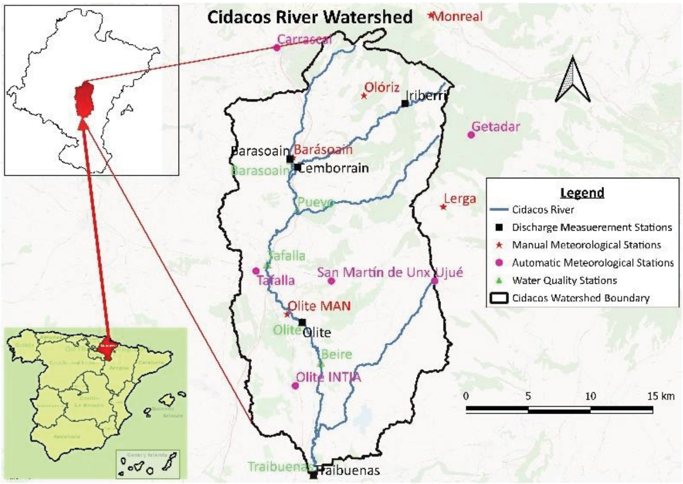

Fig. 1. The Cidacos River Watershed.

The most predominant soil types in the watershed are Haplic Calcisols soils (about 51.6%) found in various parts of the watershed, Fluvic Cambisols soils (26.1%) mainly found along the river network path and Calcaric Regosols (18%). Other soils within the watershed included: Haplic Phaeozem (1.7%), Calcic Kastanozems (1.6%), Fluvic Phaeozem (0.4%), Eutric Fluvisols (0.3%), and Dystric Cambisols (0.2%) as shown in Table 1. The most abundant soil textures were loam and clay-loam found in most agricultural areas in the watershed whereas loamy-sand and sandy-loam soils are found on the eroded hillslopes.

Table 1. Major soil distribution in the Cidacos River Watershed.

USDA Soil Name	FAO Soil Name	Symbol	Area Covered (km^2)	% Covered	Soil Texture
Typic Calcixerepts	Haplic Calcisols	CLh	246.31	51.63	Loam
Typic/ Fluventic Haploxerepts	Fluvic Cambisols	CMf	124.49	26.10	Clay-Loam
Typic/Lithic Xerorthents, Udorthent	Calcaric Regosols	RGc	85.98	18.02	Loamy-Sand
Lithic-Ruptic Haplustolls	Haplic Phaeozem	PHh	8.19	1.72	Clay-Loam
Typic calcixeroll	Calcic Kastanozems	KSk	7.47	1.56	Loam
Fluventic Haploxerolls	Fluvic Phaeozem	PHf	1.93	0.41	Loam
Typic Xerofluvent	Eutric Fluvisols	FLe	1.58	0.33	Clay-Loam
Typic Dystrudepts	Dystric Cambisols	CMd	1.08	0.23	Sandy-Loam

2.2. Description of the SWAT Model

The SWAT model is a freely available open-source software developed by the United States Department of Agriculture's Agricultural Research Service (USDA-ARS) to assist water resources managers, policy experts and decision makers to predict and quantify the impact of land use management on water and diffuse pollution in small and large watersheds, with different soil types, land use and management practices (Lévesque et al., 2008). SWAT is a data driven, semi-distributed, continuous timescale, physically and process-based hydrological model that simulates water, sediment and agricultural chemicals/pollutant yields. The model will be built on the QGIS interface through its QSWAT plugin. The hydrologic balance in SWAT is simulated for each Hydrological Response Unit (HRU). The land phase of the hydrologic model simulated by the SWAT model is based on the water balance equation as shown in equation 1 (Arnold et al., 2012; Neitsch et al., 2011).

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

Where, SW_t is the final soil water content (mm of water), SW_o is the initial soil water content on day i (mm of water), t is the time (days), R_{day} is the amount of precipitation on day i (mm of water), Q_{surf} is the amount of surface runoff on day i (mm of water), E_a is the amount of evaporation on day i (mm), W_{seep} is the amount of water entering the vadose zone on day i (mm of water), and Q_{gw} is the amount of return flow on day i (mm of water).

2.3. Data Acquisition and Model Set-up

The SWAT model requires several input dataset variables in order to be run, calibrated and validated. Both geospatial data and daily hydrometeorological data were used to set up and run the model. The geospatial data used in this study were obtained from the Government of Navarre, Spatial Data Infrastructure of Navarre (IDENA) website (https://sitna.navarra.es/geoportal/geop_sitna/geoportal.aspx). The geospatial data used included the Digital Elevation Model (DEM, 25m resolution ETRS89 UTM Zone 30N projection) of the Cidacos River (CR) Watershed (Fig. 2a), the land use/land cover (LULC, 2019) map (Fig. 2b) and soil type map data of 1:25000 scale (Fig. 2c) were used. The required hydrometeorological data was the daily meteorological data which was obtained from 25 weather stations (14 automatic stations and 11 manual stations) owned and operated by the Government of Navarre that are located inside and nearby the watershed. The meteorological data included daily data of precipitation (mm), maximum and minimum daily temperatures (˚C), solar radiation ($MJm^{-2}s^{-2}$), wind speed (ms^{-1}), and relative humidity (%) data. The daily observed streamflow data (m^3s^{-1}) at the Olite gauging station was used to calibrate and validate the model. The Olite gauging station was chosen as it was the only discharge point with a long-term data having been installed in 1988. The station is operated and maintained by the Government of Navarre and the data was obtained from their website (http://www.Navarre.es/appsext/AguaEnNavarre/ctaDatosHistoricos.aspx). The daily discharge data was for the period 2000-2020. It's imperative to note that the Olite station only covers the area of the watershed under rainfed agriculture.

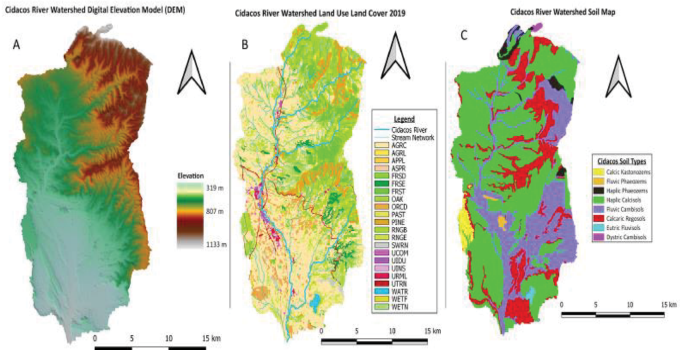

Fig. 2. The Cidacos River Watershed: (a) DEM; (b) 2019 Land Use/Land Cover (LULC) Map; (c) Soil Type Map.

The model set-up was preceded by preparation and processing of the required spatial datasets such as DEM, soil and land use grid maps as well as discharge outlet points on the QGIS 3.18 interphase. The meteorological and observed streamflow data were processed and analyzed in the R-software before being converted to the required SWAT format (text files). The streamflow data was checked for missing gaps, consistency and if there were any changes in the streamflow using the R changepoint package, *'cpt'*, following the methodology by Killick and Eckley (2014) for single changepoint detection (AMOC). The daily streamflow data was then converted into monthly averages which were used for the streamflow calibration and validation of the model. The monthly time-step was adopted since a review of previous studies (Abbaspour et al., 2018) showed that the SWAT model performed better at monthly time-step than daily time-steps. After the data preparation, the model was set up in the QSWAT3 1.1.1 interphase. The following three key steps were carried out during the model set-up in QSWAT: watershed delineation, creation of HRUs, and editing inputs and running SWAT. The outputs from QSWAT were then transferred to SWATCUP 5.1.6 which is a standalone software where the processes of parameterization, uncertainty and sensitivity analysis, calibration, validation and evaluation of the model performance was done. The multi-site, semi-automated inverse modelling routine SUFI-2 procedure (Abbaspour, 2015) was used for the model calibration and validation using observed data at a monthly time-step.

2.4. Sensitivity Analysis, Calibration and Validation

The SWAT Calibration and Uncertainty Procedures (SWAT-CUP) software with Sequential Uncertainty Fitting, version 2 (SUFI-2) algorithm (Abbaspour, 2015; Abbaspour et al., 2018) was used. SWAT-CUP consists of five different calibration routines which include: Sequential Uncertainty Fitting, version 2 (SUFI-2); Particle Swarm Optimization (PSO); Generalized Likelihood Uncertainty Estimation (GLUE); Parasol Solution (ParaSol); and Markov Chain Monte Carlo (MCMC).

These routines can be used to model SWAT outputs files as well as up to eleven different objective functions that can be carefully selected based on the study objective with an option for multi-objective calibration where any set of combination of the objectives can be chosen.

Simulation runs were carried out using the available data timeseries for 31 years with the initial 10 years from 1990-1999 being used as the model warm-up period, that is, Number of Years Skipped (NYSKIP), and then from 2000-2010 and 2011-2020 to be used for the model calibration and validation respectively. Calibration was done at a monthly time-step by setting the streamflow at the Olite gauging station as the target variable. The calibrated parameters and their uncertainty ranges were kept constant and then used for the validation of the model. The parameters to be considered for calibration were determined from the abundant existing literature (Abbaspour, 2015; Abbaspour et al., 2015, 2018; Kamali et al., 2017; Kouchi et al., 2017; Rouholahnejad et al., 2014). Streamflow parameters usually used in SWAT modeling within the Mediterranean region are detailed in in Table 2 including their model allowable ranges. Among these parameters, a set of 11 key streamflow parameters were selected for use in the calibration process after a sensitivity analysis.

Table 2. SWAT model parameters used for streamflow simulation.

Parameter	Description	Allowable Range
CN2	Initial SCS runoff CN number for moisture condition II (dimensionless)	35 - 98
ALPHA_BF	Baseflow alpha factor (1/days)	0 - 1
SOL_K	Saturated hydraulic conductivity (mm/hr.)	0 - 2000
SOL_AWC	Available soil water content (mm H_2O/mm of soil)	0 - 1
SOL_BD	Soil Bulk density (Mg/m^3 or g/cm^3)	0.9 - 2.5
SOL_Z	Depth of soil layer (mm)	0 - 3500
USLE_K	USLE equation soil erodibility (K) factor (units: 0.013 (metric ton m^2 hr.) / (m^3-metric ton cm))	0 - 0.65
CH_N2	Manning's "n" value for the channel (dimensionless)	-0.01 - 0.3
CH_K2	Channel hydraulic conductivity (mm/hr.)	-0.01 - 500
CH_COV2	Channel cover factor (dimensionless)	-0.001 - 1
SURLAG	Surface runoff lag time (days)	0.05 - 24
ESCO	Soil Evaporation compensation factor (dimensionless)	0.01 - 1
EPCO	Plant uptake compensation factor (dimensionless)	0.01 - 1
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	0 - 5000
GW_DELAY	Groundwater delays (days)	0 - 500
GW_REVAP	Ground water "revap" coefficient or coefficient of water rise to saturation zone (dimensionless)	0.02 - 0.2
SLSUBBSN	Average slope length of basin (m)	10 - 150
CANMX	Maximum canopy storage (mm H_2O)	0 - 100
SLSOIL	Slope length for lateral subsurface flow (m)	0 - 150
REVAPMN	Water depth in the aquifer for the occurrence of water rise to the unsaturated zone (mm H_2O)	0 - 500
BIOMIX	Efficiency of soil biological mix (dimensionless)	0 - 1
SOL_ALB	Soil Albedo (dimensionless)	0 - 0.25
OV_N	Manning's "n" value for overland flow (dimensionless)	0.01 - 30
HRU_SLP	Average slope steepness (m/m)	0 - 1
SOL_CRK	Crack volume potential of the soil (dimensionless)	0 - 1

The global sensitivity analysis in which all the parameters change at the same time was carried out to identify the most sensitive parameters by calculating the multiple regression computations using equation 2. This system regresses the Latin hypercube generated parameters against the objective function values (Abbaspour, 2015). A t-test was then used to identify the relative significance of each parameter, b_i.

$$g = \alpha + \sum_{i=1}^{m} \beta_i b_i \qquad (2)$$

where, $\propto = \frac{\sigma_s}{\sigma_m}$ and $\beta = \frac{\mu_s}{\mu_m}$; σ_s and σ_m are the standard deviation of simulated and measured data; μ_s and μ_m are the means of simulated and measured data; and b_i is the relative significance of each parameter. Analysis of the sensitivity of the parameters was based on the p-values and t-stat. The smaller the p-value, the more sensitive the parameter was and vice versa. The best combination is a very small p-value and a large t-value (absolute) to obtain the most sensitive parameter. Parameters that had p-values below 0.05 were considered as highly sensitive.

The sensitivity analysis was performed to help identify the most sensitive parameters that had the greatest impact on the model outputs so as to be used in the calibration process (Arnold et al., 2012). Larger parameter uncertainties were initially assumed so as to ensure that most of the observed data could be captured within the 95 Percent Prediction Uncertainty (95PPU) band (Abbaspour et al., 2018). 95PPU accounts for all the uncertainties within the model combined. The parameter ranges were then adjusted after every iteration run during the calibration phase until most of the observed data were bracketed in the 95PPU band. The model was considered satisfactory as long as more than 50% of the observed flow data were bracketed within the 95PPU, that is, p-factor > 0.5.

2.5. Model Performance Metrics

To evaluate the model's performance, several statistical performance indicator techniques were adopted. Moriasi et al. (2007) recommends the Nash-Sutcliffe efficiency (NSE), ratio of the root mean square error to the standard deviation of observed data (RSR), Coefficient of Determination (R2), and percent bias (PBIAS) as the most appropriate quantitative statistical techniques for SWAT Model evaluation. The value of NSE indicates how best the plot of observed versus simulated data fits the line 1:1. NSE values ranges between $-\infty$ to 1. A value of 1 indicates a perfect match between the observed and simulated data. RSR is calculated as the ratio of the Root Mean Square Error (RMSE) and standard deviation of observed data. RSR values vary from 0 to a large positive integer, where a value of 0 indicates no RMSE thus optimal (perfect model). RMSE shows the measure of mean residual variance. The coefficient of determination (R^2) estimates the likelihood of the simulated values corresponding to the observed data. R^2 provides an estimate of how many data points fall within the results of the best fit line formed by the regression equation. R^2 values ranges from 0 to 1, with a value of 1 being a perfect correlation. PBIAS indicates the deviation of the results from the observations expressed as a percentage. An ideal model should have a PBIAS of 0. However, models tend to have either a positive or negative PBIAS which generally implies underestimation or overestimation of the observations respectively. The model performance was considered as satisfactory, provided the values of the NSE > 0.5, RSR ≤ 0.7, $R^2 > 0.5$, and if PBIAS ±25% for streamflow.

3.- Results and Discussion

3.1. Parameterization and Sensitivity Analysis

The sensitivity analysis was used to determine which processes are most dominant in the watershed. This was achieved after five iterations with 500 simulations each in SUFI-2. Parameters that influenced the overall hydrological processes in the catchment and that need to be taken into consideration during model calibration and validation were identified (Table 3). SWAT has two types of sensitivity analyses: local (the one-at-a-time) sensitivity analysis and the global sensitivity analysis. In the local sensitivity analysis, all parameters are fixed, and change is only made to one parameter at a time. However, since the sensitivity of one parameter depends on the sensitivity of the other values, this method could yield some problems. Additionally, it is also very slow and quite time consuming hence not recommended (Abbaspour et al., 2015). Generally, the global sensitivity analysis is more acceptable and applicable. In the global sensitivity analysis, changes in all parameters are done at the same time. The larger the absolute value of t-stat, the more sensitive a parameter will be and the lower the absolute value the less sensitive the parameter is. The rejection or acceptance of the null hypothesis that a parameter is not sensitive is based on the p-values. The lower the p-values the more sensitive the respective parameter is to changes in streamflow. The parameters were ranked with the most sensitive parameters depending on their t-stat index and p-values being at the top (Table 3). The most sensitive parameters were found to be the Groundwater delays (GW_DELAY), Baseflow alpha factor (ALPHA_BF), curve number factor (CN2), the available soil water capacity (SOL-AWC), and plant uptake compensation factor (EPCO).

Table 3. Main parameters used for sensitivity analysis and calibration of SWAT model.

Parameter Name	p-value	t-stat
GW_DELAY.gw	0.0000	-42.7879
ALPHA_BF.gw	0.0000	6.6927
CN2.mgt	0.0000	6.5606
SOL_AWC.sol	0.0065	2.7318
EPCO.bsn	0.0261	2.2321
SOL_K.sol	0.1500	-1.4598
SOL_BD.sol	0.1454	1.4584
OV_N.hru	0.1598	1.4081
GWQMN.gw	0.2990	-1.0398
GW_REVAP.gw	0.8749	-0.1576
ESCO.hru	0.8960	-0.1308

To adequately consider a model validly calibrated, the parameter uncertainty ranges must be indicated (Table 4). There are three methods (parameter qualifiers) that can be used to make changes to the parameter values in SWAT: the parameter qualifier "R" which refers to a relative change of the specified parameter that increases or decreases the existing SWAT parameter value by multiplying it by (1 + fitted value) so as to obtain the new parameter value; the qualifier "V" refers to value change or replacement which means that the initial SWAT parameter value is to be directly replaced by the fitted value; and the qualifier "A" which refers to addition and means that the fitted value is added to the initial SWAT parameter value. To ensure statistical optimization of precision, SWAT-CUP suggested new values of intervals after each iteration (500 simulations) thus the calibrated values for each parameter can sometimes appear outside the initial existing intervals upon the completion of the five iterations. The model is considered calibrated once all the parameters and their respective uncertainties have been fitted in SWAT.

Table 4. Parameter adjustment method and their uncertainty ranges.

Parameter Name	Qualifier Method	Parameter Adjustment Values		
		Min. value	Max. value	Fitted value
CN2	R	-0.083	0.106	-0.066
ESCO	R	-0.039	0.054	0.033
ALPHA_BF	V	-0.318	0.561	0.523
GW_DELAY	V	13.03	39.16	28.88
GW_REVAP	V	0.049	0.147	0.107
GWQMN	V	0.397	1.193	0.820
SOL_AWC	R	-0.119	0.094	0.063
SOL_K	R	-0.662	0.046	-0.620
SOL_BD	R	-0.610	-0.203	-0.263
OV_N	R	0.050	0.151	0.120
EPCO	R	-0.221	-0.074	-0.122

R multiplies the existing value with (1+fitted value) i.e. relative change
V replaces the existing value with the fitted value i.e. value change

3.2. Simulation of Streamflow

Trend analysis of the observed streamflow data using the changepoint (cpt) method in R (Killick and Eckley, 2014) indicated that there was a slight increase in the mean of the average monthly streamflow data around 2012 as shown in Fig. 3. This correspond to the same period when the implementation of irrigation in the lower reaches of the watershed was taking place. The overall mean of the entire dataset was 0.87 $m^3 s^{-1}$ whereas the means before and after the changes were 0.61 $m^3 s^{-1}$ and 1.26 $m^3 s^{-1}$ respectively. Similar results were obtained during the model simulation with average discharge of 0.70 $m^3 s^{-1}$ and 1.05 $m^3 s^{-1}$ during the calibration and validation periods respectively. This however did not affect the simulation process since the model was evaluated only on the rainfed upper reached of the watershed which aren't influenced by irrigation.

During the simulation process, comparison in the mean monthly flow for the calibration period was estimated at 0.75 $m^3 s^{-1}$ against 0.70 $m^3 s^{-1}$ for the observed versus simulated data respectively, whereas the mean monthly flow during the validation period was estimated at 1.06 m^3

s^{-1} against 1.05 m^3 s^{-1} for the simulated versus observed data. The monthly streamflow was satisfactorily simulated in the calibration period and showed good agreement in the validation period. The model tended to underestimate most of the peak flows especially during the validation period despite simulating quite well the base flows. Previous studies have shown that SWAT model generally does not accurately predict most high flow events thus resulting to either their overestimation or underestimation (Meaurio et al., 2015; Rostamian et al., 2008; Tolson and Shoemaker, 2004).

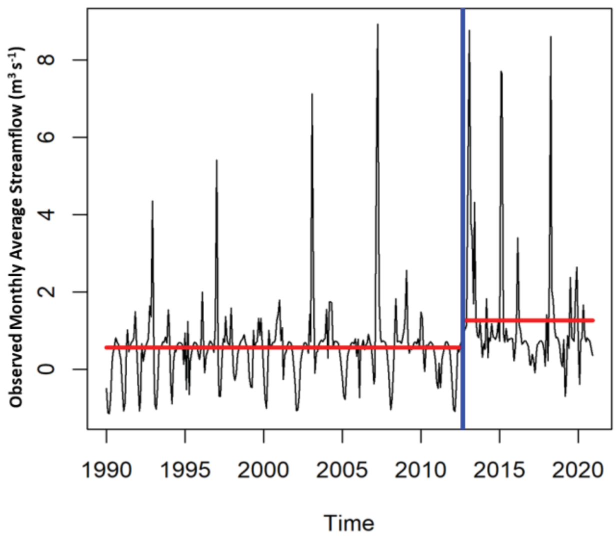

Fig 3. Changepoint analysis in the average monthly mean streamflow data at the Olite gauging station from 1990-2020.

Streamflow was calibrated and validated at a monthly time step using SUFI-2 in SWAT-CUP. The p-factor and r-factor values were 0.73 and 0.81 respectively during the calibration period (Fig. 4) and 0.86 and 0.76 respectively during the validation period (Fig.5). Studies by Abbaspour (2015) and Abbaspour et al. (2018) suggested that a p-factor value greater than 0.7 and r-factor values less than 1.2 are considered satisfactory for streamflow calibration and validation. The p-factor represents the percentage of observed data bracketed within the 95PPU which accounts for all the uncertainties during the model calibration and validation processes. The results for streamflow calibration in the Cidacos River are thus acceptable following the mentioned conditions. This implies that during calibration, 73% of the data were bracketed within the 95PPU which indicates a good model performance. Similarly, 86% of the data were bracketed within the 95 PPU during the model validation. The lower value of p-factor during calibration compared to the validation period could be attributed to the uncertainties in the input data such as precipitation data estimations for some stations within the watershed that were done to fill missing data gaps between 2000 to 2004, unlike the validation period that had a more consistent and accurate precipitation data. The r-factor represents the ratio of the average distance between the 95PPU band by the standard deviation of the observed data. The lower the r-factor values, the better the performance of the model during calibration and validation. The ideal condition should have a p-factor of 0 and an r-factor of 1 which represents a simulation that directly corresponds to the observed data. However, extremely low p-values are not recommended as it could indicate that most of the uncertainties are not being accounted for. Fig. 4 and Fig. 5 show the simulated and observed hydrographs together with their uncertainty bands as well as the precipitation for the Cidacos River Watershed at the Olite gauging station.

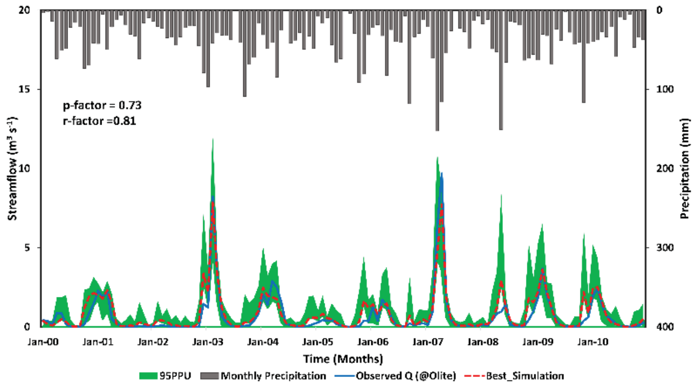

Fig. 4. Calibration results for the observed and simulated streamflow for the Cidacos River at Olite gauging station from 2000-2010.

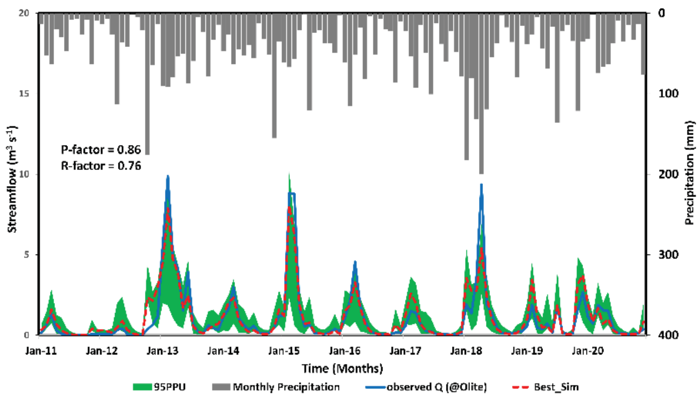

Fig. 5. Validation results for the observed and simulated streamflow for the Cidacos River at Olite gauging station from 2011-2020.

3.3. Model Performance Indicators

The statistical performance of the model during both calibration and validation were considered as good for streamflow prediction as represented in Table 5. The NSE and R^2 values of 0.77 and 0.79 respectively during calibration period and 0.78 and 0.81 respectively during validation period were very satisfactory and indicated a very good model performance (Table 5). Similarly, PBIAS of -6.5 and 0.2 during calibration and validation periods respectively were quite satisfactory. The PBIAS value indicated the general tendency of the model to overestimate the flows by 6.5% during calibration and slightly underestimate the flows by 0.2% during validation which reflects a 'very good' fit. The RSR value of 0.48 and 0.46

for calibration and validation respectively were also satisfactory as they were below the recommended threshold of 0.7 and thus indicating a good model performance. Following the results from the four statistical performance indicators, the model can thus be considered to be very good and satisfactory to simulate monthly streamflow for the Cidacos River. Better values were attained during the validation period as compared to the calibration period. This could be as a result of better input data such as rainfall and land use during the validation period. The validation period had fewer missing rainfall gaps and had the recent land use map of 2019 that was used in the model unlike the calibration period that exhibited a lot of meteorological data inconsistencies before 2004 especially for the automatic stations as most of them were only operational after March 2004.

Table 5. Model performance indicators in calibration and validation.

Performance indicator	Threshold	Calibration	Validation	Model Performance
NSE	> 0.5	0.77	0.78	Satisfactory
R^2	> 0.5	0.79	0.81	Satisfactory
PBIAS	±25%	-6.5%	0.20%	Satisfactory
RSR	≤ 0.7	0.48	0.46	Satisfactory

4.- Conclusion

In this study, the SWAT model was used to simulate streamflow in the Cidacos River from 1990-2020 at a monthly timestep. The initial first 10 years were used as warm-up period whereas calibration and validation period were carried between 2000-2010 and 2011-2020 respectively. The most sensitive parameters during streamflow calibration were Groundwater delays (GW_DELAY), Baseflow alpha factor (ALPHA_BF), curve number factor (CN2), the available soil water capacity (SOL-AWC), and plant uptake compensation factor (EPCO). The results showed that the model was capable of identifying the uncertainties in the hydrological processes using the p-factor and provided their uncertainty range (95PPU). Statistical indices indicated that the SWAT model provided satisfactory model performance and good agreement for streamflow simulation with the observed data with NSE and R2 values of 0.77 and 0.79 during calibration and 0.78 and 0.81 during the validation period respectively. It can thus be concluded that the SWAT model could be considered as an appropriate tool capable of evaluating streamflow in the Cidacos River Watershed adequately. The outcome from this study could be used to predict future hydrological impacts due to agricultural land use changes such as transformation from rainfed to irrigated agriculture.

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