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Articles

Comparison between *WEAP* and *SWAT* models in a basin at Oaxaca, Mexico

Comparación de los modelos *WEAP* y *SWAT* en una cuenca de Oaxaca, México

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Abstract

The Sordo Basin is located in the western portion of the state of Oaxaca, Mexico. This presents problems of water erosion and loss of biodiversity. The present paper aims to compare the measured runoffs at the Ixtayutla station (20021) with simulated runoff by the *WEAP* model (*Water Evaluation and Planning*) and the results of the *SWAT* (*Soil and Water Assessment Tool*) model reported for the same basin by Sánchez-Galindo, Fernández-Reynoso, Martínez-Ménez, Rubio-Granados and Ríos-Berber (2017). *WEAP*-Soil Moisture Method used the same weather data, land use and soil type than *SWAT*. The comparison was based on the statistical efficiency of both models to simulate the monthly and annual runoff during the period 1975-1985. Three efficiency indices were calculated: the coefficient of determination (r^2), Nash-Sutcliffe efficiency (*NSE*) and the percent bias (*PBIAS*). Regarding the monthly runoffs, *WEAP* presented a *NSE* = 0.73 (good); a *PBIAS* = -16.05 (satisfactory), and r^2 = 0.84. *SWAT*, for that same period, reaching a *NSE* = 0.82 (very good); a *PBIAS* = -15.92 (satisfactory), and a r^2 = 0.85. For annual runoffs, *SWAT* y *WEAP* getting a *NSE* = 0.73 and 0.3, a r^2 = 0.76 and 0.63 and a *PBIAS* = -4.65 and -16.23, respectively. Both models are satisfactory to simulate monthly runoffs and the choice between one or other will depend on the problems to study in the basin, the available data and the hydrological goals.

Keywords: *SWAT*, Soil Moisture Method, Mixteca oaxaqueña, Nash-Sutcliffe, watersheds.

Resumen

La cuenca del río Sordo, localizada al oeste de Oaxaca, México, presenta problemas de erosión hídrica y pérdida de biodiversidad. El presente trabajo tiene como objetivo comparar los escurrimientos aforados en la estación Ixtayutla (20021), con valores simulados de los modelos *WEAP* (*Water Evaluation And Planning System*) y *SWAT* (*Soil and Water Assessment Tool*). Se procuró que *WEAP*, a través del método de la humedad del suelo, utilizara los mismos datos climáticos, de vegetación y suelos que *SWAT*, reportados para esta misma cuenca por Sánchez-

Galindo, Fernández-Reynoso, Martínez-Ménez, Rubio-Granados y Ríos-Berber (2017). La comparación se basó en la eficiencia estadística de ambos modelos para simular los escurrimientos mensuales y anuales ocurridos durante el periodo 1975-1985. Se calcularon tres índices de eficiencia: el coeficiente de determinación (r^2), Nash-Sutcliffe (*NSE*) y el sesgo porcentual (PBIAS). Con respecto a los escurrimientos mensuales aforados, *WEAP* presentó un *NSE* = 0.73 (bueno); un PBIAS = -16.05 (satisfactorio), y una r^2 = 0.84. *SWAT*, para ese mismo periodo, mostró un *NSE* = 0.82 (muy bueno); un PBIAS = -15.92 (satisfactorio), y una r^2 = 0.85. Para los escurrimientos anuales, *SWAT* y *WEAP* obtuvieron un *NSE* de 0.73 y 0.3, un r^2 de 0.76 y 0.63 y un PBIAS de -4.65 y -16.23, respectivamente. Los dos modelos resultaron satisfactorios para simular escurrimientos mensuales, por lo que la elección de uno u otro modelo dependerá de la problemática de la cuenca, los datos con que se cuente y los objetivos por cumplir.

Palabras clave: *SWAT*, método de la humedad del suelo, Mixteca oaxaqueña, Nash-Sutcliffe, cuencas hidrográficas.

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Introduction

Globally, the deterioration of natural resources is becoming more severe. The causes of this problem can be both natural and anthropogenic. However, society must act to understand and evaluate the interaction between human behavior and the state of resources; especially when economic and population growth demands more natural resources.

The State of Oaxaca, Mexico is rich in natural resource diversity, but it is under serious use pressure. Specifically, the Mixtec region presents a strong degradation of its soils and vegetation cover. The Sordo River basin, a subsidiary of the Verde River, that discharge into the Pacific Ocean, covers an area of 7,751.42 km^2; which represents 54 % of the Oaxaca Mixtec region (Sánchez-Galindo *et al*., 2017).

The Sordo River basin is mainly covered by volcano-sedimentary material (70 %), has a steep relief (average slope 36.3 %), and intense rainfall (46 ± 13.3 mm hr^{-1}, annual average) derived mainly from tropical hurricanes. The presence of unconsolidated sedimentary materials, the steepness of the relief, the presence of cyclonic rains and hillside agriculture, favors erosion processes and inhibits soil's capacity to retain moisture. However, human intervention has accelerated soil degradation and decreased the density of plant cover, due to overgrazing, inadequate forestry use, and hillside agriculture (Sánchez-Galindo *et al*., 2017).

The energy of the rain derived from its intensity, and the potential energy provided by the topography, favors the detachment of soil particles; caused by drops impact and channels entrenchment which is provoked by the concentration of high-velocity runoff on sedimentary deposits. The degradation processes derived from surface runoff and the degradation of plant cover makes it necessary to understand in-depth water resources related process that occurs in the Sordo River basin. In this sense, simulation models are a useful tool to identify cause-effect relationships. Therefore, this research uses the same environmental information and *SWAT* calibrated parameters to run the *WEAP* model. The purpose of this study is to complement the hydrological analysis of the basin with the capabilities of *WEAP*. Also, to determine the performance of the *WEAP* model when simulating the same historical series of gauges used during the *SWAT* calibration.

Hydrological models are tools widely used to analyze natural processes occurring in a watershed (Singh & Woolhiser, 2002). These models are representations of the biophysical components of a basin; which, with a certain degree of confidence, simulate various outputs of the hydrological cycle (Salgado & Güitrón, 2012).

The *SWAT* and *WEAP* are leading hydrological models used to analysis basins. The *SWAT* model is a semi-distributed, process-based, continuous-time model, developed to evaluate management strategies on water resources and pollution from non-point sources in large basins. Water balance is the guideline since it affects plant growth and the movement of sediments, nutrients, pesticides, and pathogens (Cuceloglu, Abbaspour, & Ozturk, 2017). On the other hand, *WEAP* is a hybrid conceptual-physical model, with a reduced number of model parameters, that simulate the natural and intervened stream resources. It has been applied in basins of different sizes and is suitable for scenario evaluation (Hernández-Vargas, 2017).

In 2017, Sánchez-Galindo *et al*. studied the Sordo River basin using the hydrological model *SWAT*. They evaluated the tool efficiency to simulate biomass, runoff, and sediments for the period 1975 to 1985. In this study, we decided to compare the advantages of the *WEAP* model by simulating, in the same period and without calibrating parameters, the gauged runoffs through the information used and generated with *SWAT*. The purpose of using the information calibrated with *SWAT* is to observe the performance of a model like *WEAP*, which has a different hydrological conceptualization from *SWAT* regarding the calculation of surface runoff, infiltration, percolation, and surface and base flow; to complement the hydrologic analysis of the basin with processes not included in *SWAT* such as evapotranspiration, through crop coefficients and water movement with hydraulic conductivity values; and to compare the response of *WEAP*, with fewer information requirements and equal input data, with the gauge runoffs used in the calibration with *SWAT*.

As shown in other studies, it is feasible to obtain satisfactory results in *WEAP* using *SWAT*-calibrated parameters. *SWAT* and *WEAP* models were used jointly in basins in Ethiopia and Lesotho. The first one, to know the system and its hydrological behavior; meanwhile, the second one, used *SWAT* results, to quantify under different criteria the distribution of the water in the basin (Adgolign, Srinivasa-Rao, & Abbulu, 2016; Hussen, Mekonnen, & Pingale, 2018; Maliehe & Mulungu, 2017).

Materials and methods

Study area

The Sordo River basin is located in the state of Oaxaca, between the parallels 17° 37' 19.93" and 16° 29' 43.11'' north latitude and the meridians 98° 05' 54.34" and 96° 53' 17.86" west longitude. It has an altitude that goes from 274 meters a.s.l. to 3,349 meters above sea level and covers an area of 7,751.42 km^2, in which several rivers converge.

The most important rivers for its longitude are Peñoles, Labor, Cuchara, Zapote, Yolotepec, and Sordo. The Sordo-Yolotepec river discharge into Ixtlayutla (20021) hydrometric station (Figure 1).

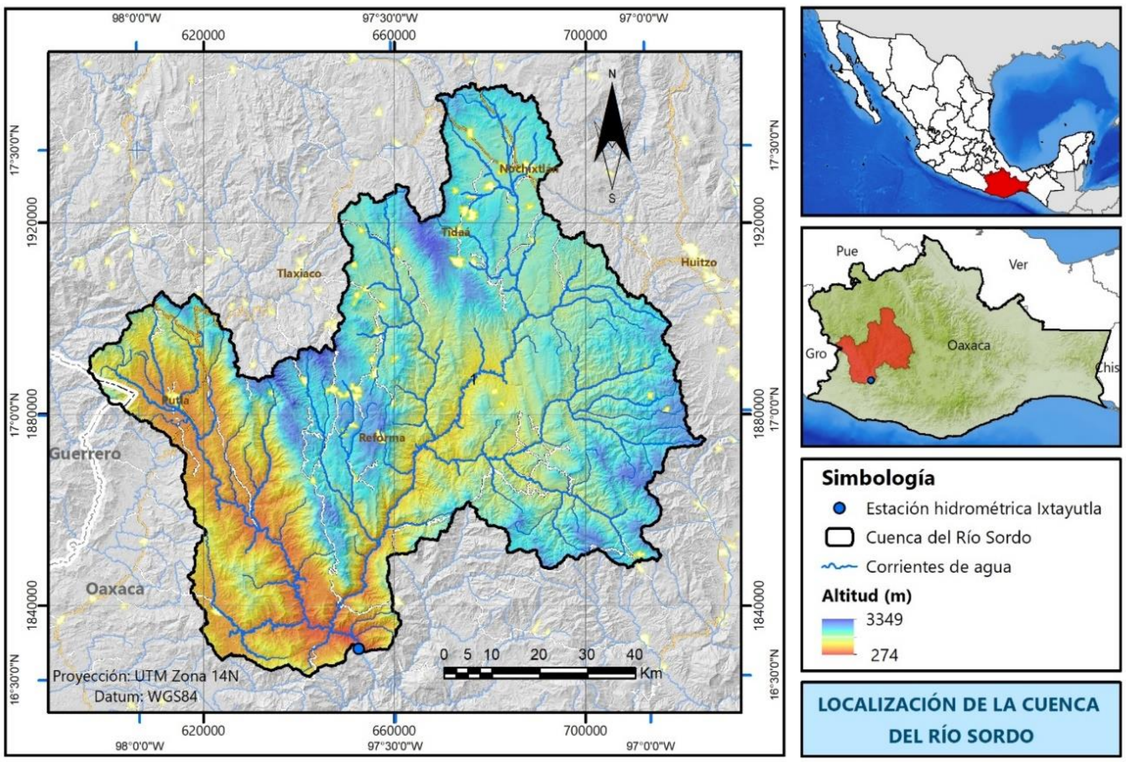

Figure 1. Location of the Sordo River basin, Oaxaca, Mexico.

This basin comprises four cultural regions: Mixteca (54.4 %), Southern Sierra (30.6 %), Central Valleys (11.7 %), and Cost (3.3 %). It is sited on two main aquifers: Nochixtlán (1 321.84 km^2) and Jamiltepec (6 269.18 km^2). The climates are humid temperate and sub-humid (48.6 %), semi-warm subhumid (34.0 %), warm sub-humid (16.0 %), and warm semiarid (1.4 %). It registers annual average temperatures that fluctuate between 10 °C and 28 °C. In the north, the rainfall goes from 400 mm to 1 600 mm in the south. It presents nine types of soils, cambisol (22.0 %), rendzina (20.3 %), acrisol (15.4 %), vertisol (10.4 %), litosol (7.7 %), fluvisol (7.5 %), luvisol (6.9 %), phaeozem (6.7 %) and regosol (3.1 %). It also has 13 types of land use and vegetation: pine-oak forest (23.1 %), pine forest (20.6 %), grassland (18.5 %), oak forest (15.6 %), rainfed agriculture (10.7 %), deciduous dry forest (6.4 %), chaparral (2.1 %), oak-pine forest (1.3 %), cloud forest (0.7 %), human settlements (0.5 %), juniper forest (0.2 %), water bodies (0.1 %) and irrigated agriculture (0.1 %).

Soil Moisture Method (*WEAP*)

The Soil Moisture Method was selected from the five methods that *WEAP* uses for water balance. This method represents the watershed through two soil layers, it characterizes the vegetation cover and the soil type, and through empirical functions, it estimates evapotranspiration, surface runoff, subsurface runoff, and deep percolation (Sieber & Purkey, 2015; Yates, Sieber, Purkey, & Huber-Lee, 2005).

In *WEAP* the basin can be divided into sub-basins, which can be subdivided into *N* areas with different types of vegetation cover j. The water balance in the root zone and deep zone are calculated according to the type of cover with equations (1) and (2), respectively (Yates *et al*., 2005).

$$Sw_j \frac{dz_{1,j}}{dt} = P_e(t) - PET(t)\ Kc_{,j}(t) \left(\frac{5z_{1,j} - 2z_{1,j}^2}{3}\right) - P_e(t)\ z_{1,j}^{\frac{LAI_j}{2}} - f_j\, k_j\ z_{1,j}^2 - \left(1 - f_j\right) k_j\ z_{1,j}^2 \quad (1)$$

$$Dw \frac{dz_{2,j}}{dt} = \left(1 - f_j\right) k_j\ z_{1,j}^2 - k_2\ z_{2,j}^2 \quad (2)$$

Where Sw_j: is soil root zone water storage capacity (mm), $z_{1,j}$: relative water storage capacity in the soils root zone, given as a fraction of the total effective storage (1, 0), $P_e(t)$: effective precipitation over time t (mm), $PET(t)$: Penman–Monteith reference crop potential evapotranspiration (mm time^{-1}), $Kc_{,j}(t)$: crop coefficient over time t (dimensionless), LAI_j: leaf area index (m^2 m^{-2}) (runoff decreases as this value increases), f_j: quasi-physical adjustment parameter related to soil type, topography, land use and vegetation that directs water horizontally

(f_j) or vertically (1-f_j) (1.0 = 100 % horizontal, 0 = 100 % vertical), and k_j: an estimate of root zone storage conductivity (mm time^{-1}), Dw: deep zone water storage capacity (mm) $z_{2,j}$: relative water storage capacity in soils deep zone, given as a fraction of the total effective storage (1, 0) (Figure 2).

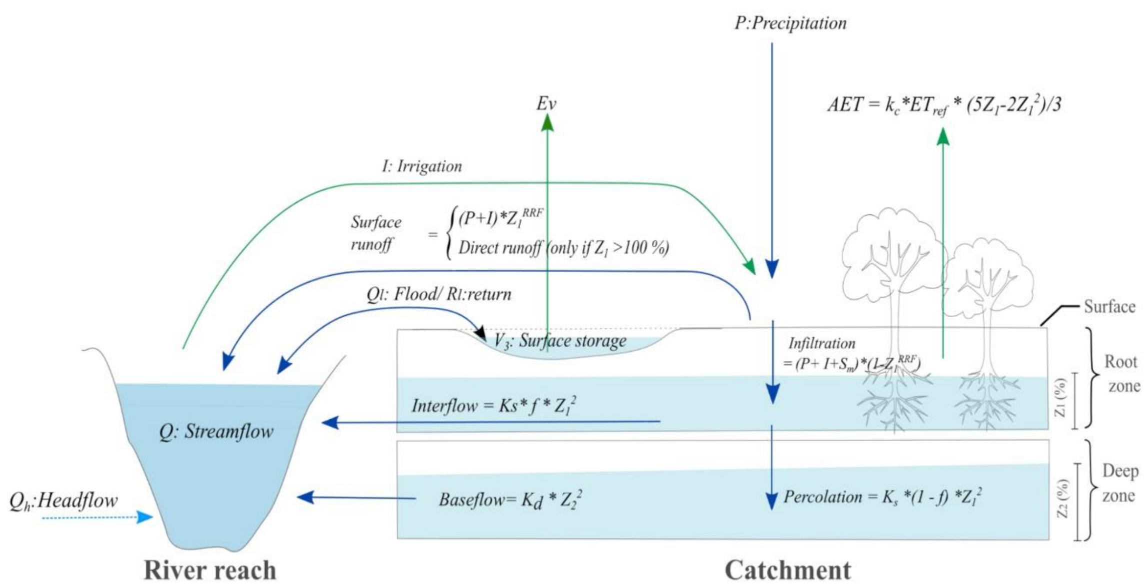

Figure 2. Scheme of the soil moisture method (Angarita *et al.*, 2018).

Model input

Figure 3 shows the methodology used to feed *WEAP*. The data generated in *SWAT* for the hydrological response units (HRU) of the Sordo River basin was calibrated by Sánchez-Galindo *et al.* (2017). Previously, these data were weighted according to the surfaces and the conversion of units to areas (branches) where *WEAP* operates.

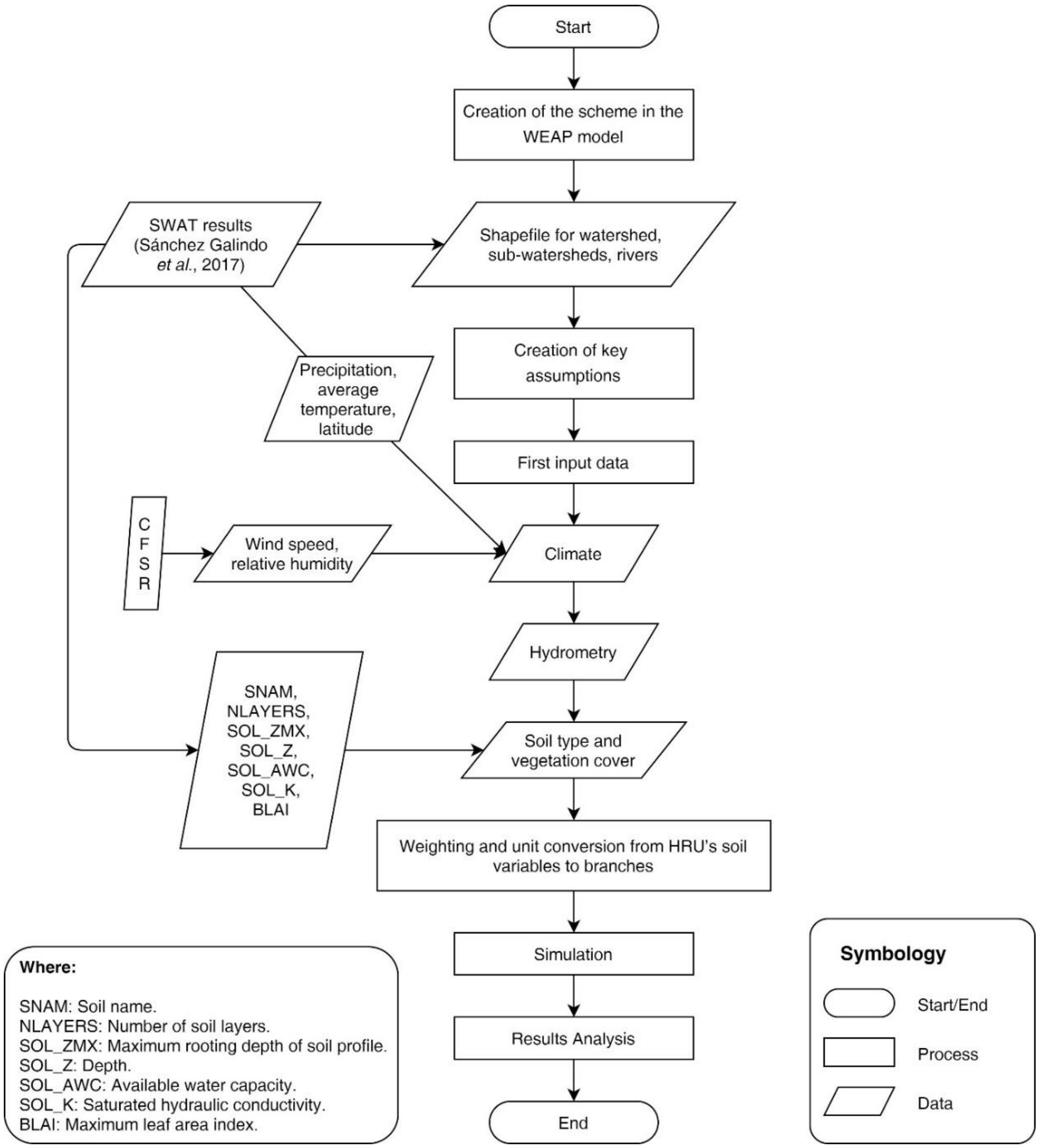

Figure 3. Methodology used on the Sordo River basin to feed the *WEAP* model from *SWAT* data.

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Based on the delimitation used in *SWAT*, the general scheme of the basin was used to operate *WEAP*, through 175 sub-basins with their main channels and the 20021 "Ixtayutla" hydrometric station. Subsequently, in *Data → Demand sites and Catchments,* 1 729 branches were manually added, which are the hydrological response units created by *SWAT*, this was done using the table generated in the "*FullHRU*" vector layer.

After the scheme, *Key Assumptions* were created for variables like precipitation, mean temperature, latitude, wind speed, relative humidity, crop coefficient, root zone water storage capacity, leaf area index (runoff resistance factor), root zone hydraulic conductivity and preferential water flow direction. The key assumptions are used when working with a large number of sub-basins that require the same information. This tool, in conjunction with the options *Export expressions to Excel* and *Import expressions from Excel*, located in the *Edit* window, facilitated data entry.

The compilation and arrangement of climatic, hydrometric, and vegetation/soil type data are described below.

From the *wgn* sheet of the *Access* book, named as the project created in *SWAT*, the weather stations used in *SWAT* for the Sordo River basin were identified (Table 1).

Table 1. Climate stations used in the hydrological modeling of the Sordo river basin.

Key	Name	Latitude N (°)	Longitude O (°)	Altitude (m)
20026	Chalcatongo de Hidalgo	17.03300	-97.58300	2 250
20038	Santiago Ixtayutla	16.56700	-97.66700	510
20044	Jalapa del Valle	17.06700	-96.88300	1 650
20076	Asuncion Nochixtlán (SMN)	17.46667	-97.21667	2 080
20094	Putla de Guerrero (CFE)	17.11667	-97.87305	1 316
20102	San Agustín Tlacotepec	17.20000	-97.51778	2 018
20105	San Esteban Atatlahuaca	17.06500	-97.67917	2 455
20126	Sta. Cruz Zenzotepec	16.53300	-97.48300	970
20130	Sta. María Yucuhiti	17.01667	-97.79972	1 876
20153	Sto. Domingo Teojomulco	16.60000	-97.21700	1 300
20159	Pedro y Pablo Teposcol.	17.50131	-97.48254	2 183
20167	Sta. Ma. Asunción Tlax. (DGE)	17.26700	-97.68300	2 065

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Key	Name	Latitude N (°)	Longitude O (°)	Altitude (m)
20178	Villa Chalcatongo, (CFE)	17.03306	-97.58305	2 428
20186	Santiago Yosondua, Stgo.Y.	16.89972	-97.59972	2 222
20187	Yutacua, Stgo. Ixtayutla	16.60361	-97.62500	437
20259	Zacatepec, Zacatepec	16.75000	-97.78300	900

The daily precipitation and temperature data entered in the *SWAT* model were converted to monthly values. Specifically for *WEAP*, between 1979 and 1985, monthly data on wind speed (VV) and relative humidity (RH) were obtained from the *Climate Forecast System Reanalysis*, a global scale network *(The National Centers for Environmental Prediction* (NCEP, 2019). The HR and VV data, corresponding to the basin, was interpolated at the monthly level (with the ArcMap *Spline* extension), and specific data was extracted for the weather stations' geographical coordinates as shown in Table 1.

The runoff data used in the calibration and validation of *SWAT* were obtained from the National Surface Water Data (Conagua-IMTA, 2019) for the Ixtayutla station (Sánchez-Galindo *et al*., 2017). They were entered into *WEAP* monthly through the route: *Supply and Resources* → *River* → *"Sordo"* → *Streamflow Gauges* → *"Ixtayutla"* → *ReadFromFile Wizard*.

The vegetation/soil variables that compose the *WEAP* model are described below. The crop coefficient (K_c) methodology was used to calculate crop evapotranspiration under standard conditions (ET_c), see equation (3). Standard conditions are those that occur in extensive fields, under excellent agronomic conditions and without limitations of soil moisture. Crop evapotranspiration (ET_c) differs from reference evapotranspiration (ET_o), generally obtained for grass, in which soil cover characteristics, vegetation properties, and aerodynamic resistance are effects incorporated into the crop coefficient K_c (Allen, Pereira, Raes, & Smith, 2006) (Table 2).

$$ET_c = K_c \, ET_o \tag{3}$$

Table 2. *Kc* values used in the Sordo River Basin. Source: Hernández-Vargas (2017).

Key	**Description**	**Crop coefficient (*Kc*)**
BENC	Oak forest	0.9
ENPI	Oak-Pine Forest	0.8
FRSD	Deciduous dry forest	1.0
FRSE	Cloud forest	1.1
MATO	Chaparral	0.6
PASI	Grassland	1.0
PIEN	Pine-oak forest	1.0
PINO	Pine forest	1.0
RIEG	Irrigated agriculture	1.1
RNGB	Juniper forest	0.8
TEMP	Rainfed agriculture	0.9
URMD	Medium density residential	1.0
WATR	Water bodies	0.7

As previously mentioned, a distinctive feature of the Soil Moisture Method is that the basin is represented through two layers of soil. Therefore, the first layer depth of each soil type, Equation (4), was obtained by considering the depths of the reference roots of each vegetation cover, contained in Table 3; the values were based on the default *SWAT* data presented by Sánchez-Galindo *et* *al*. (2017). The resulting pondering of the root depths by soil type was rounded to multiples of 50 (Table 4). On the other hand, the thickness of the deep zone of each soil type is presented as the difference between the total depth values (data obtained by Sánchez-Galindo *et al.* (2017) from the soil profile layers, series II, of INEGI) and the first layer (Table 4):

$$Pr_p = \sum_{i=1}^{n} \frac{A_i \; USV_i}{AT_s} \qquad (4)$$

Where Pr_p weighted root depth (mm), A_i: land use and vegetation area (ha), USV_i: vegetation depth (mm), AT_s: total area of the interest soil type (ha).

Table 3. Radical depths for each land use and vegetation in the Sordo River basin.

Key	Description	Depth (mm)
BENC	Oak forest	600
ENPI	Oak-Pine Forest	600
FRSD	Deciduous dry forest	500
FRSE	Cloud forest	1 000
MATO	Chaparral	400

Key	Description	Depth (mm)
PASI	Grassland	200
PIEN	Pine-oak forest	600
PINO	Pine forest	800
RIEG	Irrigated agriculture	600
RNGB	Juniper Forest	500
TEMP	Rainfed agriculture	350
URMD	Medium density residential	650
WATR	Water bodies	0

Table 4. Total and first soil layer depth, for the Sordo River basin.

Key	**Soil**	**Depth of first *WEAP* layer (mm)**	**Total depth (mm)**
AC	Acrisol	650	1 100
CM	Cambisol	600	1 250
EL	Rendzina	500	650
FL	Fluvisol	500	1 000
Hc	Phaeozem	450	1 000
Is	Litosol	500	650
Lc	Luvisol	550	1 000
Re	Regosol	500	800
Vc	Vertisol	350	1 000

The root zone (*Sw*) and deep zone (Dw_S) water storage capacity is calculated by the type of soil (Table 5) with the weighted root depth and the deep layer depth, through Equation (5) and Equation (6). The subbasin (Dw_{sub}) deep zone storage capacity values were obtained with Equation (7). The values range from 83 to 294 mm:

$$Sw = \sum_{i=1}^{n} SOL\_Z_i \; SOL\_AWC_i \tag{5}$$

$$Dw_s = \sum_{i=1}^{n} SOL\_Z_i \ SOL\_AWC_i \tag{6}$$

$$Dw_{sub} = \sum_{i=1}^{n} \frac{A_i \ Dw_{s_i}}{AT_{sub}} \tag{7}$$

Where Sw: root zone water storage capacity (mm), Dw_s: deep zone water storage capacity by soil type (mm), Dw_{sub}: sub-basin water storage capacity (mm), SOL_Z: layer depth (mm), SOL_AWC_i: layer available water capacity (mm mm^{-1}), A_i: soil type area (ha), AT_{sub}: sub-basin total area (ha).

Table 5. Root zone Values water storage capacity values (*Sw*) and deep zone (*Dw$_s$*) by type of soil, in the Sordo River basin.

Key	**Soil**	**Sw (mm)**	***Dw***
AC	Acrisol	340	340
CM	Cambisol	274	274
EL	Rendzina	291	291
FL	Fluvisol	199	199
Hc	Phaeozem	205	205
Is	Litosol	222	222
Lc	Luvisol	296	296
Re	Regosol	212	212
Vc	Vertisol	178	178

The leaf area index (LAI) represents the effect of the canopy on surface runoff; in this case, it is in the third term of *WEAP* Equation (1). This value is retaken from the *SWAT* calibration, where it is identified as a maximum leaf area index (m^2 m^{-2}), *BLAI* (Table 6).

Table 6. Leaf area index by type of coverage entered into *WEAP* for the Sordo River basin.

Key	**Description**	**IAF or RRF (m^2 m^{-2})**
BENC	Oak forest	5.7
ENPI	Oak-Pine Forest	5.7

Key	Description	IAF or RRF (m^2 m^{-2})
FRSD	Deciduous dry forest	2.1
FRSE	Cloud forest	5.6
MATO	Chaparral	2.1
PASI	Grassland	1.7
PIEN	Pine-oak forest	5.5
PINO	Pine forest	5.5
RIEG	Irrigated agriculture	3.6
RNGB	Juniper Forest	5.6
TEMP	Rainfed agriculture	3.6
URMD	Medium density residential	8
WATR	Water bodies	0.1

The saturated hydraulic conductivity of the root zone (*Ks*) and deep zone (*Kd*), is caused when the relative storage of Z1 and Z2 is respectively equal to 1.0 (saturation). The value of *Ks* is the division of the flows preferential direction in the subsurface and the percolation to the deep layer. Meanwhile, *Kd* controls the base flow movement which increases as *Kd* increases. The values by soil type of *Ks* and *Kds* (Table 7) were obtained with Equations (8) and (9), respectively. The hydraulic conductivity information comes from a previous run with *SWAT* (Sánchez-Galindo *et al*., 2017). However, the deep zone conductivity parameter was entered at the sub-basin level (*Kdsub).* Therefore, this was calculated with equation (10) with which a range between 10 and 1241 mm month^{-1} was obtained.

$$Ks = \sum_{i=1}^{n} \frac{SOL\_Z_i \; K24_i}{Pr_1} \tag{8}$$

$$Kd_s = \sum_{i=1}^{n} \frac{SOL\_Z_i \; K24_i}{Pr_2} \tag{9}$$

$$Kd_{sub} = \sum_{i=1}^{n} \frac{A_i \; Kd_{s\,i}}{AT_{sub}} \tag{10}$$

Where *Ks:* root zone hydraulic conductivity (mm month^{-1}), Kd_s: deep zone hydraulic conductivity by soil type (mm month^{-1}), Kd_{sub}: sub-basin deep zone hydraulic conductivity (mm month^{-1}), *SOL_Zi:* layer depth (mm), $K24_i$: *SOL_K* layer *(SWAT* parameter*)* multiplied by 24, Pr_1: weighted root depth by soil type (mm), Pr_2: deep layer depth by type of soil (mm), A_i: soil type area (ha), AT_{sub}: sub-basin total area (ha).

Table 7. Root zone hydraulic conductivity values (*Ks)* and deep zone (*Kds)* by soil type, for the Sordo river Basin.

Key	**Soil**	***Ks*** **(mm month $^{-1}$)**	***Kd$_s$*** **(mm month $^{-1}$)**
AC	Acrisol	32	28
CM	Cambisol	569	318
EL	Rendzina	796	10
FL	Fluvisol	1064	1331
Hc	Phaeozem	278	94
Is	Litosol	335	10
Lc	Luvisol	483	212
Re	Regosol	540	10
Vc	Vertisol	121	123

At the beginning of the simulation, the root zone (Z1) and deep zone (Z2) humidity is the relative storage of the first and second layer respectively. It is expressed as the percentage of the total effective accumulation, and for both humidities, 30 % was entered.

Evaluation of efficiency

The efficiency of the *WEAP* model was evaluated simulating annual and monthly runoff for the period 1975 to 1985, with the year 1975 being the baseline.

The models behavior and performance were evaluated by comparing the simulated runoff and the runoff measured at the exit of the catchment area (Krause, Boyle, & Bäse, 2005). The indices included in this work are described below.

Determination coefficient (r^2): describes the variation between the observed data and the data simulated by the model. The values of r^2 range from 0 to 1, a higher value indicates less error of variation, and a value higher than 0.5 is considered acceptable. This statistic is too sensitive to high extreme values and insensitive to additive and proportional differences between model predictions and measured data (Moriasi *et al.*, 2007).

Nash and Sutcliffe efficiency index (*NSE*): is a normalized statistic that determines the relative residual variance magnitude (noise) compared to the measured data variation (information). It indicates how well the graphs of the observed versus simulated data fit the line 1:1. It takes values between -∞ and 1; If the result is 1, the fit is perfect; if it is 0, the error is of the same order of magnitude as the variance of the observed data. Therefore, the mean of the observed data can have a similar capacity to predict as the model. Values below zero signify that the mean has a higher capacity to predict than the model, this implies that the simulated values are poor (Moriasi *et al*., 2007).

Percentage bias (PBIAS): calculates the model's tendency to underestimate (positive values) or overestimate (negative values) the variable of interest. Values with low magnitude indicate an accurate simulation of the model, being 0 the optimal number (Moriasi *et al.*, 2007).

Results and discussion

Monthly flows

As part of the results for the Sordo river basin, the monthly and annual flows simulated with *SWAT* (Sánchez-Galindo *et al*., 2017) and the biophysical parameters, calibrated in *SWAT*, for *WEAP* are presented.

Figure 4 shows, for the period 1976 to 1985, the flows monthly measured *versus* those simulated by *SWAT* and *WEAP* and the *NSE* y PBIAS values. It is noteworthy, that the base flows were well calculated in *WEAP*. Meanwhile, *SWAT* effectively replicated the peak flows, but the recession curve when approaching the base flow presented problems.

This *WEAP* behavior differs from the results obtained by Ingol-Blanco and McKinney (2013), who found in the Conchos river basin, that *WEAP* is better at reproducing peak runoffs than base flows. Furthermore, the *NSE* value (0.82) in *SWAT* was higher than in *WEAP* (0.73). This implies, according to Moriasi *et al*. (2007), that the *NSE* values are "very good" for *SWAT* and "good" for *WEAP*.

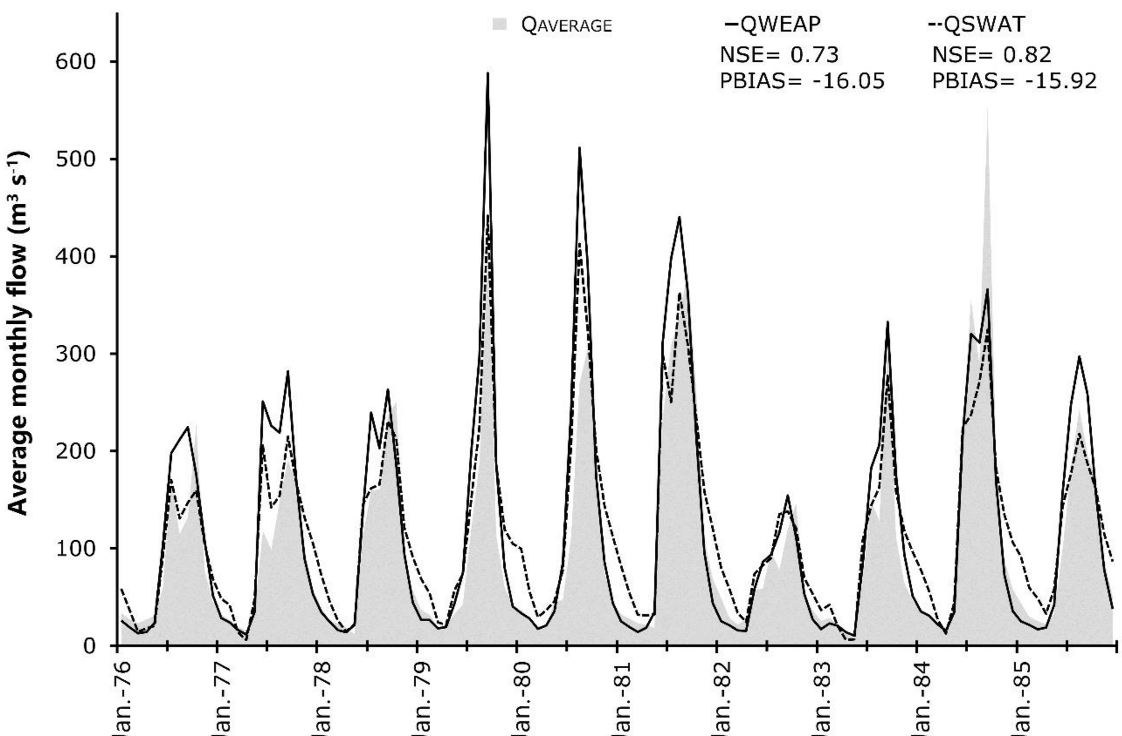

Figure 4. Average monthly flows observed and simulated by *SWAT* and *WEAP* in the Sordo River basin.

The *WEAP* index *NSE* = 0.73 is within the range of results that other authors have obtained, such as Varela-Ortega *et al.* (2016) in the Guadiana River basin, Spain, with a *NSE* > 0.7; Olsson *et al.* (2017) Chancay-Huaral basin, Peru, with a *NSE* ≥ 0.8; and Höllermann, Giertz and Diekkrüger (2010) in the Ouémé-Bonou basin, Benin, with a *NSE* ≥ 0.78.

On the other hand, the PBIAS values of -16.05 and -15.92 on *WEAP*, and *SWAT*, respectively, indicate that both tools overestimate the observed monthly flow.

Figure 5 shows that the r^2 of the average monthly runoff of *SWAT* was slightly higher than *WEAP* (0.85 *vs.* 0.84), revealing a lower variation error. However, although r^2 has been widely used for model evaluation, it only quantifies results dispersion. For example, a model that systematically overestimates or underestimates will show values close to 1.0, even if all the predictions are wrong (Krause *et al.*, 2005; Moriasi *et al.*, 2007). However, when considering the r^2 value, departing from the intercept, it is observed that *WEAP* presents a value closer to zero (6.6) than *SWAT* (34.9). Therefore, in an observed flow rate of zero, the result in *WEAP* would be 6.6 and 34.9 in *SWAT*. Likewise, the line slope reflects an over-prediction of 9.55 % for *WEAP* and an under-prediction of 15.32 % for *SWAT*.

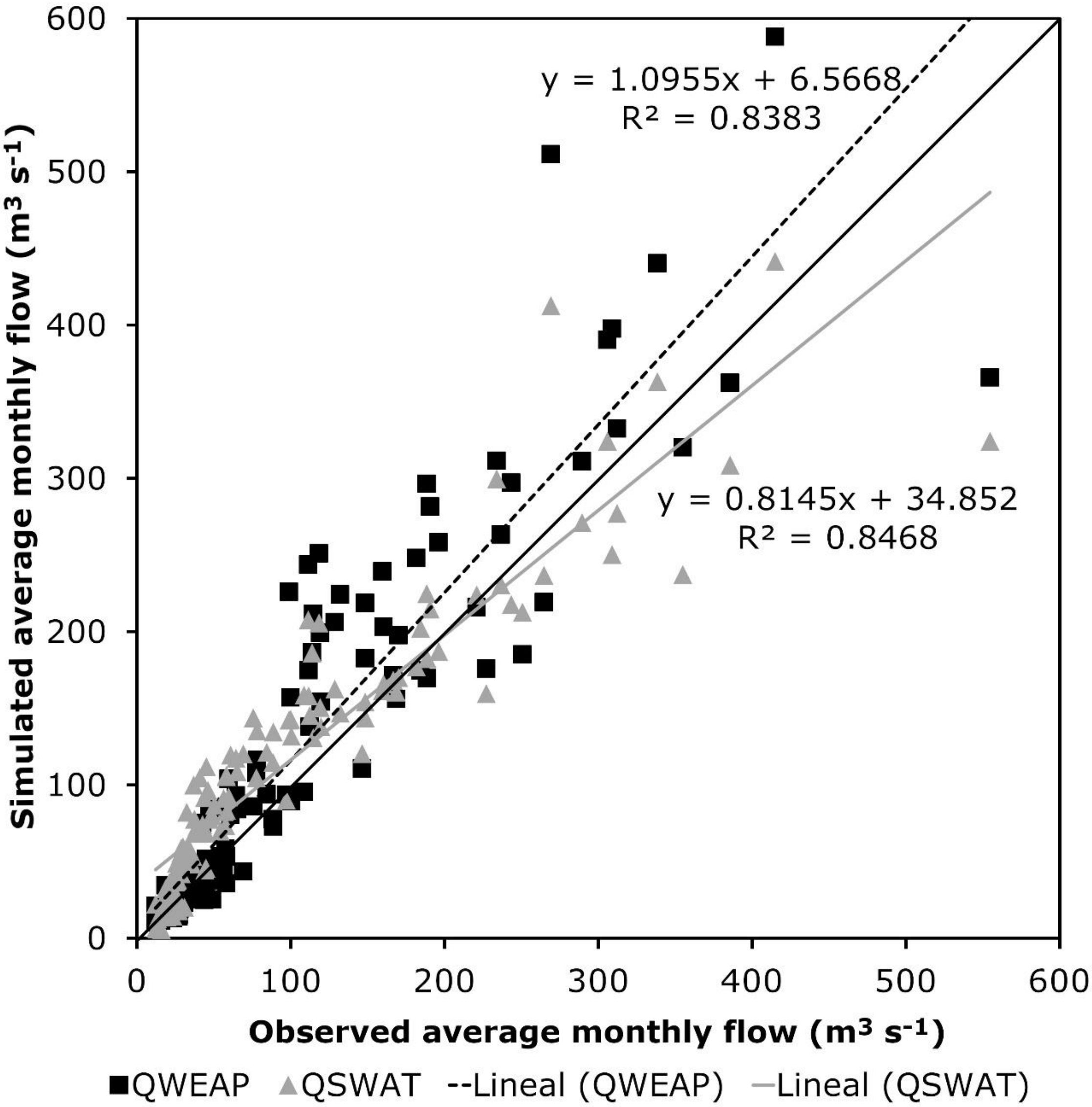

Figure 5. Relationship between observed and simulated average monthly flows by *SWAT* and *WEAP* in the Sordo River basin.

In 2016, Adgolign *et al.* assessed in the Didessa sub-basin of Ethiopia the change in water availability. As in the present study, they also used the same *SWAT* and *WEAP* tools. *SWAT* was used to fill the gaps in the measured flow data. Meanwhile, *WEAP* was used to model the allocation of surface water resources in the basin.

Hussen *et al.* (2018) calibrated and validated *SWAT's* capacity to simulate the runoff of Abaya-Chamo sub-basin, Ethiopia. In the calibration they obtained an r^2 = 0.77 and a *NSE* = 0.76, and in the validation an r^2= 0.80 and a *NSE* = 0.78. Subsequently, the *WEAP* model was implemented to assign sub-basin water resources under climate change scenarios.

The amount of surface water was assessed in the southern Phuthiatsana Basin, Lesotho. This was done by estimating flows in ungauged basins with *SWAT* and allocating resources in the basin using *WEAP*. *SWAT* was calibrated from 1979 to 2001, *NSE* = 0.59 and r^2 = 0.59, and it was validated from 2002 to 2013, *NSE* = 0.52 and r^2 = 0.66 (Maliehe & Mulungu, 2017).

Average annual flows

The annual average flows simulated in *WEAP* reached a *NSE* = 0.3. Compared to the values observed in the hydrometric station, the adjustment result is "unsatisfactory" (Moriasi *et al*., 2007), due to the effects the years 1977, 1979, and 1980 (Figure 6). On the other hand, *SWAT* reached a "good" adjustment with a *NSE* = 0.73 and a PBIAS = -4.6, which only overestimated by 4.6 %. Something comparable happened with the values of r^2, where *WEAP* obtained 0.63 meanwhile *SWAT* achieved 0.76 (Figure 7).

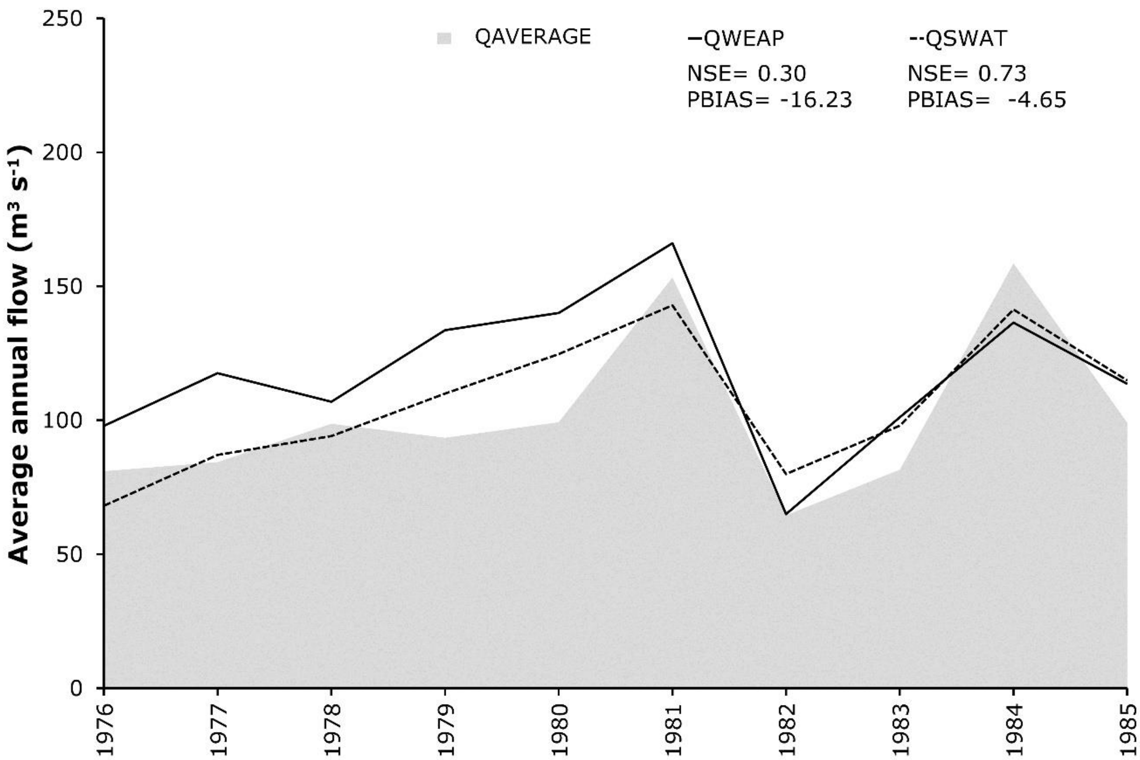

Figure 6. Observed and simulated average annual flows by *SWAT* and *WEAP* in the Sordo River basin.

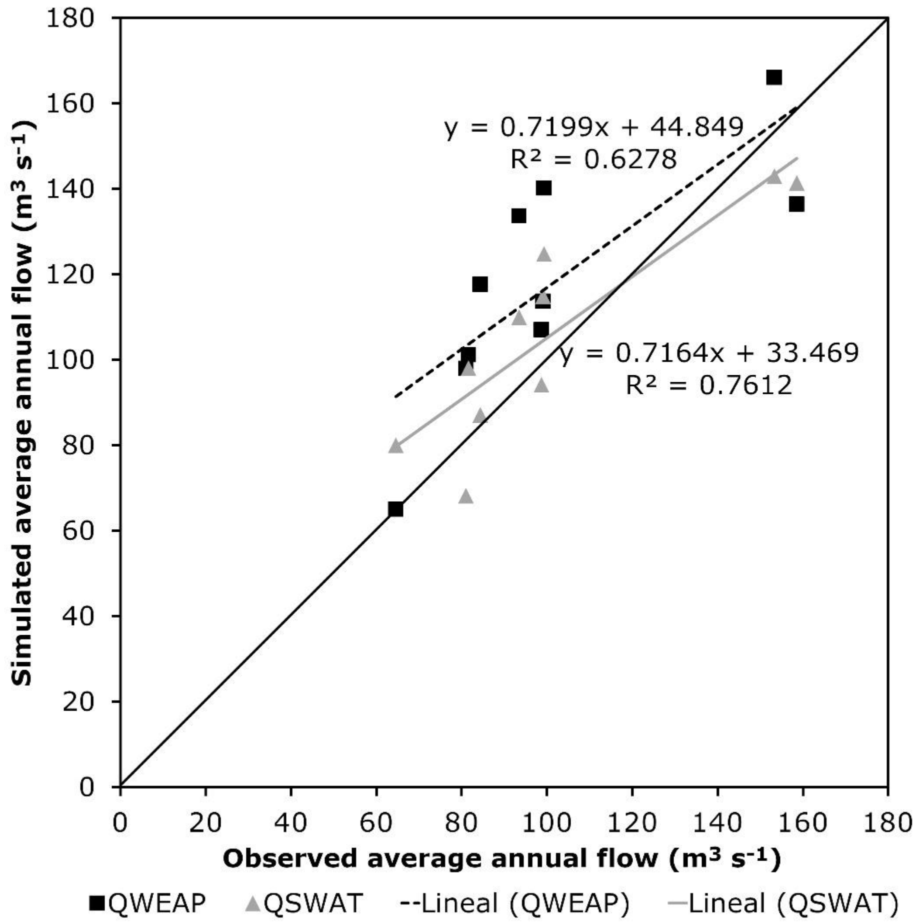

Figure 7. Relationship between observed and simulated average annual flows by *SWAT* and *WEAP* in the Sordo River basin.

In Table 8, the indices of r^2, *NSE*, and *PBIAS* demonstrate that simulations in *SWAT* and *WEAP* of monthly and annual runoff are reliable. This statement was also formulated by Faiz *et al*. (2018) who for *WEAP*, obtained values of *NSE* between 0.83 and 0.88, and of r^2 between 0.86 and 0.92; meanwhile, for *SWAT*, the values of *NSE* were 0.80 and 0.81

and of r^2 between 0.81 and 0.82. Likewise, for Sánchez-Galindo *et al.* (2017) *SWAT* successfully simulated the production of biomass and sediments. It is important to highlight, that this work profited from previously collected and used information to feed *SWAT*. However, it is feasible to feed *WEAP* without a precedent model in *SWAT*, and could even be simpler, due to the robust nature of *WEAP*. Therefore, choosing between a model depends on the available data, the study objectives, the tools the modeler, knows and the outputs of interest for decision-makers.

Table 8. Evaluation of efficiency to simulate monthly and annual runoff by *WEAP* and *SWAT* in the Sordo River basin.

Period	**Model**	r^2	***NSE***	***NSE* adjustment**	***PBIAS* (%)**	***PBIAS* adjustment**
Monthly	*SWAT*	0.85	0.82	Very good	-15.92	Satisfactory
	WEAP	0.84	0.73	Good	-16.05	Satisfactory
Annual	*SWAT*	0.76	0.73	Good	-4.65	Very good
	WEAP	0.63	0.3	Unsatisfactory	-16.23	Satisfactory

Conclusions

Hydrological modeling is a useful tool for understanding the behavior and distribution of water resources in a basin. The knowledge obtained from this process is crucial for the implementation of policies on sustainable water management and use.

The results of this study show that according to the efficiency indices r^2, *NSE*, and *PBIAS*, the *SWAT* and *WEAP* models, are capable of simulating the monthly and annual runoffs of the Sordo River basin. However, in the annual time scale, *SWAT* was superior because *WEAP* presents an $NSE = 0.3$.

The amount of data used for the employment of these two models is unequal. On one hand, *SWAT*, a physical base model, requires a huge amount of information; meanwhile, *WEAP*, a conceptual-physical base model, demands a smaller amount of data. Although this is a favorable feature for *WEAP*, its disadvantage is lack of values of these few parameters in the literature, which is contrary to what happens with *SWAT*.

From this study, we deduce that it is possible to obtain satisfactory results with *WEAP* using data from the *SWAT* tool like it has been done in other investigations. However, it is only recommended to use the information of *SWAT* to feed into *WEAP*, when there is previous information of *SWAT* in the site of interest.

It is important to emphasize that before choosing the model, the objectives of the study must be clear, and the computer tool availability, capabilities, and needs.

References

Adgolign, T. B., Srinivasa-Rao, G. V. R., & Abbulu, Y. (2016). WEAP modeling of surface water resources allocation in Didessa Sub-Basin, West Ethiopia. *Sustainable Water Resources Management*, 2, 55-70. Recovered from https://doi.org/10.1007/s40899-015-0041-4

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (2006). *Estudio FAO riego y drenaje 56. Evapotranspiración del cultivo (guías para la determinación de riego de los requerimientos de agua de los cultivos)*. Roma, Italia: Food and Agriculture Organization of the United Nations. Recovered from http://www.fao.org/3/a-x0490s.pdf

Angarita, H., Wickel, A. J., Sieber, J., Chavarro, J., Maldonado-Ocampo, J. A., Herrera-R., G. A., Delgado, J., & Purkey, D. (2018). Basin-scale impacts of hydropower development on the Mompós Depression wetlands, Colombia. *Hydrology and Earth System Sciences*, 22(5), 2839-2865. Recovered from https://doi.org/10.5194/hess-22-2839-2018

Conagua-IMTA, Comisión Nacional del Agua-Instituto Mexicano de Tecnología del Agua. (2019). *Banco Nacional de Datos de Aguas Superficiales (BANDAS)*. Recovered from https://www.imta.gob.mx/bandas

Cuceloglu, G., Abbaspour, K. C., & Ozturk, I. (2017). Assessing the water-resources potential of Istanbul by using a soil and water assessment tool (SWAT) hydrological model. *Water (Switzerland)*, 9(10), 814-832. Recovered from https://doi.org/10.3390/w9100814

Faiz, M. A., Liu, D., Fu, Q., Li, M., Baig, F., Ahmad-Tahir, A., Imran-Khan, M., Li, T., & Cui, S. (2018). Performance evaluation of hydrological models using ensemble of General Circulation Models in the northeastern China. *Journal of Hydrology*, 565, 599-613. Recovered from https://doi.org/10.1016/j.jhydrol.2018.08.057

Hernández-Vargas, M. Á. (2017). *Implementación de la herramienta WEAP al sistema Cutzamala*. Ciudad de México, México: Universidad Nacional Autónoma de México.

Höllermann, B., Giertz, S., & Diekkrüger, B. (2010). Benin 2025-Balancing future water availability and demand using the WEAP "Water Evaluation and Planning" System. *Water Resources Management*, 24(13), 3591-3613. Recovered from https://doi.org/10.1007/s11269-010-9622-z

Hussen, B., Mekonnen, A., & Pingale, S. M. (2018). Integrated water resources management under climate change scenarios in the sub-basin of Abaya-Chamo, Ethiopia. *Modeling Earth Systems and Environment*, 4(1), 221-240. Recovered from https://doi.org/10.1007/s40808-018-0438-9

Ingol-Blanco, E., & McKinney, D. C. (2013). Development of a hydrological model for the rio Conchos Basin. *American Society of Civil Engineers*, 18, 340-351. Recovered from https://doi.org/10.1061/(ASCE)HE.1943-5584.0000607.

Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences*, 5, 89-97. Recovered from https://doi.org/10.5194/adgeo-5-89-2005

Maliehe, M., & Mulungu, D. M. M. (2017). Assessment of water availability for competing uses using SWAT and WEAP in South Phuthiatsana catchment, Lesotho. *Physics and Chemistry of the Earth*, 100, 305-316. Recovered from https://doi.org/10.1016/j.pce.2017.02.014

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *American Society of Agricultural and Biological Engineers*, 50(3), 885-900.

NCEP, The National Centers for Environmental Prediction. (2019). *Global Weather Data for SWAT*. Recovered from https://globalweather.tamu.edu/

Olsson, T., Kämäräinen, M., Santos, D., Seitola, T., Tuomenvirta, H., Haavisto, R., & Lavado-Casimiro, W. (2017). Downscaling climate projections for the Peruvian coastal Chancay-Huaral Basin to support river discharge modeling with WEAP. *Journal of Hydrology: Regional Studies*, 13, 26-42. Recovered from https://doi.org/10.1016/j.ejrh.2017.05.011

Salgado, J. H., & Güitrón, A. (2012). Aplicabilidad de los modelos hidrológicos distribuidos. En: *XXII Congreso Nacional de Hidráulica* (p. 5), Acapulco, Guerrero, México.

Sánchez-Galindo, M., Fernández-Reynoso, D. S., Martínez-Ménez, M. R., Rubio-Granados, E., & Ríos-Berber, J. D. (2017). Modelo hidrológico de la cuenca del río Sordo, Oaxaca, México, con SWAT. *Tecnología y ciencias del agua*, 8(5), 141-156. Recovered from https://doi.org/10.24850/j-tyca-2017-05-10

Sieber, J., & Purkey, D. (2015). *User Guide for WEAP 2015*. Recovered from https://www.weap21.org/downloads/WEAP_User_Guide.pdf

Singh, V. P., & Woolhiser, D. A. (2002). Mathematical modeling of watershed hydrology. *Journal of Hydrologic Engineering*, 7(4), 270-292. Recovered from https://doi.org/10.1061/(asce)1084-0699(2002)7:4(270)

Varela-Ortega, C., Blanco-Gutiérrez, I., Esteve, P., Bharwani, S., Fronzek, S., & Downing, T. E. (2016). How can irrigated agriculture adapt to climate change? Insights from the Guadiana basin in Spain. *Regional Environmental Change*, 16(1), 59-70. Recovered from https://doi.org/10.1007/s10113-014-0720-y

Yates, D., Sieber, J., Purkey, D., & Huber-Lee, A. (2005). WEAP21-A Demand-, Priority-, and Preference-Driven Water Planning Model. Part 1 : Model Characteristics. *Water International*, 30(4), 487-500.