SWAT application in intensive irrigation systems: model modification, calibration and validation

Farida Dechmi[1]*, Javier Burguete[2] and Ahmed Skhiri[1]

[1] Soil and Irrigation Department (EEAD-CSIC Associated Unit), Agrifood Research and Technology Centre of Aragón, Avenida Montañana 930, 50059-Zaragoza, Spain.

[2] Soil and Water Department, Aula Dei Experimental Station, CSIC. Avenida Montañana 1005, 50059-Zaragoza, Spain.

Corresponding author: Farida Dechmi

Telephone: +34 976716802

Fax: +34 976716335

E-mail: fdechmi@aragon.es

Abstract

The Soil and Water Assessment Tool (SWAT) is a well established, distributed, eco-hydrologic model. However, using the study case of an agricultural intensive irrigated watershed, it was shown that all the model versions are not able to appropriately reproduce the total streamflow in such system when the irrigation source is outside the watershed. The objective of this study was to modify the SWAT2005 version for correctly simulating the main hydrological processes. Crop yield, total streamflow, total suspended sediment (TSS) losses and phosphorus load calibration and validation were performed using field survey information and water quantity and quality data recorded during 2008 and 2009 years in Del Reguero irrigated watershed in Spain. The goodness of the calibration and validation results was assessed using five statistical measures, including the Nash-Sutcliffe efficiency (NSE). Results indicated that the average annual crop yield and actual evapotranspiration estimations were quite satisfactory. On a monthly basis, the values of NSE were 0.90 (calibration) and 0.80 (validation) indicating that the modified model could reproduce accurately the observed streamflow. The TSS losses were also satisfactorily estimated (NSE = 0.72 and 0.52 for the calibration and validation steps). The monthly temporal patterns and all the statistical parameters indicated that the modified SWAT-IRRIG model adequately predicted the total phosphorus (TP) loading. Therefore, the model could be used to assess the impacts of different best management practices on non-point phosphorus losses in irrigated systems.

Keywords: calibration; irrigation systems; phosphorus; sediments; validation; watershed

Abbreviations: BMPs (best management practices), DRW (Del Reguero watershed), ETa (actual evapotranspiration), GWQ (baseflow), HRUs (hydrologic response units), LATQ (lateral flow), NSE (Nash-Sutcliffe efficiency), ORG_P (organic phosphorus), PBIAS (percent bias), PP (particulate phosphorus), RMSE (root mean square error), RSR (RMSE observation standard deviation ratio), SOL_P (soluble phosphorus), SWAT (Soil and Water Assessment Tool), SYLD (sediments yield), TDP (total dissolved phosphorus), TLSS (transmission losses), TP (total phosphorus), WYLD (total water yield)

1. Introduction

Excess land application of nutrients can result in the impairment of nearby water resources (Green and Griensven, 2008). In irrigated agricultural systems, the irrigation returns flows (IRF) are the major nonpoint source pollution of surface and groundwater bodies (Aragües and Tanji, 2003). For that reason, a widespread control of contaminant inputs is an effective solution to prevent further deterioration and to enhance the status of water resources. Hence, the Water Framework Directive (EU, 2000) establishes a framework for the protection of groundwater, surface, estuarine, and coastal waters. For that reason, this European Directive requires Member States to assess the ecological quality status of water bodies setting as a final objective the achievement of a “good water status” for all waters by 2015 (Borja, 2005).

The evaluation of the ecological status of water requires the establishment of a control network in the receiving bodies. In the case of agricultural watersheds, a continuous monitoring of drainage waters (quantity and quality) is indispensable to better understand the pollutants dynamics. Monitoring studies permit the identification of the actual trophic status of waters and the assessment of the effectiveness of post-implementation of best management practices (BMPs). However, conducting field experiments and collection of long-term data is very expensive (cost of instrumentation and operation) and time consuming (Santhi et al., 2006). There are uncertainties/errors associated with the measured data and also difficulty in repeating the monitoring process without additional resources and time when corrections are necessary (Santhi et al., 2006). In addition, with nonpoint source pollution emerging from large watersheds, such as the Ebro River watershed with mixed land uses and soils, it is quite difficult to associate water improvements to specific BMPs using monitoring data (Santhi et al., 2006).

The application of watershed simulation models is indispensable when pollution is generated by a non-point source. These models should be able to simulate large complex watersheds with varying soils, land use and management conditions over long periods of time. A wide range of watershed models are available to predict the impact of land management practices on water, sediment and agricultural chemical yields. Examples of these models are: the physically based event model ANSWERS (Beasley, 1991), the empirically based SWATCATCH model (Holman et al., 2001), the physically based DWSM model (Borah and Bera, 2003) and the semi-empirical SWAT model (Arnold et al., 1998; Arnold and Fohrer, 2005; Gassman et al., 2007). One common characteristic between all these models is the reproduction of the water and nutrients movement at the watershed scale.

Of all the models mentioned previously, the Soil and Water Assessment Tool (SWAT) is the most capable model for long-term simulations in watersheds dominated by agricultural land uses. This model is designed to assess the impact of land use and management practices on water, sediments and agricultural chemicals in IRF. The model has proven to be an effective tool for assessing nonpoint source pollution for a wide range of scales and environmental conditions (Gassman et al., 2007). SWAT has been widely applied across the United States (FitzHugh and Mackay, 2000; Arabi et al., 2006); Europe (Conan et al., 2003a, b; Plus et al., 2006; Nasr et al., 2007; Galván et al., 2009; Panagopoulos et al., 2011a, b) and other parts of the world (Bouraoui et al., 2005; Watson et al., 2005; Cheng et al., 2006).

SWAT has been modified and adapted to provide improved simulations of specific processes for specific watersheds (Gassman et al., 2007). Lenhart et al. (2002; 2003; 2005) modified SWAT99.2 to provide improved flow predictions (percolation, hydraulic conductivity, and interflow) for typical conditions in low mountain ranges in Germany. This SWAT-G modified version was also used to simulate sediments and phosphorus in the Dill catchment (Hessen, Germany) (Lenhart et al., 2003). The Extended SWAT (ESWAT) incorporated several modifications relative to the original SWAT model to simulate runoff and in stream processes at hourly time steps (van Griensven and Bauwens, 2003, 2005). Van Liew (2009) modified SWAT2005 to consider losses of organic nitrogen and phosphorus from bank erosion from top soil layers in three drainage areas located in the Bitterroot watershed. The Soil and Water Integrated Model (SWIM) based on the hydrological components of SWAT was designed to simulate "mesoscale" watersheds (Krysanova et al., 1998, 2005). A recent groundwater dynamics sub-model has been integrated to SWIM (Hatterman et al., 2004) to improve its simulating capability in forest systems (Wattenbach et al., 2005). Baffaut and Benson (2009) modified the SWAT code (SWAT-B&B) to simulate faster percolation in karst basins. They used transmission losses from tributary channels to represent sinking streams and ponds to depict sinkholes. Other SWAT studies described irrigations applications using an optimum irrigation management where the irrigation supply was specified by the water requirements of crops, so that IRF were not important (Cau and Paniconi, 2007; Jie et al., 2010; Kannan et al., 2011). In contrast, the application of SWAT to intensive irrigation systems where IRF are the major component of the hydrologic balance could not satisfactorily reproduce the total streamflow because of its limitations in applying maximum irrigation doses in an irrigation event when the irrigation source is outside the watershed. In this case, both SWAT versions (SWAT2005 and 2009) used irrigation doses that filled the soil layers up to field capacity. If the input irrigation doses exceeded field capacity, the excess water between soil saturation and field capacity limits returned to the source and was not considered in the daily soil water balance calculation. Thus, for the application of SWAT in such intensive irrigated systems, the irrigation subroutine source code should be modified to consider the excess irrigation water in the daily soil water balance.

The objectives of this work were to modify SWAT for its improved performance in intensive irrigated systems and to evaluate its prediction capabilities in modelling water flow and sediment and phosphorus loads. The SWAT2005 modification, calibration and validation using the Del Reguero stream watershed (NE, Spain) 2008 and 2009 data are presented in this paper.

2. Materials and methods

2.1. Study area

The Del Reguero watershed (DRW) belongs to the Alto Aragon Irrigation Scheme area located in the left bank of the middle Ebro River Basin in Spain (Fig. 1). It has a total drainage area of 18.65 km^2 with elevations ranging from 208 to 502 m and an average land surface slope of 4.4‰. The irrigation water supply is conveyed by the Pertusa Canal, itself a diversion of the Cinca Canal, the latter originating in El Grado reservoir located on the Cinca River, to the North East of the irrigation scheme. The main cultivated crops in the two studied years (2008 and 2009) were corn (41%), barley (19%), alfalfa (15%), and sunflower (9%) and represent more than 84% of the watershed irrigated area.

The climate is semiarid with an average annual precipitation and reference evapotranspiration of 391 mm and 1,294 mm, respectively. The mean annual temperature is 13.1 ºC, with a large temperature difference between winter and summer. Irrigation practices began in 1982 using sprinkler irrigation systems (mainly solid-set sprinklers). Two geomorphologic units are distinguished in the study area. The first unit corresponds to platform soils (locally called "sasos") that cover 38% of the total area. These soils are shallow, present calcareous horizons, and a high content of stones. The second unit covers the remaining of the watershed and corresponds to alluvial soils that are mostly stone-free and with soil depths varying from 0.6 m to more than 1.20 m. The soil P-Olsen concentrations were very heterogeneous ranging from 5 to 137 mg kg^{-1} in the surface layer (0 – 30 cm) with an average of 28 mg kg^{-1} and an standard deviation of 19.32 mg kg^{-1}. The drainage waters were characterized by an annual average total phosphorus concentration of 0.112 mg L^{-1}.

The seasonal average irrigation depths were 830 mm (corn), 898 mm (alfalfa), 473 mm (sunflower) and 202 mm (barley). The differences in irrigation depths between soil types and plot sizes were not significant ($P < 0.1$), indicating that farmers did not take into account these variables when irrigating. The average irrigation depth was 13 mm for all types of soils, lower than the total available water of the platform soils. The irrigation interval ranged between 1 and 3 days with an average value of 2 days in corn and alfalfa. These intervals increased at the beginning of the irrigation season and decreased during the summer to meet its high water demand during these months. Some farmers irrigated corn at night to reduce the wind drift and evaporation losses. The same behavior was observed in sunflower, with high irrigation intervals at the beginning of the irrigation season that were further reduced during the summer months. The irrigation intervals in barley ranged between 15 and 20 days with a mean value of 18 days. A more detailed study area characterisation can be found in Skhiri and Dechmi (2012).

2.2. Model Description

SWAT is a continuous time, spatially semi-distributed, physically based model (Arnold et al., 1998). The watershed is divided into multiple sub-watersheds, which are then further subdivided into specific soil/land use characteristic units that are called hydrologic response units (HRUs). The water balance of each HRU is represented by four storage volumes: snow, soil profile (0-2 m), shallow aquifer (typically 2-20 m), and deep aquifer (> 20 m). Flow generation, sediment yield, and chemical loadings from each HRU in a subwatershed are summed, and the resulting loads are routed through channels, ponds, and/or reservoirs to the watershed outlet. The soil profile is subdivided into multiple layers that consider several soil water processes including infiltration, evaporation, plant uptake, lateral flow, and percolation.

The soil percolation component of SWAT uses a storage routing technique to simulate flow through each soil layer in the root zone. Crop evapotranspiration is simulated as a linear function of potential evapotranspiration, leaf area index and root depth. Sediment yield is estimated for each HRU with the Modified Universal Soil Loss Equation (Williams et al., 1984). The Phosphorus processes are handled using a similar approach to that in the Erosion Productivity Impact Calculator (EPIC) model (Williams, 1990, 1995).

In this work, the surface runoff from daily rainfall was estimated using the modified SCS curve number (USDA-SCS, 1972) and the potential evapotranspiration (PET) was determined using the modified Penman-Monteith approach. The default values provided by the SWAT crop database were used for the crop phosphorus uptake and the optimal plant concentrations (Arnold et al., 1998).

Phosphorus can be lost in both particulate and dissolved forms (Arnold et al., 1998). The loss of dissolved phosphorus in surface runoff is estimated based on the concept of partitioning phosphorus into the solution and sediment phases as described by Leonard and Wauchope (1980) for pesticides. The amount of soluble P removed in runoff is predicted using solution P concentration in the soil top 10 mm, the runoff volume and a partitioning factor. Sediment transport of phosphorus (particulate phosphorus) is calculated with a loading function developed by McElroy et al. (1976) and modified by Williams and Hann (1978). The loading function estimates the daily organic P runoff loss based on the concentration of organic P in the top soil layer, the sediment yield, and the enrichment ratio.

2.3. SWAT input data

Three basic files were required for delineating the basin into subbasins and HRUs: a digital elevation model (DEM), a soil map, and a land use/land cover (LULC) map. The topographic parameters (slope, slope length, drainage network, watershed delimitation and number of sub-basins) were obtained from the digital elevation model (DEM) of the Ebro River Basin (20 x 20 m grid size). The land use and soil data were obtained from the special crop and soil distribution maps prepared during the study years. A total of 9 subbasins and 239 HRUs were delineated in the study area. The unique source of irrigation is from outside the watershed. The weather input data, including maximum and minimum daily air temperature, solar radiation, wind speed and relative humidity, were obtained from the Huerto meteorological station, located at a North latitude of 41º56´59´´, a West longitude of 00º08´09´´and an altitude of 390 m. Parameters of farmers' current management operations as tillage, planting dates, fertilization, irrigation and harvesting were provided as inputs to the model.

The amounts of organic and inorganic fertilizers applied to each crop grown in DRW were determined through farmer's interviews performed during the 2008 and 2009 agricultural seasons. For each crop, the dates of application and the type of fertilizers were determined. Regarding irrigation management, dates and amounts of water applied to each crop during each irrigation event were obtained from the databases facilitated by the Alconadre Irrigation District.

The crop parameter values for corn used in this study were the same as those used by Cavero et al. (2000) under meteorological conditions similar to DRW. For barley and sunflower, the crop parameter values were set according to those proposed by Cabelguenne et al. (1999) for southwestern France. In regard to alfalfa, parameter values were set according to Confalonieri and Bechini (2004).

2.4. Model modification

The application of the original SWAT2005 version in semiarid irrigated DRW using actual farmer's irrigation practices was not possible because as previously indicated the excess irrigation depths are returned to the irrigation source instead of taking them into account in the daily soil water balance calculations (Neitsch et al., 2005). Therefore the following modifications in the source code were performed in the new SWAT-IRRIG version to include the above mentioned excess water in the soil water balance calculations:

1- The maximum amount of water to be applied corresponds to the depth of irrigation water applied to each HRU as specified by the user in the irrigation operation instead of the amount of water held in the soil profile at field capacity. This modification is included in the “irrsub” subroutine as following:

Original version: $vmm = sol\_sumfc$

Modified version: $vmm = irr\_amt$

where *vmm* is the maximum amount of water to be applied (mm H_2O), *sol_sumfc* is the amount of water held in the soil profile at field capacity (mm H_2O) and *irr_amt* is the depth of irrigation water applied to each HRU (mm H_2O) as specified by the user.

2- As the original percolation calculation subroutine (percmain subroutine) included only the excess precipitation, the water excess arising from irrigation practices when the amount of irrigation exceeds field capacity was added in the percolation subroutine as follows:.

Original version: $sepbtm = sepbtm + sepday$

$$sepday = inflpcp$$

Modified version: $sepday = inflpcp + inflirr$

where *sepbtm* is the water percolating from the bottom of the soil profile (mm H_2O), *sepday* is the micropore percolation from soil layer (mm H_2O), *inflpcp* is the amount of precipitation that infiltrates the soil (mm H_2O) and *inflirr* is the amount of irrigation that infiltrates the soil (mm H_2O).

3- In the SWAT2005 source code, the subroutine “*subbasin*” that controls the simulation of the land phase of the hydrologic cycle performs the soil water balance before considering the irrigation operations from sources outside the watershed. This order doesn’t impair a change in the soil water balance since there is no excess water generated by irrigation. After making the changes in the subroutines “irrsub” and “percmain”, an excess water will be generated each time the depth of irrigation water applied is higher than field capacity. So, the simulation order of the land phase of the hydrologic cycle was changed so that the "*subbasin*" subroutine will perform the irrigation operations before the soil water balance calculations.

2.5. SWAT-IRRIG calibration and validation

Simulations were carried out from January 1st, 2007 to December 31st, 2009 using the standard split sample calibration-validation procedure (Klemeš, 1986). The period from January 1st, 2007 to January 14th, 2008 served as the warm up period for the model in order to take for granted realistic initial values for the calibration period. Data from January 15th, 2008 to December 31st, 2008 were used for the calibration and the remaining data for validation.

For every SWAT simulation, the summary input file (input.std), the summary output file (output.std), the HRU output file (output.hru), the subbasin output file (output.sub), and the main channel or reach output file (output.rch) (Neitsch et al., 2005) were generated. The output.rch file contains the summary for each routing reach in the watershed and its data were used for the calibration and validation processes.

For the hydrological model calibration and validation, the observed streamflow values were compared with the FLOW_OUT values. The simulated sediments yields (SED_OUT) were compared with the total suspended sediments measured at the DRW outlet. The simulated mineral phosphorus (MIN_P) was compared with the measured total dissolved phosphorus (TDP), while the simulated organic phosphorus (ORG_P) was compared with the measured particulate phosphorus (PP). Nevertheless particulate P does not necessarily coincide with the total organic P. However, for the P calibration process, the model parameters that give the best adjustment between total simulated (MIN_P + ORG_P) and observed phosphorus were considered.

The standard output file (.std) provides information about the average crop yields represented by the parameter YLD (Mg ha^{-1}). Therefore, the observed crop yields (Mg ha^{-1}) were compared with the YLD values. The .std file also gives the actual simulated evapotranspiration (ETa) for each crop (represented by the parameter ET). These estimates were compared with the ETa values calculated using the Irrigation Land Environmental Evaluation Tool daily soil water balance (Causapé and Pérez, 2008). These values were used for a simple comparison with those calculated by SWAT-IRRIG.

The model was run first to calibrate and validate SWAT-IRRIG crop model. In this case, only the crop parameters were adjusted. For the rest of model parameters, default values were considered. In total, seven crop parameters were adjusted to get crop yields similar to those measured in the study area (biomass energy ratio, harvest index, maximum leaf area index, optimum air temperature, base temperature, maximum root depth and light extinction factor). The observed crop yields were gathered from field surveys performed in 2008 (model calibration) and 2009 (model validation).

The separation of the measured streamflow at the DWR outlet between direct runoff and baseflow was performed because SWAT simulates separately these streamflow components. The baseflow separation technique detailed in Arnold and Allen (1999) was used to separate the simulated baseflow values from the total simulated streamflow values. This technique has been also used to estimate baseflows in several SWAT studies (Kalin and Hantush, 2006; Jha et al., 2007). In this study, the electrical conductivity (EC) of the drainage waters measured at the DWR outlet was used to separate the total streamflow into its components (Matsubayashi et al., 1993), based on the principle of water dilution during periods of high discharge.

As SWAT includes several parameters related to the site and management characteristic, a sensitivity analysis was carried out to detect the most relevant parameters in the hydrology calibration process. A parameter sensitivity analysis provides insights on which parameters contribute most to the output variance due to input variability. The sensitivity analysis method used in this study was the Latin Hypercube One-factor-At-a-Time (LH-OAT) (van Griensven et al., 2003) that combines the precision of the One-factor-At-a-Time (OAT) design (Morris, 1991) and the robustness of the Latin Hypercube (LH) sampling (McKay, 1988). A total of 27 parameters (10 intervals of LH samplings and 280 iterations) that may influence the DWR streamflow were considered (data not shown). The ranges of variation of these parameters are based on a listing provided in the SWAT manual (Neitsch et al., 2005). The analysis was performed on the daily average streamflow, for the period between January 2007 and December 2009. Sensitivity analysis was first performed without the use of observed data and next using observed data. The most sensitive ranking corresponds to the parameter that individually produced the highest average percentage of change in the objective function value of the model. The Global effect (S) produced by each parameter is classified in one of four previously defined classes according to Koskiaho et al. (2007): $S \geq 1.0$ "very high sensitivity"; $1.0 < S \geq 0.2$ "high sensitivity"; $0.2 < S \geq 0.06$ "medium sensitivity"; $S < 0.06$ "low sensitivity".

2.6. Model performance

Time series plots and five statistical methods were used to evaluate the SWAT-IRRIG performance based on the measured data. The five statistical criteria to evaluate the goodness of the calibration and validation results were: (i) the coefficient of determination (R^2), (ii) the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), (iii) the root mean square error (RMSE), (iv) the percent bias (PBIAS) (Gupta et al., 1999), and (v) the RMSE-observation standard deviation ratio (RSR) (Moriasi et al., 2007). The R^2 represents the percentage of the variance in the measured data explained by the simulated data. The NSE indicates how close are the plots of the observed versus the simulated data to the 1:1 line. The RMSE is equal to the sum of the variance of the modelled values and the square of the bias, and the smaller the RMSE the better the performance of the model. Thus, a RMSE value of 0.0 represents a perfect simulation of the observed sediments and phosphorus loadings. The PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The RSR is defined as the ratio of the RMSE to the standard deviation of the measured data (Moriasi et al., 2007). The optimal value of RSR is 0.0, which indicates zero RMSE or residual variation and therefore perfect model simulation.

The calibration objectives for streamflows and sediments and phosphorus loads were to maximize NSE and R^2, and to minimize the absolute value of PBIAS, RMSE, and RSR. Based on the guidelines proposed by Moriasi et al. (2007), the model performance can be evaluated as satisfactory if NSE > 0.5, RSR ≤ 0.70, and PBIAS < ± 25% for streamflow, < ± 55% for sediments and < ± 70% for phosphorus loads.

3. Results and discussion

3.1. Crop model calibration and validation

Table 1 shows the final values of the parameters used to calibrate the yields of corn, alfalfa, barley and sunflower. The optimum air temperature is the same for corn, alfalfa, and sunflower (25 ºC) which are summer crops; whereas for barley the optimum air temperature is set at 15.0 ºC since it is winter crop. For the same reasons, the base temperatures for corn, alfalfa and sunflower are above zero, whereas the base temperature for barley is set at 0.0 ºC.

The results indicate a good adjustment between the simulated and the observed mean crop yields obtained during the calibration and validation periods (Fig. 2). The mean simulated alfalfa yield was about 15.1 Mg ha^{-1} and the mean measured yield was 14.0 Mg ha^{-1}, indicating that SWAT-IRRIG over-estimated the alfalfa yield by 7.8%. The variability of the measured alfalfa yield (CV = 13%) was higher than the variability of the estimated alfalfa yield (CV = 5%). SWAT-IRRIG also over-estimated the mean barley yield by 9.6% (5.8 Mg ha^{-1} *vs.* 6.3 Mg ha^{-1}), and the simulated yield was less variable (CV = 3%) than the observed yield (CV = 15%). In contrast, SWAT-IRRIG under-estimated the mean corn and sunflower yield by 4.5% and 6.7%, respectively. The variability of the observed and simulated corn yields were similar (CV = 10% and 9%, respectively).

In regard to crop's actual evapotranspirations (Fig. 2), the results indicate that the mean annual ETa values simulated by SWAT-IRRIG (736, 730, 515, and 696 mm, for alfalfa, corn, barley, and sunflower, respectively) were quite similar to those calculated with the soil water balance. The differences between the simulated and calculated ETa values for corn, barley and sunflower ranged from 3.7 to 7.0%. In the case of alfalfa, the soil water balance over-estimated the value of ETa by almost 17.4%.

For all crops, the lowest values of average simulated yields and ETa were obtained in the platform soils, whereas the highest values were found in the deep alluvial soils (Fig. 3). Intermediate simulated values of crop yields and ETa were obtained in the shallow alluvial soils. Average yields of corn and alfalfa obtained in deep alluvial soils were found to be 19% and 6% higher than those obtained in platform and shallow alluvial soils, respectively. Also, higher mean sunflower yields were obtained in the deep alluvial soils than in the platform soils (3.2 Mg ha^{-1} *vs.* 2.4 Mg ha^{-1}, respectively). The mean barley yields obtained in the deep and shallow alluvial soils were similar, whereas the yields in the platform soils were 7% lower. These results were expected and could be for the most part driven by the variability of the soil types characteristics. Moreover, a Duncan's multiple comparison analysis indicated that differences in irrigation water use between soil types were not significant ($P < 0.1$) for both calibration and validation periods.

The small depth (0.6 m on average), the existence of a petrocalcic horizon limiting rooting depths, and the small average value of the soil total available water (TAW = 70 mm) of platform soils resulted in the lowest average simulated values of yields and ETa. Platform soils are stony (20% on average) so that the applied irrigation water quickly percolates through the soil profile. This explains the highest annual volumes of baseflow (GWQ) generated during the calibration and validation periods (Fig. 3). The opposite occurred in the deep alluvial soils that have a high TAW average of 179.1 mm. The mean annual GWQ values for all crops were 75.2 mm in the platform soils, and 45.9 mm in the deep and shallow alluvial soils. The soils occupied by corn and sunflower presented the highest GWQ mean annual values.

3.2. SWAT2005 *vs.* SWAT-IRRIG

Comparisons between the monthly streamflows measured and estimated using SWAT2005 and SWAT-IRRIG indicated very large differences between the observed and the SWAT2005 simulated data (Fig. 4). These differences were most important during the months where irrigation is intensive (Jun to September). The SWAT2005 predictions for the lateral flow (LATQ), baseflow (GWQ) and transmission losses (TLSS), which are the main SWAT model processes that affect the total water yield at the outlet of the system, were underestimated by 74.0, 341.1, and 6.7%, respectively (Table 2) in comparison with the SWAT-IRRIG predictions. These differences were due to the fact that during some irrigation events, the irrigation depths were higher than those needed to fill the soils up to field capacity and therefore the remaining amounts of water applied were lost and not used in the daily soil water balance calculation. As a result, the total water yield (WYLD) at the outlet of DRW was underestimated by 117.6% (Table 2). The Nash and Sutcliffe (NSE) increased from -0.50 using SWAT2005 to 0.90 using SWAT_IRRIG.

3.3. Sensitivity analysis

The sensitivity analysis performed with the observed data indicated that the effective hydraulic conductivity in main channel alluvium (CH_K2) was the highest sensitive parameter (S = 0.43). ALPHA_BF (baseflow alpha factor), SURLAG (surface runoff lag coefficient) and CN2 (curve number) have a medium sensitivity (*S* = from 0.06 to 0.20) and the remaining parameters were classified as low (*S* < 0.06). Without the use of observed data, the sensitivity of the parameters that govern groundwater and surface water flows increased and more parameters were in the "high" and "medium" sensitive classes.. The threshold depth water in the shallow aquifer for "revap" and percolation (REVAPMN) was ranked as the most sensitive parameter (*S* = 0.91), followed by the deep aquifer percolation (RCHRG_DP) and the soil evaporation compensation factor (ESCO) with *S* values of 0.74 and 0.43, respectively. The sensitivities obtained for REVAPMN, RCHRG_DP and ESCO were classified as high. These parameters were followed by six parameters with medium sensitivities, (CN2, SOL_AWC (soil available water capacity), SOL_Z (soil depth), GW_DELAY (groundwater delay time), BLAI (maximum potential leaf area index) and ALPHA_BF). The sensitivities of the remaining parameters were classified as low (*S* < 0.06).

3.4. Streamflow calibration and validation

Only those parameters with high and medium sensitivities were considered in the calibration process except for SOL_Z (Depth from soil surface to bottom of layer) and BLAI (maximum potential leaf area index for the plant). For SOL_Z the measured values were considered and BLAI was already adjusted in the process of crop parameters adjustment. The default values and the adjusted values for each parameter considered in the calibration process are presented in Table 3.

SWAT-IRRIG was manually calibrated and the daily simulated and observed streamflows at the DRW outlet were compared considering the calibration (Fig. 5A) and the validation (Fig. 5B) periods. Minor discrepancies between the observed and simulated stream discharges can be observed. During the calibration period, the calculated R^2 on a daily scale was about 0.55, which can be considered as acceptable. However the NSE value was very low (NSE = -0.23), mainly driven by the two very high stream discharges recorded on 28/10/08 and 02/11/08

(Fig. 5A). It seems that this problem in simulating high peaks flows is typical in SWAT model when implemented in particular climatic conditions as the Mediterranean ones (Panagopoulos et al., 2011b). In addition, the SWAT-IRRIG over-estimation of streamflows during high discharges might result from an underestimation of the daily precipitations (especially those events corresponding to peak stream discharges) arising from an inadequate sampling of subbasin precipitations. In fact, a comparison between the monthly precipitations recorded at the weather station located at 6 km from the study area and those measured with a pluviometer installed in the middle of the study area indicated that they were quite different in those months with high rainfall events. , If these high stream discharges were not considered, the NSE value increased to 0.47. A similar tendency was observed in the validation process. On a daily basis, the R^2 values were high (about 0.86), but the NSE was very low (-0.64) due mainly to two very high stream discharges recorded on 11/04/09 and 09/08/09 (Fig. 5B).

A good agreement between the monthly observed and simulated stream discharges was observed in the calibration and validation processes (Fig. 6B and 6D), with very high R^2 and NSE values of 0.90. The monthly RMSE and RSR were 26.38 10^3 m^3 and 0.33, respectively, and the absolute value of the PBIAS for the 2008 calibration year was 1.10%. Hence, according to the model evaluation guidelines proposed by Moriasi et al. (2007), SWAT-IRRIG simulation was “very good” for the Del Reguero stream discharge.

Values of R^2 and NSE greater than 0.8 were also found in several SWAT hydrological calibration studies (Hao et al., 2004; Kalin and Hantush, 2006; Wang and Melesse, 2006; Wang et al., 2006; Jha et al., 2007). Kalin and Hantush (2006) reported accurate surface runoff and streamflow results for the Pocono Creek watershed in eastern Pennsylvania (R^2 and NSE = 0.87). Accurate streamflow predictions were also achieved by Wang and Melesse (2006) in the Elm River North Dakota watershed (R^2 and NSE = 0.89 and 0.88, respectively).

However, NSE values obtained in other Mediterranean country were lower than 0.8 (Panagopoulos et al., 2011a).

The Baseflow calibration results at the DRW outlet also showed a good agreement with the observed baseflows. The baseflow fraction was about 0.80 of the total streamflow simulated by SWAT-IRRIG and about 0.77 for the observed data using the EC approach. A good agreement between the measured and simulated baseflows was also found by Tolson and Shoemaker (2007) in the Connonsville Reservoir watershed using the same technique of baseflow separation described by Arnold and Allen (1999).

For the validation process, the R^2 value calculated using daily data was 0.74, indicating a good agreement between observed and simulated daily streamflows. The slight discrepancy between observed and simulated data was also mainly driven by the two extreme discharge values recorded on dates of 11/04/09 and 09/08/09. The value of NSE obtained using the daily data was -0.64, and increased to 0.22 when the two high discharge values were eliminated. The SWAT-IRRIG estimations of the monthly stream discharges were classified as "very good" according to Moriasi et al. (2007): R^2 = 0.82, NSE = 0.80, RMSE = 46.31 10^3 m^3, RSR = 0.45 and PBIAS = 3.16%.

The calibration results were better than the validation results. Monthly best results achieved during the calibration period in comparison with the validation period were also found in several SWAT hydrological studies (Srinivasan et al., 1998; Arabi et al., 2006; Green et al., 2006; Kalin and Hantush, 2006). Green et al. (2006) evaluated SWAT performance in simulating the streamflow in the South Fork of the Iowa River watershed over the 1995-1998 period. The monthly values of R^2 and NSE in the calibration period were 0.9, and decreased to 0.6 and 0.5, respectively, in the validation period (Green et al., 2006). In a study performed by Srinivasan et al. (1998) for streamflow calibration and validation in the Richland-Chambers Reservoir watershed, the monthly R^2 and NSE values achieved during the validation and calibration periods were similar (R^2 and NSE monthly values of 0.82 for validation and 0.87 and 0.84, respectively, for calibration).

3.5. Sediments calibration and validation

Large discrepancies between daily observed and simulated total suspended sediment (TSS) loads were observed in the calibration process (Fig. 7A). The R^2 value was about 0.12 indicating a poor correlation between observed and simulated TSS loads. On a monthly basis the measured and simulated TSS loads were close, except in June, July and August 2008 (Fig. 7B). The R^2 value was high (0.87) showing a good correlation between simulated and observed TSS loads (Table 4). Also, the NSE and PBIAS values (0.72 and 15.87%, respectively) were considered as 'good', and the RSR value (0.38) was considered as 'very good' according to Moriasi et al. (2007).

On a monthly basis, similar sediment predictions were reported by Hao et al., (2004), and Santhi et al., (2001). Hao et al. (2004) successfully tested SWAT using sediment data collected from the Lushi watershed in China. They concluded that the agreement between observed and SWAT predicted sediment loads was good, with R^2 and NSE values of 0.72 on a monthly time step. Santhi et al. (2001) evaluated SWAT using two gauging stations located in the Bosque River watershed (Texas, USA) and found a good agreement between measured and predicted sediment loads (NSE of about 0.75).

A poor relationship between daily observed and simulated TSS loads was observed in the validation process (Fig. 7C) (R^2 = 0.18). On a monthly basis, the agreement between observed and simulated sediment yields was satisfactory (Fig. 7D). As shown in Table 4, the statistical results indicate a "satisfactory" SWAT-IRRIG performance in describing monthly sediment yields. The monthly value of R^2 was 0.93, indicating a "very good" agreement between monthly observed and simulated sediment yields. The value of NSE was 0.52, considered as "satisfactory" according to Moriasi et al. (2007). The PBIAS (1.39) and RSR (0.27) values for the validation process were considered "very good".

Monthly values of R^2 and NSE for the validation period were similar or better than other sediment modelling studies. Chu et al. (2004) found a poor agreement between observed and simulated sediment during the validation period using observed monthly data for the Warner Creek watershed. The values of R^2 and NSE were 0.19 and 0.11, respectively. Gikas et al. (2005) reported that SWAT correctly simulated the transport of sediments within the Vistonis Lagoon watershed in Greece using data for nine gauging stations. The R^2 values ranged from 0.34 to 0.98 on a monthly basis.

3.6. Total phosphorus (TP) calibration and validation

The daily observed and simulated TP loads showed a relatively good agreement (R^2 = 0.34) during the calibration process. The simulated and measured monthly TP loads were close (Fig. 8A and B). The NSE, RSR, and PBIAS values (0.66, 0.57, and - 9.75%, respectively) indicate a "good" simulation of monthly TP loadings during the calibration period (Table 4). These results are considerably better or similar than the monthly TP calibration reported by Grunwald and Qi (2006). They found lower NSE values, ranging from -0.89 to 0.07. Hanratty and Stefan (1998) calibrated SWAT phosphorus predictions using measured data collected in the Cottonwood watershed in Minnesota, and reported satisfactory TP predictions results (NSE = 0.54). Using nine gauging stations within the Vistonis Lagoon watershed (Greece), Gikas et al. (2005) found a good model performance for TP monthly loads with R^2 values ranging from 0.50 to 0.82.

The model TP validation showed a good relationship between observed and simulated TP loads (Fig. 8 C and D), with an R^2 value of 0.70 for the daily data and of 0.71 for the monthly data. The statistical results indicate a "satisfactory" SWAT-IRRIG performance in predicting monthly TP loads at the DRW outlet along the validation process (Table 4). The value of NSE was 0.76, considered as 'satisfactory' according to Moriasi et al. (2007). The percent bias (PBIAS) between simulated and observed TP loads shows that the simulated TP loads were relatively over-predicted (PBIAS of 20.8%), but the value was considered as 'very good'. The RSR measure showed a monthly value of 0.56 which is also considered as "good". Monthly values of R^2 and NSE achieved during the validation period were similar or better than those reported in other SWAT modelling studies. Saleh and Du (2004) achieved a monthly NSE value of 0.71 for the Upper North Bosque River watershed in Texas. In a study performed by Tolson and Shoemaker (2007), in the Cannonsville watershed (Texas, USA), the reported values of R^2 (from 0.72 to 0.83) and NSE (from 0.52 to 0.76) were similar to those found in Del Reguero watershed. In another study performed by White and Chaubey (2005), the values of R^2 and NSE ranged between 0.58 and 0.76 and -0.29 and 0.67, respectively, for three gauges located in the Beaver Reservoir watershed (Arkansas).

3.7. Total dissolved phosphorus (TDP) calibration and validation

Results indicated a relatively good relationship between daily observed and simulated TDP loads (R^2 = 0.35) in the calibration process. This relationship was improved when monthly observed and simulated TDP loads were considered (R^2 = 0.50). However, an underestimation of TDP loads during the February to May period was shown (PBIAS = 40.50%). This explains the relatively low NSE (NSE = 0.38) obtained (Table 4). Low values of NSE on a monthly basis were also reported in other SWAT modeling studies. Bouraoui et al. (2002) performed a study about climate change impacts on nutrient loads in the Yorkshire Ouse watershed (UK). The monthly value of NSE for TDP calibration was 0.02, which was judged as very low. Also Chu et al. (2004) achieved a negative value of monthly NSE (-0.08) for TDP predictions in the Warner Creek watershed. The percent bias (PBIAS) between simulated and observed TDP loads shows that they were under-predicted (PBIAS of 11.82%) and that the RSR was unsatisfactory (RSR of 0.74) (Table 4).

The validation results were better than the calibration results. A good relationship between observed and simulated TP loads was observed on a daily (R^2 = 0.72) and on a monthly (R^2 = 0.67) basis (Table 4). The statistical results indicate a "satisfactory" SWAT-IRRIG performance in describing monthly TDP loads at Del Reguero watershed outlet. Indeed, the NSE monthly value of 0.56 was considered 'satisfactory'. The value of PBIAS (19.96%) shows that simulated TDP loads were somewhat over-predicted, but it was considered as "very good" according to Moriasi et al. (2007).

The validation monthly values of R^2 and NSE achieved in this study are within the range of variation of those achieved in the study performed by Bracmort et al. (2006) in the Dreisbach and Smith Fry watersheds (Indiana). Performance values presented by the cited authors were 0.63 and 0.86 for R^2, whereas values of NSE ranged from 0.51 to 0.74. Values of R^2 (0.65) and NSE (0.55) found by Chu et al. (2004) for a monthly time step are similar to those found in this study. In the Upper North Bosque River watershed (Texas), Saleh and Du (2004) reported a TDP validation NSE value of 0.40 on a monthly basis.

3.8. Particulate phosphorus (PP) calibration and validation

A poor agreement between daily observed and simulated daily PP loads was obtained (R^2 = 0.04) in the calibration process, but the agreement for the monthly data was satisfactory (R^2 = 0.66). Cerucci and Conrad (2003) calibrated SWAT-PP predictions using measured data obtained for the Townbrook watershed in New York, and reported a monthly R^2 value of 0.40, if the measured data from February and March were excluded from the regression.

The monthly NSE value was about 0.66, indicating a good agreement between observed and simulated PP loads in the calibration period. This result was better than those obtained in other SWAT modelling studies. Saleh et al. (2000) evaluated SWAT using data measured at the Upper Bosque River watershed outlet. They found that the monthly calibration statistics parameters generally indicated a good model performance for PP loads (NSE = 0.54). In Texas, Saleh and Du, (2004) tested SWAT predictions of PP using measured data within the Upper Bosque River watershed. They concluded that SWAT satisfactorily simulated PP losses with a monthly calibration NSE value of 0.59. The percentage difference between simulated and observed PP loads shows that simulated PP loads were moderately over-predicted (PBIAS of 2.68%), but considered as 'very good'. The RMSE-observation standard deviation ratio (RSR) showed a monthly value of 0.61, also considered as 'satisfactory' (Table 4).

A relatively good relationship (R^2 = 0.36) was obtained between the observed and simulated daily PP loads in the validation process. On a monthly basis the relationship between observed and simulated PP loads improved (R^2 = 0.60). The NSE value was about 0.52, indicating a "satisfactory" prediction of monthly PP loads. The NSE value achieved during the validation period was within the range of variation found by Santhi et al. (2001) for the Bosque River watershed in Texas. Considering the PBIAS value (29.20%), the results show that the simulated PP loads were over-predicted, although they were considered "good" according to Moriasi et al. (2007). The RSR value (0.66) was also considered "satisfactory" at the monthly time step (Table 4).

4. Conclusions

The SWAT model does not reproduce the irrigation return flows (IRF) at the outlet of intensive irrigated watersheds when the irrigation source is outside the watershed. SWAT2005 model modifications regarding: (i) the maximum amount of irrigation water to be applied, (ii) the soil water percolation under irrigation, and (iii) the order of soil water routing were necessary for model applications to intensive irrigation watersheds such as those found in the middle Ebro River Basin (Spain). The SWAT-IRRIG modified version showed better model performance under irrigated systems. The monthly model calibration (NSE = 0.90, PBIAS = 1.1%, and RSR = 0.33) and validation (NSE = 0.80, PBIAS = 3.2%, and RSR = 0.45) statistics indicated a "very good" SWAT-IRRIG performance in describing stream discharge at the outlet of the Del Reguero study watershed. However, the model was unable to predict satisfactorily the observed streamflow peaks and, therefore, it should be further improved to obtain better estimations of sediments and particulate phosphorus. The monthly SWAT-IRRIG calibration and validation results indicated, respectively, a "good" and "satisfactory" performance in describing total phosphorus and total suspended sediment loads measured at the outlet of Del Reguero watershed. The SWAT-IRRIG model calibrated for hydrology, sediments and phosphorus can be used to determine the effects of different best management practices scenarios on phosphorus transfer from irrigated agricultural land to the IRF receiving water bodies.

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