Çukurova Tarım Gıda Bil. Der. *Çukurova J. Agric. Food Sci.*
33(2): 99-110, 2018

Evaluation of Streamflow Simulation By SWAT Model for The Seyhan River Basin

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Abstract
The Soil and Water Assessment Tool (SWAT) was used to model the hydrological water balance from the Seyhan river basin located in Turkey. The model sensitivity analysis and auto-calibration were conducted at four sites (i.e., Uctepe, Himmetli, Korkun and Zamanti) using the Sequential Uncertainty Fitting (SUFI-2), the Generalized Likelihood Uncertainty Estimation (GLUE) and Parameter Solution (ParaSol) algorithms in the SWAT-Calibration Uncertainty Programs (SWAT-CUP) package. The sensitivity analysis showed that the base-flow alpha factor (ALPHA_BF) and SCS runoff curve number (CN2) are the most sensitive parameters for this catchment. All sources of uncertainties were captured by bracketing more than 60% of the observed river discharge when using SUFI-2 and ParaSol except for ParaSol at Uctepe (57%). Streamflow calibration was done at a monthly time step for the period of 2001-2007. The results showed that ParaSol gave better results than those obtained by SUFI-2 and GLUE with regard to the Nash Sutcliffe Efficiency (NSE). Among all of the calibrated sites and the various calibration algorithms, the highest NSE (0.74) was obtained when the model was calibrated at Zamanti using the ParaSol algorithm.

Key words: Hydrologic modelling, Seyhan river basin, SWAT model, streamflow simulation

Seyhan Havzasında SWAT Modeli İle Nehir Akış Simülasyonu Ve Değerlendirilmesi

Özet
Toprak ve Su Değerlendirme Yazılımı (SWAT) Türkiye'de bulunan Seyhan nehri havzasında hidrolojik işlemleri su bütçesini temel alarak simüle etmek için kullanılmıştır. Model duyarlılık analizi ve otomatik kalibrasyonlar, SWAT-Kalibrasyon paket programında (SWAT-CUP) bulunan, Sıralı Belirsizlik Uygunluğu (SUFI-2), Genelleştirilmiş Olabilir Belirsizlik Tahmini (GLUE) ve Parametre Çözümü (ParaSol) algoritmaları kullanılarak, Üçtepe, Himmetli, Korkun ve Zamantı akarsuları için yapılmıştır. Duyarlılık analizi sonucunda, Baz Akış Alfa Faktörü (ALPHA_BF) ve SCS akış eğri numarasının (CN2) bu havza için akıma etki eden en hassas parametreler olduğunu göstermiştir. Gözlenen akım verilerinde tüm belirsizlik kaynaklarının ParaSol sonucunda Üçtepe (% 57) hariç, SUFI-2 ve ParaSol sonuçlarında %60'dan fazla olduğu görülmüştür. Akış verilerinin kalibrasyonu aylık bazda 2001-2007 dönemi için yapılmıştır. Nash Sutcliffe Katsayısına (NSE) göre ParaSol, SUFI-2 ve GLUE'ye göre daha iyi sonuçlar vermiştir. Kullanılan kalibrasyon algoritmaları arasında en iyi sonuç, (NSE=0.74) Zamanti akış verilerinin Parasol algoritması ile kalibrasyonu sonucu bulunmuştur.

Anahtar kelimeler: Hidrolojik modelleme, Seyhan havzası, SWAT modeli, nehir akış simülasyonu

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Yayın Kuruluna Geliş Tarihi: 09.10.2018
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Introduction

Hydrologic models are primarily used to understand the hydrologic processes of a basin or sub-basin and to provide valuable information to support water resources management programs. The Soil and Water Assessment Tool (SWAT; Arnold et al. 1998) is a physically based, semi-distributed, model that is used to simulate the hydrologic processes in a wide range of watersheds including those in semi-arid regions (Van Liew et al. 2007). The model was developed over a period of about 30 years by the USDA Agriculture Research Service (ARS). There have been few applications of the SWAT model to Turkish conditions: however, Akiner and Akkoyunlu (2012) tested the applicability of the SWAT model for predicting the surface flow in the Melen watershed using an Artificial Neural Network (ANN) to generate the daily precipitation for the study period. Their results gave a Nash Sutcliffe Efficiency (NSE) of 0.78 for the entire period of 1995-2008. Calibration in a hydrologic model is the process whereby model parameters are adjusted to allow the best-fit between the simulation and observations. Many studies have presented different techniques for SWAT model calibration. For example, van Griensven and Bauwens (2003) presented the ESWAT simulator using a multi-objective function. The model was applied to the Dender River (Belgium) to optimize 32 parameters. Using different statistical approaches, SWAT-CUP (Abbaspour et al. 2007a) is a public domain program that performs model sensitivity analysis, calibration, validation and uncertainty analysis of the SWAT model. The program links the Generalized Likelihood Uncertainty Estimation (GLUE; Beven and Binley 1992), Bayesian inference based on Markov Chain Monte Carlo (MCMC; Vrugt et al. 2003), Parameter Solution (ParaSol; van Griensven and Meixner, 2006) and Sequential Uncertainty Fitting (SUFI-2; Abbaspour et al. 2007b). The program has been used for model calibration in many different catchments worldwide (Schoul et al. 2008; Abbaspour et al. 2009; Rostamiani et al. 2008; Luo et al. 2011; Singh et al. 2013). The Seyhan river basin contains the largest number of fertile agricultural lands in Turkey and provides water to the fourth largest city of Turkey (Adana) (Acar and Dincer 2005). The basin is characterized by spatially heterogeneous climate, soil, land cover, and elevation. The upper area of the basin is mountainous while the lower area shows alluvial plain formation. The Mediterranean climate is the dominant climate type and is strongly present in the southern part of the basin. Seyhan Dam Lake and Catalan Dam Lake now compensate for the lack of major water bodies in the region. The Seyhan River system consists of three major streams i.e., Goksu, Zamanti and Cakit streams that merge to form the Seyhan River in the Northern of Adana. The objectives of the study reported here were to evaluate SWAT for its applicability in a Turkish Mediterranean type watershed for simulation of stream flow, to investigate the effect of multi-gauge calibration on flow prediction in a semi-arid watershed, and, finally, to examine the applicability of the three calibration algorithms in the SWAT-CUP program (i.e., SUFI-2, GLUE and ParaSol).

Materials and methods

The spatial data required for the model includes the digital elevation model (DEM), land cover map, and soil map. Daily climate data include precipitation, maximum and minimum temperature, relative humidity, solar radiation, and average wind speed. River discharge data are required for model calibration and validation. The DEM was the 30m DEM that available as the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), GDEM (Global Digital Elevation Model) and it was downloaded from http://asterweb.jpl.nasa.gov/gdem.asp. The SWAT model uses the DEM to delineate the watershed, calculate the geomorphic parameters and to create the sub watersheds and stream network. The distribution of the land covers within the basin was obtained from GlobCover 2009 v2.3 which was derived using bimonthly composites of ENVISAT MERIS acquisitions at 300m spatial resolution for the year 2009 (http://due.esrin.esa.int/globcover/). The land cover spatial data were reclassified to SWAT land use/land cover types. All soils data were obtained from the Food and Agriculture Organization of the United Nations (FAO/UNESCO 2003) Soil Map of the World. The soil map was linked to the SWAT soil database by modifying the user defined soil file because it holds soil information that is not included in the model database. A SWAT model simulation requires the input of daily precipitation, maximum and minimum temperature, solar radiation, wind speed and relative humidity. These data can be provided by the user or generated by the model. In our study, different sources of climate data were used for the period from 2000 to 2007. Daily minimum and maximum temperature and average wind speed were obtained from the US National Climatic Data Center (NCDC), Global Summary of the Day (GSOD). The data are online at: ftp://ftp.ncdc.noaa.gov/pub/data/gsod/; it was accessed in 03/2013. Data were obtained for three stations: Adana, Sivas and Nigde. The location of these stations is presented in Table 1 and Figure 1.

Table 1. List of weather stations and stream gauges sites used in the study

Station	Latitude	Longitude	Elevation (m)
Climate stations			
Adana	36° 58' 59"	35° 18' 00"	20
Sivas	39° 45' 00"	37° 01' 01"	1285
Nigde	37° 58' 01"	34° 40' 59”	1210
Stream gauges			
Uctepe (G1818)	37° 22' 50"	35° 28' 05"	127
Himmetli (G1801)	37° 51' 57"	36° 03' 34"	665
Korkun (G1820)	37° 17' 49"	35° 09' 05"	170
Zamanti (G1826)	37° 39' 46"	35° 34' 46"	347

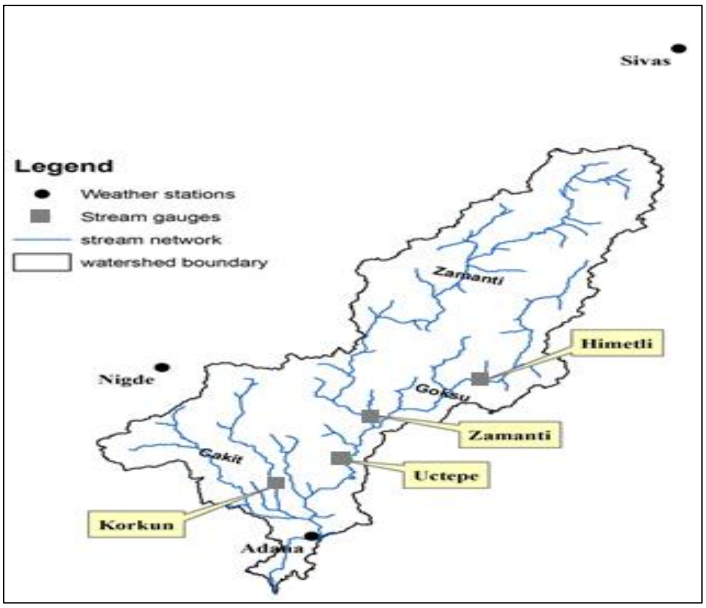

Figure 1. Location of the Seyhan River Basin and monitoring networks

Adana is the only weather station that is located within the watershed boundary; other stations that are close enough to the basin include Kahramanmaras, Gemerek, Kayseri and

Malatya. We did not use these stations because of the discontinuity of the recorded data. Because of that, we used another source of precipitation data. We used the Tropical Rainfall Measurement Mission (TRMM, product 3B42) described in Huffman et al. (2007). These data have a pixel resolution of 0.25° x 0.25°, so that only17 grid points covering the study area have been used

Relative Humidity was calculated by following Equation.

$$RH=100\frac{\exp(\frac{aTd}{b+Td})}{\exp(\frac{aT}{b+T})} \quad (1)$$

Where, *a* = 17.271; *b* = 237.7; T is average temperature (ºC); Td is dew point temperature (ºC**)** which is based on the August-Roche-Magnus approximation, considered valid for:

0 ºC < *T* < 60 ºC
1% < *RH* < 100%
0 ºC < *Td* < 50 ºC

Daily average solar radiation values were estimated using Hargreaves and Samani's (1982) equation (2) as presented by Allen (1997), which is based on temperatures. It incorporates a correction factor (Kr) based on the regional location of each weather station:

$$R_s = K_r\,(T_{max} - T_{min})^{0.5} Ra \quad (2)$$

Where T_{max} and T_{min} = mean daily maximum and minimum air temperature (°C), and Ra is extraterrestrial radiation, Allen et al. (2005) recommended using Kr = 0.16 for interior locations and Kr = 0.19 for coastal locations. Extraterrestrial solar radiation (Ra) was calculated according to Duffie and Beckman (1993).

The daily flow data for four sites of the river were obtained from by the Electrical Power Resources Survey and Development Administration of Turkey. The data from the period 2001 to 2007 was used for model calibration with a one-year warm up period. The Seyhan River Basin, shown in Figure 1, covers an area of 20164 km^2 as delineated by the SWAT model. The mean elevation of the basin is 1420 m, the land use is mainly a mosaic of crop land and vegetation (52.72 %) and the dominant soil type is loam (49.69%) followed by clay loam (36.06%). The watershed receives a mean annual precipitation of 708.5 mm with an annual average T_{max} and T_{min} of 19.7 and 7.7 °C, respectively, as determined from our input data over the period 2000-2012.

To represent spatial variability, SWAT subdivides watersheds into multiple sub-basins according to topography, which are then subdivided to create the Hydrologic Response Units (HRUs) that are based on land cover and soil characteristics. The hydrological cycle in SWAT is based on the water balance equation (Equ. 3). Model outputs include surface flow, groundwater recharge, lateral flow, sediment, and nutrient and pesticide yields. The surface runoff can be simulated by the modified Soil Conservation Service Curve Number (SCS-CN) method or the Green and Ampt infiltration model. The evapotranspiration can be estimated by the Hargreaves, the Priestly-Taylor and/or the Penman-Monteith method.

$$SW_t=SW_0+\sum_{i=1}^{t}\left(R_{day}-Q_{surf}-E_a-W_{seep}-Q_{gw}\right) \quad (3)$$

Where, SW_t = The final soil water content (mm); SW_0 = The initial soil and water content on (mm), t is the time (days); R_{day} = The amount of precipitation on day i (mm); Q_{surf} = the amount of surface runoff on day i (mm) ; E_a = The amount of evapotranspiration on day i (mm); W_{seep} = The amount of water entering the vadose zone from the soil profile on day i (mm); Q_{gw} = The amount of return flow on daily i (mm). The ArcSWAT interface for SWAT 2009 was used for the setup and parameterization of the model for this study. A complete description of this version and its capabilities is given in Douglas-Mankin et al. (2010) and Tuppad et al. (2011).

Table 2. SWAT parameters and their bounds used in sensitivity analysis and model calibration

Parameter	Description	Lower bound	Upper bound
ALPHA_BF	Base Flow alpha factor (days)	0	1
Ch_K2	Effective Channel Hydraulic Conductivity (mm/h)	0	150
Ch_N2	Manning coefficient for main channel	0	0.3
CN2*	SCS curve number for moisture condition II	-0.5	0.5
ESCO	Soil evaporation compensation factor	0	1
GW_DELAY	Ground water delay (days)	0	500
GW_REVAP	Groundwater revap coefficient	0.02	0.2
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	5000
REVAPMN	Threshold depth of water in the shallow aquifer required for revap to occur (mm)	100	500
SOL_AWC *	Available water capacity of the soil layer (mm/mm)	-0.5	0.5
SOL_K*	Soil saturated hydraulic conductivity (mm/h)	-0.5	0.5
SOL_Z *	Depth from soil surface to the bottom of layer (mm)	-0.5	0.5
OV_N	Overland Manning roughness	0	0.8
HRU_SLP*	Average slope steepness (m/m)	-0.2	0.2

The parameter sensitivity analysis was done using the SWAT-CUP program using the three algorithms i.e., SUFI-2, ParaSol and GLUE. Fourteen hydrological parameters were tested for sensitivity analysis for the simulation of the stream flow in the study area. Here, we used the default lower and upper bound parameter values as shown in Table 2. The calibration and uncertainty analysis were done using the three algorithms used for the sensitivity analysis. The methods in SWAT-CUP were chosen for their applicability for simple to complex hydrological models and their different techniques to assess the model uncertainty. ParaSol is based on a modification to the global optimization algorithm SCE-UA (Duan et al. 1992). It uses the sum of the squares of the residuals (Equ. 4) as the objective function and assesses only model parameter uncertainty:

$$SSQ = \sum_{t_i=1}^{n}\left(y_{t_i}^{M}(\theta) - y_{t_i}\right)^2 \qquad (4)$$

Where, n is the number of the observed data points, and y_{ti} and y_{ti}^{M} represent the observation and model simulation with parameters θ at time t_i, respectively. SUFI-2 and GLUE account for the uncertainty not only for the model parameters, but also to the conceptual model, input data and measured data (Setegn et al. 2010).

The output uncertainty is quantified by the 95% prediction uncertainty band (95PPU) calculated at 2.5% and 97.5% level of the cumulative distribution of an output variable obtained through Latin hypercube sampling (Abbaspour et al. 2007a). After the 95PPU is calculated the strength of a calibration is measured by p-factor which is the percentage of observation bracketed by the 95% prediction uncertainty (95PPU). Another measure quantifying the strength of a calibration or uncertainty analysis is the r-factor which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. The goodness of calibration and prediction uncertainty is judged on the basis of the closeness of the p-factor to 100% (i.e., all observations bracketed by the prediction uncertainty) and the r-factor to 1. The average thickness of the 95PPU band and the r-factor are calculated by Equation 5.

$$r - factor = \frac{\frac{1}{n}\sum_{t_i=1}^{n}\left(y_{t_{i,97.5\%}}^{M} - y_{t_{i,2.5\%}}^{M}\right)}{\sigma_{obs}} \qquad (5)$$

Where $y_{t_{i,97.5\%}}^{M}$ and $y_{t_{i,2.5\%}}^{M}$ represent the upper and lower boundary of the 95PPU, and σ_{obs} stands for the standard deviation of the measured data.

The other factor is the goodness of fit that can be quantified by the coefficient of determination (R^2) and Nash-Sutcliff Efficiency (NSE) (Nash and Sutcliffe 1970) between the observations and the final best simulations. Coefficient of determination (R^2) and Nash-Sutcliffe coefficient (NSE) are calculated by Equations 6 and 7

$$R^2 = \frac{\left[\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})\right]^2}{\left[\sum_{i=1}^{n}(O_i - \bar{O})^2\right]\left[\sum_{i=1}^{n}(P_i - \bar{P})^2\right]} \qquad (6)$$

$$NSE = \frac{\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad (7)$$

Where P_i are the predicted values, O_i are the observed values, n is the total number of observations, $\bar{O}$ is the mean of the observed data and $\overline{P}$ is the mean of the predicted data.

Results and discussion

Sensitivity analysis helps to identify the parameters that have a strong influence on the model output. In our study, sensitivity analysis was performed at all sites to determine the parameters needed to improve the model simulation and to understand the behaviour of the hydrologic system. Three algorithms (SUFI-2, ParaSol and GLUE) were used to perform the sensitivity analysis and the results are shown the ranking of the model parameters in the Table 3.

Table 3. The selected SWAT parameters and their sensitivity analysis ranking result

Parameter	G1818			G1801			G1820			G1826		
	S-2	PSol	G	S-2	PSol	G	S-2	PSol	G	S-2	PSol	G
ALPHA_BF	1	1	1	`1	2	1	2	13	3	6	4	2
Ch_K2	3	4	3	3	1	3	6	6	6	7	5	3
Ch_N2	13	11	4	5	4	4	9	11	13	10	7	7
CN2	2	8	2	2	12	2	1	1	1	2	1	1
ESCO	4	7	12	10	3	8	4	2	2	4	3	13
GW_DELAY	11	10	7	14	11	12	11	8	10	14	13	10
GW_REVAP	14	3	13	12	13	10	5	5	11	3	12	11
GWQMN	10	12	10	4	7	9	8	14	9	1	2	6
REVAPMN	8	9	6	11	5	13	10	10	8	5	9	9
SOL_AWC	12	2	9	9	8	14	12	9	5	8	8	4
SOL_K	5	14	11	7	10	5	3	7	7	12	14	5
SOL_Z	7	6	8	8	9	11	13	4	4	13	6	12
OV_N	6	13	14	6	6	7	14	12	12	11	11	14
HRU_SLP	9	5	5	13	14	6	7	3	14	9	10	8

At G1818, ALPHA_BF was ranked the most sensitive parameter using the three algorithms. At G1820, The three algorithms agreed that the most sensitive parameter is CN2, but they differently ranked the second and third most sensitive parameters. In G1826, GWQMN, CN2 and GW_Revap were the most sensitive parameters using SUFI-2, however, CN2, GWQMN and ESCO seem to be very sensitive using ParaSol. From the above results the model is very sensitive to surface runoff and base flow parameters. At G1801, again SUFI-2 and GLUE showed a similar performance in regard to ranking the most sensitive parameters and different than that obtained by ParaSol. Alpha_BF, CN2 and Ch_K2 were ranked as first, second and third most sensitive parameters, respectively, according to SUFI-2 and GLUE. Model calibration aims to adjust and optimize model parameters to achieve the pre-defined objective function. Fourteen model parameters that mostly affect surface runoff and groundwater parameters were used for the calibration. The model was calibrated on a monthly basis for the period from 2001-2007 with a one year warming up period. The model was calibrated and uncertainty analysis performed at four gauging sites (Uctepe, Himetli, Korkun and Zamanti) using three different algorithms (SUFI-2, ParaSol and GLUE through the SWAT-CUP program). Calibration results were interpreted using p-factor, r-factor, R^2 and NSE that are shown in Table 4. Although it is very sensitive to high extreme values due to the square differences, the NSE is still the best and most acceptable goodness of fit measure. According to Moriasi et al. (2007) and Cho et al. (2013), NSE value can be considered satisfactory if NSE ≥0.5, good if NSE ≥0.65 and very good if NSE ≥0.75 when comparing the observed versus the simulated flow on a monthly basis.

Table 4. Stream Flow Calibration at the four monitoring stations Using SUFI-2, GLUE and ParaSol Methods

Objective function		Stations			
		G1818	G1801	G1820	G1826
p-factor	SUFI-2	0.94	0.92	0.98	0.69
	GLUE	0.73	0.36	0.20	0.32
	PARASOL	0.57	0.71	0.62	0.68
r-factor	SUFI-2	2.52	2.13	2.59	0.92
	GLUE	0.89	0.35	0.37	0.46
	PARASOL	0.63	0.71	0.84	0.72
R^2	SUFI-2	0.65	0.57	0.55	0.71
	GLUE	0.68	0.54	0.51	0.66
	PARASOL	0.73	0.59	0.57	0.74
NSE	SUFI-2	0.64	0.56	0.52	0.67
	GLUE	0.66	0.53	0.46	0.62
	PARASOL	0.71	0.58	0.53	0.74

Comparison between observed and simulated monthly flow for seven years, showed a good agreement using the SUFI-2 algorithm. The NSE was used as an objective function where several iterations were performed until the best NSE efficiency has been met. In SUFI-2, the combined effect of all uncertainties is depicted by the final estimates of parameter uncertainties. From Table 4, at G1818 station, 94% of the observed monthly runoff values were within the 95PPU, but the r-factor was quite large (2.52) indicating large model uncertainties. The large 95PPU band (or large r-factor) necessary to bracket 94 % of the observed data indicates that the uncertainty in the conceptual model is also very important, and in our case quite large. It seems that not all processes, especially some that are important downstream of the river are not included in the model. We believe that these processes are mainly delaying the runoff and significantly contributing to higher evaporation losses. At the same site the produced NSE was 0.64 and the R^2 of 0.65.

At other stations, different p-factors and r-factors were obtained. The p-factor brackets were 92%, 98% and 69% of the observation and the r-factor equaled 2.13, 2.59 and 0.92 for G1801, G1820, and G1826, respectively. The model produced a good R^2 value and NSE efficiency for the G1826 station; 0.71 and 0.67, respectively. However, the calibration at stations G1801 and G1820 show lower R^2 (0.57 and 0.55) and NSE (0.56 and 0.52) values. This shows that the model at G1801 and G1820 is more uncertain than at the other stations (G1818 and G1826)(Figure 2,3,4,5). SUFI-2 produced the highest p-value and r-factor value for all of the studied sites when compared to ParaSol and GLUE.

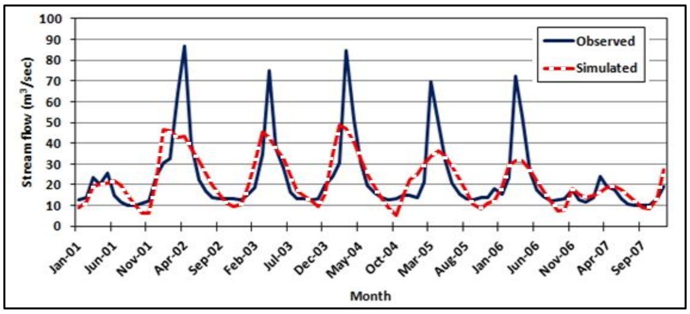

Figure 2. Comparison of monthly observed and simulated flow using SUFI-2 algorithm at G1801

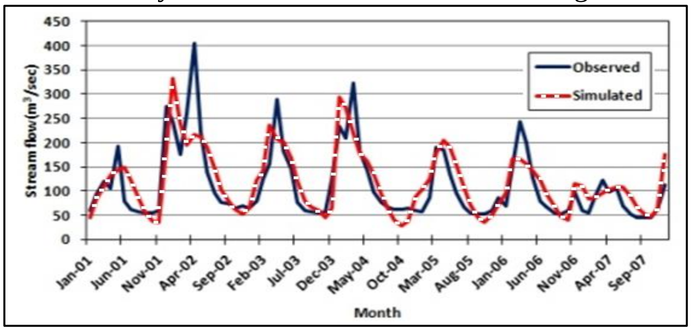

Figure 3.Comparison of monthly observed and simulated flow using SUFI-2 algorithm at G1818

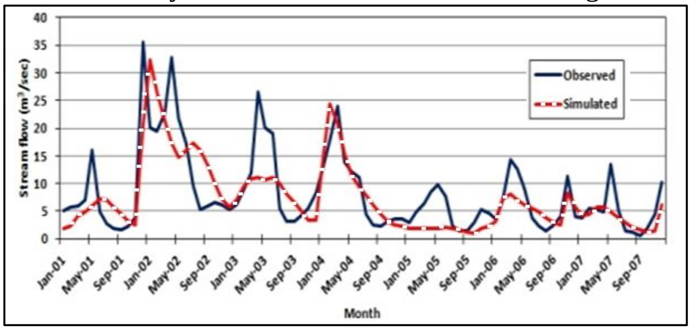

Figure 4.Comparison of monthly observed and simulated flow using SUFI-2 algorithm at G1820

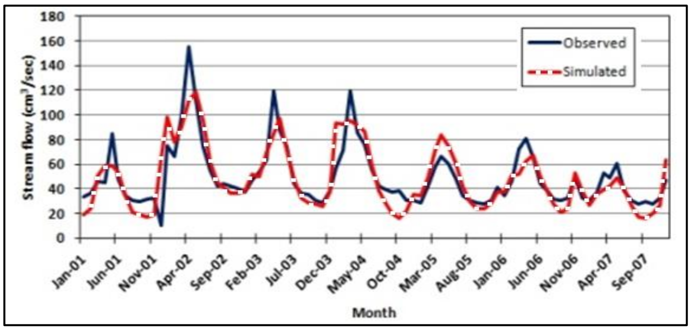

Figure 5.Comparison of monthly observed and simulated flow using SUFI-2 algorithm at G1826

Using the ParaSol algorithm, the calibration process converges within 7000 iterations. The ParaSol algorithm shows good agreement between monthly observed and simulated flows in at all the calibrated sites; this is very clear from the statistics that are given in Table 4. Using the ParaSol method, the best NSE (0.71 and 0.74) and R^2 values (0.73 and 0.74) were obtained when the model was calibrated at the G1818 and G1826 sites while the model produced satisfactory NSE values for the other stations (0.58 and 0.53) when the model was calibrated at sites G1801 and G1820. The worst p-factor (57%; which is the percentage of observations bracketed by the 95% prediction uncertainty (95PPU)), was produced when the model was calibrated at G1818 and the r-factor equals 0.63. For G1801, the p-factor brackets 71% of the observations and the r-factor equals 0.59. Other stations gave different p-factor and r-factor values; i.e., 62%, and 68% and 0.84, and 0.72 for the G1820 and G1826 stations, respectively. The ParaSol algorithm produced the highest R^2 and NSE at all of the studied sites as compared to SUFI-2 and GLUE. These results are the same as was concluded by Yang et al. (2008) and Setegn et al. (2010).

The GLUE algorithm gives bad agreement between monthly observed and simulated flows at all sites during the calibration and this is very clear from the statistics that were used in Table 4. In addition, the GLUE method yields the worst simulation results during the calibration period for all the sites Table 4. The p-values for three of the calibrated sites were very low (G1801 (36%), G1820 (20%) and G1826 (32%)). However, the method produced a reasonably good p-factor value when the model was calibrated at G1818 gave 73%. The r-factor values were also very low for G1801, G1820 and G1826 (0.35, 0.37, 0.46 respectively) but it was 0.89 for the G1818 station. When compared to the SUFI-2 and ParaSol algorithms, GLUE produced the lowest R^2
(0.54, 0.51, 0.66) and NSE (0.53, 0.46, 0.62) values at gauges G1801, G1805 and G1826, respectively. However, the method produced a higher R^2 (0.68) and NSE (0.66) at G1818 than produced by SUFI-2.

As illustrated by Yang et al. (2008), in SUFI-2 and GLUE, all source of uncertainty (for example, model structure, observation data error and model input) are captured resulting in a high p-factor value, however ParaSol only deals with the model parameters uncertainty and ignoring other source of uncertainties which lead to low p-factor and too narrow prediction uncertainty band. A higher NSE value using ParaSol and lower values using SUFI-2 and GLUE are due to that, ParaSol based on the Shuffled Complex Evaluation Method-University of Arizona (SCE-UA) is very efficient in detecting the high objective function in the response surface. However, the global sampling procedure in GLUE is inefficient to locate the maximum or maxima of the objective function, moreover the narrowed parameters range in SUFI-2 decreases the sample size and decreases the exploration of the parameter space.

The vast majority of the parameters which were used for model calibration were in relation to groundwater (baseflow release factors and groundwater delay factors) and surface water which signifies the groundwater component of the water balance in the watershed; this also highlights the fact that the interaction between surface and groundwater plays an important role in the overall dynamics of the watershed. Our results suggested that a single calibration at the watershed outlet can be misleading and requires multisite calibration to capture the heterogeneity of the watershed (in our case different results were obtained when the model was calibrated at G1818 and G1801, for example). Many studies have addressed the multisite calibration of SWAT model (Cao et al. 2006; Qi and Grunwald 2005; White and Chaubey 2005; Zhang et al. 2008; Cho et al. 2013, and Niraula et al. 2012). Cao et al. (2006) suggested that the poor results that are produced from the model when calibrated at a subwatershed level and good prediction ability at a bigger scale is due to the compensation between the differing factors (for example, climate, land cover and soil data) at large scale. As shown from the results provided above, the model has some difficulties simulating the low flow conditions at G1801 and G1820. Although we used the TRMM data as a gridded type of precipitation source to provide the spatial cover over the area of study, there was no climate station close enough to provide the other climate parameters for the contributing area of site G1801. The closest weather station is Kahramanmaras (58 km from the basin) but the station has a gap in the data (from mid-2002 to mid-2007) so that it cannot be used in this study. In general, the model underestimated the high peak flows at all sites and this might be a result of the regulations across the river, reservoirs, lakes and irrigation channels. This inability to capture the peak flows caused a lower NSE. Further inspection of the precipitation data indicates insufficient rainfall to generate the observed flow. Beside precipitation and other climate data uncertainties, other uncertainties that can impact the calibration are, for example; land use data (with a spatial resolution of 300 m), which we think it doesn’t provide enough details about the land use and the changes that has been made since 2009 (the year of our land cover data). Another source of uncertainty is the soil type data. We used the FAO digital soil map of the world which has a spatial resolution of 10 km; this doesn’t provide sufficient details about the soil characteristics and channel flow measurements. The Seyhan River, like other rivers in semi-arid regions, is more extreme and less predictable than those in humid regions as a result of the spatial and temporal variation of the flow resulted mainly from climate conditions variations.

Conclusion

The SWAT model was used to investigate the hydrologic component of the Seyhan river basin located in Turkey. The model was calibrated on a monthly basis and the uncertainty analyses were performed using the SWAT-CUP program. The results show that SUFI-2 captured the observations well during the calibration period with a p-value > 90% for gauges G1818, G1801 and G1826 and 62% for G1826. The NSE ranged from 0.52 to 0.67. ParaSol was characterized by lower p-values with a high NSE of 0.74 in the case of G1826. The model was sensitive to the base flow recession constant ALPHA_BF parameter at most of the calibrated locations which shows that more studies of the groundwater and its relation to surface water in the basin are essential. The uncertainty of the simulated flow is due to errors in input data such as rainfall, temperature and the other climate data as these data, except for rainfall, came from stations that are not within the basin boundary except for the Adana station (located downstream) which is not representative to the basin climatic conditions. Other sources of model uncertainty include diversions and regulations for which the impact is not accounted because of upstream dams and reservoirs and irrigation diversion. SWAT model was able to accurately simulate the surface flow at the studied locations.

Acknowledgment

We would like to thank TUBITAK-BIDEB (The Scientific and Technological Research Council of Turkey-Department of Science Fellowships and Grant Programmes) for their financial support to the second's author fellowship.

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