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Model selection techniques in SWAT-based hydrological modelling

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Abstract: Hydrological modeling is subject to issues of simplicity vs. complexity and accuracy vs. uncertainty. This recognition has led to a growing tendency among hydrologist to postulate several alternative hydrological models for a given problem. In this case, model selection techniques can be used as effective yet practical just-in-time approaches to rank these candidate models and select the 'best' one among them and/or attempt to construct a set of 'good' models. SWAT (soil and water assessment tool) is one of the most comprehensive large-scale watershed models with a large number of parameters capable of evaluating hydrologic processes, so its calibration is challenging. This study aims to investigate the efficiency of AIC model selection criterion for selecting a "good" calibration setting. To predict water discharge at Sirwan River Basin outlet, a SWAT model of the basin has been set-up. Depending on the number of calibration parameters and observation data, different calibration settings have been built and calibrated using sequential uncertainty fitting (SUFI) approach. The calibration settings were compared then against Nash Sutcliff, P-Factor and R-factor statistics, as well as AIC model selection criterion. Results showed that a good calibration setting is the one with less number of observations according to the AIC.

Key words: hydrological modeling, SWAT, calibration, model selection criteria

1. INTRODUCTION

Hydrological modelling plays a critical role in assessing water resources problems. During the last decades, several physically based distributed hydrological models have been emerged and applied to simulate the basin wide hydrological processes. Some of the models include System Hydrologic Europeen (SHE) (Abbott at al. 1986a, b), Variable Infiltration Capacity (VIC) (Liang et al. 1994) and Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998).

SWAT is a physics-based model with the ability of predicting the impact of land-management practices on water, sediment, and agricultural chemical yields in watersheds with varying soil, land use, and management conditions (Neitsch et al. 2011). Due to the complex nature of the hydrological processes, SWAT contains a large number of parameters, the value of some of which cannot be measured directly and should be estimated through the calibration. Indeed, the agreement between the simulated and the observed data is measured through the calibration by evaluating one or more objective functions (Zhang et al. 2008).

Characteristics of a calibration setting depend on the purpose of the study (Gong et al. 2012). Several studies have focused on single-gauge calibration for the hydrological modeling (Li et al. 2010, Sudheer et al. 2011, Bitew et al. 2012). Multiple gauges-based calibration has been documented by Abbaspour et al. (2007), Migliaccio and Chaubey (2007), and Faramarzi et al. (2015), among others. Finally, several authors have successfully applied multi-objective formulations for the calibration (White and Chaubey 2005, Bekele and Nicklow 2007, Ahmadi et al. 2014).

Model selection offers a way to draw inferences from a set of multiple competing models. These criteria discriminate among models based on how closely they reproduce hydrologic observations using maximum likelihood estimates of model parameters (favoring models that reproduce observed behavior most closely) and how many such parameters they contain (penalizing models that contain many) (Ye et al. 2008). The Akaike information criterion (Akaike, 1973) is among the most widely used criteria for model selection that estimates the Kullback–Leibler information lost by approximating full reality with the fitted model.

In this paper, SWAT model was applied to hydrologically simulate *Sirwan* River basin in Iran. In order to calibrate the model, several calibration settings were built, and an attempt was made to evaluate the impact of the number of observations as well as the number of calibration parameters on the calibration results according to AIC criteria.

The remainder of the paper is organized as follows: materials and methods are described in Section 2. Section 3 discusses results and discussion, and Section 4 describes the conclusions.

2. MATERIALS AND METHODS

2.1 Study area

With an area of about 9515 km2, Sirwan river basin, is located in west of Iran (Fig. 1). It lies between 46°1′-48° N and 34°43′-35°48′ E, where topography is complex, in that altitude varies from 3273 m to 601 m, according to the ASTER DEM (NASA and JPL 2009). Sirwan is mostly mountainous and the heterogeneous climate conditions make the hydrological modeling challenging in the basin.

2.2 SWAT model setup

The National Centers for Environmental Prediction's Climate Forecast System Reanalysis (CFSR) daily weather data (precipitation and temperature) with the resolution of 38 km have been used as input to SWAT (Saha et al. 2010). SWAT required spatial data including digital elevation model (DEM), soil map, and land cover data were driven from the Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER) DEM dataset (NASA and JPL 2009), at the resolution of 30x30 m, the digital soil map of the world (FAO 1995), and the Iranian Ministry of Energy, respectively. Precipitation, maximum and minimum temperature have been considered for 13 stations, from 1981 to 2012. In order to account for orographic effects of each subbasin on precipitation, temperature and solar radiation, five elevation bands were assigned to each subbasin. SWAT built 39 subbasins and 707 HRUs for the Sirwan basin, and it simulated the streamflow for a period of 32 years from 1981 to 2012, considering the first three years as the warm-up.

2.3 Calibration settings

For the calibration of SWAT model, SUFI-2 calibration and uncertainty analysis method (Abbaspour et al. 2004) was used, utilizing SWAT-CUP software. The period of 1985 to 2003 was chosen to perform the calibration, in which a variety of the hydrological conditions/extremes had been occurred within the watershed. Moreover, during this time period the flow was almost natural and just Gheshlagh Dam (Fig. 1) had been operating. The following 9 years i.e., 2004-2012 were considered for the validation. The Nash and Sutcliffe (NS) statistics (Nash and Sutcliffe 1970), the P-Factor (the fraction of measured data bracketed by the 95PPU band) and R-factor (the ratio of the average width of the 95PPU band and the standard deviation of the measured variable) indices (Abbaspour et al. 2004, 2007) were used in this study to evaluate the calibration. As the objective of the study was to evaluate different calibration settings utilizing AIC model selection criterion, two basic scenarios were defined, based on each of which four calibration settings were built. Overall, 8 settings were built for the calibration of the *Sirwan* river basin. The scenarios are:

Scenario 1: To consider the outlet site (gauge) for the calibration. Since in the Sirwan basin the Gheshlagh dam had been operating during the calibration time period, we had to consider the observed data of the sites 3 and 4 (Fig. 1) in the calibration (objective function) to capture the physical characteristics of the dam upstream.

Scenario 2: To consider sites located in the middle of the *Sirwan*'s tributaries in addition to the outlet site. We selected sites that were not nested and were not hydrologically connected (Table 2).

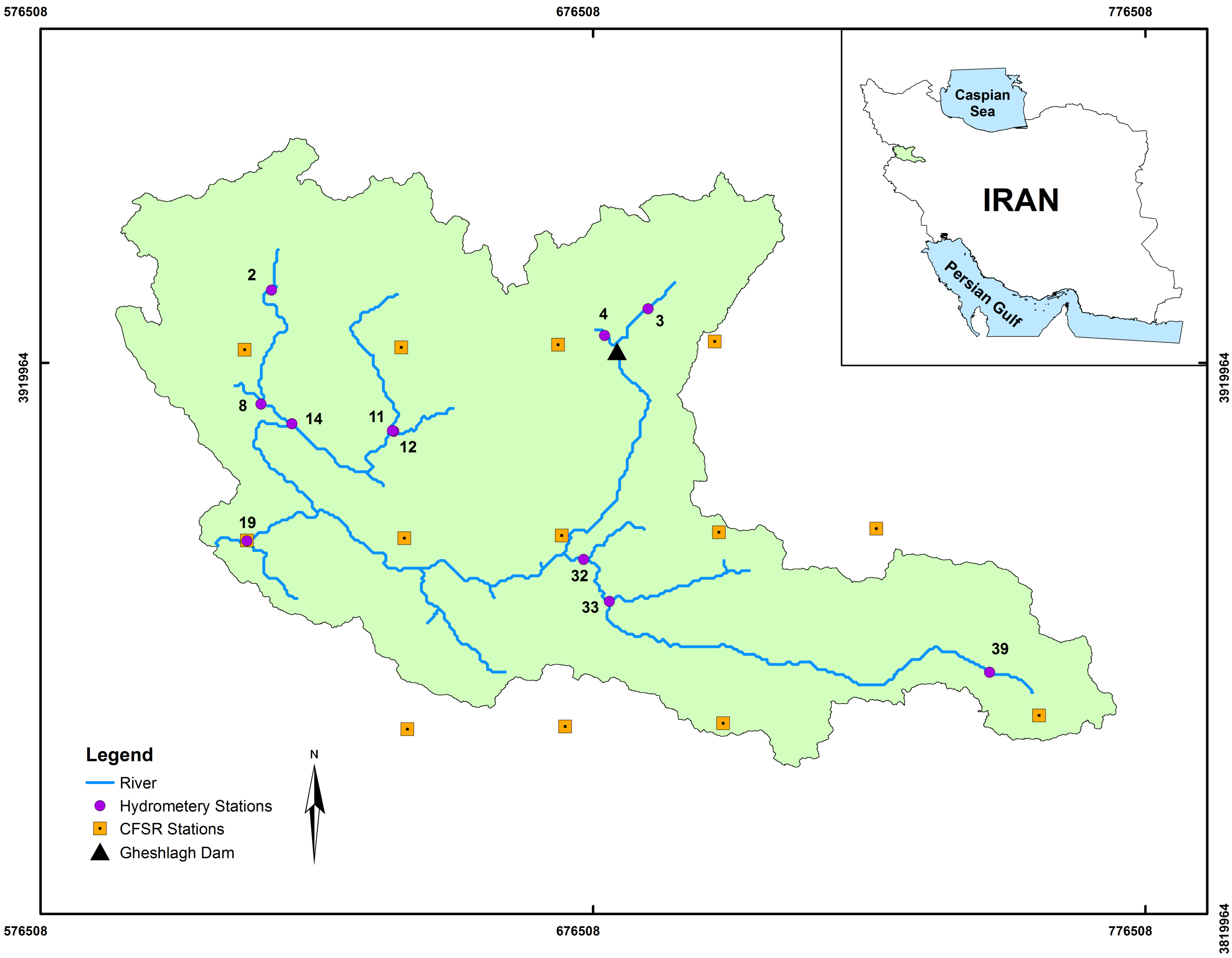

Figure 1. Study area.

For the settings built according to the basic scenarios, 28 commonly used parameters (Abbaspour et al. 2007) were considered for the calibration of discharge, and their values were initially set according to the guidelines provided by SWAT developers (Arnold et al. 2012a). These parameters and their definition can be found in Table 1. We examined each scenario for two cases and built 4 calibration settings; in the first case (Combined), we built a calibration setting considering all the sites mentioned in Table 2 in one model. In the second case (Separate), we calibrated the area upstream of each site separately. Then, we aggregated calibrated parameters into one setting. We performed one-at-a-time sensitivity analysis, reduced the number of the parameters and built another 4 settings based on the sensitive parameters. After building calibration settings, AIC model discrimination criterion (Eq. 1) was used for ranking and evaluating the set of 8 settings and also making some beneficial inferences.

$$AIC = -2 \log(\mathcal{L}) + [2K] \qquad (1)$$

where K is the number of parameters; $\mathcal{L}$ is maximum likelihood of the model.

$\Delta AIC = AIC_i - AIC_{min}$ can be used in order to rank the competing settings (Burnham & Anderson 2004). The weight of evidence or the probability that setting i is the best model is given by:

$$w_i = \Pr(model_i \mid data) = (\exp(-0.5\Delta AIC_i))/(\sum^{R}_{j=1}(\exp(-0.5\Delta AIC_j))) \qquad (2)$$

where i=1.2.….R, and R is total number of settings. These weights have a value between 0 to 1, with the sum equals 1 for all settings in the candidate set.

Table 1. Calibration parameters

Parameter Name	Definition	Sensitive or not
v__ALPHA_BF.gw	Baseflow alpha factor	Yes
v__GW_DELAY.gw	Groundwater delay time	Yes
v__GW_REVAP.gw	Groundwater "revap" coefficient	Yes
v__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	Yes
v__REVAPMN.gw	Groundwater "revap" coefficient	
r__CN2.mgt	Initial SCS runoff curve number for moisture condition II	Yes
v__CH_N2.rte	Manning's "n" value for the main channel	
v__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium	Yes
r__SOL_AWC().sol	Available water capacity of the soil layer	Yes
r__SOL_K().sol	Saturated hydraulic conductivity	
r__SOL_BD().sol	Moist bulk density	Yes
r__SLSUBBSN.hru	Average slope length	
v__OV_N.hru	Manning's "n" value for overland flow	
v__CANMX.hru (FRST)	Maximum canopy storage for the landuse "FRST"	
v__CANMX.hru (FRSE)	Maximum canopy storage for the landuse "FRSE"	
v__CANMX.hru (FRSD)	Maximum canopy storage for the landuse "FRSD"	
v__CANMX.hru (PAST)	Maximum canopy storage for the landuse "PAST"	
v__SFTMP.bsn	Snowfall temperature	Yes
v__SMTMP.bsn	Snowmelt base temperature	Yes
v__SMFMN.bsn	Melt factor for snow on December 21	Yes
v__SMFMX.bsn	Melt factor for snow on June 21	Yes
v__ESCO.bsn	Soil evaporation compensation factor	
v__EPCO.bsn	Plant uptake compensation factor	
v__SNOCOVMX.bsn	Minimum snow water content that corresponds to 100% snow cover	Yes
v__TIMP.bsn	Snow pack temperature lag factor	Yes
v__SURLAG.bsn	Snow pack temperature lag factor	
v__PLAPS.sub	Precipitation lapse rate	Yes
v__TLAPS.sub	Temperature lapse rate	Yes

Table 2. Characteristics of calibration settings

Calibration Setting	Basic Scenario	Sites considered in the calibration	Combined (C) or Separate (S)	Sensitivity Analysis	Number of observed data considered in the calibration	Number of calibration parameters	Calibration time (min)	Calibration Residual Sum of Squares (RSS)	Validation Residual Sum of Squares (RSS)
Setting1	Scenario1	3, 4, 19*	C	No	684	30[a]	711	528345.1	392117.7
Setting2	Scenario2	3, 4, 8, 14, 19, 32	C	No	1368	30[a]	584	388143.9	139920.3
Setting3	Scenario1	3, 4, 19	S	No	684	30[a]	1076	577833.6	212510.3
Setting4	Scenario2	3, 4, 8, 14, 19, 32	S	No	1368	30[a]	2446	417220.2	153447.6
Setting5	Scenario1	3, 4, 19	C	Yes	684	18[a]	375[e]	557576.1	181235.4
Setting6	Scenario2	3, 4, 8, 14, 19, 32	C	Yes	1368	18[a]	763	414032.2	161490.1
Setting7	Scenario1	3, 4, 19	S	Yes	684	18[a]	1786	612368.9	194964.6
Setting8	Scenario2	3, 4, 8, 14, 19, 32	S	Yes	1368	18[a]	3141	339383.0	141555.4

** site 19 is the outlet*

3. RESULTS AND DISCUSSION

The objective of the hydrological simulation of this study was to estimate discharge at the outlet (site 19). Therefore, 8 different calibration settings were built considering various number of observations, and parameters to find settings which better simulate discharge at the outlet. We have considered all sites in the validation procedure, but analysed the evaluation criteria for the outlet (Table 3). Low validation NS value for settings 1 (column 7 in Table 3), i. e. 0.13, shows the poor performance of this setting in simulating the outlet discharge. Close validation NS values of other settings which assert a good calibration (NS>0.55, R-factor<1.5, P-factor>0.5) (Moriasi et al. 2007), suggests the consideration of other criteria rather than NS and P-factor and R-factor for evaluation of the settings. Hence, AIC model selection criterion has been utilized to evaluate and rank calibration settings excluding setting1 (Table 3).

Results presented in Table 3 show that setting5 is prioritized as the most preferred setting, followed by setting7 and setting3. Therefore, if the watershed is calibrated under measures considered in setting5, a good simulation with a low error value and reasonable calibration effort will be achieved. Comparison of the results presented in Table 3 shows that according to AIC, consideration of 3 sites (Scenario1) in the calibration is preferred to consideration of 6 sites (Scenario2). In fact, settings with fewer observations are prior to ones with more observations. It also can be inferred from Table 3 that except for settings 2 and 6, settings with fewer parameters are prior to settings with more parameters.

Table 3. Statistical indices, Δ and w_j values for the outlet (site19)

	calibration			validation			AIC			
	p-factor	r-factor	NS	p-factor	r-factor	NS	Value	Δ	w_j	Rank
1	2	3	4	5	6	7	8	9	10	11
Setting1	0.94	1.09	0.86	0.93	1.2	0.13	N/A	N/A	N/A	N/A
Setting2	0.84	1.03	0.86	0.82	1.05	0.74	3416	1388	0.00	5
Setting3	0.88	1.13	0.82	0.7	1.16	0.55	2062	35	0.00	3
Setting4	0.81	0.54	0.85	0.59	0.52	0.69	3458	1431	0.00	7
Setting5	0.94	1.32	0.85	0.89	1.25	0.64	2027	0	1.00	1
Setting6	0.94	0.83	0.85	0.85	0.83	0.67	3430	1403	0.00	6
Setting7	0.74	0.82	0.84	0.46	0.64	0.6	2055	28	0.00	2
Setting8	0.89	0.65	0.88	0.87	0.7	0.73	3312	1285	0.00	4

4. CONCLUSION

The purpose of this study was to choose a "good" calibration setting which had low error value as well as low reasonable calibration effort. To do so, 8 calibration settings considering different number of observations and calibration parameters were built using SUFI 2 algorithm, to calibrate SWAT hydrological model of *Sirwan* river basin in Iran. The set of settings were then evaluated according to NS, P-factor and R-factor statistics. The results showed these statistics were not sufficient for the judgment of the calibration settings since their values all asserted good calibration (according to guidelines provided by Moriasi et al. (2007)). In this respect, model selection techniques can be of great advantage. Therefore, AIC model selection criteria were applied to rank the settings. According to AIC, settings with fewer number of observations were preferred to the others.

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