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Hydrology modelling in Taleghan mountainous watershed using SWAT

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Abstract

Mountainous regions in Iran are important sources of surface water supply and groundwater recharge. Therefore, accurate simulation of hydrologic processes in mountains at large scales is important for water resource management and for watershed management planning. Snow hydrology is the more important hydrologic process in mountainous watersheds. Therefore, streamflow simulation in mountainous watersheds is often challenging because of irregular topography and complex hydrological processes. In this study, the Soil and Water Assessment Tool (SWAT) was used to model daily runoff in the Taleghan mountainous watershed (800.5 km^2) in west of Tehran, Iran. Most of the precipitation in the study area takes place as snow, therefore, modeling daily streamflow in this river is very complex and with large uncertainty. Model calibration was performed with Particle Swarm Optimization. The main input data for simulation of SWAT including Digital Elevation Model (DEM), land use, soil type and soil properties, and hydro-climatological data, were appropriately collected. Model performance was evaluated both visually and statistically where a good relation between observed and simulated discharge was found. The results showed that the coefficient of determination R^2 and the Nash-Sutcliffe coefficient *NS* values were 0.80 and 0.78, respectively. The calibrated model was most sensitive to snowmelt parameters and CN_2 (Curve Number). Results indicated that SWAT can provide reasonable predictions daily streamflow from Taleghan watersheds.

Key words: *auto-calibration, Particle Swarm Optimization, snow hydrology, Soil and Water Assessment Tool, Taleghan Dam*

INTRODUCTION

Sustainable watershed management requires thorough knowledge of water resources, including streamflow [BELYANECH, ADAMOWSKI 2013; WOJAS, TYSZEWSKI 2013]. In these days, the hydrology of semi-arid mountain watersheds has become an important topic of research. In semi-arid regions such as Iran country, mountainous watersheds are the source of a large fraction of annual streamflow in river basins. Two of the more dominant mountain hydrologic processes are snowfall and snowmelt. Therefore, understanding the hydrologic processes in a watershed and its prediction are challenging tasks of hydrologists there [PHOMCHA *et al.* 2011].

Distributed hydrologic models have important applications in interpretation and prediction of the effects of land use change and climate variability on water availability and quality, since they relate model parameters directly to physically observable land surface characteristics. SWAT is a continuous simulation large scale hydrologic model that operates on a daily time step/Hydrologic Response Unit (HRU) resolution and is designed to predict the impacts of land management on the water yield of large ungauged watersheds [ARNOLD *et al*. 1998; ABBASPOUR *et al*. 2007; NEITSCH *et al*. 2011; TALEBIZADEH *et al*. 2010].

Hydrologic models, even those semi-distributed model models such as SWAT, often contain parameters that cannot be measured directly due to measurement limits and scale issues [BEVEN 2000; ZHANG *et al*. 2008). These parameters need to be estimated through an inverse method by calibration so that observed and predicted output values are in agreement. The automatic calibration of SWAT is based upon the use of optimization algorithms that perform a search for the optimal solution with respect to one or more objectives. Automatic calibration methods, which are objective and relatively easy to implement with high speed computers, have become more popular in recent years.

SWAT may be useful for evaluating the simulation of hydrology in Mountain region. SWAT ability to simulate snowmelt processes because model is supported by algorithms that account for the effects of elevation on snowmelt. AHL *et al*. [2007] calibrate SWAT in a snow-dominated mountain watershed in USA. Results indicate that the calibrated model was most sensitive to snowmelt parameters, followed in decreasing order of influence by the surface runoff lag, ground water, soil, and SCS Curve Number parameter sets. LEMONDS and MCCRAY [2007] simulated hydrology in a Small Mountain Watershed using SWAT. Results showed Snowmelt and snow formation parameters, as well as several ground-water parameters, were the most important calibration factors. PRADHANANG *et al*. [2011] used SWAT model to assess snowpack development and predict streamflow in a watershed in USA. In this research Simulations examine the effects of parameterising the SWAT snowmelt sub-model using 1, 3, and 5 elevation bands by comparison with measured snow and streamflow. Simulations of both daily and seasonal streamflow, improved when using 3 elevation bands. RAHMAN *et al*. [2013] simulated streamflow in a mountainous glacier watershed using swat in upper Rhone river watershed in Switzerland. In Taleghan watershed also HOSSEINI *et al*. [2010] used SWAT for simulation of monthly streamflow, but daily streamflow simulation and analysis effects of parameters on daily streamflow weren't considered.

The Taleghan watershed is located in the Sefidroud basin, which is an important source of water for the Taleghan reservoir dam and irrigation of agricultural lands in Qazvin Plain. Therefore, the main objective of this study is calibrating SWAT model using PSO for simulation daily streamflow and then analysis effecting change in parameter sets on stramflow simulation.

MATERIALS AND METHODS

STUDY AREA

The Taleghan watershed is located in the north west of Tehran, Iran. According to the study of FAUT [1993], most of the precipitation in the study area takes place as snow. The maximum and minimum mean annual precipitations are recorded as 814 and 454 mm at Dizan and Galinak Stations, respectively [VAFAKHAH *et al*. 2011]. Figure 1 shows the Taleghan watershed located within 36°04' to 36°21' N latitudes and 50°38' to 51°12' E longitudes.

The outlet stream gauging station is named Galinak with an area of 800.5 km^2 that was selected to performance evaluation of SWAT. Data of eight climatology stations located inside and around the catchment were analyzed.

The topographical elevation of the study area varies between 1707 and 4362 m above mean sea level with a weighted average of 2753 m. The highest proportion of the study area belongs to the elevation class of 2500–3000 m with 35% of the total area while the lowest proportion belongs to the 4000–4500 m class with 6% of the area. The land use of the study watershed comprises 90 percent under poor and good rangelands, 10 percent under orchid, agriculture and others land use. The soil textures of the watershed mainly are silt loam and loamy.

HYDROLOGIC MODEL DESCRIPTION

SWATdescribes the hydrology of a watershed divided into two major phases. The first division is the land phase of the hydrologic cycle, which controls the amount of water, sediment, nutrient, and pesticide loadings to the main channel in each sub basin. The second division is the water or routing phase of the hydrologic cycle, which considers the movement of water, sediments, etc. [NEITSCH *et al*. 2011].

In this study, surface runoff volume is predicted from daily rainfall or snowmelt by using the Soil Conservation Services (SCS) curve number equation method [NEITSCH *et al*. 2011]. Lateral subsurface flow in the soil profile is calculated simultaneously with percolation. A kinematic storage routing that is based on the degree of slope, slope length and saturated hydraulic conductivity is used to predict lateral flow in each soil layer. Lateral flow occurs when the storage in any layer exceeds field capacity after percolation. Groundwater flow contribution to total streamflow is simulated by creating shallow aquifer storage. Percolation from the bottom of the root zone is considered as recharge to the shallow aquifer. Hargreaves methods were used to determine the potential evapotranspiration (*PET*) in SWAT [NEITSCH *et al*. 2011].

The SWAT model is able to add up snow melt proportion to the water balance on the basis of the

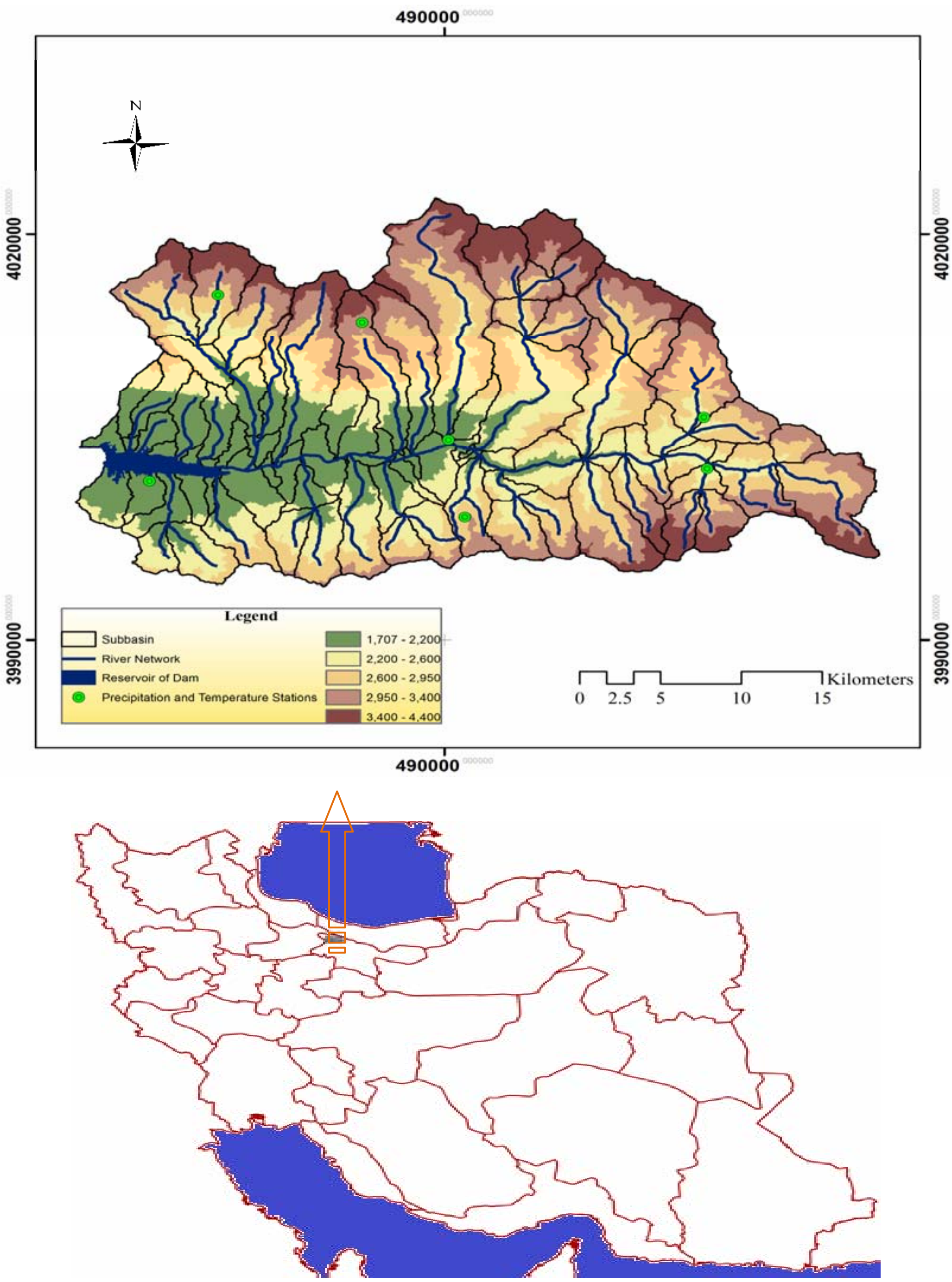

Fig. 1. Research area Taleghan river basin
with SWAT-delineated 85 subbasins; source: own study

elevation classes and their areas. Elevation is considered one of the very important variables related to meteorological parameters, not only in temperature but also snow amount. SWAT allows the sub-basin to be split into some elevation bands, and snow cover and snowmelt are simulated separately for each elevation band [NEITSCH *et al*. 2011]. Therefore, this study subdivided sub-watershed elevation into 3 classes. The lapse rate was found –6°C·km^{-1} from other study in this watershed [VAFAKHAH *et al*. 2011].

INPUT DATA REQUIRED

SWAT model needs a lot of data to be defined for the physical watershed. This would be data about topography (Digital Elevation Model), climate (daily measured and monthly statistical weather data), and both soil and land use (maps and physical parameters). Data availability as well as quality for a watershed will take effect on the accuracy of model prediction. Daily runoff, precipitation and temperature data

Table 1. List of eight selected precipitation and temperature stations in this study watershed

Station name	*X* UTM	*Y* UTM	Elevation m *
Dehdar	506043	4006472	2800
Garab	506245	4002652	2600
Joestan	490234	4004812	1990
Dizan	484904	4013508	1950
Sekranchal	475977	4015500	2200
Geliroud	491252	3999080	2150
Zidasht	471670	4002880	1750
Nesa	536767	3992344	2200

Source: FAUT [1993].

were collected from the Iranian water resources researches, Tehran. Table 1 shows positions of precipitation and temperature stations in the study watershed.

A land use map for the years around 2008 was detected from image processing using TM image. For this purpose, point sampling from land use locations in watershed was done using GPS and then a supervised method was used for land use classification. A digital elevation model (DEM) was taken from the National Cartographic Centre of Iran (grid: 30 m × 30 m); a 1:50,000 pedological soil map was available from the Faculty of Agriculture, University of Tehran [FAUT 1993] as well as some textural soil profile descriptions for all the major soils.

The first step was watershed delineation which split the basin into 85subbasins (Fig. 1) according to the terrain and river channels. Further division into multiple hydrological response units (HRUs) comprising of unique land use, soil, and land use management was based on user-defined threshold percentages [ARNOLD *et al*. 1998]. HRUs are the fundamental modeling unit within SWAT, and sub-catchments can be composed of one or several HRUs by specifying relative area thresholds for each defining component [NEITSCH *et al*. 2011]. In this study the overlay of soil and land use maps resulted in 388 HRUs. The next step was the precipitation and weather data files upload. The final stage was writing input files with required input data for the project.

This simulation passed through three consecutive separate periods. These, as well as their durations, were: (i) the setup (also known as warm-up) period (1 year); (ii) the calibration period (3 years), and (iii) the validation period (2 years).

MODEL CALIBRATION

After recognizing the most important parameter in model performance, a calibration method was needed. PSO is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling [KENNEDY, EBERHART 2001]. During the optimization process, in order to find the global optimum, each particle in the population adjusts its ‘flying’ according to its own flying experience and its companions’ flying experience. The basic PSO algorithm consists of three steps: (1) generate the positions of particles (coordinates in the parameter space) and their velocities (‘flying’ direction and speed); (2) update the velocity of each particle using the information from the best solution it has achieved so far (personal best) and another particle with the best fitness value that has been obtained so far by all the particles in the population (global best); (3) finally, the new position of each particle is calculated by adding the updated velocity to the current position [ZHANG *et al.* 2008]. In hydrologic model calibration using PSO particles are decision variables or parameters of model. Position and velocity also are current value and new range of parameters.

In this study to link between calibration algorithm and hydrologic model, we used the SWAT-CUP package.

MODEL PERFORMANCE EVALUATION

Performance was evaluated through visual interpretation of the simulated hydrographs and commonly used statistical measures of agreement between measured and simulated streamflow. Several statistical approaches were used to check the model performance, viz. coefficient of determination (R^2) and Nash-Suttcliffe efficiency (*NS*) [AHL *et al*. 2008; MORIASI *et al*. 2007; RAHMAN *et al*. 2013]. The R^2 value is an indicator of relationship strength between the observed and simulated values. Values of the *NS* coefficient can range from negative infinity to 1. *NS* coefficients greater than 0.75 are considered “good”, whereas values between 0.75 and 0.5 as “satisfactory” [RAHMAN *et al*. 2013].

RESULTS AND DISCUSSIONS

After providing the required input data, SWAT was run for daily streamflow in Taleghan River. Comparison of the estimated and observed values showed that the SWAT significantly overestimated rainfall and snowfall eventsbut, generally underestimated the streamflow in the study watershed. The mean values of observed and predicted streamflow were 13.6 and 14.1 $m^3 \cdot s^{-1}$, respectively. Ultimately, the determination coefficient was also poor (R^2 = 0.23). Figure 2 shows the initially simulated and observed time series of runoff.

In this study, 10 parameters of the SWAT affecting the streamflow were identified through a sensitivity analysis and detailed literature review especially in mountainous region with dominant snow regime [ABBASPOUR *et al*. 2007; AHL *et al*. 2008; LEMONDS, MCCRAY 2007; PRADHANANG *et al*. 2011; RAHMAN *et al*. 2013] that are shown in Table 2. In Table 2, v__ parameter name means the existing parameter value is to be replaced by the given value and r__ parameter name means the existing parameter value is multiplied

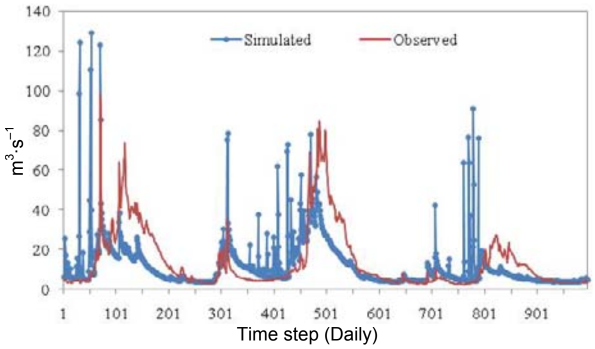

Fig. 2.Observed and simulated streamflow time series in study watershed before calibration in Taleghan watershed; source: own study

Table 2. Calibration range and final calibration estimate of selected SWAT model parameters

Variablename	Finalrange in calibration		Best value
r__CN2.mgt	–0.10	0.05	–0.085
v__ALPHA_BF.gw	0.02	0.08	0.0414
v__GW_DELAY.gw	15	35	23.2
v__SNOCOVMX.bsn	300	370	330.8
v__SMFMX.bsn	3	5	4.44
v__SMFMN.bsn	1.2	2.8	1.33
v__SNO50COV.bsn	0.55	0.65	0.61
r__SOL_AWC(1).sol	–0.35	0.10	-0.291
r__SOL_K(1).sol	–0. 35	0.10	-0.268
v__Timp.bsn	0.30	0.45	0.39

Source: own study.

by (1+ a given value). The absolute ranges of parameter values were taken directly from the SWAT user's manual [NEITSCH *et al*. 2011].

Calibration of the snow parameter set had the greatest effect on model performance. Reason for the larger sensitivities of the snow parameters is that Taleghan watershed is mountainous and snowmelt controls much of the streamflows. Five parameters including SMFMN, SMFMX, SNOCOVMX, SNO50COV and TIMP affected snow processes.

SMFMX and SMFMN, which are responsible for the maximum and minimum melt rate in summer and winter, respectively; any increase of these value results in rapid melt [PRADHANANG *et al*. 2011]. The SWAT parameter SNOCOVMX controls the minimum snow water content that corresponds to complete coverage of the watershed with snow [LEMONDS, MCCRAY 2007]. The actual volume of melt water released during a melt event depends on the potential melt volume and the extent of snow coverage. The decrease in available snow water during a melt season must be taken into account to accurately estimate the actual melt volume. The rate of snow cover depletion has been shown to be a function of how much bare ground remains covered by snow. The shape of the depletion curve is fixed before snowmelt simulation begins. The curve shape is adjusted using the input parameter SNO50COV, which is a fraction defined as the ratio of snow water at 50% areal snow cover and snow water at 100 snow cover. Varying cov_{50} between 0 and 1 allows the user to change the shape of the curve and represent different depletion curves depending on the area of interest. An area typified by wide ranging snow cover depths (such that areas devoid of snow cover exist) dictates a value of cov_{50} that approaches 1.

The lag factor (TIMP) controls the influence of the previous day's temperature on the current day's snow-pack temperature, and is an empirical lumped parameter that accounts for snow-pack density, snow-pack depth, exposure, and impacts other factors affecting snow-pack temperature [LEMONDS, MCCRAY 2007]. TIMP is constant with permissible values ranging from 0 (low reliance on air temperature during previous days) to 1 (snow pack temperature is equal to mean daily air temperature).

Setting only the snow parameters to their calibrated values (Tab. 2) clearly improved efficiency of SWAT (Fig. 3).

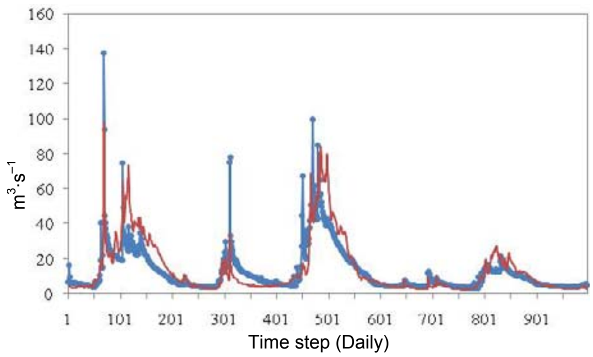

Fig. 3. Observed and simulated streamflows obtained using calibrated snow parameters in Taleghan watershed; source: own study

In Taleghan watershed, calibration of groundwater flow was controlled by ALPHA-BF and GW-DELAY. The base flow recession coefficient (ALPHA-BF) is a direct index of ground water flow response to changes in recharge. GW-DELAY is the lag between the times that water exits the soil profile and enters the shallow aquifer [NEITSCH *et al*. 2011]. Reducing ALPHA_BF slows the aquifer response to recharge, causing a reduction in the annual runoff peak during snowmelt but making more water available for streamflow later in the year. Reducing the value of the ground-water delay parameter (GW_DELAY) affects both the width of the peak discharge and the quantity of water available for base flow [AHL *et al*. 2008]. Setting only the groundwater parameters to their calibrated values slightly improved efficiency of SWAT (Fig. 4).

CN_2 is a most important parameter in calibration of SWAT [BANASIK, WOODWORD 2010; TEDELA *et al*. 2013; WOODWARD *et al*. 2006] and contributes directly to surface runoff generation. Setting only CN_2 to their calibrated values improved efficiency of SWAT (Fig. 5).

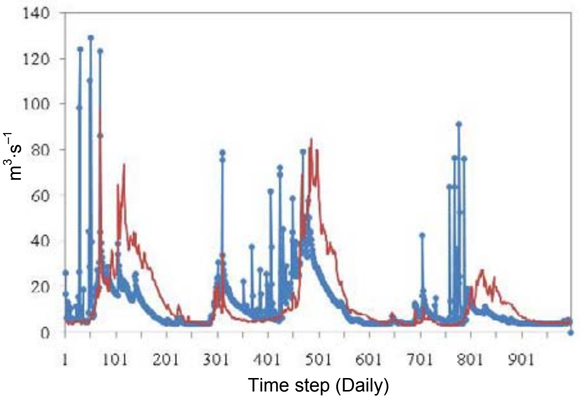

Fig. 4. Observed and simulated streamflows obtained using calibrated *GW* parameter in Taleghan watershed; source: own study

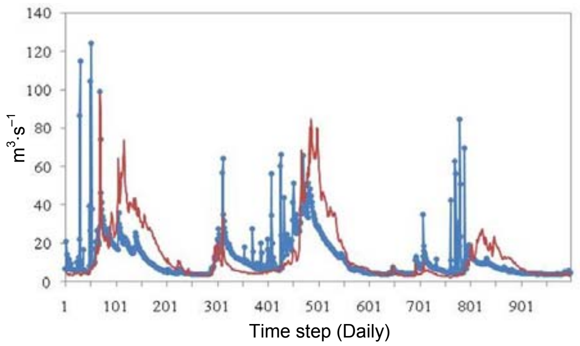

Fig. 5. Observed and simulated streamflows obtained using calibrated CN_2 parameter in Taleghan watershed; source: own study

SOL-AWC and SOL-K represent soil moisture parameters in the calibration process. SOL-AWC or plant available water is estimated as the difference in soil water content between field capacity and the wilting point. SOL-K or saturated hydraulic conductivity relates soil water flow rate to the hydraulic conductivity [NEITSCH *et al*. 2011]. Setting only the soil parameters to their calibrated values slightly improved efficiency of SWAT (Fig.6).

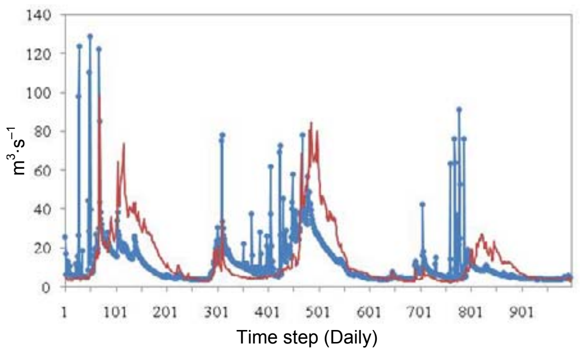

Fig. 6. Observed and simulated streamflows obtained using calibrated soil parameters in Taleghan watershed; source: own study

Finally, setting the whole set of calibrated parameters to their calibrated values clearly improved the model efficiency of SWAT. Results showed for the calibration process as a whole that measured and simulated daily streamflows have a good match with slight under-prediction in some days (Fig. 7). The statistical results for calibration and validation of streamflows were 0.8 and 0.72 for R^2 criteria and 0.78 and 0.7 for *NS* criteria. The results were higher than the recommended minimum values in the literature ($R^2 > 0.6$ and $NS > 0.5$), which illustrates that SWAT has represented the whole process that occurred in the watershed with sufficiently close output compared to the observed streamflow [MORIASI *et al*. 2007].

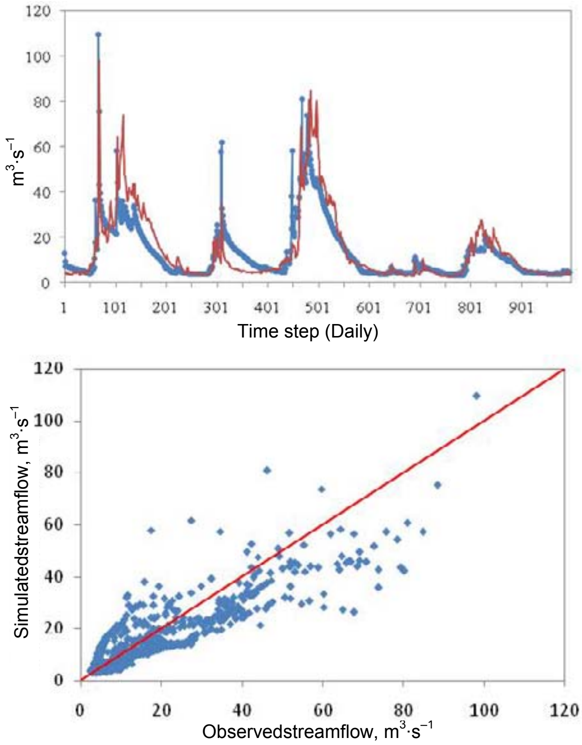

Fig. 7. Graphical presentation of observed streamflow and SWAT simulation in Taleghan watershed; source: own study

SWAT consistently underestimated daily streamflow. These trends may be explained in terms of the simple temperature-index method in snowpack and snowmelt modeling used in SWAT. Topographic effects, aspects, slope, different land use, and land cover have an effect on snow development and melt processes. Such processes are, however, not well represented in the simple temperature-index method [AKHAVAN *et al*. 2010; PRADHANANG *et al*. 2011]. Also, ground-water parameters have effect on the timing and delivery of ground water to the stream. Lowering the value of the base flow runoff coefficient (ALPHA_BF) dampened the model response to snowmelt-induced recharge, increasing the amount of runoff available for base flow later in the year. However, lowering ALPHA_BF also decreased the snowmelt runoff peak by reducing the ground-water contribution, and increased the runoff during the snowmelt recession period when runoff is rapidly changing from a shallow subsurface flow dominated regime to one dominated by groundwater flow. Reducing the value of GW_DELAY partially offset the effect of limited base flow on the runoff peak, but improvements in model performance during the base flow period were largely achieved at the expense of reduced model performance during the runoff period (see Tab. 2).

CONCLUSION

Watershed models are very useful and efficient tools for simulating the effect of hydrologic processes and management of soil and water resources. In this research the ability of the SWAT model to simulate streamflow in a mountain watershed was evaluated. Mountain watershed hydrology is critically important because of increasing water demand and because these are source watersheds for drinking water in the Iran. Due to the mountainous characteristics of the basin, it is imperative to carefully evaluate model input parameters specifically related to mountain hydrologic processes and snowmelt. In the model, elevation bands and lapserates accounted for the orographic effects in the watershed. Snowmelt parameters that were adjusted include a snowmelt lag factor, minimum and maximum snowmelt factors, and an areal snow cover coefficient. All remaining variables that were adjusted fell within reasonable ranges of accepted values. Consequently, the SWAT model can be used confidently to predict hydrology modeling and water resources management in this semi-arid mountain watershed.

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Modelowanie hydrologii górskiej zlewni rzeki Taleghan z zastosowaniem modelu SWAT

STRESZCZENIE

Słowa kluczowe: *autokalibracja, hydrologia śniegu, optymalizacja rojem cząstek PSO, system oceny gleby i wody, zapora Taleghan*

Górskie regiony Iranu są ważnymi terenami zasilania wód powierzchniowych i podziemnych. Z tego powodu dokładna symulacja procesów hydrologicznych w dużej skali ma znaczenie dla gospodarki zasobami wodnymi i planowania zarządzania zlewnią. Śnieg odgrywa ważną rolę w hydrologii górskich zlewni. Symulacja przepływów w tych zlewniach stanowi więc wyzwanie z powodu nieregularnej rzeźby terenu i skomplikowanych procesów hydrologicznych. W badaniach zastosowano system oceny gleby i wody (SWAT) do modelowania dobowego odpływu z górskiej zlewni Taleghan (800,5 km^2) położonej w Iranie na zachód od Teheranu. Większość opadów na obszarze badań stanowi śnieg, dlatego modelowanie dobowego przepływu rzeki jest złożone i obarczone znacznym stopniem niepewności. Optymalizację modelu przeprowadzono metodą roju cząstek (PSO). Zebrano odpowiednie dane wejściowe do symulacji SWAT: cyfrowy model deniwelacji (DEM), dane o użytkowaniu gruntów, typie i właściwościach gleby oraz dane hydrologiczne i klimatyczne. Działanie modelu oceniano zarówno wizualnie, jak i statystycznie. W tym drugim przypadku stwierdzono ścisłą zależność między obserwowanym i symulowanym przepływem wody. Współczynniki determinacji R^2 i Nasha-Sutcliffa *NS* wynosiły odpowiednio 0,80 i 0,78. Wykalibrowany model był najbardziej wrażliwy na parametry topnienia śniegu i CN_2. Wyniki badań wykazały, że model SWAT może zapewnić wiarygodne prognozy dobowego przepływu wody w zlewni rzeki Taleghan.