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Hydrological stream flow modeling in the Talar catchment (central section of the Alborz Mountains, north of Iran): Parameterization and uncertainty analysis using SWAT-CUP

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Abstract

There are several methods and techniques for measuring the parameters and forecasting the errors in the hydrological models. In this study, semi distributed Soil and Water Asseeement Tool (SWAT) model and SWAT-CUP (CUP – Calibration and Uncertainty Programs) have been applied using SUFI2 program. After collection of data, the whole Talar watershed located in the central section of the Alborz Mountains, north of Iran was separated into 219 hydrological response units (HRU) in 23 sub-watersheds.

In order to improve the simulation parameters and obtain better correlation of observed and simulated values, the sensitive parameters were validated to obtain finally the acceptable value of both R^2 and Nash–Sutcliffe (NS) coefficients equal to 0.93. Final P-value and t-state were also estimated for sensitive parameters. As a result, the CN2 parameter, which was critical in the initial stage of this research was replaced by the SOL-K parameter (electrical conductivity saturated soil layers) as a critical parameter in the later stage. Results of this study show that the SWAT model can be an effective and useful tool for the assessment and optimal management of water and soil resources.

Key words: *model validation, precipitation–runoff, sensitive parameters, SWAT-CUP, the Talar watershed*

INTRODUCTION

Higher standards of living, demographic changes, land and water use policies, and other external forces are increasing pressure on local, national and regional water supplies needed for irrigation, energy production, industrial uses, domestic purposes, and the environment [KLØVE *et al.* 2014]. Hydrological models are important tools for planning sustainable use of water resources to meet various demands. Sustainable watershed management requires thorough knowledge of water resources, including streamflow [BELYANEH, ADAMOWSKI 2013; NOOR *et al.* 2014; WOJAS, TYSZEWSKI 2013]. Therefore, understanding the hydrologic processes in a watershed and their prediction are challenging tasks of hydrologists [PHOMCH *et al.* 2011].

Distributed hydrologic models have important applications in interpretation and prediction of the effects of land use change and climate variability on parameters pertaining directly to physically observable land surface characteristics. In particular, physically based distributed hydrological models, whose input parameters have a physical interpretation and explicit representation of spatial variability, are used to solve complex problems in water resource management [BEVEN 1989; 2002; SOROOSHIAN, GUPTA 1995]. Initial parameters for distributed datasets describe soils, vegetation, and land use; however, these so-called physically based parameter values are often adjusted through subsequent calibration to improve streamflow simulations. In other words, some model parameters are physically based and can be measured while in some models parameters can only be estimated by calibration [ANDERTON *et al.* 2002; BEVEN 2006; BEVEN, BINLEY 1992; BEVEN, FREER 2001; BOYLE *et al.* 2000; DUAN *et al.* 1992; 1994; GUPTA *et al.* 1998; REFSGAARD 1997; YAPO *et al.* 1996].

The Soil and Water Assessment Tool (SWAT) [ARNOLD *et al.* 1998] has been applied as a physically based hydrologic model to manage and assess water resources, including arid regions of northwest China [GASSMAN *et al.* 2007; HUANG, ZHANG 2004; 2010; LI *et al.* 2009; 2010; 2011; LIU *et al.* 2012; WANG *et al.* 2003]. The SWAT program is a comprehensive, semi-distributed, continuous-time, processed-based model [ARNOLD *et al.* 2012; GASSMAN *et al.* 2007; NEITSCH *et al.* 2005]. The program can be used to build models to evaluate the effects of alternative management decisions on water resources and the non-point source pollution in large river basins.

The hydrological component of SWAT (Fig. 1) allows explicit calculation of different water balance components, and subsequently water resources (e.g., blue and green waters) at a sub basin level. In SWAT, a watershed is divided into multiple sub-basins, which are then further subdivided into hydrologic response units (HRUs) that reflect the unique land use, management, topographical, and soil characteristics. Simulation of watershed hydrology is done in the land phase, which controls the amount of water, sediment, nutrient, and pesticide loadings to the main channel in each sub-basin and in the routing phase, which is the movement of water, sediments, etc., through the streams of the sub-basins to the outlets. The hydrological cycle is climate driven and provides moisture and energy inputs, such as daily precipitation, maximum/minimum air temperature, solar radiation, wind speed, and relative humidity that control the water balance. Snow is computed when temperatures are below freezing, and soil temperature is computed because it affects water movement and the decay rate of residue in the soil.

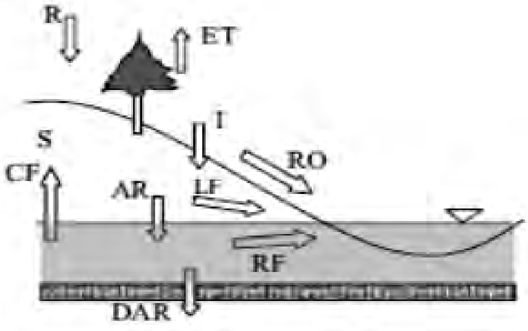

Fig. 1. Schematic illustration of the conceptual water balance model in SWAT; *R* = rainfall, *ET* = evapotranspiration, *I* = infiltration, *RO* = runoff, *RF* = return flow, *LF* = lateral flow, *CF* = capillary flow, *AR* = aquifer recharge, *DAR* = deep aquifer recharge, *S* = soil moisture; source: own elaboration

Hydrologic processes simulated by SWAT include canopy storage, surface runoff, and infiltration. In the soil the processes include lateral flow from the soil, return flow from shallow aquifers, and tile drainage, which transfer water to the river; shallow aquifer recharge, capillary rise from shallow aquifer into the root zone, and finally deep aquifer recharge, which removes water from the system. Other processes include moisture redistribution in the soil profile, and evapotranspiration. Optionally, pumping, pond storages, and reservoir operations could also be considered. The water balance for reservoirs includes inflow, outflow, rainfall on the surface, evaporation, seepage from the reservoir bottom, and diversions. Addressing vegetation growth is essential in a hydrological model as evapotranspiration is an important component of water balance, and management operations such as irrigation [FARAMARZI *et al.* 2009] and fertilization have a large impact on hydrology and water quality, respectively. SWAT uses single plant growth model to simulate growth and yield of all types of land covers and differentiates between annual and perennial plants. In addition, SWAT simulates the movement and transformation of several forms of nitrogen and phosphorus, pesticides, and sediment in the watershed. SWAT allows users to define management practices taking place in every HRU. Once the loadings of water, sediment, nutrients, and pesticides from the land phase to the main channel have been determined, the loads are transported through the streams and reservoirs within the watershed. More details on the SWAT can be found in the theoretical documentation (http://swatmodel.tamu.edu) and in paper by ARNOLD *et al.* [1998]. However, the SWAT was designed based on the soil, vegetation, and hydrological structure of North America. The databases about soil and vegetation this model comes with are different from the actual situation somewhere else. In order to efficiently and effectively apply the SWAT model, different calibration methods have been developed and applied to improve the prediction reliability of the SWAT simulations, including manual and automated calibration [BEKELE, NICKLOW 2007; CAO *et al.* 2006; ECKHARDT, ARNOLD 2001; KANNAN *et al.* 2008; LU *et al.* 2012; NIRAULA *et al.* 2012; WHITE, CHAUBEY 2005; ZHANG *et al.* 2008; 2009a, b; 2010]. For example, ZHANG *et al.* [2009a] proposed a combined method, which implemented Genetic Algorithms (GA) and Bayesian Model Averaging (BMA), to conduct calibration by comparing multiple model structures. The SWAT model was used to simulate the hydrologic processes of Yingluoxia watershed. The model uses readily available inputs, is computationally efficient for use in large watersheds and is capable of simulating long-term yields for determining the impact of land management practices [ARNOLD, ALLEN 1996]. SWAT allows a number of different physical processes to be simulated in a basin. The hydrologic routines within SWAT account for snow fall and melt, vadose zone processes (e.g., infiltration, evaporation, plant uptake, lateral flows, and percolation) and ground water flows. The hydrologic cycle that is simulated by SWAT is based on the water balance equation:

$$SW_t = SW0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{sep} - Q_{gw} \quad (1)$$

where: SW_t = the final soil water content (mm); $SW0$ = the initial soil water content on day i (mm); t = 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 day i (mm).

Figure 1 shows schematic illustration of the conceptual water balance model in SWAT.

Application of SWAT model – watershed delineation. The DEM was used to generate flow direction and flow paths within the Geographic Information System (GIS). The watershed outlet was defined at the Shirgah gauge, which is located on the mainstream and controls the runoff from the mountainous watershed. Considering that the hydrologic response units (HRUs) were often spatially discontinuous and the values of the surface runoff lag time were identical to a sub-basin in the SWAT model, the areas of the sub-basins were as small as theoretically possible. This watershed was divided into 23 subbasins (Fig. 2). In the Talar watershed, the land use types were divided into 6 categories based on the dominant species and constructive species and the soil was categorized into 36 types. The vegetation, soil and slope layers were overlaid to create hydrologic response units (HRUs) within each sub-basin. A total of 219 HRUs were created in the Talar watershed.

Fig. 2. Digital Elevation Model of Talar watershed in Mazandaran province of Iran; source: own study based on data from Mazandaran Regional Water Authority; source: own elaboration

MATERIALS AND METHODS

STUDY AREA

The Talar watershed is located in the Central section of the Alborz Mountains, north of Iran. According to the Project Report of Talar watershed [2000], most of the precipitation in the study area takes place as rain. The maximum and minimum mean annual precipitations recorded were 900 and 200 mm, respectively. Figure 1 shows the Talar watershed located within 35°44’ to 36°19’ N latitudes and 53°23’ to 52°35’ E longitudes. The outlet stream gauging station is Shirgah with an area of 2100.9 km^2 that was selected to perform evaluation of SWAT. Data of eight climatology stations located inside the catchment were analyzed. The topographical elevation of the study area varies between 215 and 3910 m a.s.l. The land use of the study watershed comprises poor and good rangelands, orchids, agriculture and others types of land use. The soil textures of the watershed are mainly silty loam, silty clay, loamy clay and clayish loam [Project... 2000].

INPUT DATA REQUIRED

SWAT model needs a lot of data to be defined for the physical watershed. The data should include topography (Digital Elevation Model), climate (daily and monthly weather data), and both soil and land use (maps and physical parameters).

Availability and quality of the data on watershed will affect the accuracy of model prediction. Daily runoff, precipitation and temperature data were collected from the Mazandaran Regional Water Authority and Mazandaran Meteorological Organization, (Tab. 1). Land use map for the recent years was derived from image processing using TM image. A digital elevation model (DEM) was taken from the organization of forest, range and watershed in Mazandaran Province (grid: 50 m × 50 m); a pedological soil map was available from the report of this organization to-

Table 1. List of selected precipitation and temperature stations in Talar watershed

Station name	Main river	Longitude	Latitude	Altitude m
Shirgah	Talar	52°53'10"	36°17'57"	220
Valikbon	Kasilian	53°10'24"	36°05'46"	1 106
Shirgah	Kasilian	52°53'14"	36°18'05"	220
Pole sefid	Talar	53°03'31"	36°06'44"	580
Palandroodbar	Sheshroodbar	52°54'08"	36°01'13"	1 218
Shirgah	Talar	52°53'10"	36°17'57"	220
Valikchal	Kasilian	53°13'00"	36°05'55"	1 500
Pole sefid	Talar	53°03'55"	36°06'24"	580
Kale	Kasilian	53°09'45"	36°04'11"	1 557
Sodkola	Kasilian	53°11'26"	36°05'45"	1 250
Darzikola	Kasilian	53°12'14"	36°04'08"	1 300
Alasht	Talar	52°50'21"	36°04'10"	1 680
Palandroodbar	Sheshroodbar	52°54'11"	36°01'13"	1 225
Shirgah	Talar	52°53'30"	36°18'20"	259
Sangdeh	Kasilian	53°13'42"	36°03'36"	1 337

Source: own elaboration.

gether with some textural soil profile descriptions for all the major soils. The first step was watershed delineation which split the basin into 23 sub basins according to the terrain and river channels. Further division into multiple hydrological response units (HRUs) comprising unique land use, soil, and land use management was based on user-defined threshold percentages [ARNOLD *et al*. 1998]. HRUs are the fundamental modeling units 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 219 HRUs. The next step was the uploading of precipitation and weather data files. 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 (4 years), and (iii) the validation period (2 years).

SWAT-CUP2 – SWAT Calibration and Uncertainty Programs

Calibration and uncertainty analysis of distributed watershed models is beset with a few serious issues that deserve the attention and careful consideration of researchers. These are:
1) parameterization of watershed models,
2) definition of what is a "calibrated watershed model" and what are the limits of its use,
3) conditionality of a calibrated watershed model,
4) calibration of highly managed watersheds, where natural processes play a secondary role,
5) uncertainty problems.

SUFI2 (Sequential Uncertainty Fitting) – Conceptual basis of the SUFI-2 uncertainty analysis routine

In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the *P* factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). As all the processes and model inputs such as rainfall and temperature distributions are correctly manifested in the model output (which is measured with some error) – the degree to which we cannot account for the measurements – the model is in error; hence uncertain in its prediction. Therefore, the percentage of data captured (bracketed) by the prediction uncertainty is a good measure to assess the strength of our uncertainty analysis. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling, disallowing 5% of the very bad simulations. As all forms of uncertainties are reflected in the measured variables (e.g., discharge), the parameter uncertainties generating the 95PPU account for all uncertainties. Breaking down the total uncertainty into its various components is highly interesting, but quite difficult to do, and as far as the author is aware, no reliable procedure yet exists. Another measure quantifying the strength of a calibration/uncertainty analysis is the *R* factor, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2 hence seeks to bracket most of the measured data with the smallest possible uncertainty band. The concept behind the uncertainty analysis of the SUFI-2 algorithm is depicted graphically in Figure 3. This figure illustrates that a single parameter value (shown by a point) leads to a single model response (Fig. 3a), while propagation of the uncertainty in a parameter (shown by a line) leads to the 95PPU illustrated by the shaded region in Figure 3b. As parameter uncertainty increases, the output uncertainty also increases (not necessarily linearly) (Fig. 3c). Hence, SUFI-2 starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially falls within the 95PPU, then decreases this uncertainty in steps while monitoring the *P* factor and the *R* factor. In each step, previous parameter ranges are updated by calculating the sensitivity matrix (equivalent to Jacobian), and equivalent of a Hessian matrix, followed by the calculation of covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered around the best simulation. The goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. Theoretically, the value for *P* factor ranges between 0 and 100%, while that of *R* factor ranges between 0 and infinity. A *P* factor of 1 and *R* factor of zero is a simulation that exactly corresponds to measured data. The degree to which we are away from these numbers can be used to judge the strength of our calibration. A larger *P* factor can be achieved at the

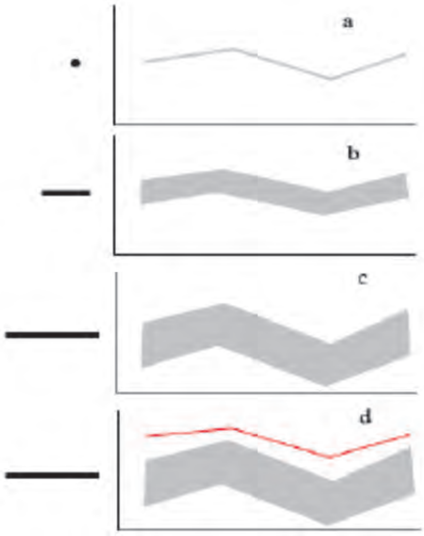

Fig. 3. Illustration of the relationship between parameter uncertainty and prediction uncertainty; a, b, c = the larger will be the 95PPU (d). If parameters are at their maximum physical limits and the 95PPU does not bracket the measured response, then model must be re-evaluated; source: own elaboration

expense of a larger *R* factor. Hence, a balance must often be reached between the two. When acceptable values of *R* factor and *P* factor are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R^2 and/or Nash–Sutcliff (NS) coefficient between the observations and the final "best" simulation. It should be noted that we do not seek the "best simulation" as in such a stochastic procedure the "best solution" is actually the final parameter ranges. If initially we set parameter ranges equal to the maximum physically meaningful ranges and still cannot find a 95PPU that brackets any or most of the data, for example, if the situation in Figure 3d occurs, then the problem is not one of parameter calibration and the conceptual model must be re-examined.

Automated model calibration requires that the uncertain model parameters are systematically changed, the model is run, and the required outputs (corresponding to measured data) are extracted from the model output files. The main function of an interface is to provide a link between the input/output of a calibration program and the model. The simplest way of handling the file exchange is through text file formats. SWAT-CUP is an interface that was developed for SWAT. Using this generic interface, any calibration/uncertainty or sensitivity program can easily be linked to SWAT. In this study we used the SWAT-CUP package [ABBASPOUR *et al.* 2008] to link between calibration algorithm and hydrologic model.

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 DISCUSSION

After providing the required input data, SWAT was run for daily streamflow in the Talar River. The first in this study, 21 parameters of the SWAT affecting the streamflow were identified through a sensitivity analysis and detailed literature review that are shown in Table 2. The absolute ranges of parameter values were taken directly from the SWAT user's manual [NEITSCH *et al.* 2011]. In the Talar 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 time 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

Table 2. Calibration range of selected SWAT model parameters

Row number	Parameter name	Minimum value	Maximum value
1	r__CN2.mgt	–0.2	0.2
2	v__ALPHA_BF.gw	0	1
3	v__GW_DELAY.gw	30	450
4	v__GWQMN.gw	0	2
5	r__GW_REVAP.gw	0.09	0.274
6	r__ESCO.hru	0.878	1.038
7	r__CH_N2.rte	0.114	0.348
8	r__CH_K2.rte	22.278	79.778
9	–r__ALPHA_BNK.rte	–0.249	0.589
10	r__SOL_K().sol	–0.8	0.8
11	r__SOL_AWC().sol	–0.2	0.2
12	r__EPCO.hru	0.01	1
13	r__PLAPS.sub	0	100
14	r__RCHRG_DP.gw	0	1
15	r__REVAPMN.gw	0	500
16	r__SFTMP.bsn	–5	5
17	r__SMFMN.bsn	0	100
18	r__SMTMP.bsn	–5	5
19	r__TIMP.bsn	0.01	1
20	r__TLAPS.sub	–10	0
21	r__SMFMX.bsn	0	100

Explanations: v means that the existing parameter value is to be replaced by the given value and r means that the existing parameter value is multiplied by (1+ a given value).
Source: own study.

the peak discharge and the quantity of water available for base flow [AHL *et al*. 2008]. CN2 is the 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. 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].

Scatter plot of *P*-value and *t*-state is shown in Fig. 4. Due to the low coefficient of R^2 (0.01) and Nash–Sutcliffe (44.15), the next step of validation of the model improve coefficient R^2 to 0.79 and Nash–Sutcliffe to 0.78. Figures 4 and 5 show scatter plots of *P* value index and *t*-state in the SWAT-CUP model validation stage. Figure 6 also shows an indicators chart of *P* value and *t*-stat calculated in the first step in the validation of selected parameters.

In fact, primary calibration and validation were the test phase of selecting sensitive parameters to perform the secondary phase of calibration and validation. Based on results of the first stage, sensitive parameter presented in Table 3 were re-calibrated and validated until simulation parameters were within acceptable limits.

Table 3. Daily stream flow of sensitive parameters and their ranges derived from calibration of SWAT-CUP model using SUFI2 software

Parameter name	Minimum value	Maximum value
r__CN2.mgt	–0.2	0.2
v__GW_DELAY.gw	30	450
v__GWQMN.gw	0	2
r__CH_K2.rte	–22.278	79.778
r__SOL_K().sol	–0.8	0.8
r__SOL_AWC().sol	–0.2	0.2
r__RCHRG_DP.gw	0	1
r__TLAPS.sub	–10	0

Source: own study.

In the first stage of calibration of sensitive parameters, R^2 and Nash–Sutcliff coefficients achieved the values of 0.02 and –38.28 respectively. Validation of sensitive parameters gave the final both R^2 and Nash–Sutcliff coefficients of 0.93. This result was in the acceptable simulation range. Figure 8 shows scatterplots of the number of sensitive parameters and Table 4 lists the rating of simulation parameters that are within acceptable simulation.

In this research, 21 parameters were selected in the calibration and validation phases. The choice of these 21 parameters was based on the role and importance of these factors in the development and creation of runoff.

Most of these important parameters such as CN2 (moisture condition curve number), SOL_(K) (saturated hydraulic conductivity of the first layer), CH_K2 (effective hydraulic conductivity in the main channel alluvium – mm·h^{-1}), ALPHA_BF (baseflow recession constant), (GW_REVAP) groundwater 'revap' coefficient, ESCO (soil evaporation compensation factor), EPCO (plant evaporation compensation factor) were also considered important by other researchers. CHEN and WU [2012] used parameters such as CN2 (percentage of SCS curve number adjustment), SURLAG surface runoff lagtime (day), CH_K2 channel hydraulic conductivity (mm·day^{-1}), SOL_AWC available water capacity of the soil. Another researchers used from 10 [WANGPIMOOL *et al*. [2013] to 27 XIE and LIAN [2013] parameters. Cited studies and those not cited show a high similarity in the selection of sensitive parameters. For example, in this study CN2 (moisture condition curve number) parameter was found significant. Here, the program SUFI2 for validation and SWAT model was used to determine the uncertainty in choosing SWAT-CUP extensions. Some researchers used other options. For example, XIE and LIAN [2013] used GLUE program of SWAT-CUP and SINGH *et al*. [2013] used SUFI2 and GLUE program for estimation of parameters and uncertainty of analysis in the Tungabhadra catchment of India. LU *et al*. [2015] in their study obtained R^2 and Nush–Sutcliff coefficients of 0.81 and 0.94 respectively. Since their study was performed in an area of similar climatic conditions, their results can be compared and contrasted with ours. The results of the final *P* value and *t*-state also varied among 8 selected parameters so that CN2 – the most sensitive parameters in the first stage, was ranked second while SOL_K (saturated hydraulic conductivity of the first layer) appeared most sensitive at this phase. After two parameters also GW_DELAY.gw, SOL_AWC.sol, RCHRG-DP.gw, GWQ Min.gw, CH_K2.rte obtained further ranking in sensitive parameters. In total, there was a good fit of simulated and observed discharges after 1500 time model simulations in the second stage of simulation. It was found that maximum precipitation related to days and months with high precipitation and in the days without precipitation, the value of simulation was zero due to the neglect of base water and groundwater of the Talar watershed by the model. During the validation process, after multiple simulations, the range of uncertainty around the default values was gradually decreasing and set in the best range of simulation model. Other researchers used different methods to evaluate the performance of calibration and analysis of uncertainty [ABBASPOUR *et al*. 2015, SETHGEN *et al*. 2010].

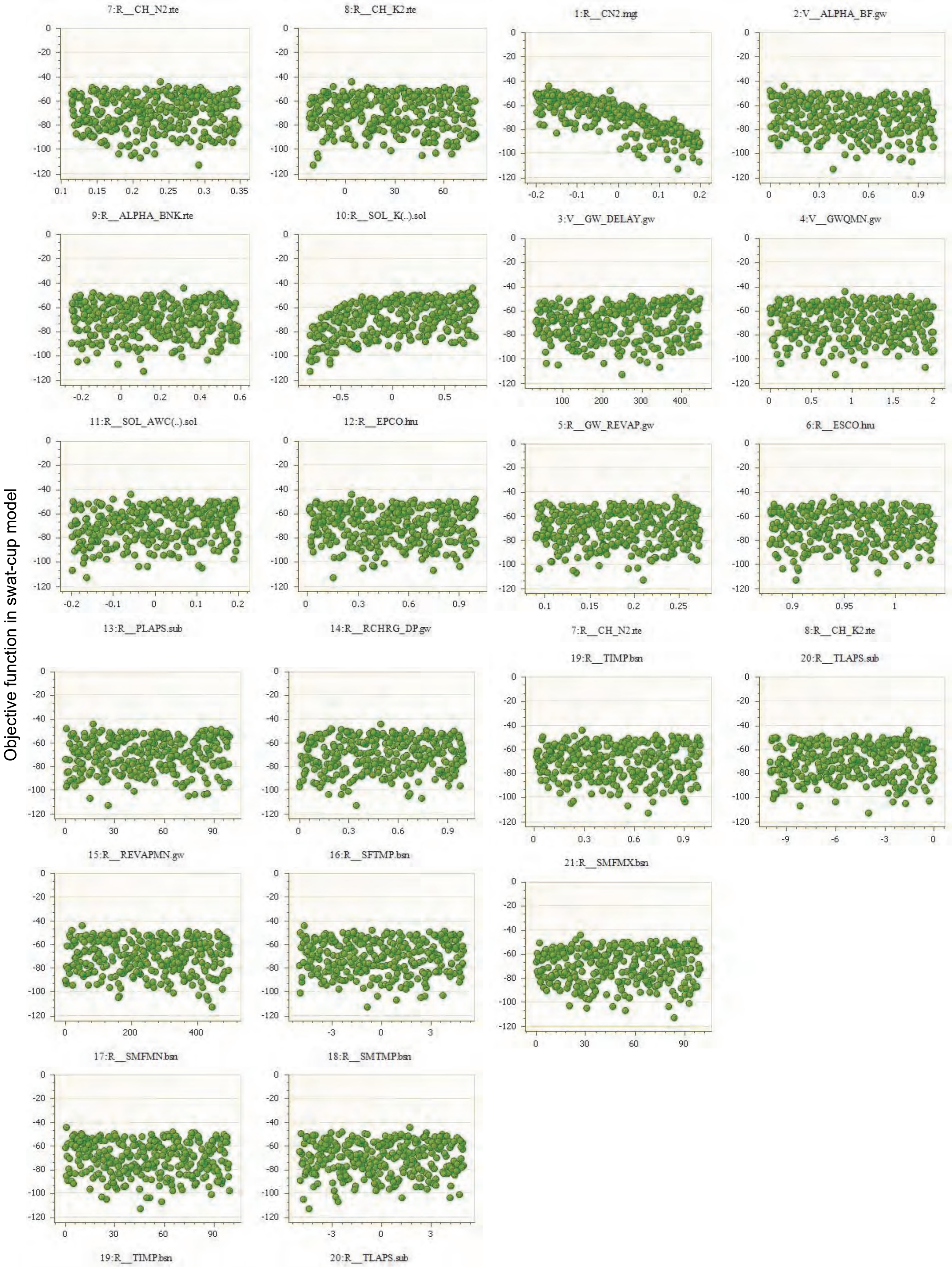

Fig. 4. Scatterplots of selected parameters in the calibration phase with SUFI2 software of SWAT-CUP model; source: own study

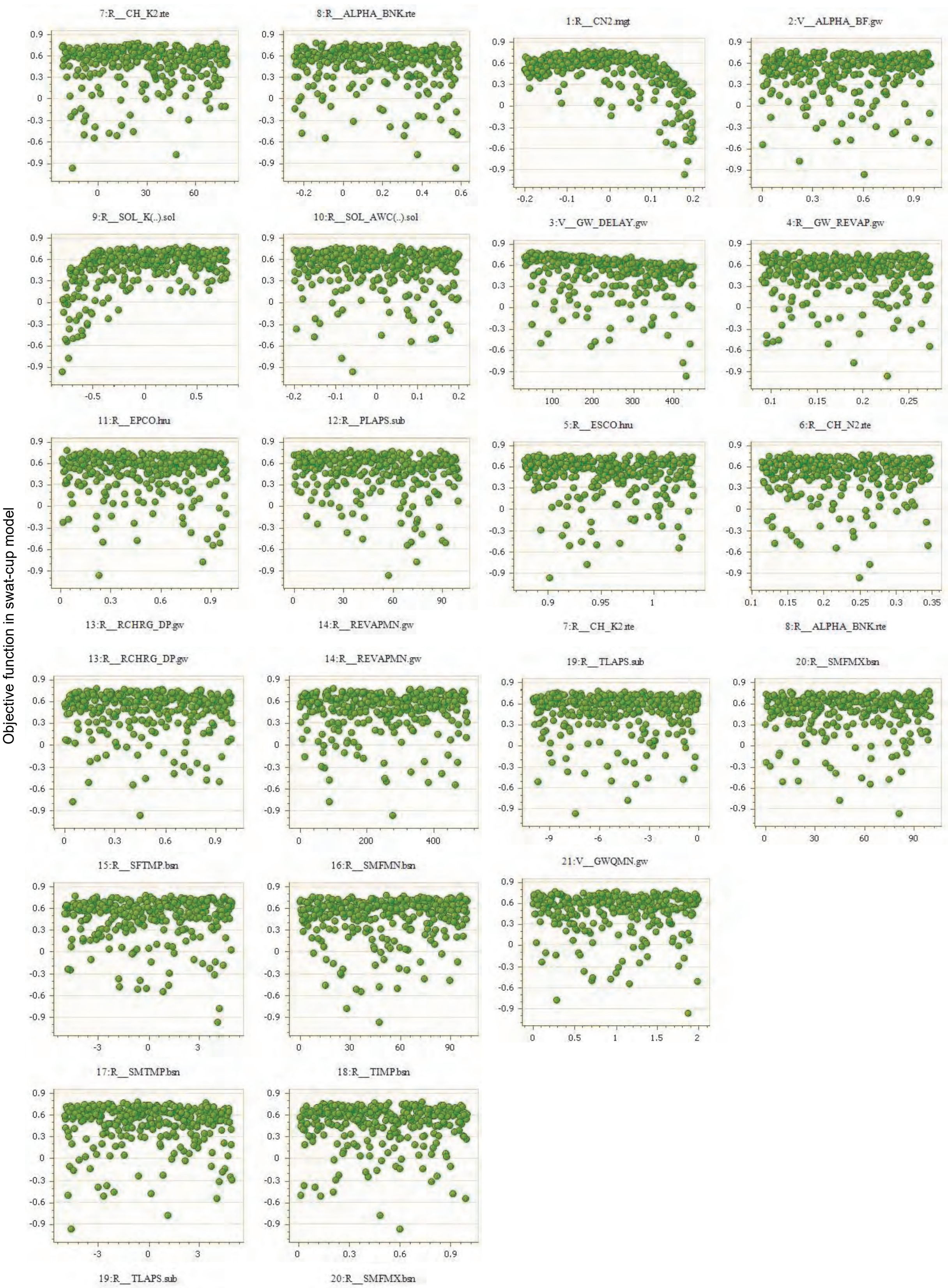

Fig. 5. Scatterplots of selected parameters in the validation phase with SUFI2 software of SWAT-CUP model; source: own study

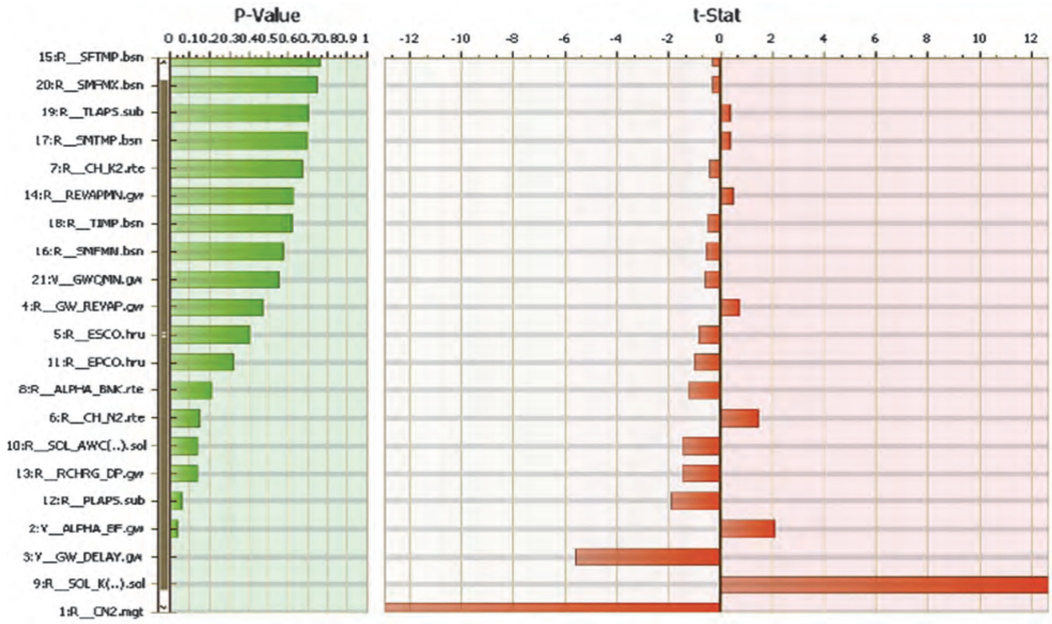

Fig. 6. Indicator chart of *P* value and *t*-stat, calculated for the first step in the validation of selected parameters; source: own study

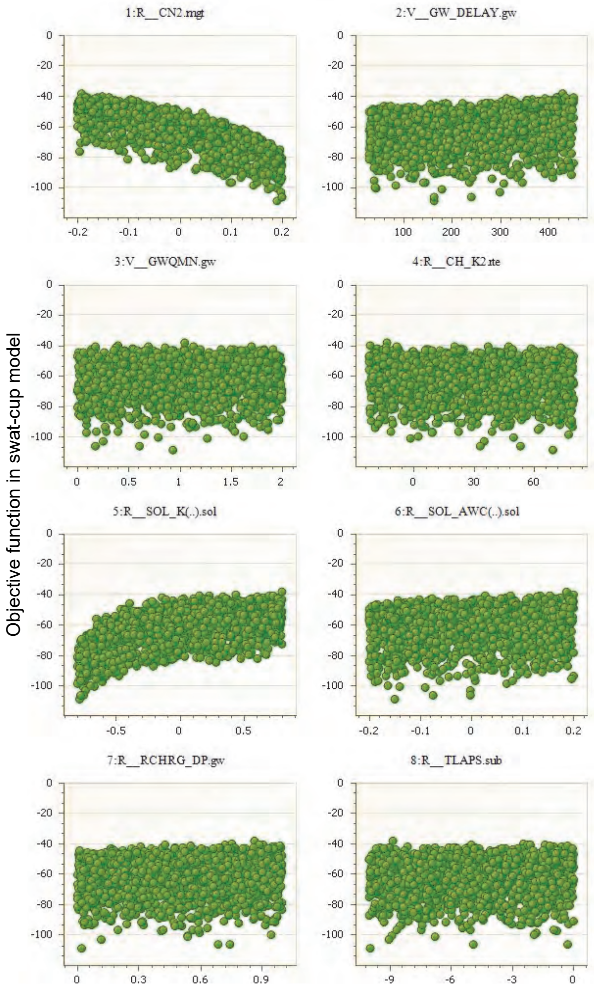

Fig. 7. Scatterplots of critical parameters in calibration SWAT-CUP model using the SUFI2 software; source: own study

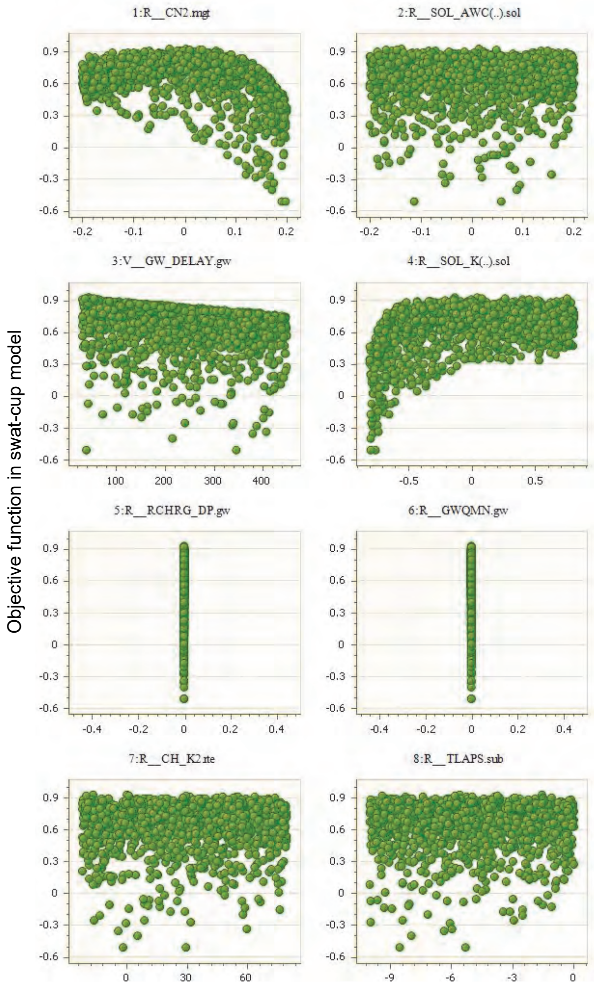

Fig. 8. Scatterplots of sensitive parameters in the model validation stage with SWAT-CUP model using the SUFI2 software; source: own study

Table4. Ranking of critical parameters in the validation phase of the model

Goal-type=Nash-Sutcliff	No-sims=1500	Best-sim-no=141	Best-goal=9.321237e-001
Parameter name	Fitted value	Min value	Max value
1- R_CN2.mgt	0/0022267	-0/200000	0/200000
2- R_SOL-AWC(..).sol2-	0/014267	-0/200000	0/200000
3- V_GW_DELLAY.gw3-	41/340000	30/000000	450/000000
4-R_SOL_K(..).sol	0/043200	-0/800000	0/800000
5- R_RCRG_DP.gw	0/000000	0/000000	0/000000
6- R_GWQMIN.gw	0/000000	0/000000	0/000000
7- R_CH_K2.rte	0/140301	-22/278000	79/778000
8- R_TLAPS.sub	-5/590000	-10/000000	0/000000
-5/0590000/0140301/0000000/0000000/41043200/0340000/0014267/0022267			
r_CN2.mgt	0/0022267		
r_SOL_AWC(..).sol	0/014267		
v_GW_DELLAY.gw	41/340000		
r_SOL_K(..).sol	043200/0		
r_RCRG_DP.gw	0/000000		
r_GWQMIN.gw	0/000000		
r_CH_K2.rte	0/140301		
r_TLAPS.sub	-5/590000		

Source: own study.

CONCLUSION

In our study we used several indexes for the determination of model efficiency for simulation. Out of 21 selected parameters, 8 gave the acceptable range after 1500 simulations. In general, good forecasting of maximum discharge by the model was not accompanied by a high correlation between the time to peak of simulated discharge and the output value especially in spring season, which was caused by a lack of fitness of the SCS method in complete simulations considering runoff of snowmelt in mountainous area [CHU, SHIRMOHAMMADI 2004; ROSTAMIAN *et al.* 2010]. Noteworthy, the difference in altitude in the study region between mountain and lowland area is about 3695 m and annual coefficient of snow factor of the area is estimated at 21.9%. It is the fact that can be examined. Base time for calibration and validation of the SWAT model was from hydrological years 2003–2004 until 2006–2007 with 4 years for calibration and hydrological years 2008–2009 until 2009–2010 with 2 years for validation model in the daily scale. Due to low values of *P* factor and *r* factor in the first stage of this research, observed values fell out of 95% confidence intervals (see weak simulation in this stage). This problem was improved in further simulations and finally decreased the range of uncertainty. Certain principles of acceptable range of coefficient R^2 are not provided, but value about 0.5 for hydrological model adopted in this study after SANTHI *et al.* [2001], increased the coefficient to 0.93. Another coefficient of the study was Nush–Sutcliff coefficient, which also was improved to 0.93 in the final stage of simulation. GASSMAN *et al.* [2007] and SANTHI *et al.* [2001] studies showed also that values above 0.5 gave the best range of this coefficient. Therefore, our results allow for the following suggestions in this regard:

1. Use a wide range of programs such as GLUE, ParaSol, MCMC of SWAT model to compare the effects of hydrological simulation.
2. Run SWAT model in regions with similar and different climatic condition and analyze the effect of those conditions on the selection and use of models.

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Abbas GHOLAMI, Mahmood HABIBNEJAD ROSHAN, Kaka SHAHEDI, Mehdi VAFAKHAH, Karim SOLAYMANI

Modelowanie przepływu w zlewni rzeki Talar (środkowa część gór Alborz w północnym Iranie): Parametryzacja i analiza niepewności za pomocą SWAT-CUP

STRESZCZENIE

Istnieje kilka metod i technik pomiaru parametrów oraz przewidywania błędów w modelach hydrologicznych. W prezentowanej pracy zastosowano modele SWAT i SWAT-CUP z użyciem programu SUFI2. Po zgro-

madzeniu danych cała zlewnia rzeki Talar, zlokalizowana w środkowej części gór Alborz w północnym Iranie, została podzielona na 219 jednostek hydrologicznych (HRU) w 23 podzlewniach.

W celu usprawnienia parametrów symulacji oraz lepszego powiązania wartości symulowanych i obserwowanych zweryfikowano parametry wrażliwe, co w efekcie doprowadziło wartości R^2 i współczynnika Nasha–Sutcliffa (NS) do akceptowalnej wartości 0,93. Dla tych parametrów ustalono także końcowe wartości *P* i *t*. W wyniku przeprowadzonej analizy parametr CN2, krytyczny na wstępnym etapie badań, został zastąpiony parametrem SOL-K (przewodnictwo elektrolityczne nasyconej warstwy gleby). Wyniki badań świadczą, że model SWAT może być wydajnym i użytecznym narzędziem w ocenie oraz optymalnym zarządzaniu zasobami wody i gleby.

Słowa kluczowe: *badanie dokładności modelu, opad-odpływ, parametry wrażliwe, SWAT-CUP, zlewnia rzeki Talar*