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Model calibration and uncertainty analysis for runoff in the Chao River Basin using sequential uncertainty fitting

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Abstract

The Chao River is one of the most important surface water sources for drinking water in Beijing. Due to the impacts of human activities and climate change, the Chao River basin is facing water scarcity. Therefore, it is very important to effectively manage water resources, while the distributed watershed model is the useful and effective tool. Soil and Water Assessment Tool (SWAT) was selected to set up hydrological model in the Chao River basin. Model calibration and uncertainty analysis were performed with Sequential Uncertainty Fitting (SUFI-2), which is one of the programs integrated with SWAT in the package SWAT-CUP (SWAT Calibration and Uncertainty Programs). Results showed that the *p-factor* was 0.85 and the *r-factor* was 1.12 in calibration period (1995-1999) while the *p-factor* was 0.83 and the *r-factor* was 2.15 in validation period (2000-2002). When values of *p-factor* and *r-factor* are accepted, further goodness of fit can be quantified by the coefficient of determination (R^2) and Nash–Sutcliffe coefficient (NS) between the observed and the final best simulated data. The results indicated that R^2 was 0.90 and NS was 0.88 in calibration period, while R^2 was 0.77 and NS was 0.74 in validation period. The results of calibration and uncertainty analysis were satisfactory.

Keywords: SWAT; Chao River; Runoff; SUFI-2; *p-factor*; *r-factor*

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1. Introduction

The Chao River basin is one of the surface water sources for drinking water in Beijing and the drainage watershed of Miyun reservoir. In recent years, the Chao River basin is facing water scarcity due to the impact of human activities and climate change. Therefore, it is very important to effectively manage water resources. Distributed watershed model is a useful and effective tool to manage water resources. In recent years, many hydrological models have been developed such as AGNPS (Agricultural None Point Source model) [1], SWAT (Soil and Water Assessment Tool) [2] and HSPF (Hydrologic Simulation Program – Fortran) [3]. These watershed models can be used in several areas including integrated watershed management, peak flow forecasting, test of the effectiveness of measures for the reduction of non-point source pollution, soil loss prediction, assessment of the effect of land use change, analysis of causes of nutrient loss, and climate change impact assessment. SWAT has extensive application all over the world because of easy availability and friendly interface [4]. For this reason, SWAT model was selected to estimate runoff in the Chao River basin.

As distributed watershed models are increasingly being used to support decisions on alternative management strategies, it is very important for these models to carry out a careful calibration and uncertainty analysis. However, calibration of watershed models is a challenging and time consuming task because of input, model structure, parameter, and output uncertainty. The definition and quantification of model uncertainty had become the subject of considerable research in recent years because distributed hydrological modelling is subject to large uncertainties. Up to now, researchers have developed various uncertainty analysis techniques for watershed models, such as, Markov chain Monte Carlo (MCMC) method [5-7], generalized likelihood uncertainty estimation (GLUE) [8], parameter solution (ParaSol) [9], and sequential uncertainty fitting (SUFI-2) [10]. SWAT-CUP (SWAT-Calibration and Uncertainty Programs) links GLUE, Parasol, SUFI-2 and MCMC procedures to SWAT. It enables sensitivity analysis, calibration, validation and uncertainty analysis of SWAT models. SUFI-2 is the more frequency used and calibration and uncertainty analysis method [7, 10-12].

Against this background, the main objective of this study was first to simulate hydrological process of the Chao River basin using SWAT. Secondly, model calibration and uncertainty analysis of SWAT model were performed using SUFI-2.

2. Materials and methods

2.1. Study area and input data

The Chao River basin is located in North China with a drainage area of 6277 km^2 (Fig. 1). The Chao River is one of two tributaries flowing into the Miyun reservoir, which is an important drinking water reservoir for Beijing City and provides nearly half of the city's water supply. The Chao River originates from the northern part of Huangqi Town located in Fengning Manchu Autonomous County in Hebei Province, flows through Luanping County, then runs down to Gubeikou Town in Miyun County and empties into Miyun reservoir near Xiahui Village. The main tributaries in upstream of the Chao River include Andamu River and Xiaotang River. There are another two tributaries. One directly flows into Maoniu River, another runs down to Qingshui River going through Xinglong County and Miyun County.

The characteristic of the climate is temperate continental and semi-arid and semi-humid. Mean air temperature is 7.3℃-10.3℃. Mean annual precipitation is 470-731 mm. Mean precipitation is 415 mm in the northwest part while the mean precipitation is 719.1 mm in the southeast part. Precipitation mainly concentrated in flood seasons from June to September, accounting for 64%-89% of the total annual precipitation. Maximum runoff is mainly concentrated in late July to mid-August, and the runoff from June to September accounts for 70% of the total annual runoff.

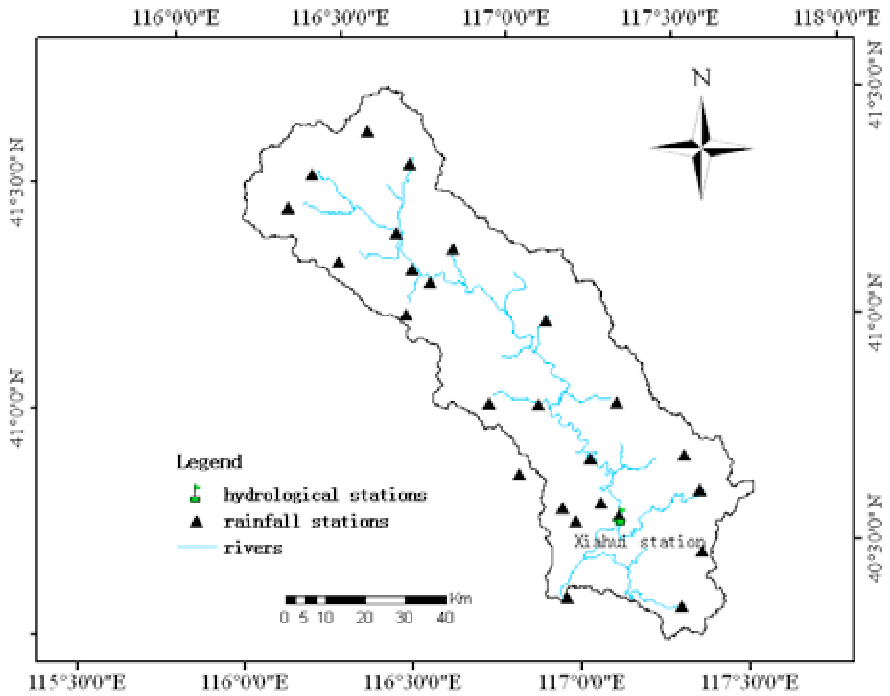


Fig.1 The map showing precipitation stations and hydrological stations in the Chao River basin

Spatial data used in the study included a digital elevation model (DEM), land use and land cover, soil type. Additionally, meteorological input data including precipitation, temperature, and solar radiation, discharge data, nonpoint sources data and point sources data, etc, are also required. The detailed information about the database was listed in table1.

Table 1 Input data required in SWAT

Data type	Data description	Sources
DEM	1:2500000; ESRI grid	Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC)
Land use and land cover map	1:1000000; Arc/Info coverage	
Soil type map	1:10000000; Arc/Info coverage	
Digital stream network	1:2500000; Arc/Info coverage	
Meteorological data	Climatic stations, precipitation, temperature, solar radiation and relative humidity data	China Meteorological Administration National Meteorological Center
Discharges data	Monthly average discharge and from 1995 to 2002	Hydrology statistical yearbooks

2.2. SWAT model

SWAT model is a basin-scale, continuous time model that operates on a daily time step and evaluates the impact of management practices on water, sediment and agricultural chemical yields in ungauged basins [2]. The model is physically based, computationally efficient, and capable of continuous simulation over long time periods. The model's major components include weather, hydrology, erosion, soil temperature and properties, plant growth, nutrients, pesticides, land management [13-14].

In SWAT model, a watershed is divided into multiple subwatersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management and soil characteristics. For each HRU, water balance was simulated for four storage volumes: snow, soil profile, shallow aquifer, and deep aquifer.

SWAT provides two methods for estimating surface runoff: SCS curve number procedure and the Green & Ampt infiltration method. Numerous methods have been developed to estimate PET. Three of these methods have been incorporated into SWAT: Hargreaves method [15], Priestley-Taylor method [16] and Penman-Monteith method [17-18]. The model can also read in daily PET values if the user prefers to apply a different potential evapotranspiration method. Groundwater flow contribution to total streamflow is simulated by creating shallow aquifer storage [19]. Percolation from the bottom of the root zone is considered as recharge to the shallow aquifer. More information about SWAT model can be found in Soil and Water Assessment Tool Theoretical Documentation or link http://swatmodel.tamu.edu/swat/.

2.3. SUFI-2 algorithm

The program SUFI-2 was used for calibration and uncertainty analysis. 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 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling.

A short step-by-step description of SUFI-2 algorithm [20] is as follows:

- (1) In the first step an objective function is defined.
- (2) The second step the physically meaningful absolute minimum and maximum ranges for the parameters being optimized are identified. Because the absolute parameter ranges play a constraining role, they should be as large as possible, yet physically meaningful.
- (3) This step involves an optional, yet highly recommended "absolute sensitivity analysis" for all parameters in the early stages of calibration.
- (4) Initial uncertainty ranges are assigned to parameters for the first round of Latin hypercube sampling. In general, the above ranges are smaller than the absolute ranges, and depend upon experience. The sensitivity analysis in step 3 can provide a valuable guide for selecting appropriate ranges.
- (5) Latin Hypercube sampling is carried out next; leading to n parameter combinations, where n is the number of desired simulations.
- (6) As a first step in assessing the simulations, the objective function is calculated.
- (7) Then a Latin Hypercube sampling is carried out in the hypercube, the corresponding objective functions are evaluated, and the sensitivity matrix *J* and the parameter covariance matrix *C* are calculated according to:

$$J_{ij} = \frac{\Delta g_i}{\Delta j_i} \quad i = 1 \ldots C_2^n, j = 1 \ldots m \tag{1}$$

where C_2^n is the number of rows in the sensitivity matrix (equal to all possible combinations of two simulations), and *j* is the number of columns (number of parameters).

$$C = s_g^2 (J^T J)^{-1} \quad (2)$$

where s_g^2 is the variance of the objective function values resulting from m model runs.

- (8)A 95% predictive interval of a parameter bj is computed as follows:

$$b_{j,lower} = b_j^* - t_{V,0.025} s_j \quad (3)$$

$$b_{j,lower} = b_j^* + t_{V,0.025} s_j \quad (4)$$

where b_j^* is the parameter b_j for the best estimates, and v is the degrees of freedom (m-n).

- (9) The 95PPU is calculated. And then two indices, i.e., the *p-factor* (the percent of observations bracketed by the 95PPU) and the *r-factor*, are calculated:

$$r - factor = \frac{\overline{d}_X}{\sigma_X} \quad (5)$$

where σ_X is the standard deviation of the measured variable X. A value of less than 1 is a desirable measure for the *r-factor*.

$$\overline{d}_X = \frac{1}{k}\sum_{l=1}^{k} (X_U - X_L)_l \quad (6)$$

where k is the number of observed data points; and X_L (2.5^{th}) and X_U (97.5^{th}) represent the lower and upper boundary of the 95PPU.

- (10) Because parameter uncertainties are initially large, the value of *d* tends to be quite large during the first sampling round. Hence, further sampling rounds are needed with updated parameter ranges calculated from:

$$b'_{j,\min} = b_{j,lower} - Max\left(\left(\frac{b_{j,lower} - b'_{j,\min}}{2}\right), \left(\frac{b'_{j,\max} - b'_{j,upper}}{2}\right)\right) \quad (7)$$

$$b'_{j,\max} = b_{j,upper} + Max\left(\left(\frac{b_{j,lower} - b'_{j,\min}}{2}\right), \left(\frac{b'_{j,\max} - b'_{j,upper}}{2}\right)\right) \quad (8)$$

where b' indicate updated values. Parameters of the best simulation are used to calculate $b_{j,lower}$ and $b_{j,upper}$. The above criteria, while producing narrower parameter ranges for subsequent iterations, ensure that the updated parameter ranges are always centered on the best estimates.

In addition, SUFI-2 is linked to SWAT (in the SWATCUP software) through an interface that includes the programs GLUE, ParaSol, MCMC algorithm. SWAT-CUP was developed by Swiss Federal Institute of Aquatic and Technology, Naprash Company and Texas A&M University.

3. Results and analysis

3.1. Sensitivity analysis

Sensitivity analysis was performed to identify key parameters in the Chao River basin, as hydrology component of SWAT involve a large number of parameters. For the sensitivity analysis, 20 parameters integrally related to stream flow were initially selected. After one iteration run, 12 parameters such as CN2, ALPHA_BF, ESCO, SOL_AWC, SOL_K, CANMX, EPCO, et al., were found more sensitive. The ranking of 12 parameters are listed in Table 2. The sensitivity analysis results obtained from this study are very similar to previous studies [21]. CN2 is the most sensitive as expected.

Table 2 Ranking of SWAT input parameters related to runoff

Ranking	Name	Definition
1	CN2.mgt	SCS runoff curve number for moisture condition II
2	ALPHA_BF.gw	Base flow alpha factor (days)
3	ESCO.hru	Soil evaporation compensation factor
4	SOL_AWC.sol	Soil available water storage capacity (mm H_2O/mm soil)
5	SOL_K.sol	Soil conductivity (mm hr^{-1})
6	CANMX.hru	Maximum canopy storage (mm H_2O)
7	EPCO.hru	Plant uptake compensation factor
8	SOL_Z.sol	Depth from soil surface to bottom of layer (mm)
9	CH_K2.rte	Effective hydraulic conductivity in the main channel (mm hr^{-1})
10	CH_N2.rte	Manning's n value for main channel
11	GW_DELAY.gw	Groundwater delay time (days)
12	GW_REVAP.gw	Groundwater revap. coefficient

3.2. Model parameters calibration and uncertainty analysis

In SUFI-2, a *p-factor* of 1 and *r-factor* of zero is a simulation that exactly corresponds to measured data. The degree to which are away from these values can be used to judge the strength of calibration. The results of monthly runoff calibration and uncertainty for the Chao River basin were presented in Figure 2. The *p-factor* was 0.85 and the *r-factor* was 1.12 in calibration period (1995-1999) (Figure 2a) while the *p-factor* was 0.83 and the *r-factor* was 2.15 in validation period (2000-2002) (Figure 2b). The percentage of data being bracketed by 95PPU (*p-factor*) was high both in calibration and validation periods, e.g. 0.85 and 0.83. Additionally, some observed data were not bracketed by the prediction band and occurred at the beginning stages of calibration and validation periods. This maybe related to the fact that SWAT model in the Chao River basin was not warmed up in this study. Warming up can define more real initial soil moisture. If SWAT model was warmed up, the results would be better.

On the other hand, a careful examination of the calibration results showed that the observed data unbracketed by the prediction band were fallen in the baseflow part. This was maybe caused by a limitation of SWAT that it does not rigorously simulate groundwater flow [22]. Groundwater recharge is important in the Chao River basin. If baseflow were better simulated, a larger *p- factor* as well as a smaller *r-factor* could be achieved for a better simulation result. Therefore, parameters such as groundwater recharge and groundwater–river interaction were important in the hydrology processes.

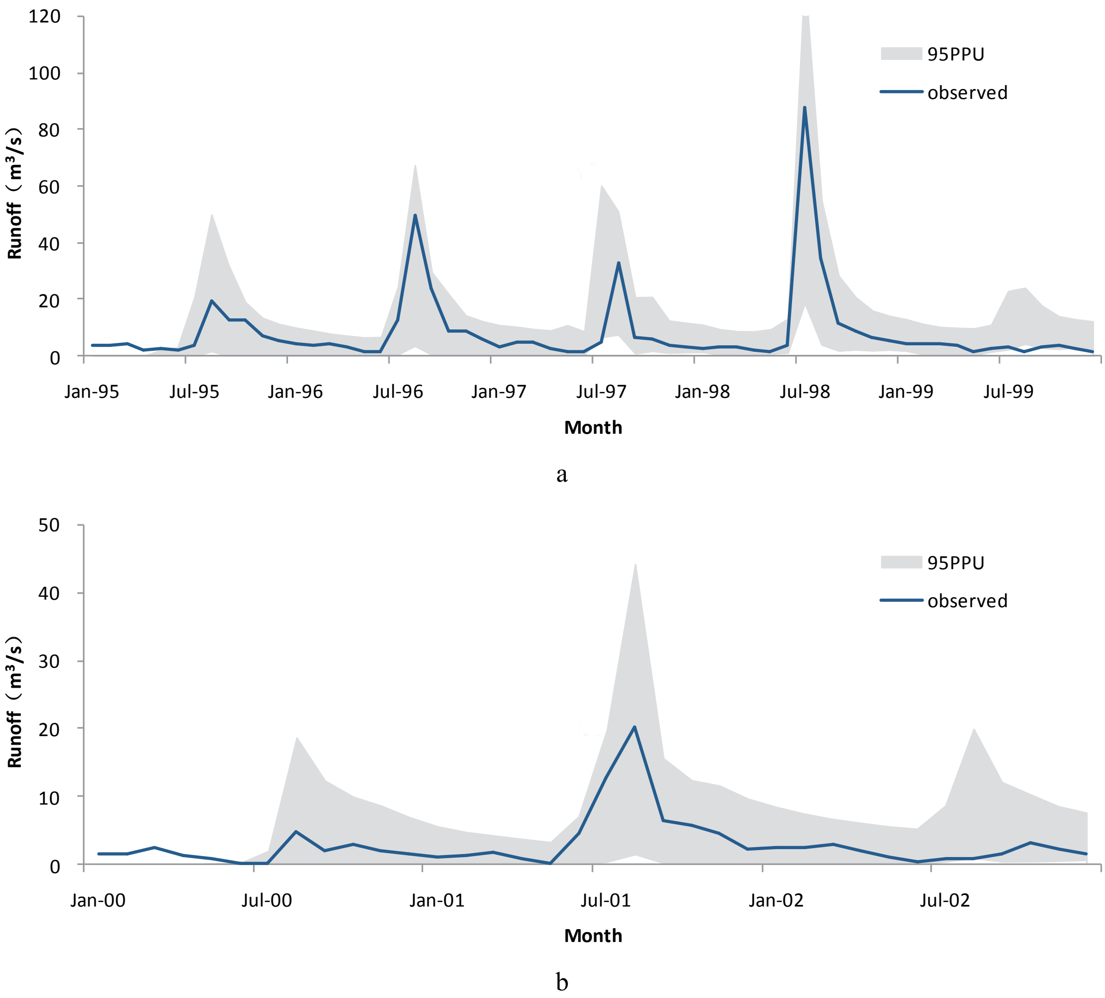
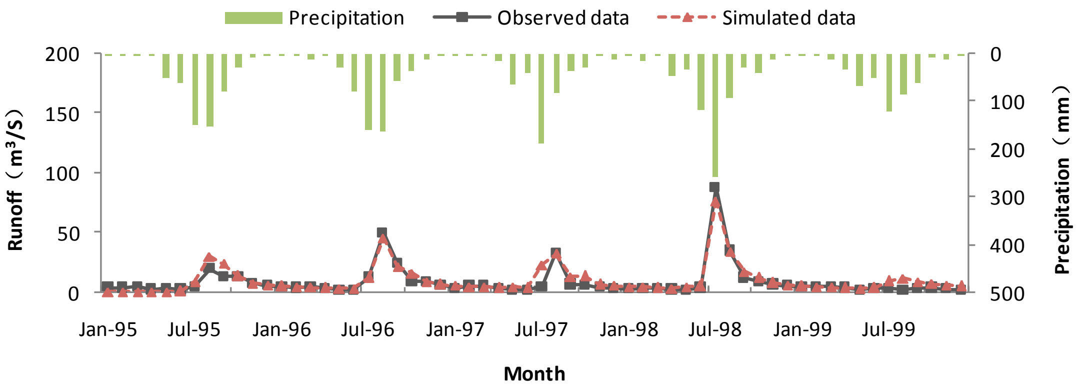


Fig.2 Monthly runoff simulation at Xiahui station (a. calibration period; b. validation period)

Figure 2 showed that the *r-factor* was 1.12 in calibration period, while the *r-factor* was 2.15 in validation period. Results showed that the SWAT model revealed large uncertainties for validation period which were in wet years, although the simulation of monthly runoff for the Xiahui station was satisfactory during the calibration period. This maybe resulted from the fact that SWAT can not well simulate extreme event. Tolson & Shoemaker reported that SWAT is not designed to simulate an extreme event and the model usually underpredicts the largest flow events [23].

When values of *p-factor* and *r-factor* are accepted, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the coefficient of determination (R^2) and Nash–Sutcliffe coefficient (NS) [24] between the observed and the final simulated data. For R^2, the closer to 1 R^2 is, the better the simulation result is. For NS, the simulation results are good when NS is larger than 0.75; the simulation results are satisfactory when NS is larger than 0.36 and smaller than 0.75; simulation results are satisfactory when NS is larger than 0.36 and smaller than 0.75; simulation results are not good when NS is smaller than 0.36. The results indicated that R^2 was 0.90 and NS was 0.88 in calibration period (Figure 3a), and R^2 was 0.77 and NS was 0.74 in validation period (Figure 3b). The simulation results were satisfactory. It should be noted that it is not necessary to seek the "best simulation" as in such a stochastic procedure the "best solution" is actually the final parameter ranges.



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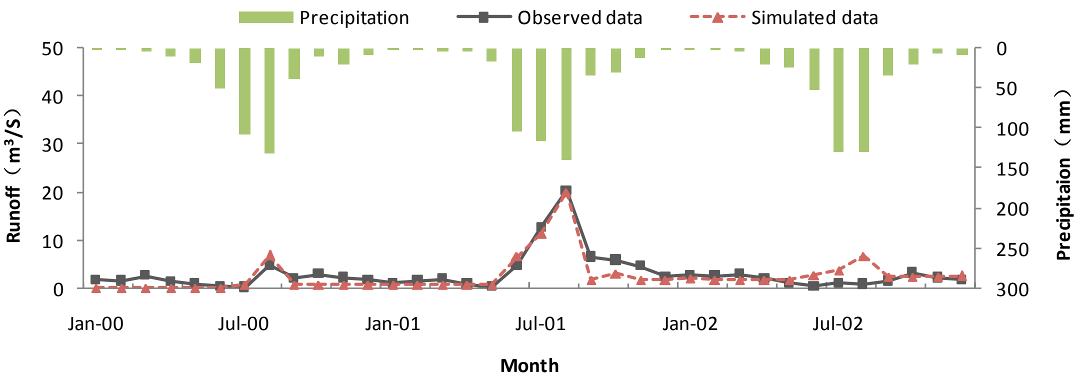

b

Fig.3 Simulated and observed hydrograph at Xiahui station in the Chao River basin (a. calibration period; b. validation period)

4. Conclusions

SWAT model was applied in the Chao River basin to simulate runoff from 1995 to 2002 in this study. The year of 1995-1999 was selected as the calibration period and the year of 2000-2002 was selected as the validation period. Then sensitivity analysis, model calibration and uncertainty analysis were performed using SUFI-2 algorithm integrated with SWAT. The following conclusions were obtained.

- (1) Results of sensitivity analysis showed that 12 parameters such as CN2, ALPHA_BF, ESCO, SOL_AWC, SOL_K, CANMX, EPCO, et al., were found more sensitive.
- (2) Results of uncertainty analysis indicated that SWAT model had large uncertainties for validation period, although the simulation of monthly runoff for the Xiahui station was satisfactory during the calibration period.
- (3) Calibration and validation results showed that R^2 was 0.90 and NS wad 0.88 in calibration period, and R^2 was 0.77 and NS was 0.74 in validation period. The simulation results were satisfactory.

References

[1] Young RA, Onstad CA, Bosch DD, Anderson WP. AGNPS – A nonpoint-source pollution model for evaluating agricultural watersheds. *J. Soil Wat. Conserv* 1989;**44**:168-73.

[2] Arnold JG, Srinivasan R, Muttiah RS, Williams JR. Large area hydrologic modeling and assessment–Part 1: Model development. *J Am Water Resour As* 1998;**34**:73-89.

[3] Bicknell BR, Imhoff J, Kittle J, Jobes T, Donigian AS. Hydrological Simulation Program–Fortran User's Manual. *USEPA* 2000.

[4] Gassman PW, Reyes MR, Green CH, Arnold JG. The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. *Transactions of the ASABE* 2007;**50**:1211-50.

[5] Kuczera G, Parent E. Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. *J. Hydrol* 1998;**211**:69-85.

[6] Vrugt JA, Gupta HV, Bouten W, Sorooshian S. A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resour Res* 2003;**39**:1201.

[7] Yang J, Reicher P, Abbaspour K C, Xia J, Yang H. Comparing uncertainty analysis techniques for a SWAT application to the Chao he Basin in China. *J. Hydrol* 2008;**358**:1-23.

[8] Beven K., Binley A. The future of distributed models –model calibration and uncertainty prediction. *Hydrol.Process* 1992;**6**:279-98.

[9] van Griensven A, Meixner T. Methods to quantify and identify the sources of uncertainty for river basin water quality models. *Water Sci Technol* 2006;**53**:51-9.

[10] Abbaspour KC, Yang J, Ivan M, Siber R, Bogner K, Mieleitner J, Zobrist J, Srinivasan R. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *J. Hydrol* 2007;**333**:413-30.

[11] Faramarzi M, Abbaspour KC, Schulin R, Yang H. Modelling blue and green water resources availability in Iran. *Hydrol.Process* 2009;**23**:486-501.

[12] Schuola J, Karim CA, Srinivasan R, Yang H. Estimation of freshwater availability in the West African sub-continent using the SWAT hydrologic model. *J. Hydrol* 2008;**352**:30-49.

[13] Arnold JG, Fohrer N. SWAT2000: current capabilities and research opportunities in applied watershed modelling. *Hydrol. Proces* 2005;**19**:563-72.

[14] Behera S, Panda, RK. Evaluation of management alternatives for an agricultural watershed in a sub-humid subtropical region using a physical process based model. *Agric. Ecosyst. Environ* 2006;**113**:62-72.

[15] Hargreaves GH, Samni ZA. Reference crop evapotranspiration from temperature. *Appl Eng Agric* 1985;**1**:96-9.

[16] Priestley CHB, Tylor RJ. On the assessment of surface heat flux and evaporation using large-scale parameters. *Mon Weather Rev* 1972;**100**:81-92.

[17] Monteith JL. Evaporation and environment, the state and movement of water in living organisms. *In: 19th symp Soc Excp Biol., Academic press,* New York; 1964.

[18] Allen RG. A Penman for all seasons. *J Irrig Drain E-ASCE* 1986;**112**:348-68.

[19] Arnold JG, Allen PM. Estimating hydrologic budgets for three Illinois watersheds. *J. Hydro* 1996;**176**:57-77.

[20] Abbaspour KC, Johnson C A and van Genuchten MTh. Estimating Uncertain Flow and Transport Parameters Using a Sequential Uncertainty Fitting Procedure. *Vadose Zone J* 2004;**3**:1340-52.

[21] Lenhart T, Kckhardt K, Fohrer, N, Frede HG. Comparison of two different approaches of sensitivity analysis. *Phys Chem Earth* 2002;**27**:645-54.

[22] Rostamian R, Jaleh A, Afyuni M, Mousavi S F, Heidarpour M, Jalalian A, Abbaspour KC. Application of a SWAT model for estimating runoff and sediment in two mountainous basins in central Iran. *Hydrolog Sci J* 2008;**53**:977-88.

[23] Tolson BA, Shoemaker CA. Watershed modeling of the Cannonsville basin using SWAT2000: model development, calibration and validation for the prediction of flow, sediment and phosphorus transport to the Cannonsville Reservoir. *Technical Report, School of Civil and Environmental Engineering, Cornell University*, New York, USA; 2004.

[24] Nash JE, Sutcliffe JV. River flow forecasting through conceptual models, Part 1- a discussion of principles. *J. Hydrol* 1970;**10**:282-90.