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RESEARCH ARTICLE

Parameters optimization based on the combination of localization and auto-calibration of SWAT model in a small watershed in Chinese Loess Plateau

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Abstract This study simulated the watershed flow and sediment responses based on calibration of the SWAT model in the semi-arid Chinese Loess Plateau (LP) where soil erosion intensively occurs. After the model's initiation and manual modification, a 7-year inconsecutively observed flow and sediment data from 1984 to 1990 was used to analyze the model's application in the selected watershed called AJW in the Chinese LP region. The model procedure included sensitivity analysis, parameter calibration and model validation. The best parameter set was finally determined based on the combination of parameter localization and auto-calibration. Then the model was assessed for its accuracy based on the NSE estimation, resulting in 0.77 and 0.67 for calibration and 0.46 and 0.32 for validation on simulations for flow and sediment, respectively, which is a moderately satisfactory accuracy among the applications of the SWAT model. Annual watershed assessment on flow and sediment with the calibrated SWAT model resulted in a multiyear averaged annual runoff coefficient of about 2.7% and an erosion modulus of 797 t/(km$^2 \cdot$a^{-1}) in the AJW, indicating a beneficial consequence from the implementation of the historical soil and water conservations.

Keywords SWAT, Anjiagou watershed, parameter localization, auto-calibration, flow and sediment assessment

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1 Introduction

Notoriously severe soil erosion in the Chinese Loess Plateau has put great pressures on the fragile regional ecosystems, resulting in land degradation (Fu et al., 2006) and adverse consequences to the environment and society (Wei et al., 2006). Therefore, soil and water conservation in the region has been considered especially important, and various measures have been implemented to protect the watersheds over the past several decades. While scientists have devoted efforts to investigating the watershed processes (McVicar et al., 2007), most of the studies are based on plot-level observations and not spatially explicit. As a result, our understanding of the effectiveness of these measures and their influences on flow and sediment dynamics has been limited.

In recent years, the application of hydrologic models has become an indispensable way (Ndomba et al., 2008; Li et al., 2010) for understanding watershed processes and quantifying watershed responses to variable restoration measures. Many models, such as TopModel (Beven and Kirkby, 1979), MIKE SHE (Singh and Woolhiser, 2002), and SWAT (Arnold et al., 1998), have been progressively developed for that purpose. These physically based distributed hydrologic models are capable of simulating not only flow and sediment processes and nutrient transmission, but also the effects of best management practices (BMP), plant growth, climate change, and land use/cover change (LUCC) on a variety of time and space scales (e.g., Chaplot, 2007; Rao et al., 2007; Bosch, 2008; Sang et al., 2008).

In all these distributed hydrologic models, SWAT (Soil and Water Assessment Tool) is well known as a computationally efficient and continuous simulation model (Kang et al., 2006), which has proven to be an effective tool for assessing water resource and nonpoint-source pollution problems for a wide range of environmental conditions across the globe (Gassman et al., 2007). In the US, the database supporting SWAT has been continually enriched for decades, leading to integrated state soil categories for almost the whole country. This has broadly promoted the tool's application and the development of its methodological components. Nowadays, SWAT has become a worldwide soil and water assessment tool, increasingly used to support nutrient transmission and Total Maximum Daily Load (TMDL) analysis (Zhang et al., 2009; Kang et al., 2006; Bosch, 2008), estimation of conservational or the BMP effectiveness (Santhi et al., 2006; Arabi et al., 2007; Guo et al., 2008; Ouyang et al., 2009; Yang et al., 2009), watershed assessment (Srinivasan et al., 1998; Di Luzio et al., 2005; Kou et al., 2007), and a wide range of other water use and water quality applications.

In this study, we use SWAT to assess the flow and sediment processes of a small-scale watershed, named Anjiagou (AJW), in the relatively data-scarce Loess Plateau region of China. Our choice of SWAT is mainly because of its ready availability and user-friendly interface for data processing (Abbaspour et al., 2007). One potential problem of applying SWAT to the Chinese Loess Plateau region is that since the model was originally calibrated in the US, parameters, such as soil properties and flux characteristics, must be modified according to the inherent features of the specific China Loess Plateau area for the simulations. This parameter modifying process is done as follows: First, we initialize the model simulation and manually calibrate it to an overall acceptable accuracy level; second, the number of key parameters is determined according to model's sensitivity analysis; third, some of the model's key parameters are defined on the basis of in situ experiments and local observations, the rest of which are optimized by SWAT auto-calibration procedure (Muleta and Nicklow, 2005), while the localized parameters are fixed to the input files in parameter screening procedure; fourth, a set of best parameters that are physically and locally representative of the watershed flow and sediment processes are defined; and fifth, we rerun the model with the best set of parameters for both model validation and flow and sediment assessment across the study watershed (Fig. 1).

2 Study site

With an area of 8.29 km^2, the AJW is located near Dingxi City of Gansu Province of China (Figs. 2(a) and (b)) between 35°33'02″–35°35'29″N and 104°38'13″–104°40'25″E. It features a hilly loess landscape and a semi-arid climate. The elevation varies from 1901 to 2231 m (Fig. 2(c)). The annual mean air temperature is 6.3°C and the annual precipitation is 427 mm while the annual potential evapotranspiration is as high as 1510 mm. About 56% of the precipitation occurs between July and September, and little runoff is observed during the dry season. The predominant gray calcareous soil developed on loess parent material with a silty loam texture has a relatively thick profile and a weak resistance to hydraulic erosion (Gong et al., 2006). The landscape is markedly heterogeneous in terms of land uses/covers. The major land use types are: terraced cropland (TC), wasteland (WA), sloping cropland (SC), grassland (GL), and woodland (WO). Hydrogeomorphically, the variations in terrains and land covers play significant roles on flow generation in the watershed (Li et al., 2005).

The AJW belongs to the rain-fed semi-arid agricultural zone. The main land use type in the watershed is cropland, with 64.87% the total watershed area for TC and 4.23% for SC (Fig. 2(d)). This makeup of cropland indicates that

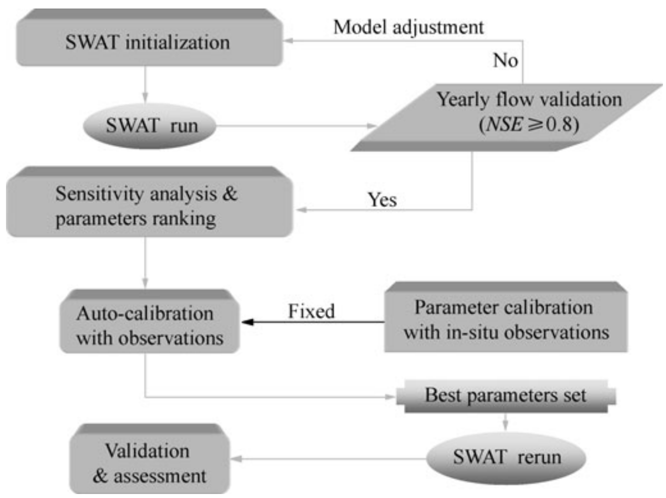

Fig. 1 Scheme map for application of SWAT model in the AJW

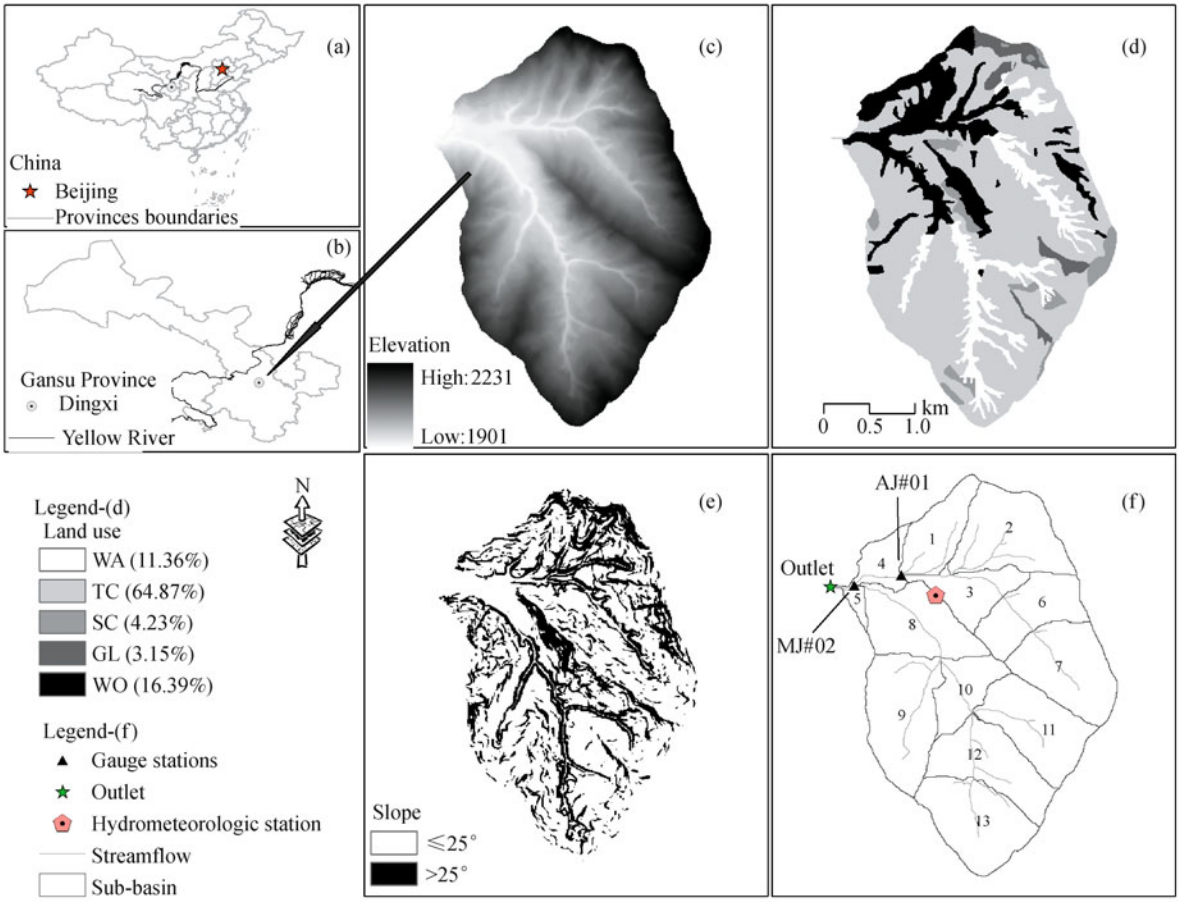

Fig. 2 Maps for location of the AJW and the distribution of its elevation, land use, slope and sub-basins

great efforts of terracing have been made to control water runoff and soil erosion in AJW. Because of the low temperature, farming practices in AJW feature single annual crops, including spring wheat (*Triticum aestivum L.*), beans (*Phaseolus vulgaris*), and potato (*Solanum tuberosum L.*). Also, 80.55% of the AJW watershed is on slopes below 25 degrees, nearly 20% on slopes from 25 to 61 degrees (Fig. 2(e)). In general, the relatively flat and easy-to-cultivate land is mainly located at the hilltops and the lower parts of the AJW, with a higher fraction of steep cropland near the gullies and streams of the watershed.

3 Method

SWAT makes use of watershed information, such as weather, soil, topography, vegetation, and land management practices, to model watershed processes, including surface and subsurface flow, erosion and sedimentation, and crop growth for customized agricultural management practices (Arnold et al., 2000). SWAT is also designed for assessing the impacts of long-term, point and non-point source pollution on water quality as reflected in such variables as sediments, nutrients, and pesticide loads (Arnold et al., 1994; Yang et al., 2008; Ullrich and Volk, 2009). Material/particle dynamics are calculated by determining the flow routing through the specific watershed.

SWAT delineates a watershed into sub-basins (Fig. 2(f)) based on topographical analysis on a Digital Elevation Model (DEM). Flow generation in a sub-basin is defined by the hydro-physical mechanism of Hydrologic Response Units (HRUs), which is an overlaid distribution of soil categories, land use/cover types and hydro-classification of slopes across the watershed. The Curve Number (*CN*) technique and the Green-Ampt method in the model are provided for a user to make a selection on flow generation estimation. The peak runoff rate is calculated using the Modified Rational Formula (Williams, 1975). Sediment yield from each sub-basin is generated using the Modified Universal Soil Loss Equation (MSULE).

The model determines the C factor of the MUSLE equation on a daily basis, by using information from the crop growth component, hence accounting for variation in plant cover during its growth cycle and its effect on erosion (Muleta and Nicklow, 2005). Flow, sediment and nutrient loadings from each HRU in a sub-basin are totaled and computationally routed through channels, ponds, and reservoirs or to the outlet of the watershed (Eckhardt and Arnold, 2001). Major components of SWAT include weather, surface runoff, return flow, percolation, evapotranspiration, transmission losses, pond and reservoir storage, crop growth and irrigation, groundwater flow, reach routing, nutrient and pesticide loads, and water transfer (Arabi et al., 2007). Table 1 provides a list of 32 parameters that are of great importance in simulating watershed flow and sediment processes (Neitsch et al., 2000).

Table 1 List of parameters used in sensitivity, uncertainty and calibration analysis for flow and sediment simulation. Min and Max refer to the lower and upper bounds of parameter

Parameter	Description	Units	Value range		Imet [b)]
			Min	Max	
Alpha_Bf.gw	Baseflow alpha factor	1/d	0	1	1
Biomix.mgt	Biologic mixing efficiency	–	0	1	1
Blai (Crop.dat)	Maximum potential leaf area index	–	0.5	10	1
Canmx.hru	Maximum canopy index	mm	0	100	1
Ch_Cov.rte	Channel cover factor	–	– 0.001	1	1
Ch_Erod.rte	Channel erodibility factor	–	– 0.05	0.6	1
Ch_K2.rte	Effective hydraulic conductivity in main channel alluvium	mm/h	– 0.01	500	1
Ch_N2.rte	Manning's "*n*" value for the main channel	–	– 0.01	0.3	1
Cn2.mgt	SCS runoff curve number for moisture condition II	%	30	98	3
Epco.bsn	Plant uptake compensation factor	–	0.01	1	1
Esco.bsn	Soil evaporation compensation factor	–	0.01	1	1
Gw_Delay.gw	Groundwater delay time	D	0	500	2
Gw_Revap.gw	Groundwater "revap" coefficient	–	0.02	2	2
Gwqmn.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	mm H_2O	0	5000	2
Revapmn.gw	Threshold depth of water in the shallow aquifer for "revap" or percolation to the deep aquifer to occur	mm H_2O	0	500	2
Sftmp.bsn	Snowfall temperature	°C	– 5	5	1
Slope.hru	Average slope steepness	m/m	0	0.6	3
Slsubbsn.hru	Average slope length	M	10	150	3
Smfmn.bsn	Minimum melt rate for snow during the year	mm/(°C·d^{-1})	0	10	1
Smfmx.bsn	Maximum melt rate for snow during the year	mm/(°C·d^{-1})	0	10	1
Smtmp.bsn	Snow melt base temperature	°C	– 5	5	3
Sol_Alb.sol	Moist soil albedo	–	0.01	1	3
Sol_Awc.sol	Available water capacity of the soil layer	mm/mm	0.01	0.4	3
Sol_K.sol	Saturated hydraulic conductivity	mm/h	0	2000	3
Sol_Z.sol	Depth from soil surface to bottom of layer	mm	0	3500	3
Spcon.bsn	Linear parameters for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	–	0.0001	0.01	1
Spexp.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	–	1	1.5	1
Surlag.bsn	Surface runoff lag coefficient	–	1	12	1
Timp.bsn	Snow pack temperature lag factor	–	0	1	1
Tlaps.sub	Temperature lapse rate	°C/km	0	50	1
Usle_C (Crop.dat)	Minimum value of USLE C factor for water erosion applicable to the land cover/plant [a)]	–	0.005	0.4	3
Usle_P.mgt	USLE equation support practice factor	–	0	1	1

a) C is the crop/vegetation and management factor. It is used to determine the relative effectiveness of soil and crop management systems in terms of preventing soil loss. The C factor is a ratio comparing the soil loss from land under a specific crop and management system to the corresponding loss from continuously fallow and tilled land. The C Factor can be determined by selecting the crop type and tillage method that corresponds to the field and then multiplying these factors together. Value range of the C factor in Table 1 was from the corresponding multiplication of minimum/maximum crop type factor and tillage method factor (http://www.omafra.gov.on.ca/); b) parameter change method when auto–calibration. 1: replace by value; 2: addition of value; 3: multiplication of value

4 SWAT procedures

4.1 Model initialization

For better matching the physical mechanism derived from the field observations, a 10m × 10m DEM is used to provide a more compatible watershed delineation for the simulation. The soil type in the AJW with the texture of silty loam is almost hydrologically uniform with clay content of about 15%. In order that the SWAT model can determine the area and hydrologic parameters for each land-soil-slope category, maps for land use, soil and slope distribution are overlaid, and the dominant land use and slope definition are used to create the dominant HRUs for each sub-basin. The simulation uses the CN technique for calculation of the flow generation, a first-order Markov Chain for rainfall distribution estimation, the Penman-Monteith method for evaporation, and the Muskingum method for channel routing. Then, the available land use data are reclassified to match the SWAT Land Cover/Plant Growth classification (Table 2). We evaluate the model performance by comparing the simulated yearly flow with the observed one at the two gauge stations (Fig. 2(f)).

Yearly flow data of 1984, 1985 and 1987 (missing data for other years) are used to manually adjust the model to a reasonable overall accuracy based on the Nash-Sutcliffe Efficiency index (NSE) (Nash and Sutcliffe, 1970). An NSE value of 0.8 was considered suitable in the early period of the model's training (Fig. 1). The NSE has been widely used to evaluate the performance of hydrologic models and is calculated as:

$$c_e = 1 - \frac{\sum_{j=1}^{n}(O_j - S_j)^2}{\sum_{j=1}^{n}(O_j - \overline{O})^2}, \tag{1}$$

where c_e is the NSE, O_j and S_j are the observed and simulated hydrological variables——flow or sediment concentration, $\overline{O}$ is the mean of observed basin response, and n is the length of the time series.

4.2 Sensitivity analysis

There are more than 30 important parameters (Table 1) included in flow and sediment calculations in SWAT (Neitsch et al., 2000). The most important step influencing the model's performance is to reduce the number of parameters for an efficient parameter set. In SWAT, a sensitivity analysis can be implemented by using the stepwise regression method, which is carried out on ranks of input-output data pairs that are generated based on the combination of One-factor-At-a-Time (OAT) Design (Morris, 1991) and Latin Hypercube (LH) sampling method (McKay et al., 2000). In light of the sensitivity analysis, those parameters that contribute most to the variability of flow and sediment yield will be identified for the parameter optimization for watershed flow and sediment simulations in the AJW. Parameter sensitivity is approximated using the Relative Sensitivity (S_r):

$$S_r = \frac{x}{y} \cdot \frac{y_2 - y_1}{x_2 - x_1}, \tag{2}$$

where x is the parameter and y is the predicted output. x_1, x_2 and y_1, y_2 correspond to ±10% of the initial parameter and the corresponding output values, respectively (James and Burges, 1982; White and Chaubey, 2005). The greater the S_r, the more sensitive a model output variable is to that particular parameter.

We use the incompletely observed flow and sediment data from 1984 to 1987 for parameter sensitivity analysis; those missing observations were replaced with the negative value of −99 in the inputting time series. The results of sensitivity analysis showed that the sensitive parameters for flow are sequentially Cn2, Ch_K2, Canmx, Sol_K, Slope, Blai, Alpha_Bf, Ch_N2, ESCO, Sol_Z and Sol_Awc; for sediment are Spcon, Ch_cov, Ch_N2, Cn2, Spexp, Surlag, Sol_Z, Canmx, Alpha_Bf, Sol_K, Slope, Blai, Esco, Timp, Smtmp, and Ch_K2. Those with $S_r \geqslant 1$ were considered as high sensitive parameters, whereas those with $0.1 \leqslant S_r < 1$ are considered as normally sensitive ones (Ndomba et al., 2008). All the parameters are listed in Table 3.

The parameter Cn2 (value of CN corresponding to the moisture condition II) has retained very sensitive levels in both flow and sediment responses, with the high S_r value of 1.98 for flow and 2.14 for sediment, ranked in the first and fourth in the important parameters list (Table 3). Sediment concentration (mg/L) was mostly sensitive to channel re-entrained linear parameter Spcon, with the

Table 2 AJW land use classes matched with the SWAT Land Cover/Plant Growth classes

Land use		SWAT Land Cover/Plant Growth	SWAT description	Dominancy rank in AJW
Acronym	Type			
TC	Terraced cropland	AGRR	Agricultural Land-Row Crops	1
WO	Woodland	FRSD	Forest-Deciduous	2
WA	Waste land	SWRN	South-western US (Arid) Range	3
SC	Sloped cropland	ALFA	Alfalfa	4
GL	Grassland	PAST	Pasture	5

Table 3 List of parameters ranks produced the relative sensitivity for SWAT outputs. Parameters in form of *Bold Italic* were what we selected for localization and auto–calibration

Par. rank	Flow/($m \cdot s^{-1}$)			Sediment/($mg \cdot L^{-1}$)		
	Par.	Sr	Sen. level	Par.	Sr	Sen. level
1	***Cn2***	1.980	High	***Spcon***	4.290	
2	***Ch_K2***	0.900	Normal	***Ch_Cov***	3.330	
3	***Canmx***	0.568		***Ch_N2***	2.780	High
4	***Sol_K***	0.495		***Cn2***	2.140	
5	Slope	0.385		***Spexp***	1.850	
6	***Blai***	0.381		***Surlag***	0.673	
7	***Alpha_Bf***	0.365		***Sol_Z***	0.516	
8	***Ch_N2***	0.255		***Canmx***	0.416	
9	***Esco***	0.188		***Alpha_Bf***	0.327	
10	***Sol_Z***	0.185		***Sol_K***	0.322	
11	***Sol_Awc***	0.141		Slope	0.300	Normal
12	Smtmp	0.079		***Blai***	0.299	
13	Timp	0.068		***Esco***	0.293	
14	Epco	0.012		***Timp***	0.236	
15	Gw_Delay	0.005		***Smtmp***	0.190	
16	Gw_Revap	0.005	Low	***Ch_K2***	0.183	
17	Biomix	0.003		Sol_Awc	0.078	
18	Surlag	0.003		Gwqmn	0.045	
19	Sol_Alb	0.002		Epco	0.028	Low
20	Slsubbsn	0.001		Biomix	0.015	
21	–	–	–	Usle_P	0.012	
22	–	–	–	Sol_Alb	0.004	

highest S_r value of 4.29 (Table 3). For the parameter Slope, we adopted a fine 10 m × 10 m DEM for the watershed delineation, the accuracy of which for calculation is fairly enough and the slope steepness will maintain spatially consistent throughout the simulation.

There were 16 parameters (Table 4) that had obvious influences on the model's outputs according to SWAT sensitivity analysis assisted by the daily observed flow and sediment data. Ignoring their rank difference in Table 3, we called them the sensitive parameters for SWAT simulation in the AJW. We defined some of them based on our past work or some in situ observations in the area for parameter localization. The rest of them will be determined by the SWAT auto-calibration function (Table 4).

4.3 Localizations for SWAT key parameters

There were 9 of those 16 sensitive parameters to be localized for the SWAT simulations in the AJW (Table 4).

4.3.1 Alpha_Bf.gw

Factor Alpha_Bf, defined as the baseflow recession constant, is a direct index of groundwater flow response to changes in recharge to main channel. The AJW is at a small watershed scale and always has a rapid channel response during the periods of recharges. The base flow can be defined by empirically dividing the hydrograph as illustrated in Fig. 3 (Rui, 2004). Parameter Alpha_Bf is calculated as (Neitsch et al., 2005):

$$\alpha_{\mathrm{BF}} = \frac{1}{BFD} \ln\left(Q_{\mathrm{B}}/Q_{\mathrm{t}}\right), \tag{3}$$

where α_{BF} is the calculated Alpha_Bf (in a unit of 1/day), *BFD* is the number of base flow days for the watershed (in days), Q_{B} is the discharge at the point B of inflection when surface flow stops, Q_{t} is the minimum channel flow responding to time t. We selected 5 observed recession processes for the determination of Alpha_Bf for the AJW, obtained an averaged BFD of about 0.25 d (6 h), and an averaged $\ln\left(Q_{\mathrm{B}}/Q_{\mathrm{t}}\right)$ of 0.23. Alpha_Bf was calculated into the value of 0.92 d^{-1}, indicating a fast response of base flow (including discharge from the lateral and the small volume of groundwater in AJW) for channel water process in the AJW.

4.3.2 *Blai* (crop.dat)

Conceptualized as maximum potential leaf area index (*LAI*), *Blai* is one of the six parameters used to

Table 4 Lists of the sensitive parameters to be localized and auto-calibrated for the SWAT model in the AJW

Sn	Parameters	Localization	Auto-calibration	
			Imet	Bound (lower / upper)
1	Alpha_Bf.gw	√		
2	*Blai* (Crop.dat)	√		
3	Canmx.hru		1	0 / 10
4	Ch_Cov.rte		1	0 / 1
5	Ch_K2.rte	√		
6	Ch_N2.rte	√		
7	Cn2.mgt	√		
8	Esco.bsn		1	0 / 1
9	Smtmp.bsn		3	– 25% / 25%
10	Sol_Awc.sol	√		
11	Sol_K.sol	√		
12	Sol_Z.sol	√		
13	Spcon.bsn		1	0 / 0.01
14	Spexp.bsn		1	1 / 2
15	Surlag.bsn	√		
16	Timp.bsn		1	0 / 1

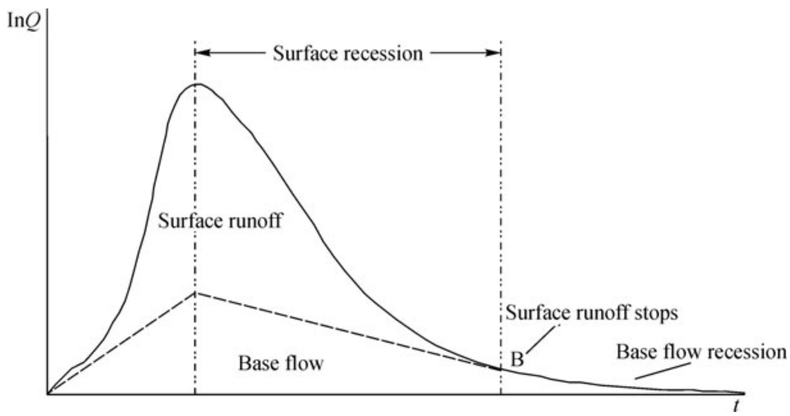

Fig. 3 Scheme for an approximate division of base flow from the hydrograph

quantify leaf area development of a plant species during the growing season. Vandijk and Bruijnzeel published their findings on the relationship between the LAI and the fractional ground cover (*GC*) (Vandijk and Bruijnzeel, 2001):

$$GC = 1 - \exp(-k \times LAI), \tag{4}$$

where *GC* is fractional ground cover for land use type, *k* is light extinction coefficient with the value of 0.55 (Zhao, 2003). The maximum LAI then can be calculated as:

$$Blai = -\ln(1 - GC)/k, \tag{5}$$

We investigated the AJW in late summer in 2005 when the land cover there reached its flourish peak in the area (corresponding to an approximate time of *Blai*), and obtained the in situ empirical estimation of *GC* for each land use type in the watershed (Table 5). Values of each land use type in AJW for parameter *Blai* were then determined according to Eq. (5) and listed in Table 5.

Table 5 Investigated *GC* value and localization of parameter *Blai*

Land use	*GC*	*Blai*
TC	0.85	3.45
WO	0.90	4.19
WA	0.50	1.26
SC	0.70	2.19
GL	0.65	1.91

4.3.3 Ch_K2.rte and Sol_K.sol

The AJW represents a moderately high loss rate in the main channel where a sand and silt mixture alluvium dominates with a very small proportion of gravels. The river is always recharged by lateral and a very small portion of groundwater during the wet season and seldom discharges to the underground water system because of the deep downcutting channel in the loess area. In the dry season, the river runs dry because of the lack of precipitation. The effective hydraulic conductivity (Ch_K2, mm/h) in AJW is defined as a positive one based on our field in situ measurements for field-saturated hydraulic conductivity by a measurement named Guelph Permeameter (GP), and as for the determination of saturated hydrologic conductivity, the parameter Sol_K (mm/h). A 2800K model GP from Soil-Moisture Equipment Corp. was used to measure saturated hydraulic conductivity (Fig. 4), which helped to have Ch_K2 and Sol_K locally parameterized for the SWAT model in the study area. Equation (6) describes how GP is used for calculating the saturated hydraulic conductivity:

$$\mathrm{Sol\_K} = 0.0041 \times X \times \overline{R}_2 - 0.0054 \times X \times \overline{R}_1, \quad (6)$$

where X is the calibrated cell constant value for the permeameter, valued as 35.2±0.18 according to the Operating Instructions for GP 2800 (www.soilmoisture.com). $\overline{R}_1$ and $\overline{R}_2$ were falling rates (in the unit of cm/s) of the water head when the Two-Head Procedure is used for measuring, which can be calculated based on the readings of the water height in the GP. The time required for the GP to reach steady-state flow is a function of the permeability of the material (Strunk, 2009). More information for a complete procedure of taking measurements and performing calculations with the GP can be found in the Model 2800K Guelph Permeameter manual (Soil Moisture Equipment Corp., 2008). We conducted the in situ experiments several times at each site. The averaged values of saturated hydraulic conductivity were 12.16 mm/h and 9.12 mm/h for parameters Ch_K2 and Sol_K, respectively.

Fig. 4 A model of 2800K GP used for measuring Sol_K in a farmland in AJW

4.3.4 Ch_N2.rte

Ch_N2 represents Manning's "n" value (Manning's Roughness Coefficient, MRC) for the main channel. Venn Te Chow has organized a very extensive list of MRC (Chow, 1959). Stream channels in AJW feature a relative winding and sluggish status and most of that are earth, we defined the main channel Ch_N2 with the value of 0.03 according to Chow's classifying and our past work in AJW (Li et al., 2005).

4.3.5 Sol_Z.sol

Sol_Z (mm) is the depth from soil surface to the bottom of a layer. Loess deposits in our study area distributes a relatively deep profile on average of more than 3000 mm, but the effective distribution of roots for modern vegetation and cultivation are mainly less than 600 mm in depth (An, 2004). Studies also revealed that in the LP area, the maximum depth of rainfall infiltration is about 1,600 mm and the average one is about 1100 mm (He et al., 2003). The information above showed a reasonable definition for the maximum effective hydrological depth of 1,600 mm. We determined the deepest value for parameter Sol_Z as 1,200 mm according to our in situ observations in 2005 (Li et al., 2010), and divided the whole depth into two layers. The top one is defined with a depth of 600 mm to represent the real modern cultivation. SWAT model was applied to each soil layer independently for simulations of soil water routing feature consisting of soil evaporation, plant uptake and transpiration, lateral flow and percolation, and so on (Neitsch et al., 2000).

4.3.6 Sol_Awc.sol

Parameter Sol_Awc (mm H_2O/mm Soil) is for available water capacity in the soil layer, also known as the plant available water and calculated by subtracting the wilting point from the field capacity (Neitsch et al., 2004):

$$\mathrm{Sol\_Awc} = \mathrm{Sol\_Fc} - \mathrm{Sol\_Wp}, \quad (7)$$

where *Sol_Fc* is the water content at field capacity, *Sol_Wp* is the water content at the permanent wilting point. We determined parameter Sol_Awc according to the openly published Soil Database with the scale of 1:1,000,000 compiled by the Nanjing Institute of Soil Science, Chinese Academy of Sciences (Shi and Yu, 2001). The empirical estimations for field capacity and wilting point were calculated as (Gupta and Larson, 1979):

$$\mathrm{Sol\_Fc} = 0.003075\mathrm{Sd} + 0.005886\mathrm{St} + 0.008039\mathrm{Cl} + 0.002288\mathrm{Om} - 0.1434\mathrm{Bd}, \quad (8)$$

$$\text{Sol\_Wp} = -0.000059\text{Sd} + 0.001142\text{St} + 0.005766\text{Cl} + 0.002228\text{Om} + 0.02671\text{Bd}, \tag{9}$$

where in both of the above two equations, the Sd, St, Cl and Om sequentially are content percentage for sand, silt, clay and organic matter, Bd is bulk density (mg/cm^3). Soil particle size distribution was analyzed with USA criterion, which is satisfied with the input requirement for the SWAT model. Sol_Fc, Sol_Wp and Sol_Awc were averaged into 0.33, 0.17 and 0.16 to a depth of 600 mm and 0.32, 0.18 and 0.14 for the depth of deeper than 700 mm which is used to parameterize the depth from more than 600 mm to 1,200 mm (Table 6).

4.3.7 Surlag.bsn

Parameter Surlag is for the estimation of the surface runoff lag for daily flow concentration. In large sub-basins with a time of concentration greater than 1 d, only a portion of the surface runoff will reach the main channel on the day it is generated. Fraction of surface runoff storage reaching to the stream observed at the outlet has a converse relationship with the watershed time of concentration (Fig. 5) (Neitsch et al., 2004). For a small scale watershed such as the AJW, the time of concentration is always less then 1 d while during the time, the surface runoff has completely reached to the outlet, the fraction of surface runoff reaching stream will then be 1.0 (Fig. 5). We adopted the method of Abac Schema (Singh, 1988) for the determination of the concentration time (*K* in Fig. 5) as is defined to the time distance between geometric centers of net precipitation to direct surface runoff (Rui, 2004), the value of K is about 1.67 h (Li et al., 2005). From the Fig. 5, parameter Surlag can be defined as 9 for the AJW.

4.3.8 Cn2.mgt

When using SCS method (*CN* technique) for the calculation of flow and sediment, parameter *Cn*2 is undoubtedly of great significance because it is the core of the SCS method and will be used throughout the simulation if the parameter *CNOP* (*CN* for management such as plant, tillage, harvest and kill operations) is not defined for the manageable options (Neitsch et al., 2004). The purpose of

Table 6 Soils properties in the AJW for SWAT parameterization

Depth/mm	Sd/%	St/%	Cl/%	Om/%	Bd/(g·cm^{-3})	Sol_Fc/(mm·mm^{-1})	Sol_Wp/(mm·mm^{-1})	Sol_Awc/(mm·mm^{-1})
0–600	39.78	45.87	14.35	0.79	1.25	0.33	0.17	0.16
> 700	37.82	46.80	15.38	0.63	1.35	0.32	0.18	0.15

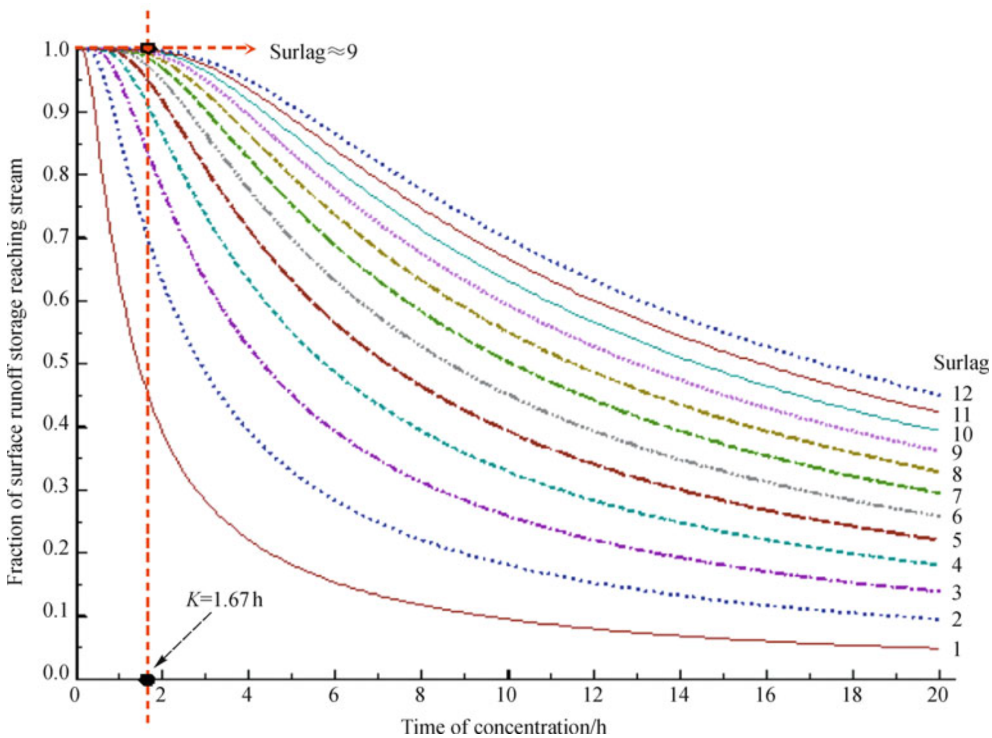

Fig. 5 Schematic illustration for determination of parameter Surlag

Fig. 6 Field plot for rainfall-runoff measurement in AJW

CN (SCS, 1956) in SCS method (Eq. (10)) is to empirically quantify the potential maximum retention since the initial abstraction was empirically defined as Eq. (11).

$$Q = \frac{(P - I_a)^2}{P - I_a + S}, \tag{10}$$

$$I_a = 0.2S, \tag{11}$$

where Q is the predicted runoff amount (mm), P is rainfall amount (mm), I_a is the initial abstraction and S, the potential maximum retention, is given by

$$S = \frac{25400}{CN} - 254. \tag{12}$$

Value of $Cn2$ can be found based on the combinations of land use and soil type in the SCS lookup table which was the achievement of a large amount of rainfall-runoff experiments at field or small watershed scale (SCS, 1956). To feature the local characteristics of surface runoff generation in the Chinese LP region, we have the parameter CN computationally valued through the inverse calculations supported by in situ rainfall-runoff observations in the AJW. By Eqs. (10)– (12), the CN is calculated as

$$CN = \frac{B + \sqrt{B^2 - 4AC}}{2A}, \tag{13}$$

$$A = (5P + 254)^2 - Q(25P - 5080), \tag{14}$$

$$B = 50800 \times (5P + 254) + 508000Q, \tag{15}$$

$$C = 25400^2. \tag{16}$$

Equation (13) represented a localization method for those that have in situ simultaneous observations of rainfall and runoff used for computing the parameter CN. AJW has been a demonstrative site for soil and water conservation since the early 1980s, which had been built with field runoff plots (Fig. 6) for the rainfall and runoff-sediment observations conducted for land uses including TC, WO, WA, SC and GL in the watershed.

Records from field plots corresponding to the Ahead Moisture Condition II (AMC II, Table 7) (SCS, 1956) were selected for the calculation of the CN values for each land use. The calculated CN values for the 5 kinds of land uses and the Relative Errors (RE, Eq. (17)) for validation are listed in Table 8, indicated a fair accuracy for runoff prediction. We used $Cn2$ values listed in Table 8 for the modification of the SWAT model before it went to auto-calibration.

$$RE = \frac{S_i - Q_i}{Q_i} \times 100\%, \tag{17}$$

where S_i is the simulated overland flow (mm), Q_i is the observed of that (mm).

Table 7 SCS AMC classes for CN

AMC classes	Total precipitation of the ahead five days/mm	
	Fallow season	Growth season
AMC I	< 12.7	< 35.56
AMC II	12.7–27.9	35.56–53.3
AMC III	> 27.9	> 53.3

4.4 Auto-calibration

After the localized determination of the above 9 parameters, SWAT was operated with the auto-calibration function (Fig. 1) for the retained 7 parameters in the sensitive list (Table 4). The Shuffled Complex Evolution-University of Arizona (SCE-UA) method (Duan et al., 1992), which had been widely used in watershed model calibration and had been applied with success on SWAT for the hydrologic parameters and hydrologic and water quality parameters (Eckhardt and Arnold, 2001; Vangriensven et al., 2006), was conducted for the auto-calibration of the model. The optimization was conducted on one or two parameter(s) at a time depending on the computation resource required for a particular simulation. The parameter range was modified either by replacement of the initial value (imet number valued as 1), addition of an absolute change (imet number valued as 2) or multiplication of a relative change (imet number valued as 3) (Table 1, Table 4). The incomplete daily flow and sediment records from 1984 to 1987 were used to this procedure as in the sensitivity analysis, resulted in relatively satisfactory NSE of 0.77 and 0.67 (Figs. 7 and 8) for the simulations of daily flow and sediment, respectively.

Table 8 Calculated CN values and the validation for their predictions by RE

Plot SN	Land use	CN	*Q*/mm		RE/%
			Observed	Simulated	
1	TC	71.79	0.53	0.57	7.55
7	WO	71.12	0.43	0.45	4.65
13	WA	76.72	1.64	1.61	– 1.83
3	SC	73.56	0.85	0.92	8.24
14	GL	74.17	0.83	0.76	– 8.43

4.5 Validation of the model

Values of the best set of the sensitive parameters including the localized and auto-calibrated were listed in Table 9. These values were used to the rerun procedure of the SWAT model (Fig. 1) for validation with another 3 y data from 1988 to 1990. The model's outputs, together with those from calibration, were considered as the source data for the watershed flow and sediment assessment.

5 Results

5.1 Values of the best parameter set and accuracy analysis

Table 9 lists the best set of the 16 sensitive parameters for the SWAT model used in the AJW. Parameters *Blai* and *Cn*2 were locally determined based on land use types.

The calibrated model with the best parameter set was operated from 1988 to 1990 for accuracy validation by comparison with the observed flow and sediment, gave the NSE values of 0.46 and 0.32 for daily flow and sediment, respectively (Figs. 7 and 8). Both represented an accurate decrease than the correspondingly calibrated value. Anyway, both of the validated accuracies were considered moderately satisfactory according to the historical SWAT utilization (Gassman et al., 2007). Based on existing inconsecutive observations for daily flows, we made the trend comparison (Fig. 7) and scatter plot (Fig. 8) for simulated and observed runoff and sediment at the gauge station of MJ#02 (Fig. 1(f)), and found that the calibrated model cannot capture the extreme runoff and sediment very well for the daily process simulation. Duration curves for runoff (Fig. 9) constructed using the data indicated an underestimation of high and moderate runoff. The reason for errors was mainly because of the lack of a finely distributed soil map for a better illustration of the hydrologic properties that influence the flow and sediment generation to a large extent. Also, the SWAT model structure is mainly based on a daily scale inadequately accounting for the hydrological extreme events, which may be another source for the simulated deviation in the

Table 9 The best parameter set for SWAT model in AJW

Parameters	Best value [c]	Localization based
Alpha_Bf.gw	0.92	√
Blai (Crop.dat) [a]	3.45, 4.19, 1.26, 2.19, 1.91	√
Canmx.hru	1.2335	
Ch_Cov.rte	0.36184	
Ch_K2.rte	12.16	√
Ch_N2.rte	0.03	√
Cn2.mgt [a]	71.79, 71.12, 76.72, 73.56, 74.17	√
Esco.bsn	0.18845	
Smtmp.bsn	1.67296	
Sol_Awc.sol [b]	0.16, 0.15	√
Sol_K.sol	9.12	√
Sol_Z.sol	600, 1200	√
Spcon.bsn	0.009946	
Spexp.bsn	1.4225	
Surlag.bsn	9	√
Timp.bsn	0.17269	

a) In a order of land use types of TC, WO, WA, SC and GL; b) 0.16 was the average value for a soil depth from 0 to 600 mm while 0.15, for the depth from 600 to 1200 mm; c) value marked with √ meant the localized parameter, others were auto-calibrated.

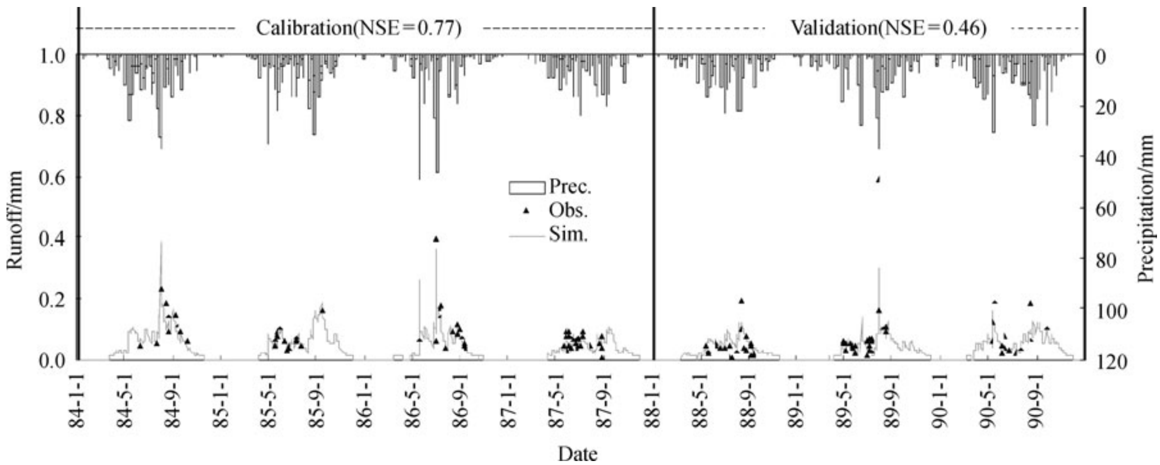

Fig. 7 Observed and simulated daily runoff for the period 1984–1990

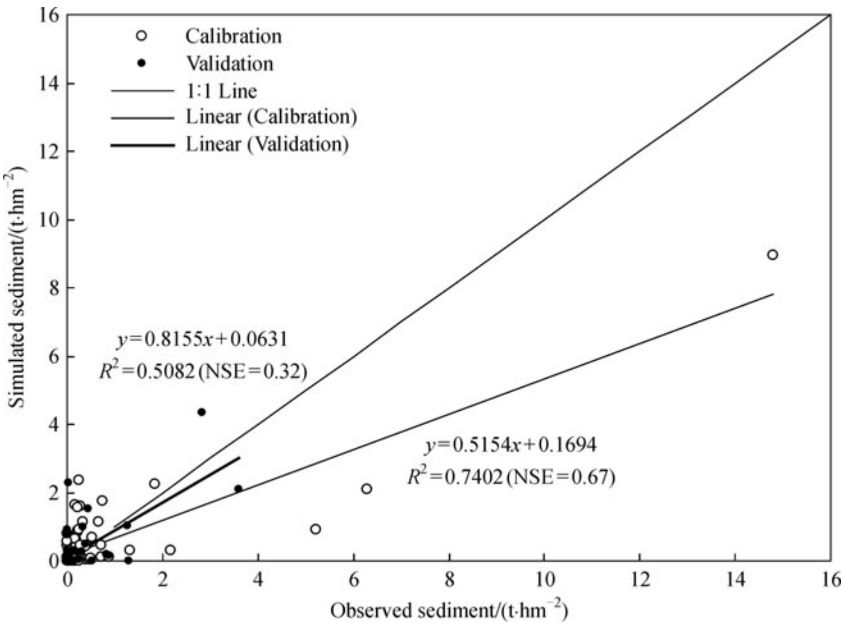

Fig. 8 Scatter plot for observed and simulated daily sediment during the period of calibration and validation

Chinese LP region where the short-term and high intensity rainfall in the wet season cause the swift surface flow and the heavy erosion primarily (Li et al., 2010). Additionally, the incomplete observed series may cause uncertainty during the model's calibration and validation. However, with a combined NSE estimation containing calibration and validation procedures, the NSE values went to 0.71 for the total flow series and 0.65 for that of the sediment simulation, quite acceptable at a multi-yearly time scale in the AJW.

5.2 Watershed flow and sediment assessments

Our additional interest in this research is to use the calibrated SWAT model for the annual assessment of the flow and sediment yield at the watershed scale for the data scarce LP area. Flow and sediment yield can be derived from SWAT outputs at a yearly scale. The simulated annual precipitation, runoff and sediment from the year 1984 to 1990 were averaged. The multiyear-averaged runoff was 12.4 mm, resulting in a runoff coefficient of about 2.7% when divided by the average annual precipitation of 458.3 mm; the average annual sediment is 7.97 t/ha, calculated in an erosion modulus of 797 t/($km^2 \cdot a^{-1}$) in the area, which is really small when compared to those that have been reported (e.g., Xu et al., 2004), mainly because of the implementation of conservation methods in this demonstrative watershed, which have affected and changed the flow and sediment processes remarkably by the modification of the surface land cover (Li et al., 2010).

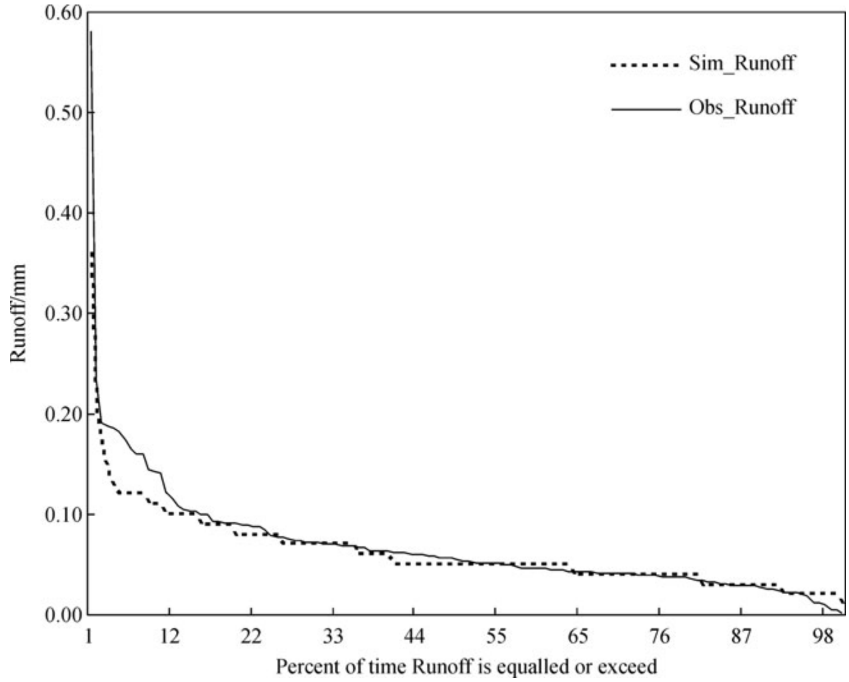

Fig. 9 Daily Runoff duration curves at MJ#02 for the period 1984–1990

6 Conclusions

The study has shown a calibration scheme for the determination of the best set of parameters for the SWAT model's utilization in the Chinese LP area. There were 16 sensitive parameters identified by using sensitivity analysis of the model in the selected watershed of AJW. Results showed that the sensitive parameters ($S_r \geqslant 0.1$) for flow simulation were sequentially *Cn*2, Ch_K2, Canmx, Sol_K, Slope, *Blai*, Alpha_Bf, Ch_N2, ESCO, Sol_Z and Sol_Awc; while that for the sediment were Spcon, Ch_cov, Ch_N2, *Cn*2, Spexp, Surlag, Sol_Z, Canmx, Alpha_Bf, Sol_K, Slope, *Blai*, *Esco*, *Timp*, Smtmp and Ch_K2. In all those sensitive parameters, the parameter *Cn*2 had retained a very sensitive level in both flow and sediment simulations, with high S_r values of 1.98 for the flow and 2.14 for the sediment, ranked in the first and fourth significance in the assessed parameter lists for flow and sediment, respectively. For a reasonable operation of the SWAT model in the AJW, the study localized 9 of the sensitive parameters based on local characteristics of the watershed in the LP region. Then the SWAT model was auto-calibrated for the other sensitive parameters while those localized were unscreened during the procedure. Finally, the best set of parameters was determined with a calibrated NSE of 0.77 and 0.67 for flow and sediment simulations during the period of 1984 to 1987. Validation for the calibrated SWAT model was conducted for another 3 y from 1988 to 1990, resulting in NSE pairs of 0.46 and 0.32 for the daily simulated flow and sediment simulation, a moderately satisfactory accuracy among the historical applications of the SWAT model. If computed during a longer time period including durations of the calibration and validation, the overall NSE values went to 0.71 and 0.65 for the application of SWAT model on daily flow and sediment in the AJW, which is quite an acceptable evaluation.

At the end of the study, the annual flow and sediment were assessed by using the calibrated SWAT model, resulting in a 7 a average runoff coefficient of about 2.7% and a soil erosion modulus of 797 t/(km$^2 \cdot$a^{-1}) in the area, indicating a relatively beneficial consequence of the historical soil and water conservations.

In this study, it was also verified that being capable of its availability and friendly-operation interface, the SWAT model was a reasonable approach to simulate soil and water dynamics across a watershed at different time scales, which is greatly helpful for people to continuously plan and manage watershed resources with more efficiency and more knowledgeable experiences. For our research, more observed data and field experiments will be useful for enhancing the model's performance. We will devote further efforts to improve our modeling approach while deriving more accurate and long-term data series for better simulations of SWAT in the Chinese Loess Plateau.

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