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Analysis of SWAT 2005 Parameter Sensitivity with LH-OAT Method

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Analysis of SWAT 2005 Parameter Sensitivity with LH-OAT Method

The Soil and Water Assessment Tool (SWAT) is widely used as watershed simulation tool, and the parameter sensitivity of the SWAT model is the foundation of model calibration. For the latest version of the SWAT model (SWAT 2005), the LH-OAT automated sensitivity analysis tool uses a stratified sampling approach and attributes the output changes to the change of a single parameter at the sampling point. But there is still some uncertainty of sensitivity result made by this tool.

A SWAT 2005 model for the Jiyunhe Basin in Tianjin of China was constructed and the LH-OAT method was applied for sensitivity analysis. The sensitivity of the predefined hydrology-related parameters was analysed. 16 sensitive parameters showed a disparity of sensitivity rank under different scenarios. The scenarios were configured considering the parameter varying methods, parameter bound, the number of intervals within parameter bound, and the random seed number. Some parameters showed evident disparity of sensitivity when different varying methods or LH-OAT configurations were applied. Under some scenarios, a single parameter's sensitivity rank changed from 14th to second and five parameters' sensitivity rank changed more than five. The nonlinearity of the relationship between the output and the parameters, the spatial distribution of the parameters and the bound inconsistency are the main causes of the sensitivity disparity of each individual parameter in the proposed scenarios. The conclusion is that the sensitivity of the hydrological-related parameters determined by the LH-OAT method is strongly influenced by the parameter varying methods and the random seed number that were required as the configuration of the LH-OAT method.

Keywords: *Sensitivity Analysis, LH-OAT, Varying Method, Parameter Bound, Number of Intervals, Random Seed*

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Introduction

The distributed hydrological model has been used more widely for considering the spatial and temporal variance (such as the spatial variances of land type or temporal variance of precipitation) in the simulation. On the other hand, this complex distributed model is always over-parameterised. For example, in the SWAT (Soil and Water Assessment Tools) model (Arnold *et al.*, 1998; Arnold and Fohrer, 2005), there are at least 61 changeable parameters that can affect the stream flow or pollutant transportation (van Griensven *et al.*, 2006). Thus, parameter sensitivity analysis was implemented so as to determine the most sensitive parameters for model calibration.

Spruill *et al.* (2000) performed a manual sensitivity analysis of 15 SWAT input parameters for a 5.5 km^2 watershed with karst characteristics in Kentucky, which showed that saturated hydraulic conductivity (SOL_K), alpha base flow factor (ALPHA_BF), drainage area (DRAINAGE_AREA), channel length (CH_L), and channel width (CH_WDR) were the most sensitive parameters that affected stream flow. Arnold *et al.* (2000) researched surface runoff, base flow, recharge, and soil ET sensitivity to curve number (CN2), soil available water capacity (SOL_AWC), and soil evaporation coefficient (ESCO) on three different 8-digit watersheds within their upper Mississippi River basin. Lenhart *et al.* (2002) reported on the effects of two different sensitivity analysis schemes using SWAT-G for an artificial watershed, in which an alternative approach of varying 44 parameter values within a fixed percentage of the valid parameter range was compared with the more usual method of varying each initial parameter by the same fixed percentage. Both approaches resulted in similar rankings of parameter sensitivity and thus could be considered equivalent (Gassman *et al.*, 2007). A sensitivity analysis method combining the Latin-Hypercube Simulation (McKay *et al.*, 1979; Iman and Conover, 1980; McKay, 1988; LH for short) and One factor-At-a-Time sensitivity analysis method (Morris, 1991, OAT design for short) was developed by ven Griensven *et al.* (2006) and was applied both in Upper North Bosque River catchment in Texas and the Sandusky River catchment in Ohio. Holvoet *et al.* (2005) used the LH-OAT method to determine the most sensitive input parameters of the 27 SWAT hydrologic-related input parameters for stream flow and atrazine for 32 km^2 Nil watershed in central Belgium. Remegio *et al.* (2007) analysed the sensitivity of the objective functions to changes in parameters in a multi-objective automatic calibration and used a Bayesian network, a graphical model for probabilistic relationships among a set of variables (Lauritzen, 2003; Remegio *et al.*, 2007), to estimate the interdependencies of the SWAT parameters. He pointed out that the interactions of parameters needed to be described in the calibration search. Most of these sensitivity analysis studies are conducted by making a variance to the parameters and analysing the simulation result accordingly. Kannan *et al.* (2007) developed a simple approach that three values (namely low, medium and high) within the appropriate range of each parameter were determined and all different value combinations were considered in the simulations. This approach is quite simple, but the 'appropriate range' is not totally objective and still difficult to be determined in different research regions or periods.

In all of these sensitivity analysis approaches mentioned above, the parameter value bound which determines the maximum and minimum value of the parameter and parameter varying methods are determined quite subjectively. Thus, a full inspection of the influences of this personally determined 'bound' or 'method' to the parameter sensitivity is needed before a convincing sensitivity result is achieved. For the LH-OAT automatic sensitivity analysis method in SWAT 2005 (Arnold and Fohrer, 2005), a configuration related to the parameter bound or varying method is made for the automated sensitivity analysis. This configuration may influence the sensitivity result of the SWAT model. For these concerns, the parameter sensitivity result determined by the LH-OAT method in different configuration scenarios is analysed and the impacts of this configuration on parameter sensitivity are evaluated in this paper.

Theory and Method

The SWAT Model Overview

The SWAT model is a physically based semi-distributed hydrological model developed by Arnold *et al.* (1998) and the latest version is SWAT 2005. In the SWAT model, a watershed is divided into a number of sub-basins which are associated with the river channels. The hydrological cycle of sub-basins is defined based on the following eight aspects, including climate, hydrology, sediment, soil temperature, plant growth, nutrients, pesticides and agriculture management (Arnold, 1998; Arnold and Fohrer, 2005). Each sub-basin is further subdivided into hydrologic response units (HRU) according to the land use and soil type. The HRU is the smallest calculation unit and the SWAT model runs a daily time step simulation on HRU.

LH-OAT Method

The LH (Latin-Hypercube Simulation) sampling method which was first established by McKay *et al.* (1979) and later improved by Iman and Conver (1980) and McKay (1988) is a sampling method based on Monte Carlo simulation but uses a stratified sampling approach. Firstly, the distribution of each parameter is subdivided into N stratums with a probability of occurrence equal to 1/N. Then, the sampling point is randomly generated from these stratums with the precondition that each interval (strata) of each of the P parameters is sampled once. So the SWAT model will run N times for each parameter. The main drawback of this method is assuming that the model output is linearly related to the changes in the parameter values. The OAT method was first established by Morris (1991) and was used as an efficient sensitivity analysis method. In the OAT design, only one parameter is changed at each sampling point, which means this method can unambiguously attribute the output variance to the changed parameter. For a set of P parameters, the model need to run P times to get the model output after each parameter changed at a sampling point, meanwhile an additional model run is needed so as to get the output at the sampling point. So, at each sampling point, the model needs to run P + 1 time to get the local sensitivity of these P parameters.

In the SWAT 2005 model, the LH sampling method an OAT design was combined by van Griensven (2006). For P parameters whose distribution is subdivided into N intervals, the local sensitivity at one sampling point can be combined to that of other sampling points so as to get the global sensitivity of each parameter with N*(P + 1) model runs.

After each model run, the output change is attributed to the change of a single parameter and the local effect at the sampling point of each parameter will be evaluated so as the global sensitivity is conducted after all the model simulations at the N sampling points are completed. Two evaluation procedures that can determine the local effect is described in the LH-OAT module for SWAT 2005. One procedure is to measure the average of the output variable (called OF for short) while the other is to calculate the percentage of time that the output variable is below the predefined threshold (called OUT for short). With each of the two sensitivity procedures, the most sensitive parameter ranks 1, while the least sensitive parameter's rank is equal to the number of the analysed parameters.

Configuration of the LH-OAT Method

The LH-OAT method needs to be configured so as to perform the sensitivity analysis. This configuration includes the method for varying the input parameters, the lower and upper bound of the parameter value, number of the intervals within the parameter distribution, parameter change for the OAT design and the random seed number for generating the sampling points.

In SWAT 2005, three methods are provided for varying the input model parameters. The first method is replacement of initial parameter by value (called Method 1), and the lower and upper bound of each parameter is required for this method. The second method is adding value to initial parameter (called Method 2), and the lower and upper bound of the adding value is required for this method; the third method is multiplying the initial parameter by value (in percentage, called Method 3), and the lower and upper bound of the percentage value is required. Some researchers will probably choose different varying methods which may result in diverse sensitivity rank of parameters, so the influence of varying methods on parameter sensitivity rank should be evaluated.

Meanwhile, the parameter bound which defines the maximum and minimum value of each parameter and the number of the intervals which defines the magnitude of value changes compared to the value at the sampling point are usually undeterminable. Thus, the bound or interval selection may lead to a variety of sensitivity for a single parameter. Furthermore, because the SWAT 2005 is written in FORTRAN language, the random seed number needs to be assigned so as to get a random number between 0 and 1, and this number is used for generating the LH sampling points. With a diversity of random seed numbers, different sets of LH sampling points will be made, and thus this influence on the model parameter sensitivity rank also should be evaluated.

In order to determine the influence of different LH-OAT configuration on the model parameter sensitivity rank, an evaluating index referred to as the Sensitivity Deviation was designed in this paper. For each of the LH-OAT configuration scenario, the sensitivity deviation is calculated as:

$$S_{sd} = \sum_{i=1}^{N_{opt}} (R_i - K_i)^2 / N_{opt} \tag{1}$$

Where S_{sd} refers to the sensitivity deviation, N_{opt} refers to the number of analysed model parameters, R_i refers to the sensitivity rank of the i_{th} model parameter and K_i refers to the sensitivity rank of i_{th} model parameter of the Reference LH-OAT Configuration Scenario, which is configured in Table 1.

	Varying Method	Parameter Bound	Number of Intervals	Parameter Change for OAT	Random Seed Number
Configuration	Method 3	[-50,50]	10	0.5	2003

Table 1 – Configuration of the Reference LH-OAT Configuration Scenario

Application

Study Area Overview

Jiyunhe Basin which is located in northeast of Tianjin, China was chosen as the study area. Jiyunhe River, one of the main tributaries in Haihe Basin, is located in North China and runs from north to south, into the Bohai Sea at the ebb-gate in east coast of Tianjin (Figs 1 and 2). The area of Jiyunhe Basin is 3,300 km^2 and is located at the northeast of the Haihe Basin (Fig 1). The north area of Jiyunhe Basin is mountainous and the south part is a lowland plain dominated by farmland with wheat and corn. Human activities have a strong influence on the watershed. The cropland accounts for more than 70% of the whole area (Fig 3). The average yearly precipitation of Jiyunhe Basin is 538.5 mm (from 1980 to 2005) and average yearly potential evaporation is between 1,000 mm to 1,300 mm in the plain area (including the intermountain basin) and between 850 mm to 1,000 mm in the mountainous area (Sang *et al.*, 2008). There is a gauge station which belongs to Tianjin Water Affairs Bureau and Hydrology Survey Centre at the ebb gate at the estuary of Jiyunhe River (Fig 2).

Construction of the SWAT Model for Jiyunhe Basin

The data needed for the SWAT model includes spatial data, climatic data and management data. The spatial data in the SWAT model for Jiyunhe Basin includes DEM data with 3″ resolution (downloaded from http://srtm.csi.cgiar.org/), 1 : 250,000 scale river network data, 1 : 100,000 scale land use map (Fig 3) and 1 : 1,000,000 scale soil type map obtained from

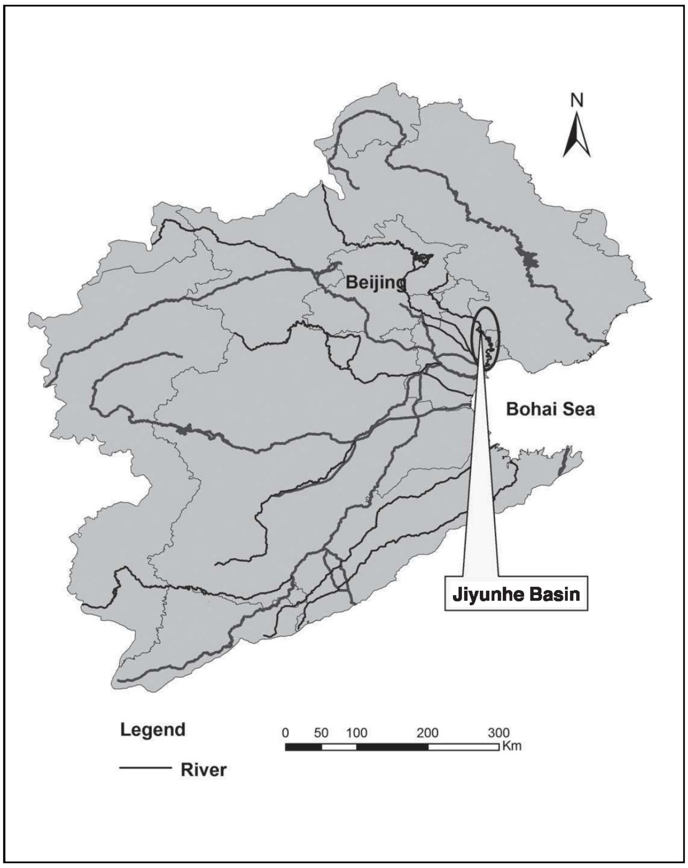

Figure 1 – Location of Jiyunhe in Haihe Basin

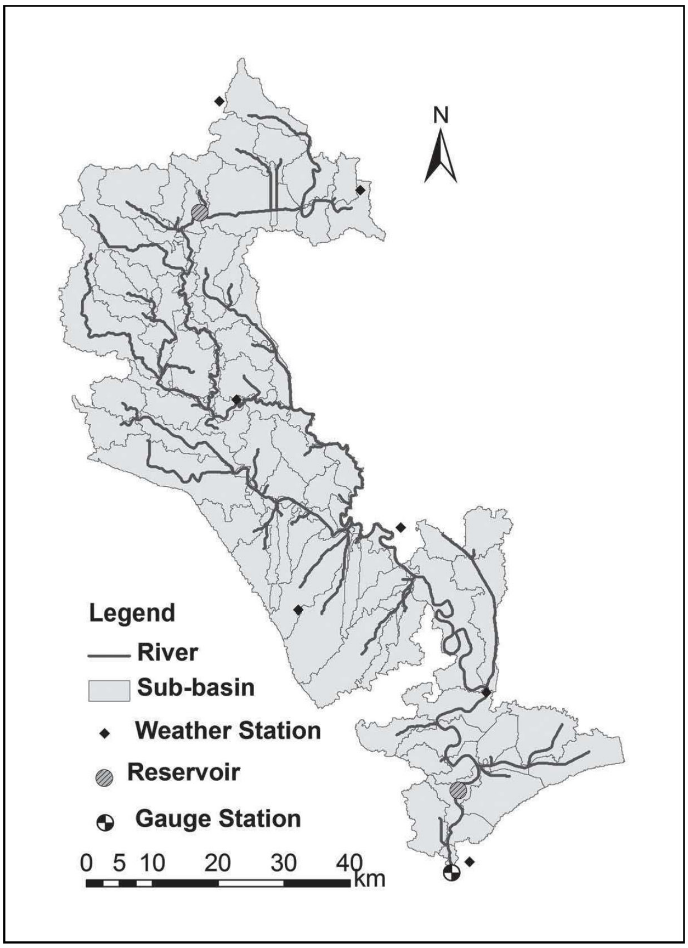

Figure 2 – Maps of Rivers in Jiyunhe Basin

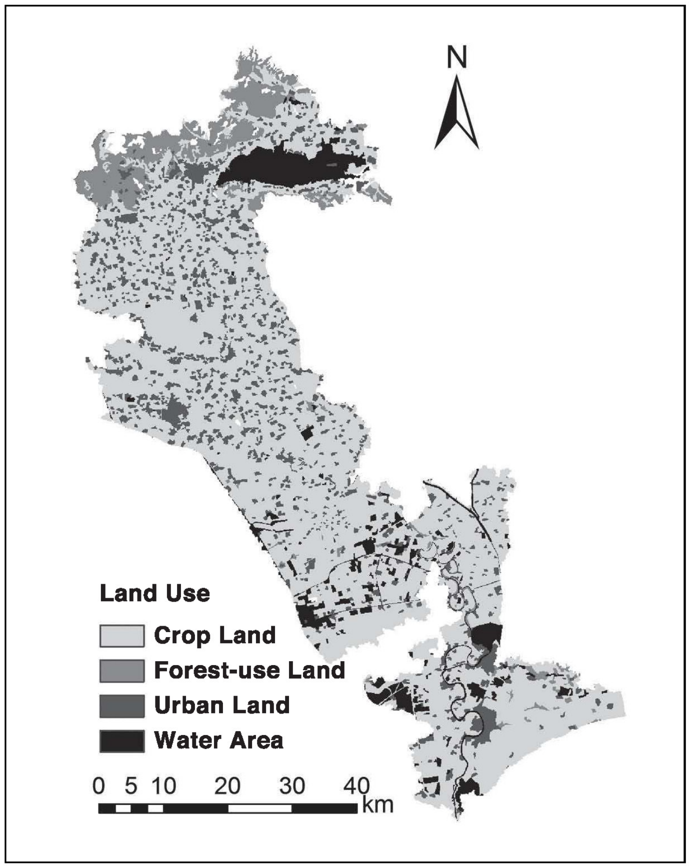

Figure 3 – Land Use Type of Jiyunhe Basin

Tianjin Water Resources Bureau (Sang *et al.,* 2008). The daily weather data (including wind speed, relative humidity, solar radiation, average daily temperature, maximum and minimum temperature during the day) were obtained from ten national weather stations and daily precipitation data were obtained from 26 rainfall stations (Sang *et al.,* 2008). The management data including parameters and management record of reservoirs in the study area and crop management operations (Sang *et al.,* 2008). The monitored daily stream flow data (from 1986 to 1988) at the gauge station is obtained from Tianjin Hydrologic Headquarter (Sang, *et al.,* 2008) for model parameters calibration and sensitivity analysis.

With the thresh hold value of the sub-basin area set as 500 ha (0.05 km^2), the Jiyunhe Basin was divided into 95 sub-basins which were further subdivided into 595 hydrologic response units (HRUs) with 'multiple Hydrological Response Units' configuration. The year of 1985 to 1988 was set as the simulation period while the year of 1985 is the warm up period for the simulation.

Parameters Selection

This approach uses the daily runoff data from 1986 - 1988 at the gauge station for sensitivity analysis, thus only the parameters related to stream flow can be analysed. According to the research of van Griensven, *et al.* (2006), changes of the following 31 hydrological-related parameters (Table 2) can affect the simulated stream flow. The value bound, the parameter definition and related hydrological process of the 31 parameters (van Griensven *et al.,* 2006b) are listed in Table 2.

The area of cropland accounts for 78% of the total area and urban land accounts for 14% of the total area (Fig 3). The nitrogen stress does not exist in the farmland and its impact on plant growth which will further influence the stream flow will only be effective in forest-use land that accounts for less than 10% of the total area. For this reason, the parameters related to nitrogen in the soil (SOL_NO3, NPERCO) are not discussed in this paper. The rest 29 parameters are analysed in the proposed scenarios. These parameters are set within their proper ranges, and when the Method 3 is applied, attention has been taken to ensure

Name	Min	Max	Definition	Process
ALPHA_BF*	0	0.95	Baseflow Alpha Factor (Days)	Groundwater
BIOMIX*	0	0.95	Biological Mixing Efficiency	Soil
CH_N*	0.01	0.6	Manning Coefficient for Channel	Channel
CN2*	20	95	SCS Runoff Curve Number for Moisture Condition II	Runoff
EPCO*	0	0.95	Plant Evaporation Compensation Factor	Evaporation
ESCO*	0	0.95	Soil Evaporation Compensation Factor	Evaporation
GW_DELAY*	0	100	Groundwater Delay (Days)	Groundwater
GW_REVAP*	0	0.6	Groundwater 'Revap' Coefficient	Groundwater
RCHRG_DP*	0	0.95	Groundwater Recharge to Deep Aquifer (Fraction)	Groundwater
REVAPMN*	0	500	Threshold Depth of Water in the Shallow Aquifer for 'Revap' to Occur (mm)	Groundwater
SLOPE*	0	0.1	Average Slope Steepness (m/m)	Geomorphology
SLSUBBSN*	0	500	Average Slope Length (m)	Geomorphology
SOL_ALB*	0	0.5	Soil Albedo	Evaporation
SOL_AWC*	0	0.5	Available Water Capacity of the Soil Layer (mm/mm Soil)	Soil
SOL_K*	0	1,000	Soil Conductivity (mm/h)	Soil
SOL_Z*	0	2,000	Soil Depth (mm)	Soil
NPERCO[a]			Nitrogen Percolation Coefficient	Soil
SOL_NO3[a]	0	5	Initial NO_3 Concentration (mg/kg) in the Soil Layer	Soil
GWQMN[b]	0	5,000	Threshold Depth of Water in the Shallow Aquifer Required for Return Flow to Occur (mm)	Groundwater
SMFMX[b]	0	10	Maximum Melt Rate for Snow during the Year (mm/°C/Day)	Snow
SMFMN[b]	0	10	Minimum Melt Rate for Snow during the Year (Occurs on Winter Solstice) (mm/°C /Day)	Snow
SFTMP[b]	0	5	Snowfall Temperature (°C)	Snow
SMTMP[b]	0	5	Snow Melt Base Temperature (°C)	Snow
TIMP[b]	0.01	1	Snow Pack Temperature Lag Factor	Snow
BLAI[b]	0	0.95	Leaf are Index for Crop	Crop
CANMX[b]	0.01	0.6	Maximum Canopy Index	Channel
CH_COV[b]	0.001	0.95	Channel Cover Factor	Erosion
CH_EROD[b]	0	0.95	Channel Erodibility Factor	Erosion
TLAPS[b]	0	50	Temperature Laps Rate (°C/km)	Geomorphology
SURLAG[b]	0	10	Surface Runoff Lag Coefficient	Runoff
USLE_P[b]	0.1	1	USLE Equation Support Practice (P) Factor	Erosion

* The sensitive parameters, their variation can change the simulated flow
a These parameters are not discussed according to dominant land type in the area
b These parameters show no sensitivity in this study

Table 2 – Parameters and the Value Bound of the Parameters Used in Sensitivity Analysis

the initial value of each parameter is not zero. With further study, the parameters with superscript of 'b' in Table 2 show no sensitivity in this study at all. Thus, only the rest 16 sensitive parameters (Table 2) are discussed in this paper.

Results and Discussion

Influence of the Varying Method of the Model Parameters

In this section, three varying methods are used in the scenarios respectively. The random seed number, the number of intervals and parameters' bound for OAT design are identical to that in the reference configuration scenario. In the Method 1 and Method 2 scenarios, the parameter distribution is same as that in Table 2, and with Method 3, the parameter distribution is same as that in the reference configuration scenario. The sensitivity rank of the 16 sensitive model parameters determined by average of the output variable (OUT) procedure is shown in Fig 4. The sensitivity rank for a single parameter shows evident differences among the three varying methods, and the sensitivity ranks of six parameters (ESCO, GW_DELAY, CH_N, SLSUBBSN, RCHRG_DP, REVAPMN) change more than 5 and the sensitivity rank of soil evaporation compensation factor (ESCO) changes from 2 in Method 3 scenario to 14 in Method 1 scenario.

As the parameters' boundaries are different and the variations of these parameters change from 0.95 to 500, and the same numerical change may cause different impacts on two parameters. For example, a numerical variation of 0.05 to the parameter of SLSUBBSN with Method 1 or Method 2 may have little impact on this parameter and the stream flow, because

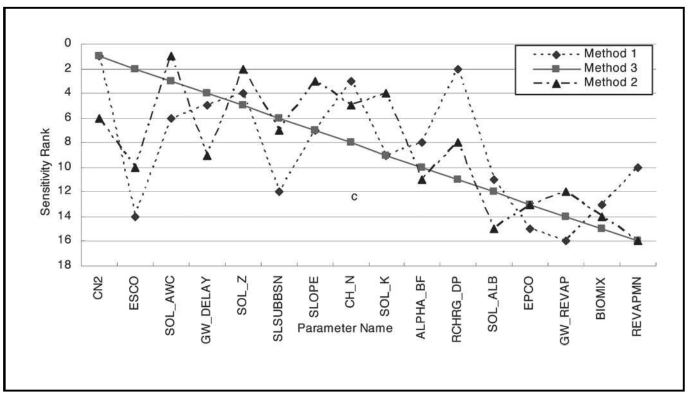

Figure 4 – Sensitivity Rank of 16 Hydrological-related Parameters Based on Three Varying Methods

the value of SLSUBBSN is several hundred larger than 0.05. Conversely, this numerical reduction of 0.05 will cut at least 50% off the parameter of SLOPE and make a considerable impact on the stream flow. Thus, the SLOPE exhibits stronger sensitivity in Method 2 scenario than that in Method 3 scenario. This can also explain that the sensitivity ranks of SOL_AWC, CH_N, RCHRG_DP, GW_REVAP and BIOMIX in Method 2 scenario are higher than those in Method 3 scenario. Meanwhile, a spatial distribution of some parameters should be considered. Only the percentage varying method (Method 3) can keep the spatial relationship among the distributed parameters (such as SOL_AWC) while the other two methods may lead to improper parameter value and sensitivity rank. Thus, considering the variations of these parameters are of different magnitudes and the spatial relationship of some parameters, the varying method in LH-OAT configuration has considerable influences on model parameter sensitivity.

Influence of Model Parameter Bound

The model parameter bounds are changed in this scenario set and the other configurations are kept the same as that in the reference configuration scenario. Here, the sensitivity rank of the 16 sensitive hydrological-related parameters is shown in Fig 5, with model parameter bounds set as [-50, 50], [-25, 25] and [-100,100] respectively. In Fig 5, the parameter sensitivity rank changes a little with different parameter bounds, the sensitivity rank of most parameters changes less than 5, except soil depth (SOL_Z) whose sensitivity rank changes from a ranking of 7 with the bound set as [-25,25] to 1 with the bound set as [-100,100].

Because the parameter bound is limited within a defined proper range (Table 2), the same percentage changes of the parameter have relatively same influence on the parameter value in the three scenarios. For those parameters who have linear relationship with the stream flow, such as SOL_AWC, SLSUBBSN, GW_REVAP, the sensitivity rank keep consistently if the values parameters are kept in reasonable ranges. The small variations of sensitivity rank of some parameters are caused by the nonlinearly relationship between the parameter changes and the stream flow variation, and the flaw of the LH-OAT method is consistently

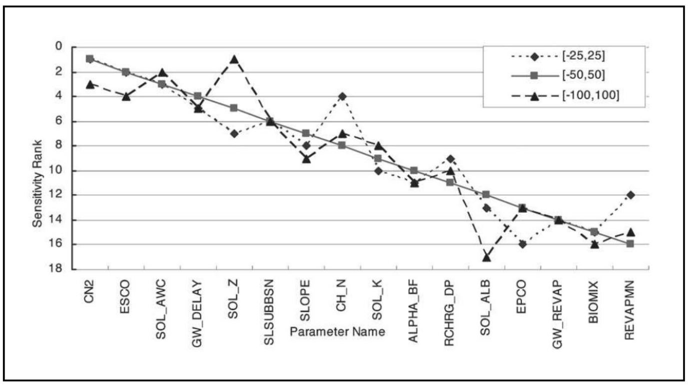

Figure 5 – Sensitivity Rank of 16 Hydrological-related Parameters Based on Three Sets of Parameter Bounds

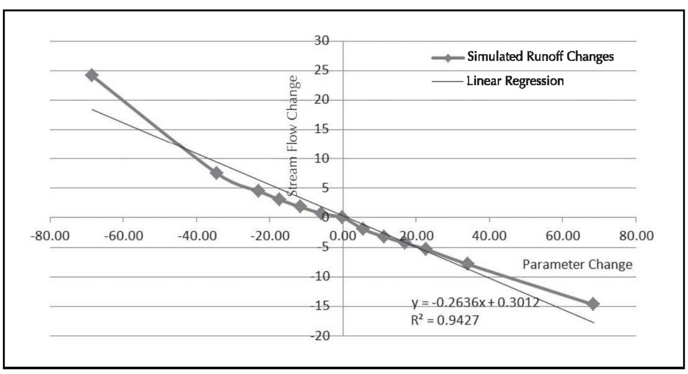

Figure 6 – The Relation between Stream Flow Changes and SOL_AWC Value Changes

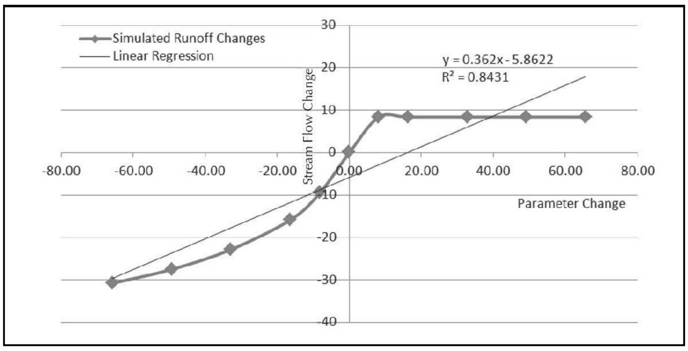

Figure 7 – The Relation between Stream Flow Changes and ESCO Value Changes

attributing the output changes linearly to the changes of input (van Griensven, A, 2006).

To demonstrate the relationship between the stream flow changes and the parameter changes, a single parameter value is changed in a series of model runs. The relationships between stream flow changes and parameter (SOL_AWC and ESCO) changes are shown in Figs 6 and 7 where the changes are expressed as the percentage of the initial value. The initial parameter value is the calibrated parameter value while the initial stream flow value is the value from the result calculated by calibrated model (details of the calibration are discussed in the end of this section). It shows that the stream flow changes are apparently linearly related to the SOL_AWC value changes in Fig 6 while the relationship between the stream flow changes and ESCO value changes exhibits poor linearity in Fig 7.

Still, as the sensitivity rank variation is not so evidently, the parameter bound in LH-OAT configuration has relatively small influence on model parameter sensitivity.

Influence of Number of Intervals within the Parameter Value Distribution

The number of intervals within the model parameter distribution are changed in this scenarios set while the other configurations are same as that in the reference configuration scenario. The sensitivity rank of the 16 sensitive hydrological-related parameters is shown in Fig 8, with the number of intervals within model parameter distribution set as 20, 10, and 5 respectively. In Fig 8, the sensitivity rank variances of all the 16 parameters with the three sets of interval numbers are within 3 except the GW_DELAY and CH_N whose sensitivity rank of different interval numbers changed more than 4.

In Method 3, the number of intervals will influence the magnitude of change to each parameter. The disparity of sensitivity rank for individual parameter in the three scenarios is caused by the nonlinear relationship between the changes of parameters and the changes of the stream flow. Compared to the influences of the varying methods, the number of intervals of model parameters in LH-OAT configuration has less influence on model parameter sensitivity.

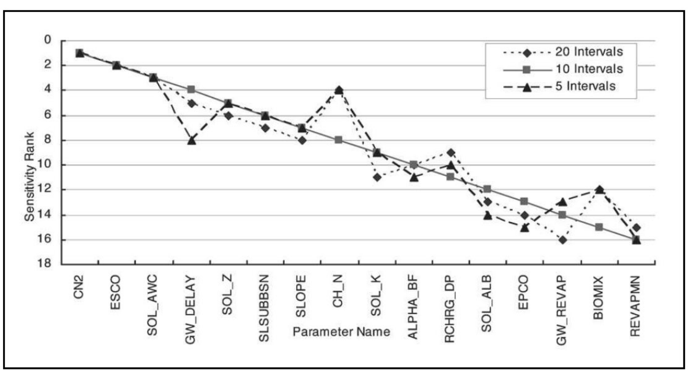

Figure 8 – Sensitivity Rank of 16 Hydrological-related Parameters Based on Three Sets of Interval Numbers

Influence of Random Seed Number

The random seed numbers are changed within the scenarios set while the other configurations are same as that in the reference configuration scenario. The sensitivity rank of the 16 sensitive hydrological-related parameters is shown in Fig 9, with the random seed number set as 2003, 1503, 1003, 503 and 3 respectively. In Fig 9, the sensitivity rank exhibits evident inconsistency among different random seed number scenarios, and there are five parameters whose sensitivity ranks change more than 5.

The random seed number determines the changes of parameters based on the sampling points in Method 3 scenarios. A small random seed number leads to a new parameter value close to the sampling point while a big random seed number leads to a new parameter value far from the sampling point. The disparity of sensitivity rank for individual parameter can be attributed to nonlinearity between the parameter changes and the output changes. The random seed number in LH-OAT configuration shows great influence on model parameter sensitivity.

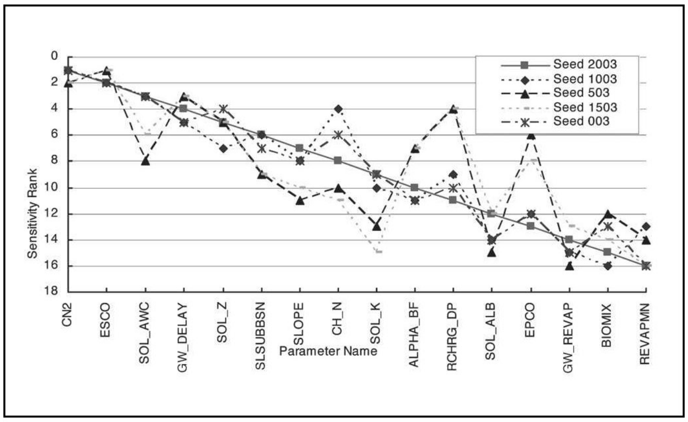

Figure 9 – Sensitivity Rank of 16 Hydrological-related Parameters Based on Five Sets of Random Seed Numbers

Sensitivity Deviation with Different LH-OAT Configuration Scenarios

In order to describe the influence of LH-OAT configuration on the model parameter sensitivity directly, the sensitivity deviation of each LH-OAT configuration scenario constructed above are calculated in this section, and the value of sensitivity deviation in each scenario are listed in Table 3. The sensitivity deviation in Table 3 is determined by both of the sensitivity determining procedures.

In Table 3, all the sensitivity deviations with Method 1 and Method 2 varying method are larger than that of other scenarios, which means the varying method has the greatest influence on model parameter sensitivity. A proper varying method should be assigned to each parameter according to the physical conception of the parameter.

The sensitivity deviations in some scenarios with different random seed numbers are equal to or larger than 10 which mean that the random seed number influences the model parameter sensitivity strongly. There are no convincing explanations for this result in this research and further study is required.

Conversely, the sensitivity deviations of scenarios of different parameter bound or number of intervals within the parameter distribution is less than 4 which means that these LH-OAT configuration values have less influences on the model parameter sensitivity than the varying method or the random seed number does. But considering the parameters' applicable bound in reality, the sensitivity analysis should keep the value within a proper range based on experimental data or investigation.

The sensitivity deviation determined by the OUT determining procedure is mostly smaller than that determined by OF procedure. Both procedures refer to the criteria of sensitivity, and the OUT procedure is suggested to be more robust than the OF procedure.

Scenario	Ssd (Determined by OF)	Ssd (Determined by OUT)
Reference Scenario	0	0
Method 1	21.875	21.125
Method 2	12.625	15.75
Bound [-25,25]	3.375	2.75
Bound [-100,100]	3.8125	3.3125
5 Intervals	3.25	1.25
20 Intervals	2.75	2
Seed 3	1.25	0.625
Seed 503	12.875	2.25
Seed 1003	2.75	6.5
Seed 1503	10.00	0.875

Table 3 – Sensitivity Deviation of Different LH-OAT Configuration Scenarios

Calibration and Validation after Sensitivity Analysis

Considering the sensitivity disparity of the analysed parameters and no convincing reason for eliminating some less sensitive parameters, all the 16 parameters are selected for model calibration which applies the SCE auto-calibration method (van Griensven *et al.,* 2006). The stream flow data measured at the gauge station from the year of 1986 - 1987 is used for calibration and the data in the year of 1988 is used for validation. The Nash-Sutcliffe Efficiency coefficient (NSE), Correlation Coefficient (R^2) and Percent Bias (PBIAS) are used to evaluate the calibration performance (Table 4). Because there are some observed peak runoff events that the model does not present during the calibration period and validation period, the values of NSE and R^2 in Table 4 are a little low. The main reason for this poor performance is that some upstream reservoir discharge events are not recorded. According to investigation on precipitation data, there was no precipitation on these days or ten days before or after these 'inconsistent days' (such as 28 March 1986, 1 April 1986, 15 October 1987, 16 October 1987, 9 November 1987). The measured sudden increased stream flow on those days (Fig 10) is caused by the unrecorded reservoir discharge and the model was not able to take this discharge into consideration for lacking of exact information. Additional information of reservoir discharge operation is required for a better simulation. Conversely, if the sudden stream flows on those days were set same as the simulated value, the NSE for the calibration period and validation period would increase to 0.53 and 0.74 respectively. Generally, this stream flow simulation is quite reasonable and those parameters determined by sensitivity analysis are applicable for model calibration.

	Calibration Period			Validation Period		
Criteria Name	NSE	R^2	PBIAS	NSE	R^2	PBIAS
Value	0.47	0.68	6.8%	0.48	0.69	10.6%

Table 4 – Performance Evaluation of the Auto-calibration with the 16 Parameters

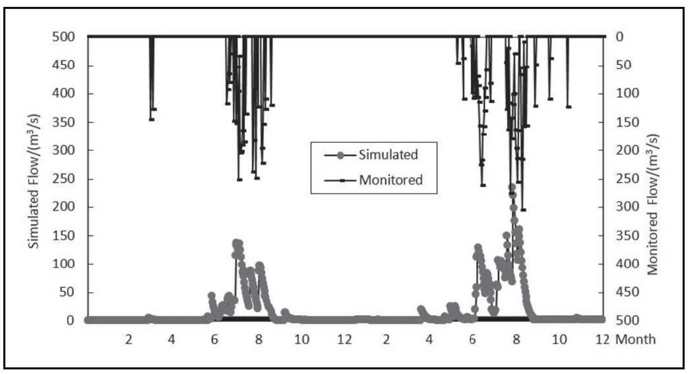

Figure 10 – Daily Stream Flow during the Calibration Period (1986 - 1987)

Conclusion

In this paper, the influences of LH-OAT configuration on SWAT model parameter sensitivity rank has been studied, and more work needs to be done for a systematic evaluation of this LH-OAT sensitivity analysis method. Though the LH-OAT sensitivity analysis method of SWAT 2005 is quite efficient, the parameter varying method and the random seed number has great influences on the parameter sensitivity and these factors should be considered when performing sensitivity analysis. The nonlinearity of the relationship between the output changes and the parameter changes, the spatial distribution of the parameters and the bound inconsistency are the main causes of the sensitivity disparity.

In the future, a proper varying method should be selected according to the parameter's physical meaning and a reasonable parameter bound should be predefined to eliminate the uncertainty of sensitivity. Furthermore, a series of tests should be taken so as to determine the most sensitive parameters from all the scenarios.

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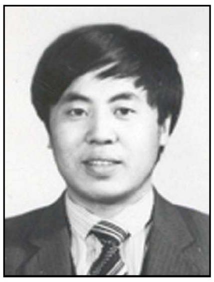

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