Hydrol. Earth Syst. Sci. Discuss., 10, 2243–2286, 2013
www.hydrol-earth-syst-sci-discuss.net/10/2243/2013/
doi:10.5194/hessd-10-2243-2013

Hydrology and Earth System Sciences
Open Access
Discussions

Assessing parameter importance of the Common Land Model based on qualitative and quantitative sensitivity analysis

J. D. Li[1], Q. Y. Duan[1], W. Gong[1], A. Z. Ye[1], Y. J. Dai[1], C. Y. Miao[1], Z. H. Di[1], C. Tong[2], and Y. W. Sun[2]

[1]College of Global Change and Earth System Science (GCESS), Beijing Normal University, Beijing, 100875, China
[2]Lawrence Livermore National Laboratory, Livermore, CA 94551, USA

Received: 27 December 2012 – Accepted: 24 January 2013 – Published: 21 February 2013

Correspondence to: Q. Y. Duan (qyduan@bnu.edu.cn), J. D. Li (lijianduo@mail.bnu.edu.cn)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Proper specification of model parameters is critical to the performance of land surface models (LSMs). Due to high dimensionality and parameter interaction, estimating parameters of a LSM is a challenging task. Sensitivity analysis (SA) is a tool that can screen out the most influential parameters on model outputs. In this study, we conducted parameter screening for six output fluxes for the Common Land Model: sensible heat, latent heat, upward longwave radiation, net radiation, soil temperature and soil moisture. A total of 40 adjustable parameters were considered. Five qualitative SA methods, including local, sum-of-trees, multivariate adaptive regression splines, delta test and Morris methods, were compared. The proper sampling design and sufficient sample size necessary to effectively screen out the sensitive parameters were examined. We found that there are 2–8 sensitive parameters, depending on the output type, and about 400 samples are adequate to reliably identify the most sensitive parameters. We also employed a revised Sobol' sensitivity method to quantify the importance of all parameters. The total effects of the parameters were used to assess the contribution of each parameter to the total variances of the model outputs. The results confirmed that global SA methods can generally identify the most sensitive parameters effectively, while local SA methods result in type I errors (i.e. sensitive parameters labeled as insensitive) or type II errors (i.e. insensitive parameters labeled as sensitive). Finally, we evaluated and confirmed the screening results for their consistence with the physical interpretation of the model parameters.

1 Introduction

Land surface model (LSM) is an integral component of any numerical weather prediction (NWP) and climate models. The ability of a LSM to represent the land surface processes accurately and reliably depends on several factors (Duan et al., 2006). The first factor is the authenticity of the model structure (e.g. the equations or parameterization schemes of the model). The second is the quality of external forcing data and the initial and boundary conditions. The third is the appropriateness of model parameter specification. How to estimate model parameters has received increasing attention from the hydrology and land surface modeling community over the recent years (Franks and Beven, 1997; Gupta et al., 1999; Duan et al., 2001, 2003; Jackson et al., 2003; Liu et al., 2004; Hou et al., 2012).

In traditional hydrological modeling, model parameters are often estimated through model calibration, i.e. a process of matching model simulation with observation by tuning model parameters. However, calibrating the parameters of complicated LSMs is a challenging task because of high dimensionality and nonlinear parameter interaction. With water, energy and, in some cases, carbon and nitrogen cycles being considered concurrently, a typical LSM usually has a large number of adjustable parameters (from 10s to 100s) that govern the model equations. Typically $10^5 \sim 10^6$ or even more model runs are required to calibrate a high-dimensional (> 10) model (Vrugt et al., 2008; Deb et al., 2002). To compound the problem, running a LSM at a large spatiotemporal scale can be very time-consuming, making traditional parameter calibration methods (e.g. genetic algorithm (GA) (Goldberg, 1989) and shuffled complex evolution method, Duan et al., 1993) impractical.

For the reasons above, we need to reduce the dimensionality by identifying which parameters have the most influences on model performance. Sensitivity analysis (SA) is a family of methods that are designed to identify the most sensitive (namely, influential) parameters from the insensitive ones (Saltelliet al., 2004). A good SA method is able to screen out the most sensitive parameters in a relative low number of model runs (Tong and Graziani, 2008).

There are two types of SA methods: qualitative and quantitative. Qualitative methods tell if a parameter is sensitive or not, while quantitative methods tell how sensitive the parameter is by computing the impact of the parameter on the total variance of model output. Qualitative methods usually need fewer model runs (hundreds or fewer) while quantitative methods require a large number of model runs (tens of thousands or even

more). In recent decades, SA methods have been applied to practical problems in many fields (Campolongo and Saltelli, 1997; De Pauw et al., 2008; Yamwong and Achalakul, 2011). For hydrological and land surface models, Collins and Avissar (1994) employed the Fourier amplitude sensitivity test (FAST) to evaluate the parameter importance to the sensible heat and latent heat in LAID land surface scheme. Bastidas et al. (1999) proposed the Multi-Objective Generalized Sensitivity Analysis (MOGSA) method and screened out 18 sensitive parameters from a total of 25 parameters in BATS model. It was demonstrated that the degradation in the quality of the calibrated model performance is negligible if the insensitive parameters were not calibrated. Tang et al. (2007) applied local and global SA methods on the lumped Sacramento soil moisture accounting model (SAC-SMA). They aimed to identify sensitivity tools that will advance the understanding of lumped hydrologic models. The relative efficiency and effectiveness of several SA methods have been analyzed and compared. Hou et al. (2012) introduced an uncertainty quantification framework to analyze the sensitivity of 10 hydrologic parameters in CLM4-SP with generalized linear model (GLM) method. They found that the simulation of sensible heat and latent heat is sensitive to subsurface runoff generation parameters. In the aforementioned work, many SA methods have shown their effectiveness in screening out important parameters. However, for large complex dynamic system models which are expensive to run, we need to be able to screen out important parameters with as fewer model runs as possible. Therefore, the goal of this study is to investigate the effectiveness and efficiency of different qualitative SA methods for parameter screening.

Several SA methods were used to evaluate the importance of 40 adjustable parameters in the Common Land Model (CoLM). The work has two objectives: (1) to test and compare different qualitative SA methods for separating sensitive parameters from insensitive ones; (2) to validate the screening results using a quantitative SA method. Towards these objectives, this study first screened out the sensitive parameters qualitatively with a small amount of samples, and then quantified the sensitivity of all parameters using a quantitative SA method.

The paper is organized as follows. Section 2 presents a brief introduction of the qualitative SA methods for parameter screening and the quantitative SA method for computing the parameter importance. Section 3 introduces the model used, CoLM, and its adjustable parameters. The study area, the forcing and validation data, and the design of sensitivity study are also described. Section 4 presents the results and discusses the performance of qualitative and quantitative SA methods. The physical interpretations of the screening results are also examined. Section 5 provides the conclusions.

2 Methods

This study employed five qualitative SA methods to do parameter screening: local method (Turanyi, 1990; Capaldo and Pandis, 1997), sum-of-trees (SOT) (Breiman, 2001; Chipman et al., 2010), multivariate adaptive regression splines (MARS) (Friedman, 1991), delta test (DT) (Pi and Peterson, 1994) and Morris method (Morris, 1991). Moreover, to validate the parameter screening results obtained by qualitative methods, the revised Sobol' method (Sobol', 1993, 2001), was applied to compute the total effects of parameters. Below, we provide a brief description of these methods. For detailed descriptions, please refer to related literature.

2.1 Local method

Local method is a derivative-based sensitivity method. The sensitivity of variable $x_i \in [a_i, b_i]$ is computed as the normalized local sensitivity scaled by the variable range: $s_i = \frac{1}{(b_i - a_i)} \frac{\partial y}{\partial x_i}\big|_{x_i = \alpha_i}$, where s_i is the local sensitivity measure, α_i is a value of x_i at which the sensitivity is evaluated, a_i and b_i are the lower and upper bounds of x_i. The variable with a high s_i value is considered to have a high impact on the model output. Obviously the value of s_i is dependent on location α_i.

2.2 Sum-of-trees (SOT) method

The SOT method is a tree-based method. A single regression tree model is a step function, which is obtained by recursively partitioning the data space and fitting a simple prediction model (generally, the average value) within each partition (Breiman et al., 1984). In the process of recursively partitioning, the variables are split to cause maximum decrease in impurity function (residual sum of squares) until the impurity function falls below a threshold. The SOT model uses a certain number of bootstrapped samples to build independent regression trees and averages them (Breiman, 2001). The total number of splits for each variable in the model stands for the importance of this variable, i.e. the variable with the most splits in the model is considered to be the most important one.

2.3 Multivariate adaptive regression splines (MARS) method

The MARS method is an extension of regression tree method. After recursively partitioning the data space, it builds localized regression models (first-order linear or second-order nonlinear) instead of step functions. Therefore, this method can produce continuous models with continuous derivatives and has better fitting ability (Friedman, 1991). This method includes a forward procedure and a backward procedure. The forward procedure builds an over-fitted model by considering all variables, while the backward procedure prunes the over-fitted model by removing one variable at a time. For each model, a generalized cross-validation (GCV) score can be computed:

$$\mathrm{GCV}(M) = \frac{1}{N} \frac{\sum_{i=1}^{N} \left(Y_i - \hat{Y}\right)^2}{\left[1 - \frac{C(M)}{N}\right]^2} \tag{1}$$

where $C(M) = 1 + c(M)d$, N is the number of observations, d is the effective degrees of freedom, and $c(M)$ is a penalty for adding a basic function.

To screen out the important variables, the increase in GCV values between the pruned model and the over-fitted model is considered as the importance measure of the removed variable (Steinberg et al., 1999). The larger the GCV increase, the more important is the removed variable.

2.4 Delta test (DT) method

DT method is a variable selection method based on the nearest neighbor approach. Let $Y = F(\boldsymbol{X}) = F(X_1, \cdots, X_m) + \boldsymbol{\varepsilon}$, where the noise $\boldsymbol{\varepsilon} = (\varepsilon_1, \cdots, \varepsilon_m)$, $\varepsilon_i (i = 1, \cdots, m)$ is independent identically distributed random variable with zero mean. The DT criterion of a variable subset $S \subseteq \{X_1, \cdots, X_m\}$, $\delta(S)$, can be computed as:

$$\delta(S) = \frac{1}{2N} \sum_{i=1}^{N} \left(Y_{N_S(i)} - Y_i \right)^2 \tag{2}$$

where $N_S(i) = \arg\min_{k \neq i} \| X^i - X^k \|_S^2$ represents the nearest neighbors of the input point X^i, Y_i is the function value corresponding to X^i, and N is the sample size. $\delta(S)$ is an estimate of the variance of the residual (converges to the true residual in the limit $N \to \infty$) when only the variables in S are selected for regression. It has been demonstrated that either adding the unrelated variables or omitting the related ones will increase the δ value (Eirola et al., 2008). Therefore, the variable subset S with the smallest DT criterion corresponds to the most important subset of variables, i.e. the most sensitive parameters.

For high dimensional problems, it is impractical to compute all possible combinations of variable subsets (e.g. for 40 variables, the total configuration of subsets is $2^{40} - 1$). Therefore, to speed up the search for the variable subset with a minimum $\delta(S)$, search algorithms such as GA are often used (Guillen et al., 2008). Thus, the reliability of DT

results depends on the effectiveness of the search algorithm applied.

2.5 Morris method

Morris method is a gradient-based SA method using an individually randomized Morris one-factor-at-a-time (MOAT) design (Morris, 1991). This study employed an enhanced Morris method (Campolongo et al., 2007). Consider a model with k independent inputs X_i $(i = 1, \cdots, k)$ whose ranges are normalized to [0, 1]. The experimentation region Ω is a discrete k-dimensional p-level grid. For a given value of point $\boldsymbol{X}^0 = (x_1, x_2, \cdots, x_k)$, the elementary effect of variable X_j is defined as

$$d_j = \frac{f\left(x_1, \cdots, x_j + \Delta, \cdots, x_k\right) - f(x_1, \cdots, x_j, \cdots, x_k)}{\Delta}, \tag{3}$$

where Δ is a value in $1/p-1, \cdots, p-2/p-1$. The sampling strategy generates a random starting point for each trajectory and then completing it by perturbing one input variable by $+\Delta$ or $-\Delta$ at a time in a random order. At the end of process, a trajectory spanning $k+1$ points is evaluated to compute the elementary effects for all k input variables. After repeating this procedure r times to construct r trajectories of $k+1$ points in the input space, the total cost of the experiment is thus $r \times (k+1)$. The mean of $|d_j|$, μ_j, and the standard deviation of d_j, σ_j, can be construed as the sensitivity indices of input variable X_j:

$$\mu_j = \sum_{i=1}^{r} |d_j(i)| \Big/ r, \quad \text{and} \quad \sigma_j = \sqrt{\sum_{i=1}^{r} \left(d_j(i) - \frac{\sum_1^r d_j(i)}{r} \right)^2 \Big/ r} \tag{4}$$

where μ_j assesses the overall influence of X_j on the output, while σ_j estimates the higher order effects (i.e. effects due to interactions) of X_j.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

2.6 Sobol' method

Sobol' method (Sobol', 1993) is a quantitative SA method based on the variance decomposition theory, which decomposes the variance of the output as $V = \sum_{i=1}^{n} V_i + \sum_{1\le i<j\le n} V_{ij} + \cdots + V_{1,2\cdots,n}$, where n denotes the total number of parameters. The Sobol' sensitivity index is defined as $S_{i_1,\cdots,i_s} = V_{i_1,\cdots,i_s}/V$, where $V_{i_1,\cdots,i_s}$ denotes the variance corresponding to $(i_1,\cdots,i_s)$, the integer s is called the order or the dimension of the index. All the values of $S_{i_1,\cdots,i_s}$ are nonnegative, and their sum is

$$\sum_{i=1}^{n} S_i + \sum_{1\le i<j\le n} S_{ij} + \cdots + S_{1,2\cdots,n} = 1 \tag{5}$$

where $S_i = V_i/V$ is the main effect (first order effect) of the ith variable, $S_{ij} = V_{ij}/V$ is the interaction effect (second order effect) of the ith and jth variables (Sobol', 2001). The total effect of the ith variable can be obtained by Eq. (6), where V_{-i} is the variance without considering the i-th variable (Homma and Saltelli, 1996).

$$S_{T_i} = 1 - \frac{V_{-i}}{V} \tag{6}$$

The total effect reflects the variable's contribution to the variance of model output. The values of those indices for important variables are generally much higher than those for unimportant ones.

The Sobol' method can provide reliable quantitative sensitivity information of the input variables. However, for a high dimensional problem, it needs a large number of samples (10^4 to 10^5 or more). If a small sample size is used, the estimates of the total effects vary greatly around the analytical values, and at times can take on unphysical negative values (Saltelli et al., 2000). To avoid unphysical variance values and to reduce the need for extremely large sample size, we carried out Sobol' analysis on the response surface model instead of the original model. The effectiveness of respond

surface model based Sobol' method (RSMSobol) has been demonstrated by Iooss et al. (2006) and Storlie et al. (2009).

To assess the importance of parameter P(i), we computed the relative values of the total effects of parameter P(i):

$$C(i) = S_{T_i} \Big/ \sum_{k=1}^{n} S_{T_k} \tag{7}$$

The cumulative importance of a subset of parameters, A, can be computed as

$$\tilde{C}(A) = \sum_{A} C(i) \tag{8}$$

3 Experimental setup

3.1 CoLM and adjustable parameters

CoLM (Dai et al., 2003) is a widely used land surface model. It combines the advantages of three existing land surface models: Land Surface Model (LSM) (Bonan, 1995), biosphere-atmosphere transfer scheme (BATS) (Dickinson et al., 1993) and Institute of Atmospheric Physics land-surface model (IAP94) (Dai and Zeng, 1997). In recent years, it has incorporated different physical processes such as glacier, lake, wetland and dynamic vegetation. It has also been successfully implemented in several global atmospheric models (Yuan and Liang, 2010).

CoLM considers the biophysical, biochemical, ecological and hydrological processes. The energy and water transmission among soil, vegetation, snow and atmosphere is well described. The model contains one vegetation layer, 10 unevenly distributed vertical soil layers, and up to 5 snow layers (depending on the snow depth). The parameterization scheme of soil thermal and hydraulic properties are derived from Farouki (1986), Clapp et al. (1978) and Cosby et al. (1984). The parameterization scheme of snow is synthesized from Anderson (1976), Jordan (1991) and Dai et al. (1997).

In this study, forty of time-invariant coefficients and exponents in CoLM, known as model parameters, are chosen as parameters that can be adjusted according to local conditions. Their physical meanings and value ranges are shown in Table 1. The adjustable parameters can be classified into 3 categories: canopy, soil and snow. The default parameters of canopy depend on the vegetation type in the 24-category (USGS) vegetation dataset. Soil parameters depend on the soil texture in 17-category (FAO-STATSGO) soil dataset. Snow parameters depend on the snow depth. In this paper, the parameter range is the lower and upper bound among all the possible types of canopy, soil and snow types (Ji and Dai, 2010). For convenience, these parameters are indexed from P1 to P40.

This study screens sensitive parameters for 6 land surface fluxes: sensible heat, latent heat, upward longwave radiation, net radiation, soil temperature and soil moisture. The objective function is the root-mean squared error normalized by the geometric mean (Parada et al., 2003):

$$\mathrm{RMSE}_i = \frac{\sqrt{\sum_{j=1}^{N}\left(y_{i,j}^{\mathrm{sim}} - y_{i,j}^{\mathrm{obs}}\right)^2}}{\sqrt{\sum_{j=1}^{N}\left(y_{i,j}^{\mathrm{obs}}\right)^2}} \tag{9}$$

where N is the number of observations, j indexes the time step, $y_{i,j}^{\mathrm{sim}}$ and $y_{i,j}^{\mathrm{obs}}$ are the simulated and observed values, i ranges from 1 to 6 standing for different flux types, respectively. All the objective functions and their descriptions are shown in Table 2. Objective function represents the performance of simulation, so a smaller RMSE means a better performance.

3.2 Study area and datasets

The study area is the A'rou observation station, which is located at the upstream of Heihe River basin in China. The geographic coordinate of A'rou is 100°28′ E, 30°08′ N (see Fig. 1), the altitude is 3032.8 m a.s.l. It belongs to the typical continental climate. The underlying surface type is alpine steppe.

The forcing data of CoLM is shown in Table 3, including downward shortwave and longwave radiation, precipitation, air temperature, relative humidity, air pressure and wind speed (Hu et al., 2008). The validation data contains observations of 6 fluxes (see Table 4). These 6 fluxes are all important physical quantities between land surface and atmosphere. The soil temperature and moisture data are available at the depth of 10 cm, 20 cm, 40 cm and 80 cm, while the soil column in CoLM is divided into 10 layers (the depths are shown in Table 5). We used the linear interpolation method to get soil temperature and moisture at the observed depths.

The data for year 2008 was used to spin up CoLM. Model simulations from 1 January 2009 to 31 December 2009 with a 3-h time step are used to evaluate model parameter sensitivity.

3.3 Design of sensitivity study

This study used a newly developed software package named Problem Solving environment for Uncertainty Analysis and Design Exploration (PSUADE) (Tong, 2005) for all SA analyses. PSUADE implements various uncertainty quantification (UQ) tools such as design of experiments, sampling methods, qualitative and quantitative sensitivity analysis, response surface, uncertainty assessment, and numerical optimization.

We conducted the SA study in two stages: qualitative parameter screening and quantitative validation. In the first stage, the study investigates the proper sampling designs and sample sizes for different qualitative SA methods. Once the proper sampling design and sample size are determined for each qualitative method, the most sensitive parameters that control each of the six flux simulations are identified. In the second stage, the quantitative method, RSMSobol, is used to validate the parameter screening results from the first stage based on the contributions of screened parameters to the total variances of model outputs. The parameter screening results are also checked for their consistency with the parameters' physical interpretations.

4 Results and discussion

4.1 Qualitative parameter screening

4.1.1 Sampling methods and sample sizes

We tested and compared different sampling methods and sample sizes (see Table 6). For SOT, MARS and DT, three sampling methods were evaluated: Monte Carlo (MC) (Hastings, 1970), Latin Hypercube (LH) (McKay et al., 1979) and LPTAU (quasi random sequences) (Statnikow and Matusov, 2002). For each sampling method, different sample sizes, 200, 400 and 1000 (i.e. 5, 10 and 25 times of the number of parameters, respectively), were investigated. Morris method has its own sampling method. The sample size of Morris method is generally set as a multiple of $n+1$, where n is the number of parameters. So this study tested three sample sizes: 205, 410 and 1025 for Morris method.

Take the results of SOT for example, which examines parameters most sensitive to sensible heat flux. The SOT sensitivity scores of 40 parameters given by different sampling designs are shown in Fig. 2. The numbers along each circle represent different parameters, with the length of the needles, which range from 0 to 100, indicating the relative sensitivities of different parameters.

From Fig. 2, we can see the most important parameters based on SOT method. With 1000 samples, all sampling methods identified the same sensitive parameters: P36, P6, P30, P2, P34 and P17. When the sample size is reduced to 400, for LH and LPTAU, the results are similar to those at 1000 samples, suggesting that a sample size

of 400 is adequate for identifying the most sensitive parameters. With 400 samples, SOT based on MC sampling method can still screen out the same parameters, but the medium sensitive parameters: P2, P34 and P17, are not as clearly identified. With 200 samples, even though SOT using all the three sampling methods can still find all sensitive parameters, the relative sensitivities of the medium sensitive parameters are too small to be seen clearly (e.g. P17). This suggests that 200 samples may not be enough for SOT method. Thus, LH and LPTAU are considered to be better sampling designs for SOT, and 400 samples are enough for these sampling designs.

Similarly, Figs. 3–5 show the results of MARS, DT and Morris methods. We have the following observations: (1) for MARS method, the results based on MC, LH and LPTAU are nearly the same, 400 samples are enough for all sampling methods; (2) LH is more suitable for DT, 400 samples are enough; (3) for Morris method, 410 samples are enough.

Based on above results, it seems clear that 10 times of the number of parameters are approximately enough for qualitative SA methods to screen 40 parameters of CoLM. In the following study, LH is chosen for SOT, LPTAU is chosen for MARS, and LH is chosen for DT. The sample size is set to 400 for these three designs. For Morris method, the sample size is set to 410.

4.1.2 Intercomparison of qualitative SA methods

The parameter screening results by all qualitative SA methods for all fluxes are summarized in Figs. 6–11. The sensitivity scores of 40 parameters are normalized to [0, 1]. The most sensitive parameters get a score of 1, while the least sensitive ones get a 0 score. The vertical axis in these figures denotes different SA methods and the horizontal axis denotes the 40 parameters. The grey scale of each grid indicates the sensitivity level of each parameter by each SA method. In Fig. 6, for example, the dark grey color for P6 and P36 indicates that they are the most sensitive parameters for sensible heat flux.

From these figures we have three interesting findings. First, for each land surface flux, the number of sensitive parameters appears to be less than 10. For latent heat and sensible heat fluxes, there are more sensitive parameters as compared to other fluxes, which have only 2–3 sensitive parameters. Second, the results of SOT, MARS and Morris methods are consistent with each other except for the case of latent heat. For latent heat, the number of sensitive parameters is relatively larger than that of other fluxes (this is confirmed in the following quantitative SA). SOT, MARS and Morris methods can reliably identify the most sensitive parameters, but there are some discrepancies in indentifying the medium sensitive parameters for latent heat. Third, the results of Local method and DT appear very different from that of other methods. Local method often takes sensitive parameters as insensitive ones (type I error, e.g. P3 for soil moisture) or the insensitive parameters as sensitive ones (type II error, e.g. P20 and P27 for sensible heat). DT can always identify the most sensitive parameters clearly, but provide uncertain results for medium sensitive parameters, especially when there are a large number of sensitive parameters (e.g. in the cases of sensible heat and latent heat). We suspected that the GA used in DT failed to find the optimal parameter subset in those cases.

4.2 Validation of parameter screening results

The qualitative SA methods identified the most sensitive parameters for different fluxes data, as shown in the previous section. Here we use RSMSobol method to confirm if these findings are reasonable. The total effect is computed by RSMSobol using 2000 samples to assess the importance of each parameter. The results are shown in Fig. 12, in which each slice of the pie chart indicating the relative importance of the parameter, as computed by Eq. (7). The RSMSobol results obtained are deemed as reliable since the training and testing errors of the response surface are below 2.5 %. We note from Fig. 12 that the number of important parameters for each flux is indeed less than 10 (i.e. 2–8). This confirms that the results of qualitative SA methods are reasonable.

Table 7 shows the cumulative importance of the 10 most sensitive parameters selected by different qualitative SA methods, as computed according Eq. (8). The SA method is regarded as effective if the cumulative importance of the 10 most sensitive parameters is close to 100 %. Obviously, local method is ineffective in screening the important parameters for sensible heat (79.74 %), latent heat (57.98 %), upward longwave radiation (51.57 %) and net radiation (85.71 %); while the other methods are effective because the cumulative importance of the 10 most sensitive parameters are close to 100 %. Furthermore, to confirm the effectiveness of global SA methods, Fig. 13 showed the cumulative importance of the top 10 sensitive parameters screened by different SA methods. X-axis is the number of parameters and y-axis is their cumulative importance. According to Fig. 13, the SOT and MARS method performed well for all the land surface fluxes as their cumulative importance curves are always higher than others.

DT is prone to selecting more parameters than other methods (commiting type II errors) and does not distinguish the medium sensitive from highly sensitive parameters. But the result of validation shows that the most sensitive parameters selected by DT are nearly the same to that given by SOT and MARS, even though the medium sensitive parameters may differ the ones identified by other SA methods. This suggests that type II error that may have committed by DT is not as damaging as type I error, as in the case of local method.

For latent heat flux, Morris method committed a type I error because it missed the second most important parameter, P18, whose importance rate is 15.82 %, resulting in a cumulative score of 80 % only. We originally thought that the 410 samples may be not enough. So we experimented more samples (1025), but still found that Morris method could not screen out P18. But after experimenting with $p = 10$ (instead of default $p = 4$ as implemented in PSUADE), we were able to identify P18 as a sensitive parameter. This suggests a limitation of Morris method is not due to its sample size but due to the fact that Morris samples are not space filling.

In summary, Local method is an unsuitable SA method for a complex model like CoLM with 40 adjustable parameters. Global SA methods are generally effective to screen the sensitive parameters reliably providing that proper sampling design and sufficient sample size are used.

4.3 The consistency of the screening results and physical interpretations

In previous sections, we used five different qualitative SA methods to identify the most sensitive parameters for all flux types. The quantitative RSMSobol method confirms that the qualitative SA results are reasonable. Here we try to explain the SA results based on physical interpretations of the screened parameters.

P6 and P3 are shown to be the most important parameters for soil moisture (see Figs. 11 and 12). From Clapp et al. (1978), P6 (Clapp and Hornberger "b" parameter) is the exponent of wetness in the formulas for soil hydraulic conductivity and water potential, and P3 (porosity) is a part of denominator in the formulas to compute the wetness. A small perturbation in these values would result in much change to soil moisture. Therefore these two parameters are sensitive for soil moisture. It should be mentioned that P2 (saturated hydraulic conductivity) and P4 (minimum soil suction) will also affect the simulation of soil moisture (see Fig. 11). But they are not as sensitive as P6 and P3, which have exponential relationship with soil moisture.

Besides soil moisture, P6 is also important for other land surface fluxes (see Fig. 12). This is because soil moisture is an important model output which is tied to the sensible heat flux, latent heat flux and radiant fluxes (Henderson-Sellers, 1996). A parameter which exerts great influence on soil moisture should have a big impact on related fluxes. This finding is also consistent with Lettenmaier et al. (1996).

P36 (aerodynamic roughness length) is another important parameter for sensible heat, latent heat, upward longwave radiation, net radiation and soil temperature (see Fig. 12). Through the influence to friction velocity, P36 affects the magnitude of the aerodynamic resistance and the near-surface drag force for the simulation of sensible heat, latent heat, and radiant fluxes, and then indirectly affects the soil temperature

(Dorman and Sellers, 1989). P17 (the inverse of square root of leaf dimension), P30 (longwave reflectance of living leaf) and P34 (longwave transmittance of living leaf) are sensitive to the simulation of surface temperature and air temperature. Accordingly they are important for sensible heat and net radiation. The sensitivity of other parameters, including P18 (quantum efficiency of vegetation photosynthesis) and P4 (minimum soil suction), to latent heat can be explained by their influence on evapotranspiration.

But not all the parameters in the screening results can be explained based on physical interpretations (e.g. P12 in screening result for latent heat). Possible reasons are: (1) due to the limitation of the SA methods and the sample sizes, the insensitive parameters might be regarded as sensitive ones; (2) due to the authenticity of the model structure, the physical processes might not be described perfectly; (3) due to local conditions or a lack of appropriate observations for sensitivity evaluation (e.g. saturated hydraulic conductivity P2 not sensitive because there is no runoff observations).

5 Conclusions

In this study, we first identified the most sensitive parameters for sensible heat, latent heat, upward longwave radiation, net radiation, soil temperature and soil moisture using five different qualitative SA methods. We investigated the proper sampling design and sample size necessary for screening the parameters effectively. Based on the SA results, there are 2–8 parameters that are deemed as most sensitive in CoLM, depending on the flux type. We employed a quantitative SA method to confirm the screening results. The results of quantitative method are consistent with those of qualitative methods. Moreover, the screening results are generally consistent with the physical interpretations of the model parameters.

By using meteorological and land surface observation data in A'rou, Heihe of Northwest China, this study demonstrates the feasibility of employing different qualitative SA methods to find the most important parameters in a complex model. For a 40-parameter CoLM, we were able to screen out the most important parameters using only about 400 samples. The kind of parameter screening approach studied here should be applicable to other complicated models. However, caution must be exercised in interpreting these results. The parameters identified in this study were obtained with data of limited length and at a single site with particular geographical conditions. Results from a different location or a different condition can be quite different from the ones shown in this study. The screened parameters are also tied to available land surface fluxes used in the study. Parameters such as saturated hydraulic conductivity (P2) were not considered as important parameters because we did not examine parameter sensitivity to runoff generation. To truly understand the parameter sensitivity for CoLM, we need to conduct a more comprehensive SA study by including more geographical locations, more observation data types and longer data sets. In future research, parameter screening of CoLM will be extended to regional and even global scale by using more available data.

Even though we identified the most important parameters for CoLM, we did not perform model calibration to obtain the most appropriate estimates for these parameters. Model calibration for complex multi-flux, high-dimensional LSMs such as CoLM can be extremely complicated. To do model calibration in such cases, future studies must explore more mathematical tools including surrogate modeling approach to save computational resources, multi-objective optimization strategy for model calibration of multi-physics models.

Acknowledgements. The authors want to acknowledge the support provided by Natural Science Foundation of China (Grant #: No. 41075075) and Chinese Ministry of Science and Technology 973 Research Program (Grant #: No. 2010CB428402). Special thanks are due to "Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China" (http://westdc.westgis.ac.cn) for providing the meteorological forcing data, to the group of Shaomin Liu at State Key Laboratory of Remote Sensing Science, School of Geography and Remote Sensing Science of Beijing Normal University for providing the surface flux validation data.

References

Anderson, E. A.: A point of energy and mass balance model of snow cover, NOAA Tech. Rep. NWS, 19, 1–150, 1976.

Bastidas, L. A., Gupta, H. V., Sorooshian, S., Shuttleworth, W. J., and Yang, Z. L.: Sensitivity analysis of a land surface scheme using multicriteria methods, J. Geophys. Res., 104, 19481–19490, doi:10.1029/1999JD900155, 1999.

Bonan, G. B.: Land surface model (LSM version 1.0) for ecological, hydrological, and atmospheric studies: Technical description and user's guide, Technical note, National Center for Atmospheric Research, Boulder, CO (United States). Climate and Global Dynamics Div., 159 pp., 1996.

Breiman, L.: Random forests, Mach. Learn., 45, 5–32, doi:10.1023/A:1010933404324, 2001.

Breiman, L., Friedman, J., Stone, C. J., and Olshen, R. A.: Classification and Regression Trees, Chapman and Hall/CRC, Bota Raton, Florida, USA, 1984.

Campolongo, F. and Saltelli, A.: Sensitivity analysis of an environmental model: an application of different analysis methods, Reliab. Eng. Syst. Safe., 57, 49–69, 1997.

Campolongo, F., Cariboni, J., and Saltelli, A.: An effective screening design for sensitivity analysis of large models, Environ. Modell. Softw., 22, 1509–1518, 2007.

Capaldo, K. P. and Pandis, S. N.: Dimethylsulfide chemistry in the remote marine atmosphere: evaluation and sensitivity analysis of available mechanisms, J. Geophys. Res., 102, 23251–23267, 1997.

Chipman, H. A., George, E. I., and McCulloch, R. E.: BART: Bayesian additive regression trees, Ann. Appl. Stat., 4, 266–298, 2010.

Clapp, R. B. and Hornberger, G. M.: Empirical equations for some soil hydraulic properties, Water Resour. Res., 14, 601–604, doi:10.1029/WR014i004p00601, 1978.

Collins, D. C. and Avissar, R.: An evaluation with the Fourier amplitude sensitivity test (FAST) of which land-surface parameters are of greatest importance in atmospheric modeling, J. Climate, 7, 681–703, 1994.

Cosby, B., Hornberger, G., Clapp, R., and Ginn, T.: A statistical exploration of the relationships of soil moisture characteristics to the physical properties of soils, Water Resour. Res., 20, 682–690, 1984.

Dai, Y. and Zeng Q.: A land surface model (IAP94) for climate studies part I: formulation and validation in off-line experiments, Adv. Atmos. Sci., 14, 433–460, doi:10.1007/s00376-997-0063-4, 1997.
Dai, Y., Zeng, X., Dickinson, R. E., Baker, I., Bonan, G. B., Bosilovich, M. G., Denning, A. S., Dirmeyer, P. A., Houser, P. R., and Niu, G.: The Common Land Model, Bull. Am. Meteorol. Soc., 84, 1013–1023, 2003.
De Pauw, D. J. W., Steppe, K., and De Baets, B.: Unravelling the output uncertainty of a tree water flow and storage model using several global sensitivity analysis methods, Biosyst. Eng., 101, 87–99, doi:10.1016/j.biosystemseng.2008.05.011, 2008.
Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE T. Evolut. Comput., 6, 182–197, 2002.
Dickinson, R., Henderson-Sellers, A., and Kennedy, P.: Biosphere–Atmosphere Transfer Scheme (BATS) version 1e as coupled to the NCAR community model, NCAR Tech. Note NCAR/TN-387+ STR, National Center for Atmospheric Research, Boulder, CO, USA, 72, 1993.
Dorman, J. and Sellers, P. J.: A global climatology of albedo, roughness length and stomatal resistance for atmospheric general circulation models as represented by the Simple Biosphere Model (SiB), J. Appl. Meteorol., 28, 833–855, 1989.
Duan, Q. Y., Gupta, V. K., and Sorooshian, S.: Shuffled complex evolution approach for effective and efficient global minimization, J. Optimiz. Theory App., 76, 501–521, doi:10.1007/BF00939380, 1993.
Duan, Q., Schaake, J., and Koren, V.: A priori estimation of land surface model parameters, land surface hydrology, meteorology, and climate: observations and modeling, Water Sci. Appl., 3, 77–94, 2001.
Duan, Q., Gupta, H. V., Sorooshian, S., Rousseau, A. N., and Turcotte, R.: Calibration of Watershed Models, American Geophysical Union, Washington, USA, 345, 2003.
Duan, Q., Schaake, J., Andreassian, V., Franks, S., Goteti, G., Gupta, H. V., Gusev, Y. M., Habets, F., Hall, A., Hay, L., Hogue, T., Huang, M., Leavesley, G., Liang, X., Nasonova, O. N., Noilhan, J., Oudin, L., Sorooshian, S., Wagener, T., and Wood, E. F.: Model Parameter Estimation Experiment (MOPEX): an overview of science strategy and major results from the second and third workshops, J. Hydrol., 320, 3–17, doi:10.1016/j.jhydrol.2005.07.031, 2006.

Eirola, E., Liitiäinen, E., Lendasse, A., Corona, F., and Verleysen, M.: Using the delta test for variable selection, In: Proceedings of ESANN 2008/16th European Symposium on Artificial Neural Networks, Bruges (Belgium), 23–25 April 2008, 25–30, 2008.
Farouki, O. T.: Thermal properties of soils, Ser. Rock Soil Mech., 11, 1–136, 1986.
Franks, S. W. and Beven, K. J.: Bayesian estimation of uncertainty in land surface-atmosphere flux predictions, J. Geophys. Res., 102, 23991–23999, doi:10.1029/97JD02011, 1997.
Friedman, J. H.: Multivariate adaptive regression splines, Ann. Stat., 19, 1–141, 1991.
Goldberg, D.: Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley Professional, Boston, MA, USA, 1989.
Guillen, A., Sovilj, D., Lendasse, A., and Mateo, F.: Minimizing the delta test for variable selection in regression problems, Int. J. High Perform. Sys. Arch., 1, 269–281, 2008.
Gupta, H., Bastidas, L., Sorooshian, S., Shuttleworth, W., and Yang, Z.: Parameter estimation of a land surface scheme using multicriteria methods, J. Geophys. Res., 104, 491–503, 1999.
Hastings, W. K.: Monte Carlo sampling methods using Markov chains and their applications, Biometrika, 57, 97–109, 1970.
Henderson-Sellers, A.: Soil moisture: a critical focus for global change studies, Global Planet. Change, 13, 3–9, 1996.
Homma, T. and Saltelli, A.: Importance measures in global sensitivity analysis of nonlinear models, Reliab. Eng. Syst. Safe., 52, 1–17, 1996.
Hou, Z., Huang, M., Leung, L. R., Lin, G., and Ricciuto, D. M.: Sensitivity of surface flux simulations to hydrologic parameters based on an uncertainty quantification framework applied to the Community Land Model, J. Geophys. Res., 117, D15108, doi:10.1029/2012JD017521, 2012.
Hu, Z. Y., Ma, M. G., Jin, R., Wang, W. Z., Huang, G. H., Zhang, Z. H., and Tan, J. L.: WATER: dataset of automatic meteorological observations at the A'rou freeze/thaw observation station, Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences, doi:10.3972/water973.0279.db, available at: http://westdc.westgis.ac.cn/water/50a8fe84-deeb-49b0-b8d8-8f784bc27a89, 2003.
Jackson, C., Xia, Y., Sen, M. K., and Stoffa, P. L.: Optimal parameter and uncertainty estimation of a land surface model: a case study using data from Cabauw, Netherlands, J. Geophys. Res., 108, 4583, doi:10.1029/2002JD002991, 2003.
Ji, D. Y. and Dai, Y. J.: The Common Land Model (CoLM) technical guide, Technical Report of Beijing Normal University, Beijing, China, 2010.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

Jordan, R.: A one-dimensional temperature model for a snow cover: technical documentation for SNTHERM, 89, DTIC Document, US Army Cold Regions Research and Engineering Laboratory Special Rep., USA, 91–16, 1991.

Lettenmaier, D., Lohmann, D., Wood, E., and Liang, X.: PILPS-2c workshop report, Princeton Univ., Princeton, NJ, 1996.

Liu, Y., Gupta, H. V., Sorooshian, S., Bastidas, L. A., and Shuttleworth, W. J.: Constraining land surface and atmospheric parameters of a locally coupled model using observational data, J. Hydrometeorol., 6, 156–172, 2005.

McKay, M., Beckman, R., and Conover, W.: A comparison of three methods for selecting values of input variables in the analysis of output from a computer code, Technometrics, 42, 55–61, 2000.

Morris, M. D.: Factorial sampling plans for preliminary computational experiments, Technometrics, 33, 161–174, 1991.

Parada, L. M., Fram, J. P., and Liang, X.: Multi-resolution calibration methodology for hydrologic models: application to a sub-humid catchment, Water Sci. Appl., 6, 197–211, 2003.

Pi, H. and Peterson, C.: Finding the embedding dimension and variable dependencies in time series, Neural Comput., 6, 509–520, 1994.

Saltelli, A., Chan, K., and Scott, E. M.: Sensitivity Analysis, Wiley, New York, 2000.

Saltelli, A., Tarantola, S., Campolongo, F., and Ratto, M.: Sensitivity Analysis in Practice: a Guide to Assessing Scientific Models, Wiley, New York, USA, 2004.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., and Tarantola, S.: Global sensitivity Analysis: the Primer, Wiley-Interscience, Chichester, UK, 2008.

Sobol', I. M.: Sensitivity analysis for nonlinear mathematical models, Math. Mod. Comput. Exp., 1, 407–414, 1993.

Sobol', I. M.: Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, Math. Comput. Simulat., 55, 271–280, 2001.

Statnikov, R. B. and Matusov, J. B.: Multicriteria Analysis in Engineering: Using the PSI Method with MOVI 1.0, Springer, Kluwer Academic Publishers, Dordrecht, The Netherlands, 2002.

Steinberg, D., Colla, P., and Martin, K.: MARS User Guide, Salford Systems, San Diego, CA, 1999.

Storlie, C. B., Swiler, L. P., Helton, J. C., and Sallaberry, C. J.: Implementation and evaluation of nonparametric regression procedures for sensitivity analysis of computationally demanding models, Reliab. Eng. Syst. Safe., 94, 1735–1763, 2009.

Tang, Y., Reed, P., Wagener, T., and van Werkhoven, K.: Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation, Hydrol. Earth Syst. Sci., 11, 793–817, doi:10.5194/hess-11-793-2007, 2007.

Tong, C.: PSUADE User's Manual, Lawrence Livermore National Laboratory, LLNL-SM-407882, Livermore, CA, USA, 2005.

Tong, C. and Graziani, F.: A practical global sensitivity analysis methodology for multi-physics applications, in: Computational Methods in Transport: Verification and Validation, 62, 277–299, 2008.

Turányi, T.: Sensitivity analysis of complex kinetic systems, tools and applications, J. Math. Chem., 5, 203–248, 1990.

Vrugt, J. A., Ter Braak, C. J. F., Clark, M. P., Hyman, J. M., and Robinson, B. A.: Treatment of input uncertainty in hydrologic modeling: doing hydrology backward with Markov chain Monte Carlo simulation, Water Resour. Res, 44, W00B09, doi:10.1029/2007WR006720, 2008.

Yamwong, W. and Achalakul, T.: Yield improvement analysis with parameter-screening factorials, Appl. Soft Comput., 12, 1021–1040, 2011.

Yuan, X. and Liang, X. Z.: Evaluation of a Conjunctive Surface-Subsurface Process model (CSSP) over the contiguous United States at regional-local scales, J. Hydrometeorol., 12, 579–599, 2011.

Table 1. Adjustable parameters and their ranges.

Index	Parameter	Physical meaning	Unit	Range
P1	dewmx	maximum ponding of leaf area	–	(0.05, 0.15)
P2	hksati	saturated hydraulic conductivity	$\mathrm{mm\,s^{-1}}$	(0.001, 1)
P3	porsl	Porosity, Fraction of soil that is voids	–	(0.25, 0.75)
P4	phi0	minimum soil suction	mm	(50, 500)
P5	wtfact	fraction of shallow groundwater area	–	(0.15, 0.45)
P6	bsw	Clapp and Hornberger "b" parameter	–	(2.5, 7.5)
P7	wimp	water impermeable when porosity is less than wimp	–	(0.01, 0.1)
P8	zlnd	roughness length for soil surface	m	(0.005, 0.015)
P9	pondmx	maximum ponding depth for soil surface	mm	(5, 15)
P10	csoilc	drag coefficient for soil under canopy	–	(0.002, 0.006)
P11	zsno	roughness length for snow	–	(0.0012, 0.0036)
P12	capr	tuning factor of soil surface temperature	–	(0.17, 0.51)
P13	cnfac	Crank Nicholson factor between 0 and 1	–	(0.25, 0.5)
P14	slti	slope of low temperature inhibition function	–	(0.1, 0.3)
P15	hlti	1/2 point of low temperature inhibition function	–	(278, 288)
P16	shti	slope of high temperature inhibition function	–	(0.15, 0.45)
P17	sqrtdi	the inverse of square root of leaf dimension	–	(2.5, 7.5)
P18	effcon	quantum efficiency of vegetation photosynthesis	$\mathrm{mol\,CO_2\ molquanta^{-1}}$	(0.035, 0.35)
P19	vmax25	maximum carboxylation rate at 25°	–	$(10\times10^{-6}, 200\times10^{-6})$
P20	hhti	1/2 point of high temperature inhibition function	–	(305, 315)
P21	trda	temperature coefficient of conductance-photosynthesis model	–	(0.65,1.95)
P22	trdm	temperature coefficient of conductance-photosynthesis model	–	(300, 350)
P23	trop	temperature coefficient of conductance-photosynthesis model	–	(250, 300)
P24	gradm	slope of conductance-photosynthesis model	–	(4, 9)
P25	binter	intercept of conductance-photosynthesis model	–	(0.125, 0.375)
P26	extkn	coefficient of leaf nitrogen allocation	–	(0.5, 0.75)
P27	chil	leaf angle distribution factor	–	(−0.3, 0.1)
P28	ref(1,1)	shortwave reflectance of living leaf	–	(0.07, 0.105)
P29	ref(1,2)	shortwave reflectance of dead leaf	–	(0.16, 0.36)
P30	ref(2,1)	longwave reflectance of living leaf	–	(0.35, 0.58)
P31	ref(2,2)	longwave reflectance of dead leaf	–	(0.39, 0.58)
P32	tran(1,1)	shortwave transmittance of living leaf	–	(0.04, 0.08)
P33	tran(1,2)	shortwave transmittance of dead leaf	–	(0.1, 0.3)
P34	tran(2,1)	longwave transmittance of living leaf	–	(0.1, 0.3)
P35	tran(2,2)	longwave transmittance of dead leaf	–	(0.3, 0.5)
P36	z0m	aerodynamic roughness length	m	(0.05, 0.3)
P37	ssi	irreducible water saturation of snow	–	(0.03, 0.04)
P38	smpmax	wilting point potential	mm	$[-2\times10^{5}, -1\times10^{5}]$
P39	smpmin	restriction for min of soil potential	mm	$[-1\times10^{8}, -9\times10^{7}]$
P40	trsmx0	maximum transpiration for vegetation	$\mathrm{mm\,s^{-1}}$	$[1\times10^{-4}, 100\times10^{-4}]$

Table 2. The objective functions.

Objective function	Description
RMSE_1	sensible heat
RMSE_2	latent heat
RMSE_3	upward longwave radiation
RMSE_4	net radiation
RMSE_5	soil temperature (average of 4 layers)
RMSE_6	soil moisture (average of 4 layers)

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

Table 3. The forcing data taken from A'rou observation station.

Forcing data	Downward shortwave	Downward longwave	Preci-pitation	Air tempera-ture (2 m)	Relative humidity (2 m)	Air pressure	Wind speed (10 m)
Unit	$\mathrm{w\,m^2}$	$\mathrm{w\,m^2}$	mm	°C	%	hPa	$\mathrm{m\,s^{-1}}$
Time period	1 January 2008 to 31 December 2009						
Time step	0.5 h	0.5 h	1h	0.5 h	0.5 h	1h	0.5 h

Table 4. The validation data.

Validation data	Sensible heat	Latent heat	Upward longwave	Net radiation	Soil temperature	Soil moisture
Unit	$\mathrm{w\,m^{-2}}$	$\mathrm{w\,m^{-2}}$	$\mathrm{w\,m^{-2}}$	$\mathrm{w\,m^{-2}}$	°C	$\mathrm{cm^3\,cm^{-3}}$
Time period	11 Jun 2008 to 31 Dec 2009		1 Jun 2008 to 31 Dec 2009		1 Jan 2008 to 31 Dec 2009	
Time step	0.5 h	0.5 h	10 min	10 min	0.5 h	0.5 h

Note: the soil temperature and moisture data contains the data of 10 cm, 20 cm, 40 cm, 80 cm and 120 cm, respectively.

Table 5. The z and Δz in each layer.

layer	1	2	3	4	5	6	7	8	9	10
z (cm)	0.71	2.79	6.23	11.89	21.22	36.61	61.98	103.80	172.76	286.46

Table 6. The experiment designs to confirm the proper sampling methods and sample size for SA methods.

SA methods	SOT MARS DT	Morris
Sampling methods	MC, LH, LPTAU	MOAT
Sample sizes	200, 400, 1000	205, 410, 1025

Table 7. The cumulative importace of the 10 most sensitive parameters screened by different qualitative SA methods.

SA method	Sensible heat	Latent heat	Upward longwave	Net radiation	Soil temperature	Soil moisture
Local	79.74 %	57.98 %	51.57 %	85.71 %	96.15 %	98.00 %
SOT	98.86 %	97.10 %	98.69 %	98.66 %	97.49 %	99.71 %
MARS	99.15 %	95.83 %	99.82 %	99.96 %	97.93 %	99.98 %
DT	96.86 %	90.60 %	98.67 %	99.12 %	95.09 %	99.73 %
Morris	99.06 %	80.01 %	99.68 %	99.51 %	98.70 %	99.93 %

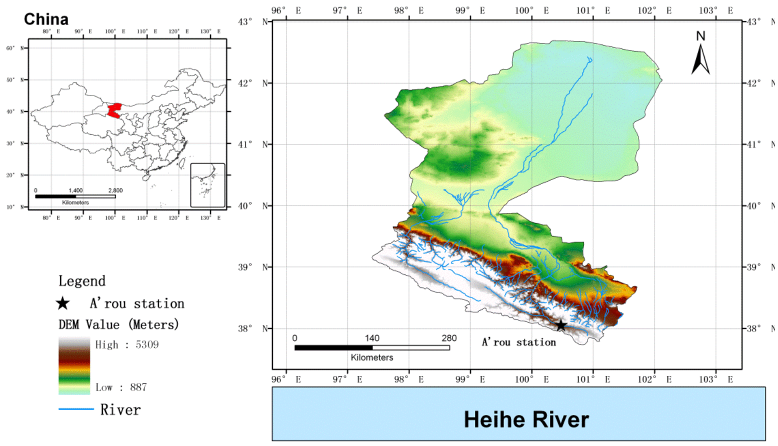

Fig. 1. The location of study area.

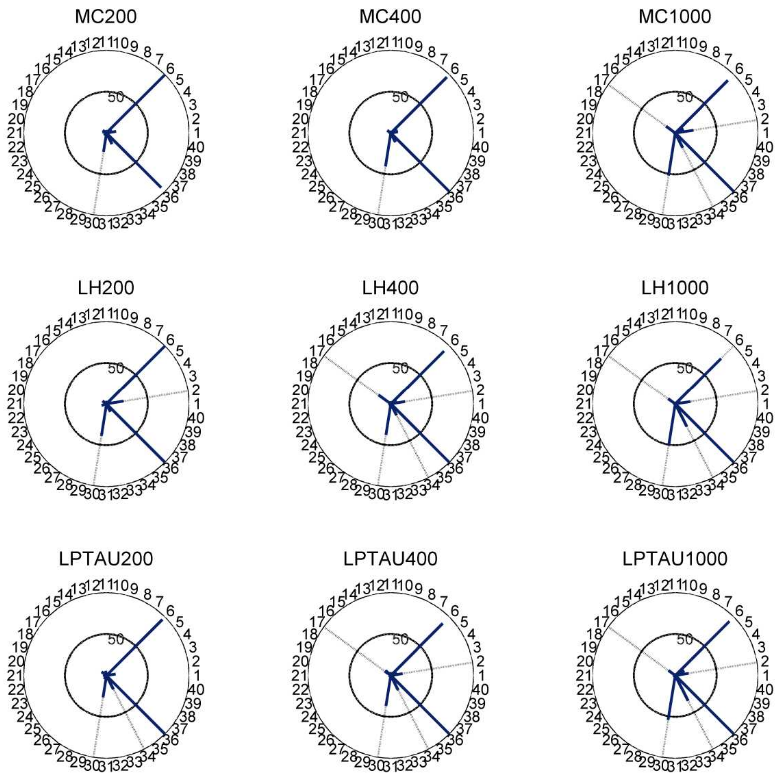

Fig. 2. The SOT parameter screening results of sensible heat.

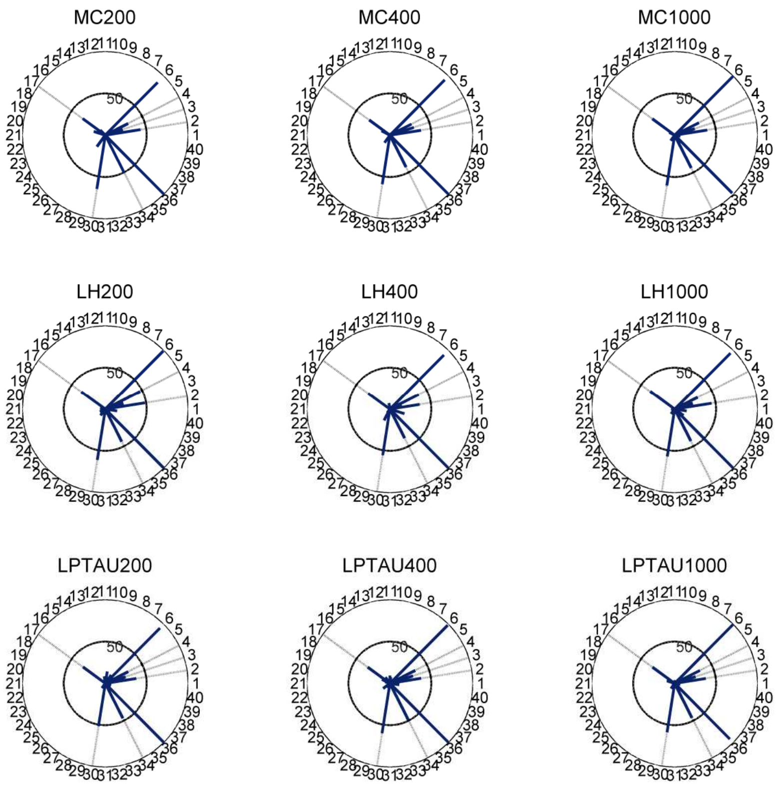

Fig. 3. The MARS parameter screening results of sensible heat.

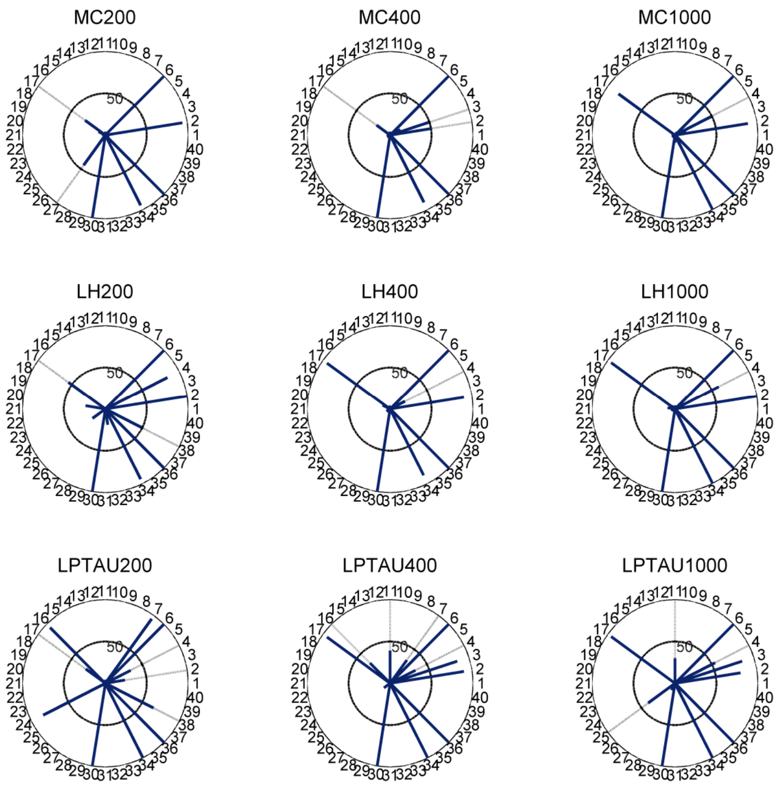

Fig. 4. The DT parameter screening results of sensible heat.

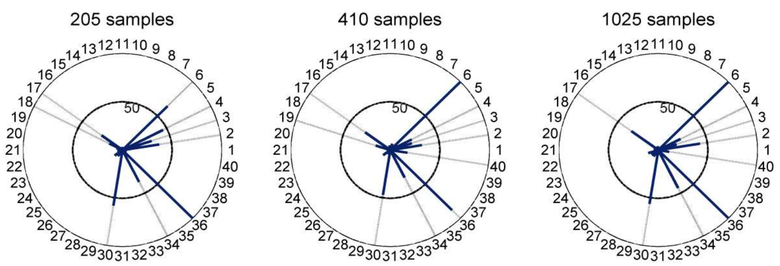

Fig. 5. The Morris parameter screening results of sensible heat.

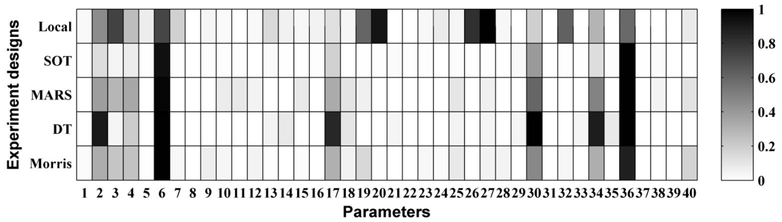

Fig. 6. The qualitative SA results of different methods for sensible heat.

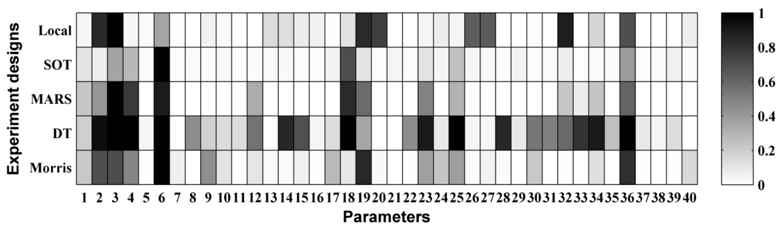

Fig. 7. The qualitative SA results of different methods for latent heat.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

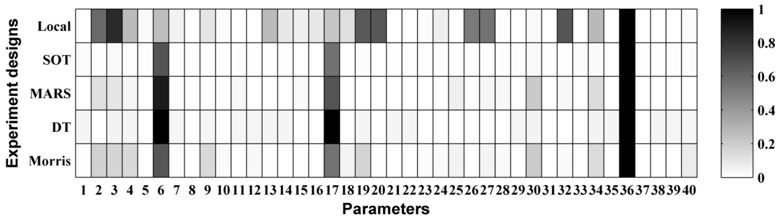

Fig. 8. The qualitative SA results of different methods for upward longwave radiation.

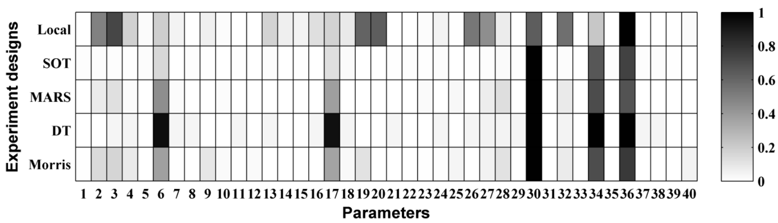

Fig. 9. The qualitative SA results of different methods for net radiation.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

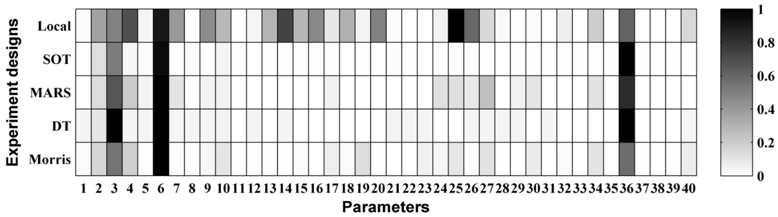

Fig. 10. The qualitative SA results of different methods for soil temperature.

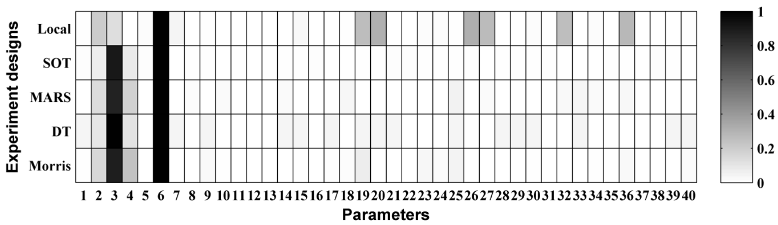

Fig. 11. The qualitative SA results of different methods for soil moisture.

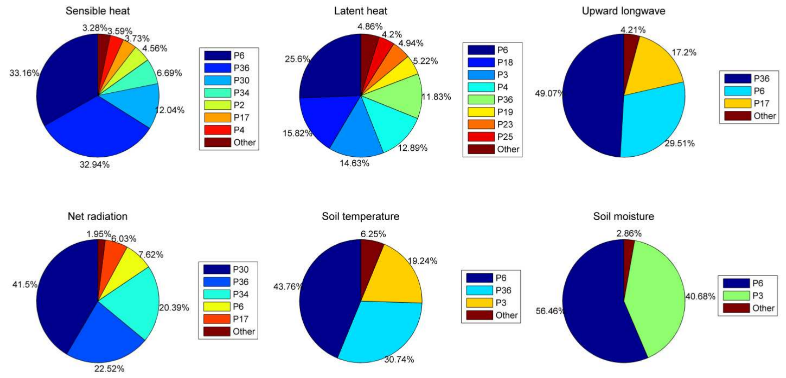

Fig. 12. The importance rates of parameters obtained by RSMSobol' total effect analysis.

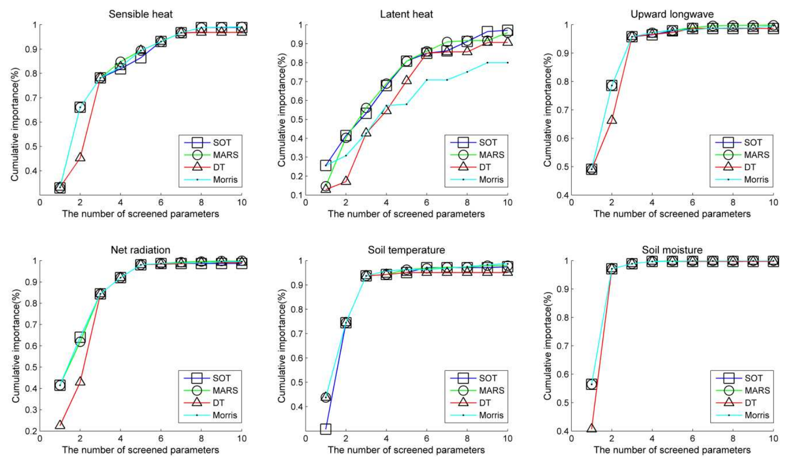

Fig. 13. The relationship between the number of screened parameter and cumulative importance for different SA methods.