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Intercomparison of land-surface parameterization schemes: sensitivity of surface energy and water fluxes to model parameters

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Abstract

In this study, sensitivities of 10 land-surface schemes (LSS) to five prescribed model parameters (i.e. the maximum soil moisture content (MSMC), effective available water content (EAWC), Clapp-Hornberger B parameter, leaf area index (LAI), and minimum stomatal resistance) are investigated based on the fractional factorial analysis method. The sensitivities of four model responses (i.e. evapotranspiration, total runoff, sensible heat flux, and soil moisture in the total zone) are evaluated as functions of these five parameters considering both individual and parameter interaction effects. To facilitate these sensitivity analyses, which are conducted for three hydroclimatic scenarios, two indices are introduced along with a criterion for measuring relative parameter effects. The two new indices are single response effect index and multiple response effect index. Results show that for the majority of LSS, the four model responses are generally most sensitive to the MSMC parameter, followed by the Clapp-Hornberger B parameter under the three different hydroclimatic scenarios. The effects of MSMC, the Clapp-Hornberger B parameter, and EAWC on the model responses are generally much larger than those of LAI and minimum stomatal resistance among most of the 10 schemes. This implies that the variations associated with the soil properties possibly due to the measurement uncertainties and/or spatial heterogeneity may play a more significant role in partitioning water and energy budgets than those associated with vegetation properties in the current generation of land-surface model parameterizations. Results also show that large sensitivities of model responses exist in relation to the choice of LSS when using the same parameter values, and in relation to the hydroclimatic scenario when using the same parameter and LSS. The differences can be sometimes quite large. In addition, the effects of parameter interactions are generally weaker than those of single parameters. The preliminary conclusions obtained from this study offer some insight on why large response differences between schemes occurred every time in the Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) phases 1, 2(a), 2(b), and 2(c) intercomparison studies, and perhaps on why each scheme performs better at its own testing site(s) than at the PILPS sites.

Keywords: Sensitivity; Model parameter; Intercomparison; Project for Intercomparison of Land-surface Parameterization Schemes; Land-surface model

1. Introduction

A series of experiments have been conducted under the framework of the Project for Intercomparison of

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Land-surface Parameterization Schemes (PILPS) in the past. Our current study is an extension of the PILPS Phase (2c) Red-Arkansas River Basin experiment (Liang et al., 1998; Lohmann et al., 1998; Wood et al., 1998). In this paper, 10 land-surface schemes (LSS) are intercompared through sensitivity analyses under three different hydroclimate conditions in the Red-Arkansas River Basin.

The goal of PILPS, as embodied in the different phases of PILPS intercomparison studies, is to understand and improve the parameterizations of the current generation of land-surface schemes used for climate and numerical weather prediction studies. The philosophy of PILPS was addressed by Henderson-Sellers et al. (1993, 1995). In the intercomparison studies, the participating land-surface schemes were provided with identical forcings and values of common model parameters. Their outputs were then intercompared among themselves and/or with available observations. The PILPS studies conducted in the past have shown that there are a variety of discrepancies among the existing land-surface schemes, and that no scheme has always performed significantly better than others in all of the aspects examined (e.g. Shao et al., 1996; Chen et al., 1997; Liang et al., 1998; Lohmann et al., 1998; Wood et al., 1998; Pitman et al., 1999). Attempts to trace back to the responsible mechanisms that caused those discrepancies proved to be very difficult if not entirely impossible. Also, we argue that it may not be appropriate to conduct the cause–effect analyses between model parameters and individual pieces of model parameterizations without taking into account of the entire model structures as a whole. The main reasons are that land-surface schemes are highly nonlinear systems, and that they differ from each other in model structures. For example, the same individual parameterizations (e.g. using Penman–Monteith approach for evapotranspiration could result in quite different evaporation patterns and parameter sensitivities if the soil moisture is parameterized differently) may perform quite differently when connected with different parameterizations/structures. Therefore, we argue that it would be more meaningful to relate the sensitivities of model responses on parameters to individual models than to individual parameterizations. In this paper, we attempt to conduct a series of systematic investigations and intercomparisons of model sensitivities on selected model parameters to understand possible sources that caused the disagreements among the PILPS participating schemes. The sensitivity analyses reported here are based on the PILPS-2C Red-Arkansas River Basin experiment from 10 participating schemes. In the past, few sensitivity intercomparison analyses have been conducted among a relatively large number of models.

The technique of sensitivity analysis has been widely used by modelers as an effective approach in individual model studies for potential improvements. Through sensitivity analysis, responses of a model to changes of different parameters can be investigated (e.g. Jacobs and DeBruin, 1992; Sun and Bosilovich, 1996; Bastidas et al., 1999) and relative importance of each parameter can be identified. Large differences in energy and water fluxes among models in the PILPS intercomparisons may be, in part, due to the different degrees of sensitivities of different models to the uncertainties associated with the model parameters.

The traditional sensitivity analysis method of varying one-factor-at-a-time is a powerful approach and has been widely used for sensitivity studies of individual models with great success (e.g. Wilson et al., 1987a,b; Liang, 1994; Pitman, 1994; Gao et al., 1996, Sun and Bosilovich, 1996). One of the important advantages of this approach (i.e. varying one-factor-at-a-time) is its availability to investigate incremental sensitivity of each parameter on a studied quantity over its parameter range where the nonlinearity effect of each single parameter on the studied quantity can be examined. Sun and Bosilovich (1996) showed a valuable study on the incremental sensitivity effects of each studied parameter on the planetary boundary layer and surface layer by applying this method. The disadvantage of this approach is that it is difficult to carry out efficient comparisons among a large number of schemes. In addition, this approach (i.e. varying one-factor-at-a-time) is not quite efficient in identifying effects of potential parameter interactions. Other methods used for the sensitivity analysis of LSS, where parameter interactions are not efficiently considered as briefly reviewed by Bastidas et al. (1999), include the Fourier amplitude sensitivity test (Collins and Avissar, 1994), and the regionalized sensitivity analysis method (Fransk et al., 1997).

Bastidas et al. (1999) presented a valuable new approach (called Bastidas et al. approach hereafter) to study model parameter sensitivities on latent and sensible heat fluxes, soil moisture, and ground temperature for BATS (Biosohere–Atmosphere Transfer Scheme) with data from the ARM-CART grassland site (5 months of data) and a semiarid site (1 year of data) in the Sonoran Desert, Arizona, respectively. Their new approach partitions the feasible parameter space (consisting of specified reasonable ranges of each studied model parameter) into behavioral and non-behavioral sets based on Pareto ranking, and performs Kolmogorov–Smirnov test to study the integrated effects of each parameter to multiple model responses (e.g. latent flux, sensible flux, soil moisture, and ground temperature). The main advantage of this approach is its ability to consider parameter interactions and the sensitivities of multiple model responses to parameters. The main disadvantage of this approach is its complexity in implementation, and thus may not be a good candidate for conducting sensitivity analyses among a large number of schemes.

Fractional factorial analysis is a method that can deal with partially the effects of parameter interactions. This method is much simpler to implement by different LSSs than the Bastidas et al. approach, and thus is a good candidate for conducting sensitivity intercomparison studies among a large number of schemes. As demonstrated by Henderson-Sellers (1993) for BATS and Liang (1994) for VIC, the fractional factorial analysis method (Box et al., 1978) may reveal not only potential interactions among parameters, but also the effects of different parameters on the energy and water budgets of the models. Similar to Henderson-Sellers (1993) and Liang (1994), Arendt et al. (1996) applied the factorial analysis framework to study the interactions of energy and moisture transfer processes of two relatively simple land-surface models used in general circulation models. The two land-surface models are simple non-vegetated models with a configuration of single-layer (Bucket type) and a configuration of double-layer, respectively. Hu and Islam (1996) also applied the fractional factorial experiment framework to study the importance and sensitivity of interactions between land-surface and atmosphere through uncoupled and coupled modes. Comparing with the approach by Bastidas et al. (1999), the main advantage of the fractional factorial analysis method is its simplicity. The effectiveness of the fractional factorial method in dealing with parameter interactions is between the approach of varying one-factor-at-a-time and the approach by Bastidas et al. (1999). The main disadvantage of the fractional factorial analysis method is that it cannot deal sufficiently with the non-linearity of a parameter or parameter combinations on model simulated quantities. Also, similar to the approach by Bastidas et al. (1999), the fractional factorial method has a drawback of obtaining sensitivities that may be contributed by unwanted combinations of parameter values within the parameter feasible space. In the Bastidas et al. approach, for example, the sensitivity result may be due to a combination of porosity at value of 0.33 (sand type) and the Clapp-Hornberger B parameter at 10.8 (clay type), since both 0.33 for porosity and 10.8 for Clapp-Hornberger B parameter are within the specified feasible parameter space used in the study (Bastidas et al., 1999). In the fractional factorial method, similar unwanted combinations could also be present. However, this drawback may not be as serious as it sounds when a model is applied to large spatial scales. This is because at large scales, each computational unit may include multiple soil classes, and also large intraclass variability may be expected. Consequently, the cross-class soil parameter combination described above may actually occur in real applications at large scales. It is worth mentioning that the disadvantage of the fractional factorial analysis method in dealing with the sensitivities of multiple model responses to parameters (compared to the approach by Bastidas et al. (1999)) is partially overcome by using multiple response effect index (MREI) that is introduced in this study.

In a brief summary, each of the three methods (i.e. varying one-factor-at-a-time method, Bastidas et al. approach, and the fractional factorial analysis method) has its own strengths and weaknesses. Despite its limitations, overall, the fractional factorial analysis method seems to be a good feasible candidate for conducting the sensitivity comparison studies with 10 different LSSs due to its simplicity and other comparable good features.

There were 16 land-surface schemes participated in the PILPS(2c) Red-Arkansas experiment, but only 10 schemes had their sensitivity model runs available for conducting the analyses here. Table 1

Table 1
List of participating models, five common parameters and four model evaluated quantities

Names	References	Parameters (factors)	Quantities evaluated
BASE (BS)	Desborough and Pitman (1998)	1. Maximum soil moisture content (MSMC)	1. Annual evapotranspiration
BATS (BA)	Yang and Dickinson (1996), Dickinson et al. (1993)	2. Effective available water content (EAWC)	2. Annual total runoff
CAPS (CP)	Ek and Mahrt (1991), Mahrt and Pan (1984)	3. Clapp-Hornberger B	3. Annual mean sensible heat flux
ISBA (IB)	Noilhan and Mahfouf (1996), Mahfouf and Noilhan (1996)	4. LAI	4. Annual mean soil moisture in total zone
MOSAIC (MC)	Koster and Suarez (1996)	5. Minimum stomatal resistance	
NCEP (NC)	Chen et al. (1996)		
PLACE (PL)	Wetzel and Boone (1995)		
SPONSOR (SP)	Shmakin et al. (1993)		
SEWAB (SE)	Mengelkamp et al. (1999)		
VIC-3L (VC)	Liang et al. (1994, 1996a,b, 1999)		

lists the names and relevant information of the 10 schemes. The general background of Red-Arkansas experiment was described by Wood et al. (1998). A brief description of the fractional factorial analysis method and the experiment design are provided in Section 2. In Section 3, two new indices based on the fractional factorial analysis method are introduced to effectively identify the model parameters that have significant effects on single and multiple model responses, respectively. In Section 4, sensitivity experiments and results among 10 participating models are systematically analyzed. Conclusions are presented in Section 5.

2. Factorial design and sensitivity experiments

For extensive and comprehensive description of the fractional factorial designs, readers are referred to the work by Box et al. (1978) and Montgomery (1991). In this section we will only briefly review the methodology of the fractional factorial design to keep the paper self-contained.

In contrast to varying 'one-factor-at-a-time' method, the factorial analysis method allows for the effects of a parameter to be estimated at several levels of other parameters. Thus, it can provide, in a relatively efficient way, a picture of the sensitivity of model responses to a parameter that is valid over a range of experimental conditions. A full factorial design can simultaneously consist of all combinations of levels of different parameters. Suppose we have two parameters X and Y, each can take values at two levels. Denote the two levels of each parameter by '+' for high level and '−' for low level, respectively. The factorial design of these two parameters can be easily illustrated with the matrix shown in Tables 2a and 2b. Only four experiment runs are needed to evaluate all of the effects of X and Y, and their interactions, XY.

Following Box et al. (1978), one can construct a calculation matrix (e.g. Table 2b) and calculate the effects of each parameter as follows

$$E_j^k = \frac{\sum_i^N S_{ij} V_i^k}{P} \tag{1}$$

Table 2a
Design matrix for a full two-level two-parameter factorial analysis. The '+' and '−' signs represent high and low levels of each parameter, respectively

Run	Parameter	
	X	Y
1	+	−
2	−	−
3	−	+
4	+	+

Table 2b
Calculation matrix for a full two-level two-parameter factorial analysis

Run	Parameters			Model responses		
	X	Y	XY	V^1	V^2	$\cdots V^k \cdots$
1	+	−	−	V_1^1	V_1^2	$\cdots V_1^k \cdots$
2	−	−	+	V_2^1	V_2^2	$\cdots V_2^k \cdots$
3	−	+	−	V_3^1	V_3^2	$\cdots V_3^k \cdots$
4	+	+	+	V_4^1	V_4^2	$\cdots V_4^k \cdots$

where E_j^k is the mean effect of the parameter in column j on the k^{th} model response V^k, $S_{i,j}$ represents the sign in column j and row i of the matrix, N is the total number of experimental runs conducted, P is the number of + signs in each column of the design matrix, and V_i^k is the value of the k^{th} model response V^k obtained from the i^{th} experimental run.

From Eq. (1), it can be seen that a positive value of E_j^k implies that over a specified parameter range, model response V^k will increase, in an average sense, if the parameter in column j increases. On the contrary, a negative value of E_j^k implies that the model response V^k will decrease if the parameter in column j increases. Therefore, a complete matrix $E = E_j^k$ ($k = 1, 2, \ldots, q$; $j = 1, 2, \ldots, p$; where q is the total number of model responses, and p is the total number of parameters under investigation) of a scheme provides a general picture of its response behaviors with respect to different parameters. Such a matrix is referred to as E matrix in this study. The E_j^k elements of E matrix with different schemes can be used to evaluate the scheme differences quantitatively and qualitatively. In addition, a two-level n-parameter experiment needs 2^n number of experimental runs.

A land-surface model generally involves many parameters for different processes, and different models may have different groups of parameters. As the number of parameters increases, the size of the experiment becomes large. Data interpretation also becomes much more cumbersome, particularly when interactions are present. Categorizing of model parameters is thus often necessary in experiment designs. The fractional factorial experiment is thus often adopted in practice.

In PILPS-2c, the sensitivity experiments were conducted on eight model parameters by each LSS. Of the eight parameters, the first five parameters are common to all of the schemes except for MOSAIC which does not use the parameter of minimum stomatal resistance. The five common parameters represent the characteristics of soil and vegetation (see Table 1). The remaining three parameters are related to the soil or vegetation properties, and are determined by each participating group. Thus, the three remaining parameters will not be the focus of this study. In the past, different sensitivity studies conducted with different models using different data sets sometimes show contradictory sensitivity results to the same model parameters. For example, Wetzel and Chang (1988) and Siebert et al. (1992) showed more sensitivity to the amount of soil water content than to vegetation, and Wilson et al. (1987a) found soil texture to be the most sensitive parameter, while Jacquemin and Noilhan (1990) found vegetation cover to be the most sensitive surface parameter. Therefore, it is important to investigate the relative sensitivities of a model response to the five common soil and vegetation related parameters among the different LSSs that use the same data sets. If a parameter is identified to be the most sensitive one to a model response for a scheme in this study, for example, it implies that this parameter is more sensitive than the other four common parameters and their parameter interactions. The identified parameter is not necessarily the most sensitive one to the scheme among all the parameters and their interactions.

In conducting the PILPS-2c sensitivity experiments by each LSS group, each of the eight parameters was pre-assigned values at two levels that were obtained by $\pm 35\%$ perturbation around its average (nominal) value. Table 3 shows the nominal values of the five common parameters. It is worth mentioning that this pre-assigned range (i.e. $\pm 35\%$) does not imply that it is the exact uncertainty range associated with each parameter, although it is consistent with the uncertainty ranges or measurement errors of the commonly selected parameters (e.g. Clapp-Hornberger B parameter (Dingman, 2002)) except for porosity and wilting point. For example, the uncertainty associated with porosity measurement at a point is generally around a range of $\pm 15\%$ (Dingman, 2002). The reason of taking porosity to be $\pm 35\%$ is because the uncertainty for the average

Table 3
The nominal values of the five common soil and vegetation parameters

Parameter names	Location 1 (wet), nominal	Location 2 (dry-1), nominal	Location 3 (dry-2), nominal
Soil porosity	0.47	0.47	0.46
Wilting point	0.11	0.12	0.10
Clapp-Hornberg B	4.37	4.83	4.31
LAI	Varied monthly	Varied monthly	Varied monthly
Minimum stomatal resistance (s/m)	100	70	110

maximum soil moisture content (MSMC) of each model grid is much larger than ±15%. Due to the fixed soil depth used in some LSS models, we thus artificially enlarge the porosity uncertainty level in order to represent a reasonable uncertainty range of the average MSMC for each model grid. For a similar reason, the uncertainty level of the wilting point is assigned to be ±35% to represent the uncertainty range for effective available water content (EAWC) for each model grid. For comparison purpose, the sensitivity results of VIC where a perturbation level of ±15% for the porosity and wilting point, respectively, are also included in this study. The results of VIC with all five parameters perturbed by ±35% are represented by 'VC1', and the ones with porosity and wilting point perturbed by ±15% are represented by 'VC2' in all of the plots. It should be noticed that the objective of this intercomparison sensitivity analysis is to study the sensitivities of the model responses to each model parameter under the same level of uncertainty, rather than the sensitivities to each parameter under different parameter ranges (i.e. the range of possibility) that are associated with different soil and vegetation types. Other model parameters such as the albedo, roughness length, and displacement height are taken to be the same among all of the participating models, and the fraction of vegetation coverage is specified as 100% or equivalent to 100%.

As discussed earlier, a full factorial experiment of eight-parameters at two-levels would require $2^8 = 256$ different model runs. However, the number of 256 model runs is unpractical and often unnecessary. As argued by Box et al. (1978) and Henderson-Sellers (1993), higher-order factor interactions are often unlikely to be significant, and could be disregarded by conducting fractional factorial analysis where only a fraction of the full factorial experiment model runs is needed. It should be pointed out that when a fractional factorial design is employed, certain tradeoff exists between the loss of information about higher order interactions and the number of experimental runs. In this study, a fractional factorial experiment design with a resolution of 4 is used. Such a design ensures that any single parameter effects on model responses will not be confounded with the effects of any two parameter interactions due to the reduction of model runs (Box et al., 1978). However, the single parameter effects can be confounded with three parameter interactions and two parameter interactions can be confounded with other two parameter interactions, and so on. With such a fractional factorial experimental design, only 16 model runs are required for each model. The calculation matrix corresponding to such an experimental design is shown in Table 4 which has the same meanings as the columns shown in Table 2b under the category of parameters. It should be mentioned that the calculation matrix shown in Table 4 would guarantee a design with resolution 4 in 16 model runs and thus is preferred (Box et al., 1978).

According to the 16 model-run fractional factorial experiment design, each modeling group was asked to conduct three sets of the 16 model runs associated with three different hydroclimatic conditions at three locations in the Red-Arkansas River Basin (Wood et al., 1998). At each location, each model runs to its equilibrium states to reduce the effects of initial conditions to the minimum extent. Among the three different hydroclimatic sites, one has much larger amount of annual precipitation than the other two (Fig. 1). The three sites are referred to as 'wet' (N33.5, W94.5; forest), 'dry-1' (N37.5, W97.5; cultivation) and 'dry-2' (N35.5, W100.5; grassland), respectively. The two drier sites (i.e. dry-1 and dry-2) have different monthly precipitation distributions. A relatively long dry period is found at dry-1 site (e.g. from August to February of next year). The reason to study the sensitivity analyses of each model under the three different hydroclimatic conditions is that land-surface schemes can be calibrated at only limited locations, but they are expected to work well at other locations in the global where the soil and vegetation conditions and the climate conditions could be quite different.

Table 4
Calculation matrix of the two-level eight-parameter factorial design. The meaning of each parameter index is given in Table 1

Model runs	Parameters and parameter-combinations														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)(2)	(1)(3)	(1)(4)	(1)(5)	(2)(3)	(2)(4)	(2)(5)
1	−	−	−	+	+	+	−	+	+	+	−	−	+	−	−
2	+	−	−	−	−	+	+	+	−	−	−	−	+	+	+
3	−	+	−	−	+	−	+	+	−	+	+	−	−	−	+
4	+	+	−	+	−	−	−	+	+	−	+	−	−	+	−
5	−	−	+	+	−	−	+	+	+	−	−	+	−	−	+
6	+	−	+	−	+	−	−	+	−	+	−	+	−	+	−
7	−	+	+	−	−	+	−	+	−	−	+	+	+	−	−
8	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
9	+	+	+	−	−	−	+	−	+	+	−	−	+	−	−
10	−	+	+	+	+	−	−	−	−	−	−	−	+	+	+
11	+	−	+	+	−	+	−	−	−	+	+	−	−	−	+
12	−	−	+	−	+	+	+	−	+	−	+	−	−	+	−
13	+	+	−	−	+	+	−	−	+	−	−	+	−	−	+
14	−	+	−	+	−	+	+	−	−	+	−	+	−	+	−
15	+	−	−	+	+	−	+	−	−	−	+	+	+	−	−
16	−	−	−	−	−	−	−	−	+	+	+	+	+	+	+

Hence, we must pay attention not only to the effects of soil and vegetation properties, but also the effects of climate conditions on model processes that may dominate under different climate conditions in calibrating, modifying, and validating LSSs. If the effects of model parameters of a LSS on model responses are quite different under different climate conditions, attention needs to be paid to the model's validations under different climate conditions. This is because the model may behave quite differently even if the soil and vegetation properties are similar under those different hydroclimatic conditions.

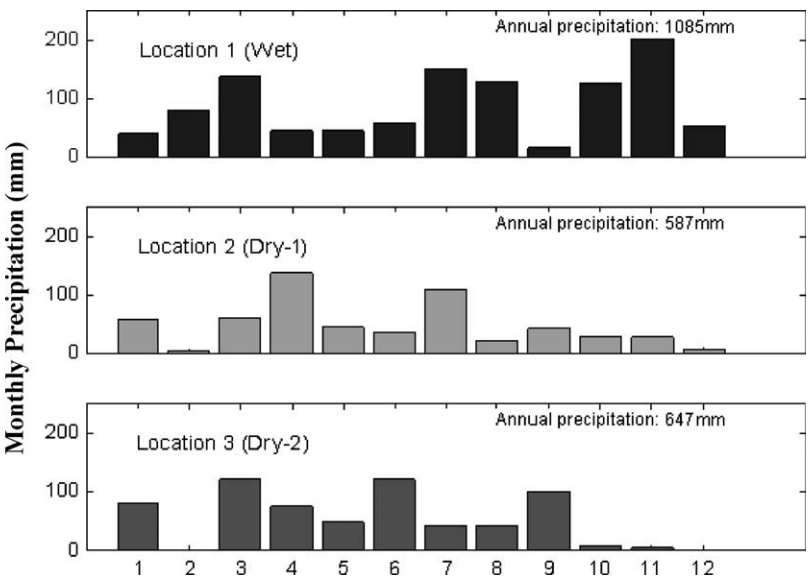

Fig. 1. Distribution of monthly precipitation at three different locations in the Red-Arkansas River Basin.

The transferability of model parameters in such cases may become very complicated.

Four model responses are selected to evaluate the effects of the five common model parameters. They are annual evapotranspiration (mm), annual total runoff (mm), annual mean sensible heat flux (W/m^2), and annual mean soil moisture in the total zone (mm/mm), respectively. Note that different model sensitivities may be expected, to the five common model parameters, if the models' responses were evaluated at a diurnal or seasonal time-scales. However, the approach used here can be easily applied to other time-scales.

3. Identification of primary parameters

One of the important objectives of conducting the sensitivity analyses is to identify the most sensitive parameters (called primary parameters here) to the model responses, since these primary parameters could play critical roles in model performance and improvement. Therefore, it is important to identify whether any changes of the values in a parameter j, for example, has any significant effect (i.e. sensitivity) on the model response V^k based on the mean effect E_j^k estimated by Eq. (1). In the previous fractional factorial sensitivity studies (e.g. Henderson-Sellers, 1993; Hu and Islam, 1996), primary parameters were identified as a group of 'outliers' using a quantity of multiple times of standard deviation (i.e. $\pm n\sigma$) as a criterion in the selection process, where the standard deviation (σ) was evaluated through an iteration procedure, and n is a positive number. Effects that were greater than the above selected criterion were identified as outliers, and the corresponding parameters were considered to have significant effects on the model responses. A disadvantage of this outlier method is that for situations where the available sample size used to calculate the standard deviation is small, the estimated standard deviation could be significantly distorted which would consequently obscure objective selections of the primary parameters. In fact, the sample size is usually small because the number of parameters to be examined together with their non-confounding parameter interactions is not large. Also, the outlier method may not be able to identify any outliers if the effects of most of the parameters (including parameter interactions) are significant but few effects fall into the category of 'experiment errors'. Arendt et al. (1996) identified parameters to be sensitive if they lie outside four times of the root mean square error range. The root mean square error is also evaluated through an iteration procedure, following the work of Henderson-Sellers (1993). As pointed out by Arendt et al. (1996), their method works reasonably well if a large number of parameter effects is minor and only a small number deviates from the normal probability line. However, if the magnitudes of the parameter effects are spread more equally, their method will not work well because the root mean square error is often higher than even the largest effect. Adjustments are then needed (Arendt et al., 1996).

In this study, we introduce two new indices to evaluate the effects of model parameters on model responses based on the mean effects obtained from Eq. (1). Let us use 'single response effect index (SREI)' and 'multiple response effect index (MREI)' to represent, respectively, the sensitivities of single and multiple model responses to the model parameters. The SREI of a model parameter is represented by its relative effect on a single model response, while the MREI of a model parameter is defined as a normalized score with respect to its relative effects on multiple model responses. The SREI of each parameter on a specified model response (e.g. annual evapotranspiration) can be easily obtained by calculating the relative effect of each parameter on the specified model response as follows

$$\mathrm{SREI}_j^k = \frac{|E_j^k|}{E_{\mathrm{cr}}^k} \tag{2}$$

where SREI_j^k is the relative effect of the j^{th} parameter on the specified k^{th} model response, and E_{cr}^k can be evaluated by the mean value ($\overline{E^k}$) expressed below

$$E_{\mathrm{cr}}^k = \overline{E^k} = \frac{1}{m}\sum_{i=1}^{m}|E_i^k| \tag{3}$$

or by the mean–median value ($E_{\mathrm{m-med}}^k$) which is expressed as

$$E_{\mathrm{med}}^k = \mathrm{median}(|E_1^k|, |E_2^k|, |E_3^k|, \ldots, |E_m^k|) = |E_l^k|$$

$$E_{\mathrm{med}-1}^k = |E_{l-1}^k|, \qquad E_{\mathrm{med}+1}^k = |E_{l+1}^k|$$

$$E_{\mathrm{cr}}^k = E_{\mathrm{m-med}}^k = \frac{1}{3}(E_{\mathrm{med}-1}^k + E_{\mathrm{med}}^k + E_{\mathrm{med}+1}^k) \tag{4}$$

where m is the maximum number of parameters (including non-confounding parameter interactions) used to calculate $\overline{E^k}$ or E^k_{med} (i.e. $m = 15$ in this case where individual parameters and two-parameter interactions are included, but the confounded patterns among two-parameter interactions are excluded), l represents the median number over the total number of m, and $l-1$ and $l+1$ are the left and right neighbors of the median number. If m is an even number, l represents the two in the middle, and $l-1$ and $l+1$ are again the two neighbors of the two numbers in the middle. The absolute values of E^k_i are used in Eqs. (3) and (4) to consider equally both the positive and negative effects of each parameter or parameter interaction on the specified k^{th} model response. For MREI, we first rank the relative effects (i.e. SREIs) of the parameters that are selected for the sensitivity study with respect to each single model response of interest, then the relative effects (i.e. SREIs) of each parameter is normalized over the selected multiple responses (e.g. over four responses in this study), which is expressed as

$$\text{MREI}_j = \frac{1}{M}\sum_{k=1}^{M}\text{SREI}^k_j \tag{5}$$

where MREI_j is the MREI for the j^{th} parameter, and M is the number of multiple responses (i.e. $M = 4$ in this study) used for calculating MREI_j. The magnitudes of MREI_j $(j = 1, 2, \ldots, m)$ thus provide an integrated sensitivity ranking among the investigated parameters with respect to the selected multiple model responses. From Eqs. (2)–(5), it can be seen clearly that the larger the value of SREI^k_j or MREI_j $(j = 1, 2, \ldots, m;$ $k = 1, 2, \ldots, M)$ is, the more sensitive the j^{th} parameter will be compared to other parameters with respect to the selected single or multiple model responses. If $\text{SREI}^k_j > 1$ (or $\text{MREI}_j > 1$) $(j = 1, 2, \ldots, m;$ $k = 1, 2, \ldots, M)$, it implies that the sensitivity of the kth single model response (or the multiple model responses) to the j^{th} parameter is greater than the averaged sensitivity ($\overline{E^k}$) or the mean–median sensitivity ($E^k_{\text{m-med}}$) depending on which one is used for E^k_{cr}. In this study, we use $E^k_{\text{m-med}}$ because the value of $\overline{E^k}$ is generally more significantly affected by extreme values in the sample than $E^k_{\text{m-med}}$. The reason to use $E^k_{\text{m-med}}$ rather than E^k_{med} is to reduce the effects of large 'jumps' in the magnitudes of E^k_i ($i = \text{med} - 1$, med, med $+ 1$) in the sample. Comparing with the criteria evaluated using $\pm n\sigma$ or using $4 \times$ root mean square error, SREI could be less affected by the sample size, the extreme values in the sample, and the situation of large root mean square error. Also, the index of MREI can reflect an integrated effect of a model parameter on multiple model responses. In this study, we define that a parameter or a parameter interaction is highly sensitive (i.e. primary) to a specified single (multiple) model response(s) if SREI (MREI) is equal to or greater than 3, and is moderately sensitive if SREI (MREI) is between 2 and 3. In other words, if a parameter or a parameter interaction has its effect three (2–3) times greater than the mean–median effect among the parameters and parameter interactions, we say that this parameter or parameter interaction is highly (moderately) sensitive to the model response(s) compared to others. It should be mentioned that the criterion of the value of 3 (2–3) is somewhat subjective, similar to the selection of the value n in the $\pm n\sigma$ approach (e.g. 3 or 4 in Henderson-Sellers, 1993, and 1 in Hu and Islam, 1996) and 4 in the root mean square error approach by Arendt et al. (1996). A more objective way could be to conduct a hypothesis test. However, for sample sizes that are small, the hypothesis test may not be a good candidate. In this study, we use both SREI and MREI to evaluate the relative importance of the model parameters of each participating scheme with the criterion of 3 (2–3) and $E^k_{\text{cr}} = E^k_{\text{m-med}}$. SREI and MREI are, in a sense, similar to the single- and multiple-criteria (Pareto ranking) of the approach by Bastidas et al. (1999).

4. Experimental results and analyses

For a land-surface scheme, effects of specified model parameters at a location can be represented by an E matrix (i.e. Eq. (1)) which includes at least 20 elements (i.e. 4 model responses $\times$ 5 common parameters for a single parameter case). However, due to the large number of E matrices (10 schemes $\times$ 3 locations), we re-organized them based on Eqs. (1), (2) and (5) so that more efficient intercomparison studies can be carried out among the schemes. The effects of the parameters and their interactions on model responses for a specific scheme, and the sensitivities of model responses of different schemes to the same parameters will be examined and analyzed in this section.

4.1. Comparison of primary parameters

Primary parameters of a scheme play a critical role in an overall performance of the scheme because these parameters are the ones whose variations in magnitudes could significantly affect the model results. Therefore, for the intercomparison study, it is important to identify the common primary parameters so that efforts could be made in the future to estimate them more adequately.

As described in Section 3, primary parameters in this study are identified as a group of single parameters or parameter interactions whose SREIs or MREIs to a specified single or multiple model response(s) are equal to or greater than 3. Fig. 2 shows the relationship of SREIs versus the five common model parameters for each scheme for the four individual model responses, respectively, at location 1 (i.e. the wet site). All the schemes have their own sensitivity patterns similar to each other on the five common model parameters with respect to the annual evapotranspiration, runoff, and sensible heat flux, except SEWAB whose SREI of MSMC is greater than 6 for the runoff, but less than 3 for the evapotranspiration and sensible heat flux. Among the other nine schemes (BASE, BATS, CAPS, ISBA, MOSAIC, NCEP, PLACE, SPONSOR, and VIC-3L) whose own patterns are similar for the evapotranspiration, runoff, and sensible heat flux, seven (BATS, CAPS, MOSAIC, NCEP, PLACE, SPONSOR, and VIC-3L) have their SREIs of MSMC greater than 3, and six (BATS, CAPS, MOSAIC, NCEP, PLACE, and VIC-3L) have MSMC to be the most sensitive parameter among the five common parameters with respect to evapotranspiration, runoff, and sensible heat flux. ISBA is the only scheme where none of the five SREIs is sensitive enough to be even greater than 2. In other words, all of the five common model parameters of ISBA have similar effects that are not significantly different from E_{cr}^{k} on each of the four model responses (i.e. evapotranspiration, runoff, sensible, and soil moisture in the total zone) at the wet site.

The sensitivity patterns to the annual mean soil moisture in the total zone for the five common model parameters vary largely from scheme to scheme, and from the patterns to the other three model responses (evapotranspiration, runoff, and sensible heat) within the same scheme. It is important that such a large sensitivity variation pattern to the soil moisture in the total zone among the schemes is identified, since soil moisture has significant impact on land–atmosphere interactions. All of the 10 schemes have the parameter of MSMC to be highly sensitive to the soil moisture in the total zone, except for ISBA and NCEP. However, in the case of NCEP, MSMC is the most sensitive parameter among the five parameters and the SREI value of MSMC is quite close to 3 (see Fig. 2d).

The next most sensitive parameter at the wet site is the Clapp-Hornberger B parameter where six (BASE, CAPS, MOSAIC, PLACE, SPONSOR, and SEWAB) of the 10 schemes have their corresponding SREIs greater than 3 for three model responses (evapotranspiration, runoff, and sensible heat flux). BASE and SPONSOR are the two schemes where the Clapp-Hornberger B parameter is the most sensitive parameter over the model responses of evapotranspiration, runoff, and sensible heat flux. For the model response of annual mean soil moisture in the total zone, the parameter of Hornberger B is identified to be highly sensitive only in three schemes (CAPS, PLACE, and SEWAB).

The vegetation related parameters of leaf area index (LAI) and minimum stomatal resistance are highly sensitive to the model responses of evapotranspiration, runoff, and sensible heat flux for SPONSOR (LAI) and SEWAB (minimum stomatal resistance). For the annual soil moisture in the total zone, only the minimum stomatal resistance of BATS shows to be highly sensitive, while the LAI and minimum stomatal resistance of SPONSOR and SEWAB are no longer identified as the highly sensitive parameters. Also, the sensitivity patterns of each scheme to the five common model parameters are more diverse to the model response of soil moisture than to the other three model responses.

From Fig. 2, it can be seen clearly that although the individual sensitivity patterns of each scheme to the five model parameters vary from each other, the four model responses of the majority of the schemes are most sensitive to the parameter of MSMC. Also, the effects of MSMC, Clapp-Hornberger B, and EAWC (i.e. soil related parameters) on the model responses are generally much larger than those of LAI and

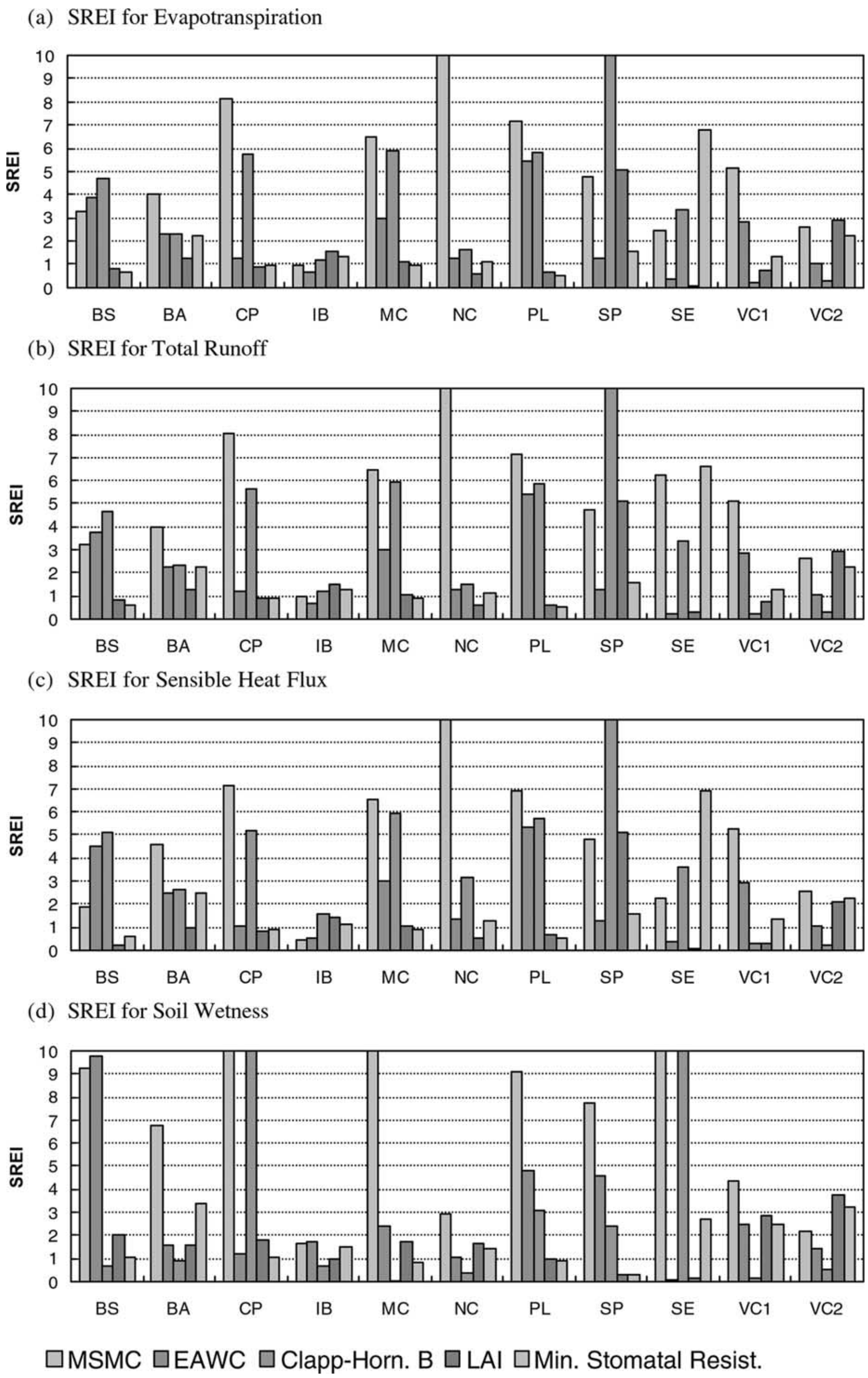

Fig. 2. SREIs of the five common model parameters of each scheme with respect to the four individual model responses (i.e. a, b, c, and d) at the wet site.

minimum stomatal resistance (i.e. the vegetation related parameters) among the majority of the schemes. Although one may argue that the variation range of porosity (0.306, 0.635) and wilting point (0.072, 0.149) taken to be $\pm 35\%$ of their nominal values may artificially exaggerate the effects of MSMC and EAWC, we argue that the variation range of $\pm 35\%$ for MSMC and EAWC is reasonable and consistent with the natural variations of the two parameters (i.e. MSMC and EAWC), and is in line with the range of other parameters. Also, the ranges of porosity (0.306, 0.635) and wilting point (0.072, 0.149) are consistent with the ranges used in other sensitivity studies, for example, the one by Bastidas et al. (1999) where their values vary over (0.33, 0.66) for porosity and (0.088, 0.542) for wilting point, respectively. In addition, varying both porosity and wilting point by only $\pm 15\%$ while keeping the rest of the three common parameters by $\pm 35\%$, we show with VIC scheme (VC2 in Fig. 2) that MSMC is the most sensitive parameter to the model response of sensible heat flux, and is the second most sensitive parameter (only slightly less sensitive than the most sensitive parameter of LAI) with respect to evapotranspiration and runoff.

If we agree on that each scheme's individual sensitivity patterns to the five common parameters are a reflection, to some extent, of each scheme's integrated model structures (parameterizations), we can see that with respect to evapotranspiration, runoff, and sensible heat flux, CAPS, MOSAIC, and PLACE have more similarities among their sensitivity patterns than other schemes; and BATS, NCEP, and VIC are relatively more similar to each other at the wet site. Also, NCEP is similar to CAPS compared to other schemes, although it is not as close as MOSAIC and PLACE to CAPS. The patterns of BASE, ISBA, SPONSOR, and SEWAB are quite different. Regarding the soil moisture in the total zone, BATS, MOSAIC, NCEP, and VIC have similar sensitivity patterns to the five model parameters, while PLACE and SPONSOR are similar to each other. The patterns of BASE, CAPS, ISBA, and SEWAB are quite different. The similarity and dissimilarity of the sensitivity patterns among the schemes indicate the importance of intercomparing the integrated effects of the schemes, in addition to the intercomparison of individual process/parameterization used by its model.

Fig. 3a shows the relationship of MREIs (i.e. over four integrated model responses of evapotranspiration, runoff, sensible, and soil moisture) versus the five common model parameters for each scheme at location 1 (i.e. the wet site). From Fig. 3a, it can be seen that the sensitivity patterns of MREIs of each scheme to the five model parameters are similar to those of SREIs shown in Fig. 2, except for BASE, SPONSOR, and SEWAB. The main reason for these three schemes to have quite different patterns is due to their very different SREI patterns with respect to the model response on soil moisture. The relationship between SREI and MREI of each scheme on the five common model parameters is similar to the ones between single- and multiple-criteria (Pareto ranking) of the approach by Bastidas et al. (1999).

One of the advantages of the factorial method is that it can be used to test the effects of parameter interactions in a simple and relatively efficient way. In the current experiment design, a two-parameter interaction could be confounded by some other two-parameter interactions. Fig. 3b shows the relationship of MREIs with seven independent two-parameter interactions (i.e. none of them is confounded with others) for each scheme at the wet site. Comparing the magnitudes of MREIs in Fig. 3a and b, we can see clearly that the effects of the parameter interactions on the four integrated model responses are not as important as the effects of the single model parameters for the 10 schemes. Specifically, only CAPS and PLACE have some of their MREIs greater than 3, BASE has some of its MREIs between 2 and 3, and all of the other seven schemes have their MREIs less than 2. Among the MREIs that are greater than 2, they are the two-parameter interactions between MSMC–EAWC (BASE and PLACE), MSMC–Clapp-Hornberger B (BASE, CAPS, and PLACE), and EAWC–LAI (BASE and PLACE), in which MSMC and Clapp-Hornberger B are the parameters identified to be the two most sensitive ones among the majority of the schemes. ISBA is the scheme that has very similar values on MREIs for single and parameter interactions at the wet site (see Fig. 3a and b). In other words, both the five common parameters and the seven interactions (except for the combination of EAWC–Min. Resist.) in ISBA have

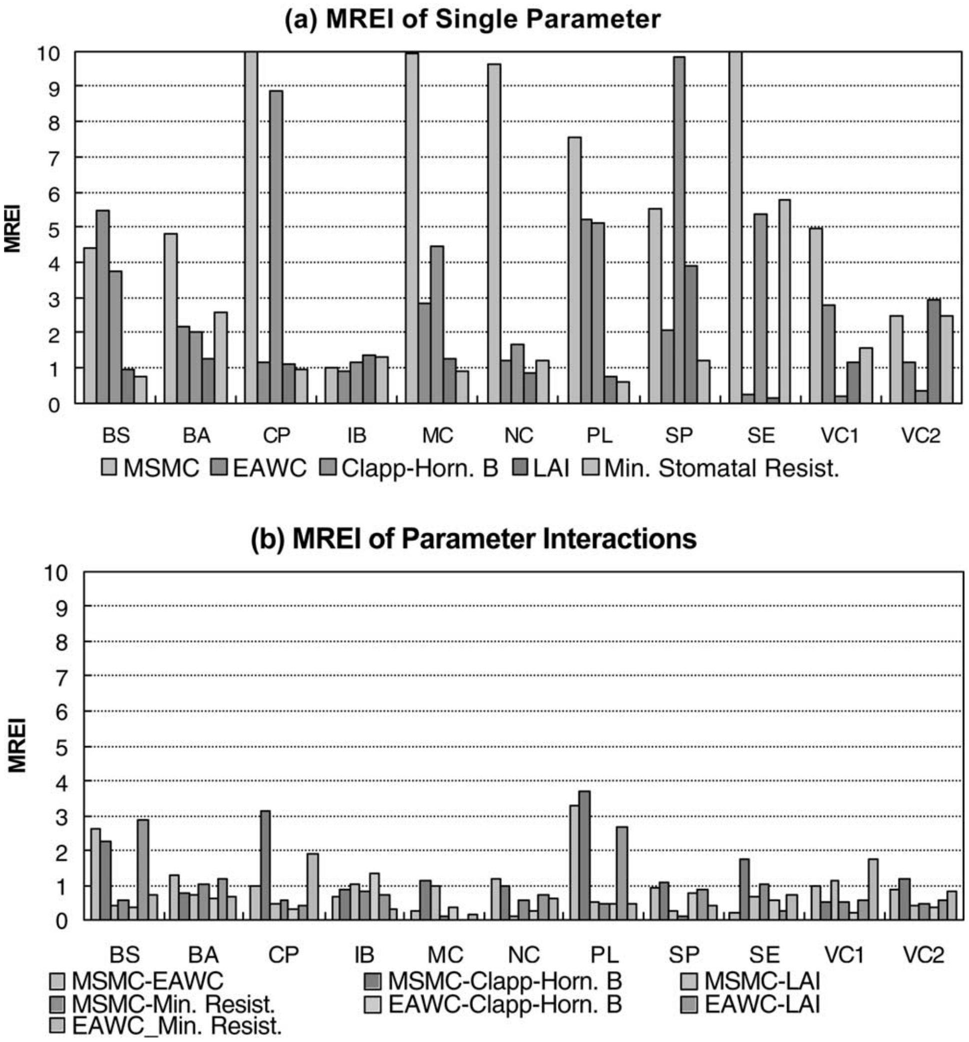

Fig. 3. MREIs of the five common model parameters and their two-parameter interactions of each scheme at the wet site.

similar degrees of sensitivities on the model responses. The pattern of the parameter interactions is another indicator of the differences of the model integrated structures among the 10 schemes, since parameter interactions could be partially affected by the model structures (parameterizations), hydroclimatic conditions, and other unknown reasons. In this study, it seems that the model responses of BASE, CAPS, and PLACE could be more significantly affected by the parameter interactions among the five common parameters than the other schemes. Ideally, one may want to eliminate or reduce the effects of parameter interactions on model responses because parameters with higher interactions may suffer from identification problems more significantly.

Fig. 4 shows the same plots of SREIs as shown in Fig. 2, but at location 2 (i.e. the dry-1 site). Unlike Fig. 2 in which nine schemes (except for SEWAB) have their own sensitivity patterns on the five common model parameters similar to each other with respect to the annual evapotranspiration, runoff, and sensible heat flux, only six schemes (BATS, CAPS, MOSAIC, PLACE, SPONSOR, and VIC) at location 2 (dry-1 site) keep similar features (i.e. have similar patterns). The other four schemes (BASE, ISBA, NCEP, and SEWAB) have their patterns quite

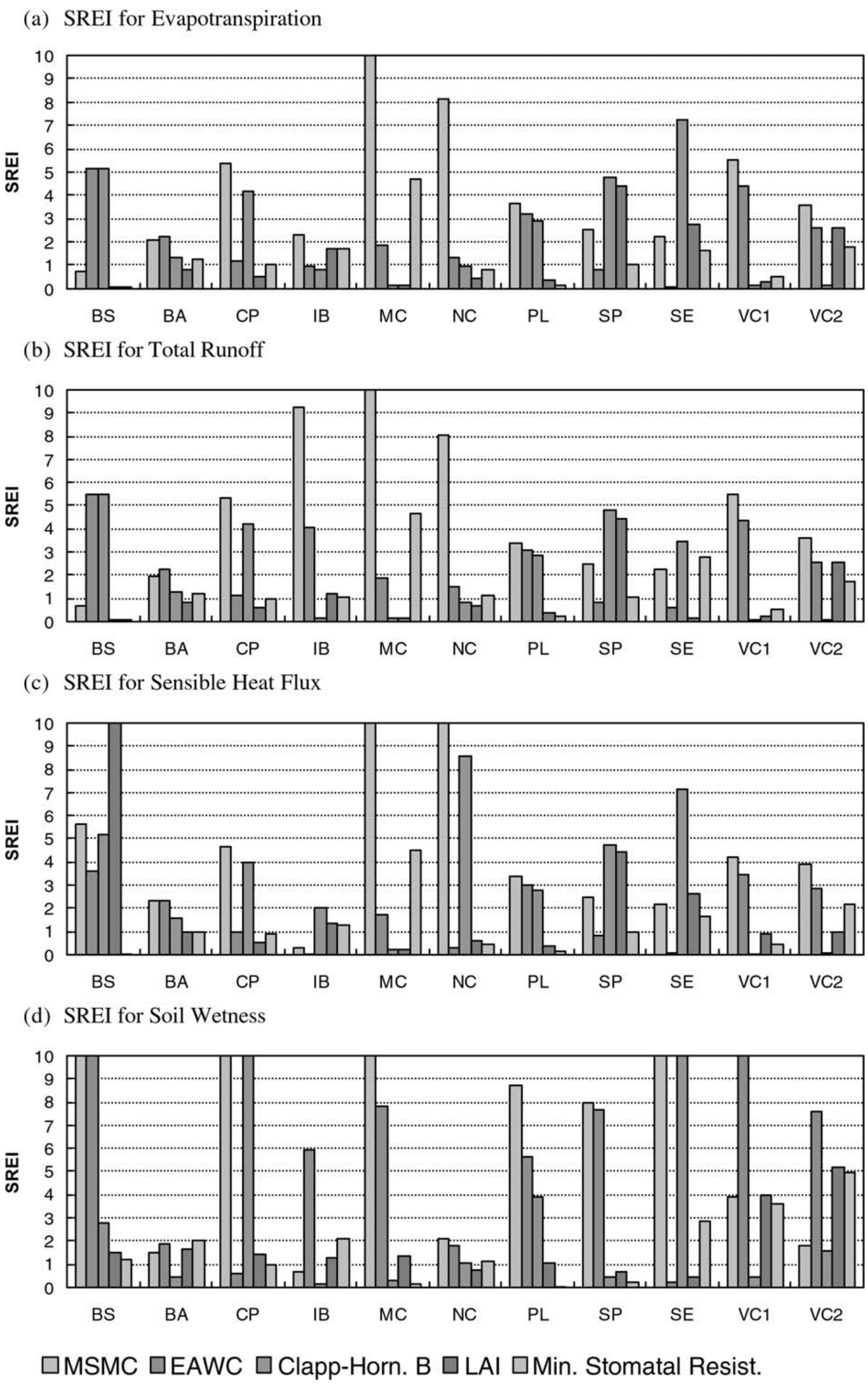

Fig. 4. SREIs of the five common model parameters of each scheme with respect to the four individual model responses (i.e. a, b, c, and d) at the dry-1 site.

different in one or more model responses with respect to the evapotranspiration, runoff, and sensible heat flux. Among the six schemes (BATS, CAPS, MOSAIC, PLACE, SPONSOR, and VIC), five models (except for MOSAIC) have their patterns, in a relative sense, similar to the corresponding ones at location 1 (the wet site), while MOSAIC is quite different. At the wet site, MOSAIC has its parameters of MSMC and Clapp-Hornberger B to be highly sensitive to the evapotranspiration, runoff, and sensible heat flux, but has MSMC and the fifth model parameter (not minimum stomatal resistance for MOSAIC) to be highly sensitive at the dry-1 site. The Clapp-Hornberger B parameter becomes the least sensitive parameter with its magnitude of SREI much smaller than 1 (Fig. 4a–c). NCEP would be identified to have similar patterns among the evapotranspiration, runoff, and sensible heat flux at dry-1 site if its SREI of the Clapp-Hornberger B parameter to the sensible heat flux did not increase to about 8.5 from less than 1 in the cases of evapotranspiration and runoff. BASE, ISBA, and SEWAB have their sensitivity patterns quite different at the dry-1 site. Unlike the wet site, ISBA has its SREI of MSMC and EAWC greater than 3 with respect to the runoff at the dry-1 site, while its SREIs are always less than 2 at the wet site. Unlike the wet site, BATS has its SREIs at the dry-1 site to be always less than 3, and only slightly greater than 2 sometimes. Although MSMC is still one of the most sensitive parameters at the dry-1 site, only five schemes have it identified as a highly sensitive parameter and also only five schemes have it to be the most sensitive one compared with seven and six, respectively, at the wet site. Similar to the wet site, the next most sensitive parameter is the Clapp-Hornberger B parameter where four schemes (BASE, CAPS, SPONSOR, and SEWAB) have their corresponding SREIs greater than 3 on three model responses (evapotranspiration, runoff, and sensible heat flux).

Similar to the wet site, the sensitivity patterns to the annual mean soil moisture in the total zone for the five common model parameters also vary widely (even more diversely than that at the wet site) from scheme to scheme, and from the patterns to the other three model responses (evapotranspiration, runoff, and sensible heat) within the same scheme. Also, similar to the wet site, the Clapp-Hornberger B parameter is identified to be highly sensitive only in three schemes (CAPS, PLACE, and SEWAB) with respect to the model response of soil moisture in total zone. All of the 10 schemes, except BATS, ISBA and NCEP, have the parameter of MSMC to be highly sensitive to the soil moisture of the total zone. The large values of SREIs to the soil moisture in total zone for many schemes suggest that a small change in the magnitudes of model parameters may result in large relative changes in soil moisture since the soil may be quite dry. BATS is the only scheme whose SREI of MSMC at the dry-1 site is much less than that at the wet site, suggesting that its soil moisture in the total zone is more sensitive to MSMC at the wet site than that at the dry-1 site.

The vegetation related parameters of LAI and the 5th model parameter are highly sensitive to the model responses of evapotranspiration, runoff, and sensible heat flux for MOSAIC (not minimum stomatal resistance) and SPONSOR (LAI). For the annual soil moisture in the total zone, only LAI and minimum stomatal resistance of VIC shows to be highly sensitive, while the 5th parameter of MOSAIC and the LAI of SPONSOR are no longer identified as the highly sensitive parameters. Similar to the wet site, the sensitivity patterns of the model response of soil moisture to the five common model parameters are more diverse than those to the other three model responses among the schemes.

From Fig. 4, it can be seen clearly again that in general MSMC is most sensitive among the five common parameters, and that the soil related parameters (i.e. MSMC, Clapp-Hornberger B, and EAWC) are more sensitive than the vegetation related parameters (LAI and minimum stomatal resistance) among the majority of the schemes. For the dry-1 site, the sensitivity patterns of VC1 and VC2 (having porosity and wilting point varying by $\pm 15\%$ only) are similar on the four model responses, and MSMC is the most sensitive parameter, in both VC1 and VC2, with respect to the model responses of evapotranspiration, runoff, and sensible heat flux.

The wider range of the sensitivity patterns at the dry-1 site, compared to the wet site, suggests that differences among the integrated model structures (parameterizations) are greater in handling the land-surface processes under dry conditions than that under wet conditions. From Fig. 4, we can see that with respect to the evapotranspiration, runoff, and sensible

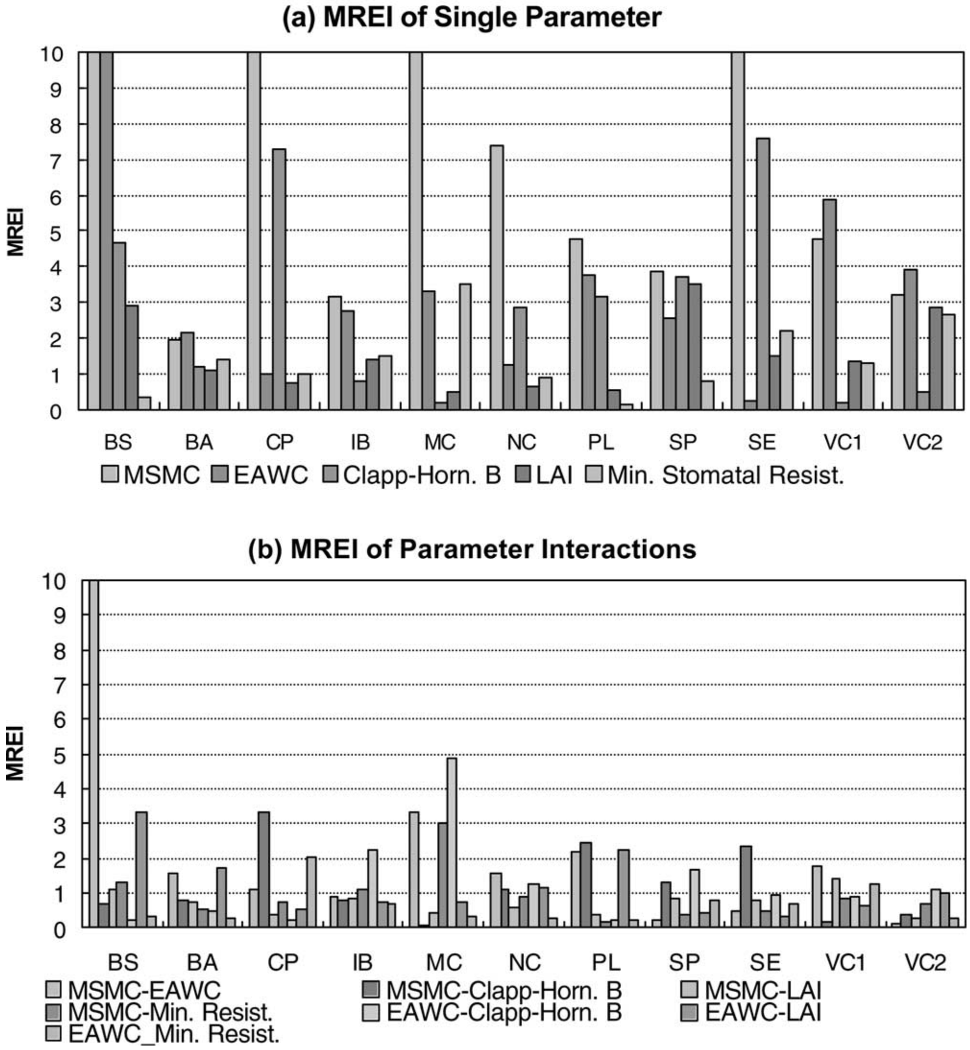

Fig. 5. MREIs of the five common model parameters and their two-parameter interactions of each scheme at the dry-1 site.

heat flux, CAPS, MOSAIC, and PLACE are no longer more similar to each other than to others in their sensitivity patterns; and so is true for BATS, NCEP, and VIC whose patterns are also quite different from each other at the dry-1 site. Except for the model response of sensible heat flux, the patterns of NCEP and CAPS are also no longer similar to each other at the dry-1 site. ISBA and VIC seem to be the two schemes whose patterns are relatively similar to each other on the model responses of evapotranspiration, runoff, and soil moisture in the total zone at the dry-1 site, although the SREI patterns of ISBA and VIC to the sensible heat flux are quite different. Regarding the soil moisture in the total zone, BATS and NCEP are the two schemes whose SREI patterns are not highly sensitive to any of the five common model parameters. However, such a phenomena does not occur in NCEP regarding the other three model responses.

Fig. 5a shows the same plots of MREIs as shown in Fig. 3a, but at location 2 (dry-1 site). From Fig. 5a, it can be seen that the sensitivity patterns of MREIs to the five model parameters are similar to those of SREIs (except for the patterns on soil moisture) shown in Fig. 4 among six schemes (BATS, CAPS, ISBA, MOSAIC, PLACE, and SPONSOR), while three schemes (BASE, SEWAB, and VIC) have their MREI patterns similar to their corresponding SREI patterns of the soil moisture in total zone due to relatively much higher values of SREIs of the model response on soil moisture in these three schemes. From Fig. 5a, it can be seen clearly again that MSMC is highly sensitive to the integrated four model responses in nine (except for BATS) out of 10 schemes at the dry-1 site, similar to that at the wet site. The second most sensitive parameter at the dry-1 site is again the Clapp-Hornberger B parameter which is highly sensitive to the model integrated responses in five (BASE, CAPS, PLACE, SPONSOR, and SEWAB) out of 10 schemes. EAWC is the third most sensitive parameter that is highly sensitive to the integrated model responses in four (BASE, MOSAIC, PLACE, and VIC) out of 10 schemes. The two vegetational related parameters (LAI and minimum stomatal resistance) are identified to be highly sensitive only in two schemes, that is in MOSAIC for its 5th model parameter (not minimum stomatal resistance, see explanation in Section 2) and in SPONSOR for LAI. Comparisons between VC1 and VC2 also show that the two vegetational related parameters are not as sensitive as the soil related parameters to the integrated model responses at the dry-1 site, although they become moderately sensitive in VC2 from VC1 (see Fig. 5a). However, the patterns of VC1 and VC2 are similar (see Fig. 5a).

Fig. 5b shows the relationship of MREIs and seven two-parameter interactions for each scheme at location 2 (i.e. the dry-1 site). Comparing the magnitudes of MREIs in Fig. 5a and b, we can see clearly again that the effects of model parameter interactions on the four integrated model responses are not as important as the effects of the single model parameters among most of the 10 schemes. However, comparing with the wet site (Fig. 3b), more schemes (three schemes (BASE, CAPS, and MOSAIC) versus two (CAPS and PLACE at the wet site)) show higher sensitivities to the two-parameter interactions. More specifically, BASE has its MREIs of MSMC–EAWC and EAWC–LAI parameter interactions greater than 3, CAPS has its MREI of MSMC–Clapp-Hornberger B parameter greater than 3, and MOSAIC has its MREIs of MSMC–EAWC, MSMC–5th parameter, and EAWC–Clapp-Hornberger B parameter interactions greater than 3. In addition, there are six MREIs of two-parameter interactions that are between 2 and 3 at the dry-1 site while only four such MREIs at the wet site. Such a comparison between Figs. 3 and 5 seems to suggest that parameter interactions could become more significant at the dry site than at the wet site. This could be due to the model structures (parameterizations) of each scheme where the processes for arid climate are represented more differently than their counterparts under moist climate. These results show some consistency with the findings by others (e.g. Gedney et al., 2000; Gan and Biftu, 2002). It should be mentioned that the results presented here do not imply that other models do not have or have less parameter interactions, but that other schemes have less two-parameter interactions among the tested five common model parameters. However, these schemes may have significant parameter interactions among other model parameters.

The SREI and MREI sensitivity patterns of eight schemes (CAPS, ISBA, MOSAIC, NCEP, PLACE, SEWAB, SPONSOR, and VIC) at the dry-2 site are between their counterparts at the wet and dry-1 sites (some schemes are closer to the dry-1 site while others are closer to the wet site). However, the SREI and MREI sensitivity patterns of BASE and BATS are different at all of the three sites. These results suggest that BASE and BATS are more sensitive to the hydroclimatic conditions comparing to the other eight schemes with respect to the five common model parameters.

It is worth mentioning that the sensitive parameters identified here for BATS are generally consistent with the results from other sensitivity studies (e.g. Henderson-Sellers, 1993; Hu and Islam, 1996; Bastidas et al., 1999), despite the differing ranges of how the same parameters were allowed to vary, the different number of parameters studied, and even the different sensitivity assessment methods used in the different studies. For example, the parameter of porosity has been shown to be highly sensitive in all of the previous studies (Henderson-Sellers, 1993; Hu and Islam, 1996; Bastidas et al., 1999), and depth of root zone to be highly sensitive in the studies by both Hu and Islam (1996) and Bastidas et al. (1999). In the study by Bastidas et al. (1999), BATS is also shown to be sensitive to the parameters of the depth of top soil layer, minimum stomatal resistance, and the Clapp-Hornberger B parameter. In addition, similar features of BATS of having different sensitivities of model responses to the same model parameters under different hydroclimatic conditions are reported by Bastidas et al. (1999) in their studies for the Tucson semiarid site and the ARM-CART grassland site. Henderson-Sellers (1993) showed similar results for BATS using fractional factorial analysis method with the criterion of $\pm n\sigma$ over three sites (i.e. tropical, temperate, and polar environments) with artificially constructed atmospheric forcing data. These results show that the findings from this study on BATS are in good agreement with the results from other studies.

In summary, the analyses here have shown that the effects of model parameters are very complicated among the schemes. Although there is no such a single parameter that is always dominant for all schemes at all of the three sites, and the sensitivities of model responses to the five common parameters could vary widely among the 10 schemes and at the three different sites for the same scheme, results here suggest that MSMC is the most sensitive parameter among the five common parameters, and that the soil related parameters (i.e. MSMC, Clapp-Hornberger B, and EAWC) are more sensitive than the vegetation related parameters (i.e. LAI and minimum stomatal resistance) among the majority of the 10 schemes.

4.2. Comparison of the effects of single parameters

Figs. 6–9 show relative effects of each of the five common parameters to the four model responses, respectively, at the three different sites (i.e. one wet and two dry sites). The relative effect is calculated as a ratio of the effect obtained from Eq. (1) for a parameter on a model response to its corresponding annual mean model response in which all of the model parameters are taken at their nominal values. From Figs. 6–9, it can be seen clearly again that MSMC has relatively greater relative effects on the four model responses (i.e. evapotranspiration, runoff, sensible, and soil moisture in the total zone) than the other four common parameters. Also, the order of magnitude (from the largest to smallest) of the relative effects of MSMC is from runoff, soil moisture in the total zone, sensible, to evapotranspiration. The reason to have the largest relative effects on runoff is due to its small amount at the nominal condition. CAPS and PLACE have their relative effects greater than 150% at all three sites, and BASE and NCEP have their effects greater than 150% at the dry-2 site. BASE has negligible relative effect at the dry-1 site while MOSAIC has its relative effect close to 120% which is the largest relative effect for MOSAIC at the three sites. SPONSOR has the smallest relative effects at all three sites among the 10 schemes (see Fig. 7a). For situations where other factors are unchanged, increase in MSMC would decrease the amount of surface runoff in general (especially at the wet site), while its effect on subsurface flow could be more complicated. Fig. 7a shows that the increase of MSMC decreases the total amount of runoff (surface and subsurface runoff combined) for all of the 10 schemes and at all three sites. Such a negative effect of MSMC also holds for sensible heat flux (Fig. 8a) for all schemes and at all three sites, although the order of magnitude is much smaller (mostly less than 30%). BASE is the scheme that has positive relative effect at the dry-1 site. However, the magnitude is very small (less than 5%) and could be considered as within the 'uncertainty range'. The reason for sensible heat flux has the negative effect with the increase of MSMC is probably related to the increase of the capability of storing water within the soil column, and thus an increase of soil moisture level. The higher soil moisture content could then lead to higher evapotranspiration which results in the decrease of sensible heat flux to keep the energy budget balanced. Comparing Figs. 6a and 8a, it can be seen that the positive feedback of MSMC on evapotranspiration has similar magnitude of negative feedback on sensible heat flux. Fig. 9a shows that the positive feedback of MSMC has the second largest effects on the soil moisture in the total zone. ISBA has negative feedback for the dry-1 site, but it is very small and could be considered as within the uncertainty range. Figs. 6–9 imply qualitatively that all of the 10 schemes have correct response directions with the change of MSMC where the increase in evapotranspiration and soil moisture, and the corresponding decrease in total runoff and sensible heat flux keep the energy and water budgets balanced within the system. However, quantitatively, large differences of the relative effects of MSMC on evapotranspiration, runoff, sensible heat flux, and soil moisture exist

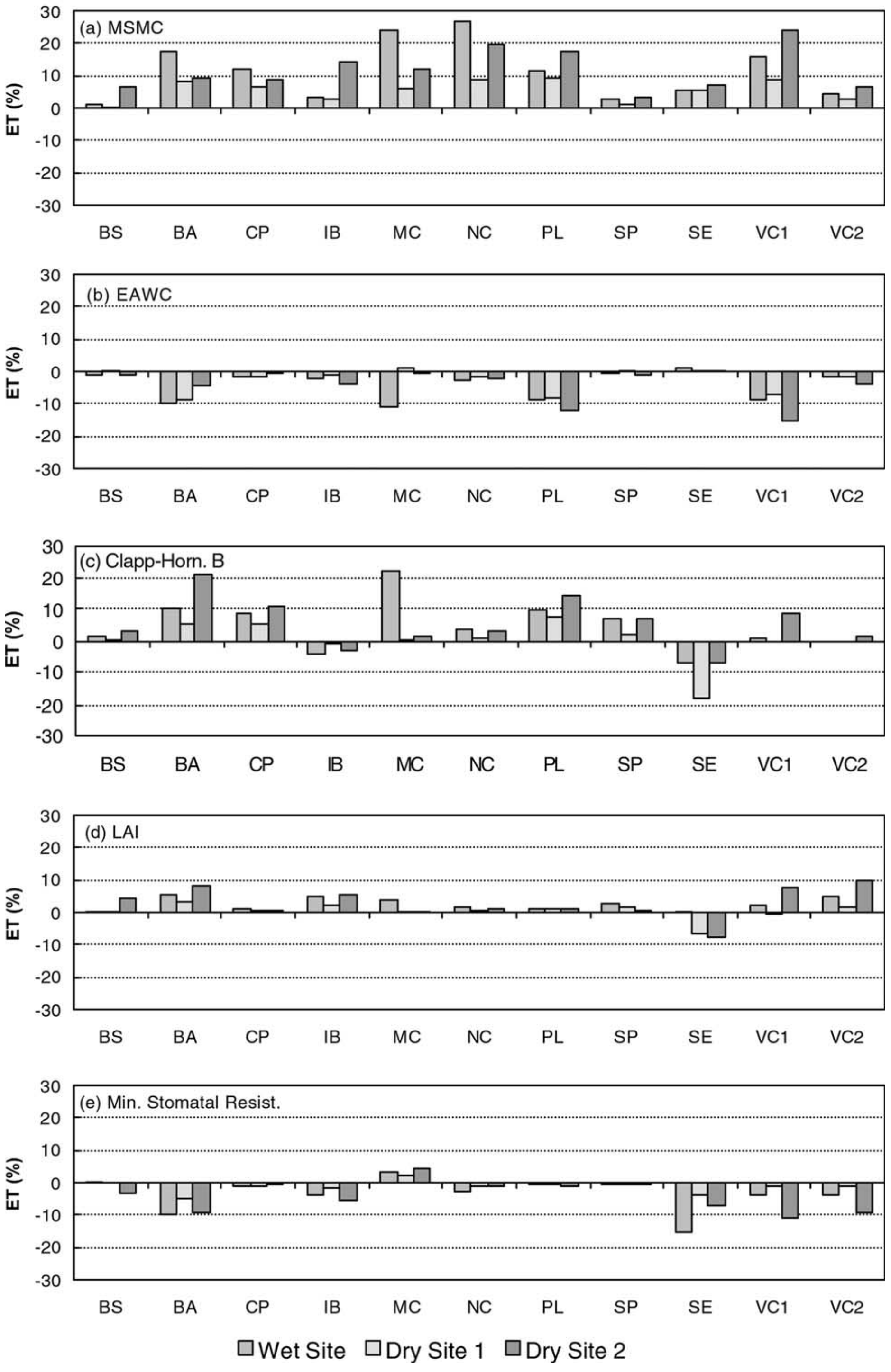

Fig. 6. Relative effects of each of the five common parameters to annual evapotranspiration at the three sites.

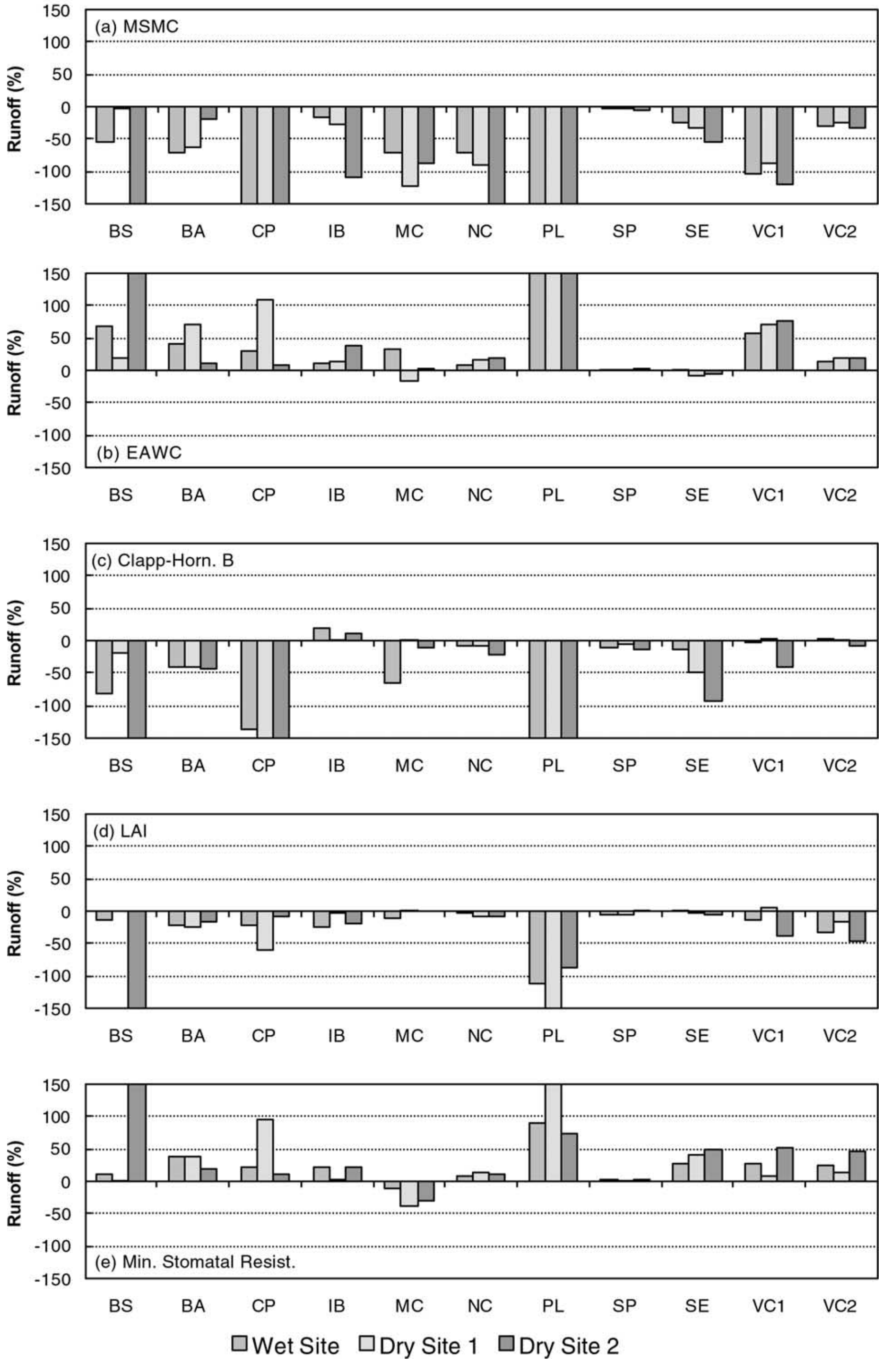

Fig. 7. Relative effects of each of the five common parameters to annual runoff at the three sites.

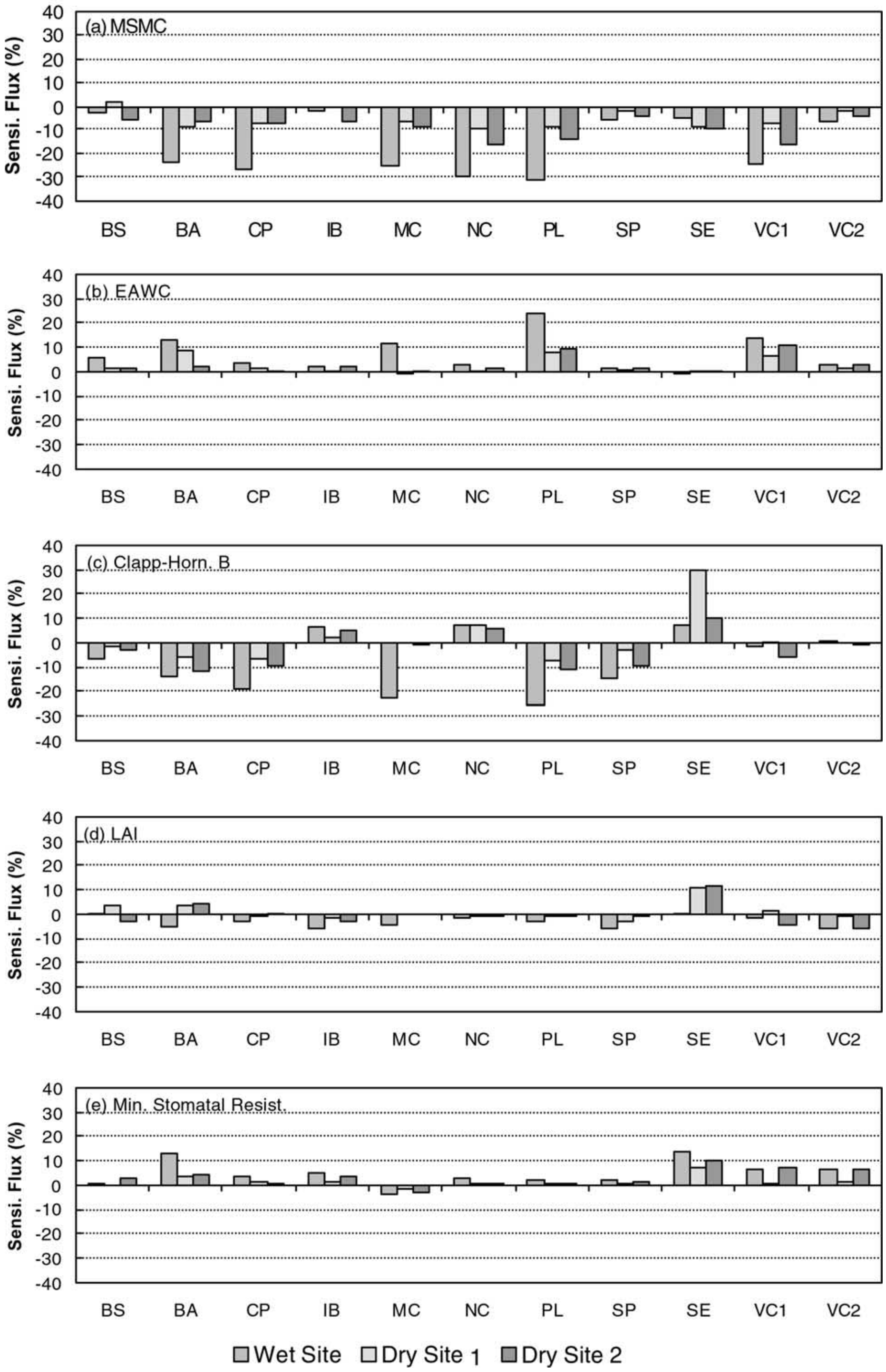

Fig. 8. Relative effects of each of the five common parameters to annual mean sensible heat flux at the three sites.

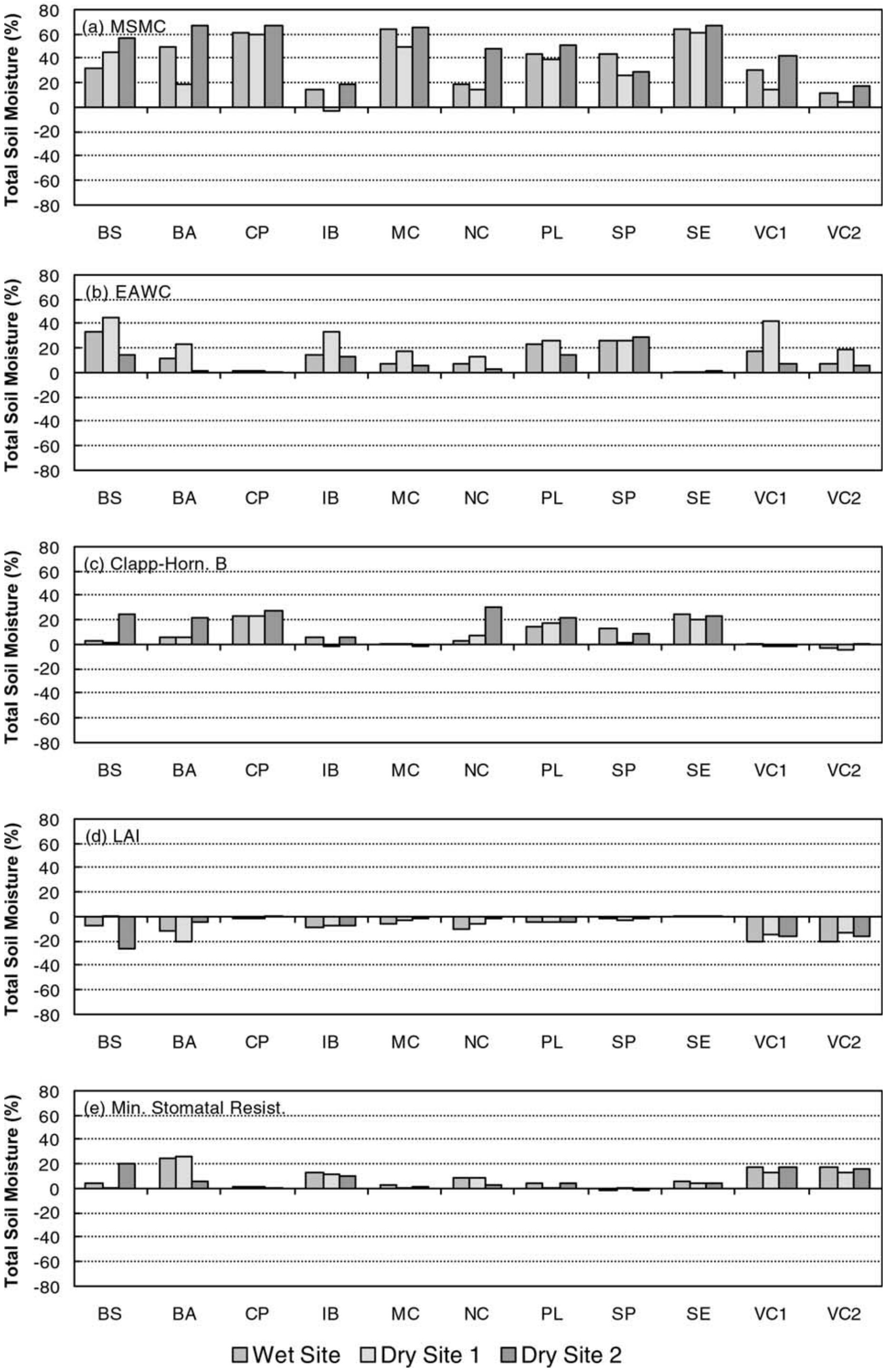

Fig. 9. Relative effects of each of the five common parameters to annual mean soil moisture in the total zone at the three sites.

among the schemes and among the three different locations for the same scheme (Figs. 6–9).

Different patterns of the relative effects associated with the three locations are present among the schemes. For MSMC, for example, its effect on annual evapotranspiration among the 10 schemes may be grouped into three different patterns: (1) largest effect at location 1 (i.e. wet site) and smallest effect at location 2 (i.e. dry-1 site) (BATS, CAPS, MOSAIC, NCEP); (2) largest effect at location 3 (i.e. dry-2 site) and smallest effect at location 2 (dry-1 site) (BASE, ISBA, PLACE, SPONSOR, VIC-3L); and (3) largest effect at location 3 (i.e. dry-2 site) and smallest effect at location 1 (i.e. wet site) (SEWAB). The first two patterns include nine schemes, and both have smallest relative effects at location 2 (dry-1 site) which has the lowest annual total precipitation and longest dry period. A qualitative explanation is that there is not much water available for evapotranspiration at location 2 (dry-1 site) (Fig. 1). The variation of MSMC at this location, therefore, would not pose a significant change in evapotranspiration. Thus, it has the smallest change in evapotranspiration with respect to the change in MSMC among the three locations. Although many factors may be responsible to the large differences in the sensitivities of model responses to the same parameter (e.g. MSMC) at the different locations, the forcings at the three locations certainly play a significant role in resulting large different relative effects of MSMC on the evapotranspiration. This is because the variation of MSMC is the same at the three locations, and that the values of MSMC and other soil parameters at the three locations are similar to each other as shown in Table 3. Other factors that may play a significant role in contributing to such large difference of model sensitivity on the evapotranspiration are the vegetation parameters of LAI and minimum stomatal resistance (see Table 3). Also, model structures (parameterizations) of each scheme in which different processes (e.g. wet processes versus dry processes) are represented may certainly play an important role. More detailed studies are needed to identify the relative roles of the forcings, vegetation parameters, and model structures in this regard. Results (Figs. 6–9) show again that for the same scheme, same parameters do not necessarily present similar sensitivities under different hydroclimatic conditions.

Comparing with the effects of MSMC on the evapotranspiration, the relative effects of the Clapp-Hornberger B parameter and EAWC are generally smaller among the participating schemes, and the effects of LAI and minimum stomatal resistance are even smaller (Fig. 6b–e). Most schemes have positive feedback on the evapotranspiration with the Clapp-Hornberger B parameter but SEWAB, which has negative feedback at all three sites (ISBA's negative feedback is very small and thus can be ignored). Five schemes (BASE, BATS, CAPS, PLACE, and VIC) have a pattern with the largest relative effect at the dry-2 site and the smallest at the dry-1 site, while MOSAIC and NCEP have the largest relative effect at the wet site and the smallest at the dry-1 site. For EAWC which represents a critical soil moisture level below which plants cannot take any water for transpiration, all the schemes have negative feedback on the evapotranspiration with an increase of EAWC because more water is retained in the soil column but not available for transpiration. ISBA, PLACE, SPONSOR, and VIC have similar patterns at the three sites where the largest relative effects occur at the dry-2 site, although the magnitudes of individual relative effects vary widely among these schemes. Such a pattern indicates that the soil moisture level among these four schemes at the dry-2 site could be closer to the originally assigned EAWC value than that at the other two sites. Increasing the EAWC value would then make the soil moisture level below the critical state for vegetation to transpire at the dry-2 site, and thus significantly reduce the transpiration amount which results in a large relative effect on the evapotranspiration at the site. However, the increase of EAWC does not necessarily have the largest relative effect on the soil moisture change in the total zone at the dry-2 site as shown in Fig. 9b. BASE, BATS, CAPS, MOSAIC, and NCEP have the largest relative effects at the wet site, also with the magnitudes of the effects varying over a wide range among the schemes. Such a pattern implies that the soil moisture level at the wet site could be closer to the originally assigned EAWC value than that at the other two sites for these five schemes. Thus, an increase in EAWC may be just large enough to stop the transpiration and hence results in the largest relative effect at the wet site for these schemes compared to the other two sites. Again, the increase of EAWC does not necessarily have the largest relative effect on the soil moisture change in the total zone for these schemes at the wet site as shown in Fig. 9b. From Fig. 9b, it can be seen clearly that the change of EAWC has the largest relative effect on the change of soil moisture at the dry-1 site for most schemes. The reason that the relative effects of EAMC on evapotranspiration is the smallest for most of the schemes at the dry-1 site could be that the soil moisture at this site is very dry and the change of EAMC would not be able to affect the switch for starting or stopping transpiration in a significant way. From these results, it can be seen clearly the binary-type of effect of EAWC on modeled evapotranspiration. Therefore, the estimation of soil moisture level and the prescribed value of EAWC (associated with the wilting point) would become critically important. Despite of the support of the binary-switch physics for EAWC (wilting point), we suggest to examine the possibilities of expressing EAWC (associated with wilting point) as a function of a range rather than one distinct value to be switched on and off, due to many uncertainties associated with the soil property measurements, root zone distributions, vegetation parameters, and so on.

The positive and negative model responses of each scheme to the five common model parameters are qualitatively correct for all of the schemes except for SEWAB sometimes. The relative effects of LAI and minimum stomatal resistance on the evapotranspiration, runoff, sensible, and soil moisture in the total zone are smaller than those of MSMC, Clapp-Hornberger B, and EAWC for most of the schemes (Figs. 6–9), although VIC has larger relative effects, in general, on the four model responses by LAI and minimum stomatal resistance than those by the Clapp-Hornberger B parameter. Such results may imply again that variations associated with the soil properties possibly due to either measurement uncertainties and/or spatial heterogeneity may play a more significant role in partitioning water and energy budgets than those associated with vegetation properties for most schemes. Note that the parameter of roughness length is not considered here to be part of the vegetation properties, but a surface property. Although hydraulic conductivity is not explicitly considered in this study, its effects are partially represented through the Clapp-Hornberger B parameter and MSMC, both of which are related to soil textures. Our analyses also showed that large response sensitivities exist in relation to the hydroclimatic conditions when using the same parameters and the same LSS for the majority of the current generation of LSSs. This implies that a scheme that performs well at its calibrated location may perform poorly at other locations under different hydroclimatic conditions if the scheme is not re-calibrated. Therefore, when all of the schemes are assigned to the same model parameter values and the same atmospheric forcings for a location that are different from the ones based on which the models were calibrated, their energy and water fluxes could respond quite differently. This is because the assigned parameter values at the location could be quite different from the best values each model should use for that location, and because the different degrees of sensitivity of each model has to the parameter variations resulted from the assigned values. This may explain why large differences occurred every time in the PILPS phase 1, 2(a), 2(b), and 2(c) intercomparison studies, and perhaps why each scheme performs better at its own testing sites than at the PILPS sites. However, it may be expected that a LSS that considers spatial variabilities of soil, vegetation and atmospheric forcings would perform better because its model parameters could be less sensitive. This argument is partially evidenced by the study of Koren et al. (1999) where the values of model parameters vary less when the model that considers spatial variabilities is applied to different spatial scales. More concrete and solid studies are needed in this aspect to test our hypothesis. Our ongoing study with VIC-3L in this respect may offer some insight in the future.

4.3. Comparison of the effects of parameter interactions

Similarly to the results shown in Figs. 3b and 5b, the significance of the relative effects of the seven two-parameter interactions (figures not shown) on the four model responses (evapotranspiration, runoff, sensible heat flux, and soil moisture in total zone) is much smaller than those of the single parameters shown in Figs. 6–9. Among the seven two-parameter interactions, only BATS (MSMC–EAWC, EAWC–LAI), PLACE (MSMC–EAWC, MSMC–Clapp-Hornberger B, EAWC–LAI), SEWAB (MSMC–Clapp-Hornberger B), and VIC (EAWC–minimum stomatal resistance) have their two parameter interactions comparable or slightly smaller than their corresponding single parameter effects on evapotranspiration at one or more sites. Here the 'corresponding single parameter effect' is taken from the one out of the two parameters (i.e. the two parameters that constitute the two-parameter interactions) that has higher relative effect on evapotranspiration at each site. For the model response of runoff, BASE, CAPS, PLACE (MSMC–Clapp-Hornberger B), BASE and PLACE (MSMC–LAI, EAWC–Clapp-Hornberger B, EAWC–LAI), BASE, CAPS, and PLACE (EAWC–minimum stomatal resistance), PLACE (MSMC–minimum stomatal resistance), and BATS (MSMC–EAWC) have comparable relative effects to their counterparts at one or more sites. For the sensible heat flux, BATS, ISBA, and PLACE (MSMC–EAWC), BASE, ISBA, PLACE, and SEWAB (MSMC–Clapp-Hornberger B), ISBA (EAWC–Clapp-Hornberger B), BATS, CAPS, ISBA, and PLACE (EAWC–LAI), and CAPS, NCEP, and VIC (EAWC–minimum stomatal resistance) have comparable relative effects to their single parameter counterparts at one or more sites. For the soil moisture in the total zone, BASE (MSMC–EAWC, MSMC–LAI), BATS (MSMC–minimum stomatal resistance), BATS and NCEP (EAWC–LAI), and BASE, BATS, and ISBA (EAWC–minimum stomatal resistance) have comparable relative effects to their single parameter counterparts at one or more sites. Due to the page limitation, all of the plots of these relative effects of the two-parameter interactions on each of the four model responses are not shown.

The effects of interactions vary among different climate conditions, and have different patterns among the schemes. However, comparing to the effects of single parameters, the effects of the interactions are again generally small. It is worth mentioning that Figs. 3b and 5b show the overall significance of the parameter interactions at two different locations based on MREIs; while the significance of the parameter interactions discussed here are expressed as the relative effects on the four individual model responses at each of the three locations (figures not shown).

5. Conclusions

In this intercomparison study, we investigate the sensitivities of model responses (i.e. evapotranspiration, total runoff, sensible heat flux, and soil moisture in the total zone) to five common model parameters (i.e. MSMC, EAWC, Clapp-Hornberger B parameter, LAI, and minimum stomatal resistance) and their interactions under three different climate conditions for 10 land-surface schemes. The sensitivities of the four model responses are evaluated based on two newly introduced indices (SREI and MREI) along with a criterion for measuring relative parameter effects. The index of SREI is used to indicate the effect of a parameter or parameter interaction on a single model response relative to a specified average level (e.g. the mean–median level is used in this study). If the effect of a model parameter or parameter interaction is three times or higher than the mean–median level, the parameter or parameter interaction is identified to have significant effect on the specified model response. The index of MREI is used to indicate the effect of a parameter or parameter interaction on a combination of selected multiple model responses (e.g. on four model responses in this study). Again, a parameter or a parameter interaction is identified to have significant effect on a combination of four model responses if its corresponding MREI is equal to or greater than 3. Also, the sensitivities of model responses to each parameter and parameter interaction are investigated by using the criterion of relative effects. The major conclusions from this study are as follows:

(1) MSMC has the largest effect and the Clapp-Hornberger B parameter has the second largest effect on most of the four model responses among most of the 10 schemes based on the criteria of SREI, MREI, and the relative effects. The effects of MSMC, Clapp-Hornberger B parameter, and EAWC are generally more significant than those of LAI and minimum stomatal resistance among most of the 10 participating schemes. This implies that the variations associated with the soil properties possibly due to the measurement uncertainties and/or the spatial heterogeneity may play a more significant role in partitioning water and energy

budgets than those associated with vegetation properties for the majority of the current generation of land-surface model parameterizations. In addition, the sensitive parameters identified in this study on BATS are generally consistent with the results from other sensitivity studies (e.g. Henderson-Sellers, 1993; Hu and Islam, 1996; Bastidas et al., 1999), despite the differing ranges of how the same parameters were allowed to vary, the different number of parameters studied, and even the different sensitivity assessment methods used in the different studies.

(2) Under different hydroclimatic conditions, most of the 10 LSSs have quite different sensitivities of model responses to the same model parameters. Similar results are also reported by Bastidas et al. (1999) for BATS at the Tucson semiarid site and at the ARM-CART grassland site. Henderson-Sellers (1993) showed similar results for BATS using fractional factorial analysis method with a criterion of $\pm n\sigma$ over three sites (i.e. tropical, temperate, and polar environments) with artificially constructed atmospheric forcing data. This study also shows that different schemes could have quite different degrees of sensitivities to the same model parameter, resulting in different sensitivity patterns under the same hydroclimatic conditions.

(3) The effects of parameter interactions are generally much smaller than those of single parameters. However, for some schemes, the parameter interactions are significant and can play an important role in the sensitivities of model responses to the model parameters. Also, results show that there are more significant parameter interactions and more differences in the sensitivity patterns at the dry sites than those at the wet site. This suggests that there are more differences among the 10 schemes in their model structures (parameterizations) under arid conditions than under moist conditions.

The preliminary conclusions obtained above may provide some insights on why large response differences between schemes occurred every time in the PILPS phases 1, 2(a), 2(b), and 2(c) intercomparison studies, and perhaps on why each scheme performs better at its own testing site(s) than at the PILPS sites. However, a LSS that considers spatial variabilities of soil, vegetation and/or atmospheric forcings may perform better because its model parameters may be less sensitive as partially evidenced by Koren et al. (1999). Also, this sensitivity study may suggest that when developing a methodology for transferring parameters from data rich areas to data sparse areas, not only should the characteristics of soil and vegetation be considered in the parameter transferring formulations, but also the climate conditions (e.g. external forcings) to partially compensate for the weaknesses of model structures (parameterizations) that are used to describe different processes in each scheme. Some of the changes associated with different climate conditions might also be reflected by the vegetation and soil properties.

Finally, it should be mentioned that results presented in this study are subject to annual scales. Different sensitivity results may be obtained if diurnal or seasonal scales are used as the model responses. For example, the effects of LAI and minimum stomatal resistance may become much more significant to surface fluxes if monthly scale is used. Also, the feedback of the planetary boundary layer on the sensitivity results is not accounted for in this study. Therefore, the sensitivities of model responses to some model parameters may be altered from those reported here if the study was to be conducted under a coupled mode between the LSSs and atmospheric models (e.g. Jacobs and DeBruin, 1992).

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