Exploring parameter sensitivities of the land surface using a locally coupled land-atmosphere model

Yuqiong Liu,[1] Hoshin V. Gupta,[1] Soroosh Sorooshian,[2] Luis A. Bastidas,[3] and William J. Shuttleworth[1]

Received 2 March 2004; revised 24 June 2004; accepted 6 August 2004; published 2 November 2004.

[1] This paper presents a multicriteria analysis that explores the sensitivity of the land surface to changes in both land and atmospheric parameters, in terms of reproducing surface heat fluxes and ground temperature; for the land parameters, offline sensitivity analyses were also conducted for comparison to infer the influence of land-atmosphere interactions. A simple "one-at-a-time" sensitivity analysis was conducted first to filter out some insensitive parameters, followed by a multicriteria sensitivity analysis using the multiobjective generalized sensitivity analysis algorithm. The models used were the locally coupled National Center for Atmospheric Research (NCAR) single-column community climate model and the offline NCAR land surface model, driven and evaluated by a summer intensive operational periods (IOP) data set from the southern Great Plains. As expected, the results show that land-atmosphere interactions (with or without land-atmosphere parameter interactions) can have significant influences on the sensitivity of the land surface to changes in the land parameters, and the single-criterion sensitivities can be significantly different from the multicriteria sensitivity. These findings are mostly model and data independent and can be generally useful, regardless of the model/data dependence of the sensitivities of individual parameters. The exceptionally high sensitivities of the selected atmospheric parameters in a multicriteria sense (and in particular for latent heat) appeal for adequate attention to the specification of effective values of these parameters in an atmospheric model. Overall, this study proposes an effective framework of multicriteria sensitivity analysis beneficial to future studies in the development and parameter estimation of other complex (offline or coupled) land surface models. *INDEX TERMS:* 1610 Global Change: Atmosphere (0315, 0325); 1719 History of Geophysics: Hydrology; 1833 Hydrology: Hydroclimatology; 3322 Meteorology and Atmospheric Dynamics: Land/atmosphere interactions; *KEYWORDS:* land-atmosphere interactions, sensitivity analysis, coupled modeling

Citation: Liu, Y., H. V. Gupta, S. Sorooshian, L. A. Bastidas, and W. J. Shuttleworth (2004), Exploring parameter sensitivities of the land surface using a locally coupled land-atmosphere model, *J. Geophys. Res.*, *109*, D21101, doi:10.1029/2004JD004730.

1. Introduction

[2] Numerical modeling of the earth system and its sensitivity to anthropogenic forcing is a highly complex scientific problem, involving the parameterization of non-resolvable physical processes such as the evapotranspiration from vegetated surfaces. If the parameterizations within a land-atmosphere model are not capable of representing the physical processes adequately well, the simulations or predictions of the model can be biased and/or unrealistic. Accordingly, model parameters, introduced by the parameterizations, can play a fundamental role in regulating the model performance. To reduce the model simulation uncertainties associated with model parameters, it is important to estimate effective values for model parameters through an appropriate procedure, such as model calibration. As the parameterizations within land-atmosphere models become more and more complex, the number of model parameters to be specified may increase significantly, which could make the estimation of model parameters a tedious and inefficient process. One way to avoid this problem is to reduce the dimension of the parameter space by conducting a sensitivity analysis (SA) of the parameters [e.g., *Bastidas et al.*, 1999; *Gupta et al.*, 1999].

[3] *McCuen and Snyder* [1986] defined *sensitivity* as the rate of change in one factor with respect to the change in another factor. In the case of a land-atmosphere model, a parameter sensitivity analysis is usually used to determine how, and to what extent, the model simulations of the internal state variables or the output fluxes change with perturbations in the model parameters. Various SA methods have been developed and applied to hydrological and land

[1]Department of Hydrology and Water Resources, University of Arizona, Tucson, Arizona, USA.
[2]Department of Civil and Environmental Engineering, University of California, Irvine, California, USA.
[3]Department of Civil and Environmental Engineering, Utah State University, Logan, Utah, USA.

0148-0227/04/2004JD004730

surface models. Among these is the elementary "one-at-a-time" (OAT) approach [*Pitman*, 1994], where only one factor is perturbed at each time while the remaining factors are kept constant. Other methods include the second-order analysis [*Sorooshian and Gupta*, 1985]; the factorial design [*Srivastava*, 1990; *Henderson-Sellers*, 1993]; the Fourier amplitude test (FAST) [*Collins and Avissar*, 1994; *Saltelli et al.*, 1999]; and adjoint methods [*Errico*, 1997; *Margulis and Entekhabi*, 2001]. However, most (if not all) of the above mentioned methods do not take into account the inter-dependences between model parameters or the interactions between model outputs or responses. *Bastidas* [1998] presented a multicriteria approach, called the multiobjective generalized sensitivity analysis (MOGSA), based on an extension of the regional sensitivity analysis (RSA) method [*Hornberger and Spear*, 1981]. Unlike other methods, the MOGSA algorithm considers the influence of the joint multiparameter and multiresponse interactions on parameter sensitivities.

[4] *Bastidas et al.* [1999] conducted a parameter sensitivity analysis for the offline Biosphere-Atmosphere Transfer Scheme (BATS 1e) [*Dickinson et al.*, 1993] using the MOGSA algorithm. An offline analysis like this allows the evaluation of the sensitivities of land surface schemes to changes in their parameters without the complications associated with the errors in the atmospheric components of a coupled global circulation model (GCM). However, it has recently been recognized that offline sensitivity analyses of land surface schemes could be of limited value in that they prevent the investigation of the interactions and feedbacks between the land surface and the overlying atmosphere. A number of studies have pointed out that offline experiments can lead to misleading results and thus do not provide reliable information on the performance of a land surface scheme in GCMs. For example, *Koster and Eagleson* [1990] found that, because of the lack of land surface-atmosphere feedbacks, the results from the offline experiments were incompatible with those from the coupled experiments with a single-column model or a GCM. *Dolman and Gregory* [1992] and *Pitman et al.* [1993] also showed that *Pitman et al.* [1990] had overestimated the sensitivity of the land surface to changes in the interception parameterization in BATS [*Dickinson et al.*, 1986] by running the model in an offline mode with prescribed atmospheric forcing. It was also pointed out in *Pitman* [1994] that the sensitivity results obtained from the "stand alone" experiments by *Henderson-Sellers* [1992] were unreliable because of lack of land-atmosphere feedbacks.

[5] In this study, we conducted a preliminary screening SA using the OAT approach and a multicriteria SA using the MOGSA algorithm, involving both land and atmospheric parameters. In light of the current infeasibility of conducting sensitivity analyses directly within a fully coupled GCM using the MOGSA algorithm, a locally coupled single-column model (SCM) was used. The primary purpose of this paper is to illustrate an effective framework for examining the sensitivities of land and atmospheric parameters in a locally coupled mode, taking into account influences of land-atmosphere interactions and multiresponse interdependences. In Section 2, the land surface model and the locally coupled SCM used in this study are briefly introduced, along with a brief description about the data. The results from the preliminary SA using the OAT approach are presented in Section 3. A brief overview of the MOGSA algorithm and the results from the multicriteria SA are presented in Section 4, followed by some concluding remarks and future recommendations in Section 5.

2. Models and Data

[6] To examine the influence of land-atmosphere interactions on parameter sensitivities, a locally coupled single-column model (the National Center for Atmospheric Research (NCAR) single-column community climate model, NCAR-SCCM, hereinafter referred to as the SCCM) and an offline version of the land surface model coupled to the SCCM (the NCAR land surface model, NCAR LSM, hereinafter referred to as the LSM) were used in this study.

2.1. Offline LSM

[7] The LSM is a one-dimensional, time-dependent model describing the momentum, energy, water, and CO_2 fluxes exchanges and interactions between land surfaces and the atmosphere [*Bonan*, 1996]. The model allows for multiple surface types in a single grid cell, accounting for ecological differences among 12 different vegetation types, and takes into account the optical, thermal, and hydraulic differences among eight different soil types with different combinations of percentages of sand, silt, and clay. The atmospheric forcing terms required to drive the model include incident direct and diffuse solar radiation, incident longwave radiation, convective and large-scale precipitation, specific humidity, temperature, pressure, wind, and reference height. When driven by these forcing terms, which can be generated by an atmospheric model or specified from observations, the LSM calculates diffuse and direct surface albedos, zonal and meridional momentum fluxes, constituent fluxes (H_2O and CO_2), surface-emitted longwave radiation, surface sensible and latent heat fluxes, soil and vegetation temperatures, and soil moisture contents. For details of the model physics, interested readers are referred to *Bonan* [1996], where a comprehensive description about the model is provided.

[8] The LSM has been used in a number of ecological, hydrological, and atmospheric studies. For example, *Bonan et al.* [1997] and *Lynch et al.* [1999] compared the LSM-simulated surface fluxes to the observations for the boreal forest sites in Canada and the tundra ecosystems in Alaska, respectively; *Lynch et al.* [2001] used a multivariate reduced form model to investigate the sensitivity of the LSM to perturbations in climate forcing. Other LSM-related studies include *Bonan* [1995a] and *Craig et al.* [1998], where the LSM was used to investigate the land-atmosphere CO_2 exchanges; *Bonan* [1995b], where the sensitivity of a GCM simulation to the inclusion of inland water surfaces was explored; and *Bonan* [1997, 1999], where the effects of land cover changes on the climate of the United States were studied.

[9] In this study, the parameterization of canopy evapotranspiration of the LSM was slightly adjusted to allow for more reasonable simulations of latent and sensible heat fluxes. Interested readers are referred to *Liu et al.* [2003] for details on the parameterization adjustment and its effects on the improvement of the model simulations.

2.2. Locally Coupled SCCM

[10] The SCCM is a single-grid column model developed from the global climate model NCAR Community Climate Model CCM3. The physical parameterizations in the SCCM, such as those of radiation, clouds, deep and shallow convection, large-scale condensation, and boundary layer processes, are the same as those in the CCM3. *Kiehl et al.* [1996] provides more details on the physical parameterization of the CCM3. The advantage of using the SCCM instead of the fully coupled CCM3 lies in that single-column model applications can avoid huge computational expenses and the difficulty of separating the effects of specific parameterizations being tested from those of other interdependent processes [*Xu and Arakawa*, 1992; *Randall et al.*, 1996]. The SCCM, however, lacks the horizontal feedbacks available in the more complicated three-dimensional CCM3, making it necessary to prescribe the horizontal advective tendencies using observations or reanalysis data. Consequently, the reliability of the SCCM simulations relies on the quality of the observed boundary conditions or reanalysis data used to drive the model. Interested readers may refer to J. J. Hack et al. (SCCM user's guide, version 1.2, 1999, available at http://www.cgd.ucar.edu/cms/sccm/sccm.html) and *Randall and Cripe* [1999] for information about specifying the effects of neighboring columns in the SCCM. Although several problems have arisen from the use of the SCCM in terms of simulating precipitation, temperature, and moisture fields [*Hack and Pedretti*, 2000; *Xie and Zhang*, 2000], in this study the SCCM provided a suitable locally coupled environment for examining the effects of land-atmosphere interactions on the sensitivity of the land surface to changes in model parameters.

2.3. Data

[11] In this study, both the offline LSM and the locally coupled SCCM were driven and evaluated using an intensive operational periods (IOP) data set from the Southern Great Plains (SGP) Clouds and Radiation Testbed (CART) of the Atmospheric Radiation Measurement (ARM) program. The data set contains both single-level (or surface) variables (e.g., surface heat fluxes and ground temperature) and multilevel (or column) fields (e.g., horizontal advective tendencies of temperature and humidity). The surface energy fluxes were obtained from the ARM Energy Balance Bowen Ratio (EBBR) stations, with a well-closed energy balance. To derive the initial atmospheric conditions and large-scale forcing terms, a constrained variational analysis was applied to the areal-averaged observations over the SCCM domain (about 370 km across) represented by a 12-sided variational analysis grid of the SGP site [*Zhang and Lin*, 1997; *Zhang et al.*, 2001]. This constrained variational analysis ensured the conservation of column-integrated mass, water, energy, and momentum.

[12] This IOP data set extends for 17.5 days from 0530 UTC 18 July 1995 (0030 in local time) to 1730 UTC 4 August 1995 (1230 in local time) and experiences various summer weather conditions, including several intensive precipitation periods. Because it is associated with a convectively active period, this data set has been used in various single-column modeling studies [e.g., *Ghan et al.*, 2000; *Hack and Pedretti*, 2000; *Xie and Zhang*, 2000]. It is worth mentioning that all the variables available in this IOP data set were interpolated at 20-min intervals on the basis of the original 3-hour observational data using cubic spline interpolation (as noted in the NetCDF data file). However, a preliminary analysis indicated that the parameter sensitivities to be investigated in this paper are not sensitive to this data provision.

3. One-at-a-Time (OAT) Sensitivity Analysis

[13] A preliminary sensitivity analysis based on the OAT approach was first conducted for a number of selected land and atmospheric parameters. As the name suggests, the OAT approach allows only one parameter to vary each time, ignoring the effects of parameter interactions and multi-response interdependences. This simple, preliminary analysis facilitated the identification a subset of potentially important parameters for the subsequent multicriteria SA.

[14] 45 land parameters and 14 atmospheric parameters were selected for the OAT sensitivity analysis. Appropriate lower and upper boundaries (the feasible ranges) for the selected parameters were carefully derived from available sources of information, mainly expert opinions (J. Jin, personal communications, 2002) and the literature. The OAT SA experiments were conducted in the following way: each model (LSM or SCCM) was run repeatedly for a number of times while varying a single parameter from the lower bound to the upper bound, increasing the parameter value by one percent of the feasible range each time; all the other parameters were fixed at a priori values. The mutual physical constraints among the parameters, necessary to be considered in subsequent MOGSA studies, were not included for this simple, preliminary sensitivity analysis. The root mean square (RMS) errors of latent heat flux (λE), sensible heat flux (H), and ground temperature (T_g) were used to evaluate the sensitivity of the land surface. Soil moisture was not included in this study because of lack of corresponding observational data.

[15] For illustration purposes, Figure 1 shows the variation in RMS errors of λE, H, and T_g in response to changes in three typical vegetation parameters (roughness length Z0MVT, displacement height ZPDVT, and top of canopy HVT) for the LSM (dashed line) and the SCCM (solid line), with the errors associated with the a priori parameter values marked by circles for the LSM and stars for the SCCM. The sensitivities of three typical soil parameters (porosity WATSAT, wilting point WATDRY, and optimal soil water content for evaporation WATOPT) are shown in Figure 2. For each subplot in Figures 1 and 2, the x axis represents a varying parameter, while the y axis gives the RMS errors of heat fluxes or ground temperature as the parameter varies from its lower bound to its upper bound independently. Hence the steeper the response surface associated with a parameter, the more sensitive the model (LSM or SCCM) to changes in that parameter in terms of simulating λE, H, and T_g.

[16] As shown in Figures 1 and 2, the response surfaces in the locally coupled case are less smooth than in the offline case due to the nonlinearities, feedbacks and/or other possible sources within the atmospheric part of the SCCM. However, generally similar response trends of the two cases can be noticed for all the selected vegetation and soil parameters. In other words, if the RMS error of a heat flux or state variable decreases (increases) as a parameter value

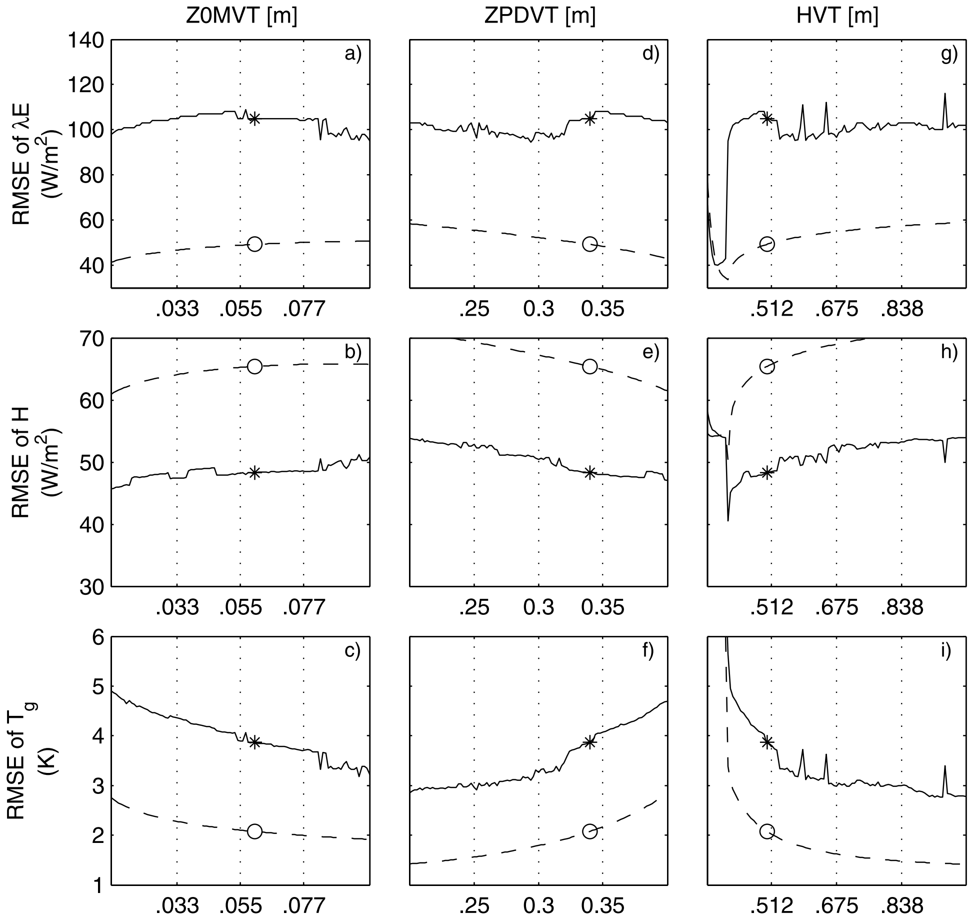

Figure 1. Response surfaces of latent heat (λE, W/m^2), sensible heat (H, W/m^2), and ground temperature (T_g, K) for three selected vegetation parameters: vegetation momentum roughness length (Z0MVT), displacement height (ZPDVT), and top of canopy (HVT). Dashed line is for the uncoupled LSM and solid line is for the coupled SCCM. The circles and the stars highlight the RMS errors corresponding to the a priori parameter values for the LSM and the SCCM, respectively.

increases in the offline case, it also does so in the locally coupled case. Figures 1 and 2 also show that, in both offline and coupled cases, the two heat fluxes and ground temperature often have opposite responses to changes in the parameters, indicating that an improvement in the simulation of the heat fluxes via adjusting a parameter could lead to a deterioration in the simulation of ground temperature, and vice versa. This trade-off is characteristic of most multiobjective calibration problems, primarily because of deficiencies in the model structures [*Bastidas*, 1998; *Gupta et al.*, 1999]. It can also be noted that Z0MVT and ZPDVT appear to be less sensitive than HVT and the three soil parameters in both offline and coupled cases. In addition, although land-atmosphere interactions existing in the coupled simulation have little impact on the sensitivities of Z0MVT and ZPDVT, the other four parameters, that is, HVT, WATSAT, WATOPT, and WATDRY, generally appear to be more sensitive in the offline case than in the coupled case.

[17] Figure 3 shows the response surfaces for λE, H, and T_g for three selected atmospheric parameters: convective available potential energy (CAPE) threshold for deep convection (CAPELMT), minimum relative humidity for low cloud formation (RHMINL*)*, and reduction on RHMINL for cloud condensation nuclei (CCN) rich land areas (RHCCN). Generally speaking, λE and T_g appear to be more sensitive to the three atmospheric parameters than H, and the response surfaces of λE and T_g for each parameter have very similar shapes. This is different from those for the land parameters for which the response surfaces of λE and T_g have opposite trends.

[18] Besides facilitating an initial perception of the model behaviors with respect to each parameter, an important purpose of this preliminary sensitivity analysis was to reduce the dimensionality of the parameter space for the subsequent more complicated multicriteria sensitivity analysis using the MOGSA algorithm. On the basis of visual comparisons of the response surfaces, 32 land parameters and 8 atmospheric parameters (as shown in Tables 1 and 2, respectively) were selected for use in the MOGSA experiments presented in Section 4. The resulting "sensitive" parameter set includes 12 vegetation parameters, 16 soil parameters, 4 initial soil moisture conditions, 4 atmospheric parameters related to deep convection, and another 4 atmospheric parameters associated with cloud fraction calculations. The remaining 13 "insensitive" land parameters and 6 "insensitive" atmospheric parameters were not included in the MOGSA experiments. These include two snow

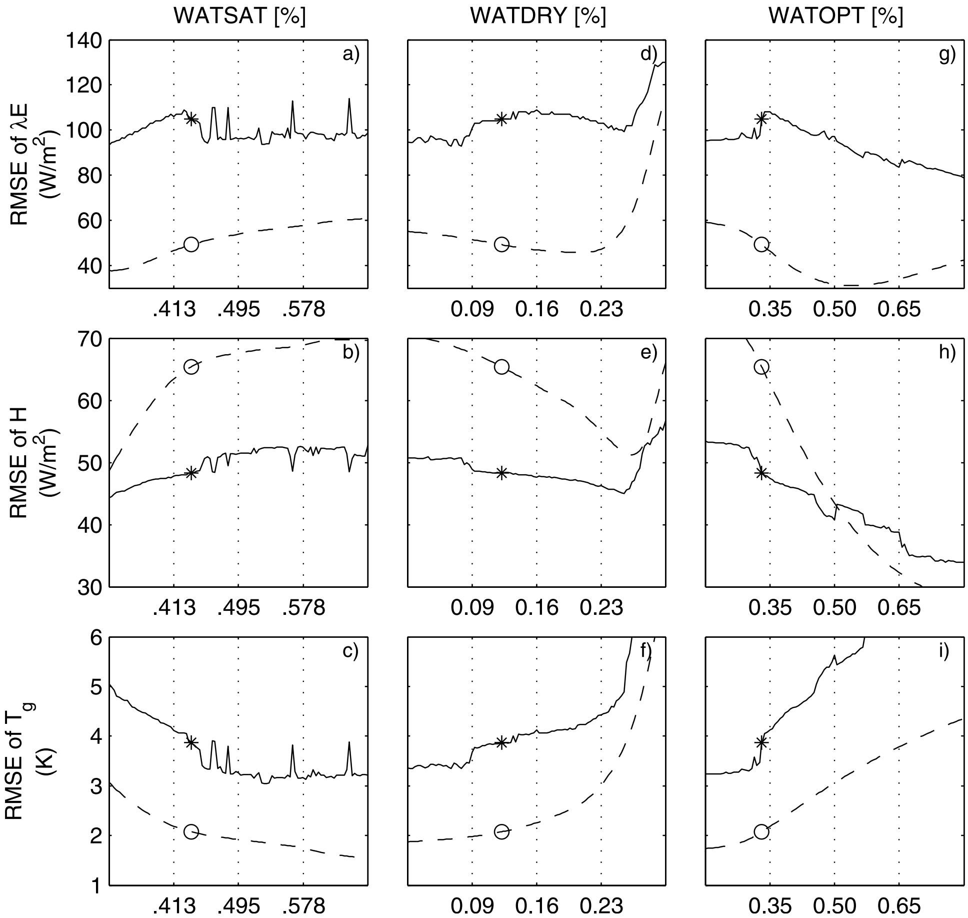

Figure 2. Same as Figure 1 but for the three selected soil parameters: porosity (WATSAT), wilting point (WATDRY), and the optimal soil water content for evapotranspiration (WATOPT).

parameters, four stem radiative parameters, the monthly leaf area index, two dry soil albedos, soil layer thicknesses and initial soil water contents for the deepest two layers, the minimum vertical diffusion coefficient, the critical Richardson number for PBL calculations, and four parameters related to shallow/middle moist convection.

4. Multicriteria Sensitivity Analysis

[19] The MOGSA algorithm was used to conduct a multicriteria SA to: 1) investigate the influence of land-atmosphere interactions on the sensitivity of the land surface to changes in land parameters, as well as the effects of multiresponse interdependences; and 2) improve the computational efficiency and effectiveness of the calibration algorithm by reducing the dimensionality of the parameter space to be used in a subsequent calibration study.

4.1. MOGSA Algorithm

[20] The multicriteria approach to model identification facilitates a more rigorous analysis of multi-input/multi-output models of dynamic earth system responses than the traditional single-criterion approach used for systems analysis [*Gupta et al.*, 1998]. The multiobjective generalized sensitivity analysis (MOGSA) algorithm [*Bastidas*, 1998] was therefore developed as a multicriteria extension of the Regional Sensitivity Analysis (RSA) approach [*Hornberger and Spear*, 1981] for testing the identifiability of environmental models. The RSA methodology investigates the sensitivities of individual parameters by examining whether a priori distributions of the parameters "separate" (are statistically differentiable) under a specific behavioral classification, via the Kolmogorov-Smirnov (K-S) two-sample test: the smaller the K-S probability, the more sensitive the parameter. By using Pareto ranking [*Goldberg*, 1989] as the technique for selecting the discriminatory threshold for behavioral and nonbehavioral parameter sets, MOGSA takes into account the multicriteria nature of typical sensitivity problems of environmental models. MOGSA also uses bootstrapping (or resampling) to minimize the influences of sampling on the outcome of the sensitivity analysis.

[21] In the implementation of MOGSA, a number of samples (i.e., parameter sets) are randomly chosen from the predefined feasible parameter space and the objective function (OF) values are calculated for each sample. On the basis of the corresponding OF values, the samples are then ranked using Pareto ranking and an arbitrary rank threshold is used to partition the samples into behavioral and nonbehavioral groups. The K-S test is performed on the two sets to estimate the multicriteria (or global) sensitivity of each parameter. The test is repeated using the bootstrapping procedure (i.e., resampling) to reduce the sampling dependence of the results. This process is repeated with succes-

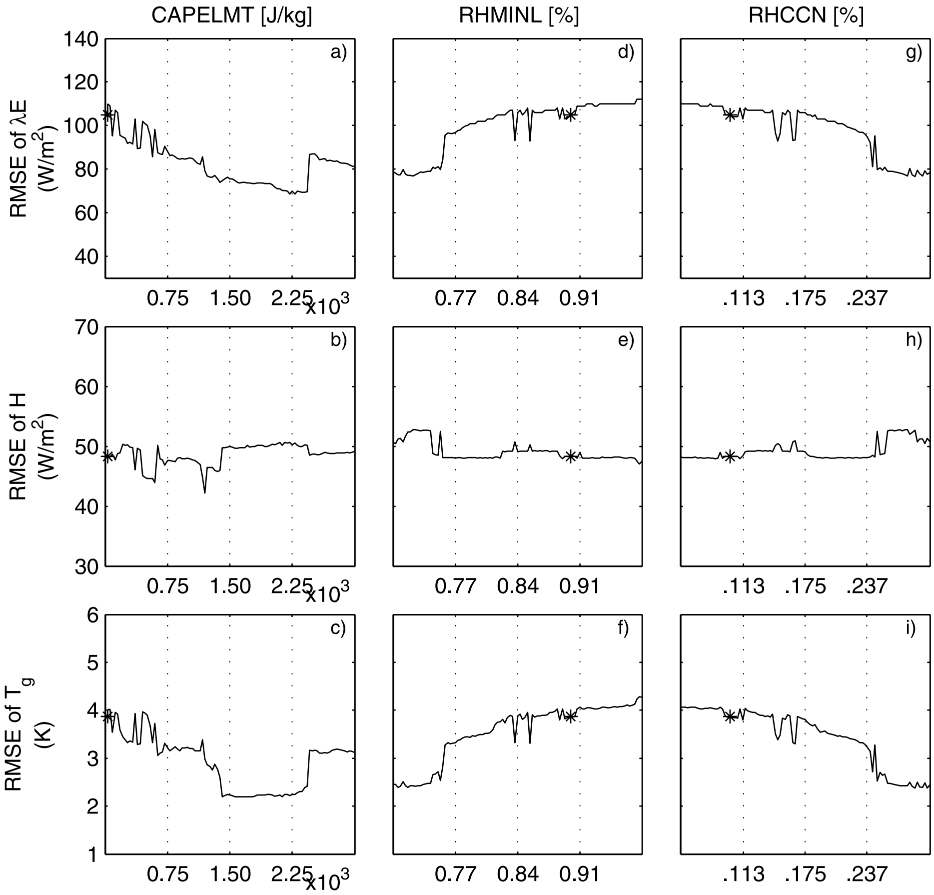

Figure 3. Response surfaces of latent heat (λE, W/m^2), sensible heat (H, W/m^2), and ground temperature (T_g, K) for three atmospheric parameters of the SCCM: the threshold of CAPE for deep convection (CAPELMT), minimum relative humidity for low clouds (RHMINL), and the reduction on RHMINL for CCN-rich areas (RHCCN).

sively larger sample sizes until the total number of sensitive parameters stabilizes. Different Pareto rank thresholds may also be used to test the sensitivity to the choice of the threshold. A certain threshold, for which the sample size required for stability is smallest and the number of sensitive parameters is largest, is then chosen to decide the final global sensitivities. Once the global sensitivities have been estimated, the corresponding quantile of the objective function value is used as the discerning threshold to decide the sensitivity of a single objective. Interested readers are referred to *Bastidas* [1998] and *Bastidas et al.* [1999] for further details.

4.2. Methodology

[22] As in the previous OAT sensitivity analysis, the RMS errors of λE, H, and T_g were used to evaluate the sensitivity of the land surface to changes in the 32 land parameters and 8 atmospheric parameters (Tables 1 and 2). When sampling parameter sets from the predefined multiparameter space, appropriate interparameter constraints were applied to ensure that the samples were biologically and hydrologically realistic. For example, vegetation displacement heights and roughness lengths should be less than vegetation heights, and soil water contents must not be higher than porosity.

[23] Three different MOGSA experiments were established and conducted:

[24] 1) Case 1: random sampling within the 32-dimensional land parameter space using the offline LSM;

[25] 2) Case 2: same as case 1 but using the locally coupled SCCM, with the eight atmospheric parameters fixed at their corresponding a priori values;

[26] 3) Case 3: random sampling within the 40-dimensional combined land and atmospheric parameter space using the locally coupled SCCM;

[27] Because the land-atmosphere parameter interdependence considered in case 3 is also a part of the overall land-atmosphere interactions, cases 2 and 3 are considered as the locally coupled cases with and without land-atmosphere parameter interdependences, respectively. The influences of land-atmosphere interactions can be inferred from a comparison of the offline case with the coupled cases, while the differences between global and single-criterion sensitivities in each single case reveal the impacts of multiresponse interdependences. Specifically, a comparison of case 1 with case 2 explores the effects of land-atmosphere interactions

Table 1. Land Parameters Selected for the MOGSA Experiments

No.	Parameter	Default[a]	Lower[a]	Upper	Description[b]
			Twelve Parameters Associated With Vegetation (Vegetation Type 11, Crop)		
1	Z0MVT	0.06	0.01	0.1	Momentum roughness length of vegetation [m]
2	ZPDVT	0.34	0.2	0.4	Displacement height [m]
3	BP	2000	1000	3000	Minimum leaf conductance [μmol/m^2/s]
4	RHOL1	0.11	0.07	0.11	Leaf reflectance in VIS
5	RHOL2	0.58	0.35	0.58	Leaf reflectance in NIR
6	TAUL1	0.07	0.05	0.07	Leaf transmittance in VIS
7	TAUL2	0.25	0.1	0.25	Leaf transmittance in NIR
8	XL	−0.3	−0.4	0.6	Leaf orientation index
9	CH2OP	0.1	0.05	0.5	Maximum intercepted water per unit LAI + SAI [mm]
10	HVT	0.5	0.35	1	Top of canopy [m]
11	AVCMX	2.4	1	3	Temperature sensitivity parameter for carboxylation
12	COVER	0.85	0.3	0.98	Vegetation cover fraction [%]
			Sixteen Parameters Associated With Soil (Soil Color 8)		
13	RLSOI	0.05	0.004	0.1	Roughness length of soil [m]
14	WATSAT	0.435	0.33	0.66	Volumetric soil water content at saturation (porosity)
15	HKSAT	4.19E-3	1.00E-5	0.1	Hydraulic conductivity at saturation [mm H_2O/s]
16	SMPSAT	−207	−750	−30	Soil matrix potential at saturation [mm]
17	BCH	5.772	3	10	Clapp and Hornberger "b"
18	WATDRY	0.122	0.02	0.3	Soil water content when evapotranspiration stops (wilting point)
19	WATOPT	0.331	0.2	0.8	Optimal soil water content for evapotranspiration
20	TKSOL	7.065	4	10	Thermal conductivity, soil solids [W/m/K]
21	TKDRY	0.15	0.1	3	Thermal conductivity, dry soil [W/m/K]
22	CSOL	2.20E + 6	2.00E + 5	5.00E + 6	Specific heat capacity, soil solids [J/m^3/K]
23	ALBSAT1	0.05	0.05	0.12	Saturated soil albedo in VIS
24	ALBSAT2	0.1	0.1	0.2	Saturated soil albedo in NIR
25	DZSOI1	0.1	0.05	0.2	Thickness of the first soil layer [m]
26	DZSOI2	0.2	0.1	0.6	Thickness of the second soil layer [m]
27	DZSOI3	0.4	0.2	1.0	Thickness of the third soil layer [m]
28	DZSOI4	0.8	0.6	2	Thickness of the fourth soil layer [m]
			Four Initial Soil Moisture Conditions		
29	H2OSOI1	0.3	0.01	0.4	Initial volumetric soil water content, first layer
30	H2OSOI2	0.3	0.1	0.5	Initial volumetric soil water content, second layer
31	H2OSOI3	0.3	0.15	0.66	Initial volumetric soil water content, third layer
32	H2OSOI4	0.3	0.2	0.66	Initial volumetric soil water content, fourth layer

[a]Read 4.19E-3 as 4.19×10^{-3}.
[b]NIR is near infrared; VIS is visible; LAI is leaf index area; and SAI is stem area index.

without land-atmosphere parameter interdependences; a comparison of case 1 with case 3 examines the influences of overall land-atmosphere interactions; and a comparison of case 2 with case 3 detects the impacts of land-atmosphere parameter interdependences.

[28] In this particular study, for all the three cases, sample sizes were successively increased from 500 to 750, 1,000, 2,000, 3,000, 5,000, 8,000, 10,000, 12,000, 15,000, 18,000 until 20,000 with 200 bootstraps for each and four different Pareto rank thresholds were tested: 5, 10, 15, and 20. The results show that rank 10 corresponded to the largest number of sensitive parameters with a minimum sample size of 10,000 in all the three cases. Consequently, the K-S probabilities obtained from the run with a sample size of 10,000 and a rank threshold of 10 were used to decide the sensitivities of each parameter. As mentioned in Section 4.1 above, the smaller the K-S probability associated with a parameter, the more sensitive the parameter is. In this study, for the convenience of analysis, we consider parameters with a K-S probability lower than 0.01 to be highly sensitive (i.e., sensitivity is significant at the 99% level) and those with a K-S probability higher than 0.05 to be insensitive. Parameters with a K-S probability between 0.01 and 0.05 are also considered to be sufficiently sensitive to be included in

Table 2. Atmospheric Parameters Selected for the MOGSA Experiments

No.	Parameter	Default	Lower	Upper	Description
					Four Parameters Associated With Deep Convection
1	CAPELMT	70	0.01	3000	Threshold value of CAPE for deep convection [J/kg]
2	TAU	7200	2400	9600	Adjustment timescale for CAPE consumption [s]
3	FMAX	0.0002	0.0001	0.0005	Maximum fractional entrainment rate of updrafts
4	ALFA	0.1	0.01	0.5	Proportionality factor for downdraft mass flux profile
					Four Parameters Associated With Cloud Fraction Calculations
5	RHMINL	0.9	0.7	0.98	Minimum relative humidity for low cloud formation
6	RHMINH	0.9	0.7	0.98	Minimum relative humidity for high/midlevel cloud formation
7	CCONV	0.035	0.01	0.06	Coefficient for calculating column convective cloud
8	RHCCN	0.1	0.05	0.3	Reduction on RHMINL for enhanced cloud drop nucleation over CCN-rich land areas

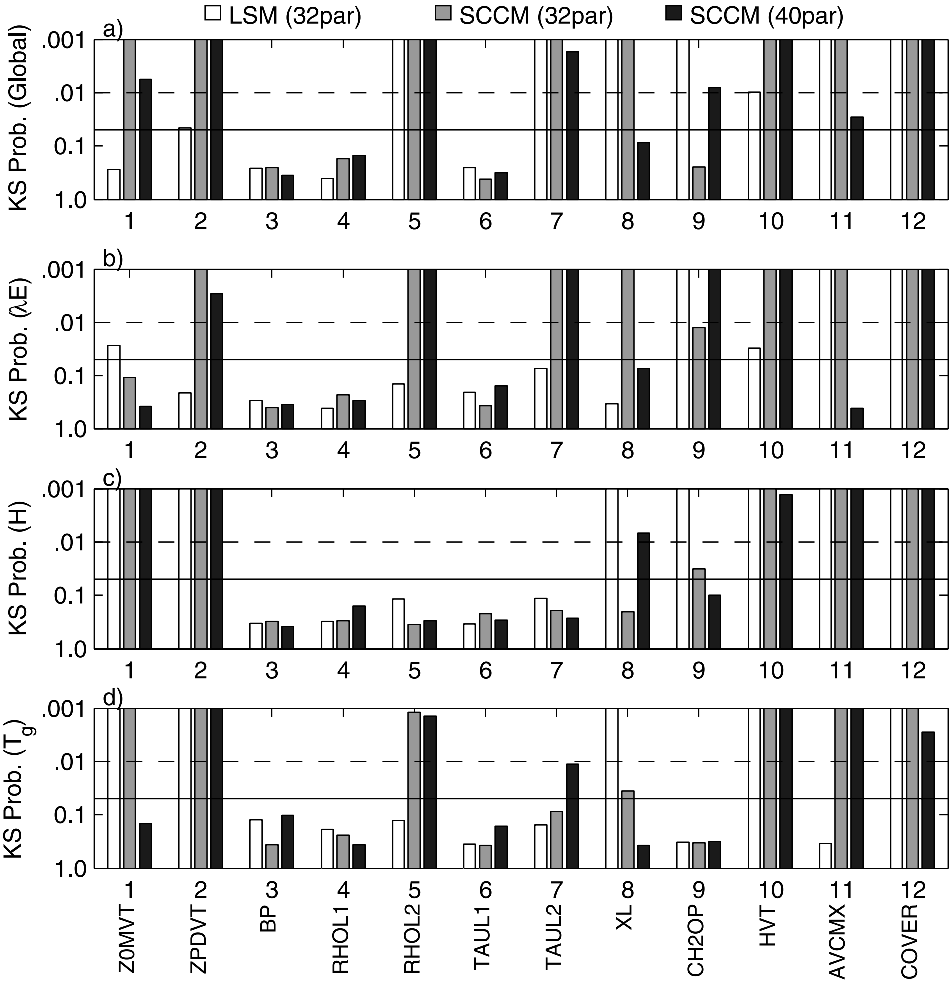

Figure 4. The K-S probabilities of the 12 vegetation parameters for (a) the global objective, (b) latent heat, (c) sensible heat, and (d) ground temperature in the offline case (white, case 1), the locally coupled case with 32 land parameters (gray, case 2), and the locally coupled case with 32 land parameters and 8 atmospheric parameters (black, case 3).

a calibration experiment. The same convention was used in previous SA studies using the MOGSA algorithm [e.g., *Bastidas et al.*, 1999].

4.3. Results

[29] Figure 4 shows the global (Figure 4a) and single-criterion (Figures 4b–4d for λE, H, and T_g, respectively) K-S probabilities of the 12 vegetation parameters for the three different cases mentioned above, while those of the 16 soil parameters, the 4 initial soil moisture conditions, and the 8 atmospheric parameters are presented in Figures 5, 6, and 7, respectively. In each subplot of these figures, the y axis is in a reverse direction (i.e., value diminishes upward) and the K-S probability values are plotted on the logarithmic scale, with the solid and dashed lines highlighting the K-S probabilities of 0.05 and 0.01, respectively. Hence, in these subplots, if a bar corresponding to a parameter reaches above the dashed line, we consider the parameter to be highly sensitive; if the bar is between the solid line and the dashed line, we consider the parameter to be sufficiently sensitive to be included in a calibration experiment; otherwise, the parameter is considered insensitive and could be omitted in a calibration experiment. For each parameter, the bars of the three different cases are grouped together for the convenience of comparison, with the white, gray, and black bars representing cases 1, 2 and 3, respectively.

[30] As shown in Figures 4–7, although a few parameters appear to be consistently highly sensitive (e.g., COVER in Figure 4) or insensitive (e.g., RHOL1 and TAUL1 in Figure 4) for all the objectives in all three cases, most of the parameters have different levels of sensitivities for different objectives (in a certain case, offline or coupled) or in different cases (for a certain objective, global or single). This indicates the considerable influences of land-atmosphere interactions and multiresponse, multiparameter interdependences on the sensitivity of the land surface to changes in model parameters. Next, the sensitivity results shown in Figures 4–7 are examined for vegetation parameters, soil parameters, initial soil moisture conditions, and atmospheric parameters, respectively, with a major focus on the analysis of the differences between the cases due to land-atmosphere interactions and/or multiresponse interdependence.

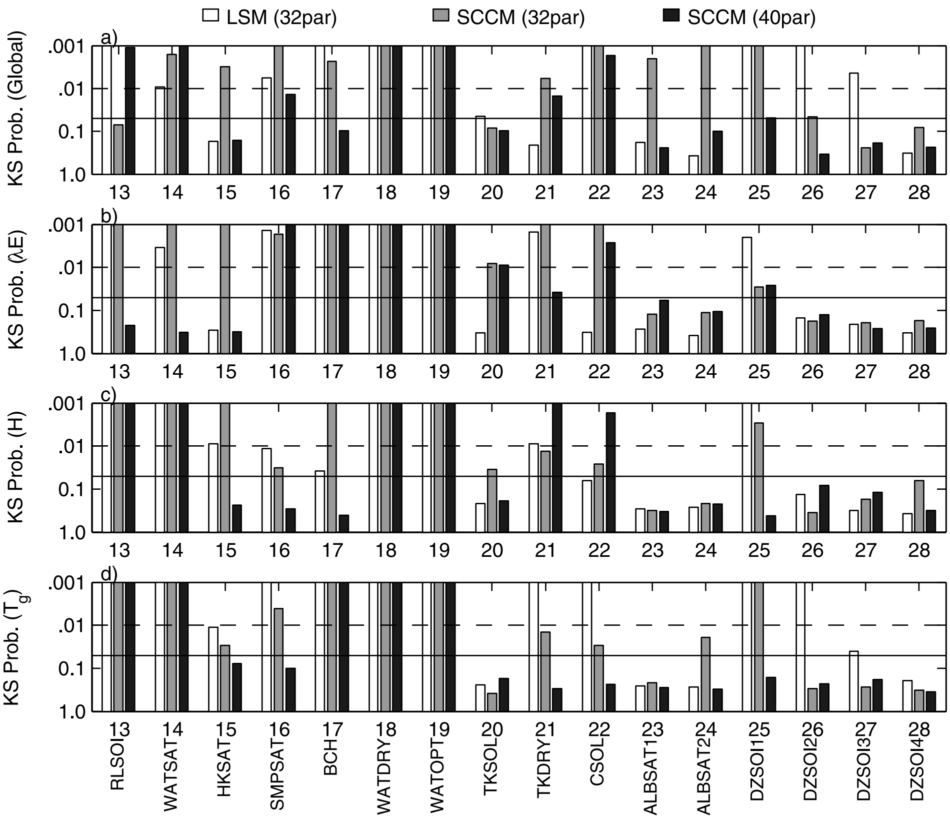

Figure 5. Same as Figure 4 but for the 16 soil parameters.

4.3.1. Vegetation Parameters

[31] As shown in Figures 4a–4d, three of the vegetation parameters, including BP (minimum leaf conductance) and RHOL1 and TAUL1 (leaf reflectance and transmittance in the visible region), remain consistently insensitive for all the objectives (global, λE, H, and T_g) in all the three cases, while another two vegetation parameters, HVT (top of canopy) and COVER (vegetation fraction), appear to be consistently highly sensitive for all the objectives across the three cases. This indicates that either land-atmosphere interactions or multiresponse interdependences have little influence on the sensitivities of these parameters. For example, it is not surprising that COVER shows high sensitivity consistently for all the objectives in all the cases: COVER controls the fraction of the grid square covered by vegetation for which the energy fluxes and temperatures can be significantly different from those of a bare soil surface and this would not change with the model used (offline or coupled) or the flux/variable evaluated.

[32] The remaining seven vegetation parameters (Z0MVT, ZPDVT, RHOL2, TAUL2, XL, CH2OP, AVCMX) have different sensitivities for different objectives and/or in different cases, due to the influences of land-atmosphere interactions and/or multiresponse interdependences. For example, the parameter ZPDVT (vegetation displacement height), which regulates the turbulence transfer of heat and water vapor between the canopy and the atmosphere, shows high sensitivity for sensible heat and ground temperature in all the cases (except for T_g in case 3); this is also true for latent heat in the two coupled cases but not the offline case. This can be partially attributed to the fact that, in the offline case, the very limited interception capability of vegetation (mainly crops) prevents the sensitivity of evapotranspiration (latent heat) but enhances the sensitivity of sensible heat and ground temperature through the turbulence transfer of heat [*Pitman*, 1994]. However, in the coupled cases, the model-generated, weaker, but more frequent precipitation helps to increase the total interception and thus enhance the sensitivity of the latent heat flux. The multiobjective sensitivity of this parameter is similar to that of latent heat: low in the offline case and high in the coupled cases.

[33] The interdependences of land and atmospheric parameters show significant influence on the sensitivities of two vegetation parameters (XL and AVCMX) for latent heat, one parameter (XL) for sensible heat, one parameter (Z0MVT) for ground temperature, and three parameters (XL, CH2OP, and AVCMX) from the multiobjective point of view (case 2 versus case 3). Overall, the influence of land-atmosphere interactions is most significant for latent heat: in the offline case, only 3 out of the 12 vegetation parameters (CH2OP, AVCMX, and COVER) appear highly sensitive, while in the coupled cases, more parameters (e.g., ZPDVT, RHOL2, TAUL2, and HVT) become sensitive for latent heat. The sensitivities for sensible heat, on the other hand, seem to be least affected by land-atmosphere interactions, with only 2 out of 12 parameters have different sensitivities in the three cases. This discrepancy regarding the sensitivities for the two heat fluxes can be at least partially attributed to the very different patterns of the

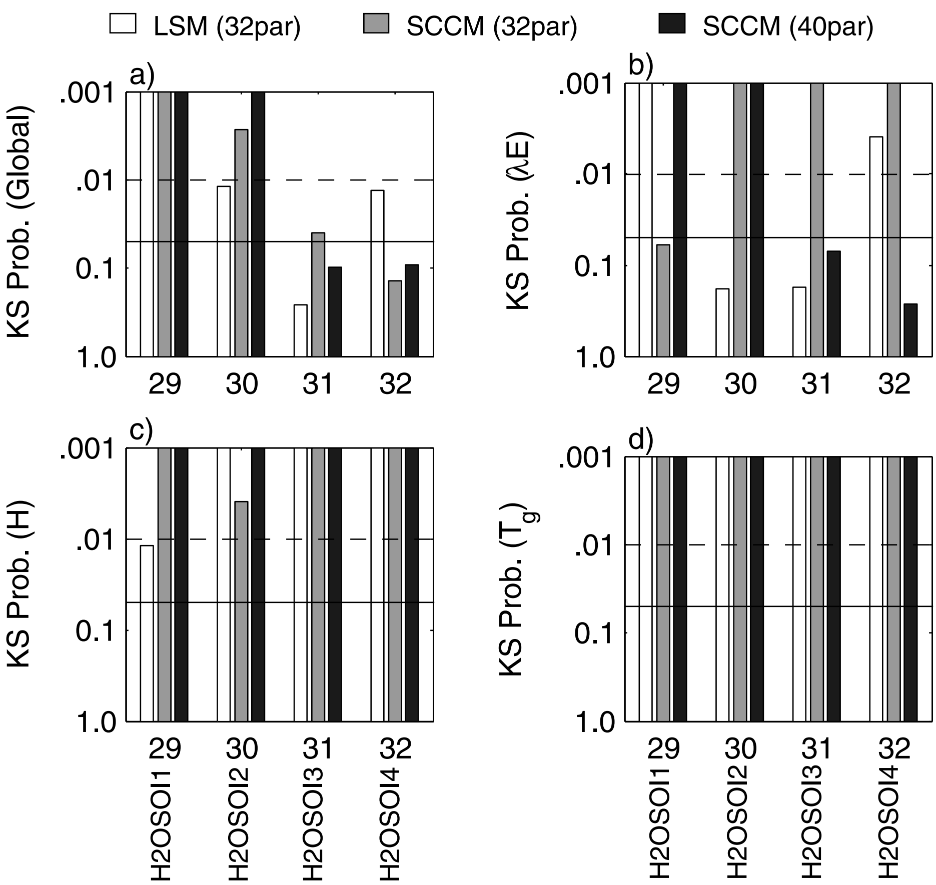

Figure 6. Same as Figure 4 but for the four initial soil moisture conditions.

model-predicted precipitation and the observed precipitation [*Xie and Zhang*, 2000], which more effectively affects the sensitivity of evapotranspiration than that of sensible heat.

4.3.2. Soil Parameters

[34] As shown in Figure 5, among the 16 soil parameters, only three parameters, namely, WATDRY (soil water content when evapotranspiration stops), WATOPT (optimal soil water content for evapotranspiration), and DZSOI4 (the thickness of the fourth soil layer), are consistently sensitive (WATDRY and WATOPT) or insensitive (DZSOI4) for all the objectives in all the three cases. WATOPT and WATDRY are used to determine leaf stomatal resistance and surface resistance, which are needed for the calculation of latent heat flux, thus playing an important role in partitioning the available energy. The insensitiveness of DZSOI4 is also not surprising, given that the forth soil layer is too deep into the soil (0.6–2 m, Table 1) to have an effect on soil evaporation and vegetation (crop) uptake within a simulation period of 17.5 days.

[35] The sensitivities of all the other 13 soil parameters are more or less affected by land-atmosphere interactions and/or multiresponse interdependences. The soil roughness length (RLSOI) shows high sensitivity for all the objectives in all cases (except for latent heat in case 3 and the global objective in case 2), while the two radiative parameters (ALBSAT1 and ALBSAT2) tend to be insensitive for all objectives in all cases (except that in case 2 they appear to be highly sensitive for the global objective). The influence of land-atmosphere interactions and multiresponse are more significant for the soil hydraulic parameters (WATSAT, HKSAT, SMPSAT, and BCH) and thermal parameters (TKSOL, TKDRY, and CSOL). The sensitivities of the thicknesses of the four soil layers (DZSOI1-DZSOI4) generally decease with the depth into the soil for all the objectives in all three cases, with the thicknesses of the soil layers appearing to be less sensitive in the coupled cases. This is not surprising, considering that most roots of crops are in the upper soil layers and soil heat in deep layers cannot diffuse to the surface as quickly. In the coupled environment, more frequent but weaker precipitation makes the soil moisture contents more homogeneous both spatially and temporally, leading to the low dependence of soil moisture/temperature on the thicknesses of soil layers.

[36] Six of the soil parameters (RLSOI, HKSAT, BCH, ALBSAT1, ALBSAT2, and DZSOI1) have different sensitivities in cases 2 and 3, due to the interdependences between land and atmospheric parameters, which also influence the sensitivities of several soil parameters for the single objectives. Overall, the land-atmosphere interactions and multiresponse interdependences seem to have more effects on the sensitivities of the soil parameters than on those of the vegetation parameters, considering that there are only 3 out of 16 soil parameters (compared to 5 out of 12 vegetation parameters) have consistent sensitivities for all objectives in all cases.

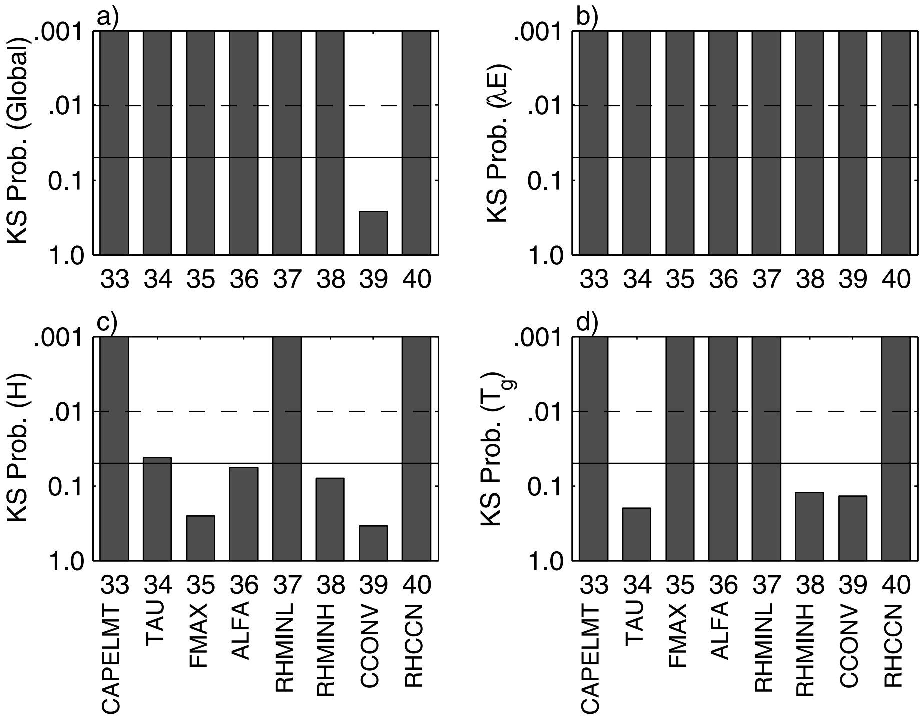

Figure 7. Same as Figure 4 but for the 8 atmospheric parameters in case 3.

4.3.3. Initial Soil Moisture Conditions

[37] Initial soil moisture conditions play an important role in regulating the energy and water transfers between the land surface and the atmosphere. In practice, when measurements of initial soil moisture are not available, a spin-up period of model simulation is usually used to allow the model to reach energy and water balances. The importance of accurate initial moisture conditions is confirmed in this study by the MOGSA experiments: the thicknesses of all the upper four soil layers (H2OSOI1-H2OSOI4) appear to be highly sensitive for sensible heat and ground temperature in all three cases (Figures 6c and 6d). From the multi-objective point of view, not surprisingly, the sensitivities of the initial soil moisture conditions generally decrease with the depth into the soil in all the three cases, with the initial soil moisture conditions of the first two layers being highly sensitive and those of the third and forth layers being insensitive or only marginally sensitive (Figure 6a). This is also true for latent heat flux in case 3 but not in the other two cases (Figure 6b): in the offline case, the sensitivity of initial soil moisture conditions first decreases with depth into the soil and then starts to increase again; in case 2, unexpectedly, the initial soil moisture of the first layer is insensitive while those of the lower three layers are all highly sensitive. This indicates the significant influence of land-atmosphere interactions and land-atmosphere parameter interdependences on the sensitivity of latent heat flux to changes in initial soil moisture conditions.

4.3.4. Atmospheric Parameters

[38] Figures 7a–7d present the global and single-criterion (λE, H, and T_g) sensitivities of the eight atmospheric parameters (Table 2) in case 3. As mentioned earlier in Section 3, these atmospheric parameters are related to deep convection or cloud fraction calculations, thus playing a critical role in simulating precipitation and net radiation, which are very important to the land surface. Although the atmospheric parameters are not directly associated with the simulation of land surface fluxes/variables, changes in these parameters can affect the atmospheric forcing of the land surface model and thus can indirectly regulate the simulation of the surface fluxes/variables.

[39] Among the eight atmospheric parameters, three parameters, including CAPELMT, RHMINL, and RHCCN, are highly sensitive for all the objectives (global and single). CAPELMT specifies the threshold value of CAPE for deep convection thus plays an important role by initiating the development of convective storms. The consistent high sensitivity of RHMINL, the relative humidity threshold for low cloud formation, can be attributed to the fact that most moisture is nearer to the earth's surface and most precipitation (in the form of rain during summer) is generated from low clouds, while high clouds are primarily composed of ice crystals rather than water drops. This also explains the high sensitivities of RHCCN, the reduction on RHMINL for CCN-rich land areas. The remaining five atmospheric parameters (TAU, FMAX, ALFA, RHMINH, and CCONV) are also highly sensitive for latent heat but may not show sufficient sensitivity for sensible heat and/or ground temperature.

[40] Overall, seven out of eight atmospheric parameters appear to be highly sensitive from the multiobjective point of view and all the eight atmospheric parameters show high sensitivities for the latent heat flux. This is not surprising considering that deep convection is the major precipitation mechanism for the specific time period at the SGP. There are five sensitive atmospheric parameters for ground tem-

perature, while only three out of eight parameters are sensitive for sensible heat. The low sensitivity of atmospheric parameters for sensible heat, shown in both OAT and MOGSA experiments partially explains what obtained from a subsequent calibration study: optimizing atmospheric parameters can significantly improve the simulation of latent heat and ground temperature but is of little advantage to the simulation of sensible heat flux. The high global sensitivities of these atmospheric parameters imply the potential advantage of including these parameters in multiobjective calibration experiments.

5. Concluding Remarks and Future Recommendations

[41] *Saltelli and Sobol* [1995] pointed out that Sensitivity Analysis (SA) can be used for 1) parameter screening to identify important factors in a system with many parameters or 2) global/local system analyses to apportion the output uncertainty to uncertainties in input parameters. In this study, a framework of using SA for both purposes was proposed and applied to a complicated locally coupled land atmosphere model (the NCAR SCCM). A preliminary OAT sensitivity analysis was performed first for parameter screening; a more advanced, multiobjective sensitivity analysis using the MOGSA algorithm was then conducted for three different cases: one offline case and two coupled cases. The framework can also be used to examine how land-atmosphere interactions and multiresponse interdependences influence the sensitivity of the land surface to changes in land parameters. Most importantly, some atmospheric parameters are also included in a coupled case to investigate the sensitivity of the land surface to changes in these parameters and the impacts of land-atmosphere parameter interdependences.

[42] The results show that OAT and MOGSA methods can be combined to effectively extract the parameter sensitivities for a complicated land-atmosphere model with a high-dimensional parameter space. Regardless of the fact that the sensitivities of individual parameters are likely model and data dependent, some findings from this study are model and data independent and can be generally useful. First, it is noted that a globally sensitive land parameter does not necessarily appear to be also sensitive for all the single objectives, and vice versa. This indicates the importance of using a multicriteria approach to take into account the multiresponse nature of most sensitivity problems. Otherwise, if only single-objective sensitivities are examined, it would be difficult to decide whether a parameter should be included in a multiobjective calibration experiment because it has different sensitivities for different objectives. In addition, a land parameter may also exhibit different levels of sensitivities when the SA is conducted in a coupled mode rather than an offline mode, implying the considerable influence of land-atmosphere interactions (including land-atmosphere parameter interdependences) and thus the importance of conducting parameter SA within a coupled (rather than offline) framework for coupled applications. While land-atmosphere interactions have been broadly acknowledged in the modeling community, most SA and calibration studies ignore the influence of these interactions [e.g., *Sen et al.*, 2000].

[43] In the particular case study presented in this paper, the selected atmospheric parameters, which are associated with deep convection and cloud formation mechanisms, are found to be highly sensitive for latent heat and from the multiobjective point of view (although not all of them are sensitive for sensible heat and ground temperature). This implies that substantial benefits could be gained by including these atmospheric parameters in the calibration of a coupled land-atmosphere model, at least in terms of reproducing the latent heat flux. The parameterization of precipitation and clouds has always been a critical yet highly complicated issue in coupled land-atmosphere modeling. Most related studies have been focused on the improvement of physical parameterizations, yet ignoring the specification of effective values of the parameters. Like parameters in a land surface model, parameters in the atmospheric part of a coupled model also deserve adequate attention and effective values of them should be used to achieve reasonable model simulations or predictions. For example, on the basis of the ARM observations, *Somerville and Iacobellis* [1999] pointed out that the use of 80% as critical relative humidity for cloud formation (the parameter RHMINL examined in this study) over land areas in many GCMs may not be appropriate and needs to be re-examined. When such observations (i.e., direct measurements of parameter values) are not available, the framework proposed in this study can be used for sensitivity analysis to identify the important parameters for calibration.

[44] This study explores the sensitivity of the land surface to model parameters within a locally coupled framework and can facilitate the testing of land-surface parameterizations in a coupled mode which is of general interest. Most importantly, the plausible results and conclusions obtained in this study suggests that this two-step sensitivity analysis methodology (first OAT and then MOGSA) holds great potential in improving our understanding of a land surface model, especially a complex, coupled land-atmosphere model. However, because only one model and one data set have been used in this study and the sensitivity results obtained are likely model and site specific, it desirable in the future research to test the methodology with other coupled land-atmosphere models and different land-surface types under different weather/climate conditions.

[45] **Acknowledgments.** This study was primarily supported by SAHRA (an NSF center for Sustainability of Semi-Arid Hydrology and Riparian Areas) under grant EAR-9876800. Additional support came from NASA EOS grants NAG5-3640-5 and NAG8-1531 and a fellowship to the first author from the Graduate College at the University of Arizona. The National Center for Atmospheric Research (NCAR) is thanked for publishing the model codes and data sets online. Special thanks are due to Drs. Andy Pitman, Brian Cosgrove, and Paul Houser for their valuable comments, and to Dr. Jiming Jin for assistance in determining the parameter boundaries.

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L. A. Bastidas, Department of Civil and Environmental Engineering, Utah State University, Old Main Hill 4110, Logan, UT 84322-4110, USA.
H. V. Gupta, Y. Liu, and W. J. Shuttleworth, Department of Hydrology and Water Resources, University of Arizona, Marshall Building, Rm. 535, 845 N. Park Avenue, P.O. Box 210158-B, Tucson, AZ 85721-0158, USA. (yqliu@hwr.arizona.edu)
S. Sorooshian, Department of Civil and Environmental Engineering, University of California, E-4130 Engineering Gateway, Irvine, CA 92697-2175, USA.