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Land-Air Interaction over Arid/Semi-arid Areas in China and Its Impact on the East Asian Summer Monsoon. Part I: Calibration of the Land Surface Model (BATS) Using Multicriteria Methods

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ABSTRACT

To improve the land surface simulation in the arid and semi-arid areas of northern China, the observational data from two field experiments in Dunhuang and Tongyu are used to optimize the parameters in the land surface model, BATS, through calibration with the multicriteria method. Sensitivity analysis to the parameters in Dunhuang and Tongyu indicates that different parameters need to be calibrated in two sites with different environmental and climate regimes. Comparison of observed sensible heat flux, latent heat flux, and ground surface temperature with the simulated ones shows the simulations with the optimized parameters have been substantially improved. Especially, the holistic simulations with the calibration of the parameter values are much closer to the observations in the arid region (Dunhuang), and the energy partition with the calibrated parameters can also be simulated well in the semi-arid region (Tongyu). Whole results demonstrate that the parameter calibration of the land surface model is important when the model is to be used to investigate the land-air interaction.

Key words: land-air interaction, the arid and semi-arid areas, BATS, multicriteria method

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1. Introduction

A monsoon is manifested as an atmospheric circulation system of ocean-atmosphere-land interaction between continents and oceans in the seasonal cycle (Yasunari, 2007). The Asian summer monsoon, the most energetic component of the Earth's climate system, exhibits distinct regional characteristics. Located in a strong monsoon region, East Asia has aperiodic and large-amplitude climate variability (e.g., Huang et al., 2003). This variability and the influence from the coupled atmosphere-ocean system have been the subject of numerous studies (e.g., Zhang et al., 1996; Lau and Weng, 2001; Chen, 2002; Huang et al., 2004). However, much less research has been devoted to the influences of the land-atmosphere interaction for the East Asian region partly due to data availability.

In recent decades, a few field experiments over the

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arid and semi-arid areas in northern China have been carried out. These include the "Heihe River Basin Field Experiment" (HEIFE; Hu and Gao, 1994), the "Field Experiment on Interaction between Land and Atmosphere over Arid Region in Northwest China" (NWC-ALIEX; Zhang et al., 2005), and the Tongyu Field Experiment, which is also one of the reference sites of the Coordinated Enhanced Observing Period (CEOP; Fu and Wen, 2002). Hence, the study of land surface processes in northern China are attracting more and more interest for the boundary layer meteorology research community as more observational data become available (Liu et al., 2004; Zhang et al., 2005). However, these studies need to be extended to the research on the influence of the land-air interaction over arid/semi-arid areas on the variabilities of the East Asian climate, in particular those related with the East Asian monsoon.

In the world, arid and semi-arid areas are very, very large and account for about 1/3 of the terrestrial area (International Institute for Environment and Development, and World Resources Institute). In China there are around 4 550 000 km^2 of arid and semi-arid areas, including grassland and desert, among which 82.8% mainly distributes in Northwest China (Hu, 1985). Over these areas, the annual rainfall is usually less than 400 mm with the minimum close to 30 mm. Cholaw et al. (2002) indicated that the sensible heat flux in the arid and semiarid areas of Northwest China is the strongest over the Eurasian continent in the summer, and the atmospheric thermodynamic process over these areas is closely related to the land surface characteristics. Yasunari (2007) pointed out that the land shows strong and rapid heating (and cooling) in the seasonal cycle, which in turn has a large impact on the seasonal atmospheric differential heating (and cooling) processes between land and ocean. The land surface processes which modulate the seasonal heating, therefore, are likely to be responsible for interannual variability of the monsoon. So far, studies are primarily relevant to the characteristics of land-atmosphere interaction in the arid and semiarid areas of China and the causes of a regional dry climate (e.g., Lu and Chen, 1999; Zhu et al., 2006). Therefore, researches on the impact of land-atmosphere interaction over arid and semi-arid areas in China on the East Asian monsoon are anticipated with available observational datasets.

Land surface modeling is considered to be a more important and more functional measure in climate change simulations and predictions (Charney, 1975; Dickinson, 1995; Houghton et al., 1996; Crossley et al., 2000). Since the 1970s, the land surface model (LSM), as an important research tool, has been developed to simulate the practical processes in different land surface conditions. Compared to the earlier simple models, recent LSMs, such as the Biosphere-Atmosphere Transfer Scheme (BATS; Dickinson et al., 1993), are more realistic and sophisticated. However, the parameters used in the models to describe the land surface have yet to be fully validated through scientific testing and comparison with observations. There is a considerable degree of uncertainty associated with the parameters derived using current procedures (e.g., Kahan et al., 2006). It was pointed out that careful calibration and selection of the physical parameters for land surface models can improve the simulation (Henderson-Sellers, 1996; Dirmeyer et al., 1999). For example, Gupta et al. (1999) used a multicriteria (MC) calibration method to estimate acceptable optimal parameter sets for the Biosphere Atmosphere Transfer Scheme (BATS), which has lead BATS to perform much better.

This paper will use data from two experiments, NWC-ALIEX and Tongyu in the arid and semi-arid areas of northern China, to calibrate the parameters required in the BATS with the MC calibration method. The objectives are to reduce the model uncertainty induced by the parameter estimation errors and investigate the contribution of observational data for the improvement of the land surface simulation in the surface conditions of the Gobi desert and the semi-arid degraded grassland areas. Then, in the accompanied paper (Part II), we will couple the calibrated BATS to a regional climate model to investigate the impact of the improved simulation on the land surface forcing on the East Asian summer monsoon.

The paper is organized as follows: a brief description of sites considered, the BATS model and the MC calibration method is given in section 2. The parameter sensitive analysis and the calibration of the BATS model to the two study sites are discussed in section 3 and section 4, respectively. Section 5 discusses the results and gives a summary.

2. Sites, model, and method

2.1 *Sites*

For this study, the model forcing data and surface flux data are used as those collected at Dunhuang and Tongyu. These sites were chosen based on the data availability and different climate and vegetation characteristics in the arid and semi-arid regions of China. Their locations are marked in Fig. 1 together with the annual precipitation distribution. It is clear that nearly half of the Chinese land area is either an arid and semi-arid region, which is mainly distributed in the northern part of China. Dunhuang is located in

Table 1. Description of the two sites and observed data.

Site	Site Location: Lat. Lon. Elevation (m)	Observed period	Observed interval (min)	Vegetation type	Soil type	Annual mean precipitation (mm)	Input data
Dunhuang	40°10′N, 94°31′E 1150 m	May–Jun 2000	30	Desert and Gobi	Pebble sand	39.9	ISR, DLR, T, q, V, P
Tongyu	44°25′N, 122°52′E 184 m	May–Sep 2003	30	Degraded grassland	light Chemozems Meadow soils, and Solonetzs	404	ISR, DLR, T, q, V, P

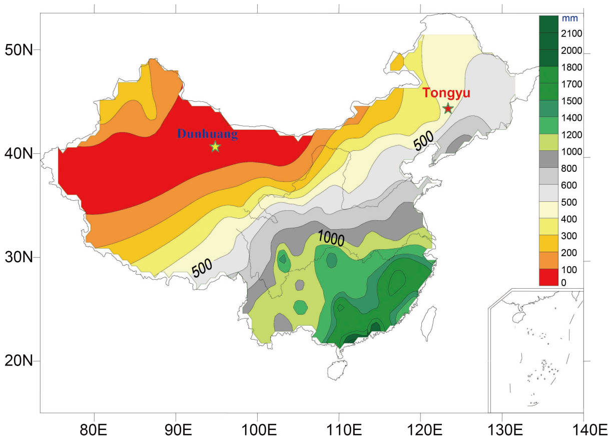

Fig. 1. The distribution of arid and semi-arid areas in China and the two sites of Dunhuang and Tongyu. Contours indicate the annual precipitation (Units: mm).

the arid region representing the Gobi desert. Tongyu is located in the semi-arid region representing degraded grassland and mixed cropland. Desert and grassland are the most common land surfaces in the arid and semi-arid regions of China, respectively. Hence, these two sites are typical and can be used to represent the land surfaces in the arid and semi-arid regions of China. At both sites, forcing data include downward longwave radiation (DLR), air temperature (T), relative humidity (q), wind speed (V), precipitation (P), and incoming solar radiation (ISR). The energy flux data include sensible and latent heat fluxes. Table 1 summarizes the location, observed periods, vegetation, climate, and input data at the two sites.

2.1.1 *Dunhuang gobi and desert site*

The Dunhuang Gobi and desert site is located at 40°10′N, 94°31′E with an elevation of 1150 m above sea level in the western edge of the Hexi corridor, in the Gansu Province in northwestern China. The climatological annual precipitation is 39.9 mm but the annual potential evaporation can reach 3400 mm. The surface is flat and pebbly, which is the typical Gobi surface in the extreme arid region of northwestern China (Hu, 1985). The forcing data were collected between April 2000 and July 2005 at 30-minute intervals. Surface energy fluxes were also collected within one intensive observation period between May and June 2000 at 30-minute intervals. For more details, refer to the description of the field experiment in Zhang et al. (2002). The available data have some gaps and several obvious errors. Since the simulation requires a continuous time series of inputs, the short gaps within 3 hours were filled by simple line interpolation, and for the longer gaps the data from a nearby site (AWS) were used to complete the series.

2.1.2 *Tongyu degraded grassland site*

The Tongyu degraded grassland site is located at 44°25′N, 122°52′E with an altitude of 184 m in the Jilin Province of northeastern China. The annual precipitation is 404 mm at this site. 40% of the surface is covered by degraded grass. The soil contains light Chernozems, Meadow soils, and Solonetzs. Tongyu has a typical semiarid surface in northern China (Liu et al., 2004). The forcing data were collected between January and September 2003 at 30-minute intervals. At the same time, surface energy fluxes were also collected. A more extensive description of the site can be found in Liu et al. (2004).

2.2 *Model*

The BATS is a comprehensive Soil-Vegetation Atmosphere Transfer Scheme (SVAT) designed for use in the NCAR CCMs to describe the role of vegetation and interactive soil moisture in modifying the surface-atmosphere exchanges of momentum, energy, and water vapor. The model consists of several interacting hydrometeorological components (three layers of soil, a canopy leaf-stem component, and so on). Together, these components simulate the various radiative, biophysical, and hydrological process at the land atmosphere interface, including the exchange of solar and long-wave radiation, precipitation inputs (rain, snow, and dew), runoff, and the surface transfer of momentum and sensible and latent heat exchanges. BATS calculates the sensible and latent heat fluxes with the classical equations, where the sensible and latent heat fluxes are proportional to the temperature gradient and the humidity gradient between the surface and the air, respectively. The two surface fluxes are also proportional to the turbulent transport coefficient. The ground heat flux is calculated as a residual from the surface energy balance, and soil temperature is calculated using the force-restore method. BATS has a global land surface classification consisting of 20 land cover types. Each land cover type is characterized by 15 parameters. BATS also has 12 global soil types, ranging from very coarse sand (= 1) to very fine clay (= 12), and 8 soil color types (each having 4 basic albedos), ranging from light (= 1) to dark (= 8). Each soil type is characterized by 8 parameters. More details on BATS can be found in Dickinson et al. (1993).

2.3 *Multi-criteria approach*

The multicriteria (MC) parameter estimation methodology was developed by Gupta et al. (1998) from a single-criteria method (Duan et al., 1994). Gupta et al. (1998) have used the MC methodology to estimate the reasonable ranges of optimal parameters for the BATS land surface model. Full details of the MC calibration methodology are given by Gupta et al. (1998) and Yapo et al. (1997), and a brief summary is presented below.

The aim of MC as an optimization procedure is to search out appropriate parameter sets that could improve a model's performance. The MC approach has been widely used to calibrate different land surface schemes at different sites with various climate systems and vegetation covers, which were chosen based on the data availability (Gupta et al., 1999; Bastidas et al., 1999; Sen et al., 2001; Xia et al., 2002; Jackson et al., 2003; Xia et al., 2004). For example, consider a model with parameters $\theta = \{\theta_1, \cdots, \theta_n\}$ that are to be calibrated by using the observed time series and the corresponding simulated variables $[Z_j(\theta, t_j), j = 1, \cdots, m]$. To measure the distance between the simulated responses Z_j and the corresponding observations O_j at a study site, a single criterion $f_j(\theta)$ for each separate model response is defined. The mathematical form of these criteria is specified depending on the problem and the goals of the user. In this work, we use two functions to measure the deviation between Z_j and O_j. One is the root-mean-square error

$$\mathrm{DMSE}_j = \left\{ (1/n) \sum_{t=1}^{n} [Z_j(\theta, t) - O_j(t)]^2 \right\}^{1/2} \quad (1)$$

The other form is defined as

$$\mathrm{DDRMS}_j = \left\{ (1/n) \sum_{t=1}^{n} \left[\frac{O_j(t) - Z_j(\theta, t)}{(1/n) \sum_{i=1}^{n} |O_j(t)|} \right]^2 \right\}^{1/2} . \quad (2)$$

The multicriteria model calibration problem as a function of the parameters can then be stated as follows:

$$\min F(\theta) = \{f_1(\theta), \cdots, f_m(\theta)\} , \quad (3)$$

where $\theta \subset \Theta$, Θ is a feasible parameter space. The aim of Eq. (3) is to find values for θ within Θ that simultaneously minimize all of the m criteria. Since MC is used for a multi-objective problem, it is unlikely to find a unique solution without stating how individual criteria should be weighted. Instead, there usually exist a range of solutions where moving from one solution to another results in improvement of one criterion while causing deterioration in another. This set is called the Pareto solution set which represents a range of the best solutions that can be found in the parameter space for each of the separate criteria. An effective and efficient method for solving the above problem is presented by Yapo et al. (1997) and it can provide an approximate representation of the Pareto set with a single optimization run.

3. Parameter estimation for Dunhuang Gobi and desert site

3.1 *Analysis of parameter sensitivities*

Before attempting any optimal parameter or uncertainty estimation of the BATS model, it may be helpful to use the cost function "profile" to display which parameters are likely to be important. The cost function profiles can also be used to objectively select parameters that most affect the uncertainty. The cost function displayed in Eq. (2) is considered a single criterion as the mismatch between the model and the observations used to evaluate model performance. A similar procedure has been used by Bastidas et al. (1999) and Jackson et al. (2003) for reducing the parameter number in the MC optimal parameter analysis.

As depicted in section 2.2, BATS contains 27 parameters. Except for three initial moisture conditions, the other 24 parameters are assigned values automatically based on the user specifications of land cover, soil texture, and soil color. These values are called the default parameters. Because the optimal parameters are unknown in advance, we use the default values for the parameters that are to be calibrated. The default values are the best guess for the parameter values based

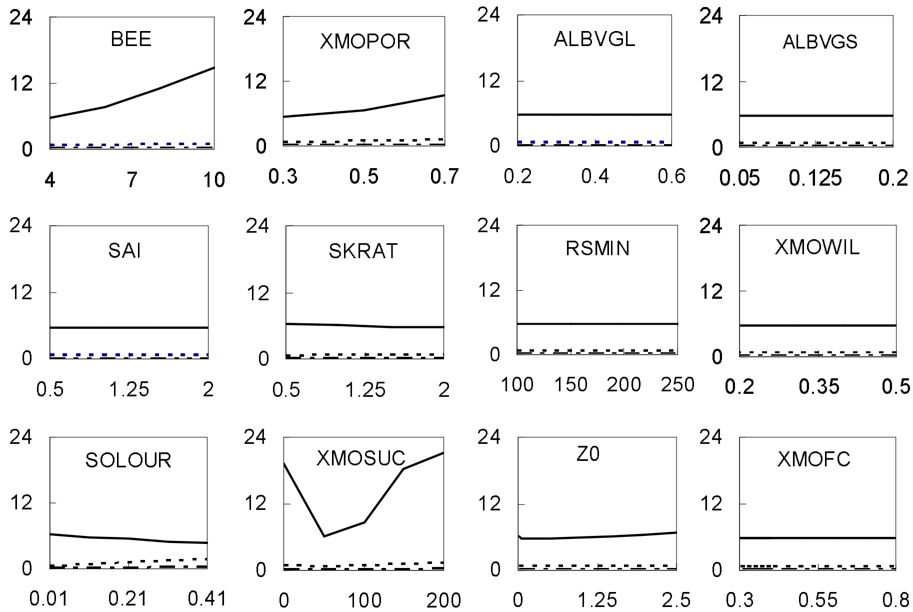

Fig. 2. Cost function profiles for 12 parameters within the BATS land surface model for the Dunhuang site (solid: SH; dashed: LH; long and short dashed: T_s).

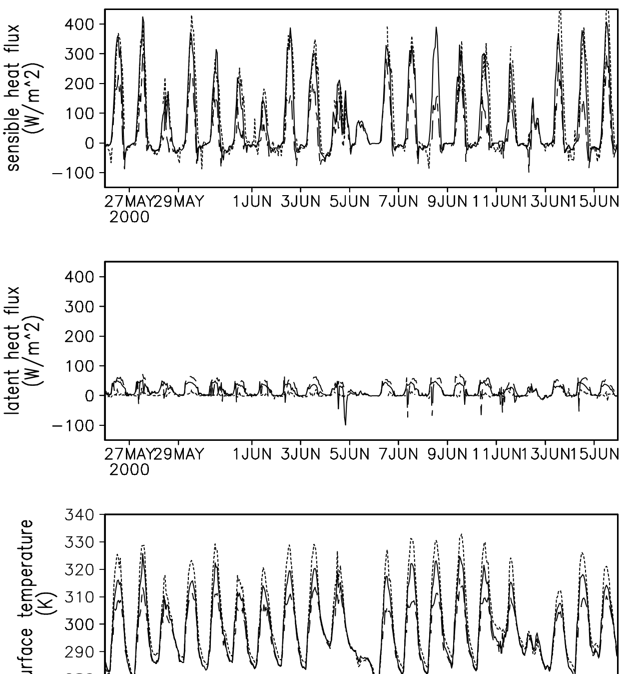

Fig. 3. Observed and simulated sensible heat fluxes, latent heat fluxes, and ground surface temperature at Dunhuang for BATS obtained using default and MC parameters, respectively (dot=observation, short and long dashed=default, solid=MC, and horizontal axis is represented with date).

on expert opinion and what can be inferred from the observations. A cost function profile is a graph of the cost function as a function of variations in a given parameter while holding the value of all other parameters constant. These graphs provide an expectation of the relative sensitivity of the model to each of the model parameters. Because Dunhuang is completely bare, the sensitivity analysis is made for 12 BATS parameters, which are mainly associated with the soil. The cost function profiles are shown in Fig. 2. For the Dunhuang Gobi and desert site, the latent heat flux and ground surface temperature are almost not sensitive to all the parameters. Thus, we mainly consider the sensitivity of the sensible heat flux. The results show that all the important parameters in Dunhuang are related to soil, among which the most important ones are XMOSUC and BEE. XMOPOR and SOLOUR have some influence on the simulation errors. In addition, Z_0 and SKRAT have a negligible effect on the simulation errors. We also found that some soil parameters in BATS have little effect on the sensible heat flux simulation errors. It is obvious that the parameters have different importance grades for different surface characteristics in BATS. The range of possible values and default settings for the above-mentioned 6 parameters are shown in Table 2.

3.2 *Multicriteria parameter estimation*

Firstly, the default BATS parameters are used to generate a control run simulation for providing a basis for comparison. Figure 3 shows the time series of the simulated sensible heat flux (SH), latent heat flux (LH), and ground surface temperature (T_s) together

Table 2. The names, default values, optimal values determined through the multicriteria approach, ranges, and descriptions of parameters of the BATS land surface model at Dunhuang.

Parameter	Default	MC	Minimum	Maximum	Description (units)
SKRAT	1.50	1.60	0.70	1.70	Ratio of soil thermal conductivity to that of loam (10^6 J m^{-3} K^{-1})
XMOPOR	0.36	0.38	0.33	0.66	Porosity
BEE	4.0	3.9	3.50	10.80	Clapp and Hornberger "b" parameter
XMOSUC	0.128	0.119	0.088	0.542	Water content at which permanent wilting point occurs
SOLOUR	0.11	0.06	0.05	0.12	Soil albedo for different colored soils
Z_0	0.05	0.0024	0.0024	1.0	Aerodynamic roughness length (m)

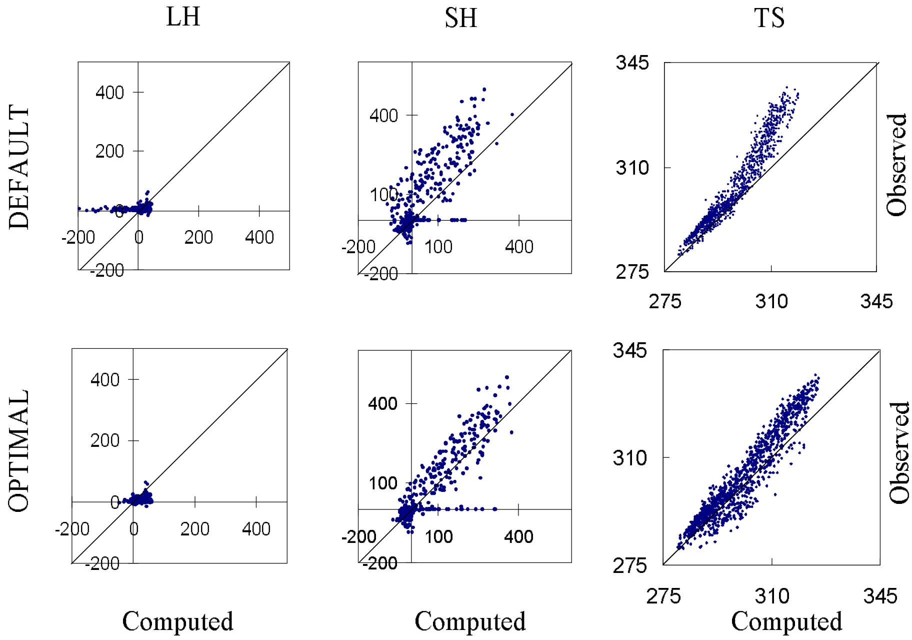

Fig. 4. Scatter plots for the simulated sensible heat fluxes, latent heat fluxes, and ground surface temperature against corresponding observations at the Dunhuang site (upper: simulation using default parameter values; lower: simulation using MC optimal parameter values).

with the observations. The result indicates that there are evident deviations of the simulated energy partitioning and T_s from the observed ones, especially during the daytime. These can also be confirmed from the scatter plots as shown in Fig. 4. The scatter plots for the entire data set show that many points are quite far from the 1:1 line. In the Dunhuang Gobi and desert site, the SH is dominant and the LH is negligible. The control run has a clear tendency toward underestimation of the SH and overestimation of the LH. With the default parameters, the model also underestimates the variations of T_s. Hence, the results show that the BATS model performance with the default parameters is poor at the Dunhuang site.

Secondly, the MC method was applied to explore the optimal values of parameters in the BATS model. Based on the results of parameter sensitivity analysis in section 3.1, a series of multi-calibration runs were conducted for the Dunhuang site, which generate the optimal parameters shown in Table 2. The results of the model simulations of SH, LH, and T_s with the MC optimal parameters are also shown in Fig. 3 together with the observations and the default parameter simulations. The results demonstrate that SH and T_s are much closer to the observed ones than the default parameter set. Again, the scatter plots as shown in Fig. 4 confirm the improvement of model performance. Even though there is poor agreement between the model simulations and the observations of LH, the poor match is not meaningful because LH at the Dunhuang Gobi and desert site is so small. Generally, LH is two magnitudes less than SH, which makes both accurate observation and accurate simulation very difficult. The values of default parameters and optimal parameters are listed in Table 2. From the table, it can be found that the values of BEE, XMOSUC, SOLOUR, and Z_0 are larger than the optimal ones and the values of SKRAT and XMOPOR are smaller than the optimal ones, but both values are within the reasonable magnitude range. However, from the time series plots and the scatter plots, the simulations with the optimal parameter set have improved the partitioning of energy, and make the ground temperature closer to the observed one. Therefore, we can argue that the BATS could have a significant improvement in the land-air interaction simulation at the arid site of Dunhuang after the calibration of parameters.

4. Parameter estimation for the Tongyu semi-arid site

4.1 *Analysis of parameter sensitivities*

In Tongyu, there is grass growing during the summer season. Hence, the sensitivity analysis is made for 20 BATS parameters. Similar to section 3, the objective is to determine the important parameters and classify them into an order of relative importance for the semi-arid degraded grassland of Tongyu. Figure 5 presents the cost function profiles. Since both SH and LH are sensitive to the variations of parameters, we consider the sensitivity of two at the Tongyu degraded grassland site. The results show that important parameters for the Tongyu degraded grassland site include VEGC, SOLOUR, XMOHYD, XMOPOR, Z_0, XLA, SAI, RSMIN, ALBVGL, ALBVGS, BEE, and SKRAT. The most important parameters in Tongyu are related to vegetation. A few parameters related to bare soil also have a significant influence on simulation errors, such as SOLOUR and XMOPOR. Other parameters in BATS have little effect on the sensible and latent heat flux simulation errors. The ranges and descriptions, and default values of these parameters are shown in Table 3.

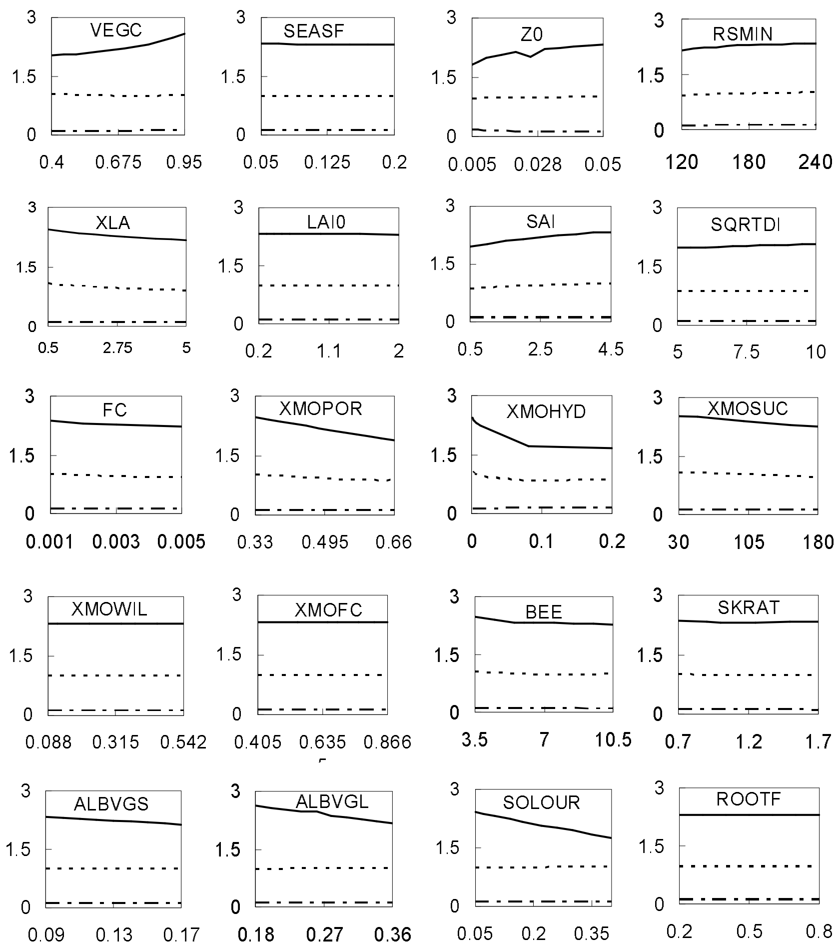

Fig. 5. Cost function profiles for 20 parameters within the BATS land surface model for the Tongyu site (solid: SH; dashed: LH; long and short dashed: T_s).

Table 3. The names, default values, optimal values determined through the multicriteria approach, ranges, and description of parameters of the BATS land surface model at Tongyu.

Parameter	Default	MC	Minimum	Maximum	Description (units)
VEGC	0.80	0.50	0.0	0.9	Vegetation cover
SEASF	0.10	0.10	0.0	0.60	Difference between VEGC and fractional cover at 296 K
Z_0	0.05	0.02	0.0024	1.0	Aerodynamic roughness length (m)
DISPLAY	0.0	0.0	0.0	18.0	Displacement height (m)
RSMIN	60.0	200.0	45.0	200.0	Minimum stomatal resistance (s m^{-1})
XLA	2.0	6.0	0.0	6.0	Maximum leaf area index
XLAI0	0.5	0.5	0.0	5.0	Minimum leaf area index
SAI	4.0	0.5	0.5	4.0	Stem area index
SQRTDI	5.0	5.0	5.0	10.0	Inverse square root of leaf dimension ($mm^{-0.5}$)
FC	0.02	0.04	0.02	0.06	Light dependence of stomatal stomatal resistance (m^2 w^{-1})
ALBVGS	0.10	0.19	0.004	0.2	Vegetation albedo for shortwave < 0.7 μm
ALBVGL	0.30	0.40	0.18	0.40	Vegetation albedo for longwave > 0.7 μm
ROOTF	0.80	0.80	0.30	0.90	Ratio of roots in upper layer to roots in root layer
XMOPOR	0.48	0.63	0.33	0.66	Porosity
XMOSUC	60.0	200.0	30.0	200.0	Minimum soil suction (mm)
XMOHYD	0.0063	0.015	0.0008	0.2	Maximum hydraulic conductivity (mm s^{-1})
XMOWIL	0.332	0.332	0.095	0.542	Water content at which permanent wilting point occurs
XMOFC	0.688	0.488	0.404	0.866	Ratio of field capacity to saturated water content
BEE	6.0	9.0	3.50	10.80	Clapp and Hornberger "b" parameter
SKRAT	1.0	1.0	0.70	1.70	Ratio of soil thermal conductivity to that of loam
SOLOUR	0.10	0.22	0.05	0.44	Soil albedo for different colored soils

4.2 *Multicriteria parameter estimation*

Similar to the Dunhuang case, the default BATS parameters as listed in Table 3 for the degraded grassland site are used to generate a control run simulation for comparison. The results are presented in Figs. 6 and 7, respectively. The time series in Fig. 6 show a representative 10 day period from the whole data. Although the model simulates SH well during the night, the simulated SH peaks during the daytime are much higher than the observations. The maximum difference can even reach about 300 W m^{-2}. However, there are only minor differences in LH and the Ts simulations. The scatter plots for the entire period of data show a clear tendency toward overestimation of the SH and a little tendency toward underestimation of both the LH and the T_s (Fig. 7). Therefore, the results demonstrate that the default parameters of the BATS model need to be calibrated at the Tongyu grassland site.

Based on the results of parameter sensitivity analysis in section 4.1, a series of multi-criteria calibration runs were conducted for the Tongyu grassland site following a similar procedure as for the Dunhuang site. Here, the whole procedure becomes more complex due to increasing vegetation parameters. The results of optimal parameters are shown in Table 3. The model simulations of SH, LH, and T_s with the MC optimal parameters are shown in Fig. 6 together with the observations and the default parameter simulations. The simulations using the optimal parameters are closer to the observations than the default parameter set except

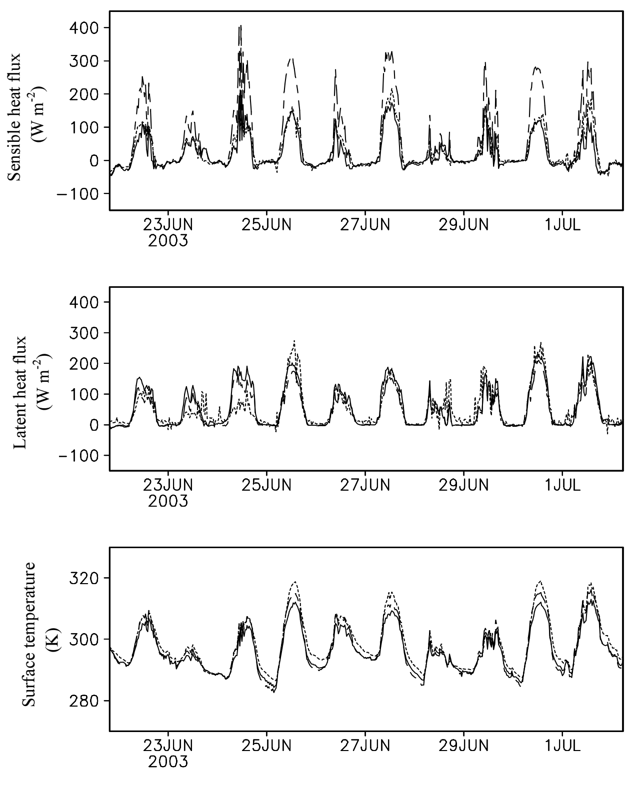

Fig. 6. Same as in Fig. 3, but for the Tongyu site.

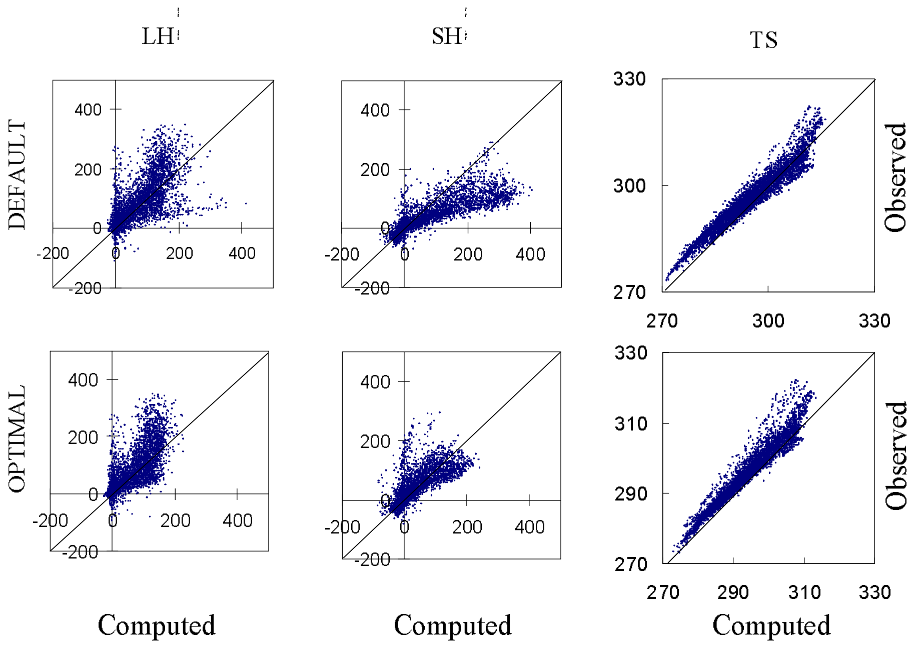

Fig. 7. Same as in Fig. 4, but for the Tongyu site.

for the T_s. Particularly the simulation of SH is substantially improved with more reasonable values during the daytime. These can also be confirmed from the scatter plots with the scatter line closer to 1:1 both for SH and LH (Fig. 7). Of course, there is a little larger error in T_s peaks, which indicates the complexity in defining the optimal model parameters at the Tongyu grassland site. Since the land surface mainly exerts its influence on the atmosphere through the SH and the LH, we take the above MC parameters as an optimal set in this study.

Further comparison between the default parameters and the optimal parameters indicates that both are within the reasonable parameter range (see Table 3). However, the value of VEGC is far above the observation at this site. A previous field observation study by Liu et al. (2004) found that the vegetation cover is about 60% during the wet season (May–September) and 40% during the dry season at the Tongyu grassland area. After the calibration the VEGC takes 50%. Clearly the optimal value is more reasonable. In addition, the values of RSMIN, XLA, ALBVGS, ALBVGL, XMOPOR, XMOHYD, BEE, and SOLOUR are smaller than the optimal ones, and the values of Z_0 and SAI are larger than the optimal ones.

5. Summary and conclusions

In this study, the ability of the MC method to estimate optimized parameters for the BATS model based on observed data is investigated. The aim at doing so is to reduce the model uncertainty induced by the errors in parameters and improve the land surface simulation in the arid and semi-arid areas of northern China.

Analysis of parameter sensitivities in Dunhuang and Tongyu indicates that various parameters for the two sites should be calibrated with different environmental and climate regimes. The sensitivity experiments can reduce the number of the parameters required to be calibrated. The result is consistent with the earlier study of Jackson et al. (2003) that stated that those important parameters affect the model uncertainty are partly a function of the observations, which are used to evaluate model performance. In the Dunhuang Gobi and desert site, the sensitivity analysis suggests that the important parameters may be ranked in a sequence from XMOSUC, BEE, XMOPOR, SOLOUR, Z_0, and SKRAT. For the Tongyu degraded grassland site, they are VEGC, SOLOUR, XMOHYD, XMOPOR, Z_0, XLA, SAI, RSMIN, ALBVGL, ALBVGS, BEE, and SKRAT.

The MC method is shown to be able to estimate the optimal parameters for both the Dunhuang Gobi and desert site and the Tongyu degraded grassland site, which represent typical arid and semi-arid land surfaces, respectively. The simulations with optimal parameters have been substantially improved by using observations of SH, LH, and T_s as criteria. In the Dunhuang Gobi and desert site, the simulations of SH and T_s are much closer to the observations after the calibration of the parameter values. The poor improvement in the LH simulation may be due to both the errors of observation and model. In the Tongyu degraded grassland site, the results show that the energy partition can be simulated well after calibration of the parameter values, especially with significant improvement in SH simulation. However, the error in T_s suggests that further model development should be conducted.

The differences between simulations and observations may be related to errors in the observations, in the model parameterization, and in the parameter values specified for the model. For example, the simulations with the calibrated parameters still have some systematical discrepancies with the observations (see Figs. 3 and 7). These discrepancies may be related to the model parameterization. Further works are needed to use different LSMs to identify the possible reasons. In this paper we only addressed the problems of the specified parameter values in the LSM of BATS. The default parameter values may be defined wrong because they are specified roughly by vegetation cover and soil type. The MC methodology provides a means to remove differences resulting from the specification of parameter values. Our results demonstrate that the difference between model simulation and observation can be reduced by the calibration of parameters values using observed data. Particularly for arid areas, the model simulations can be improved significantly by using optimal parameters. Hence, the parameter calibration of LSM is important when the model is to be used to investigate the land-air interaction.

Another important and practical issue is the spatial transferability of the calibrated parameters for the same vegetation covers. The results in the paper were derived using point-based data. However, Sen et al. (2001) have used calibrated parameters within a climate model and found improvement in the simulated climate. Therefore, the calibrated LSM in this paper may be used to improve the simulated East Asian climate. This is to be discussed in another paper.

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