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A New Approach for Parameter Optimization in Land Surface Model

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ABSTRACT

In this study, a new parameter optimization method was used to investigate the expansion of conditional nonlinear optimal perturbation (CNOP) in a land surface model (LSM) using long-term enhanced field observations at Tongyu station in Jilin Province, China, combined with a sophisticated LSM (common land model, CoLM). Tongyu station is a reference site of the international Coordinated Energy and Water Cycle Observations Project (CEOP) that has studied semiarid regions that have undergone desertification, salination, and degradation since late 1960s. In this study, three key land-surface parameters, namely, soil color, proportion of sand or clay in soil, and leaf-area index were chosen as parameters to be optimized. Our study comprised three experiments: First, a single-parameter optimization was performed, while the second and third experiments performed triple- and six-parameter optimizations, respectively. Notable improvements in simulating sensible heat flux (SH), latent heat flux (LH), soil temperature (TS), and moisture (MS) at shallow layers were achieved using the optimized parameters. The multiple-parameter optimization experiments performed better than the single-parameter experminent. All results demonstrate that the CNOP method can be used to optimize expanded parameters in an LSM. Moreover, clear mathematical meaning, simple design structure, and rapid computability give this method great potential for further application to parameter optimization in LSMs.

Key words: land surface model, parameter optimization, conditional nonlinear optimal perturbation (CNOP)

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1. Introduction

The land surface model (LSM) is an important tool in the study of interactions between land surface and atmosphere (Henderson-Sellers et al., 1995; Sun, 2002, 2005; Xue et al., 2005). However, current performances of LSMs are still not satisfactory, especially in semiarid regions characterized by dry climate, low vegetation coverage, and intense interactions between land surface and atmosphere. These regions have undergone severe aridity trends in recent decades (Fu et al., 2006; Huang et al., 2008; Liu et al., 2008). Two factors affect the performance of LSMs in semiarid regions: (1) Some physical processes in models are in-

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complete (Sun, 2005). (2) The parameter values in some physical processes are inaccurate (Sun, 2005). The inaccuracy of some physical processes has resulted from the complexity of current LSMs. The transmission processes of soil water and heat, the physiological biochemical processes of vegetation, and the exchange processes of material and energy between land surface and atmosphere are comprehensively considered in current LSMs. All of these processes involve numerous parameters; however, some parameters cannot be directly measured and therefore must be estimated using empirical methods (e.g., conductivity of soil water and aerodynamic resistance) or cannot be measured under limited conditions (e.g., proportion of sand or clay in soil).

The uncertainty of parameters restricts LSM simulation capability to a great degree. Some studies have tried to solve this problem. Xia et al. (2002, 2004a, b) examined the applicability of different parameter optimization methods in LSMs over different underlying surfaces based on the Chameleon Surface Model (CHASM). Their research indicated that parameter optimization improved LSM in some aspects and that the optimal parameter set also fitted other stations with the same vegetation cover. In addition, they also investigated the importance of calibration data in terms of length of spin-up time when estimating optimal parameters of the CHASM model and found that the sensitivity of the optimization process to data length depends on the candidate variables and that spin-up time has little effect on the optimal parameters except for the soil moisture. Bastidas et al. (2006) evaluated the multicriteria method by using four different LSMs at five stations and proved the effectiveness of this method. Consequently, parameter optimization of LSMs has become an important topics in land-surface research.

Several methods have been developed for optimizing parameters for LSMs [e.g., MC (Zhu, 2007), MOCOM (Multi-Objective Complex Evolution)-UA (Song, 2008), and EnKF (Zheng et al., 2006a, b; Nie, 2008)]. All of these methods has improved the LSMs, and each has its own respective advantages and disadvantages. Disadvantages include, for example, ambiguous mathematical and physical meanings, demands for huge computing resources, tedious programming requirements, and/or poor transferability.

The use of conditional nonlinear optimal perturbation (CNOP) was proposed to study the predictability of numerical weather and climate prediction by Chinese scientists (Mu et al., 2003a, 2006; Mu and Duan, 2003, 2005a, b; Duan et al., 2004, 2008, 2009; Duan and Mu, 2006, 2009; Mu and Jiang, 2007). CNOP is characterized by maximum nonlinear growth of initial perturbations under a specific constraint condition and has been used widely in research on the predictability of El Niño-Southern Oscillation (ENSO), the sensitivity of thermohaline circulation (THC), and initial perturbations of ensemble forecasting (Mu et al., 2003b; Duan et al., 2004; Duan and Mu, 2006). Recently, Mu et al. (2010) expanded the CNOP method to take both initial perturbation and parameter perturbation into account. In this way, it is possible to introduce the CNOP method into parameter optimization research in LSM.

Our study comprised three experiments to examine the applicability of expanded CNOP method: First, a single-parameter optimization was performed, while the second and third experiments performed triple- and six-parameter optimizations, respectively. The experiments were based on the long-term enhanced field observations during the growing seasons of 2006 and 2008, respectively, at Tongyu station in Jilin Province, China, using a sophisticated nonlinear LSM (common land model, CoLM). Tongyu station is a reference site of the international Coordinated Energy and Water Cycle Observations Project (CEOP) in semiarid regions (Dai et al., 2001, 2003). We chose soil color, sand or clay proportion of soil, and leaf-area index (LAI) as the parameters to be optimized; we chose sensible heat flux (SH), latent heat flux (LH), temperature (TS), and soil moisture (MS) at shallow layers as target variables. We employed differential evolution (DE) as the optimization algorithm (Storn and Price, 1997), and we calculated the minimum between simulated value and the observation value by calculating the negative value of the maximum nonlinear perturbation used in CNOP.

Section 2 briefly introduces the CNOP method; sections 3 and 4 show the experimental scheme and results.

2. Conditional nonlinear optimal perturbation (CNOP)

The CNOP assumes the following nonlinear models:

$$\begin{cases} \dfrac{\partial v}{\partial t} + F(v) = 0, \\ v|_{t=0} = v_0 \ , \end{cases} \tag{1}$$

where $v(x,p,t) = [v_1(x,p,t), v_2(x,p,t), \ldots, v_n(x,p,t)]$, $v \in \Omega(\Omega$ is a domain in $R^n)$ is the ensemble of model state variables, for example, SH and LH used in experiments. $x = (x_1, x_2, \ldots, x_m)$ indicates initial value, $t \in +\infty$ is the time, $p = (p_1, p_2, \ldots, p_m)$ is model parameters, and F is a nonlinear operator. If the initial value x and model state v_0 are known exactly, and the model is well designed in terms of physical meaning, then the solution to Eq. (1) for the state value v at time t is given by

$$v(t) = M_t(p) \ , \tag{2}$$

$M(t)$ propagates the initial value to the time t in the future, p is the given value of parameters, $\overline{p}$ is the initial value of parameters, p' is the parameter perturbation. If $p=\overline{p}$ and $p=\overline{p}+p'$ are the model parameters, then the transform of Eq. (2) yields

$$\begin{aligned} v(t)+v'(t) &= M_t(\overline{p}+p') \ , \\ v(t) &= M_t(\overline{p}) \ , \end{aligned} \tag{3}$$

where $v'(t)$ represents the perturbation of solution at time t caused by p'.

For a chosen norm $\|\cdot\|$, a parameter perturbation satisfies the constrain condition (is called CNOP), if and only if

$$\begin{aligned} & J(p) = \max_{\|p'\|\leqslant\delta} J(p') \ , \\ \text{where} \quad & J(p') = G(M_t(\overline{p}+p') - M_t(\overline{p})) \ . \end{aligned} \tag{4}$$

Target function $G(\cdot)$ measures the evolution of the perturbation. It can be a norm ($\|\cdot\|$) or can be designed under the artificial physical constraints. $\|p'\| \leqslant \delta$ is the constrained condition for parameter perturbation.

3. Experimental design

Typically, the kernel of CNOP method is used to obtain the optimal (O) perturbation (P) by a nonlinear (N) system under constraints. The CNOP might be the maximum or minimum, but it must be the optimum solution. Following this core principle, we expanded the CNOP method to optimize parameters. We used the real values of the range of parameters as constraints. If the parameter was assigned a range, CoLM cannot continue to work; we used DE optimization algorithm to compute the optimal parameters using the nonlinear CoLM. To expand the CNOP method into parameter optimization, we used Eq. (5) to replace Eq. (4) under the CNOP principle:

$$\begin{aligned} & J(p) = \max_{(\overline{p}+p')\in p_{\text{range}}} J(p'), \\ \text{where} \quad & J(p') = -G(M_t(\overline{p}+p') - M_t(\overline{p})) \ , \end{aligned} \tag{5}$$

where, p_{range} is the real value range of parameters, $M_t(\overline{p})$ is observation, $G(\cdot)$ is a nonnegative linear combination of subcriteria (i.e., target function, also means the criteria, referred to as T, Eq. 6a). Adding a minus sign "-" before $G(\cdot)$, the minimum value of $J(p')$ is calculated.

$$T(\theta) = \left| \frac{1}{m\left(\sum\limits_{j=1}^{n} w_j\right)} \left(\sum_{i=1}^{m} \left\{ \sum_{j=1}^{n} [w_j f_{i,j}(\theta)] \right\} \right) \right| , \tag{6a}$$

where θ stands for target variables (e.g., SH, LH, and TS), $f_{i,j}(\theta)$ means subcriteria: distance root-mean-square (DRMS), bias (BIAS), and the number of symbol change (NSC) according to these formulas:

$$\text{DRMS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(q_{\text{sim},t}(\theta) - q_{\text{obs},t}(\theta))^2} \ , \tag{6b}$$

where $q_{\text{sim},t}$ and $q_{\text{obs},t}$ are the simulation and observation of target variables, and N is simulated time.

$$\text{BIAS} = \frac{1}{N}\left|\sum_{t=1}^{N}[q_{\text{sim},t}(\theta) - q_{\text{obs},t}(\theta)]\right| \ , \tag{6c}$$

$$\text{NSC} = \left|\frac{n_1}{n_1+n_2} - 0.5\right| \ , \tag{6d}$$

where m is the number of target variables, n is the number of subcriteria, n_1 is the number of subcriteria when simulation larger than observation, n_2 is the number of subcriteria when observation is larger than simulation, and w is the weight coefficient (generally, $w-$DRMS=3, $w-$BIAS=2, and $w-$NSC=1).

According to the CNOP method, p' computed from Eq. (5) is called CNOP. We can improve the models' performances by using new parameters under the constraint conditions shown in Eq. (5). To validate the assumption above, we designed three experiments to test the application of the expanded CNOP method in parameters optimization.

3.1 *Data, model, and algorithm description*

The data used in this study were the long-term, enhanced field observations at Tongyu station, which is in Baicheng city, Jilin Province located at 44°25′N, 122°52′E, at an elevation of 184 m and with an annual mean precipitation of 404.3 mm (Liu et al., 2004). Observations from Tongyu station included surface-layer meteorological elements, moisture and temperature of soil, surface radiation, heat exchange between surface land and atmosphere, air moisture, and CO_2. Observations at Tongyu began in October 2002 continued to the present. Since 2002, Tongyu station has been qualified as one of the reference sites of CEOP.

Two sites have been established at degraded grassland and cropland areas, ~10 km away from each other. Two 20-m height meteorological observation

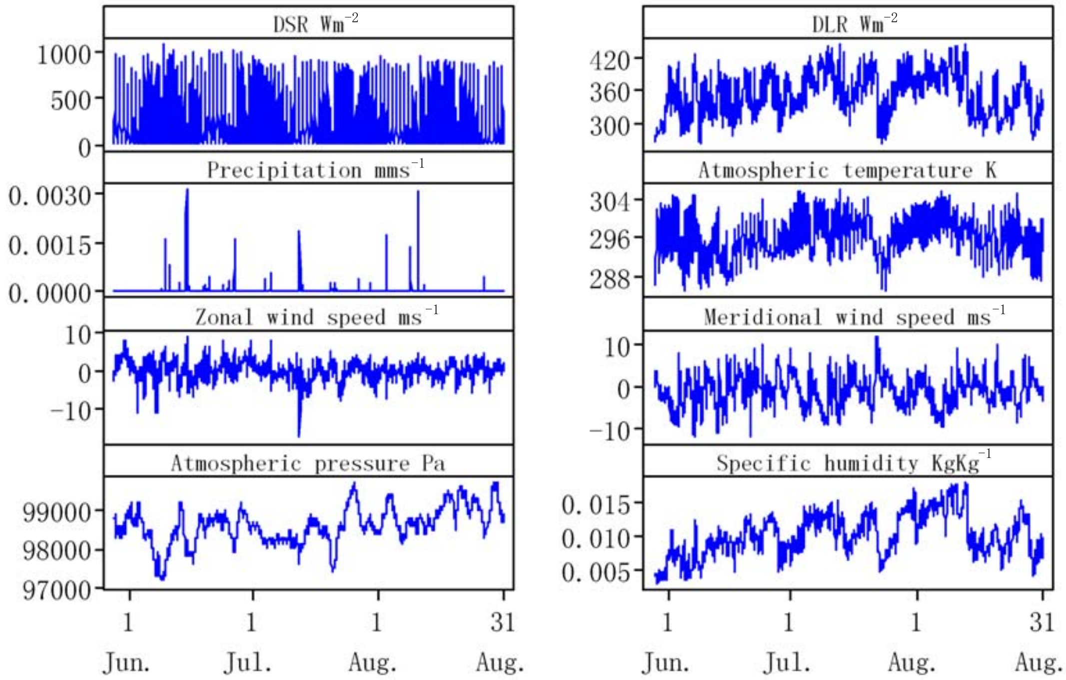

Fig. 1. Atmospheric forcing data during simulating time (DSR: downward short wave radiation, DLR: downward long wave radiation).

towers were built at each site with five sets of sensors that observe temperature, wind speed, and humidity at heights of 2 m, 4 m, 8 m, 12 m, and 17 m, and one wind-direction sensor at a height of 17 m. Surface observations include surface temperature, atmospheric pressure and precipitation, while radiation observations include upward and downward solar radiation and long-wave radiation. Radiation instruments and an eddy covariance (EC) system were installed at a height of 3.0 m over cropland and 2.0 m over degraded grassland, respectively. The non-growing season (i.e., the dry season) usually lasts from October to March of the next year, while the rainy season lasts from June to August. Since the 1960s, this region has undergone severe soil salination, grassland degradation, and desertification.

The data used in this study were the observed meteorological data and flux data at 30-minute intervals over the degraded grassland during 28 May to 31 August 2006. We used a 20-day spin-up time in our experiments. Therefore, the observation and simulation data during 16 June to 31 August 2006 were used in our optimization study. The meteorological forcing data during the simulation period are illustrated in Fig. 1.

The CoLM is a sophisticated, nonlinear, land-surface process model developed by Dai et al (Dai et al., 2001) that includes vegetation dynamics, carbon cycling, river routing, and biogeophysics schemes. Its performance has been proved in several studies (Zeng et al., 2002; Steiner et al., 2005; Meng et al., 2009).

The selection of the optimization algorithm is one of the key components in parameter optimization. An algorithm's quality could even determine whether the optimization problems can be solved eventually. Differential evolution (DE) is a simple and efficient heuristic for global optimization consisting of three steps (Fig. 2): (1) New parameter vectors are generated by adding the weighted difference between two population vectors into a new vector. This step is called "mutation." (2) Parameters are mixed; this is called

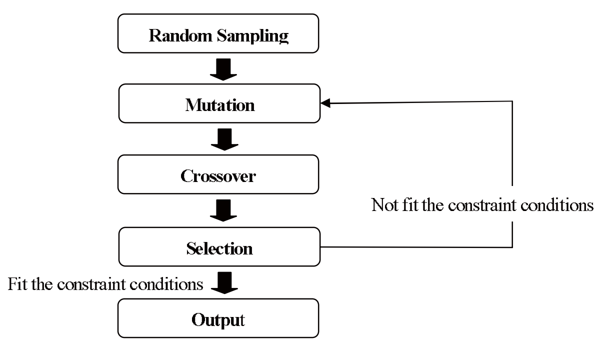

Fig. 2. Schematic map of DE.

"crossover." (3) The superior vector replaces its previous iteration; this step is called "selection".

3.2 *Experimental design*

Three experiments were designed in this study: The first was a single-parameter optimization experiment to check the practicality of the CNOP method for optimization. The second experiment used a triple-parameter optimization to examine the performance of CNOP method in multi-parameter optimization. These two experiments used data from 2006. The third experiment used a six-parameter optimization using data from 2008.

3.2.1 *Single-parameter optimization experiment*

In the first experiment, we chose soil color as the single parameter. As we know, soil color is strongly correlated with the surface albedo, which directly determines gains and distributions of surface energy to a great extent. Unfortunately, soil color has never been observed in many stations in China, so we used a roughly assigned value or estimation. This missing observation inevitably introduced uncertainties into the LSM simulation. Some results of this single-parameter optimization experiment are shown in Table 1. Notably, soil color has been optimized to the lightest value (1) corresponding to the serious salination in this region.

3.2.2 *Triple-parameter optimization experiment*

To compare the capability of the CNOP method in single- and multi-parameter optimizations, we added soil sand proportion and $\mathrm{LAI_s}$ to soil color as the three parameters of the second optimization experiment. Observations for LAI were available only for 2003. Here, $\mathrm{LAI_s}$ is a conversion coefficient between LAI and LAI of 2003, expressed by

$$\mathrm{LAI} = \mathrm{LAI}_{2003} \times \mathrm{LAI_s}\,. \tag{7}$$

Some results of the triple-parameter optimization experiment are shown in Table 2. The results show that, in addition to soil color, soil sand proportion was optimized to a high value corresponding to the desertification in this region. Because the growth of vegetation in this semiarid region is sensitive to the rainfall, LAI was optimized to a larger value corresponding to the relatively abundant precipitation in 2006.

3.2.3 *Six-parameter optimization experiment*

To further evaluate the applicability of the CNOP method, we performed a six-parameter optimization experiment using data from 2008 at Tongyu station from 1 July 2008 to 30 September 2008. To the three previous optimization parameters we added drag coefficient for soil under canopy ($\mathrm{C_{soilc}}$), maximum dew (Dew) and maximal transpiration for moisture

Table 1. Information of single-parameter optimization experiment (2006).

Parameter	Value before optimization	Range	Value after optimization	Remarks
Soil color	8	1–8	1	1→8 (Integer) light → dark

Table 2. Information of the triple-parameter optimization experiment (2006).

Parameter	Value before optimization	Range	Value after optimization	Remarks
Soil color	8	1–8	1	1→8 (Integer) light → dark
Soil sand proportion (%)	50	0–100	99	
$\mathrm{LAI_s}$	1	0.01–2.5	2.47	

Table 3. Information of the six-parameter optimization experiment (2008).

Parameter	Value before optimization	Range	Value after optimization	Remarks
Soil color	8	1–8	2	1→8 (Integer) light → dark
Soil sand proportion (%)	50	0–100	81.8	
$\mathrm{LAI_s}$	1	0.01–2.5	0.81	
$\mathrm{C_{soilc}}$	0.004	0.0004–0.04	0.013	
Dew	0.1	0.01–1	0.04	
Trsmx0	2.0×10^{-4}	2.0×10^{-5}–2.0×10^{-3}	0.0013	

(Trsmx). Results from the six-parameter optimization experiment are shown in Table 3. Compared to the two previous experiments, the optimal parameters used in this experiment were somewhat different: Soil color limit value was 2 rather than 1; sand proportion was optimized to 81.8% rather than the extreme value 99%; LAI_s was 0.81 for precipitation in 2008, almost the same as 2003, but less than that in 2006. The results indicate that more parameters in experiment can improve the modeling results.

4. Results and analysis

In this study, we used SH, LH, temperature at 2 cm below ground surface (TS), and moisture at 5 cm below ground surface (MS) of shallow-layer soil as target variables to evaluate the performance of the CoLM model. The three parameters shown in Table 2 influenced the simulation of the four target variables using CoLM model to different extent. For instance, LAI_s had a prominent influence on LH simulation. The formula of SH in CoLM is

$$H = H_c + H_g \ , \tag{8}$$

where H means the SH to the atmosphere, H_c is the SH from the foliage, and H_g is the SH from the ground.

To verify the uniqueness of this solution, we designed different experiments which were discriminated by their number of the initial random sample size. A unique solution came out after we removed results calculated by the less random sample size experiments. This solution is shown in Table 2 above in text.

Compared with the simulation before parameter optimization, the CoLM model performed better by using optimal parameters obtained from the parameter optimization experiments. Figures 3–5 show the comparison of the target variables before parameter optimization, after parameter optimization, and during the observations day by day. Obvious improvements of SH, LH, and WS can be seen in these figures, and the triple-parameter optimization shows better results than the single-parameter optimization (Table 4). For example, the population deviation decreased, and the symbol consistency increased. In addition, the simulation values are closer to the observations. These results indicate that the deviation between simulation data and observation data in the model has been modified to a certain extent and that the CNOP method is an applicable parameter-optimization approach.

To have a better view compare of the improvements, the values of sub-criteria before and after the optimization are listed in Table 4. It is This evidence shows that most sub-criteria differences reduced systematically. According to equations Eqs. 6b–6d, this

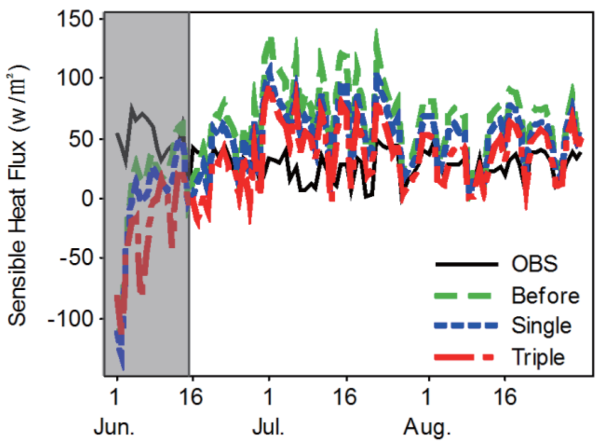

Fig. 3. Contrasts of SH before and after optimization (2006). Shadow area means spin-up period.

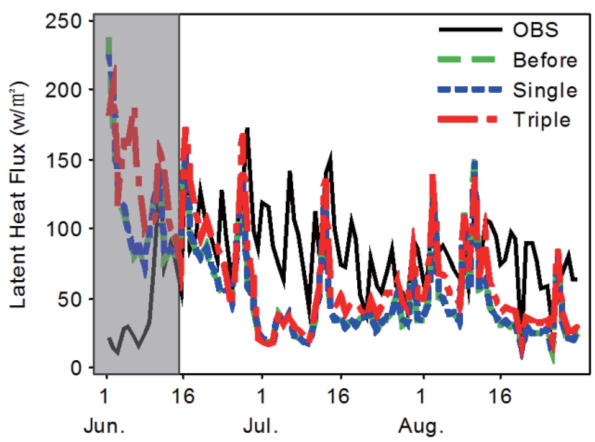

Fig. 4. Same as Fig. 3, but for LE (2006).

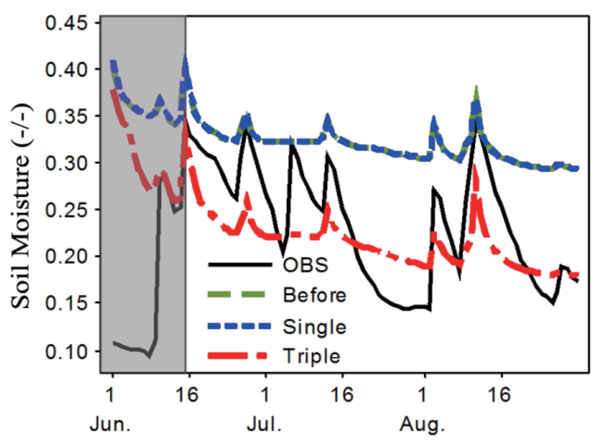

Fig. 5. Same as Fig. 3, but for MS (2006).

Table 4. Values of subcriteria before and after parameter optimization. (D: DRMS, B: BIAS, N: NSC. Values in italic means improvements relative to simulation with non-optimal parameters. Values in italic and bold mean improvements relative to single parameter optimization.)

	SH			LH			TS			WS		
	D	B	N	D	B	N	D	B	N	D	B	N
Before	72.97	38.92	0.34	91.69	37.97	0.23	11.35	10.81	0.5	0.1	0.08	0.48
Single	*55.67*	*25.18*	*0.25*	*89.31*	*37.83*	0.24	*10.68*	*10.23*	0.5	0.1	0.08	0.48
Triple	***50.73***	***12.26***	***0.01***	***76.37***	***27.21***	***0.2***	***10.37***	***9.95***	***0.5***	***0.05***	***0.02***	***0.16***

Table 5. T and correlation coefficients of target variables before and after optimization (Values in italic mean improvements relative to simulation with nonoptimal parameters. Values in italic and bold mean improvements relative to single parameter optimization. All correlation coefficients passed the significance level $p = 0.05$).

	T	SH	LH	TS	MS
Before	42.00	0.66	0.60	0.84	0.778
Single	*37.56*	*0.85*	*0.62*	*0.85*	*0.781*
Triple	***31.30***	***0.86***	***0.72***	***0.86***	***0.82***

reduction implies an a melioration in the model simulation of the model using optimal parameters under the constraint conditions.

According to Eqs. (1)–(6), T influences optimization and also the concrete form for the improvements of model using optimal parameters. It dominates the whole optimization and reflects the improvements of model by using optimal parameters. T and correlation coefficients between simulation and observation for each target variable before and after optimization are shown in Table 5. Since the optimal parameters were applied in both experiments, the value of T dropped notably: 4.44 in single-parameter optimization and 10.7 in triple-parameter optimization. Correlation coefficients are advantageous: all of the correlation coefficients increased after single optimization and further increased after triple optimization.

Details of the four target variables were simulated by CoLM with and without optimal parameter sets are discussed below, and Figs. 3 and 4 demonstrate the contrasts of SH and LH simulated by CoLM with (or without) the optimal parameter sets. Figure 3 shows that by using optimal parameter set, the simulation of SH did not get closer to observation values. The same result for LH is shown in Fig. 4. In general, improvements of SH simulation were more obvious than that of LE, and triple-parameter optimization worked better than single-parameter optimization. SH and LE heat fluxes influenced the structure of atmospheric boundary layer directly; they also affect the temperature and humidity profiles, the atmospheric stability near the surface, and the atmospheric boundary layer as well. Furthermore, SH and LH are the main contributing factors to the enrichment of low-level energy in the troposphere. Therefore, SH and LH heat fluxes play very important roles for understanding the land–atmosphere interaction. In conclusion, results of using the expanded CNOP method for parameter optimization are encouraging.

CoLM worked very well in terms of simulating TS; however, the difference before and after optimization was not noteworthy. The contrast in values of MS before and after optimization is shown in Fig. 5. No visible difference between before and after single-parameter optimization was measured. This may be due to the single parameter selected for optimization, soil color. Soil albedo was the dependent variable for soil color, but MS is influenced by the combined effect of run-off, evaporation loss, gradient flow, gravity current, pumping by roots, seepage, etc. (Dai et al., 2001). Soil color (soil albedo) does not play an important role in MS simulation. Because the two new parameters (sand or clay proportion and LAI) have strong relationship with factors that are two main factors in MS simulation, such as soil conductivity and soil matrix potential. The optimal parameter set from the triple-parameter optimization experiment resulted in great improvement in the simulation (Fig. 5). DRMS, BIAS, and NSC were reduced by 50%, 75%, and 67%, respectively. These results illustrate that triple optimization compensated for the shortcomings of single-parameter optimization in MS simulation and improved the performance of the CoLM model.

MS plays a very important role in land-surface research. In particular, it influences the exchange of energy and water between surface land and near-surface atmosphere directly (Wu et al., 2006; Song et al., 2009). The partition of SH and LH is sensitive to changes in MS. Unfortunately, the simulation of MS is usually the biggest deficiency in the current LSMs, es-

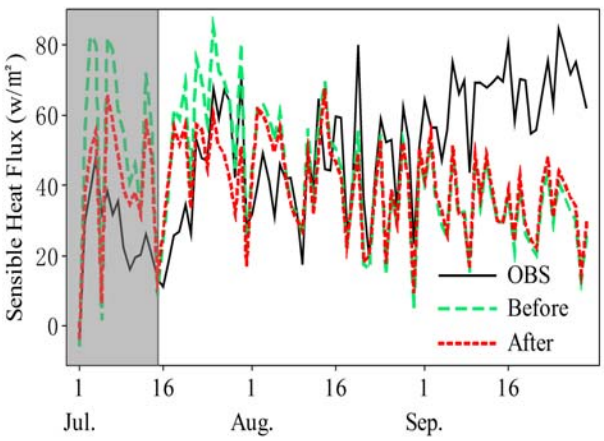

Fig. 6. Same as Fig. 3, but for SH (2008).

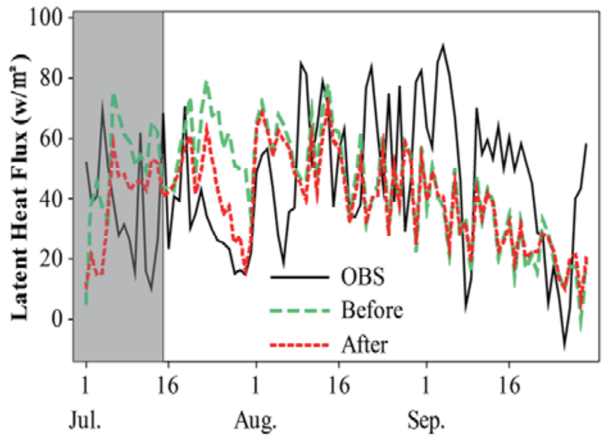

Fig. 7. Same as Fig. 3, but for LH (2008).

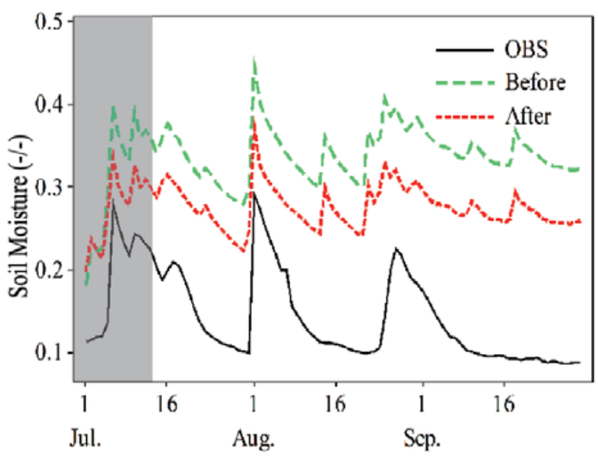

Fig. 8. Same as Fig. 3, but for MS (2008).

pecially in semiarid regions. Therefore, the expanded CNOP method raises the capability of LSM to simulate MS.

Figures 6–8 show the target variables with or without optimal parameters. Table 6 presents the details of subcriteria computed by simulations with and without optimal parameters. Results show that the optimal parameters differ in value with the results in 2006, but they also reflect the basic characteristics of the region. For example, soil color is 2 (corresponding to the salination of soil), and sand proportion is 81.8% (corresponding to the desertification of grass). Because the vegetation is highly sensitive to rainfall, the LAI_s values for 2008 were much different than those for 2006—there was less precipitation in 2008 than in 2006. By using optimal parameters in the model, the simulations of SH, LH, and MS were improved.

To examine the applicability of the optimal parameters, we used the optimal parameters (soil color, sand proportion, and LAI) gained from triple-parameter optimization in 2006 into the simulation using data of 2008 over the same region. Table 7 shows the changes in the subcriteria.

In Table 7 we see that, using the optimal parameters from 2006 in simulation of year 2008, values of subcriteria improved. For example, the DRMSs of four target variables decreased. This result indicates that the optimal parameters of 2006 data can also help to improve the simulation using data of 2008. But differences remain in the degree of improvement, shown by comparing the Tables 6 and 7. Using the six optimal parameters in LSM shows more significant improvement than using the three optimal parameters. On one hand, more parameters can further improve the simulation; on the other hand, some parameters are not suitable for common use or exchange, like the LAI.

In addition, we operated a new triple-parameter (i.e., soil color, soil sand proportion, and LAI_s) optimization experiment using the data of 2008. The optimal parameters and values of subcriteria are shown in Tables 8 and 9. The optimal parameters were more similar to those obtained using year 2006: the soil color was 1 and the sand proportion was 91.9%. Values of subcriteria show some improvement compared with those using optimal parameters of 2006. At the same time, they are worse than those using six optimal parameters. That is, the results computed from six-parameter optimization are closer to the observation data: the optimized six parameters are not as extreme as the experiments that used fewer parameters. Consistencies and differences in the values of parameters show that the number of parameters in each experiment has an important impact on the result. When

Table 6. Values of subcriteria before and after six-parameter optimization (2008). (D: DRMS, B: BIAS, N: NSC. Values in italic and bold means improvements relative to simulation with non-optimal parameters.)

	SH			LH			TS			WS		
	D	B	N	D	B	N	D	B	N	D	B	N
Before	140.8	9.4	0.21	135.3	20.4	0.20	21.4	13	0.5	0.6	0.4	0.5
After	***112.1***	17.2	***0.2***	***126.2***	***9.8***	***0.1***	***19.4***	***10.9***	0.5	***0.4***	***0.3***	0.5

Table 7. Values of subcriteria in 2008 using optimal parameters of 2006 or not. (D: DRMS, B: BIAS, N: NSC. Values in italic and bold means improvements relative to simulation with non-optimal parameters.)

	SH			LH			TS			WS		
	D	B	N	D	B	N	D	B	N	D	B	N
Before	140.8	9.4	0.21	135.3	20.4	0.20	21.4	13	0.5	0.6	0.4	0.5
After	***122.5***	13.2	***0.2***	***132.2***	***10.4***	0.2	***21.1***	21.1	0.5	***0.4***	***0.4***	0.5

Table 8. Information of triple-parameter optimization experiment (2008).

Parameter	Value before optimization	Range	Value after optimization	Remarks
Soil color	8	1–8	1	1→8 (Integer) light → dark
Soil sand proportion (%)	50	0–100	91.6	
$\mathrm{LAI_s}$	1	0.01–2.5	0.69	

Table 9. Values of subcriteria before and after triple-parameter optimization (2008). (D:DRMS, B: BIAS, N: NSC. Values in italic and bold means improvements relative to simulation with non-optimal parameters.)

	SH			LH			TS			WS		
	D	B	N	D	B	N	D	B	N	D	B	N
Before	140.8	9.4	0.21	135.3	20.4	0.20	21.4	13	0.5	0.6	0.4	0.5
After	***120.7***	16.5	***0.2***	***129.2***	***10.1***	***0.1***	***19.9***	***11.9***	0.5	***0.4***	***0.4***	0.5

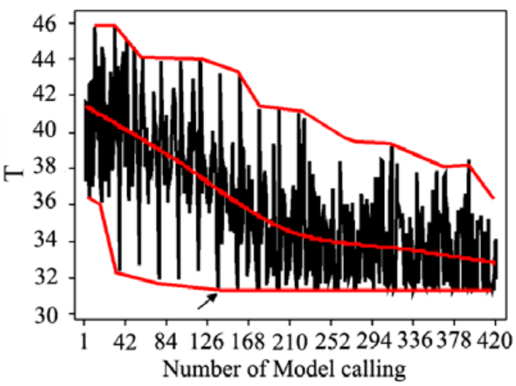

Fig. 9. Value of T changing with model calling number (for triple optimization). Red dotted lines mean the extremes, and the arrow shows the minimal value.

fewer parameters were used, the choice of parameters was more easily evaluated, but the value of parameters was somewhat extreme. When the number of parameters was increased, extreme values were avoided to some degree. All of these results show that the expanded CNOP method can be used not only in the parameter optimization approach but also to improve multi-parameter optimization.

In addition to the optimization results, the convergence rate of optimization was also an important index to judge the quality of this optimization method. Less computing time and faster convergence speed will popularize this method. The minimum value of T of triple parameter optimization approached a stable value after ~140 callings (Fig. 9). Only a few hours are required to run a triple-parameter optimization. In brief, the expanded CNOP method has adequate computing efficiency.

5. Conclusion and discussion

We expanded the CNOP method in LSM parameter optimization and checked its practicality by using CoLM model based on the long-term enhanced field observations at Tongyu station. Three experiments were designed to evaluate this method: a single-parame parameter optimization (soil color), a triple-parameter optimization using data of 2006 (i.e., soil color, soil sand proportion, and LAI_s), and a six-parameter optimization using data of 2008 (i.e., soil color, soil sand proportion), and LAI_s as parameters to be optimized and SH, LH, TS, and MS as target variables. The results indicate that the expanded CNOP method worked well in parameter optimization; for example, soil color was optimized to be close to the observed value, especially in the multi-parameter optimization experiments. Triple-parameter optimization compensated for the shortcomings of single-parameter optimization in MS simulation. To check the optimal parameters, we put optimal parameters from triple-parameter experiment into the model simulation using data of 2008. Results from the six-parameter optimization show that the application of this method using independent data sets and more parameters can improve the optimization. For example, after adding three other parameters in experiment, the soil color and sand/clay proportion approached the observation value instead of the extreme value. In addition, the expanded CNOP method also shows a rapid convergence rate (Fig. 9). In general, the expanded CNOP method is a promising application for land-surface parameter optimization.

Notably, however, some disadvantages remain in this study: the selection of constraint condition and T were under artificial control; the data period was not long enough; etc. At the same time, this study shows that, although parameter optimization can improve the performance of LSM in some aspects, the improvement of the overall parameterization scheme must be emphasized. In addition, the quality assessment and quality control of the field observations are also important for more objective and reliable evaluation of LSM model performance.

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