Parameter Sensitivities of the Community Land Model at Two Alpine Sites in the Three-River Source Region

Qi LUO\textsuperscript{1,2}, Jun WEN\textsuperscript{1,3*}, Zeyong HU\textsuperscript{1}, Yaqiong LU\textsuperscript{4}, and Xianyu YANG\textsuperscript{3}

\textsuperscript{1}Key Laboratory of Land Surface Process and Climate Change in Cold and Arid Regions, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000
\textsuperscript{2}University of Chinese Academy of Sciences, Beijing 100049
\textsuperscript{3}Chengdu University of Information Technology, Chengdu 610025
\textsuperscript{4}Key Laboratory of Mountain Surface Processes and Ecological Regulation, Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu 610041

(Received December 30, 2019; in final form April 2, 2020)

ABSTRACT

The three-river source region plays an important role on China’s ecological security and Asia’s water supply. Historically, the region has experienced severe ecological degradation due to climate change and human activities. Reasonable simulations of the energy and water cycles are essential to predict the responses of land surface processes to future climate change. Current land surface models involve empirical functions that are associated with many parameters. These parameter uncertainties will largely affect the simulation when applied to a new domain. The Community Land Model (CLM) is a widely used land surface model, and version 5.0 is the newest version. Compared to the prior version CLM4.5, CLM5.0 has largely updated plant hydraulic and stomatal conductance schemes. How these changes affect parameter sensitivities is unknown. In our work, we tested 17 key parameters in CLM4.5 and 19 parameters in CLM5.0 at two eddy flux sites in the three-river source region: the Maqu and Maduo sites. We adopted the simplest one-at-a-time changes on each parameter and quantified their sensitivities by the parameter effect (PE). We found that the Maqu site was more sensitive to vegetation parameters, while the Maduo site was more sensitive to the initial soil water content in both CLM4.5 and CLM5.0. This is because Maduo grid cell has wetland that does not respond to vegetation parameters in CLM, which may not reflect the reality. Further model development on wetland vegetation parameterization is important. Our validation on the default simulation showed CLM5.0 did not always improve the simulations. The largest difference between CLM5.0 and CLM4.5 was that soil moisture (SM) showed a much stronger decrease in response to a higher leaf area index (LAI) in CLM5.0 than in CLM4.5, suggesting that SM is more sensitive to vegetation changes in CLM5.0.

Key words: parameter sensitivities, Community Land Model (CLM), three-river source region

Citation: Luo, Q., J. Wen, Z. Y. Hu, et al., 2020: Parameter sensitivities of the Community Land Model at two alpine sites in the three-river source region. J. Meteor. Res., 34(4), 851–864, doi: 10.1007/s13351-020-9205-8.

1. Introduction

The three-river source region of the Yellow River, Yangtze River, and Lancang–Mekong is located in the Tibetan Plateau, and it is a key region for China’s ecological security and Asia’s water supply. The area of the three-river source region is about 363,000 km\textsuperscript{2}. Historically, the region has experienced severe ecological degradation due to climate change and human activities (Zhou et al., 2005; Yin et al., 2014). Since the dramatic streamflow reduction of the Yellow River in the 1990s, a series of ecological restoration and protection projects have been carried out in the three-river source region that increased grassland coverage and water supply capacity (Jiang and Zhang, 2016; Shao et al., 2017).

To quantify how such land cover change affects land surface energy and water cycles, process-based land surface models are useful tools. There are many works of land surface models that have been done over the Tibetan Plateau that improved land surface model simulations.
For example, Yang et al. (2009) implemented an advanced soil water flow scheme and considered excess resistance on heat flux in Simple Biosphere Model 2 (SiB2) that improved soil water and energy fluxes. Luo et al. (2017) introduced gravel and organic matter in the Community Land Model, version 4.5 (CLM4.5), soil parameterization and improved the simulations during the freeze–thaw process. Yuan et al. (2018) developed a new version of a Conjunctive Surface-Subsurface Process model (CSSPv2) that largely improved streamflow simulations.

However, land surface models have empirical functions that are associated with many parameters. Understanding the parameter uncertainties and sensitivities is essential for land surface model application and development (Razavi and Gupta, 2015). Most land surface models are calibrated against regions with plenty of observations but may not be well calibrated for regions with limited observations, such as in the Tibetan Plateau. In recent years, as there are increasing numbers of eddy flux observations, several studies explored parameter sensitivities and uncertainties on the Tibetan Plateau over different land surface models, such as in Noah land surface model with multiparameterization (Noah-MP; Gao et al., 2015; Li et al., 2017) and the Common Land Model (CoLM; Su et al., 2010; Peng and Sun, 2019; Peng et al., 2020). These works largely enhanced our understanding on parameter uncertainty and sensitivity in Noah-MP and CoLM. Exploring parameter uncertainty and sensitivity in other land surface models is necessary when applying the model to a new domain or using a newer version of the model.

We were interested in understanding the parameter sensitivities in the CLM. The CLM is a comprehensive land surface model that simulates biophysical (e.g., radiation transfer, energy fluxes, and hydrology) and biogeochemical processes (e.g., carbon and nitrogen dynamics). CLM5.0 is the latest version of the CLM that was released in February 2018. Compared to the prior version CLM4.5 (released in July 2013), CLM5.0 largely modified the vegetation-related processes. It replaces the Ball–Berry stomatal conductance model (Collatz et al., 1991) with the Medlyn stomatal conductance model (Medlynn et al., 2011), and it abandoned the previous simple calculations for plant water stress that were based on only soil water potential and adopted a plant hydraulic scheme that accounts for different water potential at the leaf, stem, root, and soil. CLM5.0 added a soil dry layer that largely reduced the soil evaporation that was usually overestimated in earlier version of the CLM (Swenson and Lawrence, 2014). How these changes impact parameter sensitivities is unknown.

There are several approaches that are often used to quantify parameter sensitivities in land surface models, such as the Fourier amplitude sensitivity test (Collins and Avisser, 1994), the reduced-form statistical model (Beringer et al., 2002), the distributed evaluation of a local sensitivity analysis (Rakovec et al., 2014; Zhang et al., 2017), and the variance decomposition to assess the sensitivity (Arsenault et al., 2018). However, these approaches are designed for a small set of parameters and could be computationally expensive for our 17 and 19 parameters in CLM4.5 and CLM5.0. Here, we use the simplest one-at-a-time parameter perturbation, which is a useful approach that is still widely used in international model intercomparison projects (Rosenzweig et al., 2014; Lawrence et al., 2016). We developed a parameter-effect algorithm to quantify the parameter sensitivity to ensure the equivalence of the algorithm between the two models. We set up perturbation simulations for 17 and 19 selected key parameters in CLM4.5 and CLM5.0 at two eddy flux sites, i.e., the Maqu and Maduo sites, which represent two typical land surfaces (alpine steppe and alpine marsh meadow) over the three-river source region. We tested the biophysical factors of the model, focusing on parameters that may largely affect soil and vegetation energy and water exchange.

2. Data and methods

2.1 Site descriptions

The Maqu site (33.92°N, 102.15°E) is located on a grazing alpine steppe with vegetation coverage over 92%. The elevation is 3423 m above sea level (ASL) (Fig. 1). The mean annual temperature is 1.2°C, and the mean annual precipitation is 595 mm. The soil texture is silt loam. The Maduo site (34.91°N, 97.55°E) is located over a mixed alpine wetland and meadow with vegetation coverage of approximately 70%. The elevation is 4500 m ASL. The mean annual temperature is −3.3°C, and the mean annual precipitation is within 380–470 mm. The soil texture is clay loam.

The atmospheric forcing data for the site simulations are the CLM default global forcing data (CRUNCEP). We obtained only two-year site observations, including at Maqu in 2016 and at Maduo in 2014, which could not address our goal of understanding whether parameter sensitivity changes in different years. Therefore, we used the 2014–2016 forcing data from CRUNCEP. The air temperature retrieved at the two sites from the global product well matched the site observations in 2016 for Maqu and in 2014 for Maduo, with $R^2$ higher than 0.95 at
both sites. The other forcing variables have $R^2$ within 0.78–0.94 except for the wind speed, which showed $R^2$ of only 0.01 and 0.26 for Maqu in 2016 and Maduo in 2014, respectively. However, based on our validation on the latent heat flux (LE), sensible heat flux ($H$), 5-cm soil moisture (SM), and 5-cm soil temperature (ST) at Maqu in 2016 and Maduo in 2014, the CRUNCEP forcing showed reasonable simulations on the monthly variations of these key variables.

The CRUNCEP atmospheric forcing data at the two sites in 2014–2016 were significantly different. In comparison to the Maduo site, the Maqu site had higher temperatures and precipitation due to the lower elevation. The annual temperature and precipitation were higher by 5.1°C and 170 mm at the Maqu site than at the Maduo site. The Maqu site had slightly higher specific humidity (0.0008 kg kg$^{-1}$) and a lower wind speed (0.66 m s$^{-1}$). In addition, in comparison to the Maduo site, the Maqu site also had 87-hPa higher air pressure and 11.8 W m$^{-2}$ lower downward solar radiation.

The two major land cover types in the three-river source region are alpine steppe and alpine swamp meadow. The land surface energy and water exchanges between the land and atmosphere could be very different for two such land cover types. The land surface characteristics of the Maqu and Maduo sites were also different. Maqu is an alpine meadow site, while Maduo is a mixed alpine wetland and meadow site. Therefore, in our simulation, we set the Maduo site to consist of 30% wetlands and 70% vegetation, while the Maqu site consisted of 100% vegetation. The soil textures were 10% clay, 33% silt, and 37% sand at the Maqu site, while they were 30% clay, 33% silt, and 37% sand at the Maduo site.

2.2 Experiment and parameter descriptions

We selected 17 parameters (Table 1) for CLM4.5 and 19 parameters for CLM5.0 that play important roles in canopy water and energy transfer. We created six perturbations for each parameter, including ± 25%, ± 50%, and ± 75% of default values. We also set perturbation upper and lower bounds to ensure that all the parameter perturbations are within their possible ranges that were reported in previous literature (Oleson et al., 2013; Cai et al., 2019). Then, we run perturbation single-point simulations at two observational sites (Maqu and Maduo) using CLM4.5 and CLM5.0 with the Community Land Model Satellite Phenology (CLMSP).

We cycled the 2014–2016 CRUNCEP forcing to run spin-up for 300 yr at each site to make sure the surface variables entered steady state (Yang et al., 1995). Maqu CLM4.5 (CLM5.0) reached steady state for 27 (9) yr, and Maduo CLM4.5 (CLM5.0) reached steady state for 123 (126) yr.

2.3 Sensitivity analysis

To evaluate the sensitivity of the parameters, we focused on a total of eight variables that are important for land–atmosphere interactions, including the LE, $H$, ground heat flux ($G$), SM, ST, vegetation temperature (TV), ground temperature (TG), and absorbed solar radiation (FSA). For each variable, we calculated the differences between the 3-yr averaged variable in the control simulation and in the six perturbation simulations,
\( \Delta X_{i,j,s} = \sum_{k=1}^{6} |X_{i,j,s,k} - \bar{X}_{i,s,\text{control}}|, \)

\( \text{PE}_{i,j,s} = \frac{\Delta X_{i,j,s}}{\max(\Delta X_{i,j,s})_{1\leq i\leq 8, 1\leq j\leq 17, 1\leq s\leq 4}}, \)

where \( i \) is the \( i \)th variable across the eight output variables, which include \( L, H, G, \) SM, ST, TV, TG, and \( T \); \( j \) is the \( j \)th parameter across the 17 parameters for CLM4.5 and 19 parameters for CLM5.0; \( s \) varies from 1 to 4 to represent the variation in the locations and model versions \((s = 1 \text{ for Maqu CLM4.5, } s = 2 \text{ for Maqu CLM5.0, } s = 3 \text{ for Maduo CLM4.5, and } s = 4 \text{ for Maduo CLM5.0})\); and \( k \) is the six changing factors on the parameters. The \( \text{PE}_{i,j,s} \) (parameter effect) represents the sensitivity of variable \( i \) to the parameter \( j \) in the \( s \) simulation.

### 3. Results and discussion

#### 3.1 Validation on the default simulations

We validated the default simulations (parameter un-
changed) at Maqu in 2016 and Maduo in 2014 and found CLM could reasonably capture the monthly variations. The simulations using the CRUNCEP forcing data well captured monthly variations of the site-observed LE and 5-cm ST (Table 2) with $R^2$ range in 0.81–0.98 at Maqu and Maduo. CLM poorly simulated $H$ at Maqu in both CLM4.5 and CLM5.0, where only 5%–15% variations are captured, while 58%–67% of Maduo $H$ are simulated in CLM4.5 and CLM5.0. For the 5-cm SM at Maqu, CLM reasonably captured the monthly variation with $R^2$ above 0.76, and the double peak SM pattern was also simulated in CLM (Fig. 2). At Maduo site, CLM underestimated the springtime SM, and thus $R^2$ is only 0.51–0.57. The 1-yr validation also showed that CLM5.0 does not always yield better simulations than CLM4.5. For example, LE at Maqu, SM at Maqu, and $H$ at Maduo showed increased root-mean-square error (RMSE) in CLM5.0 compared to that in CLM4.5.

### 3.2 PE analysis

The PE analysis showed that the Maqu site is more sensitive to the vegetation parameters, while the Maduo site is more sensitive to the initial soil water content. At the Maqu site, the most sensitive parameter is the LAI for both CLM4.5 and CLM5.0 (Table 3). LAI strongly affects LE, $H$, and TV, and such a sensitivity remains in CLM5.0 (Fig. 3). The SAI shows a similar sensitivity to that of LAI but with a smaller parameter score. There are two other parameters ($R_{0dm}$ and Ice) that show moderate sensitivity in CLM4.5 but are not sensitive in CLM5.0. The $R_{0dm}$ moderately affects $H$ and temperature-related variables in CLM4.5 (Fig. 3). In CLM5.0, the two new parameters in the photosynthesis (Medlynslope) and plant hydraulic scheme (rootprof-beta) largely affect LE, $H$, and TV at the Maqu site. The leafcn and slatop moderately affect LE, $H$, and TV.

In comparison to the Maduo site, the Maduo site generally shows lower sensitivity to the selected parameters. LAI still exerts moderate controls on energy fluxes and temperature, but the parameter scores are quite low. The most sensitive parameter is the initial soil liquid and ice content (Liqice), which largely affects $G$, SM, and ST. This sensitivity is stronger in CLM5.0 than in CLM4.5. The CLM5.0 photosynthesis parameter Medlynslope moderately affects LE, $H$, and TV at the Maduo site.

The lower sensitivity to vegetation parameters at Maduo is because 30% of land was covered by wetland. CLM assigns different soil columns for different land cover, and performs weighted mean on the column levels to get the grid cell outputs. The wetland soil column in CLM only responds to initial soil condition and does not respond to vegetation parameters so that the overall sensitivity to vegetation parameters is reduced at Maduo simulations. Such a weighted mean on wetland land cover and vegetation land cover in CLM may not represent the reality, where the wetland has its own specific vegetation that will affect energy and water cycles. Wetland plays an important role on ecological security, and therefore, wetland vegetation parameterizations need to be explored to better simulate the energy and water cycles.

The three soil water parameters (Liq, Liqice, and Ice) are not real parameters in CLM. They are the water state variables in initial files that were derived from the spin-up process. Our study treats them as parameters and the artificial perturbation on these soil water states could lead the soil water away from the steady state. Despite this shortcoming, our analysis confirmed the importance of soil initialization in CLM. Microwave remote sensing

---

Table 2. The RMSE (same units as the variables) and regression coefficients ($R^2$) for the four variables between simulations and observations at Maqu in 2016 and Maduo in 2014

| Variable | Maqu (RMSE) | Maqu ($R^2$) | Maduo (RMSE) | Maduo ($R^2$) |
|----------|--------------|--------------|--------------|--------------|
| LE (W m$^{-2}$) | 4.05 | 0.98 | 8.94 | 0.89 |
| $H$ (W m$^{-2}$) | 12.07 | 0.05 | 9.98 | 0.15 |
| SM (m$^3$ m$^{-2}$) | 0.05 | 0.94 | 0.06 | 0.76 |
| ST (°C) | 3.46 | 0.94 | 3.42 | 0.91 |

Table 3. The top five parameters that show strong sensitivity and their PE values [defined in Eq. (2)]

| Rank | Parameter | PE | Parameter | PE | Parameter | PE | Parameter | PE |
|------|-----------|----|-----------|----|-----------|----|-----------|----|
| 1    | LAI       | 0.55 | Liqice    | 0.30 | Medlynslope | 0.48 | Liqice    | 0.41 |
| 2    | Liqice    | 0.46 | Ice       | 0.19 | rootprof_beta | 0.44 | Ice       | 0.18 |
| 3    | $R_{0dm}$ | 0.37 | Liq       | 0.15 | Medlynslope | 0.42 | Leafcn    | 0.33 |
| 4    | flnr      | 0.25 | Leafcn    | 0.14 | Leafcn    | 0.33 | LAI       | 0.10 |
| 5    | flnitr    | 0.25 | Slatop    | 0.14 | Slatop    | 0.14 | Slatop    | 0.14 |
data have already been successfully applied in land surface models and improved SM simulations over the Tibetan Plateau (Lu et al., 2012). Other high-resolution satellite products, such as SM from Soil Moisture Active Passive (SMAP) satellite, has already been used to constrain CLM SM in the U.S. (Felfelani et al., 2018), and could also be used in the Tibetan Plateau to improve SM simulation.

There are three parameters ($R_d$, dleaf, and xl) that maintain the same values in CLM5.0 as those in CLM4.5, and their sensitivities remain the same. The parameter $R_d$ is the ratio of displacement height to canopy top height and is used to calculate the displacement height in the Monin–Obukhov similarity theory. The parameter dleaf is the characteristic dimension of the leaves in the direction of wind flow, which is directly used in the leaf boundary layer resistance (rb) calculation and hence affects the LE. The parameter xl is directly used in calculating the mean leaf inclination angle relative to the horizontal and hence affects the upward and downward radiation. When xl is closer to 1, the leaf angle is closer to horizontal and acts more like a broadleaf tree, and when xl is closer to −1, the leaf angle is closer to vertical and acts more like a deciduous tree. In comparison to vertical leaves, horizontal leaves result in larger projected areas that may absorb higher solar energy when other conditions are the same.

There are three parameters (flnr, fnitr, and $R_{z0m}$) that also have the same values but showed lower sensitivity in CLM5.0 than in CLM4.5. The flnr is the fraction of leaf nitrogen in the Rubisco enzyme. The fnitr is the foliage nitrogen limitation factor. Both flnr and fnitr are used in the calculation of the maximum rate of carboxylation at 25°C ($v_{cmax25}$), which determines the photosynthesis rate. A higher flnr or fnitr will lead to higher $v_{cmax25}$ and higher photosynthesis rates when other conditions are the same. The $R_{z0m}$ is the ratio of the momentum roughness length to the canopy top height and is used to calculate the roughness length and therefore affects the aerodynamic resistance for momentum, sensible heat, and latent heat. A higher $R_{z0m}$ results in higher roughness lengths.

Fig. 2. Validations on the CLM4.5 and CLM5.0 simulations with CRUNCEP forcing and default parameters at (left) Maqu in 2016 and (right) Maduo in 2014 for latent heat flux (LE; W m$^{-2}$), sensible heat flux ($H$; W m$^{-2}$), 5-cm soil moisture (SM; m$^3$ m$^{-3}$), and 5-cm soil temperature (ST; °C).
There are seven parameters that have different values but similar sensitivities, including LAI, SAI, leafcn, slatop, Liq, Liqice, and Ice. The LAI and SAI play important roles in radiation transfer, surface energy fluxes, hydrology within the canopy, and photosynthesis. For radiation transfer, they determine the direct beam transmitted through a canopy, reflected and absorbed radiation for sunlit and sun-shaded leaves, and canopy emissivity. For surface energy fluxes, LAI and SAI affect the sensible heat and water vapor conductance from the canopy air to the atmosphere, as well as the fraction of vegetation versus the ground. For canopy hydrology, LAI and SAI determine interception, liquid and ice throughfall, and fraction of wet or dry leaves. For photosynthesis, LAI and SAI determine stomatal resistance and canopy photosynthesis upscaling for the sunlit and sun-shaded leaves. In comparison to a low LAI and SAI, a high LAI and SAI could absorb more energy and exert stronger turbulence conductance and higher amounts of interception and transpiration when other conditions are the same. The leafcn and slatop are used in calculating the area-based leaf nitrogen concentration, which determines \( \text{vmax25} \) and then affects photosynthesis. The higher (lower) the leafcn or slatop is, the lower (higher) the leaf nitrogen and \( \text{vmax25} \) are. The Liq, Liqice, and Ice are initial soil liquid or ice contents that vary due to the spin-up.

CLM5.0 largely modified the stomatal conductance parameterization. CLM4.5 uses the Ball–Berry conductance model as described by Collatz et al. (1991), while CLM5.0 uses the Medlyn stomatal conductance model (Medlyn et al., 2011). The largest difference between the two stomatal conductance models is that the Medlyn stomatal conductance model adopts vapor pressure deficit.
and abandons the plant water stress variable (btran). In addition, soil water is influenced through plant hydraulic stress. The Medlynslope is the key parameter that varies among different plants, and the other parameter Medlyn-intercept is equal to 100 μmol m$^{-2}$ s$^{-1}$ for all plants. A higher Medlynslope could generate higher stomatal conductance when other conditions are the same.

Some parameters involved with plant water stress calculations are no longer used in CLM5.0, such as roota_par, rootb_par, smpsc, and smpso. In CLM4.5, smpsc and smpso are two soil matrix potential thresholds that lead to stomata being fully open (smpso) or fully closed (smpsc). They determine the plant wilting factor and plant water stress. The roota_par and rootb_par determine root fractions in each soil layer and are used to aggregate the plant water stress in each soil layer to the soil column plant water stress. When the root fraction is higher in a soil layer, the water stress in this layer has a higher weight for the column plant water stress.

CLM5.0 adopts new plant hydraulic processes to represent plant water stress, and rootprof_beta, psi50, psi_soil_ref, kmax, and krmax are the key parameters. The rootprof_beta is the new root distribution parameter. It affects the vertical root distribution in plant hydraulics nonlinearly. The root fraction in each soil layer increases slightly as rootprof_beta increases. However, when rootprof_beta occurs across a threshold (different for different soil layers), the root fraction could dramatically decrease. The kmax and krmax are two parameters that linearly affect hydraulic conductance. The water conductances from stem to leaf, root to stem, and soil to root decrease (decrease) as the two parameters increase (decrease). The psi50 and psi_soil_ref are two water potential references that are used for leaf, stem, root, and soil water potential calculations. Increasing psi50 and psi_soil_ref may result in strong plant water stress if the plant water potential remains the same. However, the whole plant hydraulic process is a dynamic process that balances water demand and water supply. When the soil becomes drier and water stress increases, stomatal conductance and evapotranspiration decrease.

The parameter sensitivities averaged across 2014–2016 did not show a statistically significant difference from the individual year at Maqu and Maduo in CLM4.5 and CLM5.0 (Fig. 4). PEs in each individual year are very similar to the 3-yr average. In CLM4.5, the two root parameters (roota_par and rootb_par) show relatively low parameter sensitivity, while the new root parameter

![Graphs](image-url)
in CLM5.0 (rootprof_beta) shows stronger sensitivity, where PE values increased from 0.08 to 0.44 at Maqu and 0.007 to 0.06 at Maduo from CLM4.5 to CLM5.0, respectively. The new plant hydraulic parameters (kmax, krmax, psi50, and psi_soil_ref) in CLM5.0 show relatively low sensitivities at both sites.

3.3 Key variable response to perturbations on LAI, SAI, Liqice, and Ice

The CLM5.0 and CLM4.5 models showed very similar responses to LAI at the two sites (Fig. 5). The high LAI increased the FSA, LE, and $H$, while it reduced the SM and ST. With a 75% higher LAI, FSA increases by 1.16–2.52 W m$^{-2}$, LE increases by 0.72–3.09 W m$^{-2}$, and $H$ increases by 0.37–3.0 W m$^{-2}$; SM decreases by 0.007–0.02 m$^3$ m$^{-3}$, and ST decreases by 0.03–0.36°C across the two sites and two models.

In comparison to the Maqu site, the Maduo site shows a stronger response to the initial soil water content (Liqice). At the Maduo site, 75% reduction on the initial soil water content increases the FSA by 2.15 and 2.01 W m$^{-2}$ in CLM4.5 and CLM5.0, respectively, while at Maqu site, 75% reduction on the initial water content leads to slightly lower FSA. Another different response is that with 75% increase of the initial soil water content, ST increases by 0.33–0.66°C at Maduo site, while it decreases by 0.16–0.33°C at Maqu site in the two models.

3.4 LE sensitivity analysis

The LE is a key variable in the land–atmosphere interaction and we use it as an example variable to show how the different parameter perturbation affected the LE simulation in the two models. Overall, CLM5.0 performs
better than CLM4.5 in terms of LE [less pattern root-mean-square (RMS)] at the Maqu and Maduo sites (Fig. 6). At the Maqu site, the averaged pattern RMS (averaged across the control and sensitivity simulations) is 9.67 in CLM4.5 and decreases to 5.38 in CLM5.0. At the Maduo site, the averaged pattern RMS is 13.5 in CLM4.5 and decreases to 11.33 in CLM5.0. At the Maqu site, parameter perturbation simulations show a wide range for both standard deviation and correlation. However, the Maduo site only shows a wide range in its standard deviation, and the correlation and pattern RMS do not vary largely because of lower vegetation coverage.

Using LE as an example, we show the best simulation (lowest RMS) for each parameter value among its six perturbations. The RMS of LE varies greatly at the Maqu site but does not change obviously at the Maduo site in either CLM4.5 or CLM5.0. This result is consistent with the previous finding that parameter sensitivity is higher at the Maqu site than at the Maduo site. Across the different parameter perturbations, the parameters and their changing factors that yield the lowest pattern RMS are roota_par × 0.25 at Maqu for CLM4.5, dleaf × 1.75 at Maqu for CLM5.0, Liqice × 1.5 at Maduo for CLM4.5, and Medlyslope × 1.5 at Maduo for CLM5.0 (Fig. 7).

The results suggest that adjusting the most sensitive parameters does not necessarily improve the simulation the most. Thus, changes in the insensitive parameters, such as roota_par in the Maqu CLM4.5 simulation or dleaf in the Maqu CLM5.0 simulation, generated the lowest RMS of LE. This result is because the sensitive parameters may increase or decrease the simulated value far above or below the observation. Furthermore, we tested whether the combined best-parameter simulation will generate the best simulation. The combined best-parameter simulation means that each parameter is assigned the value that generated the lowest RMS across its six perturbation simulations. We found that the combined best-parameter simulation does not yield the smallest pattern RMS compared to that of other single parameter perturbation simulations. In fact, the combined best-parameter simulation results in a large pattern RMS at Maqu for CLM5.0 and at Maduo for CLM4.5. This result indicates that one-at-a-time parameter perturbation could not be used as an overall parameter optimization.

Fig. 6. Taylor diagrams for monthly LE for the Maqu site in 2016 and for the Maduo site in 2014. The black circle on the horizontal axis (obs) is the observed LE standard deviation. The colored symbols are simulated LE and their positions are determined by their correlation to observed LE and their standard deviation. The distance between the colored symbol and the obs represents the pattern RMS defined by Taylor (2001). A smaller pattern RMS means a better simulation. The different parameters are represented by different symbols shown in the figure legend. The colors indicate different parameter perturbation ratios.
3.5 Different responses to LAI in CLM4.5 and CLM5.0

Another major difference between CLM4.5 and CLM5.0 is their different SM response to the same LAI perturbations (Fig. 8). In comparison to CLM4.5, in CLM5.0, the SM shows a much stronger decrease in response to the LAI increase at both sites. The top-layer SM decreases by 0.05 m³ m⁻³ at the Maduo site and 0.09 m³ m⁻³ at the Maqu site in response to the 10-fold higher LAI in CLM5.0 compared to CLM4.5. In CLM4.5, the averaged top-layer SM actually increases by 0.02 and 0.0004 m³ m⁻³ at the Maduo and Maqu sites, respectively, which is due to the wintertime SM increase in response to the LAI increase. The 50% higher LAI also shows a stronger decrease of the SM in CLM5.0 than in CLM4.5.

However, although CLM5.0 showed much stronger SM response to increased LAI, the LE did not show a stronger response in CLM5.0. We used the default LAI derived from the CLM global surface map. CLM4.5 and CLM5.0 have different global surface maps, so the model LAI values in CLM4.5 and CLM5.0 are slightly different at both Maqu and Maduo simulations. In general, the model LAI in Maqu simulation is much higher than LAI in Maduo simulation. The peak grid averaged LAI values are 0.76 and 0.47 m² m⁻² at Maduo in CLM4.5 and CLM5.0, respectively, while they are 1.99 and 2.70 m² m⁻² at Maqu in CLM4.5 and CLM5.0. Therefore, in the sensitivity tests, the 50% and 10-fold higher LAI mean different increments of LAI for the two sites in the two versions of CLM. However, the largest increase in LAI is...
not necessarily indicating the strongest impact. For example, LAI increases to an unrealistic value of 27 m$^2$ m$^{-2}$ at the Maqu site in CLM5.0 (Fig. 8b), but such a large increase in LAI does not result in a dramatic increase in the LE. The increase in the LE at the Maqu site in CLM5.0 is 5.26 W m$^{-2}$, only slightly higher than the 3.64-W m$^{-2}$ increase in the LE at the Maduo site in CLM5.0 as the LAI increases to a peak of 4.72 m$^2$ m$^{-2}$. The reason for the small increase of LE in CLM5.0 is because a top dry soil layer has been implemented in CLM5.0 (Swenson and Lawrence, 2014). The top dry soil layer adds resistance to the soil evaporation, which has been overestimated in the previous version of CLM.

4. Conclusions

Understanding parameter sensitivity in land surface models is an essential task for model application and development. In our study, we set up one-at-a-time parameter sensitivity tests for 17 CLM4.5 parameters and 19 CLM5.0 parameters at two eddy flux observation sites, i.e., the Maqu and Maduo sites in 2014–2016, located over two typical vegetation types on the three-river source region, Tibetan Plateau. We found that the Maqu site is more sensitive to vegetation parameters, while the Maduo site is more sensitive to the initial soil water content in both CLM4.5 and CLM5.0. The parameter sensitivities averaged across 2014–2016 did not show a statist-
A distinctly significant difference from the individual year at Maqu and Maduo in CLM4.5 and CLM5.0. There were three parameters ($R_d$, $R_{\text{def}}$, and $x_l$) that maintained the same values in CLM5.0, and their sensitivities remain the same. There were three parameters (fhn, fintr, and $R_{\text{aon}}$) that also had the same values but showed lower sensitivity in CLM5.0 than in CLM4.5. There were seven parameters that had different values but similar sensitivities, including LAI, SAI, leafcn, slatop, Liq, Liqice, and Ice. In general, in comparison to the Maqu site, the Maduo site showed lower sensitivity to vegetation parameters due to the wetland at Maduo site not responding to vegetation parameters. Such a model response may not reflect the wetland vegetation reality and therefore wetland vegetation parameterizations need to be explored to better simulate the energy and water cycles. The largest difference between CLM5.0 and CLM4.5 was that SM showed a much stronger decrease in response to a higher LAI in CLM5.0 than in CLM4.5, suggesting that SM is more sensitive to vegetation changes in CLM5.0.

Acknowledgments. We greatly acknowledge the eddy flux observations (Maqu and Maduo sites) from the Zoige Alpine Wetland Ecosystem Observation Center, Chinese Academy of Sciences (http://tpwrr.nier.cas.cn).

REFERENCES
Arsenault, K. R., G. S. Nearing, S. G. Wang, et al., 2018: Parameter sensitivity of the Noah-MP land surface model with dynamic vegetation. J. Hydrometeorol., 19, 815–830, doi: 10.1175/JHM-D-17-0205.1.
Beringer, J., S. Melfiwaite, A. Lynch, et al., 2002: The use of a reduced form model to assess the sensitivity of a land surface model to biotic surface parameters. Climate Dyn., 19, 455–466, doi: 10.1007/s00382-002-0237-9.
Cai, X. T., W. J. Riley, Q. Zhu, et al., 2019: Improving representation of deforestation effects on evapotranspiration in the E3SM land model. J. Adv. Model. Earth Syst., 11, 2412–2427, doi: 10.1029/2018MS001551.
Collatz, G. J., J. T. Ball, C. Grivet, et al., 1991: Physiological and environmental regulation of stomatal conductance, photosynthesis and transpiration: A model that includes a laminar boundary layer. Agric. For. Meteor., 54, 107–136, doi: 10.1016/0168-1923(91)90002-8.
Collins, D. C., and R. Avissar, 1994: An evaluation with the Fourier amplitude sensitivity test (FAST) of which land-surface parameters are of greatest importance in atmospheric modeling. J. Climate, 7, 681–703, doi: 10.1175/1520-0442(1994)007<0681:AEWFTA>2.0.CO;2.
Felfelani, F., Y. Pokhrel, K. Y. Guan, et al., 2018: Utilizing SMAP soil moisture data to constrain irrigation in the Community Land Model. Geophys. Res. Lett., 45, 12892–12902, doi: 10.1029/2018GL080870.
Gao, Y. H., K. Li, F. Chen, et al., 2015: Assessing and improving Noah-MP land model simulations for the central Tibetan Plateau. J. Geophys. Res. Atmos., 120, 9258–9278, doi: 10.1002/2015JD023404.
Jiang, C., and L. B. Zhang, 2016: Ecosystem change assessment in the Three-river Headwater Region, China: Patterns, causes, and implications. Ecol. Eng., 93, 24–36, doi: 10.1016/j.ecoleng.2016.05.011.
Lawrence, D. M., G. C. Hurtt, A. Arndt, et al., 2016: The Land Use Model Intercomparison Project (LUMIP) contribution to CMIP6: Rationale and experimental design. Geosci. Model Dev., 9, 2973–2998, doi: 10.5194/gmd-9-2973-2016.
Li, H. Y., C. B. Fu, and W. D. Guo, 2017: An integrated evaluation of land surface energy fluxes over China in seven reanalysis/modeling products. J. Geophys. Res. Atmos., 122, 8543–8566, doi: 10.1002/2016JD026166.
Lu, H., T. Koike, K. Yang, et al., 2012: Improving land surface soil moisture and energy flux simulations over the Tibetan Plateau by the assimilation of the microwave remote sensing data and the GCM output into a land surface model. Int. J. Appl. Earth Observat. Geoinformat., 17, 43–54, doi: 10.1016/j.jag.2011.09.006.
Luo, S. Q., X. W. Fang, S. H. Lyu, et al., 2017: Improving CLM4.5 simulations of land–atmosphere exchange during freeze–thaw processes on the Tibetan Plateau. J. Meteor. Res., 31, 916–930, doi: 10.1007/s13351-017-6063-0.
Medlyn, B. E., R. A. Duursma, D. Eamus, et al., 2011: Reconciling the optimal and empirical approaches to modelling stomatal conductance. Glob. Change Biol., 17, 2134–2144, doi: 10.1111/j.1365-2486.2010.02375.x.
Oleson, K. W., D. M. Lawrence, G. B. Bonan, et al., 2013: Technical Description of Version 4.5 of the Community Land Model (CLM). NCAR Technical Note No. NCAR/TN-503+STR, NCAR, Boulder, CO, 434 pp, doi: 10.5065/D6RR1W7M.
Peng, F., and G. D. Sun, 2019: Identifying sensitive model parameter combinations for uncertainties in land surface process simulations over the Tibetan Plateau. Water, 11, 1724, doi: 10.3390/w11081724.
Peng, F., M. Mu, and G. D. Sun, 2020: Evaluations of uncertainty and sensitivity in soil moisture modeling on the Tibetan Plateau.Tellus A, 72, 1–16, doi: 10.1080/16000870.2019.1704963.
Rakovec, O., M. C. Hill, M. P. Clark, et al., 2014: Distributed Evaluation of Local Sensitivity Analysis (DELSA), with application to hydrologic models. Water Resour. Res., 50, 409–426, doi: 10.1002/2013WR014063.
Razavi, S., and H. V. Gupta, 2015: What do we mean by sensitivity analysis? The need for comprehensive characterization of “global” sensitivity in earth and environmental systems models. Water Resour. Res., 51, 3070–3092, doi: 10.1002/2014WR016527.
Rosenzweig, C., J. Elliott, D. Deryng, et al., 2014: Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. USA, 111, 3268–3273, doi: 10.1073/pnas.1222463110.
Shao, Q. Q., W. Cao, J. W. Fan, et al., 2017: Effects of an ecological conservation and restoration project in the Three-River Source Region, China. J. Geogr. Sci., 27, 183–204, doi: 10.1007/s11442-017-1371-y.
Su, Z., J. Wen, and W. Wagner, 2010: Preface “Advances in land
surface hydrological processes—field observations, modeling and data assimilation”. *Hydrol. Earth Syst. Sci.*, 14, 365–367, doi: 10.5194/hess-14-365-2010.

Swenson, S. C., and D. M. Lawrence, 2014: Assessing a dry surface layer-based soil resistance parameterization for the Community Land Model using GRACE and FLUXNET-MTE data. *J. Geophys. Res. Atmos.*, 119, 10299–10312, doi: 10.1002/2014JD022314.

Taylor, K. E., 2001: Summarizing multiple aspects of model performance in a single diagram. *J. Geophys. Res. Atmos.*, 106, 7183–7192, doi: 10.1029/2000JD900719.

Yang, K., Y.-Y. Chen, and J. Qin, 2009: Some practical notes on the land surface modeling in the Tibetan Plateau. *Hydrol. Earth Syst. Sci.*, 13, 687–701, doi: 10.5194/hess-13-687-2009.

Yang, Z.-L., R. E. Dickinson, A. Henderson-Sellers, et al., 1995: Preliminary study of spin-up processes in land surface models with the first stage data of Project for Intercomparison of Land Surface Parameterization Schemes Phase 1(a). *J. Geophys. Res. Atmos.*, 100, 16553–16578, doi: 10.1029/95JD01076.

Yin, F., X. Z. Deng, Q. Jin, et al., 2014: The impacts of climate change and human activities on grassland productivity in Qinghai Province, China. *Front. Earth Sci.*, 8, 93–103, doi: 10.1007/s11707-013-0390-y.

Yuan, X., P. Ji, L. Y. Wang, et al., 2018: High-resolution land surface modeling of hydrological changes over the Sanjiangyuan region in the eastern Tibetan Plateau: 1. Model development and evaluation. *J. Adv. Model. Earth Syst.*, 10, 2806–2828, doi: 10.1029/2018MS001412.

Zhang, G., G. S. Zhou, and F. Chen, 2017: Analysis of parameter sensitivity on surface heat exchange in the Noah land surface model at a temperate desert steppe site in China. *J. Meteor. Res.*, 31, 1167–1182, doi: 10.1007/s13351-017-7050-1.

Zhou, H. K., X. Q. Zhao, Y. H. Tang, et al., 2005: Alpine grassland degradation and its control in the source region of the Yangtze and Yellow Rivers, China. *Grassl. Sci.*, 51, 191–203, doi: 10.1111/j.1744-697X.2005.00028.x.