Evaluation of sensitive physical parameter combinations for determining the uncertainty of fire simulations and predictions in China

Guodong Sun¹,²

¹State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China
²University of Chinese Academy of Sciences, Beijing, China

Abstract

Fires are fundamental and natural phenomena that affect terrestrial ecosystems and the global climate change. However, uncertainties in fire modeling still exist. It is important to improve the ability to simulate fires by tuning model parameters. In this study, a sensitivity analysis (SA) approach based on the conditional nonlinear optimal perturbation related to parameters (CNOP-P) is employed to find the most sensitive parameter subset. First, the maximum uncertainty in modeling fire is estimated, and it is found that the degrees of uncertainty in modeling fire are different in different regions of China. The extents of the uncertainties in modeling fire in northeastern China and northern China with arid and semiarid climate conditions are greatest, and the magnitude of the uncertainty in southern China is the smallest. The uncertainty in modeling fires in northern China with a semihumid climate condition is between the above values. Second, we find that the most sensitive parameter combination with the number of elements determined by the SA method based on the CNOP-P approach are different from the top five parameters combination via a sensitivity test using a traditional method (such as the one-at-a-time [OAT] method). The most sensitive parameter combination includes not only the parameters in the fire module (e.g., $f_{air}$) but also the parameters that could cause variations in biomass and soil moisture. The prediction skill of fire by reducing the errors of the sensitive parameter combination using the SA method based on the CNOP-P approach are different from the top five parameters combination via a sensitivity test using a traditional method (such as the one-at-a-time [OAT] method). The above results suggest that not only the parameters in the fire module but also the parameters of other physical processes (e.g., biomass and soil moisture) should be corrected and calibrated to improve simulation and prediction of fire.

Keywords

CNOP-P, fire modeling, sensitivity of parameter combinations, uncertainty and predictability
INTRODUCTION

Fires are fundamental and natural phenomena that occur over Earth’s land surfaces. They not only affect the structures of terrestrial ecosystems (Cochrane & Schulze, 1999; Nepstad et al., 2002) and the cycling of carbon but also contribute to global warming by injecting large amounts of aerosols and greenhouse gases into the troposphere (Penner et al., 2003). For these reasons, it is essential to better understand the dynamics of fires and to establish tools to simulate and predict their basic characteristics, such as frequency, intensity, and burn area. However, there is a wide gap in the results of numerical simulations and observations.

At present, fires are not modeled well compared to observations (Arora and Boer, 2005). Many studies have developed methods to describe fire occurrences, length, and frequencies in dynamic global vegetation models (DGVMs) or general circulation models (GCMs). Bachelet et al. (2003) employed two DGVMs, the MC1 and the Lund-Potsdam-Jena (LPJ) models, to simulate the average area burned in the contiguous United States. These studies found that the average areas burned in the contiguous United States were $19.1 \times 10^6$ and $33.2 \times 10^6$ ha, which were lower than that observed by Leenhoustra (1998) $(35 \times 10^6$–$86 \times 10^6$ ha). The differences in fire parameterization may be the main reason for the above results. In the MC1 model, fire is simulated as a function of fuel load and arrangement, fuel moisture, and air temperature, while in the LPJ model, fire is framed as a function of soil moisture, fuel load (litter only), length of fire season, and litter flammability. Pechony and Shindell (2009) suggested a simple global fire algorithm for GCMs using four physical parameters: precipitation, relative humidity, temperature, and vegetation density.

They indicated that a relatively simple yet effective and physically based representation of fire activity could reproduce both global fire patterns and their seasonal variations quite well compared to the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra MOD15A2 product (Garrigues et al., 2008) and Visible and Infrared Scanner (VIRS) monthly fire product with a $0.5^\circ \times 0.5^\circ$ resolution (Giglio et al., 2003). This makes us confident in simulating and predicting fire occurrence and intensity. Rogers et al. (2011) considered the fire suppression mechanism and found that the results were favorable compared with the observations of the MC1 model during the historical period. However, the MC1 fire-only model overestimated the burned area. Migliavacca et al. (2013) optimized the parameters in the fire module and announced an improvement in the estimated burned area with the regulated model. Although the fire activity could be performed well using earlier models when compared with the observations, the magnitude and timing of individual fire years were often smaller, and it was difficult to capture the temporal patterns of the burn area. Hence, simulating real fire using models is challenging. It is apparent that model errors are an important source causing uncertainties in fire simulation. If the simulation ability of fire is to be improved, the key physical processes and physical parameters should be closely analyzed. Determining the key physical processes and physical parameters is related to searching for the important sensitive physical parameters.

There are many sensitivity analysis (SA) approaches to identify the sensitivities of parameters. An easily actualized method (the one-at-a-time [OAT] method) has been employed to determine the sensitive physical parameters in atmospheric and land sciences (Pitman, 1994). However, this method fails to consider the interactions among physical parameters because one parameter floats and other parameters are fixed when to determine the sensitivities of these parameters. To take into account the interactions among physical parameters, sample methods are employed to choose all selected parameters by excluding only one parameter, according to the criterion, such as Monte Carlo-type stratified sampling, factorial design, and the Latin hypercube (Bastidas et al., 2006; Razavi & Gupta, 2015; Zaehle et al., 2005). The above methods can tell us the rank of the parameter sensitivity. However, these methods encounter obstacles in identifying sensitive parameter combination (Mu, 2013). To find the sensitive physical parameter combination, Sun and Mu (2017a) proposed a SA method based on conditional nonlinear optimal perturbation related to parameters (CNOP-P, Mu et al., 2010; Mu, 2013), which is a type of parameter perturbation that can cause maximum simulation and prediction errors at a given time. Determining sensitive physical parameter combination based on the CNOP-P involve the nonlinear effects of parameter combinations on the numerical simulation and prediction. This method has been employed to identify sensitive physical parameter subsets in land processes and improve the ability of numerical simulations (Sun & Mu, 2017b, Sun et al., 2017). In this report, this method is employed to explore the sensitive physical parameter subset of numerical simulations of fire.

MODEL AND METHOD

2.1 Lund-Potsdam-Jena wetland hydrology and methane dynamic global vegetation model (LPJ-WHyMe)

The LPJ-WHyMe v1.3.1 model is an extension of the Lund-Potsdam-Jena (LPJ) dynamic global vegetation
model (DGVM) originally proposed by Sitch et al. (2003) and Gerten et al. (2004). The LPJ model could describe the land-atmosphere carbon exchange and the hydrological cycle and simulate plant physiology, carbon allocation, decomposition, and hydrological fluxes over Earth’s land surfaces every day. Vegetation is classified by 12 plant functional types (PFTs), which include tropical broadleaved evergreen tree (TrBE), tropical broadleaved rainforest tree (TrBR), temperate needleleaved evergreen tree (TeNE), temperate broadleaved evergreen tree (TeBE), temperate broadleaved summergreen tree (TeBS), boreal needleleaved evergreen tree (BoNE), boreal needleleaved summertime tree (BoNS), boreal broadleaved summertime tree (BoBS), C3 perennial grass (C3PG), C4 perennial grass (C4PG), flood-tolerant C3 graminoid, and Sphagnum moss. Furthermore, new modules were added to the LPJ model (Wania et al., 2009a, 2009b; Wania et al., 2010). Other important characteristics enable the simulation of freeze–thaw cycles, such as the active layer depth, permafrost distribution, and water table position. A flowchart of the LPJ-WHyMe model is shown in Figure 1 (Sitch et al., 2003).

**FIGURE 1** A flowchart describes the order individual process representations in all grid cells for the LPJ-WHyMe model. It is revised according to the study of Sitch et al. (2003)
The fire module was included in the LPJ and LPJ-WHyMe models. In this section, the representation of fire in the model is explained (Figure 2). In the LPJ-WHyMe model, the probability of fire ($F_{\text{ire.prob}}$) for a grid cell with a 0.5° resolution (latitude/longitude) is the key process to determine the occurrence of fire in the fire module. There are two factors that determine the occurrence of fire: temperature and the litter moisture weighting factor ($M_f$, Equation [1]). $G_i$ is aboveground litter, $G_{\text{total}}$ is the total aboveground litter, and $F_{\text{lum}}$ is the flammability threshold. The litter moisture weighting factor is computed using the aboveground litter. The annual length of the fire season ($f_{\text{len}}$) is calculated and accumulated using $F_{\text{ire.prob}}$ (Equation [2]) when the temperature and litter moisture weighting factor are greater than zero. $S_i$ is the surface soil moisture. The annual fire index ($F_{\text{ire.index}}$) is computed by dividing the annual length of the fire season by 365. Then, the function of the fractional area burned could be obtained through Equations (3) and (4) for each grid cell with a 0.5° resolution (latitude/longitude). The carbon fluxed into the atmosphere will be calculated, and the aboveground litter due to burned biomass will be updated.

\begin{equation}
M_f = F_{\text{lum}} \times \frac{G_i}{G_{\text{total}}} \quad (1)
\end{equation}

\begin{equation}
F_{\text{ire.prob}} = e^{-x^2 \left( \frac{M_f}{M_f^*} \right)^2} \quad (2)
\end{equation}

\begin{equation}
F_{\text{ire.area}} = F_{\text{ire.index}} e^{2.43 \times F_{\text{ire.term}}^2 + 2.33 \times F_{\text{ire.term}} + 5.96 \times F_{\text{ire.term}} + 1.06} \quad (3)
\end{equation}

\begin{equation}
F_{\text{ire.term}} = F_{\text{ire.index}} - 1 \quad (4)
\end{equation}

2.2 | Determining the sensitivity parameter combination based on the CNOP-P approach

The SA approach to determining sensitive parameter combination based on the CNOP-P includes three steps (Sun & Mu, 2017a), where the last two steps are most important. The introduction of the CNOP-P method could be found in Appendix. Here, the last two steps are introduced using 28 candidate parameters within the LPJ-WHyMe model (Table 1), which are similar to the studies in Sun and Mu (2017a, 2017b), and Sun et al. (2020, 2022). To eliminate some insensitive physical parameters, the CNOP-P method is employed to calculate the maximum uncertainty in modeling the burned fraction due to each parameter. According to the extent of the uncertainty, the parameters, which each cause slight variations in fire modeling, are removed, that is, 18 parameters will be removed, and an arbitrary number of the most sensitive parameter combination is calculated. In this study, the most sensitive parameter combination with five elements is analyzed for the remaining 10 parameters. In addition to selecting five parameters, any number of parameters can be selected (Sun and Mu, 2017a, b; Sun et al., 2020, 2022). The reason why we choose five parameters is that the uncertainty of the fire simulation caused by the five parameters is equivalent to the uncertainty of the fire simulation caused by the 10 parameters and 28 parameters. However, the uncertainty of the fire simulation caused by the three or four parameters is lower than that by the 10 parameters. There are $C_5^{10} = 252$ groups of parameter combinations. All parameter combinations are computed, giving the maximum uncertainties in the modeled burned fraction for every group of parameter combinations using the CNOP-P method. The parameter combination, which leads to maximum uncertainties in modeled fire among 252 groups, is thought to be the most sensitive parameter combination. This approach of determining sensitive parameter combination based on the CNOP-P is flexible because the arbitrary number of parameter combinations could be chosen (Sun and Mu, 2018). The CNOP-P method is an optimization method (see Appendix). The maximal value should be computed for the cost function. To obtain the optimal values (CNOP-P values), the differential evolution (DE, Storn & Price, 1997) algorithm is employed. Ten groups of initial guess values are applied.
to calculate the optimal values. Among 10 optimal values, the maximal optimal values are chosen as the CNOP-P. Additional 10 groups of random perturbation are superimposed on the CNOP-P. Finally, the CNOP-P is confirmed on the basis of the above optimization processes.

### 3 | EXPERIMENTAL DESIGN

To identify the sensitivity of the parameter combination in simulating fire, 28 physical parameters, including photosynthesis, respiration, soil, hydrological processes, and a fire module within the LPJ-WHyMe model (Table 1), were used. Within the fire module, the aboveground litter and soil moisture are two important factors to control fire occurrence. Hence, the parameters related to the hydrological processes are included (such as $\alpha_m$). In addition, the aboveground litter is dependent on variations in the plant. The parameters related to photosynthesis and respiration are also considered. The parameter of the flammability threshold is directly related to the fire module.

#### TABLE 1 The chosen parameters within the LPJ-WHyMe model

| Number of Parameters (NP) | Parameter     | Standard | Minimum | Maximum | Description                                                                 |
|---------------------------|---------------|----------|---------|---------|-----------------------------------------------------------------------------|
| 1                         | $\theta^*$    | 0.7      | 0.2     | 0.996   | Co-limitation shape parameter                                              |
| 2                         | $\alpha_a$    | 0.5      | 0.3     | 0.7     | Fraction of PAR assimilated at ecosystem level relative to leaf level       |
| 3                         | $\lambda_{\text{max,C3}}$ | 0.7 | 0.6     | 0.8     | Optimal $ci = ca$ for C3 plants (all PFTs except TrH)                       |
| 4                         | $\alpha_C$    | 0.08     | 0.02    | 0.125   | Intrinsic quantum efficiency of CO$_2$ uptake in C3 plants                 |
| 5                         | $\alpha_C$    | 0.015    | 0.01    | 0.021   | Leaf respiration as a fraction of Rubisco capacity in C3 plants             |
| 6                         | $Q_{10,Ko}$   | 1.2      | 1.1     | 1.3     | q10 for temperature-sensitive parameter $ko$                               |
| 7                         | $Q_{10,Kc}$   | 2.1      | 1.9     | 2.3     | q10 for temperature-sensitive parameter $kc$                               |
| 8                         | $Q_{10,\tau}$ | 0.57     | 0.47    | 0.67    | q10 for temperature-sensitive parameter $\tau$                             |
| 9                         | $\tau_{\text{growth}}$ | 0.25 | 0.15    | 0.4     | Growth respiration per unit NPP                                             |
| 10                        | $g_m$         | 3.26     | 2.5     | 18.5    | Maximum canopy conductance analogue [mm d$^{-1}$]                           |
| 11                        | $\alpha_m$    | 1.391    | 1.1     | 1.5     | Evapotranspiration parameter                                               |
| 12                        | $k_{\text{allom1}}$ | 100 | 75      | 125     | Crown area = $k_{\text{allom1}}$height*$^{\text{krp}}$                     |
| 13                        | $k_{\text{allom2}}$ | 40   | 30      | 50      | Height = $k_{\text{allom2}}$diameter*$^{\text{allom3}}$                     |
| 14                        | $k_{\text{allom3}}$ | 0.67 | 0.5     | 0.8     | Height = $k_{\text{allom2}}$diameter*$^{\text{allom3}}$                     |
| 15                        | $k_{\text{la/ka}}$ | 6000  | 2000    | 8000    | Leaf-to-sapwood area ratio                                                 |
| 16                        | $k_p$         | 1.5      | 1.37    | 1.6     | Crown area = $k_{\text{allom1}}$height*$^{\text{krp}}$                     |
| 17                        | $k_{\text{mor1}}$ | 0.01 | 0.005   | 0.1     | Asymptotic maximum mortality rate [yr$^{-1}$]                              |
| 18                        | $k_{\text{mor2}}$ | 0.4   | 0.2     | 0.5     | Growth efficiency mortality scalar                                         |
| 19                        | $est_{\text{max}}$ | 0.24 | 0.05    | 0.48    | Maximum sapling establishment rate [m$^{-2}$ yr$^{-1}$]                     |
| 20                        | $n_0$         | 7.15     | 6.85    | 7.45    | Leaf N concentration (mg/g) not involved in photosynthesis                 |
| 21                        | $\text{dens}_{\text{wood}}$ | 200  | 180     | 220     | Specific wood density [kgC m$^{-3}$]                                       |
| 22                        | $\tau_{\text{litter}}$ | 0.35 | 0.19    | 0.81    | Litter turnover time at 10°C [yr]                                          |
| 23                        | $p_t$         | 1.32     | 1.12    | 1.52    | Priestley-Taylor coefficient                                               |
| 24                        | $\beta$       | 0.17     | 0.15    | 0.19    | Global average short-wave albedo                                           |
| 25                        | $k_2$         | 2.00     | 1.80    | 2.20    | variables in percolation equation                                          |
| 26                        | $f_1$         | 0.9      | 0.6     | 1.0     | Fraction of active fraction of roots uptaking water from top soil layer    |
| 27                        | $l_{\text{nc}}$ | 0.02 | 0.005   | 0.08    | LAI parameter, interception storage parameter                              |
| 28                        | $f_{\text{air}}$ | 0.3   | 0.15    | 0.4     | Flammability threshold                                                     |
Four regions with different dry and wet conditions (Ma & Fu, 2005) were chosen (Figure 3, Sun & Mu, 2017a). The PFTs are BoNM (BoNE and BoNS trees), TeBE, TeBS, and C3PG. The LPJ-WHyMe model was run over a 1000-year period to supply the initial condition using the new Climatic Research Unit (CRU) data (CRU TS3.25, Harris et al., 2014; https://crudata.uea.ac.uk/cru/data/hrg/), which include monthly air temperature (°C), monthly cloud cover (%), monthly wet day frequency (days) and monthly precipitation (mm) with a 0.5° resolution (latitude/longitude) for all land areas (excluding Antarctica). The model is run from 1981 to 2000 to explore the sensitivities of the parameters. The 28 physical parameters have different magnitudes of values and ranges, so the physical parameters should be normalized. The standardization formula is as follows (Sun & Mu, 2017a; Sun et al., 2020, 2022):

\[
y = \begin{cases} 
\frac{x - \text{Defvalue}}{\text{Maxvalue} - \text{Defvalue}}, & \text{when } x \geq \text{Defvalue} \\
\frac{x - \text{Defvalue}}{\text{Defvalue} - \text{Minvalue}}, & \text{when } x < \text{Defvalue}
\end{cases}
\]

Here, \(x\) and \(y\) are the prenormalization and post-normalization parameters, respectively. \(\text{Defvalue}, \text{Maxvalue}, \text{and Minvalue}\) are the standard, maximum and minimum values of the parameters, respectively. In this study, the normalized parameters are controlled by the lower and upper bounds \((-1, 1)\). For some parameters, the values are different according to different PFTs (Table 2). The parameters are normalized based on the different PFTs. To compare the differences among different methods for determining the sensitivities of each parameter, the traditional OAT approach and the CNOP-P method are employed to identify the sensitivities of every parameter due to the representative parameter perturbation value by fixing the other parameters. According to the definition of the OAT method, the uncertainty in fire modeling with the OAT stems from a single parameter. The sensitivity ranks of the parameters are determined according to these uncertainties. For the CNOP-P method, the uncertainty in fire modeling with the CNOP-P method stems from the parameter combination. The sensitivity ranks of the parameters’ combinations are determined according to these uncertainties. It is different to identify the sensitivity of parameter or parameter combination. For the identification of each parameter sensitivity, \(p\) is a parameter. For the identification of parameters combinations sensitivities, \(p\) is vector with \(m\) elements. The extent of uncertainties in parameters is ±20% of each parameter value in the study for the OAT method and the CNOP-P method. For the CNOP-P approach, the sensitivities of the parameters are measured by the differences between the modeling burned fraction with the CNOP-P-type perturbation and without the CNOP-P-type perturbation.

4 | RESULTS AND ANALYSIS

4.1 | Uncertainties in the fire simulation caused by parameter errors

The parameter errors are the main factor causing the uncertainties in fire simulation. To explore the extent of uncertainties in fire simulation, the CNOP-P approach is employed, which can find a type of parameter error that

| Parameters | BoNM | TeBE | TeBS | C3PG |
|------------|------|------|------|------|
| \(f_1\) | 0.9  | 0.7  | 0.7  | 0.8  |
| \(l_{\text{ste}}\) | 0.06 | 0.02 | 0.02 | 0.01 |
| \(f_{\text{air}}\) | 0.35 | 0.3  | 0.3  | 0.2  |
leads to the maximum simulation uncertainty given the 28 parameters in Table 1 measured by Equation (A3). The average extent of uncertainty in the modeled fire for whole study region is $2.56 \times 10^{-3}$, which represents the burning area and is a proportion of the study region (Figure 4). There are different variations in different regions for the uncertainty in the modeled fire. The extent of the fire modeling uncertainty ($3.60 \times 10^{-3}$) is the largest in northern China, which has arid and semi-arid climates, among all four regions. The area that follows the second-highest change is northeastern China, with an uncertainty of $2.73 \times 10^{-3}$. The smallest variation in uncertainty is located in southern China ($3.70 \times 10^{-4}$). The uncertainty of modeling fire in northern China, which has a semi-humid climate character, has a value between the above results ($1.82 \times 10^{-3}$) (Figure 4).

4.2 The sensitivity of each parameter for fire simulation

In northern China, which has an arid and semi-arid climate character, the most sensitive physical parameter is $i_{int}$ (Table 3) using the SA method based on the CNOP-P method, which is the leaf area index (LAI) parameter, representing the interception storage parameter for determining the soil moisture in the surface layer ($S_{1}$), as shown in Equation (2). $F_{\text{fire_probability}}$ is the fire probability, and $F_{m}$ is the litter moisture weighting factor. The second-most sensitive physical parameter in Equation (5) is $f_{air}$, which is the flammability threshold and is applied to calculate the litter moisture weighting factor and assess fire probability according to the positive and negative values of the litter moisture weighting factor. The third most sensitive physical parameter is $f_{1}$, which is the active fraction of roots taking up water from the topsoil layer and is used to calculate the effective supply function in the root zone.

$$F_{m} = \frac{L_{\text{litter}}}{L_{\text{litter_all}}} \cdot f_{air}$$

$L_{\text{litter}}$ is the aboveground litter, and $L_{\text{litter_all}}$ is the aboveground litter for all PFTs. In southern and northern China, which have humid and semihumid climates, respectively, there are similar sensitivities among the physical parameters (Table 3). There are minor differences, such as $f_{air}$ being the most sensitive physical parameter. In northeastern China, $i_{int}$ is still the most sensitive physical parameter for most cases. $r_{growth}^{*}$ is also one of the most sensitive physical parameters and is the growth respiration per unit of net primary production (NPP). For some cases, $r_{growth}^{*}$ is also the second-most sensitive physical parameter. This suggests that the parameter is important for aboveground litter ($L_{\text{litter}}$), as shown in Equation 5.

The sensitivity of each parameter is analyzed not only using the SA method based on the CNOP-P method, but also using the OAT method (Table 4). It is found that there are same sensitivity ranks about the candidate parameters using two methods for sensitivity of each parameter. This indicates that the sensitivity ranks keep unchanged without interaction among physical parameters.

4.3 Sensitive parameter combinations for fire simulation

In this section, the sensitive parameter combination is identified. First, 18 of 28 physical parameters were eliminated in the above section according to the single parameter sensitivity rank using the SA method based on the CNOP-P method. The sensitive parameter combination with five elements was assessed out of the remaining ten physical parameters. The sensitive parameter combination with five elements using the SA method based on the CNOP-P approach was found to be different from the combination with the top five parameters via the sensitivity test for all physical parameters using the traditional method (such as the OAT method, Table 4 and 5). This implies that the uncertainty in modeling fire due to the sensitive parameter combination is greater than that due to the top four parameters in the sensitivity test using the OAT method for the chosen five parameters measured by Equation (A3) (Figure 5), and the nonlinear interactions among physical parameters should be considered. In northern China, with an arid and semi-arid climate, $a_{w}^{*}$,

---

**FIGURE 4** The absolute errors of fraction of gridcell burnt in the whole and different regions due to the CNOP-P types of parameters errors for 28 parameters. WR: whole region; NEC (SH): northeastern China (semi-humid); SC (H): southern China (humid); NC (SH): northern China (semi-humid); and NC (SR): northern China (semi-arid)
| Number of Location (NL) | Location | Plant functional type | The sequence from high to low about the sensitivity of parameter |
|------------------------|----------|-----------------------|---------------------------------------------------------------|
| 1                      | 125.75   | BoNM                  | 27 9 4 10 2 28 19 1 26 5                                      |
| 2                      | 125.75   | BoNM                  | 27 9 28 4 26 10 2 19 1 12 1                                  |
| 3                      | 125.75   | BoNM                  | 27 9 28 4 26 10 2 19 1 13 19                                 |
| 4                      | 126.25   | BoNM                  | 27 28 26 25 24 23 22 21 20 19                                |
| 5                      | 126.25   | BoNM                  | 27 4 28 9 10 2 1 26 19 18                                   |
| 6                      | 126.25   | BoNM                  | 27 9 28 4 26 10 2 18 1 19                                    |
| 7                      | 126.75   | BoNM                  | 9 4 10 27 28 2 26 1 19 18                                   |
| 8                      | 126.75   | BoNM                  | 27 28 26 25 24 23 22 21 20 19                                |
| 9                      | 126.75   | BoNM                  | 27 28 26 25 24 23 22 21 20 19                                |
| 10                     | 115.75   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                                |
| 11                     | 115.75   | TeBE                  | 27 28 26 25 24 23 22 21 20 19                                |
| 12                     | 115.75   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                                |
| 13                     | 116.25   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                                |
| 14                     | 116.25   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                                |
| 15                     | 116.25   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                                |
| 16                     | 116.75   | TeBE                  | 27 28 26 25 24 23 22 21 20 19                                |
| 17                     | 116.75   | TeBE                  | 27 27 26 25 24 23 22 21 20 19                                |
| 18                     | 116.75   | TeBE                  | 27 9 28 26 4 10 2 1 19 18                                   |
| 19                     | 115.75   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                                |
| 20                     | 115.75   | TeBS                  | 9 27 28 26 4 10 2 13 1 11                                   |
| 21                     | 115.75   | TeBS                  | 27 28 26 25 24 23 22 21 20 19                                |
| 22                     | 116.25   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                                |
| 23                     | 116.25   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                                |
| 24                     | 116.25   | TeBS                  | 27 28 26 25 24 23 22 21 20 19                                |
αC3, f1, lntc, and fair comprise the sensitive physical parameter combination for all nine cases (Table 5). \( \alpha^\prime_\text{a} \) represents the fraction of photosynthetically active radiation (PAR) assimilated at the ecosystem level relative to the leaf level. \( \alpha^\prime_\text{C3} \) is the intrinsic quantum efficiency of CO2 uptake in C3 plants and is used to calculate the PAR-limited photosynthesis rate. When the nonlinear interaction among physical parameters is considered, \( \alpha^\prime_\text{a} \) and \( \alpha^\prime_\text{C3} \) exist in the sensitive parameter combination of these five elements for possibly determining the aboveground litter (Litter). f1, lntc, and fair are the three parameters that impact the soil moisture in the water balance module for soil and plants. For the sensitivity of the parameter using the OAT method, the three parameters that impact the soil moisture in the water balance module for soil and plants could be identified. However, the parameter \( \alpha^\prime_\text{a} \) failed to be determined as the sensitive parameter. The parameter belongs to the photosynthesis process, which could cause variation of the vegetation and further lead to variation of aboveground litter. The above numerical results suggest that the indirect effect on the fire modeling could be found using the SA method based on the CNOP-P method, but the fact fails using the OAT method. In northeastern China, there are four cases in which the sensitive parameter combination with five elements is similar to those in northern China with an arid and semiarid climate. However, not all cases show the same features. There are three cases in which estmax, \( \beta \), f1, lntc, and fair comprise the sensitive physical parameter combination for the remaining two cases (Table 5). Although there is a similar sensitive physical parameter combination in southern and northern China, with humid and semiarid climates, respectively, the different characteristics are also shown. For example, k2, \( \beta \), f1, lntc, and fair comprise the combination of sensitive physical parameters for nine cases (Table 5). The above results suggest that the sensitive physical parameter combinations may be different under the same climatic conditions. However, the variations

| Number of Location (NL) | Location | Plant functional type | The sequence from high to low about the sensitivity of parameter |
|-------------------------|----------|-----------------------|---------------------------------------------------------------|
| 25                      | 116.75   | TeBS                  | 27 28 26 4 2 25 24 23 22 21                                  |
| 26                      | 116.75   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                               |
| 27                      | 116.75   | TeBS                  | 9 27 4 28 10 26 2 1 13 19                                   |
| 28                      | 115.75   | C3PG                  | 27 28 9 26 4 13 2 1 11 15                                  |
| 29                      | 115.75   | C3PG                  | 27 28 26 13 4 9 1 2 11 10                                  |
| 30                      | 115.75   | C3PG                  | 27 28 26 9 13 10 1 4 5 2                                    |
| 31                      | 116.25   | C3PG                  | 27 28 26 4 13 9 1 2 11 10                                  |
| 32                      | 116.25   | C3PG                  | 27 28 26 4 1 13 2 11 15 5                                  |
| 33                      | 116.25   | C3PG                  | 27 28 26 4 10 2 1 8 9                                     |
| 34                      | 116.25   | C3PG                  | 27 28 26 4 13 9 1 2 11 10                                  |
| 35                      | 116.75   | C3PG                  | 27 28 26 9 4 13 1 2 11 10                                  |
| 36                      | 116.75   | C3PG                  | 27 28 26 9 4 13 1 2 11 10                                  |

Note: The number of the column of “The sequence from high to low about the sensitivity of parameter” corresponds to NP in Table 1.

Abbreviations: BoNM, boreal needleleaved evergreen tree and boreal needleleaved summergreen tree; C3PG, C3 perennial grass; TeBE, temperate broadleaved evergreen tree; TeBS, temperate broadleaved summergreen tree.
| Number of Location (NL) | Location | Plant functional type | The sequence from high to low about the sensitivity of parameter |
|-------------------------|----------|-----------------------|---------------------------------------------------------------|
| 1                       | 125.75   | BoNM                  | 27 9 4 10 2 28 19 1 26 5                                   |
| 2                       | 125.75   | BoNM                  | 27 9 28 4 26 10 2 19 12 1                                  |
| 3                       | 125.75   | BoNM                  | 27 9 28 4 26 10 2 1 13 19                                  |
| 4                       | 126.25   | BoNM                  | 27 28 26 25 24 23 22 21 20 19                              |
| 5                       | 126.25   | BoNM                  | 27 4 28 9 10 2 1 26 19 18                                  |
| 6                       | 126.25   | BoNM                  | 27 9 28 4 26 10 2 18 1 19                                  |
| 7                       | 126.75   | BoNM                  | 9 4 10 27 28 2 26 1 19 18                                  |
| 8                       | 126.75   | BoNM                  | 27 28 26 25 24 23 22 21 20 19                              |
| 9                       | 126.75   | BoNM                  | 27 28 26 25 24 23 22 21 20 19                              |
| 10                      | 115.75   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                              |
| 11                      | 115.75   | TeBE                  | 27 28 26 25 24 23 22 21 20 19                              |
| 12                      | 115.75   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                              |
| 13                      | 116.25   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                              |
| 14                      | 116.25   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                              |
| 15                      | 116.25   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                              |
| 16                      | 116.75   | TeBE                  | 27 28 26 25 24 23 22 21 20 19                              |
| 17                      | 116.75   | TeBE                  | 28 27 26 25 24 23 22 21 20 19                              |
| 18                      | 116.75   | TeBE                  | 27 9 28 26 4 10 2 1 19 18                                  |
| 19                      | 115.75   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                              |
| 20                      | 115.75   | TeBS                  | 9 27 28 26 4 10 2 13 1 11                                  |
| 21                      | 115.75   | TeBS                  | 27 28 26 25 24 23 22 21 20 19                              |
| 22                      | 116.25   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                              |
| 23                      | 116.25   | TeBS                  | 28 27 26 25 24 23 22 21 20 19                              |
| 24                      | 116.25   | TeBS                  | 27 28 26 25 24 23 22 21 20 19                              |
in the aboveground litter and the soil moisture are affected by the above sensitive parameter combinations. In Southern China with humid and semiarid climates, the same parameter sensitivities are shown using two methods.

### 4.4 Analysis of the benefits of fire modeling after reducing the uncertainty in the sensitive parameter combination

The aim of identifying the sensitive parameters is to enhance the modeling ability or prediction skill for fire. In this study, the sensitive parameters are determined by the SA method based on the CNOP-P and the OAT method. A theoretical experiment is implemented to explore the benefits of fire modeling due to reducing uncertainties in the sensitive parameters. The benefits of fire modeling are computed as follows:

\[
\tau = \frac{||M_T(U_0, P + p) - M_T(U_0, P)|| - ||M_T(U_0, P + \alpha p) - M_T(U_0, P)||}{||M_T(U_0, P + p) - M_T(U_0, P)||}
\]

\(\tau\) represents the benefit of fire modeling. The larger \(\tau\) is, the more effective the improvement. \(p\) is the parameter errors of the relatively sensitive parameters. \(\alpha\) (0.2, 0.4, 0.6, and 0.8) represents the extent of error reduction in correct parameters due to data assimilation or observation. \(P\) and \(p\) are different for different methods (the SA method based on the CNOP-P and the OAT method) and determine the sensitive parameters. \(P\) is the referenced
TABLE 5 The most sensitive parameter combinations using the SA method based on the CNOP-P for different plant functional types

| Number of Location (NL) | Location | Parameter combination |
|-------------------------|----------|-----------------------|
| 1                       | 125.75   | 2,4,26,27,28          |
|                         | 45.75    |                       |
| 2                       | 125.75   | 2,4,26,27,28          |
|                         | 46.25    |                       |
| 3                       | 125.75   | 2,4,26,27,28          |
|                         | 46.75    |                       |
| 4                       | 126.25   | 19,24,26,27,28        |
|                         | 45.75    |                       |
| 5                       | 126.25   | 4,18,26,27,28         |
|                         | 46.25    |                       |
| 6                       | 126.25   | 2,4,26,27,28          |
|                         | 46.75    |                       |
| 7                       | 126.75   | 4,18,26,27,28         |
|                         | 45.75    |                       |
| 8                       | 126.75   | 19,24,26,27,28        |
|                         | 46.25    |                       |
| 9                       | 126.75   | 19,24,26,27,28        |
|                         | 46.75    |                       |
| 10                      | 115.75   | 24,25,26,27,28        |
|                         | 26.25    |                       |
| 11                      | 115.75   | 24,25,26,27,28        |
|                         | 26.75    |                       |
| 12                      | 115.75   | 24,25,26,27,28        |
|                         | 27.25    |                       |
| 13                      | 116.25   | 19,24,26,27,28        |
|                         | 26.25    |                       |
| 14                      | 116.25   | 19,24,26,27,28        |
|                         | 26.75    |                       |
| 15                      | 116.25   | 19,24,26,27,28        |
|                         | 27.25    |                       |
| 16                      | 116.75   | 24,25,26,27,28        |
|                         | 26.25    |                       |
| 17                      | 116.75   | 19,24,26,27,28        |
|                         | 26.75    |                       |
| 18                      | 116.75   | 2,9,26,27,28          |
|                         | 27.25    |                       |
| 19                      | 115.75   | 24,25,26,27,28        |
|                         | 32.25    |                       |
| 20                      | 115.75   | 2,4,9,10,28           |
|                         | 32.75    |                       |
| 21                      | 115.75   | 24,25,26,27,28        |
|                         | 33.25    |                       |
| 22                      | 116.25   | 24,25,26,27,28        |
|                         | 32.25    |                       |
| 23                      | 116.25   | 24,25,26,27,28        |
|                         | 32.75    |                       |

(Continued)

| Number of Location (NL) | Location | Parameter combination |
|-------------------------|----------|-----------------------|
| 24                      | 116.25   | 19,24,26,27,28        |
|                         | 33.25    |                       |
| 25                      | 116.75   | 2,4,26,27,28          |
|                         | 32.25    |                       |
| 26                      | 116.75   | 24,25,26,27,28        |
|                         | 32.75    |                       |
| 27                      | 116.75   | 4,9,10,27,28          |
|                         | 33.25    |                       |
| 28                      | 115.75   | 24,26,27,28           |
|                         | 36.25    |                       |
| 29                      | 115.75   | 24,26,27,28           |
|                         | 36.75    |                       |
| 30                      | 115.75   | 24,26,27,28           |
|                         | 37.25    |                       |
| 31                      | 116.25   | 24,26,27,28           |
|                         | 36.25    |                       |
| 32                      | 116.25   | 24,26,27,28           |
|                         | 36.75    |                       |
| 33                      | 116.25   | 24,26,27,28           |
|                         | 37.25    |                       |
| 34                      | 116.75   | 24,26,27,28           |
|                         | 36.25    |                       |
| 35                      | 116.75   | 24,26,27,28           |
|                         | 36.75    |                       |
| 36                      | 116.75   | 24,26,27,28           |
|                         | 37.25    |                       |

Note: The number of the column of “Parameter combination” corresponds to NP in Table 1.

FIGURE 5 The absolute errors of fraction of grid cell burnt in the whole and different regions due to different types of parameters errors for chosen five parameters. WR: Whole region; NEC (SH): Northeastern China (semi-humid); SC (H): Southern China (humid); NC (SH): Northern China (semi-humid); and NC (SR): Northern China (semi-arid)

unperturbed parameters, and $p$ is the CNOP-P perturbation for different methods. The benefits of fire modeling due to reducing the uncertainties in the sensitive parameters using the SA method based on the CNOP-P are higher than those using the OAT method for all cases. The average benefit values of fire modeling for all cases using the SA method based on the CNOP-P method are 50.4%, 22.8%, 13.1%, and 6.2% for $\alpha = 0.2, 0.4, 0.6$, and 0.8, respectively. The average benefit values of fire modeling using the OAT method are 49.4%, 20.2%, 11.7%, and
In this study, the degree of uncertainty in modeling fire is estimated in China. The ranges of uncertainty in modeling fire are different in different regions in China. This implies that the ability of fire simulation is dependent on different climate conditions. In addition, the most sensitive parameter subset is identified using the SA method based on the CNOP-P. The sensitive parameter combination is different from the top-ranking parameters in the sensitivity test that includes all physical parameters using the traditional method (such as the OAT method). This suggests that for numerical fire simulation, the nonlinear interactions among parameters should be considered. In addition, the uncertainty of fire modeling could be reduced through corrected parameters determined as the sensitive parameters. Hence, some facts are revealed in the conclusion. First, the sensitivity of parameter combination is ignored for the OAT method. As a method to identify the sensitivity of physical parameters, the CNOP-P method supplies a tool to consider the interaction among physical parameters. The OAT method fails to consider it. Second, the most sensitive parameter combination using the SA method based on the CNOP-P is different from the simple combination according to the sensitivity rank of the physical parameters using the OAT method. Finally, the improvements of the fire modeling to reduce the errors of key parameters identified by the SA method based on the CNOP-P are better than those by the OAT method. We can draw three qualitative conclusions, although the magnitude is very small and the number of different combinations of sensitive parameters is small. The fire module could be applied to properly estimate parameters in all DGVMs. However, the tuned parameters may fail in future fire predictions because tuning one parameter might simultaneously lead to worse agreements with other metrics. Improving our understanding of physical fire processes, such as triggering, duration, and dying out, is an important tool. Fire modeling could actually be improved when physical fire processes are examined thoroughly. The observation or targeted observation must be implemented to comprehend the behaviors of fire. In addition, it will help to reasonably simulate the impacts of fire, such as reductions in plants, the aboveground litter term, and carbon flux into the atmosphere. The above results also indicate that the parameters in the fire module should be tuned, and the parameters of other physical processes impacting fire occurrence and duration should also be adjusted to improve the numerical simulation ability. In the future, the most sensitive parameter combination should be verified to improve the capabilities of the numerical fire model. There are many sensitivity analysis methods, such as the variance-based method. However, there is no reference state in the variance-based method. For the OAT
method and the SA method based on the CNOP-P, the reference state is employed to explore the sensitivity of parameters. In the future, a new method will be designed to compare to the variance-based method.

ACKNOWLEDGEMENTS
We thank the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics, Chinese Academy of Sciences for providing support. Funding was provided by grants from the Second Tibetan Plateau Scientific Expedition and Research program (STEP) (No. 2019QZKK0103) and the National Natural Science Foundation of China (Nos. 41975132, 42175077)

CONFLICT OF INTEREST
The authors declare that they have no competing interests.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE
Not applicable.

DATA AVAILABILITY STATEMENT
The dataset of CRU is available in Harris et al., 2014; https://crudata.uea.ac.uk/cru/data/hrg/.

REFERENCES
Arora, V.K. & Boer, G.J. (2005) Fire as an interactive component of dynamic vegetation models. *Journal of Geophysical Research*, 110, G02008. [https://doi.org/10.1029/2005JG000042](https://doi.org/10.1029/2005JG000042)
Bachelet, D., Neilson, R.P., Hickler, T., Drapek, R.J., Lenihan, J.M., Sykes, M.T. et al. (2003) Simulating past and future dynamics of natural ecosystems in the United States. *Global Biogeochemical Cycles*, 17(2), 1045. [https://doi.org/10.1029/2001GB001508](https://doi.org/10.1029/2001GB001508)
Bastidas, A.A., Hogue, T.S., Soroshian, S., Gupta, H.V. & Shuttleworth, W.J. (2006) Parameter sensitivity analysis for different complexity land surface models using multicriteria methods. *Journal of Geophysical Research*, 111, D20101. [https://doi.org/10.1029/2005JD006377](https://doi.org/10.1029/2005JD006377)
Clark, T.L., Griffiths, M., Reeder, M.J. & Latham, D. (2003) Numerical simulations of grassland fires in the Northern Territory, Australia: A new subgrid-scale fire parameterization. *Journal of Geophysical Research*, 108(D18), 4589. [https://doi.org/10.1029/2002JD003340](https://doi.org/10.1029/2002JD003340)
Chen, G., Hayes, D.J. & McGuire, A.D. (2017) Contributions of wildland fire to terrestrial ecosystem carbon dynamics in North America from 1990 to 2012. *Global Biogeochemical Cycles*, 31, 878–900. [https://doi.org/10.1002/2016GB005548](https://doi.org/10.1002/2016GB005548)
Cochrane, M.A. & Schulze, M.D. (1999) Forest as a recurrent event in tropical forests of the eastern Amazon: Effects on forest structure, biomass, and species composition. *Biotropica*, 31(1), 1–16.
Coen, J.L., Cameron, M., Michalakes, J., Patton, E.G., Riggan, P. J. & Yedinak, K.M. (2013) WRF-fire: Coupled weather–wildfire modeling with the weather research and forecasting model. *Journal of Applied Meteorology and Climatology*, 52, 16–38.
Filippi, J.B., Bosseur, F., Mari, C., Lac, C., Le Moigne, P., Cuenot, B. et al. (2009) Coupled atmosphere–wildland fire modelling. *Journal of Advances in Modeling Earth Systems*, 1, 1.1
Garrigues, S., Lacaze, R., Baret, F., Morisette, J. T., Weiss, M., Nickeson, J. E. et al. (2008) Validation and intercomparison of global Leaf Area Index products derived from remote sensing data. *Journal of Geophysical Research*, 113. [https://doi.org/10.1029/2007JG000635](https://doi.org/10.1029/2007JG000635)
Gerten, D., Schaphoff, S., Haberlandt, U., Lucht, W. & Sitch, S. (2004) Terrestrial vegetation and water balance: hydrological evaluation of a dynamic global vegetation model. *Journal of Hydrology*, 286, 249–270. [https://doi.org/10.1016/j.jhydrol.2003.09.029](https://doi.org/10.1016/j.jhydrol.2003.09.029)
Giglio, L., Kendall, J.D. & Mack, R. (2003) A multi-year fire data set for the tropics derived from the TRMM VIRS. *International Journal of Remote Sensing*, 24(22), 4505–4525. [https://doi.org/10.1080/0143116031000070283](https://doi.org/10.1080/0143116031000070283)
Harris, I., Jones, P.D., Osborn, T.J. & Lister, D.H. (2014) Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *International Journal of Climatology*, 34, 623–642. [https://doi.org/10.1002/joc.3711](https://doi.org/10.1002/joc.3711)
Kashian, D.M., Romme, W.H., Tinker, D.B., Turner, M.G. & Ryan, M.G. (2006) Carbon storage on landscapes with stand-replacing fires. *Bioscience*, 56, 598–606.
Leenhouwers, B. (1998) Assessment of biomass burning in the conterminous United States. *Conservation Ecology*, 2, 1. [http://www.consecol.org/vol2/iss1/art1](http://www.consecol.org/vol2/iss1/art1)
Ma, Z.G. & Fu, C.B. (2005) Decadal variations of arid and semi-arid boundary in China. *Chinese Journal of Geophysics*, 48, 519–525.
Mandel, J., Beezley, J.D., Coen, J.L. & Kim, M. (2009) Data assimilation for wildland fires: Ensemble Kalman filters in coupled atmosphere-surface models. *IEEE Control Systems Magazine*, 29, 47–65. [https://doi.org/10.1109/MCS.2009.932224](https://doi.org/10.1109/MCS.2009.932224)
Migliavacca, M., Dosio, A., Kloster, S., Ward, D.S., Camia, A., Houmborg, R. et al. (2013) Modeling burned area in Europe with the Community Land Model. *Journal of Geophysical Research – Biogeoosciences*, 118, 265–279. [https://doi.org/10.1002/jgrg.20026](https://doi.org/10.1002/jgrg.20026)
Mu, M., Duan, W., Wang, Q. & Zhang, R. (2010) An extension of conditional nonlinear optimal perturbation approach and its applications. *Nonlin. Processes Geophys.*, 17(2), 211–220.
Mu, M. (2013) Methods, current status, and prospect of targeted observation. *Science China: Earth Sciences*, 56(12), 1997–2005. [https://doi.org/10.1007/s11430-013-4727-x](https://doi.org/10.1007/s11430-013-4727-x)
Nepstad, D.C. et al. (2002) Large-scale impoverishment of Amazonian forests by logging and fire. *Nature*, 98, 503–508.
Penner, J.E., Zhang, S.Y. & Chuang, C.C. (2003) Soot and smoke aerosol may not warm climate. *Journal of Geophysical Research*, 108(D21), 4657. [https://doi.org/10.1029/2003JD003409](https://doi.org/10.1029/2003JD003409)
Pechony, O. & Shindell, D.T. (2009) Fire parameterization on a global scale. *Journal of Geophysical Research*, 114, D16115. [https://doi.org/10.1029/2009JD011927](https://doi.org/10.1029/2009JD011927)
Pitman, A.J. (1994) Assessing the sensitivity of a land-surface scheme to the parameter values using a single column model. *Journal of Climate*, 7, 1856–1869.
Razavi, S. & Gupta, H.V. (2015) What do we mean by sensitivity analysis? The need for comprehensive characterization of “global” sensitivity in Earth and Environmental systems models. *Water Resources Research*, 51, 3070–3092. [https://doi.org/10.1002/2014WR016527](https://doi.org/10.1002/2014WR016527)
Rogers, B.M., Neilson, R.P., Drapek, R., Lenihan, J.M., Wells, J.R., Bachelet, D. et al. (2011) Impacts of climate change on fire regimes and carbon stocks of the U.S. Pacific Northwest. *Journal of Geophysical Research*, 116, G03037. https://doi.org/10.1029/2011JG001695

Sitch, S., Smith, B., Prentice, I.C., Arneth, A., Bondeau, A., Cramer, W. et al. (2003) Evaluation of ecosystem dynamics, plant geography, and terrestrial carbon cycling in the LPJ dynamic global vegetation model. *Global Change Biology*, 9, 161–185. https://doi.org/10.1046/j.1365-2486.2003.00569.x

Storm, R. & Price, K. (1997) Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11, 341–359.

Sun, G., Peng, F. & Mu, M. (2017) Uncertainty assessment and sensitivity analysis of soil moisture based on model parameters-results from four regions in China. *Journal of Hydrology*, 555, 347–360.

Sun, G.D. & Mu, M. (2017a) A new approach to identify the sensitivity and importance of physical parameters combination within numerical models, using the Lund–Potsdam–Jena (LPJ) model as an example. *Theoretical and Applied Climatology*, 128, 587–601. https://doi.org/10.1007/s00704-015-1690-9

Sun, G. & Mu, M. (2017b) A flexible method to determine the sensitive physical parameter combination for soil carbon under five plant types. *Ecosphere*, 8(8), e01920. https://doi.org/10.1002/ecs2.1920

Sun, G. & Mu, M. (2018) Assessing the characteristics of net primary production due to future climate change and CO2 under RCP4.5 in China. *Ecological Complexity*, 34, 58–68.

Sun, G., Mu, M. & You, Q. (2020) Identification of key physical processes and improvements for simulating and predicting net primary production over the Tibetan Plateau. *Journal of Geophysical Research: Atmospheres*, 125. https://doi.org/10.1029/2020JD033128

Wania, R., Ross, I. & Prentice, I.C. (2009a) Integrating peatlands and permafrost into a dynamic global vegetation model: 1. Evaluation and sensitivity of physical land surface processes. *Global Biogeochemical Cycles*, 23, GB3014. https://doi.org/10.1029/2008GB003412

Wania, R., Ross, I. & Prentice, I.C. (2009b) Integrating peatlands and permafrost into a dynamic global vegetation model: 2. Evaluation and sensitivity of vegetation and carbon cycle processes. *Global Biogeochemical Cycles*, 23, GB3015. https://doi.org/10.1029/2009GB003413

Wania, R., Ross, I. & Prentice, I.C. (2010) Implementation and evaluation of a new methane model within a dynamic global vegetation model: LPJ-WHYMe v1.3.l. *Geoscientific Model Development*, 3, 565–584. https://doi.org/10.5194/gmd-3-565-2010

Zaehe, S., Sitch, S., Smith, B. & Hatterman, F. (2005) Effects of parameter uncertainties on the modeling of terrestrial biosphere dynamics. *Global Biogeochemical Cycles*, 19, GB3020. https://doi.org/10.1029/2004GB002395

---

**APPENDIX A**

A.1 Introduction of Conditional nonlinear optimal perturbation related to parameters (CNOP-P)

Here, we will present the details of this method for the reader’s convenience. Let the state variable $U$ be the solution of the following equations:

$$
\begin{align*}
\frac{\partial U}{\partial t} &= F(U, P) \quad U \in \mathbb{R}^n, t \in [0, T], \\
U|_{t=0} &= U_0
\end{align*}
$$

where $U_0$ is an initial value of the state variable $U$; $F$ is a nonlinear partial differential operator; and $P$ is the parameter vector. $M_r$ is the propagator of Equation (A1) above from initial time 0 to $\tau$. Then, $U(\tau) = M_r(U_0, P)$. The solution of Equation (1), which is determined by the parameter perturbation, $p$, is $M_r(U_0, P + p)$. The difference between the reference state $U(\tau)$ and the $U(\tau) + u(\tau)$ induced by $p$ is described by $u(\tau)$.

For an optimal time, $T$, and norm, $\| \cdot \|$, the perturbation, $p_0$, is regarded as the CNOP-P under the constraining condition $p \in \Omega$ if and only if,

$$J(p_0) = \max_{p \in \Omega} J(p),$$

where

$$J(p) = \| u(T) \| = \| M_r(U_0, P + p) - M_r(U_0, P) \|.$$