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Applications of CNOP-P Method to Predictability Studies of Terrestrial Ecosystems

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Abstract: In this paper, recent research on terrestrial ecosystem predictability using the conditional nonlinear optimal parameter perturbation (CNOP-P) method is summarized. The main findings include the impacts of uncertainties in climate change on uncertainties in simulated terrestrial ecosystems, the identification of key physical parameters that lead to large uncertainties in terrestrial ecosystem modeling and prediction, and the evaluation of the simulation ability and prediction skill of terrestrial ecosystems by reducing key physical parameter errors. The study areas included the Inner Mongolia region, north–south transect of eastern China, and Qinghai–Tibet Plateau region. The periods of the studies were from 1961 to 1970 for the impacts of uncertainties in climate change on uncertainties in simulated terrestrial ecosystems, and from 1951 to 2000 for the identification of the most sensitive combinations of physical parameters. Climatic Research Unit (CRU) data were employed. The numerical results indicate the important role of nonlinear changes in climate variability due to the occurrences of extreme events characterized by CNOP-P in the abrupt grassland ecosystem equilibrium state and formation of carbon sinks in China. Second, the most sensitive combinations of physical parameters to the uncertainties in simulations and predictions of terrestrial ecosystems identified by the CNOP-P method were more sensitive than those obtained by traditional methods (e.g., one-at-a-time (OAT) and stochastic methods). Furthermore, the improvement extent of the simulation ability and prediction skill of terrestrial ecosystems by reducing the errors of the sensitive physical parameter combinations identified by the CNOP-P method was higher than that by the traditional methods.

Keywords: CNOP-P; model uncertainties; predictability; terrestrial ecosystem

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1. Introduction

As a part of the Earth system, terrestrial ecosystems interact and couple with the atmosphere through water cycling and energy exchange, so terrestrial ecosystems have important impacts on weather and climate systems [1–3]. However, there are large uncertainties in current terrestrial ecosystem simulations and predictions, and these uncertainties affect our quantitative estimates of terrestrial ecosystem carbon flux and carbon storage and are an obstacle to the simulation and prediction of weather and climate events. Therefore, it is essential to conduct studies on uncertainties in terrestrial ecosystem simulations and predictions [4–8].

Model errors are one of the factors that contribute to uncertainties in the simulation and prediction of terrestrial ecosystems [9,10]. Model errors include climate forcing errors, uncertainties in the physical processes of models, and errors in the physical parameters of models. Climate change is an important factor that can induce variations in terrestrial ecosystems, especially under the background of global warming [11–13]. Climate change is reflected not only in variations in climatology but also in climate variability. However, in previous studies, linearly increased temperature and precipitation changes were employed to assess the impacts of uncertainties in climate change on uncertainties in simulated terrestrial ecosystems [14].

Recently, many studies have found that climate variability plays a key role in the variation in terrestrial ecosystems [15]. For example, Botta and Foley [16] demonstrated that climate variability resulted in changes in ecosystem structure, soil carbon, and vegetation carbon. Mitchell and Csillag [17] also emphasized that climate variability could influence the stability of grasslands and result in high uncertainty in estimating the net primary production (NPP) of grasslands. Zaghloul et al. [18] investigated the impact of climate change on river flow and showed that early spring warming caused water flow to increase in cold climate regions of Canada due to snowpack melting and gradual glacier melting. Li et al. [19] explored the climatic impact of vegetation spring phenology in China and provided important support for modeling vegetation phenology and growth in northern China. Dastour et al. [20] showed that the seasonal cycles of vegetation and climate were generally coherent but there was a time delay. Their wavelet methods also considered the observational uncertainties. Although the effects of climate variability change on terrestrial ecosystems have been investigated, the extreme effects of uncertainties in climate variability change on uncertainties in simulated terrestrial ecosystems are often neglected [21–23].

Moreover, the uncertainties of physical parameters in numerical models are a major factor contributing to the uncertainties in terrestrial ecosystem simulations and predictions. Reducing the errors of physical parameters in numerical models is an effective way to improve the simulation ability and forecasting skills of terrestrial ecosystems. The simulation ability and forecasting skill of terrestrial ecosystems can be improved by adjusting the model parameters. For example, by assimilating the parameters in the model, Rayner et al. [24] found that the model could match the seasonal cycle and annual variation in CO_2 well with the observation with the Biosphere Energy Transfer Hydrology (BETH) model. Mo et al. [25] optimized the physical parameters of the boreal ecosystem productivity simulator (BEPS) model using the ensemble Kaman filter and found that the simulation abilities of total primary productivity, total ecosystem respiration, and net ecosystem productivity were improved. From these results, it was found that the simulation capability of terrestrial ecosystems could be improved by adjusting the parameters in numerical models.

Numerical models contain a large number of parameters in dynamic vegetation models, which simulate carbon storage and cycling in terrestrial ecosystems. There are three categories for the above parameters in numerical models. The first is related to the discrete format of the model, which is independent of observations; the second is for parameters that can be determined from direct observations; and the third is for parameters that can be determined from indirect observations. For example, the random number seed parameter in the Lund–Potsdam–Jena (LPJ) numerical model [26] belongs to the first type; the co-limitation shape parameter obtained directly from observations belongs to the second type [27]; and the temperature sensitivity parameter to the Q10 obtained from indirect observations belongs to the third type [28]. The latter two types of physical parameters determined by direct and (or) indirect observation (PDOs) are the focus of attention in the above studies.

The numerical model contains a large number of PDOs, and reducing the errors of all PDOs at the same time would be very costly. Identifying which PDO errors should be reduced first is critical, and this question involves identifying the sensitivity and importance of the physical parameters. There has been ample research on how to identify the sensitivities of physical parameters in numerical models. For example, Pitman [29] analyzed the sensitivities of 18 physical parameters in the Biosphere Atmosphere Transfer Scheme (BATS) model using the one-at-a-time (OAT) method. When the sensitivity of one of the parameters was analyzed, the remaining 17 physical parameters remained unchanged.

However, the OAT approach ignores the interaction of physical processes characterized by physical parameters [30,31].

The above sensitivity analysis method was also used to analyze the sensitivity of the parameters. However, this method is based on the assumption of linearity and can be used to explore only small parameter errors and short integration times and is not valid for large parameter errors and long integration times. To consider the interaction of physical processes, some scholars have conducted sensitivity analysis of parameters with finite parameter error samples using the multiobjective generalized sensitivity analysis (MOGSA) method, Monte Carlo method, and extended Fourier amplitude sensitivity test (EFAST) method [32]. Zaehle et al. [28] applied the Monte Carlo hierarchical sample method to identify the sensitivity of model parameters. Bastidas et al. [33] used the MOGSA method to analyze the sensitivity of parameters according to different significance levels. These aforementioned methods were characterized by their low computational cost due to the use of limited samples in the parameter space to identify the sensitivities of physical parameters. However, there were certain limitations; for example, either the interaction among all physical parameters was not considered, or the sensitivity of physical parameters was identified within the parameter space using finite samples.

The responses of terrestrial ecosystems to uncertainties in climate change and physical parameters are a component of predictability studies. Although many studies have been conducted on the uncertainties of terrestrial ecosystem simulations and predictions in terms of uncertainties in climate change and physical parameters, the maximum extent of their uncertainty has rarely been determined. The conditional nonlinear optimal perturbation (CNOP) approach [34,35] is a powerful tool to study predictability. The CNOP approach is related to initial errors (CNOP-I) and model errors (CNOP-P) and has been widely applied to predictability studies in atmospheric and oceanic sciences [36–42].

In this study, the applications of the CNOP-P method to predictability studies of terrestrial ecosystems are introduced. The content includes the maximum extent of uncertainties in climate change on the simulation uncertainties in terrestrial ecosystems using the CNOP-P method. Second, key physical parameters and combinations of physical parameters that lead to uncertainties in terrestrial ecosystem simulations and predictions are identified using the CNOP-P method. Furthermore, the degree of improvement in terrestrial ecosystem simulations and projections is assessed by reducing the errors of sensitive physical parameter combinations identified by the CNOP-P method. These works are reviewed mainly to demonstrate the usefulness and adaptability of nonlinear optimization methods (e.g., the CNOP-P method) in terrestrial ecosystem predictability studies. Furthermore, it provides an outlook for more scholars to use this method to conduct uncertainty studies on numerical simulations and predictions of terrestrial ecosystems using the method.

This paper is organized as follows: studies on the influence of grassland ecosystem equilibrium on moisture index perturbation are introduced in Section 2.1. The impact of uncertainties in climate change on the uncertainties in simulated terrestrial ecosystems is presented in Section 2.2. In Section 2.3, the impact of uncertainties in physical parameters on the terrestrial ecosystem is introduced; in Section 3, the summary and conclusion are provided.

2. Results of Reviews

2.1. The Impact of Moisture Index Perturbation on the Stability of Grassland Ecosystem Equilibrium

To investigate the stability of grassland ecosystem equilibrium to climate perturbation, Sun and Mu [43] used the CNOP-P method and a five-variable grassland ecosystem model. For a grassland equilibrium state (GES) and a desert equilibrium state (DES) within the five-variable grassland ecosystem model, moisture index perturbations were generated using the CNOP-P method, and these perturbations represented the climate perturbation. They first found that the variations in the moisture index resulting from CNOP-P showed nonlinear characteristics. For instance, for the GES, the humidity index of CNOP-P gradually decreased when the amplitude of the moisture indices was small, while when the amplitude of the moisture indices was large, the humidity index of CNOP-P showed a "decreasing–increasing–decreasing" pattern and changed sharply at the end of the period. The variation in the GES also exhibited nonlinear characteristics due to the above humidity index variations.

With the small amplitude of moisture indices, grassland ecosystems returned to the grassland equilibrium state under the influence of the CNOP-P-type humidity index. There were different times required for recovery for different amplitudes of moisture indices. However, grassland ecosystems gradually evolved toward the desert equilibrium state with abrupt changes in the larger amplitude of moisture indices. Numerical results indicated that grassland ecosystems eventually evolved toward a desert state with nonlinear instability when subjected to sufficiently large climate changes. For the DES, Sun and Mu [43] also demonstrated a nonlinear character similar to that of the GES.

To further explore the nonlinear characteristics of the stability of the GES and DES to different types of climatic disturbances, Sun and Mu [43] analyzed the nonlinear evolution of grassland ecosystems under the influence of nonlinear and linear climatic disturbances (Table 1). To interpret the differences between the two, they created two linear climate perturbations that could be distinguished in light of their linear slopes, which were zero or nonzero. For the GES, they found that nonlinear climate change had a severe impact on grassland ecosystems. Grassland ecosystems degraded to a desert equilibrium state and tended to be nonlinearly unstable under the influence of the CNOP-P-type moisture indices. For the DES, they found that nonlinear moisture indices had a severe impact on desert ecosystems. The desert ecosystem influenced by the CNOP-P-type moisture index degenerated into the grassland equilibrium state and became nonlinearly unstable. All of the above work suggests that nonlinear changes in climate variability play an important role in abrupt changes in the equilibrium state of grassland ecosystems.

2.2. The Impact of Uncertainties in Climate Change on the Uncertainties in Simulated Terrestrial Ecosystems

Soil carbon, as a large carbon sink, plays an important role in the carbon cycle in terrestrial ecosystems [14,44]. Changes in soil carbon can cause large changes in atmospheric CO_2, which may further accelerate global warming. It is therefore necessary to determine the uncertainty in modeled soil carbon. Sun and Mu [45] used the CNOP-P method to analyze the maximum degree of uncertainty in the contribution of soil carbon to climate change uncertainty (both climatological change and climate variability) in China (Table 1).

Table 1. Summary of the studies of terrestrial ecosystem predictability using the CNOP-P method.

Sources of Uncertainty	Descriptions/Limitations	Reference
Moisture index	Stability analysis of grassland ecosystem equilibrium was shown due to moisture index perturbation using CNOP-P method. A theoretical model was employed.	Sun and Mu [43]
Climate condition	Uncertainties in simulated soil carbon due to temperature and precipitation perturbations were estimated using the CNOP-P method.	Sun and Mu [45]
Physical parameters	A new parameter sensitivity analysis method based on CNOP-P was proposed. The new method was applied to identify the most sensitive physical parameters set to uncertainties in simulated NPP in China. The improvement extent by reducing the errors of sensitive physical parameters set determined by the new method was evaluated.	Sun and Mu [46]
Physical parameters	The new parameter sensitivity analysis method based on CNOP-P was applied to identify the most sensitive physical parameters set to uncertainties in simulated soil carbon in China.	Sun and Mu [47]
Physical parameters	The new parameter sensitivity analysis method based on CNOP-P was applied to identify the most sensitive physical parameters set to uncertainties in simulated ET over the TP. The improvement extent by reducing the errors of sensitive physical parameters set determined by the new method was evaluated.	Sun et al. [48]

Under the background of global warming, they provided a nonlinear climate change, i.e., CNOP-P-type climate change, and a linear climate change. The key difference between the CNOP-P-type climate change and the linear climate change was whether there was a change in temperature or precipitation variability compared to a reference temperature or precipitation variability. Sun and Mu [45] showed that there were different regional responses to uncertainties in simulated soil carbon caused by CNOP-P-type and linear temperature changes.

By exploring three components of soil carbon in the LPJ model, namely, rapidly decomposing soil carbon, slowly decomposing soil carbon, and subsurface apoplastic material, they found that the decrease in subsurface apoplastic matter was probably the main reason for the decrease in soil carbon in arid and semiarid zones as a result of the two temperature climate changes. The different effects of the two temperature climate changes in southern China may be caused mainly by the rapid decomposition of soil carbon. The uncertainties in simulated soil carbon caused by the two precipitation climate changes were similar. In the arid and semiarid zones, both precipitation and climate changes led to increased uncertainty in the simulated soil carbon. This research implied that the variation in temperature variability played a crucial role in the variations in soil carbon and its components in the study region.

2.3. The Impact of Uncertainties in Physical Parameters on the Terrestrial Ecosystem

2.3.1. The Sensitivity Analysis Method Based on CNOP-P

The numerical model contains a large number of physical parameters. Finding the key physical processes and physical parameters in the numerical model is an important way to improve simulation capabilities and prediction skills. To find the most sensitive physical parameters, Sun and Mu [46] proposed a sensitivity analysis (SA) method based on CNOP-P (Figure 1, Table 1). For the SA method based on CNOP-P, there were two steps. First, some insensitive physical parameters were eliminated using the CNOP-P method. Next, among the remaining physical parameters, the combination of relatively sensitive and important physical parameters was judged using the idea of combination and the CNOP-P method. In the second step, the sensitivity of a single parameter was identified using the CNOP-P approach, which in theory was the optimal way to ensure the ranking of every parameter in terms of its sensitivity. Obviously, this method fully considered the nonlinear synergistic effects between physical parameters. Moreover, this method identified relatively sensitive and important combinations of physical parameters in the whole physical parameter space.

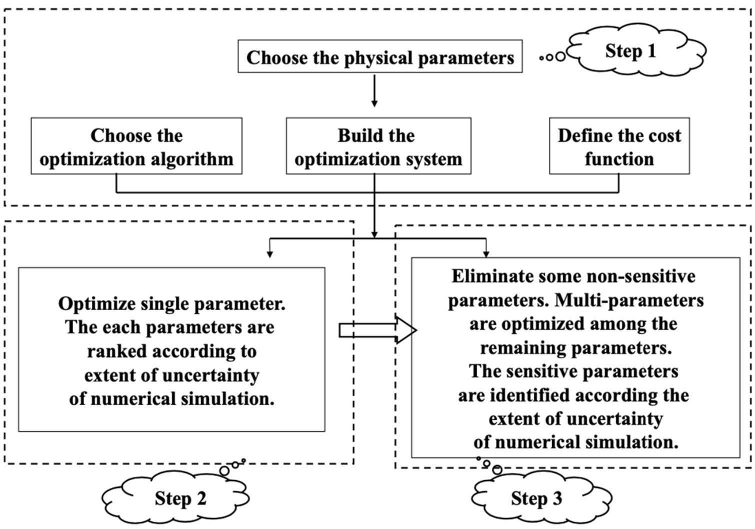

Figure 1. Flowchart depicting the steps involved in the SA method based on CNOP-P (From research findings by Sun and Mu [46]).

2.3.2. Identification of Sensitive Physical Parameters

Model errors are a critical source affecting the uncertainty in simulated terrestrial ecosystems. It is important to determine which parameter errors should be reduced to improve the simulation ability of terrestrial ecosystems. Sun and Mu [47] used the SA method based on CNOP-P to identify the most sensitive physical parameters to soil carbon. To compare the sensitivity of the parameter combination, the one-at-a-time (OAT) approach was also applied to judge the sensitivity of each parameter.

Sun and Mu [47] noted that the most sensitive parameters to soil carbon varied between plant functional types (Figure 2, Table 1, and the physical meanings of the parameters can be found in Table S1). For example, for C3 perennial grasses under semiarid conditions, the uncertainty in hydrological processes was also critical for modeling soil carbon.C3 perennial grasses are cool season grasses and are great at fixing CO_2 at cooler temperatures. However, at higher temperatures, e.g., above 90 degrees F, they are not as efficient. The most sensitive parameter combinations using the SA method based on CNOP-P differed from the highest rank of sensitivity for each parameter using the OAT method. This difference suggested that the nonlinear effects of parameter combinations were key to determining sensitive parameter combinations (Figure 3, and the physical meanings of the parameters can be found in Table S1).

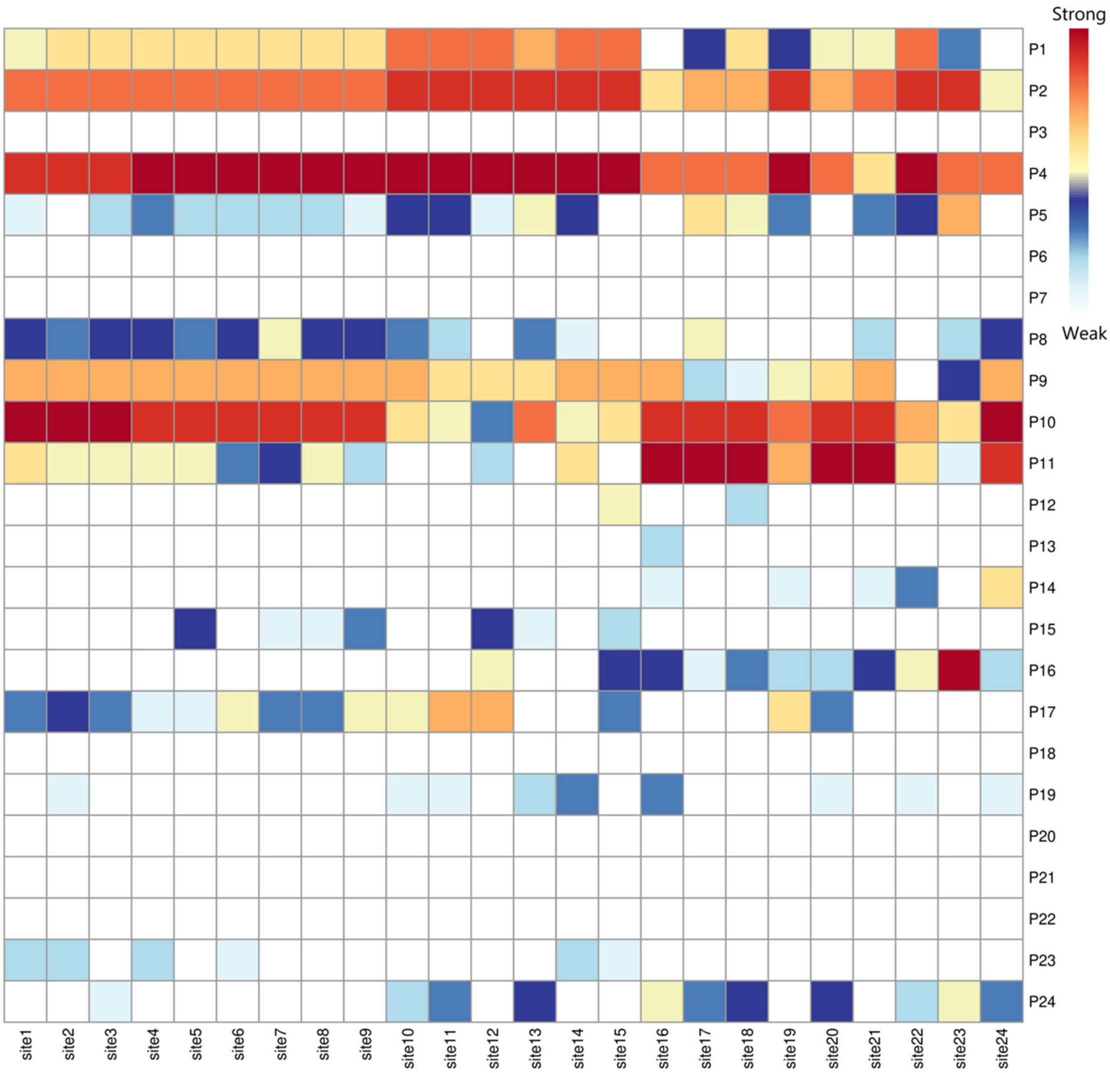

Figure 2. The sensitivity of each parameter for the simulated soil carbon using the CNOP-P method (From research findings by Sun and Mu [47]. Parameter corresponding to the number can be found in studies by Sun and Mu [47] and Table S1 in Supplementary Materials).

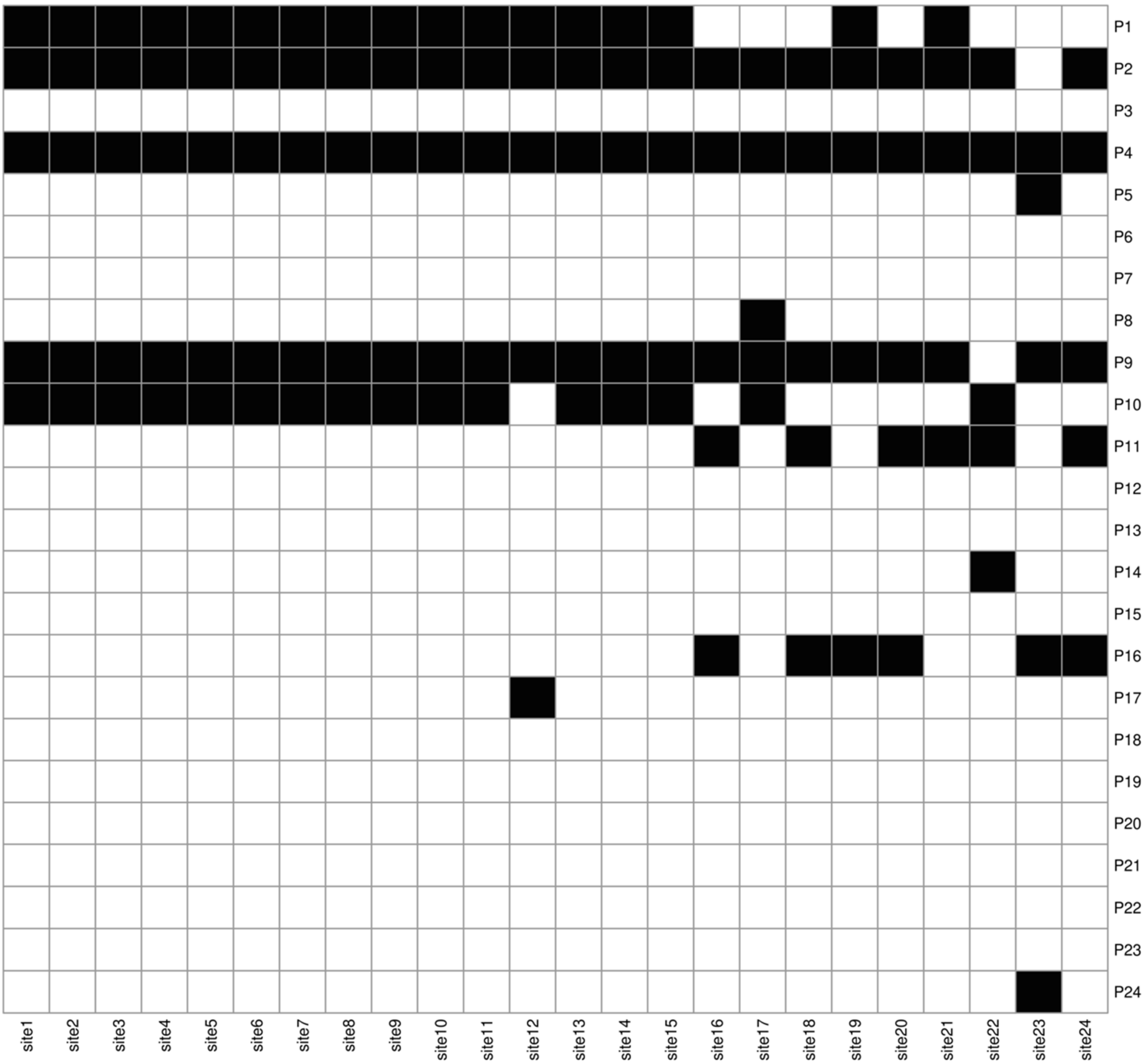

Figure 3. The sensitive parameter combination for the simulated soil carbon using the SA method based on CNOP-P (From research findings by Sun and Mu [47]. Parameter corresponding to the number can be found in studies by Sun and Mu [47] and Table S1 in Supplementary Materials).

Numerical simulations and predictions of carbon fluxes (net primary production, NPP) on the Qinghai–Tibet Plateau (TP) are still subject to large uncertainties. To reduce the uncertainty in numerical simulations and improve the predictive power of simulated NPP, Sun et al. [48] identified the key physical processes associated with uncertainty at nine stations on the TP using the SA method based on CNOP-P. In the mid-precipitation region of the Tibetan Plateau, the parameters related to photosynthesis were the main factors contributing to the large uncertainty in the NPP simulations; in regions with low and high precipitation on the Tibetan Plateau, the combined effects of the parameters related to hydrological processes and photosynthesis played an important role (Figures 4 and 5, and the physical meanings of the parameters can be found in Table S2). All the above results showed that the SA based on the CNOP-P method could reasonably identify relatively sensitive and important combinations of parameters and was more physically meaningful.

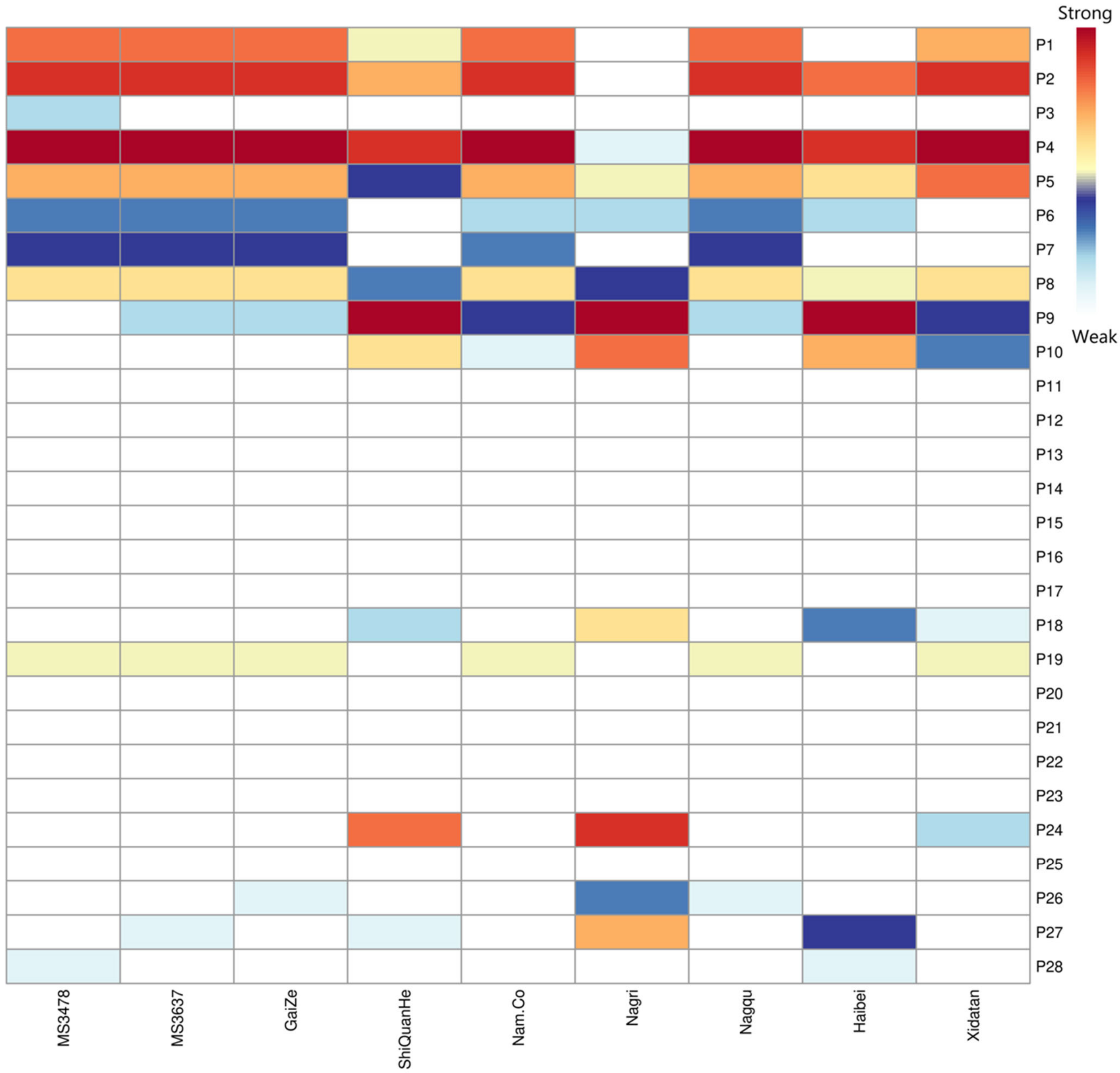

Figure 4. The sensitivity of each parameter using CNOP-P method over the TP (From research findings by Sun et al. [48]. Parameter corresponding to the number can be found in studies by Sun et al. [48] and Table S2 in Supplementary Materials).

2.3.3. Evaluation of Simulation Ability and Prediction Skill by Reducing the Errors of Sensitive Physical Parameters

An important objective of finding the sensitive parameter subset is to improve the simulation ability and prediction skill of terrestrial ecosystems. Sun et al. [48] designed an ideal numerical experiment to reduce the uncertainty in the simulation of NPP over the TP (Table 1). To explore the benefits of modeling NPP while reducing the parameter errors associated with the most sensitive parameter subset, an experiment was implemented as follows:

$$\tau = \frac{\|M_T(\boldsymbol{U}_0,\ \boldsymbol{P}+\boldsymbol{p}) - M_T(\boldsymbol{U}_0,\ \boldsymbol{P})\| - \|M_T(\boldsymbol{U}_0,\ \boldsymbol{P}+(1-\alpha)\boldsymbol{p}) - M_T(\boldsymbol{U}_0,\ \boldsymbol{P})\|}{\|M_T(\boldsymbol{U}_0,\ \boldsymbol{P}+\boldsymbol{p}) - M_T(\boldsymbol{U}_0,\ \boldsymbol{P})\|} \times 100\% \quad (1)$$

where τ represents the benefit of modeling NPP based on reducing the parameter errors of the sensitive parameter subset. A larger τ value indicates a better improvement in the NPP simulation. $\boldsymbol{P}$ is the reference state of the sensitive parameter subsets. $\boldsymbol{p}$ is the CNOP-P, which is related to the errors of five sensitive parameter subsets. α (=0.2, 0.4, 0.6, and 0.8) represents the extent of the error reduction for the correct parameters due to data assimilation or observation.

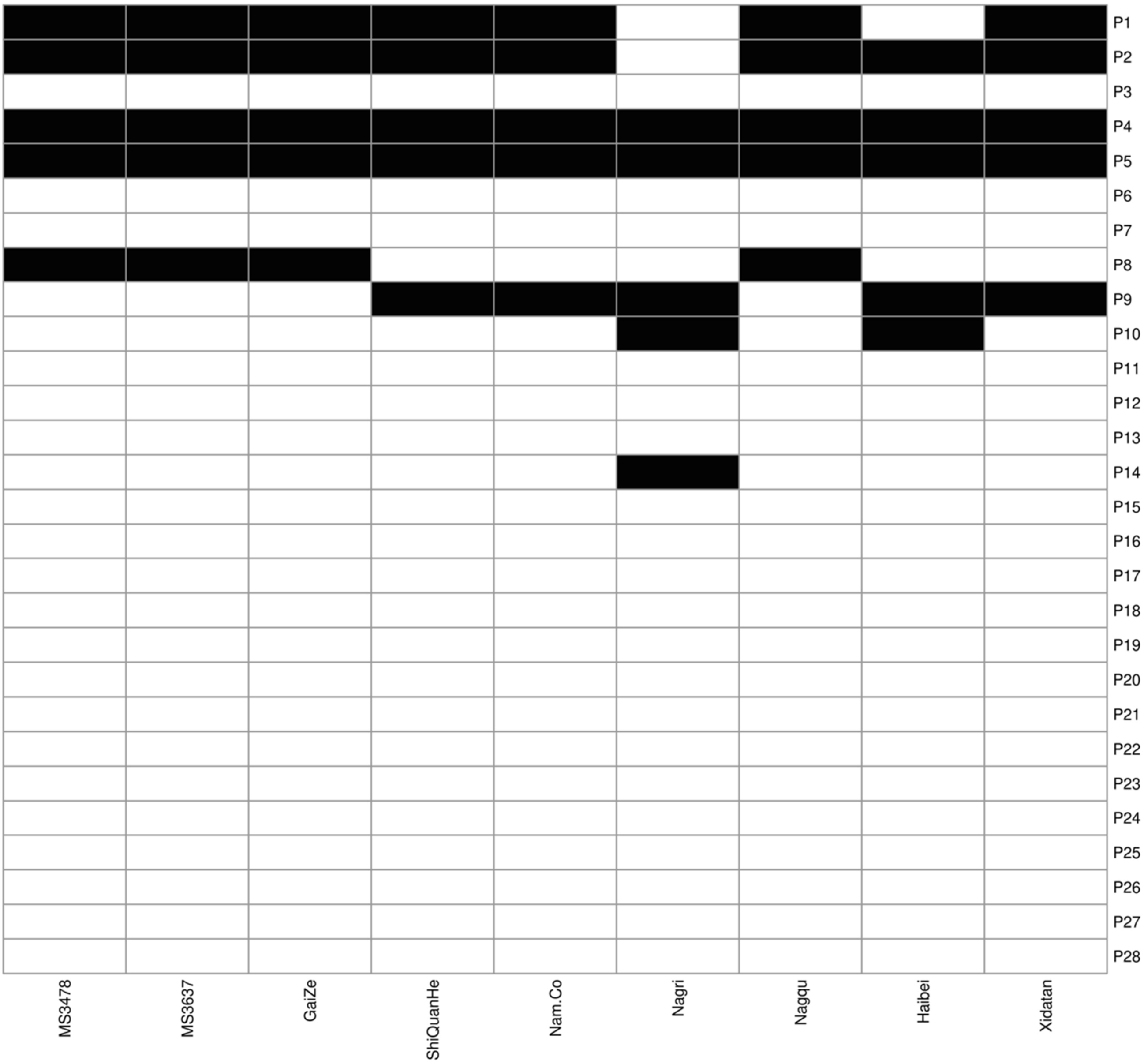

Figure 5. The sensitive parameter combination using the SA method based on CNOP-P over the TP (From research findings by Sun et al. [48]. Parameter corresponding to the number can be found in studies by Sun et al. [48] and Table S2 in Supplementary Materials).

Sun et al. [48] demonstrated that eliminating the errors associated with the most sensitive and important parameter subset with the SA method based on CNOP-P led to the maximum benefit in terms of reducing the uncertainty of simulated NPP when compared to that obtained using the traditional method. For all cases over the TP in the studies of Sun et al. [48], the numerical results showed that the simulation abilities of NPP were improved by reducing the uncertainties in sensitive physical parameters identified by the CNOP-P method compared to the OAT method. In addition, for some cases, the extent of improvement in the simulated NPP by reducing the uncertainties in sensitive physical parameters identified by the CNOP-P method was distinctly better than that by the OAT method [48]. For example, for the Ngari site, the extent of the improvement in the simulated NPP was 34.3% using the CNOP-P method and 28.6% using the OAT method. This study suggested that we should prioritize reducing the uncertainty of relatively sensitive parameter combinations among all physical parameters to improve the prediction or simulation ability of NPP over the TP. Sun et al. [48] also emphasized the importance of nonlinear interactions among sensitive parameter sets for uncertainties in the simulation ability and prediction skill of terrestrial ecosystems.

3. Discussion

Although the CNOP-P method has been studied in terms of uncertainties in terrestrial ecosystem modeling and prediction, more research should be conducted. It is not enough for studies to consider only the effects of a 2 °C temperature increase on terrestrial ecosystem variations. Climate change with multimodel prediction results should be considered. Additionally, ideal numerical experiments are implemented when studying sensitive combinations of physical parameters. In the future, studies of sensitive physical parameter combinations can be conducted with observational data. Finally, the study of the CNOP-P method in terrestrial ecosystem predictability is not limited to the above two aspects.

On the one hand, ensemble forecasting is one of the methods that can be used to improve the simulation and prediction of terrestrial ecosystems, and research on the CNOP-P method is worth exploring land carbon cycle ensemble predictions (LEPS). On the other hand, the impacts of extreme events (e.g., droughts, high temperatures, and fires) on terrestrial ecosystems have received increasing attention from scholars. Studies of terrestrial ecosystem responses to climate change imply that this approach can be used to carry out research on the effects of extreme events on terrestrial ecosystems.As the underlying surface of the Earth system, terrestrial ecosystems affect local and global climate change through land–atmosphere interactions. The impact of terrestrial ecosystems on regional and global climate change will be discussed in the future using the CNOP-P method, especially for studies of extreme events. The results reviewed in this article may not be sufficient to conclude significant findings that are part of uncertainties in simulated and predicted terrestrial ecosystems over multiple years. In this study, uncertainties in simulated and predicted terrestrial ecosystems were shown using the nonlinear optimization method (CNOP-P method). These results encourage us to further research the uncertainty and predictability of terrestrial ecosystems.

4. Conclusions

In this paper, the applications of CNOP methods in terrestrial ecosystem predictability studies are reviewed. The paper contained two main parts. First, using the CNOP method, climate changes were given where both climate state changes and climate variability changes were considered. The numerical results showed that the nonlinear changes in climate variability were considered to show more significant changes in terrestrial ecosystems. This result shows the important role of nonlinear variations in climate variability in terrestrial ecosystem changes.

Additionally, to overcome the limitations of traditional methods in studying the identification of key physical parameters for terrestrial ecosystem simulation and prediction uncertainty, a CNOP-P-based SA method for identifying combinations of sensitive physical parameters was proposed. This method can consider both the nonlinear interactions among physical parameters and the sensitivity of the parameters in the whole physical parameter error space. The sensitive physical parameter combinations identified by the CNOP-P-based SA method for identifying sensitive physical parameter combinations were more sensitive than those identified by the traditional methods. Furthermore, reducing the errors of sensitive physical parameters identified by the CNOP-P-based SA method resulted in a higher degree of improvement in terrestrial ecosystem simulation and prediction. All of these applications imply that the CNOP method is an important theoretical tool that can be used to study the uncertainties in terrestrial ecosystem simulations and predictions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/atmos14040617/s1, Table S1: The chosen physical parameters in studies of Sun and Mu [46,47]; Table S2: The chosen physical parameters in studies of Sun et al. [48].

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