Global sensitivity analysis of the APSIM-Oryza rice growth model under different environmental conditions

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Abstract

This study conducted the global sensitivity analysis of the APSIM-Oryza rice growth model under eight climate conditions and two CO2 levels using the extended Fourier Amplitude Sensitivity Test method. Two output variables (i.e. total aboveground dry matter WAGT and dry weight of storage organs WSO) and twenty parameters were analyzed. The ±30% and ±50% perturbations of base values were used as the ranges of parameter variation, and local fertilization and irrigation managements were considered. Results showed that the influential parameters were the same under different environmental conditions, but their orders were often different. Climate conditions had obvious influence on the sensitivity index of several parameters (e.g. RGRLMX, WGRMX and SPGF). In particular, the sensitivity index of RGRLMX was larger under cold climate than under warm climate. Differences also exist for parameter sensitivity of early and late rice in the same site. The CO2 concentration did not have much influence on the results of sensitivity analysis. The range of parameter variation affected the stability of sensitivity analysis results, but the main conclusions were consistent between the results obtained from the ±30% perturbation and those obtained the ±50% perturbation in this study. Compared with existing studies, our study performed the sensitivity analysis of APSIM-Oryza under more environmental conditions, thereby providing more comprehensive insights into the model and its parameters.

Keywords: Parameter sensitivity; Extended FAST; Range of parameter variation; Climate condition; CO_2 level

1. Introduction

Crop growth models have been widely used in many applications such as crop management, climate change assessment, and yield gap analysis (Holzworth et al., 2015; Lobell et al., 2015; Müller et al., 2017; Tao et al., 2018). Prior to the application of crop growth models, their parameters must be determined properly. As some parameters are hard to measure directly, parameter calibration using optimization algorithms is usually needed (Archontoulis et al., 2014; Kamali et al., 2018).

Parameter calibration needs to run a crop model many times in order to evaluate the simulation performance under different parameter combinations. The number of model runs is in proportion to the complexity of the model and the number of parameters (Zhao et al., 2014). If many parameters are involved in the calibration, a large number of model runs is needed. In this case, parameter calibration will take a long computation time. In order to reduce the number of parameters used in calibration, sensitivity analysis was introduced to determine those most influential parameters (Lamboni et al., 2009; Zadeh et al., 2017). The results of parameter sensitivity analysis can also be used to dissect the robustness of simulation methods and the balance of different components in the model, which can provide valuable information on the application and improvement of models (Cariboni et al., 2007; Confalonieri et al., 2010b; Wang et al., 2013).

The methods for parameter sensitivity analysis can be broadly divided into two classes: local methods and global methods (Saltelli et al., 2000). The local methods (e.g. simple derivative-based method) explore the responses of output variables to parameter changes by varying one parameter at each time while holding the other parameters fixed (Cariboni et al., 2007). They are easy to implement and have low computational cost, but their results heavily depend on parameter's base value and cannot capture the interactions among parameters. In contrast, the global sensitivity analysis methods overcome the shortcomings of the local methods by simultaneously exploring the whole multi-dimensional parameter space, and therefore can the give a more comprehensive view of the sensitivity of model output to parameters (Confalonieri et al., 2010a; Yang, 2011). The widely used global sensitivity analysis methods include screening-based methods such as Morris (Morris, 1991), regression-based methods such as Latin hypercube sampling (Helton et al., 2005), and variance-based methods such as Sobol' (Sobol, 1993) and extended Fourier Amplitude Sensitivity Test (extended FAST) (Saltelli et al., 1999).

Numerous global sensitivity analysis methods have been applied to different crop models (DeJonge et al., 2012; Kamali et al., 2018; Lamboni et al., 2009; Saltelli et al., 1999; Sexton et al., 2017; Zadeh et al., 2017). For example, DeJonge et al. (2012) conducted parameter sensitivity analysis for the CERES-Maize model using Morris and Sobol' global sensitivity analysis methods. Wang et al. (2013) applied the extended FAST method to the WOrld FOod STudies (WOFOST) crop growth model. These studies provided valuable information for the calibration and application of crop models.

APSIM-Oryza is a model for rice growth simulation, and it has been increasingly used in related studies because of the widely-accepted APSIM (Agricultural Production Systems sIMulator) platform (Amarasingha et al., 2015; Gaydon et al., 2012; Gaydon et al., 2017; Holzworth et al., 2014; Radanielson et al., 2018; Zhang et al., 2007). The crop growth process of APSIM-Oryza was borrowed from the Oryza2000 model (https://sites.google.com/a/irri.org/oryza2000/, Bouman et al., 2001; Bouman and Van Laar, 2006; Li et al., 2017). Although there existed some studies on the parameter sensitivity analysis of Oryza2000 and ORYZA_V3 (Soundharajan and Sudheer, 2013; Tan et al., 2016; Tan et al., 2017), these studies were all conducted at a single point. Because the sensitivity of model outputs to parameters can be influenced by environment conditions (Confalonieri et al., 2010b; DeJonge et al., 2012; Zhao et al., 2014), it is necessary to conduct sensitivity analysis of the APSIM-Oryza model under different environment conditions in order to obtain a comprehensive view of the sensitivity of model outputs to parameters, which is the objective of this study. In addition, because of the interaction between the APSIM platform and its Oryza module, the sensitivity analysis results of APSIM-Oryza may not be exactly the same as the original ORYZA model (Bouman et al., 2001; Li et al., 2017).

In this study, six sites in different regions over China and two levels of CO2 concentrations were used for the sensitivity analysis. This study aims to explore whether and to what extent the sensitivity of model outputs to parameters varies under different environmental conditions.

2. Methods

2.1 APSIM-Oryza

APSIM is a flexible modeling framework for agricultural system, which has many modules for different crops (Brown et al., 2014; Holzworth et al., 2014). The key concept in the design of APSIM is a focus on cropping systems rather than individual crops. The dynamics of soil plays an important role in APSIM as McCown et al. (1995 stated that "*Crops come and go, each finding the soil in a particular state and leaving it in an altered state*." A specific crop module can be incorporated to the framework via a plug-in mechanism.

The 'Rice' module in APSIM (APSIM-Oryza) simulates the rice growth under potential production, water-limited and N-limited simulations at a daily time-step (Gaydon et al., 2012; Gaydon et al., 2017; Zhang et al., 2007). APSIM-Oryza interacts with other components of APSIM such as soil water, irrigation, and fertilization. The main crop-growth processes include phenology, leaf area development, biomass production and allocation. Development in APSIM-Oryza is represented by DVS (development stage), which represents the plant's physiological age (Bouman and Van Laar, 2006). The key development stages of rice are emergence (DVS=0), the end of juvenile stage (DVS=0.4), panicle initiation (DVS=0.65), flowering (DVS=1), and physiological maturity (DVS=2) (Bouman et al., 2001). The parameters related to the development of rice are mainly the changes in DVS per degree day (i.e. DVRJ, DVRI, DVRP, and DVRR as shown in Table 1).

The daily CO_2 assimilation rate is calculated by integrating instantaneous assimilation rates over time and depth within the canopy. The integration assumes sinusoidal time course of radiation in the day and exponential light profile in the canopy. The net daily growth rate in kg dry matter per ha per day can be obtained by subtracting respiration requirements from the total assimilation rate. The produced dry matter is partitioned among various organs (i.e. leaves, stems, panicles and roots). The partitioning coefficients are determined experimentally according to the development stage (Bouman et al., 2001; Li et al., 2017). The related parameters mainly include FLV0.5, FLV0.75, FST1.0, DRLV1.0, DRLV2.1 and FSTR. The parameter names such as FLV0.5 were the annexation of the parameter name (e.g. FLV) and the development stage (e.g. 0.5). The parameter FLV0.5 means the fraction of shoot dry matter partitioned to the leaves at DVS=0.5. The meanings of other parameters can be found in Table 1.

The number of spikelets at flowering is proportional to the total biomass accumulated from panicle initiation to flowering. The parameter SPGF (no./kg) is used to describe the number of spikelets per unit mass of biomass. Some spikelets turn into grains with crop growth, while some others become sterile because of too high or too low temperature. The parameter WGRMX (kg/grain) is used to control the maximum individual grain weight. For leaf area growth, when LAI (leaf area index) is less than 1, LAI increases exponentially as a function of temperature sum (°Cd). The parameter RGRLMX and RGRLMN are used to calculate the relative leaf area growth rate (R_1 in Eq. 1 and Eq. 2, (°C d)$^{-1}$) in this exponential growth phase. R_1 is then used to calculate the growth in LAI (*gLAI* in Eq. 2, ha leaf/ha soil/d). The related formulas are described as follows:

$$R_1 = RGRLMX - (1 - f_N)(RGRLMX - RGRLMN) \qquad (1)$$

$$gLAI = LAI \times \mathrm{R}_1 \times HULV \qquad (2)$$

where, f_N is the reduction factor for the relative leaf area growth rate caused by nitrogen (N) limitation, *HULV* is the daily increase in temperature sum (℃d/d). When LAI exceeds 1, LAI increases linearly with the amount of carbohydrates available for leaf growth according to specific leaf area (SLA, m^2/kg). The parameters involved in the calculation of SLA include ASLA, BSLA, CSLA, DSLA and SLAMAX. The main outputs involved in the analysis include total aboveground dry matter (WAGT in the model) and dry weight of storage organs or total panicle biomass (WSO in the model). For cereals like rice, WSO is an indicator of grain yield and it is useful in crop performance evaluation

Table 1. Description of selected parameters and output variables in the APSIM-Oryza model

Name	Description	Unit	Lower bound (30%)[a]	Upper bound (30%)	Lower bound (50%)	Upper bound (50%)	Base value[b]
Parameters							
DVRJ	Development rate in juvenile phase	(℃day)$^{-1}$	0.0007	0.0013	0.0005	0.0015	0.001
DVRI	Development rate in photoperiod-sensitive phase	(℃day)$^{-1}$	0.000525	0.000975	0.000375	0.001125	0.00075
DVRP	Development rate in panicle development	(℃day)$^{-1}$	0.000595	0.001105	0.000425	0.001275	0.00085
DVRR	Development rate in reproductive phase	(℃day)$^{-1}$	0.0014	0.0026	0.001	0.003	0.002
RGRLMX	Maximum relative growth rate of leaf area	(℃day)$^{-1}$	0.00595	0.01105	0.00425	0.01275	0.0085
RGRLMN	Minimum relative growth rate of leaf area	(℃day)$^{-1}$	0.0028	0.0052	0.002	0.006	0.004
ASLA	Parameter A of the function to calculate specific leaf area (SLA, ha/kg)	-	0.00168	0.00312	0.0012	0.0036	0.0024
BSLA	Parameter B of SLA	-	0.00175	0.00325	0.00125	0.00375	0.0025
CSLA	Parameter C of SLA	-	-3.15	-5.85	-2.25	-6.75	-4.5
DSLA	Parameter D of SLA	-	0.098	0.182	0.07	0.21	0.14
SLAMAX	Maximum value of SLA	ha/kg	0.00315	0.00585	0.00225	0.00675	0.0045
FLV0.5	Fraction of shoot dry matter partitioned to the leaves at DVS= 0.5	-	0.42	0.78	0.3	0.9	0.6
FLV0.75	Fraction of shoot dry matter partitioned to the leaves at DVS = 0.75	-	0.21	0.39	0.15	0.45	0.3
FST1.0	Fraction shoot dry matter partitioned to the stems at DVS =1.0	-	0.28	0.52	0.2	0.6	0.4
DRLV1.0	Leaf death coefficient as a function of development stage at DVS = 1.0	-	0.014	0.026	0.01	0.03	0.02

DRLV1.6	Leaf death coefficient as a function of development stage at DVS = 1.6	-	0.021	0.039	0.015	0.045	0.03
DRLV2.1	Leaf death coefficient as a function of development stage at DVS = 2.1	-	0.035	0.065	0.025	0.075	0.05
FSTR	Fraction of carbohydrates allocated to stems stored as reserve	-	0.175	0.325	0.125	0.375	0.25
SPGF	Spikelet growth factor	no./kg	45430	84370	32450	97350	64900
WGRMX	Maximum individual grain weight	kg/grain	1.75E-05	0.0000325	0.0000125	0.0000375	0.000025
Outputs							
WAGT	Total aboveground dry matter	kg/ha					
WSO	Dry weight of storage organs	kg/ha					

[a] Lower bound means the base value minus 30% or 50%, upper bound means the base value plus %30 or 50%.[b] Base values are obtained from Tan et al. (2016).

2.2 Global sensitivity analysis method

The extended FAST method, a variance-based global sensitivity analysis algorithm (Saltelli et al., 1999), was used in this study. The core concept of variance-based sensitivity analysis method is that the variance of a model output (Y) can be decomposed as Eq. (3).

$$\mathrm{V(Y)} = \sum_{i=1}^{n} V_i + \sum_{1 \le i < j \le n} V_{ij} + \ldots + V_{12\ldots\mathrm{n}} \tag{3}$$

where, $V(Y)$ denotes the total variance of model output Y, V_i denotes the variance allocated to the i-th parameter P_i, and V_{ij} denotes the variance allocated to the interaction between P_i and P_j. The sensitivity of output Y to P_i , called the main or first-order index (S_i), is measured by the ratio of P_i-caused variance to total variance $V(Y)$ (as shown in Eq. (4)).

$$\mathrm{S}_i = \frac{V_i}{V(Y)} \tag{4}$$

The total sensitivity index (ST_i) measures all the effects associated with parameter P_i, including the main effect and the interactions with other parameters. It is defined by Eq. (5):

$$\mathrm{ST}_i = \mathrm{S}_i + \sum_{i \ne j} S_{ij} + \sum_{i \ne j \ne m} S_{ijm} + \ldots + S_{12\ldots\mathrm{n}} = \frac{\mathrm{V}(Y) - V_{-i}}{V(Y)} \tag{5}$$

S_{ij} denotes the second-order sensitivity index for the couple of parameter P_i and P_j, S_{ijm} denotes the third-order sensitivity index for the combination of Parameter P_i and any other two parameters, and so on. V_{-i} denotes the sum of the contributions to the variance of output that do not include parameter P_i.

The ranges of both S_i and ST_i are [0, 1]. The larger the index value is, the more influence the parameter has. $ST_i = S_i$ means that Pi does not interact with other parameters. If $ST_i = S_i$ for all parameters, the model is additive (linear). Besides the normal parameters, a "dummy parameter" also appears in the results of sensitivity analysis, which can be used to judge whether the sensitivity index of a parameter is significantly different from zero. When sampling, the dummy parameter is treated as normal parameters; when running the simulations, the dummy parameter is ignored because it neither appears in the model nor affects the model in any other way; when calculating the sensitivity index, dummy parameter is considered again. Thus the dummy parameter should ideally have a sensitivity index of zero (Marino et al., 2008). However, because of the aliasing and interference effects, the obtained index of dummy parameter would be a small but non-zero value. If the sensitivity index of a parameter is less than or equal to that of the dummy parameter, the sensitivity index of this parameter can be considered to be not significantly different from zero (Zadeh et al., 2017).

2.3 Study sites and parameter settings

There are six main cultivation regions of rice across mainland China; they include single rice in Northeast China, single rice in mid-lower Yangtze River Valley, single rice in Sichuan Basin, single rice in Yunnan-Guizhou Plateau, double rice in mid-lower Yangtze River Valley, and double rice in South China (Sun and Huang, 2011). Six sites (Fig.1) were selected accordingly to study the effects of climate and soil condition on the results of sensitivity analysis. Among these sites, double-cropping rice is planted in Yingtan and Nanhai. The climate data, including daily minimum and maximum air temperature, rainfall, and solar radiation from 1980 to 2010 were collected from CMA (China Meteorological Administration, http://data.cma.cn/). For Shenyang, Changshu, Yanting, and Yingtan, the soil data and management information (i.e. sowing date, transplanting date, fertilization and irrigation operations) were obtained from CNERN (National Ecosystem Research Network of China). For Yiliang and Nanhai, the soil data were obtained from China Soil Database (http://vdb3.soil.csdb.cn/), and the management information was obtained from the nearby agricultural meteorological stations of CMA (http://data.cma.cn/data/cdcdetail/dataCode/AGME_AB2_CHN_TEN.html).

The fertilization rules for these six sites are described as follows: all sites were fertilized one day after transplanting, and the other fertilization and corresponding amounts depended on the management information. Taking the early rice in Yingtan site as an example, 86.5 kg/ha urea N was applied after transplanting (30 days after sowing). Besides, there were another time of fertilization (75.9 kg/ha urea N) after 40 days of sowing. In Shenyang, because rice may reach maturity before the predefined fertilization date, the fertilization dates were first converted to DVS according to observed phenological phases and then DVS was used to control the fertilization dates in the simulation of this site. The maximum ponded water depth of the field was 60 mm and irrigation was applied up to 30 mm of ponded water depth once the water depth dropped to zero. If the DVS was between 0.6 and 0.65 (the late tillering stage), there would be no irrigation in order to control inefficient tillers.

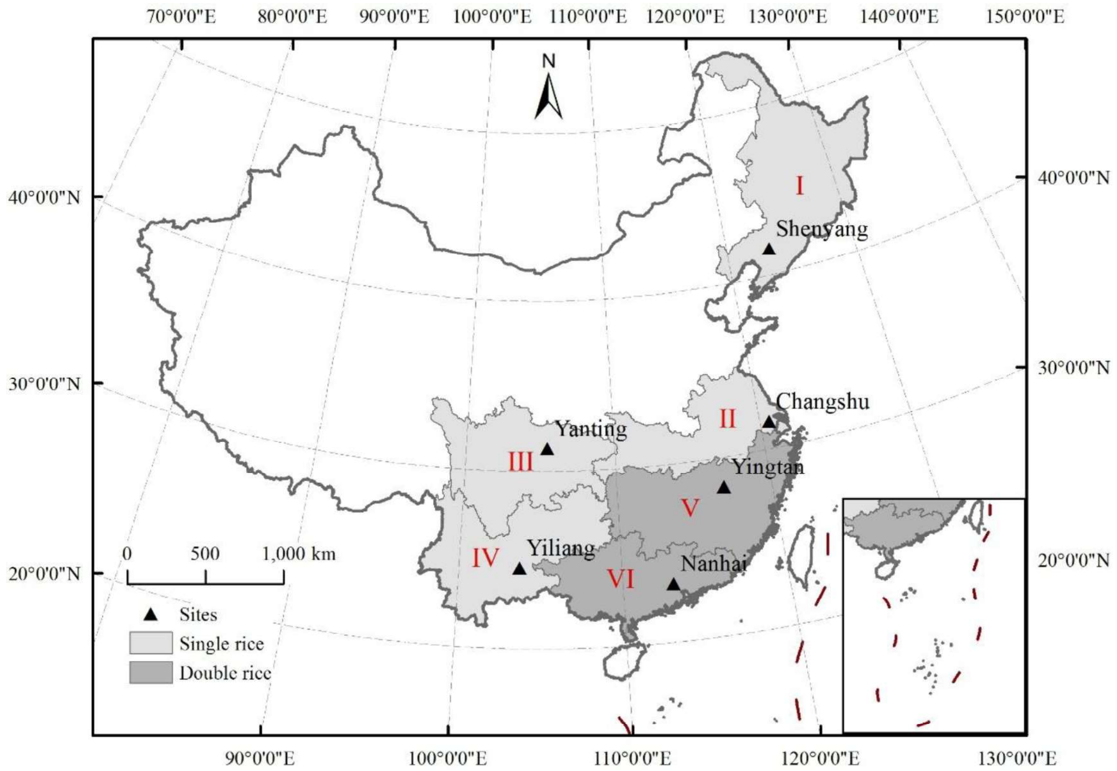

Fig.1. The spatial distribution of six rice cultivation regions across mainland China and selected sites. The six rice cultivation regions are as following: I, single rice in Northeast China, II, single rice in mid-lower Yangtze River Valley, III, single rice in Sichuan Basin, IV, single rice in Yunnan-Guizhou Plateau, V, double rice in mid-lower Yangtze River Valley and VI, double rice in South China.

Table 2 presents the information of location, growing-season climate and topsoil texture in the six selected sites. The growing-season climate values were calculated by averaging daily values between observed mean sowing dates to harvest dates. The climate data was from CMA and phenology data was from CNERN and agricultural meteorological stations. For Shenyang, Changshu, Yanting, and Yingtan, soil particle size in the top layer were obtained from CNERN. For Yiliang and Nanhai, soil particle size in the top layer were obtained from China Soil Database (http://vdb3.soil.csdb.cn/). During the growing season, the temperature in Shenyang and Yiliang were lower than other sites. The temperature in the growing season of late rice was higher than that of early rice and single rice. Shenyang had the highest daily solar radiation, and the early rice of Nanhai had the lowest one. Shenyang, Changshu and Yanting had less rainfall than other sites. The soil is mainly silt in Shenyang, Changshu and Nanhai, sand in Yanting, and clay in Yiliang.

Table 2. Location, growing-season climate and topsoil texture in the six selected sites.

	Shenyang	Changshu	Yanting	Yiliang	Yingtan	Nanhai
Rice type	Single rice	Single rice	Single rice	Single rice	Double rice	Double rice
Latitude	41.52	31.55	31.27	24.53	28.25	23.13
Longitude	123.36	120.63	105.46	103.73	116.93	113.03
Elevation(m)	38	5	489	1699	41	1
Mean daily temperature (◦C)[b]	20.30	25.95	25.04	20.09	Early: 24.81 Late: 28.12[a]	Early: 25.45 Late: 28.24
Mean daily solar radiation(MJ/m^2)	18.18	17.74	16.73	15.50	Early: 16.74 Late: 17.17	Early: 11.68 Late: 13.29
Mean rainfall (mm)	580.72	544.34	643.6	716.68	Early: 1068.55 Late: 372.75	Early: 855.73 Late: 452.53
Sand (0.05-2.0mm) (%)[c]	18.42	3.77	30.70	15.20	51.25	31.05
Silt (0.002-0.05mm) (%)	66.70	62.23	39.72	32.00	37.62	54.95
Clay (<0.002mm) (%)	14.88	34.00	20.14	52.80	11.13	14.00

[a] "Early" represents early rice, "Late" represents late rice. For example, "Late: 28.96" stands for the mean temperature of late rice in Yingtan is 28.12◦C, etc.

[b] Mean daily temperature, mean daily solar radiation and mean rainfall are the mean value in rice growth period (from observed mean sowing date to harvesting date).

[c] Soil particle size in the top layer.

The sensitivity analysis in this study involved eight climate conditions, two CO_2

levels and twenty parameters. For single rice, each site corresponds to one type of climate condition, and for double rice, each site corresponds to two types of climate conditions (i.e. early rice and late rice). The double rice was simulated as two seasons of single rice, and each season was configured with its own sowing and transplanting dates. The number of search curves for extended FAST was set to five and the number of samples per search curve was set to 97 according to existing researches (Marino et al., 2008; Saltelli et al., 2000). So for a certain climate condition, CO_2 level, and simulation period, the number of simulations was 5*(20+1)*97=10185. The number 20 in the equation means 20 parameters and the number one means the one dummy parameter. The parameter sampling strategy is the same as Saltelli et al. (1999). Simulations were conducted for 31 years from 1980 to 2010. One result of parameter sensitivity was calculated for each year, and the overall parameter sensitivity was obtained by averaging each year's result.

The base values of parameters followed Tan et al. (2016), and the parameter values for each simulation were generated randomly between the ±30% and ±50% perturbation of the base values. It should be noted that some parameter combinations may lead to simulation failure for some site-years due to cold damage caused by low temperature in late growth stage. Simulation failure here means that the simulated value of WAGT or WSO is negative. Since negative WAGT or WSO values do not make sense, thus we set negative WAGT or WSO to zero before the calculation of sensitivity indices. In this study, when the ±30% perturbation was used, there was no simulation failure. When the ±50% perturbation was used, there were a small number of simulation failures mainly for the late rice in Yingtan and Naihai (Table A.1 in the Appendix). The default CO2 concentration used in simulation is 350 ppm. Because it is widely acknowledged that the CO2 concentration in atmosphere is increasing over the past half century, two levels of CO2 concentration (i.e. 350 ppm and 429 ppm) were used to explore whether CO2 concentration has effects on the sensitivity index of parameters (Nakicenovic et al., 2000).

When the ranking of parameters is needed, ST_i was used as the criterion. For each parameter, the ST_i values of multiple years in each climate condition were first averaged, and then the ST_i values of different climate conditions were averaged to get an overall ST_i for each parameter. A threshold of 0.05 for ST_i was used to select influential parameters. In order to get the distribution of the simulation results, the Kernel Density Estimate (KDE) method (Parzen, 1962) was adopted. KDE is a nonparametric density estimator, which can learn the shape of the density from the data automatically. In this study, we used the sns Python package to plot the KDE curve, and the default settings of sns were used.

3. Results

3.1 Overall parameter sensitivity under different environmental conditions

3.1.1 The sensitivity of total aboveground dry matter to parameters

Fig. 2 shows the sensitivity indices under eight climate conditions for the output variable WAGT at maturity for the ±50% perturbation of parameter's base value, and the corresponding figure for the ±30% perturbation is shown in Fig. A.1 in the Appendix. For both perturbations, the influential parameters (with overall ST_i larger than 0.05) for all the sites were the same; they are the four development rate parameters (DVRJ, DVRI, DVRP, DVRR) and three of the leaf relevant parameters: parameter A of the function to calculate specific leaf area (ASLA), maximum relative growth rate of leaf area (RGRLMX), and the fraction of shoot dry matter partitioned to the leaves at DVS=0.5 (FLV0.5). The sensitivity indices of these parameters were much larger than those of dummy parameter, indicating that they were significantly different from zero. Other parameters showed little impacts on WAGT. The interaction indices (the blue bar in Fig.2) were low for all climate conditions except for Shenyang, suggesting that the interaction among parameters was weak. This means that the parameters affect WAGT independently, only with slight interaction with each other.

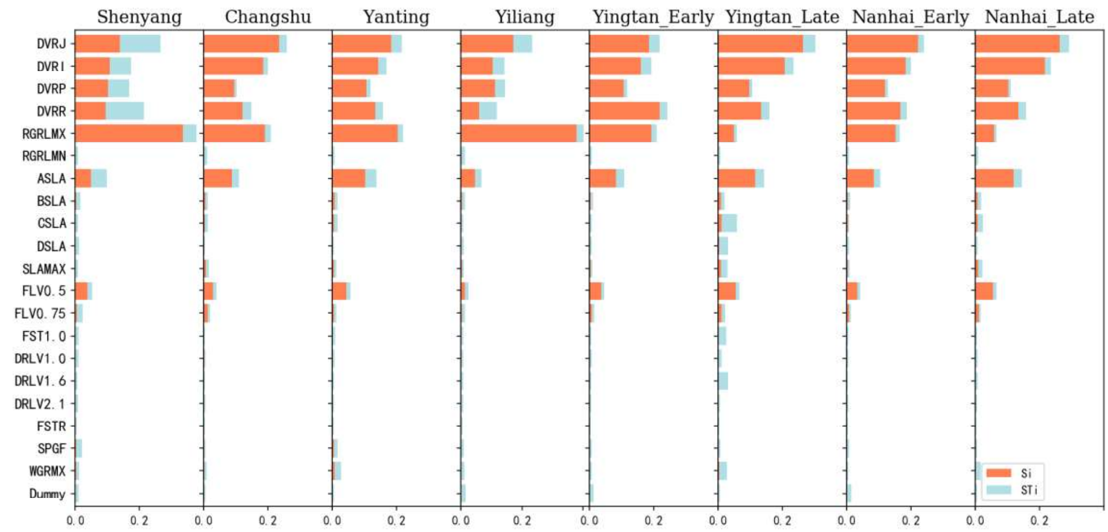

Fig.2. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WAGT (total aboveground dry matter) at maturity for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc.

The sensitivity index of RGRLMX had obvious variation among different environmental conditions. For the ±50% perturbation, the STi value of RGRLMX for Yiliang was 0.38, while those for Yingtan_Late and Nanhai_Late were less than 0.1. For double-rice sites, the overall sensitivity index of parameters was similar for early and late rices. However, there were also observable differences for the parameter DVRJ and RGRLMX. The sensitivity index of DVRJ for early rice was consistently smaller than that for late rice, while the sensitivity index of RGRLMX for early rice was larger than that of late rice.

3.1.2 The sensitivity of dry weight of storage organs to parameters

Dry weight of storage organs (WSO) is an indicator of grain yield in the APSIM-Oryza model (Bouman et al., 2001; Gaydon et al., 2012). Fig.3 shows the sensitivity indices under eight climate conditions for the output variable WSO for the ±50% perturbation of base values, and the corresponding figure for the ±30%

perturbation was shown in Fig. A.2. For both perturbations, WSO were mainly sensitive to eight parameters (with overall ST_i larger than 0.05): the four development rates (DVRJ, DVRI, DVRP and DVRR), two leaf relevant parameters RGRLMX and ASLA, two grain relevant SPFG and WRGMX. The sensitivity indices of these parameters were much larger than those of dummy parameter, indicating they were significantly different from zero. The first six were also sensitive parameters for WAGT. Four development rates (DVRJ, DVRI, DVRP and DVRR) still dominated, although their relative importance was often different. The sensitivity of WSO to RGRLMX was weaker than that of WAGT in all sites except the Yiliang site. Compared with WAGT, WSO showed greater parameter interaction. The interaction part even accounted for over half of the total sensitivity indices for some parameters (e.g. development rates of the single rice in Shenyang, Yiliang and the early rice in Yingtan). This is because that the accumulation of storage organs was the last growth stage of rice and thus determined by the combined influence of many parameters. The sensitivity index of RGRLMX, WGRMX, and SPGF showed obvious variation among different environmental conditions. In particular, the sensitivity index of RGRLMX was much larger in Yiliang than in other sites.

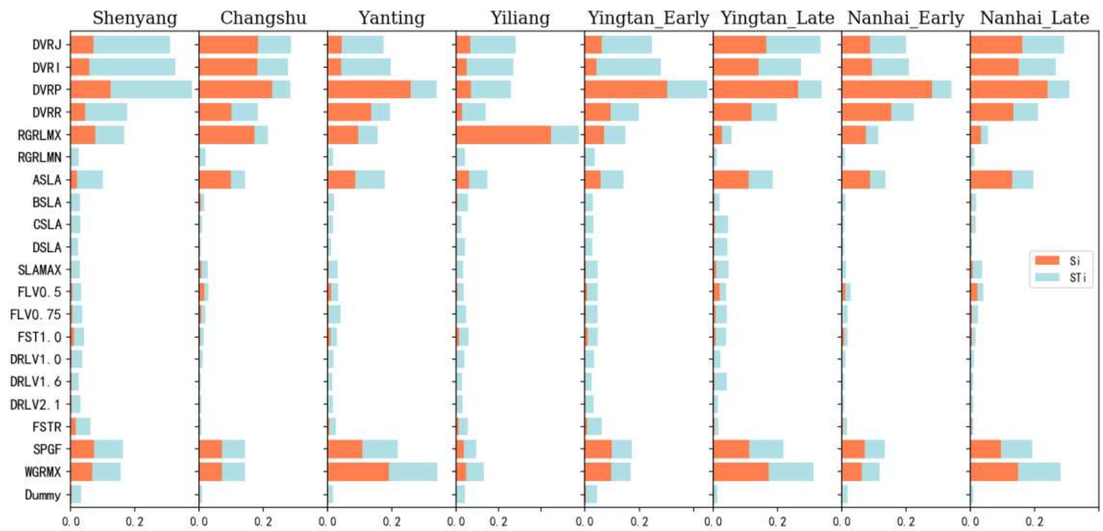

Fig.3. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WSO (dry weight of storage organs) at maturity for the ±50% perturbation of parameter’s base value. The title of each subfigure in the top of the

figure means different environmental conditions. For example, “Shenyang” means single rice in the Shenyang site, “Yingtan_Early” means early rice in the Yingtan site, etc.

3.2 Impacts of CO2 concentration on parameter sensitivity

Two levels of CO2 concentrations (350ppm and 429ppm) were used to drive the simulations under eight climate conditions, and the order of parameters was ranked by the total sensitivity index (STi) for each level. The changes of orders in absolute value under the two levels were then calculated to indicate the impact of CO2 concentration on the parameter sensitivity. Fig.4 and Fig.5 show the results for WAGT and WSO for the ±50% perturbation of parameter’s base value, respectively, and the corresponding figures for the ±30% perturbation were shown in Fig. A.3 and Fig. A.4 in the Appendix. For the influential parameters for the output variable WAGT identified in Section 3.1 (i.e. DVRJ, DVRI, DVRP, DVRR, RGRLMX, ASLA, and FLV0.5), the changes under two CO2 concentration levels were slight. For the ±50% perturbation, only 2 out of the 56 changes were two, and the others (96%) were less than or equal to one. For the influential parameters for the output variable WSO (i.e. DVRJ, DVRI, DVRP, DVRR, RGRLMX, ASLA, WGRMX and SPGF), the changes of orders were larger than those of WAGT. But there were still 75% of the changes that were less than or equal to one. For the relatively insensitive parameters, the changes of orders were sometimes large, but these parameters would not be used in the model calibration, so these changes were not important. Overall, the CO2 concentration did not have much influence on the results of sensitivity analysis for the two output variables WAGT and WSO.

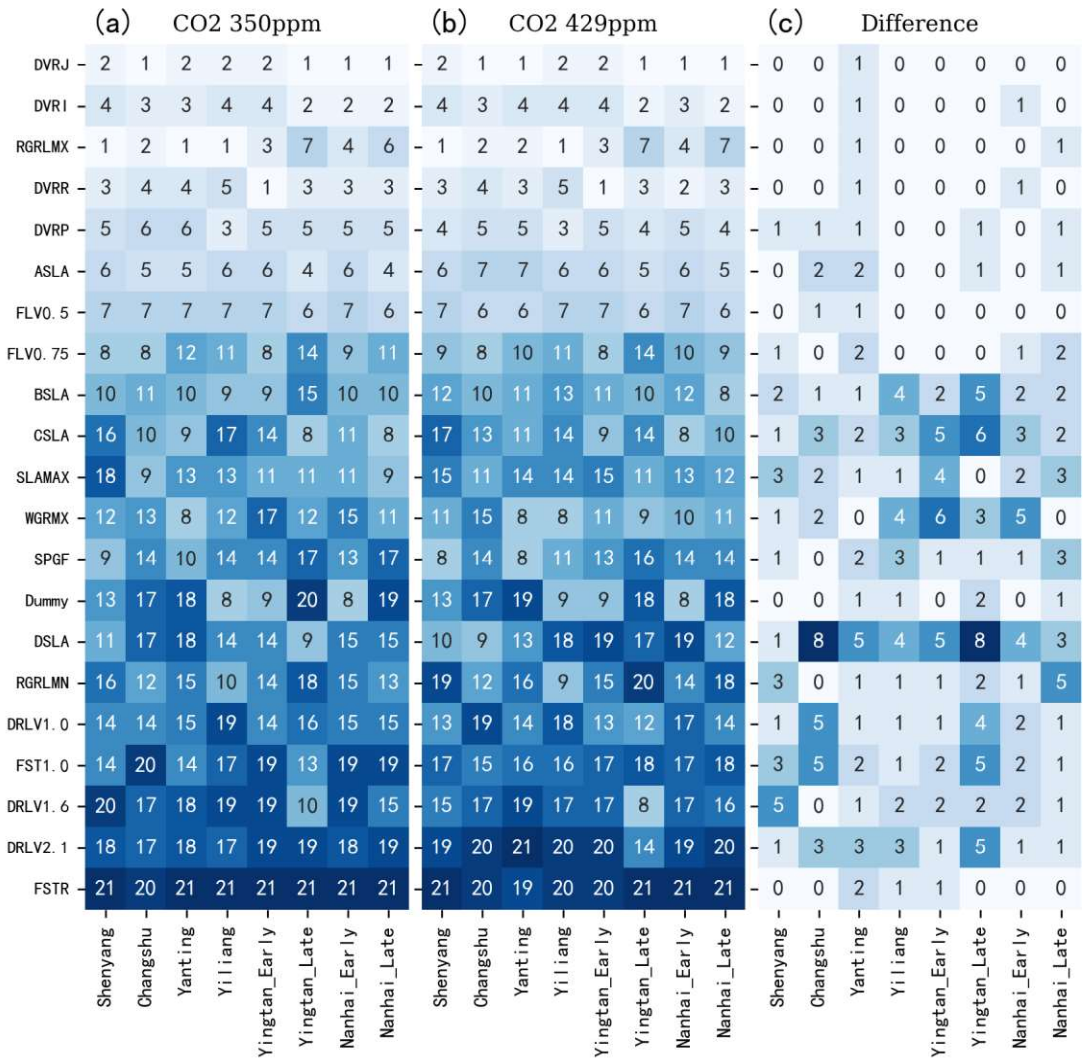

Fig.4. Impact of CO2 concentration on parameter sensitivity for WAGT (total aboveground dry matter) at maturity for the ±50% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO2 concentrations levels (i.e. 350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

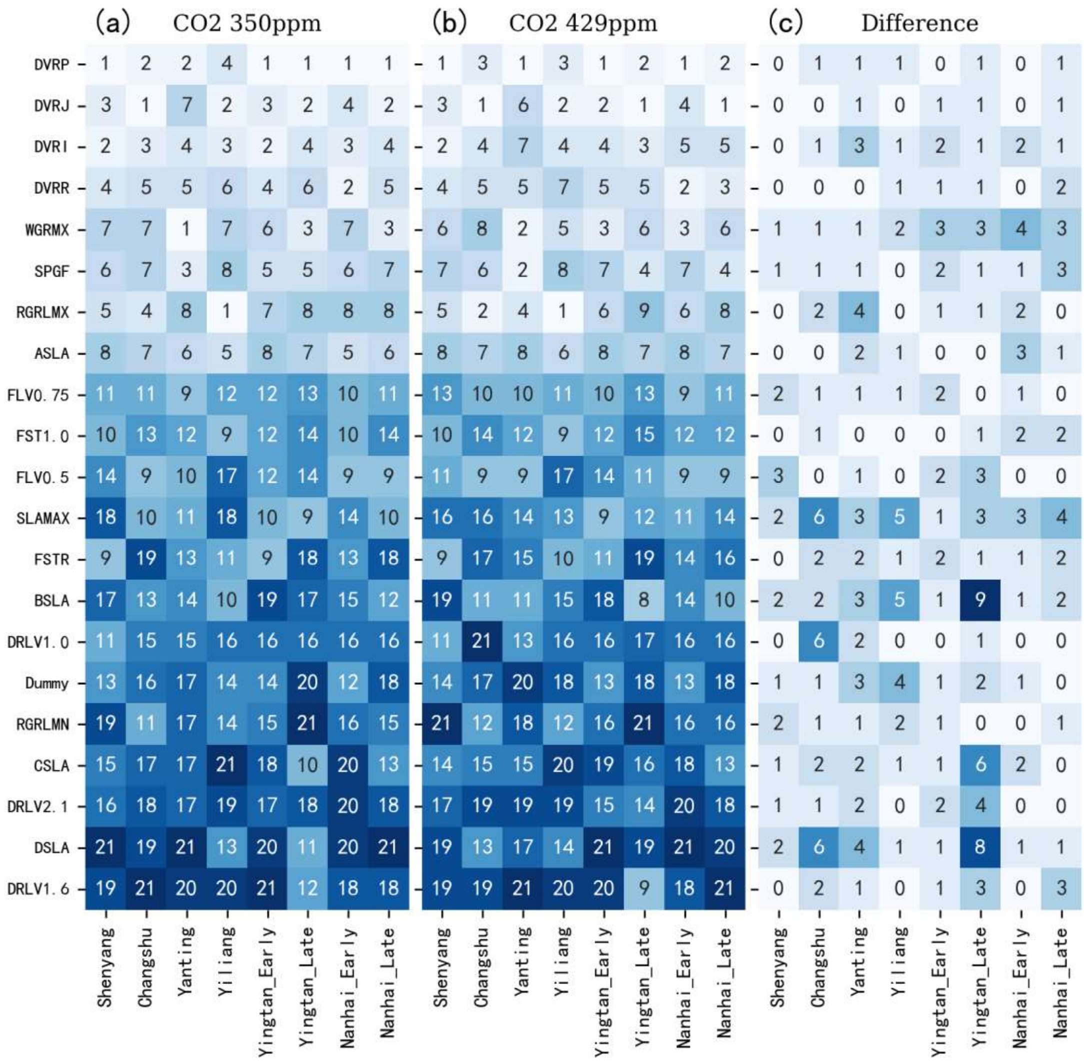

Fig.5. Impact of CO2 concentration on the parameter sensitivity for WSO (dry weight of storage organs) at maturity for the ±50% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO_2 concentrations levels (350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

3.3 Impacts of inter-annual climate variation on parameter sensitivity

To explore whether inter-annual climate variation affects the sensitivity orders of parameters, each year's sensitivity order of parameters from 1980 to 2010 was obtained, and the standard deviations (SD) of orders in these years for influential parameters for WAGT and WSO are shown in Fig. 6. A large SD indicates that inter-annual climate variation had large impacts on the sensitivity orders of parameters. The average SDs of parameter sensitivity orders across all the climate conditions and parameters were larger for WSO (1.15 for the ±30% perturbation and 0.97 for ±50% perturbation) than for WAGT (0.63 for the ±30% perturbation and 0.53 for ±50% perturbation). For each parameter, the SD in each climate condition was calculated first, and then SDs in eight climate conditions were averaged. For WAGT, the average SD of orders for RGRLMX was the largest, while those for DVRJ and FLV0.5 were relatively small. For WSO, there does not exist large differences among parameters. For both WAGT and WSO, the SDs for the ±50% perturbation were generally smaller than those for the ±30% perturbation, which indicates the sensitivity analysis results using the ±50% perturbation were more stable.

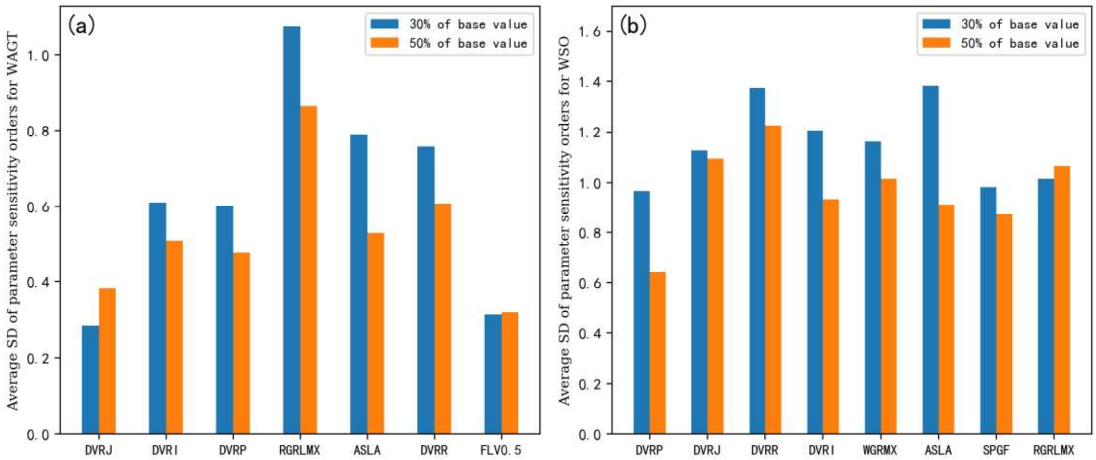

Fig.6. Average standard deviations (SD) of parameter sensitivity orders from 1980 to 2010 for influential parameters (with overall ST_i larger than 0.05) for WAGT (total aboveground dry matter, a) and WSO (dry weight of storage organs, b). For each parameter, the SD in each climate condition was calculated first, and then SDs in eight climate conditions were averaged.

Fig. 7 shows the average SDs of parameter sensitivity orders for each climate condition. For each climate condition, the SD of each parameter was calculated first, and then average SDs were calculated using the influential parameters (with overall

ST_i larger than 0.05). It can be seen the SDs for the ±50% perturbation were also smaller than those for the ±30% perturbation in most climate conditions, especially in Yiliang and Shenyang which have low growing-season temperature (Table 2).

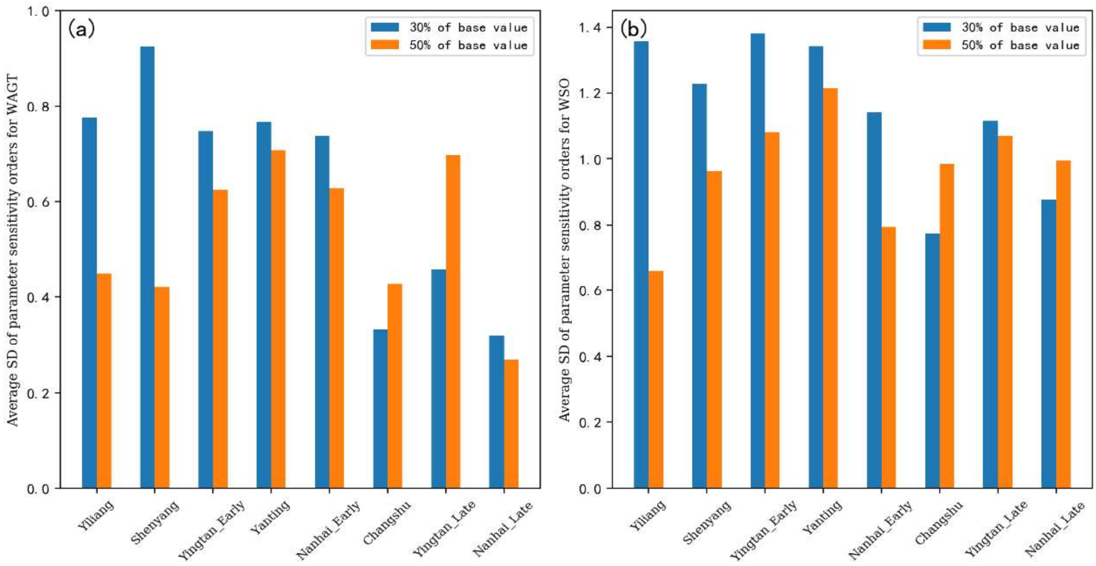

Fig. 7 Average standard deviations (SD) of parameter sensitivity orders from 1980 to 2010 for different climate conditions for WAGT (total aboveground dry matter, a) and WSO (dry weight of storage organs, b). For each climate condition, the SD of each parameter was calculated first, and then average SDs were calculated using the influential parameters (with overall ST_i larger than 0.05).

3.4 Distribution of the model outputs

Fig.8 and Fig.9 show the distribution of WAGT and WSO under the eight different climate conditions obtained by the KDE method for the ±50% perturbation of parameter's base value. The measured WAGT and yield were also shown in the figures as vertical dotted line. We can see that the measured values were located near to the peaks of the distribution of simulated values in all the sites. In addition, these figures clearly show that the values of WAGT and WSO under CO2 concentration of 429ppm were larger than those under CO2 concentration of 350ppm. Taking the WSO of Shenyang as an example, there was a peak at 8000 kg/ha under CO_2 concentration of 350ppm, while this value increased to about 9000 kg/ha under CO2 concentration of 429ppm. This can be explained by the fact that in the APSIM-Oryza model, the

CO2 assimilation rate is positively correlated with ambient CO2 concentration. It should be noted that although the peak of the distribution changed, the shape of the curve almost remained unchanged under two levels of CO_2 concentration.

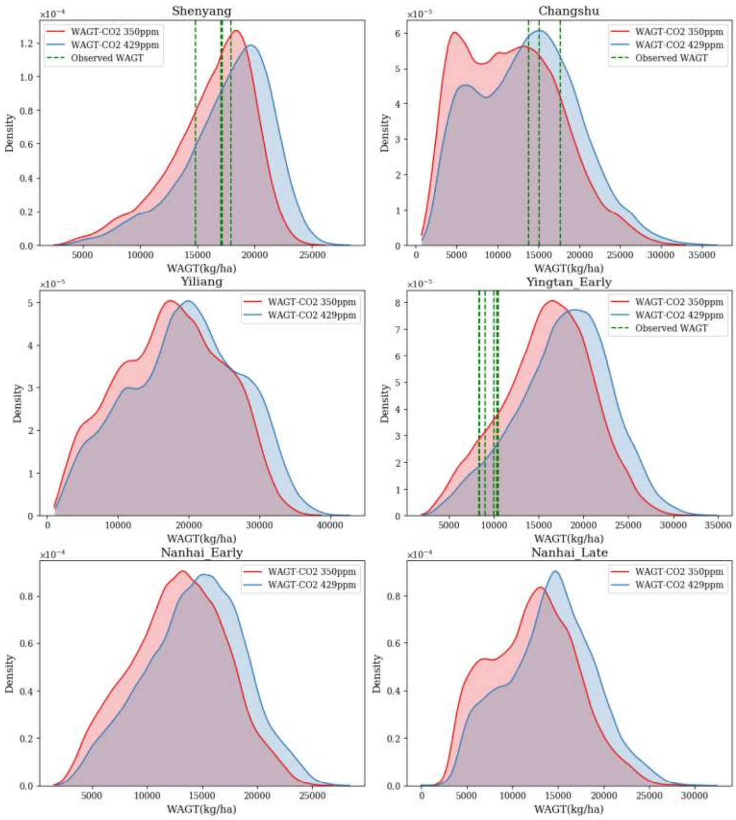

Fig.8. The distribution of WAGT (total aboveground dry matter) under eight different climate conditions obtained by the KDE (Kernel Density Estimation) method for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure represents the site and cropping system. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc. The red and blue colors represent the distributions of WAGT under CO_2 concentration of 350 ppm and 420 ppm, respectively.

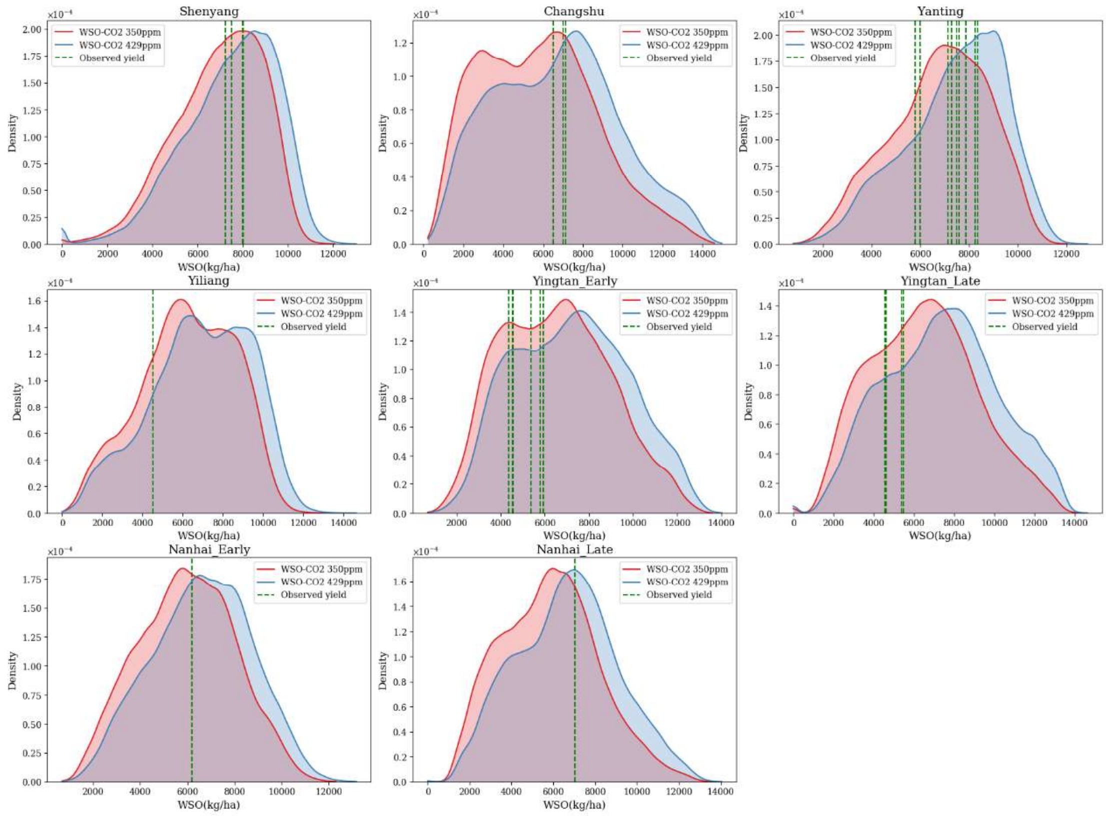

Fig.9. The distribution of WSO (dry weight of storage organs) under eight different climate conditions obtained by the KDE (Kernel Density Estimation) method for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure represents the site and cropping system. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc. The red and blue colors represent the distributions of WSO under CO2 concentration of 350 ppm and 420 ppm, respectively.

4. Discussion

4.1 Differences of parameter sensitivity among different environmental conditions

The sensitivity index of some parameters had obvious differences among the investigated eight different climate conditions. For example, the sensitivity index of RGRLMX was much larger in Yiliang, the coldest site in this study, than in other sites for both output variables WAGT and WSO. For early rice and late rice in the same site, the sensitivity index of parameters also varied. The sensitivity of WAGT and WSO to

RGRLMX for early rice was consistently larger than that of late rice.

From the viewpoint of model structure, the different sensitivity of model outputs to parameters across environmental conditions could be attributed to the interaction of environmental conditions and parameters in some simulation methods. For example, let us assume that a step in the simulation is to calculate a value $V=E\times P$, in which E is the environmental term and P is the parameter, and then the value V is compared with a threshold to determine the usage of different simulation methods in the following step. If the environmental term E is large enough, it is possible that the value V is always larger than the threshold for a defined range of parameters. In this case, the parameter P is not sensitive. If the environmental term E is moderate, whether the value V is larger than the threshold depends on the parameter P. In this case, the parameter P is sensitive. If the environmental term E is small enough, it is possible that the value V is always smaller than the threshold for a defined range of parameters. In this case, the parameter P is not sensitive again.

In this study, because the simulations were conducted under irrigation and fertilization conditions, water and soil conditions should not be the main influencing factor. The observed differences could be mainly attributed to the temperature conditions. Taking the RGRLMX parameter as an example, it was used only in calculating the relative leaf area growth rate (R_l in Eq. 1 and Eq. 2, (°C d)$^{-1}$) in the exponential growth phase when LAI is less than 1 (Bouman et al., 2001). R_l was then multiplied by LAI and HULV (i.e. daily increase in temperature sum, °C/d) to calculate the growth in LAI (*gLAI* in Eq. 2, ha leaf/ha soil/d). In cold climate, HULV will be small. If the value of R_l is also very small, gLAI will be very small which means slow growth rates of leaf area. Thus it will take a long time for LAI to grow to 1 (e.g. the end of the exponential growth phase). This will have large negative impacts on carbon assimilation and thus greatly affect the value of WAGT and WSO. In contrast, HULV will have larger values in the warm climate. Even RGRLMX is small, there is still larger possibility for gLAI to maintain a large enough value. So the dependence of WAGT on RGRLMX is relatively weak in warm conditions.

4.2 The little influence of CO2 concentration setting on parameter sensitivity

The CO2 concentration is only used in the calculation of gross CO2 assimilation rate (kg CO_2 ha^{-1} d^{-1}) in the APSIM-Oryza model. The little influence of CO2 concentration setting on parameter sensitivity could be because that on the one hand, some parameters are only used in the calculations that are not affected by CO2 concentration. For example, the phenology calculation, where the parameters DVRJ, DVRI, DVRP, and DVRR are used, and the calculation of exponential growth phase of leaf development, where the parameters RGRLMX and RGRLMN are used, do not depend on CO2 concentration. Thus CO2 concentration will not affect the sensitivity of model outputs to these parameters. On the other hand, most of the other parameters are used in the calculations that are linearly affected by CO2 concentration. For example, the gross CO2 assimilation is used to calculate the daily crop growth rate (kg day matter ha^{-1} d^{-1}) through a linear relationship, and the daily crop growth rate is then multiplied by the parameter FLV0.5 to get the growth rate of leaves. The relative changes of values in these linear relationships will not affect the sensitivity of model outputs to parameters.

4.3 The impacts of ranges of parameter variation on sensitivity analysis results

For the sensitivity analysis of crop models in existing literature, the parameter ranges were usually proportionally amplified from ±5% to ±50% perturbation of the base value (Marino et al., 2008; Richter et al., 2010; Tan et al., 2016; Tan et al., 2017; Yang, 2011; Zhao et al., 2014). Tan et al. (2017) investigated the effects of different ranges of parameter variation (i.e. ±5%, ±10%, ±20%, ±30%, ±50% perturbations of the base value) on the sensitivity analyses for ORYZA_V3 model, and recommended the ±30% perturbation when specific ranges cannot be obtained. It should be noted that this research was conducted at a single site, and the base values of some parameters (e.g. the partitioning factors, leaf death rates) were determined according to experimental observation (Tan et al., 2016).

The Yingtan site used by Tan et al., (2016, 2017) was also used in this study. Because the base values of parameters in other sites of this study were not known in advance, we used the base values of Tan et al. (2016) in all the sites, and used the ±50% perturbation of the base values besides the ±30% perturbation in order to get more robust conclusions. These parameters ranges were considered to be reasonable for the following reasons: 1) The parameter ranges using the 50% perturbation can cover the parameter values in all the predefined cultivars of APSIM-Oryza except for the DVRP parameter of cultivar BR3; 2) The measured WAGT and yield values were compared with the simulated WAGT and WSO. The results showed that the measured values were located near to the peaks of the distribution of simulated values in all the sites (Fig.8 and Fig.9), which demonstrated the ability of the model and the parameter ranges to simulate rice growth in these sites; 3) The main conclusions were consistent between the results obtained from the ±30% perturbation and those obtained the ±50% perturbation, which demonstrates the robustness of the conclusions in this study. This is consistent with Wang et al. (2013), which showed that for the WOFOST model, the perturbations of parameter's base values ranging from ±10% to ±50% did not change the sensitivity rankings of parameter.

For Yiliang and Shenyang where growing-season temperature is low, the average SDs of parameter sensitivity orders from 1980 to 2010 were much larger for the ±30% perturbation than for the ±50% perturbation. This may be because that parameter's base values of Yingtan_Late were used in all the sites of this study due to the lack of experimental observation, but these base values were not suitable for the sites with very different climate conditions. When the perturbation is not large enough, an inappropriate base value may lead to parameter sampling ranges that cannot cover the range of interest, which makes the results of sensitivity analysis not stable. When the perturbation is large enough (e.g. ±50% in this study), the parameter sampling range can cover the range of interest even an inappropriate base value is given, which makes the results of sensitivity analysis stable. This highlights the need for using a larger perturbation value when the base value of parameters cannot be specifically obtained.

5. Conclusions

In this study, the global sensitivity analysis of the APSIM-Oryza model was performed under eight different climate conditions and two CO_2 levels for a 31-year simulation period. The number (eight) of conditions considered in our study is much larger than that in existing studies (most focused on only a single condition), and thus our findings can provide additional insights into the APSIM-Oryza model and its parameters. The sensitivity of two output variables (i.e. total aboveground dry matter WAGT and dry weight of storage organs WSO) to twenty parameters was analyzed using the extended FAST method. The main findings include (1) for the output variables WAGT and WSO, the influential parameters (with overall ST_i larger than 0.05) under different climate conditions were the same, but their orders were often different; (2) the sensitivity index of some parameters (e.g. RGRLMX, WGRMX and SPGF) had obvious differences among different climate conditions. In particular, the sensitivity index of RGRLMX is larger under cold climate than under warm climate; (3) the CO2 concentration had little influence on the results of sensitivity analysis for the two output variables WAGT and WSO; (4) The range of parameter variation affected the stability of sensitivity analysis results, but the main conclusions were consistent between the results obtained from using the ±30% perturbation and those obtained the ±50% perturbation in this study.

It should be noted that in existing studies and our current study, the failed simulations in which crop does not reach maturity were treated as normal simulations. However, these failed simulations could cause great variation of simulation results and then might have large impacts on the results of sensitivity analysis. Therefore, we highlight a further scientific question about how to handle these failure simulation, which needs to be investigated in future studies.

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The Appendix

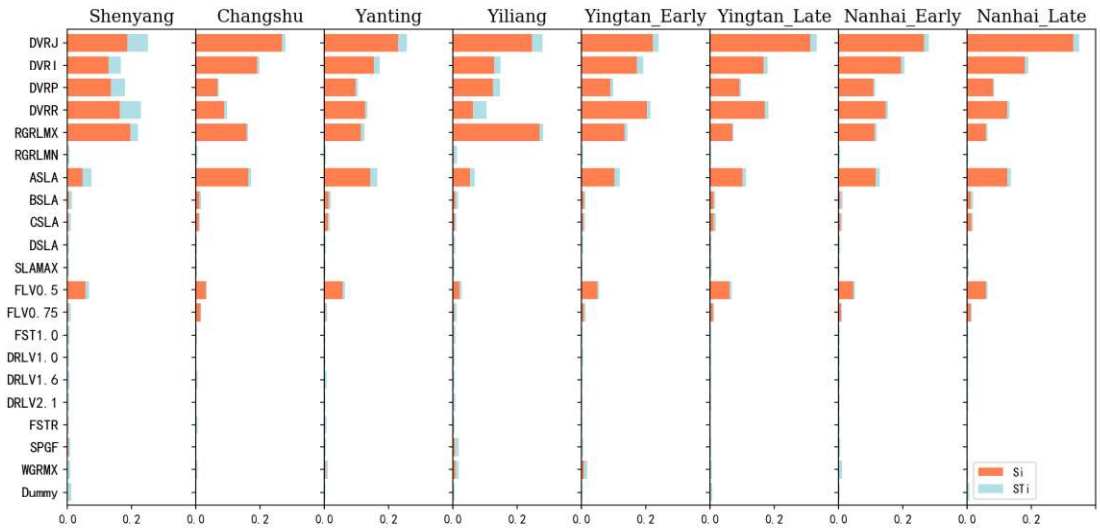

Fig. A.1. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WAGT (total aboveground dry matter) at maturity for the ±30% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc.

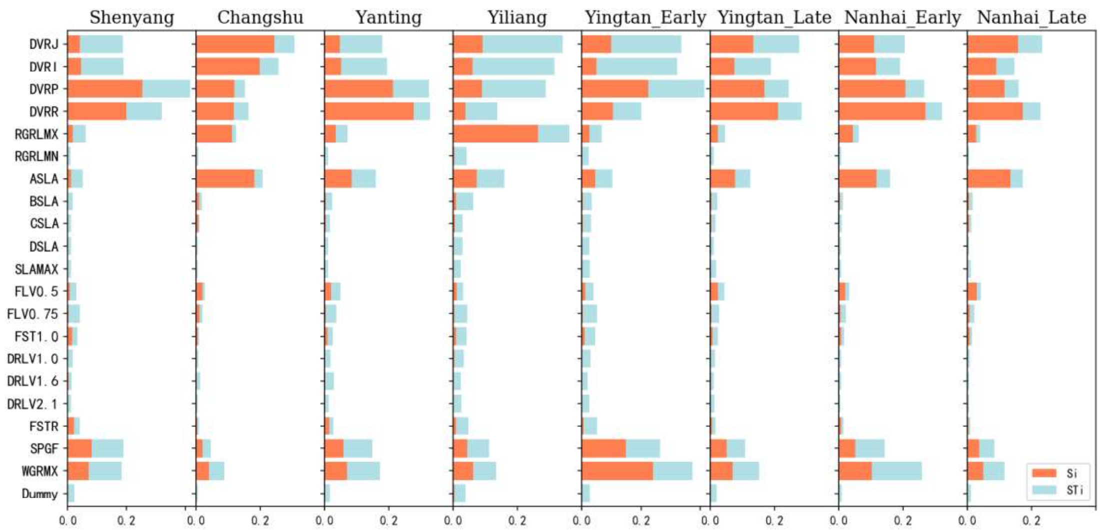

Fig. A.2. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WSO (dry weight of storage organs) at maturity for the ±30% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site.

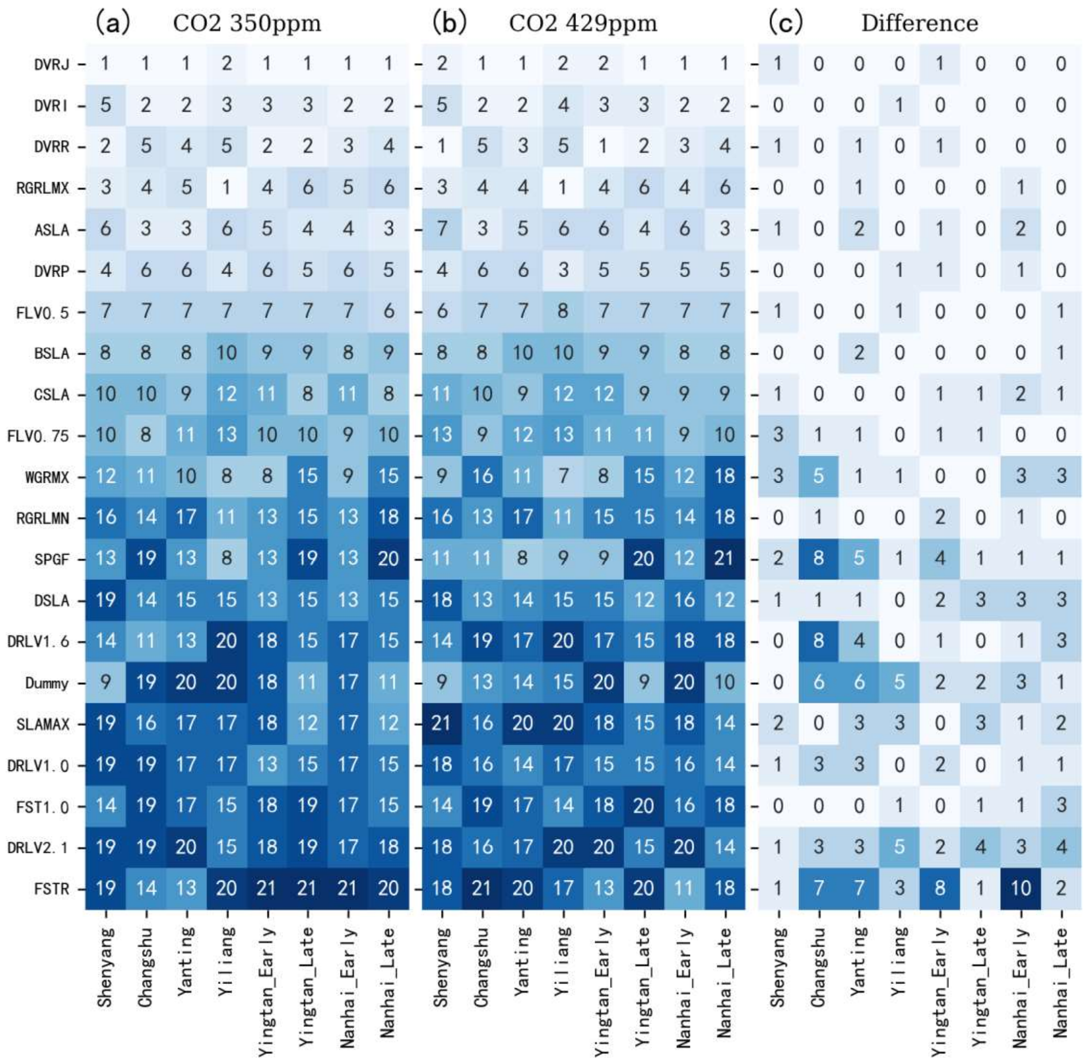

Fig. A.3. Impact of CO2 concentration on parameter sensitivity for WAGT (total aboveground dry matter) at maturity for the ±30% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO2 concentrations levels (i.e. 350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

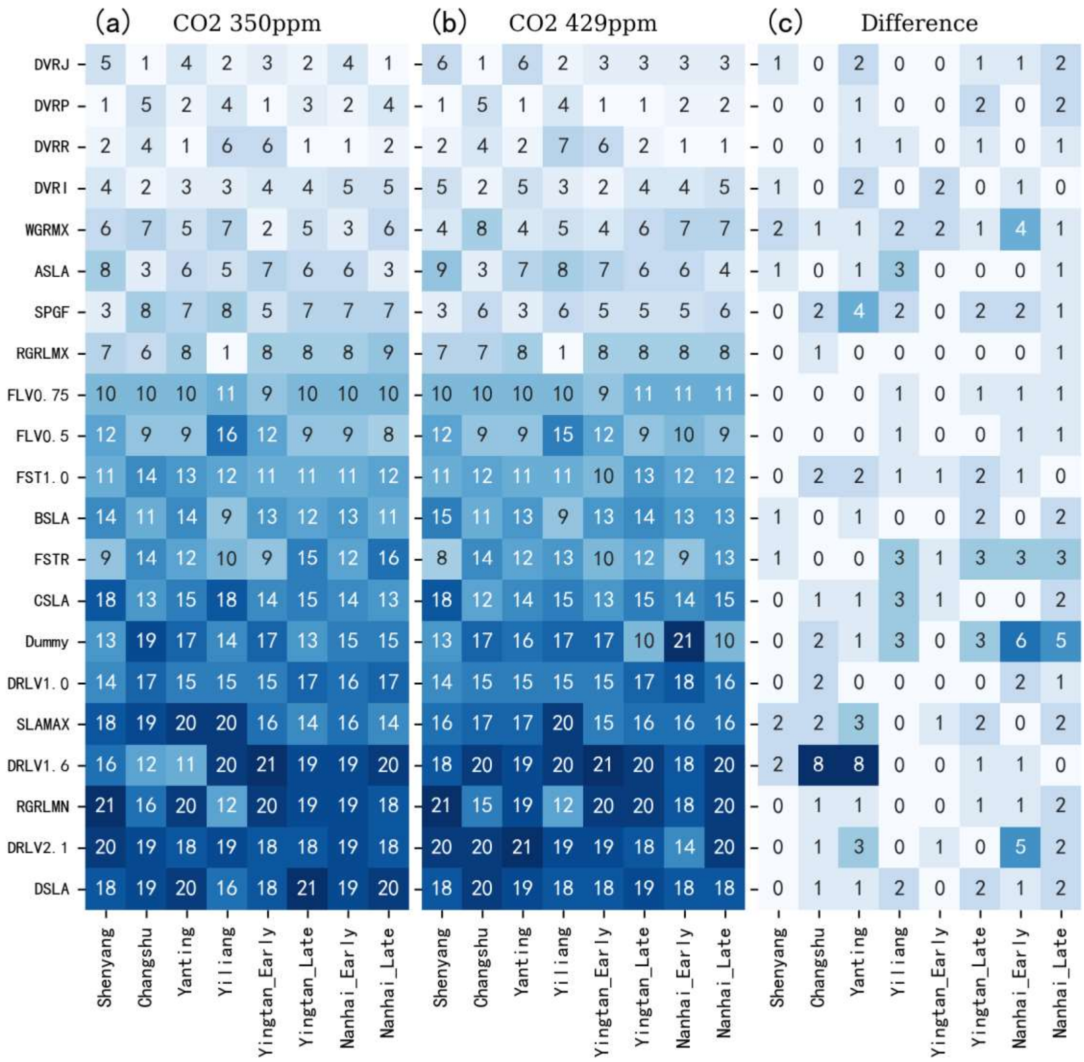

Fig. A.4. Impact of CO2 concentration on the parameter sensitivity for WSO (dry weight of storage organs) at maturity for the ±30% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO_2 concentrations levels (350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

Table A.1. Summaries of simulation failure.

Sites	Co2 condition	Failure times	Failure rate (%)
Shenyang	350 ppm	2	0.000633
	429 ppm	2	0.000633
Changshu	350 ppm	0	0
	429 ppm	0	0
Yanting	350 ppm	0	0
	429 ppm	0	0
Yiliang	350 ppm	3	0.000950
	429 ppm	3	0.000950
Yingtan_Early	350 ppm	0	0
	429 ppm	0	0
Yingtan_Late	350 ppm	471	0.149176
	429 ppm	783	0.247993
Nanhai_Early	350 ppm	0	0
	429 ppm	0	0
Nanhai_Late	350 ppm	61	0.019320
	429 ppm	87	0.027555

Table 1. Description of selected parameters and output variables in the APSIM-Oryza model

Name	Description	Unit	Lower bound (30%)[a]	Upper bound (30%)	Lower bound (50%)	Upper bound (50%)	Base value[b]
Parameters							
DVRJ	Development rate in juvenile phase	(℃day)$^{-1}$	0.0007	0.0013	0.0005	0.0015	0.001
DVRI	Development rate in photoperiod-sensitive phase	(℃day)$^{-1}$	0.000525	0.000975	0.000375	0.001125	0.00075
DVRP	Development rate in panicle development	(℃day)$^{-1}$	0.000595	0.001105	0.000425	0.001275	0.00085
DVRR	Development rate in reproductive phase	(℃day)$^{-1}$	0.0014	0.0026	0.001	0.003	0.002
RGRLMX	Maximum relative growth rate of leaf area	(℃day)$^{-1}$	0.00595	0.01105	0.00425	0.01275	0.0085
RGRLMN	Minimum relative growth rate of leaf area	(℃day)$^{-1}$	0.0028	0.0052	0.002	0.006	0.004
ASLA	Parameter A of the function to calculate specific leaf area (SLA, ha/kg)	-	0.00168	0.00312	0.0012	0.0036	0.0024
BSLA	Parameter B of SLA	-	0.00175	0.00325	0.00125	0.00375	0.0025
CSLA	Parameter C of SLA	-	-3.15	-5.85	-2.25	-6.75	-4.5
DSLA	Parameter D of SLA	-	0.098	0.182	0.07	0.21	0.14
SLAMAX	Maximum value of SLA	ha/kg	0.00315	0.00585	0.00225	0.00675	0.0045
FLV0.5	Fraction of shoot dry matter partitioned to the leaves at DVS= 0.5	-	0.42	0.78	0.3	0.9	0.6
FLV0.75	Fraction of shoot dry matter partitioned to the leaves at DVS = 0.75	-	0.21	0.39	0.15	0.45	0.3
FST1.0	Fraction shoot dry matter partitioned to the stems at DVS =1.0	-	0.28	0.52	0.2	0.6	0.4
DRLV1.0	Leaf death coefficient as a function of development stage at DVS = 1.0	-	0.014	0.026	0.01	0.03	0.02
DRLV1.6	Leaf death coefficient as a function of development stage at DVS = 1.6	-	0.021	0.039	0.015	0.045	0.03
DRLV2.1	Leaf death coefficient as a function of development stage at DVS = 2.1	-	0.035	0.065	0.025	0.075	0.05
FSTR	Fraction of carbohydrates allocated to stems stored as reserve	-	0.175	0.325	0.125	0.375	0.25
SPGF	Spikelet growth factor	no./kg	45430	84370	32450	97350	64900
WGRMX	Maximum individual grain weight	kg/grain	1.75E-05	0.0000325	0.0000125	0.0000375	0.000025
Outputs							
WAGT	Total aboveground dry matter	kg/ha					
WSO	Dry weight of storage organs	kg/ha					

[a] Lower bound means the base value minus 30% or 50%, upper bound means the base value plus %30 or 50%.[b] Base values are obtained from Tan et al. (2016).

Table 2. Location, growing-season climate and topsoil texture in the six selected sites.

	Shenyang	Changshu	Yanting	Yiliang	Yingtan	Nanhai
Rice type	Single rice	Single rice	Single rice	Single rice	Double rice	Double rice
Latitude	41.52	31.55	31.27	24.53	28.25	23.13
Longitude	123.36	120.63	105.46	103.73	116.93	113.03
Elevation(m)	38	5	489	1699	41	1
Mean daily temperature (◦C)[b]	20.30	25.95	25.04	20.09	Early: 24.81 Late: 28.12[a]	Early: 25.45 Late: 28.24
Mean daily solar radiation(MJ/m^2)	18.18	17.74	16.73	15.50	Early: 16.74 Late: 17.17	Early: 11.68 Late: 13.29
Mean rainfall (mm)	580.72	544.34	643.6	716.68	Early: 1068.55 Late: 372.75	Early: 855.73 Late: 452.53
Sand (0.05-2.0mm) (%)[c]	18.42	3.77	30.70	15.20	51.25	31.05
Silt (0.002-0.05mm) (%)	66.70	62.23	39.72	32.00	37.62	54.95
Clay (<0.002mm) (%)	14.88	34.00	20.14	52.80	11.13	14.00

[a] "Early" represents early rice, "Late" represents late rice. For example, "Late: 28.96" stands for the mean temperature of late rice in Yingtan is 28.12◦C, etc.

[b] Mean daily temperature, mean daily solar radiation and mean rainfall are the mean value in rice growth period (from observed mean sowing date to harvesting date).

[c] Soil particle size in the top layer.

Table A.1. Summaries of simulation failure.

Sites	Co2 condition	Failure times	Failure rate (%)
Shenyang	350 ppm	2	0.000633
	429 ppm	2	0.000633
Changshu	350 ppm	0	0
	429 ppm	0	0
Yanting	350 ppm	0	0
	429 ppm	0	0
Yiliang	350 ppm	3	0.000950
	429 ppm	3	0.000950
Yingtan_Early	350 ppm	0	0
	429 ppm	0	0
Yingtan_Late	350 ppm	471	0.149176
	429 ppm	783	0.247993
Nanhai_Early	350 ppm	0	0
	429 ppm	0	0
Nanhai_Late	350 ppm	61	0.019320
	429 ppm	87	0.027555

Figure
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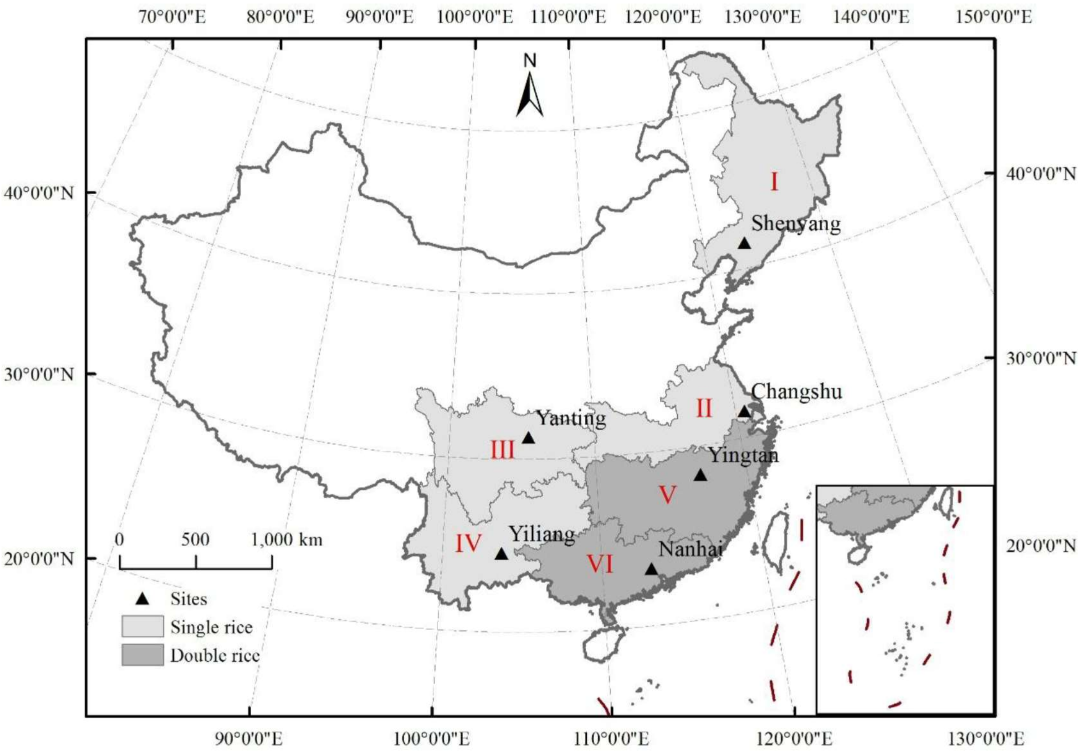

Fig.1. The spatial distribution of six rice cultivation regions across mainland China and selected sites. The six rice cultivation regions are as following: I, single rice in Northeast China, II, single rice in mid-lower Yangtze River Valley, III, single rice in Sichuan Basin, IV, single rice in Yunnan-Guizhou Plateau, V, double rice in mid-lower Yangtze River Valley and VI, double rice in South China.

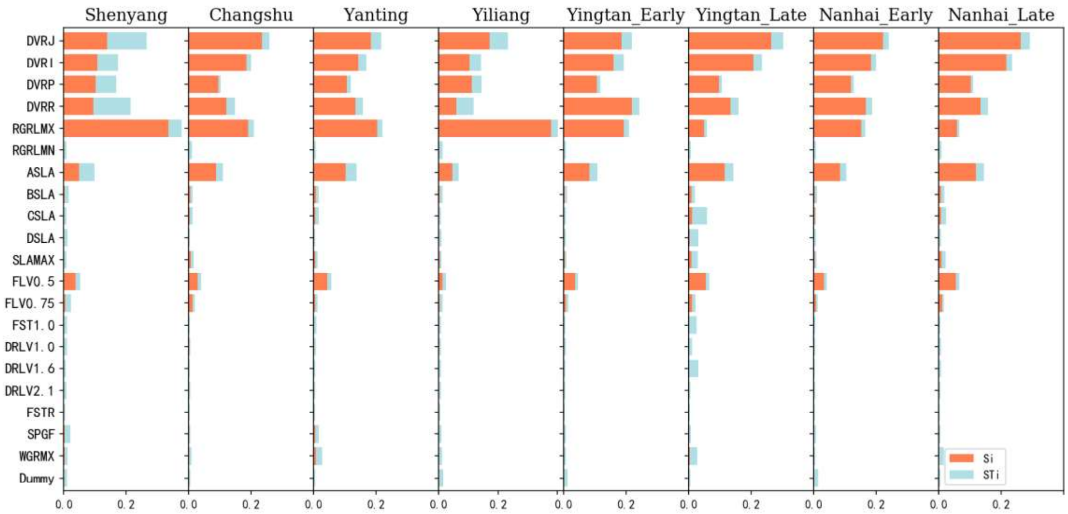

Fig.2. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WAGT (total aboveground dry matter) at maturity for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site.

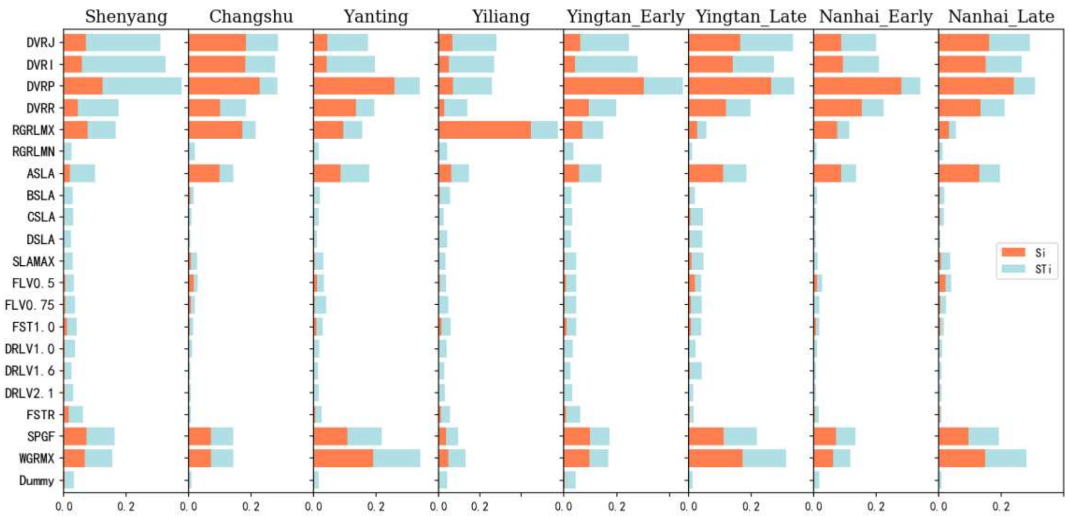

Fig.3. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WSO (dry weight of storage organs) at maturity for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site.

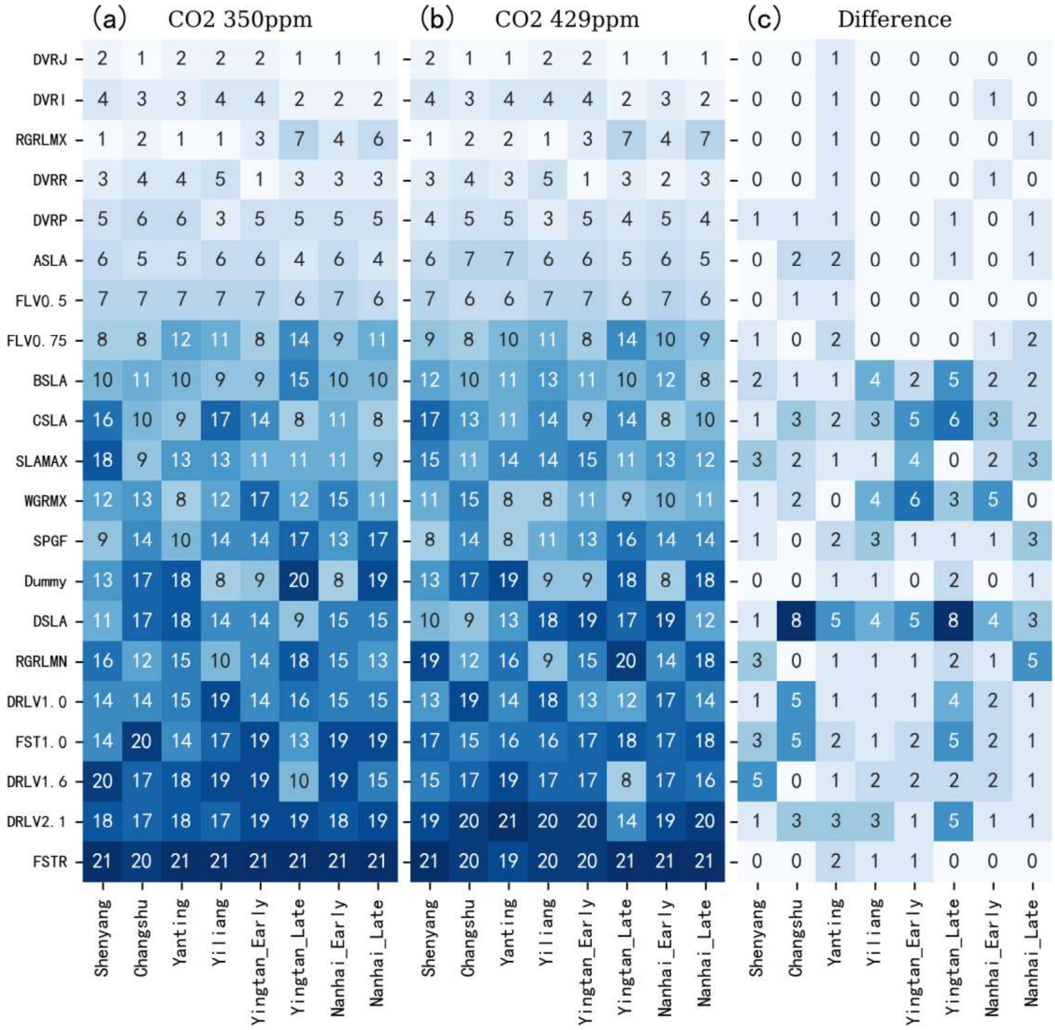

Fig.4. Impact of CO2 concentration on parameter sensitivity for WAGT (total aboveground dry matter) at maturity for the ±50% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO2 concentrations levels (i.e. 350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

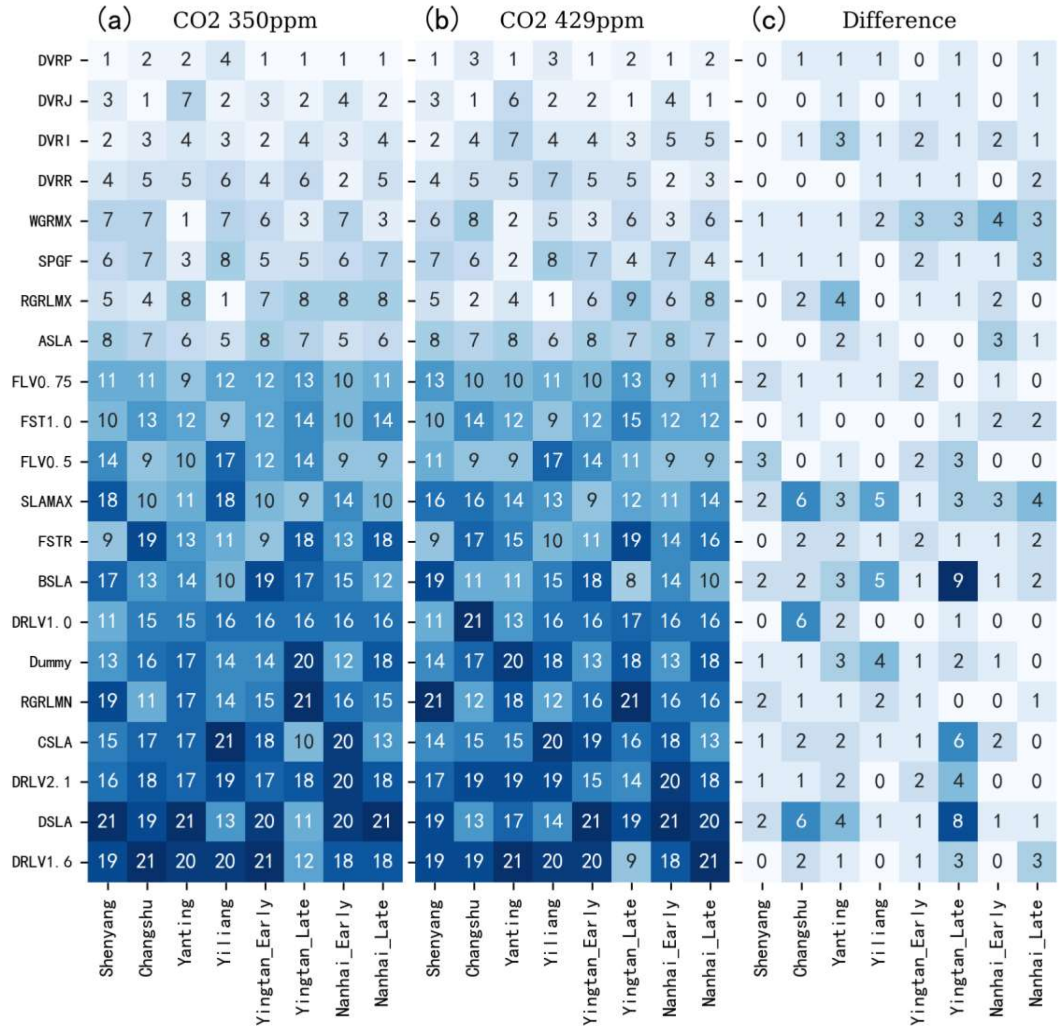

Fig.5. Impact of CO2 concentration on the parameter sensitivity for WSO (dry weight of storage organs) at maturity for the ±50% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO_2 concentrations levels (350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

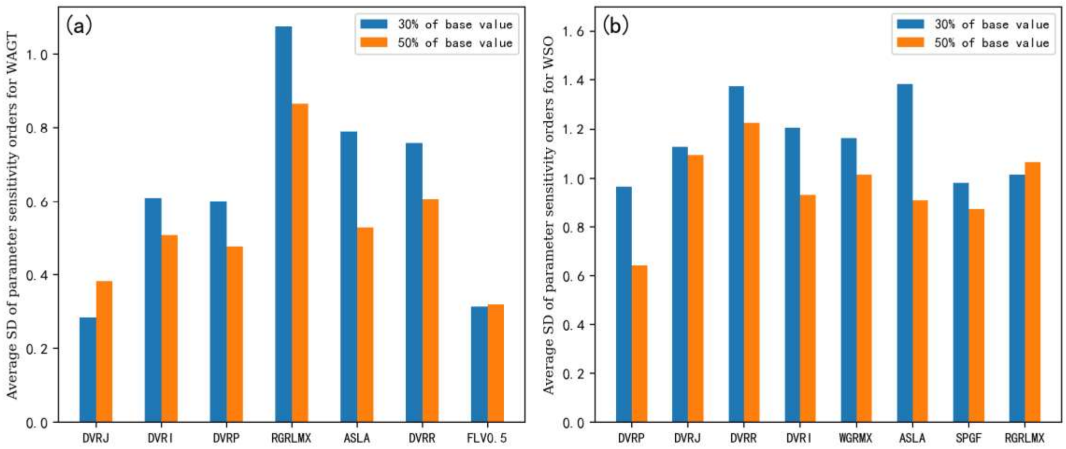

Fig.6. Average standard deviations (SD) of parameter sensitivity orders from 1980 to 2010 for influential parameters (with overall ST_i larger than 0.05) for WAGT (total aboveground dry matter, a) and WSO (dry weight of storage organs, b). For each parameter, the SD in each climate condition was calculated first, and then SDs in eight climate conditions were averaged.

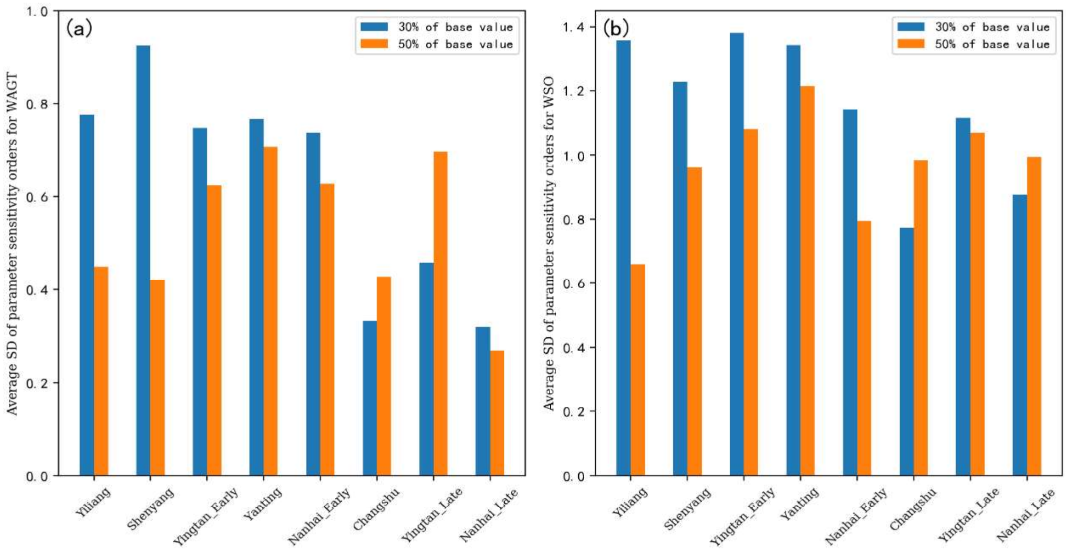

Fig. 7 Average standard deviations (SD) of parameter sensitivity orders from 1980 to 2010 for different climate conditions for WAGT (total aboveground dry matter, a) and WSO (dry weight of storage organs, b). For each climate condition, the SD of each parameter was calculated first, and then average SDs were calculated using the influential parameters (with overall ST_i larger than 0.05).

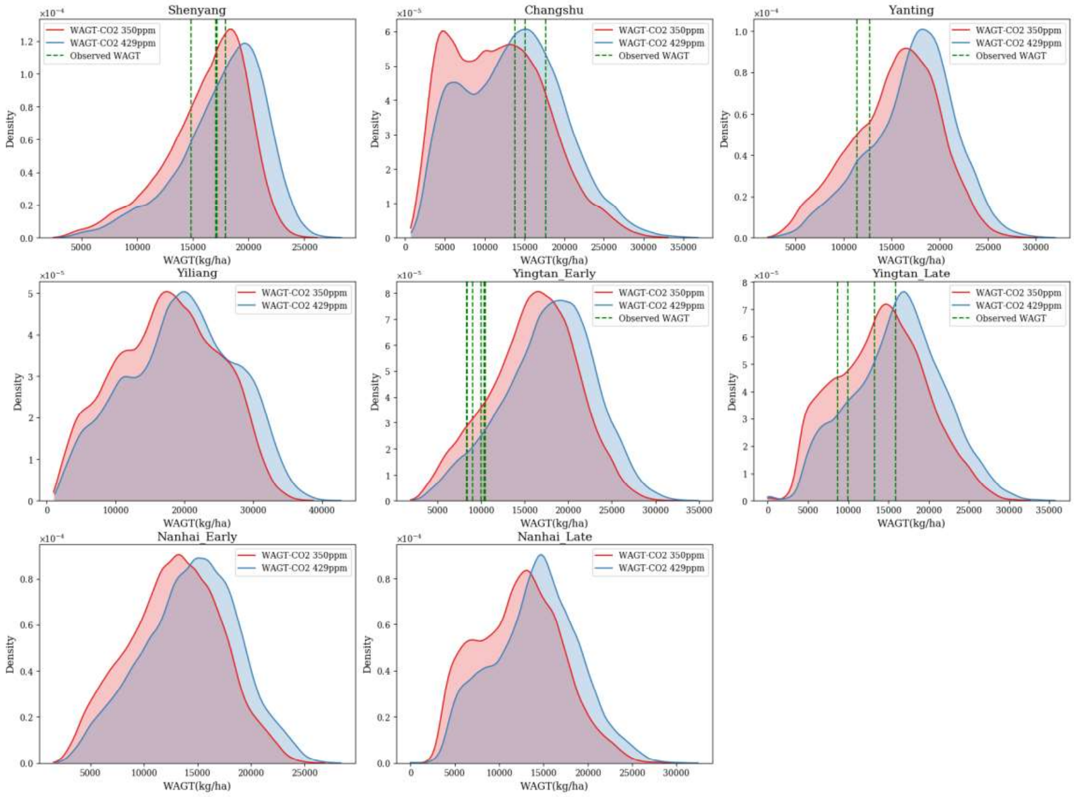

Fig.8. The distribution of WAGT (total aboveground dry matter) under eight different climate conditions obtained by the KDE (Kernel Density Estimation) method for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure represents the site and cropping system. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc. The red and blue colors represent the distributions of WAGT under CO_2 concentration of 350 ppm and 420 ppm, respectively.

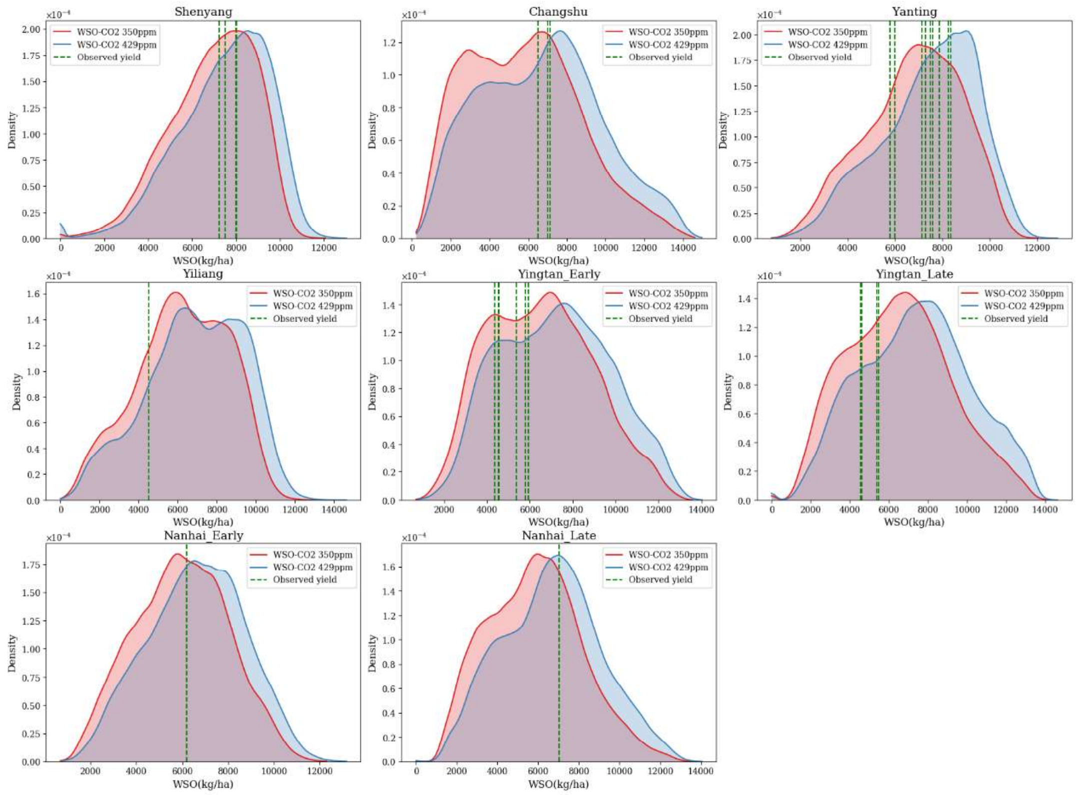

Fig.9. The distribution of WSO (dry weight of storage organs) under eight different climate conditions obtained by the KDE (Kernel Density Estimation) method for the ±50% perturbation of parameter's base value. The title of each subfigure in the top of the figure represents the site and cropping system. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc. The red and blue colors represent the distributions of WSO under CO2 concentration of 350 ppm and 420 ppm, respectively.

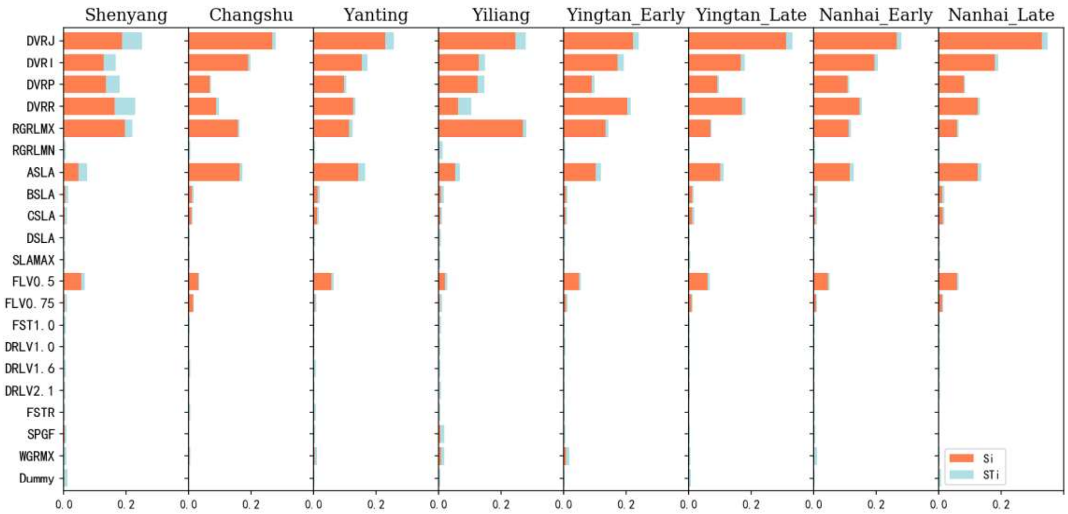

Fig. A.1. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WAGT (total aboveground dry matter) at maturity for the ±30% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site, etc.

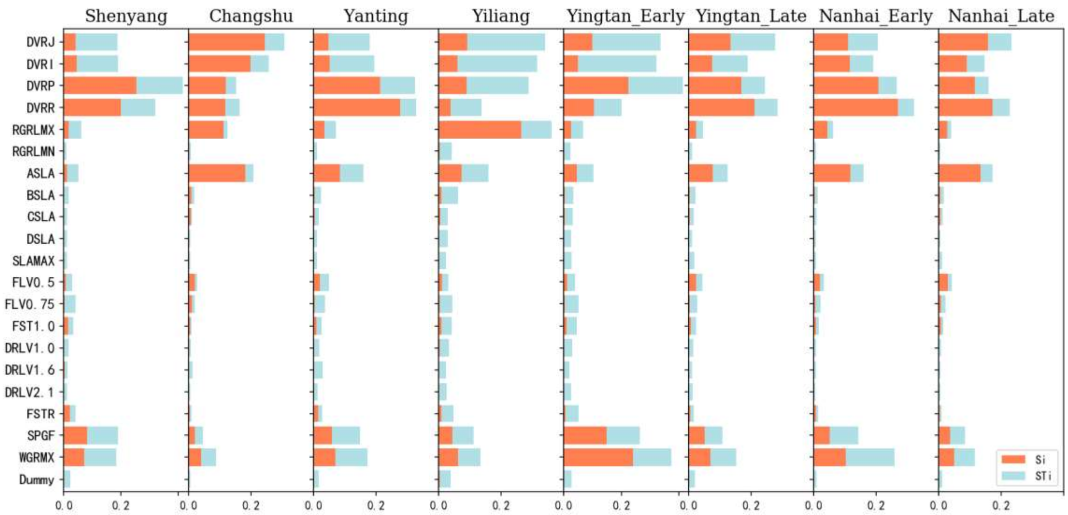

Fig. A.2. The main (Si) and total (STi) sensitivity indices under eight climate conditions for the output variable WSO (dry weight of storage organs) at maturity for the ±30% perturbation of parameter's base value. The title of each subfigure in the top of the figure means different environmental conditions. For example, "Shenyang" means single rice in the Shenyang site, "Yingtan_Early" means early rice in the Yingtan site.

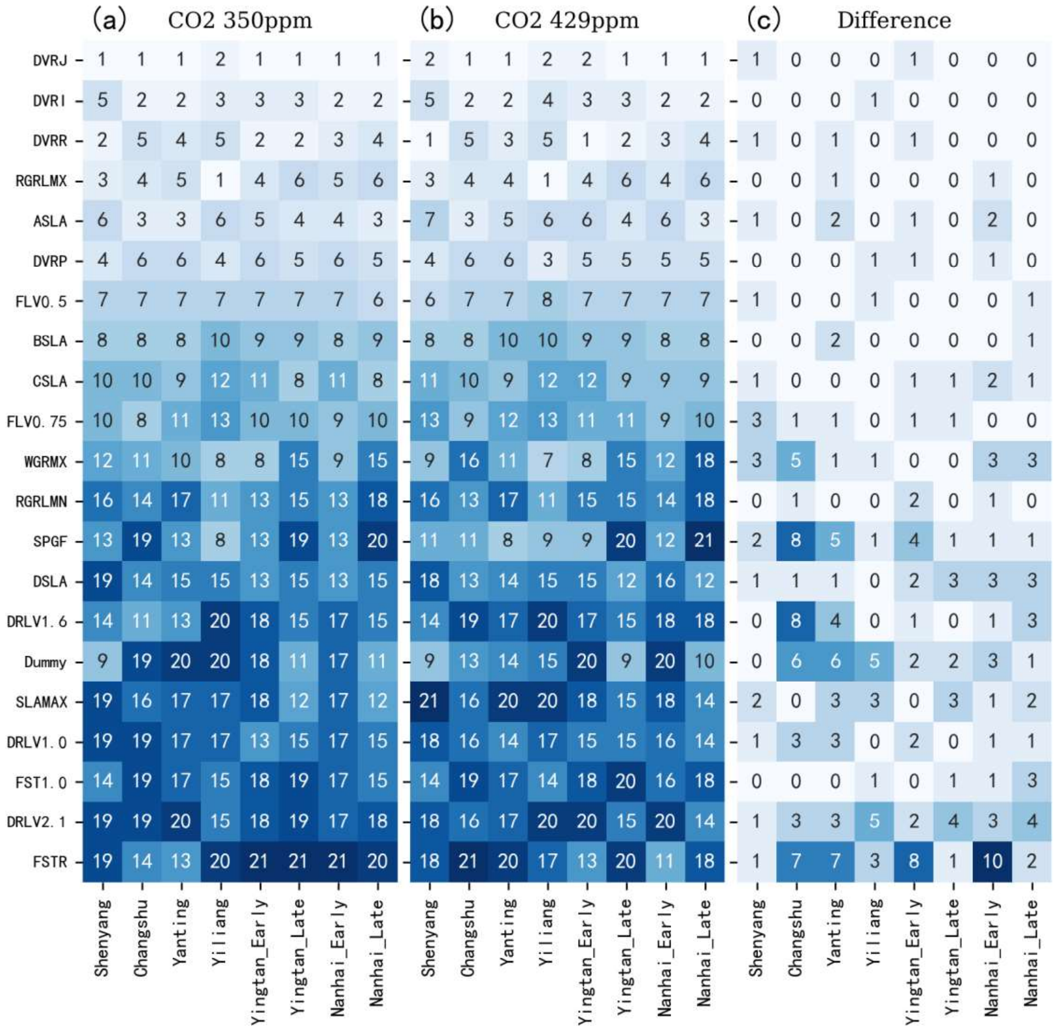

Fig. A.3. Impact of CO2 concentration on parameter sensitivity for WAGT (total aboveground dry matter) at maturity for the ±30% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO2 concentrations levels (i.e. 350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.

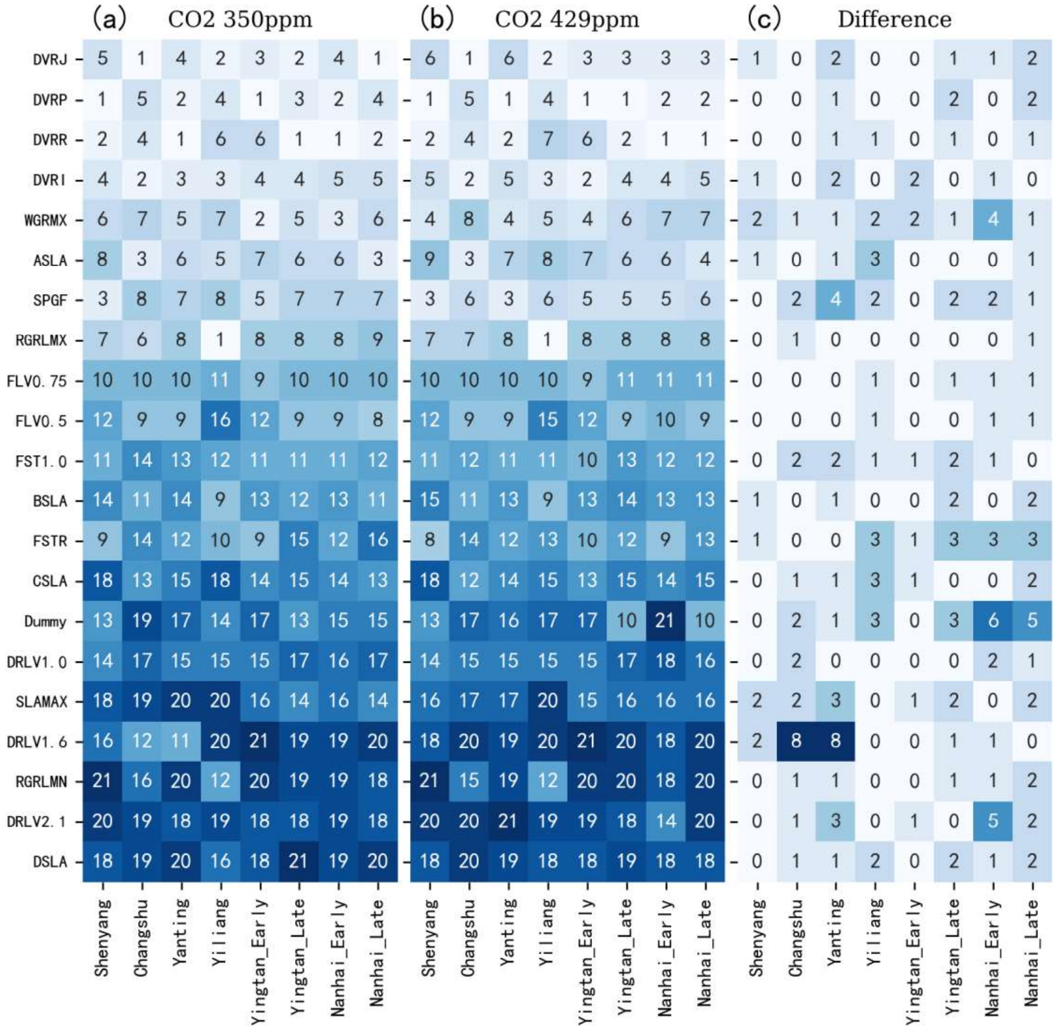

Fig. A.4. Impact of CO2 concentration on the parameter sensitivity for WSO (dry weight of storage organs) at maturity for the ±30% perturbation of parameter's base value. The numbers in Fig. (a) and (b) represent the order of parameters ranked by the total sensitivity index (STi) under two CO_2 concentrations levels (350ppm and 429ppm), and the numbers in Fig. (c) represent the changes of orders in absolute value under these two levels.