



Water Stress is a Key Factor Influencing the Parameter Sensitivity of the WOFOST Model in Different Agro-Meteorological Conditions

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Abstract

Sensitivity analysis is helpful for improving the efficiency and accuracy of the calibration of crop growth models. However, parameter sensitivity is still not well understood when combined with different meteorological and production conditions, especially adverse conditions such as water stress. This study simulated the production of winter wheat in four ecological areas in Henan Province, China. The Extend Fourier Amplitude Sensitivity Test algorithm (EFAST) was used for analyzing the sensitivity of 43 crop parameters of the WO^rld ^lFOod ^lSTudies (WOFOST) model to yield, aboveground biomass, and leaf area index (LAI) with or without water-limited conditions. The results demonstrated that yield and biomass were the objective outputs, and the main limiting factors for the model results were assimilation and dry matter conversion efficiency. Under water-limited conditions, the parameter sensitivity of related extinction coefficient, early wheat leaf area, and root growth increased with increased water stress. With the process variable LAI as the target output, the parameter sensitivity varied at different growth stages, whereas the parameter sensitivity was almost the same under different agro-meteorological conditions. Under water-limited conditions, the parameter sensitivity of wheat early extinction coefficient, maximum root depth, and death rate of the leaves also increased with increased water stress. Therefore, water stress is a key factor affecting parameter sensitivity under different agro-meteorological conditions.

Keywords Wheat · WOFOST model · Sensitivity analysis · EFAST · Water stress

Introduction

Wheat is a major food crop that is very important for food security. Wheat production in Henan Province contributes significantly to China. Based on data from the National Bureau of Statistics of China (<http://www.stats.gov.cn/>), in 2019, Henan Province accounted for 28% of China's total wheat production. Henan is a vast territory with an overlapping warm temperate zone and northern subtropical zone, and as such it has a diverse climate. In recent years in particular, the variability in climatic factors as a result of global climate change has had a great impact on wheat production (Iizumi et al., 2017), and thus accurately and quickly simulating the growth, development, and yield of wheat in

different climates is of great significance for guiding wheat production.

The crop growth model was first conceived in the 1960s (Jones et al., 2017) and describes the growth of a crop and its interaction with the environment using mathematical methods. Currently, crop growth models have been widely used in crop yield prediction (Morell et al., 2016), agricultural management decision-making (Zhang et al., 2018), agricultural production potential evaluation (Tang et al., 2018), climate change (Vanli et al., 2019), and other fields. As numerous parameters are used in the crop model to describe the growth process of the crop, it is very difficult and expensive to obtain all the parameters when the model is used (Hsiao et al., 2009). In a certain production scenario, crop growth models often contain a few parameters that have a great impact (Makler-Pick et al., 2011). Therefore, focusing on sensitive parameters can improve the accuracy and efficiency of model calibration. Sensitivity analysis can quantify the impact of model parameters on the model output and has been widely used in the calibration and development of crop growth models (Stella et al., 2014).

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Sensitivity analysis is divided into local sensitivity analysis and global sensitivity analysis (Saltelli et al., 2008). Local sensitivity analysis changes one parameter at a time, while other parameters remain fixed to estimate the influence of the parameter on the model output. It has been used extensively due to its efficiency and rapidity (Wallach et al., 2006). However, local sensitivity analysis is unsuitable for non-linear models and cannot estimate the parameter interactions (Varella et al., 2010). Global sensitivity analysis can analyze the comprehensive effects of parameters on model output based on the entire range of input parameters. It has thus gained great popularity in sensitivity analysis (Saltelli et al., 2008). Global sensitivity analysis methods can be divided into screening, regression-based, and variance-based. Among them, the Extended Fourier Amplitude Sensitivity Test (EFAST) algorithm based on the variance-based method can calculate the contribution of each parameter and its interaction with other parameters and has been widely used in sensitivity analysis (Jin et al., 2018; Wang et al., 2013; Zhao et al., 2014).

Sensitivity analysis results are mainly affected by environmental conditions (Confalonieri et al., 2010a, b) and management measures such as fertilization and irrigation (DeJonge et al., 2012; Guo et al., 2019; Liang et al., 2017). However, the performance of sensitivity analysis based on a combination of climates and production conditions is uncertain. In addition, previous sensitivity analysis studies typically used yield and aboveground biomass at maturity as objective outputs (Vanuytrecht et al., 2014; Zhao et al., 2014), while few studies have focused on process variables, such as leaf area index (LAI), which are constantly changing with crop growth.

Hu and Yin (2014) divided Henan Province into four major wheat production and ecological regions according to the temperature, radiation, precipitation, and local production characteristics as follows: the northern irrigation area, the central supplementary irrigation area, western dry farming areas, and southern rain-fed areas. Therefore, in an attempt to assess the performance of sensitivity analysis in the different ecological areas based on the World Food Studies (WOFOST) model, this study selected yield, aboveground biomass at maturity, and LAI as the objective outputs and analyzed the sensitivity parameters of WOFOST with or without water limitation.

Materials and Methods

WOFOST Growth Model

The WOFOST growth model is a dynamic, explanatory model developed by the World Food Research Center (CWFS) and Wageningen University in the Netherlands

(van Ittersum et al., 2003). It has been widely used in yield forecasting (Supit et al., 2012), climate change (Lecerf et al., 2019), and remote sensing data assimilation (Huang et al., 2019). In WOFOST, crop growth is simulated based on eco-physiological processes. The major processes are phenological development, CO₂-assimilation, transpiration, respiration, partitioning of assimilates to the various organs, and dry matter formation. The phenology of WOFOST is described by the dimensionless state variable development stage (DVS). For most annual crops, DVS is set to 0 at seedling emergence, 1 at flowering (for cereals), and 2 at maturity. WOFOST is often used to simulate crop growth under potential conditions (an optimal water supply) and water-limited (water availability limits the potential production) conditions (de Wit et al., 2019). The detailed principles and specific application of the WOFOST model have been described in the WOFOST 7.1 user manual (Boogaard et al., 2014).

Research Areas and Experimental Description

This experiment was carried out from 2019 to 2020. Four typical experimental sites, namely Neihuang (NH), Xuchang (XC), Luoning (LN), and Luoshan (LS), were selected to represent the northern Henan irrigation area and the central Henan supplementary irrigation area, western Henan dry farming areas, and southern Henan rain-fed areas. The characteristics of each site are listed in Table 1. ‘BaiNong 207’ was chosen as the test wheat variety, which is widely planted in Henan Province, and the phenological parameters were calibrated according to the observed phenology. The LAI, aboveground biomass, and yield were measured during the overwintering stage, jointing stage, anthesis stage, filling stage, and maturity.

Using meteorological data obtained from the NASA POWER database (<https://power.larc.nasa.gov/>) during October 1, 2019, to June 10, 2020, a distribution map of the main meteorological factors in Henan Province was established by interpolation (Fig. 1). The distribution of precipitation and radiation was opposite, with precipitation decreasing from south to north and radiation increasing from south to north. Both vapor pressure and accumulated temperature showed a decreasing trend from southeast to northwest. The distribution of meteorological factors resulted in sufficient sunlight, less precipitation, low vapor pressure, and low accumulated temperature in northern Henan (NH). The meteorological factors in the central and eastern regions (XC) were all at the middle level. The main features of the western region (LN) were low temperature and vapor pressure. In the southern region (LS), the temperature, precipitation, and vapor pressure were relatively high, while the total radiation was comparatively low.

Table 1 The characteristics of each experimental site

Site	NH	XC	LN	LS
Longitude	114°38'E	113°48'E	111°36'E	114°31'E
Latitude	35°30'N	34°8'N	34°17'N	32°16'N
Climate type	Warm temperate continental monsoon climate	Typical temperate monsoon climate	Temperate semi-humid arid monsoon climate	North subtropical monsoon climate
Sowing date	10/18/2019	10/18/2019	10/16/2019	10/20/2019
Flowering date	4/27/2020	4/22/2020	5/2/2020	4/16/2020
Maturity date	6/1/2020	5/27/2020	6/6/2020	5/23/2020
Water content at saturation	0.42	0.45	0.48	0.48
Field capacity	0.16	0.35	0.32	0.32
Wilting point	0.06	0.19	0.12	0.17
Irrigation date (70 mm each time)	11/20/2019 3/15/2020 4/1/2020 5/5/2020	10/28/2019 3/14/2020 5/4/2020		

The Process and Method of Sensitivity Analysis

The Process of Sensitivity Analysis

This work used SimLab (version 2.2.1) (Tarantola, 2005) software for the sensitivity analysis. The process is illustrated in Fig. 2. The main procedures were structured in the following steps: (i) the parameter range and its distribution were determined. (ii) Monte Carlo sampling was used to generate a random sample set. (iii) The sample set was used to run the WOFOST model. (iv) The results from running the WOFOST input were fed into SimLab to calculate the sensitivity of each parameter. This research mainly assessed WOFOST crop parameters under potential and water-limited production scenarios because irrigation conditions are usually the most important factors affecting wheat growth in actual production. Since the distribution of the parameters is uncertain, the uniform distribution is used for sampling. The parameter range has few effects on the ranking of the sensitivity parameters (Jin et al., 2018; Li et al., 2019a, 2019b; Wang et al., 2013), and the parameter default value fluctuates at 10% in the parameter range, as shown in Table 2.

Sensitivity Analysis Method

The EFAST method was formed based on the Fourier amplitude test method (FAST) and Sobol's method (Saltelli et al., 1999). The method integrated the merits of FAST and Sobol's algorithm. It is a method that is based on variance decomposition and considers that the variance in the model output is caused by the parameters and interaction of various parameters. Therefore, through the variance decomposition, the contribution ratio of parameters, including parameter coupling

effects to the total variance, represents the parameter sensitivity index. The basic principle is to use a certain conversion function to convert the spectrum curve of different parameter spaces expected in the model into a function curve with a common independent parameter. That is, $Y = f(x_1, x_2, x_3, \dots, x_n)$ is converted into $Y = f(s)$, converting the multidimensional space into one-dimensional space. Then the function is Fourier transformed, and the spectrum curve of the Fourier series of each frequency is extracted, following which the influence of a certain parameter change on the output variable can be obtained. It is expressed as the ratio of the variance of the result change caused by some parameters to the total variance (formula (1)).

$$V = \sum_i V_i + \sum_{i \neq j} V_{ij} + \sum_{i \neq j \neq k} V_{ijk} + \dots + V_{12\dots n}$$

where V is the total variance of the model; V_i is the variance caused by a single parameter change of the model when the other parameters are unchanged, called the first-order variance. V_{ij} is caused by the interaction between the two parameters, which is called the second-order variance. Similarly, V_{ijk} is the third-order variance.

Through normalization, the first-order (S_i), second-order (S_{ij}), and third-order (S_{ijk}) sensitivity index of the parameters was defined as:

$$S_i = \frac{V_i}{V}, S_{ij} = \frac{V_{ij}}{V}, S_{ijk} = \frac{V_{ijk}}{V}, S_{12\dots n} = \frac{V_{12\dots n}}{V}$$

The global sensitivity index of the parameter is the sum of the sensitivity indexes of each order of the parameter:

$$S_{Ti} = S_i + S_{ij} + S_{ijk} + \dots + S_{12\dots n}$$

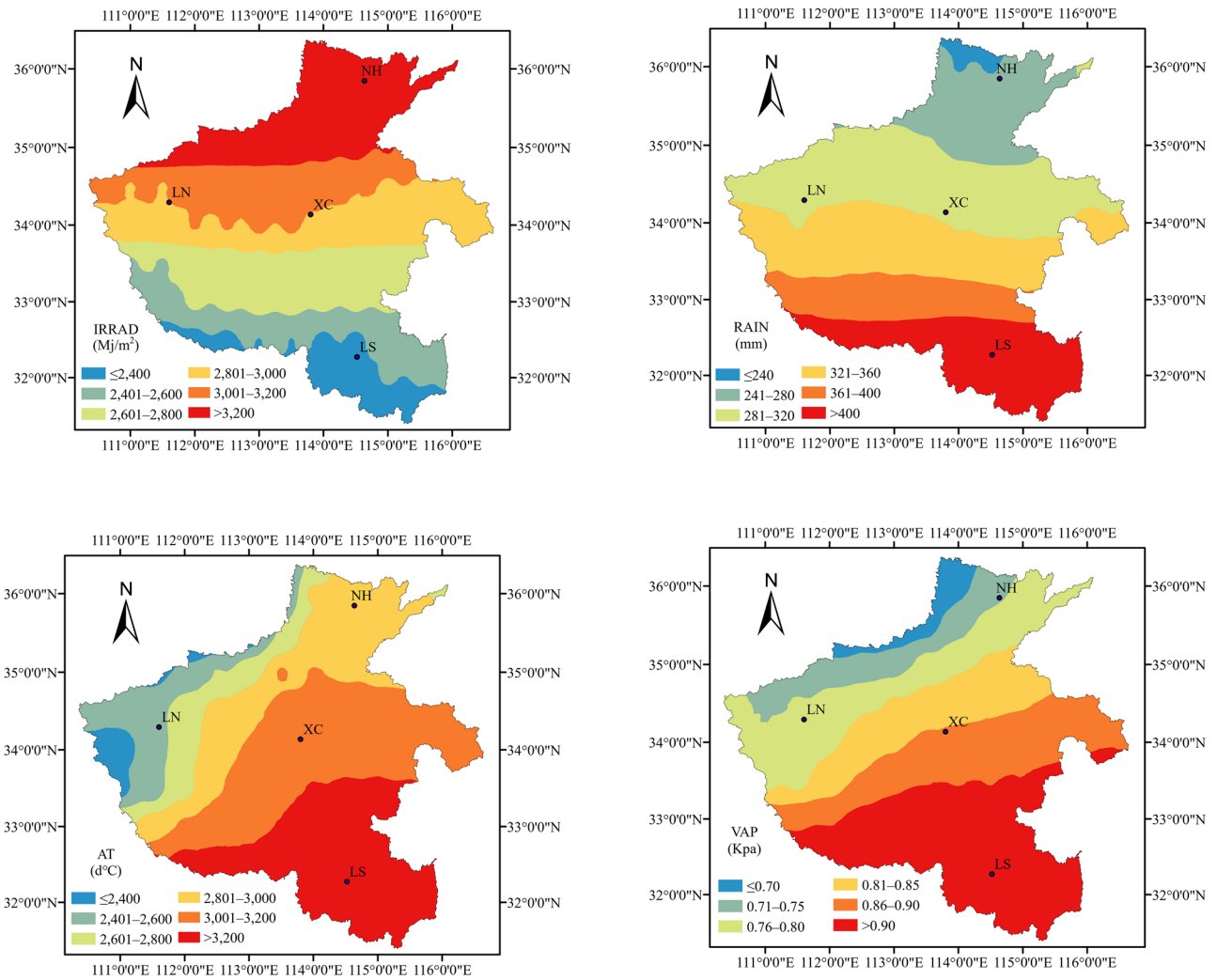


Fig. 1 Meteorological characteristics in Henan Province. IRRAR: total radiation; RAIN: precipitation; AT: accumulated temperature > 0 °C; VAP: mean vapor pressure

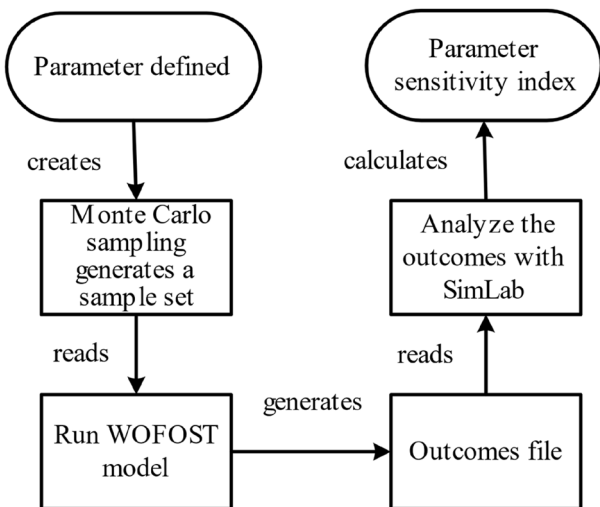


Fig. 2 Sensitivity analysis execution process

The global sensitivity can obtain the influence of the interaction of the parameters. When there is no interaction between the parameters, the interaction between the parameters is zero. The sensitivity parameters are generally considered to be the parameters with a sensitivity index > 0.1 (Lamboni et al., 2009; Richter et al., 2010; Vanuytrecht et al., 2014).

Results

Sensitivity Analysis Under Optimal Water Supply Conditions

The parameter sensitivity of yield and aboveground biomass under optimal water supply conditions is indicated in Fig. 3. The main sensitive parameters of yield and aboveground

Table 2 Input parameters of WOFOST

Parameter	Description	Unit	Minimum	Maximum
TDWI	Initial total crop dry weight	kg·hm ⁻²	189	231
LAIEM	Leaf area index at emergence	hm ² ·hm ⁻²	0.12285	0.15015
RGRLAI	Maximum relative increase in LAI	hm ² ·hm ⁻² ·d ⁻¹	0.007353	0.008987
SLATB0	Specific leaf area (DVS=0)	hm ² ·kg ⁻¹	0.001908	0.002332
SLATB0.5	Specific leaf area (DVS=0.5)	hm ² ·kg ⁻¹	0.001908	0.002332
SLATB2.0	Specific leaf area (DVS=2.0)	hm ² ·kg ⁻¹	0.001908	0.002332
SPAN	Life span of leaves growing at 35 °C	d	28.17	34.43
TBASE	Lower threshold temperature for aging of leaves	°C	-1	1
KDIFTB0	Extinction coefficient for diffuse visible light (DVS=0)		0.54	0.66
KDIFTB2.0	Extinction coefficient for diffuse visible light (DVS=2.0)		0.54	0.66
EFFTB0	Light-use efficiency of single leaf (T=0)		0.405	0.495
EFFTB40	Light-use efficiency of single leaf (T=40)		0.405	0.495
AMAXTB0	Maximum leaf CO ₂ assimilation rate (DVS=0)	kg·hm ⁻² ·h ⁻¹	32.247	39.413
AMAXTB1.0	Maximum leaf CO ₂ assimilation rate (DVS=1.0)	kg·hm ⁻² ·h ⁻¹	32.247	39.413
AMAXTB1.3	Maximum leaf CO ₂ assimilation rate (DVS=1.3)	kg·hm ⁻² ·h ⁻¹	32.247	39.413
AMAXTB2.0	Maximum leaf CO ₂ assimilation rate (DVS=2.0)	kg·hm ⁻² ·h ⁻¹	4.032	4.928
TMPFTB0	Reduction factor of AMAX (T=0 °C)		0.009	0.011
TMPFTB10	Reduction factor of AMAX (T=10 °C)		0.54	0.66
CVL	Efficiency of conversion into leaves	kg·kg ⁻¹	0.6165	0.7535
CVO	Efficiency of conversion into storage organ	kg·kg ⁻¹	0.6381	0.7799
CVR	Efficiency of conversion into roots	kg·kg ⁻¹	0.6246	0.7634
CVS	Efficiency of conversion into stems	kg·kg ⁻¹	0.5958	0.7282
Q10	Relative increase in respiration rate per 10 °C temperature increase		1.8	2.2
RML	Relative maintenance respiration rate of leaves	kg (CH ₂ O)·(kg·d) ⁻¹	0.027	0.033
RMO	Relative maintenance respiration rate of storage organ	kg (CH ₂ O)·(kg·d) ⁻¹	0.009	0.011
RMR	Relative maintenance respiration rate of roots	kg (CH ₂ O)·(kg·d) ⁻¹	0.0135	0.0165
RMS	Relative maintenance respiration rate of stems	kg (CH ₂ O)·(kg·d) ⁻¹	0.0135	0.0165
FRTB0	Fraction of total dry matter to roots (DVS=0)		0.45	0.55
FRTB0.4	Fraction of total dry matter to roots (DVS=0.4)		0.153	0.187
FRTB0.7	Fraction of total dry matter to roots (DVS=0.7)		0.063	0.077
FRTB0.9	Fraction of total dry matter to roots (DVS=0.9)		0.027	0.033
FLTB0	Fraction of aboveground dry matter to leaves (DVS=0)		0.72	0.88
FLTB0.25	Fraction of aboveground dry matter to leaves (DVS=0.25)		0.63	0.77
FLTB0.5	Fraction of aboveground dry matter to leaves (DVS=0.5)		0.45	0.55
FLTB0.646	Fraction of aboveground dry matter to leaves (DVS=0.646)		0.27	0.33
PERDL	Maximum relative death rate of leaves due to water stress	kg·(kg·d) ⁻¹	0.27	0.33
RDRRTB1.5	Relative death rate of roots (DVS=1.5001)	kg·(kg·d) ⁻¹	0.018	0.022
RDRRTB2.0	Relative death rate of roots (DVS=2.0)	kg·(kg·d) ⁻¹	0.018	0.022
RDRSTB1.5	Relative death rate of stems (DVS=1.5001)	kg·(kg·d) ⁻¹	0.018	0.022
RDRSTB2.0	Relative death rate of stems (DVS=2.0)	kg·(kg·d) ⁻¹	0.018	0.022
RDI	Initial rooting depth	cm	9	11
RRI	Maximum daily increase in rooting depth	cm·d ⁻¹	1.08	1.32
RDMCR	Maximum rooting depth	cm	112.5	137.5

Note: DVS denotes the phenological development stage; T denotes the temperature

biomass were consistent across the four regions. For yield (Fig. 3a), the parameter efficiency of conversion into storage organ (CVO), maximum assimilation rate (AMAXTB1.3), and light-use efficiency (EFFTB40) were the main sensitive

parameters. Among them, the effect of the efficiency of conversion into storage organ (CVO) was extremely significant in each region, and the parameter sensitivity indices all exceeded 0.4. The effect of light-use efficiency (EFFTB40)

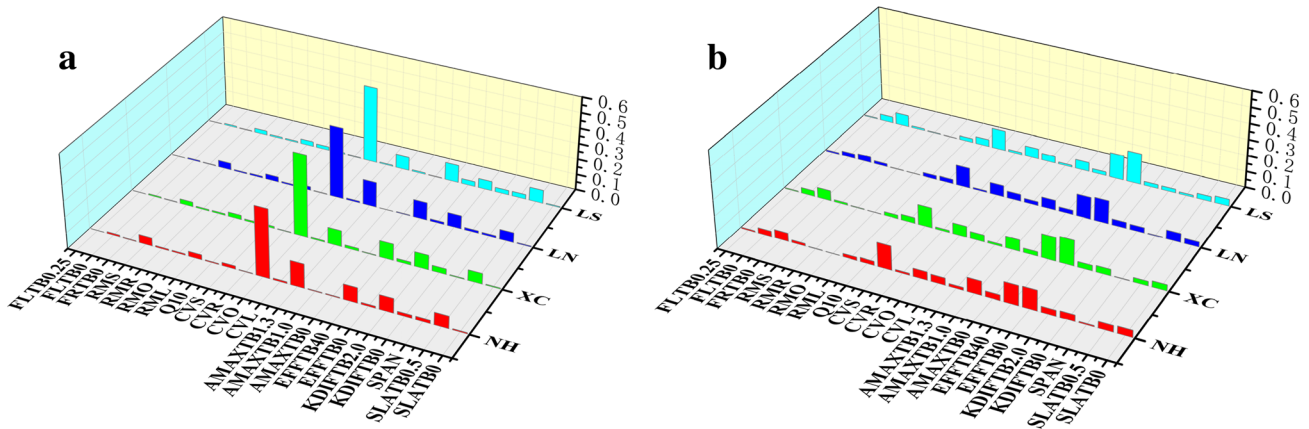


Fig. 3 Total sensitivity index of parameters under optimal water supply conditions: **a** yield; **b** aboveground biomass. Parameters whose sensitivity index to yield and biomass was less than 0.01 are not shown in the figure

was slightly lower in NH with a sensitivity index 0.098, and the sensitivity index of maximum assimilation rate (AMAXTB1.3) in LS was 0.087. Additionally, the parameter sensitivity of extinction coefficient (KDIFTB2.0) and specific leaf area (SLATB0.5) was also sensitive in the four regions. The sensitivity indices ranged between 0.06 and 0.10.

For aboveground biomass (Fig. 3b), the main sensitive parameters were light-use efficiency (EFFTb0, EFFTb40) and efficiency of conversion into stems (CVS) in the four regions, but the parameter ranking of the four regions differed. There was CVS > EFFTb0 > EFFTb40 in NH. The other three areas were EFFTb0 > EFFTb40 > CVS. There were also some parameters, including extinction coefficient and assimilation rate (KDIFTB0, KDIFTB2.0, AMAXTB0, AMAXTB1.0), specific leaf area (SLATB0, SLATB0.5), efficiency of conversion into leaves and storage organ (CVL,

CV), root and leaf dry matter distribution (FRTB0, FLTB0), and relative increase in respiration rate per 10 °C temperature increase and relative maintenance respiration rate of the leaves (Q10, RML), which had some effects on the results, and the sensitivity indices were between 0.02 and 0.09. Other parameters had little or no influence on the results.

Sensitivity Analysis Under Water-limited Production Scenarios

The results of the global sensitivity analysis based on yield and aboveground biomass under water-limited conditions are depicted in Fig. 4. The sensitive parameters were quite different in the four regions. Compared with the sensitivity analysis results of yield under optimal water supply conditions, the efficiency of conversion into storage organ (CVO) and light-use efficiency (EFFTb40) remained the sensitive

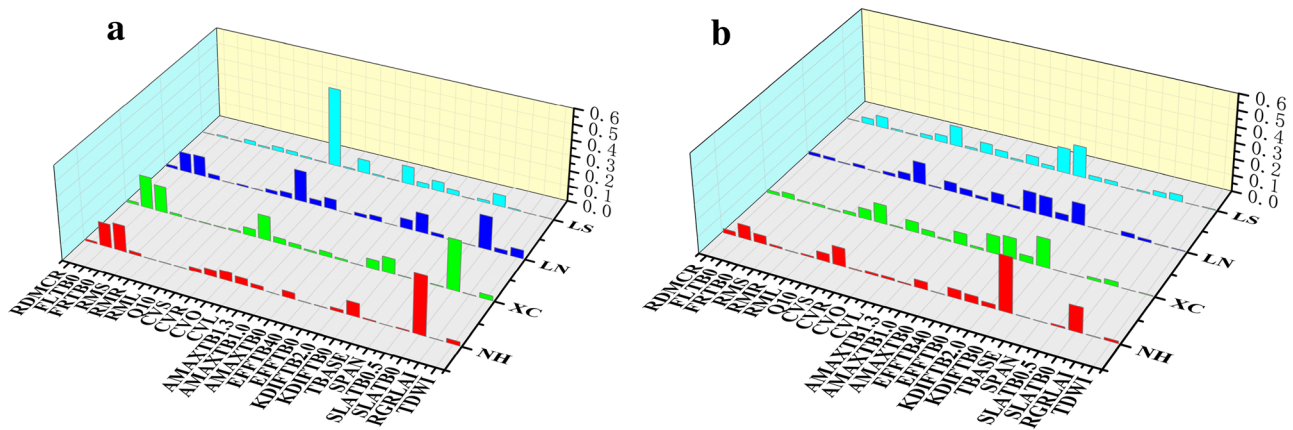


Fig. 4 The total sensitivity index of parameters under water-limited production scenarios. **a** yield; **b** aboveground biomass. Parameters whose sensitivity index to yield and biomass was less than 0.01 are not shown in the figure

parameters in LS, whereas efficiency of conversion into storage organ (CVO), light-use efficiency (EFFTB40), and maximum assimilation rate (AMAXTB1.3) decreased to different degrees in LN, XC, and NH. Furthermore, specific leaf area (SLATB0) and root and leaf dry matter distribution (FRTB0, FLTB0) became sensitive parameters in LN, XC, and NH. In addition, the parameters of extinction coefficient (KDIFTB0) in LN, XC, and NH were also sensitive, with sensitivity indices ranging between 0.09 and 0.13.

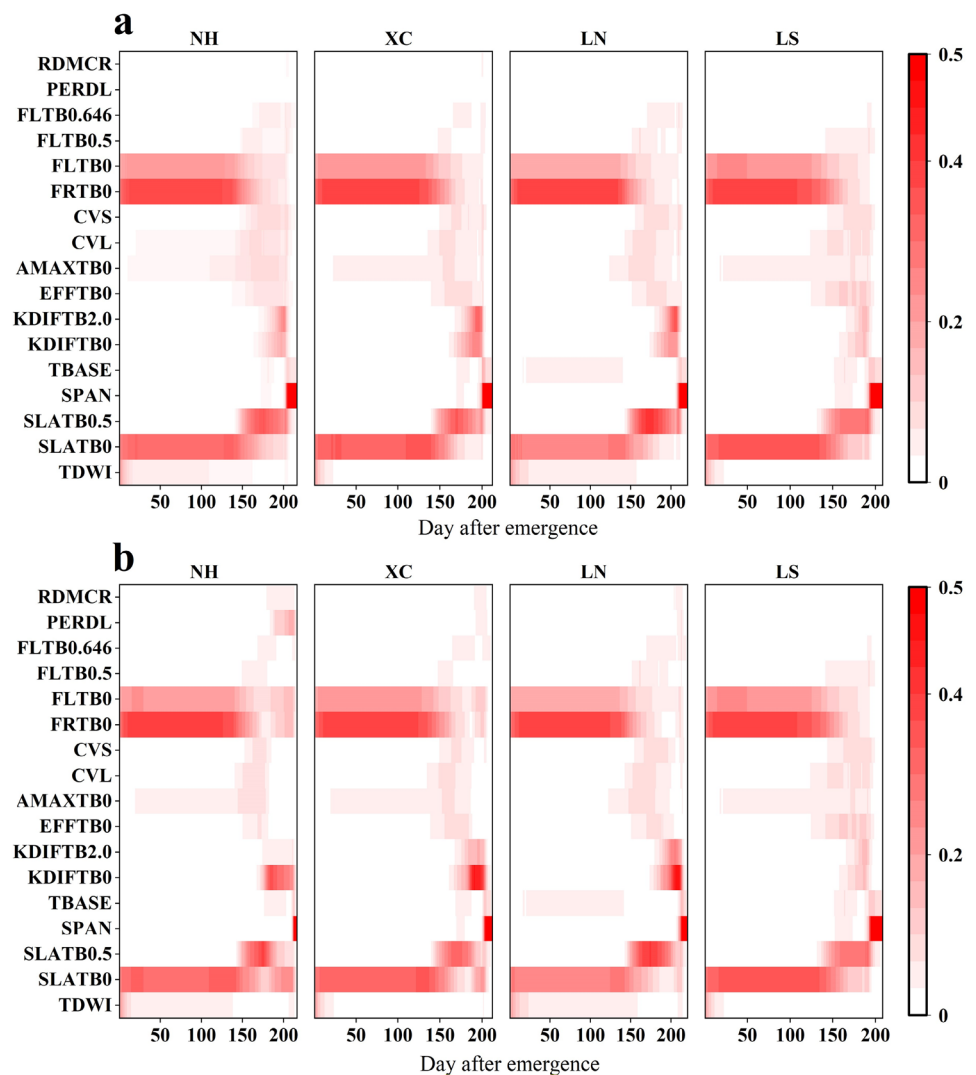
The sensitive parameters concerning aboveground biomass were also different from those under optimal water supply conditions (Fig. 4b). Aboveground biomass had similar sensitive parameters in LS, LN, and XC, and the sensitivity indices of light-use efficiency (EFFTB0, EFFTB40) and efficiency of conversion into stems CVS were all greater than 0.1. The difference in these three regions was that the sensitivity indices of extinction coefficient (KDIFTB0) were 0.18, 0.13, and 0.02 in XC, LN, and LS, respectively. The sensitive parameters of NH were quite different from the

other regions. Extinction coefficient (KDIFTB0), specific leaf area (SLATB0), and efficiency of conversion into stems (CVS) were the sensitive parameters. Among them, extinction coefficient (KDIFTB0) had the largest effect, with a sensitivity index of 0.33. Compared with optimal water supply conditions, the sensitivity indices of light-use efficiency (EFFTB0, EFFTB40) dropped below 0.1.

Sensitivity Analysis of LAI During the Entire Growth Period

The WOFOST model is a dynamic model that is simulated according to a one-day step size. It is continuous in the time series. Therefore, it is necessary to analyze the parameter sensitivity of the process variables. The effects of the parameter on LAI were assessed (Fig. 5). The results demonstrated that the sensitive parameters of LAI differed in the different growth stages. Under optimal water supply conditions, from emergence to 150 days after emergence (DAE), the wheat

Fig. 5 The total sensitivity index of the parameters of the LAI during the entire growth period: **a** Optimal water supply conditions; **b** Water-limited production scenarios. The parameters whose sensitivity index was less than 0.05 are not shown in the figure



plants had been experiencing emergence to overwintering. In this stage, the main sensitive parameters were specific leaf area (SLATB0) and root and leaf dry matter distribution (FRTB0, FLTB0) in the four regions. Only in LN did the lower threshold temperature for aging of leaves (TBASE) have a higher sensitivity than the others. From overwintering to about 200 DAE, the specific leaf area (SLATB0.5) was the most sensitive parameter, and the highest sensitivity indices were all above 0.28 in the four regions. The effects of extinction coefficient (KDIFTB0 and KDIFTB2.0) showed high sensitivity when the leaf area began to decrease (about 180 DAE). Additionally, the sensitivity of extinction coefficient (KDIFTB0 and KDIFTB2.0) was lower in LS than in the others. In the 10 days before wheat maturity, the life span of leaves (SPAN) was the most important parameter affecting LAI, and the highest sensitivity indices were all above 0.89 in the four regions. Under water-limited conditions, the sensitive parameters did not change much in LS. However, in LN, XC, and NH, the influence of extinction coefficient (KDIFTB0) increased, while the influence of extinction coefficient (KDIFTB2.0) weakened. Furthermore, the impact time of the life span of leaves (SPAN) was also shorter. Compared with optimal water supply conditions, the sensitivities of maximum relative death rate of leaves due to water stress (PERDL) and maximum rooting depth (RDMCR) were increased in LN, XC, and NH, although their effects were still very low.

Model Calibration for Aboveground Biomass and Yield

Based on the sensitivity analysis results, the yield and biomass of the four sites were calibrated using the SUBPLEX algorithm (Fig. 6). It must be noted that in LN there was no irrigation; hence, the parameters concerning early light interception [e.g., extinction coefficient (KDIFTB0), specific leaf area (SLATB0), and leaf and root allocation coefficient (FLTB0, FRTB0)] were given priority. At other sites, yield and aboveground biomass were used to construct cost functions to optimize parameter dry matter conversion efficiency (CVO, CVS), light-use efficiency (EFFTB0, EFFTB40), maximum assimilation rate (AMAXTB1.0, AMAXTB1.3), and extinction coefficient (KDIFTB2.0); and the specific leaf area (SLATB0, SLATB0.5), leaf and root allocation coefficient (FLTB0, FRTB0), extinction coefficient (KDIFTB0, KDIFTB2.0), and the life span of leaves (SPAN) were used to calibrate LAI. The results showed that the aboveground biomass and yield were well simulated. The calibrated biomass R^2 ranged between 0.97 and 0.99, the RMSE was between 0.72 and 1.06 ton/ha, and the absolute error of the yield was 0.01 ton/ha, 0.09 ton/ha, 0.48 ton/ha, and 0.16 ton/ha in NH, XC, LN, and LS, respectively.

Discussion

This research improves the applicability of the WOFOST model at the regional scale through sensitivity analysis under different meteorological and water supply conditions. In the case of sufficient water supply, the sensitive parameters of the model included parameters related to assimilation and dry matter conversion efficiency, which is consistent with the findings of Wang and Ma on WOFOST (Ma et al., 2013; Wang et al., 2013). The sensitive parameters were the same among different regions, though their rankings differed. Liu et al. (2019) reported similar findings in rice. Under water-limited conditions, the sensitivity results varied greatly among the different regions.

Under optimal water supply, the sensitivity of maximum leaf assimilation rate (AMAXTB) and extinction coefficient (KDIFTB2.0) in NH with strong radiation was higher than that in LS with low radiation. This is mainly because the WOFOST model divides the canopy into different leaf layers to calculate the assimilation rate of each layer (Boogaard et al., 2014). Therefore, when the radiation is strong, the upper leaves can easily reach the maximum assimilation rate, thereby reducing the use efficiency of light energy. At the post-growth stage of wheat, a reasonable extinction coefficient can increase the transmittance of the upper leaves, improve the radiation received by the lower leaves, and improve the use efficiency of light energy. The extinction coefficient can be affected by leaf angle (Wang et al., 2007) and row spacing (Flénet et al., 1996), but the effect of leaf angle and row spacing on the extinction coefficient is not considered in the WOFOST model (Boogaard et al., 2014). Therefore, it is essential to calibrate the extinction coefficient in model application.

Compared with optimal water supply, the results of the sensitivity analysis under water-limited conditions were inconsistent across the different regions, and the degree of variation in parameter sensitivity was especially greater under water-stressed conditions. The parameters relating to early light interception, such as specific leaf area (SLATB0), root and leaf dry matter partition coefficient (FRTB0, FLTB0), and extinction coefficient (KDIFTB0), had a great influence on the model output under water stress. This result is in line with the findings of Gilardelli et al. (2018). and Richter et al. (2010). Transpiration is the loss of water from a plant to the atmosphere. A crop reacts to water stress with closure of the stomata. As a consequence, the gas exchange between the crop and the atmosphere diminishes, and hence assimilation is reduced (Boogaard et al., 2014). Our results demonstrated that water stress reduces the sensitivity of assimilation-related parameters. Light interception depends on the leaf area and extinction coefficient, which leads to the extinction

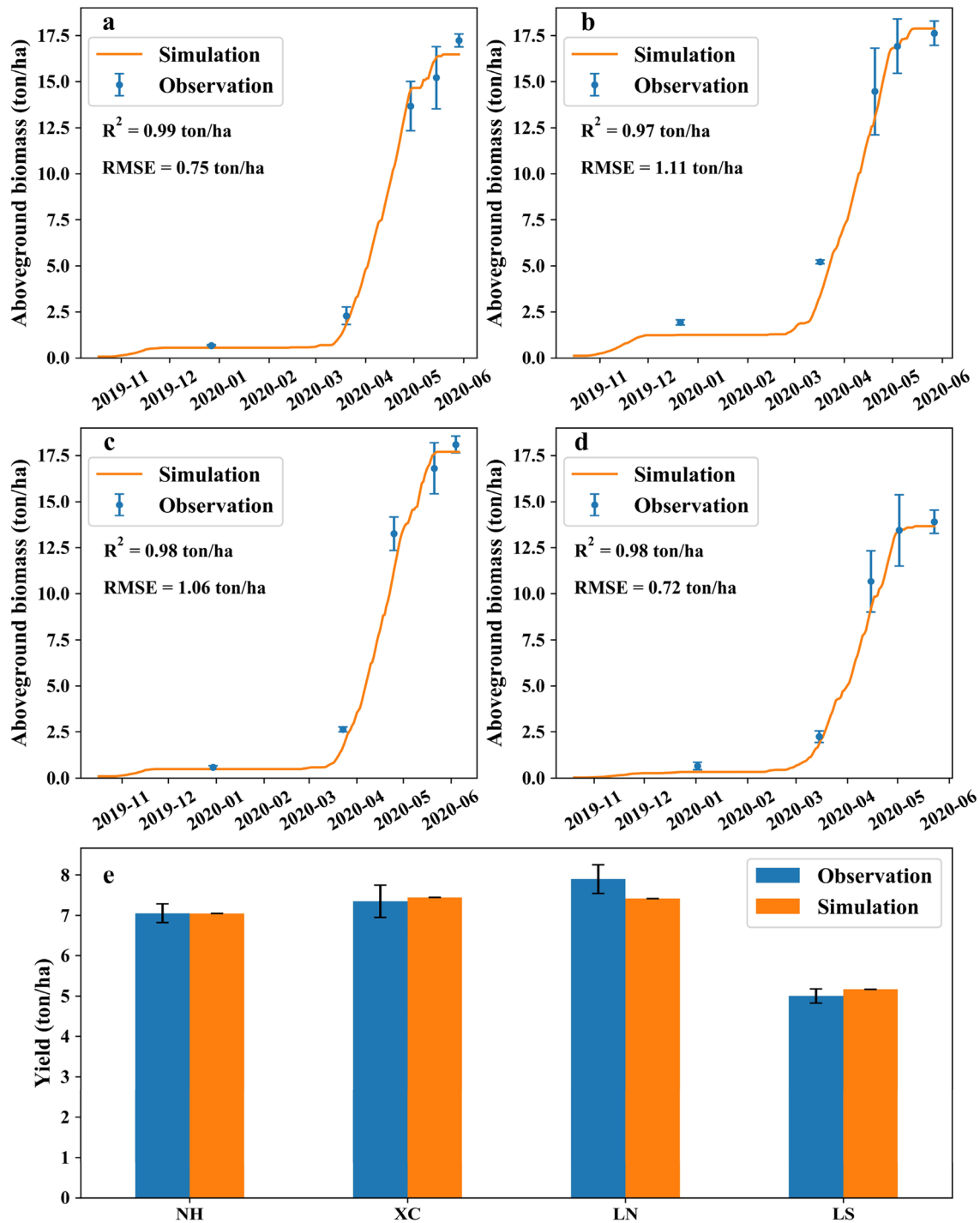


Fig. 6 Relationships between simulated and the measured values based on the calibrated model results: **a** aboveground biomass at NH site, **b** aboveground biomass at XC site, **c** aboveground biomass at LN site, **d** aboveground biomass at LS site, **e** yield at the four sites

coefficient (KDIFTB0) and parameters concerning leaf expansion becoming important factors affecting water consumption. Therefore, when the model is applied and calibrated in water-deficient areas, parameters involved in

early light interception (extinction coefficient, KDIFTB0) and specific leaf area (SLATB0, etc.) should be prioritized.

The sensitive parameters of LAI changed in the different growth stages, and thus the temporal characteristics

of parameter sensitivity are very important for model calibration. Process variables such as LAI are often used as intermediate variables for the assimilation of crop growth models and remote sensing data (Huang et al., 2019; Jin et al., 2016; Ma et al., 2013). Sensitivity analysis can increase the understanding of model process variables (Li et al., 2019a, 2019b; Specka et al., 2019). Under water stress, the extinction coefficient in the early stage (KDIFTB0), death rate of leaves due to water stress (PERDL), and maximum rooting depth (RDMCR) become more sensitive to LAI. The extinction coefficient (KDIFTB) is not only related to transpiration and assimilation but also related to the self-shading death of leaves (de Wit et al., 2019). Therefore, when calibrating LAI, the characteristics of sensitivity parameters at different growth stages should be considered in the selection of calibration parameters.

This study analyzed the differences in parameter sensitivity under water stress and provided a useful reference for WOFOST calibration. When calibrating the model, the phenology must first be calibrated. Second, the water supply situation should be analyzed based on the meteorological and production conditions. Third, calibration parameters should be selected based on water supply: when water is sufficient, dry matter conversion efficiency (CVO, CVS), light-use efficiency (EFFTB0, EFFTB40), maximum assimilation rate (AMAXTB1.0, AMAXTB1.3), and extinction coefficient (KDIFTB2.0) have a great influence on yield and aboveground biomass. The specific leaf area (SLATB0, SLATB0.5), leaf and root allocation coefficient (FLTB0, FRTB0), extinction coefficient (KDIFTB0, KDIFTB2.0), and the life span of leaves (SPAN) are sensitive to LAI. When water is deficient, priority should be given to parameters concerning early light interception, such as extinction coefficient (KDIFTB0), specific leaf area (SLATB0), and leaf and root allocation coefficient (FLTB0, FRTB0), following which it should be determined whether to consider parameters related to assimilation and matter conversion efficiency, as these parameters may result in assimilation-related parameters with small effects on the model results. This also illustrates that reasonably early light interception might reduce water stress. For example, in LN with low precipitation and no irrigation, due to the low water consumption in the early stage (due to the low biomass and LAI in the early stage), a high yield was ultimately achieved. Measures that adjust the sowing density (Li et al., 2019a, 2019b) and sowing date (Frieler et al., 2017) have also been used to adjust the early growth of wheat to reduce water stress and improve water use efficiency. Finally, the cost function of the observed value should be calculated and simulated to calibrate LAI, aboveground biomass, and yield.

Conclusion

This study integrated different environmental conditions and water supply conditions to analyze the sensitivity characteristics of the yield, aboveground biomass, and LAI of the 43 parameters of the WOFOST model. The results illustrated that for yield and aboveground biomass, the influential parameters under optimal water supply were consistent across the different environments, but changed dramatically under water-limited conditions. The parameters related to early light interception [e.g., specific leaf area (SLATB0), fraction of dry matter to leaves (FLTB0), fraction of dry matter to roots (FRTB0), and extinction coefficient (KDIFTB0)] had a strong influence on parameter sensitivity under water stress. For LAI, the sensitivity of parameters varied over the wheat growing season, and these changes were closely correlated with wheat growth stage. The sensitivity of parameters [extinction coefficient (KDIFTB0), death rate of leaves due to water stress (PERDL), and maximum rooting depth (RDMCR)] increased with increased water stress. Finally, the yield was calibrated based on the sensitivity results, and a calibration strategy of the WOFOST model under different moisture conditions was proposed.

The improvements offered by this study were as follows: (i) analyze the parameter sensitivity of the WOFOST model under different agro-meteorological and water supply conditions (ii) determine the sensitive parameters of the model to water stress in WOFOST, and (iii) propose model calibration strategies under different water supplies.

The purpose of this study was to reduce the complexity of model use and provide guidance for model calibration. The results illustrated that water stress is a key factor affecting the sensitivity of WOFOST model parameters under different meteorological conditions. Therefore, when calibrating WOFOST, the water supply situation should be considered first, particularly water-deficient conditions, to better calibrate the WOFOST crop model. In the future, research should combine geographic information systems, remote sensing, big data, and other information technologies to strengthen the analysis of meteorological and production conditions, improve the adaptability of the model, and promote the application of the model on a regional scale.

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Availability of data and materials The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

Declaration

Competing interests The authors declare that they have no competing interests.

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