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RESEARCH ARTICLE

Estimation of summer maize biomass based on a crop growth model

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ABSTRACT

The challenge in the field of agricultural remote sensing monitoring has always been how to use crop growth models to quantitatively analyze the dynamic changes of regional summer maize biomass (referring to aboveground biomass weight, AGBW). In this study, we constructed a summer maize biomass process simulation model (SM_{SMBP}) to analyze AGBW and its change characteristics at different growth stages of field summer maize in Jianghuai regional along the east coast of China. First, the initial biomass simulation model was used to estimate AGBW of summer maize from the seedling emergence to the jointing stage, from the jointing to the tasseling stage, and from the tasseling to the grain filling stage. Then, the biomass simulation model parameters were adjusted based on measured leaf area index and AGBW data at the jointing stage of summer maize. Finally, the adjusted model was used to estimate AGBW from jointing to tasseling and from tasseling to filling. The results showed that the relative errors of the predicted and measured values of summer maize AGBW from seedling emergence to before jointing, during the early stage of jointing, before tasseling, and during the grain filling stage were 3.35%, 11.56%, 23.26%, and 15.83%, respectively. For the adjusted model, the root mean square error (RMSE) between the predicted and the measured values before tasseling was 219.43 kg/hm^2 and the relative error was 4.18%, and the relative error between the predicted and the measured values during the grain filling stage was 3.44%. Adjusting the model parameters using data from the maize jointing stage improved the prediction from jointing to tasseling and from tasseling to grain filling. This study provides a reference for the prediction of AGBW and its dynamic changes in different growth stages of summer maize, and could assist agricultural management department to adjust production measures.

Keywords: Biomass; Estimation; Planting areas along the east coast of China; Process simulation model; Summer maize

INTRODUCTION

Crop process simulation models (also known as the crop growth simulation model) are dynamic mathematical models established by combining crop, environmental, and cultivation measurement as a whole. They apply the principles and methods of system analysis to comprehensively summarize and quantify the developmental processes of crop phenology, photosynthetic production, organ formation, yield, and quality formation and their relationships with climate. Many such models has been developed, including crop–environment–resources synthetic system (CERES; United States) (Ma et al., 2017), the ORYZA model (Netherlands) (Larijani et al., 2011), the O'Lerry model (Australia) (O'Lerry et al., 1985), a simulation model for rice–weather (SIMRIW; Japan) (Zhang and Tao, 2012), the rice cultivation simulation optimization decision–making system (RCSODS; China) (Gao et al., 1992), and the WheatGrow model (China) (Zhang et al., 2016). The formation of crop process simulation models is conducive to a quantitative understanding of crop growth dynamics. Crop process simulation models can be used to predict crop stage development, dry matter accumulation, and grain yield under different weather, soil, and cultivation conditions (Qi et al., 1994; Zhou et al., 2019; Li, 2013).

When the climatic environmental conditions and cultivation measures are ideal for crop growth, the prediction accuracy of crop process simulation models is higher; however, crops are often affected by uncertain factors such as climate, environment, or production management measures during the field growth process, which results in a large deviations in the predicted values from the crop process simulation models. In recent years, in order to achieve the effective and accurate application of the models, some scholars have adjusted the parameters of crop process

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simulation models to reduce the prediction error by using some easily obtained model operating variable data (such as leaf area index [LAI]). For example, Ma et al. (2013) assimilated LAI data from the moderate-resolution imaging spectral-radiometer (MODIS) into the World Food Study (WOFOST) crop process model, and reduced the estimation error of winter wheat yield by optimizing the model parameters for seedling emergence, initial AGBW, and soil moisture content. Machwitz et al. (2014) combined the crop process model APSIM (Australia) with the radiation transfer model PROSAIL and effectively estimated maize AGBW by adjusting model parameters (seedling emergence period, initial AGBW, and initial soil moisture). Cheng et al. (2016) assimilated the time series HJ-1 A/B data into the WOFOST model to optimize the LAI model and its parameters, which improved the estimation accuracy of spring maize yield. Ren et al. (2011) used LAI as the combination point to integrate the shuffled complex evolution-University of Arizona (SCE-UA) global optimization algorithm into the environmental policy integrated climate (EPIC) model, and achieved an accurate estimation of regional maize yield per unit area by adjusting the sowing date, planting density, nitrogen fertilizer application, and other parameters. It can be seen that the effective application of crop process simulation models requires regional adjustment or optimization of model operating parameters (also called parameter regionalization). Therefore, some assimilation methods of model and quantitative characteristics of change in crop AGBW need to be studied in depth (Nearing et al., 2012; Huang et al., 2016; Xie et al., 2016; Li et al., 2011).

We previously investigated the feasibility of combining crop growth models with remote sensing inversion information to estimate winter wheat AGBW in Jianghuai region of China during critical growth periods. However, there are still limitations in using crop growth models to quantitatively estimate the dynamic changes in summer maize AGBW (Zhuang et al., 2013; Yin et al., 2018; Wang, 2018). In this study, Yancheng City, Jiangsu Province, located on the coast of the East China Sea, was selected as the study area and summer maize was selected as the research object. Based on the physiological and ecological process of summer maize, we aimed to construct a simulation model of summer maize AGBW formation process. Based on the analysis of AGBW and its variation characteristics at multiple growth stages of summer maize, the feasibility of using measured LAI and AGBW data to adjust the parameters of the biomass simulation model were discussed. We aimed to provide a basis for the next step in the use of remote sensing inversion data to assimilate crop process simulation models, which is convenient for assisting county-level agricultural management departments to adjust farming and planting practices to increas production and efficiency.

MATERIALS AND METHODS

Research area and data survey

Yancheng City, Jiangsu Province, along the coast of the East China Sea was selected as the research area (120°13'–120°56' E and 32°56'–33°36' N; Fig. 1). It is located in a silt plain, with an altitude of 1.9–4.5 m. The terrain is higher in the east and lower in the west; higher in the south and lower in the north; and is located in the transitional area of the subtropical and warm-humid zone. The four seasons are distinct, the annual average temperature is 14.1 °C; and the average annual precipitation is 1042.2 mm; and the annual average sunshine is more than 2238.9 h. The regional climate and soil is suitable for crop growth, and the agricultural production conditions are excellent. The land-use types in Yancheng City are mainly dry land, paddy fields, rivers, lakes, woodlands, construction land, and coastal wetlands.

In 2016, 14 field maize study sites (all the following maize in this article refers to summer maize) were established in Yancheng City using a GPS instrument (Trimble, USA). The distance between each study site was approximately 2 km. The maize varieties were Ningyu 16 and Jinhai 5 (experimental data presented are mixed data of the two varieties). The LAI and AGBW were observed, measured, and sampled every two days during maize growth. The dates of emergence, jointing, tasseling and filling were recorded in the growth period view. The LAI was measured with a Sun Scan (Delta-t, England). Each study site was measured using the plum diagonal method, and the average value was calculated after five measurements. The AGBW of the study sites was collected according to the 5-point plum blossom

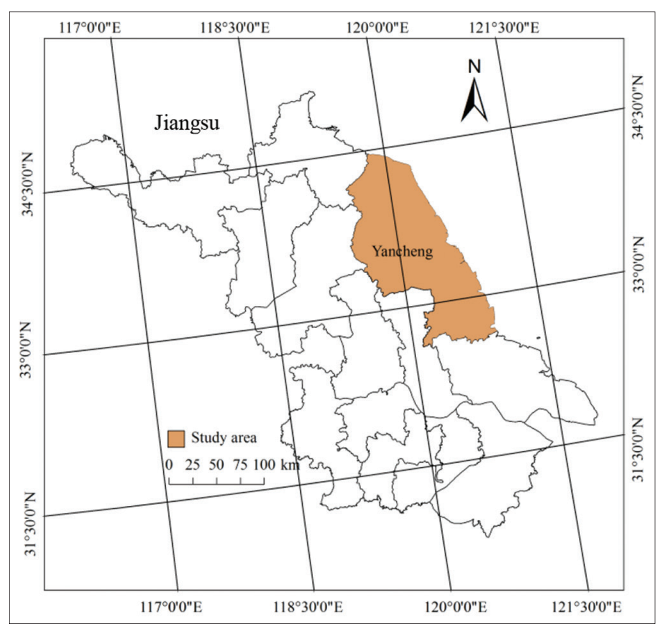

Fig 1. Location of Yancheng city in Jiangsu province of China

method. Five above-ground plants were harvested and placed in the sample bag, put in an indoor oven at 105 °C for 20 min, further dried at 75 °C, and then weighed. The specific calculation method is described by Li et al. (2009) and Li et al. (2020). Meteorological data (including total daily solar radiation, daily maximum temperature, daily minimum temperature, and daily average temperature) were provided by the local meteorological department, and technicians from the district agricultural department assisted in the experiment. The measured LAI and AGBW data were used for model parameter adjustment, verification and comparison.

Construction of the biomass simulation model

The total amount of organic matter produced after photosynthesis is called biomass, including the roots, stems, leaves, and ears. Biomass can be divided into two types: aboveground part (stems, leaves, and ears) and the belowground part (root). In this study, only the AGBW of maize was studied by combining the biomass simulation algorithm in the crop yield estimation model with Li et al. (2011) to construct a simulation model of the biomass formation process of summer maize. The model is called the simulation model of biomass process of summer maize (SM_{SMBP}). During the growth of maize, AGBW can be obtained using the following equation:

$$\mathrm{AGBW}_i = \sum_{k=1}^{k=i} \Delta\mathrm{AGBW}_i \,, \tag{1}$$

where AGBW_i represents the total accumulation of dry matter above the ground (kg/hm^2) for the ith day, $\Delta\mathrm{AGBW}_i$ is the increase of dry matter above the ground of the maize plant on the ith day (kg/(hm^2·d)), and k represents the number of days from seedling emergence to grain filling. $\Delta\mathrm{AGBW}_i$ is calculated using the following equation:

$$\Delta\mathrm{AGBW}_i = \Delta\mathrm{DPAW}_i - \mathrm{RG}_i - \mathrm{RM}_i \,, \tag{2}$$

where $\Delta\mathrm{DPAW}_i$ is the daily plant assimilation weight kg/(hm^2·d), which represents the total amount of organic matter produced by photosynthesis of maize plants on the ith day; and RG_i is the daily growth wasting weight (kg/(hm^2·d)), which represents the consumption of organic matter by the growth and respiration of maize plants on the ith day; and RM_i is the daily maintaining wasting weight (kg/(hm^2·d)), which represents the consumption of organic matter by the maize plant to maintain respiration on the ith day. RG_i and RM_i can be calculated using the following equations:

$$\mathrm{RG}_i = Gr\cdot\, \Delta\mathrm{DPAW}_i \text{ and} \tag{3}$$

$$\mathrm{RM}_i = Mr\cdot Q10^{\frac{Tem-25}{10}} \cdot \mathrm{AGBW}_i \,, \tag{4}$$

where G_r is the maize growth respiration coefficient, M_r is the maintenance respiration coefficient, $Q10$ is the temperature coefficient of respiration, and Tem is the daily average temperature (°C). G_r, M_r, and $Q10$ are model parameters.

The process by which plants form organic matter and store energy through photosynthesis is called photosynthetic assimilation. Visible light that can be used by plants for photosynthesis accounts for 47% to 48% of the total solar radiation (average 47.5%) (Yin et al., 2018), and solar radiation is partly lost due to the reflection of the plant canopy. Therefore, the effective daily use of solar radiation by the plant is described by the daily photosynthetic active radiation (DPAR, MJ/m^2) using the following equation:

$$\mathrm{DPAR}_i = \mu\cdot\mathrm{DR}_i\cdot(1-\alpha)\,, \tag{5}$$

where μ is the ratio of the visible light radiation to the total solar radiation, with a value of 0.475 (47.5%). DR_i is the total daily solar radiation per unit area (MJ/m^2); and α is the population reflectivity of summer maize (model parameter).

$\Delta\mathrm{DPAW}_i$ is the daily plant assimilation weight, which is calculated using the core algorithm of Gao et al. (1992).

$$\Delta\mathrm{DPAW}_i = \frac{B}{K\cdot A}\cdot\mathrm{Ln}\left(\frac{1+D}{1+D\cdot\mathrm{Exp}\left(-K\cdot LAIi\right)}\right) \text{ and } \cdot\mathrm{DL}\cdot\delta\cdot\min(\mathrm{FN},\mathrm{FW}) \tag{6}$$

$$D = A\cdot\frac{\mathrm{DPAR}_i}{\mathrm{DL}}\,, \tag{7}$$

where K is the population extinction coefficient (model parameter), LAI_i is the leaf area index, and δ is the conversion coefficient between CH_2O and CO_2, with a value of 0.68 (Gao et al., 1992). B and A are model parameters (or coefficients). FN and FW are the nitrogen influencing factor and moisture influencing factor, respectively. Specific calculation methods and steps are described in the literature (Wang, 2018; Guo et al., 2012). DL is the day length and β is the solar declination, which can be calculated using the following equations:

$$\mathrm{DL}=2\bullet\alpha\cos[-(\tan\varphi)\bullet\tan\beta]/15 \text{ and} \tag{8}$$

$$\beta=23.5\bullet\sin\,[360\bullet(n+284)/365], \tag{9}$$

where φ is the geographical latitude, and n is the Confucian calendar day (n=1, 2, 3, ···, 365).

Model parameter adjustment

The initial parameters of the model are difficult to obtain when the model is initially run, so the experience model parameter values refer to the rice–wheat model literature (Gao et al.,1992; Li et al.,2011; Yin et al.,2018) of the research team, namely, the growth respiration coefficient (G_r=0.35) and the maintenance respiration coefficient (M_r= 0.019), temperature coefficient of respiration (Q10=2), population extinction coefficient (K=0.68), population reflectivity (α=8%), model parameter (B=21) and model parameter (A=4.9). Due to the abundance of fertilizer and water in each test site, it can better meet the growth of maize seedlings, so the initial FN and FW values of the model operation were both set to 1.

The AGBW and LAI were the two main growth variables in the maize biomass simulation model. In this study, the measured AGBW and LAI data at the jointing stage of maize were selected, and the least squares method was used to adjust the simulation model parameters. When the relative error (RE) between the model prediction data and the measured data was between −5% and 5%, the output model parameters were the adjusted model parameters. The model parameters (or model variables) adjusted at the jointing stage included the initial LAI (LAI_1) at seedling emergence, G_r, M_r, Q10, K, α, B, A, FN, and FW.

Model accuracy test

The relative error (%), root mean square error (RMSE), and coefficient of determination (R^2) were used as evaluation indicators for model calibration and accuracy verification. RMSE represents the fitting accuracy of the predicted and the measured values, and the smaller the value, the better the fitting accuracy. The model was calibrated using the measured AGBW and LAI data at the jointing stage, and the accuracy of the AGBW change estimation was verified using the measured AGBW data from germination to grain filling.

RESULTS

Changes of maize AGBW from seedling emergence to jointing

Meteorological data (daily solar radiation, daily maximum temperature, daily minimum temperature, and daily average temperature) from maize emergence to jointing stage and the initial parameters of the model were input into the maize biomass simulation model to predict maize AGBW, and got the predicted data of maize AGBW from seedling emergence to jointing, as shown in Fig. 2. The dynamic change curve in Fig. 2a is the predicted data (average value, the same below) of maize AGBW at 14 study sites. We found that the accumulation of maize AGBW at this stage was a dynamic accumulation process.

The overall AGBW of maize showed an upward trend from the seedling emergence to the jointing stage in Fig. 2a. For the first 7 days (seedling emergence to the threeleaf stage), maize was in the weaning period, most plant nutrients come from seeds; therefore, the AGBW growth was slow. Assuming that the increase of maize AGBW from the seedling emergence to the three-leaf stage was a uniform linear growth process, the daily AGBW increase (or the daily change of AGBW) of maize could be estimated using the ratio of the increase of maize AGBW from the seedling emergence to the three-leaf stage to the number of days required from the seedling emergence to the three-leaf stage, that is, the daily average growth rate of maize during this period was 2.46 kg/(hm^2·d), which was relatively low. Soil moisture during the weaning period of maize is a key factor affecting seedling emergence.

After the three-leaf period, the maize AGBW began to increase rapidly. From seedling emergence to the jointing stage, maize mainly undergoes a vegetative growth and differentiation of roots, stems, and leaves. In this stage, the growth of aboveground stems and leaves increased slowly, mainly due to the development of the maize root system. Assuming that the growth of maize AGBW from the three-leaf stage to the initial jointing stage was a uniform growth process, the daily AGBW increase of maize could be estimated using the AGBW growth from the three-leaf stage to the jointing stage compared with the number of days required for the three-leaf to the jointing stage, that is, the daily average AGBW growth rate of maize during this period was 38.13 kg/(hm^2·d). The growth rate from the three-leaf stage to the jointing stage of maize was 19 times that from the seedling emergence to the three-leaf stage, and the maize AGBW increased rapidly from the three-leaf stage to the jointing stage. From the three-leaf stage to the jointing stage, maize shifts from relying on the energy and nutrients in the seed to taking up energy and nutrients from the environment, which makes the AGBW increase significantly compared with the seedling emergence to the three-leaf stage. Consequently, suitable water and fertilizer conditions are the premise and necessary for the formation of strong seedlings.

The scattered data in Fig. 2a is the measured AGBW data (the average value of 14 study sites, the same below) of maize from the seedling emergence to the jointing stage (20 days after seedling emergence). From the scattered data in Fig. 2a, it can be seen that after about 7 days of the seedling emergence, the maize reached the three-leaf stage, and the maize AGBW increased slowly. From 7th – 19th d, the maize AGBW started to increase, and there was a basic agreement between the measured data of maize AGBW and the predicted dynamic curve, showing a regular change trend. In the early stage of jointing, the difference between the predicted and measured maize AGBW increased. The measured data were more consistent with the predicted data, the RMSE was 18.31 kg/hm^2, and the relative error

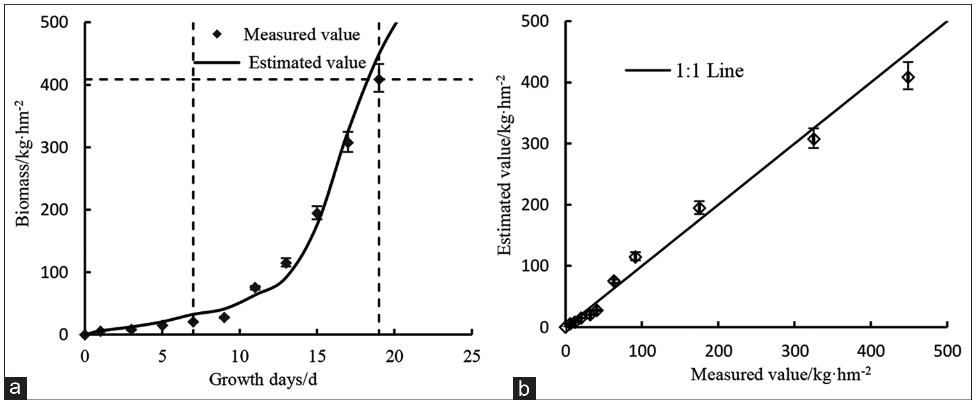

Fig 2. Changes of AGBW from seedling emergence to jointing stage in maize. (a) Dynamic changes of AGBW. (b) Comparison of measured and estimated values

was 3.35%. This shows that the maize biomass simulation model can accurately estimate the AGBW before the jointing stage of maize.

Changes in maize AGBW from the jointing to the tasseling stage and model adjustment

The meteorological data and model parameters from the jointing stage to the tasseling stage (50 d after emergence) were input into the maize biomass simulation model to predict the maize AGBW from the jointing stage to the tasseling stage, and obtained the predicted AGBW data from jointing to tasseling stage, as shown in Fig. 3. Fig. 3a shows the accumulation process of maize AGBW from the jointing stage to the tasseling stage. It can be seen that the maize AGBW showed a rapid upward trend in this period. Within 20–25 d after seedling emergence, the maize was in the early stage of nodal growth, and AGBW accumulated relatively gently. 25-30 d after seedling emergence, maize AGBW increased rapidly. The predicted AGBW of maize at the initial jointing stage was 535.5 kg/hm^2 and that at the tasseling stage was 7036.46 kg/hm^2. Assuming that the increase of maize AGBW from the jointing stage to the tasseling stage was a uniform linear growth process, the growth of daily AGBW could be estimated, that is, the average daily growth rate of the predicted value of maize AGBW from jointing to tasseling was 216.70 kg/(hm^2·d), which was approximately five times higher than the average daily growth rate of maize from seedling emergence to jointing. Maize leaf growth mainly occurs from seedling emergence to the pre-jointing stage. Then, from the jointing stage to the tasseling stage, the stem nodes extend and the number of nodes increases. The mass density of nodes is greater than that of leaves, which leads to a rapid accumulation of AGBW from the jointing stage to the tasseling stage. At this stage of maize, due to the rapid accumulation of AGBW, a large amount of water and nutrients are needed to ensure vigorous growth. Therefore, the early stage of jointing is a critical period of fertilizer and water management. Proper fertilizer and water management are conducive to the development of maize stalks and spikes, which is the premise and necessary to improve the seed setting rate and yield.

It can be seen that the predicted AGBW values of the model were clearly higher than the measured values. The predicted maize AGBW in the early stage of jointing was 535.5 kg/hm^2 and the measured value was 480 kg/hm^2, with a relative error of 11.56%. The predicted maize AGBW at the mid-joint stage was 3799 kg/hm^2 and the measured value was 3082 kg/hm^2, with a relative error of 23.26%. The predicted maize AGBW in the early stage of tasseling was 7036 kg/hm^2 and the measured value was 5794 kg/hm^2, with a relative error of 21.44%. The RMSE between the predicted and measured values from the jointing to the tasseling stage was 825.94 kg/hm^2, which was quite different between the predicted and measured values. The difference between predicted and measured values could be because the maize biomass simulation model was based on the ideal state (using empirical initial parameters), it was different from the actual field growth. Therefore, it was necessary to adjust the model parameters at this stage.

The parameters of the maize biomass simulation model were adjusted using the measured AGBW and LAI data from the jointing stage. LAI_1, G_r, M_r, $Q10$, K, α, B, A, FN, and FW were adjusted to 0.3, 0.35, 0.021, 2, 0.56, 12%, 24.3, 5.1, 0.86, and 0.92, respectively. The maize biomass simulation model after parameters adjustment was re-run to simulate the AGBW from the jointing stage to the tasseling stage, and obtained the predicted maize AGBW, as shown in Fig. 3a. After adjusting the model parameters, the predicted maize AGBW at the beginning of the tasseling stage was 6036 kg/hm^2, which was close to the measured value (5794 kg/hm^2); the relative error was 4.18%; and the RMSE was 219.43 kg/hm^2. From the relationship between

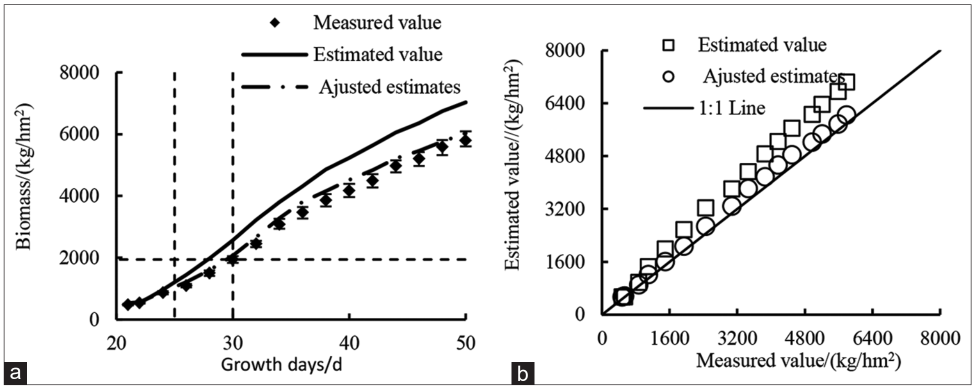

Fig 3. Prediction of AGBW change from jointing to tasseling in maize before and after adjustment of model parameters. (a) Dynamic changes of AGBW. (b) Comparison of measured and estimated values

the predicted and measured values after adjusting model parameters, it can be seen that the predicted values of the adjusted model were more consistent with the measured values, and were evenly distributed on the 1:1 line. The predicted effect was better than that before adjusting the model parameters. This indicated that the parameters of the maize biomass simulation model need to be adjusted in the early stage of tasseling.

Validation of the adjusted model (Changes in maize AGBW from the tasseling to the grain filling)

Both the initial model parameters and adjusted model parameters were used to run the maize biomass model, respectively, and input the meteorological data from the tasseling to the grain filling stage (90 d after seedling emergence), then obtained the predicted AGBW for the growth stage of maize from the tasseling to the grain filling stage (milk maturity), as shown in Fig. 4a. Combining with the AGBW dynamic change curve after adjusting the parameters in Fig. 4a, we could find that maize AGBW accumulation continuously increased after tasseling. From 50–70 d after seedling emergence, the maize AGBW increased relatively rapidly, showing almost a linear growth trend. From 70–90 d after seedling emergence, maize began to enter the grain filling stage. The predicted maize AGBW values from the adjusted model were similar to the measured values after sdjusting the model parameters. The predicted maize AGBW was 6036 kg/hm^2 at tasseling, and that was 10251 kg/hm^2 at the beginning of grain filling. Assuming that the increase of the predicted maize AGBW from the tasseling to the beginning of grain filling was a uniform linear growth process, it can be estimated that the daily increase of the predicted AGBW was 175.63 kg/(hm^2·d) at this stage. Similarly, the predicted maize AGBW at the end of grain filling stage was 11156 kg/hm^2, and the daily change of AGBW during the grain filling stage was 64.64 kg/(hm^2·d), which was 0.3 times higher than the daily increase of AGBW from the jointing to the tasseling stage. From the tasseling to the grain filling stage, vegetative growth ceases and reproductive growth begins; therefore, the maize AGBW accumulation rate slows down than that in the previous period.

A 1:1 linear relationship diagram was made according to the predicted and measured maize AGBW values from the tasseling to the grain filling stage, as shown in Fig. 4b. From Fig. 4b, the dynamic change of the aboveground AGBW accumulation from the adjusted model of maize biomass simulation was consistent with the overall trend of the measured data from the tasseling to the grain filling stage. The R^2 was 0.978 and the RMSE was 182.95 kg/hm^2. The predicted maize AGBW at the early stage of tasseling was 6036 kg/hm^2 and the measured value was 5794 kg/hm^2, with a relative error of 4.18%. The predicted maize AGBW at the grain filling stage was 11156 kg/hm^2 and the measured value was 10785 kg/hm^2, with a relative error of 3.44%. The predicted maize AGBW was 12492 kg/hm^2 before parameters adjustment, with a relative error of 15.83%. The predicted maize AGBW was little difference with the measured maize AGBW after parameters adjustment, which indicated that the prediction effect of the model after parameters adjustment was better.

DISCUSSION

Crop process simulation models have good mechanism, dynamics, and predictability due to the systematic and quantitative expression of crop growth and development process. When the climatic environmental conditions and cultivation measures are suitable (ideal state) for crop growth, the prediction accuracy of the crop process simulation models are higher. When crop grow in not ideal conditions, the prediction data of the crop process simulation models will be greatly biased. In fact, crop growth can be affected by multiple factors, such as climate (e.g. temperature, light, and rainfall), environment (e.g. soil texture, soil moisture), and production management measures (e.g. sowing amount, planting density, and

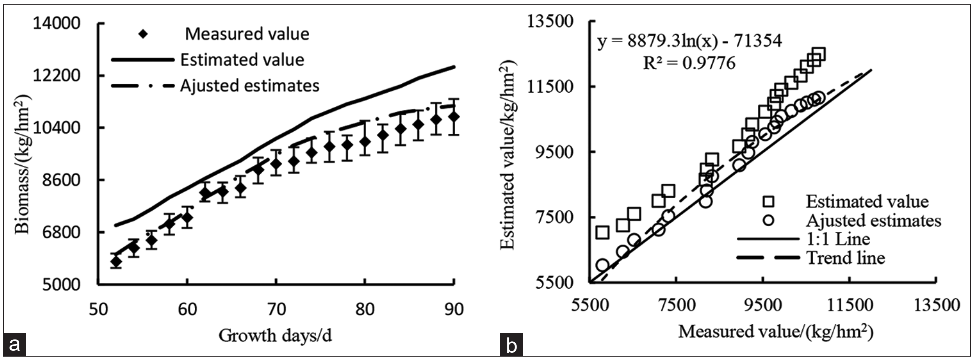

Fig 4. Changes of AGBW from tasseling to grain filling in maize before and after model adjustment. (a) Dynamic changes of AGBW. (b) Comparison of measured and simulated values

fertilization). Therefore, reasonable adjustment of model parameters has become an effective choice for improving the prediction accuracy of crop process simulation models.

Most studies cited foreign models (e.g. CERES model, ORYZA model, WOFOST model) (Ma et al., 2013; Mirima et al., 2014; Li et al., 2011; Yin et al., 2018; Pan et al., 2019; Guo et al., 2012; Ma et al., 2013), and used the LAI as a constraint condition or combination point to adjust the parameters of the crop process simulation models, that is to say, compared predicted LAI from the model with measured LAI, when the two values were similar or met the expected expectations, obtained adjusted model parameters. Used adjusted model parameters could effectively estimation crop AGBW or yield. Before jointing, summer maize maninly grows leaves, LAI changes obviously and is easy to obtain. It is ideal to use LAI as the constraint condition for adjusting the model parameters. After jointing, joint elongation occurs, the number of joints increases, and ear length increases, the growth of LAI slows down, and the increase in AGBW changes obviously. Taking the bivariate LAI and AGBW as the constraints to adjust model parameters at the same time is more conducive to the convergence of the simulation model operation and gets the appropriate model parameters. This study used the experimental data of field summer maize AGBW in Yancheng City, Jiangsu Province along the east coast of China, with the help of Gao Liangzhi's crop photosynthesis core algorithm (Gao et al., 1992), a simulation model of the summer maize biomass formation process was constructed, which was inheritance and redevelopment of the free intellectual property model of the research and development unit of the project. With the aid of the summer maize biomass formation process simulation model, based on the trend analysis of the summer maize AGBW at multiple growth stages, the parameters of the maize biomass model were adjusted by using the bivariate LAI and AGBW at the jointing stage to better achieved the effective estimation of AGBW of two growth stages, from jointing to tasseling stage and from tasseling to grain filling stage, which also provids a reference for subsequent research on the assimilation of remote sensing data and crop models.

The combination of remote sensing data and crop process simulation models to estimate regional crop AGBW or yield is an important issue in agricultural remote sensing research (Li et al., 2020; Guo et al., 2012; Li et al., 2018; Zhi et al., 2014). Maize occupies the second largest crop area in the Jianghuai region of China, after rice and winter wheat. Using remote sensing methods to effectively monitor the growth dynamics of field maize in time is conducive to improving the information level of county production management (Gu et al., 2016; Zhi et al., 2014; Kross et al., 2015; Li et al., 2014). This study used a crop process simulation model to analyze the trend of AGBW change in the three growth stages of summer maize, from seedling emergence to jointing, from jointing to tasseling, and from tasseling to grain filling, and clarified the AGBW accumulation regular and nutrient absorption characteristics in the corresponding growth stages, which can assist county-level agricultural management departments to rationally adjust fertilizer and water management measures, increasing grain production. Subsequent research will further consider using remote sensing data to retrieve LAI and AGBW (Pan et al., 2019; Li et al., 2008), and study the assimilation and application of remote sensing data and crop process simulation model to enhance the universality and effectiveness of maize biomass process simulation model in maize planting district along the east coast of China.

CONCLUSION

We examined summer maize on the coast of the East China Sea. Based on the physiological and ecological processes of maize, a simulation model of the biomass process of summer maize (SM_{SMBP}) was constructed. Based on the simulated and predicted AGBW in three stages of maize, from seedling emergence to jointing, from jointing to tasseling, and from tasseling to the grain filling, we used the concept of daily average growth rate (kg/(hm^2·d)) to quantitatively analyze the characteristics of AGBW accumulation and its dynamic change features in three different growth stages of maize. Using the initial model parameters to run the simulation model of the maize biomass formation process, the predicted effect of AGBW from seedling emergence to jointing was better, but the AGBW prediction errors for the other two growth stages from jointing to tasseling and from tasseling to grain filling were significantly higher than measured data. After adjusting the model parameters using the measured LAI and AGBW at the jointing stage to run the simulation model, the predicted AGBW values were more consistent with the measured data in two growth stages from jointing to tasseling and from tasseling to grain filling. The original predicted AGBW was 7036.46 kg/hm^2, the measured AGBW was 5794 kg/hm^2 before tasseling, with a relative error was 23.26%; and the predicted AGBW was 6036kg/hm^2 after adjusting parameters, with a relative error was 4.18%. The original predicted AGBW was 12492 kg/hm^2, the measured AGBW was 10785 kg/hm^2 during the grain filling stage, with a relative error was 15.83%; and the predicted AGBW was 11156 kg/hm^2 after adjusting parameters, with a relative error was 3.44%. The new model operating parameters were as follows: LAI_1, 0.3; G_r, 0.35; M_r, 0.021; $Q10$, 2; K, 0.56; α, 12%; B, 24.3; and A, 5.1. These parameter values could be conducive to run simulation models of maize biomass formation in similar summer maize study areas.

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Authors' contribution

All the authors participated equally in the design of the experiment, collection and analysis of experimental, writing and reversion of manuscript.

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