The Journal of Animal & Plant Sciences, 28(6): 2018, Page: 1813-1824
ISSN: 1018-7081

IMPROVING THE SIMPLACE MODELLING FRAMEWORK FOR SUNFLOWER SIMULATION UNDER SALT STRESS

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ABSTRACT

Soil salinization is a major environmental challenge for crop growth. To monitoring salt stress in crops and benefit agricultural managements, SIMPLACE Modelling Framework was improved by modifying (i) water stress coefficient (TRANRF); (ii) radiation use efficiency (RUE); (iii) specific leaf area (SLA) and (iv) both RUE and SLA. The improved model was calibrated and validated using two years field trial data of sunflower collected at the Yichang experimental station in Hetao Irrigation District (HTD), Inner Mongolia, China. Sunflowers were planted in six salt affected plots and the salinity levels were denoted as saturated electrical conductivity (EC_e). Crop characteristics included biomass and leaf area index (LAI) were measured several times during the growth period. We firstly obtained the TRANRF, RUE, and SLA for sunflower in potential conditions and then modified the TRANRF and scale factors of RUE and SLA (designated by prefix S to indicate SRUE and SSLA) to fit the measurements respectively. Results indicated that all these modifications could give relative accurate simulations for biomass and LAI but modifying SRUE and SSLA together gave us the most accurate predictions. Meanwhile, the simulation accuracy also varied with target variables, with more accurate biomass simulation by employing biomass as a target variable, and vice versa. In addition, we averaged the SRUE and SSLA results by using biomass and LAI as target variables respectively to balance the simulation accuracy and found that the averaged SRUE and SSLA results could obtain both acceptable biomass (RMSE=56.4-205.3 $g \cdot m^{-2}$) and LAI (RMSE=0.44-1.47) simulations. In addition, SRUE and SSLA had linear relationship with soil salt (EC_e) and natural logarithm of EC_e respectively. Meanwhile, using EC_e of 0-10 cm depth could obtain higher accuracy for both biomass (averaged RMSE=268.6 $g \cdot m^{-2}$ vs 274.9 $g \cdot m^{-2}$) and LAI (averaged RMSE=1.89 vs 1.95) predictions of sunflower than using EC_e of 0-100 cm depth.

Key words: Modelling, radiation use efficiency, salt stress, sunflower, specific leaf area.

INTRODUCTION

Soil salinity is a major environmental constraint to reduce crop, horticulture and forage productivity in arid and semiarid regions(Paul and Lade, 2014; Farooq *et al*., 2015; Zeng *et al*., 2015; Elgallal *et al*., 2016; Zeng *et al*., 2016c; Acosta-Motos *et al*., 2017). Taking Hetao Irrigation District (HTD) in China as an example, there are over 0.43 million hectares soils are suffering from salinization while the total amount of land of HTD are only about 1.16 million hectares (Li *et al*., 2016). Moreover, due to global climate changes and as a consequence of many irrigation practices, the saline soils are still increasing (Rengasamy, 2006; Cong *et al*., 2017). Therefore, the sustainable development of agriculture and increasing crop production in saline soils require a complete and thorough understanding of the crop response to soil salinity and finding out the relationship between crop and some agricultural factors such as moisture content and fertilizer supply under salt stress(Kumar *et al*., 2015; Cong *et al*., 2017). It is well known that field experimental data with different crops under varying soil, water and environmental parameters are important to understand the growth of crop under salt stress (Kitchen *et al*., 1999; Shani and Dudley, 2001). However, long term field experiments to acquire continuous data becomes expensive and a cumbersome activity. In this context, crop simulation models calibrated using the data acquired from short term field experiments and prediction could be an alternative mean for rapid assessment of crop growth under salt stress over a wide range of environmental and management conditions(Flowers, 2004; Kumar *et al*., 2015). A plethora of crop simulation models have been reported in the literatures(Timsina and Humphreys, 2006;

Confalonieri *et al*., 2009; Hammer *et al*., 2010; Lizaso *et al*., 2011; Paredes *et al*., 2015; Casadebaig *et al*., 2016; Confalonieri *et al*., 2016). However, due to the complex mechanisms of crop response under salt stress, few crop models can be applied in saline soils (Jiang *et al*., 2011; Zeng *et al*., 2016a). In these crop models, the effect of salinity on crop yield is defined by a critical salinity level below which no salt stress is assumed to occur, while the increase of salinity could potentially reduce the root water uptake above the critical salinity, which further leads to crop yield reduction. However, a common feature of this method of considering salt stress is the requirement for highly detailed input data, but information about soil hydrodynamic properties that are not available in most locations worldwide. Recently, researchers proposed that some very small modifications could endow the ability of simulating the effects of salinity on crop for present process-oriented crop growth models. For example, Hochman *et al*. (2004) pointed out that the effect of salinity on wheat (*Triticumaestivum* L.) can be simulated by modifying crop lower limit (CLL). Our previous study also pointed out that the modification of the pattern of root exploration in the soil profile (XF), and the water-extraction coefficient (KL) in APSIM could also consider salt stress for sunflower, which is a moderate salt tolerance crop and widely planted in saline soils(Katerji *et al*., 2000; Hochman *et al*., 2007; Zeng *et al*., 2016a). All of these modifications are based on the assumption that the adverse effects of high salt content could be considered by the parameters for water stress (e.g. CLL and KL). Meanwhile, previous studies also proved that excess salts directly have adverse effects on crop growth characteristics such as leaf area index (LAI) and radiation use efficiency (RUE) (Curtis and Lauchli, 1986; Wang *et al*., 2001; Freschet *et al*., 2015).Based on the above assumptions, we hypothesize that the modifications of parameters about LAI and RUE in crop models could also reflect the salt stress on crops as well as water limitation factor. This hypothesis could be assessed with the SIMPLACE modeling framework, includingthe LINTUL-5 crop growth model(Wolf, 2012), which has been used in various studies at field, country and continental scales for water and nitrogen limitations resulting from different irrigation and fertilizer strategies (Gaiser *et al*., 2013; Zhao *et al*., 2015; Faye *et al*., 2018a; Faye *et al*., 2018b; Webber *et al*., 2018).In addition, compared with other present crop models, SIMPLACE modeling framework is more flexible and it can be easily configured with different components based on various research questions (*Gaiser et al.,* 2013). Therefore, the present research aims to: (i) evaluate whether the effect of salinity on crop growth and production could be modelled by modifying parameters such asLAI and RUE as well as water limitation factor in SIMPLACE modeling framework and (ii) investigate whether the LAI and RUE parameters can be expressed as functions of soil salinity to improve the applicability of crop models.

MATERIALS AND METHODS

Site description: The study area is located in the Hetao Irrigation District (HID) of Inner Mongolia, China (41°07′ N, 108°00′ E). The climate is temperate continental monsoon and the average annual precipitation is around 139–222 mm, with approximately 60% rainfall in July and August. The annual potential evaporation is approximately 2200–2400 mm. Strong evaporation forces the groundwater and soil water to migrate upward constantly, eventually resulting in salt accumulation on the soil surface after the evaporation.

Field experiments: Field experiments were conducted in 2015 and 2016 at the Yichang experimental station in HID. Six plots (7.5m×4.5m) with naturally different salinity levels were established in farmers' fields. Saturated electrical conductivity (EC_e) was measured to indicate the salinity levels of each plot (Table 1).

Table 1. Basic soil physical properties of the Yichang experimental station.

Depth cm	BD[1] g/cm^3	Sand %	Silt %	Clay %	OM[2] g/kg	Total N mg/kg	EC_e[3] dS/m	Moisture cm^3/cm^3
10	1.35	10.28	71.67	18.05	14.64	590	12.11±9.48	0.26±0.05
20	1.38	7.85	72.29	19.86	15.14	610	7.49±5.83	0.31±0.02
30	1.44	6.85	78.88	14.28	10.74	590	5.68±3.63	0.32±0.03
40	1.55	20.2	61.34	18.46	10.6	550	6.75±3.75	0.37±0.06
60	1.61	16.51	77.82	5.67	12.86	550	5.05±2.85	0.40±0.05
80	1.59	10.36	66.31	23.33	11.47	630	6.94±8.57	0.38±0.03
100	1.52	11.89	33.05	55.06	10.24	590	4.63±2.21	0.39±0.04

Note: 1. BD is bulk density; 2. OM is organic matter; 3. EC_e is saturated electrical conductivity. EC_e and Moisture are expressed as mean±standard deviation.

Study factors of field experiments were soil salinity and nitrogen application. Specifically, the average EC_e of 0-10 cm soil depths for six plots (denoted as: P1-P6) were 6.8, 2.2, 13.6, 10.4, 9.8, and 29.8 dS·m^{-1}.

Meanwhile, the average EC_e of 0-100 cm soil depths for P1-P6 were 3.6, 2.0, 7.4, 6.1, 5.3, and 14.8 $dS \cdot m^{-1}$. Salinity levels for both 0-10 cm and 0-100 cm depths indicated that experimental plots were ranged from non-saline soils (EC_e<4.5 $dS \cdot m^{-1}$), high (9< EC_e<18 $dS \cdot m^{-1}$) to severe (EC_e<18 $dS \cdot m^{-1}$) saline soils (Zeng *et al*., 2015). About one month before sowing, all fields in our study site had sufficient spring irrigation and no irrigation was applied during sunflower growth period. Furthermore, each plot was covered with three plastic films (1.0 m width, with a 0.25m interval), and two rows of sunflower were sown through holes in each plastic film on May 28th 2015 and June 4th2016, respectively and maturity on September 4th 2015 and September 15th 2016, respectively. Plant density in 2015 and 2016 were about 5 and 4.28 plants per square meter, respectively. The cultivar of sunflower in 2015 was GL601 but JK601 cultivar was used in 2016 because JK601 improvedthe seed plumpness of GL601 and almost all local farmers planted this cultivar in 2016. In 2015, there were two nitrogen application rates for six plots before sowing. Specifically, 45 kg N ha^{-1} for P1, P3, P5 and 135 kg N ha^{-1} for P2, P4, and P6. In 2016, due to the misoperation by local farmer, all six plot were applied 180 kg N ha^{-1} as base fertilizer. Fortunately, based on our measurements, the soil basal nitrogen supply wassufficient (Table 1) and we can assume that soil salinity was the main factor reducing sunflower growth in our experiments. Other management practices, including insect and weed control, were performed according to local agronomic practices, unless otherwise indicated.

Description and setup of SIMPLACE modelling framework: SIMPLACE<LINTUL-5, SlimWater> used in this study combines the LINTUL-5 crop growth model, the water balance model, SlimWater fromAddiscott and Whitmore (1991). The code for SIMPLACE and the model components used in this study can be assessed from http://www.simplace.net/Joomla/index.php/documentation/simplace-framework-for-software-developers. In LINTUL-5, daily temperature sums and crop-specific requirements are used to simulate crop develop stage (DVS) and progression from emergence (DVS=0.0) to anthesis (DVS=1.0) and maturity (DVS=2.0). Leaf area index (LAI) expansion is exponential until DVS=0.2 and LAI<0.75 are reached, limited only by temperature. After that, daily increase in leaf biomass, specific leaf area (SLA), leaf death rates, and nitrogen and water stresses would affect LAI growth (Liu *et al*., 2018). The model uses the radiation use efficiency (RUE) to determine daily biomass increment and biomass is partitioned to roots, stems, leaves, and storage organs as a function of DVS(Chakwizira *et al*., 2018). In LINTUL-5, water stress is considered by a water stress reduction factor (TRANRF) which affects the actual transpiration (Ezui *et al*., 2018). In our study, sunflower parameters were determined based on the default values from LINTUL-5. To be specific, we firstly calibrated the phenology parameters ofTSUM1 and TSUM2 which indicated temperature sums from emergence to anthesis and from anthesis to maturityrespectively using the observations of sowing, anthesis and maturity date (Table 2). After that, observed biomass and LAI of P2 (non-saline) in both 2015 and 2016 were regarded as potential condition of sunflower growth in our study site to obtain the potential SLA and RUE values (Fig. 1, Table 3). During the calibration for potential condition, TRANRF was set to 1.

Table 2. Phenology data and parameters of sunflower in 2015 and 2016 respectively. TSUM1 indicates temperature sums from emergence to anthesis. TSUM2 indicates temperature sums from anthesis to maturity.

Year	Cultivar	Sowing	Anthesis	Maturity	TSUM1	TSUM2
—	—	DOY	DOY	DOY	℃	℃
2015	GL601	148	210	247	1050	700
2016	JK601	155	228	258	1350	520

Table 3. Parameters of radiation use efficiency (RUE) and specific leaf area (SLA) for sunflower under potential condition.

Year	Growth stage	RUE	SLA
2015	0	4.8	0.03
	1	4.8	0.02
	1.22	4.8	0.02
	2	1.6	0.02
2016	0	6.07	0.03
	1	6.07	0.02
	1.22	6.07	0.02
	2	2.02	0.02

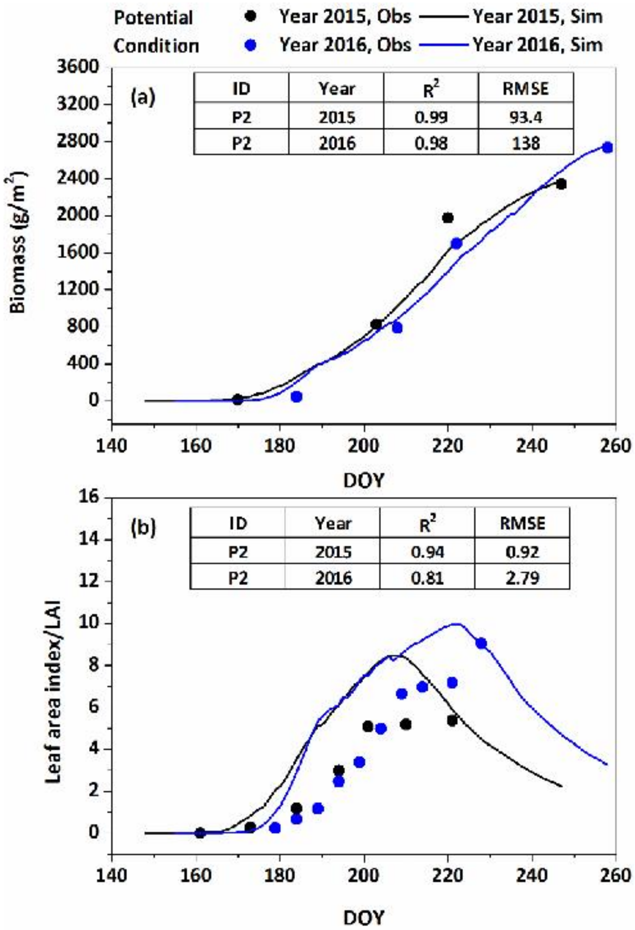

Fig. 1. Performance of SIMPLACE model framework for biomass and leaf area index (LAI) simulations under potential condition of sunflower in 2015 and 2016.

Hypotheses testing: Generally, the capability of crop to overcome soil resistance and absorb soil water would be limited under high saline environment. Meanwhile, some specific salt ions may also restrain crop growth. We tested four methods to represent these processes in the model by carrying out four modelling experiments (SE)changing (i) TRANRF; (ii) RUE; (iii) SLA and (iv) RUE and SLA together.

In modelling experiment 1 (SE1), TRANRF was changed from 0 to 1 while RUE and SLA were kept as potential value. In modelling experiment 2 (SE2) and 3 (SE3), TRANRF was kept as 1 and RUE and SLA were multiplied by a scale factor (SRUE and SSLA) respectively. In modelling experiment 4 (SE4), we modified SRUE and SSLA simultaneously while kept TRANRF as 1. In addition, for each experiment, we used Generator and Selector tools in SIMPLACE to determine these parameters with target variable of observed biomass and LAI in 2015 respectively.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(Y_i^{obs} - Y_i^{sim}\right)^2}{n}} \quad (1)$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y_i^{obs}}\right)\left(Y_i^{sim} - \overline{Y_i^{sim}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y_i^{obs}}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} - \overline{Y_i^{sim}}\right)^2}} \right)^2 \quad (2)$$

The relationship between SRUE, SSLA and the soil salinity was then established using linear or nonlinear regression analysis, and the established relationships were evaluated using the measurements of biomass and LAIin 2016. In addition, the root mean square error (RMSE, Eq. (1)) and the coefficient of determination (R^2, Eq. (2)) were used to evaluate the precision of the model for simulating biomass and LAI in both 2015 and 2016. In Eqs (1-2), *n* is the number of samples, Y_i^{mea} is the *i*th measured value, Y_i^{sim} is the *i*th simulated value, and $\overline{Y_i^{mea}}$ and $\overline{Y_i^{sim}}$ are the means of the measured and simulated values, respectively.

RESULTS

Effects of modifying TRANRF: The calibrated TRANRF varied from different plots and target variables. Specifically, when observed biomass in 2015 was set as target variable, calibrated TRANRF for P1, P3, P4, P5 and P6 were 1, 0.875, 0.996, 0.783, and 0.628, respectively. Furthermore, when the target variable was observed LAI in 2015, the calibrated TRANRF for five plots were 0.771, 0.69, 0.803, 0.642, and 0.534, respectively. The performance of the SIMPLACE was shown in Fig. 2when only TRANRF was modified. No matter target variable was observed biomass or LAI, modifying TRANRF accounted for more than 97% of the variability in biomass at different growth stages. However, large difference was found of RMSEs for two target variables except P2, which is potential condition and TRANRF is set as 1. For example, when target variable was observed biomass, the RMSE of biomass for other five plots ranged from 40.8 to 177.9 g m^{-2} (Fig. 2a), but it increased to 323.6 to 573.2 g m^{-2} when observed LAI was the target variable (Fig. 2b). For the accuracy of LAI, similar results were found with biomass. When the target variable was observed LAI, the lowest R^2 was still 0.84 and the largest RMSE was only 1.14 (Fig. 2d). But when observed biomass replaced LAI as target variable for the SIMPLACE calibration, the lowest R^2 and largest RMSE were 0.71 and 2.71 respectively (Fig. 2c).

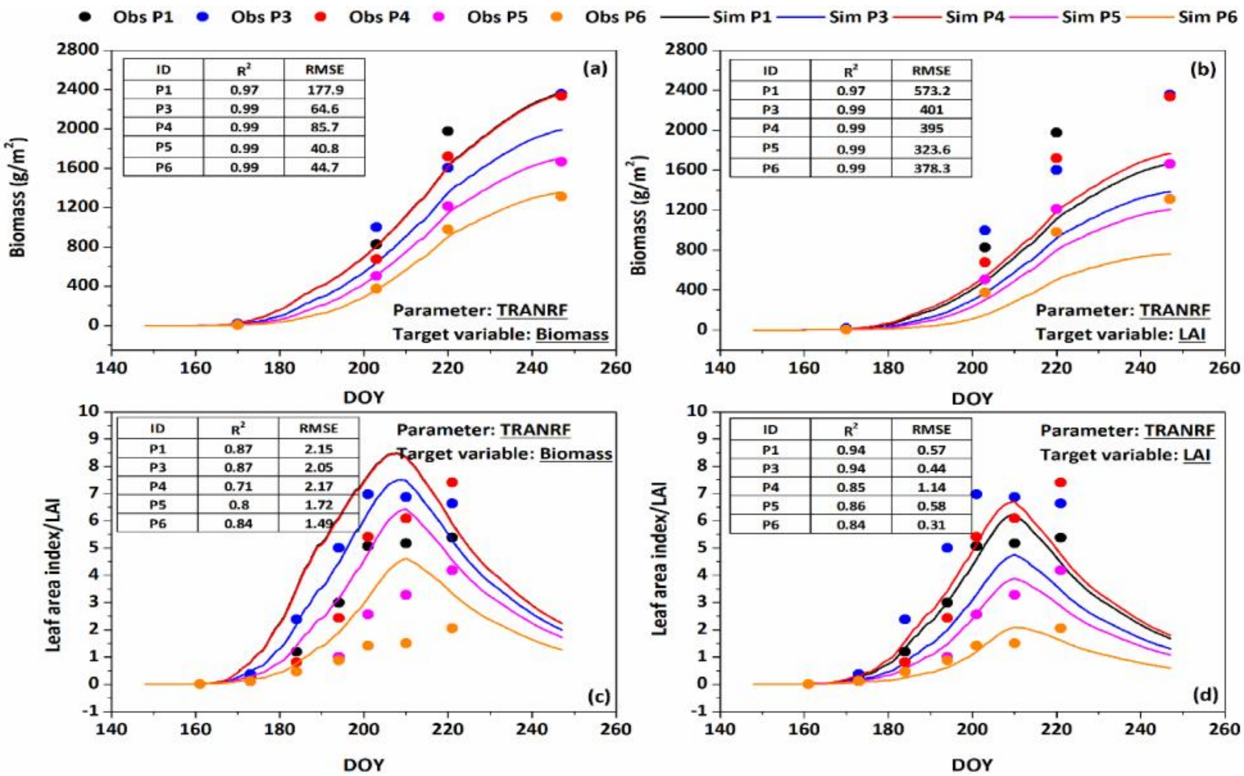

Fig. 2. Modification of the water stress factor (TRANRF) for simulating sunflower growth in salt-affected soils with trial data in 2015.

Effects of modifying SRUE: The calibrated scale factor of RUE (SRUE) also varied from different plots and target variables. Specifically, calibrated SRUE for P1, P3, P4, P5 and P6 were 1, 0.846, 0.996, 0.733, and 0.596 respectively with using observed biomass in 2015 as target variable. Furthermore, when the target variable was observed LAI in 2015, the calibrated SRUE for five plots were 0.58, 0.434, 0.636, 0.37, and 0.216, respectively. The performance of the SIMPLACE when only SRUE was modified was shown in Fig. 3. Similar with modifying TRANRF, no matter target variable was observed biomass or LAI, modifying SRUE also accounted for more than 97% of the variability in biomass at different growth stages. However, large difference was found of RMSEs for two target variables except P2, which is potential condition and SRUE is set as 1. More exactly, when target variable was observed biomass, RMSE of biomass for other five plots ranged from 43.7 to 177.9 g m^{-2} (Fig. 3a). But it increased to 587.4 to 781.7 g m^{-2} when observed LAI was the target variable (Fig. 3b). For the accuracy of LAI, similar results were found with biomass. When the target variable was observed LAI, the lowest R^2 was still 0.76 and the largest RMSE was only 1.32 (Fig. 3d). But when observed biomass replaced LAI as target variable for the SIMPLACE calibration, the lowest R^2 and largest RMSE were 0.7 and 2.57, respectively (Fig. 3c).

Effects of modifying SSLA: The calibrated scale factor of SLA (SSLA) also varied from different plots and target variables. Specifically, calibrated SSLA for P1, P3, P4, P5 and P6 were 1, 0.499, 0.911, 0.374, and 0.313 respectively using observed biomass in 2015 as target variable. Furthermore, when the target variable was observed LAI in 2015, the calibrated SSLA for five plots were 0.636, 0.515, 0.685, 0.459, and 0.337, respectively. The performance of the SIMPLACE when only SSLA was modified was shown in Fig. 4. Similar to the results of modifying SRUE, no matter target variable was observed biomass or LAI, modifying SSLA also accounted for more than 97% of the variability in biomass at different growth stages. However, large difference was found of RMSEs for two target variables except P2, which is potential condition and SSLA is set as 1. For instance, when target variable was observed biomass, the RMSE of biomass for other five plots ranged from 40.6 to 177.9 g m^{-2} (Fig. 4a),but it increased to 59.2 to 267.7 g m^{-2}, when observed LAI was the target variable (Fig. 4b). For the accuracy of LAI, similar results were found with biomass. When the target variable was observed LAI, the lowest R^2 was still 0.82 and the largest RMSE was only 1.24 (Fig. 4d),but when observed biomass replaced LAI as target variable for the SIMPLACE calibration, the lowest R^2 and largest RMSE were 0.74 and 2.15, respectively (Fig. 4c).

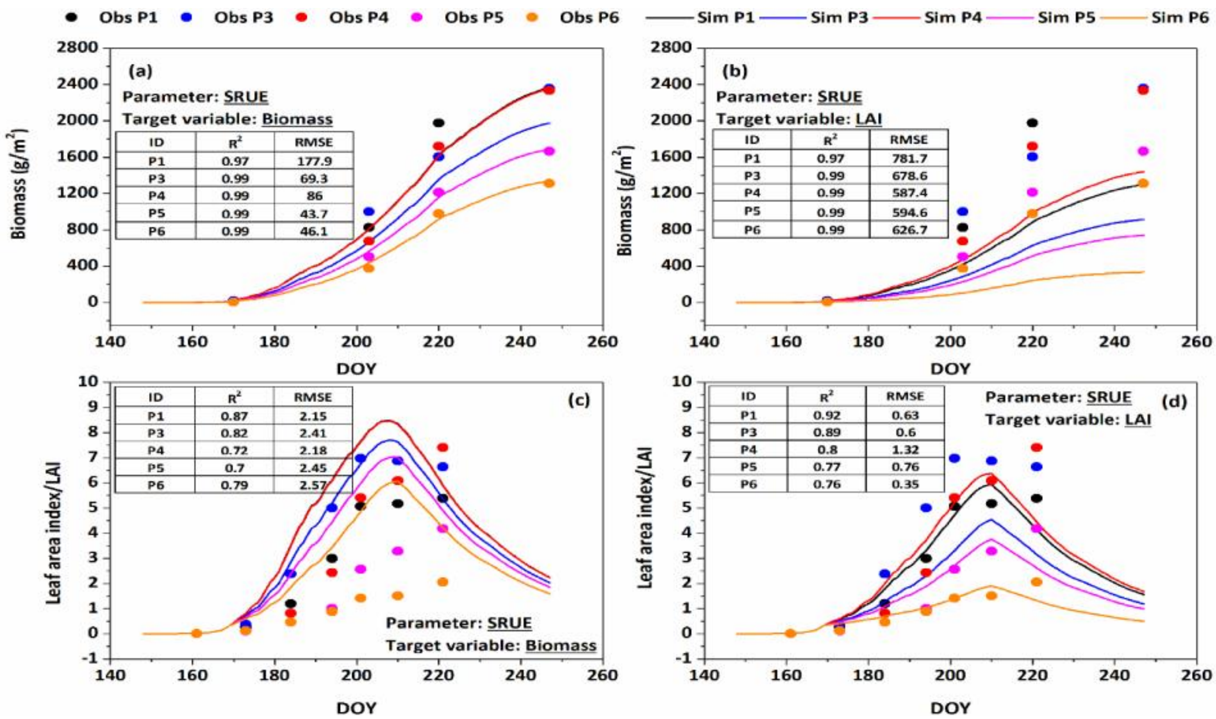

Fig. 3. Modification of the scale factor of radiation use efficiency (SRUE) for simulating sunflower growth in salt-affected soils with trial data in 2015.

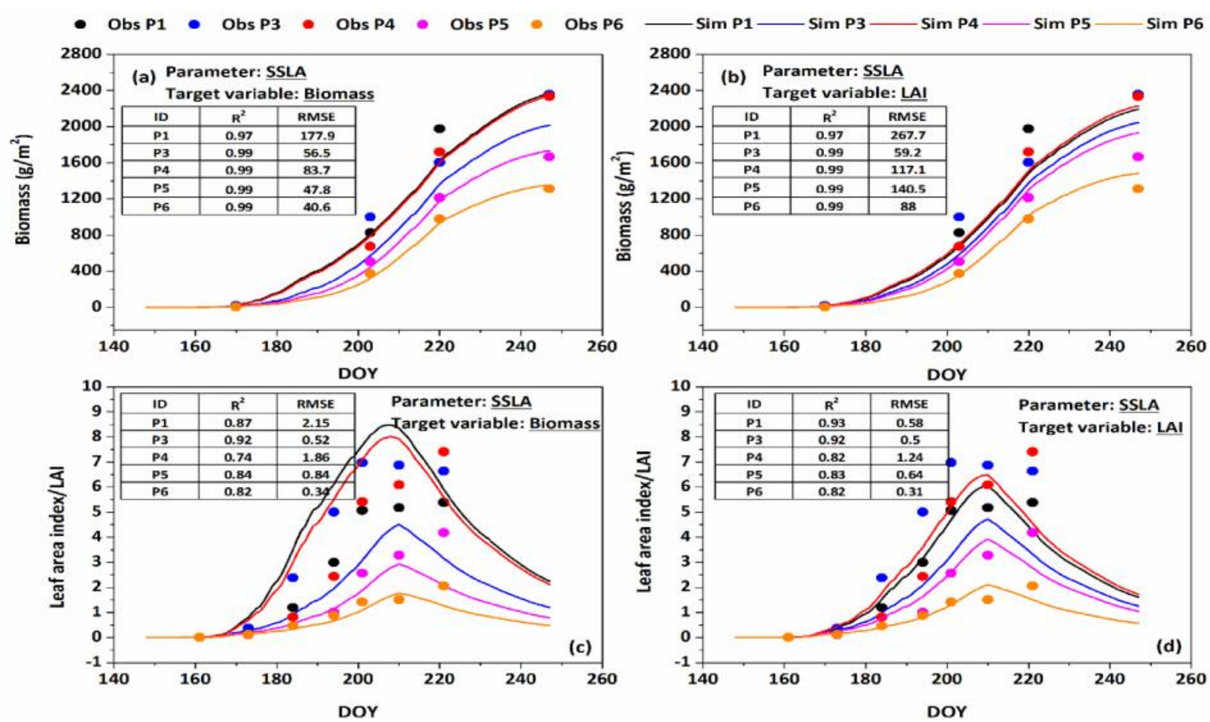

Fig. 4. Modification of the scale factor of specific leaf area (SSLA) for simulating sunflower growth in salt-affected soils with trial data in 2015.

Effects of modifying SRUE and SSLA simultaneously: Because RUE and SLA are two parameters associate with crop growth, we modified the scale factor of RUE and SLA (SRUE and SSLA) at the same time in simulation experiment 4. When observed biomass was the target variable, the calibrated SRUE for P1, P3, P4, P5 and P6 were 1, 0.984, 1, 0.804, 0.739 and the calibrated SSLA for the five plots were 1, 0.527, 0.918, 0.657, 0.527, respectively. The R^2 of biomass for all plots were larger than 0.97 and the lowest RMSE of biomass was only 33.7 $g \cdot m^{-2}$ (P6) (Fig. 5a). Meanwhile, R^2 of LAI ranged from 0.74 to 0.92 and RMSE of LAI ranged from 0.5 to 2.15 (Fig. 5c). Similar with other simulation experiments, when the target variable was observed LAI, the accuracy for LAI simulation increased. For example, in our study when the LAI replaced biomass as the target variable,the largest RMSE of LAI decreased from 2.15 to 1.24 while the lowest R^2 increased from 0.74 to 0.82 (Fig. 5d).

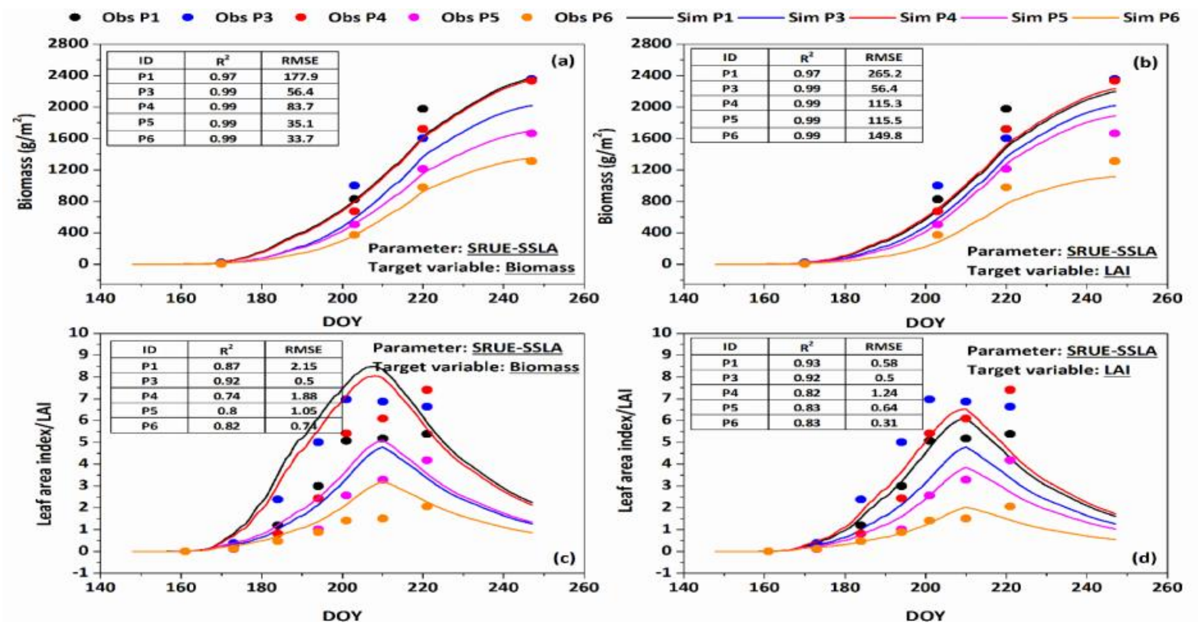

Fig. 5. Modification of the scale factor of radiation use efficiency (SRUE) and specific leaf area (SSLA) together for simulating sunflower growth in salt-affected soils with trial data in 2015.

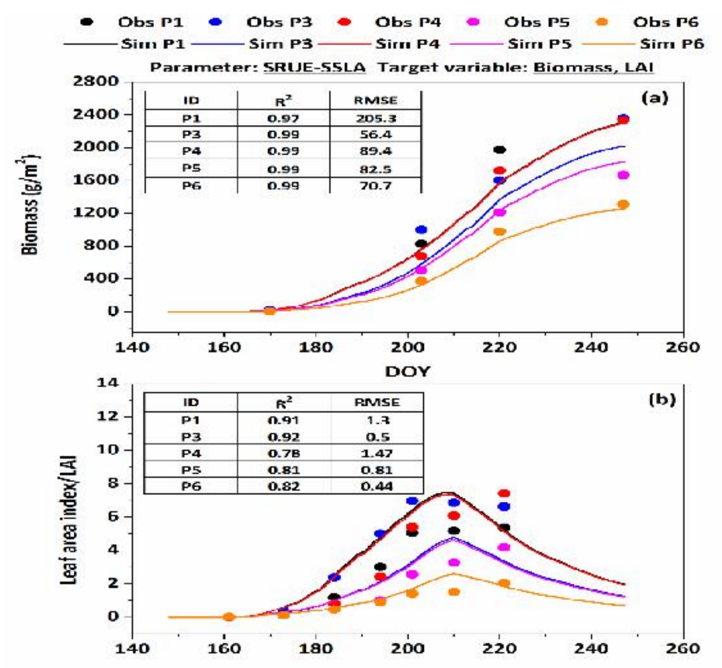

Fig. 6. Using averaged value of the modified scale factor of radiation use efficiency (SRUE) and specific leaf area (SSLA) with two different target variables for simulating sunflower growth in salt-affected soils with trial data in 2015.

Considering the differences for calibrated SRUE and SSLA with different target variable, we averaged the SRUE and SSLA calibrations to seek a balance between these two target variable. The averaged SRUE for P1, P3, P4, P5 and P6 were 1, 0.984, 1, 0.894, and 0.747 while the averaged SSLA for these five plots were 0.821, 0.527, 0.804, 0.559 and 0.47, respectively. The performance of averaged SRUE and SSLA was shown in Fig. 6. R^2 for all plots were also larger than 0.97 for biomass simulation and the lowest R^2 for LAI was 0.78, which was between 0.74 (target variable: biomass) and 0.82 (target variable: LAI). The RMSE ranges of biomass and LAI simulations were 56.4-205.3 g·m^{-2} and 0.44-1.47, respectively, which were also between the simulations with two target variables.

Modelling sunflower growth from soil salt content: The relationship between SRUE, SSLA and soil salinity was shown in Fig. 7. Two salinity indicators including EC_e of 0-10 cm and 0-100 cm were used as independent variables, respectively. SRUE could be predicted from EC_e of 0-10 cm or 0-100 cm linearly (R^2>0.76), while SSLA had linear relationship with the natural logarithm of EC_e of 0-10 cm (S10) or 0-100 cm (S100) (Eqs. (3)-(6), R^2>0.77).

$$SRUE = -0.0093S10 + 1.0468 \quad (3)$$

$$SSLA = -0.217\ln(S10) + 1.1801 \quad (4)$$

$$SRUE = -0.0193S100 + 1.0602 \quad (5)$$

$$SSLA = -0.27\ln(S10) + 1.1525 \quad (6)$$

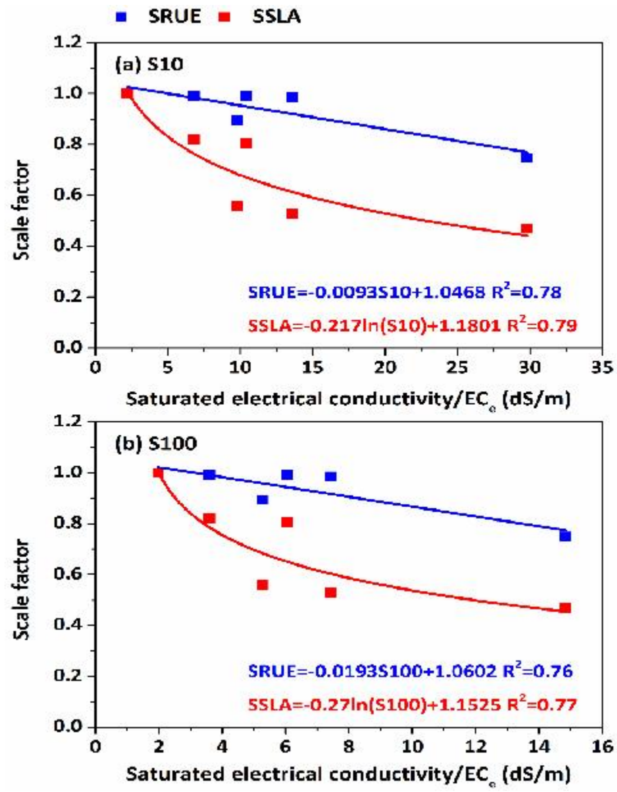

Fig. 7. Relationship between the scale factor of radiation use efficiency (SRUE) and specific leaf area (SSLA) and the initial soil salinity level of 0-10 cm (a) and 0-100 cm (b) depths respectively.

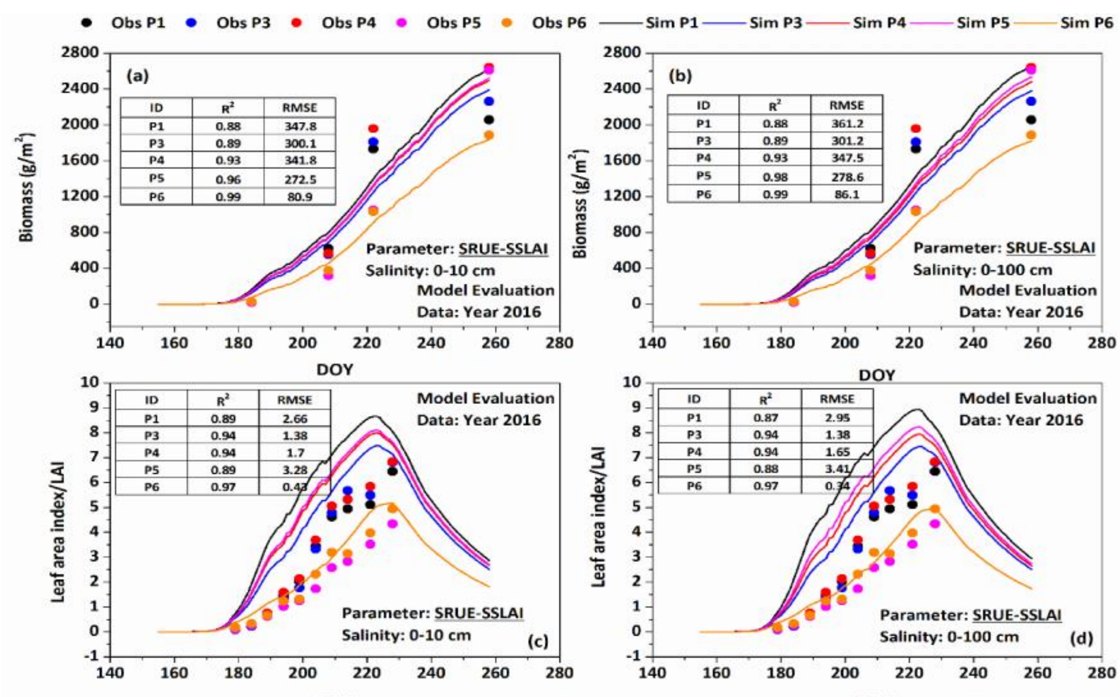

Fig. 8. Evaluation of the relationship between the scale factor of radiation use efficiency (SRUE) and specific leaf area (SSLA) and the initial soil salinity level of 0-10 cm (a) and 0-100 cm (b) depths using 2016 trial data.

The evaluation of the established SRUE and SSLA model using 2016 measurements was shown in Fig. 8. For biomass, R^2 of six plots ranged from 0.88 to 0.99 and the RMSE ranged from 80.9 to 347.8 g m^{-2} when independent variable was EC_e of 0-10 cm (Fig. 8a). However, when using EC_e of 0-100 cm as independent variable, the accuracy of biomass was not improved. More exactly, the R^2 of six plots also ranged from 0.88 to 0.99 but the smallest and largest RMSEs were 86.1 g m^{-2} and 361.2 g m^{-2}, which increased about 6.4% and 3.8% compared with using EC_e of 0-10 cm as independent variable (Fig. 8b). Similar results were found for LAI simulation, EC_e of 0-10 cm and 0-100 cm both obtained R^2 of 0.81-0.97 (Fig. 8c, d). However, the RMSEs ranged from 0.43 to 3.28 with EC_e of 0-10 cm while 0.34 to 3.41 with EC_e of 0-100 cm (Fig. 8c, d).

DISCUSSION

Our study indicated that the effect of salt stress on sunflower growth could be simulated by SIMPLACE by modifying some crop parameters. However, the accuracy for both biomass and LAI simulation under salt stress varied from the modified crop parameters. When target variable was observed biomass, the average RMSEs of biomass simulations (P1, P3, P4, P5, and P6) for modifying TRANRF, SRUE, and SSLA were 82.7 $g \cdot m^{-2}$, 84.6 $g \cdot m^{-2}$, and 81.3 $g \cdot m^{-2}$ respectively. Meanwhile, the highest accurate biomass estimation was obtained by modifying SRUE and SSLA together (SE4); the RMSE was only 77.4 $g \cdot m^{-2}$ and if we ignored P1, in which TRANRF, SRUE, and SSLA were 1 and RMSE was as much as 177.9 $g \cdot m^{-2}$; the average RMSE for SE4 was only 52.2 $g \cdot m^{-2}$. These differences of accuracy might be caused by the concept of the parameters and the interaction between the parameters and crop model (LINTUL-5).Taking TRANRF as an example, it was used to indicate crop water stress in LINTUL-5(Wolf, 2012), which is very similar with the α(h) in the root water uptake model proposed by Skaggs *et al*. (2006) (Eq. (7)).

$$S(z) = \beta(z)\alpha(h)\alpha(\pi)T_p \qquad (7)$$

In Eq. (7), S(z) and T_p represented the actual and potential root water uptake, β(z) was the normalized root density distribution, α(π) and α(h)are dimensionless stress coefficients that reflects salt and water stress on root water uptake, respectively.

Our study assumed that TRANRF could also reflect the effect of salt stress on sunflower growth, which is amount of α(π)×α(h)in Eq. (7). However, SE1 in our study considered that TRANRF was constant during the whole crop growth period, which was also a possible reason of reducing simulation accuracy. Actually, LINTUL-5 can be calculated from daily TRANRF by coupling with another module named Lintul Water Stress (Wolf, 2012). Lintul Water Stress firstly used crop coefficient approach to determine the potential crop transpiration (T_{cp}), then calculated the actual crop transpiration (T_{ca}) from water balance theory, and the TRANRF was T_{ca}/T_{cp}. This method for water stress factor was also widely used in almost all crop models. However, this method failed to capture the two processes including osmotic stress and ion toxicity in saline soils. Meanwhile, determining the salt affected daily TRANRF by experiments or even by model calibration is very difficult. Therefore, we proposed to directly modifyingRUE or SLA in order to reflect salt stress. Many previous studies have proved that the effect of salinity on crop's RUE or SLA. For example, Wang *et al*. (2001) indicated that salinity could reduce the amount of absorbed radiation and might also result in darker leaves of soybean. Hashem *et al*. (2016) also pointed out that salinity has negative effects on the synthesis of photo assimilates and hence reduce the growth of leaf area. Our study also obtained the similar results and modifying SRUE and SSLA together could obtain very accurate simulation for sunflower's biomass in saline soils.

Our study also pointed out that different target variables could lead to different simulation accuracy for both biomass and LAI. Overall, using biomass as target variable could get more accurate biomass simulation and vice versa. But it's worth noting that R^2 for biomass of each plot was all very high no matter which target variable was used. For one thing, it showed that our modification could capture the tread of biomass during the sunflower growth stages in saline soils. For another, because the biomass was only observed four times, it is possible to over fit the biomass in the calibration. In addition, big difference of simulation accuracy with different target variable also indicated there might be some system errors of biomass and LAI calculations in LINTUL-5 model. This phenomenon also occurred in other models. For example, our previous study also indicated that APSIM model failed to give accurate simulations for biomass and LAI simultaneously in saline soils (Zeng *et al*., 2016a). Therefore, it is necessary to balance the calculation of biomass and LAI if we still want to apply present crop model in saline soils. This study proposed an effective method by averaging the SRUE and SSLA obtained from two different calibration process using biomass and LAI as target variables, respectively.

Meanwhile, our study also found very good relationship between SRUE, SSLA and soil salinity levels and these relationships could also be verified by independent experimental data (Fig. 8). As it should be, the accuracy of both biomass and LAI in Fig. 8 were a little lower than the calibration process (e.g. Fig. 6). Besides the change of weather conditions between 2015 and 2016, some other factors might also be the reason. For example, although based on many other studies, the soil salinity level of fields in study area is stable(Kong, 2004; Wu *et al*., 2008; Li *et al*., 2010; Zeng *et al*., 2014; Zeng *et al*., 2016a; Zeng *et al*., 2016b), there are still some changes of soil salinity during crop growth period in both 2015 and 2016. In addition, the cultivar of sunflower in 2015 and 2016 was different. But at the other extreme, Fig. 8 indicated our proposed method might be used for different sunflower cultivars. It is also interesting that using 0-10 cm initial soil salt could obtain higher accuracy for both biomass and LAI prediction of sunflower than using 0-100 cm initial soil salt. This might be caused by two factors. Firstly, main roots of sunflower assembled in the upper layer of saline soils, especially in 0-10 cm depth, which is similar with the studies of Hu *et al*. (2006), Kaya *et al*. (2006), and Zhao *et al*. (2014).Secondly, salt stress in the early growth stage could be more harmful to sunflower's biomass and LAI when compared with salt stress occurring in later growth stages. Therefore, it is important to thoroughly irrigate fields to leach soil salt and make an appropriate environment for crop in salt affected regions.

Conclusions: Overall, modifying TRANRF, RUE, and SLA of LINTUL-5 crop model in SIMPLACE could improve the ability to predict sunflower's biomass and LAI in saline soils, and modifying the scale factor of RUE and SLA (SRUE, SSLA) together obtained the highest accurate simulation. Meanwhile, the simulation accuracy also varied from target variables. Using biomass as target variable could get more accurate biomass simulation and vice versa. To balance the different simulation accuracy caused by target variables, we average the SRUE and SSLA obtained from two different calibration process using biomass and LAI as target variables, respectively and found that by averaging the SRUE and SSLA models could obtain both acceptable biomass (RMSE=56.4-205.3 $g\cdot m^{-2}$) and LAI (RMSE=0.44-1.47) simulations. Meanwhile, the averaged SRUE and SSLA could be expressed as a function of the soil salinity and using EC_e of 0-10 cm depth as independent variable was a little more accurate than using EC_e of 0-100 cm depth. However, our present work still have some limitations. Firstly, only LAI and biomass were considered, which might cause some uncertainties and reduce the reliability of our model improvements. Secondly, it is still necessary to improve accuracy for simulating biomass and LAI in saline soils simultaneously. Therefore, additional experiments with more crop measurements are required to further evaluate the model and find out the internal linkages between crops parameters and specific soil salt components (e.g. cation, anion), and other soil properties (e.g. pH, organic matter, pore). In addition, future studies should also focus on the improvement of the mechanism of present crop models and develop some specific modules to consider salt stress.

Acknowledgements: This work was made possible by support from the State Natural Science Fund of China (grant No. 51609175, 51879196 and 51790533) and the Open Research Fund of State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin (China Institute of Water Resources and Hydropower Research) (grant no. IWHR-SKL-KF201814)

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