Effects of Optimized Root Water Uptake Parameterization Schemes on Water and Heat Flux Simulation in a Maize Agroecosystem

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ABSTRACT

As root water uptake (RWU) is an important link in the water and heat exchange between plants and ambient air, improving its parameterization is key to enhancing the performance of land surface model simulations. Although different types of RWU functions have been adopted in land surface models, there is no evidence as to which scheme most applicable to maize farmland ecosystems. Based on the 2007–09 data collected at the farmland ecosystem field station in Jinzhou, the RWU function in the Common Land Model (CoLM) was optimized with scheme options in light of factors determining whether roots absorb water from a certain soil layer (W_x) and whether the baseline cumulative root efficiency required for maximum plant transpiration (W_c) is reached. The sensibility of the parameters of the optimization scheme was investigated, and then the effects of the optimized RWU function on water and heat flux simulation were evaluated. The results indicate that the model simulation was not sensitive to W_x but was significantly impacted by W_c. With the original model, soil humidity was somewhat underestimated for precipitation-free days; soil temperature was simulated with obvious interannual and seasonal differences and remarkable underestimations for the maize late-growth stage; and sensible and latent heat fluxes were overestimated and underestimated, respectively, for years with relatively less precipitation, and both were simulated with high accuracy for years with relatively more precipitation. The optimized RWU process resulted in a significant improvement of CoLM's performance in simulating soil humidity, temperature, sensible heat, and latent heat, for dry years. In conclusion, the optimized RWU scheme available for the CoLM model is applicable to the simulation of water and heat flux for maize farmland ecosystems in arid areas.

Key words: root water uptake, land surface model, water flux, heat flux, maize agroecosystem

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1. Introduction

Plant root water uptake (RWU) is an important component of the surface water cycle (Feddes et al., 2001), partitioning precipitation among evaporation, transpiration, and penetration, and playing an important role in regulating the surface energy balance through its close link with the carbon cycle made possible by the coupling with photosynthesis (Dickinson et al., 1998; Jobbágy and Jackson, 2000). An in-depth study of RWU and its parameterization will promote understanding of surface hydrology and land surface processes, and facilitate improvements in the simulation performance of land surface models and even climate models (Laio et al., 2006). RWU parameterization schemes relate to root distribution and soil water availability. The former determines the RWU distribution at different soil depths (Schenk and Jackson, 2002; Lee et al., 2005; Zheng and Wang, 2007), which, though important, has often led to a simplification or even negligence of the root distribution function in models owing to a lack of available data due to whole-root observation difficulties (Jackson et al.,

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1996; Zeng, 2001; Jing et al., 2013). The latter is often represented by the root water use efficiency function (Lai and Katul, 2000), also known as the water stress function (Li et al., 2006), which has been continually improved upon as a result of the in-depth research conducted by a number of scholars (e.g., Saleska et al., 2003; Baker et al., 2008; Li et al., 2012). Most existing land surface process models contain an RWU scheme based on transpiration weight, which partitions transpiration volume in the soil profile by a certain weight factor in view of the RWU causal relationship. Since variables associated with the weight factors are important parameters for the soil–plant–atmosphere continuum flow equation, such models are strongly empirical but nonetheless widely used (Table 1). These models were built upon the Molz and Romson (1970) and Feddes et al. (1976, 1978) models, emphasizing the linear change of RWU intensity with the soil profile proportional to the transpiration rate, root density, and soil water diffusivity, but ignoring the impact of soil water potential. Luo et al. (2000) improved these linear models by introducing the soil water potential impact function represented by diffusivity. Then, on the basis of these linear models, nonlinear models, such as the Molz (1981) and Chandra and Rai (1996) models, incorporated considerations of the root distribution function, potential transpiration, hydraulic conductivity, suction of roots and soil, and a soil water suction function model upon the termination of transpiration, and were of better performance. Kang et al. (1992) and Li et al. (2001) put forward an RWU model that took into account the crop type, potential transpiration rate, soil water availability, and root density in water stress conditions, and significantly raised the accuracy of soil moisture simulation. In addition, a nonlinear function coupled with the potential and actual evapotranspiration in the description of the root water use efficiency function was proposed by Lai and Katul (2000), and was able to simulate the dynamic variation of soil water content within the root zone well, which further improved the RWU function. Ju et al. (2006) improved the simulation of carbon, water, and energy fluxes on different timescales in dry years in a boreal aspen forest by considering the influence of both root fraction and soil water availability in different soil layers on stomatal conductance. He et al. (2014) optimized the soil water stress factor for rain-free days over a white pine forest ecosystem, and showed that the optimized soil water stress factor was largely explained by soil water content in the summer.

Existing mainstream land surface process models, such as the Common Land Model (CoLM) (Ji and Dai, 2010), the Community Land Model version 3 (CLM3) (Oleson et al., 2004), the Community Atmosphere Biosphere Land Exchange (CABLE) (Wang et al., 2010), and Simple Biosphere (SiB) series of models (Sellers et al., 1986; Baker et al., 2008), use only simple linear functions to describe soil water availability, leading to an underestimation of evapotranspiration to varying degrees, particularly in drought conditions (Saleska et al., 2003; Baker et al., 2008; Li et al., 2012). In light of the fact that under dynamic RWU circumstances root self-regulation of water uptake enables the remaining roots to absorb adequate water to allow for potential transpiration, even if part of the roots are under water stress, Skaggs et al. (2006) and Zheng and Wang (2007) brought models even closer to the actual situation by introducing such parameters as the overall root effectiveness threshold, RWU threshold, and enhanced water use efficiency into their studies based on forest ecosystems, to improve the simulation performance of the models. A comparison conducted by Jing et al. (2013) regarding the three RWU parameterization schemes proposed respectively by Lai and Katul (2000), Li et al. (2006), and Zheng and Wang (2007), showed that the latter of the three schemes exhibited higher simulation accuracy than the other two in a desert ecosystem. Currently, studies of RWU parameterization schemes mainly cover forest (Zheng and Wang, 2007), desert (Jing et al., 2013), and wheat (Li et al., 2006) underlying surfaces, and the conclusions thus reached lack universal applicability and require further verifications against more land surface types. Among all vegetation types, maize as an annual crop stands out for its significant representativeness in land surface process studies(Choietal.,2010;Lietal.,2011)becauseofthedynamic variation of canopy height, leaf area index (LAI), vegetation coverage (F_v), and root structure with plant growth and development, which may trigger a series of physical changes in radiation, water, and heat transfer (Cai et al., 2015). Up to now, there have been few RWU studies based on maize farmland ecosystems, suggesting that further studies are required as to whether the parameterization schemes that are applicable to other underlying surfaces can generate the desired simulation results with maize. The present study had three objectives:

(1) To investigate the sensibility of parameters in the RWU function proposed by Zheng and Wang (2007) and to determine the most reasonable parameters for maize farmland ecosystems.

(2) To optimize CoLM with the RWU schemes of Zheng and Wang (2007), and to assess the effects of such optimization on the simulation results of maize farmland water and heat flux processes, by comparing CoLM's performance before and after the RWU scheme optimization.

Table 1. Summary of relevant root water uptake (RWU) research

Study	Vegetation type/location	Experiment duration	RWU function	Key result
Molz and Remson (1970)	Sorghum	Not mentioned	Considered root depth and soil water diffusivity but not root efficiency function	Extraction term models were computationally and physically feasible and gave insight into the mechanics of the overall moisture extraction process
Feddes et al. (1976)	Crop field	Not mentioned	Considered the effect of soil water content on RWU, but not root distribution	Although the model did not predict the distribution of soil water content with depth particularly accurately, the cumulative effect over the entire depth was simulated well
Selim and Iskandar (1978)	Not mentioned	Not mentioned	Considered soil hydraulic conductivity and effective root length density	The model can be used as a tool to predict the fate of nitrogen in land treatment systems; model sensitivity to changes in the rate of nitrification, ammonium ion exchange, and rate of plant uptake of nitrogen, was also described
Molz (1981)	Not mentioned	Not mentioned	Considered soil pressure head, root distribution, and water potential of the root xylem	Not mentioned
Lai and Katul (2000)	Grass-covered forest/Durham, North Carolina, USA	22 May to 10 July 1997	Proposed a root efficiency function	The proposed RWU model reproduced well measured time–depth soil moisture content dynamics within the root zone well; the RWU model captured preferential water uptake from the top layers well when water was freely available, and was able to permit high extraction rates from deeper layers despite limited rooting density in those layers
Luo et al. (2000)	Winter wheat/Yucheng, China	24 April to 6 May 1999	Molz-Remson model and Selim-Iskandar model were modified with the Feddes reduction function, and the Feddes model was modified with root length density	Modifications made to the Molz–Remson model and Iskandar model did not achieve any improvements to the model behavior, but those to the Feddes model achieved great success in lifting its prediction ability
Li et al. (2001)	Wheat–fallow rotation/Saskatchewan, Canada	1967–84	Introduced the parameter λ = 0.5 as the exponent of root fraction	The modified RWU model accounted for the distribution of water stress in the soil profile, and simulated soil water contents accurately, particularly at lower depths
Li et al. (2006)	Spring wheat/Swift Current, Saskatchewan; soybean/Simcoe, Ontario; grass/Ottawa, Canada	1967–84	Soil water pressure head and soil water content were introduced into the root efficiency function	The new module was particularly useful when integrated into large-scale regional and global modeling efforts
Zheng and Wang (2007)	Forest/Amazonia	1992–93	Dynamic RWU was considered by using a threshold value to enable potential transpiration when part of the root system experienced water stress, and defined a water uptake flag determining whether roots absorb water from a certain soil layer	The latent heat flux simulation was closer to observations with the impact of dynamic RWU
Li et al. (2012)	Temperate forest/southeastern Australia; subtropical forest/South China; tropical forest/Brazil	2003–06; 2003–05; 2001–03	The alternative RWU function proposed by Lai and Katul (2000) was used to optimize the default version of CABLE (Wang et al., 2010)	The alternative function for RWU allowed roots in deep soil to take up water more efficiently per unit root mass
Jing et al. (2013)	Desert shrub Tamarix and irrigated cropland/central Asia	2007–09	RWU functions proposed by Lai and Katul (2000), Li et al. (2006), and Zheng and Wang (2007)	Replacing the default RWU function with that of Zheng and Wang (2007) and considering the observed vertical root distribution in CLM led to a significant improvement in the model's performance.
Li et al. (2013)	Desert shrub Tamarix and irrigated cropland/central Asia	2007–09	Described RWU efficiency as an exponential function of soil water potential matrix with a power m in CLM	A modified empirical RWU function improved CLM's performance for both latent and sensible heat fluxes

(3) To investigate the applicability of the optimized CoLM to the ecosystem studied with measured data from the farmland ecosystem field observation station in Jinzhou.

2. Data and methods

2.1 *Research site*

The farmland ecosystem field station in Jinzhou, located in the Northeast China maize belt with typical brown soil (loam), has a representative temperate monsoon climate with an annual mean temperature of 282.65 K and annual rainfall of 565.9 mm, calculated based on corresponding data from 1971 to 2000. The dominant vegetation is rain-fed maize, without any irrigation and with a growing period extending from May to September. Built within the station are a 3.5-m high eddy covariance observation system equipped with a three-dimensional sonic anemometer and a fast response infrared CO_2/H_2O analyzer for observations of water, heat, and CO_2 flux; and a 5-m high gradient meteorological observation system capable of temperature, humidity, and wind speed observations at 3.5- and 5-m heights, photosynthetically active radiation observations at 4.5-m height, net radiation observations at 3.5-m height, wind observations at 5-m height, soil temperature monitoring at soil depths of 10, 20, 30, 40, 50, and 80 cm, and surface heat fluxes at a soil depth of 8 cm (Li et al., 2007; Cai et al., 2012).

2.2 *Research data*

Land surface model–driven data included specific humidity, wind speed, air temperature, precipitation, solar radiation (R_s), downward longwave radiation (R_l), barometric pressure, and LAI data (Fig. 1) from 2007 to 2009. The specific humidity data exhibited obvious seasonal variations: relatively low in winter (below 0.005 kg kg^{-1}) and high in summer (maximum value of about 0.02 kg kg^{-1}). Daily maximum wind speed fluctuated between 3 and 15 m s^{-1}, being high in winter, when the maximum value occurred, and relatively low in summer. There were marked year-to-year variations in daily average temperature, with a low of 240 K in winter and a high of 310 K in summer. Precipitation mainly concentrated in summer, with large interannual differences: growing-season precipitation was 454, 563, and 295 mm in 2007, 2008, and 2009, respectively, with remarkably less rainfall in 2009 than in the other two years. R_l fluctuated between 170 and 460 W m^{-2} throughout the year, as compared with a growing-season R_s that ranged from 800 to 1000 W m^{-2} and a winter R_s value of around 400 W m^{-2}, both demonstrating obvious seasonal variations but small interannual differences.

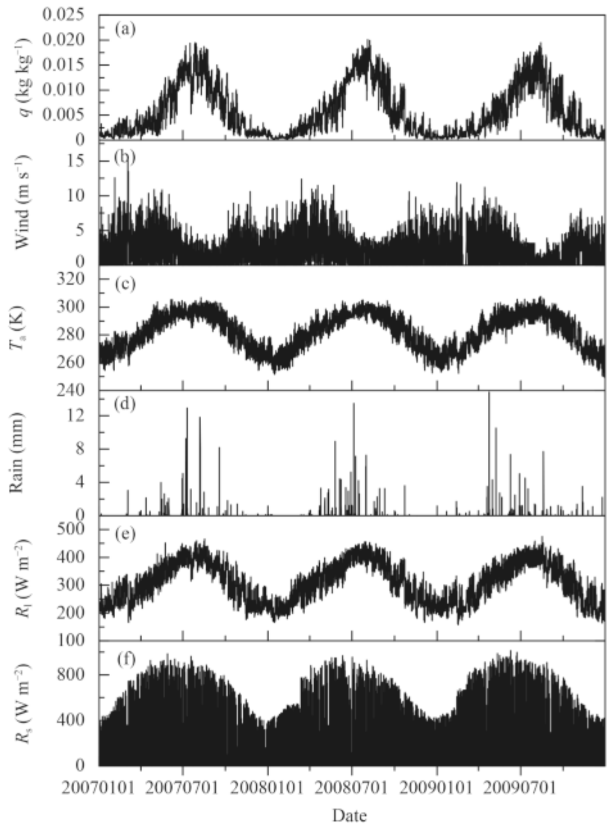

Fig. 1. Dynamic change features of model-driven data: (a) specific humidity (q; kg kg^{-1}); (b) wind speed (wind; m s^{-1}); (c) air temperature (T_a; mm); (d) precipitation (rain; mm); (e) longwave radiation (R_l; W m^{-2}); and (f) shortwave radiation (R_s; W m^{-2}).

LAI and F_v, as important canopy parameters, were poorly simulated with the scheme from CoLM (Cai et al., 2012), which will play an important role in decreasing the simulation performance of model. Therefore, we obtained day-to-day LAI by simulation based on the observed data. More specifically, LAI was obtained based on the measured data at different maize growth stages and daily mean temperature data via the effective cumulative temperature approach (Cai et al., 2011); and in light of the relationship between LAI and fractional F_v (Cai et al., 2014), the day-to-day LAI values were then applied in calculations to obtain the day-to-day F_v values (Fig. 2). As can be seen from Fig. 2, LAI and F_v experienced the same seasonal variation; that is, in terms of plant growth, they both reached peaks of around 3.7 m^2 m^{-2} and 1 for 2007 and 2008, and 4.8 m^2 m^{-2} and 1 for 2009, respectively, in the tasseling stage, and then decreased gradually until the end of the growth period.

Model verification data included the 5- and 10-cm soil

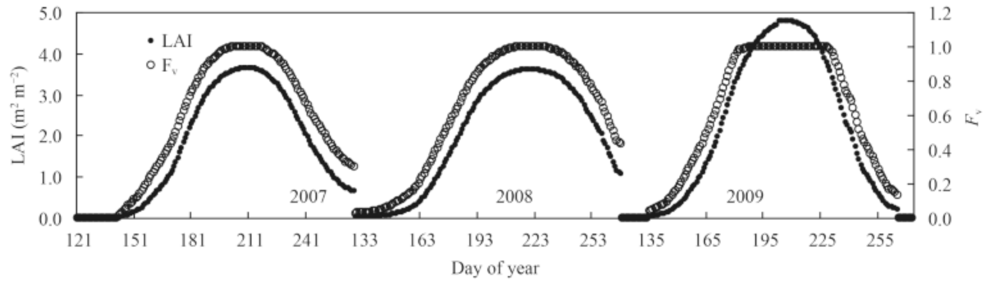

Fig. 2. Dynamics of leaf area index (LAI) (represented by solid points) and fractional vegetation cover (F_v) (represented by hollow points) during growth seasons of 2007–09.

temperature, the 30-min average sensible heat and latent heat fluxes under such quality controls as high-frequency attenuation correction and hydrothermal correction, and 0–50-cm soil humidity measured with the soil auger method every five days. For the great many latent heat flux data absent for the 2009 growing season, reference tables were used as a supplement (Gu et al., 2005). Considering nighttime data were inferior to daytime data in quality, for accuracy, this study adopted data during the period 0630–1800 Beijing Time only, except for the sensitivity analysis where whole-day data were required.

2.3 *Model description*

The land surface model used in this study was CoLM (Ji and Dai, 2010), finely tuned to the ecological and hydrological processes for a proper description of soil–vegetation–snow–atmosphere energy and water transmission, covering a layer of photosynthetic vegetation, 10 uneven vertical soil layers reaching to a depth of 3.43 m underground, and 5 snow layers. The two-big-leaf model was used to calculate the leaf surface temperature and leaf stomatal resistance; two-stream approximation was used in the solution of the singular points created by vegetation surface albedo, and the radiation calculation was differentiated between the sunny and shady vegetation sides; the new iterative algorithm was used to calculate the leaf surface temperature; convective precipitation and large-scale precipitation were dealt with separately in the calculation of foliar interception and retention values; turbulent transport under the canopy was taken into consideration; and soil bedrock thickness, surface runoff, subsurface runoff, the impact of root distribution, and water pressure on water uptake were considered for the water and heat conduction processes of the soil. All model parameters and variables are listed in Table 2.

2.4 *Default RWU parameterization scheme for the model*

Water movement in soil is calculated with Darcy's law in CoLM, and its equation can be written as

$$\frac{\partial \theta_i}{\partial t} = -\frac{\partial}{\partial z_i}\left(K_i - D_i \frac{\partial \theta_i}{\partial z_i}\right) - E_{x,i}, \tag{1}$$

where θ_i represents the volumetric water content of soil, K_i is the hydraulic conductivity, D_i is the soil water diffusivity, z_i is soil depth, t is time, and $E_{x,\,i}$ is the RWU:

$$E_{x,i} = T\eta_i. \tag{2}$$

Here, T stands for plant transpiration and η_i is the contribution of each water-uptake soil layer to the total amount of transpiration.

$$T = W_t \times T_{\text{pot}}. \tag{3}$$

T_{pot} stands for potential plant transpiration and W_t is the accumulated root efficiency factor.

$$W_t = \sum_{i=1}^{n} f_{\text{root},i} f_{\text{sw},i}, \tag{4}$$

$$\eta_i = \frac{f_{\text{root},i} f_{\text{sw},i}}{W_t}, \tag{5}$$

where $f_{\text{root, i}}$ is the proportional factor of the ith root layer, whose equation can be written as

$$f_{\text{root},i} = \frac{1}{1 + \left(\frac{z}{d_{50}}\right)^c}, \tag{6}$$

where c is a dimensionless root profile configuration parameter,

$$c = \frac{-1.27875}{(\lg d_{95} - \lg d_{50})}, \tag{7}$$

in which d_{50} and d_{95} represent soil depths with $f_{\text{root},\,i}$ = 50% and 95%, respectively. Cai et al. (2015) proposed that the changes of these two parameters among different growth stages of maize can barely affect model performance. As a result, they are set with the original model values; that is, 15.7 and 80.8 cm, respectively.

The parameter $f_{\text{sw},\,i}$ represents the soil water availability of the ith soil layer, which is linear to the soil matric potential in CoLM:

$$f_{\text{sw},i} = \frac{\phi_{\max} - \phi_i}{\phi_{\max} + \phi_{\text{sat}}}, \tag{8}$$

where φ_{max}, φ_{sat}, and φ_i stand for soil water potential at the time of wilting, actual and saturated soil water content, respectively.

2.5 *Methods for optimization of RWU function*

Zheng and Wang (2007) proposed an empirical nonlinear RWU scheme, in which two threshold parameters are adopted to reflect the dynamic root water use efficiency. The default method of CoLM was adopted to determine the root efficiency of each soil layer, while the accumulated root efficiency W_t was redefined as

$$W_{t,\ \mathrm{adjusted}} = \begin{cases} 1.0, & W_t \geqslant W_c \\ W_t/W_c, & W_t < W_c \end{cases}, \tag{9}$$

where W_c is a tunable threshold value between 0 and 1.0. This equation indicates that when W_t is higher than or equal to W_c, the plants could be enabled to reach potential transpiration even if part of the root system suffered water stress. $T_{pot} \times W_{t,\ \mathrm{adjusted}}$ is used to determine the total RWU. In order to determine the water uptake allocation, a water uptake flag $\alpha(i)$ is defined and expressed in the following equation:

$$\alpha(i) = \begin{cases} 0, & f_{\mathrm{sw},i} < \min(f_{\mathrm{sw,max}}, W_x) \\ 1.0, & f_{\mathrm{sw},i} \geqslant \min(f_{\mathrm{sw,max}}, W_x) \end{cases}, \tag{10}$$

where $f_{\mathrm{sw,\ max}}$ stands for the water availability of the most humid soil layer, while W_x stands for the water availability threshold parameter. Equation (10) indicates that when the water availability of a certain soil layer is less than the W_x threshold value, no water will be absorbed by the roots unless it is the wettest layer of the whole root

Table 2. Parameters and variables for models in this paper

Symbol	Description	Value	Unit
LAI	Leaf area index		$m^2\ m^{-2}$
F_v	Vegetation fraction	0–1	
θ_i	Volumetric of soil water content		$m^3\ m^{-3}$
z_i	Soil depth	0–3.5	m
$E_{x,\ i}$	Water extraction		$m\ s^{-1}$
K_i	Hydraulic conductivity		$m\ s^{-1}$
D_i	Soil moisture diffusivity		$m^2\ s^{-1}$
T	Actual transpiration		$m\ s^{-1}$
W_t	Accumulated root resistance factor	0–1	
T_{pot}	Potential transpiration		$m\ s^{-1}$
η_i	Soil water availability within layer *i*	0–1	
$f_{\mathrm{root},\ i}$	Root fraction within soil layer *i*	0–1	
$f_{\mathrm{sw},\ i}$	Soil water availability	0–1	
$f_{\mathrm{sw,\ max}}$	Soil water availability factor in the wettest layer of the root zone	0–1	
c	A dimensionless shape-parameter		
i	Soil layer	1–10	
d_{50}	Depth above which 50% of all roots were located	15.7	cm
d_{95}	Depth above which 95% of all roots were located	80.8	cm
φ_{max}	Soil water potential at wilting point within soil layer *i*	-1.5×10^5	mm
φ_{sat}	Saturated soil water potential		mm
φ_i	Soil water potential		mm
$W_{t,\ \mathrm{adjusted}}$	Redefined W_t	0–1	
W_c	A threshold determining whether the baseline cumulative root efficiency required for maximum plant transpiration (W_c) is reached		
W_x	A threshold parameter determining whether roots absorb water from a certain soil layer		
k	A tunable parameter used in the optimized RWU scheme	4	
$\alpha(i)$	A variable to determine the water uptake allocation	0–1	
EBR	Energy balance closure rate	0–1	
R	Correlation coefficient	0–1	
b_0	Intercept of linear regression		
b_s	Slope of linear regression		
o	Observation		
p	Simulation		
RMSE	Root-mean-square error		
NS	Nash-Sutcliffe efficiency coefficient	$-\infty$–1	
t	Time		
n	Data number		
R_n	Net radiation		$W\ m^{-2}$
G	Soil heat flux		$W\ m^{-2}$
LE	Latent heat flux		$W\ m^{-2}$
H	Sensible heat flux		$W\ m^{-2}$

zone. In Eq. (5) in the original model, η_i is redefined as

$$\eta_i = \frac{f_{\mathrm{root}}(i) f_{\mathrm{sw},\,i}^{k} \alpha(i)}{\sum_{j=1}^{n} f_{\mathrm{root}}(j) f_{\mathrm{sw},\,i}^{k} a(i)}, \tag{11}$$

where the tunable parameter k is equal to or larger than 1.0 and, when larger than 1.0, k reflects the nonlinear relationship between water availability and water uptake. Setting k to a value larger than 1 ensures that a larger proportion of water is absorbed by roots in relatively wet soil layers. As Zheng and Wang (2007) set the reasonable k value at 4, arguing that increasing the k value had little impact on the model simulation results, the value was also set at 4 in this study.

2.6 *Sensitivity analysis*

At the time, they put forward the RWU function, Zheng and Wang (2007), by comparing two groups of W_c and W_x parameters, reported that model simulation accuracy was the highest when $W_c = 0.4$ and $W_x = 0.6$. Given that no sensitivity analysis had been conducted on the two parameters, this study made equal interval adjustments to the two parameters based on the parameter settings, as is shown in Table 3. Simulations corresponding to different settings were defined as M1–M6; the simulation with the original model was M0. Considering the absence of measured latent heat data for 2009, whole-day data for the 2007 and 2008 growing seasons were adopted for comparison of accuracy in the sensitivity analyses.

2.7 *Statistical analysis methods*

Flux data obtained from the research site were assessed for their energy balance closure situation by using the energy balance closure rate with the following equation:

$$\mathrm{EBR} = \frac{\sum_{i=1}^{n}(\mathrm{LE}+H)}{\sum_{i=1}^{n}(R_{\mathrm{n}}-G)}. \tag{12}$$

To provide a more graphic assessment of the consistency between the simulated and measured values, the linear correlation coefficient (R), root-mean-square error (RMSE), and Nash–Sutcliffe (NS) coefficient (Gordon, 2003; Moriasi et al., 2007) were used as judgment indicators. The NS coefficient was used to assess model performance, ranging from minus infinity to 1: when the variance between the simulated and measured values exceeds the observational variance, NS < 0; when the variance approaches 0, NS approaches 1, indicating that the model performs a perfect simulation of the observational values. The equations for the statistical methods used in this study are:

Table 3. Model parameter sensitivity configuration

Simulation	W_c	W_x
M0	–	–
M1	0.8	0.2
M2	0.8	0.4
M3	0.6	0.2
M4	0.6	0.4
M5	0.4	0.4
M6	0.4	0.6

$$R = \frac{\sum_{i=1}^{n}(o_i-\bar{o})(p_i-\bar{p})}{\sqrt{\sum_{i=1}^{n}(o_i-\bar{o})^2 \sum_{i=1}^{n}(p_i-\bar{p})^2}}; \tag{13}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(p_i-o_i)}{n-1}}; \tag{14}$$

$$\mathrm{NS} = 1 - \frac{\sum_{i=1}^{n}(p_i-o_i)^2}{\sum_{i=1}^{n}(o_i-\bar{o})^2}. \tag{15}$$

3. Results

3.1 *Energy balance closure scenario*

Since the latent heat flux data for the 2009 growing season were supplemented reference data that could barely reflect the actual energy closure scenario, only flux data for the 2007 and 2008 growing seasons were analyzed for their energy closure status. Figure 3 shows that LE+H for both growing seasons was below R_{n}–G, indicating that the sum of sensible and latent heat measured from eddy covariance was lower than the available energy. The regression coefficients (R) of the two stood at 0.92 and 0.89, respectively, and EBR at 0.83 and 0.88, respectively, indicating energy nonclosure existed to a certain extent, and with interannual differences.

3.2 *Parameter sensitivity of the optimized model*

Judgments were made on the parameter sensitivity of the optimized model through a comparison of the simulation accuracy of the models with different parameter configurations. It is apparent from Table 4 that for each of the three groups, i.e., M1 and M2, M3 and M4, and M5 and M6, the R values were identical; the RMSEs were slightly different; and the NS coefficients were virtually identical. Whereas, the R, RMSE, and NS values differed

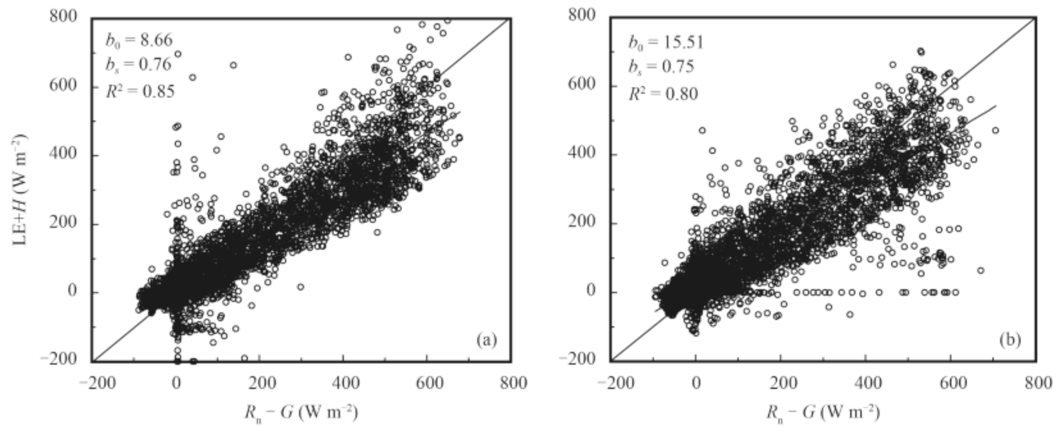

Fig. 3. Energy closure situations for the research site with (a) b_0= 8.66 and (b) b_0=15.51. Refer to Table 2 for the definitions of the parameters.

significantly between different groups, suggesting that the model was barely sensitive to W_x but very sensitive to W_c. Among others, the simulation accuracy of the sensible heat and latent heat for 2007, and the latent heat for 2008, increased with a decrease of W_c. The case for sensible heat in 2008 was precisely the opposite, which might have been caused by energy imbalance in the flux observations (Li et al., 2013). From a comparative point of view, when W_c = 0.4, the improvements in the optimized RWU schemes in terms of flux simulation were most obvious. When W_x was insensitive, W_c values were identical to the results of Zheng and Wang (2007) for forest, in that both exhibited better model simulation performance with the decrease in W_c. According to this finding, both W_c and W_x were set at 0.4 in the simulations used for comparison of the optimization effects over the three years.

3.3 *Effects of optimized RWU function on soil humidity simulation*

According to soil stratification (Table 5) in the model, the third layer in the model corresponds to soil humidity observation at the depth of 10 cm; the fifth layer, 20–30 cm; and the sixth layer, 30–50 cm.

Considering soil water content varies little within the day, the average daily soil water content values for the 2007–09 growing seasons were used for comparison of the simulation accuracy before and after the optimization. As can be seen from Fig. 4, either at the depth of 10 or 20–30 cm, there was an underestimation, to varying degrees, of the simulated soil water content for the 2007 and 2008 growing seasons, as compared to the actual measured values: in terms of the 10-cm soil humidity, errors were small on days with large-scale precipitation, large on precipitation-free days, and grew with the increase in the number of precipitation-free days. Measured soil water content values suffered scarcely any influence from small daily precipitation amounts, which might be attributable to the fact that surface water uptake cannot bring the precipitation influence down to a depth of 10 cm, as compared to more sensitive reactions in the simulated value, indicating the model's inaccurate description of this process might be a factor contributing to the errors in soil water content simulation. As a result, there was almost no difference in the simulated values at various soil depths under the small daily precipitation conditions for 2007 and 2008 before and after the optimi-

Table 4. Comparison of models with different parameter configurations in terms of simulation accuracy

Simulation	LE (2007)			*H* (2007)			LE (2008)			*H* (2008)		
	R^2	RMSE	NS	R^2	RMSE	NS	R^2	RMSE	NS	R^2	RMSE	NS
M0	0.662	70.959	0.647	0.679	47.032	0.337	0.771	56.318	0.743	0.717	32.661	0.693
M1	0.654	71.968	0.637	0.676	48.132	0.305	0.769	56.827	0.738	0.714	32.778	0.690
M2	0.654	71.973	0.637	0.676	48.137	0.305	0.769	56.827	0.738	0.714	32.778	0.690
M3	0.672	70.284	0.654	0.679	45.753	0.372	0.777	56.345	0.743	0.706	33.005	0.686
M4	0.672	70.289	0.653	0.679	45.756	0.372	0.777	56.345	0.743	0.706	33.005	0.686
M5	0.687	68.602	0.670	0.686	43.623	0.429	0.779	56.107	0.745	0.706	32.972	0.687
M6	0.687	68.638	0.670	0.686	43.648	0.429	0.779	56.100	0.745	0.706	32.970	0.687

Table 5. Soil stratification in the model

The order number of soil layer	1	2	3	4	5	6	7	8	9	10
Soil depth (m)	0.018	0.045	0.091	0.166	0.289	0.493	0.829	1.383	2.296	3.433
Soil layer thickness (m)	0.018	0.028	0.046	0.075	0.124	0.204	0.336	0.554	0.913	1.137

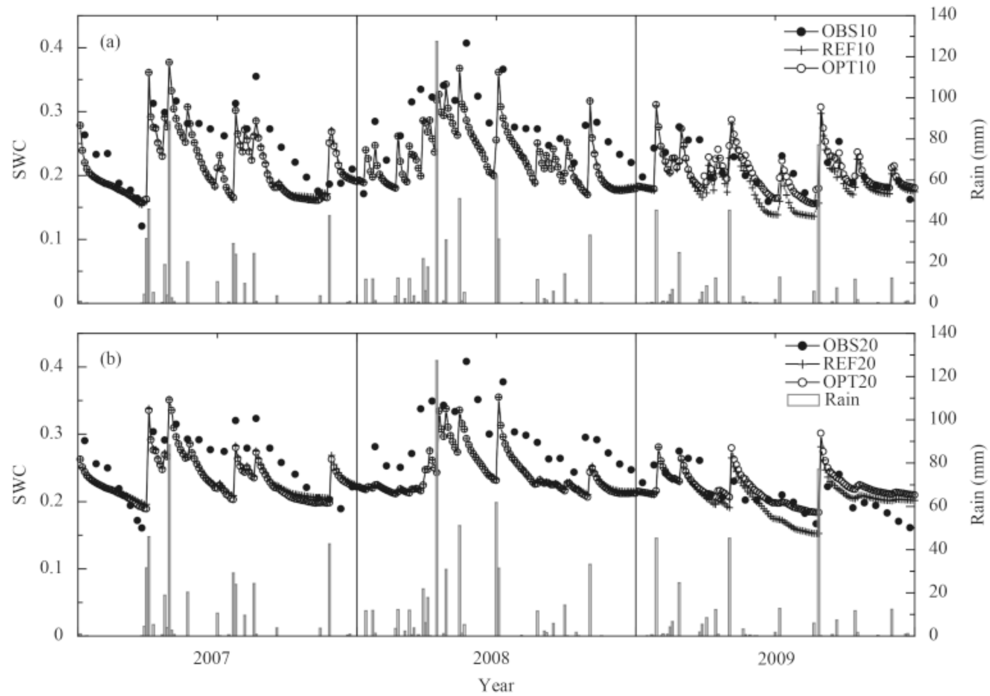

Fig. 4. Comparison of the simulated and measured soil water content (SWC) values at the depths of (a) 10 cm and (b) 20–30 cm before and after the optimization. Filled circles stand for measured values (OBS); crosses and open circles stand for simulated values before (REF) and after the optimization (OPT), respectively.

zation.

The case was different in 2009. Errors caused by the underestimation of the simulated soil water content at 10-cm depth were small, and the simulated values after the optimization were even closer to the measured values, indicating that the optimization significantly helped to improve the simulation of the upper-layer soil humidity. Simulated soil water content at 20–30-cm depth was overestimated with the original model for the latter part of the growing season, and underestimated in other stages; there were no marked changes in the simulation accuracy after the optimization for the earlier part of the growing season, marked improvements for the middle part, and rather large errors in the latter part. The effects of the optimized models at the two levels were more obvious during the continuous non-precipitation days of July and August when maize required a great deal of water, whereas RWU was greatly restricted for long-term lack of precipitation. The optimized model generated larger simulated soil water content values for this period, with enhanced simulation accuracy. In contrast, the optimized model did not enhance the soil water content simulation accuracy over the continuous non-precipitation periods in 2007 and 2008, which might be attributable to the higher soil water availability in these two years than in 2009. That is to say, the effects of the optimized models show up only when soil humidity is below a certain threshold.

To more clearly reflect the changes in soil water content simulation performance after the optimization, the vertical variation of the simulated soil water content values for each month of the 2009 growing season was analyzed (Fig. 5). However, this revealed that there was almost no change in the simulated soil humidity values for different layers in June; an increase to varying degrees in July and August, with a decreasing margin corresponding to the increase in soil depth; and a marked difference in September, with the margin of increase maximizing in the fifth and sixth layers, and diminishing both ways for the upper and lower layers. The findings from the causal analysis of the above situations were: In June, the maize plants were small, so changes in soil water content were caused mainly by surface evaporation rather than RWU, making it impossible to show the effects of the optimized models. July and August marked the reproductive growth stage when maize became water-consuming and changes in soil water content were attributed mainly to plant transpiration, making it possible to best reflect the effects of the optimized RWU parameterization schemes. September presented a different picture from July and August: as leaves fell, transpiration no longer played the leading role, and soil water content was subject to the combined influence of surface evaporation and plant transpiration. At the surface level, where surface evaporation predominates, the effects of the optimized RWU

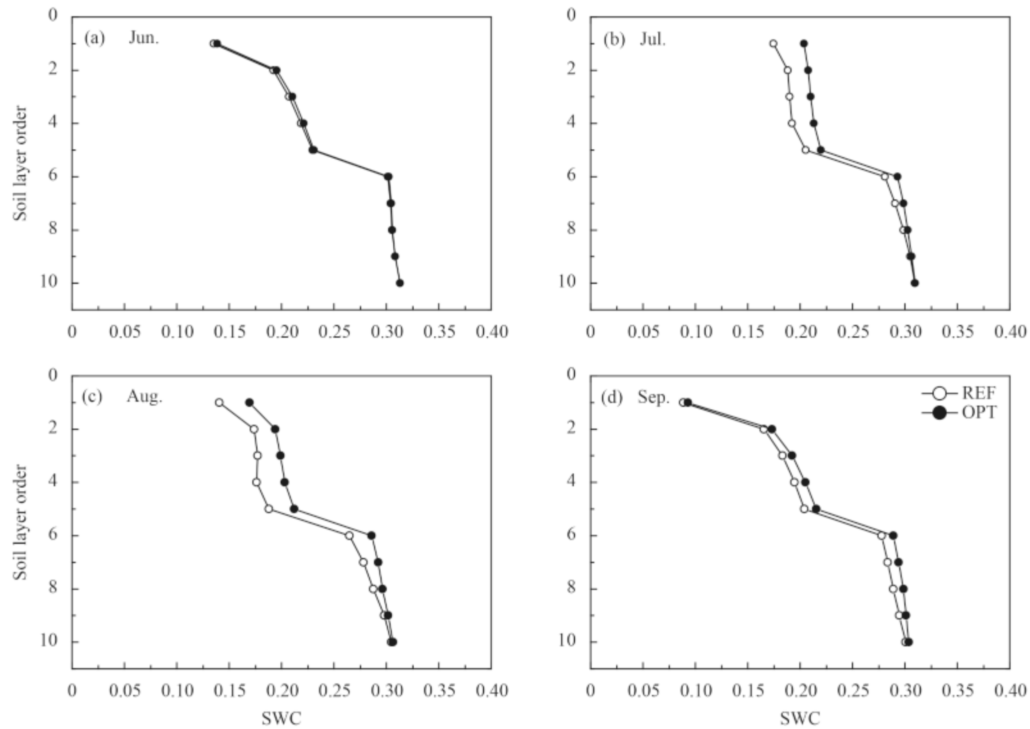

Fig. 5. Comparison of the vertical variation in monthly average simulated soil water content (SWC) values before (REF) and after the optimization (OPT) in (a–d) June–September 2009.

model barely took hold; but with the increase in soil depth, transpiration dominated again in affecting soil water content to fully reveal the optimization effects. The case with the lower layers was rather the same as that in July and August; that is, the optimization effects on soil water content weakened with the increase in soil depth.

3.4 *Effects of optimized RWU function on soil temperature simulation*

The case was different with soil temperature, which took on a marked daily dynamic feature, and so monthly average daily variations were taken into account in the simulation accuracy comparison (Fig. 6). In terms of simulation accuracy, the original model achieved the largest simulation errors in June 2007, August 2009, and September of all three years, with daily variation simulated values rather close to the measured values for the remaining time, even though simulation performance varied significantly from year to year and seasonally. The optimized model generated increased soil temperature simulation accuracy at the depths of 5 and 10 cm in August 2009 only. Overall, soil temperature simulation correlated with the soil humidity simulation to some extent.

3.5 *Effects of optimized RWU function on latent and sensible heat flux simulation*

In terms of latent and sensible heat flux simulation, the original model exhibited high simulation accuracy for either variable in 2008 (Fig. 7), with simulated values identical to measured values of latent heat for July and August, and sensible heat for June and August. In 2007, the simulated July and August latent heat and July sensible heat values also reflected the measured daily change well; however, there were considerable errors in both variables in June and September. In 2009, latent heat flux was underestimated, except in June, and to a wide margin in August and September; whereas, sensible heat flux was overestimated, to varying degrees, from June to August. The optimized model enhanced the latent and sensible heat simulation accuracy slightly for 2007, barely for 2008, and most remarkably for 2009, which was reflected by the simulated July and August latent heat values increasing remarkably to hold the underestimation of the original model in check, and the simulated July and August sensible heat values decreasing significantly to better correlate with the soil temperature situations and to further demonstrate that optimization effects vary in different maize growth stages. Although the supplemented reference data of the 2009 latent heat flux might not reflect the actual case, the sensible heat flux data were obtained from actual observations, and so improved simulation accuracy in this regard might well prove the effects of the optimized model on heat flux simulation.

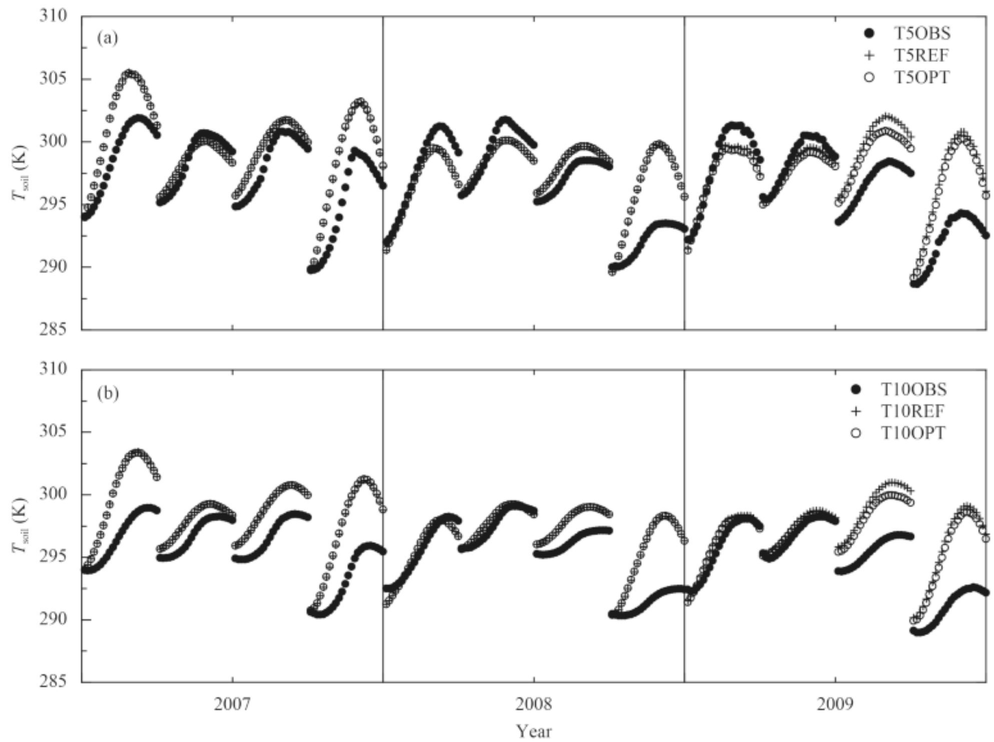

Fig. 6. Comparison of the simulated and measured values (OBS) of the monthly average diurnal patterns of (a) 5- and (b) 10-cm soil temperature before (REF) and after the optimization (OPT).

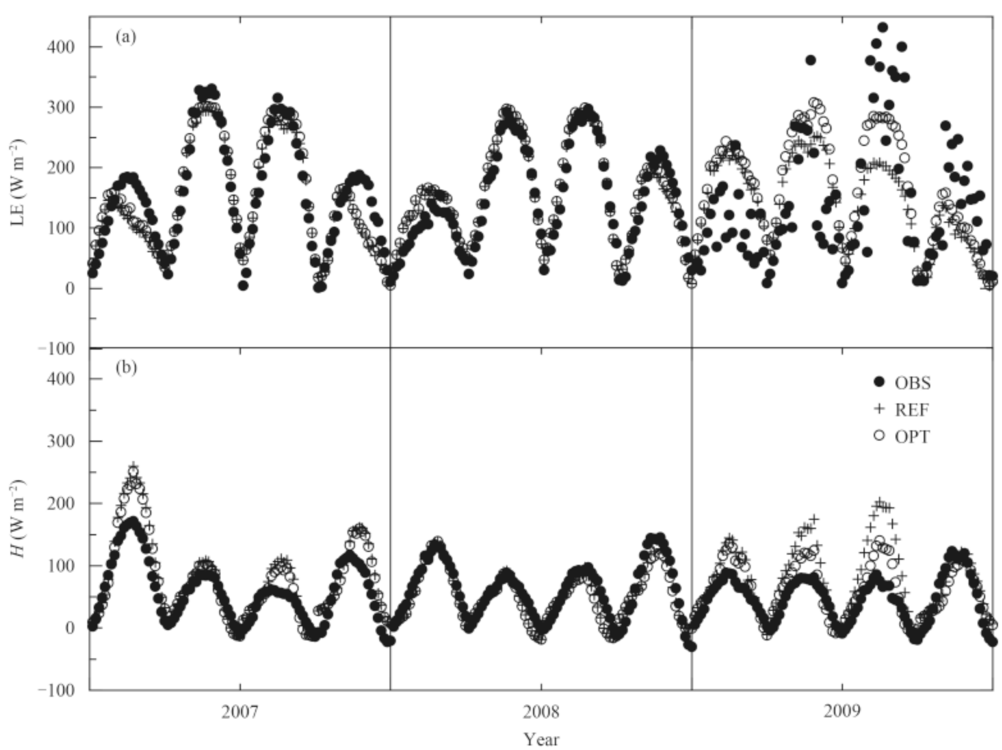

Fig. 7. As in Fig. 6, but for the diurnal variation of (a) latent and (b) sensible heat fluxes averaged on the monthly scale.

For a more graphic reflection of the optimization effects, the R, RMSE, and NS values were used to assess the latent and sensible heat flux simulation accuracy from a quantitative point of view (Table 6). In terms of simulation accuracy, with regard to either latent or sensible heat data, the maximum RMSE, the minimum NS,

Table 6. Comparison of the latent and sensible heat flux simulation accuracy before and after optimization

Year	Variable	Default CoLM			Modified CoLM		
		RMSE	NS	R	RMSE	NS	R
2007	LE	93.621	0.457	0.724	90.060	0.497	0.747
	H	63.074	0.017	0.768	57.992	0.169	0.777
2008	LE	74.980	0.604	0.815	74.663	0.608	0.822
	H	42.719	0.562	0.814	43.211	0.552	0.809
2009	LE	144.343	−0.468	0.277	140.589	−0.392	0.406
	H	90.229	−1.508	0.516	68.495	−0.445	0.528

and R values all occurred in 2009, and the minimum RMSE, the maximum NS, and R values in 2008, with the 2007 figures falling between. This indicates that the simulation accuracy was highest in 2008, followed by 2007, and then 2009, and that model performance varied from year to year. A comparison of the statistics before and after the optimization showed that, except for sensible heat in 2008, the simulation accuracy for all variables was higher-slightly for 2007, and remarkably for 2009. We can confidently conclude that the optimized model has its poorest effects under high soil water availability situations and its best effects during times of drought, which is consistent with the findings of Li et al. (2013).

4. Discussion

Agricultural ecosystems are representative in that they are found everywhere and are most severely affected by human activities. Climate change is likely to have a wide range of impacts on agricultural productivity in many regions of the world (IPCC, 2007). Compared with forests, grasslands, and other ecosystems scarcely influenced by human activities, maize farmland ecosystems are more intensively managed, leading to some complex and varied interactions of physical processes with the atmosphere (Li et al., 2011). However, no definite conclusion has been reached as to how well land surface models can be applied to the simulation of maize farmland ecosystems, and there have been few RWU-related studies conducted.

Even though various RWU functions have been introduced by scholars (e.g., Jackson et al., 2000; Li et al., 2006; Zheng and Wang, 2007) into land surface models, they exhibit limited applicability because different ecosystems cope differently with different soil water availability scenarios. For instance, in the Amazon rain forest, water redistribution is an effective mechanism to maintain transpiration (Lee et al., 2005; Oliveira et al., 2005); and in central Asia, high root water use efficiency is an effective way for desert shrubs to adapt to the arid environment (Xu et al., 2007). In the case of the Jinzhou farmland ecosystem in different maize growth stages, the simulation results of CoLM with the default RWU function show that the simulation accuracy of soil moisture is higher on precipitation days but tends to reduce during continuous non-precipitation periods. The simulation accuracy of soil temperature varies significantly from year to year and seasonally, with remarkable low accuracy in the late growth stages of maize and a higher simulation accuracy for other time periods. In years of little rainfall, there is an underestimation of sensible heat and latent heat; whereas, in years of normal rainfall, heat flux simulations tend to be more accurate.

To overcome this defect of poor simulation performance with respect to various variables during drought, this study introduced the RWU function proposed by Zheng and Wang (2007) for optimization of the model. The results demonstrate that the W_x parameter used in the optimized function to determine whether roots absorb water from certain soil layers has scarcely any effect on the simulation of sensible and latent heat, indicating that RWU at different soil depths has nothing to do with heat flux. However, the W_c parameter, used to determine whether the baseline cumulative root efficiency required for maximum plant transpiration is reached, is very sensitive to the heat flux simulation. As far as the research site is concerned, when this parameter is valued at 0.4, the model simulation accuracy is highest. In fact, the optimized model did not generate better simulation results under all soil water availability conditions, but did make an obvious difference in the 2009 growing season, characterized by a relatively low level of soil moisture, suggesting that the effects show up only when soil water content reaches a certain threshold, which might not be a fixed value but is closely related to canopy structures or physiological properties in the given plant growth stage. In short, from a qualitative point of view, the optimized RWU function generated notably better simulation results of maize water uptake in times of drought, with soil moisture and latent heat simulation accuracy significantly improved, suggesting that proper RWU schemes have obvious effects in enhancing the simulation of land–atmosphere water and heat flux. Although sensible heat simulation at certain points dropped in accuracy after the optimization, this does not necessarily mean that the optimized schemes are not good enough; rather, it means that land surface models might have other parameterization schemes that are inaccurate and should be held accountable, such as those related to runoff, infiltration, and transpiration (Zheng and Wang, 2007), proving that in the evaluation of the effectiveness of physical process parameterization schemes, the single most important prerequisite is an accurate description of some associated processes.

Based on this research, a suitable parameterization scheme for simulations conducted for Northeast China maize farmland ecosystems has basically been determined, which helps to enhance our understanding of the RWU process and provides a reference for similar studies. Nevertheless, because of the lack of or inadequacy of some important variables used to determine the effects of the optimized model, such as measured soil water content data at different depths and canopy evapotranspiration data associated with the total amount of RWU, some of the simulation results reported in this paper cannot be fully accounted for, meaning that related conclusions are somewhat uncertain. In addition, whether or not a parameterization scheme is good enough requires verification with data from different observation sites. Therefore, future studies should focus on collecting year-to-year data from other maize farmland ecosystems, to further test and assess the simulation performance of the RWU parameterization schemes.

5. Conclusions

Based on the 2007–09 data collected at the farmland ecosystem field station in Jinzhou, we optimized CoLM with the RWU scheme of Zheng and Wang (2007). We then investigated the sensibility of parameters in the optimized RWU function and evaluated the effects of the optimized RWU function of this model on the simulation of land–atmosphere water and heat flux. The following conclusions were drawn:

(1) In the optimized RWU function, the soil water availability parameter used to determine whether roots absorb water from a certain soil layer has scarcely any effect on the simulation of heat, whereas the parameter used to determine whether the lower limit of cumulative root efficiency required for maximum plant transpiration is reached is very sensitive to the land surface process simulation: simulation accuracy increases with a decrease in this parameter.

(2) The optimized RWU function significantly improves CoLM's performance in simulating soil humidity, temperature, and sensible heat and latent heat fluxes in years of little rainfall, particularly on continuous non-precipitation days at a time when maize growth becomes most water-consuming. This indicates that the optimized CoLM RWU process is highly applicable to simulating water and heat flux in maize farmland ecosystems under arid conditions.

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