Agricultural Water Management 103 (2012) 140–149

Contents lists available at SciVerse ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Calibrating RZWQM2 model for maize responses to deficit irrigation

Liwang Ma[a,*], Thomas J. Trout[b], Lajpat R. Ahuja[a], Walter C. Bausch[b], S.A. Saseendran[c], Robert W. Malone[d], David C. Nielsen[e]

[a] USDA-ARS, Agricultural Systems Research Unit, Fort Collins, CO 80526, United States
[b] USDA-ARS, Water Management Unit, Fort Collins, CO 80526, United States
[c] Department of Soil and Crop Sciences, Colorado State University, Fort Collins, CO 80523, United States
[d] USDA-ARS, National Laboratory for Agriculture and the Environment, Ames, IA 50011, United States
[e] USDA-ARS, Central Great Plains Research Station, Akron, CO 80720, United States

ARTICLE INFO

Article history:
Received 24 May 2011
Accepted 6 November 2011
Available online 9 December 2011

Keywords:
Crop modeling
Irrigation scheduling
RZWQM
DSSAT
CERES-maize
Soil hydraulic properties
Systems modeling

ABSTRACT

Parameterizing a system model for field research is a challenge and requires collaboration between modelers and experimentalists. In this study, the Root Zone Water Quality Model-DSSAT (RZWQM2) was used for simulating plant responses to water stresses in eastern Colorado. Experiments were conducted in 2008, 2009, and 2010 in which maize (*Zea Mays* L.) was irrigated to meet a certain percentage (100%, 85%, 70%, 55%, and 40%) of the estimated crop evapotranspiration (ETc) demand during a growing season. The model was calibrated with both laboratory-measured and field-estimated soil water retention curves (SWRC) and evaluated for yield, biomass, leaf area index (LAI), and soil water content under five irrigation treatments in all three years. Simulated results showed that field-estimated SWRC provided better model responses to irrigation than laboratory-measured SWRC. The results also showed that there were multiple sets of plant parameters that achieved acceptable simulations when only one irrigation treatment was used for calibration. Model parameterization can be improved when multiple treatments and multiple years of data are included. The parameterized RZWQM2 model was capable of simulating various irrigation treatments in all years and could be used to schedule irrigation based on ETc requirement.

Published by Elsevier B.V.

1. Introduction

It is a challenge to parameterize a system model that can be applied to other soil and weather conditions without re-calibration. An agricultural system model is seldom calibrated to a high accuracy for all of its components due to inadequacy of the model, methods of calibration, lack of measured data for all system components, and variability in field measurements. Another common difficulty is the lack of evaluation for a variety of conditions after a model is calibrated. Most often, a system model is at best partially calibrated due to lack of data collected for all system components. If experimental data were available for all the system components, calibration of a model for such a comprehensive dataset may help improve the science used in the model, especially the interactions among system components. In addition, the majority of model calibration schemes involve a degree of trial and error without a rigorous optimization algorithm that accounts for uncertainties and correlation among parameters. As such, the calibrated model parameters may not be unique, and many combinations of model parameters may produce similar results (Fang et al., 2010).

Although a few studies used an optimization algorithm to obtain model parameters (Fang et al., 2010; Malone et al., 2010), it took considerable time to set up the optimization scheme for a study and to come up with the right objective function (Nolan et al., 2011). Therefore, a system model is usually calibrated manually and the goodness-of-calibration depends on the experience of model users. For example, the same model may be calibrated differently on the same dataset by two different users based on their personal experience (Ma et al., 2009; Thorp et al., 2007). A model user may be more competent to calibrate soil parameters than plant parameters. He or she may achieve a calibration of soil parameters which leaves the plant parameters at their default values. On the other hand, a user may choose to calibrate the dataset by adjusting the plant parameters and leave the soil parameters at their default settings. Without extensive evaluation and using measured soil and plant parameters, it is difficult to judge which calibration is more reasonable than the others. In addition, the manual calibration procedure usually is not reported in modeling studies.

Parameterization of a system model includes both calibration and evaluation. Usually one dataset is used for calibration and another independent dataset for evaluation or validation. A model user may use one year's data for calibration and the rest for model evaluation (Ma et al., 2003; Saseendran et al., 2004) or use one treatment for model calibration and the rest for model evaluation (Hu

* Corresponding author. Tel.: +1 970 492 7339.
E-mail address: Liwang.Ma@ars.usda.gov (L. Ma).

0378-3774/$ – see front matter. Published by Elsevier B.V.
doi:10.1016/j.agwat.2011.11.005

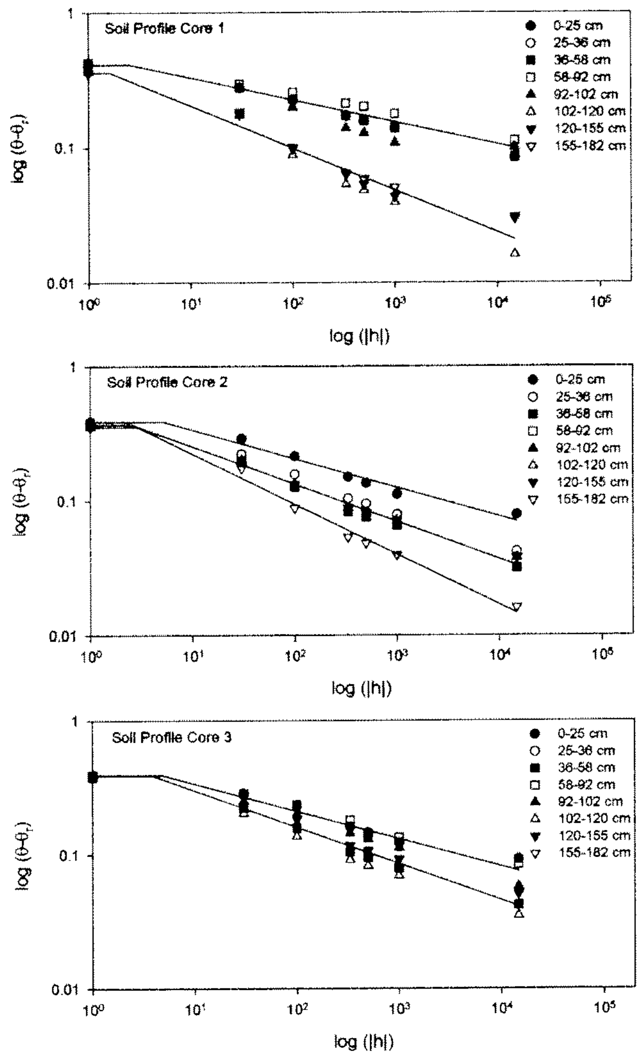

Fig. 1. Laboratory-measured soil water retention curves (SWRC) and fitted Brooks–Corey curves for the three soil profile cores.

conductivity (K)-suction head (h) curve (cm), and N_2 is the slope of the $\log(K) - \log(h)$. C_2 is obtained by imposing continuity at h_{bk}:

$$C_2 = K_{sat} h_{bk}^{N_2} \tag{4}$$

N_2 in RZWQM2 is calculated as:

$$N_2 = 2 + 3\lambda \tag{5}$$

The parameters h_b and h_{bk} were assumed to be equal and θ_r was assumed to be 0.039 cm^3 cm^{-3} for the soil texture based on Rawls et al. (1982). Table 1 shows the physical properties and fitted Brooks–Corey parameters for each soil core. Fitted porosity was then used to calculate an average bulk density using $\rho_b = (1 - \theta_s)\rho_p$, where θ_s is saturated soil water content (or porosity) and ρ_b and ρ_p (=2.65 g cm^{-3}) are bulk density and particle density, respectively.

To compare with laboratory derived SWRCs, SWRCs were also obtained from field estimated field capacity (water content approximately 24 h after a large water application, assumed to be equal to 33 kPa soil water content) and by assuming that 50% of field capacity is wilting point (1500 kPa soil water content), which is close to the average ratio between 1500 kPa water content and 33 kPa water content measured in the laboratory cores and as reported by Rawls et al. (1982) and Ma et al. (2009).

$$\lambda = \frac{\ln[(\theta_{1/3} - \theta_r)/(\theta_{15} - \theta_r)]}{\ln(15,000/333)} \tag{6}$$

$$h_b = \exp\left[\frac{\ln(\theta_{1/3} - \theta_r) - \ln(\theta_s - \theta_r) + \lambda\ \ln(333)}{\lambda}\right] \tag{7}$$

where θ_{15} and $\theta_{1/3}$ are soil water contents at 1500 kPa and 33 kPa suctions, respectively. The latter is assumed to be at field capacity (FC).

Root mean squared deviation (RMSD) or relative RMSD (RRMSD) was used to quantify the goodness of fit of the predicted results to the field measured results for a given calibration.

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}} \tag{8}$$

$$\text{RRMSD} = \frac{\text{RMSD}}{O_{avg}} \tag{9}$$

where N is the number of observations. P_i and O_i are the model predicted and experimental measured points, respectively, and O_{avg} is the averaged observed value.

3. Model description and parameterization

The Root Zone Water Quality Model (RZWQM2, version 2.0) with the DSSAT 4.0 crop modules was used in this study (Ma et al., 2006). The model requires SWRC and saturated hydraulic conductivity (K_{sat}). The model provides options to calculate hourly and daily potential evapotranspiration (PET) based on the Shuttleworth–Wallace method (Shuttleworth and Wallace, 1985). In this study, the K_{sat} values were obtained from table values based on soil texture (Rawls et al., 1982) and the hourly PET calculation was used. As done previously in the literature, RZWQM2 was calibrated manually at first. The manual calibration procedure included matching simulation results with measured soil water, anthesis and maturity dates, maximum LAI, and final biomass and yield. The soil root growth factor (SRGF) was assumed to obey the following equation (Ma et al., 2009) with $wcg = 3$ and $z_{max} = 200$ cm.

$$\text{SRGF} = \begin{cases} 1 & z \le 15\,\text{cm} \\ \left(1 - \dfrac{z}{z_{max}}\right)^{wcg} & z > 15\,\text{cm} \end{cases} \tag{10}$$

Three model calibration studies were conducted (Fig. 2). *First*, fitted SWRCs in Fig. 1 were used. Instead of taking an average of the SWRCs at respective soil depths from the three soil cores (Fig. 1), we built soil profiles by randomly selecting a SWRC at each soil horizon from one of the three soil cores. The soil profile that provided the best simulation of soil water content was then used. Then, the plant parameters were manually calibrated for the 100% ET treatment (#1) in 2008.

Second, field-estimated water holding capacity for each soil horizon was used as 33 kPa soil water content (assumed to be DUL). The SWRC was derived from the 33 kPa soil water contents and 1500 kPa (assumed to be LL) soil water contents based on Eqs. (6) and (7). Initial calibration was for the 100% ET treatment (#1) in 2008 and the calibrated plant parameters were then evaluated for the other treatments in 2008 and all treatments in 2009 and 2010. If the calibrated model did not simulate well for other treatments, the plant parameters were recalibrated until the model responded to water stresses with simulation error within 10% of measured yield and biomass.

The *third* calibration was an ordered search of plant parameters in a given range for each parameter in Table 2, using field estimated SWRC as in the second calibration study. Each plant parameter was

Table 3
Soil parameters estimated from field measured soil water contents.

Soil depth (cm)	Bulk density ρ_b (g cm^{-3})	θ_s (cm^3 cm^{-3})	$\theta_{1/3}$ (cm^3 cm^{-3})	θ_{15} (cm^3 cm^{-3})	h_b (cm)	λ
0–15	1.492	0.437	0.262	0.131	20.04	0.182
15–30	1.492	0.437	0.249	0.124	15.15	0.182
30–60	1.492	0.437	0.220	0.110	7.75	0.182
60–90	1.568	0.408	0.187	0.093	4.64	0.182
90–120	1.568	0.408	0.173	0.086	2.95	0.182
120–150	1.617	0.390	0.162	0.081	2.71	0.182
150–200	1.617	0.390	0.198	0.099	8.04	0.182

September. Simulated RMSD was 0.778 for LAI, 0.039 cm^3 cm^{-3} for soil water content, and 3.20 cm for soil profile water. Since simulated soil water did not deviate further from measurements after adjusting the plant parameters, the calibration was accepted even though the LAI was not predicted well towards the end of growing season.

After the calibration, the model was used to simulate other irrigation treatments in 2008. To our disappointment, simulated yield and biomass did not respond to irrigation treatments (Fig. 3). The LAI also did not change with irrigation treatment. To find out why the calibrated model did not respond to irrigation, we compared measured and simulated average plant available water (PAW)

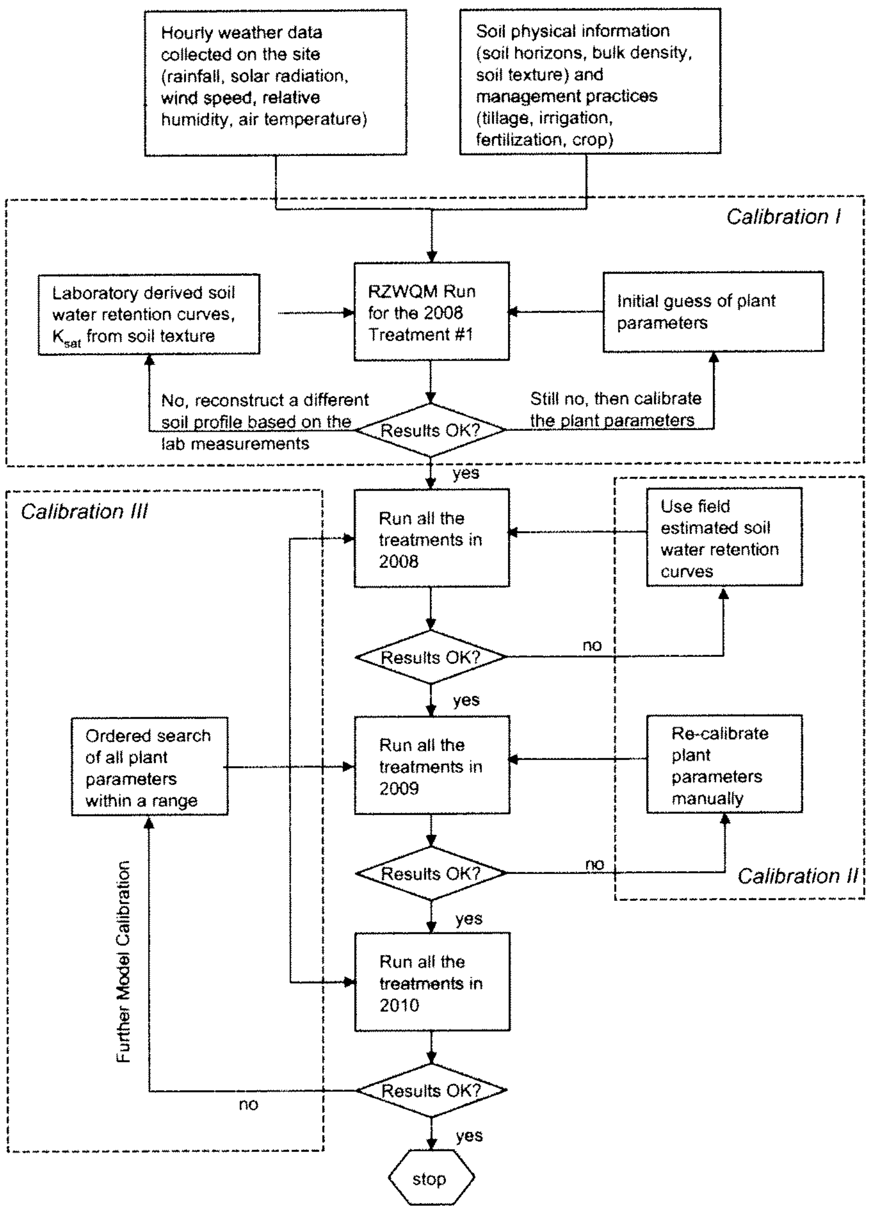

Fig. 2. A flow chart of calibration procedure used in the study.

length sensitivity coefficient improved biomass simulation. In addition, we used the default 38.9 °C-days phylochron interval (PHINT). These parameters improved yield and biomass responses to irrigation amounts (Figs. 3, 5 and 7). The RMSD across all the five treatments were 0.037 $cm^3 cm^{-3}$ for soil water content and 3.7 cm for profile soil water for 2008, which were comparable to those using laboratory-measured SWRC (0.043 $cm^3 cm^{-3}$ for soil water content and 3.8 cm for profile soil water). Although maximum LAI simulated for the treatment #1 was close to measured (4.5 compared to 4.6), the peak LAI was 10 days early compared to maximum canopy cover. Both simulated anthesis and maturity dates were also early by a week compared to observed dates.

For 2009, the simulated anthesis date was 85 compared to 84 DAP observed and maturity date was 143 compared to 147 DAP observed. The simulated RMSD was 387 $kg\,ha^{-1}$ for yield and 1400 $kg\,ha^{-1}$ for biomass. Simulated relative difference between treatment #1 and #5 was 4353 $kg\,ha^{-1}$ compared to 5206 $kg\,ha^{-1}$ for yield and 8136 $kg\,ha^{-1}$ compared to measured difference of 8091 $kg\,ha^{-1}$ for biomass (Fig. 5). Simulated soil water content and profile soil water were slightly better than those for 2008 with RMSD of 0.030 $cm^3 cm^{-3}$ and 2.4 cm, respectively. The worse simulation of soil water in 2008 could be due to the measurement error in treatment #5 (Fig. 4). The better response of crop growth to irrigation using field estimated 33 kPa soil water was due to the correct relationship between PAW and TPAW (i.e., TPAW > PAW; Figs. 4 and 6). When laboratory-measured SWRCs were used, PAW was always higher than TPAW. Therefore, no water stress was simulated. However, when field-estimated SWRC was used, TPAW was higher than average seasonal PAW although the simulated PAW was close to TPAW for the 100% treatments in both 2008 and 2009, for the three soil profile depths shown (90, 120, and 180 cm).

These calibrated parameters simulated maize yield well in 2010 for treatments #3, #4, and #5, but under-predicted yield for treatments #1 and #2 with an overall RMSD of 1722 $kg\,ha^{-1}$. On the contrary, the model predicted biomass well in 2010 for #1 and #2,

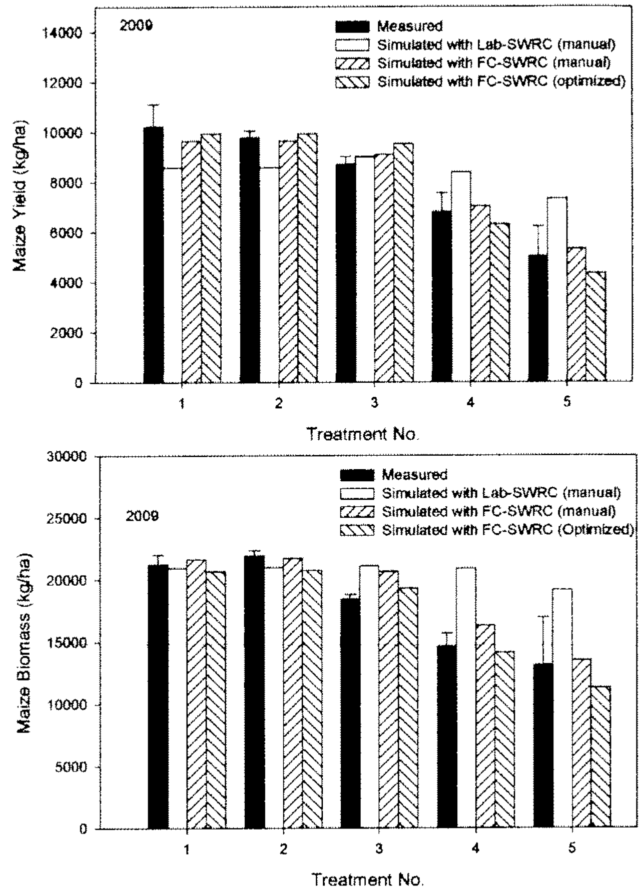

Fig. 5. Measured and simulated maize yield and biomass with field and laboratory measured soil water retention curves (SWRC) and plant parameters calibrated manually and automatically in 2009.

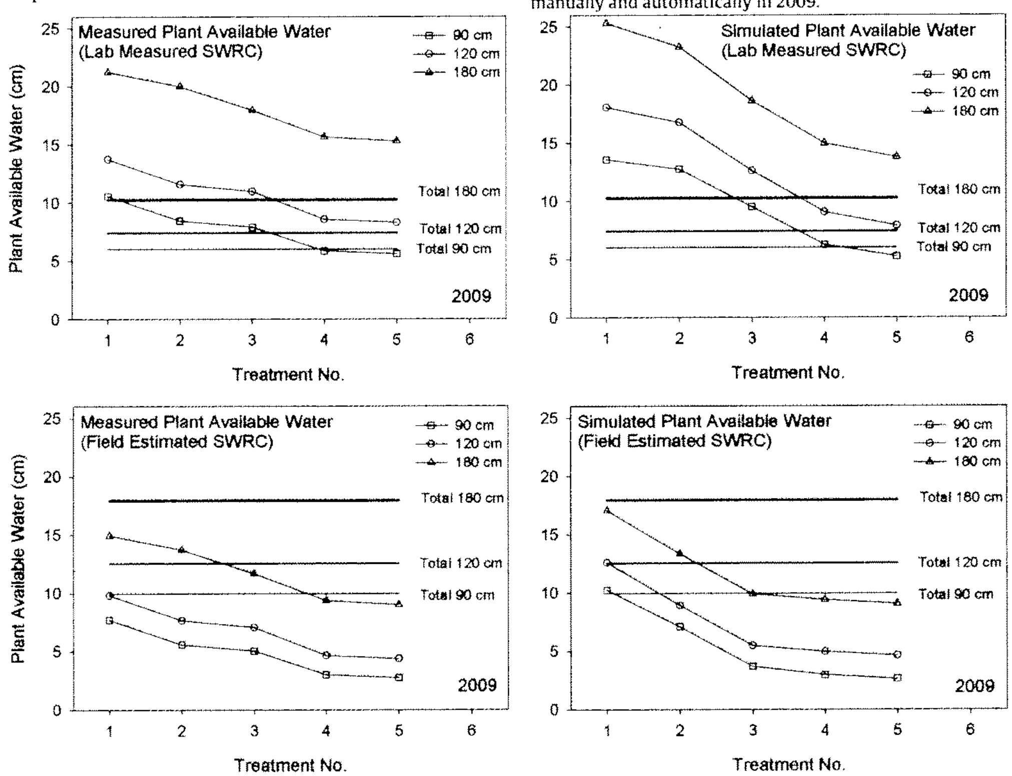

Fig. 6. Measured and simulated average plant available water (PAW) during the growing season from laboratory and field estimated SWRC in 2009. The horizontal lines are total plant available water (TPAW) in the 90, 120, and 180 cm soil profiles.

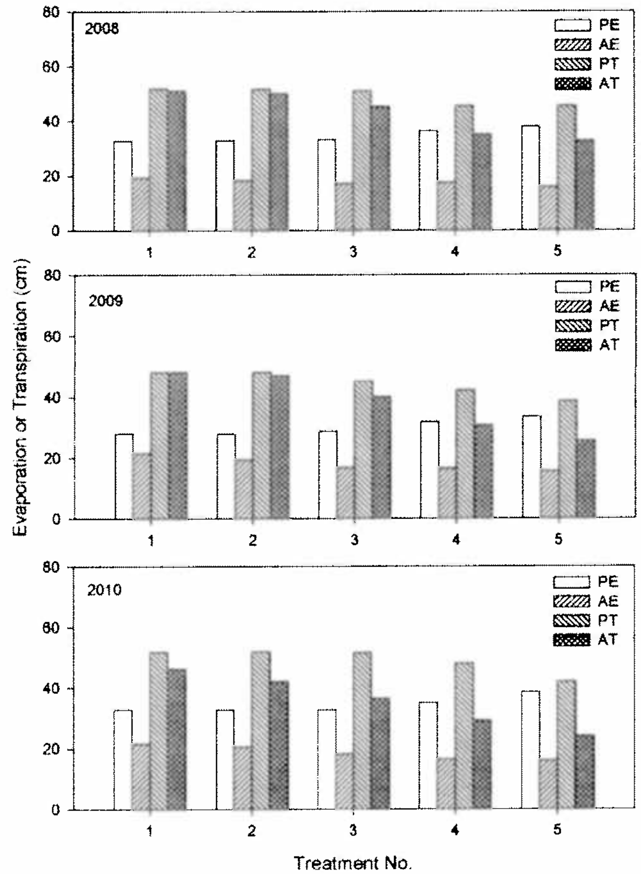

Fig. 9. Simulated potential evaporation (PE), potential transpiration (PT), actual evaporation (AE) and actual transpiration (AT) in 2008, 2009, and 2010.

field estimated transpiration for the three years (63–100% in 2008, 56–100% in 2009, and 52–100% in 2010). The only discrepancy was the wettest treatment in 2010 where the model simulated only 90% of PT, which was in agreement with the simulated water stress in early June and lower simulated yield in RZWQM2.

Thus, the model should be capable of scheduling irrigation events based on ETc requirements. As a test case, we used the calibrated model to schedule weekly irrigation amounts for the five ETc treatments of 100%, 85%, 70%, 55%, and 40% – the same as in the field experiment except that there was no 20% hold back of the projected irrigation amounts during the vegetative stage for use in the reproductive stage. Since RZWQM2 does not simulate ETc using the FAO 56, the Shuttleworth–Wallace PET was used instead. Weekly irrigation amount was determined in the model to meet a certain percentage of the weekly Shuttleworth–Wallace PET of previous week less the rainfall during the same period of time. However, unlike the field irrigation schedule where approximately 20% of the prescribed irrigation amount for the stressed treatments were withheld during the vegetative stage and added back during reproductive stage (with some flexibility from week to week), the stressed treatments in the model were uniformly irrigated based on the Shuttleworth–Wallace PET throughout the growing seasons. As shown in Fig. 10, simulated irrigation amounts were very close to the actual amounts applied in the field with $r^2 = 0.92$. In addition, simulated yield and biomass were also close to those simulated with actual irrigation amounts with $r^2 = 0.92$ and 0.93, respectively (Fig. 11), especially at high ETc treatments. For the low ETc treatments (stressed treatments), the simulated irrigation amount under-predicted yield and biomass somewhat, which implied that redistributing 20% irrigation water from the vegetative

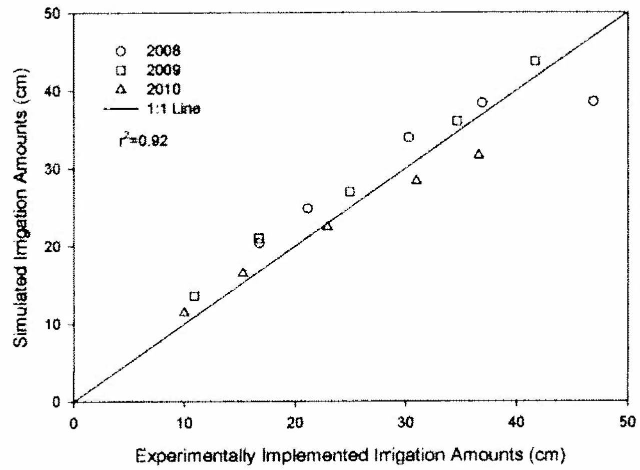

Fig. 10. Irrigation amount as simulated by RZWQM2 and as scheduled in the field in 2008, 2009, and 2010.

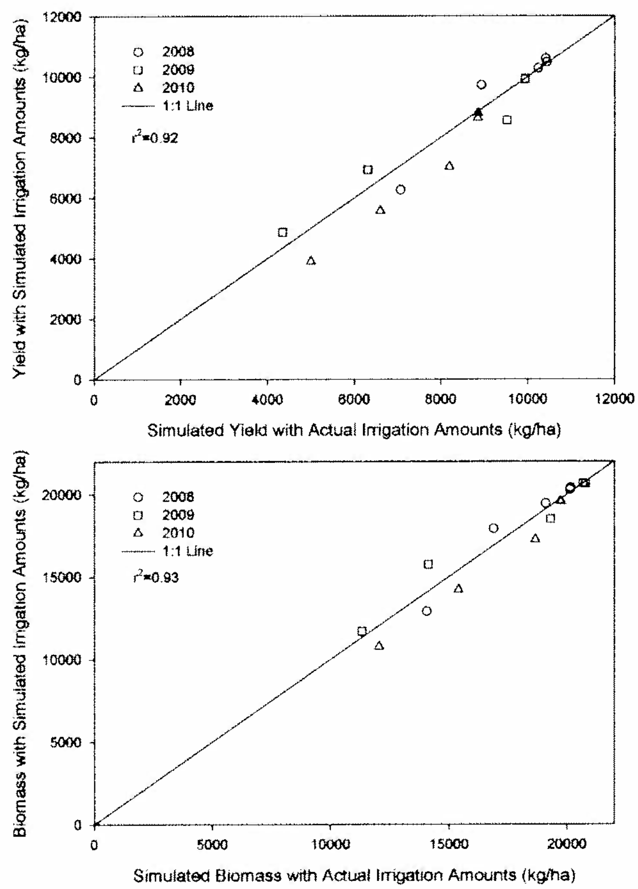

Fig. 11. Simulated yield and biomass with simulated irrigation events and actual irrigation events.

stage to the reproductive stage in the field experiment increased yield at low ETc treatments, but not at high ETc treatments.

5. Conclusion

This study showed that laboratory-measured SWRCs were not capable of simulating plant water responses. However, using field-estimated SWRCs, the model simulated the response of yield and biomass to all irrigation levels adequately in both 2008 and 2009,