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Simulating Maize Yield and Biomass with Spatial Variability of Soil Field Capacity

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ABSTRACT

Spatial variability in field soil properties is a challenge for system modelers who use single representative values, such as means, for model inputs, rather than their distributions. In this study, the root zone water quality model (RZWQM2) was first calibrated for 4 yr of maize (*Zea mays* L.) data at six irrigation levels in northern Colorado and then used to study spatial variability of soil field capacity (FC) estimated in 96 plots on maize yield and biomass. The best results were obtained when the crop parameters were fitted along with FCs, with a root mean squared error (RMSE) of 354 kg ha^{-1} for yield and 1202 kg ha^{-1} for biomass. When running the model using each of the 96 sets of field-estimated FC values, instead of calibrating FCs, the average simulated yield and biomass from the 96 runs were close to measured values with a RMSE of 376 kg ha^{-1} for yield and 1504 kg ha^{-1} for biomass. When an average of the 96 FC values for each soil layer was used, simulated yield and biomass were also acceptable with a RMSE of 438 kg ha^{-1} for yield and 1627 kg ha^{-1} for biomass. Therefore, when there are large numbers of FC measurements, an average value might be sufficient for model inputs. However, when the ranges of FC measurements were known for each soil layer, a sampled distribution of FCs using the Latin hypercube sampling (LHS) might be used for model inputs.

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Knowledge of soil hydraulic properties, mainly the soil water retention curve and hydraulic conductivity, is essential for crop modeling and can influence simulated crop responses to soil water status (Ma et al., 2012a). Due to a lack of their measurement or inadequate estimation from pedotransfer functions for a field, the soil hydraulic parameters in a model are, most often, calibrated along with crop parameters (Ma et al., 2012a, 2012b). However, an important aspect of the soil hydraulic properties is their high spatial variability in a field. For example, as much as two orders of magnitude variation in saturated hydraulic conductivity (K_s) was observed in a field (Rienzner and Gandolfi, 2014). This field spatial variability needs to be considered when a model is used to evaluate management effects (e.g., of irrigation levels). There are more studies on the effects of soil spatial variability on simulated N leaching than on crop production. Djurhuus et al. (1999) found that a geometric mean or a stochastic mean of hydraulic conductivity was sufficient for simulating N leaching using the Daisy model. Similarly, Hansen et al. (1999) demonstrated that simulated N leaching using average soil parameters (e.g., clay content and soil organic C) was comparable to that averaged from 25 Daisy runs with parameters sampled from distributions using Monte Carlo sampling.

Irrespective of spatial variability, field measured soil hydraulic properties were better in simulating crop yield than the laboratory measured values (Gijsman et al., 2003; Ma et al., 2012a). On the other hand, using a simple crop production model, Hakojarvi et al. (2013) found that observed yield variation in the field could not be explained by the variation of field soil hydraulic properties alone. Other factors such as lodging, slopes, and rainfall variability, also contributed to yield variability. However, spatial variability of soil in the field is likely the major factor in most cases, and it is important to know the contribution of spatial variability of soil hydraulic properties to

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Abbreviations: DSSAT: decision support system for agrotechnology transfer; EPIC: environmental policy integrated climate; ET: evapotranspiration; FC: soil field capacity; LAI: leaf area index; LHS: Latin hypercube sampling; PEST: Parameter Estimation software; RMSE: root mean squared error; RZWQM2: root zone water quality model; SHAW, simultaneous heat and water; TDR; time domain reflectometry; WP, soil wilting point.

total yield variability and to see if such contribution interferes with simulated management effects.

Few studies have been published in the literature on how to account for the effects of spatial variability of measured soil properties on simulated crop yield variability. Using the EPIC model, Perez-Quezada et al. (2003) found that FC and wilting point (WP) were the key soil parameters for simulating spatial variability of yield. Using the CERES-Maize model, Sadler et al. (2000) found that the model was not sensitive enough to soil type (hence, soil FC, WP, and K_s) to be used for site-specific water management purposes although simulated yield was responsive to rainfall. They proposed that the insensitivity was due to one of two reasons–either the CERES-Maize soil parameters did not adequately describe the soils or the simulated soil processes did not adequately match those occurring in the field. On the contrary, Basso et al. (2001) found that spatial distribution of soybean [*Glycine max* (L.) Merr.] yield among the gridded field sections could be predicted from soil parameters (i.e., FC and WP) and plant population for each grid. Thus, more studies are needed to identify the sensitivity of crop models to soil properties so that modelers can focus on the critical parameters for precision farming.

In addition to soil parameters, correct plant parameters are also important for model application in precision farming. Unfortunately, several of the plant parameters are conceptual and difficult to measure directly. Therefore, they are usually calibrated from one or more experimental data sets. The uncertainty of these parameters decreases with the number of data sets used in model calibration (Ma et al., 2012b; Pathak et al., 2012). It is also important to use an automated optimization algorithm so that user bias will not affect the calibration results. Pathak et al. (2012) applied the generalized likelihood uncertainty estimation (GLUE) method with the CSM–CROPGRO–Cotton model and derived plant parameters for a cotton cultivar grown across three locations in Georgia and Florida that simulated yields better than the original parameters. Ma et al. (2012b) used the Parameter Estimation software (PEST) (Doherty, 2010) to obtain better simulation of maize yield than previous calibration with the manual trial-and-error method for the RZWQM2 model (Ma et al., 2012a).

The RZWQM2 simulates soil water balance based on the Green–Ampt and Richards' Equations. This detailed soil water movement approach should simulate the soil water balance better and enhance the sensitivity of the CERES-Maize crop growth model in RZWQM2 to soil types compared to the CERES-Maize model in decision support system for agrotechnology transfer (DSSAT) that Sadler et al. (2000) used in their study. The objectives of this study were to (i) obtain representative parameters for a maize cultivar (Dekalb 52-59) grown in eastern Colorado under 4 yr of full and deficit irrigation (2008–2011) using the RZWQM2 and PEST; and (ii) investigate the effects of spatial variability of FC on simulated maize yield using measured FC from 96 plots in the experimental field site.

MATERIALS AND METHODS

Field Experimental Design

The 4-yr field experiment was initiated in 2008 near Greeley, CO (40.45° N, 104.64° W, 1450 m above sea level). The site contains three major soil types: Nunn (fine, smectitic, mesic Aridic Argiustoll), Olney (fine-loamy, mixed, superactive, mesic Ustic Haplargid), and Otero (coarse-loamy, mixed, superactive, calcareous, mesic Aridic Ustorthent). Weather data were recorded on site with a standard Colorado Agricultural Meteorological Network (http://ccc.atmos.colostate.edu/~coagmet/) weather station (GLY04), including hourly solar radiation, precipitation, air temperature, wind speed, and relative humidity. Missing weather data at the beginning of the study were estimated with data from a station 800 m to the east (GLY03).

The 4-ha field was divided into four sections (A, B, C, D from left to right in Fig. 1) and each section was then subdivided into four replicate blocks (top to bottom), which were subdivided into six 9 by 44 m small plots to which water

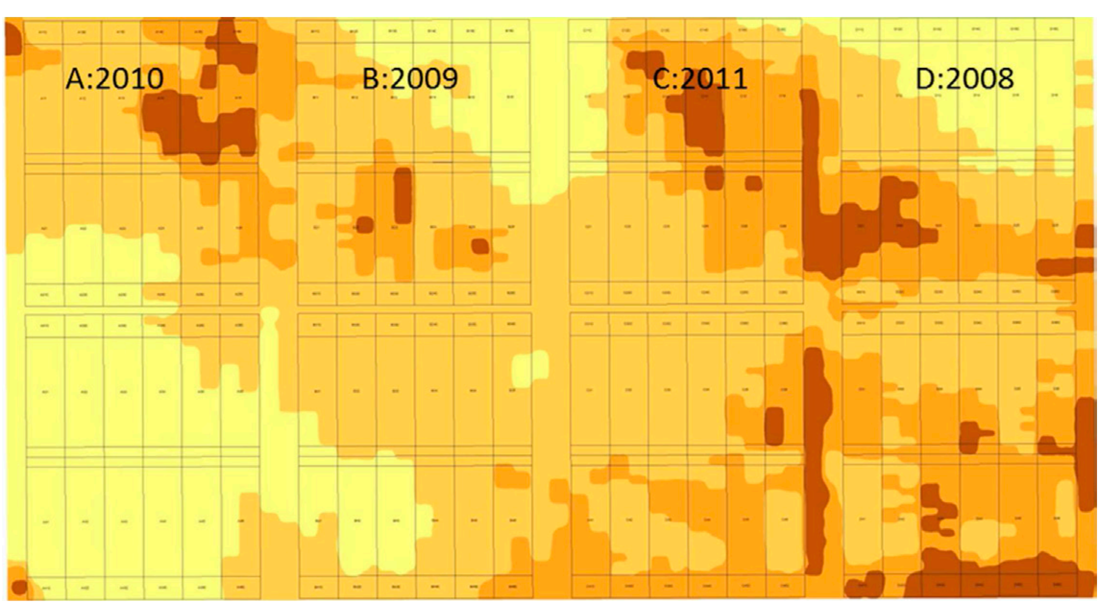


Fig. 1. Layout of the 96 plots in sections A, B, C, and D, planted to maize from 2008 to 2011. The filled color represents electrical conductivity (EC) measured for the 0- to 90-cm soil profile in 2012 to show the spatial variability of the soil. Darker colors represent higher EC values.

treatments were randomly assigned (randomized complete block), resulting in 24 plots per section and a total of 96 plots. Maize was planted to a different section in the order of D, B, A, and C from 2008 to 2011 in rotation with wheat (*Triticum aestivum* L.), sunflower (*Helianthus annuus* L.), and Pinto bean (*Phaseolus vulgaris* L.). Thus, each of the sections and all the 96 plots were planted to maize once during the 4 yr (Fig. 1). As shown by the electrical conductivity map (EC) in Fig. 1, there was just as much variability within plots as between plots. Before planting, each plot was irrigated to make sure initial soil water contents were similar among treatments.

Maize (Dekalb 52-59) was planted at 81,000 seeds ha^{-1} with 0.76 m row spacing. Six irrigation treatments (T1-T6; micro-irrigation with surface drip tubing adjacent to each row) with four replicates each were designed to meet a certain percentage of crop evapotranspiration (ETc) requirements (Allen et al., 1998, 2005, 2007) during the growing seasons: 100% (T1), 85% (T2), 70% (T3), 70% (T4), 55% (T5), and 40% (T6) of ET_c. Except for T1 and T3, approximately 20% of the projected irrigation amount during the vegetative stage was saved for use during the reproductive stage. The ET_c requirement was estimated on a daily basis from the product of the alfalfa (*Medicago sativa* L.) referenced evapotranspiration (ET_r) and a crop coefficient, and irrigations were applied every 3 to 7 d. Treatments T3 and T4 were designed to compare the differences in water allocation between vegetative and reproductive stages on crop production under deficit irrigation.

The amount of crop water use (actual ET) for each treatment was calculated on a daily basis based on irrigation, rainfall, soil water content, and atmospheric demand (FAO 56, Allen et al., 1998). Soil water content was measured near the center of each plot twice a week during the growing season with a portable time domain reflectometry (TDR) moisture meter (MiniTrase, Soil Moisture Equipment Corp., Santa Barbara, CA) for the 0- to 15-cm soil layer and with a neutron attenuation moisture meter (CPN-503 DR Hydroprobe, InstroTek Inc., Concord, CA) between 15 and 200 cm below the soil surface at 30 cm intervals (30, 60, 90, 120, 150, and 200 cm). The neutron moisture meter was calibrated for the site soils and calibration verified annually. Field capacity for each plot at each depth was estimated as the measured soil water content about 1 d after a large irrigation or rainfall event that resulted in increased soil water content at deeper depth. The soil water content at wilting point was assumed to be 50% of FC based on Allen et al. (1998) and Rawls et al. (1982) and verified by pressure plate measurements of soils from the field. Since maize was planted in different plots each year, a total of 96 sets of FC values were estimated for each depth increment (6 treatments × 4 replicates × 4 yr).

Fertilizer as urea-ammonium-nitrate was applied at planting and then with irrigation water during the growing seasons as needed based on estimated plant growth and expected N uptake. Nitrogen was only applied to the plots when irrigation water was required for all plots so that equal amount of N was applied to all the treatments. Total N applied was 134 kg N ha^{-1} in 2008, 160 kg N ha^{-1} in 2009, 146 kg N ha^{-1} in 2010, and 178 kg N ha^{-1} in 2011 for all treatments. Total irrigation amounts were 46.9, 36.9, 31.3, 30.3, 21.1, and 16.7 cm in 2008; 42.7, 35.6, 30.7, 25.9, 18.7, and 12.9 cm in 2009; and 38.6, 33.3, 28.3, 24.9, 18.3, and 13.0 cm in 2010; and 50.5, 40.8, 34.8, 32.6, 24.2, and 17.7 cm in 2011 for T1 through T6, respectively.

Canopy cover was measured both with a photosynthetically active radiation sensor (AccuPAR LP-80, Decagon Devices, Pullman, WA) and was converted to leaf area index (LAI) (Ma et al., 2012a). Grain yield was measured by hand harvesting the ears from the center 15 m of the center four rows of each plot (46 m^2). Grain was threshed with a stationary thresher, weighed, and subsampled for moisture content determination. Plant population (plants ha^{-1}) was measured by counting the number of plants in the center 15 m of the center four rows of each plot (46 m^2). Final aboveground biomass (kg ha^{-1}, dry weight) was measured by cutting 10 (2008 and 2011) or 15 (2009 and 2010) adjacent plants 10 cm above the soil surface in each plot (four replications), separating the biomass into ears and stover; drying the ears and a subsample of the stover; threshing the grain; redrying the cobs and adjusting the stover and grain weights for moisture content; and summing the dry weight of the stover, grain, and cobs. Average biomass per plant was multiplied by the plant population for each plot. More details on the experimental design are available in Ma et al. (2012a), Fang et al. (2014), and Saseendran et al. (2014).

Root Zone Water Quality Model and Parameter Estimation Software Optimization

The RZWQM2 model is a whole system model with detailed soil C/N dynamics, plant growth, water and solute transport, and heat flow (Ahuja et al., 2000). The model also includes surface energy balance from the simultaneous heat and water (SHAW) model and plant growth from the DSSAT family (Ma et al., 2012b). Recently, the PEST software was coupled into RZWQM2 to facilitate model calibration. In this study, the CERES-Maize model from the DSSAT family in RZWQM2 was used to simulate maize production. The model was run for each treatment starting 1 January for each year with the same initial soil condition after the soil organic pools were initialized by running the model for 10 yr (Ma et al., 1998). Simulation results from all treatments and years were pooled together to define an objective function for PEST optimization. As a result, calibrated parameters should be applicable to all the years and treatments and are less biased due to variability in weather and soil conditions (Ma et al., 2012b; Pathak et al., 2012).

To run the CERES-Maize model in RZWQM2, drained upper limit and lower limit of plant available water were assumed to be FC and wilting point, respectively (Ma et al., 2006). Saturated soil hydraulic conductivity (K_s, cm h^{-1}) was calculated from the following equation (Ahuja et al., 1989):

$$K_s = 764.5(\theta_s - FC)^{3.29} \quad [1]$$

where θ_s is soil water contents at saturation (cm^{3}cm^{-3}). The ranges of FC for each soil layer and plant parameters are listed in Tables 1 and 2, respectively, based on field measurements and a previous study on the site (Ma et al., 2012a). An overall objective function was defined in the following form (Nolan et al., 2011):

$$\Phi = \sum_{i=1}^{n} \sum_{j=1}^{m_i} w_i^2 (y_{i,j} - y'_{i,j})^2 \quad [2]$$

Table 1. Calibrated and averaged soil field capacity (FC) for each soil layer in this study, in comparison to the calibrated FC used in previous studies (Ma et al., 2012a; Saseendran et al., 2014).

Soil depth	Bulk density ρ_b	θ_s	Ranges of FC used for PEST calibration	Final calibrated values of FC using PEST	Averaged FC from the 96 sets of measured FC for each plot	Averaged FC from the 100 LHS sampled FC	FC used in previous studies
cm	g cm^{-3}				cm^{3}cm^{-3}		
0–15	1.492	0.437	0.18–0.32	0.231	0.258	0.241	0.262
15–30	1.492	0.437	0.14–0.32	0.242	0.239	0.214	0.249
30–60	1.492	0.437	0.13–0.38	0.230	0.211	0.225	0.220
60–90	1.568	0.408	0.13–0.37	0.206	0.185	0.222	0.187
90–120	1.568	0.408	0.13–0.32	0.205	0.182	0.206	0.173
120–150	1.617	0.390	0.13–0.31	0.263	0.183	0.202	0.162
150–200	1.617	0.390	0.13–0.31	0.310	0.209	0.203	0.198

where n is the number of output variables to optimize and m_i is the number of observations for each variable, w_i is the assigned weight for each observation, and $y_{i,j}$ and $y'_{i,j}$ are paired observed and simulated values. In this study, four output variables were included in the Φ value; maize yield, maize biomass, LAI, and total soil water content in the soil profile, with weights (w_i) of 0.0017, 0.0051, 0.60, and 4.18, respectively. These weights were initially determined using an error-based approach (Hill and Tiedeman, 2007) as the inverse of the standard deviation of each group of observations, and then adjusted such that no observation group dominated or was dominated by the other groups. The end result was that the four observation groups (output variables) had about the same sum of squares contribution to the objective function (Φ) value.

Root mean squared error was used to quantify the goodness of fit of the predicted results to the field measured results for a given observation i:

$$\mathrm{RMSE}_i = \sqrt{\frac{\sum_{j=1}^{m_i} (y_{i,j} - y'_{i,j})^2}{m_i}} \qquad [3]$$

Distributions and Sampling of Estimated Field Capacity

After the model was calibrated for treatment average experimental data for grain yield, biomass, LAI, and soil water content (Fang et al., 2014), it was then used to examine FC variability effect on simulated maize production, using the 96 sets of field-estimated FC data. Four modeling exercises (Case 1–4 shown below) were conducted in this study using the same plant parameters as calibrated:

1. Case 1: Scenarios for each irrigation treatment (six treatments) and each year (2008, 2009, 2010, and 2011) were run with all the 96 sets of estimated FCs. Since the 96 sets of FCs were estimated from the 96 plots in the field, this exercise was designed to study spatial variability of FCs in a field on crop yield simulation. A total of 2304 model runs were conducted (6 treatments × 4 yr × 96 sets of FC values).
2. Case 2: Instead of using the 96 sets of measured FCs directly as in Case 1, we sampled 100 sets of FCs using the Latin hypercube sampling (LHS) method, by assuming a log-normal distribution of FC (Ma et al., 2000; Hansen et al., 1999). Similar to Case 1, scenarios for each treatment and each year were run with the 100 sampled values of FC values, which resulted in a total of 2400 model runs (6 treatments × 4 yr × 100 sampled FC values).
3. Case 3: Instead of running each treatment and each year for all the 96 sets as in Case 1 or 100 sets as in Case 2, we ran each

Table 2. Cultivar coefficients of the CERES-maize model in root zone water quality model (RZWQM2) as calibrated in this study and in previous studies (Ma et al., 2012a; Saseendran et al., 2014).

Acronyms used and definitions of traits.	Units	Range	Final values	Values used by Saseendran et al. (2014)	Values used by Ma et al. (2012a)
P1- Degree days (base temperature of 8°C) from seedling emergence to end of juvenile phase.	ptd†	100–450	245.6	260	260
P2- Day length sensitivity coefficient [the extent (days) that development is delayed for each hour increase in photoperiod above the longest photoperiod (12.5 h) at which development proceeds at maximum rate].		0–2	0.156	0.6	0.2
P5- Degree days (base temperature of 8°C) from silking to physiological maturity	ptd	600–1000	704	620	570
G2- Potential kernel number	kernel number per plant	440–1000	994	1000	920
G3- Potential kernel growth rate	mg (kernel d)$^{-1}$	5–16	6.24	6.9	7
PHINT- Degree days required for a leaf tip to emerge (phyllochron interval)	ptd	38–55	52.89	43.0	50

† Photothermal days.

plot with its respective estimated FCs. A total of 96 model runs were conducted (6 treatments × 4 yr × 4 replicates).
4. Case 4: Taking an average of the 96 sets of measured FCs for each soil layer, we then ran the model for each treatment and each year using the averaged FC. A total of 24 runs were completed (6 treatments × 4 yr).

RESULTS AND DISCUSSION

Calibration of Root Zone Water Quality Model

In earlier simulation studies with the same experimental data set, the RZWQM2 parameters were calibrated manually by Saseendran et al. (2014) using the trial-and-error method and by Ma et al. (2102a) with semi-automation. In this study, the fully automated calibration algorithm from PEST was used to minimize the objective function in Eq. [2]. Detailed procedure of PEST model calibration for this data set is available from Fang et al. (2014). The PEST-calibrated FC ($\theta_{1/3}$) was slightly lower for the top 30-cm soil profile and slightly higher for the other layers compared to those used by Ma et al. (2012a) and Saseendran et al. (2014) (Table 1). Calibrated plant parameters were similar to those used by Ma et al. (2012a) and Saseendran et al. (2014), especially parameters P1, G2, and G3 (Table 2). Across the 4 yr and all treatments, the PEST-calibrated model simulated grain yield, final biomass, peak LAI, and soil water content with RMSEs of 354 kg ha^{-1}, 1202 kg ha^{-1}, 0.78 cm^2 cm^{-2}, and 0.036 cm^{3}cm^{-3}, respectively. Goodness of calibration in terms of relative deviation (RMSE/average measured yield) showed an increasing trend as irrigation level decreased from 100% ET to 40% ET for both yield (3–8%) and biomass (5–13%).

Averaging across the 4 yr, measured yield was 10,635, 10,303, 9369, 8754, 6763, and 5140 kg ha^{-1} for T1 through T6, respectively. Corresponding simulated yield was 10,619, 10,318, 9334, 8894, 6921, and 5267 kg ha^{-1}. Similarly, average measured aboveground biomass was 21,232, 20,670, 18,479, 17,321, 13,158, and 11,746 kg ha^{-1} for T1 through T6, respectively, and corresponding average simulated biomass was 20,416, 20,005, 18,563, 17,338, 13,626, and 11,242 kg ha^{-1}. Both measured and simulated results showed that T3 produced slightly better crop growth than T4, which was probably due to the intended water saving during vegetative stage not being fully replaced in the reproductive stage in T4 and the resulting slightly higher total irrigation water for T3 than for T4. These results were better than those obtained by the trial-and-error method (Saseendran et al., 2014). Simulated anthesis dates for year 2008, 2009, and 2011 were 82, 84, and 88 d after planting (DAP), respectively, which were close to the observed anthesis dates of 85, 84, and 90 DAP. Potential error in field observation was 3 d due to frequency of field observations. The simulated anthesis date for 2010 was 76 DAP compared to 83 in field observation. Anthesis dates did not change with irrigation treatments in either observed or simulated results.

Simulated soil water storage in 0 to 200 cm was on average higher than measured (Fig. 2). However, given the average experimental variation of 5.5 cm among replicates, simulated soil water storage was reasonable with a RMSE of 3.5 cm. The model overpredicted LAI at early growth stages when LAI was low and under-simulated LAI when LAI was high with an average RMSE of 0.78 cm^{2}cm^{-2} (Fig. 2), which has been reported earlier for the CERES-Maize model (Yu et al., 2006; Saseendran et al., 2005). In general, simulated evapotranspiration (ET) was lower than ET estimated from soil water balance during the crop seasons. The ET was closely simulated in 2008 except for the 100% ET$_c$ irrigation treatment followed by 2009 ET simulations where T2, T3, and T4 were adequately simulated (Fig. 3). The RMSE for ET simulation was 5.6 cm, which was close to the standard error of 5.5 cm in soil water measurements. More detailed comparison between simulated and measured yield, biomass, and crop responses to irrigation management is available in Fang et al. (2014).

Effects of Field Capacity on Simulated Yield and Biomass

To investigate the effect of spatial variability in the estimated FC on the uncertainty of simulated yield and biomass, we used the calibrated plant parameters above without further modification, especially as these values were close to those in previous studies (Ma et al., 2012a; Saseendran et al., 2014). Figure 4 shows the distributions of FC estimated from field measurements in the 96 plots planted to maize from 2008 to 2011, and Fig. 5 shows the distributions sampled with LHS based on the ranges listed in Table 1. Average LHS sampled FCs were 0.241, 0.214, 0.225, 0.222, 0.206, 0.202, and 0.203 cm^{3}cm^{-3} for the 0 to 15, 15 to 30, 30 to 60, 60 to 90, 90 to 120, 120 to 150, and 150 to 200 cm soil layers, respectively. Corresponding average FCs from field estimation was 0.258, 0.239, 0.211, 0.185, 0.182, 0.183, and 0.209 cm^{3}cm^{-3}. Although these two sets of FCs were similar, the field-estimated FC values were lower than the calibrated FC values for the 60- to 150-cm soil depth (Table 1). It is quite possible that field-measured FC was lower because the lower soil layers might not have reached FC in the semiarid Colorado climate. It should also be noted that the average set of FCs from the LHS sampling was closer to the PEST-calibrated FCs (0.231, 0.242, 0.230, 0.206, 0.205, 0.263, and 0.310 cm^{3}cm^{-3}) (Table 1).

Results from running the calibrated model for all the 96 sets of FCs (Case 1) are shown in Fig. 6. The average simulated yield and biomass had a simulated RMSE of 376 and 1504 kg ha^{-1}, respectively, which were slightly higher than those using FC values calibrated with PEST (354 and 1202 kg ha^{-1}). Similar to calibrated results, relative deviation of simulation error (RMSE/average measured value) ranged from 3 to 9% for yield and 6 to 18% for biomass as irrigation water decreased from 100% ET to 40% ET. Standard deviations of simulated yield and biomass among the 96 sets of FCs ranged from 47 to 561 kg ha^{-1} and from 142 to 1167 kg ha^{-1}, respectively, which were smaller than standard deviations of measured yield (from 150 to 1200 kg ha^{-1}) and biomass (from 60 to 3800 kg ha^{-1}). We also noted that there was no pattern in the standard deviation of measured yield and biomass in relation to irrigation treatments. In contrast, simulated standard deviations increased as the irrigation deficit increased from 100% ET$_c$ to 40% ET$_c$, suggesting that the soil parameters were less important when there was enough precipitation and irrigation (Angulo et al., 2014). As shown in Fig. 6, average simulated yield and biomass were very close to the measured average yield. Therefore, it was possible to run the model with field-measured FC without the need to calibrate soil parameters, allowing users to focus on the plant parameters only.

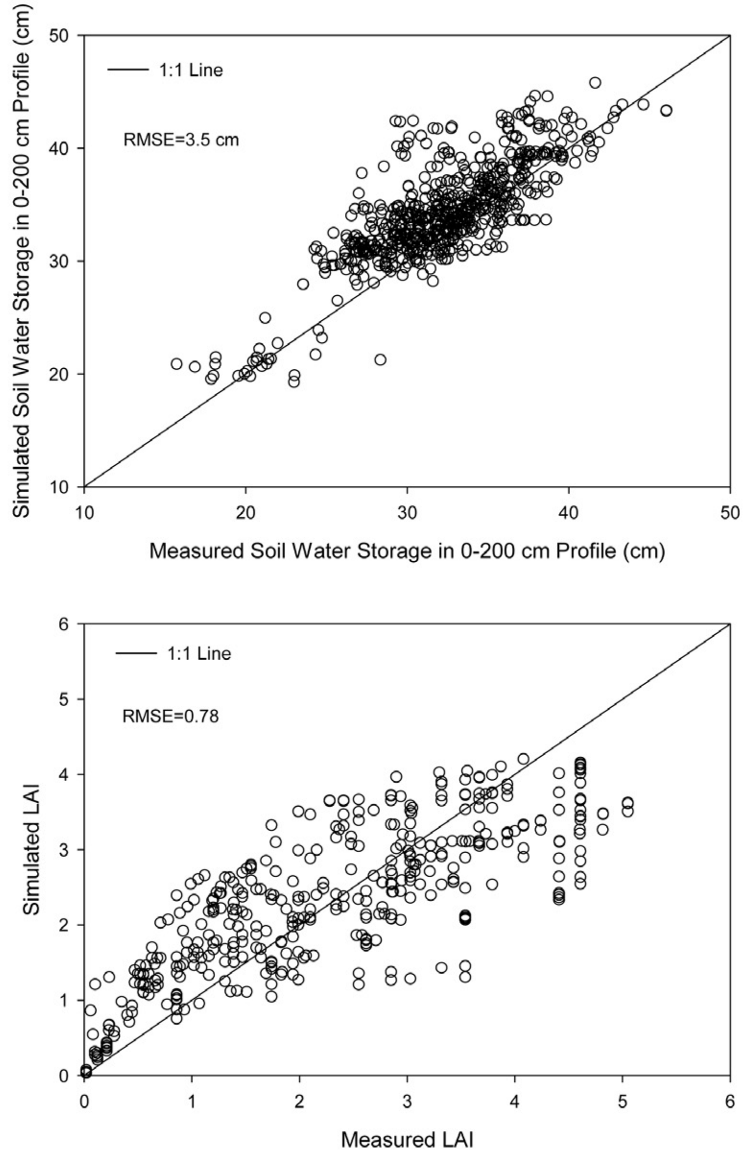


Fig. 2. Root zone water quality model (RZWQM2) simulated vs. measured profile (0–200 cm) (top) soil water storage and (bottom) leaf area index (LAI) from 2008 to 2011 for all treatments.

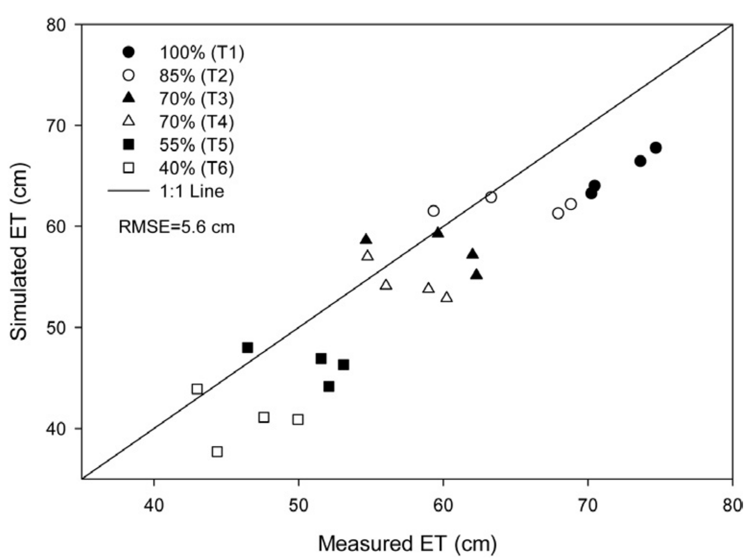


Fig. 3. Root zone water quality model (RZWQM2) simulated vs. estimated evapotranspiration (ET) during the crop seasons from 2008 to 2011 for all the treatments.

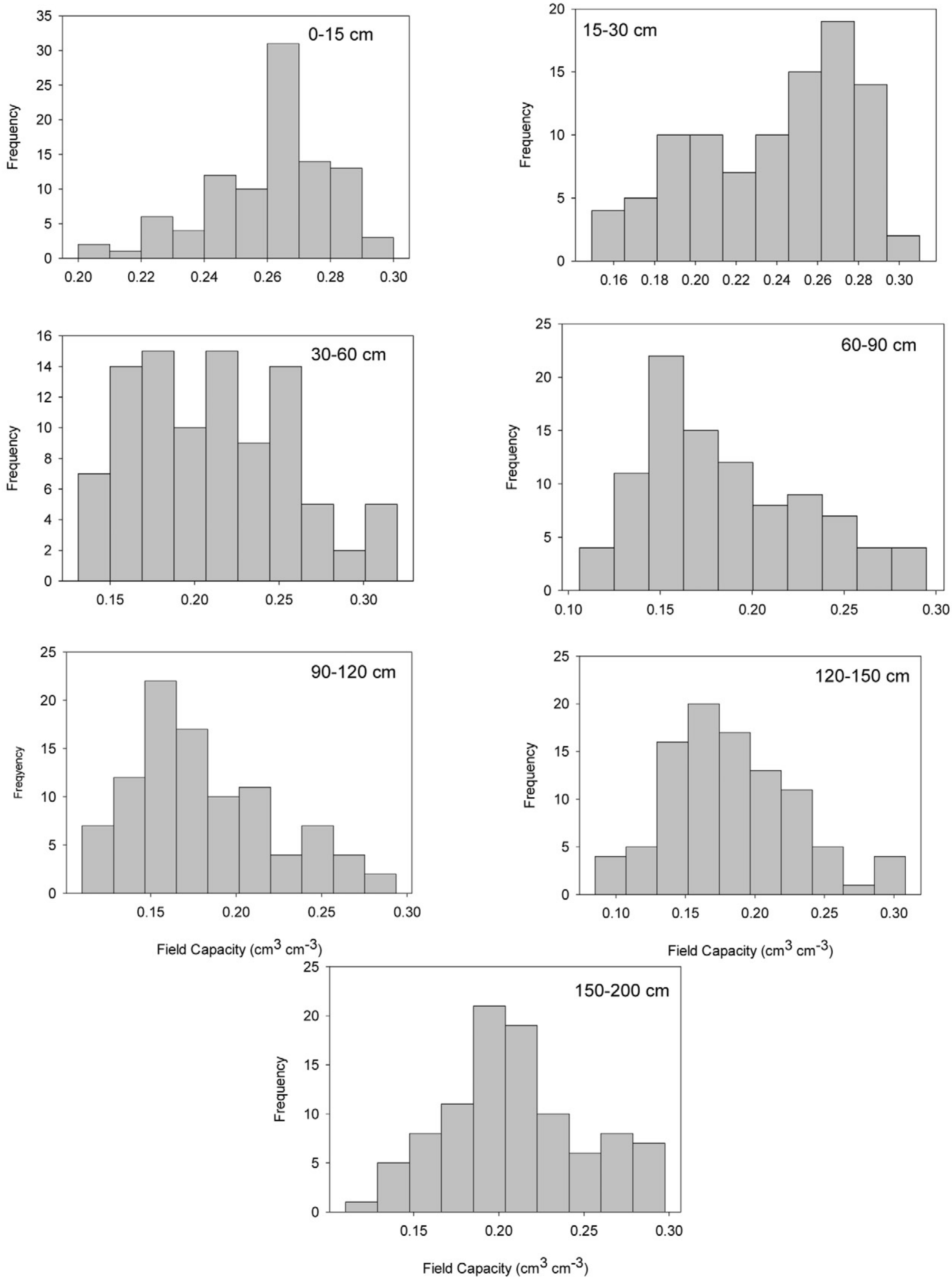


Fig. 4. Field capacity (FC) distributions as estimated in the field for each soil layer.

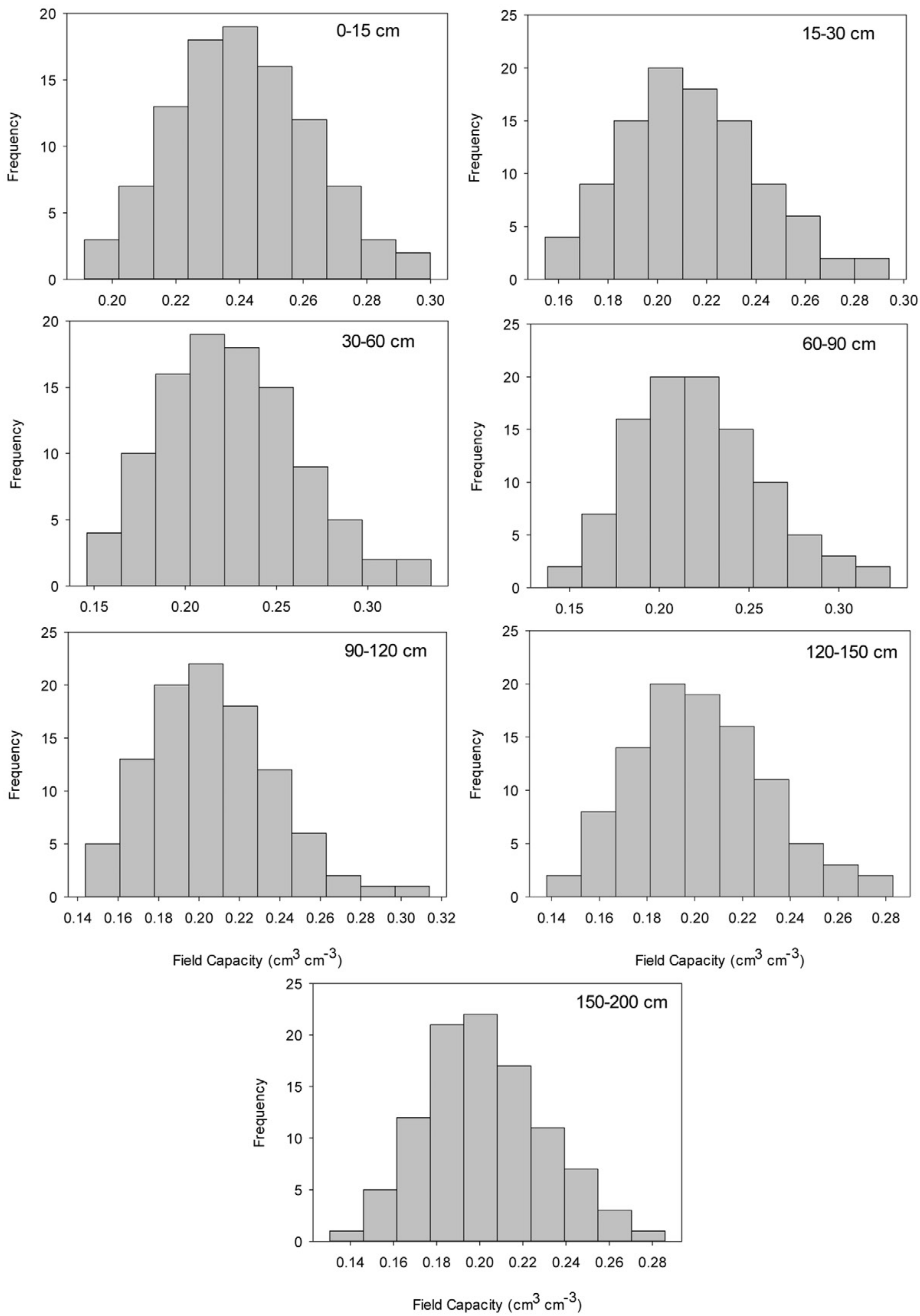


Fig. 5. Field capacity distributions for each soil layer as sampled using Latin hypercube sampling (LHS) given the observed range in Table 1.

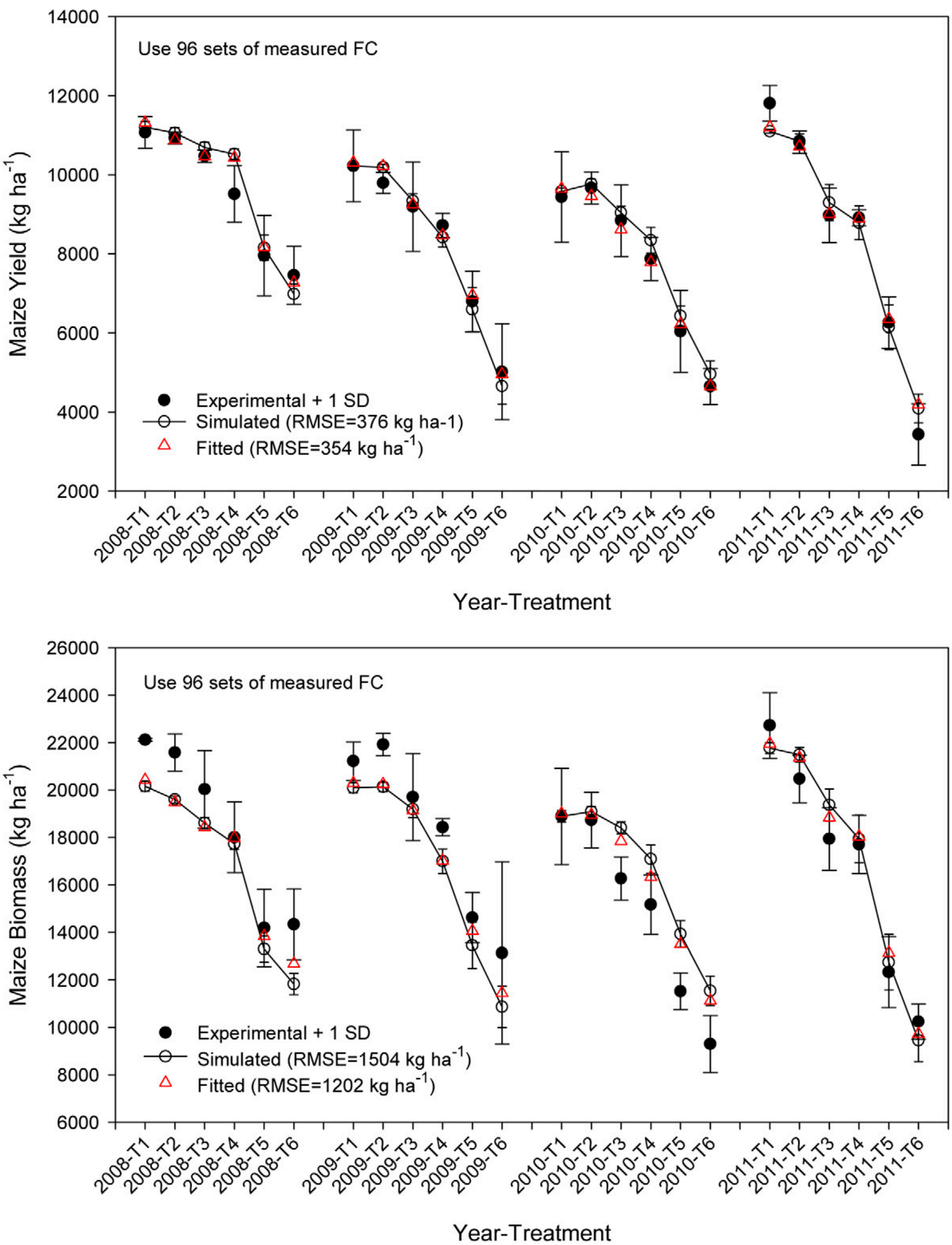


Fig. 6. Simulated maize yield (top) and biomass (bottom) by running each treatment with the 96 sets of field capacity for the soil profile as estimated in Fig. 4 (Case 1), in comparison with measured and calibrated yield and biomass. The vertical bars are 1 SD from the mean.

The average simulated maize grain yield from the 100 sets of LHS sampled FCs (Case 2) had higher RMSE (544 kg ha^{-1}) than the calibrated yield (354 kg ha^{-1}). Simulated average biomass was also a little worse, with RMSE = 1632 kg ha^{-1} compared to 1202 kg ha^{-1} for the calibrated biomass. These RMSEs were slightly larger than those in Case 1 where measured FCs were used directly as model inputs. Again, model performance became worse as irrigation decreased from 100% ET to 40% ET with relative RMSE increased from 3 to 13% for yield and 6 to 16% for biomass. Standard derivations among simulated yield and biomass were higher for the two lowest irrigation treatments (T5 and T6) than for the four highest irrigation treatments (Fig. 7). The standard deviation of the simulated yields due to the 100 sets of FCs ranged from 30 to 600 kg ha^{-1} and of the simulated biomass from 130 to 1200 kg ha^{-1}, which were smaller than standard deviations of measured treatment yields (from 150 to 1200 kg ha^{-1}) and biomass (from 60 to 3800 kg ha^{-1}). As shown in Fig. 7, averaging simulated values from the LHS sampling provided comparable results in 2008 and 2009. However, both yield and biomass were overpredicted for the lowest four deficit irrigation treatments in 2010 and 2011 (T3, T4, T5, T6), in comparison with calibrated yield and biomass. Since the average simulated yield and biomass with the LHS generated FC values were generally within one standard deviation of the measured results, it was reasonable to conclude that the spatial variability in FC did not affect our simulated management effects (i.e., irrigation).

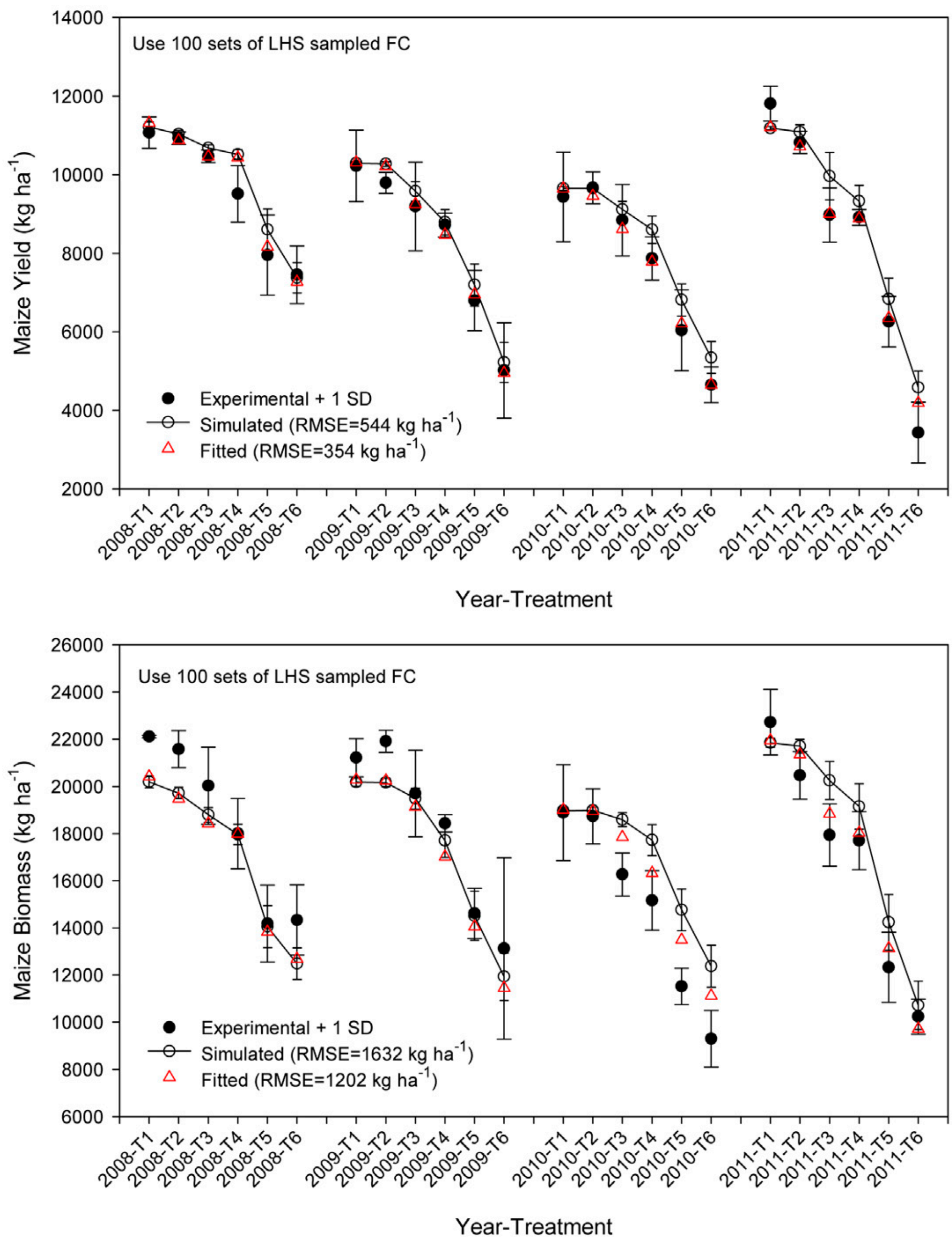
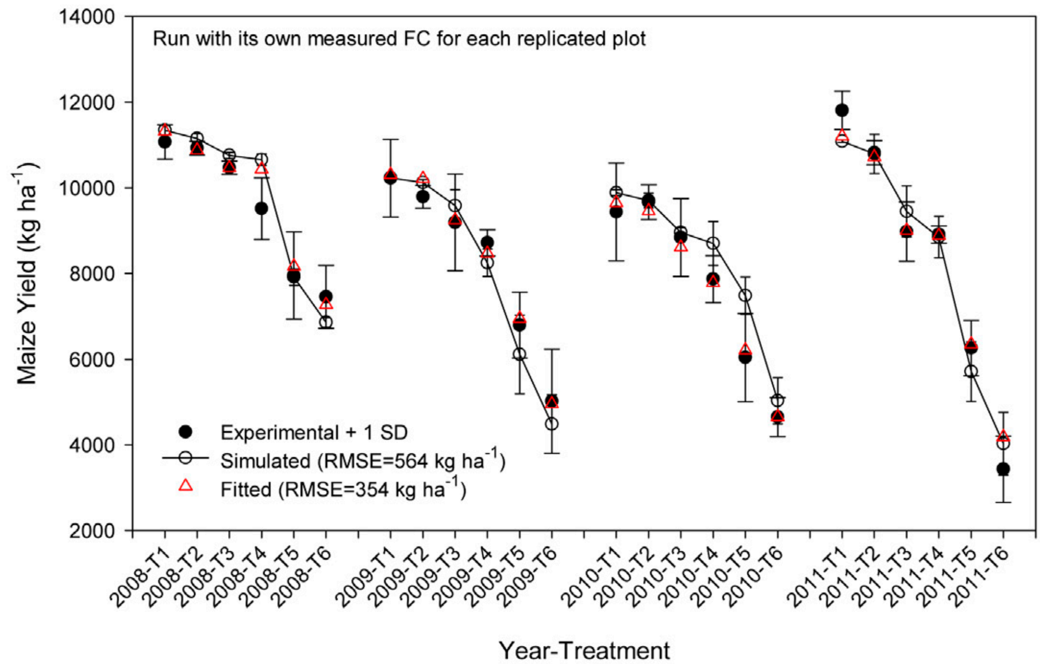


Fig. 7. Simulated maize yield (top) and biomass (bottom) by running each treatment with 100 sets of field capacity for the soil profile as generated in Fig. 5 (Case 2), in comparison with measured and calibrated yield and biomass. The vertical bars are 1 SD from the mean.

When the model was run for each plot (four replicated plots) with its respective field estimated FCs (Case 3), the average yield and biomass for each treatment from the four replicated plots showed the highest RMSEs (564 kg ha^{-1} for yield and 1867 kg ha^{-1} for biomass) (Fig. 8). Simulated standard deviation among replicated plots increased as water deficit increased. Relative RMSE between simulated and measured values also increased from 4 to 10% for yield and from 6 to 20% for biomass as irrigation decreased from 100% ET to 40% ET. The only noticeable differences between Case 3 and Case 1 were biomass simulation for the 40% ETc treatment in 2008 and the 55% ETc treatment in 2009 (Fig. 8). Therefore, for practical purposes, running individual plots (replicates) and then averaging the simulation results provided comparable results as running the model with an averaged FC for each of the 96 plots. This point was further illustrated when the averaged FCs of 0.258, 0.239, 0.211, 0.185, 0.182, 0.183, and 0.209 cm^{3}cm^{-3} from each of the soil layers were used (Case 4, Fig. 9), where simulated yield and biomass had RMSEs of 438 and 1627 kg ha^{-1}, respectively. In terms of relative RMSE, simulated errors increased from 4 to 11% for yield and 6 to 20% for biomass as irrigation water decreased from 100 to 40% ET, which were similar to other Cases. Given the nonlinearity of the processes simulated, the ability to use an average set of FC values to simulate crop production is an unexpected feature but useful to users (Hansen et al., 1999, Djurhuus et al., 1999).



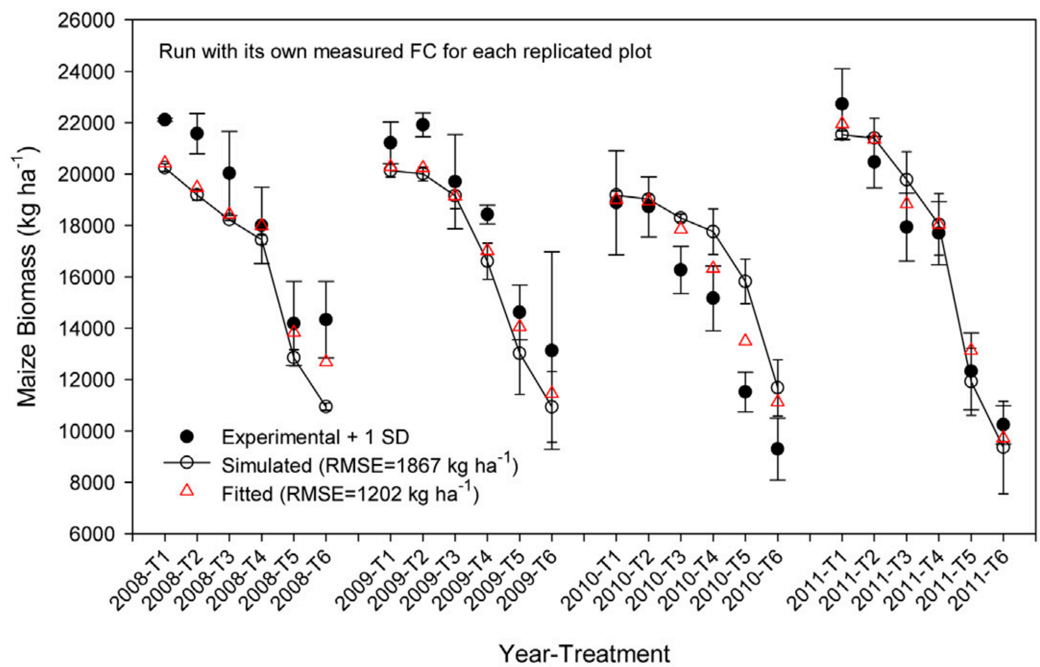


Fig. 8. Simulated average maize yield (top) and biomass (bottom) by running each individual plot with its respectively estimated field capacity (Case 3), in comparison with measured and calibrated yield and biomass. The vertical bars are 1 SD from the mean.

Effects of Field Capacity on Simulated Leaf Area Index and Soil Water Content

In general, simulated biomass and LAI were improved as RMSE of simulated yield became smaller (Fig. 10). However, RMSE of simulated soil water content did not respond linearly to RMSE of simulated yield. Therefore, some of the FC sets might produce good simulation of yield with poor soil water simulation, which was more so for Case 1 where the measured FCs were used directly for simulations than for Case 2 where FCs were sampled from a distribution. In addition, some of the FC sets simulated higher RMSEs in yield, LAI, and biomass when they were sampled from the prescribed distributions. It was also worthwhile noting that the relationship between yield and FC depended on irrigation treatment and year. For example, a weak positive relationship between yield and FC (either 0–30-cm or 0–60-cm soil depth) was observed for the 100% ET treatments for all the years. On the other hand, a weak negative correlation between yield and FC (either 0–30-cm or 0–60-cm soil profile) was simulated for the 40 and 55% ET treatments for all the years. However, there was no consistent correlation between yield and FC (either 0–30- or 0–60-cm soil profile) for the 85 and 70% ET treatments across the 4 yr.

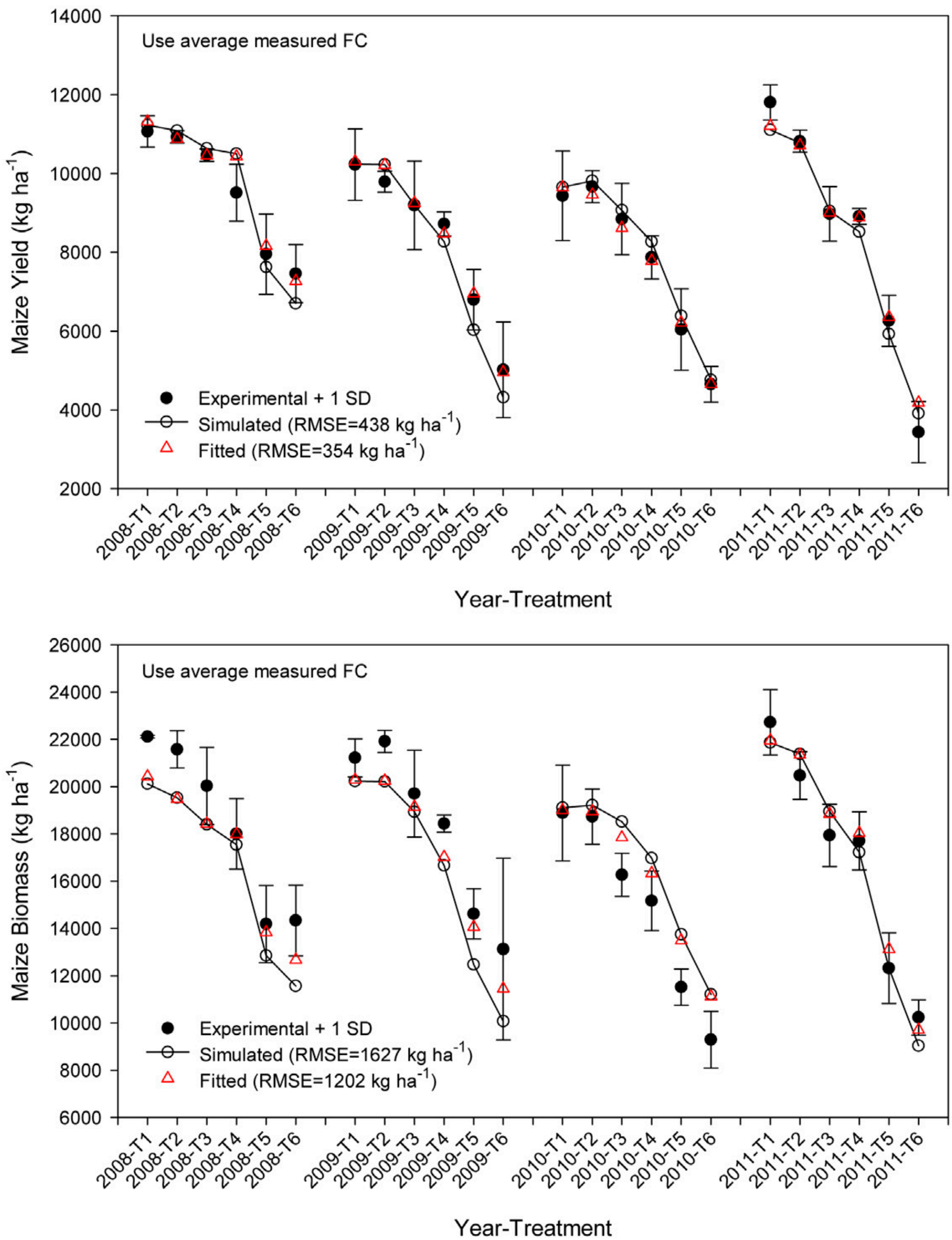


Fig. 9. Simulated maize yield (top) and biomass (bottom) by running the model with an average field capacity from Fig. 4 (Case 4), in comparison with measured and calibrated yield and biomass. The vertical bars are one standard deviation (SD) from the mean.

Simulated yield did not correlate to average FC for 0- to 90-, 0- to 120-, or 0- to 200-cm soil depths, which was expected because irrigation amount was just enough to replace potential ET without excess water for leaching to deeper soil layers. Therefore, it was the combination of FC in the soil profile that determined simulated yield, not FC from an individual soil layer or an average FC for the soil profile.

As expected, the lowest RMSEs for yield, biomass, LAI, and soil water content were obtained when PEST was employed to fit all the data (solid upward triangle in Fig. 10). Using an average FC set from the measured FCs, the RMSEs were almost as good as the fitted ones (solid square symbols in Fig. 10). The worse RMSEs were found when the model was run individually for each plot with its respective FCs and then averaged the simulated yield values for each treatment (solid circle in Fig. 10). These results demonstrated that a large number of measurements were needed to represent a field. Furthermore, since the plots are 9 by 44 m, there is as much variability within the plots as between plots (Fig. 1). Averaging across plots is needed to reflect even within plot variability.

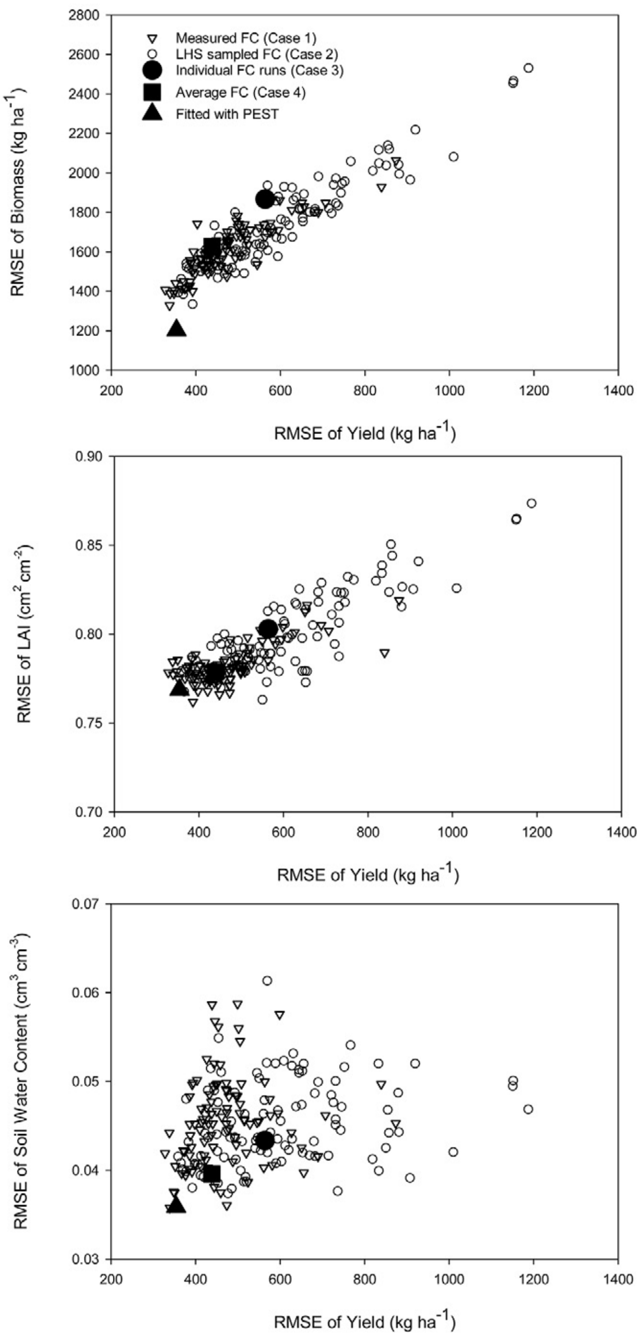


Fig. 10. Lumped RMSE across all treatments and years as simulated by various sets of field capacity (FC). The solid symbols are for Case 3, Case 4, and fitted with Parameter Estimation software (PEST).

CONCLUSION

Using a calibrated system model, RZWQM2, we demonstrated the effect of spatial variability of soil properties on maize production in terms of yield and biomass. We found that using a mean FC by soil layer measured in the field was sufficient for practical purposes when a large number of field measurements were taken, with 438 and 1627 kg ha^{-1} for yield and biomass, respectively. However, simulation results were improved when distributed inputs were used for FC instead of average values, with 376 and 1504 kg ha^{-1} for yield and biomass, respectively. So, when only the ranges of FC are available in a field, it is better to create a distribution of the FC from these ranges using a statistical sampling technique as model inputs. As a result, users need only to focus on optimizing plant parameters.

The above results were obtained for a well-controlled drip-irrigation experiment. The spatial variability of FCs may have less influence on both measured and simulated yield and biomass under an efficient irrigated condition than under rainfed conditions, as the controlled irrigation is scheduled such that applied water stays within the root zone. In the 40% ET treatment in this experiment, which was close to a rainfed treatment, the spatial variability resulted in a much greater variability in simulated yield and biomass. The variability in yield and biomass as simulated by the model due to spatial distribution in FCs was less than observed variability in the field. Therefore, field variability in yield and biomass could not be fully explained by FC variability alone. Other soil properties, such as bulk density, nutrient level, and uneven distribution of irrigation water, might have contributed to the larger variation in measured yield and biomass.

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