ABSTRACT

YANG, ZHENGYU. Estimating CSM-CERES-Maize Genetic Coefficients and Soil Parameters and Evaluating Model Response to Varying Nitrogen Management Strategies under North Carolina Conditions. (Under the direction of Dr. Gail Wilkerson.)

CSM-CERES-Maize has been extensively used to simulate corn growth and grain production in various locations worldwide, but has not been evaluated previously for use in North Carolina. The first objective of this study were to calibrate CSM-CERES-Maize soil parameters and genetic coefficients using Official Variety Trial data from 60 site-years for 53 maize genotypes, and to determine the suitability of the fitting technique and variety trial data for model calibration. A stepwise calibration procedure with grid search algorithm was utilized: 1) two genetic coefficients which determine anthesis and physiological maturity dates were adjusted based on planting date and growing degree day requirements for each hybrid; and 2) plant available soil water and rooting profile were adjusted iteratively with two genetic coefficients affecting yield. Cross validation was used to evaluate the suitability of this approach for estimating soil parameters and genetic coefficients.

Results indicate that the CSM-CERES-Maize model can be used in North Carolina to simulate corn growth under non-limiting nitrogen conditions and Official Variety Trial data can be used to estimate genetic coefficients, although the CSM-CERES-Maize over-estimated yield for low yield environments and under-estimated it for high yield environments for some hybrids.

The second objective of this study was to examine the ability of the CSM-CERES-Maize model to simulate corn response to varying irrigation and nitrogen

application strategies. Yield data for a total of 88 irrigation/nitrogen treatments with only one cultivar (Pioneer 31G98) from three fields in Lewiston, North Carolina were available for comparison. Procedures were: 1) develop realistic soil profiles for the three fields; 2) compare simulated CSM-CERES-Maize corn yields to measured yields for all 88 treatments; 3) adjust soil parameters in an iterative process in order to improve simulation of corn yields for these treatments; and 4) determine the importance of each soil parameter to simulated crop yields.

Simulated yields did not match observed yields well using our initial soil profiles, with Relative Root Mean Square Error (RRMSE) values of 17.5, 38.4, and 50.1% for the three fields. The iterative adjustment of soil parameters was successful in determining a set of soil parameters for each field such that the RRMSE values for yield improved to 8.2, 7.8, and 7.4%, respectively. Simulated yield using these optimized parameters generally fell within ±Standard Error (SE) of the measured yield. The soil fertility factor, SLPF, ranged from 1.27 to 1.34 for these fields, much higher than the default value of 1.0. SRGF, the root growth factor, also had a very different pattern than the expected exponential pattern, which begins with a value of 1.0 in the top 15 cm of soil and declines to 0.078 by 135 cm. The optimized pattern of SRGF for all three fields started with a value of 0.1 in the layers above 45 cm, with larger values in the deeper layers.

The importance of each adjusted soil parameter was investigated by setting it back to its starting value while the other adjusted parameters were left at the optimized value. When SRGF was returned to an exponential pattern, simulated yields for irrigated treatments which received a side dressing of N at visual tasseling were lower than those for an irrigated treatment which did not receive this second application. Because new root length is distributed across the soil profile by the model, we recommend necessary changes to CSM-CERES-Maize in order for the model to be used to predict crop response to split applications of N.

Estimating CSM-CERES-Maize Genetic Coefficients and Soil Parameters and Evaluating Model Response to Varying Nitrogen Management Strategies under North Carolina Conditions

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DEDICATION

To my wife for her full hearted support, love and patience.

To my parents for their encouragement and support in my goal.

BIOGRAPHY

Zhengyu Yang was born in Beijing, the People's Republic of China, in 1969. He graduated the Beijing 96 High School in 1988. In 1992, after graduated from the Computer College, the Beijing University of Technology, he entered the Institute of Botany, Chinese Academy of Science. By working in computer system management, he produced geographical data editing module under Environmental Digital Library System, to support geographical and environmental data input, output and maintenance management. In 1998, while working in the same institute and interested in ecological research, he past Graduate School Entrance Exam and became a Mater student of the institute, major in ecology. Four years later, he got the degree of Mater Science and entered PhD program in Crop Science department, North Carolina State University.

He has worked as volunteer in developing the kernel code and database in North Carolina Wild Flower System. Beside the experience in programming and database management, he has broad and great interest and experience in life science modeling, including ecological modeling, crop modeling, eco-geographical modeling, and eco-agricultural modeling.

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I would like to extend my thanks to Greg Buol for his help in manipulating the model simulation and data base management, and advising in various aspects of soil module in the crop model. I would also like to thanks Mike Sturgill in helping me maintaining me computers for smooth running under heavy load of crop simulation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

Introduction and Literature Review

Corn is one of the most important crops in the US and in North Carolina. The US grew nearly 30 million hectares (73 million acres) of corn in 2003 (NASS, 2004). In North Carolina, corn was planted on 300 thousand hectares in 2003 (740 thousand acres) (NASS, 2004). Hectarage of corn planted in North Carolina increased substantially to 425 thousand hectares in 2007 (Schnitkey, 2007). In the US, continuing improvement in the interaction between genotype and management of maize in recent years has resulted in a yield raise from about 1 Mg ha^{-1} in the 1930s to about 7 Mg ha^{-1} in the 1990s (Tollenaar et al., 2002). Tollenaar et al. (2002) attributed this increase predominantly to genetic improvement of hybrids, resulted from the improvement in genotype and management interaction, which is associated with both stress tolerance and yield stability increase during the past 70 years.

Corn grain is used in North Carolina by the livestock industry, with demand exceeding the supply which can be produced locally (NCDA&CS Agricultural Statistics Division, 2007). It is expected that alternative fuel production will lead to increased demand for corn. A company is currently constructing a corn based fuel refinery in Aurora, North Carolina, and planning to build two more plants of the same size in the Virginia / North Carolina / South Carolina area (Pease, 2007). USDA/NASS estimated that these three plants would consume three-fourths of the current corn crop in the region, i.e. around 6.8 billion kg each year (Pease, 2007).

To satisfy both livestock feed and alternative fuel demands, yields must be increased, either through increasing land area planted or through increasing yields per unit area. Yields can be increased by promoting water and nitrogen (N) use efficiency, and reducing or removing water and N stresses throughout the growing season. It requires a large amount of N to maintain high yields. Over four billion kilograms (9.5 billion lb) of N were applied to corn in the US in 2003 (NASS, 2004). In North Carolina, 43.5 million kilograms (95.9 million lb) of N were applied to corn planted in 2003 (NASS, 2004). Corn is also very sensitive to drought stress during critical development periods (Brownie, 1993). Any stress to corn coming from drought, insufficient N, or N uptake difficulty can result in low yields.

As the demand for corn has increased and the selling price has risen in recent years, so too has the cost of N fertilizer. N prices in 2007 were nearly double those of 2002 (USDA, ERS, 2007). High levels of NO_3-N in groundwater in the southeastern Coastal Plain have made groundwater contamination from excess application of fertilizers an important environmental issue (Hubbard and Sheridan, 1989). The necessity of limiting N usage while maintaining high production complicates N management, and has driven an interest in utilizing precision applications to optimize N usage (Sripada et al., 2005, 2006).

Multiple split applications of inorganic N have been shown to produce higher corn yields compared to one at-planting application (Binder et al., 2000; Sripada et al., 2005, 2006). Crozier (2000) recommends that North Carolina corn producers apply 0.57 kg of N for every 25.4 kg of expected yield. One fourth should be applied before planting and the remainder prior to silking (Crozier, 2000). NCDA&CS gave guidelines of 168-179 kg N ha^{-1}

for sandy plain soils, 146-168 kg N ha^{-1} for Piedmont and mountain soils, and 134-146 kg N ha^{-1} for organic soils (Crozier, 2000).

Many North Carolina farms have potential water quality problems due to N leaching from fertilizer applications. A large proportion of the ground water pollution has been found to be from fertilizer N leaching as nitrate (Singh and Sekhon 1979). N has become one of the primary nutrients affecting water quality (Lilly and Crozier 1996). Studies have indicated that North Carolina estuaries almost always have excessive amounts of N, which entered the system at rates 10 to 100 times greater by agricultural runoff than from forested, non-developed conditions (Lilly and Crozier 1996). Excessive nitrate (NO_3) in drinking water causes issues to human and babe health (Baird 1990), and it has been reported to cause methemoglobinemia in infants (Comly, 1945). Although the U.S. Environmental Protection Agency has established a drinking-water standard for well water of 10 mg L^{-1} of nitrate or less (USEPA, 2001) according to the standard from 1962 (United States Department of Health, Education, and Welfare, 1962), a 2002 study of well samples in Albemarle-Pamlico Drainage Basin of North Carolina found inorganic fertilizer to crops was one of the main identified sources of nitrate N contamination (Spruill et al. 2002). Hubbard and Sheridan (1989) reported an environmental concern that high levels of NO_3-N in groundwater in the southeastern Coastal Plain have made groundwater contamination from excess application of fertilizers. In 2002, the Farm Bill proposed that a site rating of Leaching Index (LI) and/or Phosphorus Index (PI) should be recorded for each field. “Plans for nutrient management shall specify the source, amount, timing and method of application of nutrients on each field to achieve realistic production goals, while minimizing movement of nutrients and other potential contaminants to surface and/or ground waters." (NRCS, USDA, 2006). For all of the land where plant nutrients are applied and soil management included, the nutrient management plan should be applied (NRCS, USDA, 2007).

Climate fluctuations in North Carolina can also put stress on corn development, and further influence the need for N and the potential yield. In the drought year 2002 at the Salisbury Research Station, the measured yield for corn hybrid Pioneer 31G98 was only 2265 kg ha^{-1} (Bowman, 2002), compared to a yield of 8954 kg ha^{-1} the previous year at the same location (Bowman, 2001). This large gap between the two yields in adjacent years at the same site indicates the difficulty of balancing the need for sufficient N to maximize yield in a good year against the need to minimize leaching risk and lower production costs in a year when climatic conditions limit N uptake and final yield.

CERES-Maize Model. Given the complicated interactions between many factors which affect crop growth and yield, such as planting date, cultivar selection, seeding rates, soil type, fertilizer and irrigation strategies, and seasonal weather patterns, field experiments can only go so far in identifying management strategies which might increase the potential for higher yields while minimizing production costs. Crop models can be a powerful tool for evaluating various N application and irrigation strategies across a wide range of environments. These models not only allow researchers to explore crop response to numerous alternative management practices under specific environmental conditions, without really doing it in the field, but also provide researchers with the opportunity to understand and evaluate the multi-dimensional relationship between simulations and field observations.

The CERES-Maize model was first introduced by Jones and Kiniry (1986). Over the years, the model has been improved and included as a module in the software package DSSAT-CSM, the Decision Support System for Agrotechnology Transfer – Crop Simulation Model (Ritchie et al 1998; Hoogenboom et al., 2003; Jones et al., 2003). CSM-Ceres-Maize simulates corn growth on a daily basis in response to weather, soil, and environmental conditions, fertilizer rates, and other field management strategies. It simulates plant phenological development, biomass accumulation and partitioning, and final yield production. The CSM-CERES-Maize model can provide a prompt assessment to support decisions in crop production systems that involve risk (Jagtap et al. 1999), and has been widely used in various agricultural environments in a number of locations in the United States and in cultivation regions all over the world (Jones et al., 2003).

CERES-Maize has been widely used to investigate various aspects of corn growth, including leaf area calculation (Ben Nouna, et al., 2003; Muchow and Carberry 1989, 1990; Carberry et al., 1989; Carberry, 1991), leaf expansion and senescence (Lizaso, et al., 2003a), leaf level canopy assimilation (Lizaso et al., 2005), light capture (Lizaso, et al., 2003b), kernel number (Ritchie, et al., 2003; Lizaso, et al., 2001, 2007; Andrade et al., 1999, 2000), and silage (Braga et al., 2008).

Since CERES-Maize was released in 1986, there have been a number of research studies in which it was extensively used in simulating corn growth and predicting potential yield under various environmental conditions both in the US corn belt and in many other countries, including Brazil (Liu et al. 1989), China, Nigeria (Gungula et al., 2003; Jagtap et al., 1993, 1999); Argentina (Bert et al., 2007; Andrade et al., 2000); Australia (Carberry et al., 1989;

Carberry 1991); South Africa (Walker and Schulze, 2006); Spain (Mantovani et al., 1995), and Thailand (Asadi and Clemente, 2003). The original CERES-Maize (STANDARD version) was a model without N-supply subroutines in which N was assumed to be non-limiting (Jones and Kiniry, 1986). Carberry et al. (1989) compared the performance of this original CERES-Maize (STANDARD version) to a revised version which improved the accuracy in various aspects of the simulation model, including phenology, leaf growth and senescence, assimilation production, grain growth, and soil water balance. This revised version of Ceres-Maize was shown to do a better job of simulating corn growth under various field environments (Carberry et al. 1989; Carberry 1991).

Liu et al. (1989) assessed the capability of CERES-Maize to simulate yields and growth stages of the corn hybrid DINA 10 for five years (from 1983 to 1987) under Brazilian weather and soil conditions. The CERES-Maize model could simulate yields well under normal germination, but it did a better job of simulating the number of days from silking to physiological maturity than the number of days from emergence to the end of the juvenile stage.

The N sub model in CERES-Maize (Version 2.10) was evaluated for ability to simulate N mineralization, nitrate leaching, and N uptake by Bowen et al. (1993). This study included 10 different organic N sources, incorporated from legume green manures ranging from 25 to 300 kg ha^{-1} at C/N ratios between 13 and 37. They modified the N module for N leaching process and N uptake process. Original N model generally predicted well inorganic N release from organic sources across the soil profile. The modified N leaching module simulated inorganic N in soil profile more accurately for the wet season. The modified N uptake module in CERES-Maize could realistically simulate legume N release, but N uptake was over-predicted at high levels of available N.

Lin et al. (2000) used CERES-Maize as a tool to analyze denitrification in corn field soil environment. The simulations demonstrated that soil moisture and soil temperature were two of the most influential factors leading to N loss in denitrification.

A technique of spatially varying N application in grid-cells was developed by Paz et al. (1999) in an Iowa corn field, and the CERES-Maize model was used to characterize corn yield in response to the spatial variation of N application rates. Simulated grid-cell corn yields for all years were in agreement with measured yields for the spatially-varied N rates application.

Xevi et al. (1996) compared CSM-CERES-Maize performance with another model SWATRER-SUCROS in terms of biomass yield, LAI, soil water content, and above ground biomass for a cultivar grown in a field in Nebraska in 1988. Soil moisture content between 0 to 120 cm depth at the field was used in calibrating the soil and records of above ground biomass, LAI and soil water content were used in statistical comparisons. Using fixed genetic coefficients, the CSM-CERES-Maize model predicted soil moisture content, leaf area, and above ground biomass well within 95% confidence limits of field data. The soil moisture content was predicted better by CSM-CERES-Maize than by SWATRER-SUCROS, though the leaf area index and above ground biomass were not predicted better by CSM-CERES-Maize than by SWATRER-SUCROS.

Garrison et al. (1999) introduced an improved subroutine for tile drainage to correct the excessive LAI and water stress that was predicted by the original version of CERES-Maize (might be version 3.0). The soil water balance module was modified, and the soil-water and nitrate leaching was evaluated for subsurface tile drainage conditions typically found in the Mid-West USA. The modified model showed good predictions of cumulative tile-nitrate flow and soil-nitrate concentrations. But the method used in the modified model required calibration using field measurements of soil-moisture, nitrate content, tile-water and nitrate flow, which limited its further wide spread utilization.

Ben Nouna et al. (2000) found that the CERES-Maize model (Jones and Kiniry, 1986) predicted corn LAI, biomass and grain yield unsatisfactorily under soil water stress with weather and soil conditions for a semi-arid Mediterranean environment. They suggested modification in leaf growth and senescence function and soil water deficit function for adopting the CERES-Maize model to the Mediterranean environment. Ben Nouna et al. (2003) and Mastrorilli et al. (2003) both introduced calibrated formulae of functions for LAI and water stress separately into the original modules (CERES-Maize v3.0) to form four new versions of the model: V0 (original version), V1 (only leaf development modified), V2 (only water stress calculations modified), and V3 (both leaf development and water stress modified). Ben Nouna et al. (2003) reported that the newly revised LAI module improved LAI prediction compared to the module in original model, and the new water stress function calculated less severe water stress compared to the original module in the CERES-Maize model. Mastrorilli et al. (2003) concluded that the modified functions for LAI (V1) and water stress (V2) performed better when compared to the original version, and the combination version (V3) performed best among the four models.

In validating CERES-Maize, model phenology and genetic parameters are important in matching simulated yield with recorded yield. Gungula et al. (2003) assessed performance of the phenology module in CERES-Maize in a low-N soil in a tropical region, in experiments including seven late-maturing cultivars grown under five N levels of 0, 30, 60, 90, and 120 kg ha^{-1}. CERES-Maize correctly predicted maize phenology, including days to silking and maturity, and length of the grain-filling period, within two days deviation, as well as maximum number of leaves under the higher-N conditions. However, they found a low N rate (below 90 kg ha^{-1}) affected corn phenology very much for most varieties in the field, but had no effect on simulated phenology. They concluded that a N stress factor needed to be incorporated into the CERES-Maize model to better simulate phenology under low-N conditions.

CERES-Maize Calibration. In general, before any model can be used to simulate crop growth in a new environment or location, it will require some calibration of parameters under local field conditions (Hoogenboom et al. 1994). Two different approaches, or some combination of these approaches, have generally been used to calibrate crop models to local environments. In the first approach, genetic coefficients and / or soil parameters are selected through trial and error comparisons of simulated to measured crop growth and yield values. As each new set of coefficients / parameters is simulated, goodness of fit to observed values is assessed visually and influences the selection of the next set of coefficients / parameters. A more structured approach to calibration has involved using various optimization procedures to estimate multiple genetic coefficients and/or soil parameters across a range of possible values, searching the parameter space until the simulated growth / yield match observed values within acceptable error bounds. There are several systematic and automatic searching algorithms designed for computer-aided parameterization for crop models, including a grid search, the downhill simplex method, and simulated annealing.

The grid search algorithm, the principal searching algorithm used in current research, sets up a potential range of values for each parameter, then divides this range into a predetermined number of equal intervals. Simulations are made using each level setting for the parameter. For example, suppose the reasonable range for a particular parameter value is from 1 to 5. If 5 different values are to be simulated for this parameter, then values of 1, 2, 3, 4, and 5 will be simulated. If 9 different values are to be simulated, then values of 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, and 5 will be simulated. The parameter setting which yields the minimum root mean squared error between simulated values and measured values is selected as the optimum parameter value. It is the simplest method in parameter optimizing manipulation. It has the added advantage in storing the simulated results in a big logically rectangular grid format of table, which allows rapid and repeated reuse of the simulated result of multiple variables while avoiding redundant simulations. This saves storage space and simulation time, which promotes the efficiency of the searching algorithm upon the simulated results.

The downhill simplex method was introduced by Caldwell (1959), Nelder and Mead (1965), and Bach (1969). This method has been applied in phenological parameterization research by Piper et al. (1996a, 1996b) and Grimm et al (1993, 1994). This algorithm determines the direction of search and the search is terminated when the objective function falls within the pre-defined tolerance level. This algorithm is relatively simple, always converges, and provides potentially more precision in searching result compared to the grid search. However, sometimes the method encounters dilemma (Bach, 1969), such as saddle point, valley and hollow, which might break down the algorithm process. There is no guarantee that the method will find the unique and global optimum solution, because this algorithm might be trapped by local extreme near the initial starting point for the search, and does not have rules or method to get out of the local extreme.

Simulated annealing (Goffe, 1994; Fleischer, 1995) is also known as Monte Carlo annealing, probabilistic hill climbing, statistical cooling, and stochastic relaxation (Aarts and Korst, 1989), and has been applied in many disciplines. The algorithm is described as targeting a minimum energy state while cooling a substance with moderate speed to avoid undesirable state (Paz et al., 1999). It is a combinatorial optimization algorithm, and not sensitive to local extremes. This algorithm is very independent of starting parameter values, and capable of escaping from local optima to reach the global optimum. Despite the advantages, the number of simulation runs and the simulation run time cannot be determined beforehand, in contrast to the grid search. Especially when considering crop growing in multiple locations, the environmental factors, such as soil extractable water, will have to be optimized individually each time, and the simulation for the same sets of parameter values have to be redundantly rerun for each location.

Asadi and Clemente (2003) calibrated five genetic coefficients for CERES-Maize using a trial and error approach. They used data from a laboratory experiment to estimate soil parameters related to water-holding capacity. Their simulations targeted yield, N uptake, and N leaching of the simulated field in Thailand during 1999 and 2000.

Using 1982 data for average planting, tasseling, and maturity dates, and average measured yields, Hodges et al. (1987) calibrated five genetic coefficients for the CERES-Maize model for each of 51 locations in the US corn belt. The adjustment to the five genetic coefficients was made by trying each of eight sets of pre-defined fixed coefficient values. The best set of values for these coefficients was determined for each location, representing all hybrids grown there, rather than any specific hybrid. The CERES-Maize model demonstrated success in estimating production for the state and the corn belt from 1982 to 1985, using these coefficients.

Liu et al. (1989) calibrated genetic coefficients in standard version of CERES-Maize model for one Brazilian hybrid using crop and weather data from 1983 collected at one site in Brazil, using methods similar to those applied by Hodges et al. (1987). Data used included grain yield, phenological cycle, plant population density, sowing depth, photoperiod sensitivity, dates of sowing, silking, and physiological maturity. The soil data included drained upper limit, lower limit of plant extractable soil water, saturated soil water content by volume, upper limit of Stage 1 soil evaporation, and soil rooting depth. The phenological parameters were adjusted using a limited pre-defined set of coefficient values until simulated silking and maturity dates were in close agreement with observed values. Then, one coefficient which affects grain filling was adjusted until simulated yields were within 2% of observed yields.

A program named GENCALC was developed for use with the CERES models to estimate genetic coefficients for any cultivar (Hunt et al. 1993). GENCALC was designed to iteratively run the related model with the approximate genetic coefficients and match the measured values, and under each iteration, the genetic coefficients were changed until the predicted matched the measured within acceptable range of difference. Roman-Paoli et al. (2000) investigated two different methods for estimating CERES-Maize phenological parameters, degree days from emergence to end of juvenile phase and photoperiod sensitivity coefficient, for five hybrids grown at Rossville, Kansas, during 1995: the Uniform Covering by Probabilistic Region (UCPR), and Genetic Coefficient Calculator (GENCALC) (Hunt et al. 1993). A joint confidence region for the two parameters corresponding to a goodness-of-fit threshold level was delineated using UCPR. They simulated silking dates using degree days from emergence to end of juvenile phase and photoperiod sensitivity coefficient values obtained by the two methods. Both UCPR and GENCALC underestimated degree days from emergence to end of juvenile phase values compared to field data from the Kansas Corn Performance Tests, which might be due to the model's propensity to overestimate leaf number. Although UCPR was difficult to use for more than three parameters, it was superior to GENCALC for three or fewer parameters to produce a realistic joint confidence region along with better point estimates.

Piper et al. (1998) estimated soybean cultivar coefficients for SOYGRO Version 5.42 by performing an iterative stepwise procedure, which used the downhill simplex method to optimize temperature functions and visual fitting to optimize cultivar coefficients. Overall results were compared using independently collected data and the mean squared error of prediction (MSEP).

Irmak et al. (2000) and Welch et al. (2002) used a computationally efficient approach to estimating genetic coefficients for large sets of hybrids. This method involves making all crop model simulations first and storing results for an iterative grid search procedure. Irmak et al. (2000) first optimized one coefficient related to flowering by minimizing the errors between simulated and observed anthesis dates. They retained the optimized value of this parameter while optimizing two coefficients that affect maturity date. They next evaluated hybrid coefficients affecting yield through a two way grid search, which was similar to the method described in Mavromatis et al. (2001, 2002). Welch et al. (2002) estimated values for several genetic coefficients and the crop rooting profile in CROPGRO-Soybean by setting the genetic coefficients with the normal maturity group values first while searching for the optimal rooting profile and then fixing the resulting rooting profile while searching for optimal genetic coefficients. The estimation stopped when the relative improvement was less than 0.1% in any iteration step.

Mavromatis et al. (2001) optimized CROPGRO-Soybean genetic coefficients and soil parameters with a stepwise procedure using a combination of linear grid searches and simulated annealing. Mavromatis et al. (2002) used two-dimensional linear grid searches to determine cultivar coefficient values which minimized root mean squared errors (RMSE).

Calmon et al. (1999) reported successful optimization in root growth and soil water extraction parameters for dynamic crop model by applying the adaptive simulated annealing algorithm. Ferreyra (2004) proposed a modified version of simulated annealing used by Ferreyra et al. (2002), with data reuse to avoid repeated simulation and redundant storage of simulated results. This increased the searching speed by 25% to 75%, depending on the geometry of the simulation domain.

Using fixed genetic coefficients, Braga and Jones (2004) tried two different methods for calibrating soil parameters in the CERES-Maize model: one which used grain yield as the objective function, and a second which used soil-water content measured 12 times during the season in each 15 cm increment of the soil profile as the objective function. Simulated annealing was used in both methods as the optimization procedure. Grain yield estimates using the grain yield objective function were acceptable, but the simulations of soil water content, particularly in the bottom layer, were not. The use of soil-water content measurements as the objective function resulted in both simulated yield and soil water content values which were acceptable.

Miao et al. (2006) determined optimal nitrogen rates for four management zones, 2 hybrids, and 2 years using CERES-Maize (version 3.5) after calibration of four soil profile parameters for each of four management zones using 3 years of experimental data. Simulated annealing was used to minimize the sum of squared errors between measured and simulated yields (Miao et al., 2006). Calibrated soil parameters included SCS curve number, effective tile drainage, saturated hydraulic conductivity, and fraction available soil water. The genetic coefficients were set to those for a known generic cultivar in spite of the potential for introducing errors. Simulated yields were 10% lower than measured and the model accounted for 58.7% yield variability in the three simulated years.

Validation. Once soil parameters and/or genetic coefficients have been calibrated for a new location or cultivar, it still must be shown that these parameters / coefficients will work well when used to simulate crop growth and yield compared to field data sets not used in the fitting process. Liu et al. (1989) used data from 1983 to fit CERES-Maize genetic coefficients, then used data from 1984 to 1987 to validate that these fitted coefficients resulted in simulated silking and physiological maturity dates, LAI, and grain number and grain yield values which were within reasonable error bounds.

Carberry et al. (1989) validated the accuracy of simulated corn plant development and yield values using independent experiment measurements, including days to silking, days to maturity, dry weight at silking, LAI at silking, leaf number, grain yield, grain size, grain number, biomass at maturity, stover at maturity and LAI at maturity, for the standard CERES-Maize model and an improved model version. Root mean square deviation (RMSD), the mean weighted difference between observed and predicted values was used to judge model fit. Pang et al. (1998) validated CERES-Maize ability to simulate grain yield, N uptake, and nitrate leaching for Pioneer 3921 planted under control and 3 N rates with two irrigation strategies in a Minnesota field in 1991 and 1992. The simulated and measured yields and N uptake were close without significant difference in both years, but the nitrate leaching was significantly different between simulated and measured values.

Jagtap et al. (1999) tried three N inputs of 60, 90, and 120 kg ha^{-1} (due to unknown N inputs from records) in simulating yields for three rain fed locations during 1992-1995 with

CERES-Maize (Version 2.1). The linear regression of the observed vs. the simulated yields indicated that the simulated yields more closely approximated the measured yields when the 90 kg ha^{-1} N input was assumed. R^2 values for all three N inputs were over or equal 0.987, but only the 90 kg ha^{-1} level possessed a slope value close to 1.0.

Cross validation is frequently used to investigate model prediction quality. Cross validation performs resampling from the complete dataset where data are repeatedly grouped into pairs of a larger and a smaller one, for estimating the parameters and the prediction variance, respectively (Irmak et al., 2000). Iteration to the resampling process leads to improved estimation in parameters and prediction variance (Irmak et al., 2000).

After calibrating four soil parameters, Miao et al. (2006) validated the CERES-Maize model by simulating the yields for two hybrids grown under five N treatments in four management zones in 2001 and 2003. The model performed unsatisfactorily for non-fertilized treatments, with simulation error varying from -34% to 112%, but performed well for non-zero N rates.

Sensitivity to Changes in Model Parameters and Model Inputs. Sensitivity analysis is a systematic investigation of the variation in model output in response to changes in model parameter values. Boote et al. (2001) demonstrated CERES-Maize model sensitivity to changes in each of three genetic coefficients for one cultivar. Changes in value settings to any one of the three parameters resulted in proportional change to the simulated yield for the cultivar. The increase of 10% in degree days from silking to physiological maturity increased simulated yield 12-13%.Decreases of 10% in potential kernel number resulted in 6-7%

decrease in simulated yield. A 10% decrease in potential kernel growth rate (mg / kernel d) generated 8-9% decrease in simulated yield.

Bert et al. (2007) investigated the CSM-CERES-Maize sensitivity in yield to soil and climate related variables by running the CERES-Maize model on 31 years of historical weather data for a field in Argentine Pampas. They examined the soil N content at sowing, soil organic matter content, soil water storage capacity, soil water content at sowing, soil infiltration number, and daily solar radiation, each varied within designed boundary, respectively. Although the model demonstrated sensitivities to soil variables, much higher sensitivity was reported to changes in daily solar radiation. The normalized sensitivities in daily solar radiation for rainfed and irrigated condition were -0.69 and 0.45, respectively, compared to 0.20-0.28 for that of the soil variables.

Liu et al. (1989) investigated the sensitivity of CERES-Maize response in grain yield and available soil water to changes in plant population, sowing depth, rooting depth, and plant-extractable lower limit soil water one at a time while holding all other parameters unchanged. Their results demonstrated that grain yield increased with population increase, but decreased when population was higher than 10 plants m^{-2}. Highest simulated yield occurred at sowing depth of 4 cm, with a yield decrease when sowing depth either decreased from 4 to 3 cm, or increased from 5 to 6 cm. The yield was less affected when rooting depth increased from 65 to 95 cm than when roots were shallower than that. A mixed response of yield to changes in plant extractable soil water was found, with an increase to the highest level tested actually resulting in a decrease in yield. They also detected a delay in physiological maturity of 10 days when drought happened.

In a study by Sadler et al. (2000), the performance of CERES-Maize (version 3.5) was evaluated in the SE coastal plain of the US; and simulated yield sensitivity of the model to various factors was reported. This study found the model to be largely insensitive to changes in soil type, depth to clay, N, and plant population, but rather sensitive to soil water, rainfall, and canopy temperature. The model also reported sensitivity of yield to depth of clay layer. The authors suggested that further work on modeling crop phenology and runoff was needed.

Using CERES-Maize to Evaluate Management Strategies. Once a model has been calibrated and validated for use in a particular location or situation, it can be used to evaluate management strategies, such as cultivar selection, planting practices, nutrient applications, or weed and pest control under various weather patterns and field conditions. These studies can assist corn producers in making management decisions in order to maximize economic return, as well as to minimize cultivation cost and environmental contamination. Especially in recent years, studies have been concerned with the genetic coefficients of corn hybrids and with factors affecting corn development (fertilizer, weather, and soil type, among others) under various field conditions.

Mantovani et al. (1995) used CERES-Maize to investigate yield response to irrigation amount and uniformity. The optimum irrigation amount was reported highly related to sprinkler irrigation spatial uniformity and the ratio between production price and water cost.

Thornton and MacRobert (1994) used CERES-Maize (version V2.1) to evaluate the design in timing and amount of N schedules in order to investigate the optimum N application schedules and estimate corresponding profit returns. They utilized 10 time slots for possible N applications during the growing season. N application amounts varied from 49 to 240 kg ha^{-1}. There was potential moderate economical benefit over long-term, if using best-bet N schedules for long-term fertilizer for all seasons based on the ten year weather data sets from 1978 to 1987 used in the study.

Evaluation is also necessary to investigate the applicability of crop model in site-specific research (Pang et al., 1998). The sensitivity of the predicted yield and nitrate leaching in response to three irrigation management strategies (irrigation triggered at 40, 60, or 80% of the available water remaining in soil) and 31 years climate changes were analyzed by Pang et al. (1998). The simulated corn grain yield was not significantly different at irrigation trigger in soil water deficit at 30% and above, but leaching amount in nitrate was increased with the increase in irrigation trigger level.

Simulating maize yield over 20 years of weather, Jagtap et al. (1999) evaluated CERES-Maize (V 2.1) model in three savanna locations under three N input strategies (0, 60, and 120 kg ha^{-1}). By using cumulative probability distribution method, they analyzed N use efficiency and variety yields for medium duration varieties and late duration varieties. Under rain fed savanna and N fertilizer input condition, medium duration varieties had better yield and nitrogen use efficiency than late duration varieties in Mokwa and Ibadan in Nigeria. There was no advantage in varying N input strategy for a specific variety. The N use efficiency was best at 60 kg ha^{-1} N input strategy.

Thorp et al. (2006) used CERES-Maize to examine the environmental and economical risks of management strategies that either maximized the farmer’s marginal net return, or insured that the N left in harvested soil would not exceed 40 kg ha^{-1} in most growing seasons. They concluded that the difficulty in precision N management was highly related to the dynamics of N movement, to soil spatial variability, and to weather uncertainties.

Miao et al. (2006) evaluated economical optimum N rates varied from 70 to 250 kg ha^{-1}, for two hybrids, and concluded that N application at year specific, hybrid specific, and management zone specific EONR increased net return by $49and $52 for two hybrids, respectively, when compared to uniform N application of 170 kg ha^{-1}.

Based on the above research, there is an opportunity to utilize CSM-CERES-Maize to improve within-season N management decision making. This research will determine if CSM-CERES-Maize can be used to provide recommendations on precise and timely within-season N application for improving final corn yield and net returns in a precision agricultural system, while minimizing and optimizing N fertilizer usage. This research should assist farmers with N application strategies based on corn growth stage, current crop N status and biomass, as well as soil type, and expectation of crop yield potential. In relation to the main objective, specific objectives include:

1) Determine if the CSM-CERES-Maize model can be used to accurately simulate yield of corn hybrids grown in several North Carolina environments under non-limiting N conditions.

2) Determine if the CSM-CERES-Maize model can be used to simulate yield of a specific hybrid, Pioneer 31G98 (P31G98), in several North Carolina environments under non-limiting N conditions.

3) Certify that the CSM-CERES-Maize model can accurately simulate response of P31G98 to variations in N and irrigation timing and amount.

REFERENCES

Andrade, F.H., C. Vega, S. Uhart, A. Cirilo, M. Cantarero, and O. Valentinuz. 1999. Kernel Number Determination in Maize. Crop Sci. 39:453-459.

Andrade, F.H., M.E. Otegui, and C. Vega. 2000. Intercepted radiation at flowering and kernel number in maize. Agron. J. 92:92-97.

Aarts, E., J. Korst. 1989. Combinatorial optimization. pp11. *In:* Emile Aarts and Jan Korst, Simulated annealing and Boltzmann machines: a stochastic approach to combinatorial optimization and neural computing. Wiley. Chichester.

Asadi, M.E., and R.S. Clemente. 2003. Evaluation of CERES-Maize of DSSAT model to simulate nitrate, yield and soil moisture content under tropical condition. Food, Agric & Environ. 1:270-276.

Bach, H. 1969. On the downhill method. Comm. ACM. 12:675-677.

Baird, J.V. 1990. Soil facts nitrogen management and water quality. North Carolina cooperative extension service. Publication AG-439-2. Available on-line at: http://www.soil.ncsu.edu/publications/Soilfacts/AG-439-02/

Ben Nouna, B., N. Katerji, and M. Mastrorilli. 2000. Using the CERES-Maize model in a semi-arid Mediterranean environment. Evaluation of model performance. Eur. J. Agron. 13:309-322.

Ben Nouna, B., N. Katerji, and M. Mastrorilli. 2003. Using the CERES-Maize model in a semi-arid Mediterranean environment. New modeling of leaf area and water stress functions. Eur. J. Agron. 19:115-123.

Bert, F.E., C.E. Laciana, G.P. Podesta, E.H. Satorre, and A.N. Menendez. 2007. Sensitivity of CERES-Maize simulated yields to uncertainty in soil properties and daily solar radiation. Agric. Syst. 94:41–150.

Binder, D.L., D.H. Sander, and D.T. Walters. 2000. Maize response to time of nitrogen application as affected by level of nitrogen deficiency. Agron. J. 92:1228–1236.

Boote, D.L., K.J., M.J. Kropff, and P.S. Bindraban. 2001. Physiology and modelling of traits in crop plants: implications for genetic improvement. Agric. Syst. 70:395–420.

Bowen, W.T., J.W. Jones, R.J. Carsky and J.O. Quintana. 1993. Evaluation of the nitrogen submodel of CERES-Maize following legume green manure incorporation. Agron. J. 85:153-159.

Bowman, D. T. 2001. Corn and corn silage 2001. North Carolina measured crop performance (Crop Science Research Report No. 195).

Bowman, D. T. 2002. Corn and corn silage 2002. North Carolina measured crop performance (Crop Science Research Report No. 201).

Braga, R. P., and J. W. Jones. 2004. Using optimization to estimate soil inputs of crop models for use in site−specific management. Trans. ASAE 47:1821−1831.

Braga, R.P., M.J. Cardoso, and J.P. Coelho. 2008. Crop model based decision support for maize (Zea mays L.) silage production in Portugal. Eur. J. Agron. 28:224-233.

Brownie, C., D.T. Bowman, and J.W. Burton. 1993. Estimating spatial variation in analysis of data for yield trials: A comparison of methods. Agron. J. 85:1244-1253.

Caldwell, G.C. 1959. A note on the downhill method. J. ACM. 6:223 – 225.

Calmon, M.A., J.W. Jones, D. Shinde, and J.E. Specht. 1999. Estimating parameters for soilwater balance models using adaptive simulated annealing. Applied Engineering in Agric. 15:703-713.

Carberry, P.S. 1991. Test of leaf-area development in CERES-Maize: a correction. Field Crops Res. 27:159-167.

Carberry, P.S., R.C. Muchow and R.L. McCown. 1989. Testing the CERES-Maize simulation model in a semi-arid tropical environment. Field Crops Res. 20:297-315.

Comly, H.H. 1945. Cyanosis in infants caused by nitrates in well water. J. Amer. Medical Assoc. 129:112–116.

Crozier, C. 2000. Fertilizer and lime management. *In*:The North Carolina corn production guide 2000. N. C. Coop. Ext. Service, N. C. State Univ. Available at: http://www.ces.ncsu.edu/plymouth/cropsci/cornguide/Chapter3.html.

Ferreyra, R.A. 2004. A faster algorithm for crop model parameterization by inverse modeling: simulated annealing with data reuse. Trans. ASAE 47:1793−1801.

Ferreyra R.A., H.P. Apezteguı´a, R. Sereno, and J.W. Jones. 2002. Reduction of soil water spatial sampling density using scaled semivariograms and simulated annealing. Geoderma. 110:265– 289.

Garrison, M.V., W.D. Batchelor, R.S. Kanwar, and J.T. Ritchie. 1999. Evaluation of the CERES-Maize water and nitrogen balances under tile-drained conditions. Agric. Syst. 62:189-200.

Goffe, W.L., G.D. Ferrier, J. Rogers. 1994. Global optimization of statistical functions with simulated annealing. J. Econom. 60: 65-99.

Grimm, S.S., J.W. Jones, K.J. Boote, and John D. Hesketh. 1993 Parameter estimation for predicting flowering date of soybean cultivars. Crop Sci. 33:137-144.

Grimm, S.S., J.W. Jones, K.J. Boote, and B.C. Herzog. 1994. Modeling the occurrence of reproductive stages after flowering for four soybean cultivars. Agron. J. 86:31-38.

Gungula, D.T., J.G. Kling, and A.O. Togun. 2003. CERES-Maize predictions of maize phenology under nitrogen-stressed condition in Nigeria. Agron. J. 95:892-899.

Hodges, T., D. Botner, C. Sakamoto, and J. Hays Haug. 1987. Using the CERES-Maize model to estimate production for the US Corn Belt. Agric. For. Meteorol. 40:293-303.

Hoogenboom, G.J., J.W. Jones, P.W. Wilkens, W.D. Batchelor, W.T. Bowen, L.A. Hunt, N. Pickering, U. Singh, D.C. Godwin, B. Baer, K.J. Boote, J.T. Ritchie, and J.W. White. 1994. Crop models. pp. 95-242. *In* G.Y. Tsuji, G. Uehara, and S. Balas (ed.) DSSAT v3. Vol. 2–2. Univ. of Hawaii, Honolulu.

Hoogenboom, G., J.W. Jones, C.H. Porter, P.W. Wilkens, K.J. Boote, W.D. Batchelor, L.A. Hunt, and G.Y. Tsuji (Editors). 2003. Decision Support System for Agrotechnology Transfer Version 4.0. Vol. 1. Univ. of Hawaii, Honolulu, HI.

Hubbard, R.K. and J.M. Sheridan. 1989. Nitrate movement to groundwater in the southeastern Coastal Plain. J. Soil and Water Conserv. 44:20-27.

Hunt, L.A., S. Pararajasingham, J.W. Jonges, G. Hoogenboom, D.T. Imanmura, and R.M. Ogoshi. 1993. GENCALC: software to facilitate the use of crop models for analyzing field experiments. Agron. J. 85:1090-1094.

Irmak, A., J.W. Jones, T. Mavromatis, S.M. Welch, K.J. Boote, and G.G. Wilkerson. 2000. Evaluating methods for simulating soybean cultivar responses using cross validation. Agron. J. 92:1140-1149.

Jagtap, S.S., F.J. Abamu, and J.G. Kling. 1999. Long-term assessment of nitrogen and variety technologies on attainable maize yields in Nigeria using CERES-Maize. Agric. Syst. 60:77-86.

Jagtap, S. S., M. Mornu & B. T. Kang. 1993. Simulation of growth, development and yield of maize in the transition zone of Nigeria. Agric. Syst. 41:215-229.

Jones, C.A., and J.R. Kiniry. 1986. CERES-Maize, a simulation model of maize growth and development. Texas A&M Univ. Press, College Station.

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. 2003. The DSSAT cropping system model. Eur. J. Agron. 18:235-265.

Lilly, J. P. and C.R. Crozier. 1996. SoilFacts Agriculture and coastal water quality. North Carolina Cooperative Extension Service. Publication AG-439-10. http://www.soil.ncsu.edu/publications /Soilfacts/AG-439-10/

Lin, C, C. Chen, W. Hsiang, and T.L. Hu. 2000. A model and its implications for denitrification in soil environment. Proc. Natl. Sci. Counc. 24:136-142.

Liu. W.T.H., D.M. Botner, and C.M.Sakamoto. 1989. Application of CERES-Maize model to yield prediction of a Brazilian maize hybrid. Agric. Forest Meteorol. 45:299-312.

Lizaso, J.I., A.E. Fonseca, and M.E. Westgate. 2007. Simulating source-limited and sink-limited kernel set with CERES-Maize. Crop Sci. 47:2078-2088.

Lizaso, J.I., W. D. Batchelor, K. J. Boote, M. E. Westgate, P. Rochette, and A. Moreno-Sotomayor. 2005. Evaluating a leaf-level canopy assimilation model linked to CERES-Maize. Agron. J. 97:734–740.

Lizaso, J.I., W.D. Batchelor, and M.E. Westgate. 2003a. A leaf area model to simulate cultivar-specific expansion and senescence of maize leaves. Field Crops Res. 80:1-17.

Lizaso, J.I., W.D. Batchelor, M.E. Westgate, and L. Echarte. 2003b. Enhancing the ability of CERES-Maize to compute light capture. Agric. Syst. 76:293-311.

Lizaso, J.I., W.D. Batchelor, and S.S. Adams. 2001. Alternate approach to improve kernel number calculation in CERES-Maize. Trans. ASAE 44:1011-1018.

Mavromatis, T., K. J. Boote, J. W. Jones, A. Irmak, D. Shinde, and G. Hoogenboom. 2001. Developing genetic coefficients for crop simulation models with data from crop performance trials. Crop Sci. 41:40–51.

Mavromatis, T., K. J. Boote, J. W. Jones, G. G. Wilkerson, and G. Hoogenboom. 2002. Repeatability of model genetic coefficients derived from soybean performance trials across different states. Crop Sci. 42:76–89.

Mantovani, E.C., F.J. Villalobos, F. Orgaz, and E. Fereres. 1995. Modelling the effects of sprinkler irrigation uniformity on crop yield. Agric. Water Manage. 27:243-257

Mastrorilli, M., N. Katerjib, and B. Ben Nouna. 2003. Using the CERES-Maize model in a semi-arid Mediterranean environment. Validation of three revised versions. Eur. J. Agron. 19:125-134.

Miao, Y., D.J. Mulla, W.D. Batchelor, J.O.Paz, P.C. Robert, and M. Wiebers. 2006. Evaluating management zone optimal nitrogen rates with a crop growth model. Agron. J. 98:545-553.

Muchow, R.C. and P.S. Carberry. 1989. Environmental control of phenology and leaf growth in a tropically adapted maize. Field Crops Res. 20:221-236.

Muchow. R.C. and P.S. Carberry. 1990. Phenology and leaf-area development in a tropical grain sorghum. Field Crops Res. 23: 221-237.

NASS (National Agricultural Statistics Service). 2004. Agricultural Chemical Usage 2003 Field Crops Summary. http://usda.mannlib.cornell.edu/reports/nassr/other/pcu-bb/agcs0504.pdf,

NCDA&CS Agricultural Statistics Division, 2007. Statistics - Crops summary. Available at: http://www.agr.state.nc.us/stats/crops/cropsum.html

Nelder, J. A., and R. Mead. 1965. A simplex method for function minimization. Comput. J. 7:308-313.

NRCS (Natural Resources Conservation Service), USDA. 2006. Conservation Practice Standard. Nutrient Management (Ac.). Code 590. Available on-line at: http://efotg.nrcs.usda.gov/references/public/RI/NutrientManagement590.doc.

NRCS (Natural Resources Conservation Service), USDA. 2007. Title 190, Part 402 Nutrient management. Available on-line at: http://www.nrcs.usda.gov/technical/ecs/nutrient/gm-190.html.

Pang, X.P., S.C. Gupta, J.F. Moncrief, C.J. Rosen, and H.H. Cheng. 1998. Evaluation of nitrate leaching potential in Minnesota glacial outwash soils using the CERES-Maize model. J. Environ. Qual. 27:75-85.

Paz, J.O., W.D. Batchelor, B.A. Babcock, T.S. Colvin, S.D. Logsdon, T.C. Kaspar, and D.L. Karlen. 1999. Model-based techniques to determine variable rate nitrogen for corn. Agric. Syst. 61:69-75.

Pease, J. 2007. Ethanol and corn. Available on-line at: http://www.ext.vt.edu/news/periodicals/fmu/2007-02_03/ethanol.html.

Piper, E.L., K.J. Boote, and J.W. Jones. 1998. Evaluation and improvement of crop models using regional cultivar trial data. Applied Engineering in Agric. 14:435-446.

Ritchie, J.T., Singh, U., Godwin, D.C., Bowen, W.T., 1998. Cereal growth, development and yield. pp. 79–98. *In:* Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Ritchie, J.T., and G. Alagarswamy. 2003. Model concepts to express genetic differences in maize yield components. Agron. J. 95:4-9.

Roman-Paoli, E., S.M. Welch, and R.L. Vanderlip. 2000. Comparing genetic coefficient estimation methods using the CERES-Maize model. Agric. Syst.65:29-41.

Sadler, E.J., B.K. Gerwig, D.E. Evans, and W.J. Busscher. 2000. Site-specific modeling of corn yield in the SE coastal plain. Agric. Syst. 64:189-207.

Schnitkey, G. 2007. Projected 2007 corn acres. *In*: Illinois farm economics: facts and opinions. Dept. Agric. and Consumer Econ., College of Agric., Consumer and Environ. Sci., Univ. of Illinois at Urbana-Champaign. Available on-line at: http://www.farmdoc.uiuc.edu/manage/newsletters/fefo07_07/fefo07_07.html.

Singh, B. and G.S. Sekhon. 1979. Nitrate pollution of groundwater from farm use of nitrogen fertilizers - a review. Agric. Environ. 4:207-225.

Spruill, T.B., W.J. Showers, and S.S. Howe. 2002. Application of classification-tree methods to identify nitrate sources in ground water. J. Environ. Qual. 31:1538-1549.

Sripada, R.P., R.W. Heiniger, J.G. White, and R. Weisz. 2005. Aerial color infrared photography for determining late-season nitrogen requirements in corn. Agron. J. 97:1443–1451.

Sripada, R.P., R.W. Heiniger, J.G. White, and A.D. Meijer. 2006. Aerial color infrared photography for determining early in-season nitrogen requirements in corn. Agron. J. 98:968–977.

Thornton, P.K., and J. F. MacRobert. 1994. The value of information concerning near-optimal nitrogen fertilizer scheduling. Agric. Syst. 45: 315-330.

Thorp, K.R., W.D. Batchelor, and J.O. Paz. 2006. Methodology to link production and environmental risks of precision nitrogen management strategies in corn. Agric. Syst. 89:272-298.

Tollenaar, M., and E.A. Lee. 2002. Yield potential, yield stability and stress tolerance in Maize. Field Crops Res. 75:161-169.

United States Department of Health, Education, and Welfare. 1962. Drinking water standards. Revised. Public Health Serv. Publ. 956. United States Dept. Health, Educ., and Welfare, Washington, DC.

USDA (U.S. Department of Agriculture), ERS (Economic Research Service). 2007. U.S. fertilizer use and price. Available on-line at: http://www.ers.usda.gov/Data/fertilizeruse

Walker, N.J., R.E. Schulze. 2006. An assessment of sustainable maize production under different management and climate scenarios for smallholder agro-ecosystem in KwaZulu-Natal, South Africa. Physics and Chemistry of the Earth. 31:995-1002.

Welch, S.M., G. Wilkerson, K. Whiting, N. Sun, T. Vagts, G. Buol, T. Mavromatis. 2002. Estimating soybean model genetic coefficients from private-sector variety performance trial data. Trans. ASAE 45(4):1163-1175.

Xevi, E., J. Gilley, and J. Feyen. 1996. Comparative study of two crop yield simulation models. Agric. Water Manage. 30:155- 173.

CHAPTER 2

Calibrating the CSM-CERES-Maize Model for Simulating Yield under Non-limiting Nitrogen Conditions in North Carolina Environments

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ABSTRACT

CSM-CERES-Maize has been extensively used to simulate corn growth and grain production in various locations worldwide, but has not been evaluated previously for use in North Carolina. The objectives of this study were to calibrate CSM-CERES-Maize soil parameters and genetic coefficients using official variety trial data, to evaluate model performance in North Carolina, and to determine the suitability of the fitting technique and variety trial data for model calibration. Yield data from 60 site-years for 53 maize genotypes were used in the study. A stepwise calibration procedure was utilized: 1) two genetic coefficients which determine anthesis and physiological maturity dates were adjusted based on planting date and growing degree day requirements for each hybrid; and 2) plant available soil water and rooting profile were adjusted iteratively with two genetic coefficients affecting yield. Cross validation was used to evaluate the suitability of this approach for estimating soil and genetic coefficients. The root mean squared errors of prediction (RMSEP) were similar to fitting errors. Results indicate that the CSM-CERES-Maize model can be used in North Carolina to simulate corn growth under non-limiting nitrogen conditions and official variety trial data can be used to estimate genetic coefficients, although the CSM-CERES-Maize over-estimated yield for low yield environments and under-estimated it for high yield environments for some hybrids. Root mean squared errors were sufficiently large for several site-years that data from these locations could not be used in fitting genetic coefficients. In some cases, this could be attributed to a weather event, such as a late-season hurricane.

Abbreviations: DAP, days after planting; DSSAT, Decision Support System for Agrotechnology Transfer ; GDD, growing degree days; RMSE, root mean squared error; RMSEP, root mean squared error of prediction; RRMSE, relative root mean squared error; MRRMSE, mean of the relative root mean squared error; SD, standard deviation.

INTRODUCTION

The CSM-CERES-Maize model, which is part of Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.0 (Jones and Kiniry, 1986; Jones et al., 2003; Hoogenboom et al., 2003), is a process-oriented corn growth model that has been widely used in simulation studies of varied agricultural environments in a number of different states in the US and in locations worldwide (Jones et al., 2003). The CSM-CERES-Maize model simulates corn phenological stages, growth and development, biomass production, and grain yield based on information about initial soil conditions, soil profile characteristics, daily weather, fertilizer applications, irrigations, planting date, plant population, and other management strategies.

Before the CSM-CERES-Maize model can be used in simulation studies of corn production in North Carolina, it must be calibrated and evaluated for suitability in simulating growth of the currently available, locally grown corn hybrids under North Carolina environmental conditions and field management practices. CSM-CERES-Maize uses a set of six genetic coefficients to characterize the response of different corn hybrids to variations in environmental conditions (Hoogenboom et al., 2003). The genetic coefficients for most of the corn hybrids grown in North Carolina are not known and are not included with the CSM-CERES-Maize model distributed in DSSAT v4.0 (Hoogenboom et al., 2003).

A number of different approaches have been used to estimate genetic coefficients for use in crop growth models when coefficients are needed for large numbers of hybrids, but only limited information is available. This is the case when data from crop variety trials, either public or private, are to be used in the fitting process. At best, anthesis and maturity dates may have been recorded, but often only final yield data are available for each hybrid. Piper et al. (1998) estimated soybean cultivar coefficients for SOYGRO Version 5.42 by performing an iterative stepwise procedure, which used the downhill-simplex method (Nelder and Mead, 1965) to optimize temperature functions, and visual fitting to optimize genetic coefficients. Overall results were compared using independently collected data and the mean squared error of prediction (MSEP). Mavromatis et al. (2001) optimized CROPGRO-Soybean genetic coefficients and soil parameters with a stepwise procedure using a combination of linear grid searches and simulated annealing. Mavromatis et al. (2002) used two-dimensional linear grid searches to determine cultivar coefficient values which minimized root mean squared errors (RMSE).

Irmak et al. (2000) and Welch et al. (2002) used a computationally efficient approach to estimating genetic coefficients for large sets of cultivars. This method involves making all crop model simulations first and storing results for an iterative search procedure. Irmak et al. (2000) first optimized one coefficient related to flowering by minimizing the errors between simulated and observed anthesis dates. They retained the optimized value of this parameter while optimizing two coefficients that affect maturity date. They next evaluated hybrid coefficients affecting yield through a two way grid search, which was similar to the method described in Mavromatis et al. (2001, 2002). Welch et al. (2002) estimated values for several genetic coefficients and the crop rooting profile in CROPGRO-Soybean by setting the genetic coefficients with the normal maturity group values first while searching for the optimal rooting profile and then fixing the resulting rooting profile while searching for optimal genetic coefficients. The estimation stopped when the relative improvement was less than 0.1% in any iteration step.

Roman-Paoli et al. (2000) investigated using two different methods for estimating CERES-Maize phenological parameters, P1 and P2, for five hybrids: the Uniform Covering by Probabilistic Region (UCPR), and Genetic Coefficient Calculator (GENCALC). Both UCPR and GENCALC underestimated P1 values compared to field data from the Kansas Corn Performance Tests, which might be due to the model's propensity to overestimate leaf number.

Since the genetic coefficients of the CSM-CERES-Maize model have not been widely investigated, especially for use in North Carolina, the objectives of this study were to i) calibrate CSM-CERES-Maize soil parameters and genetic coefficients using official variety trial data, ii) evaluate model performance in North Carolina for locally grown hybrids, and to iii) determine the suitability of the fitting technique and variety trial data for model calibration.

MATERIALS AND METHODS

The performance of CSM-CERES-Maize (Hoogenboom et al., 2003) was examined under North Carolina weather conditions, field environments, and management practices, for locally grown hybrids. The silking stage is the most critical phase for corn production in determining the corn plant kernel number and the final grain production level. Our overall approach was to first estimate two genetic coefficients (phenological parameters) that primarily determine time of anthesis and physiological maturity, using variety trial data and calculated RMSE. Using these optimized coefficients, a large matrix of simulations was performed in which soil parameters for each field included in the trials and two genetic coefficients affecting yield were varied across reasonable ranges. Results of these simulations were organized in hybrid-specific databases and iterative searches were made to determine optimal values for both soil parameters and genetic coefficients. The performance of the CSM-CERES-Maize model was evaluated in terms of yield and/or phenological stage predictions over all hybrids, over all site-years in North Carolina. Cross validation was used to examine the ability of the fitting approach to estimate hybrid coefficients. The simulations were managed and controlled by Crop Simulation DataBase (CSDB) (Buol et al., 2006), a program developed to facilitate management of weather, soil, and field experimental data and use of the data in simulations studies using CSM-CERES-Maize or other DSSAT 4.0 crop models (Buol et al., 2006).

Variety Trial Data

The corn yield data used in this study were collected from trials performed on eleven research stations in North Carolina from 1994 through 2003 (Table 1a, and Figure 1) in the Official Variety Testing Program (Bowman, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003). Planting dates varied from March 28 to April 27 across locations and years. The row spacing was 91.4 cm; and corn plant population ranged from 3.12 to 8.13 plants/m^2. N-P-K fertilizer was applied to each field pre-plant or at planting. A sidedressing application of N was made to most fields prior to silking. These applications were accepted agronomic practices for their areas.

Since the dates of anthesis and physiological maturity were not recorded in the official variety trials, the "observed" phenological dates were calculated using Growing Degree Days (GDD). The calculated phenological dates were used as field observed anthesis and physiological maturity dates in this study. GDD is defined as thermal time which governs the rate of corn plant development. Besides comprehensive discussion of GDD by Arnold (1960) and Wang (1960), Cross and Zuber (1972) and Gilmore and Rogers (1958) gave 22 and 15 methods for calculating the GDD for application in determining corn development stages, respectively. The "observed" dates of phenological development stages were derived from two published sources of GDD requirements (Heiniger et al., 2000; Pioneer Hi-Bred International, 2004) for each corn hybrid, and recorded daily min/max temperatures and planting dates for each site-year. GDD has been defined in terms of a base temperature threshold of 10 ℃ (50 ℉) by Heiniger et al. (2000):

$$GDD = \frac{(T_{Max} + T_{Min})}{2} - 50 \qquad [1]$$

where T_{max} is the maximum temperature of the day and T_{min} is the minimum temperature encountered during the day. T_{min} is replaced with 50 ℉ if it is lower than 50 ℉. If T_{max} is above 86 ℉, it is replaced with 86 ℉, limiting GDD accumulation on any day to between 0 and 18.

Variety trial data were checked for problems prior to inclusion in this study. First, we eliminated corn hybrids for which we lacked information on GDD requirements. Next, we removed hybrids which were grown in fewer than five site-years. Several site-years were removed because they included fewer than five hybrids meeting the above criteria.

We found that some site-years had unexplainably low or high measured yields for all corn hybrids. We were unable to simulate these yields within the boundaries we had set for soil parameters and genetic coefficients. These sites were removed from the data set before estimation of genetic coefficients affecting yield. Any site-year, with RRMSE in yield over 3SD (SD of the RRMSE) from the mean of RRMSE (MRRMSE) across all site-years, was removed, where RRMSE is RMSE as a percentage of the average measured yield. These site-years with unexplained high or low measured yields could have been due to unrecorded irrigations, extreme weather events (e.g., hurricanes in 1999), or pest damage (e.g. bear damage in some plots in 1997). Any cultivar with less than five site-years was also removed. After these were removed, the Estimation Data Set consisted of trial data from 60 site-years, and 49 hybrids, composing a total of 905 treatments.

CSM-CERES-Maize Model Inputs

Weather Data

Historical weather data were obtained from the National Climatic Data Center (NCDC, 2004). For trials that were performed on agricultural research stations, on-station data were available. For trials that were performed on-farm (Belhaven, Four Oaks, and McLeansville) weather data were obtained from the recording station nearest to the farm. The reliability of the weather data, particularly precipitation, depended on the distance between the field and weather recording site. This distance was at most 24 km (15 miles) (for McLeansville). Missing weather data were filled in with data from the nearest recording station. For all site-years, daily solar radiation was estimated from latitude, daily minimum and maximum air temperature, and day of the year (Hargreaves et al., 1985; Welch et al., 2002).

Soil Data

For each field, only soil series and soil surface texture were reported by Bowman (1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003). Pedon data from the National Map Unit Interpretation Record (MUIR) Database (USDA, 1994) were used to provide estimates of bulk density, organic carbon, and percent sand, silt, and clay in each layer. The methods of Saxton et al. (1986) were used to estimate volumetric soil water content at lower and upper limits and saturated hydraulic conductivity for each soil layer. We assumed a maximum soil profile depth of 2.0 m for all soils and set layer depths to 5, 15, 30, 45, 60, 75, 90, 105, 120, 135, 150, 165, 180, and 200 cm. Soil albedo (SALB), runoff potential (SLRO), and drainage rate (SLDR) were estimated according to the procedures outlined in DSSAT documentation (Hoogenboom, 2003). The soil fertility factor (SLPF), which affects photosynthetic rate, was assumed to be 1.0 in all simulations. The soil surface evaporation limit (SLU1) was set to 3.0 mm day^{-1} for all site-years. Initial soil water content was assumed to be at field capacity in all simulations.

Nitrogen

The simulated timing of phenological events is not affected by nitrogen stress in CSM-CERES-Maize (Hoogenboom et al., 2003). Gungula et al. (2003) were able to fit genetic coefficients and soil parameters for the CSM-CERES-Maize model to a reasonable degree for their high-nitrogen treatments (90 and 120 kg ha^{-1}), but did find that CSM-CERES-Maize predicted faster development than actually occurred under low-nitrogen conditions. In the North Carolina official variety trials, N was applied pre-plant or at planting, and as a sidedressing application prior to silking based on soil test results (e.g. Bowman, 2004). We assumed N to be non-limiting in all simulations, since some of the information required to simulate N dynamics was unavailable (e.g., date of application).

Irrigation

We assumed no irrigation was applied for all official variety trial locations and years for which an irrigation schedule was not available. Under non-irrigated settings, some site-years had low simulated yields and high water stress due to drought conditions during some portion of the growing season. Any site-year with a RRMSE for yield over 3SD from the mean of RRMSE across all site-years, was removed.

Estimating Hybrid Genetic Coefficients and Soil Parameters

Genetic Coefficients Values

Six genetic coefficients are used by the CSM-CERES-Maize model for each corn hybrid, with four of them shown in Table 2. Corn development is influenced by both photoperiod and temperature in CSM-CERES-Maize (Hoogenboom et al., 2003). The model uses a formula similar to Equation 1 to calculate GDD, but normally uses a base temperature of 8 ℃ (46.4 ℉). Development rate reaches a maximum at a temperature of 34 ℃ (93.2 ℉). Although it is possible in DSSAT 4.0 to change the base and maximum temperature values and to remove the effect of photoperiod on development by setting P2 to zero, we did not feel comfortable assuming that all the corn hybrids grown in North Carolina were insensitive to photoperiod. It seemed preferable to us to leave the CSM-CERES-Maize base and maximum temperatures set to their normal values, assume photoperiod does indeed affect development, adjust genetic coefficients, and determine whether simulated anthesis and physiological maturity matched the dates calculated using Equation 1.

In this study, PHINT and P2 were set to constant values, while the other four coefficients were estimated according to procedures explained below. The value of 38.9 was assigned to PHINT in all hybrid simulations. This is the value assigned to PHINT for most of the hybrids included with DSSAT 4.0 data files. Although PHINIT values as high as 42.50 have been specified for some of the hybrids included with DSSAT 4.0, setting PHINT higher did not significantly affect yield and phenology in our preliminary simulations.

Considering the setting of 0.5 h^{-1} by Jones and Kiniry (1986) and Pang et al. (1997), P2 was set to 0.45 for all hybrid simulations. In a preliminary sensitivity trial of the effect of changes in P2 on simulated yield, we found that simulated yield leveled off when P2 was set less than 0.39, or higher than 0.50 (Figure 2). Since yield appeared to change linearly for values of P2 between 0.39 and 0.50, we assigned a value of 0.45 to this coefficient in order to achieve yields in the middle of the variability range.

Soil Drained Upper Limit

The soil drained upper limit (SDUL) parameter was chosen to allow variations in soil water holding capacity. Values of this parameter contained in the initial soil profiles for each site-year were modified using the formula:

$$SDUL_{Actual} = SLLL_{Default} + (SDUL_{Default} - SLLL_{Default}) \times (1+X) \qquad [2]$$

where $SDUL_{Default}$ and $SLLL_{Default}$ were based on starting default soil profile, calculated from Saxton et al. (1986) method according to soil series and soil surface texture reported by Bowman (1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003). SLLL represents the soil water drained lower limit, and X represents the proportional percent change in plant available soil water.

Soil Root Growth Factor

The soil root growth factor (SRGF), the other soil parameter selected for variation in this study, is used in DSSAT models to determine the maximum rooting depth and the relative distribution of new root mass across the profile. The values used in various soil layers in this study are listed in Table 3. Based on previous work with soybean (Welch et al., 2002), we chose to set SRGF in each layer either to 0 or to 1. If set to 0, no root growth will occur in that layer. Setting SRGF to 1 in all layers specifies that once roots extend into a layer, they will grow with equal preference in all layers if water is non-limiting.

Reducing the Number of Simulations

Before a large number of simulations are performed to fit multiple parameters, each of which has a wide range of possible values, a group of preliminary simulations is necessary to determine reasonable bounds for each factor. In this study, the sensitivity of simulated yield and phenological dates to variations in each parameter was investigated to determine the most likely range for each factor. Once this boundary had been determined, the number of values to include from within this range was determined based on limiting the total number of simulations to a reasonable number.

As has been the case in other studies in which genetic coefficients have been estimated for a large number of hybrids using data from multiple locations and years (Irmak et al., 2000; Mavromatis et al., 2001; Welch et al., 2002), finding a way to reduce the number of simulations required to fit parameters was a necessity in this study. Fitting four genetic coefficients and two soil parameters simultaneously for hybrids grown in 60 site-years would require over 106 million simulations, if only 10 increments (11 levels) were simulated for each variable, far exceeding our computer capabilities.

To avoid this huge number of simulations, a strategy was adopted to reduce the total simulation dimension. Instead of simulating and analyzing in a six dimensional space at the same time, the two genetic coefficients affecting timing of anthesis and physiological maturity (P1 and P5) were separated from the other genetic coefficients and soil parameters, and two-dimensional grid searches were used. A preliminary sensitivity analysis demonstrated that anthesis and physiological maturity were not affected by variations in the genetic coefficients G2 and G3 or by variations in the soil parameters, making this a reasonable approach to reducing the number of simulations required. Simulating P1 values between 200 and 300 in 21 increments and P5 values from 700 to 1000 in 61 increments resulted in only 79422 simulations for fitting P1 and P5 for each hybrid.

A disadvantage of fitting P1 and P5 for each hybrid prior to fitting the genetic coefficients G2 and G3 and the soil parameters SDUL and SRGF was that each hybrid had to be simulated separately at each location, resulting in 905 simulations (number of hybrid-site-year combinations) for each set of G2 and G3 values and soil parameters. We performed further sensitivity analyses to limit the number of simulations required to fit G2, G3, SDUL, and SRGF.

Estimating Phenological Parameters P1 and P5

In simulations to determine optimized values of P1 and P5 for each hybrid, G2 and G3 were set to the default settings for the medium maturity group for all hybrids. Since soil water availability does not affect simulated phenology in CSM-CERES-Maize (Hoogenboom et al., 2003), we used the default soil settings when optimizing the parameters related to timing of anthesis and physiological maturity.

The optimal values for P1 and P5 were determined by finding the parameter values which resulted in the minimum value for RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(D_{Simulated} - D_{Observed})^2} \qquad [3]$$

where $D_{Simulated}$ represents simulated days after planting and $D_{Observed}$ represents observed days after planting for phenological stages (anthesis or physiological maturity). N was the number of site-years where the hybrid was grown. For each hybrid, RMSE values were calculated for P1 and P5, respectively. The minimized summation of RMSE for P1 and P5 was used to determine the optimized setting of P1 and P5 for the hybrid.

Estimating Genetic Coefficients G2 and G3 and Soil Parameters

A sensitivity analysis was performed to check the simulated yield response to variations in SRGF and SDUL. Since maize roots generally grow deeper than 50 cm and simulated yield generally did not increase once maximum rooting depth exceeded 135 cm (Figure 3), we decided upon 6 values for SRGF that simulated a maximum rooting depth of 60, 75, 90, 105, 120, and 135 cm. The sensitivity trials also showed that varying X in Equation 2 from -20% to +20% would likely be sufficient. Using 11 levels for X results in plant available soil water values that are 80, 84, 88, 92, 96, 100, 104, 108, 112, 116, and 120% of the initial value for each soil.

Based on the sensitivity trials and information contained in DSSAT 4.0 data files and documentation, boundaries for G2 and G3 were set as indicated in Table 2. We settled on nine levels for each of the two coefficients, respectively. This resulted in 6.5 million simulations in this stage, requiring about a week using three PCs.

Once all simulations had been conducted, an iterative process of two-dimensional grid searches was used to estimate G2, G3, SDUL, and SRGF. In the first step, yields simulated using default settings of G2 and G3 for the medium maturity group were searched. Optimal values for the soil parameters (SDUL, SRGF) for all 60 site-years were determined by minimizing RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(Y_{Simulated} - Y_{Observed})^2} \qquad [4]$$

where N represents the number of hybrids grown at the location, $Y_{\text{Simulated}}$ is the simulated hybrid yield, and Y_{Observed} is the observed hybrid yield.

The second step involved searching the yields simulated for each hybrid using the values of SDUL and SRGF obtained in the first iteration. Optimal values for G2 and G3 were determined by minimizing RMSE as computed in Equation 4 with N representing the number of site-years in which a hybrid was grown, $Y_{Simulated}$ representing the simulated hybrid yield for each site-year, and $Y_{Observed}$ representing the observed hybrid yield. These steps were repeated until we obtained optimized settings of soil parameters for all site-years, and optimized genetic coefficient settings for all hybrids, with which the current simulated yields obtained less than 1% improvements from previous simulated yields (Welch et al. 2002).

Cross Validation Analysis

Once cultivar coefficients had been estimated for all hybrids contained in the Estimation Data Set and soil parameters had been estimated for all site-years using the iterative technique described above, a cross validation procedure was performed on an Evaluation Data Set. Four corn hybrids were included in this analysis: Novartis N8811, Pioneer 31G98, Pioneer 32K61, and S. States SS 827. No data from these four hybrids were used in fitting the soil parameters for each site-year.

The cross validation procedure involved estimating optimal genetic coefficients N_H different times for hybrid H using data from N_H -1 site-years each time. In each iteration, a different site-year was left out when estimating the optimal coefficients P1, P5, G2, and G3. Optimal coefficients were determined by finding the minimum RMSE according to Equations 3 and 4. Once optimal coefficients had been determined for hybrid H using data for all site-years except for site j, predicted anthesis, physiological maturity, and yield for site j were determined from the simulated growth at site j using these optimal coefficients. This resulted in N_H values for predicted anthesis, physiological maturity, and yield. The root mean squared error of prediction (RMSEP) was calculated as follows:

$$RMSEP = \sqrt{\frac{1}{N_{\mathrm{H}}}\left(\sum_{k=1}^{N_{\mathrm{H}}}(P_{\mathrm{Hjk}} - O_{\mathrm{Hjk}})^2\right)} \qquad [5]$$

where N_H is the number of site-years where the hybrid H was grown, P_{Hjk} is the predicted value for site-year j, and k represents anthesis, physiological maturity, or yield. O_{Hjk} is the observed value for hybrid H for site-year j.

RESULTS AND DISCUSSION

Estimating Phenological Parameters P1 and P5

There were 49 hybrids and 60 site-years included in the Estimation Data Set for the final analysis (Table 1). The minimum RMSE for P1 ranged from 0.9 d to 3.5 d for these 49 hybrids, and that for P5 ranged from 0.7 d to 3.5 d. The minimum sum of the RMSE for these two phenology parameters ranged from 1.6 d to 6.8 d. The estimation error for anthesis and physiological maturity appear reasonable and in line with results of other studies in which field data were used to estimate genetic coefficients (Irmak et al., 2000; Roman-Paoli et al., 2000; Mavromatis et al., 2001; Mavromatis et al., 2002; Gungula et al., 2003). Since most hybrids require more than 100 days to reach physiological maturity, the sum of RMSE for P1 and P5 was less than 7% of the measured value. The optimized P1 values ranged from 235 to 295 with an average of 270. Optimized P5 ranged from 795 to 990 with an average of 900. Both of these averages were higher than the averages were for the default hybrids included with DSSAT 4.0.

Simulated days from planting to anthesis and physiological maturity appear to match observed days reasonably well (Figures 4 and 5). The slope of the regression line between simulated and observed days was less than 1.0 in both cases, indicating that there was a slight tendency by the model to overestimate days to anthesis and maturity when the measured days was low, and to underestimate days when measured days was longer. Whether this bias is a function of the CSM-CERES-Maize model or of our approach to estimating the "measured" anthesis and maturity dates using GDD is unknown. Roman-Paoli et al. (2000) found that CERES-Maize in DSSAT V3.0 underestimated longer durations to silking, when two different estimation methods were used to estimate P1 and P2.

Estimating Soil Parameters and Genetic Coefficients G2 and G3

In all, 5,371,520 simulations were made using nine different values for G2 and G3 for each hybrid, six rooting profiles, and 11 values of SDUL for each site-year. The minimum RMSE of yield ranged from 398 to 1108 kg ha^{-1}, averaging 701 kg ha^{-1} across all 49 hybrids. RRMSE for each site-year is shown in Table 4. This ranged from a minimum of 3.7% in Salisbury 2003 to a high of 24.3% in Salisbury in 1998. RRMSE was generally below 15%. We judged that conditions in most site-years were suitable for estimating genetic coefficients.

The estimation of G2 and G3 utilized large step sizes: G2 values varied 50 between levels, and G3 varied 0.5 between levels. The resulting RRMSE was below 19% for all 49 hybrids. The average across all hybrids was 10.2%, with a minimum of 4.6% and a maximum of 18.8%, indicating that even with these large step sizes reasonably good estimates of these coefficients were found. The average of G2 was higher than that of the defaults in DSSAT 4.0 data sets. G3 values were distributed across the range of the ones in DSSAT.

Simulated vs. measured yields for all hybrid-site-year treatments are shown in Figure 6. The slope of the regression line is 0.85, indicating that the model had a tendency to overestimate yields under low-yielding conditions, and to underestimate yields under high-yielding conditions. When simulated and measured yields were averaged across all hybrids for each site-year (Figure 7), the slope of the regression line improved to 0.92. In general, CSM-CERES-Maize performed well in simulating average yield of each site-year across all hybrids. As can be seen in Figure 7, trials were performed in very different environments: both simulated and measured average yields covered a wide range, from ~3000 kg ha^{-1} to over 10000 kg ha^{-1}.

In general, CSM-CERES-Maize did a good job of capturing the response of different hybrids across all environments. As can be seen in Figure 8, average simulated yield for each hybrid across all site-years matched observed yield well, with a slope for the regression line of 0.92 and a coefficient of determination (r^2) of 0.89. The strategy for fitting both soil parameters and genetic coefficients worked well for all high-, low- and average-yielding hybrids, as well as for early-, medium- and late-maturing ones. As can be seen in Figs. 7 and 8, the average yields for site-years were spread across a wider range (from about 3280 kg ha-1 to 10800 kg ha^{-1}) than were the average hybrid yields (from 4300 kg ha^{-1} to 9383 kg ha^{-1}). Differences in environmental conditions between site-years contributed more to variations in yield than did differences between hybrids.

Four corn hybrids in the Estimation Data Set (Mycogen 7885, Pioneer 31B13, Pioneer 3167, and Pioneer 32R25) were selected to demonstrate details of the calibration results. Table 5 shows a summary of optimized genetic coefficients for these four hybrids. Mycogen 7885 could be considered an average hybrid, with not only an average RRMSE, but also a measured yield which was very close to average yield at each site (Figure 9a). Simulated yield of this hybrid was higher than the measured under low-yielding conditions, but lower under high-yielding conditions (Figure 9b). Although the coefficient of determination (r^2) was 0.80, the slope of the regression line was only 0.81. Even though CSM-CERES-Maize simulated yield well in the middle portion of the yield range for this hybrid, it was biased in both the higher and lower portions of the yield range.

Pioneer 3167 had a high RRMSE (14.7), with almost the lowest average yield across site-years (Figure 10a). Among those hybrids which were grown in more than five site-years, Pioneer 3167 possessed the highest RRMSE. The slope of the regression line of its measured yields compared to site-average yields (Figure 10a) was close to 1.0, but the negative intercept of this regression line indicates that this is a lower-yielding hybrid than the average across environments. The measured yield for the hybrid was never higher than 8500 kg ha^{-1}. Even though measured yield of this hybrid was below the average hybrid yield, simulated yields were overestimated in low-yielding environments and underestimated in high-yielding environments. The r^2 value was 0.80, but the slope of the regression line was only 0.75 (Figure 10b). Considering that the intercept of the regression line is 1534 kg ha^{-1}, the yield simulation for Pioneer 3167 was among the most biased.

Pioneer 31B13 had a relatively high RRMSE (12.1), as well as a high average grain yield across site-years. The measured yield of this hybrid was generally higher than the site-average yield (Figure 11a). In only four of the 38 site-years where Pioneer 31B13 was grown was the measured yield below the site-average yield. With the slope of the regression line above 1 and the intercept above 0, this hybrid clearly performed better than the average hybrid, especially under high-yielding environments. The CSM-CERES-Maize model simulated higher yield than measured for this hybrid in low-yielding environments, but simulated lower yield than measured in high-yielding environments (Figure 11b). With a slope of 0.82 and an intercept of over 1300 kg ha^{-1}, the regression line indicates a substantial overestimation of yield under low-yielding conditions.

Pioneer 32R25 had almost the lowest RRMSE (7.3%), and almost the highest average yield across site-years. The measured yield for Pioneer 32R25 was relatively high, averaging 8167 kg ha^{-1} across all site-years. The slope and intercept of the regression equation indicate that this hybrid does worse than average under low-yielding conditions, and better than average under high-yielding conditions (Figure 12a). It should be noted, however, that this hybrid was only included in one trial for which the measured site-average yield was below 6000 kg ha^{-1}. As with other hybrids, the regression line indicates that CSM-CERES-Maize underestimated yields in the higher portion of the yield range, and overestimated yields in the lower portion of the range (Figure 12b). However, results for one site-year for which measured yield was 3865 kg $ha^{-1}$and simulated yield was 5288 kg ha^{-1}greatly influenced this result.

We were unable to find genetic coefficient values in the literature to compare to those estimated in this study except in a few cases. The optimized values determined in this study for phenological parameters P1 and P5 for Pioneer 33Y09 and Pioneer 3394 were similar to those reported by Lizaso et al. (2001). Lizaso et al. (2001) reported P1 and P5 values of 245 and 905 for Pioneer 33Y09, respectively, which were similar to the optimized values determined in this study of 260 and 895. Lizaso et al. (2001) gave P1 and P5 values of 240 and 900 for Pioneer 3394, respectively, which are both larger compared to values of 235 and 860 from this study. Pioneer 3394 was recognized as an even shorter maturing cultivar than reported by Lizaso et al. (2001). Pioneer 33Y09 had relatively larger values of P5 compared to Pioneer 3394 in both studies. The P1 value of 280 obtained in our study for Pioneer 31G98 is relatively larger than that for both of the cultivars mentioned above, which allows this hybrid longer time to accumulate more biomass before silking, .

However, genetic coefficients G2 and G3 optimized for Pioneer 33Y09 and Pioneer 3394 did not agree with those reported by Lizaso et al. (2001). On the other hand, the value of G2 estimated for Pioneer 3245 was similar (800 seeds/plant) to the maximum grain number (693±134 seeds/plant) reported by Kiniry and Knievel (1995). The phenological parameters for Pioneer 31G98 which were included in the DSSAT cultivar description file were much lower than those for the short maturity cultivar Pioneer 3394, which was unrealistic for the long maturity cultivar Pioneer 31G98. It was also noticed that the phenological parameters of Pioneer 31G98 in the DSSAT file were apparently estimated from a one-year study performed in a laboratory chamber environment.

Cross Validation Analysis

The four hybrids in the Evaluation Data Set had optimized phenological parameters P1 and P5 which yielded relatively low average RMSE and RMSEP values (Table 6). The RMSEP values for silking ranged from 2.2 d to 3.8 d; those for maturity ranged from 2.5 to 3.6. In each of the cultivars, the RMSEP in silking and/or physiological maturity days were always greater (only the same for Novartis N8811 at silking days) than that of average RMSE. This indicated that the phenology stages were closely predicted for all four hybrids across all site-years.

Novartis N8811 had a RMSEP of yield prediction of 979 kg ha^{-1}, which at 14.1% is the highest relative prediction error among the four evaluation hybrids. Eleven of the site-years had their RMSE smaller than RMSEP (979 kg ha^{-1}), but that of all other 23 site-years were larger than the RMSEP. Average RMSE for all site-years for this hybrid was the same as RMSEP. Southern States SS 827 had a RMSEP of 689 kg ha^{-1}, which is 10.3% of measured yield. RMSEP for yield was larger than RMSE for all but one site-year, and bigger than the average RMSE (677 kg ha^{-1}) across all site-years. Pioneer 32K61 had a RMSEP of yield of 886 kg ha-1, 12.6% of measured yield. The average RMSE (809 kg ha^{-1}) and the RMSEs from all site-years were smaller than the RMSEP.

Results indicate that Pioneer 31G98 was one of the highest yielding hybrids included in this study (Figure 13a). The only other comparable hybrids, Pioneer 32R25 and Pioneer 31B13, had average measured yield across all site-years higher than 8000 kg ha^{-1}. Pioneer 31G98 had an average measured yield of 8775 kg ha^{-1}, which was close to the average simulated yield of 8793 kg ha^{-1} (Figure 13b). The RMSEP of 783 kg ha^{-1}, which represented 8.9% of measured yield, was relatively low compared to the other Evaluation hybrids. The RMSEP was smaller than the average RMSE (767 kg ha^{-1}) and RMSEs for most site-years, except for the RMSE (827 kg ha^{-1}) for Clinton 2002.

In most cases, it did not matter which site-year was left out of the dataset when estimating P1, P5, G2, and G3 coefficients: the values estimated for all four coefficients were identical across site-years. However, in one case for Novartis N8811 (Salisbury 1994), a different set of coefficient values was optimal. A P5 value of 930 was optimal when Salisbury 1994 was the site-year left out of the estimation process, compared to a value of 925 for all other 33 site-years. For Pioneer 31G98, with 24 site-years, the genetic coefficients for only 2 site-years (Sampson 2002 and Kinston 2002) were different from those of the other 22 site-years. Estimated values for all four genetic coefficients were different when either of these two site-years were not included in the estimation process. For S. States SS 827, estimated genetic coefficients were identical for 25 site-years. A second set of genetic coefficients was chosen as optimal for three site-years, and a third set was optimal for one site-year. The set chosen when Kinston 1995 was not included in the estimation process was quite different from the coefficients chosen for all other site-years. For Pioneer 32K61, 16 of 31 site-years yielded estimates of genetic coefficients which were identical to the optimum genetic coefficient settings for the hybrid across all site-years. Eleven more of the site-years had estimated coefficients which were very close to the optimum setting. The remaining four site-years had quite different estimates for the genetic coefficients. Sampson and Kinston in 2002 were among these four, which indicated that the genetic coefficients estimated when these two site-years were left out were quite different from those estimated when the other site-years were removed for both Pioneer 31G98 and Pioneer 32K61.

CONCLUSIONS

The approach presented in this paper for estimating genetic coefficients appears to work well. RMSE and RMSEP were comparable to those obtained in other studies using other fitting techniques. Varying soil rooting profiles and DUL provided enough flexibility that yield data from most site-years could be satisfactorily simulated and G2 and G3 could be accurately estimated. The average simulated yield for each hybrid across all site-years (Figure 8) closely matched the average measured one well with a regression slope of 0.92 and an r^2 value of 0.89. We were able to parameterize the CSM-CERES-Maize model to successfully simulate corn growth and phenological development for 49 hybrids in the Estimation Data Set and another four hybrids in the Evaluation Data Set across a broad range of conditions in North Carolina.

The optimized phenological parameters yielded a RMSE for anthesis ranging from 0.9 to 3.5 days, which was mostly within 6.6% of the mean anthesis days for all hybrids. RMSE for physiological maturity varied from 0.7 to 3.5 days. This is comparable to results for soybean which Irmak et al. (2000) obtained using CROPGRO-Soybean, in which RMSE for anthesis varied from 2.4d to 3.1d and for harvest maturity from 3.8d to 5.1d.

The optimized genetic coefficients G2 and G3 generated simulated yields with a RMSE within 24.3% of the measured yield for all hybrids, under normal weather conditions and field management in North Carolina. At a few locations, there were unknown factors affecting the final measured yield which prevented CSM-CERES-Maize from accurately simulating growth and yield. These locations were discarded before final data analysis. In considering the slopes of the regression lines of simulated versus measured yields for all hybrids discussed above, the CSM-CERES-Maize model tended to underestimate yield under high-yielding conditions, and overestimate it under low-yielding conditions. This is probably due to some unknown or un-considered factors, rather than to soil parameter or genetic coefficient estimation procedures. A similar bias has been noted in at least one earlier study (Liu et al., 1989).

The cross validation procedure successfully demonstrated that the methodology used in this study can successfully estimate hybrid genetic coefficients which can be used to predict growth and yield under other North Carolina environments. Compared to RMSE values ranging from 398 kg ha^{-1} to 1108 kg ha^{-1} for the 49 hybrids in the Estimation Data Set, values of RMSEP for the four hybrids in the Evaluation Data Set ranged from 689 to 979 kg ha^{-1}. Cross validation results, with a yield prediction error below 14.1% for all four hybrids, support the approach of utilizing official variety trial data for hybrids grown under varying environmental conditions to estimate genetic coefficients and then use these coefficients to simulate growth and predict yield under different environments.

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Thanks to Sandra B. Donaghy for providing maize measured yield records in electronic form.

REFERENCES

Arnold, C.Y. 1960. Maximum-minimum temperatures as a basis for computing heat units. Proc. Am. Sot. Hort. Sci. 76: 292-682.

Bowman, D.T. 1994. Corn and corn silage 1994. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 148. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 1995. Corn and corn silage 1995. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 154. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 1996. Corn and corn silage 1996. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 161. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 1997. Corn and corn silage 1997. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 169. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 1998. Corn and corn silage 1998. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 174. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 1999. Corn and corn silage 1999. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 180. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 2000. Corn and corn silage 2000. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 186. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 2001. Corn and corn silage 2001. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 195. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 2002. Corn and corn silage 2002. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 201. Crop Sci. Dep., North Carolina State Univ.

Bowman, D.T. 2003. Corn and corn silage 2003. North Carolina measured crop performance, corn and corn silage. Crop Sci. Res. Rep. No. 208. Crop Sci. Dep., North Carolina State Univ.

Buol, G.S., G. Wilkerson, and M.C. Sturgill. 2006. CSDB Ver1.0: Database and Software for Managing Data Used by ICASA/DSSAT Crop Models. ASA-CSSA-SSSA 2006 International Meetings Abstracts CD ROM, Abstract 1905b. ASA, Madison, WI.

Cross, H.Z., and M.S. Zuber. 1972. Prediction of flowering dates in maize based on different methods of estimating thermal units. Agron. J. 64:351-355.

Gilmore, EC. Jr., and J.S. Rogers. 1958. Heat units as a method of measuring maturity in corn. Agron. J. 50:611-615.

Gungula, D.T., J.G. Kling, and A.O. Togun. 2003. CERES-Maize predictions of maize phenology under nitrogen-stressed condition in Nigeria. Agron. J. 95:892-899.

Hargreaves, G. L., G. H. Hargreaves, and J. P. Riley. 1985. Irrigation water requirements for Senegal River basin. J. Irrigation and Drainage Engineering. 111(3):265–275.

Heiniger, R.W., J.F. Spears, D.T. Bowman, E.J. Dunphy, and D.T. Bowman. 2000. Crop management. *In* The North Carolina corn production guide 2000. N. C. Coop. Ext. Service, N. C. State Univ. Available on-line at: http://www.ces.ncsu.edu/plymouth/cropsci/cornguide/Chapter2.html.

Hoogenboom, G., J.W. Jones, C.H. Porter, P.W. Wilkens, K.J. Boote, W.D. Batchelor, L.A. Hunt, and G.Y. Tsuji (Editors). 2003. Decision Support System for Agrotechnology Transfer Version 4.0. Vol. 1: Overview. University of Hawaii, Honolulu, HI.

Irmak, A., J.W. Jones, T. Mavromatis, S.M. Welch, K.J. Boote, and G.G. Wilkerson. 2000. Evaluating methods for simulating soybean cultivar responses using cross validation. Agron. J. 92:1140-1149.

Jones, C.A., and J.R. Kiniry. 1986. CERES-Maize, a simulation model of maize growth and development. Texas A&M University Press, College Station.

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. 2003. The DSSAT cropping system model. European J. Agron. 18:235-265.

Kiniry, J.R., and D.P. Knievel. 1995. Response of maize seed number to solar radiation intercepted soon after anthesis. Agron. J. 87:228-234.

Liu, W.T.H., D.M. Botner, and C.M. Sakamoto. 1989. Application of CERES-Maize model to yield prediction of a Brazilian maize hybrid. Agric. and Forest Meteorol. 45:299-312.

Lizaso, J.I., W.D. Batchelor, and S.S. Adams. 2001. Alternate approach to improve kernel number calculation in CERES-Maize. Trans. ASAE. 44:1011-1018.

Mavromatis, T., K.J. Boote, J.W. Jones, A. Irmak, D. Shinde, and G. Hoogenboom. 2001. Developing genetic coefficients for crop simulation models with data from crop performance trials. Crop Sci. 41:40-51.

Mavromatis, T., K.J. Boote, J.W. Jones, G.G. Wilkerson, and G. Hoogenboom. 2002. Repeatability of model genetic coefficients derived from soybean performance trials cross different states. Crop Sci. 42:76-89.

NCDC (National Climate Data Center). 2004. Available at: www.ncdc.noaa.gov. Accessed 02 February 2004.

Nelder, J., and R. Mead. 1965. A simplex method for function minimization. Computer J. 7:308-311.

Pang, X.P., J. Letey, and L. Wu. 1997. Irrigation Quantity and Uniformity and Nitrogen Application Effects on Crop Yield and Nitrogen Leaching. Soil Sci. Soc. Am. J. 61:257-261.

Pioneer Hi-Bred International, Inc. 2004. Available at www.pioneer.com. Accessed 20 July 2004.

Piper, E. L., K. J. Boote, and J. W. Jones. 1998. Evaluation and improvement of crop models using regional cultivar trial data. American Society of Agricultural and Biological Engineers. 14(4): 435-446.

Roman-Paoli, E., S.M. Welch, R.L. Vanderlip. 2000. Comparing genetic coefficient estimation methods using the CERES-Maize model. Agric. Syst. 65:29-41.

Saxton, K.E., W.J. Rawls, J.S. Romberger, and R.I. Papendick. 1986. Estimating generalized soil water characteristics from texture. Soil Sci. Soc. Am. J. 50(4):1031–1036.

USDA. 1994. National Map Unit Interpretation Record (MUIR) Database. USDA Natural Resources Conservation Service, Fort Worth, TX.

Wang, J.Y. 1960. A critique of the heat unit approach to plant response studies. Ecology 41:785-790.

Welch, S. M., G. Wilkerson, K. Whiting, N. Sun, T. Vagts, G. Buol, and T. Mavromatis. 2002. Estimating soybean model genetic coefficients from private–sector variety performance trial data. Trans. ASAE 45:1163-1175.

Table 1. Number of hybrids at each location which were used in this study each year between 1994 and 2003. Data are from North Carolina official variety trials (Bowman, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003).

	Year									
Field site	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Belhaven										8
Four Oaks	15	16		24			19	13		
Clinton	15	16				22	19		7	8
McLeansville	9	10	12	13						
Kinston	15	16		24	24	22	19	13	7	8
Lewiston	15	16	17	24			19	13		8
Plymouth, mineral soil	15	18	19	23						
Rocky Mount					24	22	19	13	7	
Salisbury	9	10	12	13	14			13		8
Plymouth, organic soil	15	18	19	23		13		13	7	8
Whiteville					24		19	13		8

Table 2. Genetic coefficients definition (Hoogenboom et al., 2003; Jones et al., 2003) and values.

Symbol	Definition	Lower boundary	Upper boundary	Interval size	Levels
G2	Maximum possible number of kernels per plant	600	1000	50	9
G3	Kernel fill rate during linear fill stage under optimal conditions	6.0	10.0	0.5	9
P1	Thermal time from emergence to the end of juvenile phase	200	300	5	21
P5	Thermal time from silking to physiological maturity	700	1000	5	61

Table 3. Values of soil root growth factor (SRGF) used in simulations.

Layer	SLB †	SRGF1‡	SRGF2‡	SRGF3‡	SRGF4‡	SRGF5‡	SRGF6‡
	cm						
1	5	1.0	1.0	1.0	1.0	1.0.	1.0
2	15	1.0	1.0	1.0	1.0	1.0	1.0
3	30	1.0	1.0	1.0	1.0	1.0	1.0
4	45	1.0	1.0	1.0	1.0	1.0	1.0
5	60	1.0	1.0	1.0	1.0	1.0	1.0
6	75	0.0	1.0	1.0	1.0	1.0	1.0
7	90	0.0	0.0	1.0	1.0	1.0	1.0
8	105	0.0	0.0	0.0	1.0	1.0	1.0
9	120	0.0	0.0	0.0	0.0	1.0	1.0
10	135	0.0	0.0	0.0	0.0	0.0	1.0
11	150	0.0	0.0	0.0	0.0	0.0	0.0
12	165	0.0	0.0	0.0	0.0	0.0	0.0
13	180	0.0	0.0	0.0	0.0	0.0	0.0
14	200	0.0	0.0	0.0	0.0	0.0	0.0

†SLB: Depth (cm), Soil Layer Base.

‡SRGF1, SRGF2, SRGF3, SRGF4, SRGF5, SRGF6: one of six settings for 14 layers of soil profile.

Table 4. Relative root mean squared errors (RRMSE) for yield for each site for which soil parameters were estimated in this study. Data are from North Carolina official variety trials (Bowman, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, and 2003).

	Year									
Field site	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
	%									
Belhaven	†	†	†	†	†	†	†	†	†	5.9
Four Oaks	12.2	12.3	†	15.5	†	†	9.3	8.2	†	†
Clinton	3.9	6.8	†	†	†	12.7	11.2	†	14.8	4.1
McLeansville	6.7	14.2	20.1	13.9	†	†	†	†	†	†
Kinston	12.4	5.9	†	11.0	11.2	14.8	5.4	5.5	5.5	4.6
Lewiston	7.4	9.2	19.4	17.3	†	‡	12.7	6.3	‡	7.6
Plymouth, mineral soil	8.5	17.2	9.2	8.2	†	†	†	†	†	†
Plymouth, organic soil	5.9	17.9	12.2	8.3	‡	7.9	‡	12.1	13.9	9.7
Rocky Mount	†	†	†	†	9.0	11.7	15.8	9.1	17.4	‡
Salisbury	6.6	10.5	12.0	17.3	24.3	†	‡	6.9	‡	3.7
Plymouth, normal soil	5.9	17.9	12.2	8.3	‡	7.9	‡	12.1	13.9	9.7
Whiteville	†	†	†	†	5.9	‡	6.9	5.1	†	10.4

† No available data

‡ The RRMSE of yield for this site-year was over 3SD (SD of the RRMSE, 4.6%) from the mean of RRMSE (MRRMSE, 10.5%) across all site-years.

Table 5. Coefficient estimates for four hybrids, which are representative of the results of the calibration procedure for all hybrids.

Variety	Sites	G2	G3	P1	P5	Silking RMSE	Physiological Maturity RMSE	Yield RMSE	Yield Average	Yield RRMSE
						---- days ----		---- kg/ha ----		-- % --
Mycogen 7885	18	800	6	275	915	3.4	3.4	705	6602	10.7%
Pioneer 31B13	38	600	9.5	285	880	1.8	2.2	980	8066	12.1%
Pioneer 3167	35	700	6	290	985	2.6	3.0	835	5666	14.7%
Pioneer 32R25	18	1000	6	280	865	2.5	2.3	613	8416	7.3%

Table 6. Evaluation of the cross validation results for the four hybrids used in this procedure.

		Novartis N8811	Pioneer 31G98	Pioneer 32K61	S. States SS 827
Site-years		34	24	31	29
Silking, days after planting	RMSEP	2.2	2.7	2.1	3.8
	Average RMSE	2.2	2.4	2	3.4
	Simulated	79.3	75.3	78.2	76.8
	Observed	78.8	74.4	77.5	75.6
Physiological Maturity, days	RMSEP	2.5	2.3	2.2	3.6
	Average RMSE	2.4	2	2.1	3.3
	Simulated	130.6	125.3	126.7	127.7
	Observed	130.8	125.3	126.5	127.5

Table 6 (continued).

		Novartis N8811	Pioneer 31G98	Pioneer 32K61	S. States SS 827
Yield, kg ha^{-1}	RMSEP	979	783	886	689
	Average RMSE	979	767	809	677
	Simulated	6882	8793	7025	6597
	Observed	6946	8775	7013	6705
	r^2	0.7	0.8	0.84	0.82

List of Figures

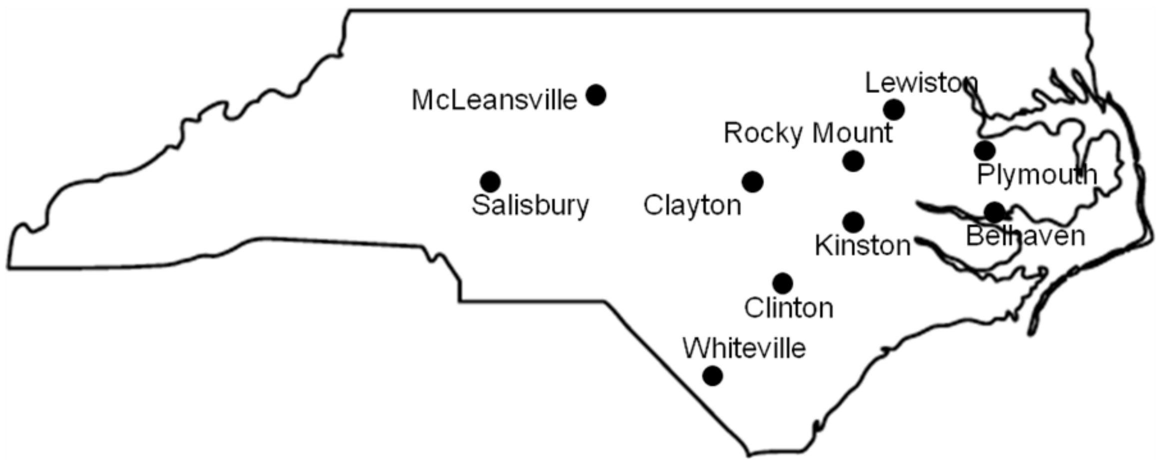

Figure 1. Location of official variety trial sites used in this study.

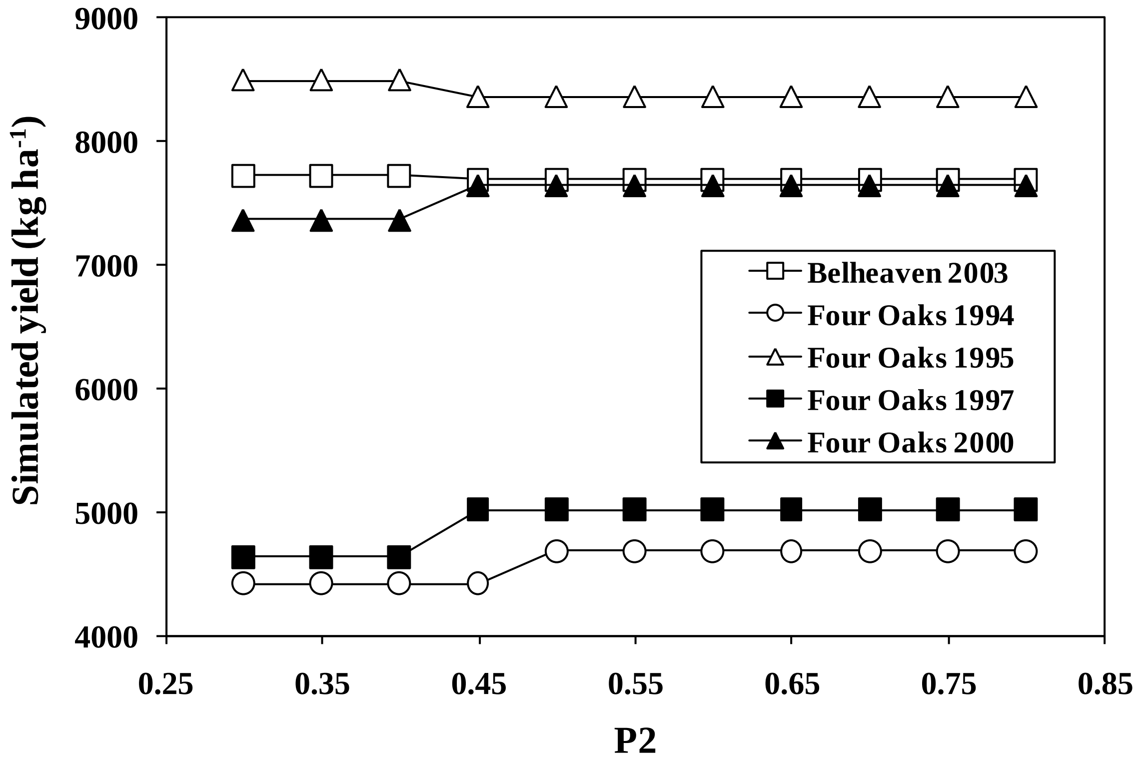

Figure 2. Simulated yield changes due to changes in P2 from 0.25 to 0.85 for several site-years included in this study.

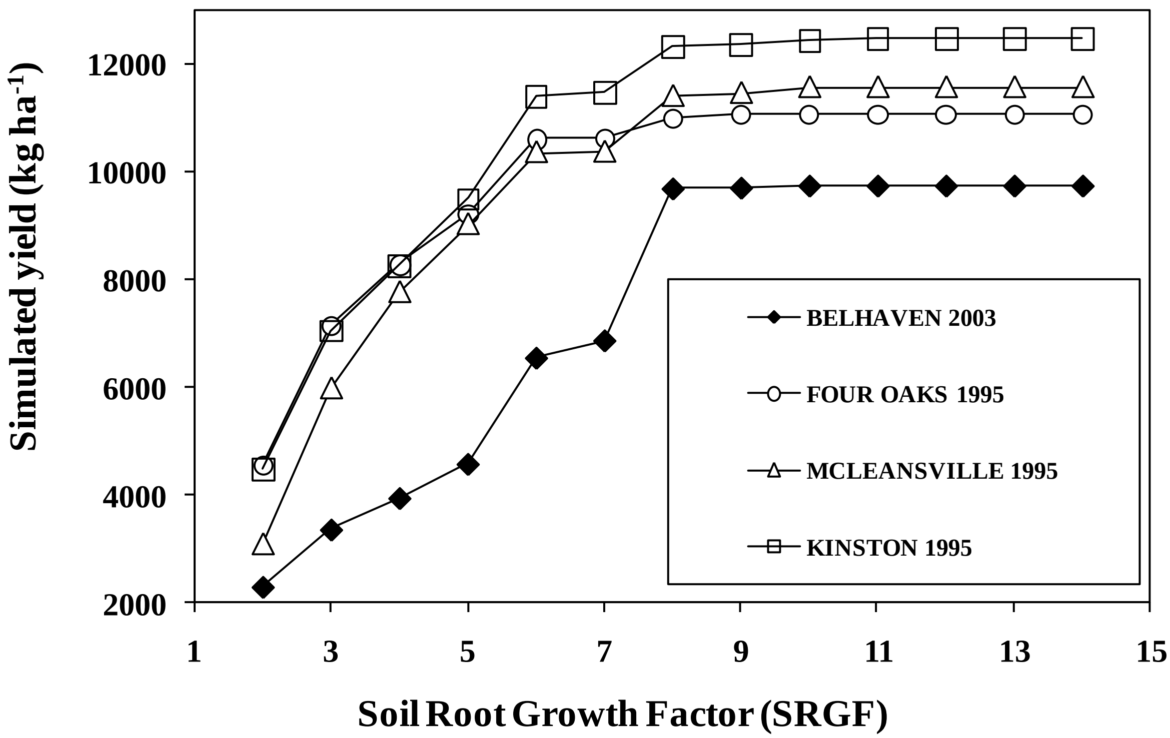

Figure 3. Simulated yield response to changes in maximum rooting depth for several site-years included in this study.

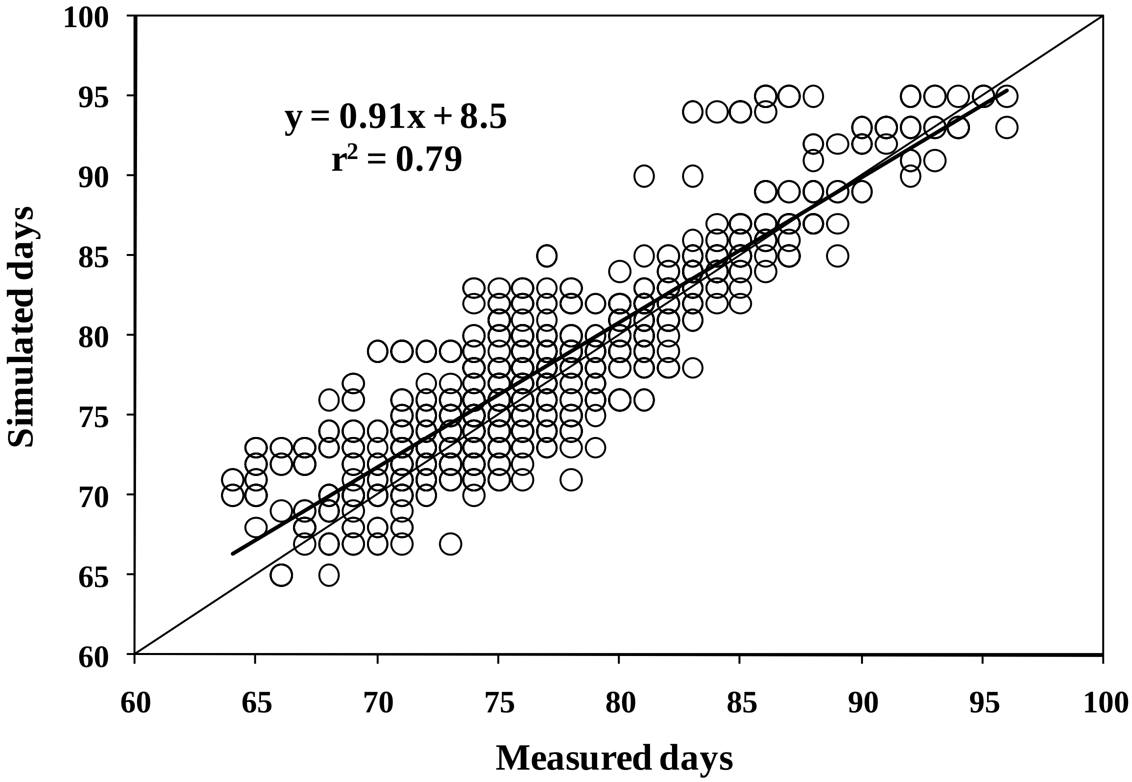

Figure 4. Simulated vs. measured days from emergence to anthesis for all hybrid-site-year combinations.

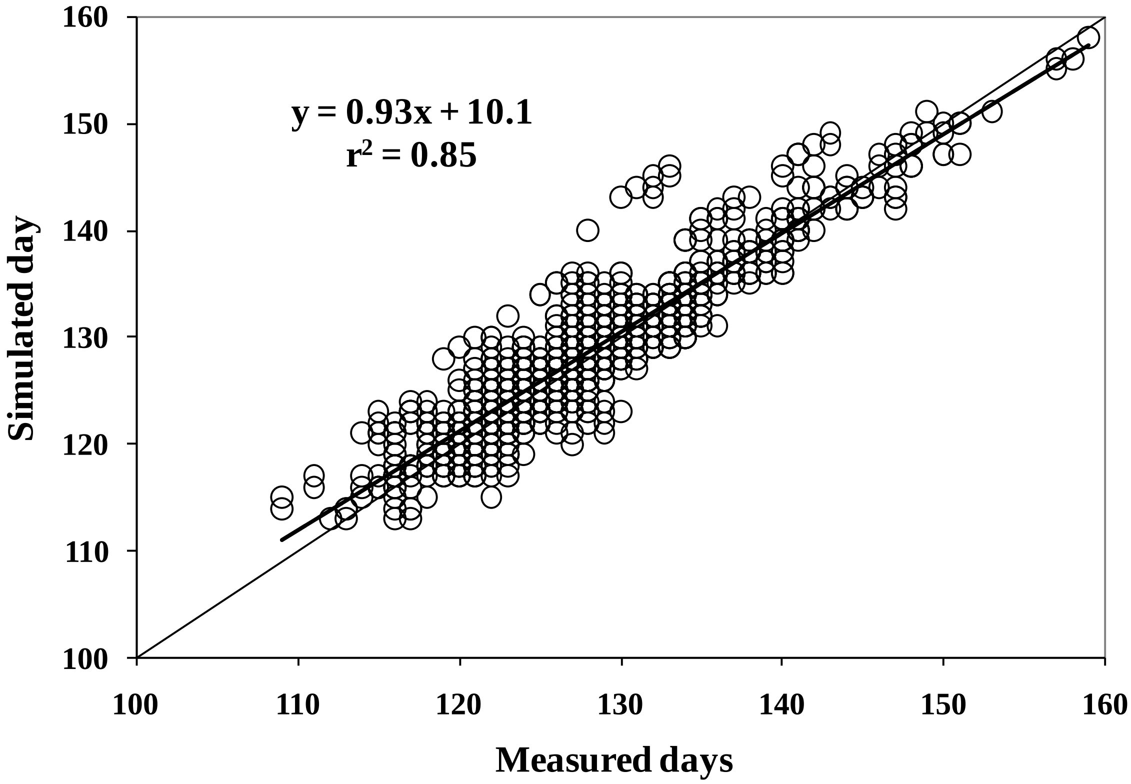

Figure 5. Simulated vs. measured days to physiological maturity for all hybrid-site-year combinations.

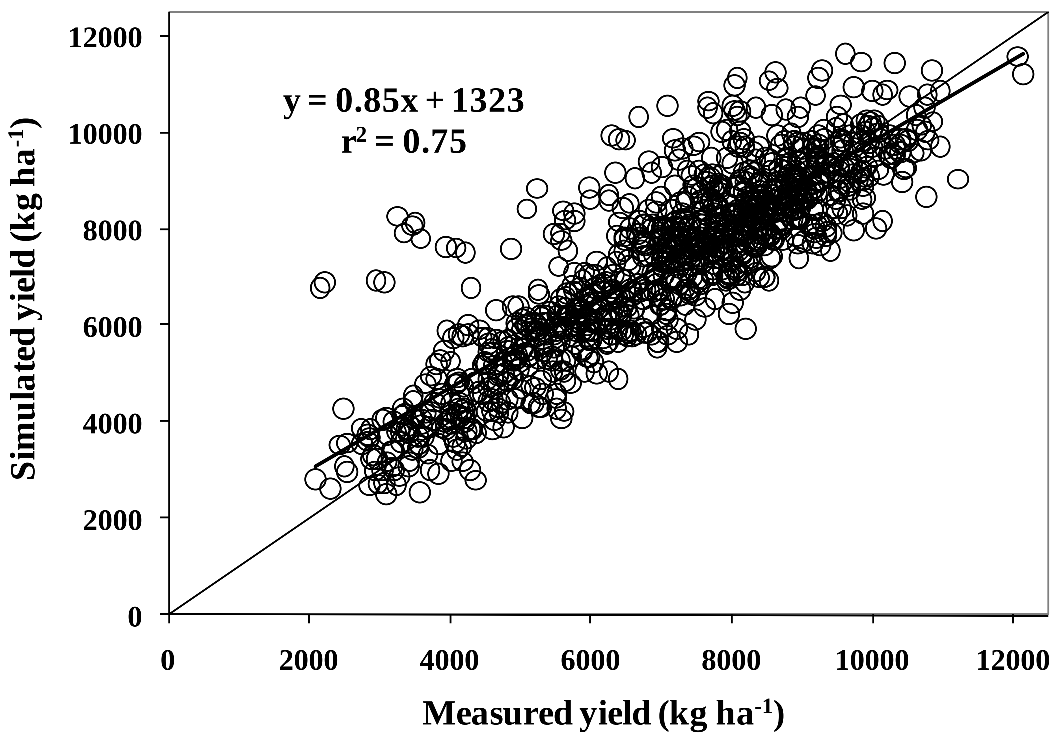

Figure 6. Simulated vs. measured yields of all hybrid-site-year treatments

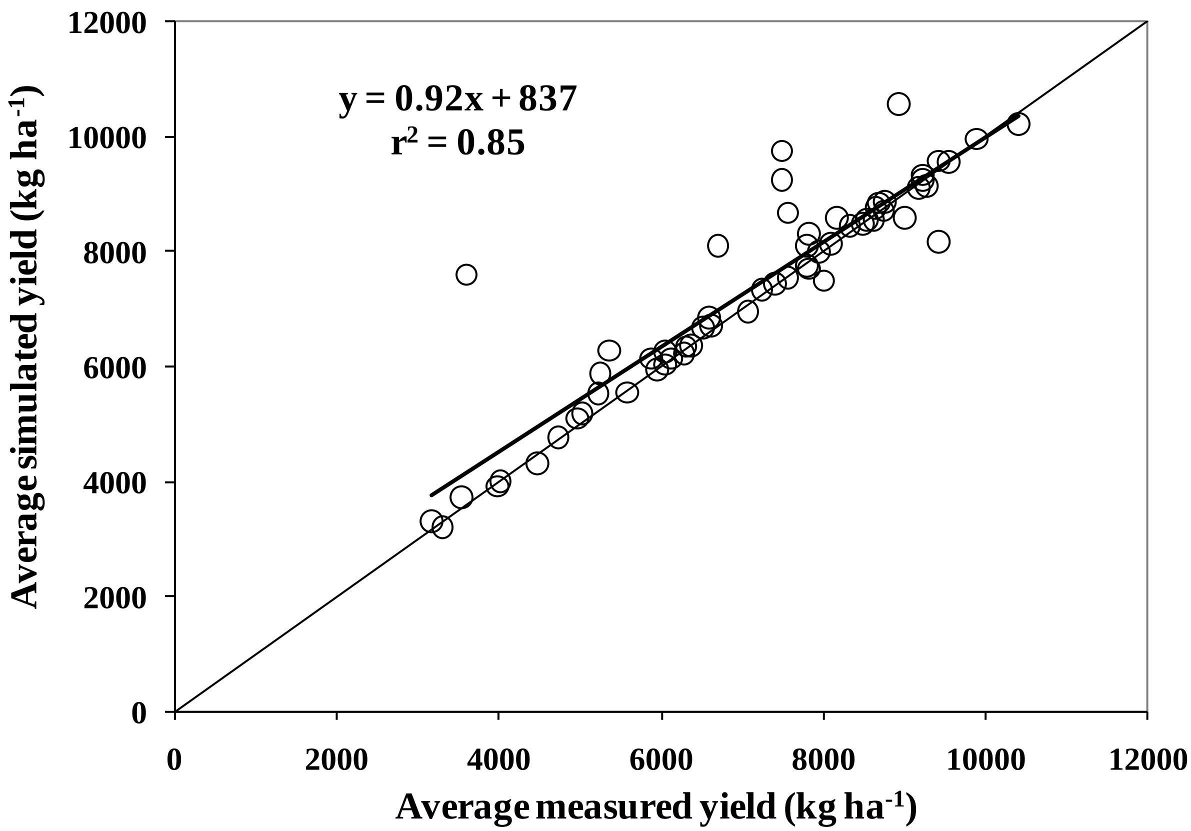

Figure 7. The average simulated yield vs. average measured yield of each site-years across all hybrids

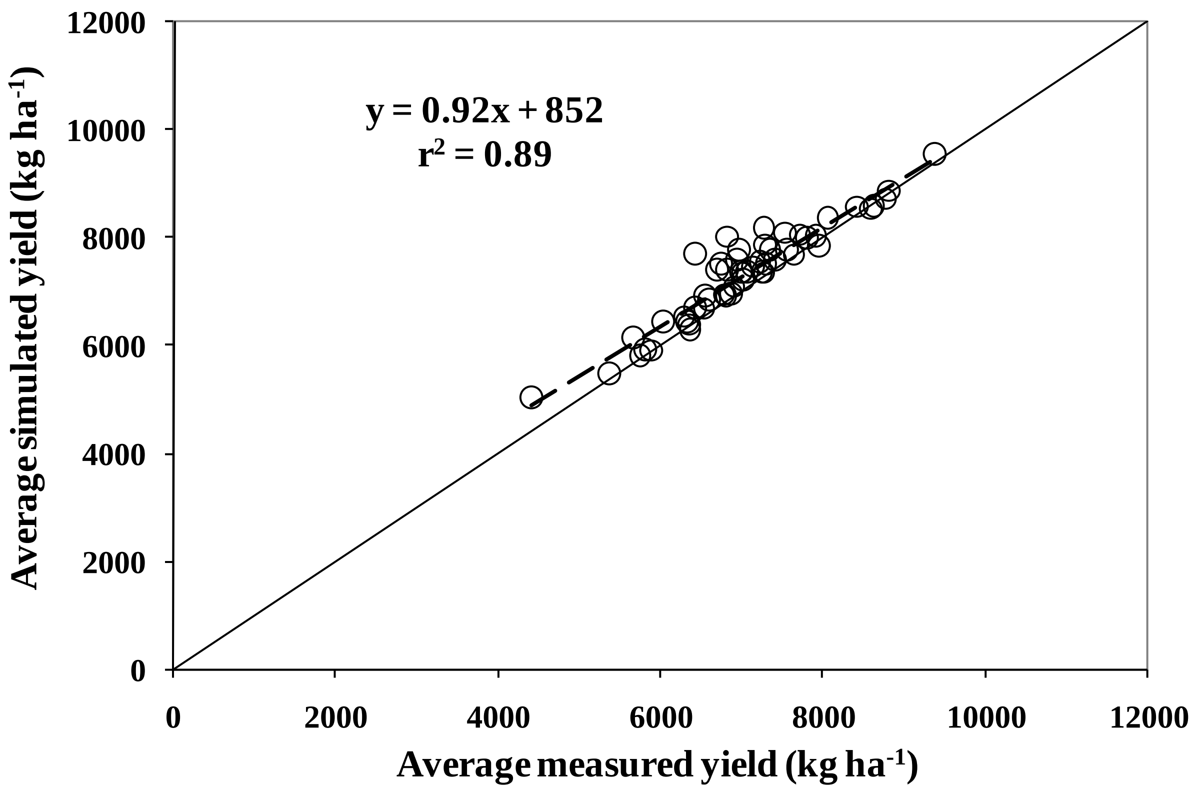

Figure 8. Average simulated yield vs. average measured yield of each hybrid across all site-years in which the hybrid was grown.

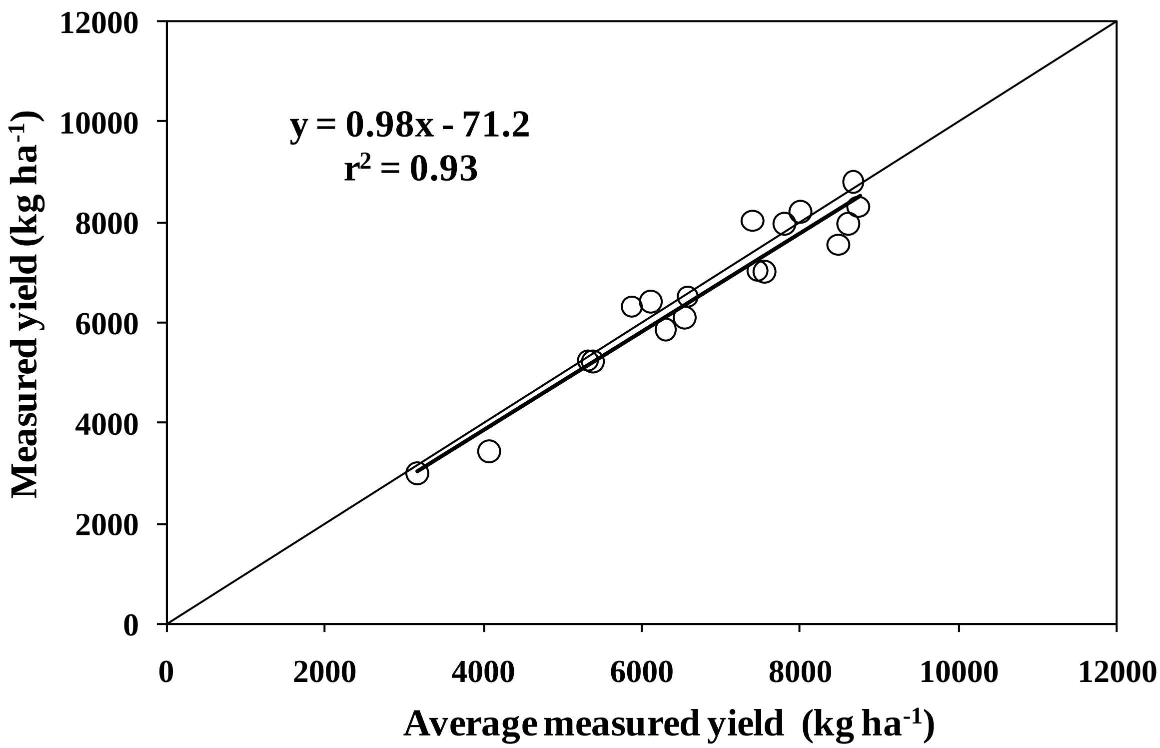

Figure 9a. Comparison of measured yield for Mycogen 7885 for each site-year vs. the average measured yield across all hybrids for each site-year.

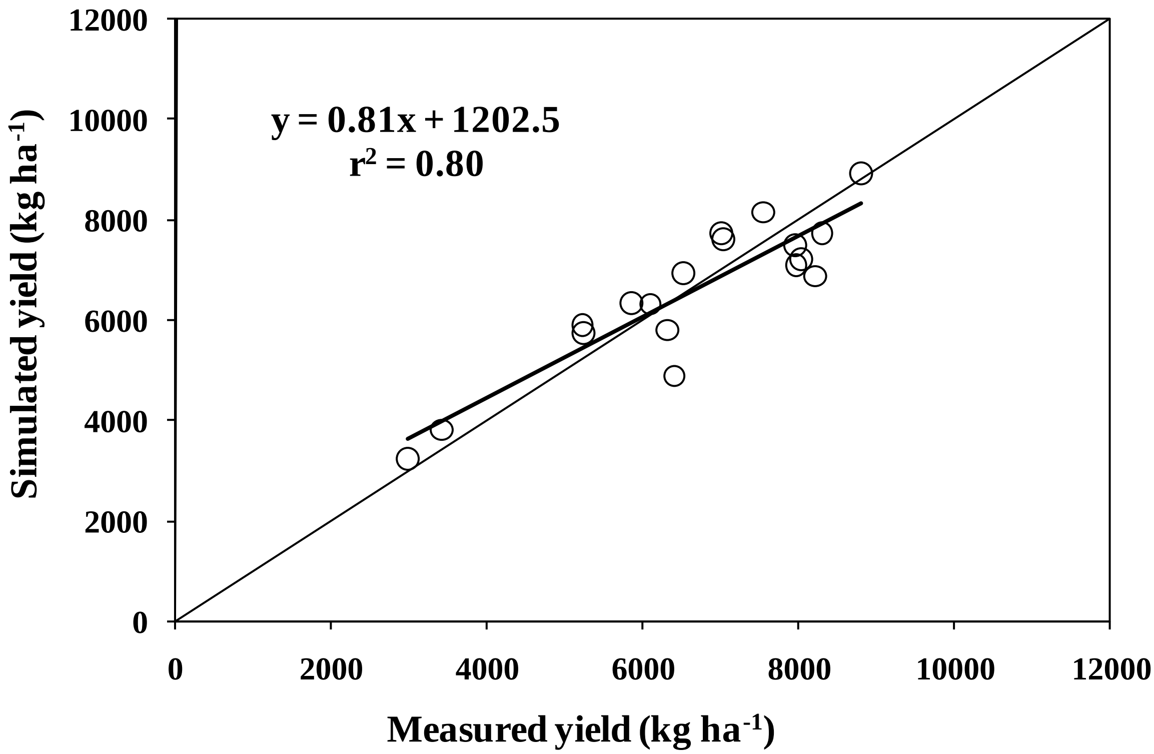

Figure 9b. Comparison of simulated vs. measured yield for Mycogen 7885 for all site-years.

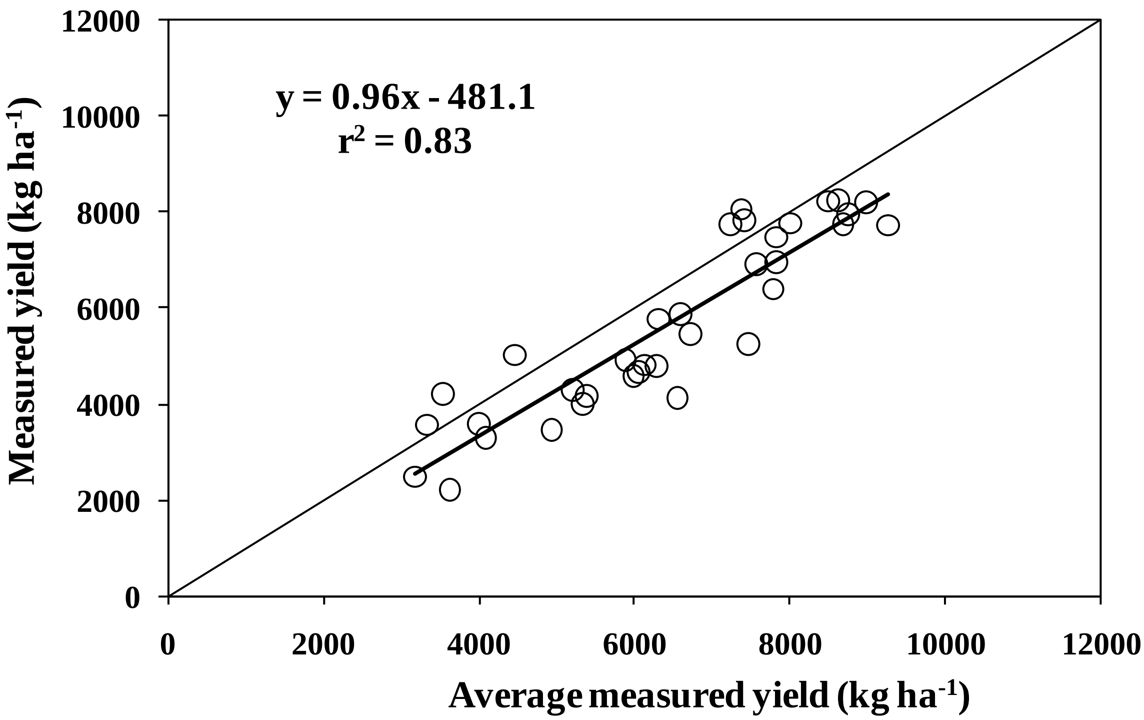

Figure 10a. Comparison of measured yield for Pioneer 3167 for each site-year vs. the average measured yield across all hybrids for each site-year.

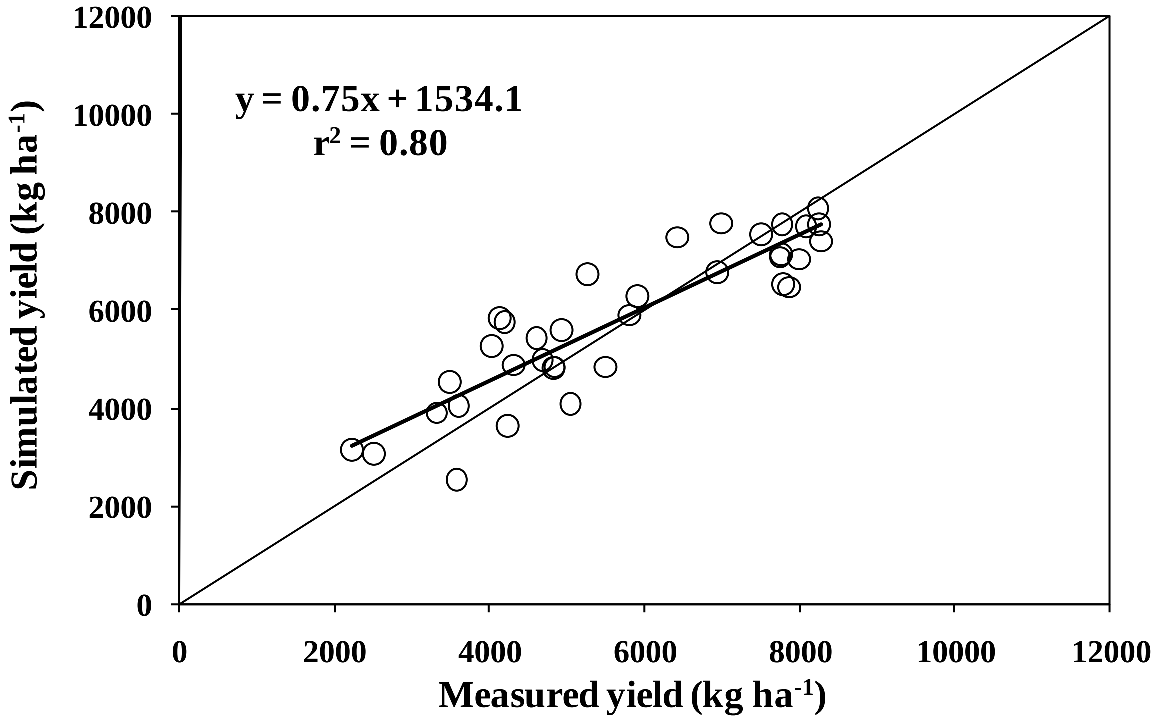

Figure 10b. Comparison of simulated vs. measured yield for Pioneer 3167 for all site-years.

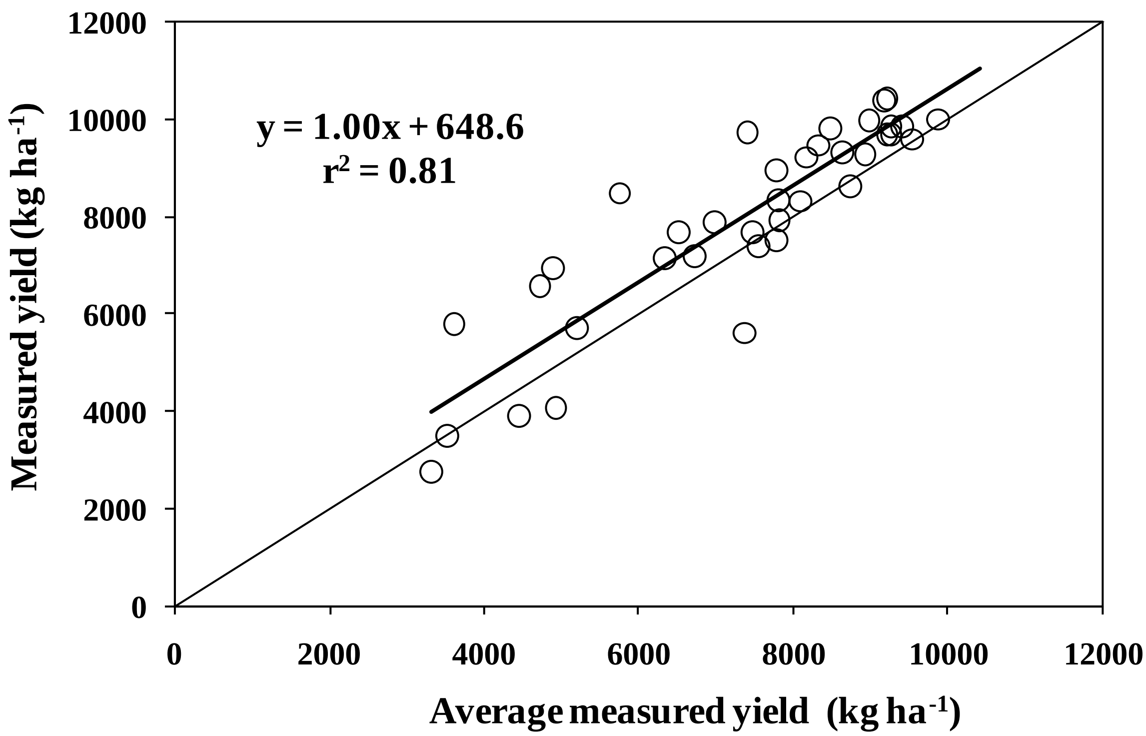

Figure 11a. Comparison of measured yield for Pioneer 31B13 for each site-year vs. the average measured yield across all hybrids for each site-year.

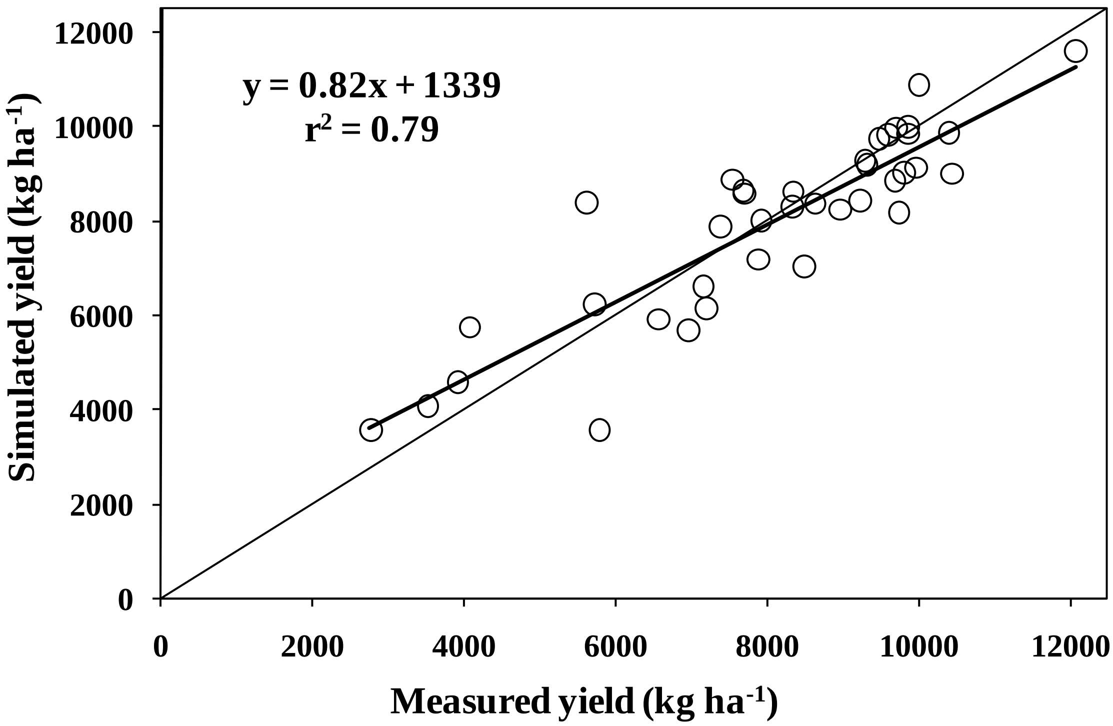

Figure 11b. Comparison of simulated vs. measured yield for Pioneer 31B13 for all site-years

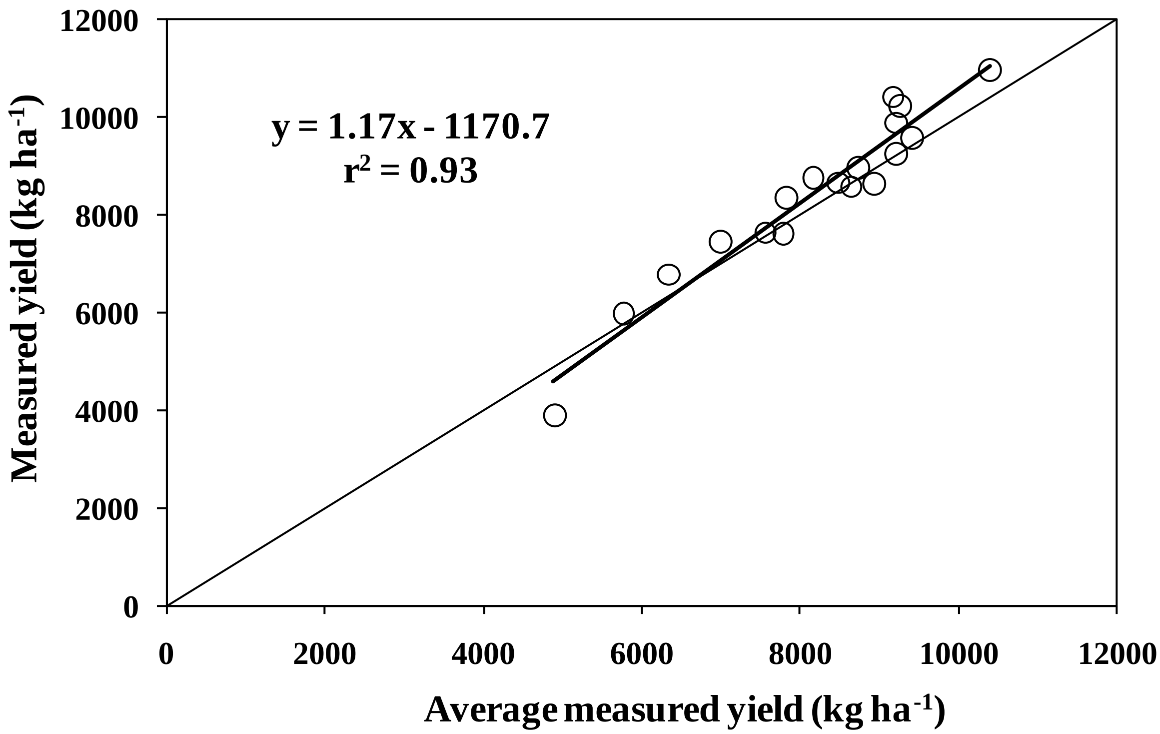

Figure 12a. Comparison of measured yield for Pioneer 32R25 for each site-year vs. the average measured yield across all hybrids for each site-year.

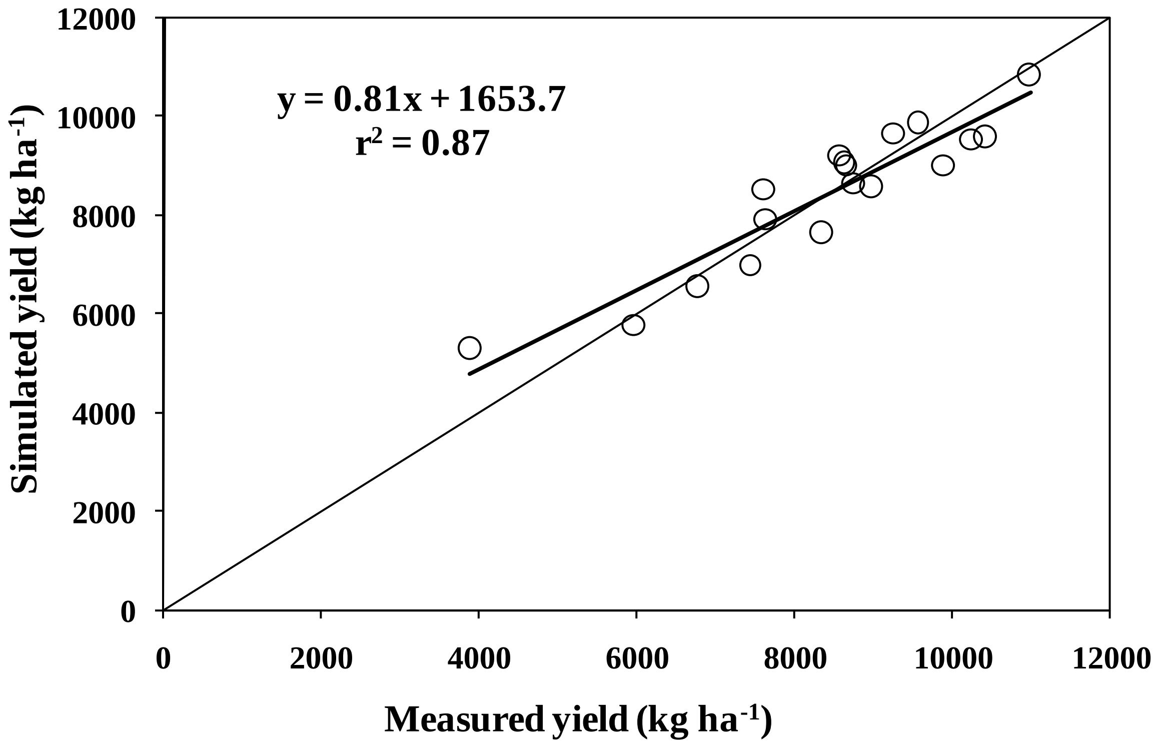

Figure 12b. Comparison of simulated vs. measured yield for Pioneer 32R25 for all site-years.

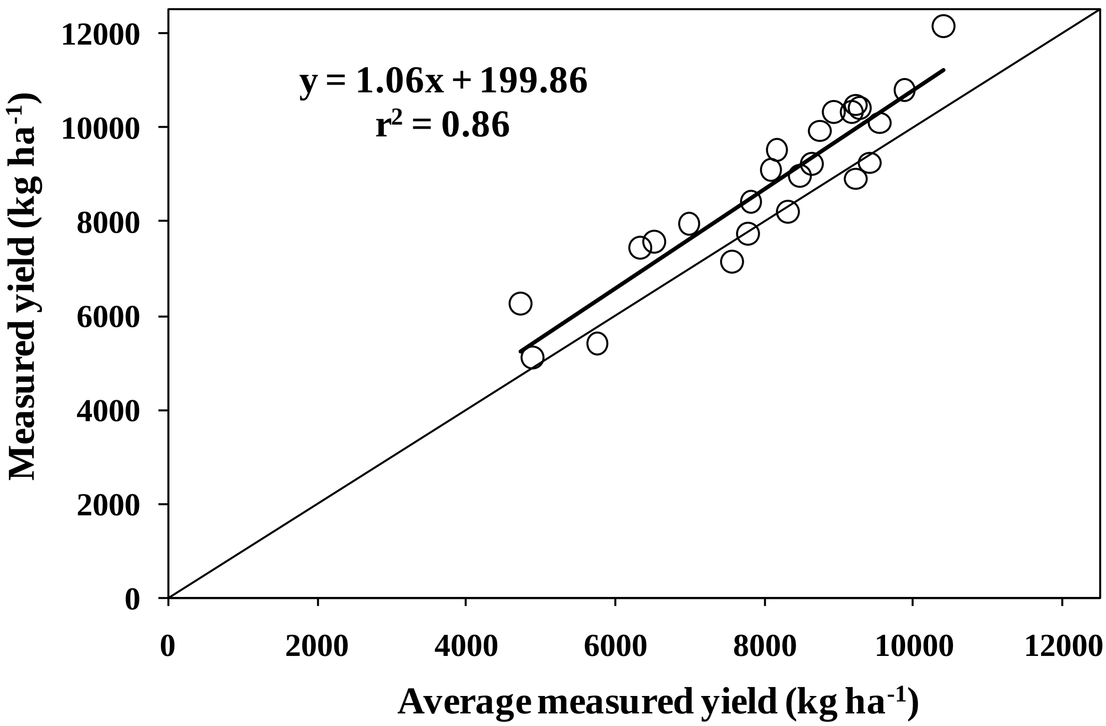

Figure 13a. Comparison of measured yield of Pioneer 31G98 for each site-year vs. the average measured yield across all hybrids for each site-year.

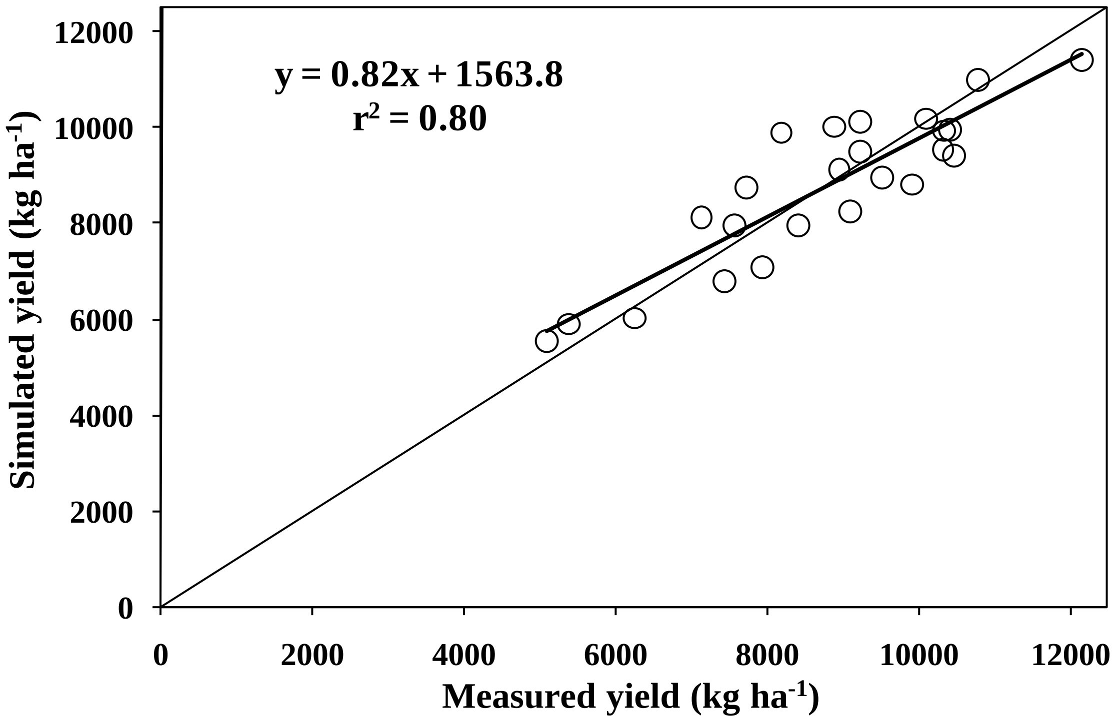

Figure 13b. Comparison of simulated vs. measured yield for Pioneer 31G98 for all site-years.

CHAPTER 3

Estimating CSM-CERES-Maize Soil Parameters and Evaluating Model Response to Varying Nitrogen Management Strategies under North Carolina Conditions

Zhengyu Yang, Gail G. Wilkerson,* Ron. Heiniger, and Gregory S. Buol

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ABSTRACT

The CSM-CERES-Maize model had been widely used all over the world, but hasn't been used previously in North Carolina. In this study, we examined the ability of the CSM-CERES-Maize model to simulate corn response to varying irrigation and nitrogen application strategies. Yield data for a total of 88 irrigation/nitrogen treatments from three fields in Lewiston, North Carolina were available for comparison. Our objectives were: 1) develop realistic soil profiles for the three fields; 2) compare simulated CSM-CERES-Maize corn yields to measured yields for all 88 treatments; 3) adjust soil parameters in an iterative process in order to improve simulation of corn yields for these treatments; and 4) determine the importance of each soil parameter to simulated crop yields. Simulated yields did not match observed yields well using our initial soil profiles, with relative root mean squared error (RRMSE) values of 17.5, 38.4, and 50.1% for the three fields. The iterative adjustment of soil parameters was successful in determining a set of soil parameters for each field such that the RRMSE values for yield improved to 8.2, 7.8, and 7.4%, respectively. Simulated yield using these optimized parameters generally fell within ±SE of the measured yield. Despite this agreement between simulated and observed yields, we think that the optimized values for two of the four adjusted parameters were outside reasonable bounds. The soil fertility factor, SLPF, ranged from 1.27 to 1.34 for these fields, much higher than the default value of 1.0. SRGF, the root growth factor, also had a very different pattern than the expected exponential pattern, which begins with a value of 1.0 in the top 15 cm of soil and declines to 0.078 by 135 cm. The optimized pattern of SRGF for all three fields started with a value of 0.1 in the layers above 45 cm, with larger values in the deeper layers. The importance of each

adjusted soil parameter was investigated by setting it back to its starting value while the other adjusted parameters were left at the optimized value. When SRGF was returned to an exponential pattern, simulated yields for irrigated treatments which received a side dressing of N at visual tasseling were lower than those for an irrigated treatment which did not receive this second application. We determined that these results were due to the manner in which new root length is distributed across the soil profile by the model. Modifications to CSM-CERES-Maize are necessary, if it is to be used to predict crop response to split applications of N.

Abbreviations: ASW, plant available soil water; DOY, day of year; EFIR, irrigation efficiency factor; N_{init}, N present in soil profile prior to initial N application; $N_{(Initial,Second)}$, treatment with "Initial" amount of N applied at planting, and "Second" amount of N applied at either V_7 or V_T; RMSE, root mean squared error; RRMSE, relative root mean squared error; SDUL, volumetric soil water content, drained upper limit; SLLL, volumetric soil water content, lower limit; SLPF, soil fertility factor; SRGF, soil root growth factor; V_7, layby; V_T, visual tasseling.

INTRODUCTION

Corn has traditionally been one of the most important crops grown in North Carolina. Hectarage had declined to 253 thousand hectares by 2001, but has gradually recovered since then (NCDA&CS Agricultural Statistics Division, 2007). Among all crops grown in North Carolina, corn was the third largest in planted hectarage in 2005 and 2006, with about 304 and 320 thousand hectares, respectively (NCDA&CS Agricultural Statistics Division, 2007). The hectarage increased substantially to 417 thousand hectares in 2007 (Schnitkey, 2007). This reflected the nationwide trend, with acreage up across US by 15 percent from 2006 (Schnitkey, 2007).

Corn grain is used in North Carolina by the livestock industry, with demand exceeding the supply which can be produced locally (NCDA&CS Agricultural Statistics Division, 2007). Furthermore, production of alternative fuels is likely to increase demand in North Carolina. Three corn-based fuel refineries are either under construction or being planned for the Virginia / North Carolina / South Carolina area (Pease, 2007). USDA/NASS has estimated that these three plants will consume three-fourths of the corn currently being produced in the Virginia / North Carolina / South Carolina region (Pease, 2007).

To satisfy the demand for both livestock feed and fuel production, yields must be increased, either by continuing to expand acreage or by increasing grain yield per hectare. Yields are highly dependent on water and nutrient availability, and growers might increase yields per hectare by installing irrigation equipment, or by modifying management practices such as planting date, plant population, cultivar selection, or irrigation and nutrient application strategies. Severe droughts in 2002 and 2007 in most areas of North Carolina have highlighted the importance of water availability and water management to corn growth and yield. As the demand for corn has increased and the selling price has risen in recent years, so too has the cost of N fertilizer. High levels of NO_3-N in groundwater in the southeastern Coastal Plain have made groundwater contamination from excess application of fertilizers an important environmental issue (Hubbard and Sheridan, 1989). The necessity of limiting N usage while maintaining high production complicates N management, and has driven an interest in utilizing precision applications to optimize N usage (Sripada et al., 2005, 2006). Multiple split applications of inorganic N have been found to increase crop yields over those obtained with one at-planting application (e.g. Cassman et al., 1994).

Crop models have long been used to explore the effects of proposed changes in management strategies across a diversity of environments and weather conditions (e.g., Swaney et al., 1983; Retta et al, 1996; Hodges et al. 1987; Sinclair and Muchow, 2001; Andales et al, 2003; Asseng et al., 2003; Cavero et al., 2000; Feng et al., 2003; Kucharik and Brye, 2003; Abrahamson et al., 2006; Baumhardt and Howell, 2006; Baumhardt et al., 2007). CSM-CERES-Maize has been widely used to simulate corn growth under various environmental conditions, both in the United States and in cultivation regions all over the world (Jones and Kiniry, 1986; Vigil et al., 1991; Bowen et al. 1993; Smart et al., 1993; Vigil and Kissel, 1995; Kiniry and Williams 1997; Pang et al., 1997a, 1997b, 1998; Ritchie, 1998; Kiniry and Bockholt, 1998; Fortin and Moon, 1999; Andresen et al., 2001; Xie et al., 2001; Gungula et al., 2003; Hoogenboom et al., 2003; Jones et al., 2003; Löffler et al., 2005; Saseendran et al., 2005; Miao et al., 2006; López-Cedrón et al., 2008).

CERES-Maize was first released in 1986 by Jones and Kiniry (1986), and is now available as CSM-CERES-Maize in DSSAT, Decision Support System for Agrotechnology Transfer (Ritchie et al., 1998; Jones et al., 2003; Hoogenboom et al., 2003). CSM-CERES-Maize simulates corn development, biomass accumulation, and final yield production in response to soil conditions, local weather, and management decisions, including N application and irrigation strategies.

The N module in CERES-Maize was investigated by Bowen et al. (1993) in predicting the ability to simulate N mineralization, N leaching, and N uptake based on experiments incorporating 10 different legume green manures which varied from 25 to 300 kg ha^{-1} with C/N ratio from 13 to 37 in 8 soil layers to 1.2 m depth. They concluded that the N sub-model in CERES-Maize realistically simulated legume N release, and N leaching predicted using the improved model. N uptake was over-predicted at high levels of available N.

Thornton and MacRobert (1994) used CERES-Maize to estimate maximum economic gross margins by simulating various N application rates and timing for each year from 1978 to 1987. They found the optimum N application was highly dependent on weather, with total amount varying from 49 kg ha^{-1} to 240 kg ha^{-1}.

Research was conducted to determine optimum N application rates for 224 grid cells in a 16 ha field using CERES-Maize (Paz et al., 1999). After simulations were made for 22 years of historical weather, they concluded that N fertilizer rates from 141 to 161 kg ha^{-1} were optimum.

Bert et al. (2007) studied the sensitivity of CERES-Maize to uncertainties in soil and weather conditions, using simulations of one cultivar grown in one field in Argentina. Daily solar radiation and soil conditions, including soil water storage capacity, N and water content at sowing, organic matter content and soil infiltration curve number were varied under rainfed and non-limiting water conditions in simulations using 31 years of weather. This study concluded that the CERES-Maize model had similar sensitivities to different tested soil conditions, but much higher sensitivity to variations in radiation.

In general, before any model can be used to simulate crop growth in a new location or environment, it is necessary to calibrate multiple parameters (Hoogenboom et al. 1994). CSM-CERES-Maize has recently been parameterized for 53 hybrids grown under typical North Carolina soil and environmental conditions using 60 site-years of data from the North Carolina official variety trials (Yang et al., 2008). N was applied at planting and as a side dressing according to soil test results (e.g., Bowman, 2001, 2002, 2003). N was therefore assumed to be non-limiting when genetic coefficients were estimated using these trial data and the model appeared to adequately simulate response of the hybrids to varying soil and environmental conditions (Yang et al., 2008).

Although CSM-CERES-Maize has been used widely all over the world under a variety of field conditions, it has not been evaluated for a complex combination of N application and irrigation strategies. In this project, we evaluated the ability of the CSM-CERES-Maize model to simulate corn response to different irrigation and N application strategies under North Carolina conditions. Specific objectives included: 1) develop realistic soil profiles for three North Carolina fields; 2) compare simulated CSM-CERES-Maize corn yields to measured yields for a total of 88 different N and irrigation treatments applied in these three fields; 3) adjust soil parameters in an iterative process in order to improve simulation of corn yields for these treatments; and 4) determine the importance of each soil parameter to simulated crop yields. Although other researchers have evaluated the ability of CSM-CERES-Maize or its predecessors to simulate response to different N or irrigation strategies, none has evaluated its performance for such a large collection of N and irrigation treatments applied to the same or neighboring fields.

MATERIALS AND METHODS

Field Description

Data were obtained from trials performed in three fields at the Peanut Belt Research Station in Lewiston-Woodville, Bertie County, North Carolina in two consecutive years (Heiniger, unpublished data; Sripada et al., 2005, 2006). The research fields were located at latitude 36.132 °and longitude -77.176 °with an elevation of 15m. Soil classification, planting details, and irrigation and N application strategies for these fields are listed in Table 1. The hybrid 'Pioneer 31G98' was planted at a population of 60000 seeds ha^{-1} (6 seeds m^{-2}) on 6 April 2001 and on 9 April 2002. The 2001 experiment had three replicates for each treatment, and the 2002 experiments had five replicates. In every treatment plot, the center two rows of the four rows were harvested to determine grain yield.

In all three fields, several N application strategies, varying in timing and amount, were used (Table 1). N application was scheduled to occur during critical developmental stages as defined by Ritchie and Hanway (1982). A urea-ammonium nitrate solution (UAN, 30% N) was surface-applied at planting and/or at or near tasseling (V_T) in 2001, and/or at layby (V_7) in 2002 using a CO2–pressurized backpack sprayer. For convenience, the notation $N_{(Initial,Second)}$ is used to denote the amount of N applied initially at planting and on the second application date (either V_7 in 2002 or V_T in 2001). For example, a treatment with an initial N application of 56 kg ha^{-1}, and a second application of 224 kg ha^{-1} would be denoted $N_{(56,224)}$. In 2001, irrigation strategy was the main plot effect, with subplots for N level at planting, and sub-sub-plots for N level at V_T (Table 1). In 2002, one field was irrigated, the other was not. Seasonal irrigation and rainfall are shown in Figure 1 for 2001, and Figure 2 for 2002.

CSM-CERES-Maize Model

The CSM-CERES-Maize model, included in DSSAT Version 4.0.2, was used in this study (Ritchie et al., 1998; Jones and Kiniry, 1986; Jones et al., 2003; Hoogenboom et al., 2003). The CSM-CERES-Maize model utilizes a one-dimensional soil profile which may be divided into as many as 20 layers (Jones et al., 1998; Ritchie et al., 1998). Daily changes in volumetric soil water content are calculated for each layer by adding precipitation and rainfall amounts, and subtracting water lost through evaporation, transpiration, runoff, or infiltration and drainage through the profile (Porter et al., 2004). The soil N module computes a daily soil N balance, based on organic and inorganic fertilizer and residue placement, decomposition rates, and nutrient fluxes between various pools and soil layers. Soil nitrate and ammonium concentrations are updated on a daily basis for each layer (Hoogenboom et al., 2003). The crop module simulates plant processes, including phenology, daily growth and partitioning, and plant N and carbon demands. Daily plant growth is computed by converting intercepted photosynthetically active radiation into plant dry matter using a radiation use efficiency parameter. Additions of dry matter each day may be reduced due to limitations in water or N, or by unfavorable temperatures (Hoogenboom et al., 2003). Above-ground biomass has priority for carbohydrate each day, but roots receive at least a stage-dependent minimum. Kernel numbers per plant are computed based on the cultivar's genetic potential, canopy weight, and average rate of carbohydrate accumulation during flowering, and temperature, water and N stresses (Hoogenboom et al., 2003).

Soil Profile Parameterization

When we started this project, we hoped to be able to extract starting soil profiles for each field from the NRCS database (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture, 2004), and then visually calibrate a few soil parameters using a very limited subset of the experimental treatment data which were available to us. We planned to use the remaining treatment data to validate the ability of CSM-CERES-Maize to simulate different irrigation and N application strategies under North Carolina conditions. Unfortunately, this expectation was primarily a result of our naiveté with regards to the complexities injected into the calibration process when N dynamics are simulated.

In our previous study (Yang et al., 2008) in which we utilized data from the North Carolina official variety trials and iteratively adjusted crop genetic coefficients and soil parameters in order to estimate genetic coefficients for many corn hybrids, we were quite successful using soil profiles drawn from NRCS, and adjusting only two soil parameters (rooting depth and soil water holding capacity). However, in this previous study, all treatments were well-fertilized, and we were able to assume that N was non-limiting in all simulations.

We were forced to quickly abandon the simple approach to soil parameterization which we had planned for this current study. It became clear that when the N balance model is turned on in CSM-CERES-Maize, many soil parameters become important and must be set to reasonable values. We found, for example, that if soil pH has not been defined for the soil profile, then CSM-CERES-Maize assumes a pH of 7.0 for all layers. While this may be appropriate for a mid-western soil, it is not at all appropriate for the acidic mineral soils of North Carolina. Soil pH has no effect on simulated yields when N dynamics are not simulated in CSM-CERES-Maize, but has significant effects when the N dynamics model is utilized. Since we had very limited information about the soils in the fields in which the experiments were conducted, we found ourselves faced with a daunting task of estimating many soil parameters which all had impact on simulated N dynamics and crop growth. We therefore undertook a more structured approach to create our starting soil profiles and to optimize soil parameters than originally planned. Eventually we utilized all of the treatment data to some extent in the parameter fitting exercise.

Initial Soil Profiles

CSM-CERES-Maize utilizes field-specific soil profiles which define soil physical and chemical properties. Parameters which influence water and N dynamics are defined in Table 2. When developing an initial soil profile for the three fields utilized in this study, we relied upon information provided by a study conducted by Broome (1969) at the same research station.

When the N model is turned on, soil pH, bulk density, organic carbon, and distribution of initial soil N through the profile become important. In the starting profile of the three fields, the soil organic matter and soil pH were estimated using information supplied by Broome (1969). The texture information for all three fields in sand, clay and silt fraction, as a starting point for simulation and calibration, was determined in the Soil Texture Triangle (NRCS, USDA, 2008). The sand-clay-silt distribution across layer profile in depth was referenced according to field description in the station documentation (Kleiss et al., 1982), and co-referenced the soil texture information from soil data in Broome (1969) research. The soil bulk density was calculated from soil organic matter and mineral bulk density in equation presented by Rawls et al. (1985). The soil water properties, including soil water lower limit, soil water drainage upper limit, soil saturation, and soil hydraulic conductivity were estimated from equations in Saxton (1986) and Rawls et al. (1982) in consideration of soil texture characteristics derived above.

Although rainfall can bring 9.2 to 31 kg ha^{-1} of N to the soil each year (Clark and Kremer, 2005; Ayars and Gao, 2007), study has shown bulk deposition of N at 30.6 kg N ha^{-1} around Beijing agricultural area in China (Liu et. al., 2006). Jenkinson et al. (2004) also found non-fertilizer N input by atmospheric deposition to Rothemsted was 39 kg ha^{-1} annually by long term experiment method, which was comparable to the finding (45 kg ha^{-1}) in nitrogen deposition to winter cereals at Rothamsted by Goulding et al. (1998) under 154 years of experiment since 1843. In another long term experiment located at Halle, Germany, Weigel et al. (2000) estimated the total annual N deposition to be 60 kg ha^{-1}. Weigel et al. (2000) even measured a 65 kg ha^{-1} airborne N deposition with ^{15}N aided ITNI-system in 1998. Considering all above research about N deposition, the initial soil N was set to a total of 50 kg ha^{-1} (Table 5), based also on the opinions of those familiar with the site. We expected the three fields at the same station in Lewiston, North Carolina to have similar soil N distributions prior to the start of the growing season.

One of the inputs required by CSM-CERES-Maize is the method of N application. DSSAT offers a list of possible application methods. In the field experiments used in this study, N was applied as urea nitrate ammonia solution. In preliminary simulations, when we selected this application method, we discovered that CSM-CERES-Maize predicted high levels of volatilization for this application method. Prior field tests performed at the site had shown that excessive volatilization did not occur, possibly due to differences between the particular form of liquid N used in the NC field experiments and the form used when CSM-CERES-Maize was being developed and tested. To minimize the amount of volatilization simulated by CSM-CERES-Maize, we found it necessary to specify that the fertilizer was incorporated, even though it was not incorporated in actuality.

The soil root growth factor (SRGF) represents the relative suitability of each soil layer for root growth, if no N or water deficits are present. For each layer, SRGF was calculated according to the exponential equation used in the SBuild tool contained in DSSAT 4 (Uryasev et. al., 2003). This equation results in decreases in SRGF with depth (Wilkens et al., 2004). The soil fertility factor (SLPF) for all three fields was set to 1.0, based on the previous study by Yang et al. (2008). The irrigation efficiency factor (EFIR) was set to 0.75, since a sprinkler irrigation system was used in all fields.

Simulation and Data Analysis

The Crop Simulation Database Program (CSDB) was used to store field data, make all model runs, and store model results in multiple Microsoft Access databases (Buol et al., 2006). This program facilitated the construction and processing of simulation experiments in which soil parameters were varied across the specified range using the given number of steps. A custom program was written using Microsoft Visual Basic 6.0 to analyze results, including querying the databases generated by CSDB, calculating relevant statistics, and determining the optimal parameter values.

Optimization Procedures

Simulations Using Default Soil Settings for All Three Fields.

Initial simulations for the three fields were made using the default settings for soil physical properties (Tables 3 and 4), and initial soil N conditions (50 kg ha^{-1}) from Table 5. Other parameters were set as previously described. The root mean squared error (RMSE) for each field was calculated to determine the difference between simulated and measured yields, according to the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(Y_{Simulated} - Y_{Observed})^2} \qquad [1]$$

where n represents the number of treatments, $Y_{Simulated}$ is the simulated yield for a treatment, and $Y_{Observed}$ is measured yield. Bar graphs comparing simulated to measured yields for each N treatment were also generated.

The relative root mean squared error (RRMSE) was also calculated according to the following formula:

$$RRMSE = \frac{RMSE}{Y_{Average}} \times 100\% \qquad [2]$$

where RMSE was calculated from equation [1]. $Y_{Average}$ was the average measured yield.

General Approach to Limit Number of Simulations.

When deciding upon an approach for calibrating uncertain soil profile parameters for these three fields, it was clear that some strategy for limiting the parameter search space would be required. The simulation number would be huge if we considered straight forward strategy in parameter setting and simulation control for constructing the simulations. For example, if the parameter SRGF was assigned 10 possible values from 0.1 to 1.0 for each of the 10 soil layers, this would generate 10^{10} levels. Moreover, considering three fields, there might be 3 * 10^{10} total possible settings if only SRGF was varied for the target field soils. Using a computer which can make 2.5 simulation runs per second, it would require 138,889 days to simulate one setting for DUL, one value of SLPF, and one N_{init} value for all these values of SRGF and all 88 treatments. It was necessary to reduce both the range and number of levels for each parameter, while still trying a sufficient number of parameter settings to generate acceptable soil profiles.

After simulations using the default settings for each field proved unsatisfactory, we used simulations of the 2002 irrigated field to determine reasonable parameter ranges to use in the remaining two fields. Previous work has shown that CSM-CERES-Maize responds accurately to different levels of water stress under North Carolina conditions when N is non-limiting (Yang et al., 2008). We decided to concentrate first on defining a soil profile for a well-irrigated field, with the expectation that this would simplify fitting of soil parameters for accurate simulation of different N application schedules.

The general approach for fitting parameters to this field was an iterative process of multiple simulations followed by analysis, adjustment of parameter ranges, and additional simulations and analysis. Preliminary simulations using treatments $N_{(0,0)}$ and $N_{(224,0)}$ identified starting ranges for soil parameters being varied. To maximize the number of parameter values which could be simulated within these boundaries, simulations using all parameter values were made for only seven of the 20 treatments: $N_{(0,0)}$, $N_{(0,56)}$, $N_{(0,112)}$, $N_{(0,224)}$, $N_{(56,0)}$, $N_{(112,0)}$, and $N_{(224,0)}$. The 196 sets of parameter values with the lowest values for RMSE from these runs were then used to simulate the remaining 13 treatments, and the set of parameters with the lowest RMSE across all 20 treatments was used to determine if additional changes in parameter values were needed.

Optimization Procedure for Irrigated Field in 2002

First set of simulations. Initially, we chose to vary three parameters: N_{init}, SDUL, and SRGF. Based on the preliminary simulations using treatments $N_{(0,0)}$ and $N_{(224,0)}$, N_{init} was increased from the default value of 50 kg ha^{-1}. Three levels (70, 80, and 90 kg ha^{-1}) were included in the first set of simulations, and were set proportional to the setting of 50 kg ha^{-1}. The soil drained upper limit (SDUL) parameter was chosen to allow variations in soil water holding capacity. Values of this parameter contained in the initial soil profiles for each site-year were modified using the formula:

$$SDUL_{Actual} = SLLL_{Default} + (SDUL_{Default} - SLLL_{Default}) \times (1+X) \qquad [3]$$

where SLLL represents the soil water drained lower limit, and X represents the proportional change in plant available soil water (ASW). ASW was varied ±20% (-20%, -10%, 0%, +10%, +20%) in all layers, using the method described in Yang et al. (2008). All layers were multiplied by the same adjustment factor, so that there were only 5 levels for this parameter.

SRGF required a different approach. It is known that the corn plant grows a larger volume of roots in the upper soil layers, and develops less root volume in deeper soil layers. Varying the default values in all layers by a proportional amount, as done for SDUL, did not appear to be an effective strategy, based on the preliminary simulations. The range for SRGF in upper layers was set to 0.1 - 0.9, but in deeper layers it ranged from 0.1 - 0.4 (Table 6). Simulations were made for seven N treatments, resulting in a total of 393,750 runs using 2137 different levels of SRGF (Table 6). The sets of parameter values which resulted in the 196 lowest values of RMSE across these 7 treatments were used to simulate all 20 N treatments.

Second set of simulations. Based on RMSE values and graphs of simulated and observed yields for each treatment, we decided that additional parameter values needed to be explored. The new values for SRGF in each layer are shown in Table 6. In these new simulations, the value of SRGF was set to 0.1 in the first four layers, and a total of 10,000 different values of SRGF were tried in layers 5 to 10. ASW was fixed at 120% of the default value in each layer, and N_{init} was fixed at 70 kg ha^{-1}, resulting in an additional 70,000 simulations for the seven N treatments. The 196 parameter sets with the lowest values of RMSE were again run for all 20 N treatments.

Third set of simulations. When RMSE values were again judged to be unacceptable, we decided to explore the effect of varying the soil fertility factor SLPF on simulation results. Using the optimized parameter settings for ASW, SRGF, and N_{init}, SLPF was varied from 1.10 to 1.80 in interval increment of 0.1.

Based on results of these simulations, further simulations with the optimal parameter settings for ASW, and N_{init} were made in which SLPF values varied ranging from 1.22 – 1.36 in step size of 0.01, and SRGF was set according to Table 6, resulting in 45,360 simulations for the seven N treatments.

Fourth set of simulations. In a final series of simulations, N_{init} used values of 65, 70, 75, and 80 kg ha^{-1}, ASW varied ±8% (-8%, -4%, 0%, +4%, +8%) of the default value, SLPF was set to 1.34, and values of SRGF were set to values displayed in Table 6 for the seven N treatments.

Optimization Procedure for 2002 Non-irrigated Field and 2001 Field

For both of these fields, the results for the irrigated field in 2002 were used to determine the range of values of N_{init}, ASW, SRGF, and SLPF to try. For the non-irrigated field in 2002, ASW was varied from the default level by ±20% in 5 levels (-20%, -10%, 0%, +10%,

+20%) in all layers according to Equation 3. N_{init} values of 70, 75, and 80 kg ha^{-1} were tried. SLPF varied from 1.22 to 1.36 in increments of 0.01. Values for SRGF are shown in Table 6. In 2001, ASW was varied from the default level by ±20% in 9 levels. N_{init} values of 70, 75, 80, 85, 90, 95 kg ha^{-1} were tried. SLPF varied from 1.21 to 1.36 in increments of 0.01. Values for SRGF are shown in Table 6. All parameter sets were run for all 48 N and irrigation treatment levels.

Exploring the Impact of Changes in Each Parameter on Overall Yield Simulation

After all parameters, including N_{init}, ASW, SRGF, and SLPF, were optimized for each field, the impact of each parameter on simulated yields was examined. Each of these four parameters was reset to the default setting (Tables 3, 4, and 5), while the other three parameters remained at the optimized setting.

RESULTS AND DISCUSSION

Simulations Using Default Soil Settings

In general, the initial simulations using the default set of soil parameters resulted in an under-prediction of yield for most treatments in all three fields (Figure 3). The sole exception was the simulation of non-irrigated treatments in 2001 (Figure 3a). In 2002, the simulated yield was ~6000 kg ha^{-1} for all irrigated treatments with 56 kg ha^{-1} or more total N (Figure 3d). Results for the 2002 non-irrigated field were even worse, with simulated yields of ~2000 kg ha^{-1} for treatments receiving 112 kg ha^{-1} or more total N, and higher simulated yields for treatments with a total of 56 kg ha^{-1} (Fig 3e). With N_{init} set to 50 kg ha^{-1}, the simulated yield was lower than measured in all three fields for the $N_{(0, 0)}$ treatment, except for the normal-irrigation treatment in 2001. These poor results are reflected in the RMSE and RRMSE values listed in Table 7 for all three fields. In 2002, the regression lines for simulated versus observed yields for both fields had very low r^2 and slope values, indicating a large amount of bias. The slope of the regression line for the 2002 non-irrigated field was actually negative. Although the r^2 and slope values for the 2001 field were much better than those for the 2002 fields, the RRMSE was still over 17%.

Optimization for Irrigated Field in 2002

In preliminary simulations using treatments $N_{(0, 0)}$ and $N_{(224, 0)}$, results appeared better if N_{init} in all three fields was set to 80 kg ha^{-1}. Therefore, in later simulations N_{init} values between 70 and 90 kg ha^{-1} were used.

Allowing N_{init} to vary between 70 and 90 kg ha^{-1}, ASW to vary between 80% and 120% of the default value, and SRGF to vary between 0.1 and 0.9 in the top soil layers, and between 0.1 and 0.4 in deeper layers (Table 6) resulted in considerable improvement in RMSE, r^2, and slope values for the irrigated field in 2002. RMSE was decreased to 1697 kg ha^{-1} compared to 3272 kg ha^{-1} for the default soil settings (Table 7). The r^2 value improved to 0.65. The optimal value of ASW was120% of the default value. The lowest RMSE was obtained using low values for SRGF in soil layers above 60 cm in depth, and larger values in the deeper layers (Table 8).

When SRGF was set to 0.1 in the top four layers and the value was allowed to vary between 0.4 and 0.8 in the lower layers, with N_{init} set to 70 kg ha^{-1}, and ASW to 120% of the default value (Table 6), results continued to improve. RMSE improved to 940 kg ha^{-1}, the r^2

value to 0.86, and the slope of the regression line to 0.94, much lower than the values obtained in the initial optimization runs and in the simulations using default soil settings (Table 7). The optimized SRGF, with a fixed value of 0.1 in the upper four layers, had larger values in deeper layers (Table 8). A value of 120% of the default setting for ASW was still best. The best value of N_{init} changed to a lower value of 70 kg ha^{-1}, when compared to N_{init} in previous simulations.

When reviewing the graphs of simulated versus observed yield for the best set of parameters identified above, we noticed that the model did not differentiate much between treatments with observed yields above 8000 kg ha^{-1} (Fig 4a). We experimented with values of SLPF between 1.10 and 1.80 (but only showed result for SLPF at 1.10, 1.20, 1.30, and 12.40), using the set of soil parameters which yielded the minimized RMSE in the simulations above. RMSE decreased from 940 for an SLPF of 1.0, down to 780 for an SLPF of 1.3, then increased again to 970 kg ha^{-1} for an SLPF of 1.4. At the same time, the r^2 value increased from 0.87 to 0.95 as SLPF rose (Figure 4). The slope of the regression line declined from 1.03 when SLPF was 1.10 to 0.68 when SLPF was 1.4.

In simulations in which SLPF was varied between 1.22 and 1.36 in increments of 0.01, a minimum RMSE of 743 kg ha^{-1} was obtained for an SLPF of 1.34. One final set of simulations was made during which N_{init} was 65, 70, 75, 80 kg ha^{-1}, SRGF was set as shown in Table 6, and ASW 92, 96, 100, 104, 108% of the default value were varied and SLPF was fixed at 1.34. A final optimized value for RMSE of 665 kg ha^{-1} was obtained in these simulations (Table 7), with ASW set at 96%, and N_{init} set to 75 kg ha^{-1} (Table 8). A comparison of simulated and observed yields using these optimized soil parameter settings is shown in Figure 5. With a relatively high r^2 of 0.93 and a regression slope of 1.00, we judged model performance to be satisfactory for the irrigated field in 2002. The slope of 1.00 demonstrates a lack of bias in predictions of yield across all N treatments. In both the field and in the simulations, there was no significant response to increasing N above a total N level of 224 kg ha^{-1} (Figure 5b). As shown in Figure 5b, yield was overestimated for treatments $N_{(56, 56)}$, $N_{(56, 112)}$, and $N_{(112, 56)}$. It was underestimated for treatments $N_{(0, 0)}$ and $N_{(0, 224)}$. For all other treatments, simulated yield was within the SE of the mean observed treatment yield.

Optimization for Non-irrigated Field in 2002

Using the much-reduced procedure described above for fitting soil parameters for the non-irrigated field in 2002 was successful, with a RMSE of 334 kg ha^{-1}, a regression slope of 0.83, and an r^2 value of 0.75 (Table 7, Figure 7a). The r^2 value was lower than that for the irrigated field in the same year. However, all simulated yields were within the SE of the average measured yields for each treatment (Figure 7b). SE was relatively large for most treatments. There was little difference in either simulated or observed yield for treatments with total N of 112 kg ha^{-1} or above. The optimized SRGF, although different in absolute values from those fit to the irrigated 2002 field, were similar in pattern, with higher values in deeper layers than in shallower layers (Table 8). It was necessary to include fewer layers, with a maximum rooting depth of 105 cm. A value of 80% for ASW also provided the best results, indicating a need for less available soil water in order to match the observed yields with SLPF set to 1.34. Given the low value for RRMSE and the high SE for treatments in this field, we determined that no further simulations were required for this field.

Optimization for the 2001 Field

In this field, there were three irrigation treatments and 16 N treatments, for a total of 48 treatments. The optimization procedure resulted in an r^2 value of 0.91, a slope for the regression line of 1.02, and a minimized RMSE of 850 kg ha^{-1} (Table 7 and Figure 7a). The simulated and observed yields were similar for all treatments with total N applications of 280 kg ha^{-1} or above for a given irrigation treatment (Figure 7b-d). The simulated yields at total N levels from 168 kg ha^{-1} to 336 kg ha^{-1} had eight over-estimations and five under-estimations. This miss-estimation in the middle yield portion made the treatments hard to simulate and optimize. In the irrigated treatments, yield was generally under-estimated for treatments with 0 kg ha^{-1} N applied at planting (Figure 7c-d). Yields were over-estimated for irrigated treatments $N_{(112, 0)}$, $N_{(168, 0)}$, $N_{(224, 0)}$, and $N_{(112, 112)}$. Yield was overestimated for all treatments with 112 kg ha^{-1} N applied at planting in the non-irrigated block (Figure 7b). The pattern for SRGF which yielded the best results was similar to that for the other two fields (Table 8). SLPF was lower than for the other two fields, and the default value for ASW worked well.

Impact of Changes in Each Parameter on Overall Yield Simulation

Returning to the default value of ASW

As might be expected, when ASW was raised from the optimized value of 80% of the default value back up to the default value, while all other parameters were left at their optimized value, simulated yields for the non-irrigated field in 2002 increased substantially for all N levels except the non-fertilized treatment, resulting in an increase in RRMSE from

7.42% to 31.91% (Table 7). The failure of an increase in ASW from 80% to 100% to increase simulated yield for the non-fertilized treatment is likely due to N stress serving as the limiting factor to growth. The increases in ASW did not offset N stress for this treatment.

In contrast to results for the non-irrigated field in 2002, simulated yields for the irrigated field did not change much for any of the N treatments, because the optimized ASW for this field was 96% of the original starting ASW. In the 2001 field, the optimized ASW in 2001 was 100% of the starting setting, so there was no need to investigate changing ASW for this field.

Returning to the default value of N_{init}

Changing N_{init} back to the default value of 50 kg ha^{-1} decreased simulated yields for low N treatments, while having little effect on the remaining treatments. This resulted in fairly small increases in RRMSE (Table 7). The low N treatments were sensitive to initial soil N status at or before planting, but the high N treatments were not sensitive to the initial soil N status. The effect of initial soil N was similar for all three fields.

Returning to the default value of SLPF

After SLPF was reset to the starting value of 1.0 from the optimized soil settings for the three fields, simulated yields reached a plateau for total N levels of 112 kg ha^{-1} or above in the irrigated 2002 field, and for N levels of 56 kg ha^{-1} or above for the non-irrigated 2002 field (Figure 8a-b). A similar trend was observed for the 2001 field (data not shown). However, yields for the low N treatments remained similar to those simulated using an SLPF of 1.34 for all three fields. The decrease in simulated yields for medium and high N treatments resulted in substantial increases in RRMSE for all three fields (Table 7). SLPF is one of the factors which serves as a multiplier in the calculation of crop growth rate in CSM-CERES-Maize, and is supposed to be used to account for the effect of soil nutrients other than N (Hoogenboom, 2003). That we had to raise it to 1.34 in two fields and to 1.27 in the other was surprising to us, since it normally is expected to be between 0 and 1.0.

Returning to the default value of SRGF

In CSM-CERES-Maize model, the root growth factor, SRGF, which determines the propensity of roots to grow in each layer of the soil profile, is normally assumed to be exponential, with roots being much more likely to grow in the upper layers than in lower ones. An exponential SRGF has been used in many studies (like Sau et al., 2004; López-Cedrón, 2008), but Jagtap et al. (1999) used 1.0 for first two layers and 0.5 for rest deeper layers (from 3 to 6), to deepest of 65 cm in soil profile.

We were also surprised by the need to create very different patterns for SRGF than the exponential one which served as the default for all three fields (Tables 3, 4) (Fig 9a,b). Even though the increases in RRMSE were lower when SRGF was changed back to the default setting than were the increases when SLPF was changed (Table 7), model response was more difficult to explain. Yields in 2001 were generally over-estimated for treatments with total N of 112 – 280 kg ha^{-1} while yields of the zero N treatment and of treatments with total N above 280 kg ha^{-1} were generally unaffected by returning SRGF to the default values (Figure 10a~c). Treatments with zero N application at planting and 112, 168 or 224 kg ha^{-1} on the second application date exhibited a large increase in simulated yield using the exponential

SRGF, compared to the optimized setting. In simulations using the optimized SRGF setting, much higher N stress occurred from about a month after planting until kernel number was determined for these treatments. There was less simulated N stress using the exponential SRGF. This lower N stress was accompanied by greater increases in LAI and leaf weight, so that the cumulative plant growth during flowering was much higher in simulations using the exponential SRGF. This resulted in a higher final kernel number for these treatments when the exponential SRGF was used.

Results were similar for the irrigated field in 2002, with an overestimation of yields for treatments with total N from 56 – 168 kg ha^{-1}. However, in this field yields of treatments with higher levels of N were now under-estimated (Figure 10d). Simulated yield was actually higher for the three treatments receiving a total of 112 kg ha^{-1} of N than for any other treatments (Figure 10d). We noticed this same pattern in the preliminary simulations using default soil parameters (Fig 3d and Fig 3e) for both fields in 2002. However, we did not realize what was causing this strange result, until we combined the default starting SRGF exponential setting with the other optimized soil parameter settings.

When comparing time series graphs for the $N_{(112, 0)}$ and the $N_{(112, 280)}$ treatments, we noticed that kernel number was higher for the $N_{(112, 0)}$ treatment. Simulated kernel number for the $N_{(112, 280)}$ treatment using an exponential SRGF was only 4581 m^{-2}, but the simulated kernel number was 5064 m^{-2} for the $N_{(112, 0)}$ treatment.

In the CSM-CERES-Maize model, kernel number is a function of genetic potential, canopy weight, rate of carbohydrate accumulation during flowering, and temperature, water, and N stresses (Hoogenboom, 2003), and is determined during a period around silking (Ritchie et al., 1998; Edmeades and Daynard, 1979; Lizaso et al., 2003, 2007). In the case of our simulations of the 2002 irrigated field, kernel numbers were determined on DOY of 184 (3 July 2002) based on values for the above factors during the period from flowering (DOY 176, 23 June 2002) until DOY 184 (Hoogenboom, 2003; Tsuji et. al., 1994). Genetic potential and temperature stresses were identical for the two treatments. A differentiation in simulated canopy weight between the two treatments was observed on DOY 155 (4 June 2002), about a week after the second N application. Canopy weight was slightly higher for treatment $N_{(112, 280)}$ by day 174, but was lower from day 178 onward. As expected, the N stress factor was higher for treatment $N_{(112, 0)}$ throughout the kernel-setting period. However, water stress was greater for the $N_{(112, 280)}$ treatment than for the $N_{(112, 0)}$ treatment during this period (Figure 11a). Water stress appeared to be the primary factor contributing to fewer kernels being set in the $N_{(112, 280)}$ treatment, which resulted in lower final yield. Root density for treatment $N_{(112, 0)}$ was lower in layer 1, and virtually identical to that of treatment $N_{(112,28\ 0)}$ in layers 2 – 5 during this period. Root densities in layers 2 - 5 had reached the maximum density allowed (4 cm root cm^{-3} soil) in both N treatments. However, after DOY 160 (9 June 2002), root growth proceeded at a much faster pace in the 6th layer for treatment $N_{(112, 0)}$ (Figure 11b). As roots penetrated into soil layers 7 - 9, the growth rate was also much higher in these layers for treatment $N_{(112,0)}$.

We were unable to find any information in the DSSAT and CSM-CERES-Maize documentation to explain this model behavior. Since model developers had provided us with a copy of the CSM-CERES-Maize source code, we were able to trace this model response to the equations which determine partitioning of new root length into the various soil layers. It appears that the model first calculates the amount of new root length which is available each day based on the amount of root biomass which is added. It then calculates what might be called a "favorability factor" for root growth: the proportion of this root length (cm root cm^{-3} of soil) which should go to each soil layer. This proportion is a function of the value of SRGF in each layer, and the calculated water and N stress factors for each layer:

$$\Delta RLV_i = \Delta RL_{Total} \times \frac{SRGF_i \times \min\left(NS_i, WS_i\right)}{\sum\left[SRGF_i \times \min\left(NS_i, WS_i\right) \times DLAYR_i\right]} \quad [4]$$

where ΔRLV$_i$ represents increase in root length (cm) per cm^3 of soil in layer i, ΔRL$_{Total}$ is the increase in root length across all layers (cm root cm^{-2} ground area), SRGF$_i$ denotes the SRGF value in layer i, NS$_i$ represents N stress factor in layer i, WS$_i$ represents soil water stress factor in layer i, and DLAYR$_i$ stands for thickness of layer i (cm). If the root length density in a given layer has reached 4 cm cm^{-3}, then no additional root length is added to this layer. However, this unused root length is not added to any other layer either.

In our simulations of these two treatments, once the second N application was made to treatment N$_{(112, 28\ 0)}$ the calculated favorability factor for root growth increased in the upper layers. Since there was less than 4 cm cm^{-3} of root density in the topmost layer, more roots grew in this layer for this treatment than for treatment N$_{(112,\ 0)}$. However, no more roots were able to grow in layers 2 – 5, in spite of the calculated favorability of these layers for root growth. Since the calculated favorability factor in layers 1 – 5 was lower for treatment N$_{(112,\ 0)}$ than for treatment N$_{(112,28\ 0)}$, this resulted in a higher relative favorability factor for the lower layers and a higher proportion of root growth occurring in the lower layers. For example, on DOY 165, the calculated favorability factor for layer 6 for $N_{(112,280)}$ was 0.039 / 28.842. For $N_{(112,0)}$, this factor was 0.039 / 11.023, which was 2.5 times higher than that of $N_{(112,280)}$. The lower amount of root growth in these lower layers for treatment $N_{(112, 28 0)}$ generated more water stress compared to treatment $N_{(112, 0)}$ during the period of kernel number determination.

In the non-irrigated 2002 field, simulated yields became very flat for all treatments except the one with zero N when the exponential SRGF was used (Figure 10e). It was noticed that the rooting factor in the top four layers determined root growth during the first month. The high value of SRGF in the upper soil layers resulted in rooting depth increasing more quickly than when the optimized values of SRGF were used. This resulted in early overgrowth of both canopy and roots, and exhausted water in those layers more quickly. The early draw-down of water in the first four layers had a bad effect over the whole growing period for all treatments receiving total N of more than 56 kg ha^{-1}. In general, we found that using SRGF values greater than 0.50 in the upper soil layers resulted in more water and N stress during the kernel-setting period.

It is clear that all of the four parameters, N_{init}, ASW, SRGF, and SLPF investigated above needed to be varied in tandem, since a change in one required an adjustment in the others, if yield was to be well-simulated. For these fields, we found that CSM-CERES-Maize was very sensitive to changes in SLPF. During the optimization process, we noticed that a change in SLPF of only 0.01 could result in a substantial change in RMSE. When SLPF was changed from 1.00 to 1.34 in the 2002 irrigated field, the optimal value for ASW decreased from 120% to 96% of the default value, resulting in ASW in the rooting zone of 107.25 mm. Although the 2002 fields possessed different soil types, the same SLPF of 1.34 worked well for both, but a lower value of ASW, i.e. 84.15 mm, was necessary for the non-irrigated field. However, an SLPF of 1.27 and ASW of 100% proved optimal for the 2001 field, which had the same soil type as the irrigated field in 2002. Differences between years might depend partially on differences in weather patterns between years.

CONCLUSIONS

Although we were able to estimate soil parameters which yielded reasonable RMSE and r^2 and slope values for the regression equations, it appears unlikely that the optimized values for SLPF and SRGF are a true reflection of soil physical and chemical characteristics. There is no reason to believe that the soils at this research station in North Carolina are 27 – 34% more fertile that the soils present in field experiments used to develop and validate the CSM-CERES-Maize model. Also, there is nothing about a Norfolk or Goldsboro soil which would suggest that the lower soil layers are more suitable for root growth than the upper layers, as the pattern of SRGF fitted to these fields indicates. Although we were able, after hundreds of thousands of simulations, to adjust soil parameters and obtain good agreement between simulated and observed yields for these fields, SLPF and SRGF were outside reasonable bounds. It appears that these unrealistic values of SLPF and SRGF were required to compensate for problems in the way new root length is distributed among soil layers after a second N application. The root distribution module in CSM-CERES-Maize Version 4.0.2 needs to be re-examined and revised to better simulate root growth and distribution, especially when a second N application is made during the season. Until changes are made in this module, researchers should exercise caution in utilizing the model to predict crop response to split applications of N.

REFERENCES

Abrahamson, D.A., D.E. Radcliffe, J.L. Steiner, M.L. Cabrera, D.M. Endale, and G. Hoogenboom. 2006. Evaluation of the RZWQM model for simulating tile drainage and leached nitrate in the Georgia Piedmont. Agron. J. 98:644-654.

Andales A.A., L.R. Ahuja, and G.A. Peterson. 2003. Evaluation of GPFARM for dryland cropping systems in eastern Colorado. Agron. J. 95:1510-1524.

Andresen, J.A., G. Alagarswamy, C.A. Rotz, J.T. Ritchie, and A.W. LeBaron. 2001. Weather impacts on maize, soybean, and alfalfa production in the great lakes region, 1895–1996. Agron. J. 93:1059-1070.

Asseng, S., N.C. Turner, T. Botwright, and A.G. Condon. 2003. Evaluating the impact of a trait for increased specific leaf area on wheat yields using a crop simulation model. Agron. J. 95:10-19.

Ayars, J., and Y. Gao. 2007. Atmospheric nitrogen deposition to the Mullica River-Great Bay Estuary. Marine Environ. Res. 64:590–600.

Baumhardt, R.L., and T.A. Howell. 2006. Seeding practices, cultivar maturity, and irrigation effects on simulated grain sorghum yield. Agron. J. 98:462-470.

Baumhardt, R.L., J. A. Tolk, T. A. Howell, and W. D. Rosenthal. 2007. Sorghum management practices suited to varying irrigation strategies. Agron. J. 99:665-672.

Bert, F.E., C.E. Laciana, G.P. Podesta, E.H. Satorre, and A.N. Menendez. 2007. Sensitivity of CERES-Maize simulated yields to uncertainty in soil properties and daily solar radiation. Agric. Syst. 94:41–150.

Bowen W.T., J.W. Jones, R.J. Carsky and J.O. Quintana. 1993. Evaluation of the nitrogen submodel of CERES-Maize following legume green manure incorporation. Agron. J. 85:153-159.

Bowman, D. T. 2001. Corn and corn silage 2001. North Carolina measured crop performance. Crop Sci. Res. Rep. No. 195, North Carolina State Univ.

Bowman, D. T. 2002. Corn and corn silage 2002. North Carolina measured crop performance. Crop Sci. Res. Rep. No. 201, North Carolina State Univ.

Bowman, D. T. 2003. Corn and corn silage 2003. North Carolina measured crop performance Crop Sci. Res. Rep. No. 208, North Carolina State Univ.

Broome, S.W. 1969. The efficiency of fertilizer in corn production as influenced by time and method of application and source of nutrient. Dissertation, North Carolina State Univ.

Buol, G.S., G. Wilkerson, and M.C. Sturgill. 2006. CSDB Ver1.0: Database and Software for Managing Data Used by ICASA/DSSAT Crop Models. ASA-CSSA-SSSA 2006 International Meetings Abstracts CD ROM, Abstract 1905b. ASA, Madison, WI.

Cassman, K.G., M.J. Kropff and Y. Zhende. 1994. A conceptual framework for nitrogen management of irrigated rice in high-yield environments. p. 81–96. *In* S.S. Virmani (ed.)

Selected papers from the international rice research conference 1994. International Rice Research Institute. Los Baños, Philippines.

Cavero J., I. Farreb, P. Debaekec and J.M. Faci. 2000. Simulation of maize yield under water stress with the EPICphase and CROPWAT models. Agron. J. 92:679-690.

Clark, H., and J.N. Kremer. 2005. Estimating direct and episodic atmospheric nitrogen deposition to a coastal water body. Marine Environ. Res. 59:349–366.

Edmeades, G.O., and T.B. DayNard. 1979. The relationship between final yield and photosynthesis at flowering in individual maize plants. Can. J. Plant Sci. 59:585-601.

Feng, G,L., A. Meiri, and J. Lettey. 2003. Evaluation of a model for irrigation management under saline conditions: I. Effects on plant growth. Soil Sci. Soc. Am. J. 67:71-76.

Fortin, M., and D.E. Moon. 1999. Errors associated with the use of soil survey data for estimating plant-available water at a regional scale. Agron. J. 91:984-990.

Goulding, K.W.T., N.J. Bailey, N.J. Bradbury, P. Hargreaves, M. Howe, D.W. Murphy, P.R. Poulton, and T.W. Willison. 1998. Nitrogen deposition and its contribution to nitrogen cycling and associated soil processes. New Phytol. 139:49–58.

Hodges, T., D. Botner, C. Sakamoto, and J. Hays Haug. 1987. Using the CERES-Maize model to estimate production for the US Corn Belt. Agric. Forest Meteorol. 45:293-303.

Hoogenboom, G., J.W. Jones, C.H. Porter, P.W. Wilkens, K.J. Boote, W.D. Batchelor, L.A. Hunt, and G.Y. Tsuji (Editors). 2003. Decision Support System for Agrotechnology Transfer Version 4.0. Vol. 1. Univ. of Hawaii, Honolulu, HI.

Hoogenboom, G.J., J.W. Jones, P.W. Wilkens, W.D. Batchelor, W.T. Bowen, L.A. Hunt, N. Pickering, U. Singh, D.C. Godwin, B. Baer, K.J. Boote, J.T. Ritchie, and J.W. White. 1994. Crop models. pp. 95-242. *In* G.Y. Tsuji, G. Uehara, and S. Balas (ed.) DSSAT v3. Vol. 2–2. Univ. of Hawaii, Honolulu.

Hubbard, R.K. and J.M. Sheridan. 1989. Nitrate movement to groundwater in the southeastern Coastal Plain. J. Soil and Water Conserv. 44:20-27.

Jagtap, S.S., F.J. Abamu, and J.G. Kling. 1999. Long-term assessment of nitrogen and variety technologies on attainable maize yields in Nigeria using CERES-Maize. Agric. Syst. 60:77-86.

Jenkinson, D.S., P.R. Poulton, A.E. Johnston, and D.S. Powlson. 2004. Turnover of nitrogen-15-labeled fertilizer in old grassland. Soil Sci. Soc. Am. J. 68:865–875.

Jones, C.A., and J.R. Kiniry. 1986. CERES-Maize, a simulation model of maize growth and development. Texas A&M University Press, College Station.

Jones, J., G. Tsuji, G. Hoogenboom, L. Hunt, P. Thornton, P. Wilkens, D. Imamura, W. Bowen, and U. Singh. 1998. Decision support system for agrotechnology transfer; DSSAT v3. pp. 157-177. *In* G.Y. Tsuji, G. Hoogenboom, P.K. Thornton (eds.) Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. 2003. The DSSAT cropping system model. Eur. J. Agron. 18:235-265.

Kiniry, J.R. and A.J. Bockholt. 1998. Maize and sorghum simulation in diverse Texas environments. Agron. J. 90:682-687.

Kiniry, J.R. and J.R. Williams. 1997. Evaluation of two maize models for nine U.S. locations. Agron. J. 89:421-426.

Kleiss, H.J., F.G. Averette, and R.E. Horton. 1982. Soils of the peanut belt research station, Lewiston, North Carolina. Their technical and usability classification. North Carolina Agric. Res. Service, North Carolina Agric. Ext. Service, North Carolina Dep. Agric. U. S. Dep. Agric., Cooperating.

Kucharik, C.J. and K.R. Brye. 2003. Integrated BIosphere Simulator (IBIS) yield and nitrate loss predictions for wisconsin maize receiving varied amounts of nitrogen fertilizer. J. Environ. Qual. 32:247–268.

Liu, X., X. Ju, Y. Zhang, C. He, J. Kopsch, Z. Fusuo. 2006. Nitrogen deposition in agroecosystems in the Beijing area. Agriculture, Ecosystems and Environment. 113:370–377.

Lizaso, J.I., M.E. Westgate, W.D. Batchelor, and A. Fonseca. 2003. Predicting potential kernel set in maize from simple flowering characteristics. Crop Sci. 43:892-903.

Lizaso, J.I., A.E. Fonseca, and M.E. Westgate. 2007. Simulating source-limited and sink-limited kernel set with CERES-Maize. Crop Sci. 47:2078-2088.

Löffler, C.M., J. Wei, T. Fast, J. Gogerty, S. Langton, M. Bergman, B. Merrill, and M. Cooper. 2005. Classification of maize environments using crop simulation and geographic information systems. Crop Sci. 45:1708-1716.

López-Cedrón, F.X., K.J. Bootec, J. Piñeirob, and F. Sau. 2008. Improving the CERES-maize model ability to simulate water deficit impact on maize production and yield components. Agron. J. 100:296-307.

Miao, Y., D.J. Mulla, W.D. Batchelor, J.O. Paz, P.C. Robert and M. Wiebers. 2006. Evaluating management zone optimal nitrogen rates with a crop growth model. Agron. J. 98:545–553.

NCDA&CS Agricultural Statistics Division, 2007. Statistics - Crops summary. Available at: http://www.agr.state.nc.us/stats/crops/cropsum.html

NRCS (Natural Resources Conservation Service). USDA. 2008. Texture Triangle and Particle-Size Limits of AASHTO, USDA, and Unified Classification Systems (Exhibit 618.08). http://soils.usda.gov/technical/handbook/contents/part618ex.html#ex8. In: Detailed Table of Contents (NSSH).

Pang, X.P., J. Letey, and L. Wu. 1997a. Yield and nitrogen uptake prediction by CERES-Maize model under semiarid conditions. Soil Sci. Soc. Am. J. 61:254-256.

Pang, X.P., J. Letey, and L. Wu. 1997b. Irrigation quantity and uniformity and nitrogen application effects on crop yield and nitrogen leaching. Soil Sci. Soc. Am. J. 61:257-261.

Pang, X.P., S.C. Gupta, J.F. Moncrief, C.J. Rosen, and H.H. Cheng. 1998. Evaluation of nitrate leaching potential in Minnesota glacial outwash soils using the CERES-Maize model. J. Environ. Qual. 27:75-85.

Paz, J.O., W.D. Batchelor, B.A. Babcock, T.S. Covin, and S.D. Logsdon. 1999. Model-based technique to determine variable rate nitrogen for corn. Agric. Syst. 61:69-75.

Pease, J. 2007. Ethanol and corn. Available on-line at: http://www.ext.vt.edu/news/periodicals/fmu/2007-02_03/ethanol.html.

Porter, C. H., J. W. Jones, G. Hoogenboom. 2004. Chapter 3: DSSAT v4 DSSAT model comparison utility (CropTest). *In:* James W. Jones, Gerrit Hoogenboom, Paul W. Wilkens, Cheryl H. Porter, Gordon Y. Tsuji. DSSAT v4, A Decision Support System for Agrotechnology Transfer, Volume 3, ICASA Tools. International Consortium for Agricultural Systems Applications. University of Hawaii.

Rawls, W.J., and D.L. Brakensiek. 1985. Prediction of soil water properties for hydrologic modeling. p.293-299. *In* E.B. Jones, and T.J. Ward (eds.) Proc. Symp. watershed management in the eighties. April 30-May 1, 1985, Denver, CO. Am. Soc. Civil Eng., New York, NY.

Rawls, W.J., D.L. Brakensiek, and K.E. Saxton. 1982. Estimation of soil water properties. Trans. ASAE 25:1316-1328.

Retta, A., R.L. Vanderlip, R.A. Higgins, and L.J. Moshier. 1996. Application of SORKAM to simulate shattercane growth using forage sorghum. Agron. J. 88:596-601.

Ritchie, J.T., U. Singh, D.C. Godwin, and W.T. Bowen. 1998. Cereal growth, development and yield. p. 79–98. *In* G.Y. Tsuji, G. Hoogenboom, P.K. Thornton, (eds.) Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Ritchie, S.W., and J.J. Hanway. 1982. How a corn plant develops. Spec. Rep. 48 (Rev. Feb. 1982). Iowa State Univ Coop. Ext. Service, Ames, IA.

Saseendran, S.A., L. Ma, D.C. Nielsen, M.F. Vigil, and L.R. Ahuja. 2005. Simulating planting date effects on corn production using RZWQM and CERES-Maize models. Agron. J. 97:58-71.

Sau, F., K.J. Boote, W.M. Bostick, J.W. Jones, and M.I. Minguez. 2004. Testing and improving evapotranspiration and soil water balance of the DSSAT crop models. Agron. J. 96:1243–1257.

Saxton, K.E., W.J. Rawls, J.S. Romberger, and R.I. Papendick. 1986. Estimating generalized soil water characteristics from texture. Soil Sci. Soc. Am. J. 50(4):1031–1036.

Schnitkey, G. 2007. Projected 2007 corn acres. *In*: Illinois farm economics: facts and opinions. Dept. Agric. and Consumer Econ., College of Agric., Consumer and Environ. Sci., Univ. of Illinois at Urbana-Champaign. Available on-line at: http://www.farmdoc.uiuc.edu/manage/newsletters/fefo07_07/fefo07_07.html.

Sinclair, T.R., and R.C. Muchow. 2001. System analysis of plant traits to increase grain yield on limited water supplies. Agron. J. 93:263-270.

Smart, J.R., A. Weiss, and D.A. Mortensen. 1993. Modeling the influence of postdirected sethoxydim on corn yields. Agron. J. 85:1204-1209.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. 2004. Official Soil Series Descriptions. Available on-line at: http://soils.usda.gov/technical/classification/osd/index.html.

Sripada, R.P., R.W. Heiniger, J.G. White, and R. Weisz. 2005. Aerial color infrared photography for determining late-season nitrogen requirements in corn. Agron. J. 97:1443–1451.

Sripada, R.P., R.W. Heiniger, J.G. White, and A.D. Meijer. 2006. Aerial color infrared photography for determining early in-season nitrogen requirements in corn. Agron. J. 98:968–977.

Swaney, D.P., J.W. Jones, W.G. Boggess, G.G. Wilkerson, and J.W. Mishoe. 1983. Real time irrigation decision analysis using simulation. Trans. ASAE. 26:562-568.

Thornton, P.K., and J.F. MacRobert. 1994. The value of information concerning near-optimal nitrogen fertilizer scheduling. Agric. Syst. 45:315-330.

Tsuji, G.Y., G. Uehara, and S. Balas. 1994. Decision Support System for Agrotechnology Transfer (DSSAT) Version 3, Vol. 2. University of Hawaii, Honolulu, Hawaii.

Uryasev, O., J.W. Jones, M. Medany, G. Hoogenboom, S. Irmak, and C. Porter. 2004. Chapter 1: DSSAT v4 Introductory Crop Simulation Tool (ICSIM). *In:* James W. Jones, Gerrit Hoogenboom, Paul W. Wilkens, Cheryl H. Porter, Gordon Y. Tsuji. DSSAT v4, A Decision Support System for Agrotechnology Transfer, Volume 3, ICASA Tools. International Consortium for Agricultural Systems Applications. University of Hawaii.

Vigil, M.F., D.E. Kissel, and S.J. Smith. 1991. Field crop recovery and modeling of nitrogen mineralized from labeled sorghum residues. Soil Sci. Soc. Am. J. 55:1031-1037.

Vigil, M.F., and D.E. Kissel. 1995. Rate of nitrogen mineralized from incorporated crop residues as influenced by temperature. Soil Sci. Soc. Am. J. 59:1636-1644.

Weigel, A., R. Russow, and M. Kerschens. 2000. Quantification of airborne N-input in long-term field experiments and its validation through measurements using ^{15}N isotope dilution. J. Plant Nutr. and Soil Sci. 163:229-333.

Wilkens, P.W., G. Hoogenboom, C. Porter, J.W. Jones, O. Uryasev. 2004. DSSAT v4, A Decision Support System for Agrotechnology Transfer, Volume 2, DSSAT v4, Data Management and Analysis Tools. International Consortium for Agricultural Systems Applications. University of Hawaii.

Xie, Y., J.R. Kiniry, V. Nedbalek, and W.D. Rosenthal. 2001. Maize and Sorghum Simulations with CERES-Maize, SORKAM, and ALMANAC under water-limiting conditions. Agron. J. 93:1148–1155.

Yang, Z.Y., G.G. Wilkerson, G.S. Buol, and D.T. Bowman, R. Heiniger. 2008. Calibrating the CSM-CERES-Maize model for simulating yield under non-limiting nitrogen conditions in North Carolina environments. (In review)

Table 1. Field descriptions for the experimental sites in Lewiston, North Carolina in 2001 and 2002.

Year	Soil series	Soil taxonomic classification	Irrigation strategy†	N rates First	N rates Second	N timing‡
				------------kg ha^{-1}	------------	
2001	Norfolk sandy loam	fine-loamy, siliceous, thermic Typic Paleudults	none, normal, and twice normal	0, 112, 168, 224	0, 112, 168, 224	planting, V_T
2002	Goldsboro-Lynchburg loamy sand	fine-loamy, siliceous, thermic, Aquic Paleudults	none	0, 56, 112, 224	0, 56, 112, 224, 280	planting, V_7
2002	Norfolk sandy loam	fine-loamy, siliceous, thermic Typic Paleudults	normal	0, 56, 112, 224	0, 56, 112, 224, 280	planting, V_7

† The normal irrigation in 2001 occurred weekly from June 26 to July 16, and the twice normal irrigation occurred twice weekly.

‡ The first nitrogen application was scheduled at planting for all fields. The second nitrogen application was at visual tasseling (V_T) in 2001 or at layby (V_7) in 2002.

Table 2. Soil parameter definitions, units, and values used in CSM-CERES-Maize.

Parameter	Unit	Definition
SLPF		Soil fertility factor, used to adjust for nutrients besides N
N_{init}	g N Mg^{-1} soil	Soil N content at start of simulation, including both ammonium and nitrate
SLLL	cm^3 cm^{-3}	Volumetric soil water content, lower limit at 1500 kPa
SDUL	cm^3 cm^{-3}	Volumetric soil water content, drained upper limit at 33 kPa
SSAT	cm^3 cm^{-3}	Volumetric soil water content at saturation
SRGF		Root growth factor
SSKS	cm h^{-1}	Saturated hydraulic conductivity
SBDM	g cm^{-3}	Moist bulk density
SLOC	%	Organic carbon
SLCL	%	Clay fraction (<.002 mm)
SLSI	%	Silt fraction (.002 to .05 mm)
SLHW		pH in water

Table 3. Initial Norfolk sandy loam soil profile used for the 2001 field and the 2002 irrigated field in Lewiston, North Carolina.

Layer	SLB†	SLLL‡	SDUL‡	SSAT‡	SRGF‡	SKSS‡	SBDM‡	SLOC‡	SLCL‡	SLSI‡	SLHW‡
	cm	------------ $cm^3\ cm^{-3}$		-----------	0 to 1	$cm\ h^{-1}$	$g\ cm^{-3}$	-------------- %		----------------	
1	5	0.076	0.160	0.388	1.000	4.1	1.62	0.64	8.0	10.0	5.8
2	15	0.076	0.160	0.388	1.000	4.1	1.62	0.64	8.0	10.0	5.8
3	30	0.076	0.160	0.388	0.638	4.1	1.62	0.17	8.0	10.0	5.7
4	45	0.110	0.200	0.430	0.472	1.3	1.51	0.09	15.0	13.0	5.6
5	60	0.142	0.239	0.461	0.350	0.5	1.43	0.09	23.0	15.0	5.0
6	75	0.142	0.239	0.461	0.259	0.5	1.43	0.09	23.0	15.0	5.0
7	90	0.142	0.239	0.461	0.192	0.5	1.43	0.09	23.0	15.0	4.8
8	105	0.159	0.257	0.473	0.142	0.4	1.40	0.09	27.0	15.0	4.8
9	120	0.159	0.257	0.473	0.105	0.4	1.40	0.06	27.0	15.0	4.8
10	135	0.159	0.257	0.473	0.078	0.4	1.40	0.06	27.0	15.0	4.7

† Soil depth to layer base.

‡ Defined in Table 2.

Table 4. Initial Goldsboro-Lynchburg loamy sand soil profile, used for the 2002 non-irrigated field in Lewiston, North Carolina.

Layer	SLB†	SLLL‡	SDUL‡	SSAT‡	SRGF‡	SKSS‡	SBDM‡	SLOC‡	SLCL‡	SLSI‡	SLHW‡
	cm	------------ $cm^3\ cm^{-3}$		-----------	0 to 1	$cm\ h^{-1}$	$g\ cm^{-3}$	------------ %		------------	
1	5	.110	0.20	0.430	1.000	1.31	1.51	0.64	15.0	13.0	5.8
2	15	.110	0.20	0.430	1.000	1.31	1.51	0.64	15.0	13.0	5.8
3	30	.110	0.20	0.430	0.638	1.31	1.51	0.17	15.0	13.0	5.7
4	45	.142	0.239	0.461	0.472	0.51	1.43	0.09	23.0	15.0	5.6
5	60	.159	0.257	0.473	0.350	0.35	1.40	0.09	27.0	15.0	5.0
6	75	.171	0.28	0.484	0.259	0.29	1.37	0.09	30.0	20.0	5.0
7	90	.171	0.28	0.484	0.192	0.29	1.37	0.09	30.0	20.0	4.8
8	105	.171	0.28	0.484	0.142	0.29	1.37	0.09	30.0	20.0	4.8
9	120	.171	0.28	0.484	0.105	0.001	1.37	0.06	30.0	20.0	4.8
10	135	.171	0.28	0.484	0.078	0.0	1.37	0.06	30.0	20.0	4.7

† Soil depth to layer base.

‡ Defined in Table 2.

Table 5. Distribution of initial soil nitrogen (50 kg ha^{-1}) in all three fields for starting simulations.

Layer base depth	Ammonium (KCL)	Nitrate (KCL)
cm	---------- g N Mg^{-1} soil ----------	
5	0.3	2.0
15	0.7	4.2
30	1.2	6.2
45	1.4	3.7
60	1.4	4.2

To distribute the initial soil N across layers: In each layer, the sum of ammonium and nitrate was multiplied by the thickness of the layer, the number of cubic centimeters of soil in this layer across one hectare, and the soil bulk density. For example: for the second layer from 5 cm to 15 cm, the sum of ammonium and nitrate is 4.9 g N Mg^{-1} soil. This is multiplied by the layer thickness of 10 cm and by 100,000,000 cm^2 $hectare^{-1}$, and by the bulk density of 1.51 g cm^{-3} from Table 4, generating 7399 g N. Accumulating across layers results in 48.8 kg N.

Table 6. Parameter values which were tried in the optimization procedure for the 2002 irrigated field.

	Parameter set 1	Parameter set 2	Parameter set 3	Parameter set 4
SLPF	1.0	1.0	1.22 - 1.36	1.34
ASW	80, 90, 100, 110, 120%	120%	120%	92, 96, 100, 104, 108%
N_{init}	70, 80, 90 kg ha^{-1}	70 kg ha^{-1}	70 kg ha^{-1}	65, 70, 75, 80 kg ha^{-1}
SRGF				
5 cm	0.1, 0.3, 0.5, 0.7, 0.9	0.1	0.1	0.1
15 cm	0.1, 0.3, 0.5, 0.7, 0.9	0.1	0.1	0.1
30 cm	0.0, 0.1, 0.3, 0.5, 0.7, 0.9	0.1	0.1	0.1
45 cm	0.0, 0.1, 0.3, 0.5, 0.7, 0.9	0.1	0.1	0.1
60 cm	0.0, 0.1, 0.3, 0.5, 0.7	0.6, 0.7, 0.8, 0.9	0.1, 0.15, 0.2, 0.25, 0.3	0.15, 0.2
75 cm	0.0, 0.1, 0.3, 0.5, 0.7	0.6, 0.7, 0.8, 0.9	0.0, 0.2, 0.4, 0.6, 0.8	0.4, 0.6, 0.8
90 cm	0.0, 0.1, 0.2, 0.3, 0.4	0.4; 0.5; 0.6; 0.7; 0.8	0.0, 0.2, 0.4, 0.6, 0.8	0.2, 0.4, 0.5, 0.6, 0.8
105 cm	0.0, 0.1, 0.2, 0.3, 0.4	0.4; 0.5; 0.6; 0.7; 0.8	0.0, 0.2, 0.4, 0.6, 0.8	0.2, 0.4, 0.5, 0.6, 0.8
120 cm	0.0, 0.1, 0.2, 0.3, 0.4	0.4; 0.5; 0.6; 0.7; 0.8	0.0, 0.2, 0.4, 0.6, 0.8	0.4, 0.6, 0.8
135 cm	0.0, 0.1, 0.2, 0.3, 0.4	0.4; 0.5; 0.6; 0.7; 0.8	0.0	0.0

Table 7. Results of the optimization process for the three fields in Lewiston, North Carolina.

Condition and setting	Field	r^2	Slope	Intersect	RMSE	RRMSE
				----- kg ha^{-1}-----		%
Default setting	2001 field	0.7	1.02	1043	1826	17.54
	2002 irrigated field	0.1	0.75	3936	3272	38.38
	2002 non-irrigated field	0.1	-0.3	5041	2661	59.09
Parameter set 1	2002 irrigated field	0.7	1.22	-774	1697	19.9
Parameter set 2	2002 irrigated field	0.9	0.94	250	940	11.03
Parameter set 3	2002 irrigated field	0.9	1	197	749	8.78
Optimized parameters (Parameter set 4)	2002 irrigated field	0.9	0.93	647	665	7.8
	2002 non-irrigated field	0.8	0.91	400	334	7.42
	2001 field	0.9	0.89	1012	851	8.17
Optimized parameters, but with starting SRGF†	2001 field	0.9	0.89	1012	1588	15.25
	2002 irrigated field	0.9	0.93	647	1191	13.97
	2002 non-irrigated field	0.8	0.91	400	983	21.83

Table 7 (continued).

Condition and setting	Field	r^2	Slope	Intersect	RMSE	RRMSE
				----- kg ha^{-1} -----		%
Optimized parameters, but with starting SDUL†	2001 field	0.9	0.89	1012	851	8.17
	2002 irrigated field	0.9	0.93	648	675	7.92
	2002 non-irrigated field	0.7	0.55	1285	1437	31.91
Optimized parameters, but with starting N_{init}‡	2001 field	0.9	0.78	2652	1150	11.04
	2002 irrigated field	0.9	0.91	1031	929	10.9
	2002 non-irrigated field	0.7	0.53	2038	640	14.21
Optimized parameters, but with starting SLPF†	2001 field	0.8	1.14	422	2048	19.67
	2002 irrigated field	0.7	1.69	-2643	2472	28.99
	2002 non-irrigated field	0.6	1.91	-1233	1575	34.98

† SLPF, SRGF and SDUL were defined in table 2.

‡ N_{init}: Soil nitrogen at initial soil condition, also refers to Table 5.

Table 8.The optimized settings for the three fields in Lewiston, North Carolina.

Field	Simulation step	N_{init}‡	SLPF†	SW†	SRGF†
		kg ha^{-1}		%	
2001 field	Starting	50	1.00	100	1.0,1.0,0.64,0.47,0.35,0.26,0.19,0.14,0.11,0.08
2002 irrigated field	Starting	50	1.00	100	1.0,1.0,0.64,0.47,0.35,0.26,0.19,0.14,0.11,0.08
2002 non-irrigated field	Starting	50	1.00	100	1.0,1.0,0.64,0.47,0.35,0.26,0.19,0.14,0.11,0.08
2002 irrigated field	Parameter Set 1	70	1.00	120	0.1, 0.1, 0.1, 0.1, 0.7, 0.7, 0.4, 0.4, 0.4, 0.4
2002 irrigated field	Parameter Set 2	70	1.00	120	0.1, 0.1, 0.1, 0.1, 0.6, 0.6, 0.4, 0.4, 0.5, 0.4
2002 irrigated field	Parameter Set 3	70	1.34	120	0.1, 0.1, 0.1, 0.1, 0.2, 0.4, 0.2, 0.2, 0.8
2001 field	Optimized	75	1.27	100	0.1, 0.1, 0.1, 0.1, 0.2, 0.35, 0.5, 0.8
2002 irrigated field	Optimized (Parameter Set 4)	75	1.34	96	0.1, 0.1, 0.1, 0.1, 0.15, 0.4, 0.2, 0.4, 0.8
2002 non-irrigated field	Optimized	75	1.34	80	0.1, 0.1, 0.5, 0.5, 0.3, 03, 0.9, 0.9

† SLPF, SRGF and SDUL were defined in table 2.

‡ N_{init}: Soil nitrogen at initial soil condition, also refers to Table 5.

Table 9.Comparison between simulations using the optimized soil parameters and. simulations using the optimized parameter set except for SRGF† being set to the exponential (default) setting, for treatments $N_{(112, 0)}$ and $N_{(112,28 0)}$ for the 2002 irrigated field.

		Optimized setting but with starting SRGF		Optimized setting (include optimized SRGF)	
Parameters	DOY‡	$N_{(112,0)}$ §	$N_{(112,280)}$ ¶	$N_{(112,0)}$ §	$N_{(112,280)}$ ¶
WSPDAvg4#	175~183	0.126	0.205	0.114	0.102
WSPDAvg††	99-222	0.136	0.198	0.146	1.141
LAIDAvg4‡‡	175-183	2.351	2.317	2.003	2.352
LAIDAvg §§	99-222	1.412	1.470	1.158	2.090
Grain number	184	5064	4581	3442	5206
Measured yield	222	9612	8558	6966	10254

† Soil Root Growth Factor, refers to Table 3.

‡ DOY: Day of year.

Table 9 (continued).

§ $N_{(112,0)}$: First N application of 112 kg ha^{-1} at planting, second N application of 0 kg ha^{-1} at layby (V_7).

¶ $N_{(112,280)}$: First N application of 112 kg ha^{-1} at planting, second N application of 280 kg ha^{-1} at V_7.

WSPDAvg4: Average water stress in photosynthesis during flowering.

†† WSPDAvg: Average water stress factor for photosynthesis during whole growing season,.

‡‡ LAIDAvg4: Average leaf area index during flowering.

§§ LAIDAvg: Average leaf area index during whole growing season.

List of Figures

Figure 7. Comparison of simulated and observed yields for the 2001 field in Lewiston, NC using the optimized soil parameters: a) all N treatments with 1:1 and trend lines, and b) non-irrigated N treatments grouped by total amount of N applied, c) treatments with normal irrigation grouped by total amount of N applied, and d) treatments with twice-normal irrigation grouped by total amount of N applied.

Figure 8. Comparison of simulated and observed yields using optimized soil profile settings, except with SLPF=1.0, with treatments grouped by total amount of N applied for the a) irrigated and b) non-irrigated field in 2002.

Figure 9. Comparison of the default (exponential), and optimized rooting factors (SRGF) for the irrigated field in 2002, North Carolina, Lewiston station.

Figure 10. Comparison of simulated and observed yields using optimized soil profile settings, except for using the default SRGF setting, with treatments grouped by total amount of N applied for the a) non-irrigated treatments in 2001, b) normally-irrigated treatments in 2001, c) twice-normally irrigated treatments in 2001, d) irrigated field in 2002, and e) the non-irrigated field in 2002.

Figure 11. Comparison between a) the water stress factor WSPD, and b) the simulated root length density in the 6th soil layer for treatments $N(_{112,0})$ and $N(_{112,\ 280})$, in simulations using an exponential rooting factor (SRGF) with all other soil parameters set to the optimized values for the irrigated field of 2002.

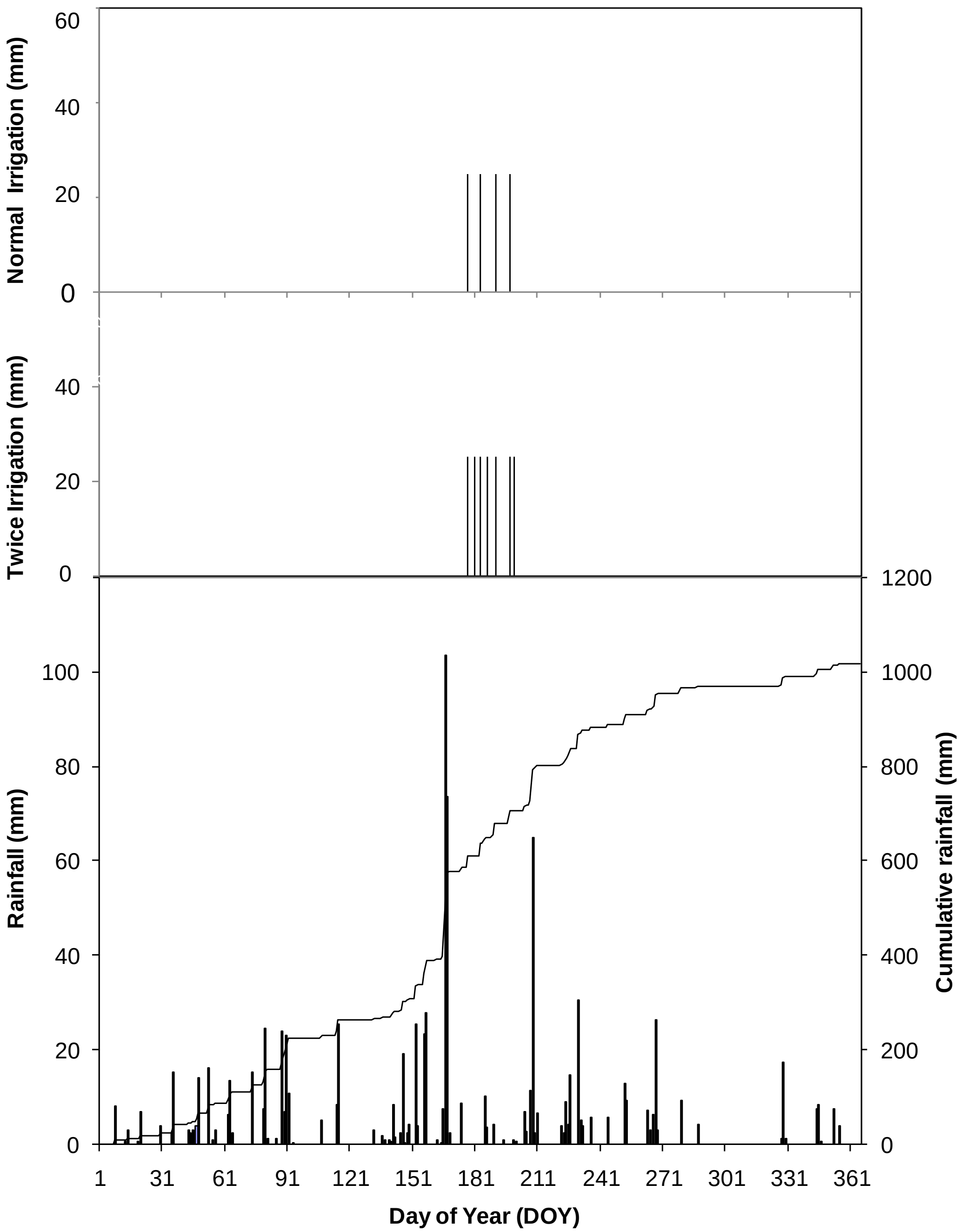


Figure 1. Rainfall and irrigation amounts for the field in Lewiston, NC in 2001: a) irrigation amounts for the normal-irrigation treatments, b) irrigation amounts for the twice-normal irrigation treatments, and c) daily rainfall amounts and cumulative rainfall.

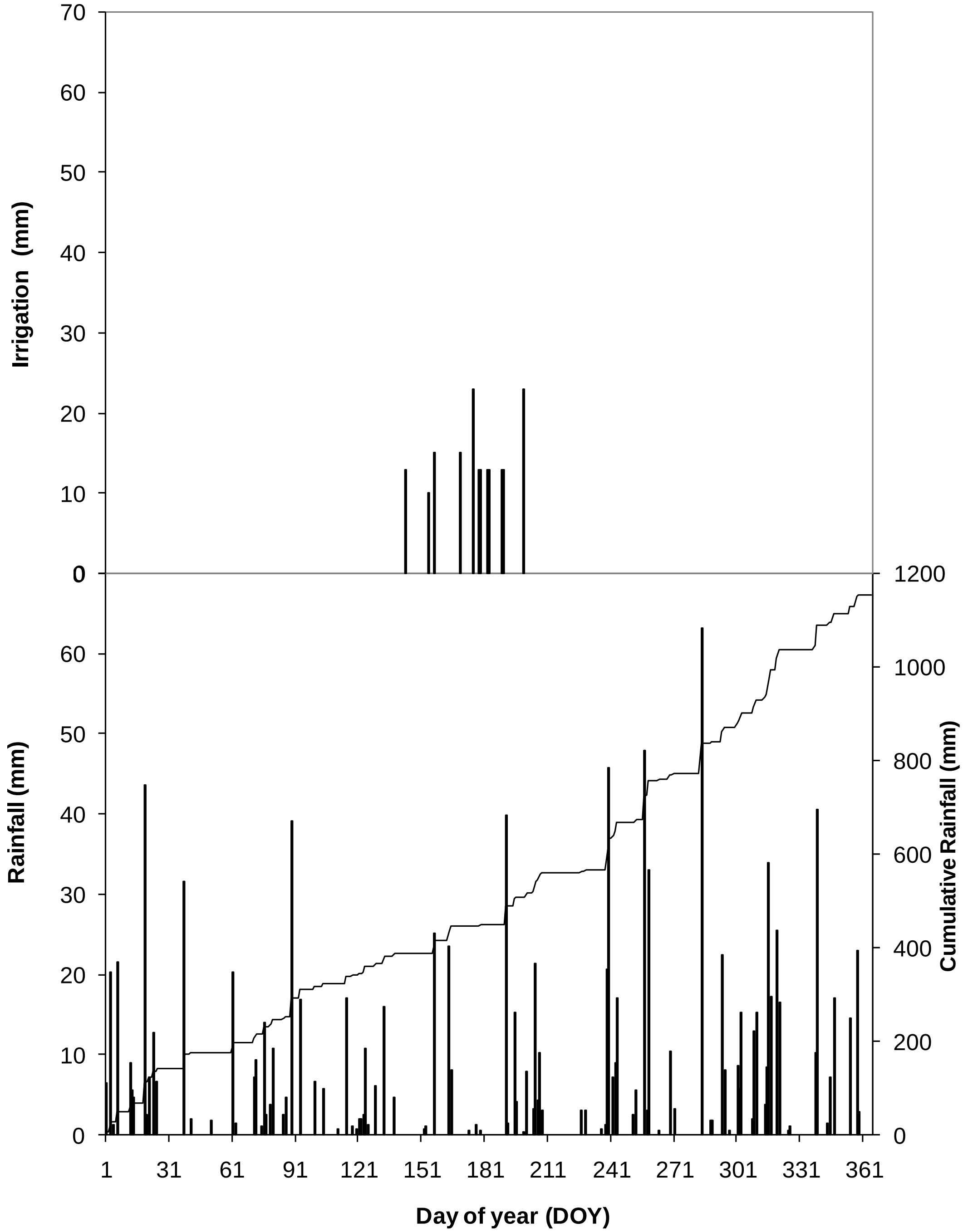


Figure 2. Rainfall and irrigation amounts for the field in Lewiston, NC in 2002. a) irrigation amounts for the irrigated treatments, and b) daily rainfall amounts and cumulative rainfall.

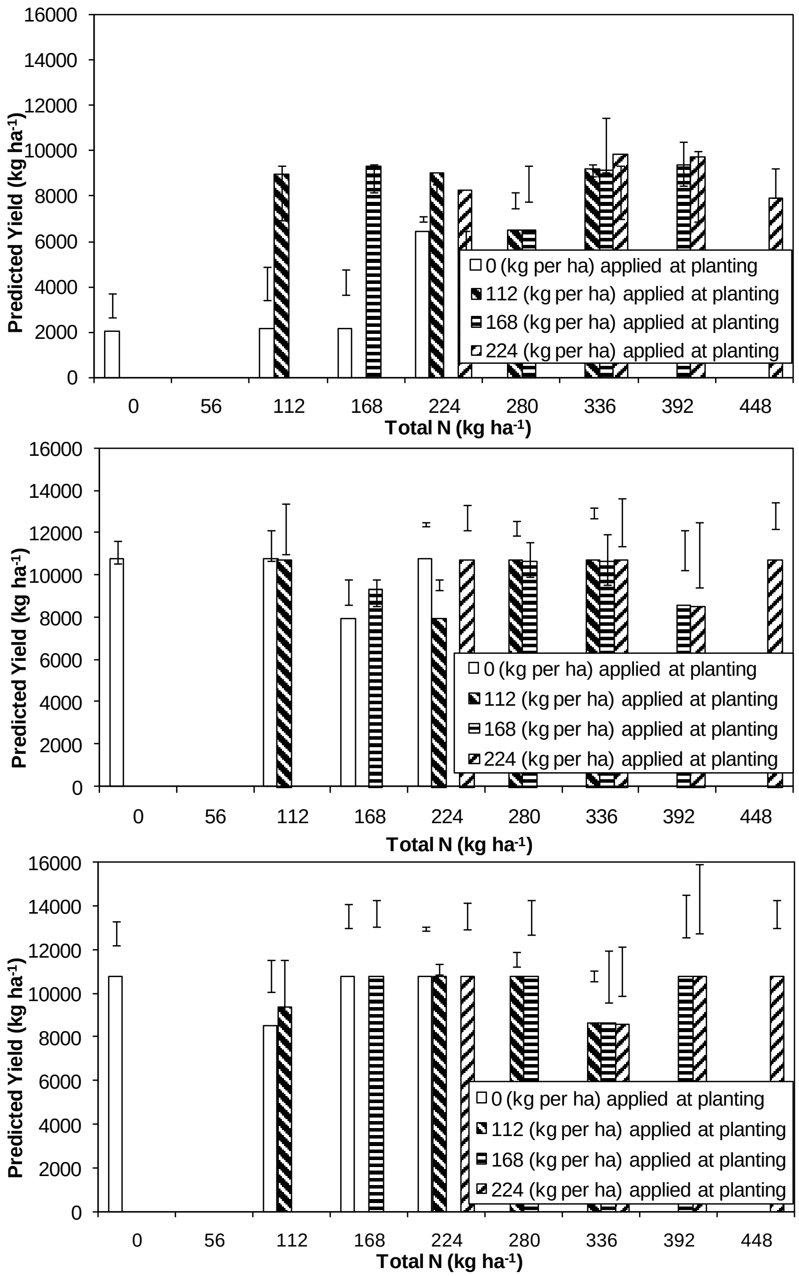


Figure 3. Comparison between simulated and measured yields using the initial (default) soil parameters for the three fields in Lewiston, NC: a) non-irrigated treatments in 2001, b) treatments receiving normal irrigation amounts in 2001, c) treatments receiving twice-normal irrigation amounts in 2001.

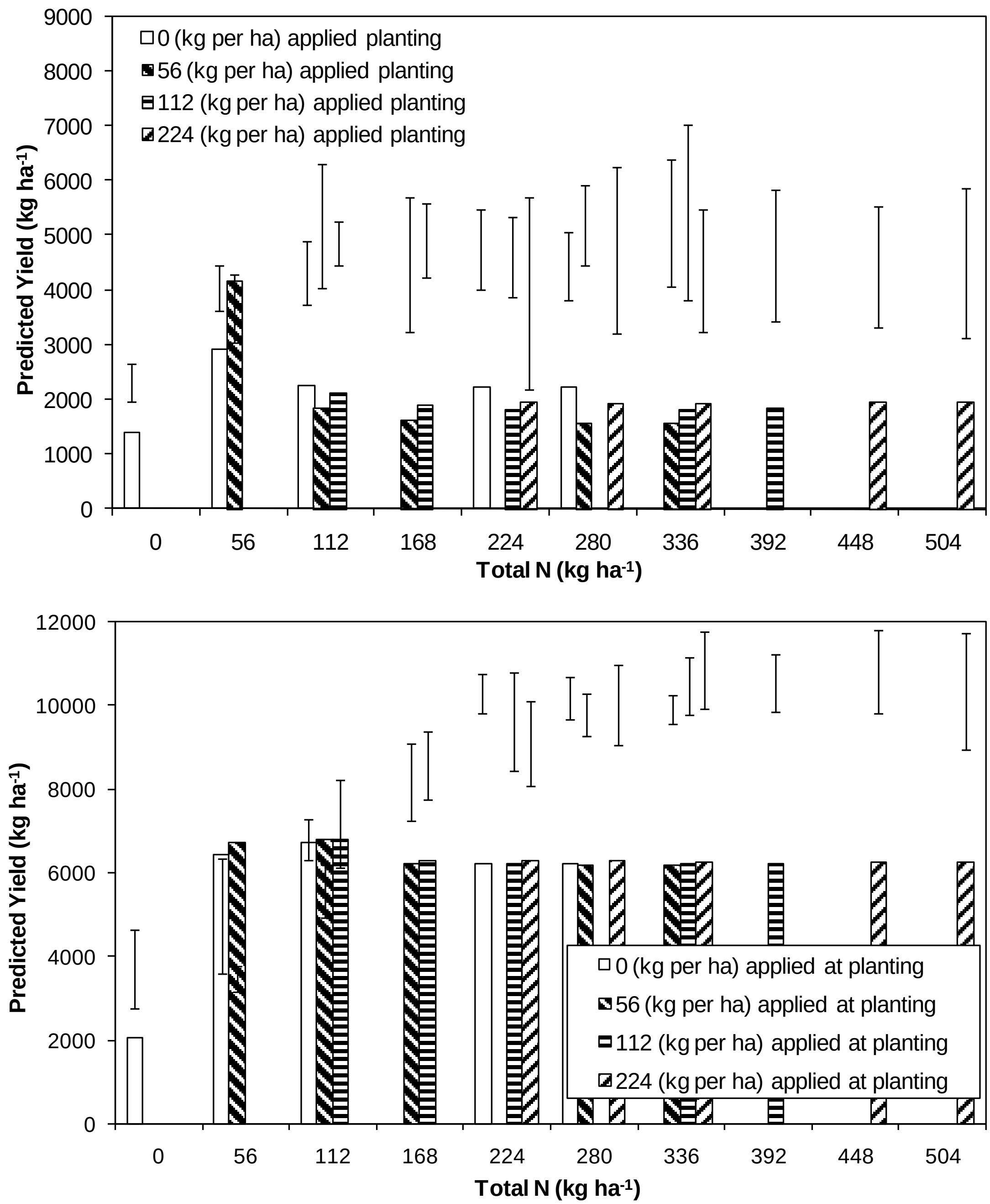


Figure 3. Comparison between simulated and measured yields using the initial (default) soil parameters for the three fields in Lewiston, NC: d) non-irrigated field in 2002, and e) irrigated field in 2002.

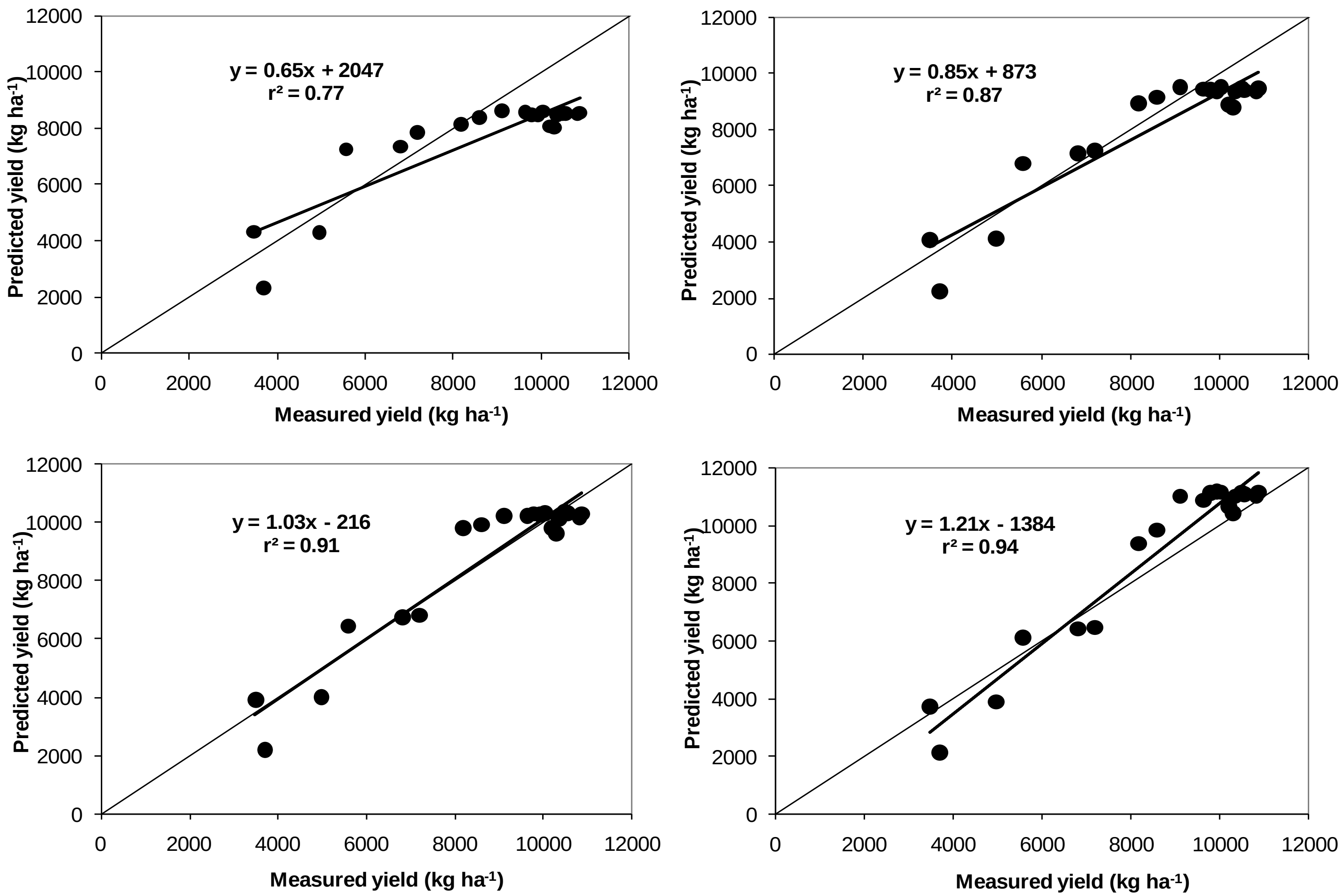
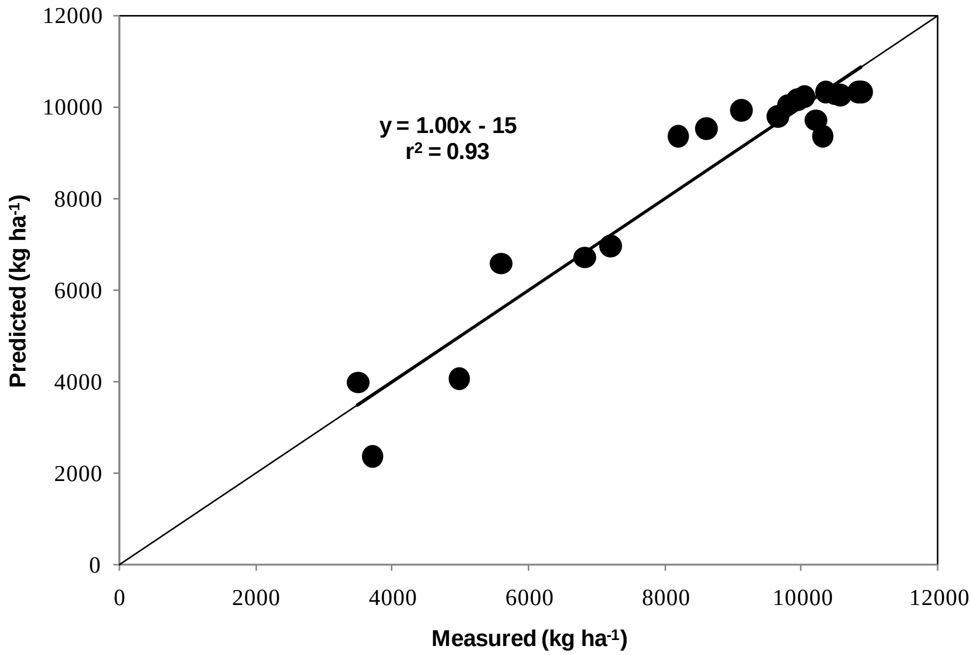


Figure 4. Comparison between simulated and observed yields for the 2002 irrigated field using the preliminary set of optimized parameters (Table 7) and SLPF values of: a) 1.1, b) 1.2, c) 1.3, and d) 1.4.



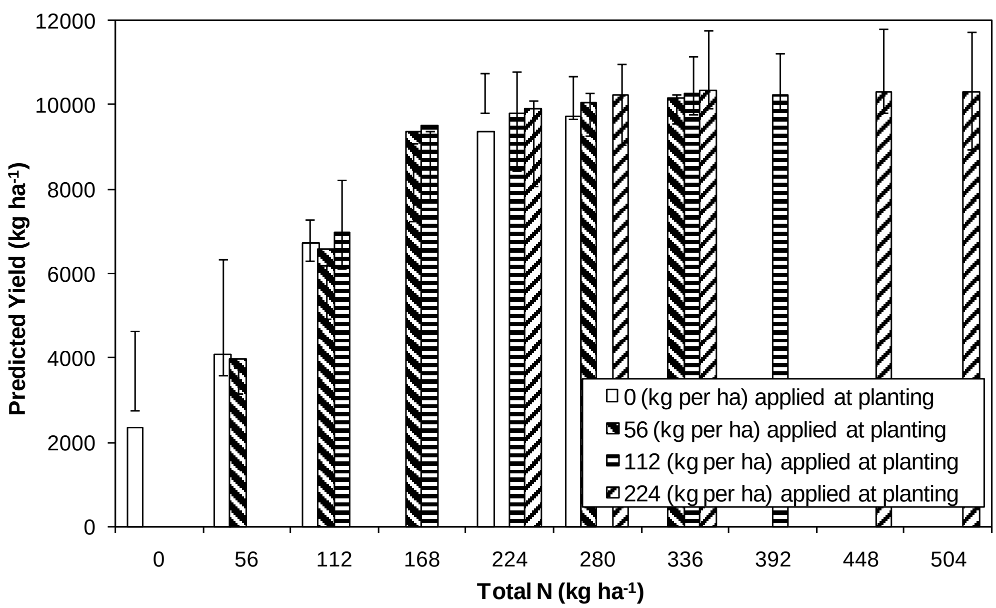
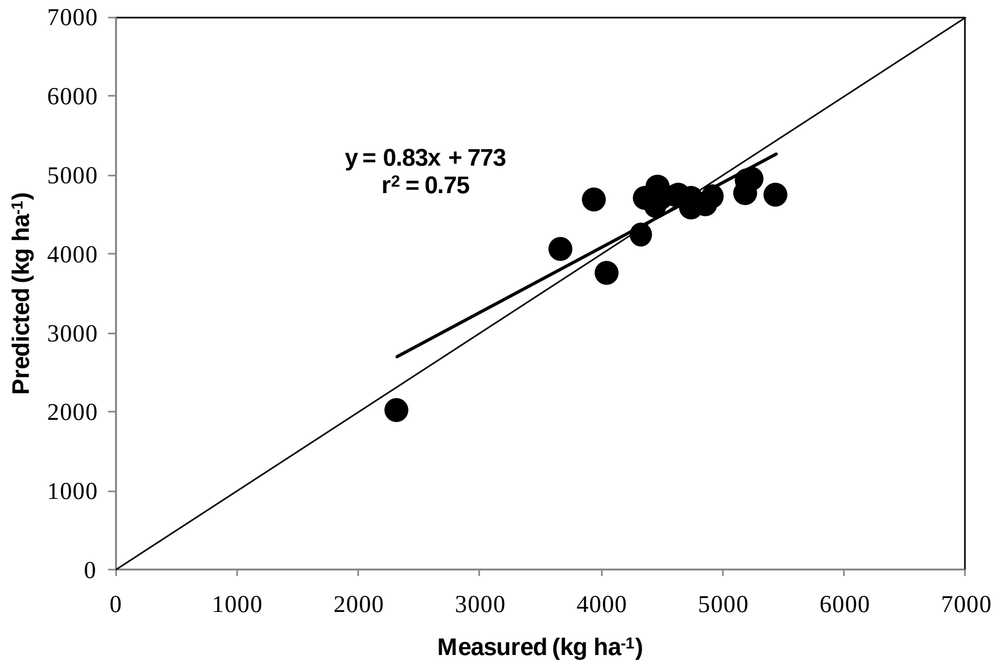


Figure 5. Comparison of simulated and observed yields for the 2002 irrigated field in Lewiston, NC using the optimized soil parameters: a) all N treatments with 1:1 and trend lines, and b) treatments grouped by total amount of N applied.



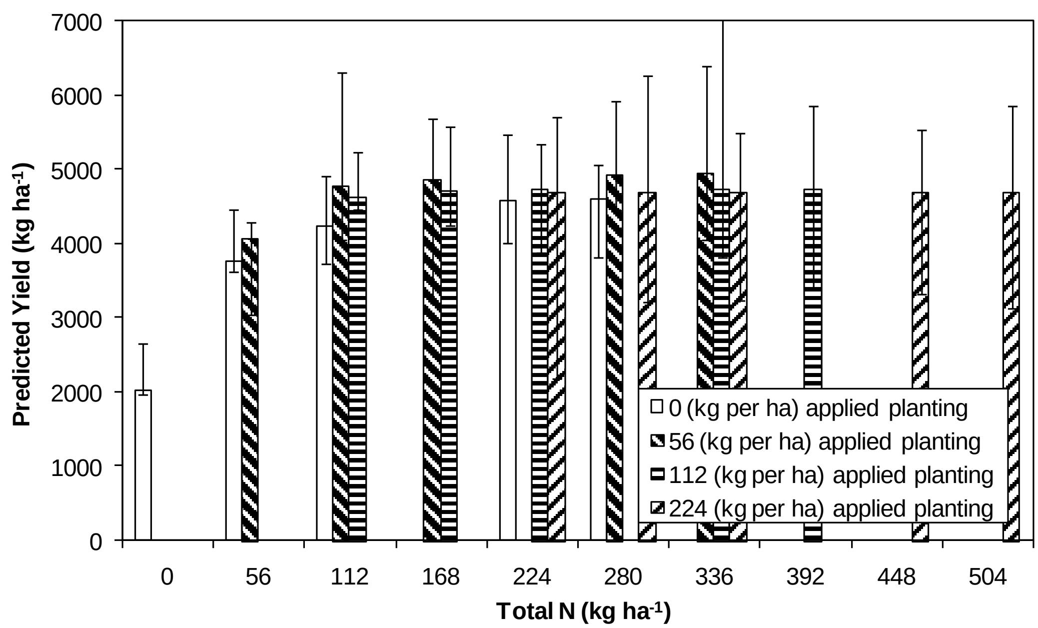
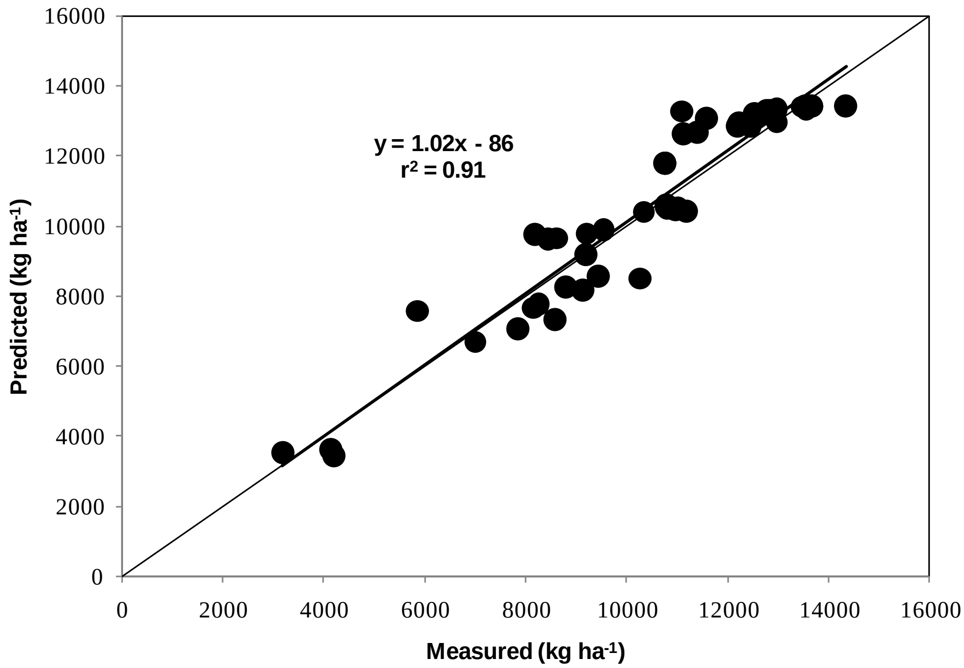


Figure 6. Comparison of simulated and observed yields for the 2002 non-irrigated field in Lewiston, NC using the optimized soil parameters: a) all N treatments with 1:1 and trend lines, and b) treatments grouped by total amount of N applied.



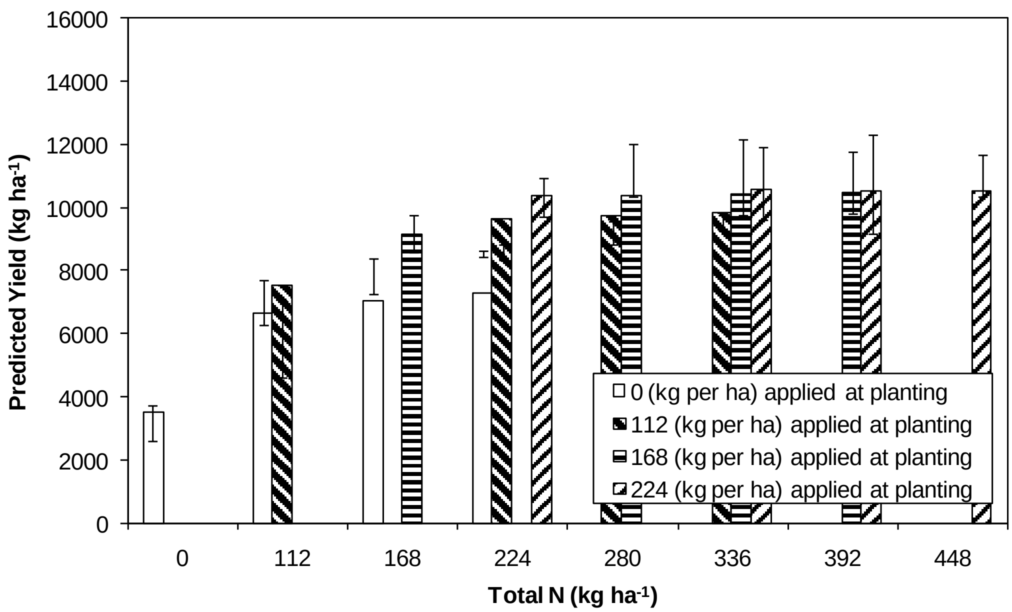


Figure 7. Comparison of simulated and observed yields for the 2001 field in Lewiston, NC using the optimized soil parameters: a) all N treatments with 1:1 and trend lines, and b) non-irrigated N treatments grouped by total amount of N applied.

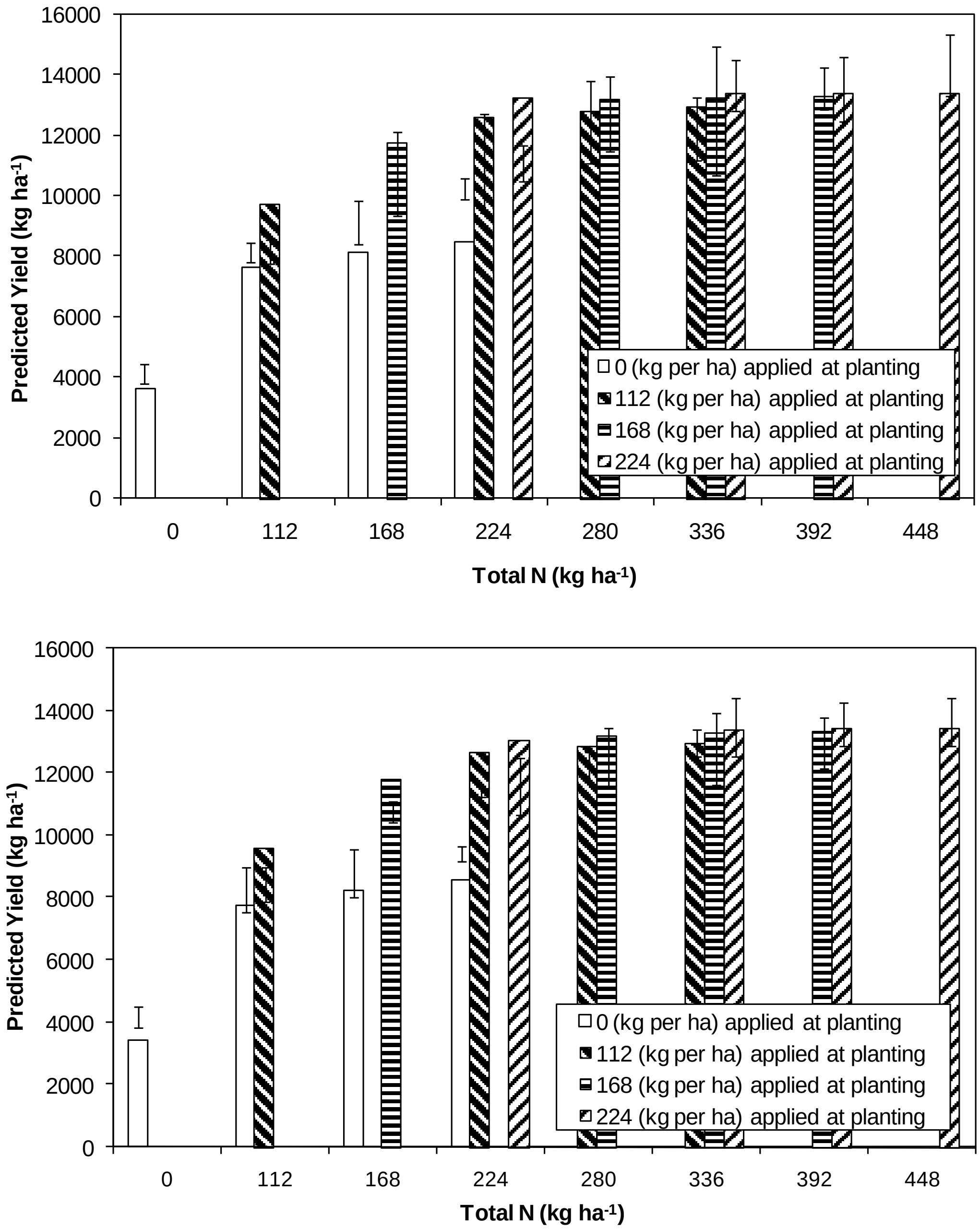


Figure 7. Comparison of simulated and observed yields for the 2001 field in Lewiston, NC using the optimized soil parameters: c) treatments with normal irrigation grouped by total amount of N applied, and d) treatments with twice-normal irrigation grouped by total amount of N applied.

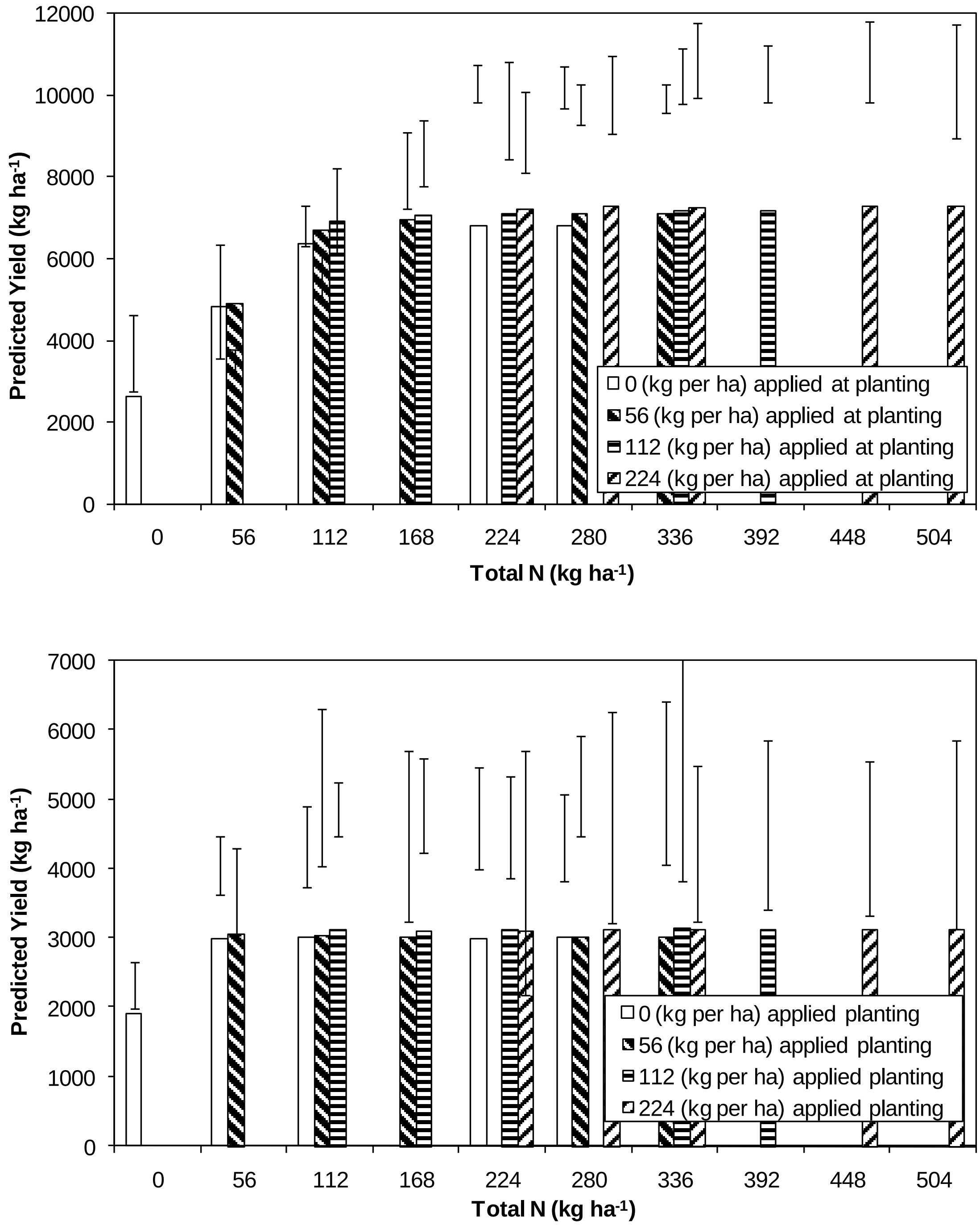
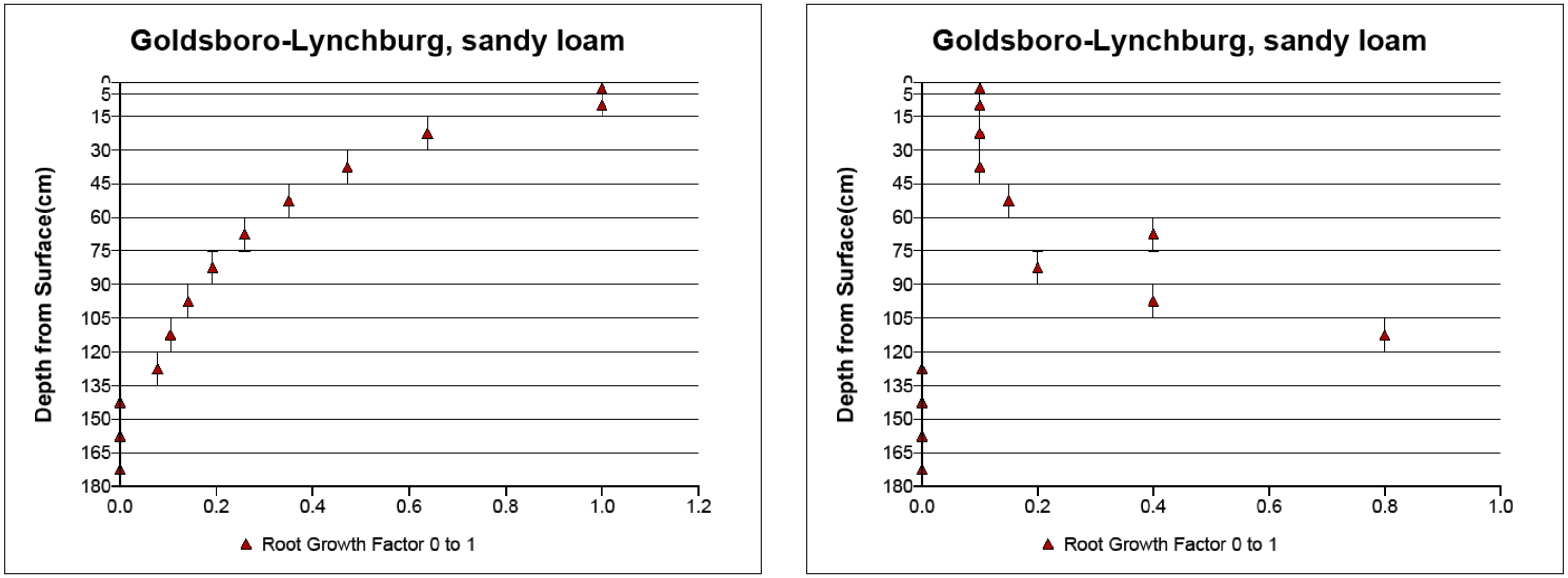


Figure 8. Comparison of simulated and observed yields using optimized soil profile settings, except with SLPF=1.0, with treatments grouped by total amount of N applied for the a) irrigated and b) non-irrigated field in 2002.



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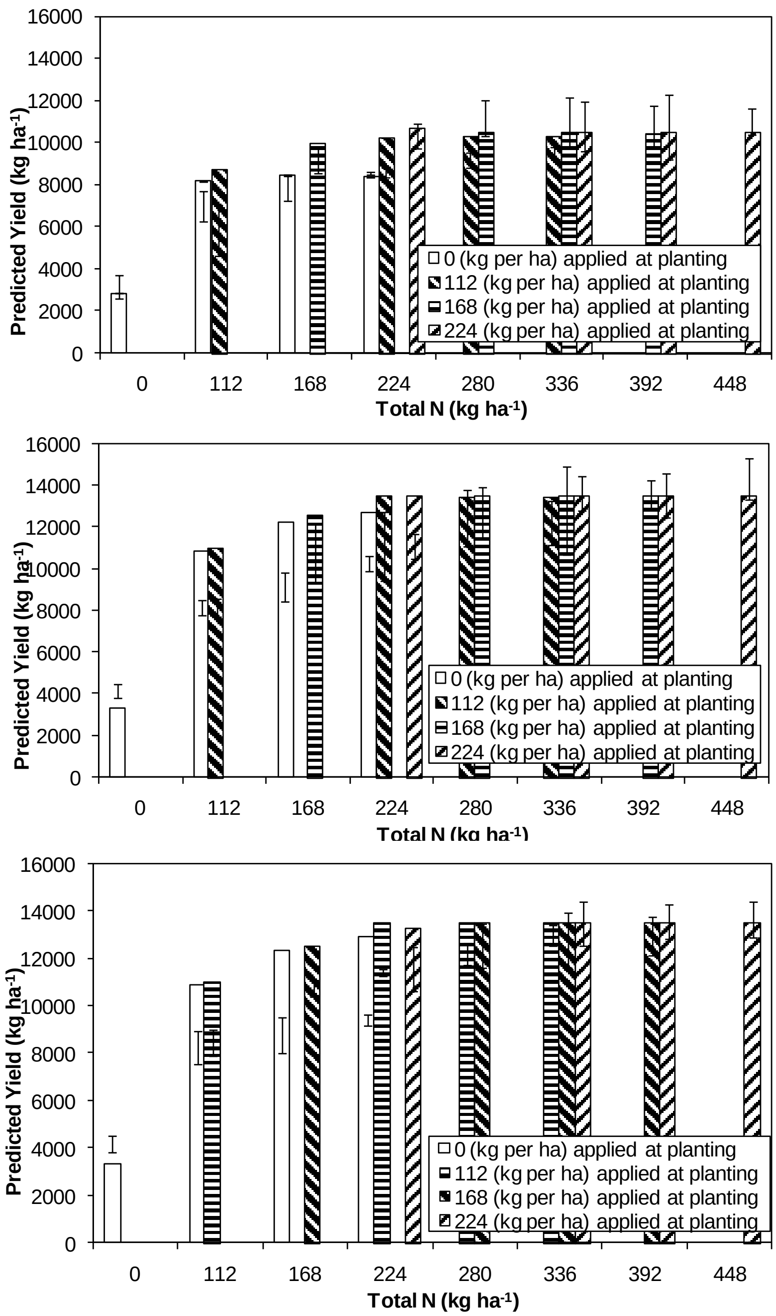
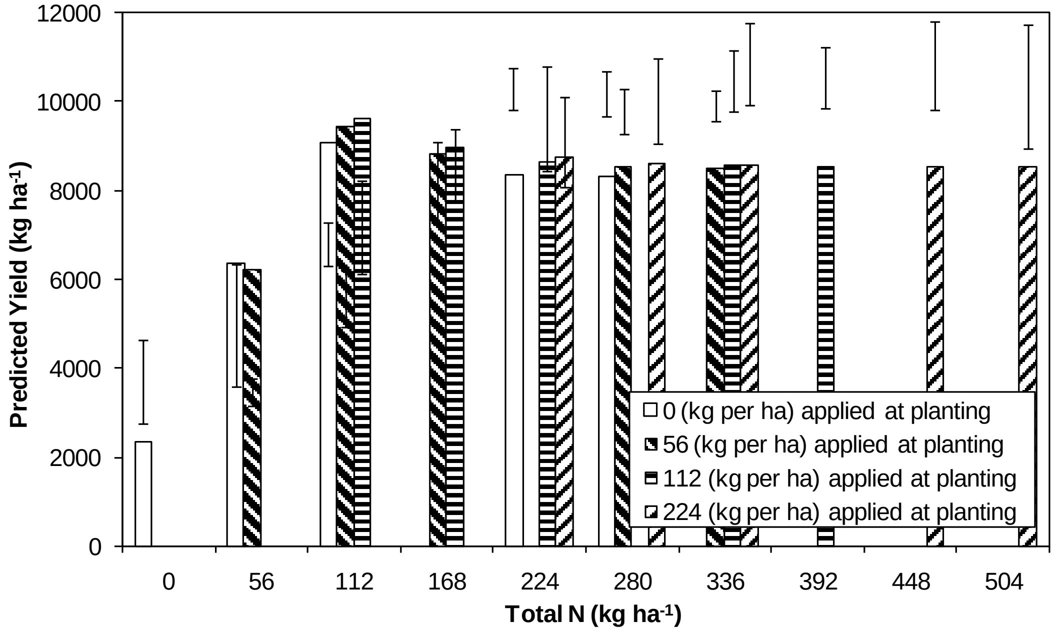
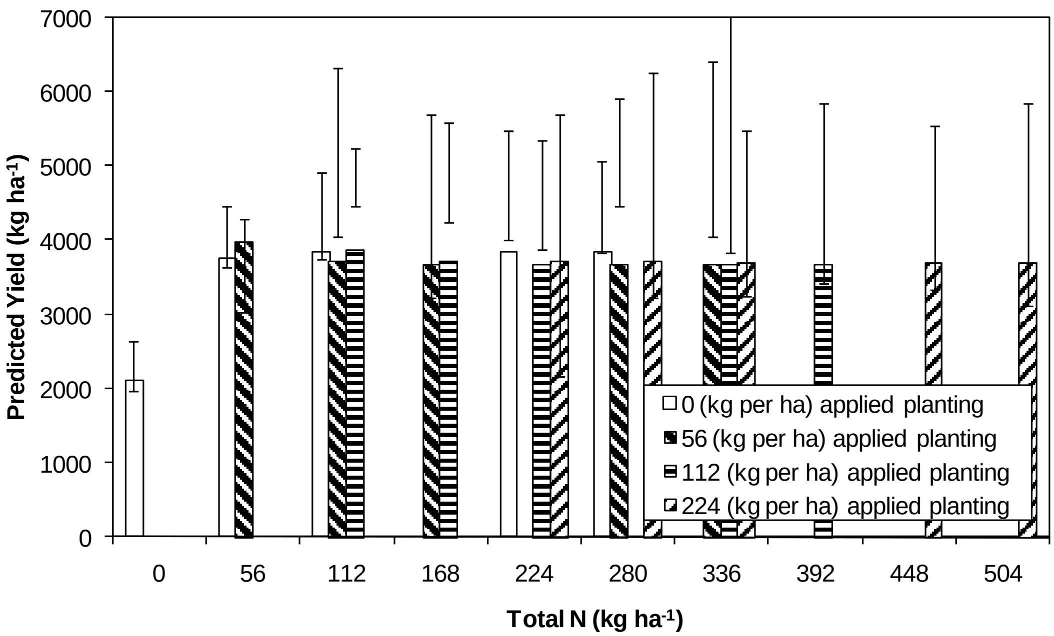


Figure 10. Comparison of simulated and observed yields using optimized soil profile settings, except for using the default SRGF setting, with treatments grouped by total amount of N applied for the a) non-irrigated treatments in 2001, b) normally-irrigated treatments in 2001, c) twice-normally irrigated treatments in 2001.





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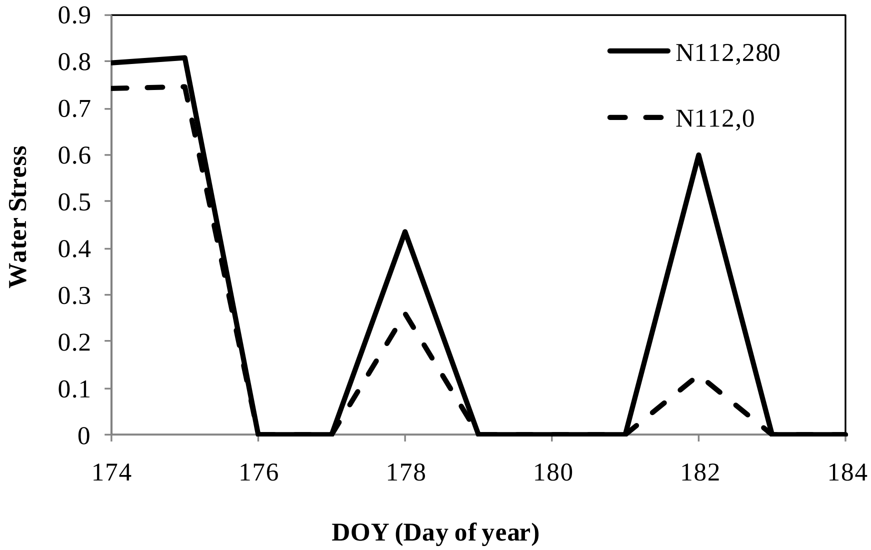

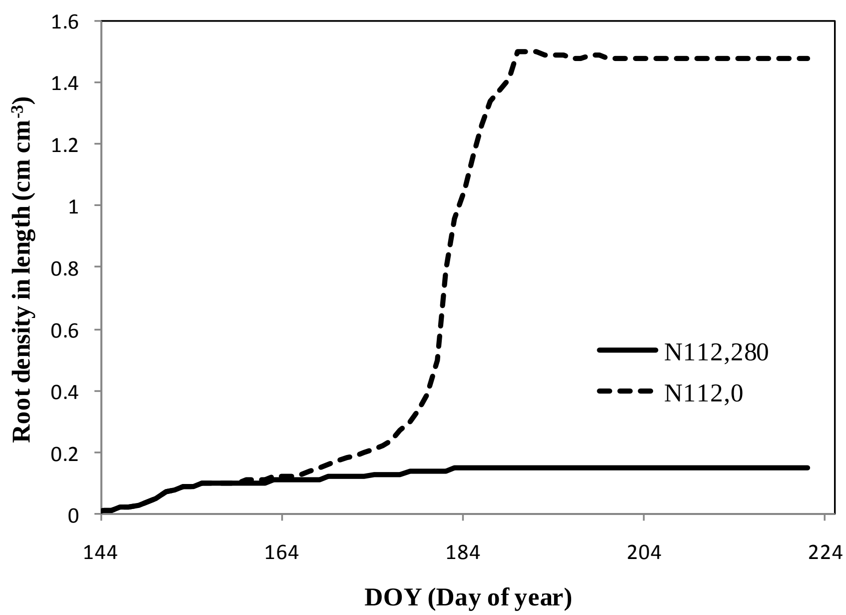

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APPENDIX

APPENDIX

All of the tables listed here, from Table 2.1 to Table 2.5, are additional information only as reference for understanding Chapter 2.

Table 2.1. Nearest meteorological stations to field sites.

Field Site	Experiment Station	County	Longitude	Latitude	Elevation (m)	Nearest weather Station	Longitude	Latitude	Elevation (m)
Belhaven	Circle Grove Farms	Beaufort	76.683	35.5	2	Belhaven	76.683	35.5	2
Clayton	San Wood Farms, Route 2, Four Oaks	Johnston	78.5	35.65	101	Clayton Wtp	78.467	35.633	91
Clinton	Horticultural Crops Research Station	Sampson	78.283	35.017	48	Clinton 2 NE	78.283	35.017	48
Kinston Ag	Lower Coastal Plain Tobacco Research Station	Lenoir	77.55	35.367	18	Kinston Ag	77.55	35.367	18
Lewiston	Peanut Belt Research Station	Bertie	77.167	36.133	15	Lewiston	77.167	36.133	15

Table 2.1 (continued).

Field Site	Experiment Station	County	Longitude	Latitude	Elevation (m)	Nearest weather Station	Longitude	Latitude	Elevation (m)
McLeansville	Farm	Guilford	†	†	†	Burlington Fire Stn #5, at Alamance, VA	79.45	36.067	201
Plymouth	Tidewater Research Station	Washington	76.65	35.867	6	Plymouth 5 E	76.65	35.867	6
Rocky Mount	Upper Coastal Plain Research Station	Edgecombe	77.72	35.9	34	Rocky Mount 8 ESE	77.683	35.9	34
Salisbury	Piedmont Research Station	Rowan	80.62	35.7	251	Salisbury 9 WNW	80.617	35.7	251
Whiteville	Border Belt Research Station	Columbus	78.8	34.4	27	Whiteville 7 NW	78.783	34.417	27

† No longitude, latitude, or elevation were available for the farm in McLeansville.

Table 2.2. Planting and harvest dates for each site-year and RMSE and RRMSE for yield.

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
Belhaven	2003	Belhaven	22-Apr	29-Aug	8	514	8580	6.0
Clinton	1994	Norfolk and Goldsboro sandy loam	07-Apr	25-Aug	15	338	8643	3.9
Clinton	1995	Norfolk, Orangeburg and Toisnot loamy sand	29-Mar	24-Aug	16	579	8567	6.8
Clinton	1999	Rains fine sandy loam	06-Apr	31-Aug	22	638	5028	12.7
Clinton	2000	Norfolk sandy loam	11-Apr	13-Sep	19	904	8068	11.2
Clinton	2002	Norfolk sandy loam	09-Apr	23-Aug	7	926	6256	14.8
Clinton	2003	Norfolk sandy loam	04-Apr	28-Sep	8	391	9446	4.1
Four Oaks	1994	Norfolk sandy loam	05-Apr	06-Sep	15	975	7997	12.2
Four Oaks	1995	Norfolk sandy loam	29-Mar	30-Aug	16	751	6130	12.3

Table 2.2 (continued).

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
Four Oaks	1997	Norfolk sandy loam	03-Apr	15-Sep	24	688	4453	15.5
Four Oaks	2000	Norfolk sandy loam	08-Apr	08-Sep	19	772	8308	9.3
Four Oaks	2001	Norfolk sandy loam	11-Apr	07-Sep	13	751	9174	8.2
Kinston	1994	Lynchburg sandy loam	04-Apr	24-Aug	15	394	3175	12.4
Kinston	1995	Goldsboro sandy loam	28-Mar	21-Aug	16	510	8719	5.9
Kinston	1997	Goldsboro sandy loam	07-Apr	09-Sep	24	820	7427	11.0
Kinston	1998	Goldsboro sandy loam	08-Apr	24-Aug	24	836	7462	11.2
Kinston	1999	Goldsboro sandy loam	01-Apr	28-Aug	22	1401	9476	14.8
Kinston	2000	Lynchburg sandy loam	06-Apr	11-Sep	19	536	9877	5.4
Kinston	2003	Lynchburg sandy loam	03-Apr	03-Sep	8	398	8602	4.6

Table 2.2 (continued).

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
Lewiston	1994	Goldsboro and Lynchburg sandy loam	12-Apr	08-Sep	15	556	7482	7.4
Lewiston	1995	Norfolk sandy loam	10-Apr	23-Aug	16	546	5911	9.2
Lewiston	1996	Goldsboro and Lynchburg sandy loam	15-Apr	24-Sep	17	782	4038	19.4
Lewiston	1997	Goldsboro and Lynchburg sandy loam	08-Apr	08-Sep	24	605	3496	17.3
Lewiston	2000	Goldsboro sandy loam	10-Apr	14-Sep	19	591	4641	12.7
Lewiston	2001	Goldsboro sandy loam	10-Apr	30-Aug	13	566	8929	6.3
Lewiston	2003	Goldsboro sandy loam	16-Apr	09-Sep	8	575	7624	7.6
McLeansville	1994	Enon fine sandy loam	21-Apr	04-Oct	9	521	7840	6.7

Table 2.2 (continued).

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
McLeansville	1995	Enon fine sandy loam	17-Apr	06-Sep	10	873	6140	14.2
McLeansville	1996	Enon fine sandy loam	18-Apr	19-Sep	12	801	3976	20.1
McLeansville	1997	Enon fine sandy loam	15-Apr	17-Sep	13	739	5306	13.9
Plymouth, mineral soil	1994	Portsmouth fine sandy loam and Cape Fear loam	11-Apr	12-Sep	15	385	6540	5.9
Plymouth, mineral soil	1995	Cape Fear loam	11-Apr	24-Aug	18	973	5421	17.9
Plymouth, mineral soil	1996	Portsmouth fine sandy loam	22-Apr	23-Sep	19	801	6597	12.2
Plymouth, mineral soil	1997	Cape Fear loam	11-Apr	10-Sep	23	686	7766	8.8
Plymouth, organic soil	1994	Portsmouth fine sandy loam and Cape Fear loam	11-Apr	13-Sep	15	524	6189	8.5

Table 2.2 (continued).

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
Plymouth, organic soil	1995	Portsmouth fine sandy loam	11-Apr	24-Aug	18	905	5274	17.2
Plymouth, organic soil	1996	Portsmouth fine sandy loam	22-Apr	23-Sep	19	783	8501	9.2
Plymouth, organic soil	1997	Portsmouth fine sandy loam	11-Apr	10-Sep	23	740	9023	8.2
Plymouth, organic soil	1999	Portsmouth fine sandy loam	14-Apr	15-Sep	13	445	5602	7.9
Plymouth, organic soil	2001	Portsmouth fine sandy loam	16-Apr	06-Sep	13	973	8074	12.1

Table 2.2 (continued).

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
Plymouth, organic soil	2002	Portsmouth fine sandy loam	17-Apr	09-Sep	7	969	6966	13.9
Plymouth, organic soil	2003	Portsmouth fine sandy loam	24-Apr	10-Sep	8	754	7809	9.7
Rocky Mount	1998	Aycock fine sandy loam	21-Apr	26-Aug	24	686	7606	9.0
Rocky Mount	1999	Norfolk loamy sand	08-Apr	27-Aug	22	790	6735	11.7
Rocky Mount	2000	Norfolk loamy sand	11-Apr	29-Aug	19	1037	6549	15.8
Rocky Mount	2001	Norfolk loamy sand	12-Apr	23-Aug	13	701	7748	9.1
Rocky Mount	2002	Norfolk loamy sand	16-Apr	05-Sep	7	862	4960	17.4
Salisbury	1994	Hiwassee clay	20-Apr	19-Sep	9	475	7174	6.6
Salisbury	1995	Hiwassee clay	27-Apr	05-Sep	10	633	6018	10.5

Table 2.2 (continued).

Location	Year	Soil Type	Planting Date	Harvest Date	Hybrids	RMSE kg ha^{-1}	Average Yield (kg ha^{-1})	RRMSE %
Salisbury	1996	Hiwassee clay	18-Apr	19-Sep	12	724	6011	12.0
Salisbury	1997	Hiwassee clay	10-Apr	16-Sep	13	582	3370	17.3
Salisbury	1998	Hiwassee clay	16-Apr	25-Aug	14	878	3610	24.3
Salisbury	2001	Davidson clay loam	09-Apr	11-Sep	13	582	8477	6.9
Salisbury	2003	Davidson clay loam	17-Apr	11-Sep	8	342	9273	3.7
Whiteville	1998	Norfolk fine sandy loam	31-Mar	25-Aug	24	466	7949	5.9
Whiteville	2000	Norfolk fine sandy loam	07-Apr	12-Sep	19	656	9526	6.9
Whiteville	2001	Norfolk fine sandy loam	02-Apr	27-Aug	13	528	10305	5.1
Whiteville	2003	Norfolk fine sandy loam	02-Apr	26-Aug	8	947	9077	10.4

Table 2.3. Optimized P1 and P5 and corresponding RMSE, respectively.

Hybrid	P1	P5	P1 RMSE	P5 RMSE	Days to Anthesis	Days to Maturity
			------------- days --------------			
AgraTech ATX 725	260	885	2.49	2.80	77	127
AgraTech ATX 787	295	880	2.75	2.78	79	128
Agripro AP9707	285	965	1.20	1.67	81	134
Agripro HS9843	280	950	2.19	2.68	77	131
Agripro HS9977	295	965	2.68	3.10	80	134
Agripro HY9646	280	865	2.24	2.06	77	126
Agripro HY9919V	290	960	2.92	3.02	79	134
Asgrow RX 770 (1)	255	825	1.65	1.31	78	123
Asgrow RX 897	295	880	2.10	2.18	81	129
Augusta A285	215	800	2.28	2.28	67	111
Cargill 7770	260	795	2.65	3.00	80	126
DeKalb DK 585	255	850	1.81	1.89	75	121
DeKalb DK 595(1)	255	925	1.29	0.91	76	126
DeKalb DK 626	255	865	3.54	2.83	71	123
DeKalb DK 632	250	945	1.90	2.14	73	123
DeKalb DK 658	250	945	1.56	2.14	74	125
DeKalb DK 679	275	970	1.70	2.08	77	129
DeKalb DK 683	280	970	3.06	3.54	78	133

Table 2.3 (continued).

Hybrid	P1	P5	P1 RMSE	P5 RMSE	Days to Anthesis	Days to Maturity
			------------- days --------------			
DeKalb DK 687	280	965	1.93	1.85	75	131
DeKalb DK 714	280	990	3.41	3.30	76	133
Mycogen 7250	260	900	3.10	2.66	75	126
Mycogen 7885	275	915	3.38	3.44	73	124
Mycogen 8460	280	970	2.98	2.77	78	132
Novartis N63-G7	240	895	2.33	2.62	72	122
Novartis N6800BT	210	965	4.10	2.35	75	125
Novartis N73-Q3	265	930	0.91	0.71	78	128
Novartis N75-T2	265	930	1.11	1.82	76	128
Novartis N79-L3	250	950	2.34	2.40	73	127
Novartis N79-P4	250	960	1.73	2.32	72	124
Novartis N83-N5	275	930	2.22	2.39	75	129
Novartis N8811	295	925	2.15	2.35	79	131
Pioneer 3140	290	855	2.92	3.01	79	128
Pioneer 3156	265	915	3.27	3.33	74	126
Pioneer 3163	280	915	2.76	2.84	77	129
Pioneer 3167	290	985	2.56	2.92	79	134
Pioneer 31B13	285	880	1.83	2.20	79	128

Table 2.3 (continued).

Hybrid	P1	P5	P1 RMSE	P5 RMSE	Days to Anthesis	Days to Maturity
			------------- days --------------			
Pioneer 31G20	275	910	1.41	1.85	75	127
Pioneer 31G66	275	855	2.60	1.80	76	124
Pioneer 31G98	280	885	2.41	2.02	74	125
Pioneer 31R88	260	910	2.22	2.22	74	125
Pioneer 3223	280	875	2.49	2.64	78	128
Pioneer 3245	275	875	3.01	3.14	76	125
Pioneer 32H58	235	940	2.39	1.81	74	127
Pioneer 32K61	280	865	2.05	2.07	78	127
Pioneer 32R25	280	865	2.47	2.34	75	124
Pioneer 32W86	250	910	2.51	1.56	73	121
Pioneer 3310	250	910	2.32	2.90	79	133
Pioneer 3394	260	830	2.90	2.72	74	121
Pioneer 33G26	265	880	1.64	1.99	75	124
Pioneer 33J56	260	860	2.35	2.32	73	123
Pioneer 33K81	260	845	2.29	2.43	75	124
Pioneer 33M54	250	890	2.85	1.50	74	122
Pioneer 33V08	260	855	1.86	1.46	77	124
Pioneer 33V15	265	820	2.92	1.90	75	121

Table 2.3 (continued).

Hybrid	P1	P5	P1 RMSE	P5 RMSE	Days to Anthesis	Days to Maturity
			-------------	days	-------------	
Pioneer 33Y09	260	895	1.62	1.85	78	127
Pioneer 34A55	255	850	2.04	2.04	75	123
Pioneer 34B97	240	820	2.04	1.96	69	114
Pioneer 34T14	255	850	1.90	2.18	74	122
S. States SS 747	275	900	2.12	1.41	83	136
S. States SS 827	260	930	3.26	3.38	76	128
S. States SS 943	295	940	3.00	2.92	77	130

Table 2.4. Optimized G2 and G3, with RMSE of simulated yields and RRMSE.

Variety	Sites	G2	G3	RMSE	Yield	RRMSE
				---- kg/ha ----		--- % ---
AgraTech ATX 725	13	650	7.0	826	6872	12.0
AgraTech ATX 787	25	800	6.5	552	6543	8.4
Agripro AP9707	8	800	6.0	679	6819	10.0
Agripro HS9843	33	600	7.5	733	6809	10.8
Agripro HS9977	24	600	7.0	924	6360	14.5
Agripro HY9646	21	950	6.0	691	6998	9.9
Agripro HY9919V	29	650	6.5	560	5892	9.5
Asgrow RX 770 (1)	6	800	7.5	501	6966	7.2
Asgrow RX 897	17	600	8.5	620	6337	9.8
Cargill 7770	10	1000	6.0	554	5756	9.6
DeKalb DK 626	6	800	6.0	772	5809	13.3
DeKalb DK 658	6	650	7.0	721	6825	10.6
DeKalb DK 679	7	600	7.5	490	6423	7.6
DeKalb DK 683	26	600	7.5	542	6538	8.3
DeKalb DK 687	15	800	6.0	802	6753	11.9
DeKalb DK 714	30	600	7.5	676	6906	9.8
Mycogen 7250	12	800	6.0	808	6435	12.6
Mycogen 7885	18	800	6.0	705	6602	10.7
Mycogen 8460	19	650	7.0	790	6786	11.6

Table 2.4 (continued).

Variety	Sites	G2	G3	RMSE	Yield	RRMSE
				---- kg/ha ----		--- % ---
Novartis N63-G7	21	650	7.5	618	7255	8.5
Novartis N75-T2	10	600	9.0	1108	7809	14.2
Novartis N79-L3	27	600	8.0	811	7912	10.3
Novartis N83-N5	20	700	7.0	595	7536	7.9
Pioneer 3140	29	600	9.5	609	6295	9.7
Pioneer 3156	12	650	7.5	742	6366	11.7
Pioneer 3163	48	900	6.0	659	7225	9.1
Pioneer 3167	35	700	6.0	835	5666	14.7
Pioneer 31B13	38	600	9.5	980	8066	12.1
Pioneer 31G20	13	900	6.0	692	7276	9.5
Pioneer 31G66	7	1000	6.0	582	8821	6.6
Pioneer 31R88	24	600	8.0	983	7957	12.4
Pioneer 3223	38	650	9.0	731	7719	9.5
Pioneer 3245	23	800	7.0	759	7068	10.7
Pioneer 32H58	7	850	6.0	713	9383	7.6
Pioneer 32R25	18	1000	6.0	613	8416	7.3
Pioneer 32W86	11	850	6.0	527	7648	6.9
Pioneer 3310	5	600	7.0	829	4409	18.8
Pioneer 3394	40	650	8.5	678	7277	9.3

Table 2.4 (continued).

Variety	Sites	G2	G3	RMSE	Yield	RRMSE
				---- kg/ha ----		--- % ---
Pioneer 33G26	13	900	6.0	887	7348	12.1
Pioneer 33J56	21	800	7.0	903	7565	11.9
Pioneer 33K81	17	600	8.5	630	7302	8.6
Pioneer 33M54	7	600	8.5	489	8629	5.7
Pioneer 33V08	12	950	6.5	481	7286	6.6
Pioneer 33V15	7	600	9.5	398	8596	4.6
Pioneer 33Y09	20	600	9.0	678	7135	9.5
Pioneer 34A55	18	600	9.0	773	7005	11.
Pioneer 34T14	10	900	6.5	516	7408	7.0
S. States SS 747	7	850	6.0	903	5369	16.8
S. States SS 943	22	750	6.0	694	6039	11.5

Table 2.5. Evaluation of genetic coefficients based on simulations of 50 levels for G2 and 50 levels for G3, by cross validation algorithm.

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Novartis N8811	600	8.0	Clinton-1994	9302	8773	990
Novartis N8811	600	8.0	Clinton-1995	8910	8801	994
Novartis N8811	600	8.0	Clinton-1999	4963	4641	993
Novartis N8811	600	8.0	Clinton-2000	6315	7504	973
Novartis N8811	600	8.0	Four Oaks-1994	8319	7653	988
Novartis N8811	600	8.0	Four Oaks-1995	5497	6757	970
Novartis N8811	600	8.0	Four Oaks-1997	4321	4944	988
Novartis N8811	600	8.0	Four Oaks-2000	8440	9670	971
Novartis N8811	600	8.0	Kinston-1994	2880	3053	994
Novartis N8811	600	8.0	Kinston-1995	8701	8966	993
Novartis N8811	600	8.0	Kinston-1997	7771	7305	991

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Novartis N8811	600	8.0	Kinston-1998	6612	8800	919
Novartis N8811	600	8.0	Kinston-1999	7909	8237	993
Novartis N8811	600	8.0	Kinston-2000	9278	8949	993
Novartis N8811	600	8.0	Lewiston-1994	7765	7955	994
Novartis N8811	600	8.0	Lewiston-1995	6361	5260	976
Novartis N8811	600	8.0	Lewiston-1996	4289	4144	994
Novartis N8811	600	8.0	Lewiston-1997	3733	4329	989
Novartis N8811	600	8.0	Lewiston-2000	5627	6030	992
Novartis N8811	600	8.0	McLeansville-1994	8145	6265	939
Novartis N8811	600	8.0	Plymouth, mineral soil-1994	6367	7003	988
Novartis N8811	600	8.0	Plymouth, mineral soil-1995	6003	4982	978
Novartis N8811	600	8.0	Plymouth, mineral soil-1996	8343	8600	993

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Novartis N8811	600	8.0	Plymouth, mineral soil-1997	8723	8774	994
Novartis N8811	600	8.0	Plymouth, organic soil-1994	6909	6540	992
Novartis N8811	600	8.0	Plymouth, organic soil-1995	6402	4305	925
Novartis N8811	600	8.0	Plymouth, organic soil-1996	6229	6504	993
Novartis N8811	600	8.0	Plymouth, organic soil-1997	7950	8169	994
Novartis N8811	600	8.0	Rocky Mount-1998	6214	6263	994
Novartis N8811	600	8.0	Rocky Mount-1999	4049	5993	935
Novartis N8811	600	8.0	Rocky Mount-2000	7788	5651	922
Novartis N8811	600	8.0	Salisbury-1994	7408	7410	978
Novartis N8811	600	8.0	Whiteville-1998	7879	8032	994
Novartis N8811	600	8.0	Whiteville-2000	8600	9892	969
Pioneer 31G98	1000	6.0	Belhaven-2003	9498	9234	780

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Novartis N8811	600	8.0	Plymouth, mineral soil-1997	8723	8774	994
Novartis N8811	600	8.0	Plymouth, organic soil-1994	6909	6540	992
Novartis N8811	600	8.0	Plymouth, organic soil-1995	6402	4305	925
Novartis N8811	600	8.0	Plymouth, organic soil-1996	6229	6504	993
Novartis N8811	600	8.0	Plymouth, organic soil-1997	7950	8169	994
Novartis N8811	600	8.0	Rocky Mount-1998	6214	6263	994
Novartis N8811	600	8.0	Rocky Mount-1999	4049	5993	935
Novartis N8811	600	8.0	Rocky Mount-2000	7788	5651	922
Novartis N8811	600	8.0	Salisbury-1994	7408	7410	978
Novartis N8811	600	8.0	Whiteville-1998	7879	8032	994
Novartis N8811	600	8.0	Whiteville-2000	8600	9892	969
Pioneer 31G98	1000	6.0	Belhaven-2003	9498	9234	780

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Pioneer 31G98	1000	6.0	Clinton-2000	8240	9103	761
Pioneer 31G98	650	8.5	Clinton-2002	6449	5383	827
Pioneer 31G98	1000	6.0	Clinton-2003	10119	9240	760
Pioneer 31G98	1000	6.0	Four Oaks-2000	9899	8196	696
Pioneer 31G98	1000	6.0	Four Oaks-2001	9961	10416	776
Pioneer 31G98	1000	6.0	Kinston-2000	11016	10790	780
Pioneer 31G98	1000	6.0	Kinston-2001	9940	10331	777
Pioneer 31G98	600	9.0	Kinston-2002	6992	7433	756
Pioneer 31G98	1000	6.0	Kinston-2003	8809	9921	747
Pioneer 31G98	1000	6.0	Lewiston-2000	6014	6255	780
Pioneer 31G98	1000	6.0	Lewiston-2001	9557	10328	765
Pioneer 31G98	1000	6.0	Lewiston-2003	8121	7136	754

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Pioneer 31G98	1000	6.0	Plymouth, organic soil-2001	8953	9524	773
Pioneer 31G98	1000	6.0	Plymouth, organic soil-2002	7069	7937	761
Pioneer 31G98	1000	6.0	Plymouth, organic soil-2003	8757	7730	752
Pioneer 31G98	1000	6.0	Rocky Mount-2000	7949	7569	778
Pioneer 31G98	1000	6.0	Rocky Mount-2001	7953	8413	776
Pioneer 31G98	1000	6.0	Rocky Mount-2002	5521	5092	777
Pioneer 31G98	1000	6.0	Salisbury-2001	9129	8954	781
Pioneer 31G98	1000	6.0	Salisbury-2003	10026	8896	745
Pioneer 31G98	1000	6.0	Whiteville-2000	10194	10093	781
Pioneer 31G98	1000	6.0	Whiteville-2001	11434	12161	767
Pioneer 31G98	1000	6.0	Whiteville-2003	9418	10471	750
Pioneer 32K61	900	6.0	Clinton-1999	5062	5580	824

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Pioneer 32K61	900	6.0	Clinton-2000	7283	8255	811
Pioneer 32K61	900	6.0	Clinton-2002	5833	4501	767
Pioneer 32K61	850	6.5	Four Oaks-1997	4321	4014	825
Pioneer 32K61	850	6.5	Four Oaks-2000	9014	7566	784
Pioneer 32K61	900	6.0	Four Oaks-2001	8809	9546	819
Pioneer 32K61	850	6.5	Kinston-1997	7745	7018	816
Pioneer 32K61	850	6.5	Kinston-1998	7656	6411	795
Pioneer 32K61	900	6.0	Kinston-1999	7930	9442	783
Pioneer 32K61	900	6.0	Kinston-2000	9681	10190	825
Pioneer 32K61	850	6.5	Kinston-2001	9054	9135	827
Pioneer 32K61	900	6.0	Kinston-2002	5634	4960	795
Pioneer 32K61	850	6.5	Lewiston-1997	3699	3310	824

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Pioneer 32K61	850	6.5	Lewiston-2000	5353	3811	778
Pioneer 32K61	850	6.5	Lewiston-2001	8890	7750	801
Pioneer 32K61	850	6.5	McLeansville-1997	5618	4816	814
Pioneer 32K61	900	6.0	Plymouth, mineral soil-1997	8205	8970	818
Pioneer 32K61	900	6.0	Plymouth, organic soil-1997	7531	8162	822
Pioneer 32K61	900	6.0	Plymouth, organic soil-1999	4482	5519	808
Pioneer 32K61	900	6.0	Plymouth, organic soil-2001	7887	8145	803
Pioneer 32K61	900	6.0	Plymouth, organic soil-2002	6447	6989	824
Pioneer 32K61	850	6.5	Rocky Mount-1998	8307	7873	823
Pioneer 32K61	900	6.0	Rocky Mount-1999	5365	6880	782
Pioneer 32K61	850	6.5	Rocky Mount-2000	7269	5989	793
Pioneer 32K61	900	6.0	Rocky Mount-2001	6993	8400	789

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted[†]	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
Pioneer 32K61	850	6.5	Rocky Mount-2002	5050	4911	827
Pioneer 32K61	850	6.5	Salisbury-1997	3150	3173	827
Pioneer 32K61	850	6.5	Salisbury-2001	8311	8215	827
Pioneer 32K61	900	6.0	Whiteville-1998	7772	8475	794
Pioneer 32K61	850	6.5	Whiteville-2000	9269	9287	827
Pioneer 32K61	850	6.5	Whiteville-2001	10170	10109	827
S. States SS 827	650	7.5	Clinton-1994	9351	9315	680
S. States SS 827	650	7.5	Clinton-1995	8913	9507	671
S. States SS 827	600	8.0	Four Oaks-1994	8035	8687	755
S. States SS 827	600	8.0	Four Oaks-1995	7369	5579	686
S. States SS 827	650	7.5	Four Oaks-1997	4154	5333	642
S. States SS 827	650	7.5	Kinston-1994	3124	3338	679

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				-------------------- kg/ha	-----------------	
S. States SS 827	850	6.0	Kinston-1995	10161	9242	666
S. States SS 827	650	7.5	Kinston-1997	6999	7564	672
S. States SS 827	650	7.5	Kinston-1998	7601	8125	673
S. States SS 827	650	7.5	Lewiston-1994	7826	8583	665
S. States SS 827	650	7.5	Lewiston-1995	6215	6178	680
S. States SS 827	650	7.5	Lewiston-1996	4040	3700	677
S. States SS 827	650	7.5	Lewiston-1997	3659	4382	666
S. States SS 827	600	8.0	McLeansville-1994	8703	9351	755
S. States SS 827	650	7.5	McLeansville-1995	7469	7784	677
S. States SS 827	650	7.5	McLeansville-1996	4186	4116	680
S. States SS 827	650	7.5	McLeansville-1997	5486	4757	666
S. States SS 827	650	7.5	Plymouth, mineral soil-1994	6696	7608	658

Table 2.5 (continued).

Hybrid Name	G2	G3	Site-year Omitted†	Simulated Yield	Observed Yield	RMSE
				------------------- kg/ha	----------------	
S. States SS 827	650	7.5	Plymouth, mineral soil-1995	6064	5271	663
S. States SS 827	650	7.5	Plymouth, mineral soil-1996	8512	9218	667
S. States SS 827	650	7.5	Plymouth, organic soil-1994	7428	7557	680
S. States SS 827	650	7.5	Plymouth, organic soil-1995	6547	5550	653
S. States SS 827	650	7.5	Plymouth, organic soil-1996	6647	7159	673
S. States SS 827	650	7.5	Rocky Mount-1998	5483	5779	678
S. States SS 827	650	7.5	Salisbury-1994	7765	7753	680
S. States SS 827	650	7.5	Salisbury-1995	6872	6485	676
S. States SS 827	650	7.5	Salisbury-1996	5547	6567	652
S. States SS 827	650	7.5	Salisbury-1997	3045	2743	678
S. States SS 827	650	7.5	Whiteville-1998	7427	7228	679

† Current site-year was omitted when estimating G2 and G3 for the specified hybrid. Simulated yields used coefficients estimated using all other site-years.