SPATIAL APPLICATION OF A COTTON GROWTH MODEL FOR ANALYSIS OF SITE-SPECIFIC IRRIGATION IN THE TEXAS HIGH PLAINS

A Dissertation

by

RANDY WAYNE CLOUSE

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2006

Major Subject: Biological and Agricultural Engineering

SPATIAL APPLICATION OF A COTTON GROWTH MODEL FOR ANALYSIS OF SITE-SPECIFIC IRRIGATION IN THE TEXAS HIGH PLAINS

A Dissertation

by

RANDY WAYNE CLOUSE

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Stephen W. Searcy
Committee Members,	J. Tom Cothren
	James R. Gilley
	Clyde R. Munster
Head of Department,	Gary L. Riskowski

May 2006

Major Subject: Biological and Agricultural Engineering

ABSTRACT

Spatial Application of a Cotton Growth Model for Analysis of Site-Specific Irrigation in the Texas High Plains. (May 2006)

Randy Wayne Clouse, B.S., The Pennsylvania State University;

M.S., Virginia Polytechnic Institute and State University

Chair of Advisory Committee: Dr. Stephen Searcy

Limited water supplies for agriculture in the Texas High Plains will require new irrigation technologies and techniques for agriculture to continue in this area. The potential for using one such technology, site-specific irrigation, was evaluated using the Cotton2k crop simulation model. This model and two other simulation models were evaluated for their ability to track water movement and usage over three growing seasons. The models were tested for sites in Lubbock and Hale County, Texas. Cotton2k performed well compared to the other two models on tests of cumulative evapotranspiration and applied water yield relations and equal to the other models for tracking soil water profiles.

A global optimization method, simulated annealing, was tested for its ability to spatially calibrate soil water parameters of Cotton2k. The algorithm found multiple parameter sets for the same objective function results. This result runs contrary to expectations for the simulated annealing algorithm, but is possibly from the relationship between available water capacity and crop yield. The annealing algorithm was applied to each sampling point at the Hale County site and improved yield predictions for 32 of 33 points as compared to simulations made with soil textural information alone.

The spatially calibrated model was used with historic weather from five seasons to evaluate a site-specific strategy where water was shifted from lower to higher yielding areas of fields. Two irrigation strategies, one with irrigations weekly and one with irrigations applied when 30% of available water was depleted, were tested. With site-specific management, the weekly interval strategy produced higher yields for two of three water levels, as compared to uniform management. With the soil moisture depletion strategy, site-specific management produced lower yields than uniform management for all three water levels examined. Yield improvement and water savings were also demonstrated for implementing site-specific irrigation when non-producing portions of fields were previously being watered.

DEDICATION

To my parents, for everything they did for me growing up.

To my wife, for her patience.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Steve Searcy, for his guidance through my graduate program. I also would like to thank my committee members, Tom Cothren, Jim Gilley and Clyde Munster, for their help and assistance while here at Texas A&M. The Salyer Fellowship in Cotton Research at Texas A&M University was a great aid to this project.

I would like to thank the sources of data used in this project. These include Jim Bordovsky, Robert Lascano, and Don Wanjura. Also invaluable were Jill Booker, Doug Nesmith, and Bill Webb for taking time to answer my questions on all the details of the data sets. Kit Boone, Javed Iqbal, Avishalom Marani, Pierre Martin, Joel Paz, and Dana Porter were very helpful in answering various questions on crop modeling, optimization, and site-specific irrigation.

I am grateful for the opportunity to assist with and learn about teaching while a teaching assistant with Don Reddell, Wayne Lepori, and Cady Engler along with Jim Gilley, Clyde Munster, and Steve Searcy from my committee.

Thanks to David Geiger, Bobby Hardin and Marcello Stabile for the chats and discussion while here at A&M.

TABLE OF CONTENTS

LIST OF FIGURES

FIGURE Page

LIST OF TABLES

TABLE Page

CHAPTER I

INTRODUCTION

Water usage is an important issue in Texas as projected water demand will exceed projected water supply (TWDB, 2002). Irrigated agriculture is currently the state's largest water user. In 2000, irrigation consumed over 9,600,000 acre-feet of water. Irrigation usage is predicted to decrease to 8,497,706 acre-feet by the year 2050. Projected decreases in irrigation usage come from increasing efficiency in surface water conveyance systems and in on-farm irrigation systems, declining groundwater resources and the voluntary transfer of historic water rights to other uses. Even with large decreases in irrigation usage by 2050, overall projected water demand for the state will exceed projected water supply by 6,000,000 acre-feet of water per year. The assumption of water use efficiency increases for irrigated agriculture in these projections plus the potential for large reallocations of water away from agriculture will necessitate the need for more irrigation methods that more efficiently use water to create crop yield in agricultural production.

Precision agriculture has the potential to improve the economic efficiency of crop production inputs as compared to uniform applications of inputs (Plant, 2001). Agricultural mechanization in the twentieth century led to the adoption of uniform management of farm fields. Observations of factors that influence yield and monitoring of yields themselves indicate that large amounts of variability exist within these uniformly managed fields. Only recently with the advent of technologies such as global positioning systems (GPS), geographic information systems (GIS), and yield monitors

---

This dissertation follows the style of *Transactions of the ASAE.*

has it become feasible for farmers to easily identify variability in fields. This increase in information about variability has also increased the complexity of decision-making for farm managers. Precision agriculture is one term given to application of information technologies in agriculture for the management of crops at scales less than a field-scale. Management of agricultural inputs at less than field-scale could potentially alleviate areas of over- and under-application of inputs.

Irrigation water is one example of a cropping system input whose usage could be optimized through precision agriculture technologies (Evans et al., 1996). Demonstrations of the ability to vary water applications with moving irrigation systems have been made in research settings. Commercial adoption of site-specific irrigation has occurred in Georgia; however, that area is much different in climate and soils than the Texas High Plains. For farm managers in the High Plains region to adopt site-specific irrigation, demonstrated improvements in their production potential are needed. Goals for farm managers include maximizing yields, profits, or the efficiency of input usages.

An illustration of a typical management scenario will show how uniform water applications could fail to meet the manager's goals. The field in this illustration is sixty percent silt loam, thirty percent clay loam, and ten percent silty clay loam. In a uniform management scenario, applications could justifiably be made based on any of the three soil types individually or based on various combinations of the three soil types. One potential scenario would use the predominant soil type as the basis for scheduling. While this scenario may optimize growth on the majority of the field, it could create runoff of irrigation water and agrichemicals from the relatively impermeable clay soil types. If the field is managed to avoid runoff from the slow draining clay soil types, drainage from the silt loam portion of the field could leave less water available for plant uptake, thus reducing potential crop yields. Scheduling could also be made based on combinations of measurements from all the soil types but this scenario would fail to optimize yields or prevent runoff from any of the soil types. This example used one of thousands of combinations of soil types that could exist in a selected field. Management tools that integrate spatial variability of soils with other interacting factors would allow managers to make decisions regarding site-specific irrigation for their individual sites.

Crop growth models offer opportunities for evaluating effects of soils, management, and weather on plants. They have been used to test hypotheses about causes of yield variability across space. A drawback to applying crop growth models on a spatial basis is obtaining the many inputs for the models. Techniques for dealing with this drawback have included linking crop growth models with remotely sensed imagery and using optimization techniques for determining the best combination of parameters.

On a theoretical basis, site-specific irrigation (SSI) offers opportunities for increasing water use efficiencies in agriculture, which could potentially benefit the state of Texas and the productivity of individual farmers. Underlying this idea is the assumption that spatially varying water applications leads to spatial variations in crop yields that can be managed to benefit individual farmers and society as a whole. Each farm where SSI could be applied will be a unique situation. Potential outcomes from SSI systems will be affected by individual soil types, proportions of these soil types across fields, management objectives, and weather patterns which could all be efficiently studied with crop growth models. Improvements in the applications of crop growth models on a spatial basis are needed however. Cotton was the crop studied in this project due to its economic importance in the High Plains of Texas, where potential water shortages exist. This study focused on development of techniques for applying crop growth models on a spatial basis to assess and improve irrigation management for cotton production in Texas through the following objectives:

1) Assess applicability of three cotton simulation models for prediction of the effects of site-specific irrigation in the Texas High Plains.
2) Evaluate the simulated annealing optimization method for improving spatial prediction of cotton yield with a cotton simulation model.
3) Evaluate net returns for site-specific irrigation with a cotton simulation model across multiple years of historic weather data.

CHAPTER II

BACKGROUND

IRRIGATION

Irrigation scheduling is defined as determination of the timing of and quantity of water applications (Martin et al., 1990). Scheduling is affected by complex interactions between soils, plants, weather, and management objectives. Water movement through this system is affected by the type of plant, genotype of the plant, growth stage, soil type, time of day, temperature, solar radiation, wind, rainfall, and initial water level. Common methods/triggers for scheduling include Management Allowed Depletion (MAD), soil water potential, leaf water potential, high frequency irrigation, water stress indices, and real time scheduling with crop growth models (Martin et al., 1990). Despite the possibility of crop growth models being used for real-time irrigation scheduling, applications of crop growth models for irrigation scheduling have tended to focus on determining irrigation strategies based on historic weather data (McClendon et al., 1996, Hook, 1994). Rogers and Elliott (1989) examined net return for three irrigation strategies for a cost/loss risk analysis procedure using both probabilistic and climatological weather with a sorghum crop model. While this model made future predictions of management effects on yield, the analysis also used historic weather data. The McClendon et al. (1996) study demonstrated the use of both sequential control search optimization and neural networks for determining irrigation schedules.

The scheduling techniques described so far assume that adequate water is always available to refill the root zone when an irrigation event occurs. In some areas, such as those in Texas supplied by water from the Ogallala Aquifer, sufficient water supplies may not be available to meet these demands. Irrigation in which water applications are less than the evapotranspiration (ET) rate is known as deficit irrigation. Deficit irrigation can be beneficial if the reduction in crop yield is less than the decrease in evapotranspiration rate. An equation to represent this relation is:

$$\frac{Y}{Y_m} = 1 - k_y \left[1 - \frac{ET_a}{ET_m} \right] \tag{2-1}$$

from Kirda (2002) where Y and Y_m are expected and maximum crop yields, ET_a and ET_m are actual and maximum evapotranspiration and k_y is a crop yield response factor. Water deficits can occur throughout a growing season or at one or more growth stages. Different crops have different sensitivities to stress at different growth stages (Doorenbos and Pruitt, 1977). The order of critical stages for cotton is: flowering and boll formation > early stages of growth > after boll formation. Irrigation scheduling in deficit situations can incorporate soils information such as water content and potential indicators of crop stress such as crop water potential and canopy temperature (English et al., 1990). Scheduling techniques that account for one or more of these information sources include Management Allowed Depletion (MAD) (Merriam, 1966) and Stress Day Index (SDI) (Hiler and Clark, 1971).

Irrigation planning studies using historic weather data in deficit situations have been conducted using dynamic programming. Epperson et al. (1993) combined dynamic programming with the CERES-Maize crop growth model to optimize net return over twelve years of historic weather. They examined irrigation quantities for six irrigation triggers at each vegetative growth stage and up to four levels for each trigger. Dynamic programming was used by Rao et al. (1988) to allocate water within crop growth stages using a dated water production function. These dynamic programming applications are for long-term decision making and do not demonstrate how the concepts can be used for in-season scheduling. Dynamic programming also suffers from a large state space size, thus the number of factors included in applications of it are often smaller than in real-world situations. An alternative scheduling approach to dynamic programming was presented by Gowing and Ejieji. (2001). This research utilized a crop growth model, a soil water deficit based trigger, seven day weather forecasts, and long term historic weather to generate yield estimates past the period of observed weather.

CROP YIELD VARIABILITY

Observations of variability of crops across fields have anecdotally been noted over a number of time periods and farming systems. Farmers in Africa often manage small areas of fields differently than other portions of fields based on observations of termite mounds and old livestock corral locations (Lowenberg-DeBoer and Swinton, 1997). Some ranges of observed variability in crop yield from research studies are listed in table 2-1. Current methods of identifying field-scale variability in crop yield include yield monitoring systems and high-altitude remotely sensed images of reflectance and emitance from crop canopies (Plant, 2001).

Table 2-1. Ranges in observed crop yield variability.

Location	Quantity	Range	Reference
Washington state	Wheat yield	2.0 – 6.0 Mg ha^{-1}	Bhatti et al., 1991
South Carolina	Corn yield	3.5 – 8.5 Mg ha^{-1}	Sadler et al., 1995
Mississippi	Cotton yield	1.01 – 2.13 Mg ha^{-1}	Kepple, 1988
Minnesota	Corn yield	4.09 – 9.59 Mg ha^{-1}	Khakural et al., 1999
Minnesota	Soybean yield	1.40 – 2.70 Mg ha^{-1}	Khakural et al., 1999
Nebraska	Corn yield	8.44 – 13.82 Mg ha^{-1}	Coelho et al., 1999

Crop yield variability has often been related to variability in soil properties and topography. Specific soil properties which potentially affect crop yield variability include soil water potential, hydraulic conductivity, soil moisture availability, drainage status, soil compaction, topsoil depth, and landscape position (Mulla and Schepers, 1997). Ranges of variation in soil properties vary based on how much the soil property is affected by management. Properties such as sand, clay, or total phosphorus which are not affected by management have coefficient of variations (CV) of 20% or less (Beckett and Webster, 1971), while the properties most affected by management, such as potassium, phosphorus, magnesium, and calcium have CV of 60%.

Data on soil properties are typically collected via discrete point sampling (Plant, 2001). When fields are managed on a whole-field basis, results of individual samples may be averaged together or the individual samples composited together. In site-specific management, samples are often collected on regularly spaced intervals with interpolation methods used to fill in unsampled areas. Simple grid, stratified grid, or directed sampling schemes can be used for identifying where samples will be collected (Plant, 2001). Interpolation methods that can be used for estimating property values between sampled points include inverse-distance weighting and kriging. The variogram used in determining the kriging weighting factors can also provide other information about variability of a property. The range of the variogram indicates the distances that properties are correlated over (McBratney and Pringle, 1997). Point sampling is time consuming so research on continuous proximate sensing of soil properties is ongoing. Soil electrical conductivity, which can be correlated with other properties such as clay content, is an example of a variable that is obtained with continuous proximate sensing (Sudduth et al., 1995).

Soil properties relate to crop yield variability in different degrees depending on the specific site and growing year studied. Since no one factor can be identified as a main causation agent for crop variability, techniques for analyzing relations between these factors and crop yield for each specific field are needed. Regression of static measurements of soil, management, or plant properties against grid level yields has been performed by Cambardella et al. (1996) and Khakural et al. (1999) among others. Plant et al. (1999) determined spatial variability causes for wheat fields using classification and regression trees. Examination of variability along transects across fields with time-series analysis techniques is called state-space analysis. This form of analysis was used to analyze spatial variability in yield in wheat and corn by Nielsen et al. (1999). The static spatial analysis techniques listed above fail to incorporate potential variations with time, however. Studies have found significant variations in crop yield maps from year to year (Sadler et al., 1995). Temporal yield variability with different climate extremes can be up to an order of magnitude (Huggins and Alderfer, 1995). Crop simulation models have been advocated for studies of crop yield variability (Paz et al., 1998) because they:

1. can be used to test hypotheses about yield variability
2. can integrate effects of dynamic and multiple stresses when inputs are properly characterized
3. following validation, can be used to develop management prescriptions
4. can be used to assess economic and environmental impact of prescriptions

MANAGEMENT OF SPATIAL VARIABILITY

Management of agricultural fields to account for observed variability has been termed site-specific management (SSM) by Lowenberg-DeBoer and Swinton (1997). The working definition that they provide for SSM is “electronic monitoring and control applied to data collection, information processing, and decision support for the temporal and spatial allocation of inputs for crop production.” They also note the following terms used to refer to these technologies, including: precision agriculture, site-specific farming, prescription farming, and variable rate technology. For SSM to be adopted the following conditions need to be met (Miller, 1999):

1. significant within field variability exists in factors that influence crop yield
2. causes of this variability can be identified and measured
3. information from these measurements can be used to modify crop-management practices to increase profit or decrease environmental impact

The basis of control for application of variable inputs depends on the factor(s) identified as causing the variation. If one primary factor is identified, maps of this factor can be created and used for applications of the input. If multiple factors are identified, areas with similar groups of these factors can be created (McCann et al., 1996). These groupings are called management zones. Criteria for defining management zones include: “yield differences between zones must be substantially greater than those within zones” and “the principal set of factors that influence yield within a zone must be the same” (Plant et al., 1999). Maps of single factors or management zones could then be used with a form of variable rate-application technology (VRT) to spatially apply an input.

Potential methods for assessing the economics of site-specific management were described by Lowenberg-DeBoer and Swinton (1997). They proposed starting with a partial budget analysis for a typical year. Changes in farm revenue and costs from implementing SSM could be included in the partial budget. Further analysis could be made by adding in annualized capital costs. Additional considerations before SSM is implemented could include environmental impacts and the feasibility of farm labor and management to effectively use the SSM tools.

Studies of the economics of SSM have been made using yields determined from crop model predictions and field studies. The potential effect of variations in weather on the profitability of site-specific management of fertilizer was examined in a case study by Braga et al. (1999). This study showed little overall difference between net returns for site-specific management as compared to uniform management for the proportions of soil types used in the study. They noted that one soil had a larger response to nitrogen applications than the other soils. If a larger area of the field had been the soil with the larger response the return for site-specific management could have been higher. Comparisons between gross incomes for site-specific and uniform irrigation management of potatoes were made by King et al. (2002). An increase in gross income of \$165 ha^{-1} was determined for site-specific irrigation as compared to uniform irrigation. Increased gross income is only a portion of the partial budget analysis presented by Lowenberg-DeBoer and Swinton (1997). Comparison of gross income figures to the cost of implementing the site-specific system is needed to better determine if SSM is profitable.

Agricultural inputs examined for SSM systems include fertilizers (Yang et al., 2001), water (King et al., 2002), herbicides (Eberlein et al., 2000) and seeds (Bauer et al., 2000). Commercial development of precision agriculture systems has been most common for fertilization applications. Potential contributing factors for this development include the relative stability of soil fertility parameters over time, confluence of technologies for consistently locating specific points in the field, and ease of implementing spatial applications through equipment modifications or through services from a fertilizer dealer.

Research on variable rate irrigation has occurred throughout the United States. A summary of key characteristics of site-specific irrigation is shown in tables 2-2 and 2-3. Research has centered on development of hardware capabilities allowing for variation in water applications across fields. Sprinklers in the systems are either pulsed on/off or in multiple manifold arrangements. Testing of these systems has centered on their capabilities for satisfactorily varying application depths across fields. Bases for spatially varying water for these systems have included pre-season soil sampling, user-defined management zones, and soil moisture sensing. Reeder (2002) developed a closed loop control system for site-specific irrigation with a Kalman filter to schedule irrigations so that soil moisture was maintained at greater than 65% of available soil water in the crop root zone. Soil moisture was measured in each management zone for this test. Field tests from this study indicated that site-specific management produced greater yields than uniform management for the same amount of water. Irrigation thresholds that maximized gross margins for soybeans in different management zones over 25 years of historic weather were determined by Nijbroek et al. (2003). The Nijbroek study showed that site-specific irrigation produced the highest average gross margin over the twenty-five-year period of the study. These results did not include the cost of implementing the site-specific system and could be affected by the irrigation scheme examined, individual field characteristics, climate and the crop grown. Due to the complex nature of the interactions among the factors affecting the results of these two studies, further tests are needed to confirm that the results hold for different situations.

CROP MODELS

Process-oriented crop growth models are composed of mathematical equations which represent processes in crop growth and development. Fundamental processes simulated include the plant carbon balance, soil-plant-water balance, soil-plant-nitrogen balance and energy balance (Boote et al., 1998). Examples of process-oriented crop growth models include CERES-Maize (Jones and Kiniry, 1986), CROPGRO-Soybean (Boote et al., 1998), and GOSSYM (Baker et al. 1983). Model uses have been grouped into the broad categories of research knowledge synthesis, crop decision management, and policy analysis by Boote et al. (1996). Crop growth models have been used for determining optimum management schemes for fertilization and irrigation, and testing hypotheses about causes for variability in fields.

Recent research for improving model usage has included modifications of models to more effectively describe observed plant growth processes, linkages of models with geographic information systems, optimization methods for parameter determination, and

Table 2-2. Site-specific irrigation research characteristics – I.

Location	Control Element Size	Nozzle Type	Control Type	Positioning	Citation
Ft. Collins, CO	22 m x 53 m	Pulsed	PLC*	(Laboratory Tests)	Fraisse, et al., 1992
Aberdeen, ID	Tests at 18.3 m to 38 m x 6 degrees	Multiple manifold	Single board micro-computer	Absolute position encoder	King et al., 1999
Florence, SC	9.1 m	Multiple manifold (3)	PLC*	Angular positions from Valmont CAMS	Camp and Sadler, 1998
Proser, WA	6-12 m x 0.5 degrees	Pulsed	Custom controller	Differential GPS; Electronic compass	Evans et al., 1996; Evans and Harting, 1999
Tifton, GA	15 m	Pulsed	Farmscan Canlink 3000™	Non-differentially corrected GPS	Perry et al., 2002
Lubbock, TX	174 m x 3 degrees	Multiple manifold (3)	PLC*	Incremental encoder	Bordovsky and Lascano, 2003

* PLC = Programmable Logic Controller

Table 2-3. Site-specific irrigation research characteristics – II.

Location	Variation Basis	Research Justification	System Tests
Ft. Collins, CO	(Laboratory tests)	Water management research	Water distribution patterns
Aberdeen, ID	Soil moisture sensor	Need to improve efficiency of water management	Coefficient of uniformity (74-75%)
Florence, SC	Soil water potential (Sadler et al. 2002)	Plant –available soil water is major yield variability factor	Tested distribution uniformity along manifold
Proser, WA	Soil type / % sand from 30 m grid sampling	Reduce leaching from over-watering in sandy soils	Coefficient of uniformity (72 – 89%)
Tifton, GA	User "painted" management zones	Eliminate suboptimal application efficiencies from variety of factors	Coefficient of uniformity
Lubbock, TX	Soil texture and slope down furrow; soil electrical conductivity	Better utilization of water which is affected by non-uniform soils and topography	Application rate and positioning tests

combinations of models with remotely sensed imagery. Shen et al. (1998) added a tile drainage component to the CROPGRO-soybean model to adapt the model for use in Iowa where subsurface tile drainage is an important management tool. The simulation of root development with the CROPGRO-soybean model was modified to reflect impedance to root growth and non-uniform distribution of roots by Calmon et al. (1999). Modifications to processes simulated by the model can allow for adaptation of models for new situations and also incorporate new understanding of crop growth processes into the models.

Crop growth models have typically been developed for modeling uniform areas of soils and management. For spatial applications, multiple simulations of the model are made at point locations across fields. To manage the spatial simulations, crop growth models have been linked with geographic information systems. Predictions of spatial yields for potatoes and nitrogen leaching were made by linking PC ARC/INFO with the SIMPOTATO model by Han et al. (1995). GOSSYM was linked to the ARCView GIS and used for demonstrating potential yield improvements when simulations were made with the COMAX expert system by McKinion et al. (2001). While these two examples demonstrate the power of being able to visualize spatial patterns in yield and environmental factors, they failed to quantitatively evaluate the spatial performance of the models. Models can also be run multiple times to represent spatial variability with no connections to a GIS and the results displayed as an ordered series (Paz et al. 1998) or two dimensional map (Basso et al. 2001) using external software. These applications are generally in research settings and would not be desirable for producer applications of the model.

One drawback to using crop growth models, especially for spatial applications, is the amount of data required for use in the model. Inputs for crop growth models such as GOSSYM (Baker et al., 1983) include initial upper and lower limits of soil water content, soil fertility parameters such as nitrate, ammonium and organic matter, and saturated hydraulic conductivity. In the case of GOSSYM, each input can be uniquely specified for multiple soil depths at each modeling location. The inputs listed for GOSSYM could be obtained through hand-sampling at each location where the model is to be run. While such hand-sampling is done in research situations, it is doubtful that producers would go to the time or expense to obtain these inputs on a spatial basis. Inputs not measured can be adjusted to better match observed plant growth and crop yield through a process called calibration. Calibrating unmeasured input variables for spatial applications models can also be tedious, time-consuming, and may not be reproducible unless consistent methods are used.

Optimization methods which select a combination of inputs to best satisfy an objective function have been used with crop simulation models. Optimization methods for input selection avoid time consuming sampling. These methods are split into two groups: local search methods and global search methods (Royce et al. 2001). While local search methods are efficient, if multiple local optima exist they fail to converge to the global optimum solution (Royce et al., 2001). Examples of local search methods include the Nelder-Mead simplex algorithm and Powell's conjugate directions, while global search algorithms include genetic algorithms and simulated annealing (Royce et al., 2001). The Nelder-Mead simplex algorithm was used by Paz et al. (1998) for optimizing saturated hydraulic conductivity, soil drainage rate coefficient, and maximum rooting depth for spatial predictions of soybean yield. Simulated annealing was used for selecting split applications of nitrogen which produced the highest net return for four soil types over 35 years of historic weather data by Braga et al. (1999). A modification of simulated annealing termed adaptive simulated annealing was used for selecting values for soil impedance factor, root hospitality factor, and rooting weighing factor to match observed and predicted volumetric soil water content by Calmon et al. (1999). While able to find global optimum values, simulated annealing can be time consuming with reports of multi-year spatial simulations taking three weeks of computation time to reach a solution (Paz et al. 1998). The approach for spatial model simulation used in the Paz et al. (1998) study potentially causes the model to be rerun for the same combination of parameters multiple times. Irmak et al. (2001) proposed a method for spatial adjustment of parameters in which a database of yield predictions for all combinations of variable soil inputs are generated and then searched based on rules that utilize information on soil texture. These examples have demonstrated a number of different numerical techniques for parameter selection in crop growth models.

In the parameter selection studies described above, techniques used for comparing model results with observed values included coefficients of determination (R^2), percent differences between measured and predicted yield values, and qualitative comparison between trends in measured and predicted yields along transects (Paz et al., 1998 and

Paz et al., 1999). The coefficients of determination of greater than 0.57 in both of these studies indicate that adjusting parameters related to water stress and plant populations can account for large amounts of observed variability in crop yield. Field level estimates of yield were within 14% of observed corn yields in the Paz et al. (1999) study, while grid level estimates of soybean yield were within 20% of observed yield 92% of the time in the Paz et al. (1998) study. Other evidence of the ability of these crop growth models and techniques to account for spatial variability included the mirroring of trends between measured and predicted yields along transects over multiple years. The examples from Paz et al. (1998) and Paz et al. (1999) indicate that crop growth models applied on point bases can describe portions of the spatial variability observed in field-scale crop yields.

While crop growth models can account for many dynamic interactions in plant growth, applying them on point bases may not provide enough spatial resolution for all situations. Research on remedying this problem has been made by combining crop growth models with remotely sensed (RS) imagery. Moulin et al. (1998) noted four ways that remote sensing and crop models can interact, which are:

1. Obtaining a model input from RS data
2. Adjusting a state variable using RS data
3. Adjusting initial model conditions with RS data
4. Calibrating model inputs so that RS estimates and model predictions match better

For the first category to work RS data would need to be available on a time step matching that of the crop simulation model. Crop simulation models often operate at daily time steps or less, which is more frequent than RS data can realistically be obtained. Barnes et al. (1997) exemplified the second type of interaction, by adjusting model predicted leaf area index (LAI) to match a RS estimate of LAI in the CERES-Wheat model. Limitations on the procedure presented by Barnes et al. (1997) include the need for LAI modifications to occur within ten days of anthesis and the inability to adjust model predictions if the model was under-predicting LAI. Adjustment types three and four are combined and applied to the adjustment of water content and field capacity for matching RS-estimated and model-predicted ET by Moran et al. (1995).

In order for site-specific management to be adopted, the ability to make management decisions that optimize each farm manager's objectives based on observed spatial variability are needed. Results of site-specific management for individual farms will be affected by a number of factors including: climate, individual soils, crop grown, and management strategy used. Crop simulation models offer an attractive solution to answering question about effects of management strategies in a timely, cost-effective, manner. Tests of crop models for soybeans and corn have been made that have shown the potential of these models for site-specific applications. The techniques used in these tests have not been used with cotton simulation models. Numerous research sites with the capability for applying site-specific irrigation were noted in the literature. Limited studies have been made on the effects of site-specific irrigation on achieving management objectives, however. Studies were noted on the effect of site-specific irrigation on profitability of soybeans and potatoes, but not for cotton. Further research is needed to test site-specific techniques with the use of a cotton simulation model and then to use the model to explore the effects of site-specific irrigation on management objectives.

CHAPTER III

MODEL ASSESSMENT

INTRODUCTION

Agricultural water usage from the Ogallala Aquifer is a pressing concern for the state of Texas as water levels in the aquifer continue to decline. Agriculture uses 95% of the water from the aquifer in this area (Martin et al., 2005). Large amounts of variability have been observed in farm fields. Evidence of this variability includes observations of past farming practices affecting present crop growth patterns and the large ranges of yields from yield monitors. Evidence of variability in plant water needs across fields comes from variation in soil properties that affect water holding capacity and studies showing variations in crop temperature across fields indicating crop water stress. Despite the evidence of this variability, farm fields have had inputs such as water and fertilizer applied uniformly for many years resulting in areas of over and under application of each input. The ability to manage this within-field variability has only arisen with the convergence of global positioning systems, geographic information systems, and control technologies in recent years. Site-specific agriculture involves adjusting inputs at specific locations in fields rather than applying inputs uniformly across fields. Site-specific farming could potentially reduce inefficiencies in the usage of farm inputs and improve farm profitability. Implementing irrigation site-specifically could allow Southern High Plains farmers to more efficiently use their irrigation water and/or improve farm profit.

Implementing site-specific agriculture increases the number of management decisions that producers will have to make. Each management zone in a field could potentially receive different quantities and timings of inputs. In the case of irrigation, which requires management decisions throughout the growing season, the task of decision making could become quite daunting. One possible method of determining the effects of each strategy used in a field would be to conduct in-field tests from year to year. This method of decision making is slow and affected by yearly weather patterns, however.

Use of crop models for producer decision making could be faster than field experiments and allow producers to deal with the larger number of decisions that will need to be made in a site-specific production environment. Process-based crop simulation models try to include processes at one level above the process of interest, ie., if the response of the entire plant is desired, processes at the plant organ level are included in the model. Despite the best efforts of model developers, models still represent some degree of empiricism in the equations included. Model relations are developed from data sets that represent specific locations, management conditions, and plant genotypes. Only after being tested in other settings and scenarios can models be deemed suitable for these new settings and scenarios.

Typically for usage at a site, crop models will need inputs specific to the site and will have the inputs or internal parameters calibrated for that site to be used for prediction of further scenarios. Acquiring initial inputs and then calibrating a model for specific field locations will require large amounts of information gathering and techniques for using common data sources for the calibration process.

Cotton growth simulation models developed in past years include GOSSYM, COTONS, and Cotton2k. GOSSYM was the first developed of the three models. The other two models used the framework developed in GOSSYM but used different equations within this framework. Development of another model, CPM, was started but validation of it has not been completed. The first three models were selected for study because: 1) they represent the cotton growth models with the most recent development 2) they have the most complete representation of cotton growth processes available 3) they have readily available software and 4) validation studies exist for them.

The overall goal for this project is to develop a set of tools so that individual producers could examine the potential for the use of site-specific irrigation on their farms. The objective for this part of the project was to select the best cotton simulation model from GOSSYM, COTONS, and Cotton2k for the examination of site-specific irrigation in the Texas High Plains. To meet this objective, the models will need to accurately predict the movement of water in the soil, through evapotranspiration, and the use of water by plants for producing lint yield.

BACKGROUND

Crop growth models have been developed in many settings and for many applications. While the goal is a universally applicable model that will allow producers to make decisions for their sites, current models need to be tested when applied to new situations. Model evaluation has often been based on visual evaluation of agronomic information such as plant height, leaf area index, and fruiting development.

For modeling cotton growth, the most widely used model in the United States is GOSSYM (Baker et al., 1983). More recent model development has occurred in the COTONS (Jallas et al., 1999) and the Cotton2k models (Marani, 2004). Both of these models were derived from GOSSYM, but each has different modifications. All three models are dynamic, process-oriented simulation models of crop development and yield. GOSSYM and COTONS primarily use a daily time step for calculations, while Cotton2k computes and uses weather information on an hourly basis. Weather inputs used in the models are daily maximum and minimum temperature, rainfall, solar radiation, and wind speed. Other inputs in the models include management practices such as irrigation, fertilizer, and chemical applications, and a soil profile description. New concepts in COTONS include simulation of plant populations and competition among plants rather than single plant simulations. Cotton2k is based on the CALGOS model which has been developed and tested in California growing conditions (Marani et al., 1992a, Marani et al., 1992b, Marani et al., 1992c). Equations modified from GOSSYM to Cotton2k include leaf growth, boll growth, evapotranspiration, and water stress effects on growth processes.

Water Balance Methods

Movement of water through the soil-plant-air system will be important for analyzing variable rate irrigation. The effect of having less than a full soil moisture profile on plant growth will also be important. The amount of soil moisture in a soil profile can be modeled by the soil water balance. A general equation for describing the overall soil profile water balance (Martin et al., 1991) is:

$$D_e = D_b + R_e + I_n + U_f - ET - P_d \tag{3-1}$$

where

D_e = depth of soil water at the end of the period
D_b = depth of soil water at the beginning of the period
R_e = rainfall during the period
I_n = net irrigation during the period
U_f = amount of upward flow of water from lower depths
ET = combined evaporation from the soil and transpiration from plants
P_d = deep percolation or drainage

GOSSYM, COTONS, and Cotton2k model the soil profile by dividing it into multiple cells both horizontally and vertically. In GOSSYM and COTONS, the array of soil cells represents a cross section from plant row to plant row, with plants on the outer edges. In Cotton2k, the soil cell array models row middle to row middle, with the plant in the center of the array. Initial water movement following a rainfall or irrigation event is by gravity flow from layer to layer. In the following days, movement is based on differences in soil water pressure potentials between cells.

The relation between water content and soil pressure potential in GOSSYM and COTONS is modeled by the Marani soil-moisture-release equation. This equation is defined as:

$$\theta_i = \theta_{AD} + (\theta_{FC} - \theta_{AD})(h_{FC} / h_i)^{TEMP} \tag{3-2}$$

where

$$TEMP = \frac{Ln((-15 / h_{FC}))}{Ln((\theta_r - \theta_{AD}) / (\theta_{FC} - \theta_{AD}))}$$

θ_r = residual (15 bar) water content (cm^3 soil cm^{-3} H_20)
θ_{FC} = water content at field capacity (cm^3 soil cm^{-3} H_20)

θ_{AD} = air-dry water content (cm^3 soil cm^{-3} H_20)
θ_i = current water content (cm^3 soil cm^{-3} H_20) ($\theta_{AD} \leq \theta_i \leq \theta_{FC}$)
h_i = current soil water potential (bar)
h_{FC} = soil water potential at field capacity (bar)
Ln = natural log

In Cotton2k, the soil moisture release curve is modeled with the Van Genuchten equation:

$$\frac{\theta - \theta_r}{\theta_s - \theta_r} = \frac{1}{\left[1 + (\alpha\psi)^n\right]^m} \tag{3-3}$$

where
θ = water content at soil water potential ψ ($\theta_r \leq \theta_i \leq \theta_s$)
θ_r = residual water content (cm^3 soil cm^{-3} H_20)
θ_s = saturated water content (cm^3 soil cm^{-3} H_20)
α, m , and n are empirical constants that can be varied with specific soil properties
m = 1-1/n

When irrigating in a semi-arid climate, it is assumed that evapotranspiration is much larger than other components in the equation; therefore, components such as upward flow is often negligible while deep percolation might not occur. Thus, from a management stand point, the comparison between the water inputs of irrigation and rainfall and the water leaving the system in the form of evapotranspiration is important. The amount of evapotranspiration is also important because it is highly correlated with the overall yield.

The GOSSYM and COTONS models use equations from Ritchie (1972) for prediction of potential evapotranspiration. The Ritchie model partitions total evapotranspiration into two parts – a below canopy portion and an above canopy portion. The above canopy evaporation is calculated with,

$$E_o = \left[\frac{\Delta}{\gamma}R_{no} + 0.262*(1+0.0061*u)(e_o - e_a)\right](\frac{\Delta}{\gamma}+1)^{-1} \tag{3-4}$$

where

E_o = potential evaporation – canopy

Δ = slope of the saturation vapor pressure curve at mean air temperature

γ = constant of the wet and dry bulb psychrometric equation

R_{no} = net solar radiation above the canopy, mm day^{-1}

u = wind speed at height of 2 m

e_o = saturation vapor pressure at mean air temperature, millibars

e_a = mean vapor pressure of the atmosphere calculated from wet bulb and dewpoint temperatures as measured during a day, millibars

In these two models, the mean vapor pressure is calculated at the minimum daily temperature rather than the wet bulb or dewpoint temperatures. This difference can reduce the potential evapotranspiration rate predicted by the model as compared to the original Ritchie equation.

For constant rate soil evaporation, GOSSYM and COTONS use the following equation:

$$E_{so} = \left[\frac{\Delta}{\Delta+\gamma}\right]\left((1-INT)-(1-INT)*\lambda_s\right)*RS \tag{3-5}$$

where

E_{so} = potential evaporation rate below the plant canopy at the soil surface, mm day^{-1}

Δ = slope of the saturation vapor pressure curve at mean air temperature

γ = constant of the wet and dry bulb psychrometric equation

INT = fraction of light intercepted by plant leaves

λ_s = soil albedo; the fraction of incident radiation reflected by the soil

RS = solar radiation

The above equation for constant rate soil evaporation differs from the original equation used by Ritchie (1972):

$$E_{so} = \left[\frac{\Delta}{\Delta+\gamma}\right]R_{no}e^{-0.398L_{ai}} \tag{3-6}$$

where

E_{so} = potential evaporation rate below the plant canopy at the soil surface, mm day^{-1}

Δ = slope of the saturation vapor pressure curve at mean air temperature
γ = constant of the wet and dry bulb psychrometric equation
R_{no} = net solar radiation above the canopy, mm day^{-1}
L_{ai} = leaf area index

The equation for constant rate soil evaporation used by these two models uses fraction of light interception rather than LAI along with a different form of the equation.

For the falling rate portion of soil evaporation, GOSSYM and COTONS, used the following equation from Ritchie (1972):

$$\sum E_{s2} = \alpha * (t^{1/2} - (t-1)^{1/2}) \tag{3-7}$$

where
E_{s2} = evaporation rate from the soil surface during stage 2 evaporation on a day when precipitation < $\sum E_{s2}$, mm day^{-1}
α = the slope of the curve plotting cumulative soil evaporation against the square root of time
t = time, days

Cotton2k uses a version of the Penman equation for plant evapotranspiration that is modified for hourly calculations (Snyder and Pruitt, 1985, Dong et al., 1992):

$$E_o = \left(\frac{\Delta}{\Delta+\gamma}\right) * \left(\frac{R_{net}}{878.61 - 0.66915 * (T + 273.161)}\right) + \left[1 - \left(\frac{\Delta}{\Delta+\lambda}\right)\right] * (e_s - e) * \mathrm{FU2} \tag{3-8}$$

where
E_o = potential evaporation – canopy
Δ = slope of the saturation vapor pressure curve at hourly air temperature
γ = constant of the wet and dry bulb psychometric equation
T = hourly average air temperature in degrees celsius
R_{net} = net radiation in w m^{-2}
e_s = saturation vapor pressure at the hourly average air temperature
e = vapor pressure in kilopascals
FU2 = wind speed function
FU2 = 0.125+0.0439(U2) for net radiation <0
FU2 = 0.030+0.0576(U2) for net radiation >0
U2 = wind speed at height of 2 m

Soil evaporation in Cotton2k is calculated with the following relationship:

$$ES = ES1HOUR[IHR] * RRACOL[K] + ES2HOUR[IHR] \qquad (3\text{-}9)$$

where

ES = potential evaporation from soil surface of a column, mm per hour.
ES1HOUR[24] = part of hourly Penman evapotranspiration affected by net radiation, in mm per hour.
ES2HOUR[24] = part of hourly Penman evapotranspiration affected by wind and vapor pressure deficit, in mm per hour
RRACOL[K] = relative radiation reaching a given column

Since all three models use a form of a combination evapotranspiration equation, the results of the calculations should be similar. The total potential evapotranspiration is removed from the soil cells with roots capable of moisture uptake. As soil water in each cell is reduced, the soil water potential in the cell is adjusted based on the new soil moisture.

The soil water balance method changes from GOSSYM to Cotton2k give Cotton2k potential advantages in prediction for the High Plains environment. The temperature inputs to the evapotranspiration equations in GOSSYM and COTONS use the daily minimum temperature rather than dewpoint temperature, which will cause under-prediction of evapotranspiration. Cotton2k accounts for dewpoint temperature by predicting it from other inputs on an hourly basis. Daily minimum temperature is often much higher than dewpoint temperature. The higher temperature is also related to a higher air vapor pressure which would allow less potential water uptake in the air. The change in plant location from the center to the edge of the soil column in Cotton2k is better for the High Plains because it removes the assumption that same amount of water is applied on both sides of a row. The ability to use asymmetrical water patterns in

Cotton2k allows for modeling of skip-row irrigation patterns that are used in the High Plains region.

Plant Development Processes

In GOSSYM and COTONS, the plant emergence is modeled as a deterministic process with the time of emergence input by the user. In Cotton2k this process has been changed to the following relationship:

$$T = \frac{1}{x^2 a\sqrt{2\pi}} e^{-\frac{1}{2}\left[(1/x-b)/a\right]^2} \quad (3\text{-}10)$$

where

T = time of development, days since sowing

x = random variable

a = $0.0054272 + 0.0000125\overline{T^{\circ}}^{2}$

b = $\dfrac{\overline{T^{\circ}}^{2}}{4.3767\overline{T^{\circ}} + 2182.2939}$

$\overline{T^{\circ}}$ = average temperature since planting date, degrees celsius

The light interception model in GOSSYM is:

$$IL_p = 1.0756*Z*PLTSP \quad (3\text{-}11)$$

where

IL_p = light intercepted by a plant

Z = plant height

PLTSP = plant spacing in the row

In COTONS, the light interception model has changed to:

$$IL_p = \left(1 - \frac{\sqrt{H^2 + (ROWSP - PWIDTH)^2} - H}{ROWSP - PWIDTH}\right) * \left(1 - e^{-KL'}\right) * PLTSP * PWIDTH \quad (3\text{-}12)$$

where

IL_p = light intercepted by a plant

H = plant height
ROWSP = row spacing
PWIDTH = maximum branch length
K = light extinction coefficient
L' = effective leaf area index (LAI/(1-light transmitted to ground without traversing canopy)
PLTSP = plant spacing in the row
PWIDTH = water stress reduction factor

In Cotton2k the light interception varies based on the magnitude of the leaf area index. The two potential equations for describing light interception are:

ZINT = 1.0756 * PLANTHEIGHT/ ROWSPACE (3-13)
or
LFINT = 0.80 * LEAFAREAINDEX for LAI<0.5
LFINT = 1 - exp(0.07 - 1.16 * LEAFAREAINDEX) for LAI>0.5

where
LFINT = light interception computed from leaf area index.
ZINT = light interception computed from plant height

LFINT and ZINT are compared and if LFINT is greater than ZINT, the light intercepted is the average of the two values. In the case that ZINT is greater than LFINT, the light intercepted will be LFINT if LAI is increasing or ZINT if LAI is decreasing.

All three models use their form of light interception in the following equation which relates potential photosynthesis to gross photosynthesis accounting for the amount of light actually intercepted and reductions due to water stress

P_g = PSTAND*(IL_p)*PTSRED*PNETCOR*0.001 (3-14)

where
P_g = gross photosynthesis
PSTAND = potential gross photosynthesis per unit area of canopy intercepting light
IL_p = light intercepted by a plant
PLTSP = plant spacing in the row
PTSRED = water stress reduction factor
PNETCOR = [CO_2] correction factor

0.001 = grams conversion

The water stress reduction factors in the gross photosynthesis equations are also calculated differently between GOSSYM and COTONS and Cotton2k. In GOSSYM and COTONS, PTSRED is calculated with the following series of equations:

$$\Psi_l = -12.63 + 0.01799 * R_{inc} - 26.1097 * \psi_{soil} - 0.00001553 * R_{inc} * R_{inc} - 18.289 * \psi_{soil} * \psi_{soil} + 0.025497 * R_{inc} * \psi_{soil} \quad (3\text{-}15)$$

$$\Psi_{lin} = -3.82193 - 0.00333224 * R_{inc} \quad (3\text{-}16)$$

$$P_{index} = -0.101235 + R_{inc} * (0.0234135 - R_{inc} * 0.000017396) \quad (3\text{-}17)$$

$$P_{mois} = 0.24 * (\Psi_{lin} - \Psi_l) \quad (3\text{-}18)$$

$$PTSRED = (P_{index} - P_{mois}) / P_{index} \quad (3\text{-}19)$$

where

Ψ_l = minimum leaf water potential for the day
ψ_{soil} = the soil water potential affecting photosynthesis
R_{inc} = incident radiation in watt m^{-2}
Ψ_{lin} = minimum leaf water potential for the day in well watered soil
P_{index} = index photosynthesis under well watered conditions
P_{mois} = change in photosynthesis due to moisture stress

In Cotton2k the water stress reduction factor is:

$$PTSRED = -3.0 + AVERAGELWPMIN * (3.229 + 1.907 * AVERAGELWPMIN) \quad (3\text{-}20)$$

where

AVERAGELWPMIN = running average of minimum (at noon) leaf water potential for the last 3 days

Equations for the calculated leaf growth and boll growth in Cotton2k are among those modified from GOSSYM and COTONS. The leaf growth equation for GOSSYM is:

$$PFDWLD(J) = PFAL(J)*RADAY*DAYTYM*WSTRSD*WTF \quad (3\text{-}21)$$

where

PFDALD(J) = the potential change in area
PFAL(J) = the current area of the leaf at prefruiting node J
RADAY = rate of area growth during day time

DAYTYM = fraction of day with daylight
WSTRSD = water stress day. Fraction of day time period during which leaf is turgid enough (above -7 bars) for growth
WTF = temperature dependent factor for converting from leaf area to weight

In the above equation, if the day time temperature is greater than 24 degrees Celsius RADAY is calculated as follows:

$$RADAY = -1.14277 + TDAY*(0.0910026 - TDAY*0.00152344) \quad (3\text{-}22)$$

If the daytime temperature is less than 24 degrees Celsius, RADAY is calculated as:

$$RADAY = -0.317136 + TDAY*(0.0300712 - TDAY*0.000416356) \quad (3\text{-}23)$$

where
TDAY = average day time temperature

The leaf growth equation for Cotton2k is:

$$R = SMAX * C * P * \exp(-C * T^{P} * T^{(P-1)}) \qquad (3\text{-}24)$$

where
R = the daily leaf growth rate
SMAX = the potential cultivar maximum growth rate
C = 0.00137566 + 0.025 * JP1 * (JP1 – 0.00005)
P = 1.6
T = time (leaf age)
JP1 = node counter

The selection of the monomolecular equation form of leaf growth for Cotton2k (Marani et al., 1992c) was made based on data from Constable and Rawson (1980). This equation was selected because another candidate equation (Richards, 1979) did not have a point of inflection appropriate for cotton leaf growth data.

The boll growth equation in GOSSYM is as follows:

$$PDWBOD = BOLWGT * DUMY \qquad (3\text{-}25)$$

where
PDWBOD = potential change in weight of boll during the day

BOLWGT = current weight of boll
DUMY = intermediate variable
DUMY = (0.0160791*TDAY-0.2120865)*DAYTYM*WSTRSD, if <7 days after beginning of boll development
DUMY = (0.0312*TDAY-0.0508125)*DAYTYM*WSTRSD, if >7 days after beginning of boll development and temperature < 28.5 Degrees Celsius
DUMY = (2.73285-0.082857*TDAY)*DAYTYM*WSTRSD, if >7 days after beginning of boll development and temperature > 28.5 Degrees Celsius

where
TDAY = average daytime temperature
DAYTYM = fraction of day with daylight
WSTRSD = water stress day. Fraction of day time period during which leaf is turgid enough (above -7 bars) for growth

The boll growth equations for Cotton2k are:

$$RATEBOL = 4 * RBMAX * PEX / (1 + PEX)^2 \qquad (3\text{-}26)$$

where
RBMAX = the potential maximum rate of boll growth (g seeds plus lint dry weight per physiological day) at this age.
PEX = auxiliary variable
PEX = exp(-4 * RBMAX* (T - AGEMAX) / WBMAX)
T = the physiological age of the boll after bloom
AGEMAX = the age of the boll (in physiological days after bloom) at the time when the boll growth rate is maximal.
WBMAX = maximum possible boll weight

The leaf and boll growth equations for the three models are affected by water stress also. In GOSSYM this stress is calculated as:

$$WSTRSD = (-2.5/(PSIAVG - 1.6)) + (0.0005*PSIAVG*TDAY) - (0.001*RN) \qquad (3\text{-}27)$$

where
WSTRSD = water stress day. Fraction of day time period during which leaf is turgid enough (above -7 bars) for growth
PSIAVG = average water potential of the root zone, in bars
TDAY = average daytime temperature
RN = net radiation in watts m^{-2}

In Cotton2k, this leaf water stress is calculated as:

$$WSTRLF = WATERSTRESS * (1 + 3.0 * (2 - WATERSTRESS)) – 3.0 \qquad (3\text{-}28)$$

where

WSTRLF	= water stress reduction factor for leaf growth rate
WATERSTRESS	= -0.10 - AVERAGELWP * (1.230 + 0.340 * AVERAGELWP)
AVERAGELWP	= running average of minimum and maximum leaf water potentials for the last 3 days.

The potential leaf growth is multiplied by the water stress factor above. Boll growth is not a factor of water stress in Cotton2k, but burr growth is reduced by a multiplicative factor of stress.

The models all calculate the potential amount of water used by plants from weather inputs. This potential amount is affected by: the location and quantity of water in the root zone, the location and age of roots to uptake water and the crop canopy available for transpiration and shading the soil thus preventing evaporation. In turn, the growth rates of plant components such as leaves, stems, and fruit are affected by water stress through differences between soil and leaf water potentials at field capacity and less than field capacity. The interrelationship of the water and growth factors in each of the models makes determining a singular relationship between any two individual factors difficult.

Modifications to light interception for COTONS and water stress effects on crop growth for Cotton2k should make these two models predict better than the original GOSSYM model. Modifications to COTONS include sensitivity to row spacing and modification of light interception to account for young age effects in cotton (response to higher gross photosynthesis, higher light penetration, and heliotropism during the earliest days of growth). Modifications to water stress effects on photosynthesis and growth equations in Cotton2k compared to the other two models were intended to improve model predictions for plants that are stressed over extended periods of time, which are conditions that would be expected for plants grown in the High Plains.

Model Validation

The GOSSYM model was originally developed in a humid Mississippi climate. Overall model performance was confirmed by qualitatively comparing time series of plant height, number of squares, and number of bolls with measured data. Tests of the agronomic components of the model have been made for the semi-arid Arizona climate (Fye et al., 1984). For the model to work in this region, coefficients in the model for a number of equations were adjusted. The model was then run for Mississippi conditions and one by one the adjustments removed. After these adjustments, the following differences still existed in the model equations between the two sites: the effect of water stress on canopy photosynthesis, potential root growth rate, growth rate of plant height, and growth rate of the leaves.

Other tests of this model for semi-arid regions including the Texas High Plains have been made with differing results. Wanjura and McMichael (1989) used the model for a nitrogen level study in this region. Relationships adjusted in this calibration were: "temperature-node equations that determine the time interval for initiating main stem nodes, squares, and bolls", minimum leaf water potential, average night time temperature, and lint yield composition. Staggenborg et al. (1996) found that the model under-predicted evaporation in this region and recommended that it be modified to utilize weather information on humidity.

Tests of CALGOS, an earlier version of Cotton2k, were made with field data from the San Joaquin Valley of California (Marani et al., 1992a, 1992b, 1992c). Qualitative assessment was made of the following model components: distribution of water in the root zone, midday leaf water potential, LAI, and green boll weight. These tests indicate improvement in model performance over the previous equations, but potential need for work on water stress effects on boll shedding.

Evaluation of the model components modified from GOSSYM to COTONS was made by Jallas (1998). The modified light interception component was compared to the original GOSSYM light interception equation on a relative basis for data sets in Mississippi. Qualitative evaluation of the results showed that light interception calculated with the two equations was similar. Evaluation of other model changes were made by examining the variability in yield, number of nodes, and number of bolls with each modified component (emergence, node appearance, and abscission) turned on separately and seeing if it seemed reasonable.

Only one of the three candidate models for this study, GOSSYM, has been used in studies in the High Plains region. Both COTONS and Cotton2k have modifications from GOSSYM in their water balance and plant growth that will make them behave differently than GOSSYM. The Texas High Plains region is an important cotton growing region and the ability to use the best cotton growth model possible would greatly aid producers in making management decisions.

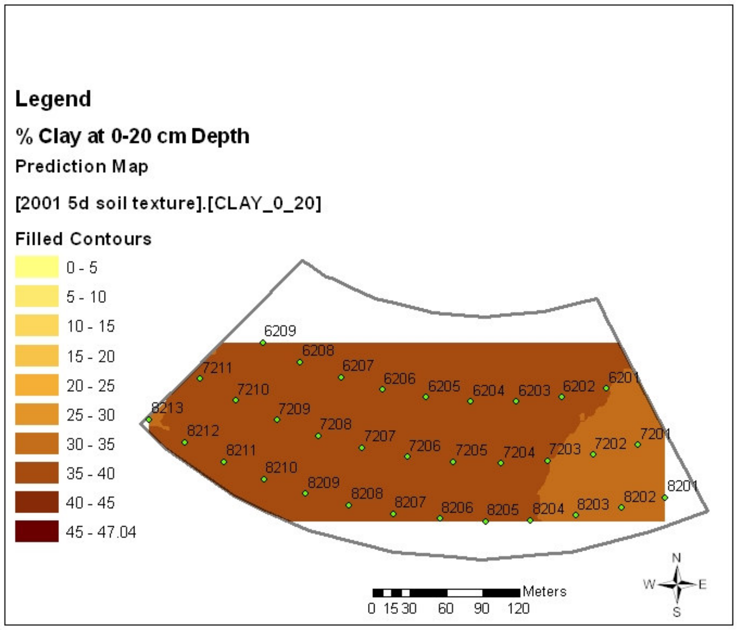
METHODOLOGY

Site Description and Field Experiments

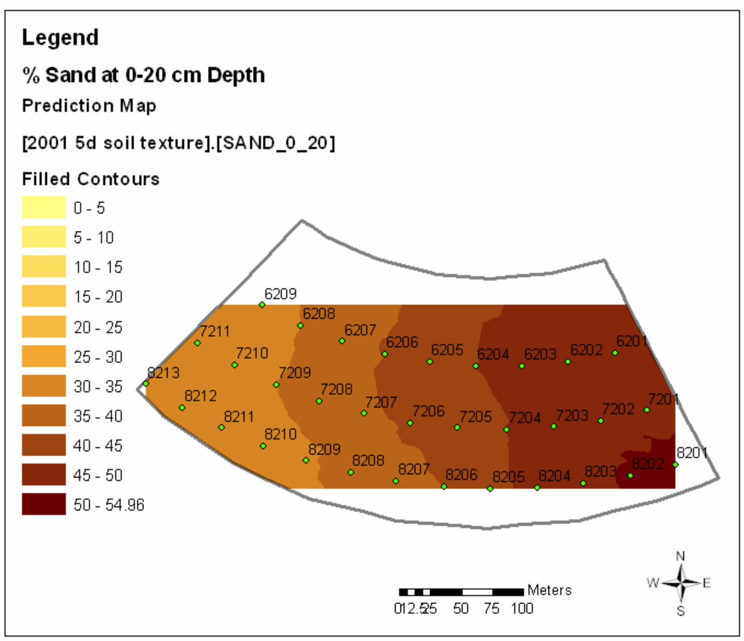
Data available for model evaluation were from sites at the Texas Agricultural Experiment Station at Halfway, Texas and a USDA experimental site in Lubbock County, Texas. The experiment on Helms Farm at the Halfway site was conducted on a 4.86 ha section of a field in a corn-cotton rotation. The soil survey map unit for this site was a Pullman sandy clay loam. Soil textures for individual points for the field were obtained by Robert Lascano (2004, personal communication) and provided for use in this study. Graphs showing the variation in percent clay and percent sand at 20-cm depth increments across the field appear in figures 3-1 and appendix A-1 to A-3.

Helms Farm

The Helms data set was from a field-scale variable rate irrigation study with the goal to "level lint yields by reducing irrigation in areas of high SWHC (soil water holding capacity) and adding water to areas of low SWHC (soil water holding capacity)" (Bordovsky and Lascano, 2003). Fields were irrigated with a LEPA center pivot system with its center point at 34° 9'6"N 101°56'52"W. The experimental area covered three pivot spans, each with three manifolds capable of being controlled separately. In the 2001 growing season, manifolds were used with variable rate and uniform rate water application strategies. For this season, three management zones for the variable rate applications were determined from soil texture and slope (Bordovsky and Lascano, 2003). Water application rates of 75%, 100%, and 125% of the uniform rate (UR) were applied to the management zones with applications occurring on average every four days



(a) percent clay



(b) percent sand

Figure 3-1. Soil composition at 0-20 cm depth: a) percent clay and b) percent sand in Helms Farm field 5D. Numbers from 6201 through 8213 indicate sampling locations.

from the middle June through the end of August. Irrigation timing was based on the time required for the pivot to travel around the field with adjustments in pivot movement following rainfall events. The water application rate for the UR areas was 80% of evapotranspiration calculated from a modified Penman-Monteith equation. Figure 3-2 shows the areas where each water rate was applied. This map shows that strips of variable rate and uniform rate irrigations were alternated across the center pivot manifolds at the site. Further description of the experiments at the site in 2001 can be found in Bordovsky and Lascano (2003). Management information for the site is summarized in table 3-1. Weather data for the simulations were obtained from a weather station at the Halfway Experiment Station (South Plains Evapotranspiration Network, 2004) and are summarized in table 3-2. This weather station was located 3.22 km from the research field; therefore, there is the potential for discrepancies between the quantity of rain in the weather data and the quantity that actually fell at the site. Both plant and soil data were obtained as a part of this experiment by Robert Lascano (personal communication, 2004). Measured data on soil water content by depth was obtained from bi-weekly sampling with neutron probes. Plant parameters collected as a part of this experiment included plant height, leaf area index, and square and boll mapping.

Lubbock County

The data from Lubbock County was part of a multiple level water and fertilization study in the 1997-2000 growing seasons. Data from the 1999 and 2000 growing seasons were included in initial examinations of data but later excluded due to the effects of insect and hail damage on crop yields. This site is located 5 km east of the Texas

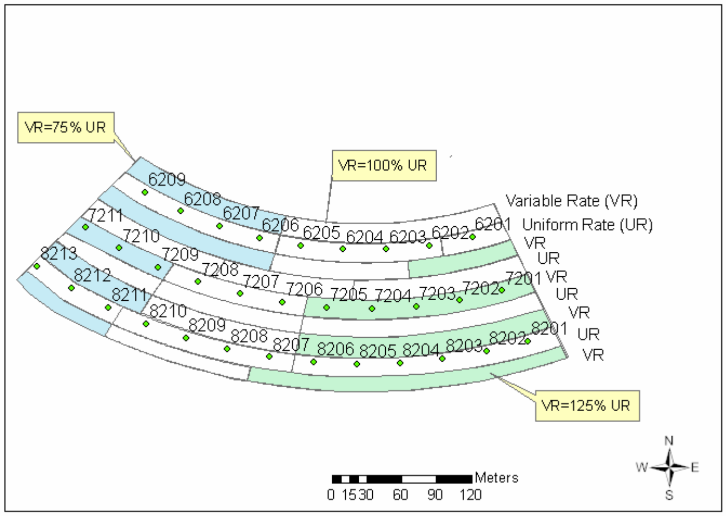


Figure 3-2. Soil sampling points and control management zones in 2001 for field 5D at Helms Farm site.

Table 3-1. Experimental management parameters for Helms Farm study.

	2001
Plant date	May 15
Harvest date	Oct. 18
Row spacing	76.2 cm
Plants per meter	10.8
Irrigation date range	May 26 – Aug. 30
Fertilizer quantity	143.4 kg N ha^{-1}

Table 3-2. Average weather conditions during simulation periods.

Year	Average Daily Maximum Temperature	Average Daily Minimum Temperature	Total Rainfall
	(°C)	(°C)	(cm)
Lubbock County study			
1997	29.0	15.4	26.3
1998	34.0	21.5	21.5
Helms Farm study			
2001	31.5	16.7	18.3
Historic average over approximate simulation periods			
(May 1 – October 15)	30.4	16.3	31.4

Agricultural Experiment Station at Lubbock at 33°41’7”N 101°41’10”W. An Olton clay loam soil (fine mixed thermic *Aridic Paleustoll*) was located at this site. Treatments in this experiment were divided into 12.2 m x 12.2 m plots. Crops were planted on May 16 in 1997 and May 14 in 1998. A Paymaster HS26 variety was planted in 1997 and Paymaster 2326 in 1998. Other management information for the site during 1997 and 1998 is summarized in table 3-3. The irrigation levels specified as WL2, WL3, and WL4 in this table correspond to irrigation applications of 1/3, 2/3 and 1.0 times PET. A subsurface drip irrigation system was used for these experiments. Irrigation treatments included dryland and 1.0 times PET irrigation levels each year. Weather data for simulations at this site were obtained from Wanjura (2004, personal communication) and are also shown in table 3-2. The weather station for these experiments was located next to the plots. Crop data obtained from this experiment included plant height, plant mapping, and crop yield. This data set did not include any soil sampling. The field experiments have been described previously in Wanjura et al. (2002).

Table 3-3. Experimental management parameters for Lubbock County study.

	1997	1998
Plant date	May 14	May 14
Harvest date	October 30	October 26
Row spacing	1.02 m	1.02 m
Plant population		
Dryland (pl/m)	11.29	13.4
W2 (pl/m)	12.24	
W3 (pl/m)	12.7	
W4 (pl/m)	12.14	10.8
Irrigation date range	July 1 – Sept. 15	May 27 – Sept. 18
Fertilizer quantity	89.6 kg N ha^{-1}	168 kg N ha^{-1}

Input File Creation

Each crop simulation model tested consisted of an executable program that read in text files for input then executed to simulate output on crop growth and yield parameters. Inputs are organized into files for soils, management, weather, and initial conditions. Soil inputs for all three models were organized by soil layers. The soil hydrology inputs for the three models are shown in table 3-4. Inputs that were the same for all three models were percent sand, percent clay, saturated water content, and residual water content. The differences in required soil inputs were due to different soil moisture retention curve equations used by the three models.

Table 3-4. Cotton model soil input variables.

GOSSYM and COTONS	Cotton2k
Percent sand	Percent sand
Percent clay	Percent clay
Bulk density	Bulk density
Hydraulic conductance	Hydraulic conductivity at saturation
	Hydraulic conductivity at field capacity
Diffusivity at -15,000 cm potential	
Saturated volumetric water content	Saturated volumetric water content
Volumetric water content at field capacity	
Volumetric water content at -15,000 cm potential	
Residual volumetric water content	
Volumetric water content at air dry	Volumetric water content at air dry
	Alpha coefficient for the Van Genuchten equation
	Beta coefficient for the Van Genuchten equation

Management parameters for all three models include timing and quantity of fertilizer applications, and timing and depth of irrigations. The GOSSYM and COTONS inputs differed from Cotton2k inputs because GOSSYM fertilizer quantities were entered as total quantity of fertilizer applied, while Cotton2k used entries for the quantity of each specific form of nitrogen applied.

Weather inputs for the three models included daily solar radiation, daily maximum and minimum temperature, daily precipitation, and daily wind run. In Cotton2k, the daily weather inputs are converted to hourly values for its hourly calculations based on work by Ephrath et al. (1996). A fifth text file, the profile file, which contains the names of each of the other input files required for a simulation, that was used by each model. Simulation start and stop dates were also contained in the profile file.

GOSSYM and COTONS contained information for the HS26 variety and its derivatives used in the field experiments for these tests. Cotton2k did not have any data for this variety, however. The equations in Cotton2k that use variety dependent parameters are different than in GOSSYM; therefore, using the same variety inputs in both models is not possible. Cotton2k simulations made with different variety inputs were compared to field measurements of LAI, plant height, number of main stem nodes, and number of green bolls. The measured data was from a field experiment conducted in Lubbock Texas during the 2002 growing season that used the HS26 variety. This test was part of a time-temperature threshold irrigation test. It was conducted on an Amarillo loamy fine sand soil at the USDA Cropping Systems Research Laboratory in Lubbock. Varieties with information in Cotton2k were Germaine 510, Delta Pine 61, and Delta

Pine 77. Predicted and measured data were compared qualitatively (figures 3-3 through 3-6) and quantitatively (table 3-5). The Germaine 510 variety performed best for the plant height and LAI parameters, but was the worst of the three varieties for predicting number of main stem nodes and number of bolls. The Delta Pine 61 variety performed best for predicting main stem nodes, but had large under-predictions for plant height. The Cotton2k predictions with the Delta Pine 77 variety were best for prediction of number of bolls and second best for all the other parameters. Based on having the most consistent predictions across all four parameters, the Delta Pine 77 variety was selected for use in further tests.

Points were selected for analysis at the Helms Farm site so that all three irrigation treatments were analyzed in an effort to account for as much of the variability in sand and clay contents (figure 3-1) as possible. Points 7202 and 8202 were from the east side of the field and points 7210 and 8210 from the west portion of the field.

Soils files were created based on soil texture information that was sampled to 80-cm depths in 20-cm increments (Robert Lascano 2004, personal communication). From 80 to 201 cm, the soil texture used was from the Pullman sandy clay loam based on the soil survey map unit (USDA-SCS, 1974). A summary of the soil textures from the points used for evaluating the three models appears in table 3-6. The sampled soil textures were used with tabular lookups and calculations based on the soil water retention relationships in the model to create the remaining soil inputs. The source of each soil input for the GOSSYM and COTONS models is shown in table 3-7 and for Cotton2k in table 3-8. Soil inputs varied for the three models due to different equations and soil

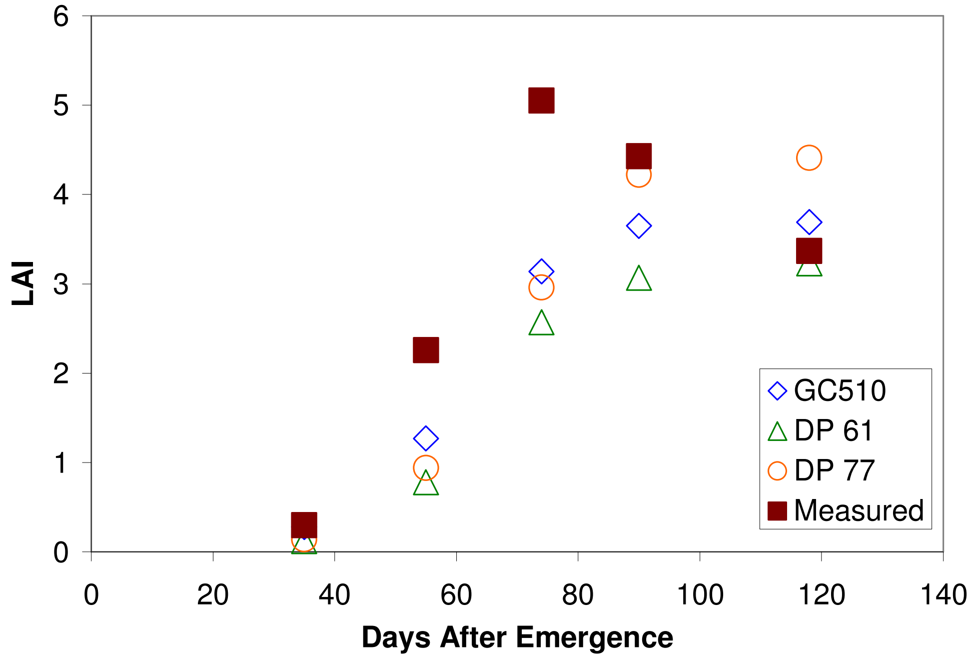


Figure 3-3. Measured and Cotton2k predicted LAI for 2002 Lubbock County experiment.

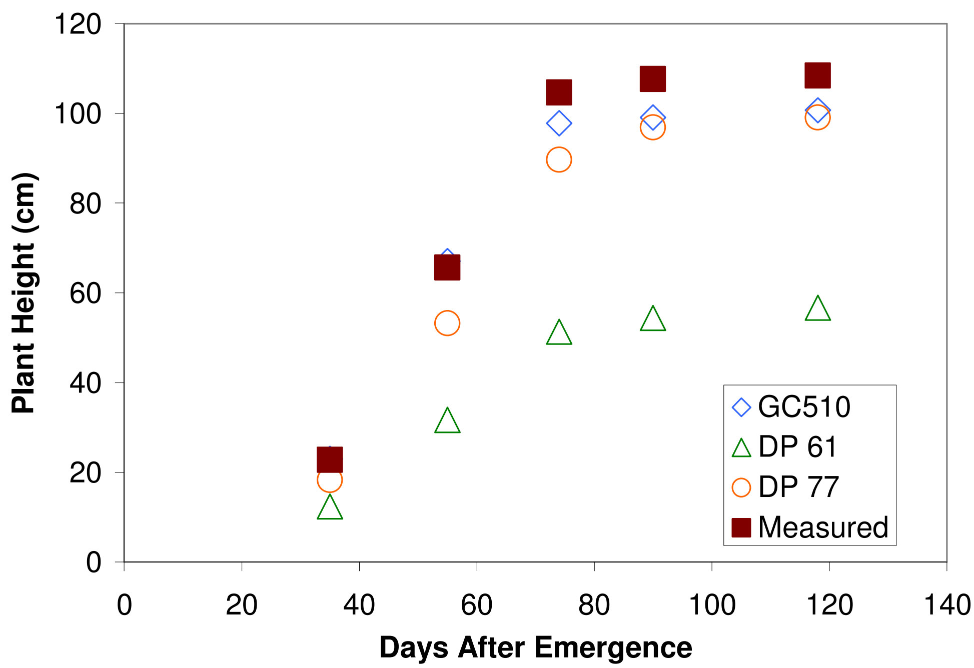


Figure 3-4. Measured and Cotton2k predicted plant height for 2002 Lubbock County experiment.

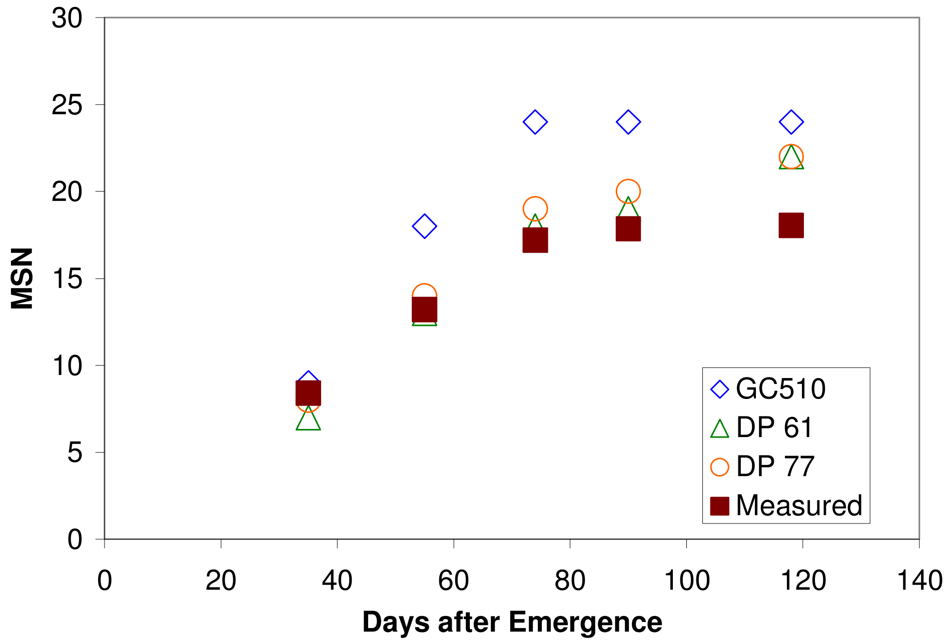


Figure 3-5. Measured and Cotton2k predicted main stem nodes (MSN) for 2002 Lubbock County experiment.

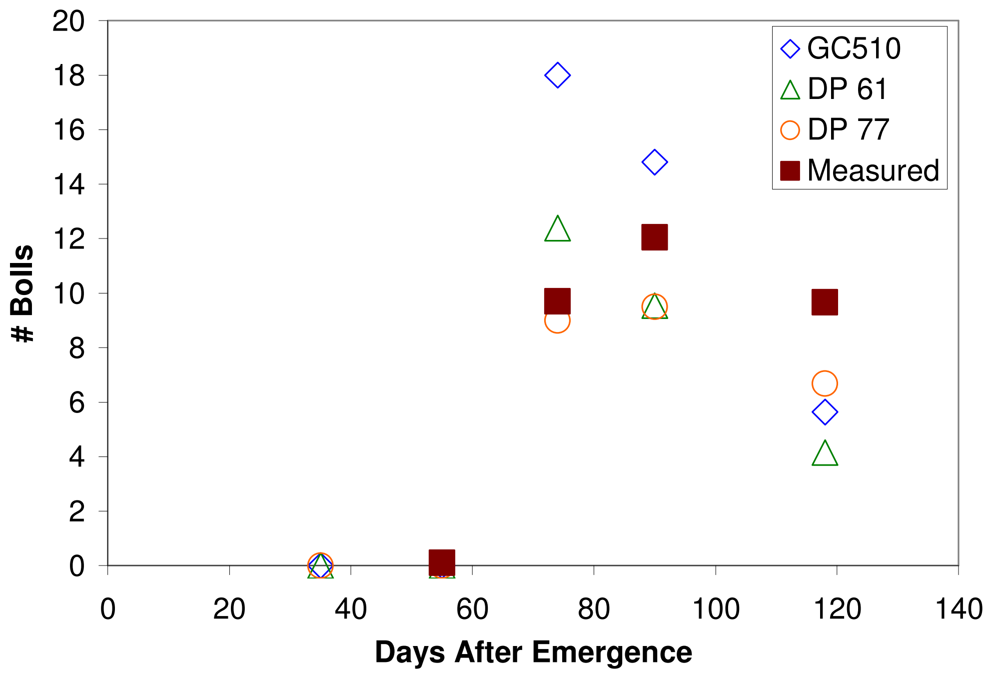


Figure 3-6. Measured and Cotton2k predicted number of bolls (# Bolls) for 2002 Lubbock County experiment.

Table 3-5. RMSE between measured and Cotton2k predicted physiology parameters with different variety inputs for 2002 Lubbock County experiment.

	Variety		
Parameter:	GC510	DP 61	DP 77
Main Stem Nodes	5.35	1.98	2.20
Bolls	4.31	2.97	1.79
Plant Height	6.08	43.90	11.00
LAI	1.03	1.43	1.21

Table 3-6. Helms Farm experiment soil textures.

LOCATION	Depth (cm)	% Sand	% Clay	Texture
7202	20	51	34	Sandy Clay Loam
7202	40	36	36	Clay Loam
7202	60	46	36	Sandy Clay
7202	80	48	36	Sandy Clay
7202	201	33	33	Clay Loam
7210	20	37	41	Clay
7210	40	40	39	Clay Loam
7210	60	54	35	Sandy Clay Loam
7210	80	62	29	Sandy Clay Loam
7210	201	33	33	Clay Loam
8202	20	55	31	Sandy Clay Loam
8202	40	31	45	Clay
8202	60	33	47	Clay
8202	80	35	42	Clay
8202	201	33	33	Clay Loam
8210	20	27	47	Clay
8210	40	27	49	Clay
8210	60	30	50	Clay
8210	80	36	44	Clay
8210	201	33	33	Clay Loam

Table 3-7. GOSSYM model soil input sources for Helms Farm simulations.

Input	Source
Percent sand	Soil sampling
Percent clay	Soil sampling
Bulk density	Soil Water Characteristic program, Saxton et al. (1986)
Diffusivity at -15,000 cm potential	Calculated from Gardner-Mayhugh equations using soil water retention curve points generated with Saxton calculator
Volumetric water content at -15,000 cm potential	Calculated from Van Genuchten equation at -15000 cm
Hydraulic conductance	Calculated from Gardner-Mayhugh equations using soil water retention curve points generated with Saxton calculator
Saturated volumetric water content	Table 3 in van Genuchten et al. (1991) by soil texture
Volumetric water content at field capacity	Calculated from Van Genuchten equation
Residual volumetric water content	Table 3 in van Genuchten et al. (1991) by soil texture
Volumetric water content at air dry	Calculated from Van Genuchten equation

Table 3-8. Cotton2k model soil input sources for Helms Farm simulations.

Input	Source
Percent sand	Soil sampling
Percent clay	Soil sampling
Bulk density	Soil Water Characteristic program, Saxton et al. (1986)
Volumetric water content at air dry	Calculated from Van Genuchten equation
Saturated volumetric water content	From table 3 in van Genuchten et al. (1991) by soil texture
Alpha coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Beta coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at saturation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at field capacity	Soil Water Characteristic program, Saxton et al. (1986)

water potentials used to describe the soil moisture release curve. Values for van Genuchten equation parameters for the Cotton2k soil inputs were obtained for each sampling point based on tables from van Genuchten et al. (1991). The remaining Cotton2k inputs of saturated water content, hydraulic conductivity, and bulk density were obtained from the Soil Water Characteristic program that was based on Saxton et al. (1986). Soil moisture retention curve parameters for GOSSYM and COTONS were calculated from the van Genuchten equation at the soil water potentials used in GOSSYM and COTONS for field capacity and wilting point. The soil water potential used for wilting point was -15,000 cm. and for field capacity it was – 300 cm.

Initial model soil moisture conditions were manually selected based on average water content profiles from the Helms Farm site. The initial soil water content is entered as a percent of field capacity for all three models. Soil water content data for the first sampling date from ten points in both 2001 and 2003 were averaged together (figure 3-7). Percent field capacity in the initial condition files was selected to match average water contents from a combination of the soil water content profiles in the two years. Other initial soil inputs for residual nitrate, ammonia and organic matter (table 3-9) were kept as in the generic initial file that came with GOSSYM.

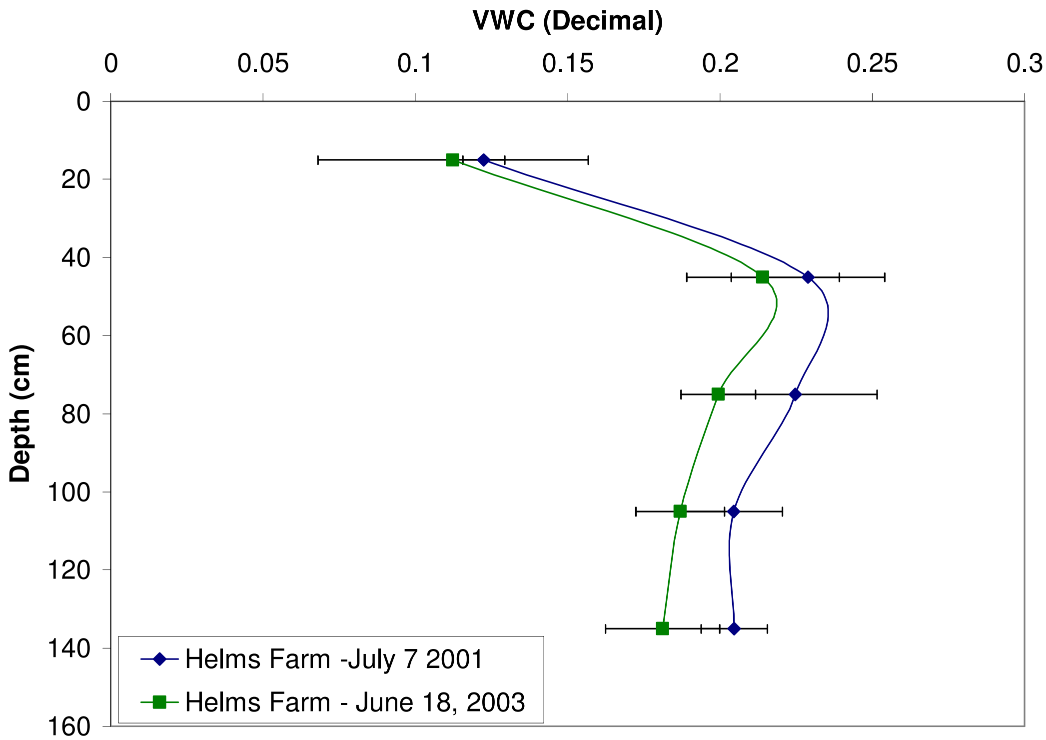


Figure 3-7. Volumetric water content (VWC) for Helms Farm site on July 7, 2001 and June 18, 2003 – averaged across ten sampling points with +/- one standard deviation error bars.

Table 3-9. Initial cotton model soil fertility and water content inputs by depth.

Bottom Layer Depth	NH_4 (kg ha^{-1})	NO_3 (kg ha^{-1})	Organic Matter, % by weight	Water Content, % of field capacity
15	2.69	26.904	0.74	60
30	1.23	13.23	0.72	80
45	1.00	10.09	0.67	85
60	0.79	7.40	0.43	85
75	0.79	7.40	0.37	85
90	0.79	7.40	0.30	85
105	4.93	4.93	0.00	85
120	4.93	4.93	0.00	85
135	4.93	4.93	0.00	85
150	4.93	4.93	0.00	85
165	4.93	4.93	0.00	85
180	4.93	4.93	0.00	85

Soil sampling information was not available for the Lubbock County experiment. A previously sampled profile for the soil survey mapping unit located at the site that was included with the GOSSYM model was used as input for GOSSYM and COTONS. Cotton2k soil inputs were created from this profile based on tabularized data by soil texture and from software based on Saxton et al. (1986). The exact source of each Cotton2k soil input is identified in table 3-10.

Table 3-10. Cotton2k model soil input sources for Lubbock County Farm simulations.

Input	Source
Percent sand	GOSSYM input file
Percent clay	GOSSYM input file
Bulk density	GOSSYM input file
Volumetric water content at air dry	From table 3 in van Genuchten et al. (1991) by soil texture
Saturated volumetric water content	From table 3 in van Genuchten et al. (1991) by soil texture
Alpha coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Beta coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at saturation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at field capacity	GOSSYM input file

Evaluation Tests

The models were compared for their ability to track water movement and use in the soil-plant-atmosphere continuum on a point by point basis. Data for this examination came from both the Helms Farm and Lubbock County sites. Data for soil moisture and yield evaluations were available at the Helms Farm site and for yield evaluations at the Lubbock County site. Model predictions were compared against measured values of cumulative evapotranspiration (ET), soil water content by depth in the soil profile, and yield by applied water quantity. Model predictions were made for individual sampling points within the field. Seasonal cumulative ET allowed for assessment of the model's tracking of long term plant water use. Data from the Helms Farm site was used with this assessment. ET from the field experiments was not measured directly but was determined from a soil water balance using the neutron probe data. In the determination of the soil water balance, it was assumed that no soil water drained through the bottom of the soil profile or that any surface runoff occurred. The soil water balance tracking was begun on the first day of soil moisture measurement. The soil moisture values to start the soil water balance were from averages of predicted soil water contents from the three models on this date. Soil water content by depth provided more detail about the location of water in the soil than the total quantity of water leaving through evapotranspiration. Model predictions of soil water content at the measured depths were determined from soil water profile map model output.

Applied water – yield relations are valuable to assess model performance because yield is an aggregation of all the processes in the model, not just soil moisture movement. Thus, if yield predictions are accurate over a range of conditions the entire model, including the soil moisture components, should be working correctly.

Model evaluations were made both qualitatively and quantitatively with graphs and summary statistics. Root Mean Square Error (RMSE) was used for the quantitative evaluation of the soil water parameters examined. RMSE is defined as:

$$\text{RMSE} = \left[\frac{1}{n} \sum_{i=1} \left(y_i - \hat{y}_i \right)^2 \right]^{1/2} \tag{3-29}$$

where
y_i = measured values,
$\hat{y}_i$ = predicted values
n = the number of values compared.

RESULTS AND ANALYSIS

Helms Farm Tests

Points 7202, 7210, 8202, and 8210 were used for testing the three cotton models. Point 7202 was under the 75% UR management, point 7210 under 125% of UR management, and the remaining two points were under 100% of UR management.

Measured and predicted cumulative evapotranspiration for four points from the 2001 growing season are shown in Figures 3-8 through 3-11. RMSE between measured and predicted cumulative ET for these four points are located in table 3-11. Trends in the ordering of the model predictions are consistent on all four graphs. GOSSYM predicted the lowest cumulative ET, COTONS the middle cumulative ET, and Cotton2k the highest cumulative ET. Comparisons of the predicted ET curves to measured values vary between the four points. For points 7202, 8202, and 8210, the Cotton2k predicted curves matched the measured ET curves best. For point 7210, the predicted curve from

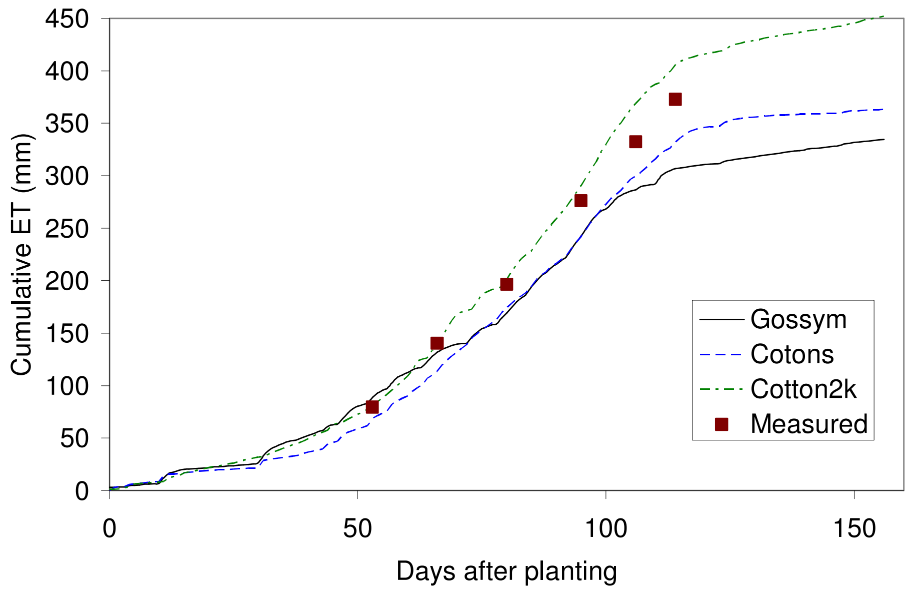


Figure 3-8. Measured and predicted cumulative ET in 2001 growing season at point 7202. Point 7202 was in a 100% ET management zone.

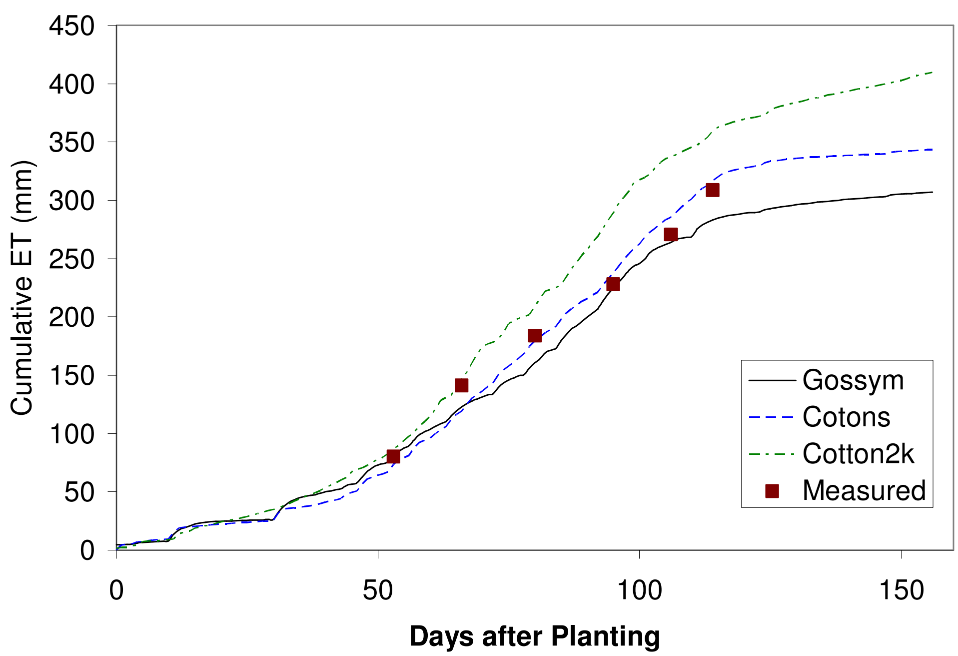


Figure 3-9. Measured and predicted cumulative ET in 2001 growing season at point 7210. Point 7210 was in a 60% ET management zone.

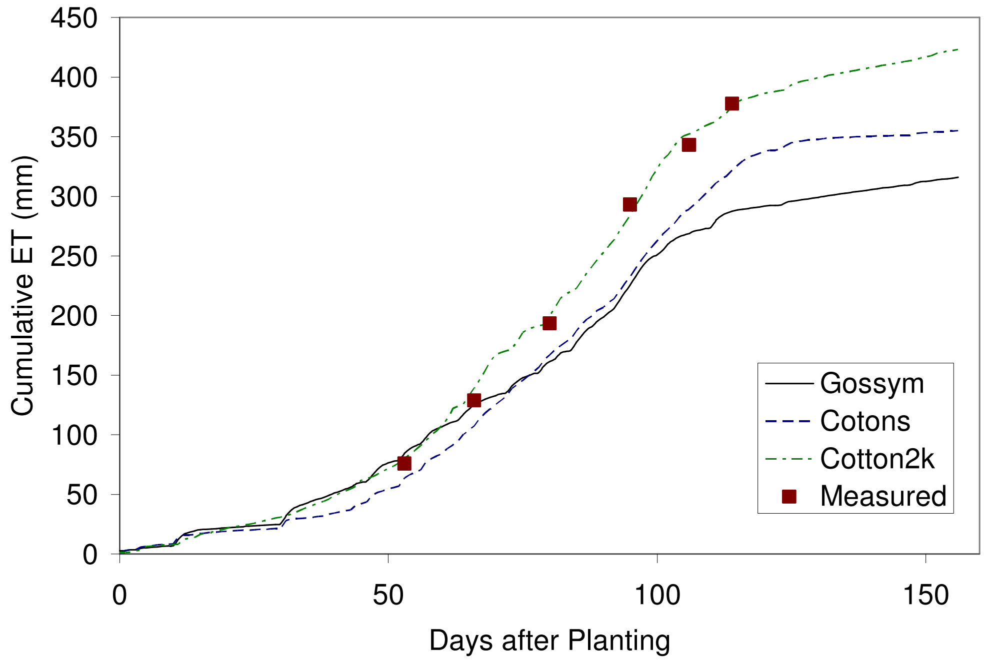


Figure 3-10. Measured and predicted cumulative ET in 2001 growing season at point 8202. Point 8202 was in an 80% ET management zone.

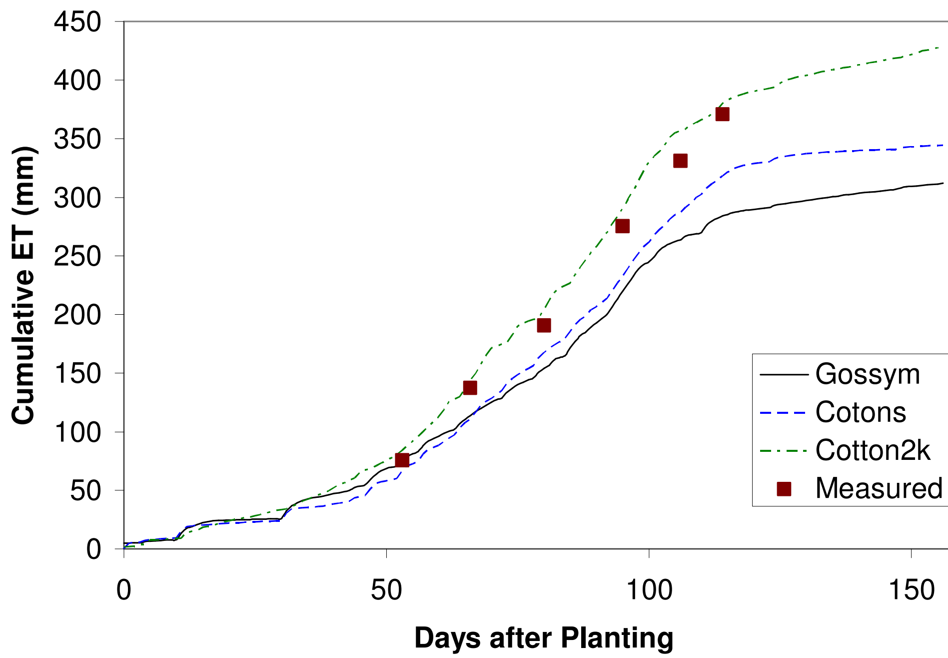


Figure 3-11. Measured and predicted cumulative ET in 2001 growing season at point 8210. Point 8210 was in an 80% ET management zone.

Table 3-11. RMSE between measured and predicted cumulative ET in 2001 season.

Point	GOSSYM	COTONS	Cotton2k
7202	41.05	32.22	22.86
7210	17.74	13.36	47.96
8202	62.03	46.67	8.03
8210	89.13	73.05	38.61

COTONS matched the measured data best based on the graphical and RMSE criteria. For point 7210 the measured ET was 63 mm less than for any other point, however. This observation suggests that the soils are allowing drainage or different initial soil water conditions are needed for this point.

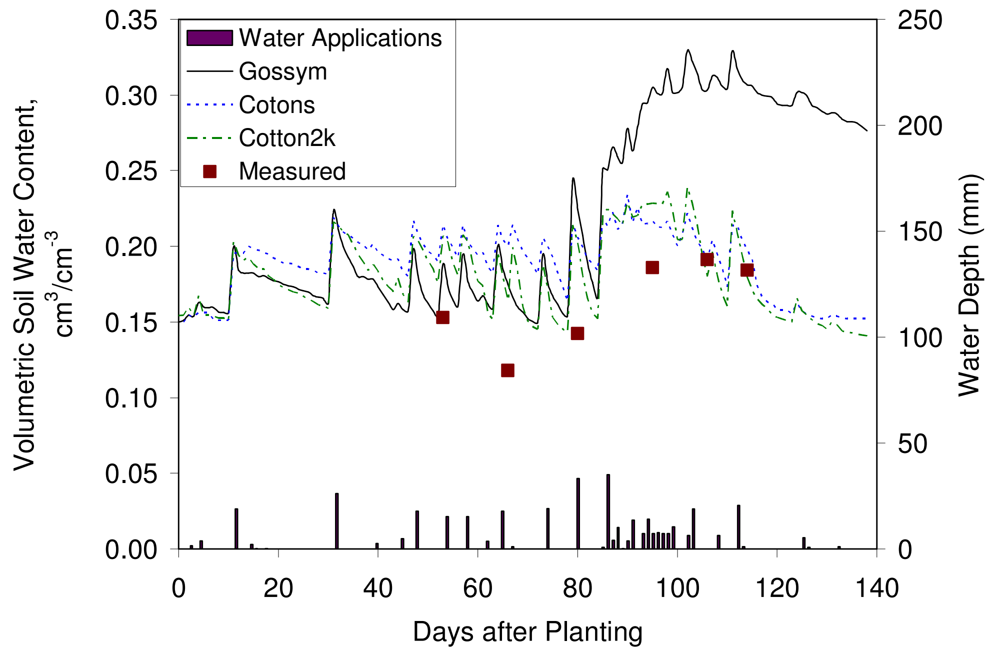
The evapotranspiration equations used between GOSSYM and COTONS are identical. The modified light interception component in COTONS would cause the differences in ET between GOSSYM and COTONS by increasing the COTONS prediction of light interception. Cotton2k on the other hand used similar equations as GOSSYM for the prediction of light interception, but predicted higher cumulative ET than GOSSYM. Cotton2k utilized an hourly form of the Penman equation rather than the Ritchie form, which is possibly the cause of Cotton2k's higher, and generally more accurate, cumulative ET predictions.

Soil water contents by layer for point 7202 are shown in figures 3-12 and 3-13. RMSE between measured and predicted values of soil water content appear in table 3-12. The increase in water contents between 80 and 100 days after planting for the 30-60 cm depths (figure 3-12b) indicates that plants at this point were not using all the water that had been applied and thus were not being stressed in this treatment. Differences in initial water contents between the three models occurred due to differences in breakpoints between categories in the soil water outputs for the three models. Model predictions were within +/-0.025 cm^3 cm^{-3} of water for the majority of the soil depths and measurement days. This margin of error is acceptable because observed initial water contents varied by a similar amount even though an average value was used as a model input.

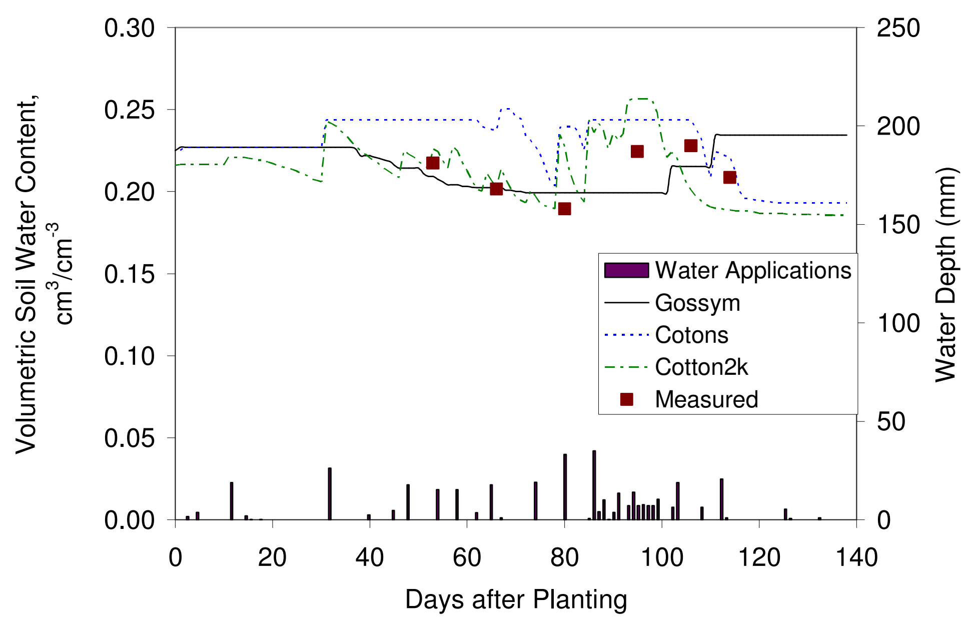
GOSSYM and COTONS did not follow measured data trends for several layers. For the 0-30 cm depth at point 7202, GOSSYM spiked up above the other models after day 80. COTONS also showed a spike above the predictions of the other two models for the 90-120 cm depth for this same sampling point. Cotton2k followed decreasing trends in soil water content for this point for depths below 60 cm. Cotton2k had better RMSE's between measured and predicted values for three of the four points examined.

Figure 3-14 shows yield response to the three levels of water applied in the 2001 Helms Farm experiments. Measured yields on this graph are averages of point yields for each water level. Predicted values are based on predictions made with soil survey map unit input files. GOSSYM predictions of yield are a fraction of the measured values, while COTONS predictions are approximately half the measured values. Cotton2k predictions were closer to the measured yields for all three points, though the prediction of yield for the lowest value was only about 60% of the measured value. The RMSE's between predicted and measured yields in table 3-13 showed that Cotton2k had the closest predictions to measured yields followed by COTONS then GOSSYM.

Water levels in the soil profile are related to the soil water potential of the soil. Soil water potentials are related to leaf water potentials in the model, which are used to

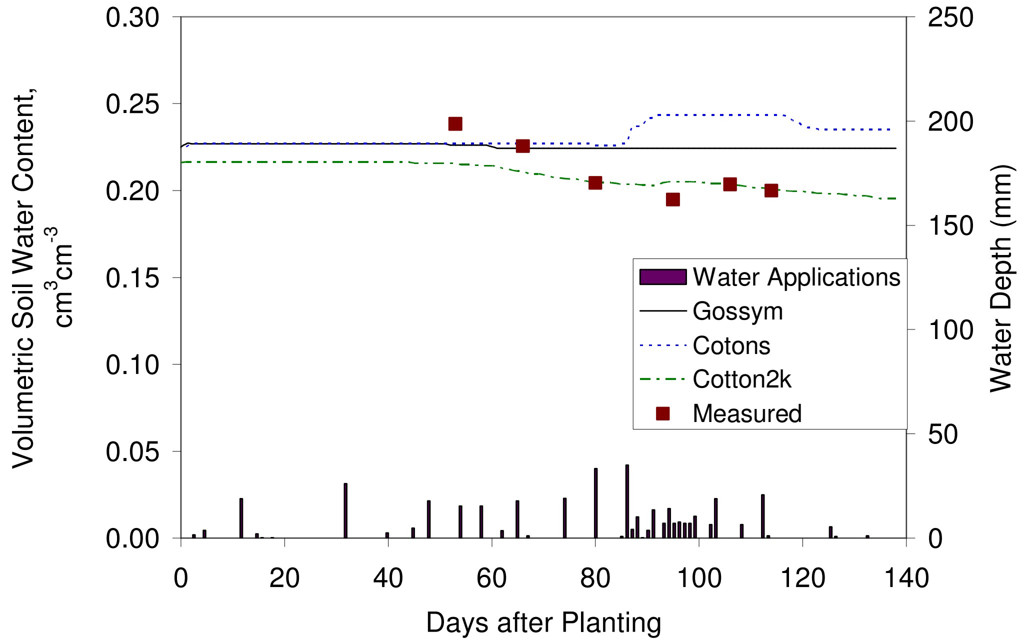


(a) 0-30 cm

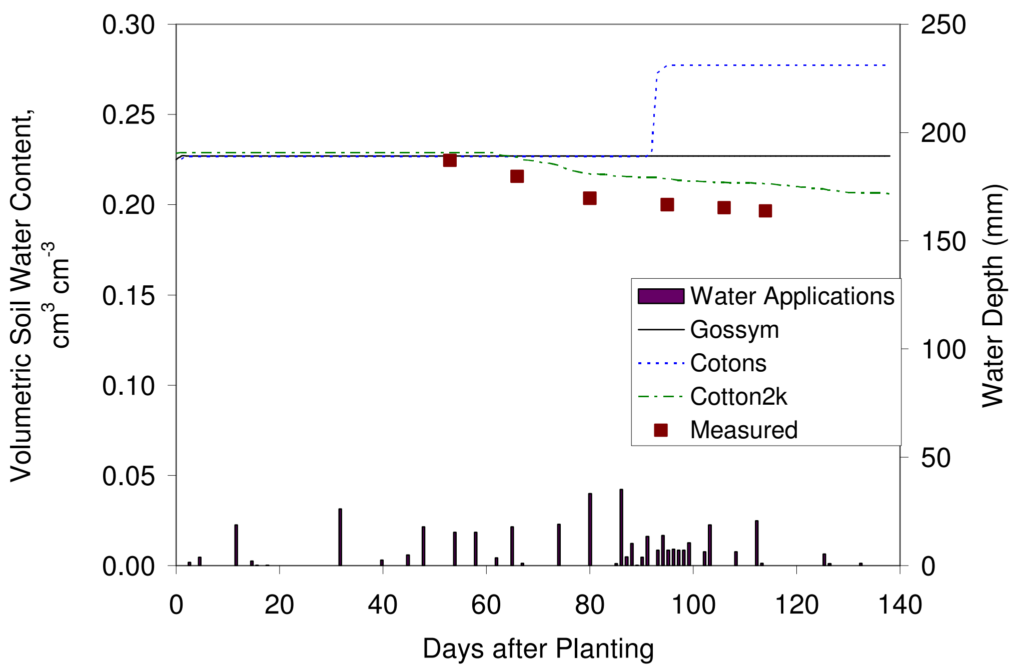


(b) 30-60 cm

Figure 3-12. Measured and predicted volumetric water content by depth for point 7202 in 2001 season. Layers shown are (a) 0-30 cm and (b) 30-60 cm.



(a) 60-90 cm



(b) 90-120 cm

Figure 3-13. Measured and predicted volumetric water content by depth for point 7202 in 2001 season. Layers shown are (a) 60-90 cm and (b) 90-120 cm.

Table 3-12. RMSE between measured and predicted volumetric soil water content by layer in 2001 season.

Point	GOSSYM	COTONS	Cotton2k
7202	0.0473	0.0452	0.0257
7210	0.0587	0.0622	0.0589
8202	0.0589	0.0650	0.0314
8210	0.0704	0.0654	0.0393

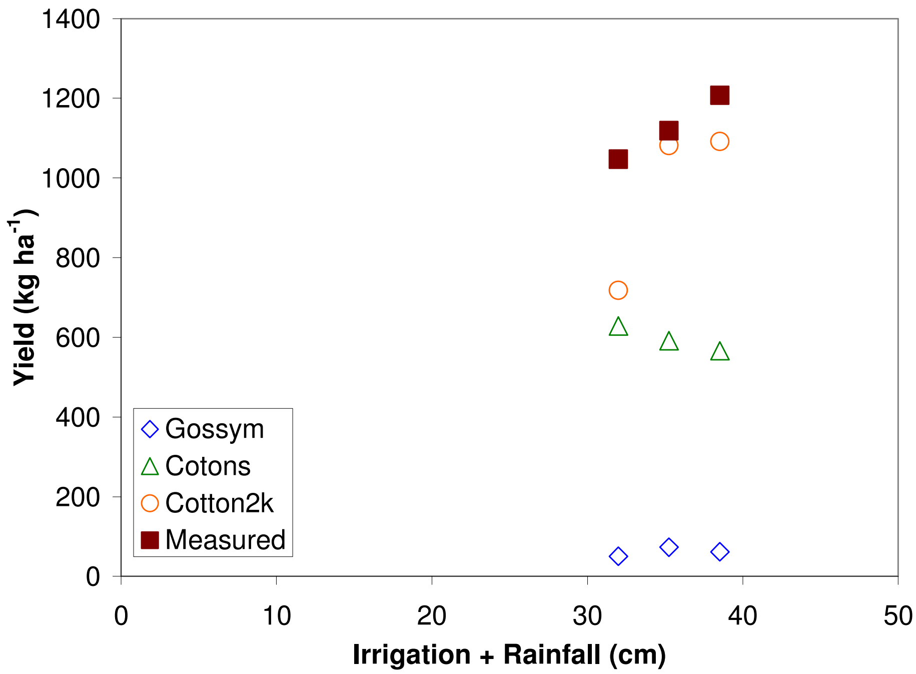


Figure 3-14. Measured and predicted applied water – yield relations for Helms Farm variable rate irrigation experiments in 2001 growing season. 60, 80, and 100% ET Treatments were 32, 35, and 39 cm, respectively.

Table 3-13. RMSE between measured and predicted yield for Helms Farm variable rate irrigation experiments.

Model	RMSE
GOSSYM	1064.4
COTONS	536.9
Cotton2k	202.4

indicate stress affecting plant growth. Actual plant growth is determined by multiplying stress factors for water and carbohydrate stresses by growth rates for different components of plant organ development. The stress factors vary from zero to one for each day with zero being a stressed plant and one being a non-stressed plant.

Water stress indices calculated by the three models were very closely related to the predicted yields for the Helms Farm field tests. The accumulated seasonal water stress index for the three models is shown in figure 3-15. This figure shows the accumulation of 1- the water stress index used in the models, so that higher values indicate greater stresses. The stress index in this figure is the summation of daily stress indices throughout the model simulation period. The R^2 values between this index and predicted yields were 0.89, 0.96, and 0.99, for GOSSYM, COTONS and Cotton2k, respectively.

Lubbock County Tests

The Lubbock County tests covered a wider range of applied water levels than the Helms Farm tests. The ability to predict yields over this range of water levels is important to allow producers to explore all possible watering options when using models. Measured and predicted applied water yield relations are shown in figure 3-16. GOSSYM under-predicted the measured yields for all water levels. GOSSYM did not have non-zero model predictions until greater than 40 cm of water was applied. The COTONS model showed markedly different trends depending on the level of applied water. Below 51.5 cm of applied water, the COTONS yield predictions were all less than 200 kg ha^{-1}, despite measured yields ranging up to 1200 kg ha^{-1}. Above 51.5 cm of applied water, the model predictions were within 25% of measured yield, though all

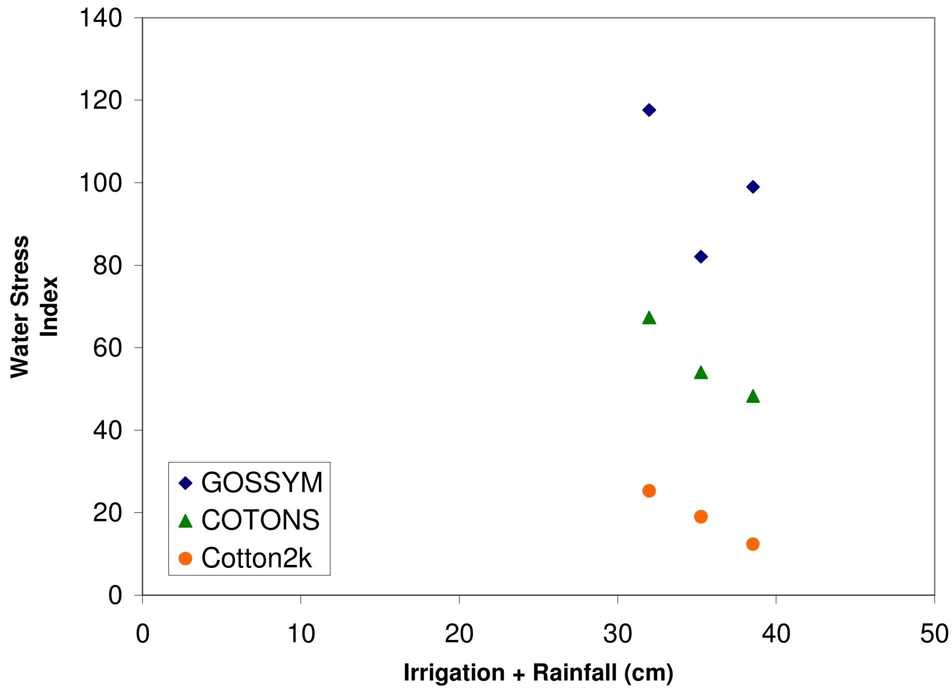


Figure 3-15. Cumulative water stress across water levels in Helms Farm experiment. Total water includes irrigations and rainfall events.

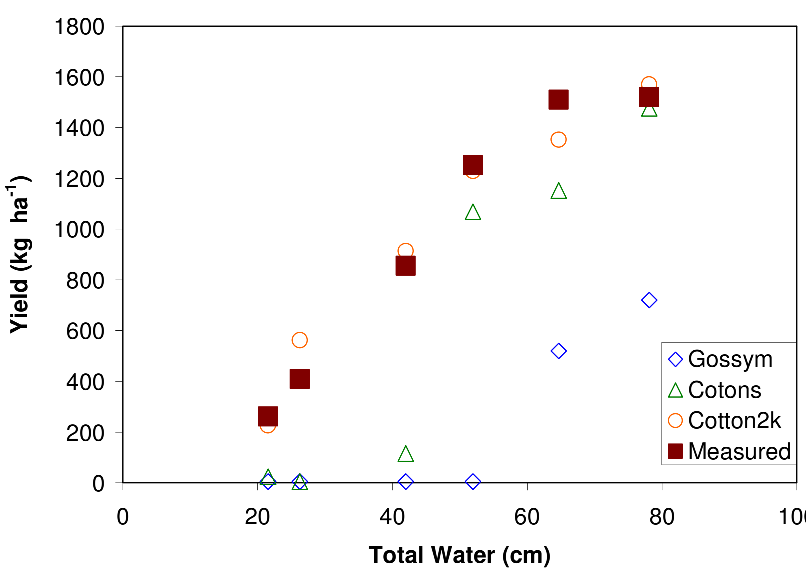


Figure 3-16. Measured and predicted applied water-yield relations for Lubbock county drip irrigation experiments in 1997 and 1998 growing seasons. Total water includes irrigations and rainfall events.

Table 3-14. RMSE between measured and predicted yield for Lubbock County applied water-yield relations.

Model	RMSE
GOSSYM	829.0
COTONS	393.1
Cotton2k	96.6

values were still under-predicted. Cotton2k predictions were close to measured yield for all six of the data points. Table 3-14 shows that Cotton 2k also had the lowest RMSE values, thus indicating better model prediction performance for yield, than the other two models.

Cotton2k produced much better yield predictions than the other two models. A portion of the differences in model predictions was from differences in evapotranspiration equations between the three models. GOSSYM predicted cumulative ET an average of 19.4% less than measured cumulative ET for the points examined. The lower ET predictions of GOSSYM and COTONS are likely from the use of daily minimum temperature in the Ritchie ET equation rather than dewpoint temperature. COTONS ET predictions were closer to measured values than GOSSYM predictions showing that the modified light interception component in it did improve model predictions. The improvements in ET predictions with the COTONS light interception equations were not as great as the improvements in Cotton2k with the use of dewpoint temperatures in the evapotranspiration equations and the use of the hourly evapotranspiration equation. The large difference in yield predictions at different water application levels between COTONS and GOSSYM and Cotton2k indicates that the modifications to water stress effects in Cotton2k makes it better for yield predictions in a semi-arid environment.

CONCLUSIONS

GOSSYM, COTONS, and Cotton2k were tested for their ability to track water as it moved through the soil and predict yield. Tests were conducted on data from two sites in areas with three different soil textures, at multiple water levels and across three years of weather information from the High Plains region. From these tests, Cotton2k is the most suitable choice for simulating the effects of site-specific irrigation on cotton for the Texas High Plains. These results illustrate the need for evapotranspiration prediction in semi-arid regions to use dewpoint temperature rather than some other temperature, such as daily minimum temperature. The ability of Cotton2k to match yield predictions at different levels of water application as compared to the other two models indicates the need for accurate description of stress factors in the development of simulation models

CHAPTER IV

USE OF SIMULATED ANNEALING FOR SELECTION OF SOIL INPUTS FOR A COTTON MODEL

INTRODUCTION

Crop models were created with a number of purposes and application methods in mind. They typically are intended to be applied with a single set of soil properties and management practices. The convergence of technologies that has enabled site-specific management has also provided the ability to apply crop models to areas with varying input conditions. Application of crop models in a site-specific manner can potentially showcase their decision making capabilities to situations where field experiments and user judgment do not work well. Applying crop models in a site-specific fashion requires a range of input values that describe the varying field conditions rather than a single value that represents an entire field. Techniques for acquiring large amounts of spatial data on farm fields include yield mapping, detailed sampling, and remote sensing.

Combining a crop model's ability to account for temporal interactions with a spatial data set can create an efficient site-specific decision tool. For crop models to be used as a site-specific management tool for individual farms, sampling of model inputs for specific sites or calibration of inputs for these sites is necessary. If the model inputs being calibrated do not directly relate to the output used for calibration, the process is known as inverse modeling. The adjustment of model inputs is made with a global optimization method. One type of global optimization that has been used with crop models is simulated annealing. The annealing name of this technique draws from analogies relating the solution of combinatorial optimization problems to annealing in metallurgy. Annealing in optimization deals with large numbers of combinations of variables, while in metallurgy it deal with large numbers of particles. In simulated annealing, the test solutions that fail to optimize an objective function are accepted with a certain probability allowing the technique to escape local solution minima. Similarly in metallurgy, materials will adjust to suboptimal energy levels in the process of moving to the overall lowest energy level.

An example of the need for input optimization is the soil properties used in crop models. While a soil series may be known for a given area, the variability of textures, horizon depth, and other factors can contribute to inaccuracy in yield estimations. The use of yield monitor data can provide a data source for an inverse modeling process that optimizes soil inputs spatially.

The objective for this study is to evaluate one type of global optimization method, simulated annealing, for its ability to improve spatial prediction of yield from a cotton simulation model. For this test it is assumed that spatially variable water stress is a key part of spatial yield variability, therefore parameters that affect the ability of the soil to hold and move water will be adjusted.

BACKGROUND

Optimization Techniques for Inverse Modeling

One method for obtaining site-specific inputs for crop simulation models is inverse modeling (Braga and Jones, 2004). This technique used an optimization method to minimize differences between model predictions and observed values by iteratively changing model inputs.

Optimization techniques are categorized as local and global techniques. Local techniques such as the Nelder-Mead simplex algorithm and Powell's conjugate directions (Royce et al., 2001) are quick but stop searching when a local maxima/minima is located. Global optimization methods can escape local optima, but require more runs and time than local techniques. In the past, global techniques such as genetic algorithms (Mayer et al., 1996) and simulated annealing (Paz et al., 1998) have been applied in determining solutions for agricultural production and crop simulation models. One advantage with the version of simulated annealing described by Goffe et al. (1994) is that it can be implemented with readily available code.

Examples of Crop Model Parameter Selection with Inverse Modeling

Applications of inverse modeling to crop simulation models have involved different crops, models, optimization algorithms, model inputs adjusted, and objective functions. Paz et al. (1998) used a down-hill simplex method to optimize rooting depth, saturated hydraulic conductivity in the bottom soil layer, and soil drainage rate coefficient. This study was made using the Cropgro-Soybean model. The goal of this study was to test the hypothesis that spatially variable water stress caused yield variability. To test this hypothesis, the inputs being adjusted were tested in one and two parameter combinations to see which had the most effect on crop yield. This study found that optimizing drainage rate and rooting depth explained 69% of yield variability.

Paz et al. (1999) tested whether the combination of soil water related stress and plant population influenced crop yield variability. This test used the simulated annealing optimization algorithm with the CERES-Maize model to optimize inputs based on three years of yield data. Inputs optimized in this study were saturated hydraulic conductivity, effective tile drain spacing, and plant population. Once inputs were optimized for this field, the model was rerun using 22 years of historic weather data and different levels of nitrogen to determine the profit maximizing nitrogen rate for this field. A rate of 202 kg ha^{-1} was determined as the optimum rate.

A study by Calmon et al. (1999) used a third type of optimization algorithm and tested soil water content in the objective function rather than yield. This study used adaptive simulated annealing in an effort to see if the search space could be sampled more efficiently than with the Goffe et al. (1994) version of simulated annealing, thus speeding up the process. This test of inverse modeling was for a single point in space as compared to the spatial calibrations in the previous two examples. Two versions of the Cropgro-Soybean model were used in this test. In one version, soil impedance and root hospitality factors were optimized, while in the other version a root weighting factor was optimized. In this work, 100,000 cycles of the optimization algorithm were used to obtain each solution. Use of the optimization algorithm allowed the model to fit the time series of water content.

Braga and Jones (2004) examined optimization using spatial water content and yield objective functions. This study used the CERES-Maize crop model with a simulated annealing optimization algorithm. Model inputs optimized in this work were lower limit, drained upper limit, saturation, and root growth factor for each soil layer to effective soil depth and the hydraulic conductivity in the deepest soil layer. Objective functions in this test used only one year of each type of data. The procedure was used for two separate years of data and then the results validated with comparisons to the second year of data. This study found that when grain yield was used as an objective function yield predictions were acceptable, while soil water content predictions were not accurate. Since soil water contents predicted with adjustment of site-specific soil parameters were adequate, research on different ways to use yield-based estimation procedures was recommended.

Previous studies of inverse modeling with crop models have found success in calibrating models across multiple years of yield data and against soil water content data. Inverse modeling tests have been conducted with corn and soybean crops in humid regions of the United States. Tests have not been made of inverse modeling for cotton crops or in semi-arid climates.

METHODOLOGY

Simulated Annealing Algorithm

In metallurgy, annealing is a process by which metals are heated then cooled slowly to create a stable form. Simulated annealing (SA) is an optimization algorithm for combinatorial optimization problems (Kirkpatrick et al. 1983). It draws parallels to metallurgical annealing in that both deal with large numbers of possible combinations of parameters and both allow selection of suboptimal states in order to obtain an overall optimal state. In the case of metallurgy, the escape from suboptimal states allows the system to continue cooling to a lower overall energy state. In the optimization algorithm, the equation for determining the acceptance of non-optimal parameter sets is known as the "Metropolis Criterion." This criterion is shown in equation 4-1:

$$p = e^{(f' - f)/T} \tag{4-1}$$

where
- p = probability
- f = the previous parameter set function value
- f' = the test parameter set function value
- T = simulated annealing temperature parameter

If the value for p obtained from this equation is less than a uniformly distributed random number selected from between 0 and 1, the set of parameters is accepted. The number of non-optimal parameter sets accepted is reduced as the optimization temperature parameter is reduced during the annealing runs.

A flow diagram for the SA algorithm from Corana et al. (1987) appears in figure 4-1. The algorithm operates by selecting a point from the step length of each input parameter, determining the resulting objective function based on the selected input parameter set, and then keeping or rejecting the selected input parameter set if the objective function was improved or if the Metropolis criterion was met. The input process is repeated for a set number of cycles until the step length for each input parameter is adjusted so that only half of the possible inputs are kept. Following a set number of step length adjustments, the Metropolis criterion temperature is reduced by the temperature reduction factor. A run of the algorithm is terminated when the number of cycles exceeds a set number, or the best function value at the end of four consecutive temperature levels is within the given error tolerance of the overall optimum function value.

No exact method of determining the temperature parameter has been established. Recommendations for its determination include performing a trial run with the temperature reduction factor equal to 1.5 and the temperature parameter equal to 1.0 then adjusting the temperature parameter to produce a large step length vector (Goffe et al. 1994) or selecting the temperature parameter so that it is the same order of magnitude as the standard deviation of the objective function (Corana et al. 1987).

Crop Model

The crop simulation model used in these tests was the process-oriented cotton growth model Cotton2k (Marani, 2004). The model uses inputs of weather, soils, and management practices to simulate fruiting development of the cotton plant. Cotton2k was derived from the GOSSYM model (Baker et al., 1983) with modifications to allow it to work better in arid environments such as California and Israel (Marani et al., 1993a, 1993b, 1993c).

Model inputs are stored in text files separate from model executable code. There are input files for soil hydrology, management practices, weather, and initial soil conditions plus a profile input file that organizes run information and links to the other files. The weather inputs to the model are daily solar radiation, maximum temperature, minimum temperature, precipitation, and wind run. Management practices input into the model include the timing and quantity of irrigations and fertilization, variety, and plant population. Inputs for describing soil water movement and the soil water characteristic

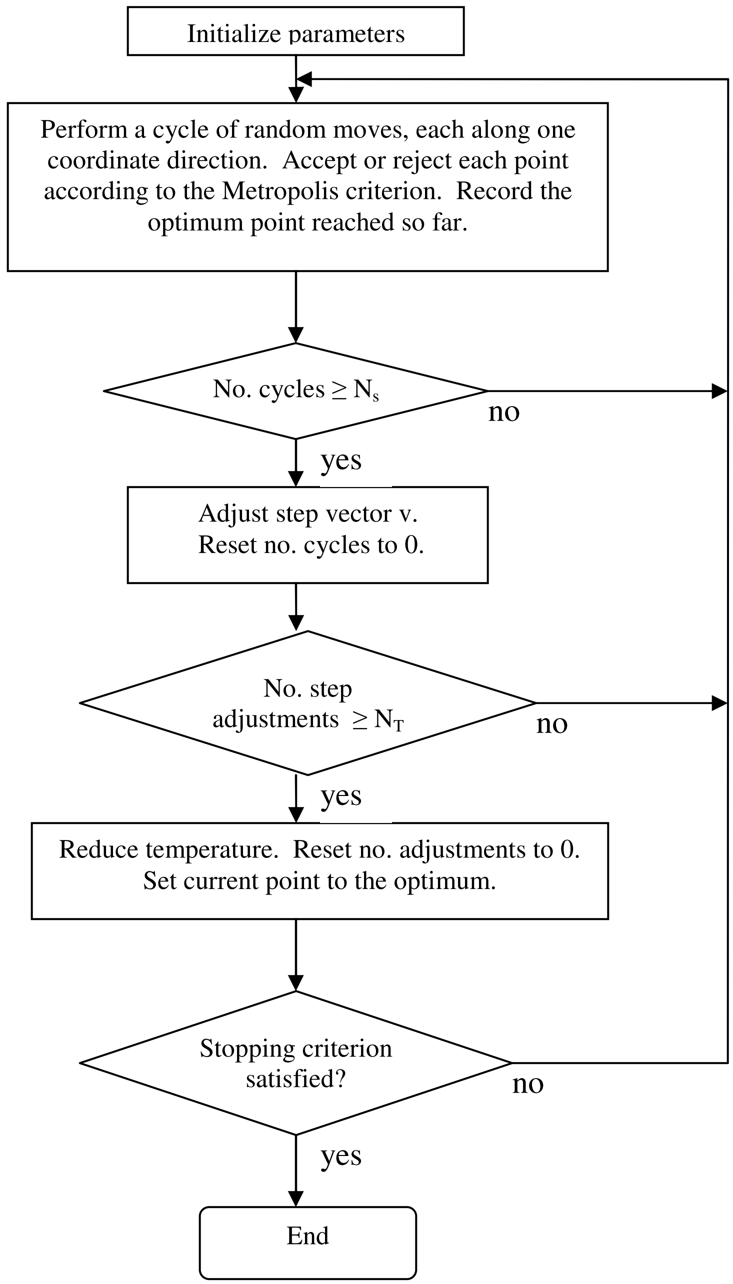


Figure 4-1. Simulated annealing algorithm (from Corana et al. 1987).

curve in Cotton2k are listed in table 4-1. The description of the soil water characteristic curve in Cotton2k is based on van Genuchten (1980), and therefore includes model inputs for residual and saturated water content and the soil texture-based empirical coefficients alpha and beta. The equation as defined by van Genuchten is:

$$\frac{\theta-\theta_r}{\theta_s-\theta_r}=\frac{1}{\left[1+(\alpha\psi)^n\right]^m} \tag{4-2}$$

where

θ = water content at soil water potential ψ
θ_r = residual water content
θ_s = saturated water content
ψ = soil water potential
α, m, and n = fitting parameters
m = 1-1/n

The use of beta in Cotton2k corresponds to the definition of n in the van Genuchten (1980) version of the equation.

Table 4-1. Cotton2k soil input variables.

Soil Input Variables
Percent sand
Percent clay
Bulk density
Hydraulic conductivity at saturation
Hydraulic conductivity at field capacity
Saturated volumetric water content
Volumetric water content at air dry
Alpha coefficient for the Van Genuchten equation
Beta coefficient (n) for the Van Genuchten equation

Cotton2k was selected for this application based on tests of its ability to predict soil moisture movement, evapotranspiration, and yield for data sets from the Texas High Plains region. Models tested in the selection process were GOSSYM, COTONS (Jallas et al., 1999) , along with Cotton2k. Data from Helms Farm field at the Halfway Texas Agricultural Experiment Station and a site in Lubbock County were used in the selection tests. For three of four test points at the Helms Farm site, Cotton2k predicted cumulative ET closer to measured cumulative ET than the other two models. All three models predicted similar values of soil water content by layer for the Helms Farm site, though Cotton2k followed trends over time better at lower depths than the other two models. In tests of yield prediction, Cotton2k was very close to measured yields, while the other two models under-predicted yields, especially for lower water levels.

Crop Simulation Model – Simulated Annealing Linkage

The computer code for implementing the version of the simulated annealing algorithm used in these tests was created by Goffe et al., (1994). A list of parameters that are set in the annealing algorithm with definitions for them (Goffe et al., 1994) is shown in Appendix B. The algorithm is implemented in the FORTRAN programming language. It was modified for use with the CERES-MAIZE crop model by Joel Paz (personal communication, 2005).

In the implementation of the algorithm for this project, the objective function from the Goffe et al. (1994) version was replaced by a subroutine that called Cotton2k. This subroutine transferred model parameters being optimized in the SA routine to the soil hydrology input file for Cotton2k. After Cotton2k executed, this routine would access the yield generated from the Cotton2k output file and transfer it to the SA routine. The core code of the Cotton2k model was executed with its command line interface. The Cotton2k code was recompiled to work with the SA algorithm to eliminate windows that appear during the execution of the model. The code was compiled in static form so that dynamic link libraries were not required.

Field Experiments

Tests of objective functions with the simulated annealing algorithm were made with single and multiple year combinations of data sets from the Helms Farm site. The data sets used were from the 2001 and 2003 growing seasons. Helms Farm is located 3.22 km from the Halfway Texas Agricultural Experiment Station with the center point of the center pivot irrigation system located at 34° 9’6”N 101°56’52”W. The data sets for this analysis were from experiments on field-scale variable rate irrigation. The soil survey map unit for this site was a Pullman sandy clay loam. Percent sand and percent clay were sampled at 33 points across the field by Robert Lascano (personal communication, 2004). Percent sand variation from this sampling ranged from 15 to 25 percent while percent clay varied from 20 to 30 percent. Soil water content information in 30-cm depth increment was obtained for each sampling point in the 2001 growing season with a neutron probe by Robert Lascano (personal communication 2004). Yield was collected at each sampling location by hand for each growing season.

Weather information for the experiments was obtained from a weather station located at the Halfway experiment station. Weather conditions in the 2001 and 2003 growing seasons are summarized in table 4-2. Planting dates for the two seasons were May 16 in 2001 and May 14 in 2003. Management operations that occurred during this growing season are listed in table 4-3. The irrigation system at the site was a Low Energy Precision Agriculture (LEPA) system with modifications that allowed site-specific control of the water applications (Bordovsky and Lascano, 2003). In 2001 and 2003, three irrigation levels, 60% evapotranspiration (ET), 80% ET, and 100% ET were used at the site. ET for this experiment was calculated with a modified Penman-Monteith equation (J. Booker, personal communication, 15 February 2005). Zones for the three irrigation levels were determined based on a combination of soil texture and slope down the furrow. The quantity of irrigation for each management zone is shown in table 4-4. The irrigation control management zones for section 5D in 2001 are shown in figure 4-2 and in 2003 in figure 4-3.

Model Inputs – Non-Optimized

Weather data and management information were entered in Cotton2k to match data from the field experiments at Helms Farm. The source of each soil input for these tests is shown in table 4-5. Soil inputs used for these tests were based on a combination of point-specific sand and clay percentages sampled by Robert Lascano (personal communication 2004) and pedotransfer functions. The sampled sand and clay percentages were used in conjunction with tabular information from Van Genuchten et al. (1991) and the Soil Water Characteristic program developed by Saxton et al. (1986).

Table 4-2. Weather conditions used for simulations compared to southern High Plains historic weather conditions.

Year	Average Daily Maximum Temperature (°C)	Average Daily Minimum Temperature (°C)	Total Rainfall (cm)
2001	31.5	16.7	18.3
2003	30.1	14.4	15.3
Historic Average (May 1 – October 15)	30.4	16.3	31.4

Table 4-3. Experimental management parameters – Helms Farm study.

	2001	2003
Plant date	May 15	May 5
Harvest date	Oct. 18	Nov. 3
Row spacing	76.2 cm	76.2 cm
Plants per meter	10.8	10.3
Irrigation date range	May 26 – Aug. 30	May 7 – Aug. 29
Fertilizer quantity	143.4 kg N ha^{-1}	109.4 kg N ha^{-1}

Table 4-4. Irrigation quantities for control management zones during 2001 and 2003 growing seasons.

Year	Treatment	Irrigation (cm)	Total Applied Water (Irrigation + Rain) (cm)
2001	60 % ET	24.1	42.4
	80 % ET	27.3	45.6
	100 % ET	30.6	48.9
2003	Base Rate – 20 %	22.5	37.8
	Base Rate	27.4	42.7

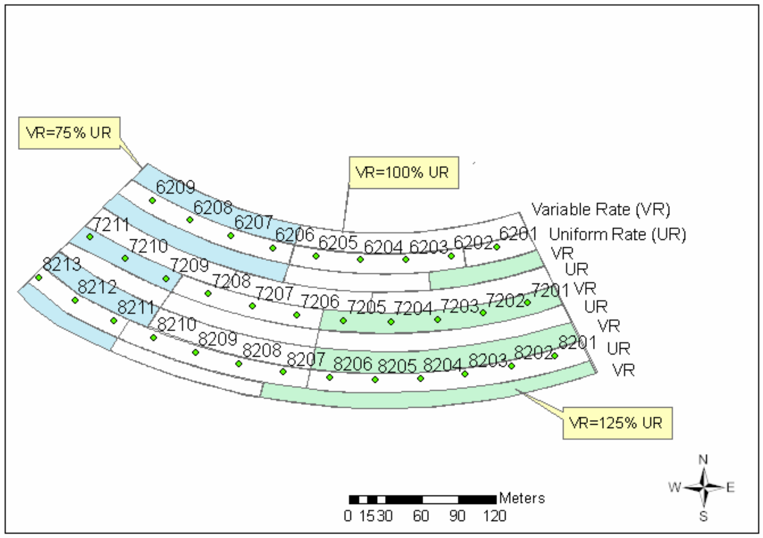


Figure 4-2. Soil sampling points and control management zones in 2001 for field 5D at Helms Farm site.

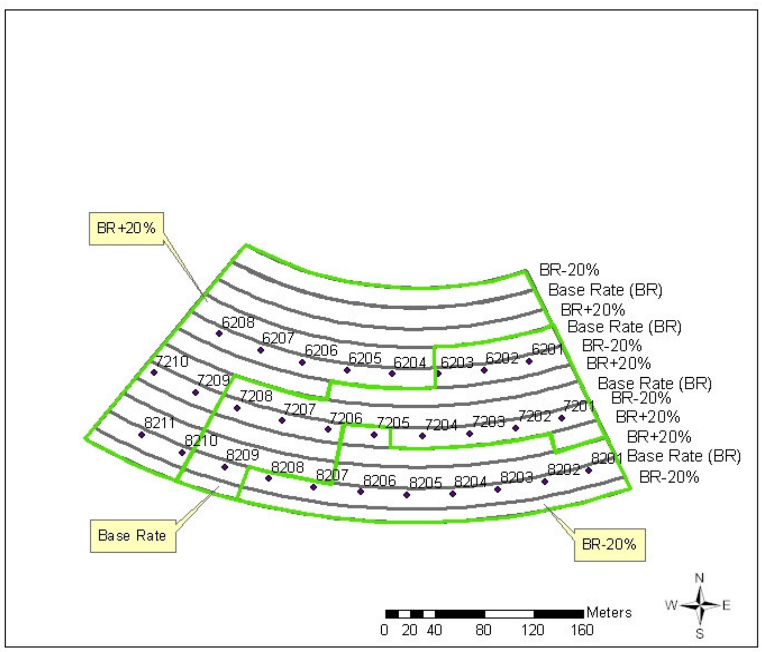


Figure 4-3. Soil sampling points and control management zones in 2003 for field 5D at Helms Farm site.

Table 4-5. Cotton2k model soil input sources for simulated annealing tests.

Input	Source
Percent sand	Soil sampling
Percent clay	Soil sampling
Bulk density	Soil Water Characteristic program, Saxton et al. (1986)
Volumetric water content at air dry	*Calculated from Van Genuchten equation
Saturated volumetric water content	*From table 3 in van Genuchten et al. (1991) by soil texture
Alpha coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Beta coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at saturation	*From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at field capacity	Soil Water Characteristic program, Saxton et al. (1986)

* Initial source of data. These values were optimized in the study.

The Soil Water Characteristic program uses a series of equations developed based on the data set analyzed by Rawls et al. (1982) to relate soil water content, hydraulic conductivity, and soil water potential to percent sand and percent clay. The relations for soil water content and soil water potential between 1500 and 10 kPa are:

$$\Psi = \mathrm{A}\ \Theta^{B} \tag{4-3}$$

$$A = \exp[a + b(\%\mathrm{C}) + c(\%\mathrm{S})^2 + d(\%\mathrm{S})^2(\%\mathrm{C})]\ 100.0 \tag{4-4}$$

$$B = e + f(\%\mathrm{C})^2 + g(\%\mathrm{S})^2(\%\mathrm{C}) \tag{4-5}$$

where

Ψ	= water potential, kPa
Θ	= water content $m^3\ m^{-3}$
A, B	= soil water characteristic equation coefficients
a, b, c, d, e, f, g	= empirical coefficients
% C	= percent clay
% S	= percent sand

The equation relating hydraulic conductivity, percent sand, percent clay, and water content is

$$K = 2.778\times10^{-6} \{\exp [12.012 - 0.0755 (\% S) + [-3.8950 + 0.03671 (\% S) - 0.1103 (\% C) + 8.7546\times10^{-4} (\% C)^2] (1/\Theta)]\} \quad (4\text{-}6)$$

where
- K = unsaturated hydraulic conductivity m s^{-1}
- Θ = water content $m^3\ m^{-3}$
- % C = percent clay
- % S = percent sand

Using equations such as 4-3 through 4-6 for hydraulic conductivity and soil water potential is not a perfect way of determining soil inputs for a crop model. Producers using crop models will likely not have as much sampled information as in this study. Potential alternatives to determining model inputs for producers could include the use of data bases based on soil map unit, such as SSURGO (USDA-NRCS, 1995). These databases present only ranges for potential inputs such as saturated hydraulic conductivity and available water capacity. Selection of inputs from ranges will also lead to errors between values used in crop models and actual values in fields . Use of database information with other site-specific information in an inverse modeling procedure could be better than use of either technique alone.

Soil moisture was initialized for all test points based on the average of soil water contents for ten sampling points on the first sampling date in the 2001 and 2003 growing seasons. Initial values of ammonium, nitrate, and organic matter in sample files with Cotton2k were used with these tests. The input values are listed in table 4-6.

Table 4-6. Initial Cotton2k model soil fertility and water content inputs by depth for simulated annealing tests.

Bottom Layer Depth	NH_4 (kg ha^{-1})	NO_3 (kg ha^{-1})	Organic Matter, % by weight	Water Content, % of field capacity
15	2.69	26.904	0.74	60
30	1.23	13.23	0.72	80
45	1.00	10.09	0.67	85
60	0.79	7.40	0.43	85
75	0.79	7.40	0.37	85
90	0.79	7.40	0.30	85
105	4.93	4.93	0.00	85
120	4.93	4.93	0.00	85
135	4.93	4.93	0.00	85
150	4.93	4.93	0.00	85
165	4.93	4.93	0.00	85
180	4.93	4.93	0.00	85

SA Control Parameter Tests

Three possible values of four SA control parameters were tested to evaluate their effect on optimized model inputs and outputs. The four control parameters tested were the number of cycles (NS), initial search length (ISTP), error tolerance for termination (EPS), and maximum number of function evaluations (MaxEval). Table 4-7 shows the three values tested for each control parameter. The control parameters were tested with two types of initial values, one based on sampled soil sand and clay measurements and one based on the midpoint of the search range being used in SA. The two cases represent different levels of information to start SA with in order to see if more or less information affects the outcome of the SA process. Beginning the SA algorithm with different initial parameter sets also tests whether it is an effective global optimization technique based on whether both start points reach the same input parameter set.

Table 4-7. Simulated annealing control parameters tested with Helms Farm point 7202 single year yield data.

SA Parameter	Values Tested
NS	20, 42, 84
ISTP	0.005, 0.02, 0.04
EPS	3, 6, 10
MaxEval	3050, 6050, 8050

Input Parameter Tests

Crop water stress and soil properties related to soil water holding capacity have been shown to vary spatially; therefore, the input parameters that were modified were related to soil water holding and transport capacity. Three combinations of inputs with from three to six input parameters adjusted were tested for their effects on the optimization routine. The combinations of input parameters tested for use with the SA algorithm are shown in table 4-8 along with the range of values searched over for each parameter. Ranges were based on ranges in each parameter across all soil textures from Rawls et al. (1982) and van Genuchten et al. (1991). Tests with the different input parameter combinations were conducted on point 7202 from the Helms Farm site. One point was selected due to the time required to conduct the test. This point was located in the 100% PET management zone, which the model should perform best in thus minimizing the effects of model errors on the SA test.

The six parameter test set looked at adjusting saturated and residual water content for three 20-cm layers from 0-60 cm deep in the soil profile. While saturated water content and residual water content do not directly describe available water capacity, they are related to available water capacity through the van Genuchten soil water characteristic

Table 4-8. Cotton2k inputs varied with simulated annealing algorithm.

Variable	Definition	Parameter Search Ranges
6 Parameter Test Set		
Variable 1	Saturated water content – layer 1	0.22 – 0.50 $cm^3\ cm^{-3}$
Variable 2	Saturated water content – layer 2	0.22 – 0.50 $cm^3\ cm^{-3}$
Variable 3	Saturated water content – layer 3	0.22 – 0.50 $cm^3\ cm^{-3}$
Variable 4	Residual water content – layer 1	0.02 - 0.18 $cm^3\ cm^{-3}$
Variable 5	Residual water content – layer 2	0.02 - 0.18 $cm^3\ cm^{-3}$
Variable 6	Residual water content – layer 3	0.02 - 0.18 $cm^3\ cm^{-3}$
5 Parameter Test Set		
Variable 1	Saturated hydraulic conductivity – layer 1	1-500 cm day^{-1}
Variable 2	Saturated hydraulic conductivity – layer 2	1-500 cm day^{-1}
Variable 3	Residual water content – layer 3	0.02-0.18 $cm^3\ cm^{-3}$
Variable 4	Saturated water content – layer 3	0.22-0.50 $cm^3\ cm^{-3}$
Variable 5	Depth to caliche layer – layer 5	81 – 151 cm
3 Parameter Test Set		
Variable 1	Saturated water content – layer 1	0.22 – 0.50 $cm^3\ cm^{-3}$
Variable 2	Saturated water content – layer 2	0.22 – 0.50 $cm^3\ cm^{-3}$
Variable 3	Saturated water content – layer 3	0.22 – 0.50 $cm^3\ cm^{-3}$

equation. The alpha and beta coefficients of the van Genuchten equation vary with soil texture, but not continuously, and therefore would not be suitable for use with the SA algorithm. The three parameter test set was selected to examine the effectiveness of adjusting only one rather than both limits related to available water capacity. The five parameter set tested a hypothesis that the combined effect of variation in soil moisture in deep soil layer and a caliche layer could affect crop yield. Caliche is a hard calcium carbonate layer that occurs in semi arid areas such as the High Plains. The first two variables in this test set, saturated water conductivity for the top two layers in the Cotton2k soil profile, affect how fast water moves through the profile. The third and fourth parameters are the saturated and residual water contents for the third soil layer.

The fifth parameter is the depth of the caliche layer, which would affect the depth at which water could build up in the soil profile since it could constrict water flow.

Objective Function Tests

Six combinations of input parameters and output parameter objective functions were evaluated, with two annealing starting points, for their ability to optimize crop model inputs. The model outputs used in the SA objective functions are shown in table 4-9. Both yield and water content based objective functions were examined. Yield data was tested as an objective function because of the increasing availability of yield monitor data in farming operations. Measured yield used in this test was based on hand-sampled measurements. Yields for the Helms Farm were available for each point in 2001 and for each treatment in 2003. Soil moisture measurements, however, are more closely related to the input parameters being adjusted than yield and thus should produce more accurate parameter estimates. Measured soil water contents were from neutron probe measurements from the 2001 Helms farm experiments. Predicted soil water contents for comparison to the measured values were from the Cotton2k soil water data output file. As with the SA control parameter tests, one sampling location was used with this test, due to time required to run the SA algorithm. Sampling location 7202 was also used with this test.

Table 4-9. Objective functions used with simulated annealing algorithm.

Number	Description
1	Single year yield using 2001 season
2	Two year yield using 2001 and 2003 seasons
3	Water content throughout 2001 season

Whole Field Optimization

Spatial application of crop models will require the determination of inputs for many model runs. Utilizing an optimization method with an available spatial data set for an output could aid in optimizing these inputs. This method of obtaining model inputs on a spatial basis was tested with the 33 sampled data points from the Helms Farm field experiments. The points used for the test are shown in figure 4-2. The points are located in areas managed with three levels of water applications, 60% ET, 80% ET, and 100% ET from the 2001 growing season.

One of the objective function / input parameter combinations was selected for application to points across the entire field. The selection was made based on: 1) the quality of the predictions made, 2) the time required for the optimization algorithm to run, 3) the reasonableness of the crop model inputs obtained from the optimization algorithm, and 4) the ease with which the parameter data could be obtained. The single year yield objective function was selected for application to the optimization of soil properties for the entire field. This objective function produced the best yield predictions, used the type of data that would be most readily available to producers today, and the 2001 yield data that was available was collected for each point rather than management zone.

RESULTS AND ANALYSIS

Crop Simulation Model – Simulated Annealing Linkage

Use of the SA algorithm involved selection of values for model input parameters, testing of algorithm control parameters, selection of which model inputs to use for optimization and selection of appropriate objective functions. Learning to link Cotton2k with the SA algorithm was a trial and error process with many decisions made along the way. It was originally envisioned that optimum values for several simulation locations could be optimized on one computer each day. The combination of SA with maximum number of evaluations of 6050 with Cotton2k took approximately 20 hours to run for one point on a 2.2 GHz desktop computer. Eventually multiple computers were used to complete the simulations.

SA Control Parameter Tests

Annealing algorithm control parameter test results are shown in table 4-10 and 4-11. Table 4-10 contains SA tests that began searching at residual and saturated water content values based on soil texture information, while the SA search used for the data in table 4-11 began at the midpoint of the specified search range. The initial parameter sets for both types of start points are similar to each other for this point. In 15 of the 18 runs in these two tables, the SA algorithm found parameter sets that allowed model predicted yields to match measured yields exactly. Yield predictions for all 18 runs were within one standard deviation of the measured yields in this management zone (101 kg ha^{-1}). This indicates that the SA algorithm was capable of finding optimum parameter sets when used with the crop simulation model. Input parameter sets obtained with the SA

Table 4-10. Soil parameter sets for point 7202 obtained with simulated annealing algorithm for objective function with single year of yields. Starting points were based on soil textures. SA control parameters used for the base simulation were: NS = 42, ISTP = 0.04, EPS = 10, MaxEval = 6050, Initial Temperature = 75, Temperature Reduction Multiplier = 0.85.

Annealing Parameter Modified	Variable 1 *	Variable 2 *	Variable 3 *	Variable 4 **	Variable 5 **	Variable 6 **	AWC (cm)†	Predicted Yield (kg ha^{-1})††	Stop Criteria***	Trials
Initial Values	0.330	0.390	0.321	0.068	0.075	0.109	19.08			
Base	0.321	0.349	0.381	0.064	0.166	0.037	19.12	1258.2	Term Crit.	4536
NS = 20	0.300	0.438	0.252	0.069	0.040	0.0526	19.38	1252.8	MaxEval	6050
NS = 84	0.311	0.368	0.452	0.065	0.159	0.118	19.10	1258.2	MaxEval	6050
ISTP =0.02	0.317	0.386	0.336	0.088	0.035	0.109	19.24	1258.2	Term Crit.	4536
ISTP = 0.005	0.314	0.400	0.374	0.081	0.064	0.101	19.44	1258.2	MaxEval	6050
EPS = 6	0.321	0.349	0.381	0.064	0.166	0.037	19.12	1258.2	MaxEval	6050
EPS = 3	0.3208	0.349	0.381	0.064	0.166	0.037	19.12	1258.2	MaxEval	6050
MaxEval = 3050	0.3208	0.349	0.381	0.064	0.166	0.037	19.12	1258.2	MaxEval	3050
MaxEval = 8050	0.3208	0.349	0.381	0.064	0.166	0.037	19.12	1258.2	Term Crit.	4536

* Variables 1, 2, 3 = Saturated water content – layers 1, 2, 3, respectively
**Variables 4, 5, 6 = Residual water content – layers 1, 2, 3, respctively
*** Term. Crit. = the SA search ended because the termination criteria in the algorithm was reached
*** MaxEval. = the SA search evaluated the crop model the maximum number of times specified without reaching the termination criteria.
† AWC = Available Water Capacity
†† Measured Yield = 1258.2 kg ha^{-1}

Table 4-11. Soil parameter sets for point 7202 obtained with simulated annealing algorithm for objective function with single year of yields. Starting points were based on middle of search range. SA control parameters used for the base simulation were: NS = 42, ISTP = 0.04, EPS = 10, MaxEval = 6050, Initial Temperature = 75, Temperature Reduction Multiplier = 0.85.

Annealing Parameter Modified	Variable 1 *	Variable 2 *	Variable 3 *	Variable 4 **	Variable 5 **	Variable 6 **	AWC (cm)†	Predicted Yield (kg ha^{-1})††	Stop Criteria***	Trials
Initial Values	0.360	0.360	0.360	0.100	0.100	0.100	19.06			
Base	0.488	0.376	0.400	0.100	0.157	0.167	19.49	1258.2	MaxEval	6050
NS = 20	0.440	0.314	0.341	0.089	0.164	0.050	19.16	1258.0	Term Crit.	2160
NS = 84	0.471	0.387	0.308	0.149	0.171	0.031	19.30	1258.2	MaxEval	6050
ISTP =0.02	0.317	0.391	0.320	0.088	0.036	0.102	19.25	1258.2	MaxEval	6050
ISTP = 0.005	0.347	0.334	0.403	0.091	0.081	0.103	19.20	1169.1	MaxEval	6050
EPS = 6	0.488	0.376	0.400	0.100	0.157	0.167	19.49	1258.2	MaxEval	6050
EPS = 3	0.488	0.376	0.400	0.100	0.157	0.167	19.49	1258.2	MaxEval	6050
MaxEval = 3050	0.488	0.376	0.400	0.100	0.157	0.167	19.49	1258.2	MaxEval	3050
MaxEval = 8050	0.488	0.376	0.400	0.100	0.157	0.167	19.49	1258.2	Term Crit.	7560

* Variables 1, 2, 3 = Saturated water content – layers 1, 2, 3, respectively

** Variables 4, 5, 6 = Residual water content – layers 1, 2, 3, respectively

*** Term. Crit. = the SA search ended because the termination criteria in the algorithm was reached

*** MaxEval. = the SA search evaluated the crop model the maximum number of times specified without reaching the termination criteria.

† AWC = Available Water Capacity

†† Measured Yield = 1258.2 kg ha^{-1}

algorithm did not match one another between the different SA algorithm control parameters tested or between the two different starting points tested. Not finding matching parameter sets between optimum yield runs with different algorithm starting points contrasts with previous tests of global optimization methods with crop simulation models (Braga and Jones, 2004). In the previous global optimization tests, a systematic search method found the same parameter set as the global optimization method. The different parameter sets for residual and saturated water content produced similar available water contents however. The water contents for all the tests in tables 4-10 and 4-11 had a range of 0.37 cm3 cm-3 for the same predicted yield. Several unique combinations of soil water parameters producing the same output is similar to an analysis of the relationship between wheat yield and available water capacity done by Wassenaar et al. (1999), however. While a single logarithmic relation between these two variables was developed in the Wasenaar et al. (1999) study, the raw data showed that the same yield values could be derived from different available water capacities.

Of the control parameters tested, the number of cycles had the most effect on the input parameters with Cotton2k soil parameters varying up to 0.012 cm^3 cm^{-3} between the three values for the number of cycles. The number of cycles had a strong influence on the optimization results because it controlled how each region is searched and it affects how fast the different temperature levels are moved through. The initial step had a smaller effect on the results because it only directly affects the initial searches. The initial step having an effect on the parameters selected was an indication that the optimum parameter set was located early in the search process for this combination of parameters and objective function. Adjusting termination error tolerance and maximum number of function evaluations had no effect on the Cotton2k soil parameters selected. The result with the error tolerance was not surprising because the selected error tolerance values were more stringent than the error tolerance for the base parameter set in Tables 4-10 and 4-11. The results in table 4-11 showed similar trends to those in table 4-10. Table 4-12 lists the cycle number at which an optimal solution was obtained for each trial in tables 4-10 and 4-11. Numbers in this table indicate that the optimal solution was found before cycle 2500 for the majority, but not all the tests. These results indicate that large amounts of computer time was wasted after an optimal parameter set was obtained.

Table 4-12. Cycle number that optimal objective function was obtained on in SA control parameter tests.

	Texture Start Point	Middle of Search Range Start Point
Base	615	899
NS = 20	6037	220
NS = 84	755	349
ISTP =0.02	842	2437
ISTP = 0.005	1642	5998
EPS = 6	615	899
EPS = 3	615	899
ME = 3050	615	899
ME = 8050	615	899

Input Parameter and Objective Function Tests

Objective function test results for point 7202 are shown in tables 4-13 for a soil texture-based algorithm starting point and in table 4-14 for an algorithm beginning at the middle of the search range. As with the SA algorithm control parameter tests, there were

Table 4-13. Soil parameter sets for point 7202 obtained with simulated annealing algorithm for objective function tests. Starting points were based on soil textures. Annealing parameters used in the tests were: NS = 42, Initial Temp. = 75, Temp. Reduction Multiplier = 0.85, EPS = 10, and MaxEval = 6050.

Input Parameter Set and Objective Function	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	AWC (cm)†	Predicted Yield – 2001 (kg ha^{-1})††	Predicted Yield – 2003 (kg ha^{-1}) †††	RMSE, Water Content
6 Parameter 1 Year Yield *	0.321	0.349	0.381	0.064	0.166	0.038	19.08	1258.2		
6 Parameter 2 Year Yield *	0.452	0.405	0.342	0.025	0.046	0.104	20.7	1219.0	1561.0	
6 Parameter 1 Year Water Content*	0.225	0.286	0.333	0.022	0.024	0.053	18.82	967.9		0.00846
5 Parameter 1 Year Yield **	347.3	2.7	0.047	0.498	102.8	--	20.68	1248.2		
5 Parameter 2 Year Yield **	1.301	9.2	0.053	0.388	136.8	--	19.93	1192.2	1700.9	
5 Parameter 1 Year Water Content **	234.3	1.40	0.020	0.359	149.8	--	19.95	1185.5		0.0431
3 Parameter 1 Year Yield ***	0.301	0.402	0.369	--	--	--	19.32	1258.2		
3 Parameter 2 Year Yield ***	0.492	0.494	0.406	--	--	--	21.48	1180.6	1586.0	
3 Parameter 1 Year Water Content ***	0.237	0.231	0.301	--	--	--	17.31	1053.7		0.0157

* Row 1-3 Variables 1, 2, 3 = Saturated water content – layers 1, 2, 3
Row 1-3 Variables 4, 5, 6 = Residual water content – layers 1, 2, 3

** Row 4-6 Variables 1, 2, = Saturated hydraulic conductivity – layers 1, 2
Row 4-6 Variable 4 = Residual water content – layer 3
Row 4-6 Variable 5 = Saturated water content – layer 3
Row 4-6 Variable 6 = Depth of caliche layer, cm

*** Row 7-9 Variables 1, 2, 3 = Saturated water content – layers 1, 2, 3

† AWC = Available Water Capacity

†† Measured Yield for point in 2001= 1258.2 kg ha^{-1}

†††Measured Yield for management zone in 2003 = 1012.67 kg ha^{-1}

Table 4-14. Soil parameter sets for point 7202 obtained with simulated annealing algorithm for objective function tests. Starting points were based on middle of search range. Annealing parameters used in the tests were: NS = 42, Initial Temp. = 75, Temp. Reduction Multiplier = 0.85, EPS = 10, and MaxEval = 6050.

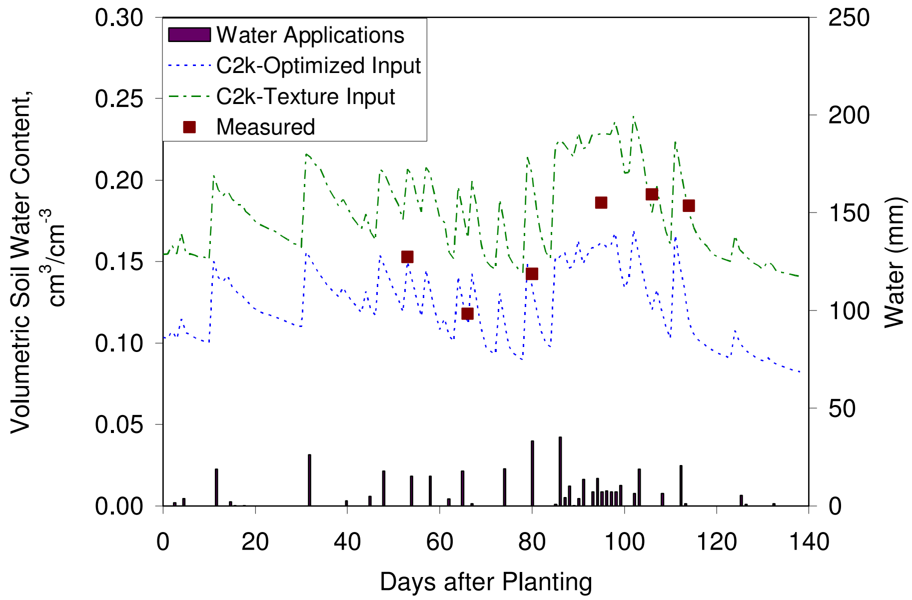
Input Parameter Set and Objective Function	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	AWC (cm)†	Predicted Yield – 2001 (kg ha^{-1})††	Predicted Yield – 2003 (kg ha^{-1}) †††	RMSE, Water Content
6 Parameter 1 Year Yield *	0.488	0.376	0.400	0.100	0.157	0.167	19.49	1258.2		
6 Parameter 2 Year Yield *	0.494	0.360	0.488	0.041	0.021	0.156	21.38	1185.4	1549.2	
6 Parameter 1 Year Water Content *	0.221	0.291	0.354	0.022	0.028	0.028	19.08	1218.1		0.00832
5 Parameter 1 Year Yield **	2.0	9.4	0.021	0.259	81.5	--	19.29	1239.5		
5 Parameter 2 Year Yield **	103.0	123.1	0.027	0.391	132.8	--	20.82	1192.8	1698.9	
5 Parameter 1 Year Water Content **	461.4	379.8	0.105	0.321	148.8	--	19.15	1130.2		0.0362
3 Parameter 1 Year Yield ***	0.418	0.348	0.430	--	--	--	20.16	1217.4		
3 Parameter 2 Year Yield ***	0.343	0.473	0.372	--	--	--	20.09	1213.3	1533.4	
3 Parameter 1 Year Water Content ***	0.225	0.223	0.296	--	--	--	17.13	921.1		0.0159

* Row 1-3 Variables 1, 2, 3 = Saturated water content – layers 1, 2, 3
Row 1-3 Variables 4, 5, 6 = Residual water content – layers 1, 2, 3
** Row 4-6 Variables 1, 2, = Saturated hydraulic conductivity – layers 1, 2
Row 4-6 Variable 4 = Residual water content – layer 3
Row 4-6 Variable 5 = Saturated water content – layer 3
Row 4-6 Variable 6 = Depth of caliche layer, cm
*** Row 7-9 Variables 1, 2, 3 = Saturated water content – layers 1, 2, 3
† AWC = Available Water Capacity
†† Measured Yield for point in 2001= 1258.2 kg ha^{-1}
†††Measured Yield for management zone in 2003 = 1012.67 kg ha^{-1}

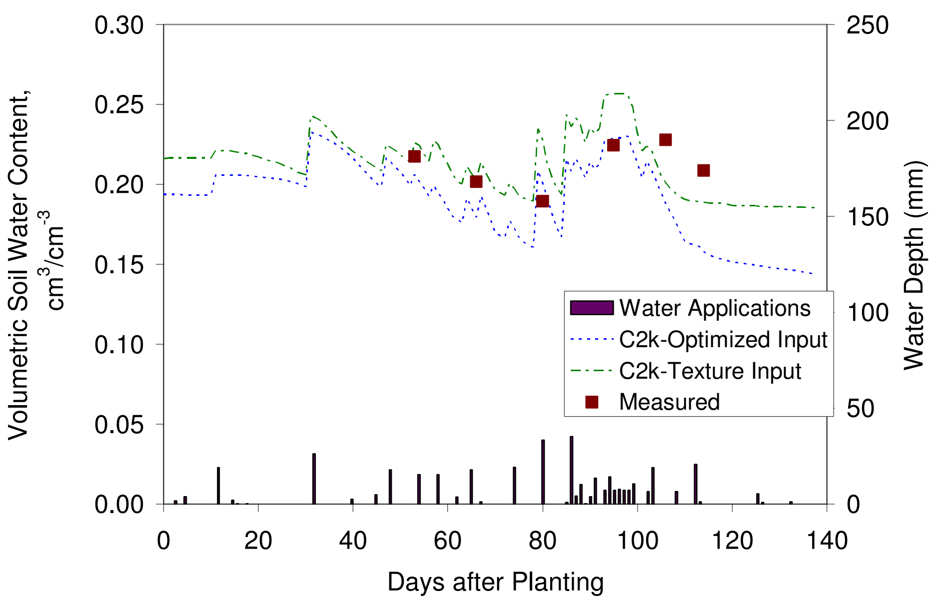
no matches in the input parameter sets selected between tests. One year yield objective function tests matched the measured yield of 1258.2 kg ha^{-1}. All four of the predicted yields from yield based objective functions were within one standard deviation of the field measured yield. With the two year yield objective function the yield was generally over-predicted for the 2003 growing season. The errors in this test may be due to the use of average measured yields across areas rather than point-specific measured yields. Comparisons among the three types of objective functions for the six combinations of number of parameters and starting points showed that the water content objective functions produced the yield predictions the furthest away from the measured yields for five out of the six combinations. The difference between measured and model predicted soil water content for 30-cm depth increments are shown in figures 4-4 and 4-5. The optimization algorithm affected model predictions most in the top 60 cm, lowering the model soil water content predictions by nearly 0.05 cm^3 cm^{-3}. Available water capacity in tables 4-13 and 4-14 was calculated from the van Genuchten soil water characteristic equation using the residual and saturated water contents obtained with the optimization algorithm. The available water capacity from the water content objective functions was the lowest of the three objective functions for five of the six combinations of objective function and the input parameter combinations.

Whole Field Optimization

Input parameters obtained using SA for the calibration of soil water parameters for each point across Helms Farm field 5D are shown in table 4-15. Predicted yields were within 5 kg/ha of measured yields for 20 out of 33 points. Three points had differences

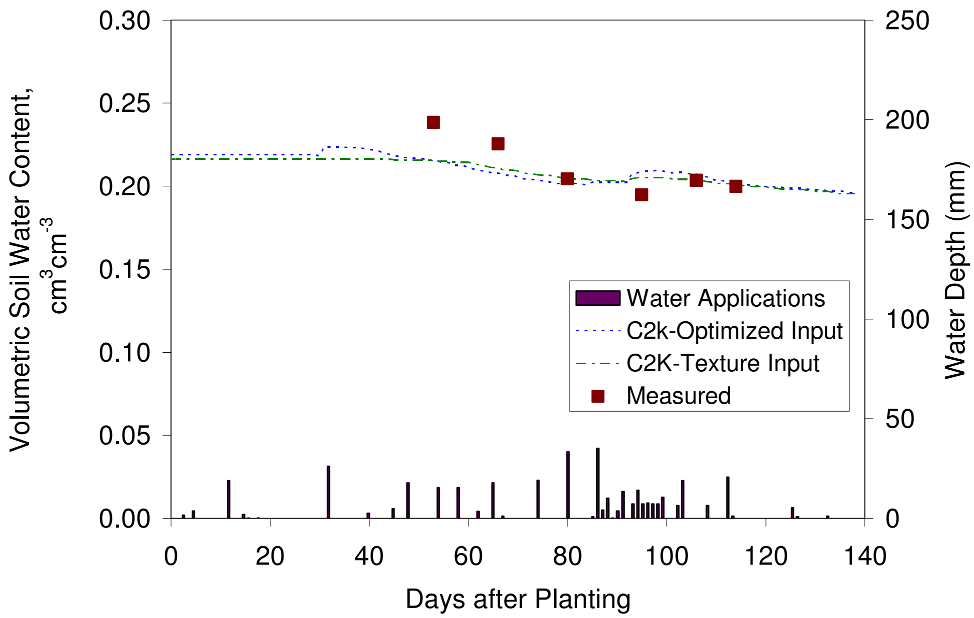


(a) 0-30 cm

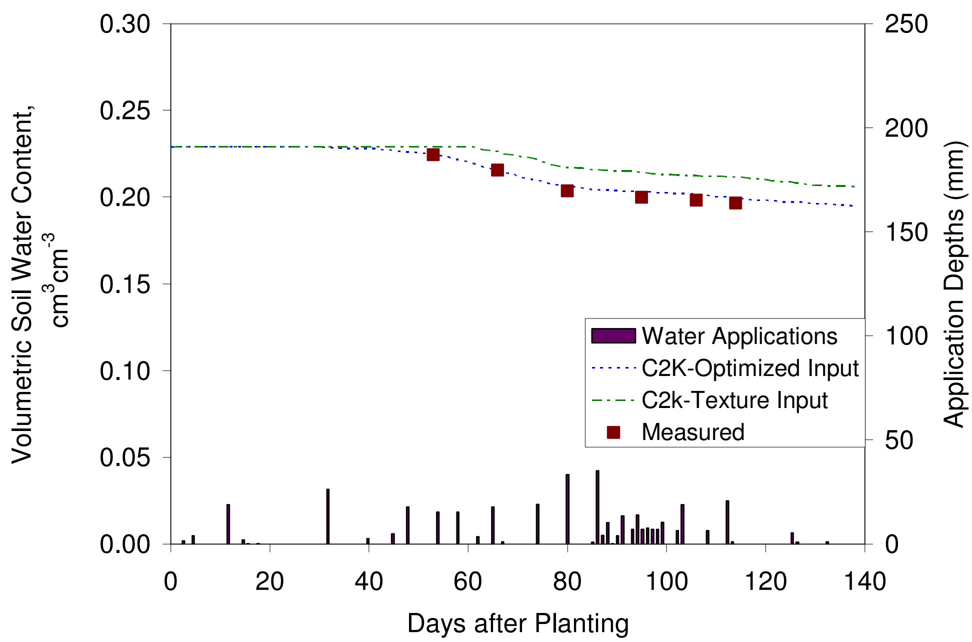


(b) 30-60 cm

Figure 4-4. Measured and predicted volumetric water content by depth for point 7202 in 2001 season before and after optimization. Layers shown are (a) 0-30 cm and (b) 30-60 cm.



(c) 60-90 cm



(d) 90-120 cm

Figure 4-5. Measured and predicted volumetric water content by depth for point 7202 in 2001 season before and after optimization. Layers shown are (a) 60-90 cm and (b) 90-120 cm.

Table 4-15. Soil parameter sets for field optimization obtained with simulated annealing algorithm using a single year yield objective function. Annealing parameters used in the tests were: NS = 42, Initial Temp. = 75, Temp. Reduction Multiplier = 0.85, EPS = 10, and MaxEval = 6050.

Point	Var. 1	Var. 2	Var. 3	Var. 4	Var. 5	Var. 6	Pred. Yield (kg ha^{-1})	Meas. – Pred. Yield (kg ha^{-1})
6201	0.338	0.324	0.424	0.022	0.102	0.175	1148.0	18.1
6202	0.345	0.348	0.500	0.069	0.030	0.179	1151.0	54.4
6203	0.438	0.265	0.454	0.140	0.150	0.023	1156.2	-0.2
6204	0.381	0.457	0.287	0.051	0.085	0.063	1109.9	0.0
6205	0.344	0.455	0.319	0.124	0.121	0.147	1164.4	34.6
6206	0.253	0.396	0.260	0.135	0.113	0.069	1146.2	0.0
6207	0.325	0.495	0.309	0.137	0.079	0.046	1140.0	6.2
6208	0.326	0.449	0.492	0.142	0.059	0.027	1137.1	-0.2
6209	0.288	0.396	0.279	0.172	0.029	0.086	1189.6	0.03
7201	0.439	0.350	0.453	0.099	0.024	0.040	1129.0	0.0
7202	0.321	0.349	0.381	0.064	0.166	0.037	1258.2	0.0
7203	0.321	0.310	0.374	0.054	0.102	0.051	1203.6	0.0
7204	0.406	0.404	0.350	0.100	0.035	0.108	1148.9	150.4
7205	0.406	0.440	0.375	0.071	0.120	0.092	1144.4	0.0
7206	0.285	0.347	0.394	0.098	0.180	0.158	1017.5	0.0
7207	0.412	0.404	0.446	0.048	0.093	0.046	1116.4	0.0
7208	0.390	0.285	0.313	0.109	0.082	0.102	931.4	0.0
7209	0.364	0.424	0.326	0.023	0.065	0.074	789.4	196.9
7210	0.452	0.419	0.481	0.042	0.043	0.103	844.9	183.4
7211	0.349	0.457	0.442	0.158	0.081	0.129	697.9	428.5
8201	0.326	0.347	0.484	0.050	0.095	0.116	1025.6	-26.0
8202	0.336	0.327	0.488	0.058	0.089	0.074	1025.7	-47.4
8203	0.291	0.382	0.247	0.120	0.055	0.116	1063.9	0.0
8204	0.363	0.312	0.384	0.053	0.127	0.087	1082.2	0.0
8205	0.280	0.369	0.313	0.114	0.068	0.169	1181.8	0.0
8206	0.282	0.466	0.413	0.131	0.168	0.062	1113.6	0.0
8207	0.428	0.379	0.412	0.116	0.104	0.050	993.0	110.5
8208	0.339	0.439	0.371	0.170	0.062	0.023	1155.6	5.0
8209	0.336	0.428	0.314	0.154	0.033	0.026	1143.3	0.0
8210	0.335	0.412	0.477	0.163	0.059	0.021	1161.5	12.0
8211	0.355	0.431	0.491	0.139	0.125	0.020	1054.7	161.7
8212	0.329	0.413	0.347	0.062	0.162	0.100	1111.5	0.0
8213	0.378	0.389	0.400	0.046	0.094	0.047	1113.5	12.7

between predicted and measured yields of greater than 180 kg ha^{-1}. These points were located on the west side of the field and were all under the 60% PET management. The large under predictions for these points could indicate that some factor other than soil water is having more influence on yield or that estimates of initial conditions for these points were in error. Measured versus optimized and deterministic predicted yields are shown in figure 4-6. Optimization improved the yield predictions for 32 of the 33 points, with the remaining yield prediction not changing. Table 4-16 shows the variation in available water capacity across the Helms Farm field before and after simulated annealing was used to optimize inputs for the model. The range of AWC across the field more than doubled going from 1.97 cm to 4.3 cm with the use of the annealing optimization routine.

Variables that affected how much storage space was available for soil water and how fast soil water moved through a soil profile were adjusted with the annealing algorithm. Tests of the SA control algorithm parameters, which input parameters to adjust, and use of yield or water content based objective function were made. The number of cycles control parameter had the largest effect on algorithm results since model inputs selected with this control parameter showed the most variation. SA control parameters used in the input parameter and objective function tests and the whole field optimization were number of cycles = 42, initial step = 0.02, error tolerance for termination = 10, and maximum number of function evaluations = 6050. These parameters could be used to apply the SA algorithm and Cotton2k to the calibration of soil water parameters for other fields. Using the SA algorithm with other crop models, input parameters, and objective

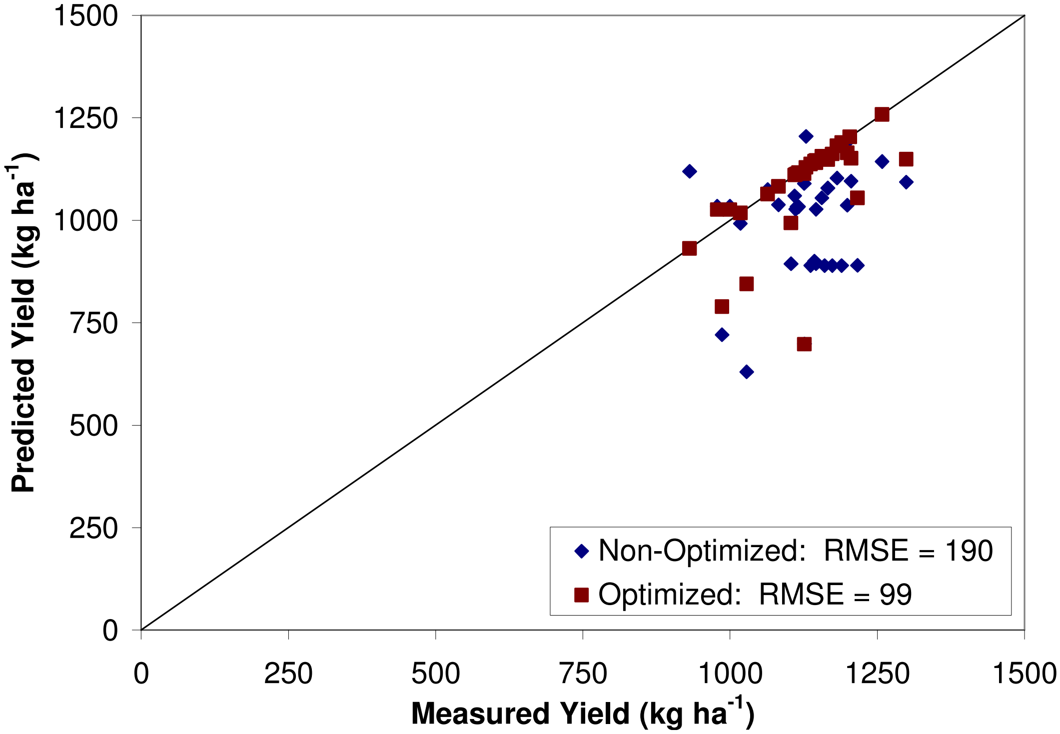


Figure 4-6. Predicted versus measured cotton yield for Helms Farm with soil texture class and simulated annealing optimized soil moisture release curve parameters.

Table 4-16. Available water capacity variation across Helms Farm between soil textural class and simulated annealing optimized soil inputs in top 200 cm of soil.

	Available Water Capacities			
Model input basis	Average (cm)	Maximum (cm)	Minimum (cm)	Standard deviation (cm)
Soil textural class	19.55	20.24	18.27	0.38
Simulated annealing optimized	19.64	21.86	17.52	1.00

functions would require further testing of control parameters, however.

Comparisons of combinations of input parameters and objective functions showed that the algorithm could adjust predicted yields very close to measured yields with one year of yield data. Yield predictions with the two year yield objective functions were not as good as for the single yield objective function, possibly due to the quality of the yield data used for the second year of optimization. Differences occurred in yield predictions between the yield and water content-based objective functions. The single year yield objective function with six input parameters adjusted was selected for use in optimizing all points in the Helms Farm field based on its performance in the tests and the quality of data available for further testing. Good results were obtained when applying the algorithm across the field with the exception of three locations which indicates that the SA optimization algorithm has proved to be a useful tool.

CONCLUSIONS

The combination of simulated annealing with the Cotton2k crop simulation model showed potential for spatial calibration of model input parameters based on its ability to improve yield predictions when used with a single year of yield data. Limitations to the use of the algorithm such as the amount of time to run the algorithm were evidenced, however. The computing time problem could be alleviated over time as computing speeds increase or through the use of an alternative optimization algorithm. The tests indicate that multiple unique input data sets can be obtained with the algorithm for a single year of data. This result is more likely from the relationships in the cropping system being modeled than failure of the optimization algorithm. Differences in input parameter sets and yield predictions between the yield and water content based objective functions indicate the need for different ways of using data sets for setting up simulated annealing runs and determining the objective functions in the runs.

CHAPTER V

SITE-SPECIFIC IRRIGATION ANALYSIS

INTRODUCTION

Water levels in the Ogallala aquifer continue decreasing each year. Irrigated agriculture uses a large portion of this water. For agriculture to continue in the areas above the aquifer, techniques for reducing water use are needed. Site-specific irrigation represents a technique to potentially reduce inefficiencies in water use in irrigation applications. Improved irrigation water use efficiencies could result in lower quantities of water needed to grow crops or improved profit from crop production. For site-specific irrigation to be implemented, producers will want to know if it is a profitable practice for their situation and how different portions of their fields should be managed.

A potential method to help producers answer these questions is to simulate the effect of potential management scenarios on yields and thus profit for their farms. Crop simulation models would be more timely and cost effective for this purpose than conducting on-farm tests of the producer's desired management strategies. Additionally, the producer could test the effects of various weather scenarios on their potential management strategies.

Previous studies of variable rate management had looked at better matching of optimum application rates to specific points in the fields. These studies assumed that a point maximizing yield on an irrigation response curve could be reached. In water limited areas of the world, such as the High Plains of Texas, reaching an optimal point on an irrigation response curve is often not possible; therefore, deficit irrigation practices should be considered.

The objective of this study was to evaluate the economic and water use effects of a site-specific irrigation scenario in the Texas High Plains growing environment. This analysis was made using a cotton simulation model across multiple years of historic weather data.

BACKGROUND

Site-specific irrigation

Most research on site-specific irrigation has been focused on designing and implementing irrigation systems capable of this type of irrigation application. Systems have been developed at sites at Colorado (Fraisse, et al., 1992), Washington State (Evans et al., 1996), Idaho (King et al., 1999), South Carolina (Camp and Sadler, 1998), Georgia (Perry et al., 2002) and Texas (Bordovsky and Lascano, 2003). These systems have fallen into categories of multiple manifolds (Idaho, South Carolina, and Texas) or on/off cycling of sprinkler heads (Idaho, Georgia, Washington). One company is offering a site-specific retrofit for center pivots based on the design used in Georgia. While hardware for site-specific systems has been developed, control strategies and studies of economic feasibility are needed.

In tests of site-specific management at the existing sites, management zones were created from user knowledge, soil properties, topography, and soil moisture sensing. Reeder (2002) controlled a site-specific system with in-season soil moisture sensing that through a feedback loop allowed soil moisture levels to be controlled within specified limits. Determination of irrigation strategies for use with site-specific irrigation was made based on maximized long term gross margins in a crop modeling study by Nijbroek et al. (2003). This study found that for a soybean crop in Georgia, site-specific irrigation was more profitable than other scheduling options, but the difference between site-specific irrigation and other options was very small. Feinerman and Voet (2000) examined the effects of management unit size on the water usage for site-specific irrigation and found that decreasing management unit size did not decrease the amount of water usage.

Deficit Irrigation

Irrigation scheduling under limited water availability is more complex than keeping the soil profile filled with water. Different water application levels will affect crop development differently depending on the crop growth stage (Doorenbos and Pruitt, 1977). The order for cotton stages most affected by water deficits are: flowering and boll formation > early stages of growth > after boll formation. Scheduling of irrigations under deficit conditions has been simulated using dynamic programming techniques (Epperson et al., 1993, Rao et al., 1988) and with a crop growth model with long term historic weather (Gowing and Ejieji 2001). Crop growth models can be important tools in deficit irrigation studies due to their ability to integrate the stress effects of varying timings and quantities of irrigations on final yield predictions. In addition to considering when and what quantity of water should be applied, producers may consider leaving portions of fields fallow or planting fields in skip-row patterns to take better advantage of available soil moisture (Heneggeler, 1998).

Crop Models

Benefits of implementing site-specific management will vary on a field by field basis (Lowenber-Deboer and Swinton, 1997). Use of a crop model to analyze the effects of site-specific management would be more timely and efficient than conducting field experiments of different management options. Crop models have been used in a number of ways in relation to analyzing irrigation scheduling and site-specific management. Studies have been made with a number of different crops, uses of weather information, and management objectives. Net profit, water use, and yield were analyzed with long term weather records and for in-season decisions with the SOYGRO crop model by Swaney et al. (1983). The SORGF sorghum simulation model was tested with a cost risk analysis procedure for determining best irrigation strategy by Rogers and Elliott (1989). The effect of site-specific irrigation management on yield, drainage, and profit was tested with the CROPGRO-Soybean for a field in the Georgia Coastal Plain by Nijbroek et al. (2003). Strategies were tested across 25 years of historic weather. The strategies tested included ones that produced the highest yield for the entire field, for field areas that showed stress first, and for the largest field area possible.

Crop models have also been used for determining management strategies for inputs other than water. Braga and Jones (1999) used the CERES-Maize model, 35 years of historic weather and a simulated annealing optimization algorithm to select the optimal nitrogen rate for a Michigan corn crop. This same model was also tested with site-specific management of nitrogen for fields in Iowa by Paz et al. (1999). In this test the simulated annealing algorithm was used to calibrate soil parameters at individual points in a field. The calibrated model at each point was then run with 22 years of historic weather data to generate nitrogen rate-net return curves to use for determining the best nitrogen rate for each point.

Management of site-specific irrigation in a water-limited area will require the ability to understand the effect of different levels and timing of water stress on crop yield. Techniques noted earlier for delineating management zones, such as soil properties and real-time monitoring fail to examine the interactions between water stress and end-of-season yield. Using crop simulation models for examining irrigation scheduling would allow producers to examine the effect of different water stresses on crop yield. The resulting differences in crop yield between different management strategies could be used in an economic analysis to determine the profitability of each strategy.

METHODOLOGY

Crop Model

The crop simulation model used in this study was the process-oriented Cotton2k model (Marani, 2004). Cotton2k was selected over GOSSYM (Baker et al., 1983) and COTONS (Jallas et al., 1999) based on tests with data from the High Plains region in the 2001 growing season. Prediction of cumulative ET and soil water content profiles were examined for four points at the Texas A&M Halfway Agricultural Experiment Station. The points tested represented different areas of field 5D at the Helms Farm site and three separate water application levels. For three of the four points tested, Cotton2k had the best predictions of cumulative ET. For soil water profile predictions at 30-cm. depth increments, Cotton2k followed soil water profile trends more consistently than the other two models. Predictions of yield for different water application levels were examined for the 2001 Halfway experiments and for experiments in 1997 and 1998 in Lubbock county. In these tests, GOSSYM vastly under-predicted yield at all water levels, COTONS under-predicted yields at lower water levels, and Cotton2k predicted yields consistently close to measured yields.

This model was created with modifications to the GOSSYM crop model for the semi-arid climate of California (Marani et al., 1993a, 1993b, 1993c). The model determines plant water usage for a non-water stressed plant using hourly evapotranspiration equations. Actual water use is determined as a percentage of the potential water use based on the leaf water pressure potential. The leaf water pressure potential is related to the soil water pressure potential. The soil profile is split into a 40 cell deep by 20 cell wide grid. Water movement is by mass balance immediately following rain and irrigation events and by the difference in soil water potential gradients between cells afterwards. In addition to reductions in the actual growth rate from water stress, deficiencies in nitrogen can reduce plant growth.

Crop Model Inputs – Weather and Management

The site used as the example for this analysis was the Helms Farm site at the Halfway Texas Agricultural Experiment Station. The Helms Farm site is a 53.85 ha area under a LEPA center pivot system. The analysis focused on a 1/6 portion of the field that was designated as section 5D. The center of the irrigation system is located at 34° 9’6”N, 101°56’52”W. The layout of the field along with sampling sites is shown in figure 5-1. Management parameters for this analysis were typical for the High Plains environment and were based on averages of actual management practices used in the 2001, 2002, and 2003 growing seasons at Helms Farm. Under this management the crop was planted on May 16 on a 76.2 cm spacing and received 126 kg of nitrogen during the growing season. A summary of these parameters is shown in table 5-1. Weather data for the 1997-2000 and 2002 growing seasons were obtained from a Lubbock area weather station (South Plains Evapotranspiration Network, 2004). Weather data from the 2001 growing season was not used for variable rate irrigation tests because it was used for selection of site-specific soil parameters. A summary of the average temperatures and rainfall from each year is shown in table 5-2. On average the weather was 1.2° Celsius above normal for maximum daily temperature and 8.3 cm below average in rainfall over these years. Much of the above average temperature was driven by temperatures in one year where the temperature was over 3° Celsius above average. The below average rainfall for the entire simulation period was more consistent with four of the five years being 7 cm or more below average.

Table 5-1. Model management input parameters for all years for site-specific irrigation study for Helms Farm field 5D.

Simulation start date	May 9
Emergence date	May 16
Simulation end date	Oct. 6
Row spacing	76.2 cm
Plants per meter	10.5
Fertilizer quantity	126.6 kg N ha^{-1}

Table 5-2. Average weather conditions during simulation periods – Halfway Experiment Station 1997- 2000 and 2002.

Year	Average Daily Maximum Temperature	Temperature – Departure from Average	Total Rainfall	Rainfall – Departure from Average
	(°C)	(°C)	(cm)	(cm)
1997	30.0	-0.4	24.0	-7.4
1998	33.6	3.2	14.1	-17.3
1999	30.8	0.4	37.7	6.3
2000	32.3	1.9	21.0	-10.4
2002	31.1	0.7	18.8	-12.6
Historic average *	30.4		31.4	

* Historic average taken from May 1 – October 15

Crop Model Inputs – Soils

The soil survey map unit for this site is a Pullman sandy clay loam (USDA-SCS, 1974). Percent sand and percent clay was obtained through sampling for 33 points in the Helms Farm field 5-D (Robert Lascano, personal communication). The points where the sampling occurred are shown in figure 5-1. The soil inputs for the simulations were based on a combination of sampling for percent sand and percent clay, soil parameters obtained with the Soil Water Characteristic calculator (Saxton et al., 1986), and site-specifically optimized soil residual and saturated water content as shown in table 5-3. The sand and clay percentages for the top 20-cm of the soil profile are in table 5-4. The soil profile for the model input consisted of four 20 cm layers plus a fifth 120-cm layer. The four 20-cm layers were chosen to reflect the depths at which soil texture information was obtained. The remainder of the soil profile was completed with information from the soil survey for this mapping unit.

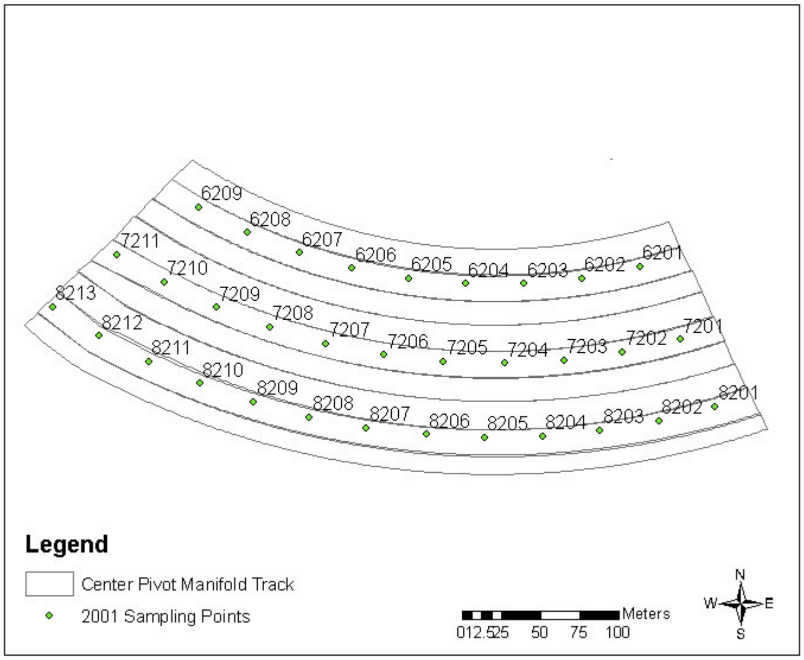


Figure 5-1. Sampling locations in field 5D at Helms Farm.

Table 5-3. Cotton2k model soil input sources for site-specific irrigation simulations.

Input	Source
Percent sand	Soil sampling
Percent clay	Soil sampling
Bulk density	Soil Water Characteristic program, Saxton et al. (1986)
Volumetric water content at air dry	Calculated from Van Genuchten equation
Saturated volumetric water content	From table 3 in van Genuchten et al. (1991) by soil texture
Alpha coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Beta coefficient for the Van Genuchten equation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at saturation	From table 3 in van Genuchten et al. (1991) by soil texture
Hydraulic conductivity at field capacity	Soil Water Characteristic program, Saxton et al. (1986)

Table 5-4. Soil properties for Helms Farm sampling points – percent sand and percent clay in top 20 cm. and available water capacity in top 200 cm.

Location	Soil Texture	% Sand	% Clay	Available Water Capacity
6201	Sandy Clay Loam	50	34	19.69
6202	Sandy Clay Loam	49	36	20.37
6203	Sandy Clay Loam	49	34	20.04
6204	Sandy Clay Loam	49	34	20.09
6205	Clay Loam	41	38	18.89
6206	Clay Loam	37	38	17.52
6207	Clay	35	41	19.14
6208	Clay	34	43	20.60
6209	Clay	32	43	18.39
7201	Sandy Clay	48	36	21.37
7202	Sandy Clay Loam	51	34	19.08
7203	Sandy Clay	47	36	19.42
7204	Clay	41	40	19.64
7205	Clay	42	40	20.55
7206	Clay Loam	43	36	18.03
7207	Clay Loam	44	37	21.01
7208	Sandy Clay	47	35	18.89
7209	Sandy Clay Loam	51	34	20.73
7210	Clay	37	41	21.86
7211	Clay	39	41	19.79
8201	Sandy Clay Loam	49	31	19.95
8202	Sandy Clay Loam	55	31	20.16
8203	Sandy Clay Loam	51	33	18.69
8204	Sandy Clay Loam	48	31	19.08
8205	Sandy Clay	45	35	18.30
8206	Clay Loam	36	37	19.22
8207	Clay Loam	35	39	18.54
8208	Clay	34	41	19.73
8209	Clay	28	41	19.54
8210	Clay	27	47	20.25
8211	Clay	28	45	20.32
8212	Clay Loam	37	39	18.66
8213	Clay Loam	40	36	20.72

Residual and saturated water content inputs for each point were obtained by optimizing model yield against measured yield for the 2001 growing season. Optimization was made using a simulated annealing algorithm. The optimization was performed for both parameters in the top three layers of the model input soil profile. Available water capacities determined from the optimized residual and saturated water contents ranged from 17.52 to 21.86 cm (tables 5-4 and 5-5). The available water capacity for an average Pullman soil based on soil survey information is 17.85 cm.

Initial moisture conditions are entered as a percent of field capacity in Cotton2k. The initial soil moisture conditions (table 5-6) used in this study were based on averages of the first neutron probe soil moisture sampling in the 2001 and 2003 growing seasons. Basing initial soil moisture values on measured data from a field scale was to ensure that these values reflect what a typical producer would experience in the High Plains region. Values used for initial conditions for these simulations were 60 percent of field capacity for the top 15 cm, 85 percent for the next 15 cm, and 80 percent for the remaining depths. This set of initial conditions represented 60 percent of the available water capacity for a Pullman clay loam soil. Initial values used for ammonium, nitrate and organic matter (table 5-6) represented typical starting conditions based on sample model files and were not adjusted for High Plains soils.

Table 5-5. Available water content at Helms Farm between simulated annealing optimized soil inputs and Pullman soil.

Model input basis	Average (cm)	Maximum (cm)	Minimum (cm)	Standard deviation (cm)
Pullman soil	17.85			
Simulated annealing optimized	19.64	21.86	17.52	1.00

Table 5-6. Initial Cotton2k soil inputs for site-specific irrigation simulations.

Bottom Layer Depth	NH_4 (kg ha^{-1})	NO_3 (kg ha^{-1})	Organic Matter, % by weight	Water Content, % of field capacity
15	2.69	26.904	0.74	60
30	1.23	13.23	0.72	80
45	1.00	10.09	0.67	85
60	0.79	7.40	0.43	85
75	0.79	7.40	0.37	85
90	0.79	7.40	0.30	85
105	4.93	4.93	0.00	85
120	4.93	4.93	0.00	85
135	4.93	4.93	0.00	85
150	4.93	4.93	0.00	85
165	4.93	4.93	0.00	85
180	4.93	4.93	0.00	85

Irrigation Strategies

Two irrigation strategies were examined for each growing season. The first strategy was a weekly interval strategy with one irrigation a week after planting and then irrigations beginning in the last week of June and ending in the last week of August for a total of 11 irrigation events. Water levels were varied from 6.35 mm to 31.75 mm, in 6.35-mm increments, with all irrigations occurring on the same dates. This strategy was chosen because in a semi-arid area such as the High Plains producers will turn on their pivots and, if water is available, allow the pivots to cycle across the field, passing the same point on a consistent basis. Irrigations in this strategy were not altered by rainfall events.

The second irrigation strategy used a soil moisture depletion threshold to determine the timing of each irrigation event using a soil water balance. Timings were based on 30% soil moisture depletion with 25.4 mm of replenishment for each irrigation event. Rainfall affected irrigation timing in this strategy by increasing the amount of water in the soil profile, thus potentially delaying irrigation events depending on the rainfall quantity. Application rates were examined in 6.35-mm increments from 6.35 to 31.75 mm with irrigation events occurring on the same day as the 25.4 mm irrigation schedule. This strategy is typical of soil moisture-based irrigation scheduling to minimize stress effects on yield. Crop evapotranspiration quantities for each year were determined from reference evapotranspiration quantities calculated from the Van Bavel (1966) evapotranspiration equation for reference evapotranspiration and cotton crop coefficients based on Allen et al. (1998). The reference evapotranspiration is available at the South Plains Evapotranspiration Network (2004). Irrigation timings were determined using the 25.4 mm irrigation quantity. This irrigation strategy was affected by climatic conditions in each year, therefore different numbers of irrigation events occurred in each year with different intervals between each event. The number of irrigation events varied from 14 in 1999 and 2000 to 20 in 1998 (table 5-7).

Table 5-7. Number of irrigation events for weekly and soil moisture depletion irrigation strategies.

Year	Weekly Interval	Soil Moisture Depletion
1997	11	16
1998	11	20
1999	11	14
2000	11	14
2002	11	19

The results from the two irrigation strategies will be different due to differences in the number of irrigations and the timing of each individual irrigation event. Because the soil moisture depletion strategy applied more water more frequently, it therefore should up to a point produce higher yields than the weekly irrigation strategy. More water allows for production of more plant mass, while increased frequency decreases periods of stress that can reduce yield potential.

Uniform and Site-Specific Scheduling

The two irrigation schedules, average management parameters, and site-specific soil information were used as inputs to the Cotton2k crop model. Yields were simulated for combinations of each point, five water levels in 6.35 mm increments, and five years of historic weather information. Estimates of field level yield responses were obtained by averaging yield responses for individual points in the field together. In the analysis, uniform management was when each point in the field had the same quantity of water applied to it.

Site-specific irrigation management was modeled two ways. The first type of site-specific management was for the case where the entire field was in production and the irrigations could be adjusted so that higher yielding portions of the field received more water. In this hypothetical case, the split between higher and lower yielding portions of the field was made at half the field. The procedure for determining the field-level response to this site-specific strategy for each water application level was:

1) Generate yield for each point and water application level with Cotton2k

2) Compute the difference in yield between one irrigation level above and one irrigation level below the water level being examined

3) Rank the yield differences from highest to lowest.

4) Compute the average field yield with the points with the highest yield differences receiving the higher water level and the points with the lowest yield differences receiving the lower water level.

Analysis of site-specific irrigation was performed for water application levels of 12.7, 19.05, and 25.4 mm since yield responses at water levels higher and lower than each of these levels had been created in the uniform irrigation simulations.

The second form of site-specific management was for the case where a portion of the field was a non-yielding playa lake. In this case, 10% of the field was considered to be in non-yielding areas. Field averages of yield for this scenario did not include yield responses for these areas. In this scenario, it was assumed that no water applications occurred in the playa lake areas, allowing for water savings or yield gains if the water was redistributed. In the water redistribution case, the 10% of the points which had the highest potential yield increase with a 6.35 mm addition of water would receive the additional water applications. The 6.35 mm water depth in this analysis was chosen to match irrigation depth increments used in earlier model simulations.

Economic Analysis

Simulation results were analyzed with model output of crop yield, water usage, and potential net return on a field basis. Net return was calculated with the following equation (adapted from Braga et al., 1999):

$$NR = Y*C_p - Y*H_c - V_c - F_c - SSC \qquad (5\text{-}1)$$

where
- NR = net return (\$ ha^{-1})
- Y = crop yield in (kg ha^{-1})
- C_p = cotton price in (\$ kg^{-1})
- H_c = the harvest cost (\$ kg^{-1})
- V_c = other variable costs (\$ ha^{-1})
- F_c = the fixed cost (\$ ha^{-1}) and
- SSC = additional cost for site-specific management (\$ ha^{-1}).

Values used for this equation were: C_p = 1.10 (\$ kg^{-1}), H_c = \$0.10 (\$ kg^{-1}) (Cotton Economics Research Institute, 2005), F_c = 416.07 (\$ ha^{-1}) (Texas Cooperative Extension 2000), V_c = 504 (\$ ha^{-1}) (Texas Cooperative Extension 2000), and SSC = 37.05 (\$ ha^{-1}). Included in the variable costs are fuel costs for irrigation system operation. The site specific cost was based on \$20,000 for a site-specific system over the cost of the base center pivot system. It was assumed that the cost would be spread over the entire 53.85 ha area of the field and over a ten year planning period. Interest was not factored into this analysis.

RESULTS AND ANALYSIS

Yield response curves across the five growing seasons are shown in figures 5-2 and 5-3. Yields vary from 600 kg ha^{-1} to about 1700 kg ha^{-1} for the 30 percent moisture depletion schedule and from 300 to 1600 kg ha^{-1} for the weekly interval schedule. The

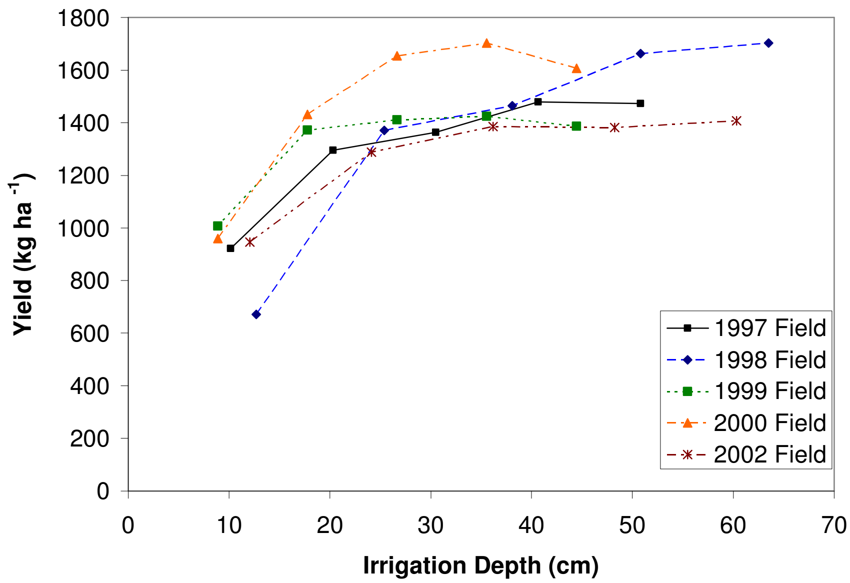


Figure 5-2. Irrigation – average yield response curves for all data points in 1997, 1998, 1999, 2000, and 2002 growing seasons. A soil moisture depletion irrigation schedule was used to generate the curves.

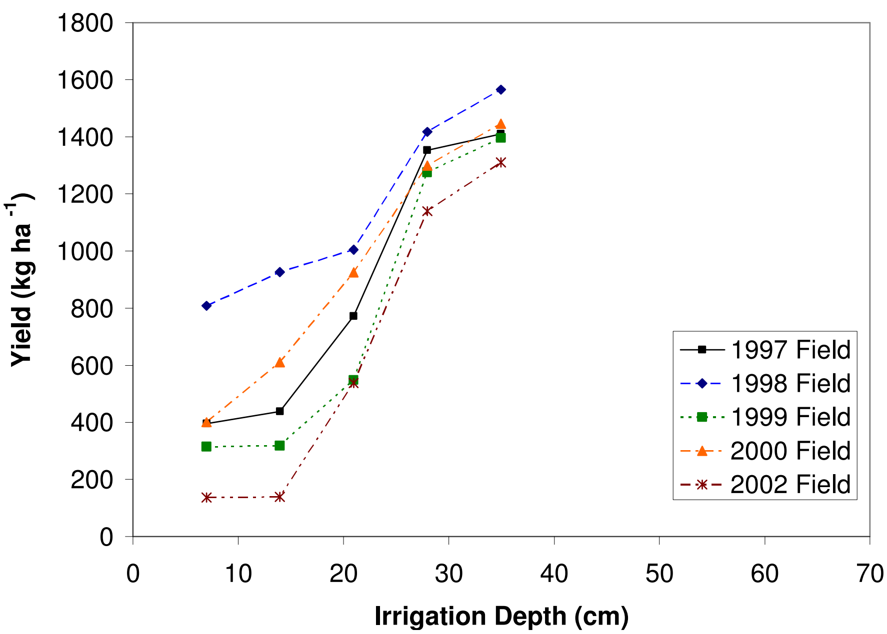


Figure 5-3. Irrigation – average yield response curves for all data points in 1997, 1998, 1999, 2000, and 2002 growing seasons. An irrigation schedule with weekly irrigation applications were used to generate the curves.

difference in peak yield between the two strategies can be attributed to the larger quantity of water applied in the soil moisture depletion strategy. The soil moisture depletion strategy tended to have high yields for the initial point on the response curve and flatter response curves than the constant interval strategy. The differences between the curves for the two strategies indicate the effect that irrigation timing will have on yield responses. For seasonal irrigation levels less than 20 cm, the soil moisture depletion strategy consistently produced higher yields than the weekly irrigation interval strategy. Since the soil moisture depletion strategy had more frequent irrigations than the weekly strategy, the results indicate that especially when water is limited more frequent irrigations can provide higher yields.

The response curves for four individual points and the field average yield response curve for both irrigation schedules for the 1997 growing season are shown in figures 5-4 and 5-5. Individual points have response curves that are nearly parallel to the field average response curves. One exception is point 7210 for the soil moisture depletion schedule between the 6.35 mm and 12.70 mm irrigation rates, where the point response curve decreases while the field average response curve increases. One standard deviation error bars are also shown on each of these graphs. For the soil moisture depletion schedule the error bars decreased as the amount of irrigation increased. Error bars for the weekly irrigation schedule were similar throughout the range of irrigations. The smaller error bar widths at the higher irrigation quantities for the soil moisture depletion schedule, could come from the reduction in water stress for more points at this water level. Not all point irrigation response curves fell within the one standard

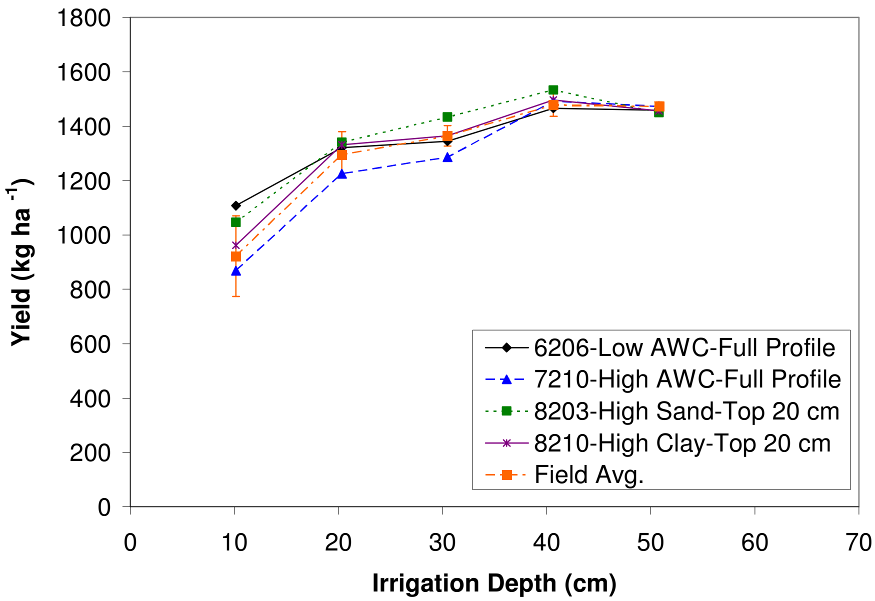


Figure 5-4. Irrigation – yield response curves for points 6206, 7210, 8203, 8210, and field average for the 1997 growing season. A soil moisture depletion irrigation schedule was used to generate the curves.

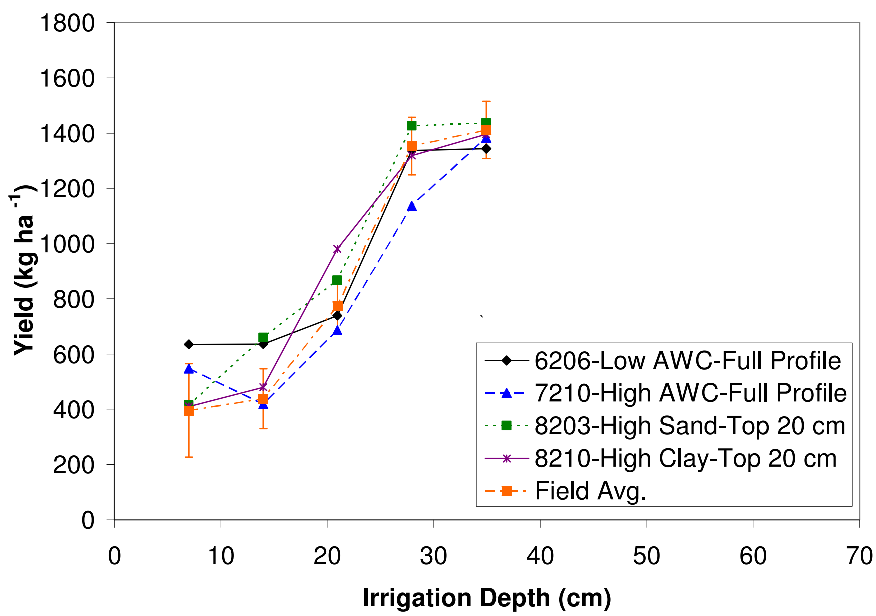


Figure 5-5. Irrigation – yield response curves for points 6206, 7210, 8203, 8210, and field average for the 1997 growing season. An irrigation schedule with weekly irrigation applications were used to generate the curves.

deviation error bars, as evidenced by the response curves for points 6206 and 7210 being outside the error bars for the soil moisture depletion graph. One anomaly in model predictions noted on figure 5-5 is that yields decrease when going from the 6.35 mm irrigation depth to the 12.70 mm irrigation depth for point 6206. With the additional water, plant height increased nearly 9 cm and LAI increased by over 0.9. At the higher water application depth, the number of open bolls decreased by seven and the amount of abscised fruit decreased by 40 kg ha^{-1}. These observations indicate that stress effects on boll growth and abscission likely caused the lower yield for the higher water depth.

An illustration of the point ranking and water allocation procedure for the weekly irrigation strategy in the 1997 growing season is shown in table 5-8. Soil differences are the cause of the difference in yield response for each point in table 5-8 since soil inputs were the only inputs that varied for each point.

Another way to perform site-specific scheduling across fields would be to average the rankings of yield responses across years. An example of average rankings obtained with this method appears in table 5-9. Allocation of water with rankings based on multiple years of response curve data would be made as in the single year example shown in table 5-8 with higher ranked points receiving water first. The soil textures for each 20-centimeter depth for each point are given in table 5-10. Points that had higher yield responses at this irrigation level were more likely to have a clay soil texture in the 20-80 cm depth range. Points with the lowest yield responses tended to have a sandy clay loam texture in the 40-80 cm depths.

Table 5-8. Ranking of yield differences for different application rates in 1997 for selection of points to apply higher irrigation quantities – weekly interval irrigation strategy.

Point Number	6.35 mm per Irrigation Yield (kg ha^{-1})	12.70 mm per Irrigation Yield (kg ha^{-1})	19.05 mm per Irrigation Yield (kg ha^{-1})	Yield Difference 6.35 mm to 19.05 mm (kg ha^{-1})	Yield Difference 6.25 mm to 19.05 mm Rank
8206	378.7	760	1067.4	688.7	1
6208	423.1	497.8	1010.4	587.3	2
8210	409.7	480	980.2	570.5	3
6203	281.3	419.4	846.2	564.9	4
8208	399.3	484.4	917.4	518.1	5
8205	293.3	558.6	810.2	516.9	6
7206	240.5	448.3	755	514.5	7
7211	313.2	443	824.3	511.1	8
6205	267.6	444.4	777.6	510	9
7202	295.7	420.3	802.1	506.4	10
6207	350	463.8	850.3	500.3	11
8209	373.5	462.3	873	499.5	12
8211	394.7	372.5	852.6	457.9	13
8203	415.5	659.5	867.1	451.6	14
7209	550.6	624.4	974.7	424.1	15
8202	394.3	401.3	785.5	391.2	16
6202	471.8	419.3	856.4	384.6	17
8201	389.6	401.5	758.5	368.9	18
6209	515.8	653.2	863.9	348.1	19
7203	341	301.3	659.7	318.7	20
8207	208.4	148.7	520.7	312.3	21
8212	280	289.6	578.5	298.5	22
6201	473.3	464.4	753.5	280.2	23
7207	392.7	334.6	664.7	272	24
7208	329	250.3	567.2	238.2	25
8204	374.8	337	607.2	232.4	26
7205	415.6	323.9	618.7	203.1	27
7204	370.1	313.1	568.3	198.2	28
7201	494.2	433.5	677.1	182.9	29
8213	506.6	365.6	681.3	174.7	30
6204	542.7	439.7	699.9	157.2	31
7210	546.8	418.7	685.6	138.8	32
6206	634.2	636.4	739.3	105.1	33

Table 5-9. Point yield potential rankings averaged across five years for site-specific management with 12.70 mm water application level.

Point Number	1997	1998	1999	2000	2002	Average 5 Year Ranking	Range in Rankings Across Years
6201	23	1	17	33	24	23	32
6202	17	2	12	18	19	11	17
6203	4	15	4	3	12	2	12
6204	31	3	18	32	27	26	29
6205	9	19	20	23	10	18	14
6206	33	9	32	20	3	22	30
6207	11	17	15	25	14	20	14
6208	2	27	2	4	13	4	25
6209	19	10	23	28	2	20	26
7201	29	30	16	17	25	29	14
7202	10	11	21	14	18	16	11
7203	20	14	13	11	15	14	9
7204	28	32	29	26	32	32	6
7205	27	33	31	24	33	33	9
7206	7	22	27	2	5	7	25
7207	24	31	25	19	28	30	12
7208	25	23	22	13	21	24	12
7209	15	6	8	29	16	16	23
7210	32	7	33	31	30	31	26
7211	8	18	14	21	7	11	14
8201	18	5	11	9	23	9	18
8202	16	13	10	10	22	12	12
8203	14	12	26	22	4	17	22
8204	26	8	24	27	26	26	19
8205	6	4	30	15	6	6	26
8206	1	29	1	1	1	1	28
8207	21	28	27	8	29	27	21
8208	5	26	6	12	8	5	21
8209	12	24	9	16	11	13	15
8210	3	21	3	5	9	3	18
8211	13	25	5	6	17	9	20
8212	22	20	19	7	20	21	15
8213	30	16	7	30	31	28	24

Table 5-10. Soil textures by depth for points ranked by yield differences between 6.35 mm and 19.05 mm water application rates. Rankings are based on yield responses averaged across five years of yield data.

Point Number	Yield Ranking	0-20 cm depth	20-40 cm depth	40-60 cm depth	60-80 cm depth
8206	1	CL	C	C	C
6203	2	SCL	SC	SCL	SCL
8210	3	C	C	C	C
6208	4	C	C	C	C
8208	5	C	C	C	C
8205	6	SC	SCL	C	C
7206	7	CL	SC	C	C
8201	8	SCL	C	C	C
8211	9	C	SCL	C	C
6202	10	SCL	CL	SC	SCL
7211	11	C	C	SC	SCL
8202	12	SCL	C	C	C
8209	13	C	C	C	C
7203	14	SC	C	CL	SCL
7202	15	SCL	CL	SC	SC
7209	16	SCL	CL	SCL	SCL
8203	17	SCL	CL	C	CL
6205	18	CL	C	SC	SCL
6207	19	C	C	C	SC
6209	20	C	C	C	C
8212	21	CL	C	C	SC
6206	22	CL	C	C	SC
6201	23	SCL	SCL	SCL	SCL
7208	24	SC	SC	SCL	SCL
6204	25	SCL	SC	SCL	SC
8204	26	SCL	C	CL	SC
8207	27	CL	C	C	C
8213	28	CL	CL	SC	SCL
7201	29	SC	CL	CL	SC
7207	30	CL	C	C	C
7210	31	C	CL	SCL	SCL
7205	32	C	CL	SC	CL
7204	33	C	CL	C	SC

C = Clay; SCL = Sandy Clay Loam; CL = Clay Loam; SC = Sandy Clay

Differences in yield and profit between uniform and site-specific management with water allocations based on the five year rankings in table 5-10 are shown in tables 5-11 and 5-12. For the soil moisture depletion strategy, average yield and profit across all five years decreased for site-specific management for all three water application levels. With the weekly irrigation strategy average yield and profit increased with site-specific management for the 12.70- mm and 19.05-mm water application levels. This result is specific to the characteristics found in this field and would potentially vary for other fields that are examined. Greater variability in soil properties could represent greater potential for improving yields with site-specific irrigation.

The effects of reallocating irrigation water from non-producing areas such as playa lakes on yield and profit are shown for the two strategies in tables 5-13 and 5-14. The point rankings for these tables were also based on average yield responses across five years of weather data. For the weekly interval strategy and 10% of the field not in production, field average yields would have improved by at least 20 kg ha^{-1} if a site-specific irrigation system were used to reallocate water to different portions of the field. The yield increases would have increased profit per hectare slightly. With the soil moisture depletion strategy and 10% of the field not in production, reallocating irrigations would have increased yield by at least five kg ha^{-1} across all three water application levels examined. This increase in yields would not have overcome the cost of implementing site-specific irrigation, however.

The amount of water that would be saved in the field if water from non-producing areas of the field was not reallocated is shown in table 5-15. For 10% of the field not in

Table 5-11. Yearly yield difference between uniform and site-specific irrigation management.

	12.35 mm per irrigation			19.05 mm per irrigation			25.4 mm per irrigation		
Year	Uniform (kg ha^{-1})	SS (kg ha^{-1})	Difference (kg ha^{-1})	Uniform (kg ha^{-1})	SS (kg ha^{-1})	Difference (kg ha^{-1})	Uniform (kg ha^{-1})	SS (kg ha^{-1})	Difference (kg ha^{-1})
Soil Moisture Depletion Strategy									
1997	1295	1159	-136	1364	1396	32	1478	1435	-44
1998	1370	1103	-267	1464	1530	66	1663	1591	-72
1999	1371	1226	-145	1410	1419	9	1423	1394	-30
2000	1431	1335	-96	1654	1596	-58	1703	1649	-54
2002	1288	1172	-116	1385	1340	-44	1382	1397	15
Average:	1351	1199	-152	1455	1456	1	1530	1493	-37
Weekly Interval Strategy									
1997	439	633	195	773	902	130	1353	1134	-219
1998	926	909	-17	1005	1180	175	1418	1299	-118
1999	318	454	136	548	816	268	1275	993	-282
2000	611	674	64	925	959	35	1300	1201	-98
2002	139	368	229	537	665	128	1139	963	-176
Average:	486	608	121	758	905	147	1297	1118	-179

Table 5-12. Yearly profit difference between uniform and site-specific irrigation management.

Year	12.35 mm per irrigation			19.05 mm per irrigation			25.4 mm per irrigation		
	Uniform ($ ha^{-1})	SS ($ ha^{-1})	Difference ($ ha^{-1})	Uniform ($ ha^{-1})	SS ($ ha^{-1})	Difference ($ ha^{-1})	Uniform ($ ha^{-1})	SS ($ ha^{-1})	Difference ($ ha^{-1})
Soil Moisture Depletion Strategy									
1997	375.44	201.84	-173.60	444.25	439.10	-5.14	558.90	478.06	-80.84
1998	450.56	146.50	-304.06	544.57	573.31	28.74	743.65	634.06	-109.58
1999	451.78	269.34	-182.43	490.75	462.74	-28.01	503.86	437.12	-66.73
2000	511.06	378.21	-132.84	734.81	639.28	-95.53	783.76	692.36	-91.40
2002	368.40	215.10	-153.30	465.04	383.55	-81.49	462.25	439.88	-22.37
Average:	431.45	242.20	-189.25	535.88	499.60	-36.28	610.48	536.30	-74.18
Weekly Interval Strategy									
1997	-481.67	-324.06	157.61	-147.43	-54.83	92.60	433.18	177.08	-256.10
1998	6.19	-48.32	-54.51	85.58	223.64	138.07	497.95	342.66	-155.29
1999	-602.23	-502.75	99.48	-372.07	-140.93	231.14	355.25	36.51	-318.74
2000	-309.49	-282.86	26.63	4.64	2.44	-2.20	380.00	244.56	-135.44
2002	-781.23	-588.96	192.27	-382.79	-291.88	90.91	219.39	6.18	-213.22
Average:	-433.69	-349.39	84.30	-162.41	-52.31	110.10	377.15	161.40	-215.76

Table 5-13. Difference in yields for variable rate irrigation with 10% of field as non-producing area.

	12.35 mm per irrigation			19.05 mm per irrigation			25.4 mm per irrigation		
Year	Uniform ($kg\ ha^{-1}$)	SS ($kg\ ha^{-1}$)	Difference ($kg\ ha^{-1}$)	Uniform ($kg\ ha^{-1}$)	SS ($kg\ ha^{-1}$)	Difference ($kg\ ha^{-1}$)	Uniform ($kg\ ha^{-1}$)	SS ($kg\ ha^{-1}$)	Difference ($kg\ ha^{-1}$)
Soil Moisture Depletion Strategy									
1997	1178	1184	5	1239	1255	15	1343	1344	1
1998	1249	1261	13	1333	1347	14	1512	1521	9
1999	1253	1258	5	1284	1288	4	1295	1289	-5
2000	1302	1328	26	1507	1518	11	1547	1541	-6
2002	1172	1185	12	1261	1262	2	1261	1262	1
Average:	1231	1243	12	1325	1334	9	1392	1391	0
Weekly Interval Strategy									
1997	399	437	37	706	769	63	1227	1234	7
1998	848	856	8	916	957	42	1290	1310	20
1999	286	319	32	495	575	80	1158	1183	25
2000	556	591	35	841	879	38	1183	1195	12
2002	125	179	54	496	563	67	1039	1059	20
Average:	443	476	33	691	749	58	1179	1196	17

Table 5-14. Difference in profit for variable rate irrigation with 10% of field as non-producing area.

	12.35 mm per irrigation			19.05 mm per irrigation			25.4 mm per irrigation		
Year	Uniform ($ ha-1)	SS ($ ha-1)	Difference ($ ha-1)	Uniform ($ ha-1)	SS ($ ha-1)	Difference ($ ha-1)	Uniform ($ ha-1)	SS ($ ha-1)	Difference ($ ha-1)
Soil Moisture Depletion Strategy									
1997	259	227	-32	320	298	-22	424	387	-37
1998	329	305	-24	413	390	-23	593	564	-28
1999	333	301	-32	364	331	-33	375	333	-42
2000	382	371	-11	587	561	-26	627	584	-43
2002	252	228	-25	341	305	-36	341	305	-36
Average:	311	286	-25	405	377	-28	472	435	-37
Weekly Interval Strategy									
1997	-521	-521	0	-214	-188	26	307	277	-30
1998	-72	-101	-29	-4	0	4	370	353	-17
1999	-634	-639	-5	-425	-382	43	239	226	-12
2000	-364	-366	-2	-79	-78	1	263	239	-25
2002	-795	-778	17	-424	-394	30	119	102	-17
Average:	-477	-481	-4	-229	-208	21	260	239	-20

Table 5-15. Water savings if 10% of Helms Farm field 5D was not watered.

	12.35 mm per irrigation (ha-cm)	19.05 mm per irrigation (ha-cm)	25.4 mm per irrigation (ha-cm)
Weekly Interval Strategy			
All Years	6.80	10.19	13.58
Soil Moisture Depletion Strategy			
1997	9.88	14.82	19.76
1998	12.35	18.53	24.70
1999	8.65	12.97	17.29
2000	8.65	12.97	17.29
2002	11.73	17.59	23.47
Average:	10.25	15.37	20.50

production this would result in water savings of at least 6.80 hectare-centimeter with the weekly interval strategy and on 8.65 hectare-centimeter with the soil moisture depletion strategy.

The site-specific analysis used here may not exactly resemble the procedure producers would use in their fields. Different levels of water applications could be tested along with strategies that adjust irrigation event timing. Using historic weather as a crop model input allows for the analysis of long-term effects of a selected management strategy. Producers could potentially use the results of the long term analysis as a guide for in-season management decisions. Alternatively, they could create new response curves by coupling in-season weather with historic weather ranges for the remaining portion of the growing season.

CONCLUSIONS

Two situations for using site-specific irrigation were examined through the use of point specific irrigation yield response curves generated with a crop simulation model. In the first situation the entire field was in production and water was reallocated from lower to higher yielding areas of the field. In the second situation, non-yielding field areas were considered and water either reallocated to high yielding field areas or saved.

This study illustrates the benefits of using a crop modeling approach for analyzing site-specific irrigation. The model utilized incorporated soils, plant, and weather components in the analysis. Each of these components affects the results of the yield responses from the system and therefore is important to include in the analysis. The flexibility of this approach would allow it to be applied at other levels of spatial homogeneity or with other water application levels or timing strategies.

These tests showed that results from implementing site-specific irrigation varied on a year-by-year basis with the practice increasing profit in some years and being unprofitable in other years. Comparison between the two strategies for this field indicated that for seasonal water application levels less than 20 cm irrigating more frequently than once per week at a lower application rate would be a better management practice than adopting point-based site-specific irrigation. Adding site-specific irrigation equipment to center pivot systems does offer the potential for yield gains and/or water usage reductions when applied to control of irrigations on non-producing portions of fields.

CHAPTER VI

CONCLUSIONS

Three crop simulation models, GOSSYM, COTONS, and Cotton 2k were tested for their ability to simulate water movement in the soil-plant-air continuum for the Texas High Plains environment. Cotton2k predictions of ET were closest to measured ET for three of four points examined. Cotton2k's performance in this test was likely from the inclusion of dewpoint temperature in the ET calculations as compared to the use of daily minimum temperature by the other two models. Cotton2k performed much better than the other two models for predicting applied water-yield relations. Its predictions were nearly identical to measured yields for plot level field experiments and much closer in magnitude than the other two models for field-scale experiments. Cotton2k's improved ability to predict yield was likely due to better description of water stress relations in model equations than the other two models. Overall, Cotton2k was the most suitable model of the three for the Texas High Plains environment.

The simulated annealing optimization algorithm was tested with the Cotton2k model for its ability to calibrate the model for parameters related to available water capacity. The algorithm could determine optimum parameter sets for yield-based objective functions. Consistent parameter sets were not obtained with different starting points, however. This result is likely from different water holding capacities leading to the same yield. Optimization results were better for one year rather than two years of yield data. In this case the results may reflect the use of yields from management zones rather than from individual points. Whole-field tests of the annealing optimization procedure improved model predictions of yield for the majority of points evaluated. When simulated annealing is applied with Cotton2k for spatial calibration up to two days was required to obtain a solution for a single location. Increases in computer speed or alternative optimization algorithms will be needed to make this form of spatial calibration practical for producers.

The spatially calibrated model was used to assess the potential profit and water usage effects of implementing site-specific irrigation. Simulations showed that site-specific irrigation could increase yields over uniform irrigation but the increases did not make site-specific irrigation more profitable than uniform irrigation. Site-specific irrigations with the weekly strategy at irrigation rates of 19.05 mm and below were not profitable even though yields were increased. The highest average profits of 610 $ ha^{-1} per year were obtained with a uniform spatial management strategy and a 25.4 mm irrigation rate. Site-specific irrigation was shown to increase yields if used to reallocate water from non-producing field areas to the most productive points in the field. The yield increase was not enough to make the weekly interval strategy profitable or to be more profitable than the uniform spatial management for the soil moisture depletion strategy. Usage of crop model generated response curves for site-specific decision making could be used either for pre-season guidance for decision rules for where to apply irrigations or used with curves created with in-season weather data.

FUTURE RECOMMENDATIONS

The variety used for the model assessment tests of the Cotton2k model was selected by comparing data from field experiments with current varieties to model simulations with older variety information. Field and laboratory experiments to determine current variety information for Cotton2k would be beneficial for making it more usable for current producers. The use of simulated annealing with the Cotton2k model took nearly two days to complete optimization runs for a single field location. This length of simulation is impractical for use in a typical producer situation. Alternative methods of optimization that perform searches faster than simulated annealing, such as adaptive simulated annealing should be tested for use with optimization of soil parameters for Cotton2k. Alternatively, the stopping criteria in the simulated annealing algorithm could be modified to avoid large amounts of computing time after an optimal parameter set is obtained.

Results of the site-specific irrigation tests are presented for only one portion of one field in the Texas High Plains region. Other fields in the Texas High Plains that have wider variety in soil textures could be identified and tested for the outcomes of implementing site-specific irrigation on them using the procedure created in this study. The irrigation schedules used in the site-specific irrigation tests were developed separate from the Cotton2k model. Application of an optimization technique to the management portion of inputs would allow for testing of a wider variety of management strategies with the model. In order for Cotton2k to be more useful for producers for site-specific management, the model should be integrated with a geographic information system to better store and manage the increased amounts of data required for site-specific management.

REFERENCES

Allen, R. G., L.S. Pereira, D. Raes, and M. Smith. 1998. Crop evapotranspiration: guidelines for computer crop water requirements. Irrigation and Drainage Paper 56. Rome, Italy: Food and Agriculture Organization of the United Nations.

Baker, D. N., J. R. Lambert, and J. M. McKinion. 1983. GOSSYM: A simulator of cotton crop growth and yield. South Carolina Agricultural Experiment Station Technical Bulletin 1089. Clemson, South Carolina: Clemson University,

Barnes, E.M., P.J. Pinter, Jr., B.A. Kimball, G. W. Wall, R. L. LaMorte, D.J. Hunsaker, F. Adamsen, S. Leavitt, T. Thompson, and J. Mathius. 1997. Modification of CERES-Wheat to accept leaf area index as an input variable. ASAE Paper No. 973016. St. Joseph, Michigan: ASAE.

Basso, B., J.T. Ritchie, F.J. Pierce, R. P. Braga, and J.W. Jones. 2001. Spatial validation of crop models for precision agriculture. *Agricultural Systems* 68: 97-112.

Bauer, M. G., J. G. Davis, K. A. Sudduth, and S. T. Drummond. 2000. Agronomic and economic evaluation of variable-rate seeding on Missouri soils. In *Proc. of the Fifth International Conference on Precision Agriculture* (cd-rom). Madison, Wisconsin: SSA-CSSA-SSA

Beckett, P. H. T. and R. Webster. 1971. Soil variability: a review. *Soils and Fertilizers* 34(1): 1-15.

Bhatti, A. U., D. J. Mulla, B. E. Frazier. 1991. Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and thematic mapper images. *Remote Sensing of Environment* 37: 181-191.

Boote, K. J., J. W. Jones, and G. Hoogenboom. 1998. Simulation of crop growth: CROPGRO model. In *Agricultural Systems Modeling and Simulation*, 651-692. R. M. Peart, and R. B. Curry, eds. New York, New York: Marcel Dekker, Inc.

Boote, K. J., J. W. Jones, and N. B. Pickering. 1996. Potential uses and limitations of crop models. *Agronomy Journal* 88: 704-716.

Bordovosky, J. P. and R. J. Lascano. 2003. Variable-rate irrigation using low energy precision application. In *Proc. of the 2003 Beltwide Cotton Conferences*, 563-571 D. Richter, ed. Memphis, Tennessee: Cotton, Inc.

Braga, R. P. and J. W. Jones. 2004. Using optimization to estimate soil inputs of crop models for use in site-specific management. *Transactions of the ASAE*. 47(5): 1821-1831.

Braga, R. P., J. W. Jones, and B. Basso. 1999. Weather induced variability in site-specific management profitability: a case study. In *Proc. of the Fourth International Conference on Precision Agriculture*, 1853-1863. P.C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Calmon, M. A., J. W. Jones, D. Shinde, J. E. Specht. 1999. Estimating parameters for soil water balance using adaptive simulated annealing. *Applied Engineering in Agriculture* 15(6): 703-713.

Cambardella, C. A., T. S. Colvin, D. L. Karlen, S. D. Logsdon, E. C. Berry, J. K. Radke, T. C. Kaspar, T. B. Parkin, and D. B. Jaynes, 1996. Soil property contributions to yield variation pattern. In *Proc. of the Third International Conference on Precision Agriculture*, 189-195. P. C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSA.

Camp, C. R. and E. J. Sadler. 1998 Site-specific crop management with a center pivot. *Journal of Soil and Water Conservation* 53(4): 312-314

Coelho, A.M., J. W. Doran, and J. S. Schepers. 1999. Irrigated corn yield as related to spatial variability of selected soil properties. In *Proc. of the Fourth International Conference on Precision Agriculture*, 441-452. P.C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Constable, G. A. and Rawson, H. M. 1980. Carbon production and utilization in cotton: inferences from carbon budget. *Australian Journal of Plant Physiology* 7: 539-553.

Corana, A., M. Marchesi, C. Martini, and S. Ridella. 1987. Minimizing multimodal functions of continuous variables with the "Simulated Annealing" algorithm. *ACM Transactions on Mathematical Software* 13(3):262-280.

Cotton Economics Research Institute. 2005. Cotton harvest cost calculator. Lubbock, Tx.: Cotton Economics Research Institute. Available at: http: //www.aaec.ttu.edu/CER-Institute. Accessed 12 August 2005.

Dong, A., S. R. Grattan, J. J. Carroll, and C. R. K. Prashar. 1992. Estimation of daytime net radiation over well-watered grass. *Journal of Irrigation and Drainage Engineering* 118(3): 466-479.

Doorenbos, J. and W. H. Pruitt. 1977. *Crop water requirements*. FAO Irrigation and Drainage Paper 24. Rome, Italy: Food and Agriculture Organization of the United Nations.

Eberlein, C.V., B.A. King, and M.J. Guttieri. 2000. Evaluating an automated irrigation control system for site-specific herbigation. *Weed Technology* 14: 182-187.

English, M. J., J. T. Musick, and V. V. N. Murty. 1990. Deficit Irrigation. In *Management of Farm Irrigation Systems*, 631-663. G. J. Hoffman, T. A. Howell, and K. H. Solomon, eds. St. Joseph, Michigan: ASAE.

Ephrath, J. E. J. Gourdriaan, and A. Marani. 1996. Modelling diurnal patterns of air temperature, radiation, wind speed and relative humidity by equations from daily characteristics. *Agricultural Systems* 51(4): 377-393.

Epperson, J. E., J. E. Hook, and Y. R. Mustafa. 1993. Dynamic programming for improving irrigation scheduling strategies of maize. *Agricultural Systems* 42: 85-101.

Evans, R. G. and G. B. Harting. 1999. Precision irrigation with center pivot system on potatoes. In *Proc. of the International Water Resources Engineering Conference, Environmental and Water Resources Institute*, R. Walton and R. E. Nece, eds., 11 p. Seattle, WA, 8-12 Aug. (on CDROM: htm\IS\IS04_505.pdf)

Evans, R. G., S. Han, S. M. Schneider, and M. W. Kroeger. 1996. Precision center pivot irrigation for efficient use of water and nitrogen. In *Proc. of the Third International Conference on Precision Agriculture*, 75-84. P. C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin:ASA-CSSA-SSSA.

Feinerman, E. and H. Voet. 2000. Site-specific management of agricultural inputs: an illustration for variable-rate irrigation. *European Review of Agricultural Economics* 27(1): 17-37.

Fraisse, C. W., D. F. Heermann, and H. R. Duke. 1992. Modified linear move system for experimental water application. In *Proc. of Advances in Planning, Design, and Management Irrigation Systems as Related to Sustainable Land Use*, Vol. 1: 367-376. Leuven, Belgium, 14-17 September.

Fye, R. E., V. R. Reddy, and D. N. Baker. 1984. The validation of GOSSYM: part 1 – Arizona conditions. *Agricultural Systems* 14:85-105.

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

Gowing, J. W. and C. J. Ejieji. 2001. Real-time scheduling of supplemental irrigation for potatoes using a decision model and short-term weather forecasts. *Agricultural Water Management* 47: 137-153.

Han, S., R. G. Evans, T. Hodges, and S. L. Rawlins. 1995. Linking a geographic information system with a potato simulation model for site-specific crop management. *Journal of Environmental Quality* 24: 772-777.

Heneggeler, J. C. 1998. Managing cotton when water is limited. In *Proc. of the 1998 Beltwide Cotton Conferences*, 641-645 D. Richter, ed. Memphis, Tennessee: Cotton, Inc.

Hiler, E. A. and R. N. Clark. 1971. Stress day index to characterize effects of water stress on crop yields. *Transactions of the ASAE* 14(4): 757-761.

Hook, J. E. 1994. Using crop models to plan water withdrawals for irrigation in drought years. *Agricultural Systems* 45: 271-289.

Huggins, D. R. and R. D. Alderfer. 1995. Yield variability within a long-term corn management study: implications for precision farming. In *Proc. of Site-specific Management for Agricultural Systems*, 417-426. P. C. Robert, R. H. Rust, W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Irmak, A., J. W. Jones, W. D. Batchelor, and J. O. Paz. 2001. Estimating variable soil properties for application of crop models in precision farming. *Transactions of the ASAE* 44(5): 1343-1353.

Jallas, E. 1998. Improved model-based decision support by modeling cotton variability and using evolutionary algorithms. Ph.D. Dissertation. Starkville, Mississippi: Mississippi State University.

Jallas, E., R. Sequeira, P. Martin, M. Cretenet, S. Turner, and J. McKinion. 1999. Virtural Cotons, the firstborn of the next generation of simulation model. In *1999 Proc. Beltwide Cotton Conferences, Volume I*, 393-395.P. Dugger and D. Richter, eds. Memphis, Tennessee: National Cotton Council.

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

Kepple, D. D. 1988. Unlocking mysteries of cotton yield variation. *Agrichemical Age* 8:24A-24B.

Khakural, B. R., P. C. Robert, and D. R. Huggins. 1999. Variability of corn/soybean yield and soil/landscape properties across a southwestern Minnesota landscape. In *Proc. of the Fourth International Conference on Precision Agriculture*, 573-579. P.C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

King, B. A., I. R. McCann, C. V. Eberlein, and J.C. Stark. 1999. Computer control system for spatially varied water and chemical applications studies with continuous move irrigation systems. *Computers and Electronics in Agriculture* 24: 177-194.

King, B. A., R. E. Reeder, R.W. Wall, and J. C. Stark. 2002. Comparison of site-specific and conventional uniform irrigation management for potatoes. ASAE Paper No. 022175. St. Joseph, Michigan: ASAE.

Kirda, C. 2002. Deficit irrigation scheduling based on plant growth stages showing water stress tolerance. In *Deficit Irrigation Practices*, 3-10. Water Reports No. 22. Rome, Italy: Food and Agriculture Organization of the United Nations

Kirkpatrick, C. D. Gelatt, and M. P. Vecchi. 1983. Optimization by simulated annealing. *Science.* 220:671-680.

Lowenberg-DeBoer, J., and S. M. Swinton. 1997. Economics of site-specific management of agronomic crops. In *The State of Site-Specific Management for Agriculture*. 369-396. F. J. Pierce and E. J. Sadler, eds. Madison, Wisconsin: ASA-CSSA-SSSA

Marani, A. 2004. Cotton2k Model Version 4.0. The Robert H. Smith Institute of Plant Sciences and Genetics in Agriculture, Hebrew University. Available at: http://departments.agri.huji.ac.il/fieldcrops/cotton Accessed on 9 October, 2004.

Marani, A., G. E. Cardon, and C. J. Phene. 1992a. CALGOS, a version of GOSSYM adapted for irrigated cotton. I. Drip irrigation, soil water transport, and root growth. In *1992 Proc. of the Beltwide Cotton Conferences*, 1352-1357. C. P. Dugger and D. A. Richter, eds. Memphis, Tennessee: National Cotton Council of America.

Marani, A., G. E. Cardon, and C. J. Phene. 1992b. CALGOS, a version of GOSSYM adapted for irrigated cotton. III. Leaf and boll growth routines. In *1992 Proc. of the Beltwide Cotton Conferences*, 1361 - 1364. C. P. Dugger and D. A. Richter, eds. Memphis, Tennessee: National Cotton Council of America.

Marani, A., C. J. Phene, and G. E. Cardon. 1992c. CALGOS, a version of GOSSYM adapted for irrigated cotton. II. Leaf water potential and the effect of water stress. In *1992 Proc. of the Beltwide Cotton Conferences*, 1358-1360. C. P. Dugger and D. A. Richter, eds. Memphis, Tennessee: National Cotton Council of America.

Martin, D. L., E. C. Stegman, and E. Fereres. 1990. Irrigation scheduling principles. In *Management of Farm Irrigation Systems*, 155-203. G. J. Hoffman, T. A. Howell, K. H. Solomon, eds. St. Joseph, Michigan: ASAE.

Martin, D. L, J. R. Gilley, and R. W. Skaggs. 1991. Soil water balance and management. In *Managing Nitrogen for Groundwater Quality and Farm Profitability*, 199 – 341. R. F. Follett, D. R. Keeney, and R. M. Cruse, eds. Madison, Wisconsin: SSSA.

Martin, R, V. Lansford, and E. Segarra. 2005. Economic evaluation of integrated cropping systems with cotton. In 2005 *Proc. of the Beltwide Cotton Conferences*, 379 - 382. C. P. Dugger and D. A. Richter, eds. Memphis, Tennessee: National Cotton Council of America

Mayer, D. G., J. A. Belward, and K. Burrage. 1996. Use of advanced techniques to optimize a multi-dimensional dairy model. *Agricultural Systems*. 50:239-253.

McBratney, A. B. and M. J. Pringle. 1997. Spatial variability in soil – implications for precision agriculture. In *Precision Agriculture 1997. Volume I. Spatial variability in soil and crop*. Papers presented at the First European Conference on Precision Agriculture, 3-31. A. B. McBratney and M. J. Pringle, eds. Oxford, United Kingdom: Bios Scientific Publishers Ltd.

McCann, B. L., D. J. Pennock, C. van Kessel, and F. L. Walley. 1996. The development of management units for site-specific farming. In *Proc. of the Third International Conference on Precision Agriculture*, 295-302. P. C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSA.

McClendon, R. W., G. Hoogenboom, and I. Seginer. 1996. Optimal control and neural networks applied to peanut irrigation management. *Transactions of the ASAE* 39(1): 275-279.

McKinion, J. M., J. N. Jenkins, D. Akins, S. B. Turner, J. L. Willers, E. Jallas, and F. D. Whisler. 2001. Analysis of a precision agriculture approach to cotton production. *Computers and Electronics in Agriculture* 32: 213-228.

Merriam, J. L. 1966. A management control concept for determining the economical depth and frequency. *Transactions of the ASAE* 9(4): 492-498.

Miller, R. O., S. Pettygrove, R. F. Denison, L. Jackson, M. Cahn, R. Plant, and T. Kearny. 1999. Site-specific relationships among flag leaf nitrogen, SPAD meter values and grain protein in irrigated wheat. In *Proc. of the Fourth International Conference on Precision Agriculture*, 113-122. P.C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA

Moran, M. S., S. J. Maas, P. J. Pinter, Jr. 1995. Combining remote sensing and modeling for estimating surface evaporation and biomass production. *Remote Sensing Reviews* 12: 335-353.

Moulin, S., A. Dondeau, and R. Delecolle. 1998. Combining agricultural crop models and satellite observations from field to regional scales. *International Journal of Remote Sensing* 19(6): 1021-1036.

Mulla, D. J. and J. S. Scheppers. 1997. Key processes and properties for site-specific soil and crop management. In *The State of Site-Specific Management for Agriculture*, 1-18. F. J. Pierce and E. J. Sadler, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Nielsen, D. R., O. Wendroth, F. J. Pierce. 1999. Emerging concepts for solving the enigma of precision farming research. In *Proc. of the Fourth International Conference on Precision Agriculture*, 303-318. P.C. Robert, R. H. Rust, and W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Nijbroek, R., G. Hoogenboom, and J. W. Jones. 2003. Optimizing irrigation management for a spatially variable soybean field. *Agricultural Systems.* 76:359-377.

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

Paz, J. O., W. D. Batchelor, T. S. Colvin, S. D. Logsdon, T. C. Kaspar, and D. L. Karlen. 1998. Analysis of water stress effects causing spatial yield variability in soybeans. *Transactions of the ASAE* 41(5): 1527-1534.

Perry, C., S. Pocknee, O. Hansen, C. Kvien, G. Vellidis, and E. Hart. 2002. Development and testing of a variable-rate pivot irrigation control system. ASAE Paper No. 022290. St. Joseph, Michigan: ASAE.

Plant, R. E. 2001. Site-specific management: the application of information technology to crop production. *Computers and Electronics in Agriculture* 30: 9-29.

Plant, R. E., A. Mermer, G. S. Pettygrove, M. P. Vayssieries, J. A. Young, R. O. Miller, L. F. Jackson, R. F. Denison, and K. Phelps. 1999. Factors underlying grain yield spatial variability in three irrigated wheat fields. *Transactions of the ASAE* 42(5): 1187-1202.

Rao, N. H., P. B. S. Sarma, and S. Chander. 1988. Irrigation scheduling under a limited water supply. *Agricultural Water Management* 15: 165-175.

Rawls, W. J., D. L. Brakensiek, and K. E. Saxton. 1982. Estimating soil water properties. *Transactions of the ASAE* 25(5): 1316-1320 and 1328.

Reeder, R. 2002. Artificially intelligent site-specific irrigation for potatoes. Master's thesis. Moscow, Idaho: University of Idaho.

Richards, F. J. 1979. A flexible growth function for empirical use. *Journal of Experimental Botany* 10: 290-300.

Ritchie, J. T. 1972. Model for predicting evaporation from a row crop with incomplete cover. *Water Resources Research* 8(5): 1204-1213

Rogers, D. H. and R. L. Elliott. 1989. Irrigation scheduling using crop growth simulation, risk analysis, and weather forecasts. *Transactions of the ASAE.* 32(5):1669-1677.

Royce, F. S., J. W. Jones, and J. W. Hansen. 2001. Model-based optimization of crop management for climate forecast applications. *Transactions of the ASAE* 44(5): 1319-1327.

Sadler, E. J., E. M. Barnes, W. D. Batchelor, J. Paz, and A. Irmak. 2002. Addressing spatial variability in crop model applications. In *Agricultural System Models in Field Research and Technology Transfer* L. R. Ahuja, L. Ma, and T. A. Howell, eds. Boca Raton, Florida: Lewis Publishers.

Sadler, E. J., W. J. Busscher, and D. L. Karlen. 1995. Site-specific yield histories on a SE coastal plain field. In *Site-specific management for agricultural systems*. 153-166. P. C. Robert, R. H. Rust, W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Sadler, E. J., C. R. Camp, D. E. Evans, and J. A. Millen. 2002. Spatial variation of corn response to irrigation. *Transactions of the ASAE* 45(6): 1869-1881.

Saxton, K. E., W. J. Rawls, J. S. Romberger, and R. I. Papendick. 1986. Estimating generalized soil-water characteristics from texture. *Soil Science of America Journal.* 50(4):1031-1036.

Shen, J., W. D. Batchelor, J. W. Jones, J. T. Ritchie, R. S. Kanwar, and C. W. Mize. 1998. Incorporation of a subsurface tile drainage component into a soybean growth model. *Transactions of the ASAE* 41(5): 1305-1313.

Snyder, R. L. and W. O. Pruitt. 1985. Estimating reference evapotranspiration with hourly data. In *Land Air and Water Resource Papers* 10013-A, 10013-B, 10013-C. Davis, California: University of California.

South Plains Evapotranspiration Network. n.d. South Plains Evapotranspiration Network climate data. Available at: http://lubbock.tamu.edu/irrigate/et/archive.html. Accessed December, 2004.

Staggenborg, S. A., R. J. Lascano and D. R. Krieg. 1996. Determining cotton water use in a semiarid climate with the GOSSYM cotton simulation model. *Agronomy Journal*. 88:740-745.

Swaney, D. P., J. W. Jones, W. G. Boggess, G. G. Wilkerson, and J. W. Mishoe. 1983. Real-time irrigation decision analysis using simulation. *Transactions of the ASAE*. 26(2): 562-568.

Sudduth, K. A., N. R. Kitchen, D. F. Hughes, and S. T Drummond. 1995. Electromagnetic induction sensing as an indicator of productivity on clay pan soils. In *Proc. of Site-Specific Management for Agricultural Systems*. 671-681. P. C. Robert, R. H. Rust, W. E. Larson, eds. Madison, Wisconsin: ASA-CSSA-SSSA.

Texas Cooperative Extension. 2000. Cotton, sprinkler irrigated (heavy textured soils), Texas High Plains, 2000 projected costs and return per acre. Texas crop and livestock budgets. College Station, Texas.: Texas Cooperative Extension. Available at: agecoext.tamu.edu. Accessed 12, August 2005.

TWDB. 2002. Water for Texas – 2002. Volumes I-III. Document No. GP-7-1. Austin, Texas: Texas Water Development Board.

USDA-NRCS. 1995. Soil survey geographic (SSURGO) Database: Data Use information. Natural Resources Conservation Service Miscellaneous Publication 1527.

USDA-SCS. 1974. Soil survey of Hale County, Texas. Washington, D.C.:USDA-SCS and Texas Agricultural Experiment Station.

Van Bavel, C. H. M. 1966. Potential evaporation: the combination concept and its experimental verification. *Water Resources Research* 2(3): 455-467.

Van Genuchten, M.Th. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Science Society of America Journal* 44:892–898.

Van Genuchten, M.Th., F.J. Leij and S.R. Yates. 1991. The RETC code for quantifying the hydraulic functions of unsaturated soils. EPA 600/2-91/065. Washington, D.C.: United States Environmental Protection Agency.

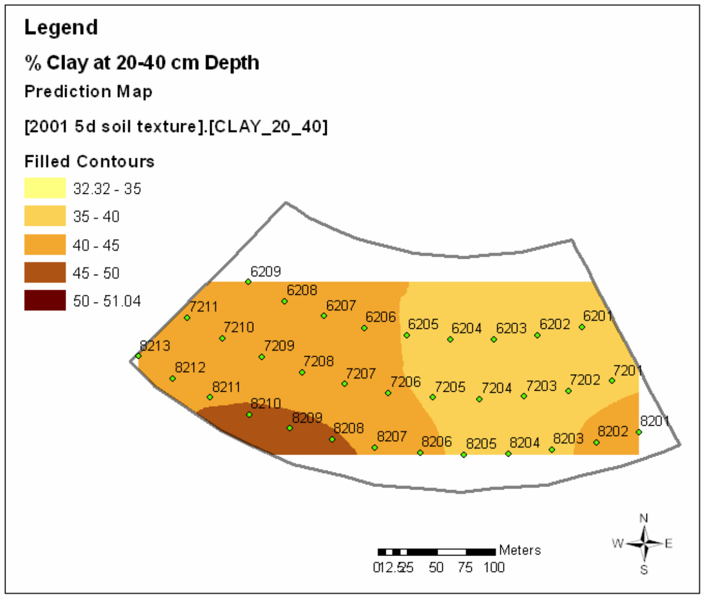
Wanjura, D. F. and B. L. McMichael. 1989. Simulation analysis of nitrogen application strategies for cotton. *Transactions of the ASAE* 32(2): 627-632.

Wanjura, D. F., D. R. Upchurch, J. R. Mahan, and J. J. Burke. 2002. Cotton yield and applied water relationships under drip irrigation. *Agricultural Water Management* 55: 217-237.

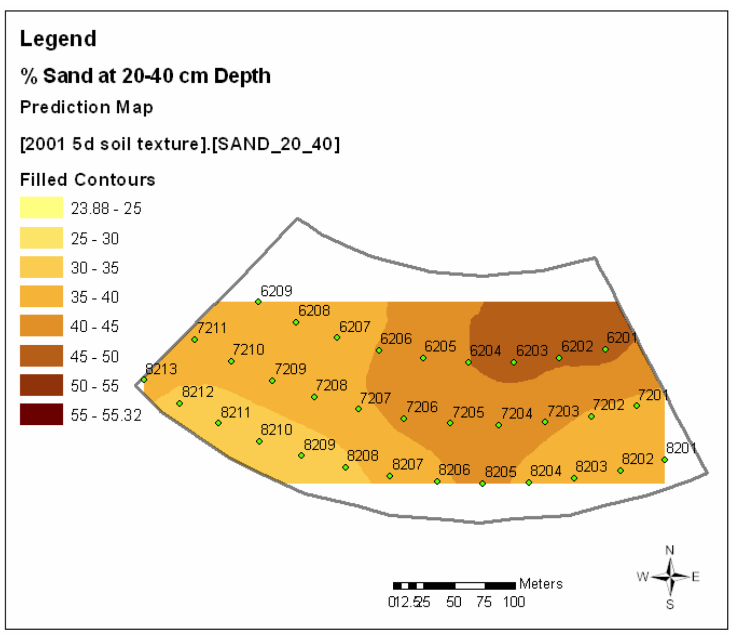
Wassenaar, T., P. Lagacherie, J. P. Legros, M. D. A. Rounsevell. 1999. Modelling wheat yield responses to soil and climate variability at the regional scale. *Climate Research*. 11: 209-220.

Yang, C., J.H. Everitt, and J.M. Bradford. 2001. Uniform and variable rate applications of nitrogen and fertilizer for grain sorghum. *Transactions of the ASAE* 44(2): 201-209.

APPENDIX A

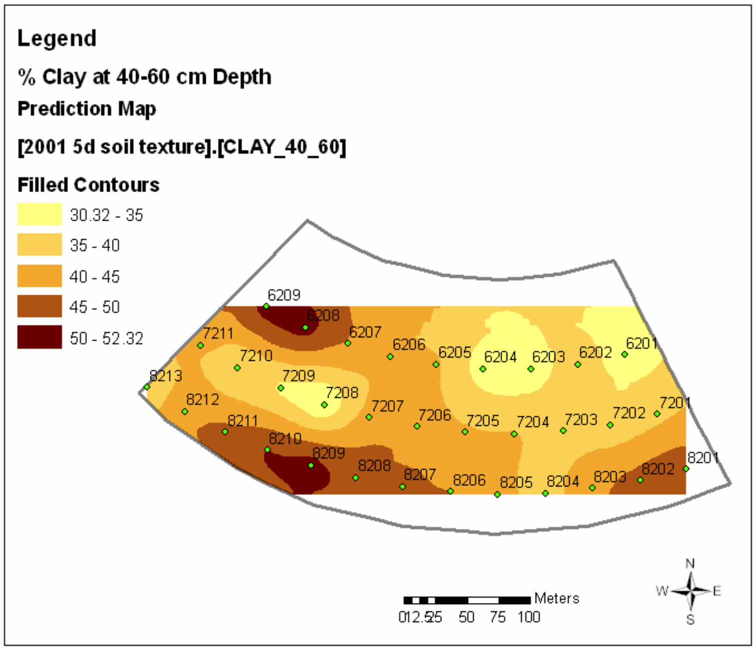


(a) percent clay

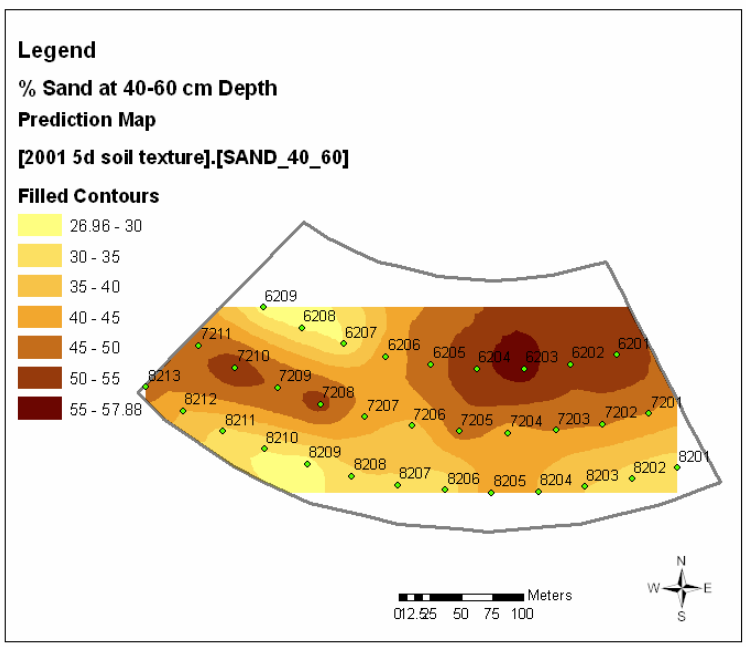


(b) percent sand

Figure A-1. Soil composition at 20-40 cm depth: a) percent clay and b) percent sand in Helms Farm field 5D. Numbers from 6201 through 8213 indicate sampling locations.

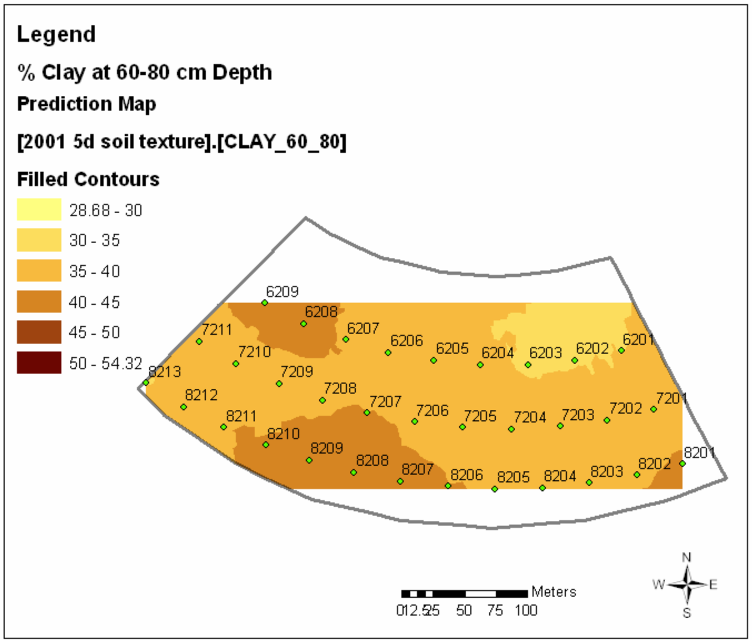


(a) percent clay

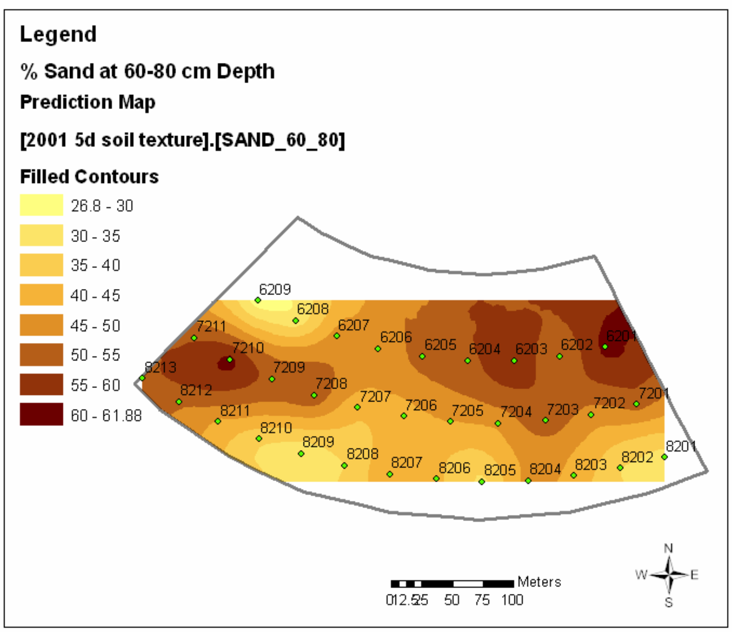


(b) percent sand

Figure A-2. Soil composition at 40-60 cm depth: a) percent clay and b) percent sand in Helms Farm field 5D. Numbers from 6201 through 8213 indicate sampling locations.



(a) percent clay



(b) percent sand

Figure A-3. Soil composition at 60-80 cm depth: a) percent clay and b) percent sand in Helms Farm field 5D. Numbers from 6201 through 8213 indicate sampling locations.

APPENDIX B

SIMULATED ANNEALING VARIABLE DEFINITIONS

Variable definitions in Simulated Annealing algorithm as taken from http://temper.stat.cmu.edu/general/simann (Goffe et al., 1994))

Input Parameters:

Note: The suggested values generally come from Corana et al. (1987) to drastically reduce runtime, see Goffe et al. (1994), pp. 90-1 for suggestions on choosing the appropriate RT and NT.

N - Number of variables in the function to be optimized.
X - The starting values for the variables of the function to be optimized.
MAX - Denotes whether the function should be maximized or minimized. A true value denotes maximization while a false value denotes minimization. Intermediate output (see IPRINT) takes this into account.
RT - The temperature reduction factor. The value suggested by Corana et al.(1987) is .85. See Goffe et al. for more advice.
EPS - Error tolerance for termination. If the final function values from the last neps temperatures differ from thecorresponding value at the current temperature by less than EPS and the final function value at the current temperature differs from the current optimal function value by less than EPS, execution terminates and IER = 0 is returned.
NS - Number of cycles. After NS*N function evaluations, each element of VM is adjusted so that approximately half of all function evaluations are accepted. The suggested value is 20.
NT - Number of iterations before temperature reduction. After NT*NS*N function evaluations, temperature (T) is changed by the factor RT. Value suggested by Corana et al. is MAX(100, 5*N). See Goffe et al. (1994) for further advice.
NEPS - Number of final function values used to decide upon termination. See EPS. Suggested value is 4.
MAXEVL - The maximum number of function evaluations. If it is exceeded, IER = 1.
LB - The lower bound for the allowable solution variables.
UB - The upper bound for the allowable solution variables. If the algorithm chooses X(I) .LT. LB(I) or X(I) .GT. UB(I), I = 1, N, a point is from inside is randomly selected. This focuses the algorithm on the region inside UB and LB.Unless the user wishes to concentrate the search to a particular region, UB and LB should be set to very large positive and negative values, respectively. Note that the starting vector X should be inside this region. Also note that LB and UB are fixed in position, while VM is centered on the last accepted trial set of variables that optimizes the function.

C - Vector that controls the step length adjustment. The suggested value for all elements is 2.0.

IPRINT - controls printing inside SA.
Values: 0 - Nothing printed.
1 - Function value for the starting value and summary results before each temperature reduction. This includes the optimal function value found so far, the total number of moves (broken up into uphill, downhill, accepted and rejected), the number of out of bounds trials, the number of new optima found at this temperature, the current optimal X and the step length VM. Note that there are N*NS*NT function evaluations before each temperature reduction. Finally, notice is also given upon achieving the termination criteria.
2 - Each new step length (VM), the current optimal X (XOPT) and the current trial X (X). This gives the user some idea about how far X strays from XOPT as well as how VM is adapting to the function.
3 - Each function evaluation, its acceptance or rejection and new optima. For many problems, this option will likely require a small tree if hard copy is used. This option is best used to learn about the algorithm. A small value for MAXEVL is thus recommended when using IPRINT = 3.
Suggested value: 1
Note: For a given value of IPRINT, the lower valued options (other than 0) are utilized.

ISEED1 - The first seed for the random number generator RANMAR.0 .LE. ISEED1 .LE. 31328.

ISEED2 - The second seed for the random number generator RANMAR.0 .LE. ISEED2 .LE. 30081. Different values for ISEED1 and ISEED2 will lead to an entirely different sequence of trial points and decisions on downhill moves (when maximizing). See Goffe et al. (1994)on how this can be used to test the results of SA.

Input/Output Parameters:

T - On input, the initial temperature. See Goffe et al. (1994) for advice. On output, the final temperature.

VM - The step length vector. On input it should encompass the region of interest given the starting value X. For point X(I), the next trial point is selected is from X(I) - VM(I) to X(I) + VM(I). Since VM is adjusted so that about half of all points are accepted, the input value is not very important (i.e. is the value is off, SA adjusts VM to the correct value).

Output Parameters:

XOPT - The variables that optimize the function.

FOPT - The optimal value of the function.

NACC - The number of accepted function evaluations.

NFCNEV - The total number of function evaluations. In a minor point, note that the first evaluation is not used in the core of the algorithm; it simply initializes the algorithm.

NOBDS - The total number of trial function evaluations that would have been out of bounds of LB and UB. Note that a trial point is randomly selected between LB and UB.

IER - The error return number.
Values:
- 0 - Normal return; termination criteria achieved.
- 1 - Number of function evaluations (NFCNEV) is greater than the maximum number (MAXEVL).
- 2 - The starting value (X) is not inside the bounds (LB and UB).
- 3 - The initial temperature is not positive.
- 99 - Should not be seen; only used internally.

VITA

Randy Wayne Clouse

<u>Education:</u>

Texas A&M University, College Station, TX 77843
Ph.D. in Biological and Agricultural Engineering, May 2006.

Virginia Polytechnic Institute and State University, Blacksburg, VA 24060
M.S. in Biological Systems Engineering, May 1996.

The Pennsylvania State University, University Park, PA 16802
B.S. in Agricultural Engineering, May 1993.

<u>Professional Experience:</u>

Texas A&M University
Graduate Teaching/ Research Assistant (September 2001 – present)

Patton, Harris, Rust, and Associates
Design Engineer (September 1998 – August 2001)

Commonwealth of Virginia, Dept. of Mines, Minerals, and Energy
Orphaned Land Nonpoint Source Pollution Coordinator (May 1996 – September 1998)

Virginia Polytechnic Institute and State University
Graduate Research Assistant (January 1994-April 1996)

Walt Disney World – The Land pavilion at EPCOT Center
Biological Engineering Intern (June 1993 – December 1993)

<u>Permanent Address:</u>

Biological and Agricultural Engineering Department
MS 2117
Texas A&M University
College Station Texas, 77843