2000

Analysis of spatial yield variability and economics of prescriptions for precision agriculture: a crop modeling approach

Joel Obien Paz

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Analysis of spatial yield variability and economics of prescriptions for precision agriculture: a crop modeling approach

by

Joel Obien Paz

A dissertation submitted to the graduate faculty in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY

Co-majors: Agricultural Engineering; Water Resources

Major Professors: William D. Batchelor and Carl E. Anderson

Iowa State University

Ames, Iowa

2000

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This is to certify that the Doctoral dissertation of

Joel Obien Paz

has met the dissertation requirements of Iowa State University

Signature was redacted for privacy.

Co-major Professor

Signature was redacted for privacy.

Co-major Professor

Signature was redacted for privacy.

For the Co-major Program

Signature was redacted for privacy.

For the Co-major Program

Signature was redacted for privacy.

For the Graduate College
DEDICATION

I dedicate this work to my wife Margie and our children Jed, Jenna, and Jeramie.
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Non-uniformity of soil properties, soil moisture and rooting depth, and other factors such as pest and disease pressures can cause significant soybean and corn yield variability within a field. In this study, two crop growth models were used to characterize factors that cause spatial yield variability in soybeans and corn, and to evaluate economic consequences of variable rate management prescriptions. Analysis of yield data from 224 grids within a 16-hectare field in Boone, Iowa focused on water stress effects using CROPGRO-Soybean and CERES-Maize models for soybean and corn, respectively. Water stress explained 69% of the variability in soybean, and population and water stress explained 57% of corn yield variability. Grid-level optimum nitrogen fertilizer rate prescriptions for corn were also developed. Distribution of optimum nitrogen fertilizer prescription was highly spatially varied. Optimum nitrogen rates were found to range from 141 to 160 kg ha\(^{-1}\) in 64 of 224 grids (28.6%) which are typical fertilizer rates farmers apply for corn in Iowa. Based on model predictions, grid-level nitrogen fertilizer management used lower amounts of nitrate, produced higher yields and was more profitable than either transect- or field-level (single rate) fertilizer application. In another study, four factors affecting soybean yield variability namely, water stress, soybean cyst nematode (SCN), soil pH, and weeds, were examined in each of 100 grids within a 20-hectare field in Perry, Iowa using the CROPGRO-Soybean model. Average estimated yield loss due to the combined effects of water stress, SCN, pH, and weeds in each 0.2-hectare grid was 842 kg ha\(^{-1}\). Water stress had the biggest impact on soybean yield with an average yield reduction of 626 kg ha\(^{-1}\). Yield impact and economic consequences of three strategies namely, variable plant population density (PPD), soybean cyst nematode (SCN) resistant and susceptible varieties, and irrigation management schemes,
were evaluated using 34 years of weather data. Implementing the best PPD for each year produced higher grid-level soybean yield and net return compared to using the 34-year average optimum rate. Achieving maximum net return may not be possible on a yearly basis due to uncertainties in weather condition. Using a SCN-resistant variety resulted in significant yield increase over that of a susceptible variety. Several grids had a significant increase (>350 kg ha\(^{-1}\)) in average yield with some grids having as much as 995 kg ha\(^{-1}\) (17 bu ac\(^{-1}\)) yield increase when a SCN-resistant variety was used. Irrigating when available soil moisture reached a value of 40% and 50% significantly increased average field-level soybean yields by 1585 and 1619 kg ha\(^{-1}\), respectively. Excluding the cost of equipment, irrigation would significantly increase net return.
CHAPTER 1. GENERAL INTRODUCTION

Variability denotes differences or non-uniformity of a particular form or feature with respect to a specific scale of spatial reference. An intriguing question that farmers and researchers have faced for many years is why yields vary within a field. Yield variability can be caused by a non-uniform distribution of soil properties, soil moisture, pest pressure, rooting depth, and other factors (Sawyer, 1994). Variations in landscape features, soil properties, and soil moisture within a specific land area contribute to unevenness in plant growth and stand. The challenge for farmers is to identify factors that they can control and manage, and make appropriate management decisions to increase profits. The goal of precision (site-specific) farming is to optimize returns using spatially variable inputs. Recent advancements in the field of precision agriculture have opened the doors for farmers to further increase the productivity of their agricultural lands. Still, both farmers and researchers must wrestle with the problem of significant yield variability within a field.

Spatial yield variability is a complex interaction of many factors, including soil properties, weather, pests, fertility, and management. There is an abundance of studies pertaining to relationships between yield and soil characteristics, landscape features and other parameters in efforts to characterize spatial variability and provide solutions to the problem of yield variability. There is, however, an apparent lack of methods that can incorporate varying levels of stresses over the season to evaluate the effects of interactive stress on growth, development, and yield. Furthermore, it is difficult to account for temporal interactions of stress on growth using traditional statistical analysis.

Process-oriented crop growth models are a promising tool to help identify relationships between environment, management, and yield variability. Crop models can be
used to synthesize research knowledge, or as tool for crop system decision management (Whisler et al., 1986; Boote et al., 1996). The CROPGRO-Soybean (Hoogenboom et al., 1994) and CERES-Maize (Jones and Kiniry, 1986) models were developed to compute growth, development, and yield on homogeneous units (either plot, field, or regional scale), and have been demonstrated to adequately simulate crop growth at a field or research plot scale. These models require inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall and solar radiation). From this information, daily growth of vegetative, reproductive, and root components are computed as a function of daily photosynthesis, growth stage, and water and nitrogen stress.

Characterization of yield variability requires analysis of both spatial and temporal behavior of soil, weather, management, and environmental factors. Crop models are excellent tools to evaluate individual factors and the complex interactions of several factors, and provide insight into causes of spatial yield variability. Extending the use of crop models to examine within-field spatial yield variability is an intriguing challenge. The general objectives of this research were to use crop growth models to analyze factors affecting corn and soybean yield variability, and to evaluate management prescriptions in the context of precision agriculture.

**Dissertation Organization**

This dissertation is a compilation of journal manuscripts submitted or intended for submission to refereed scientific journals. Each manuscript addresses a specific objective. Chapter 2 focuses on the analysis of field-level yield variability in soybeans due to water
stress using the CROPGRO-Soybean model. Chapter 3 presents a new concept of using a calibrated corn crop growth model, CERES-Maize model, to evaluate variable rate nitrogen for corn. Chapter 4 presents a modeling approach to quantify the effects of several spatial yield variability factors namely, water stress, SCN, soil pH, and weeds. Chapter 4 also examines several calibration and validation strategies for yield prediction using the soybean crop growth model. Development and evaluation of different management prescriptions for soybean is presented in Chapter 5. Chapter 6 summarizes all the major conclusions obtained from the four journal manuscripts. A discussion of recommended future work is also included in the final chapter of the text.

References


CHAPTER 2. ANALYSIS OF WATER STRESS EFFECTS CAUSING SPATIAL
YIELD VARIABILITY IN SOYBEANS

A paper published in the Transactions of the ASAE\textsuperscript{1}

J.O. Paz, W.D. Batchelor, T.S. Colvin, S.D. Logsdon,
T.C. Kaspar, and D.L. Karlen

Abstract

Soybean yields have been shown to be highly variable across fields. Past efforts to correlate yield in small sections of fields to soil type, elevation, fertility, and other factors in an attempt to characterize yield variability have had limited success. In this paper, we demonstrate how a process oriented crop growth model (CROPGRO-Soybean) can be used to characterize spatial yield variability of soybeans, and to test hypotheses related to causes of yield variability. In this case, the model was used to test the hypothesis that variability in water stress corresponds well with final soybean yield variability within a field. Soil parameters in the model related to rooting depth and hydraulic conductivity were calibrated in each of 224 grids in a 16 ha field in Iowa using 3 years of yield data. In the best case, water stress explained 69\% of the variability in yield for all grids over 3 years. The root mean square error was 286 kg ha\textsuperscript{-1} representing approximately 12\% of the 3-year mean measured yield. Results could further be improved by including factors that were not measured, such as plant population, disease, and accurate computation of surface water runon into grids. Results of this research show that it is important to include measurements of soil moisture holding capacity, and drainage characteristics, as well as root depth as data layers that should be considered in any data collection effort.

\textsuperscript{1}Transactions of the ASAE 41(5):1527-1534 (1998)
Introduction

The advent of yield monitors and global positioning systems that can create spatial yield maps has generated much excitement and controversy among farmers and researchers. Site-specific field management promises to maximize field level net return and minimize environmental impact by managing fields using spatially variable management practices. The success of site-specific field management depends upon discovery of relationships between environment, management, and resulting yield variability, and ultimately, how these relationships can be exploited to compute optimum prescriptions. Farmers are faced with trying to determine how to manage variability to improve profits. Researchers are trying to develop methods to analyze causes of yield variability, and determine how to develop prescriptions for fertility, and cultural practices to capitalize on variability across field. While environmental, management, soil, and pest factors have been studied for many years, researchers are just beginning to determine how these factors vary across fields, contributing to spatial yield variability.

Several studies have focused on establishing spatial relationships between crop yields and soil and site characteristics. Cambardella et al. (1996) used two multiple linear regression procedures to analyze the effect of soil properties on crop yield variability within a 16 ha field. They found that aggregate size distribution contributed significantly to yield variability in seven out of seven years. Bulk density, soil moisture, and soil texture contributed significantly to yield variability in four out of seven years. Sudduth et al. (1996) found that soybean yield response curves generated by two methods, pursuit projection
regression and neural network analysis, agreed well with measured yields. Ambuel et al. (1994) developed a fuzzy logic model to relate soil characteristics to describe yield variability within two 16-ha fields in Central Iowa.

Soil moisture related stress (drought or excess water) can cause significant variability due to variations in soil moisture holding characteristics, rooting depth and distribution, and drainage patterns across a field. This can be deduced through several studies which have shown good correlation between yield and elevation, yield and soil type, and yield and position on the landscape (Khakural et al., 1996; Jones et al., 1989).

Interactions between soil moisture content, water table depth, and root depth and distribution play a role in determining the extent of water stress, especially late in the season when seed filling dominates root growth in terms of sink demand. In Iowa, many fields in the Clarion-Nicollette-Webster soil group are tile drained. This creates spatially variable water table depths (James and Fenton, 1993), which can limit rooting depth, across fields. This scenario leads to the following hypothesis for these tile drained fields: high soil moisture content limits rooting depth, which leads to spatially variable water stress late in the season as soil moisture contents are reduced due to drainage, root water uptake, and limited rainfall.

One complexity in analyzing yield variability is the lack of methods that can incorporate varying levels of stresses over the season to evaluate the effects of interactive stress on growth, development, and yield. It is difficult to account for temporal interactions of stress on growth using traditional statistical analysis. For instance, while some success has been achieved to show relationships between soil type or elevation with yield variability
by regression approaches, these approaches do not directly account for the dynamic interaction of soil moisture availability, root water uptake, and water related stresses that can occur and affect plant growth each day during the season. Understanding the temporal interaction between stresses and plant growth processes is imperative to understanding and quantifying yield variability. Methods to accurately compute interactions of stress on growth will ultimately lead to the ability to determine optimum prescriptions.

Process oriented crop growth models can be used to study temporal and spatial crop response to stress (Batchelor, 1996; Allen et al., 1996). Crop models offer several advantages over traditional statistical methods to evaluate growth and yield response to environment and management:

1. They can be used as a tool to explore hypotheses related to yield variability.
2. When inputs are properly characterized, they can integrate the effects of dynamic and multiple stress interactions with crop growth processes, and subsequently, yield.
3. After being validated for a field, these models can be used to develop and evaluate prescriptions including factors such as optimum variety selection, fertilizer and irrigation application rates, plant populations, planting date, and row spacing.
4. They allow analysis of what-if scenarios and assist in the identification of appropriate prescriptions.
5. They can be used to assess economic and environmental impact of prescriptions.

The CROPGRO-Soybean (Hoogenboom et al., 1994) and CERES-Maize (Jones and Kiniry, 1986) crop models were developed to compute growth, development, and yield on homogeneous units (either plot, field, or regional scale), and have been demonstrated to
adequately simulate crop growth at a field or research plot scale. These models require inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall and solar radiation). From this information, daily growth of vegetative, reproductive, and root components are computed as a function of daily photosynthesis, growth stage, and water and nitrogen stress. Soil moisture and nitrogen balance models are used to compute water and nitrate levels in the soil as a function of rainfall and soil moisture holding properties.

Process-oriented crop growth models are a promising tool to help researchers search for relationships between environment, management, and yield variability. The objective of this study was to demonstrate the use of a soybean crop growth model to test the hypothesis that water stress creates significant yield variability in a soybean field in Iowa.

**Procedures**

**Hypothesis**

We hypothesize that wet spring weather leads to high soil moisture content in Clarion-Nicollette-Webster tile drained fields in Iowa. High soil moisture leads to higher water tables, which are typically observed under these conditions. High water tables restrict maximum rooting depth. In addition to this, upward water redistribution due to perching of the water table may cause oxygen depletion in saturated layers with existing roots, which may impede root growth and cause root senescence. This leads to spatial variability in maximum rooting depth. During grain fill, rainfall usually diminishes, and shallow roots lead to water stress during the critical grain filling period. Variability in rooting depth and
soil moisture availability in the root zone leads to variable water stress, which results in yield
variability.

We used the CROPGRO-Soybean (Hoogenboom et al., 1994) model to test this
hypothesis. The model computes a complete water balance based on daily rainfall (Figure
1a). Water is redistributed through the soil based on principles outlined in Kiniry and Jones
(1986) for the CERES-Maize model. The soil is divided into approximately 10 layers, and
the user specifies the lower limit, drained upper limit, saturated moisture holding capacity,
saturated hydraulic conductivity, and proportion of layer that is mined by roots (root
weighting factor) for each layer. Downward flow of water is computed based on the amount
the water content in a layer exceeds the drained upper limit, and how much water the next
layer can hold. Maximum water movement from a layer is limited by either a drainage
coefficient (fraction of water than can be drained from a layer in a day under free drainage
conditions) or saturated hydraulic conductivity. Perched water tables can be created by
setting the saturated hydraulic conductivity ($K_{sat}$) in a deep soil layer in the profile (usually
150-180 cm depth) to a small value. This reduces water outflow from the bottom of the
profile, and causes water to perch upward in the profile during rainfall events. Using this
technique, wet spring conditions can fill up the profile, creating shallow water tables of 50-
100 cm depths.

In the model, daily increase in root depth is a function of soil temperature and soil
moisture. A maximum increase in rooting depth per day is computed, and reduced under
cool temperatures. In addition to this, when the soil water content approaches the saturated
moisture holding capacity, oxygen depletion reduces root growth into a layer. This approach
allows a water table (defined by a saturated layer) to limit rooting depth. A maximum root depth can be specified for a soil, which limits rooting depth due to physical constraints in the soil or physiological constraints of the plant. Currently, the model does not reduce leaf expansion, photosynthetic rate, or senescence of roots under oxygen depleted conditions.

One unknown factor is the distribution of roots in the soil profile. A root distribution factor is used in the model to define the fraction of water and nutrients in a soil layer that can be mined by roots in each soil layer. Thus, a factor of 1.0 in a layer indicates that roots in that layer can mine 100% of available water and nutrients, while a factor of 0.1 indicates only 10% can be mined. Root water uptake in a soil layer is a function of available water, root length volume, and root distribution factor in the soil layer. In this research, we assume a triangular root distribution shown in Figure 1b. Roots are distributed evenly in the top 30-cm, and propagation of roots decreased linearly with respect to depth from 30 cm to the bottom of the root zone. The bottom of the root zone is limited by either a user selected depth, water table depth, or carbon limitations.

Water stress is computed each day in the model by dividing potential water uptake by evapotranspiration demand. This results in a factor ranging from 0 under total water stress, to 1.0 under no water stress conditions. This factor is then used to directly reduce daily photosynthesis, and to modify certain water stress sensitive developmental stages. In the model, water stress can also increase carbon partitioning to roots, thereby increasing rooting depth and allowing plant roots to search for more water. The implementation of water stress effects on photosynthesis is the key to implementation of the above outlined hypothesis in the model.
Site Description

Spatial yield distribution of soybean (*Glycine max.* [L.] Merr) was investigated in a 16 ha field in Boone County, IA. The field used a conventional farming method consisting of a corn (*Zea mays* L.) - soybean rotation, conventional tillage, and application of commercial fertilizer and pesticides. The field, which is the southwest (SW) quadrant of the Baker farm, was discussed in Colvin et al. (1995). Figure 2 shows the arrangement of the eight transects and the location of depressions and hilltops within the field. Each transect consists of 28 soybean yield plots or grids. This gave a total of 224 grids with measured yields. Each grid was 12 m wide and 46 m long. Final soybean yield was measured from the 5 center rows in each grid using a plot combine and weigh wagon for 1992, 1994, and 1996. Yield from each strip was used to represent yield in the larger grid. Data from grids with missing yield, or measured yield of 0 kg ha⁻¹ were eliminated. Thus, 213 of the 224 available grids were included in the analysis.

Data on measured daily solar radiation, maximum and minimum air temperatures, and rainfall were collected from the Ames, Iowa weather station. Cumulative growing degree days and rainfall amounts were determined for each soybean production year (Figure 3).

Soil Properties

The site is typical of low-relief swell and swale topography characteristic of broad areas of the Des Moines lobe surface (Steinwand and Fenton, 1995). The field contains nine soil classes which are predominantly from the Clarion-Nicollet-Webster soil association (Table 1). A detailed soil map of the field (Steinwand, 1992) was obtained from the National Soil Tilth Laboratory (NSTL) in Ames, IA. Estimates of soil physical properties were
provided by Logsdon (1995 unpublished) of the NSTL. Thus, estimates were available for lower limit, drained upper limit, saturated moisture content, saturated hydraulic conductivity, bulk density, and organic carbon at several depths for each soil type. Properties for the predominant soil type in each grid was used to represent soil properties in each grid.

**Crop Growth Model**

Three soil parameters can be adjusted in the model to test our hypothesis. These parameters primarily affect water table depth and rooting depth progress. In this study, we used the saturated hydraulic conductivity ($K_{sat}$) of the bottom layer of the soil profile (180-200 cm) to create perched water tables. High values of $K_{sat}$ in a grid create better drainage conditions resulting in lower water tables. Low values reduce drainage out the bottom of the profile and create higher water tables, which can restrict rooting depth. The second parameter is the soil drainage rate coefficient (SLDR), which represents the number of days required for a soil layer to fully drain down to the drained upper limit. Drainage through a soil layer is limited by either $K_{sat}$ or SLDR, whichever gives the slowest rate. SLDR can be used to create a slow draining soil, which mimics the effects of tile drainage in a grid. High values represent more freely drained soils. Low values can reduce rate of rooting depth increases by creating soil layers that remain above the drained upper limit for longer periods of time. The third soil parameter is the maximum rooting depth, which limits the depth of soil, and subsequently, total water available for uptake. In all grids, we assume a triangular function to estimate the root growth factor (fraction of water that can be mined by roots in a layer) for each grid as a function of maximum rooting depth. In the top 30 cm, it is assumed that roots can mine 100% of the water and nutrients available. From 30 cm down to the
maximum rooting depth, this fraction is computed assuming a linear decreasing fraction (Figure 1b).

The crop model was linked to a multi-dimensional minimization program to solve for the optimum set of combinations of these three soil parameters for each of the 224 grids in the 16 ha Baker field required to set up and test this hypothesis. The downhill simplex method (Nelder and Mead, 1965), an algorithm that determines the minimum of a function of more than one independent variable, was used in this study. The generic source code (AMOEBA) of the optimization algorithm was taken from the Numerical Recipes handbook (Press et al., 1992).

Three combinations of changes to these three soil parameters were used to test the hypothesis. These scenarios (Table 2) represented changing three different combinations of model inputs to create the conditions required to test the hypothesis. Parameters were optimized in each of the 224 grids to minimize the sum of square error between predicted and measured yield for 1992, 1994, and 1996. The objective function established for the model simulations is written as:

\[
\text{Min: } SSE = \sum_{i=1}^{3} (Y_{mi} - Y_{pi})^2
\]

where \( SSE \) is the sum of square error between \( Y_m \) (measured yield) and \( Y_p \) (predicted yield), and \( i \) is the \( i \)th year.

In Case 1 (Table 2), water tables were established using low values of SLDR, which reduced drainage. Rooting depth was used to create limitations in total soil volume and soil moisture that can be mined by roots. In Case 2, only rooting depth was adjusted in each grid.
The SLDR was set to 0.2 d⁻¹ or 20% of the excess volume is drained per day in each layer. In Case 3, both $K_{sat}$ of the bottom layer and rooting depth were adjusted. Spatial variability in drainage and water table depths were created by adjusting $K_{sat}$ of the bottom layer. In combination with setting the maximum rooting depth (which can be modified by water table depth), this created a condition that limited rooting depth and imposed water stress during seed filling.

**Results and Discussion**

**Whole Field Soybean Yield**

Following the procedures outlined above, soil and root parameters were optimized for each case and for each grid over 3 years to minimize the RMSE between predicted and measured yields in each grid. The first test of the hypothesis was to compare field level predicted and measured yields. The sum of the predicted grid level yields in each grid was close to the measured field level yields for each year. The average field level predicted yield over all 3 years was close to the average 3 year measured field yield of 3098 kg ha⁻¹ (Table 3). The predicted soybean yield for each of the three cases (3042, 2978 and 2959 kg ha⁻¹) compared favorably with the three-year average measured soybean yield for the Baker farm (3098 kg ha⁻¹). This indicates that the model, in all cases, performed well in predicting field level yields based on summing predicted yields for each grid. Predicted and measured whole field yields showed that the model slightly underpredicted whole field yields in 1992 by approximately 10%, while giving good estimates of whole fields in 1994 and 1996 (within 3% of measured yield) (Table 4). In other studies, we have noticed a tendency for the model
to underpredict yields in 1992. This is likely due to the model not responding properly to the very cool temperatures which occurred during 1992 (Sexton et al., 1997).

Grid Level Soybean Yields

The RMSE between predicted and measured yields in each grid over 3 years (Table 3) for Case 1 (392 kg ha⁻¹) was lower than Cases 2 (464 kg ha⁻¹) and 3 (487 kg ha⁻¹). This indicates that Case 1 gave better predictions of grid level yield in the 213 individual grids than Case 2 and Case 3. In fact, the RMSE of Case 1 represents approximately 12% of the field level measured yield for each year. This further indicates that changing SLDR and rooting depth better mimicked soil-water-plant relationships compared to Case 2 and Case 3 for this version of the model. Figure 4 shows predicted versus measured yields for each grid over 3 years for Case 1. Overall, the model gave good results with respect to describing yield variability as a function of spatially variable water stress. Variable levels of water stress were computed by the model across the field, which created spatially variable yields across the field. It is interesting to note that there were several data points with high predicted yields, but low measured yields. In testing this hypothesis, we had no information other than estimates of soil properties and measured yield. Low measured yields could have resulted from other factors such as low plant population, and effects of pest and diseases that were not measured nor considered in the analysis.
Error Distribution

In the next analysis, grids with low measured yields were eliminated because low yields were likely caused from factors not related to water stress (i.e. low populations, disease, or weed pressure). This resulted in 207 grids with yields greater than 1000 kg ha\(^{-1}\). Overall, the error in predicted yields in these 207 grids were better for case 1, than for case 2 or 3 (Table 5). Case 1 has lower RMSE and higher \(R^2\) (0.69) values than cases 2 and 3. These results indicate that characterizing drainage rate and rooting depth (and consequently, root growth factors) across the 16 ha field likely mimics soil moisture dynamics, and accounts for much of the variability in soybean yield for the three production years analyzed in this study. Approximately 69% of the variability in yield could be accounted for by the water stress hypothesis tested with the crop model (Figure 5).

Using the optimized set of drainage rate and rooting depth values for case 1, the model predicted soybean yield within ±10% of the measured yield for 84% of the grids and within ±20% of the measured yield for 92% of the grids (Table 6). The large number of grids with highly variable yields falling within ±10% or ±20% of measured yield indicates the ability of the model to describe spatial and temporal stresses and reinforces our approach of using the crop model in predicting yield variability on a sub-field level.

Yield Trend Along Transects

Measured yield, rooting depth, and elevation of each grids along selected transects (1 and 7) are shown in Figure 6. Yields along transect 7 appears to follow the same pattern as rooting depth. A high positive correlation between predicted rooting depth and soybean yield
(Table 7) strongly supports our observation. In general, there was good agreement in the trend of predicted and measured yields along different transects in the field. Figures 7a and 7b show an example of the predicted and measured yield trends along two of the transects which had the largest difference between the lowest and highest measured yields. Generally, the model followed the measured yield trend very well in all transects over all years. There are areas along some transects, especially transect 7 (Figure 7b), where there were larger differences between measured and predicted yield. However, the model captured the trend of high and low yields along the transect, which is reflected in the low RMSE values presented in Table 5.

Predicting the correct yield trend is likely more important than predicting the absolute yields along a transect if the model is to be used to develop and evaluate prescriptions. In determining the economic consequences of prescriptions, such as optimal plant population or variety for each grid, the analysis should focus on determining the yield response in a grid resulting from different prescriptions. The difference in net return for two prescriptions should be determined by evaluating the cost of each prescription and the value resulting from the yield response between the prescriptions. Thus, as long as the model responds in a realistic way to changes in prescriptions, the resulting net return between two prescriptions should be realistic.
Summary and Conclusions

This work demonstrates the value of using a process oriented crop growth model to test hypotheses related to causes of spatial yield variability of soybeans. The hypothesis that water stress creates yield variability within a soybean field was examined. The crop model reduced growth due to spatially variable water stress, resulting in predictions of spatial yield variability. In the best case, water stress explained approximately 69% of the variability in soybean yield over 3 years in 207 grids within a 16 ha field in Iowa. Predicted field level soybean yields compared favorably with the three-year average measured soybean yield for the Baker farm, as well as with the measured yields each year.

Overall, the model gave good predictions in the trend in yields along each of 8 transects in the field. There were instances where the model showed poor agreement between predicted and measured yield on several grids, notably those in low lying areas along transect 7. A possible explanation is the inability of the model to account for surface run-on or subsurface flow to a grid coming from several neighboring grids. Another possible explanation is the non-inclusion in the modeling analysis of above ground factors, i.e. plant population, pests and diseases, that may have an effect on yield reduction. Nonetheless, this study has shown that the crop growth model can be used to predict yield variability with reasonable accuracy on a sub-field level.

Finally, the strength of this work is that it characterizes yield variability using a process oriented crop growth model. This is superior to traditional regression oriented approaches, such as regressing yield and soil type or nutrient levels, that are being used in
other research efforts. The advantage of this approach is that process oriented models, unlike regression models, can be used to evaluate the yield response resulting from changes in management practices in individual grids. This leads to the ability to compute optimum prescriptions including optimum planting date, plant population, and variety. Procedures outlined in this work can be extended to evaluate other models and other crops.

References


Table 1. Soil series, classification, and drainage class for detailed soil map units identified at the Baker farm southwest field

<table>
<thead>
<tr>
<th>Soil Series</th>
<th>Taxonomic Classification*</th>
<th>Drainage Classb</th>
</tr>
</thead>
<tbody>
<tr>
<td>Okoboji tax.</td>
<td>Fine-loamy Cumulic Haplaquoll</td>
<td>VPD</td>
</tr>
<tr>
<td>Terril</td>
<td>Fine-loamy Cumulic Hapludoll</td>
<td>MWD</td>
</tr>
<tr>
<td>Nicollet</td>
<td>Fine-loamy Aquic Hapludoll</td>
<td>SWP</td>
</tr>
<tr>
<td>Storden</td>
<td>Fine-loamy (calcareous) Typic Udorthent</td>
<td>WD</td>
</tr>
<tr>
<td>Harps tax.</td>
<td>Fine-loamy Cumulic Calciaquoll</td>
<td>PD</td>
</tr>
<tr>
<td>Webster</td>
<td>Fine-loamy Typic Haplaquoll</td>
<td>PD</td>
</tr>
<tr>
<td>Clarion</td>
<td>Fine-loamy Typic Hapludoll</td>
<td>WD</td>
</tr>
<tr>
<td>Canisteo tax.</td>
<td>Fine-loamy (calcareous) Cumulic Haplaquoll</td>
<td>PD</td>
</tr>
<tr>
<td>Zenor</td>
<td>Coarse-loamy Typic Hapludoll</td>
<td>SED</td>
</tr>
</tbody>
</table>

* All except Okoboji tax. were in the mixed, mesic family; Okoboji is in the montmorillonitic family.

b VPD, very poorly drained; PD, poorly drained; SWP, somewhat poorly drained; MWD, moderately well drained; WD, well drained; SED, somewhat excessively drained.


Table 2. Three scenarios used to make modifications to the soil parameters in each grid.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>SLDR fraction per day</th>
<th>Rooting depth, cm</th>
<th>Ksat in bottom layer, cm/hr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimized SLDR and optimized rooting depth</td>
<td>Optimized</td>
<td>Optimized</td>
<td>Measured</td>
</tr>
<tr>
<td>2</td>
<td>Optimized rooting depth</td>
<td>Measured</td>
<td>Optimized</td>
<td>Measured</td>
</tr>
<tr>
<td>3</td>
<td>Optimized rooting depth and optimized Ksat in bottom layer</td>
<td>Measured</td>
<td>Optimized</td>
<td>Optimized</td>
</tr>
</tbody>
</table>
Table 3. Summary of error between predicted and measured three-year average field level yields for each case. The three-year average measured yield was 3098 kg ha\(^{-1}\).

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>Predicted Yield*, kg ha(^{-1})</th>
<th>S.D.</th>
<th>RMSE, kg ha(^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimized Drainage Rate (SLDR) and Rooting Depth</td>
<td>3042</td>
<td>511</td>
<td>392</td>
</tr>
<tr>
<td>2</td>
<td>Optimized Rooting Depth</td>
<td>2978</td>
<td>539</td>
<td>464</td>
</tr>
<tr>
<td>3</td>
<td>Optimized Rooting Depth and Bottom Layer (K_{sat}) (Saturated Hydraulic Conductivity)</td>
<td>2959</td>
<td>536</td>
<td>487</td>
</tr>
</tbody>
</table>

*Predicted yield represents three-year field average.
Table 4. Field level measured and predicted yield for each soybean production year and each optimization scenario.

<table>
<thead>
<tr>
<th>Production Year</th>
<th>Measured Yield, kg ha⁻¹</th>
<th>Predicted Yield, kg ha⁻¹ and Error, %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Case 1</td>
</tr>
<tr>
<td>1992</td>
<td>3076</td>
<td>2888 (-6.1)</td>
</tr>
<tr>
<td>1994</td>
<td>3119</td>
<td>3075 (-1.4)</td>
</tr>
<tr>
<td>1996</td>
<td>3099</td>
<td>3169 (1.6)</td>
</tr>
</tbody>
</table>

Table 5. Summary of results for 3 optimization scenarios using soybean data without poor-yielding grids. Total number of grids was 207.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>Predicted Yield*, kg ha⁻¹</th>
<th>RMSE, kg ha⁻¹</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimized Drainage Rate (SLDR) and Rooting Depth</td>
<td>3076</td>
<td>286</td>
<td>0.69</td>
</tr>
<tr>
<td>2</td>
<td>Optimized Rooting Depth</td>
<td>3007</td>
<td>392</td>
<td>0.51</td>
</tr>
<tr>
<td>3</td>
<td>Optimized Rooting Depth and Bottom Layer Kᵢₙₑₜ (Saturated Hydraulic Conductivity)</td>
<td>2989</td>
<td>399</td>
<td>0.50</td>
</tr>
</tbody>
</table>

*Predicted yield represents three-year field average.
Table 6. Number and percentage of grids falling within a specific yield prediction error range for Case 1 determined for the three soybean production years.

<table>
<thead>
<tr>
<th>Error Range</th>
<th>Number of Grids in Range</th>
<th>Percentage*</th>
</tr>
</thead>
<tbody>
<tr>
<td>± 5%</td>
<td>386</td>
<td>61</td>
</tr>
<tr>
<td>±10%</td>
<td>533</td>
<td>84</td>
</tr>
<tr>
<td>±20%</td>
<td>584</td>
<td>92</td>
</tr>
<tr>
<td>±30%</td>
<td>610</td>
<td>96</td>
</tr>
</tbody>
</table>

*Total number of data points is 639. (213 grids x 3 years).

Table 7. Correlation analysis between soybean yield and rooting depth, drainage rate, and elevation. Total number of grids included in the analysis is 213.

<table>
<thead>
<tr>
<th>Rooting depth, m</th>
<th>Drainage Coefficient</th>
<th>Elevation, m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992 Yield</td>
<td>0.69</td>
<td>0.08</td>
</tr>
<tr>
<td>1994 Yield</td>
<td>0.81</td>
<td>-0.17</td>
</tr>
<tr>
<td>1996 Yield</td>
<td>0.77</td>
<td>0.32</td>
</tr>
</tbody>
</table>
Figure 1. Diagram showing the different processes that affect water availability, and root development.
Figure 2. A map of the harvest plots for the Baker farm southwest field showing the eight transects. Contours are in meters.
Figure 3. Cumulative (a) growing degree days and (b) rainfall amounts for the soybean production years.
Figure 4. Predicted versus measured soybean yield for optimization case 1. Total number of grids was 213.
Figure 5. Predicted versus measured yield for optimization case 1 excluding low yielding grids. Total number of grids was 207.
Figure 6. Plots of (a) measured soybean yield, (b) rooting depth, and (c) elevation of each grid position along transects 1 and 7.
Figure 7. Comparison of soybean yield along transects (a) number 1 and (b) number 7 for 1996 production year.
CHAPTER 3. MODEL-BASED TECHNIQUE TO DETERMINE VARIABLE RATE NITROGEN FOR CORN

A paper published in the Agricultural Systems\textsuperscript{1}

J. O. Paz, W.D. Batchelor, B.A. Babcock, T.S. Colvin, S.D. Logsdon, T.C. Kaspar, and D. L. Karlen

Abstract

Past efforts to correlate yield from small field plots to soil type, elevation, fertility, and other factors have been only partially successful for characterizing spatial variability in corn (\textit{Zea mays} \textit{L.}) yield. Furthermore, methods to determine optimum nitrogen rate in grids across fields depend upon the ability to accurately predict yield variability and corn response to nitrogen. In this paper, we developed a technique to use the CERES-Maize crop growth model to characterize corn yield variability. The model was calibrated using 3 years of data from 224 grids in a 16 ha field near Boone, IA. The model gave excellent predictions of yield trends along transects in the field, explaining approximately 57\% of the yield variability. Once the model was calibrated for each grid cell, optimum nitrogen rate to maximize net return was computed for each location using 22 years of historical weather data. Results show high spatial distribution of optimum nitrogen fertilizer prescription for grids across the field. Grid-level nitrogen fertilizer management used lower amounts of fertilizer, produced higher yields and was more profitable than either transect- or field-level (single rate) fertilizer application.

\textsuperscript{1} Agricultural Systems 61:69-75 (1999)
**Introduction**

The advent of yield monitors and global positioning systems that can create spatial yield maps has generated excitement and controversy among farmers and researchers. Site-specific field management promises to maximize field level net return and minimize environmental impact by managing fields using spatially variable management practices. The success of site-specific field management depends upon discovery of relationships between environment, management, and resulting yield variability, and ultimately, how these relationships can be exploited to compute optimum prescriptions. Farmers are faced with trying to determine how to manage variability to improve profits. Researchers are trying to develop methods to analyze causes of yield variability, and determine how to develop prescriptions for fertility, and cultural practices to capitalize on variability across field. While environment, management, soil, and pest factors have been studied for many years, researchers are just beginning to determine how these factors vary across fields and contribute to spatial yield variability.

Initial efforts to study yield variability have focused on taking static measurements of soil, management, or plant properties and regressing these values against grid level yields (Cambardella et al., 1996; Khakural et al, 1996; Sudduth et al., 1996; Jones et al., 1989). However, these efforts have proven to be illusive in determining causes of yield variability. The reason for this is apparent: crop yield is influenced by temporal interactions of management, soil properties, and environment. Traditional analytical techniques, which regress static measurements against yield do not account for temporal interactions of stress on crop growth and yield. Some successes have been achieved in developing relationships
between soil type or elevation and yield variability by using regression approaches. However, these do not directly account for the dynamic interaction of available soil moisture, root water uptake, and water related stresses that can occur and affect plant growth processes. Developing this knowledge is imperative to understanding and quantifying yield variability. Soil moisture stress (drought or excess water) can cause significant variability due to variations in soil moisture holding characteristics, rooting depth and distribution, and drainage patterns across a field. Methods to accurately compute interactions of stress on growth will ultimately lead to the development of optimum site-specific prescriptions.

Assessment of spatial variability within a given field is necessary prior to implementation of variable rate fertilization (VRF). Process-oriented crop growth models are a promising tool to help researchers search for relationships between environment, management, and yield variability. In a recent study, Paz et al. (1998) used a crop growth model and found differences in water availability explained up to 69% of yield variation within transects in a central Iowa soybean (*Glycine max* (L.) Merr.) field.

The objective of this study was to demonstrate the use of a corn crop growth model in characterizing corn yield variability and evaluate variable nitrogen prescriptions for a field in Iowa.

**Procedures**

**Site Description**

Spatial yield distribution of corn was investigated in a 16 ha field in Boone County, IA. The field, which is the southwest (SW) quadrant of the Baker farm, used a conventional farming method consisting of a corn-soybean rotation, conventional tillage, and application
of commercial fertilizer and pesticides. Figure 1 shows the arrangement of the eight transects in the field. Each transect consists of 28 corn yield plots or grids. This gave a total of 224 grids with measured yields. Each grid was 12 m wide by 46 m long. Final corn yield was measured from 3 rows in each grid using a plot combine with weigh tank for 1989, 1991, and 1995.

The site is typical of low-relief swell and swale topography characteristic of broad areas of the Des Moines lobe surface (Steinwand and Fenton, 1995). The field contains nine soil classes that are predominantly from the Clarion-Nicollet-Webster soil association (Steinwand, 1992). A detailed soil map of the field was obtained from the National Soil Tilth Laboratory (NSTL) in Ames, IA. Estimates of soil physical properties were provided by Logsdon (1995, unpublished) of the NSTL, namely: lower limit (LL), drained upper limit (DUL), saturated moisture content (SAT), saturated hydraulic conductivity (K$_{sat}$), bulk density (BD), and organic carbon (OC) at several depths for each soil type. Properties for the predominant soil types were used to represent soil properties in each grid.

Data Collection

In this study, planting date, nitrogen application date and rate, and final yield in each grid were collected for 1989, 1991, and 1995. It is important to note that soil water content, initial nutrient levels, and plant population and barrenness were not collected for each grid. In the following analysis, we assumed uniform initial nitrate and soil water content levels across all grids.
Crop Growth Model

In this study, the CERES-Maize (Jones and Kiniry, 1986) crop growth model was used to characterize yield variability across the corn field. The model computes growth, development, and yield on homogeneous units (either plot, field, or regional scale), and has been demonstrated to adequately simulate crop growth at a field or research plot scale. The CERES-Maize model requires inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall and solar radiation).

We assumed that two factors dominate spatial and temporal yield variability: water related stress and population differences among grids. In order to test this hypothesis, we developed a technique to calibrate several input parameters of the corn model to minimize error between predicted and measured yields in each of the 224 grids. Two soil parameters were adjusted to mimic water table and tile drainage dynamics in each grid. These parameters primarily affect water table depth and rooting depth progress. The first parameter, saturated hydraulic conductivity ($K_{sat}$) of the bottom layer of the soil profile (180-200 cm), was calibrated in conjunction with the second parameter, effective tile drain spacing, to attempt to mimic the soil water dynamics in each grid (Garrison et al., 1998). High values of $K_{sat}$ in a grid create better drainage conditions resulting in lower water tables. Low $K_{sat}$ values reduce drainage out the bottom of the profile and create higher water tables, which can restrict rooting depth. Effective tile drain spacing (FLDS) affects the rate of daily tile flow when the water table is above the tile drain. A third model parameter, plant population (PPOP), was also adjusted in each grid to provide relative yield differences due to consistently poor emergence or barrenness between grids. Thus, three parameters were
derived for each grid to give the best fit between predicted and measured yields over a 3 year period.

Model Calibration

A control program containing the simulated annealing algorithm was linked with the CERES-Maize model. The program was used to solve for the optimum set of these three parameters for each of the 224 grids in the 16 ha Baker field. Simulated annealing is a very robust algorithm (Goffe et al., 1994) and is used in solving complex combinatorial optimization problems. The algorithm is based on the metaphor of how annealing works: reach a minimum energy state upon cooling a substance, but not too quickly in order to avoid reaching an undesirable state. This study used simulated annealing routine as described by Corana et al. (1987) and implemented by Goffe et al. (1994).

Model parameters were optimized in each of the 224 grids to minimize the sum of square error between predicted and measured yield for 1989, 1991, and 1995. The objective function established for the model simulations was written as:

\[
\text{Min: } \text{SSE} = \sum_{i=1}^{3} (Y_{m_i} - Y_{p_i})^2
\]  
[1]

where \( \text{SSE} \) is the sum of square error between \( Y_m \) (measured yield) and \( Y_p \) (predicted yield), and \( i \) is the \( i \)th year.

Economic analysis

After calibrating the model for each grid in the field, we conducted a simple analysis to determine optimum nitrogen application rate in each of the 224 grids within the field. Our strategy was to determine the nitrogen rate that maximized profit over 22 years (1975-1996)
of historical weather data. Soil nitrate and ammonium contents of each grid measured in April 1997 were used as initial values for the series of model runs. A total of 21 nitrogen rates (50-280 kg ha\(^{-1}\)) were tested for each of the 22 years. The annual net return ($ ha\(^{-1}\)) for each grid was computed for each nitrogen rate using the following function:

\[
\text{Net Return} = Y \times P_c - N \times P_n
\]  \[2\]

where \(Y\) is corn yield (kg ha\(^{-1}\)), \(P_c\) is the price of corn ($0.086 kg\(^{-1}\)), \(N\) is nitrogen application rate (kg ha\(^{-1}\)), and \(P_n\) is the cost of nitrogen fertilizer ($0.10 kg\(^{-1}\)).

**Results and Discussion**

**Yield Predictions**

The model gave very good results for the average field level corn yields. Field level predicted yields were within ±14% of measured yields for each of the three corn production year (1989, 1991, and 1995). The percent error between field level predicted and measured yields were 6.9, -13.5, and -0.4% for 1989, 1991, and 1995, respectively (Table 1). The three-year field-level predicted yield of 9027 kg ha\(^{-1}\) was only -2.4 percent off the average measured yield of 9248 kg ha\(^{-1}\).

The calibrated model generally gave excellent predictions of grid-level yields over all years, especially for yields in the range of 6000 and 11000 kg ha\(^{-1}\) (Figure 2). The model over-predicted corn yields in grids with measured yields of 6000 kg ha\(^{-1}\) or less for the 1991 production year. This likely occurred because low yields were probably a result of poor plant stand. The actual plant population were not measured and we estimated a population for each grid as outlined above.
The model gave good predictions with regard to yield trends along transects in the field for all production years except 1991. Figure 3 shows an example of yield trends along transect 7. There were instances where the model gave poor agreement between predicted and measured yield on several grids, notably those in low lying areas. However, predicted and measured yield trends generally matched. A possible explanation is the inability of the model to account for surface water run-on or sub-surface water flow to a grid from several neighboring grids, and plant death due to flooding.

Overall, the model explained approximately 57% of the yield variability in all grids over 3 years. This indicates that the adjustments of soil parameters, which induced variable water stress across the grids, as well as the adjustment of plant population, which scaled the relative yields in grids, accounted for a significant amount of the spatial and temporal yield variability across the field. While these results are not as good as those found by Paz et al. (1998) for soybean, where the CROPGRO-Soybean model (Hoogenboom et al., 1994) explained 69% of the yield variability in the same field, they are promising. The interaction of water and nitrogen stresses, as well as the difficulty in computing plant barrenness, significantly complicates yield prediction in corn. Plant population data were not available and these likely became limiting assumptions, especially for 1991, where the model did not perform as well as the other years.

**Optimum Nitrogen Rate and Net Return**

Net return for 21 nitrogen rates was computed using equation 2 and was then averaged over all 22 years for each grid, to develop the average net return for each nitrogen rate. This response is shown in Figure 4 for one grid-cell (transect 1 grid 19) in the field.
The average line shows the 22-year average profit reached a maximum at a nitrogen rate of 157 kg ha⁻¹, and slightly decreased for higher nitrogen application rates. The average line shows the 22-year average profit reached a maximum at a nitrogen rate of 202 kg ha⁻¹, and slightly decreased for higher nitrogen application rates. Also shown in Figure 4 are the profit curves for the best (1987) and worst (1976) year in the 22 year period. Profit functions for grids were different, resulting in different optimum nitrogen rates across the field.

The optimum nitrogen fertilizer rate was determined by choosing the rate that maximized net return on average over 22 years. Results show high spatial distribution of optimum nitrogen fertilizer prescription for grids across the field (Figure 5a). Net return for each grid corresponding to the optimum nitrogen fertilizer rate is shown in Figure 5b. Nitrogen rates of 141 to 160 kg ha⁻¹ were found to be optimum in 64 of 224 grids (28.6%) (Table 2). These nitrogen rates are typical of what farmers apply for corn in Iowa.

The 22-year average predicted corn yield of greater than 10000 kg ha⁻¹ accounted for 195 of the 224 grids (87%) in Baker Farm (Table 3). Only one grid (0.4%) had low average yield (< 8000 kg ha⁻¹).

Comparison of net returns for different levels of spatial resolution shows that grid-level nitrogen fertilizer application to be more profitable ($796.04 ha⁻¹) than transect ($781.13 ha⁻¹) or field-level ($780.38 ha⁻¹) management (Table 4) over the 22 year period. Overall, fertilizing by grid rather by field (single rate) reduced the average fertilizer rate 11 kg per hectare, and increased expected yield 97 kg per hectare which increased profit by $15.66 per hectare. However, soil sampling and analysis costs were not included in the economic analysis.
Conclusion

Characterization of spatial variability within a given field is necessary prior to implementation of variable rate fertilization. Our efforts have shown the value of using a crop growth model in determining spatial yield variability. Grid-level corn yield predictions for all years were in good agreement with measured yields especially between the range of 6000 and 11000 kg ha\(^{-1}\). The model had problems predicting yields for 1991 especially in grids with low (<6000 kg ha\(^{-1}\)) and very high (>11000 kg ha\(^{-1}\)) measured yields. The model gave good predictions with regard to yield trends along transects in the field for all production years except 1991. There were instances where the model showed poor agreement between predicted and measured yield on several grids, notably those in low lying areas. A possible explanation is the inability of the model to account for surface run-on or sub-surface flow to a grid coming from several neighboring grids, and plant death due to flooding.

Distribution of optimum nitrogen fertilizer prescription was highly spatially varied. Nitrogen rates of 141 to 160 kg ha\(^{-1}\) were found to be optimum in 64 of 224 grids (28.6%) which are typical fertilizer rates farmers apply for corn in Iowa. Grid-level nitrogen fertilizer management used lower amounts of fertilizer, produced higher yields and was more profitable than either transect- or field-level (single rate) fertilizer application.

Our efforts have demonstrated the use of a crop growth model as a viable and powerful tool in developing and evaluating management prescriptions across a field. The model allows yield prediction using historical weather data and provides information necessary to make decisions on management strategies that must be employed based on risk and economic benefit. The applicability of the model can be extended by developing prescriptions for different management strategies (e.g. plant population, phosphorus fertilizer
application) and different crops (e.g. soybean), and analyzing other important model output parameters including nitrate leaching potential under each management strategy.

References


Table 1. Average field-level measured and predicted yield for each corn production year.

<table>
<thead>
<tr>
<th>Production Year</th>
<th>Measured Yield, kg ha⁻¹</th>
<th>Predicted Yield, kg ha⁻¹ and Error, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>9303</td>
<td>9946 (6.9)</td>
</tr>
<tr>
<td>1991</td>
<td>9343</td>
<td>8080 (-13.5)</td>
</tr>
<tr>
<td>1995</td>
<td>9097</td>
<td>9056 (-0.4)</td>
</tr>
<tr>
<td>3 years</td>
<td>9248</td>
<td>9027 (-2.4)</td>
</tr>
</tbody>
</table>

Table 2. Distribution of grids with corresponding optimum nitrogen fertilizer rates.

<table>
<thead>
<tr>
<th>Nitrogen Rates, kg ha⁻¹</th>
<th>Number of Grids</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 60</td>
<td>38</td>
<td>17.0</td>
</tr>
<tr>
<td>80</td>
<td>10</td>
<td>4.5</td>
</tr>
<tr>
<td>100</td>
<td>7</td>
<td>3.1</td>
</tr>
<tr>
<td>120</td>
<td>13</td>
<td>5.8</td>
</tr>
<tr>
<td>140</td>
<td>21</td>
<td>9.4</td>
</tr>
<tr>
<td>160</td>
<td>64</td>
<td>28.6</td>
</tr>
<tr>
<td>180</td>
<td>47</td>
<td>21.0</td>
</tr>
<tr>
<td>200</td>
<td>16</td>
<td>7.1</td>
</tr>
<tr>
<td>220</td>
<td>8</td>
<td>3.6</td>
</tr>
</tbody>
</table>
Table 3. Distribution of 22-year average corn yield groups for grids in Baker farm.

<table>
<thead>
<tr>
<th>Yield (kg ha(^{-1}))</th>
<th>Number of Grids</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 8000</td>
<td>1</td>
<td>0.4</td>
</tr>
<tr>
<td>8000 - 8500</td>
<td>14</td>
<td>6.3</td>
</tr>
<tr>
<td>8501 - 9000</td>
<td>5</td>
<td>2.2</td>
</tr>
<tr>
<td>9001 - 9500</td>
<td>1</td>
<td>0.4</td>
</tr>
<tr>
<td>9501 - 10000</td>
<td>6</td>
<td>2.7</td>
</tr>
<tr>
<td>10001 - 10500</td>
<td>119</td>
<td>53.1</td>
</tr>
<tr>
<td>10501 - 11000</td>
<td>78</td>
<td>34.8</td>
</tr>
</tbody>
</table>

Table 4. Comparison of net return, optimum nitrogen rate, and yield for different levels of spatial management resolution.

<table>
<thead>
<tr>
<th>Spatial Resolution</th>
<th>Net Return, $ ha(^{-1})</th>
<th>Nitrogen Rate, kg ha(^{-1})</th>
<th>Yield, kg ha(^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grid</td>
<td>$ 796.04</td>
<td>134.6</td>
<td>10237</td>
</tr>
<tr>
<td>Transect</td>
<td>$ 781.13</td>
<td>142.8</td>
<td>10127</td>
</tr>
<tr>
<td>Field</td>
<td>$ 780.38</td>
<td>145.6</td>
<td>10140</td>
</tr>
</tbody>
</table>
Figure 1. Contour map and layout of yield transects and grids in Baker farm. Contour intervals are in meters.
Figure 2. Predicted versus measured corn yields for the 224 grids in Baker Farm using three years of data.
Figure 3. Measured and predicted corn yields of each grid position along transect 7 for the different production years.
Figure 4. Diagram showing minimum, average, and maximum net returns for each nitrogen fertilization scheme, for grid number 1-19.
Figure 5. Optimum variable nitrogen rate prescription for corn (a), and corresponding net return (b) of individual grids in Baker field.
CHAPTER 4. A MODELING APPROACH TO QUANTIFY THE EFFECTS OF SPATIAL SOYBEAN YIELD LIMITING FACTORS

A paper to be submitted to the Transactions of the ASAE

Joel O. Paz and William D. Batchelor

Abstract

Spatial yield variability is a complex interaction of many factors, including soil properties, weather, pests, fertility, and management. Crop models are excellent tools to evaluate these complex interactions and provide insight into causes of spatial yield variability. The goal of this study was to use a soybean crop growth model to determine the contribution of four factors that cause spatial yield variability, and to test several calibration and validation strategies for yield prediction. Two procedures were developed to calibrate the CROPGRO-Soybean model, and to compare predicted and measured soybean yields assuming that water stress, soybean cyst nematodes, weeds, and soil pH were the dominant yield limiting factors. Each procedure involved calibrating drainage properties and rooting depth over 3 seasons for each grid. These procedures were tested on 77 grids (0.2 Ha in size) in the McGarvey field in Perry, Iowa for 1995, 1997, and 1999. Predicted soybean yields were in good agreement with measured yield for both one-parameter ($R^2 = 0.63$) and three-parameter ($R^2 = 0.80$) model calibrations. The effects of four yield-limiting factors were then computed for 1997 using the three-parameter calibrated model. The maximum soybean yield potential in 1997 was estimated by running the calibrated model with no water, SCN, or weed stress, and assuming that soil pH was at an optimum level. The model was then run for 1997, turning each yield-limiting factor off to assess its relative impact on yield reduction. Average estimated yield loss due to the combined effects of water stress, SCN, pH, and
weeds in each grid was 842 kg ha\(^{-1}\) (14.4 bu ac\(^{-1}\)). Soybean yields were significantly reduced by an average of 626 kg ha\(^{-1}\) (10.7 bu ac\(^{-1}\)) as a result of water stress. The presence of SCN in several grids accounted for an average yield reduction of 105 kg ha\(^{-1}\) (1.8 bu ac\(^{-1}\)). The effects of both soil pH and weeds on soybean yield were not significant during the specified year (1997) of analysis.

**Introduction**

Spatial yield variability is a complex interaction of many factors including water stress, rooting depth, soil and drainage properties, weather, pests, fertility, and management. The challenge for farmers is to identify the factors that they can control and manage, and make appropriate management decisions to increase profits. Recent improvements in farm technology have given farmers the tools and capabilities to effectively map their fields, record yield histories and even vary inputs/management strategies in response to variations in soil and environmental factors in the field. Research advancements in the field of precision agriculture (PA) have opened the doors for farmers to further increase the productivity of their agricultural lands. Still, both farmers and researchers must wrestle with the problem of significant yield variability within a field.

Process-oriented crop models such as CROPGRO-Soybean (Hoogenboom et al, 1994) were designed to study the interactions of weather, soil, management and genetics on yields. In precision farming, crop models can be used to 1) identify yield loss due to interacting factors, 2) evaluate consequences of management prescriptions, and 3) forecast spatial yields during the season. Recently, researchers have demonstrated the use of crop models to identify spatial yield limiting factors for both corn and soybeans (Batchelor and
Paz, 1998; Fraisse et al., 1998; Paz et al. 1998, Paz et al., 1999). Paz et al. (1998) used a modified version of the CROPGRO-Soybean model and evaluated the role of spatial water stress in causing spatial yield variability in a single field utilizing multiple years of yield data. Soil parameters related to rooting depth and hydraulic conductivity were calibrated in the model in each of 224 grids in a 16 hectare field in Iowa using 3 years of yield data. They found that water stress explained 69% of the variability in yield for all grids over 3 years. Paz et al. (1999) implemented similar procedures to evaluate the interaction of corn population and water stress on spatial yield variability. Fraisse et al. (1998) used the approach developed by Paz et al. (1998) to examine water stress effects on corn yield variability in Missouri. Their calibration procedure involved adjusting the soil water upper and lower limits, saturated hydraulic conductivity, and root hospitality factor.

From the previous work, and from much anecdotal evidence, water stress is a dominant soybean yield-limiting factor. Very little can be done to control this problem in the non-irrigated Midwest. However, other stresses such as soybean cyst nematodes (SCN), weeds, and soil pH can also create significant spatial yield variability, and can be controlled through proper management. There has been no published effort extending crop modeling procedures to evaluate more complex interactions among these factors and to determine their relative impact on spatial soybean yield variability.

In order for the models to be adopted by farmers and industry, an assessment needs to be made to determine the ability to predict spatial yields in independent environments. To date, all published work has focused on calibrating the models to predict within-field yield variability and evaluate yield-limiting factors. Furthermore, there have been no studies demonstrating the performance of crop models when calibrated to predict yields across fields.
using several seasons of crop management and yield data, and tested for independent seasons.

Objectives

The objectives of this study were to: 1) quantify the effects of water stress, SCN, soil pH and weeds on soybean yield variability and to 2) test several calibration and validation scenarios to assess the ability of the CROPGRO model to predict yields in an untested environment.

Procedures

Model Description

The CROPGRO-Soybean crop model (Hoogenboom et al., 1994) was developed to compute growth, development, and yield on homogeneous units (either plot, field, or regional scale), and have been demonstrated to adequately simulate crop growth at a field or research plot scale. This model requires inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall and solar radiation). From this information, daily growth of vegetative, reproductive, and root components are computed as a function of daily photosynthesis, growth stage, and water and nitrogen stress. Soil moisture and nitrogen balance models are used to compute water and nitrate levels in the soil as a function of rainfall and soil moisture holding properties. Because the model is process-oriented, it is relatively simple to couple additional processes, such as impact of pests, to daily calculation of state variables.
Yield Limiting Factors

Soybean cyst nematode (SCN), *Heterodera glycines* Ichinohe, is the single most damaging pest of soybeans in the United States. It is responsible for significant economic losses in soybean production throughout the United States. SCN may decrease yields substantially without inducing obvious symptoms. In determining the effects of SCN, this study used the SCN damage routine proposed by Fallick (1999). The CROPGRO-Soybean model calculates photosynthesis as a function of photosynthetically active radiation (PAR). The relationship is of the form:

\[
PTS_{\text{max}} = PHT_{\text{max}} \cdot \left(1.0 - e^{-\frac{\text{PAR}}{\text{PAR}_{\text{max}}}}\right)
\]  

[1]

Where \(PTS_{\text{max}}\) is the potential photosynthesis based on PAR, \(PHT_{\text{max}}\) is a constant defining the maximum possible photosynthetic rate, and \(\text{PAR}_{\text{max}}\) is a light saturation constant. Gross photosynthesis (Pg) is calculated using the following equation:

\[
P_g = PTS_{\text{max}} \cdot \prod_i^{N} RFAC_i
\]  

[2]

where \(RFAC_i\) are a series of reduction factors (\(i = \text{leaf N factor, canopy factor, leaf age factor, etc.}\)). Fallick (1999) used a constant damage factor that was calculated as a function of the initial population density of SCN eggs in the soil and applied to CROPGRO-Soybean model. SCN-damage was coupled to photosynthesis through RFAC.

The CROPGRO-Soybean model was modified to include a new relationship that focuses on the effects of soil pH on photosynthesis. The new concept suggests a linear increase in relative yield (0-1.0) as soil pH level increases from 4.0 to 6.0, and a linear decrease in relative yield as soil pH increases from 7.5 to 8.1 (Batchelor, 1999; unpublished).
The reduction factor applied on photosynthesis (PHFAC1) as a result of soil pH decreases exponentially with time after V5 stage and is of the form:

$$PHFAC1 = 1 - (1 - PHFAC) \cdot e^{-kt}$$  \[3\]

where PHFAC is the photosynthetic factor due to soil pH, k is coefficient (0.5), and t is the photothermal time after the V5 stage. A diagram showing the temporal change in PHFAC is shown in Figure 1b.

A computer-based weed management system, WeedSOFT (Mortensen et al., 1999), was used to estimate the effects of weeds on soybean yield. Information regarding weed species and weed density rating in each cell were used as inputs to WeedSOFT which then estimated the amount of yield loss. To simplify weed damage, yield loss was added after calibration and was not integrated into model runs.

**Site Description**

In 1996, a project was initiated to study causes of corn and soybean yield variability at three sites in Iowa. One of those sites, the McGarvey field near Perry, Iowa, was selected for this study. The field was divided into 100 grids 0.2-ha in size for studying the effects of soil and pest variability on yields.

Yield data were collected from 1994 to 1999 (1994 and 1995 data were collected by the farmer prior to the initiation of the project). Relevant crop management (e.g. plant population, fertilizer rate) and soil information were collected in 1996-1999. In addition, soybean cyst nematode (SCN) spring egg count, weed species and density data were obtained from each grid in 1997. This information allowed us to identify specific areas within the field where SCN and weed infestation were high and may have significantly affected
soybean yield. Furthermore, information on SCN and weed population allowed us to identify causes of yield variability other than water stress.

Seven soil types were identified in the McGarvey field (Figure 2). Basic soil layer information such as soil texture and bulk density was obtained from county soil survey report (Soil Conservation Service, 1981). In the absence of field-measured soil water limits, values for lower limit (LL), drained upper limit (DUL), and saturated upper limit (SAT) were determined by using a database (Ratliff et al, 1983) of soil water limits for different textural classes. Soil nutrient (nitrogen, phosphorus, and potassium) and soil pH data were obtained from analysis of soil samples taken from each grid in 1997.

Methods to Compute Yield Limiting Factors

For this exercise, we developed several methods designed to calibrate the model for each grid across three seasons of yield data. The idea was to calibrate the model with all available seasons of data in order to obtain the best description of the interactions. The model databases were populated with soybean final yield, crop management and soil data obtained in each of the 100 grids at the McGarvey Field for model calibration. However, only 77 out of 100 grids had three years (1995, 1997, and 1999) of yield data. Thus, analysis was focused only on grids that had complete sets of data. However, there is a lack of hydraulic information in the field (i.e. tile flow characteristics and water table characteristics), which is a primary factor in creating yield variability. Paz et al. (1998 and 1999) demonstrated that several model parameters related to tile drainage can be estimated by minimizing error between predicted and measured yields over several seasons of data. Based on the work of Paz et al. (1998) and Shen et al. (1998), we elected to calibrate three model parameters in
each grid to minimize error in predicting yields over three seasons. Those parameters were: FLDS - effective tile drain spacing (m), KSAT - hydraulic conductivity of the bottom soil layer (cm day\(^{-1}\)), and RHRF - root depth and distribution (cm).

Paz et al. (1998) developed methods to adjust RHRF to fit spatial yield data. However, they ignored spatial tile flow and water table dynamics in their analysis. Shen et al. (1999) developed methods to adjust FLDS and KSAT to fit measured cumulative tile drainage flow and soil water content data. In this exercise, we combined the results of the two previous studies to obtain a better representation of water table and rooting depth interactions. The saturated hydraulic conductivity of an impermeable layer and effective tile drain spacing was adjusted to force the soil to saturate early in the season and allow the water to slowly drain from the soil between the tile and impermeable layers. In combination, these parameters create water stress conditions by simulating a perched water table. In addition, root growth is favored or limited corresponding to an increase or decrease in root hospitality factor.

We calibrated the CROPGRO-Soybean model and examined two model calibration scenarios. The first scenario involved calibrating the model to fit predicted and measured yields by adjusting only one parameter, which is root depth and distribution (RHRF). In the second scenario, we calibrated the model by adjusting the values of three model parameters (RHRF, FLDS, and KSAT). A control program containing the simulated annealing algorithm was linked with the CROPGRO-Soybean model. Simulated annealing is a very robust algorithm (Goffe et al., 1994) and is used in solving complex combinatorial optimization problems. This study used simulated annealing routine as described by Corana et al. (1987) and implemented by Goffe et al. (1994). Model parameters were optimized in
each of the 77 grids to minimize the sum of square error between predicted and measured yield for 1995, 1997, and 1999. The objective function established for the model simulations was written as:

$$\text{Min : } \text{SSE} = \sum_{i=1}^{i=3} (Y_{m_i} - Y_{p_i})^2$$  \hspace{1cm} [4]

where SSE is the sum of square error between $Y_m$ (measured yield) and $Y_p$ (predicted yield), and $i$ is the $i$th year. In each case, SCN population and pH effects were coupled directly to the model, and the estimated yield loss due to weeds were subtracted from the predicted yield prior to computing the SSE.

**Methods to Test Validity of Yield Predictions**

The techniques developed for predicting the yield loss due to different interacting stresses is based strictly on model calibration. For the model to be useful for other applications, it is important to determine if the model calibrated for one set of conditions can predict yield behavior for other seasons. The McGarvey field offers the best data set for beginning to define the validity of this approach for predicting yields. We expanded the previous procedures to encompass a calibration and validation step. We then made a series of model runs, using two seasons of data for calibration and the third season for validation (Table 1). In all cases, SCN, pH and weeds were handled as outlined previously. It should be noted, however, that in 1999, the farmer planted an SCN resistant soybean cultivar, thus, there is no yield loss associated with SCN.
Results and Discussion

Yield Limiting Factors

Predicted soybean yields were in good agreement with measured yield for both one-parameter ($R^2 = 0.63$) and three-parameter ($R^2 = 0.80$) model calibrations (Figure 3). The effects of four yield-limiting factors were then computed for 1997 using the three-parameter calibrated model. Figure 4 shows a comparison of predicted and measured yield under different conditions of yield limiting factors. The maximum potential soybean yield (+ symbol) in 1997, determined using the 3-parameter calibrated model, ranged from 3700 to 3800 kg ha$^{-1}$ or roughly 63 to 65 bu ac$^{-1}$. The values vary slightly from grid to grid because of differences in plant population. Predicted yields using the calibrated model for 1997 with all of the stresses (water stress, SCN, pH, and water) taken into account are indicated by the dark triangle (△). For a specified grid, subtracting the △ value from the + value indicates the estimated yield loss due to the combined effects of water stress, SCN, pH, and weeds. A similar approach was taken in determining the effects of each yield limiting factor. For example, yield reduction due to water stress in a grid was determined by subtracting △ from the ◊ value. Average estimated yield loss (over all grids) due to the combined effects of water stress, SCN, pH, and weeds in each 0.2-hectare (0.5-acre) grid was 842 kg ha$^{-1}$ (14.4 bu ac$^{-1}$) [Table 2]. A significant number of grids had high yield reduction of greater than 1170 kg ha$^{-1}$ (20 bu ac$^{-1}$) [Figure 5].

Among the yield limiting factors examined, water stress had the biggest impact on soybean yield. Soybean yields were significantly reduced by an average 626 kg ha$^{-1}$ (10.7 bu ac$^{-1}$) as a result of water stress condition. Eight grids had high yield losses ranging from 877
to 1461 kg ha\(^{-1}\) (15-25 bu ac\(^{-1}\)) [Figure 6]. Grids with poorly drained (Harps) and very poorly drained (Okoboji) soils tended to have higher yield loss due to water stress.

In 1997, the presence of soybean cyst nematode in several grids accounted for an average yield reduction of 105 kg ha\(^{-1}\) (1.8 bu ac\(^{-1}\)). Yield loss due to SCN ranged from 30 to 410 kg ha\(^{-1}\) (0.5 to 7.0 bu ac\(^{-1}\)) [Figure 7]. Soil pH levels in all grids in the McGarvey field were within the optimum range of 6.0 to 7.5 and thus, did not have any effect on yield. Similarly, weeds did not have any significant adverse effect on soybean yield (Table 2). This outcome does not, however, rule out the possibility of these factors having significant effects on any other production year.

The previous calibration of the CROPGRO-Soybean model produced relatively high R\(^2\) for both one-parameter (R\(^2\) = 0.63) and three-parameter (R\(^2\) = 0.80) model calibrations using three years of yield data. For the three-parameter model, this result implies that water stress, SCN, soil pH and weeds could account for approximately 80% of the variability in yield. These results reflect an improvement in model calibration compared to a previous study (Paz et al., 1998) that found 69% of soybean yield variability was attributed to water stress alone.

Using the three-parameter calibrated model, errors in soybean yield prediction for 1997 were very low (±5%) in most grids in the McGarvey field (Figure 8). Interestingly, grids that were grossly underpredicted (-20 to -30%) have poorly drained (Harps) or very poorly drained (Okoboji) soils that are predominant in depressions or potholes.
Model Validation

Tables 3 and 4 summarize the results of calibrating the model for two years and predicting yields for a third independent season for both one-parameter and three-parameter model calibrations, respectively. Comparing both scenarios using two years of yield data, it was clear that calibrating three parameters (FLDS, KSAT, and RHRF) was better than calibrating one parameter (RHRF) [Figures 9 and 10]. The three parameter model calibration had significantly better $R^2$ values (0.90, 0.42, 0.86) for all calibration years (1995 and 19997, 1995 and 1999, 1997 and 1999) than those of the one parameter model calibration (0.74, 0.17, 0.67).

Using the calibrated three parameter model, yield predictions for the independent years 1995 and 1999 produced decent $R^2$ values of 0.47 and 0.39, respectively (Figure 10). The model calibrated using 1995 and 1999 data, did not perform well in terms of predicting 1997 yield. Closer examination of the cumulative rainfall amounts for the calibration (1995, 1999) and prediction (1999) years shows that 1995 and 1999 had similar distribution (Figure 11). However, in 1997, cumulative rainfall amount was very small (64.3 mm) from day 166 to 222 (June 15-August 10) indicating that the soybean plants may have been under severe drought stress. Therefore, a model calibrated using two years of similar weather patterns may not perform very well in a year when long periods of no rainfall may occur as in the case of 1997. These results indicate the need to use three or more years of yield, crop management and weather data for model calibration to be able to encompass a wider range of plant response to different weather conditions.
Conclusions and Recommendations

Four factors affecting soybean yield variability namely, water stress, soybean cyst nematode (SCN), soil pH, and weeds, were examined in a central Iowa soybean field using the CROPGRO-Soybean model. We calibrated three parameters (FLDS, KSAT, and RHRF) that affect water stress, and incorporated the other three yield variability factors (SCN, soil pH and weeds). Calibration of three model parameters (FLDS, KSAT, and RHRF) using three years of data had better $R^2$ than that of a single model parameter (RHRF). With the model calibrated using two years, the relatively poor results in the validation year uncovered the need for a least three or more years of yield and crop management data for crop modeling purposes.

Among the yield variability factors that were examined in this study, water stress clearly, had a big impact on yield production. However, one cannot discount the effect of other factors such as SCN and weeds. Information on soil pH, SCN and weed population allowed us to identify causes of yield variability other than water stress, and the degree at which these factors may have affected model prediction. The technique presented in this study shows the value of using a crop growth model in quantifying the individual as well as combined effects of yield variability factors. There is a need, however, to further test the model using another year of data and also, examine the performance of the model in other sites. A bigger challenge is how to take a crop growth model and develop grid-level management prescriptions, and analyze the economic impact of such prescriptions.
References


Table 1. Description of several modeling scenarios tested in Heck Farm McGarvey soybean field.

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Calibrate 1995 and 1997; predict 1999</td>
</tr>
<tr>
<td>2</td>
<td>Calibrate 1995 and 1999; predict 1997</td>
</tr>
<tr>
<td>3</td>
<td>Calibrate 1997 and 1999; predict 1995</td>
</tr>
<tr>
<td>4</td>
<td>Calibrate 1995, 1997, and 1999</td>
</tr>
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</table>

Table 2. Average estimated soybean yield loss in 1997 due to the effects of water stress, SCN, soil pH, and weeds.

<table>
<thead>
<tr>
<th>Yield Reduction Factors</th>
<th>Yield Loss (kg/ha)</th>
<th>Yield Loss (bu/ac)</th>
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</thead>
<tbody>
<tr>
<td>Water Stress</td>
<td>626</td>
<td>10.7</td>
</tr>
<tr>
<td>Soybean cyst nematode (SCN)</td>
<td>105</td>
<td>1.8</td>
</tr>
<tr>
<td>Soil pH</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>Weeds</td>
<td>18</td>
<td>0.3</td>
</tr>
<tr>
<td>Water Stress + SCN + soil pH + weeds</td>
<td>842</td>
<td>14.4</td>
</tr>
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</table>
Table 3. Results of one-parameter calibration and subsequent validation of CROPGRO-Soybean model in McGarvey field.

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Calibration Years</th>
<th>$R^2$</th>
<th>Validation Year</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1995 and 1997</td>
<td>0.74</td>
<td>Predict 1999</td>
<td>0.38</td>
</tr>
<tr>
<td>2</td>
<td>1995 and 1999</td>
<td>0.17</td>
<td>Predict 1997</td>
<td>0.10</td>
</tr>
<tr>
<td>3</td>
<td>1997 and 1999</td>
<td>0.67</td>
<td>Predict 1995</td>
<td>0.39</td>
</tr>
<tr>
<td>4</td>
<td>1995, 1997, and 1999</td>
<td>0.63</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Results of three-parameter calibration and subsequent validation of CROPGRO-Soybean model in McGarvey field.

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Calibration Years</th>
<th>$R^2$</th>
<th>Validation Year</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1995 and 1997</td>
<td>0.90</td>
<td>Predict 1999</td>
<td>0.39</td>
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<tr>
<td>2</td>
<td>1995 and 1999</td>
<td>0.42</td>
<td>Predict 1997</td>
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<tr>
<td>3</td>
<td>1997 and 1999</td>
<td>0.86</td>
<td>Predict 1995</td>
<td>0.47</td>
</tr>
<tr>
<td>4</td>
<td>1995, 1997, and 1999</td>
<td>0.80</td>
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</table>
Figure 1. Diagrams showing a) the effect of soil pH on soybean yield and b) the degree (0-1.0) at which photosynthetic factor is affected after a specified photothermal time (Batchelor, unpublished).
Figure 2. Map showing the dominant soil type for each grid-cell in McGarvey field.
Figure 3. Comparison of measured and predicted soybean yield after calibrating a) one parameter (RHRF), and b) three model parameters (FLDS, KSAT, RHRF), and using three years of yield data.
Figure 4. Maximum potential soybean yield in 1997 and variations in predicted soybean yield as affected by SCN, pH, weeds, and water stress.
Figure 5. Grid distribution of estimated yield loss in 1997 due to the combined effects of SCN, pH, weeds and water stress.
Figure 6. Estimated yield loss in each grid due to water stress in 1997.
Figure 7. Estimated yield loss in each grid due to soybean cyst nematode (SCN) in 1997.
Figure 8. Error in soybean yield prediction in 1997 for McGarvey Field
Figure 9. Performance of CROPGRO-Soybean model for different soybean production years in McGarvey field after calibrating RHRF and using two years of yield data.
Figure 10. Performance of CROPGRO-Soybean model for different soybean production years in McGarvey field after calibrating 3 model parameters (FLDS, KSAT, and RHRF) and using three years of yield data.
Figure 11. Cumulative (a) growing degree days, and (b) rainfall amounts for the soybean production years.
CHAPTER 5. ESTIMATING POTENTIAL ECONOMIC RETURN FOR VARIABLE RATE MANAGEMENT IN SOYBEANS

A paper to be submitted to the Transactions of the ASAE

Joel O. Paz and William D. Batchelor

Abstract

The CROPGRO-Soybean model was calibrated and used to develop management prescriptions for a 20-hectare (50-acre) soybean field in central Iowa. Yield impact and economic consequences of three strategies namely, variable plant population density (PPD), soybean cyst nematode (SCN) resistant and susceptible varieties, and irrigation management schemes, were evaluated using 34 years of weather data. Implementing the best PPD for each year produced higher grid-level yield and net return compared to using the 34-year average optimum rate. Selecting the PPD is contingent on a priori knowledge of the weather information. Achieving maximum net return may not be possible on a yearly basis due to uncertainties in weather condition. A comparison was made between SCN resistant and susceptible varieties. Using a SCN-resistant variety resulted in significant yield increase over that of a susceptible variety. Several grids had a significant increase (>350 kg ha⁻¹) in average yield with some grids having as much as 995 kg ha⁻¹ (17 bu ac⁻¹) yield increase when a SCN-resistant variety was used. Finally, the value of variable rate irrigation was computed. Two irrigation management scenarios were compared to the base scenario of no irrigation. Irrigating when available soil moisture reached a value of 40% and 50% significantly increased average field-level soybean yields by 1585 (27.1 bu ac⁻¹) and 1619 (27.7 bu ac⁻¹) kg ha⁻¹, respectively. Excluding the cost of equipment, irrigation would significantly
increase net return. However, high initial investment and prohibitive cost of equipment may not justify the implementation of variable rate irrigation for this field.

Introduction

Farm management and production decisions are affected by several factors including farmers' goals, financial constraints, farm size, and availability of farm equipment. Yield limiting factors within and at the field-level must be identified and controlled, and appropriate management decisions must be made to increase profitability. The anticipated increase in crop yields and economic profits usually influence decisions on implementing or adopting specific management strategies. Developing prescriptions for small scale, grid-level management have proven to be a challenge for researchers in the field of precision agriculture.

In precision farming, crop models can be used to 1) identify yield loss due to interacting factors, 2) evaluate consequences of management prescriptions, and 3) forecast spatial yields during the season. Crop growth models provide for the integration of spatial and temporal aspects of complex crop systems and are useful in the analysis of alternative management options for different crops such as sorghum, wheat, rice, corn and soybean (Pandey, 1994; Lansigan et al. 1997; Paz et al., 1999). Lansigan et al. (1997) used a rice growth model, ORYZA_W, to estimate probability distributions of rice yield under different management scenarios including water storage capacities and seedling age. They applied stochastic dominance analysis to identify management options. Paz et al. (1999) used the CERES-Maize model to develop variable nitrogen fertilizer rate in each of the 224 grids in a corn field in central Iowa. They used a calibrated model to predict yields using different
nitrogen fertilizer rates over 22 years of weather data, and identified the fertilizer rate that maximized the average net return.

Paz et al. (1998) used the CROPGRO-Soybean crop growth model (Hoogenboom et al., 1994) to identify water stress effects on soybean yield variability. The CROPGRO-Soybean model requires inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall and solar radiation). Paz and Batchelor (2000) outlined a methodology of quantifying the individual and combined effects of yield limiting factors using CROPGRO-Soybean. An objective evaluation of specific management strategies is needed before they are considered for implementation. The objectives of this study were to develop grid-level management prescriptions for soybean using the CROPGRO-Soybean model and to evaluate the economic consequences of these prescriptions.

Procedures

The CROPGRO-Soybean model was calibrated to fit measured historical yield variability over 3 years for the McGarvey field in Perry, Iowa (Paz and Batchelor, 2000). They included the effects of four yield limiting factors namely, water stress, soybean cyst nematode (SCN) stress, soil pH and weed pressure. Three model parameters namely, field tile drain spacing (FLDS), saturated hydraulic conductivity (KSAT), and root hospitality (RHRF), were calibrated using three years (1995, 1997, 1999) of yield and crop management data. The calibration technique was outlined by Paz and Batchelor (2000) in a recent related study and will be not presented in this study. The McGarvey soybean field consists of 77
0.2-ha size grids with extensive data to run the model. In this research, the calibrated model was used to evaluate several management strategies including variable plant population density (PPD), selection of SCN resistant or susceptible soybean varieties, and selection of irrigation scheme based on different available soil moisture conditions.

**Plant Population Density**

Soybean seed yield is influenced by several management factors including planting date, pattern, and population density. Plant population density has a significant effect on soybean node and pod numbers, leaf area index, crop growth rate, and total biomass. Parvez et al. (1989) found seed yields were significantly increased with increasing plant population density up to a threshold PPD. In this study, the CROPGRO-Soybean model was used to run two different plant population management scenarios for each grid using thirty four (34) years of weather data (1966-1999). The model was run for each grid using 6 different populations ranging from 100,000 to 150,000 plants per acre in increments of 10,000 plants per acre. Profit was computed for each combination as:

\[ P_n^t = Y_n^t * Pr - R_n^t * C \]  

where \( P_n^t \) is the profit for grid \( n \) in year \( t \), \( Y_n^t \) is the predicted yield (bu ac\(^{-1}\)) for grid \( n \) in year \( t \), \( Pr \) is the selling price ($ bu^{-1} $), \( R_n^t \) is the soybean population (plants m\(^{-2}\)) for grid \( n \) and year \( t \) at harvest, and \( C \) is the cost of seeds ($ bag^{-1} $). A bag of soybean has 125,000 seeds. A price of $5.00 per bushel of soybean was assumed in the calculation of profit.

Two scenarios were considered in the analysis of variable population rate, namely: determining the variable rate (VR) that maximizes the average grid-level profit over 34 years of simulation, and determining the rate that maximizes profit for each year.
Soybean Cyst Nematode

Three management scenarios involving soybean varieties with different degrees of resistance to SCN were considered and evaluated. For each soybean variety (e.g. SCN-resistant, moderately resistant and susceptible), the model was used to predict yields in each grid using 34 years of historical weather data (1966-1999). Grid-level SCN egg count and plant population data, measured in 1997 and used in the model calibration (Paz and Batchelor, 2000), was used as inputs to the model. It was assumed that the SCN population would stay constant throughout the simulation period (1966-1999). Net return for a susceptible variety provided a baseline for the comparison of economic gain or loss of using a resistant or moderately resistant variety. Methods to simulate the effect of SCN damage in the CROPGRO model were outlined by Fallick et al. (1999).

Irrigation Management Schemes

To determine the impact of irrigation on soybean, the calibrated CROPGRO-Soybean model was used to predict yield, the number of irrigation events (IR#M) and cumulative irrigation (IRCM) for each under three different water availability scenarios. The first scenario provides a baseline reflecting a typical central Iowa condition wherein soybean plants are rainfed. The second scenario involved simulating an irrigation event in each grid when the threshold level (ITHRL) of soil water dropped to 40% of the available moisture. The third irrigation management scheme sets the ITHRL to 50% of available moisture and triggers an irrigation event when soil water goes below this threshold level. Cumulative amount of irrigation water was estimated for each year from 1966 to 1999. Comparison of yields and net returns for the different schemes were made.
Results and Discussion

Model Calibration

Calibration of the CROGPRO-Soybean model by Paz and Batchelor (2000) yielded a good R^2 value (0.80) [Figure 1]. This result implies that water stress, SCN, and weeds could account for approximately 80% of the variability in yield in this field. Furthermore, this reflects an improvement in model calibration compared to a previous study (Paz et al., 1998) that found 69% of soybean yield variability was attributed to water stress alone.

Plant Population Density

The first plant population management scenario searches for the best rate for each year by selecting the rate that results in the highest net return for each grid. Figures 2 and 3 show the potential loss in dollars per acre for grids 10 and 13, respectively, for different population densities in comparison to the optimum prescription for a specific year. For example, 110,000 plants per acre was found to be the best rate for grid 10 in 1980. This value was determined by searching for the maximum net return for that year only. The potential loss was calculated by subtracting the net return for each population from the net return for 110,000 plants per acre. An amount of $6.62 ac^{-1} for a PPD of 150,000 plants ac^{-1} indicates that a farmer will likely lose this amount if he used this rate instead of using a PPD of 110,000 plants ac^{-1} for this grid and weather year. A similar approach was used for each year from 1966 to 1999. Hence, a specific grid may have different optimum populations in different years. Figure 3 shows two different optimum PPD of 130,000 and 110,000 plants ac^{-1} for grid 13 in 1976 and 1991, respectively.
In the second plant population management scenario, an optimum rate was established for each grid by determining the rate that maximized the net return for each grid. Therefore, a specific grid would have a single optimum rate. The potential loss is calculated by taking the net return using the optimum rate and subtracting the net return of non-optimum rates. Figures 4a and 4b shows examples for grids 10 and 13, respectively. For grid 10, using a PPD of 140,000 each year would result into a potential loss of $1.40 compared to the optimum rate of 100,000. Similarly for grid 13, a farmer would incur a potential loss of $0.80 per acre if a PPD of 140,000 was used instead of the optimum rate of 110,000.

Table 1 presents a comparison of cumulative field-level profit averaged over 34 years for different plant population densities. By determining the best PPD for each year, a farmer can maximize his profit over all 34 years. For example, at a PPD of 120,000 plants per acre, a farmer would have a cumulative (34-year) profit of $1.94 per acre if he used the best PPD each year compared to only $0.46 per acre if he used the 34-year optimum rate. Although these results provide a view that favors implementing an optimum rate each year, it should be noted that a farmer would have to know the type of weather for the coming year. Risk-averse farmers, however, may be contented with using the typical (average) soybean population rate for his/her field since predicting whether a year would be wet or dry is very difficult. Therefore, determining and implementing the best PPD each would be a challenge for farmers and subsequently, achieving maximum net return may not be possible on a yearly basis.
SCN Resistant Varieties

The cumulative distribution function (CDF) of the 34-year average grid-level soybean yields was determined for each of the three levels of SCN resistant varieties (Figure 5). In general, a resistant variety produced higher grid-level soybean yields than a susceptible variety. At $P=0.50$, yields using resistant variety were significantly higher than either moderately resistant or susceptible variety. At higher probabilities ($P > 0.90$), estimated yields for all three varieties would be about the same. It should be noted that the calibrated model was setup using an SCN-susceptible variety for 1997.

Figure 6 shows the spatial distribution of yield increase due to an SCN-resistant variety. Several grids had a significant increase (>350 kg ha$^{-1}$) in average yield with some grids having as much as 995 kg ha$^{-1}$ (17 bu ac$^{-1}$) yield increase when a SCN-resistant variety was used. This analysis demonstrates that this field would benefit greatly using an SCN resistant variety, and would suffer significant yield loss for a susceptible variety.

Irrigation

In simulating soybean under different irrigation schemes, an irrigation event is triggered when soil moisture at the top 30 cm of the soil profile reaches below a specified level of available soil moisture (e.g. 40%, 50%). A comparison of the 34-year average grid-level yield under different irrigation management schemes is presented in Table 2. Compared to a no irrigation scheme, irrigating at a threshold value (ITHRL) of 40% and 50% increased soybean yields of 1585 (27.1 bu ac$^{-1}$) and 1619 (27.7 bu ac$^{-1}$) kg ha$^{-1}$, respectively. An ITHRL of 40% of the available soil moisture indicates a condition wherein the plant is subjected to more water stress because the soil is drier compared to a scenario of ITHRL of
50%. This translates into fewer irrigation events and lower cumulative irrigation water applied onto the field (Figures 7a and 7b). Most of the grids (74) under an ITHRL of 50% had an average of 5 or more irrigation events during a year while 68 grids under an ITHRL of 40% had an average of 4 events or less. A significant number of grids (59) under ITHRL of 40% used less water (< 140 mm) than those grids under ITHRL of 50%. Despite being water stressed, average soybean yields at ITHRL=40% were not significantly different from the other irrigation management strategy (Figure 8).

Choosing the best irrigation management scheme involves weighing the benefit of increased yield due to supplemental irrigation versus the cost of applying additional irrigation water. Figure 9 depicts the behavior of the average field-level net return (gross return minus seed cost) with respect to the price of soybean. The chart also shows the costs of applying varying amounts (depths) of water. The results show that for a specified price of soybean, a fixed cost of buying an irrigation system should be less than the net return indicated by the dark triangle (▲) minus the variable cost of irrigation water (horizontal lines) for an irrigation management scheme to be considered profitable. For example at a soybean price of $5.00 per bushel and irrigating 4.7 in (120 mm), the fixed cost must be lower than $14.66 per acre for a system to be profitable. Inclusion of the fixed cost of acquiring an irrigation system (e.g. center-pivot) would have dramatic implications on the profit analysis. A typical center-pivot system with a diesel engine costs $70 to $96 per acre (Colbert, 1978). Such system would be considerably more expensive in today's market. These values include initial investment, cost of ownership, loss of land, and additional production costs. The burden of covering the cost of equipment makes it difficult for a farmer to justify implementing an irrigation system for this field.
Conclusions

The calibrated CROGPRO-Soybean model was used to develop several management strategies including variable plant population density (PPD), selection of SCN resistant or susceptible soybean varieties, and selection of irrigation scheme based on different available soil moisture conditions.

Selecting and implementing the optimum PPD for each year offers higher yields and profits than using the 34-year average optimum rate. Decision on implementing the best rate is contingent on the fact that farmers must have prior knowledge of the weather for a specific year. Because of the unpredictable nature of weather, achieving maximum net return may not be possible on a yearly basis. Risk-averse farmers, however, may opt to use the typical (average) 34-year optimum rate that would provide a favorable net return albeit not the maximum.

In general, a resistant variety produced higher grid-level soybean yields than a susceptible variety. Several grids had a significant increase (>350 kg ha⁻¹) in average yield with some grids having as much as 995 kg ha⁻¹ (17 bu ac⁻¹) yield increase when a SCN-resistant variety was used.

Two irrigation management schemes were compared to the baseline scenario of no irrigation. Irrigation significantly increased grid-level yields regardless of the soil moisture threshold levels (ITHRL=40 and ITHRL=50%). Excluding the cost of equipment, irrigation would significantly increase net return. However, high initial investment and prohibitive cost of equipment may not justify the implementation of irrigation for this field. Farmers would
have difficulty shouldering the amortized payment for the irrigation equipment and additional costs.

References


Table 1. Comparison of cumulative field-level profit ($/ac\(^{-1}\)) averaged over 34 years for different plant population density.

<table>
<thead>
<tr>
<th>Management</th>
<th>Plant Population (x 1000 plants ac(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100</td>
</tr>
<tr>
<td>Best Rate Each Year</td>
<td>$1.94</td>
</tr>
<tr>
<td>34-Yr Optimum Rate</td>
<td>$0.22</td>
</tr>
</tbody>
</table>

Table 2. Comparison of 34-year average field level soybean yields under different irrigation management scenarios.

<table>
<thead>
<tr>
<th>Irrigation Management Scenario</th>
<th>Average Yield kg ha(^{-1}) (bu ac(^{-1}))</th>
<th>Yield Increase Compared to Base Scenario</th>
<th>Yield Increase Compared to ITHRL = 40 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>No irrigation (base)</td>
<td>2422 (41.4)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Irrigate at ITHRL = 40%</td>
<td>4007 (68.5)</td>
<td>1585 (27.1)</td>
<td>-</td>
</tr>
<tr>
<td>Irrigate at ITHRL = 50%</td>
<td>4040 (69.1)</td>
<td>1619 (27.7)</td>
<td>33 (0.6)</td>
</tr>
</tbody>
</table>
Figure 1. Comparison of measured and predicted soybean yield after three model parameters (FLDS, KSAT, RHRF), and using three years of yield data (From: Paz and Batchelor, 2000).
Figure 2. Potential loss in profit for a sample grid (grid 10) given the condition that population rates other than the best rate of a) 110,000 plants ac$^{-1}$ and b) 120,000 plants ac$^{-1}$ were used in 1980 and 1991, respectively.
Figure 3. Potential loss in profit for a sample grid (grid 13) given the condition that population rates other than the best rate of a) 130,000 plants ac$^{-1}$ and b) 110,000 plants ac$^{-1}$ were used in 1976 and 1991, respectively.
Figure 4. Potential loss in profit for a) grid 10 (optimum rate of 100,000 plants ac$^{-1}$), and b) grid 13 (optimum rate of 110,000 plants ac$^{-1}$) if rates other than the optimum were used over 34-years.
Figure 5. Cumulative distribution of the 34-year average grid-level soybean yields for different levels of soybean cyst nematode (SCN) resistant varieties.
Figure 6. Yield increase averaged over 34 years if an SCN-resistant variety was planted instead of an SCN-susceptible
Figure 7. Distribution of a) number of irrigation events and b) 34-year average cumulative irrigation of different grids under two irrigation management schemes.
Figure 8. Distribution of the 34-year average predicted yield of different grids under two different irrigation management schemes.
Figure 9. Net return and cost of varying amounts of irrigation water for different soybean prices.
CHAPTER 6. GENERAL CONCLUSIONS

The following are the major conclusions from this study:

1. The CROPGRO-Soybean model was used to test the hypothesis that water stress creates yield variability within a soybean field. Water stress explained approximately 69% of the variability in soybean yield over 3 years in 207 grids within a 16 ha field in Iowa. Predicted field level soybean yields compared favorably with the three-year average measured soybean yield for the Baker farm, as well as with the measured yields each year. The model gave good predictions in the trend in yields along each of 8 transects in the field. There were instances where the model showed poor agreement between predicted and measured yield on several grids, notably those in low lying areas. A possible explanation is the inability of the model to account for surface run-on or sub-surface flow to a grid coming from several neighboring grids. Another possible explanation is the non-inclusion in the modeling analysis of above ground factors, i.e. plant population, pests and diseases, that may have an effect on yield reduction.

2. The CERES-Maize model was used to examine corn yield variability and to develop variable-rate nitrogen fertilizer prescription. The model was calibrated using 3 years of data (1992, 1994, and 1996) from 224 grids in a 16 ha field near Boone, Iowa. Grid-level corn yield predictions for all years were in good agreement with measured yields especially between the range of 6000 and 11000 kg ha\(^{-1}\). The model had problems predicting yields for 1991 especially in grids with low (<6000 kg ha\(^{-1}\)) and very high (>11000 kg ha\(^{-1}\)) measured yields. The model gave good predictions with regard to yield trends along transects in the field for all production years except 1991. The model gave excellent predictions of yield trends along transects in the field, explaining approximately 57% of the yield variability.
Once the model was calibrated for each grid cell, optimum nitrogen rate to maximize net return was computed for each location using 22 years of historical weather data. Distribution of optimum nitrogen fertilizer prescription was highly spatially varied. Nitrogen rates of 141 to 160 kg ha\(^{-1}\) were found to be optimum in 64 of 224 grids (28.6%) which are typical fertilizer rates farmers apply for corn in Iowa. Grid-level nitrogen fertilizer management used lower amounts of fertilizer, produced higher yields and was more profitable than either transect- or field-level (single rate) fertilizer application.

3. Four factors affecting soybean yield variability namely, water stress, soybean cyst nematode (SCN), soil pH, and weeds, were examined in a soybean field in Perry, Iowa using the CROPGRO-Soybean model. We calibrated three parameters (FLDS, KSAT, and RHRF) that affect water stress, and incorporated the other three yield variability factors (SCN, soil pH and weeds). Calibration of three model parameters (FLDS, KSAT, and RHRF) using three years of data had better \(R^2\) than that of a single model parameter (RHRF). With the model calibrated using two years, the relatively poor results in the validation year suggest the need for at least three or more years of yield and crop management data for crop modeling purposes.

Average estimated yield loss due to the combined effects of water stress, SCN, pH, and weeds in each 0.2-hectare grid was 842 kg ha\(^{-1}\). A significant number of grids had high yield reduction of greater than 1170 kg ha\(^{-1}\). Among the yield limiting factors examined, water stress had the biggest impact on soybean yield. Soybean yields were significantly reduced by an average 626 kg ha\(^{-1}\) as a result of water stress condition.

4. The calibrated CROGPRO-Soybean model was used to develop several management strategies including variable plant population density (PPD), selection of SCN
resistant or susceptible soybean varieties, and selection of irrigation scheme based on different available soil moisture conditions.

Selecting and implementing the optimum PPD for each year offers higher yields and profits than using the 34-year average optimum rate. Decision on implementing the best rate is contingent on the fact that farmers must have prior knowledge of the weather for a specific year. Achieving maximum net return may not be possible on a yearly basis due to weather uncertainties. Risk-averse farmers, however, may opt to use the typical (average) 34-year optimum rate that would provide a favorable net return albeit not the maximum. A resistant variety produced higher grid-level soybean yields than a susceptible variety. Several grids had significant increase in average yield (> 350 kg ha\(^{-1}\) or 6 bu ac\(^{-1}\)) with some grids having as much as 995 kg ha\(^{-1}\) (17 bu ac\(^{-1}\)) when a SCN-resistant variety was used.

Two irrigation management schemes were compared to the baseline scenario of no irrigation. Irrigation significantly increased grid-level yields regardless of the soil moisture threshold levels (ITHRL=40% and ITHRL=50%). Excluding the cost of equipment, irrigation would significantly increase net return. However, high initial investment and prohibitive cost of equipment may not justify the implementation of irrigation for this field. Farmers would have difficulty shouldering the amortized payment for the irrigation equipment and additional costs.

**Recommendations for Future Research**

Modeling a complex system to analyze what causes yield variability requires good soil and crop information as well as management and historical yield data. Results of this research have shown the value of using crop growth models to characterize yield variability,
and economic consequences in the context of precision agriculture. Information on soil pH, SCN and weed population allowed us to identify causes of yield variability other than water stress, and the degree at which these factors may have affected model prediction. There is a need, however, to examine and quantify the effects of other factors such as pest pressures (e.g. corn borer) on corn, genetic differences in soybean, and interactions of several factors. In addition, there is a need to further test the model using additional years of data and also, examine the performance of the model in other sites.
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