Development and utilization of irrigation simulation with CERES-Maize in a central Iowa cornfield

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Development and utilization of irrigation simulation with CERES-Maize in a central Iowa cornfield

by

Kendall Craig DeJonge

A thesis submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
MASTER OF SCIENCE

Major: Agricultural Engineering

Program of Study Committee:
Amy Kaleita, Major Professor
Matt Helmers
Tom Colvin
Michael Duffy

Iowa State University
Ames, Iowa
2006

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This is to certify that the master’s thesis of

Kendall Craig DeJonge

has met the thesis requirements of Iowa State University

Signatures have been redacted for privacy
for my mother

“Success is not final, failure is not fatal: it is the courage to continue that counts.”

-Sir Winston Churchill
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## ABSTRACT

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ABSTRACT

Crop models have emerged as a method to evaluate different crop management practices such as irrigation without costly and time-consuming onsite experiments. A decision support system called APOLLO has been developed in past years to assist researchers in using the CERES-Maize crop model to simulate precision farming methods for corn. Past experiments have used APOLLO to develop precision population and nitrogen application prescriptions for maximum yield. In this work, an additional module was created for APOLLO to automate spatially variable irrigation scenarios. This module has the capability of simulating blanket scheduled uniform irrigations or precision irrigations based on percent of available soil water. In a Windows-based interface, the user can input desired irrigation application efficiency, irrigation amount, and threshold and management depth used for automatic applications. The module was successfully tested using several years of data and various schedules, application thresholds, irrigation amounts, and management depths. This simulation may be a very powerful tool in studying irrigation feasibility, deficit irrigation, and varying irrigation management strategies.

Few studies have been done considering the possibility of irrigation systems in Iowa or other humid regions. Recent technological progress in precision agriculture may allow irrigation in these areas to become more economically feasible. In this study, the newly developed irrigation module in the APOLLO program was used to evaluate potential improved yield in a central Iowa cornfield on a spatially and temporally variable basis. Five years of historical yield and weather data were used to calibrate the model for the 20.25 ha field over 100 spatially variable grids. This calibrated model then used 28 years of historical weather data to simulate three irrigation scenarios: no irrigation, scheduled uniform irrigation, and precision irrigation. 30 mm irrigations were applied when the percent of available soil water fell below 50 percent. Irrigation improved yield by at least 1000 kg ha\(^{-1}\) in half of the years simulated, and also showed to have less variability both spatially and temporally. Precision irrigation showed slightly higher yields than scheduled uniform irrigation. Spatial variability of yield was most influence by topography, with the largest improvements occurring on steep sideslopes and hilltops. Assuming use of a center pivot
irrigation system, irrigation showed economic returns in only three of the 28 years included in the study. High capital costs were the leading restrictor of economic feasibility.
CHAPTER 1. GENERAL INTRODUCTION

1.1. Introduction

Water is one of the most important resources when considering the production of agricultural crops. Most semi-arid regions require irrigation to obtain high yields, while many other areas such as Iowa rely exclusively on rainfall to water their crops. The average rainfall in Iowa is normally sufficient for crop production, and an estimated 35 percent of the land is drained to remove excess moisture (Zucker and Brown, 1998). However, Or (1998) found that in countries with large amounts of rainfall, temporal variation in storm frequency and production do not always coincide with crop needs. Therefore, it can be assumed that an artificial watering system such as irrigation could improve yields by providing consistent watering, but it is not clear whether these increased yields would offset the cost of installation and maintenance for such a system.

Few studies have been done considering the possibility of irrigation systems in Iowa or other humid regions. Schwab et al. (1958) studied the yield response of corn and soybeans to gravity irrigation in Iowa fields from 1951 to 1955, finding a slight increase in corn yields for most years studied. Martin et al. (1985) evaluated several irrigation strategies for corn in humid regions using the CERES-Maize crop model. Johnson et al. (1987) analyzed the economics of center pivot irrigation systems used in Southeastern U.S. peanut fields.

Although these older studies showed limited economic return for irrigation in humid areas, recent technological progress in precision agriculture may allow irrigation in Iowa and other humid areas to be economically feasible. Precision agriculture is already being used to increase farm production in other ways. For example, utilization of precision nitrogen and pesticide application has become more prevalent in recent years. Using similar methods including GPS, remote sensing, and variable-rate spray nozzles, some researchers are focusing on variable-rate precision irrigation systems as well (Sadler 2005). Most of these systems in development utilize center-pivot irrigation technology, mainly because of its potential to mount real-time sensing equipment, vary application rates, and cover the entire field.
Climate and water availability are major determining factors in corn production (Morgan et al., 2003). Paz et al. (1998, 2001) found water stress to be one of the greatest limiting factors in the yield of soybean. Spatial variability of soil characteristics may also contribute to the variation in yield. For example, Sadler et al. (2000, 2002, 2005) found that spatial variation in soil water relations directly contributes to spatial variation in grain yield and a large amount of spatial variation under drought stress, indicating that water relations are not homogeneous within the observed area. Sadler suggests use of crop models for analysis of this relationship.

One advantage of crop models is the ability to predict the outcomes of various crop management processes without performing large-scale, costly, and time-consuming experiments. Several crop model simulations such as this have been used in terms of irrigation, for example Guerra et al. (2004) successfully used the EPIC model to simulate crop yield and irrigation demand for several crops in Georgia. Also, Nijbroek et al. (2000) used crop models to determine optimum irrigation management strategies in soybean. Considering the spatial variability in the field, best results were found when applying the irrigation schedule for the largest management zone to the entire field.

Other research indicates a need for further evaluation of crop models for irrigation studies. For example, Heinemann et al. (2000) used the CROPGRO simulation for various irrigation practices, but stated that scenarios considering different weather conditions and soil types are necessary for a wider acceptance of the simulation. In addition, Sadler et al. (2005) discusses the possibility of variable-rate irrigation systems, but also indicates that decision support systems are needed to enhance the viability of such precision irrigation.

The CERES-Maize crop model (Jones and Kiniry, 1986) is a computer program developed to simulate the effects of various inputs, including rainfall and irrigation, on corn growth and yield. The model calculates growth and development of the corn plant in a daily time step. Inputs for the model include management practices (genetics, population, row spacing, planting and harvest dates, fertilizer and irrigation application amounts and dates), environmental factors (soil type, drained upper limit and lower limit, saturated hydraulic conductivity), and weather (daily minimum and maximum temperature, solar radiation, and precipitation). CERES-Maize has been shown to perform sufficiently on plot-level, field-
level, and regional scales for a wide variety of corn hybrids, climatic conditions, and soil
types around the world (Hodges et al., 1987; Carberry et al., 1989; Liu et al., 1989; Jagtap et
al., 1993; Pang et al., 1998; Garrison et al., 1999; Paz et al., 1999; Fraisse et al., 2001).

One limitation of CERES-Maize is its ability to evaluate only one uniform area at a
time. To remedy this drawback, researchers at Iowa State University have developed a new
decision support software called APOLLO, or Application of Precision Agriculture for
Field Management Optimization (Batchelor et al., 2004). This Windows-based software is
capable of automating the CROPGRO-Soybean and CERES-Maize models to analyze
several plots at a time, thereby allowing for the simulation of precision farming practices for
soybean and corn. APOLLO has the capability to calibrate models to simulate historic
spatial yield variability, validate these models for years not used in calibration, and estimate
responses to nitrogen and plant population prescriptions. Recent studies have used the
program for nitrogen and population prescriptions for maximum yield (Paz et al., 1999).

With increased focus on precision agriculture, new research is underway involving
spatially variable irrigation systems. Several prototype systems for variable-rate irrigation
application have been developed, but adequate decision support systems have not (Sadler
2005). In order to increase practical functionality of precision irrigation, real-time
monitoring, decision, and control systems must be improved. This research utilizes the
APOLLO decision model to evaluate the potential benefits from such irrigation systems
without developing the monitoring and control systems themselves.

An additional module was created in APOLLO specifically for this study that will
automate spatially variable irrigation scenarios. This study uses APOLLO and the CERES-
Maize crop model to predict the potential yields on an Iowa cornfield assuming an optimum
amount of available water, inherently predicting the effects of an irrigation system on a
typical Iowa cornfield. Three management scenarios were evaluated in this study: no
irrigation, scheduled uniform irrigation, and precision irrigation. Specific objectives were to
evaluate potential yield improvement, spatial variability, and economic viability that would
result from irrigation occurring in this cornfield.
1.2. Thesis Organization

This thesis is a compilation of two journal manuscripts intended for submission to refereed scientific journals. Chapter 2 focuses on the development and validation of an automatic irrigation module for the APOLLO program. This chapter is intended as part of a forthcoming paper about the development of the APOLLO program. Chapter 3 is a case study in which this module is utilized to simulate irrigation in a central Iowa cornfield over 28 historical years.

1.3. References


CHAPTER 2. DEVELOPMENT OF A SPATIALLY-VARIABLE IRRIGATION SIMULATION FOR CERES-MAIZE

A paper to be submitted to Agronomy Journal

K.C. DeJonge, A.L. Kaleita, and W.D. Batchelor

2.1. Abstract

Crop models have emerged as a method to evaluate different crop management practices such as irrigation without costly and time-consuming onsite experiments. A decision support system called APOLLO has been developed in past years to assist researchers in using the CERES-Maize crop model to simulate precision farming methods for corn. Past experiments have used APOLLO to develop precision population and nitrogen application prescriptions for maximum yield. In this work, an additional module was created for APOLLO to automate spatially variable irrigation scenarios. This module has the capability of simulating blanket scheduled uniform irrigations or precision irrigations based on percent of available soil water. In a Windows-based interface, the user can input desired irrigation application efficiency, irrigation amount, and threshold and management depth used for automatic applications. The module was successfully tested using several years of data and various schedules, application thresholds, irrigation amounts, and management depths. This simulation may be a very powerful tool in studying irrigation feasibility, deficit irrigation, and varying irrigation management strategies.

2.2. Introduction

In recent years, computer crop models have been implemented to predict the outcomes of various crop management processes without performing large-scale, costly, and time-consuming experiments. With these crop models, several seasons of data can be developed in a relatively short period of time, compared to an entire growing season required to acquire a single dataset in actual field tests. Testing with crop models also offers the
opportunity to evaluate the feasibility of nonstandard management practices with limited investment.

The CERES-Maize crop model (Jones and Kiniry, 1986) is a computer program developed to simulate the effects of various inputs in corn growth and yield. The model calculates growth and development of the corn plant in a daily time step. Inputs for the model include management practices (genetics, population, row spacing, planting and harvest dates, fertilizer and irrigation application amounts and dates), environmental factors (soil type, drained upper limit and lower limit, saturated hydraulic conductivity), and weather (daily minimum and maximum temperature, solar radiation, and precipitation). CERES-Maize has been shown to perform effectively on plot-level, field-level, and regional scales for a wide variety of corn hybrids, climatic conditions, and soil types around the world (Hodges et al., 1987; Carberry et al., 1989; Liu et al., 1989; Jagtap et al., 1993; Pang et al., 1998; Garrison et al., 1999; Paz et al., 1999; Fraisse et al., 2001).

One limitation of CERES-Maize is its ability to only evaluate one uniform plot at a time. To remedy this drawback, researchers at Iowa State University have developed a new decision support software called APOLLO (Batchelor et al., 2004), or A pPlication of P recision AgricuLture for FieLd Management O ptimization. This Windows-based software is capable of using the CROPGRO-Soybean and CERES-Maize models to analyze precision farming for soybeans and corn by evaluating several uniform management zones with relative ease. APOLLO has the capability of independently evaluating over 100 management zones, or “grids,” at once, allowing the user to easily evaluate various management practices in a precision agriculture context. APOLLO has the ability to calibrate models to simulate historic spatial yield variability, validate these models for years not used in calibration, and estimate responses to nitrogen and plant population prescriptions. Recent studies have used the program for nitrogen and population prescriptions for maximum yield (Paz et al., 1999).

Crop model simulations have been used in terms of irrigation, but are in need of further evaluation. For example, Heinemann et al. (2000) used the CROPGRO simulation for various irrigation practices, but stated that scenarios considering different weather conditions and soil types are necessary for a wider acceptance of the simulation. Additionally, increased focus on precision agriculture has created a significant interest in
spatially variable irrigation systems. Several prototype systems for variable-rate irrigation application have been developed, but adequate decision support systems have not (Sadler 2005).

The objective of this work is to create an additional module for APOLLO to automate spatially variable irrigation scenarios. This module would allow the user to prescribe scheduled irrigations or automatic irrigations based on the available soil water of each grid.

2.3. Development

APOLLO uses a Windows-based visual interface to input various management strategies, as shown in Figure 2.1. The irrigation simulation run through APOLLO was developed to simulate specific irrigation strategies to all years and grids evaluated. This function follows much the same logic as that of the nitrogen and population prescriptions developed by Batchelor et al. (2004). APOLLO obtains values from the prescription user interface shown in Figure 2.2 and formats them into a data file, which is acquired by CERES-Maize prior to any simulations. The user-chosen parameters then overwrite any parameters listed in the standard input files for CERES-Maize. A flowchart of the irrigation simulation is shown in Figure 2.3.

Several input parameters are available in the APOLLO visual interface. An option button allows the user to choose between several different irrigation scenarios, including no irrigation, scheduled irrigation, and automatic irrigation with fixed irrigation amounts (simulating precision irrigation). The user can also adjust irrigation efficiency, application amount, and in the case of precision application the management depth and percent of available soil water threshold used for automatic applications. The value for percent of available soil water is found by:

$$\%ASW = \frac{(SW - PWP)}{(FC - PWP)}$$  \hspace{1cm} (3.2)

where \(\%ASW\) is the percentage of available soil water, \(SW\) is the soil water content in the layer (cm\(^3\)/cm\(^3\)), \(PWP\) is the permanent wilting point or lower limit of water available to
plants (cm$^3$ cm$^3$), and $FC$ is the field capacity or drained upper limit of water available to plants (cm$^3$ cm$^3$). All of these water content values are evaluated over the management depth specified by the user.

Figure 2.1. APOLLO prescription module visual interface.

In order to evaluate the performance of various simulation schemes, output files were created within the CERES-Maize subprocedures to output seasonal data specifically pertinent to irrigation simulations. Such data includes year, grid number, yield, number of irrigations, total amount irrigated, rainfall, evapotranspiration, runoff, and drainage.
One method used to create irrigation schedules was to create a new field assuming average properties of the grids contained within the field. This new field, assumed as a single grid, can then be run with automatic irrigations when required. A separate output file contains the daily irrigation schedule for the simulation. This schedule is then applied to each grid of the spatially-variable field, thus simulating scheduled uniform irrigation. Typical management decisions are made in a similar manner in which a farmer will irrigate when the field, on average, indicates a need for supplemental water.
2.4. Model Performance

In order to validate adequate performance of the irrigation prescription, it was necessary to confirm appropriate responses to model inputs. To perform this task, an additional output file was created to track available soil water on a daily time step. This test was performed on both nonirrigated and irrigated scenarios. While this file was integral in
the evaluation of model performance, it is not required in the overall simulation and was disabled in subsequent model runs due to excessive computing time required.

As 1983 was historically a very dry year with high temperatures, one would expect the available soil water to deplete over the summer. Using the output file mentioned above, the percent of available soil water was graphed using an automatic irrigation scenario in 1983 in a 20.25 ha field near Perry, IA, and is shown in Figure 2.4. This scenario used a management depth of 1 m, a threshold for automatic applications set at 50 percent available soil water, and irrigation application amount of 30 mm, typical values used in irrigation. The grid used for this simulation was a composite of the 100 available grids to model the average response over the entire field. Figure 2.4 shows that under the automatic irrigation scenario, irrigations occur regularly whenever the available soil water falls below the 50 percent threshold. Around Julian Day 257 (September 14), the available soil moisture dips to below 40 percent; this is expected because all irrigations are disabled outside of the growing season. A scheduled irrigation scenario is also plotted with 30 mm irrigations occurring on Julian Days 200, 220, and 230, to show the functionality of the irrigation schedule option in APOLLO. Figure 2.4 also shows rainfall data for the season. Soil water response with rainfall was appropriate: large rainfalls caused large increases in percent of available soil water, while smaller rainfalls cause smaller increases and drought periods caused depleting amounts of soil water. To further validate the functionality of the irrigation simulation, this test was successfully repeated on several years with various application thresholds, application amounts, and management depths, as well as with scheduled irrigation.
Figure 2.4. Daily rainfall and variability in percent of available soil water for three scenarios over 1983 growing season.

2.5. Conclusions

An irrigation simulation was successfully added to the APOLLO visual interface. Automatic irrigations were appropriately triggered at the user-defined value of percent of the available soil water within a user-defined management depth. Soil water response was appropriate for both rainfall and artificial irrigation. This simulation can be a very powerful tool in irrigation feasibility studies such as Chapter 3 of this thesis, deficit irrigation studies, and irrigation management strategies.

2.6. References


3.1. Abstract

Few studies have been done considering the possibility of irrigation systems in Iowa or other humid regions. Recent technological progress in precision agriculture may allow irrigation in these areas to become more economically feasible. Crop models have emerged as a method to evaluate different crop management practices such as irrigation without costly and time-consuming onsite experiments. In this study, the CERES-Maize crop model was used in conjunction with APOLLO, a shell program developed at Iowa State University, to evaluate potential improved yield in a central Iowa cornfield on a spatially and temporally variable basis. Five years of historical yield and weather data were used to calibrate the model over 100 spatially variable grids for nonirrigated conditions in the 20.25 ha field. This calibrated model then used 28 years of historical weather data to simulate three irrigation scenarios: no irrigation, scheduled uniform irrigation, and precision irrigation. 30 mm irrigations were applied when the percent of available soil water fell below 50 percent. Irrigation improved yield by at least 1000 kg ha\(^{-1}\) in half of the years simulated, and also showed to have less variability both spatially and temporally. Precision irrigation showed slightly higher yields than scheduled uniform irrigation. Spatial variability of yield was most influence by topography, with the largest improvements occurring on steep sideslopes and hilltops. Assuming use of a center pivot irrigation system, irrigation showed economic returns in only three of the 28 years included in the study. High capital costs were the leading restrictor of economic feasibility.
3.2. Introduction

Water is one of the most important resources when considering the production of agricultural crops. Most semi-arid regions require irrigation to obtain high yields, while many other areas such as Iowa rely exclusively on rainfall to water their crops. The average rainfall in Iowa is normally sufficient for crop production, and an estimated 35 percent of the land is drained to remove excess moisture (Zucker and Brown, 1998). However, Or (1998) found that in countries with large amounts of rainfall, temporal variation in storm frequency and production do not always coincide with the crop needs. Therefore, it can be assumed that an artificial watering system such as irrigation could improve yields by providing consistent watering, but it is not clear whether these increased yields would offset the cost of installation and maintenance for such a system.

Few studies have been done considering the possibility of irrigation systems in Iowa or other humid regions. Schwab et al. (1958) studied the yield response of corn and soybeans to gravity irrigation in Iowa fields from 1951 to 1955, finding an average increased yield of 34.3 bu ac$^{-1}$ on one field and 21.1 bu ac$^{-1}$ on another, when comparing the best yields of each plot. Martin et al. (1985) evaluated several irrigation strategies for corn in humid regions using the CERES-Maize crop model. Johnson et al. (1987) analyzed the economics of center pivot irrigation systems used in Southeastern U.S. peanut fields.

Although these older studies showed limited economic return for irrigation in humid areas, recent technological progress in precision agriculture may allow irrigation in Iowa and other humid areas to be economically feasible. Precision agriculture is already being used to increase farm production in other ways. For example, utilization of precision nitrogen and pesticide application has become more prevalent in recent years. Using similar methods including GPS, remote sensing, and variable-rate spray nozzles, some researchers are focusing on variable-rate precision irrigation systems as well (Sadler et al., 2005). Most of these systems in development utilize center-pivot irrigation technology, mainly because of its potential to mount real-time sensing equipment, vary application rates, and cover the entire field.
Climate and water availability are major determining factors in corn production (Morgan et al., 2003). Paz et al. (1998, 2001) found water stress to be one of the greatest limiting factors in the yield of soybeans. Spatial variability of soil characteristics may also contribute to the variation in yield. For example, Sadler et al. (2000, 2002, 2005) found that spatial variation in soil water relations directly contributes to spatial variation in grain yield and a large amount of spatial variation under drought stress, indicating that water relations are not homogeneous within the observed area. Sadler suggests use of crop models for analysis of this relationship.

One advantage of crop models is the ability to predict the outcomes of various crop management processes without performing large-scale, costly, and time-consuming experiments. Several crop model simulations such as this have been used in terms of irrigation. For example, Guerra et al. (2004) successfully used the EPIC model to simulate crop yield and irrigation demand for several crops in Georgia. Also, Nijbroek et al. (2000) used crop models to determine optimum irrigation management strategies in soybeans. Considering the spatial variability in the field, best results were found when applying the irrigation schedule for the largest management zone to the entire field.

Other research indicates a need for further evaluation of crop models. For example, Heinemann et al. (2000) used the CROPGRO simulation for various irrigation practices, but stated that scenarios considering different weather conditions and soil types are necessary for a wider acceptance of the simulation. In addition, Sadler et al. (2005) discusses the possibility of variable-rate irrigation systems, but also indicates that decision support systems are needed to enhance the viability of such precision irrigation.

When considering the use of irrigation in a crop model, characteristics influencing the decision to irrigate are major inputs to be included. Machado et al. (2000) watered corn according to two irrigation regimes, based on plant 50 percent and 80 percent evapotranspiration demand according to the Penman-Monteith equation. They found that yields were consistently high when irrigating based on the larger evapotranspiration demand. Steele et al. (2000) studied four different irrigation scheduling methods, including one based on CERES-Maize estimates of plant-extractable soil water and another based on real-time sensor feedback. Due to climactic variation between years, Steele suggested that future
irrigation scheduling should follow real-time monitoring or modeling of crop water use. Guerra et al. (2004) used three options to trigger irrigation: plant water stress, soil water tension in the plow layer, and soil water deficit in the root zone. In one of the few documented irrigation experiments occurring in Iowa, Schwab et al. (1958) applied irrigations when the soil moisture dropped to 60 percent of the total water available to plants in the soil. Management Allowed Depletion (MAD) is one of the most used criteria for irrigation scheduling (Martin et al., 1990); estimation of MAD is based on crop type and maximum daily evapotranspiration rate.

The CERES-Maize crop model (Jones and Kiniry, 1986) is a computer program developed to simulate the effects of various inputs, including rainfall and irrigation, on corn growth and yield. The model calculates growth and development of the corn plant in a daily time step. Inputs for the model include management practices (genetics, population, row spacing, planting and harvest dates, fertilizer and irrigation application amounts and dates), environmental factors (soil type, drained upper limit and lower limit, saturated hydraulic conductivity), and weather (daily minimum and maximum temperature, solar radiation, and precipitation). CERES-Maize has been shown to perform sufficiently on plot-level, field-level, and regional scales for a wide variety of corn hybrids, climatic conditions, and soil types around the world (Hodges et al., 1987; Carberry et al., 1989; Liu et al., 1989; Jagtap et al., 1993; Pang et al., 1998; Garrison et al., 1999; Paz et al., 1999; Fraisse et al., 2001).

One limitation of CERES-Maize is its ability to evaluate only one uniform area at a time. To remedy this drawback, researchers at Iowa State University have developed a new decision support software called APOLLO, or Application of Precision Agriculture for Field Management Optimization (Batchelor et al., 2004). This Windows-based software is capable of automating the CROPGRO-Soybean and CERES-Maize models to analyze several plots at a time, thereby allowing for the simulation of precision farming practices for soybeans and corn. APOLLO has the capability to calibrate models to simulate historic spatial yield variability, validate these models for years not used in calibration, and estimate responses to nitrogen and plant population prescriptions. Recent studies have used the program for nitrogen and population prescriptions for maximum yield (Paz et al., 1999).
With increased focus on precision agriculture, new research is underway involving spatially variable irrigation systems. Several prototype systems for variable-rate irrigation application have been developed, but adequate decision support systems have not (Sadler 2005). In order to increase practical functionality of precision irrigation, real-time monitoring, decision, and control systems must be developed and honed. This research utilizes the APOLLO system with the CERES-Maize crop model to evaluate the potential benefits from such irrigation systems without developing the monitoring and control systems themselves.

An additional module was created in APOLLO specifically for this study that will automate spatially variable irrigation scenarios. This study uses APOLLO and the CERES-Maize crop model to predict the potential yields on an Iowa cornfield assuming an optimum amount of available water, inherently predicting the effects of an irrigation system on a typical Iowa cornfield.

The purpose of this study is to simulate three irrigation scenarios in Central Iowa and their effect on corn yield. These scenarios include no irrigation, scheduled uniform irrigation, and automatic irrigation with fixed irrigation amount. Specific objectives are:

1) Determine the potential yield improvement as a result of irrigation, in terms of quantity and frequency. Also, determine if increases in yield cause more consistent yields over time.

2) Evaluate potential changes in spatial variation of yield due to irrigation, and determine what factors lead to such changes if they exist.

3) Compare economic benefits of improved yield with capital and maintenance costs of irrigation systems, and determine the overall economic viability of adding irrigation to the test field.

3.3. Methods

3.3.1. Data

The test field, 20.25 ha near Perry, IA, USA (41.93080° N, 94.07254° W), was separated into 100 even grids, each 45 m by 45 m. Five years of complete historical
management, weather and spatially variable yield data for corn were available (1994, 1996,
1998, 2000, and 2002), with the years in between on a soybean rotation. As discussed below,
these years were used to calibrate the model by adjusting soil properties and minimizing error
between simulated and observed yield for each grid. A digitized soil survey indicated five
primary soil types present in the test field: Canisteo silty clay loam, Clarion loam, Okoboji
soil, Harps loam, and Okojois silty clay loam. Each of the 100 grids was assigned the soil
type that was the most dominant within the grid. A soil map of the field is shown in Figure
3.1, along with elevation.

Weather data for the calibration years were collected daily using a weather station at
the test site. Also available were 28 years (1966 through 1993) of historical weather data
collected from a weather station at the Perry grain elevator, 10 km from the study site. Using
the calibrated model, this second set of weather data was used to simulate crop growth with
and without irrigation from 1966 to 1993. These are referred to as simulation years.

Initial soil water content and nutrient levels were not available for this field. Therefore,
appropriate levels were assumed and assigned throughout the study area. Initial
soil water content was set at 0.35 cm$^3$ cm$^{-3}$, a value near the drained upper limit for the soils
of the field. Initial nutrient levels were set arbitrarily at 0.1 g elemental N, P, and K per Mg
soil; this amount of initial nutrients was set to be negligible because it is assumed that spring
fertilizer applications would supply nutrients for adequate growth. Plant population for each
grid was collected during the 1996 growing season only, and these population values were
used to approximate the plant population for all other years of the calibration. Simulation
years' populations were set at the average population for 1996 to eliminate any modeling
error between grids due to population differences. Calibration model inputs for management
practices (planting and harvest date, fertilizer application rate and dates) were set according
to the producer's actual practice in each of the five growing seasons. Management inputs for
the simulation years were assumed by taking mean values from the calibration years.
3.3.2. Model Calibration

Model calibration is the process of adjusting soil properties within their range of uncertainty to minimize error between simulated and measured yield for each grid over the five years (Batchelor et al., 2004). Because this study relies heavily on the hydraulic properties of the soil, effective tile drainage rate (day$^{-1}$) and saturated hydraulic conductivity
of the deep impermeable layer (cm day\(^{-1}\)) were chosen for calibration parameters. All other properties were assumed as values provided in the input files for the field.

Calibration with APOLLO utilizes the simulated annealing algorithm (Corana et al., 1987; Goffe et al., 1994), which solves for parameter values that minimize the RMSE between measured and simulated yield. The model evaluates each grid (100 total) individually to find the best fit; therefore each grid has its own ideal values for the calibration parameters. During the calibration sequence, APOLLO evaluates one grid at a time. Given default parameter values, APOLLO will run CERES-Maize for each available year and compare the simulated yield with the actual yield for that grid and year. APOLLO then goes through an iteration procedure to minimize root mean square error (RMSE) for that grid, using Formula 3.1:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Y_{m,i} - Y_{s,i})^2}
\]  

where \(N\) = total number of years evaluated, and \(Y_{m,i}\) and \(Y_{s,i}\) stand for the respective measured and simulated yield for the given grid in the \(i^{th}\) year. This process was repeated up to 1500 maximum iterations for all 100 grids in the available five-year dataset, an acceptable number of iterations according to Batchelor et al. (2004).

The calibration was performed using all five available datasets to ensure optimal simulation performance. Using the same field as this study, Thorp et al. (2005) researched leave-one-out (LOO) cross validation, a statistical procedure used to validate crop models in the instance of limited measured data. Thorp determined that the ability of a calibrated model to simulate an independent dataset is vastly improved when the calibration dataset spans a wide range of weather conditions.

The calibration parameters closely modeled the yield for all of the calibration years, as shown in Figure 3.2. The \(R^2\) value for the calibration was 0.69. Simulated yield for the years 1996 and 1998 reached the maximum potential yield for the field, as shown by the "ceiling" reached by nearly all of the grids in those respective years, while year 2002 yields were underestimated. These differences from measured yield were likely an affect of the
process used in calibration. As calibration parameters are assumed, the model will minimize the error between measured and simulated yield; however, varying the parameters can not completely negate all error. With five individual years available for calibration, such large differences in simulated yield can be expected.

Figure 3.2. Simulated vs. measured yield for calibration.

3.3.3. Irrigation Inputs

In the irrigation module developed for APOLLO, the user defines various irrigation parameters depending on the scheme desired. Some parameters influence all irrigation scenarios, such as application efficiency and growth stage for end of applications. Other parameters may or may not be used, depending on the scenario desired.

The application efficiency was set at 85 percent for all scenarios, as typical center pivot systems have an efficiency of 75-90 percent (Martin et al., 1990). Management depth for automatic applications was set at 100 cm, as effective rooting zone for maize is typically 1.0-1.7 m (Fangmeier et al., 2006). The amount of available soil water is calculated at this depth.
The threshold for automatic application is a percentage of available soil water within the management depth that triggers irrigation. The value for percent of available soil water is found by:

\[
\%ASW = \frac{(SW - PWP)}{(FC - PWP)}
\]

where \(\%ASW\) is the percentage of available soil water, \(SW\) is the soil water content in the layer (cm\(^3\) cm\(^{-3}\)), \(PWP\) is the permanent wilting point or lower limit of water available to plants (cm\(^3\) cm\(^{-3}\)), and \(FC\) is the field capacity or drained upper limit of water available to plants (cm\(^3\) cm\(^{-3}\)). All of these water content values are evaluated over the management depth specified by the user.

The irrigation threshold used for this investigation was based on the Management Allowed Depletion, or MAD, of the available water. Using a maximum daily ET of 7 mm day\(^{-1}\) for July (Scherer, 1999), typical for the climate in Iowa, the MAD is found to be 0.50 (Doorenbos and Kassam 1979). With an allowable depletion of 50 percent, the default irrigation threshold value for this study was set at 50 percent of available soil water. Similar values have been used in other crop modeling research (Jones and Ritchie, 1990).

Amount per irrigation was set at 30 mm for all scenarios. This value is typical for most center pivot irrigation systems, where often approximately one inch is applied over a three-day period (Steele et al., 2000).

3.3.4. Irrigation Scenarios

The three irrigation scenarios used in this study include no irrigation, scheduled uniform irrigation on reported dates, and precision irrigation that automatically applies a fixed amount when required by an individual grid.

The scheduled uniform scenario will irrigate based on a user-defined irrigation schedule. This schedule, normally obtained from the input files, contains irrigation date, amount, and other irrigation parameters. To simplify the functionality of this irrigation
simulation, an additional input file is used that contains the desired irrigation schedule. The same amount is applied to all days on the schedule.

In order to apply an appropriate schedule for all 28 years of the simulation, a schedule first had to be created. Assuming the entire field as one grid, an arithmetic mean of all soil properties was taken, as well as average values for calibration years including yield. The field, evaluated as one single grid, was then calibrated using the same process as any other calibration. Because only one grid was calibrated, the calibration produced only one value for each calibration parameter.

Once the single grid was calibrated, the model was run for all of the test years using the precision irrigation scenario and 30 mm applications. This simulates automatic applications to the entire field on the same days; much like current management decisions are made. An output file recorded all days irrigated throughout all years of the model. Using this output file, the full model with 100 grids was run to simulate the same schedule; however, this simulation evaluated each grid individually, modeling the spatial variability of a fixed irrigation schedule.

The precision irrigation scenario will apply 30 mm of water when the available soil water in each grid reaches a level of 50 percent. This scenario evaluates each grid independently and is intended to simulate a precision irrigation system.

3.3.5. Economics

Overall costs of irrigation systems were compared with net returns based on improved yield. Due to widespread use in the irrigation industry and recent developments in precision irrigation systems, center pivot irrigation costs were chosen as an economic basis. Cost estimates of center pivot irrigation systems vary, and estimates in this study were developed by Scherer (2005). All costs and benefits were compared on an annual dollar per acre basis.

Fixed costs were based on normal capital costs of irrigation systems:

- Depreciation on system was calculated assuming a 25 year life of the center pivot and zero salvage value.
- Depreciation on the well, pump, motor, pipe, electric panel, and wires were also calculated assuming a 25 year life and zero salvage value.
Interest on investment, or opportunity cost, was calculated using a 5 percent annual interest rate on the total capital costs.

Insurance was assumed as $0.50 per $100 of capital investment.

Labor costs were estimated at $10 per hour, with 0.75 hours of annual labor per acre.

Annual maintenance was assumed as 1.5% of the capital cost.

Modern center pivot systems usually use diesel or electricity to pump water from a well. An electric motor and pump were assumed for this study. Electric costs can be separated into energy costs and power demand costs.

Energy costs are typically billed per Kilowatt-Hour (KWH) used, and in this case is a function of the amount of water used and the time applied. The first step to determine the energy requirements is to find the water horsepower (WHP) used by the pump. This is found by:

$$WHP = \frac{Q \cdot TH}{3960} \tag{3.3}$$

where $WHP$ = water horsepower, $Q$ = discharge in gpm, $TH$ = total head in feet, and 3960 is a conversion constant. Total head is normally assumed as the depth of the well, in this case assumed to be 100 ft for a basis of comparison. Brake horsepower ($BHP$) is the actual horsepower requirement when taking inefficiencies of the pump and drive into consideration. The $BHP$ is calculated by:

$$BHP = \frac{WHP}{E_{\text{pump}} \cdot E_{\text{drive}}} \tag{3.4}$$

where $BHP$ = brake horsepower, $E_{\text{pump}}$ = pump efficiency at operating conditions, and $E_{\text{drive}}$ = drive efficiency between the pump and the power unit. Assumed values for $E_{\text{pump}}$ and $E_{\text{drive}}$ were 0.75 and 1.00, respectively. Actual horsepower experienced at the power meter is often
higher than brake horsepower due to electric demand, etc. This phenomena is fixed by using a power adjustment factor:

\[ MHP = \frac{BHP}{PF} \]  

where \( MHP = \) meter horsepower and \( PF = \) an adjustment factor assumed to be 0.90.

Horsepower is then converted to energy by multiplying the meter horsepower by the total time used at that horsepower. In this study, average horsepower during use was calculated and then multiplied by the total time used, assuming the pivot would run 24 hours for each day irrigations occurred. Total energy use is found by:

\[ E = MHP \cdot t \cdot 0.746 \]  

where \( E = \) energy in KWH, \( t = \) time in hours, and 0.746 is a conversion factor. Assumed billing for energy was $0.045 per KWH.

Power demand costs are billed on a monthly basis, based on the maximum demand experienced within the month. In most irrigation systems, this typically occurs upon starting of the pump. In this study, the demand was assumed to be the power needed to pump the maximum amount of water required for that month. This value, in kilowatts (KW), can be found by multiplying the maximum daily \( WHP \) for the given month (equation 3.3.1) by a conversion factor of 0.746. Assumed charge for power demand was $9 per KW per month. If irrigation did not occur in the given month, this value was assumed to be zero for that month.

Economic benefit was determined exclusively from improved yields and increased costs due to irrigation. A value of $2 per bushel was assumed as a baseline corn price. Net return due to irrigation was determined by

\[ NR = P \cdot Y - C \]  

(3.7)
where $NR =$ net return in $/ac, $P =$ corn price in $/bu, $Y =$ corn yield in bu/ac, and $C$ is total irrigation cost in $/ac.

3.4. Results and Discussion

3.4.1. Yield Improvement

Overall, irrigation was shown to improve yields over the duration of the study, as shown in Figure 3.3. Average annual yield is the mean yield of all 100 grids for the given year and scenario.

These improvements were more dramatic in many years with low nonirrigated yields, such as 1977 and 1980. However, other years with historically low yields such as 1983 and 1988 showed a less dramatic increase in yield. This could be due to a low maximum yield from extremely undesirable growing conditions independent of available rainfall or supplemental irrigation. For example, 1988 not only had low amounts of rainfall, but also had the highest temperatures and greatest amount of solar radiation when compared to all other years in the study.
The improvement in yield was plotted against the nonirrigated yield, as shown in Figure 3.4. As shown by the linear regression lines, seasons with nonirrigated yields of 11,000 kg ha\(^{-1}\) or less (or all the years included in the study) could potentially benefit from artificial irrigation. Again, difference in response between uniform scheduled uniform irrigation and precision irrigation seemed to be relatively insignificant, although precision irrigation showed slightly higher yield improvement and also had a higher R\(^2\) value, showing more uniformity in yield. Ten years of the 28 simulated showed very little improvement in yield; all of these years had nonirrigated yields of at least 8000 kg ha\(^{-1}\). The year 1977 showed the largest improvement in yield, with 5499 and 5501 kg ha\(^{-1}\) for scheduled and precision irrigation, respectively.

![Figure 3.4. Yield improvement vs. nonirrigated yield.](image)

Comparing yield improvement in both irrigation scenarios, a normal probability plot was created and is shown in Figure 3.5. A curve was fit to the data for ease of interpretation. This plot shows that there is little to no improvement in yield in about 30 percent of years,
but 50 percent of years the improved yield will be roughly 1000 kg/ha or greater, and 30 percent of years the improvement will be approximately 2000 kg/ha or greater.

Figure 3.5. Normal probability of yield improvement by irrigation.

A normal probability plot of average annual yield shows that irrigation will create not only higher yields, but more temporally consistent yields (Figure 3.6). One important note about this graph is because it is a normal probability, the years do not necessarily line up with each other (i.e. the lowest nonirrigated yield is not necessarily the lowest irrigated yield). However, it does show the consistency in yields to be expected over the duration of the study. Irrigated yield is greater than 10,000 kg ha\(^{-1}\) in 68 percent of the years and greater than 8,000 kg ha\(^{-1}\) in 96 percent of the years, whereas nonirrigated yield is greater than 10,000 kg ha\(^{-1}\) in only 32% of the years and greater than 8000 kg ha\(^{-1}\) in only 71 percent of the years.
Over the 28 year duration of the study, the average nonirrigated yield was 8817 kg ha\(^{-1}\). Irrigation scenarios increased the average yield by 1398 and 1425 kg ha\(^{-1}\) for scheduled and precision irrigation, respectively. Improved yield by precision irrigation was slightly better than scheduled irrigation and had slightly less temporal variability.

Table 3.1. Yield and irrigation means and standard deviations for irrigation scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Yield, kg ha(^{-1})</th>
<th>Total Irrigation, mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>No irrigation</td>
<td>8817</td>
<td>2016</td>
</tr>
<tr>
<td>Scheduled uniform irrigation</td>
<td>10215</td>
<td>1267</td>
</tr>
<tr>
<td>Precision irrigation</td>
<td>10242</td>
<td>1184</td>
</tr>
</tbody>
</table>
3.4.2. Spatial Variability

Yield was spatially variable in this field for all irrigation scenarios. The leading contributor to spatial variability in yield was likely the topography of the field based on relative elevation and slope. It is important to note that because CERES-Maize evaluates each grid independently, runoff is calculated and assumed to “disappear” rather than move laterally to adjacent cells or to lower elevations; also, subsurface flow is assumed only to be in the vertical direction and does not flow between cells. Nonetheless, the calibrated model still responds appropriately in areas of the field because of yield variation in calibration years. In the calibration process, the calibration parameters are adjusted to minimize error between simulated and measured yield. Therefore, when certain areas of the field experience high or low yield in reality, these trends will be reflected in the simulations.

Figure 3.7 shows the nonirrigated average yield over all years simulated for each grid. Areas with the highest yield occurred in two sections on the western half of the field, both at the lower elevations. This trend is not surprising, as runoff will likely provide these areas with the most water, and excess water will be drained. High yields also occurred at high elevation with more gradual slopes. The lowest yields occurred on the steep sideslopes of the hills in silty clay loams, possibly due to increased erosion and depletion of topsoil nutrients.

Both irrigated scenarios behaved similar to the nonirrigated scenario, in that the areas of high and low yield occurred at the same places. This trend is shown in Figure 3.8. However, the yield improvement for these scenarios occurred in different places, as shown in Figure 3.9. The greatest improvement in yield under irrigation occurred on the side slopes on the field, in the same grids with low yield under no irrigation. Significant improvement also occurred at the hilltops, while the least improvement occurred at the bottoms of the hills where yield was already high without irrigation. Scheduled irrigation showed more variability in yield improvement than precision irrigation, an expected trend due to equal applications of irrigation water to each grid where water needs are potentially unequal.
Figure 3.7. Nonirrigated average yield over 28 years.
Figure 3.8. Average yield for scheduled uniform (a) and precision (b) irrigation over 28 years.
In terms of spatial variability, irrigation not only proved to increase average yield in each grid, but also decreased the yield variability within each grid. Figure 3.10 plots yield standard deviation for each grid versus yield average for each grid over the 28-year duration of the study. It is interesting to note that there is an inverse linear relationship between these two variables in all three scenarios. This trend occurs because in many cases, the yield in most grids approaches the yield potential, or a maximum potential yield. Because the yields are near the yield potential, any grids that will deviate from the yield potential must be a decrease in yield. In other words, larger standard deviations nearly always occur due to many grids having large negative differences from the yield potential.
3.4.3. Economic Analysis

Fixed costs per acre were found to be $70.47 and $84.46 for scheduled uniform and precision irrigation, respectively. Fixed costs for precision irrigation were higher because of extra equipment costs. The criteria used to find these values can be found in Table 3.2. In both cases, the largest contributors to the fixed costs were the capital recovery costs, totaling approximately 70 percent of fixed costs.

Variable costs of electricity per acre ranged from zero to $27.76 for scheduled uniform irrigation and from $3.55 to $17.73 for precision irrigation. Electric costs were typically less for precision irrigation because of lower demand costs. Under precision irrigation, there were many more days where irrigation occurred but rarely would irrigate all
100 grids evaluated, thus creating a lower maximum demand each month. Neither scenario showed any significant water savings over the other, as shown in Figure 3.11.

Table 3.2. Fixed costs.

<table>
<thead>
<tr>
<th>CAPITAL COSTS:</th>
<th>Scheduled Uniform</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Life (yrs)</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>Acres Irrigated (in 160)</td>
<td>130</td>
<td>130</td>
</tr>
<tr>
<td>Irrigation System Cost</td>
<td>$50,000.00</td>
<td>$50,000.00</td>
</tr>
<tr>
<td>Well, Pump, Motor</td>
<td>$30,000.00</td>
<td>$30,000.00</td>
</tr>
<tr>
<td>Pipe, Meter, Valves</td>
<td>$3,000.00</td>
<td>$3,000.00</td>
</tr>
<tr>
<td>Electric Panel and 1,400 ft of Wire</td>
<td>$7,000.00</td>
<td>$7,000.00</td>
</tr>
<tr>
<td>Precision Equipment Retrofitting</td>
<td>$0.00</td>
<td>$20,000.00</td>
</tr>
<tr>
<td>TOTAL CAPITAL COST</td>
<td>$90,000.00</td>
<td>$110,000.00</td>
</tr>
<tr>
<td>CAPITAL COST PER ACRE</td>
<td>$692.31</td>
<td>$846.15</td>
</tr>
<tr>
<td>OWNERSHIP COST (per acre)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual cost using capital recovery method(^a)</td>
<td>$49.12</td>
<td>$60.03</td>
</tr>
<tr>
<td>Insurance ($0.50/$100)</td>
<td>$3.46</td>
<td>$4.23</td>
</tr>
<tr>
<td>TOTAL ANNUAL OWNERSHIP COST</td>
<td>$52.58</td>
<td>$64.27</td>
</tr>
<tr>
<td>OPERATING COSTS (per acre)(^b)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power (electric)</td>
<td>variable</td>
<td>variable</td>
</tr>
<tr>
<td>Labor (@$10.00/hr, 0.75 hr/acre)</td>
<td>$7.50</td>
<td>$7.50</td>
</tr>
<tr>
<td>Maintenance (1.5% New Cost)</td>
<td>$10.38</td>
<td>$12.69</td>
</tr>
<tr>
<td>TOTAL ANNUAL OPERATING COST(^b)</td>
<td>$17.88</td>
<td>$20.19</td>
</tr>
<tr>
<td>OPERATING AND OWNERSHIP COST(^b)</td>
<td>$70.47</td>
<td>$84.46</td>
</tr>
</tbody>
</table>

\(^a\) Includes both interest and depreciation, assuming 5% compounded annually
\(^b\) Not including variable power costs

Overall, irrigation was found unprofitable in both irrigation scenarios, as shown in Figure 3.12. Scheduled irrigation and precision irrigation showed respective annual net losses of $41.76 and $51.02 per acre over the duration of the study. Only in three individual years did irrigation show to be profitable in both scenarios (1975, 1977, and 1980), all of which were dry years showing increased yields of at least 4400 kg/ha. Profitability was highly limited by the large capital costs of the irrigation systems and the ability to create
large improvement in yields. To overcome fixed costs alone over the duration of the study, a corn price of $4/bu would be required.

![Figure 3.11. Annual water consumption for both irrigation scenarios.](image)

A decrease in capital costs could possibly improve the economic viability of irrigation in this field. However, in order to break even over the duration of the study, the total capital costs would have to be decreased to $30,315 for scheduled uniform irrigation and $37,070 for precision irrigation. As both of these values are one-third of assumed current costs, it is highly unlikely that the costs will ever fall this low.
3.5. Conclusions

Overall, irrigation was shown to improve corn yield over the duration of the study. The improvement in yield was at least 1000 kg ha\(^{-1}\) in half of the years simulated for both irrigation scenarios, and at least 2000 kg ha\(^{-1}\) in one-third of the years simulated. Precision irrigation showed slightly higher overall yields than scheduled uniform irrigation. Irrigation not only improved yield over time, but created more consistency in yield between years, as yield was at least 8000 kg ha\(^{-1}\) in all years simulated but one whereas nonirrigated yield was less than 8000 kg ha\(^{-1}\) in 8 of the 28 years. Spatial variability in yield was mainly
influenced by slope and field location. With no irrigation, yield was typically the highest at the bottoms of hills and the lowest on the sides of hills. This trend was also true with irrigation, but the greatest yield improvement was found on the sideslopes. Irrigation not only caused less variability temporally, but spatially as well. Neither irrigation scenario showed overall economic viability, and only three of the 28 simulation years showed positive cashflow due to irrigation. The largest economic limitation was the capital cost for a center pivot irrigation system, with fixed annual costs of $70.47 and $84.46 per acre for scheduled uniform and precision irrigation, respectively.

While this study was helpful in determining the feasibility of irrigation in a cornfield near Perry, IA, some recommendations can be made for further research. First, it would be interesting to perform a similar study on a field more suited for irrigation need, such as fields in western Iowa with sandier soils and drier climates. Also, as the irrigation module used in this project is run alongside previously developed nitrogen prescription modules, an opportunity presents itself to research irrigation and nitrogen management simultaneously.

3.6. References


CHAPTER 4. GENERAL CONCLUSIONS

4.1. Conclusions

An irrigation simulation was successfully added to the APOLLO visual interface. Automatic irrigations were appropriately triggered at the user-defined value of % of the available soil water within a user-defined management depth. Soil water response was appropriate for both rainfall and artificial irrigation. This simulation can be a very powerful tool in irrigation feasibility studies, deficit irrigation studies, and irrigation management strategies.

Overall, irrigation was shown to improve corn yield over the duration of the study. The improvement in yield was at least 1000 kg ha\(^{-1}\) in half of the years simulated for both irrigation scenarios, and at least 2000 kg ha\(^{-1}\) in one-third of the years simulated. Precision irrigation showed slightly higher overall yields than scheduled uniform irrigation. Irrigation not only improved yield over time, but created more consistency in yield between years, as yield was at least 8000 kg ha\(^{-1}\) in all years simulated but one whereas nonirrigated yield was less than 8000 kg ha\(^{-1}\) in 8 of the 28 years. Spatial variability in yield was mainly influenced by slope and field location. With no irrigation, yield was typically the highest at the bottoms of hills and the lowest on the sides of hills. This trend was also true with irrigation, but the greatest yield improvement was found on the sideslopes. Irrigation not only caused less variability temporally, but spatially as well. Neither irrigation scenario showed overall economic viability, and only three of the 28 simulation years showed positive cashflow due to irrigation. The largest economic limitation was the capital cost for a center pivot irrigation system, with fixed annual costs of $70.47 and $84.46 per acre for scheduled uniform and precision irrigation, respectively.

4.2. Recommendations

While the CERES-Maize crop model is a very powerful tool in evaluating management practices, several factors hinder its practical functionality. Limitations having particular interest to this study deal with water balance procedures. First, CERES-Maize evaluates each grid independently, which does not reflect reality especially in terms of water
balance. The model does calculate runoff, but simply assumes this water disappears instead of moving to an adjacent area. This methodology is somewhat acceptable when only evaluating a single grid, plot, or field, but is undesirable for a spatially variable application such as APOLLO. As an additional limitation, runoff is calculated using the SCS Curve Number Method. After runoff is calculated, infiltration is calculated and irrigations are applied. The sequence of such events not only omits the possibility of runoff due to irrigation, but also is backwards from a reality in which runoff occurs after saturation due to infiltration capacity.

One alternative recommendation for this study is to calibrate using SCS Curve Number as an additional calibration parameter. Another more involved recommendation is an update of the CERES-Maize and APOLLO models to transport runoff water to adjacent grids. Such a process would have to use a “top down” methodology in terms of elevation and would likely require several times the computing power for both calibration and simulations. However, such changes would be instrumental in more closely modeling actual water balance interactions.

Two other recommendations have been formed which are less involved in the computer programming aspect of this project. First, it would be interesting to perform a similar study on a field more suited for irrigation need, such as fields in western Iowa with sandier soils and drier climates. Also, as the irrigation module developed in this project is run alongside previously developed nitrogen prescription modules, an opportunity presents itself to research irrigation and nitrogen management simultaneously.
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