VALUING WEATHER INFORMATION IN IRRIGATED AGRICULTURE

by

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(Under the Direction of Jeffrey D. Mullen)

ABSTRACT

Agricultural production is risky because it depends on weather which can vary from day to day. Thus, the risk associated with agricultural production can potentially be reduced by using historic weather data for a particular location to plan strategically to take advantage of favorable weather conditions or to avoid adverse weather conditions. This study uses historic weather information to explore and develop optimal irrigation and planting date for irrigated corn, cotton, peanut and soybeans in Southwestern Georgia. The value of such weather information is also estimated for the Georgia AEMN weather station at Camilla by developing a methodology that is able to estimate the value of site-specific weather information. The methodology involves the use of DSSAT and GIS. The analysis indicates that the estimated value of the weather information from the Camilla AEMN station is $847,502 per year for irrigated corn, cotton, peanut and soybeans.

INDEX WORDS: Camilla, Corn, Cost, Cotton, Crop simulation, DSSAT, Georgia Automated Environmental Monitoring Network (AEMN), GIS, Irrigation, Kriging, Optimal Management, Peanut, Planting Date, Value, Weather Information, Soybeans, Zonal Statistics.

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DEDICATION

This Thesis is dedicated to the memory of my late father (Alhassan Yakubu)

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background

Weather and climate information are vital inputs in many human endeavors throughout the world. Virtually all economic sectors and many public and private activities are affected to some extent by changes in weather and climate (Williamson et al., 2002). For instance, weather and climate variability affect our health and determine our heating and cooling requirement, clothing and nutritional needs (Maddison and Bigano, 2003). In particular, weather events can have a profound and dramatic effect on agricultural production across all regions of the world. Of all economic activities, agriculture is the most dependent on weather and climatic conditions (Adams et al., 2004).

The day-to-day variation in weather conditions represents a major source of risk and uncertainty in many agricultural production systems around the world. In fact, in the United States, weather events such as too much or too little rainfall accounts for the majority of crop failures (Ibarra and Hewitt, 1999). Variation in weather conditions is also associated with other forms of agricultural risks. Weather conditions such as high temperatures, high humidity or higher than normal rainfall, can create the right environment for the outbreak of diseases. They can also improve the conditions for insects and other pest that consume and weaken crops and spread diseases across fields (Fraisse et al., 2006). Similarly, unexpected factors such as drought, crop failure or abundance can result in dramatic changes in the prices of crops across markets.

Farmers do not have a choice over what weather condition they get in the next growing season and also do not know with certainty what weather conditions to expect across their fields. Thus, farmers and other decision makers in the agricultural sector make production decisions based on their understanding of the general weather pattern for their region (Jones et al. 2000). This uncertainty usually results in conservative strategies that sacrifice some productivity to reduce the risk of production losses (Jones et al. 2000).

Since seasonal variation in weather plays an important role in the risks faced by the agricultural sector, one way to reduce that risk is to apply weather information to guide the decision making process in agricultural production. Over the years, the National Oceanic and Atmospheric Administration (NOAA) and many other experimental and research institutions have made significant progress towards enhancing the accuracy of weather and climate prediction (Williamson et al, 2002). However, the potential for producers to benefit from this progress depends on their flexibility and willingness to adapt farming operations to the forecast, timing and accuracy of the forecast, and the effectiveness of the communication process (Fraisse et al, 2006).

Some farmers, especially the resourceful ones, are capable of adjusting their management decisions such as choice of cultivars, planting dates, irrigation water application, and rate and timing of fertilizer application among others, to take advantage of expected favorable conditions or reduce unwanted impacts, if they have timely and reliable predictions of weather into the season. It is now possible to model crop production at specific locations (if site-specific data are available) to provide farmers and other agricultural decision makers with the tools they need to make important production decisions. Given historic daily weather information, the Decision Support System for Agro technology Transfer (DSSAT V4.5) model can be used to evaluate the optimal crop management decisions that will yield the maximum returns for a given crop at a given location. The DSSAT, which is well calibrated and tested at many locations around the world, is increasingly becoming popular among researchers (Amissah-Arthur, 2005). This approach, alongside other techniques is used by this study.

This current study uses historic daily weather information through crop simulation to explore and develop optimal irrigation and planting date for irrigated corn, cotton, peanut and soybean in Southwestern Georgia. The agricultural value of such weather information is also estimated for the Georgia Automated Environmental Monitoring Network (Georgia AEMN) weather station at Camilla by developing a methodology that is able to estimate the value of site-specific weather information.

### 1.2 Weather and Climate Information

Even though weather and climate are often conflated in the popular media, these terms are different concepts and mean different things. The difference between weather and climate is basically the measure of time. Climate describes the long-term pattern of weather in a particular area (Paz and Hoogenboom, 2008). A period of 30 years is usually used to assess the climate of a given location.

Weather, on the other hand, is the day-to-day state of the atmosphere and its short (minute to minute) variation. There are a lot of components to weather. Weather includes sunshine, rain, cloud cover, snow, flooding, wind, hail, sleet, freezing rain, blizzards, ice storms, thunderstorms, steady rain from a cool front and from a warm front, excessive heat, heat waves and many more. In many places, the weather can change from minute-to-minute, hour-to-hour, day-to-day and even from season-to-season. Climate, however, is the average of weather over a long period of time and over a large area. In summary, climate is what one expects, like a hot summer, and weather is what one gets, like a hot day with pop-up thunderstorms on a hot day (Paz and Hoogenboom, 2008).

### 1.3 Weather and Climate Information Based Decisions in Agriculture

The main concern in crop production is crop yield and as a result farmers make weather based decisions almost on daily basis to prevent crop failure and to protect their investment. The consequences of such decisions are often not known with certainty until sometime after the decision is made, and the resultant outcome can either be better or worse than expected (Fraisse et al, 2004). Weather-based decisions involve activities that should occur in a relatively shorter period of time into the future, usually in less than a week. Examples of such agricultural activities include; irrigation, frost protection, fertilizing, and harvesting. On the other hand, climate-based decisions are usually pre-season decisions and tend to be more strategic in nature (Fraisse et al, 2004). Examples of climate-based agricultural decisions include; choice of variety to plant, acreage allocation, pre-purchase of inputs, and marketing.

There has been an improvement in recent years in weather and climate predictions. However, there is still more room for improvement. It is currently not possible to forecast before the start of the season on which day a locality will have precipitation, storms or extreme temperature even though scientists have developed some ability to predict anomalies in the season average of the weather (Fraisse et al, 2004). The accuracy of weather and climate forecasts generally decreases as the lead-time increases. Weather forecasts are fairly accurate for the coming one to two days. As lead-time increases to three, four, or five or more days, accuracy decreases and there is only a small amount of accuracy with lead-time of five to seven days (Fraisse et al, 2004).

The Virtual Academy for the Semi Arid Tropics (VASAT) has grouped weather forecasts into three main categories: short range forecast - up 48 hours; extended forecast - up to 5 days; and long range forecast – from 30 days to the entire season. Forecast accuracy of short range forecast is generally 70-80%. This is reduced to 60-70% and 60% for extended and long range forecast respectively (http://vasatwiki.icrisat.org/index.php/Types_of_weather_forecasting). Each type of forecasting has a role to play in farm operations and planning of agricultural activities. These are presented in Table 1.1.

Timing and accuracy of climate or weather forecasts are necessary for such forecasts to be useful to farmers and other users of climate and weather information. Perfect forecast information is useless if it is delivered to a farmer after the window of time for making decisions, and the same thing can be said of inaccurate forecasts delivered within the decision time window (Fraisse et al, 2004).

**Table 1.1: Types of Weather and their Application in Agriculture**

| Type of Forecast | Forecast emphasis is on: | Forecast Accuracy | Agricultural Application |
|---|---|---|---|
| **24-48 hours forecast** | • High and low Temperature<br>• Wind velocity and direction<br>• Sunshine duration<br>• Time and amount of rain<br>• Relative humidity | 70-80% | • Timing of field operations.<br>• Soil workability.<br>• Drying rate of soil.<br>• Irrigation scheduling.<br>• Spray application.<br>• Labor efficiency-working hours.<br>• Frost Management |
| **Up to 5 days forecast** | • Change in weather type<br>• Sequence of rainy days<br>• Strong wings<br>• Extended dry wet spells | 60-70% | • Determined depth of sowing for optimal seedling emergence.<br>• Decide whether to sow or not.<br>• Plan irrigation based on the expected rainfall.<br>• Ensure maximum efficiency of spraying.<br>• Decide to harvest or not to harvest.<br>• Management of labor and equipment.<br>• Plan for animal feed requirement.<br>• Livestock protection from cold and heat. |

Source: (http://vasatwiki.icrisat.org/index.php/Types_of_weather_forecasting)

**Table 1.1: Continued**

| Type of Forecast | Forecast emphasis is on: | Forecast Accuracy | Agricultural Application |
|---|---|---|---|
| **30 days forecast** | • Abnormalities in temperature and rainfall | 60% | • Soil moisture management.<br>• Pasture management.<br>• Determine irrigation frequency.<br>• Short term storage after harvest.<br>• Decide to store for short term or market perishable products after harvest.<br>• Avoiding chemical sprays if insects or disease are likely. |
| **Seasonal weather Forecast** | • Abnormalities in temperature and rainfall | 60% | • Crop planning-marginal crops vs. normal crops.<br>• Choose crop varieties to suit the expected weather.<br>• Determine expected crop yield.<br>• Plan area to be cultivated to get the required crop produce. |

Source: (http://vasatwiki.icrisat.org/index.php/Types_of_weather_forecasting)

### 1.4 The Georgia Automated Environmental Monitoring Network

Weather information is, and will continue to be an important input in the management decision making process of many human activities including agriculture. At the national level, the National Weather Service (NWS) is charged with the responsibility of weather monitoring and recording. The NWS is the lead forecasting outlet for the nation's weather and supplies more than 25 different types of reports, warnings and weather watches (Paz and Hoogenboom, 2008).

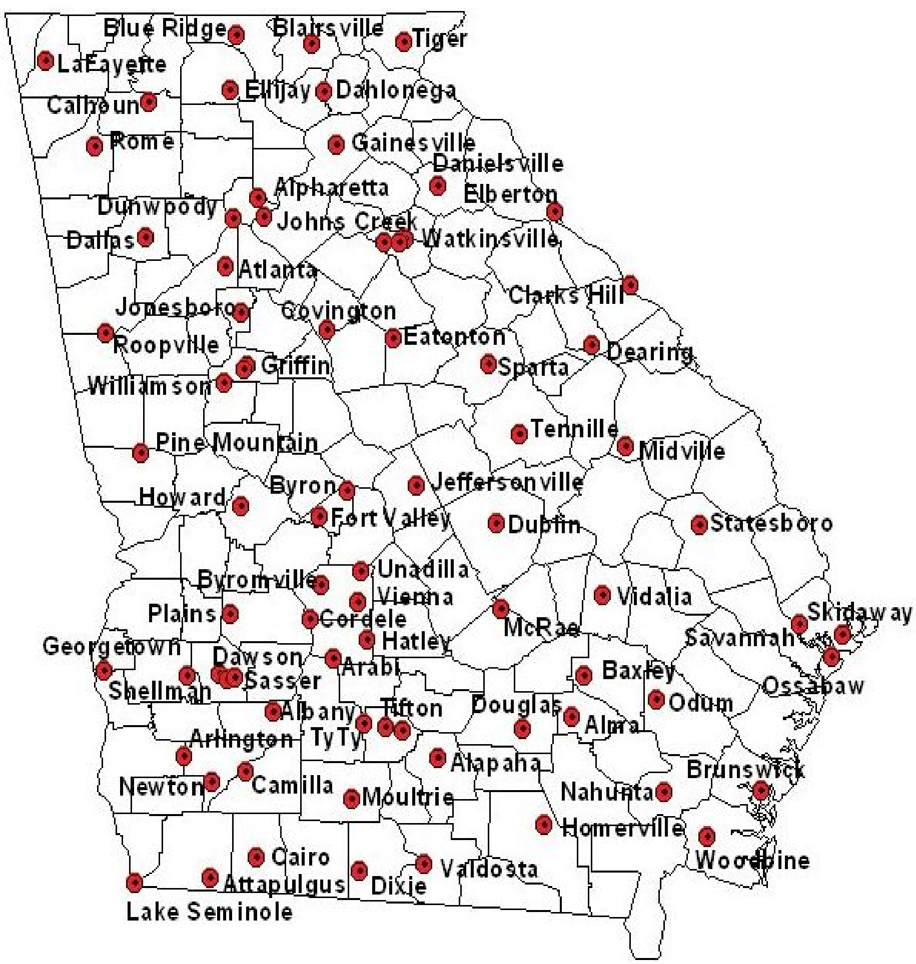
In the state of Georgia, the NWS is the main supplier of short-term weather information. It operates the Automated Surface Observing System (ASOS) at major airports such as the Hartsfield-Jackson International Airport in Atlanta and many others locations across the State of Georgia (Hoogenboom et al., 2003). In addition, the NWS also manages a Cooperative Weather Observer Network that is operated mostly by volunteers (Hoogenboom et al., 2003).

The weather information provided by the NWS, in some cases, has a limited application to agriculture and other natural resource management. This is because the ASOS are located at or near major metropolitan airports. Most airports have a history of site relocations and instrument changes and/or are located within changing urban environments which has degraded the continuity of the long-term data. In addition, urbanization and the resulting heat island influence (artificial warming) has made airport data unsuitable for agricultural use. Also, the Cooperative Weather Observer Network weather data, in most cases, are not available for weeks or months after the observations are taken and data quality may be an issue due to obsolete equipment and lack of effective quality control (NWS, 2009).

In the light of these problems, an interdisciplinary committee, consisting of the University of Georgia's Agricultural Experimental Stations, the University of Georgia's Agricultural Extension Service, the United States Department of Agriculture (USDA)-Agricultural Research Service, and the National Weather Service (NWS), was formed in 1987 to study the need for a University of Georgia Automated Weather Station Network (Hoogenboom et al., 1991). The committee concluded in its final report that continuous long-term weather records are needed for many locations in Georgia and that real time data are also needed for applications in agricultural research management (Westbrook et al., 1988).

Following the recommendation of this committee, the College of Agriculture and Environmental Sciences of the University of Georgia in 1991 established the Georgia Automated Environmental Monitoring Network (Georgia AEMN) with the installation of four automated weather stations in Griffin, Tifton, Watkinsville and Midville (Hoogenboom, 2003). The number of Georgia AEMN weather stations increased steadily over time and by September of 2002 the 50th weather station was installed at Homerville in South Georgia (Hoogenboom, 2003). The network currently has 79 weather stations across the State of Georgia. The distribution of these weather stations is shown on figure 1.1.

**Figure 1.1: Georgia Automated Environmental Monitoring Network Stations**



The main objective for establishing the Georgia AEMN Stations is to collect reliable weather data and other environmental variables for agriculture and related applications (Hoogenboom, 1993). The Georgia AEMN stations are designed to collect air and soil temperature, barometric pressure, solar radiation, wind speed and direction, rainfall, relative humidity and soil moisture. Each Georgia AEMN station is a stand-alone unit that is powered by a battery. The battery is recharged with a solar panel during day light hours. Each station also has a modem and a dedicated phone line. There are also dedicated computers that download and process the weather data from the weather stations. The processed data is then disseminated to the public in near real-time via the web at www.georgiaweather.net (Hoogenboom, 2003).

### 1.5 Problem Statement

Since its establishment in 1991, the Georgia Automated Environmental Monitoring Network has produced quality weather products for different applications in agriculture, natural resource management and other entities. The weather data recorded by the Georgia AEMN are made available to the public through the web at www.georgiaweather.net. This web site offers many different calculators, including growing degree-days, chilling hours, water balance, soil temperature, heating degree-days, cooling degree-days, rainfall, and average temperature (Hoogenboom, 2003). The website also provides a unique application of weather information on agricultural production by offering a crop simulation and yield analysis tool (Paz, et al., 2008). With this tool, users can estimate crop growth and yield as a function of their local weather conditions and management options. Weather products from the Georgia AEMN are also utilized by utility companies to manage their operations. Weather information from the Georgia AEMN also played a crucial rule in the organization and overall success of the 1996 Olympic Games held in Atlanta Georgia in 1996 (Hoogenboom et al., 1998).

Operating and maintaining weather stations that records accurate weather information requires sufficient personnel and financial resources. Cuts in budgetary allocations to many institutions in recent times due to the economic slowdown, has the potential to affect the operations of existing Georgia AEMN weather stations and could possibly lead to the termination of some of these weather stations. The question then is, what will be the revenue lost for losing a Georgia AEMN weather station?

### 1.6 Objectives of the Study

The overall objective of this thesis is to develop a methodology that is able to estimate the value of site-specific weather information for irrigated agricultural management. This methodology is then applied to irrigation management in Southwest Georgia, although the methodology is applicable wherever the relevant data are available. The application of the methodology in Camilla entails the following specific objectives.

1. To determine, in an expected utility framework, the optimal planting date and irrigation threshold for irrigated corn, cotton, peanut and soybean production in Camilla.
2. To simulate average crop yield and estimate expected revenues for the four crops under consideration based on the optimal planting date and irrigation threshold.
3. To estimate the lost revenue for losing the Camilla Georgia AEMN weather station, forcing growers in the study area to use weather data from other neighboring GEORGIA AEMN weather stations to make optimal irrigation decisions.

### 1.7 The Study Area

Georgia is a coastal State located in the Southern part of the Unite States of America. The State of Georgia can be divided in to eight soil provinces or Major Land Resource Areas (MLRA) geographically. These include the Southern Appalachian, Sand Mountain, Blue Ridge, Southern Coastal Plain, Black Lands, Southern Piedmont, Sand Hill, and Atlantic Coast Flatwoods. A humid subtropical climate with mild winters and moist summers is characteristic of most of Georgia. These, combined with the variety of soil types from the coast to the mountains, makes Georgia an ideal place to produce a diverse variety of crops. The annual average rainfall varies from 40 inches in central Georgia to more than 75 inches in Northeast Georgia. Monthly average temperatures range from a high of $92.2^0$ F to a low of $32.6^0$ F.

Georgia is an important agricultural state and ranks first in the United States in the production of peanuts, pecans, broilers, and watermelons (USDA). In fact, Georgia produces almost half of all the peanuts produced in the United States each year (Georgia Farm Bureau). Georgia's top ten commodities in order of their rank within the state are broilers, cotton, eggs, timber, horses, peanuts, dairy, greenhouse and container nursery. This ranking is based on the farm gate value of the commodities.

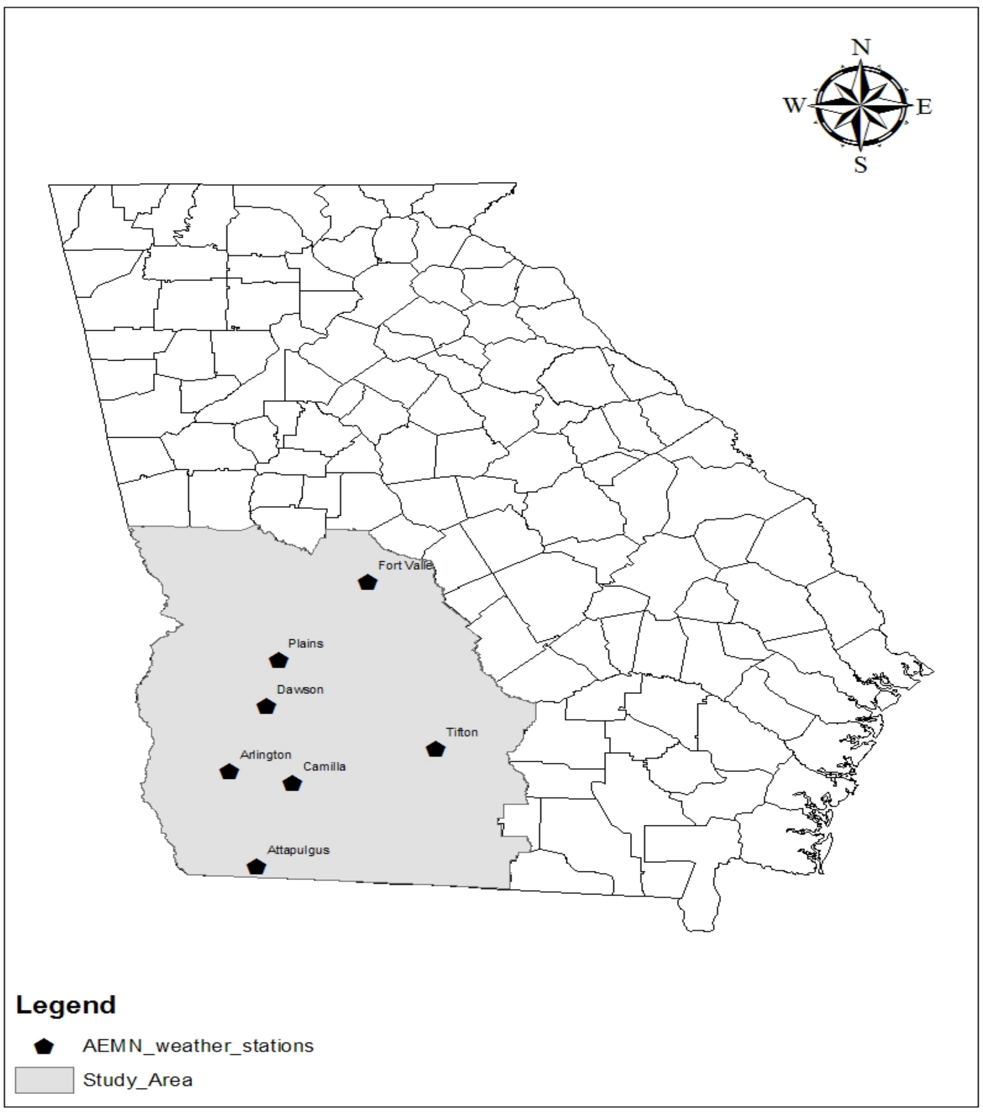
Irrigated agriculture is an important part of Georgia's agricultural system. Over the years the number of farms and acres under irrigation in the State has increased significantly. According to USDA statistics, a total of 773, 066 acres of harvested cropped land were irrigated in 1997. This rose to 1,017,773 acres in 2007 representing about 32% increase in irrigated acres of all harvested crops in the Georgia over the period. At the individual crop level, 210,608 acres of harvested corn were irrigated in 2007. All cotton under irrigation in 2007 was 309,442 acres. The number of harvested acres under irrigation in 2007 for peanut and soybean were 182,332 and

35,285 acres respectively. Irrigated peanut, cotton, soybean and corn acres therefore accounted for about 72% of all harvested irrigated crops in Georgia in 2007 (USDA 2007 Census of Agriculture-County Data). Irrigated crops usually do better than non-irrigated crops under similar management practices and can therefore increase overall farm revenue if well managed. Irrigated agriculture can also reduce the risk and uncertainty associated with agricultural production generally.

Weather information is an important input in making optimal irrigation decisions for a particular location and for a particular crop. Site-specific weather information if available can be used as input in DSSAT to analyze and develop an efficient irrigation schedule for specific crops. This is important not only for efficient use of water but also for insuring that applied nutrients are not leached out by excessive watering or under utilized by crops for inadequate watering.

The actual study area location as shown on figure 1.2 is the Southwestern corner of the State of Georgia, consisting of seven Georgia AEMN weather stations at Fort Valley, Plains, Dawson, Arlington, Camilla, Attapulgus and Tifton. These weather stations are located either directly on a farm or at a research station (www.georgiaweather.net) and thus provide weather data that are representative for agricultural and environmental research and management. The selected stations also have at least ten years of continuous records of daily weather data, making it possible to assess crop yield over ten years using crop simulation models. The Georgia AEMN weather station at Camilla in Mitchell County is the main focus within the study area and referred to as the reference weather station. Mitchell County ranks third in Georgia based on the market value of its crop products (USDA 2007 Census of Agriculture-County Data). In addition, about 42% of all harvested cropland are irrigated in the County, making it an appropriate region for a study that involves irrigated agriculture. Furthermore, significant number of acres of corn, cotton, peanut and soybean are under irrigation in the area. Specifically, the USDA statistics indicates that 12,452 acres of corn were irrigated in Mitchell County in 2007. This represents 68% of all irrigated harvested corn in the County. The same statistics also shows that the percentage of irrigated cotton, peanut and soybean are about 34%, 40% and 26% respectively.

**Figure 1.2 A Map of Georgia Showing the Study Area**



### 1.8 Organization of the Study

This thesis is organized into six chapters. Chapter one showcases a general introduction to the study. The review of exiting body of literature on value of weather information studies is presented in chapter two while the methodology is presented in chapter three. Chapter four showcases model specification, data sources and description. The empirical results is presented and discussed in chapter five. Conclusions and policy recommendations are drawn and presented in chapter six.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

The review of literature for this thesis begins with a look at the benefits associated with the use of weather information and the economic sectors that enjoy these benefits. There are potential impediments that could limit the use of weather information. These impediments are also reviewed and presented in this chapter. Also discussed in this chapter are the determinants of the value of weather information, value of weather information in efficient water management and the methodological approaches used by previous researchers to value weather information. The chapter concludes by looking at the values of weather information from different studies specific to the agricultural sector.

## 2.2 Benefits and Beneficiaries of Weather Information

The benefits as well as the beneficiaries of weather information are many and varied. There are many economic sectors that use weather information to make decisions regularly. For example, producers in the agricultural sector use weather information such as precipitation, temperature, and frost to determine when to plant their corps, when to irrigate and when to mitigate for frost damages (Houston et al., 2004). The agricultural sector is sensitive to changes in weather and therefore stands to benefit from the use of accurate and timely weather information. Accurate and timely weather information on precipitation for instance, can increase irrigation efficiencies and result in significant saving. Similarly agricultural producers can use historic weather information for a given location to help guide them plant their crop to avoid unfavorable weather events.

The aviation, trucking and shipping sectors also use weather information to make important routing decisions. The aviation sector is particularly vulnerable to weather induced traffic delays because bad weather in cities with major airports can have impacts that affect the whole system (Houston et al., 2004). The use of weather information allows air traffic control to make more efficient use of the air space, thereby reducing delays and flight cancellations (NOAA, 2003). It is also expected that the use of weather information in a timely manner will increase efficiencies in the trucking business and allow vessels to decrease transit times and reduce cargo losses due to severe weather conditions.

Governments, their ministries and agencies also use weather information in policy making, strategic and tactical planning that is aimed at the overall national well being of the economy. The use of weather information at the governmental level could be for mitigation or adoption to large-scale disasters such as epidemics, floods, drought, desertification, major snowfalls and icing of the waterways.

Other users or beneficiaries of weather information are the energy sector which utilizes weather information to estimate peak demand for energy and the household sector which uses weather forecast to make decisions such as what to wear, and when and where to go for vacation. In addition, international aid and donor agencies, and the banking, insurance, forestry, fisheries, tourism sectors all relay on weather information to make certain decisions. Finally, the Meteorological Department and other private institutions that produce and supply weather information and services may also benefit commercially from the activity.

## 2.3 Impediments to the Use of Weather Information

Despite the potential benefits associated with the use of weather information, weather information, regardless of how accurate it is, has no value if it cannot be understood and used by the recipients to support the decision making process. Significant impediments exist in the use of weather information, even in advanced technological societies.

For most individual users of weather information, some of these impediments include a lack of awareness of the availability or incorrect belief about weather information availability. According to Changnon et al. (1988), users are either commonly unaware of what weather information is available or there is lack of knowledge about where to go to obtain more specific information.

The second impediment is related to the use of weather information. There is a continuous impression by some users about the quality of weather information. This may stem from a lack of atmospheric training and familiarity with weather information (Changnon et al., 1988). Little belief in the accuracy (quality) of weather information could also stem from personal experiences, hearsay or bad publicity. In addition, most firms lack the flexibility in their operational systems and decision making models to utilize improved weather information. Furthermore, weather information provided to users may be too general and not spatially refined. This presents a challenge to the users in terms of difficulty of interpretation and sufficient application of such weather information to address their particular needs. These impediments need to be addressed for decision makers to reap the full benefits from use of weather information.

## 2.4 Determinants of Value of Weather Information

Macaulay (2006) states that the value of information is essentially an outcome of choice in uncertain situations. Individual decision makers such as a farmer, a businessperson or a trucking company may be willing to pay for information depending on how uncertain they are about the weather, and what is at stake in the event of unfavorable weather. These individuals may be willing to pay for additional or improved information provided the expected cost is lower than the expected gain of the information (Macaulay, 2006). Specifically, the general conclusions from models of information such as (Hirshleifer et al., 1979 and McCall, 1982) are that the value of information depends on a variety of factors.

One factor that affects the value of weather information is how uncertain decision makers are. The value of information depends on the mean and spread of uncertainty surrounding the decision in question (Macaulay, 2006). Harris (2002) illustrates that the value of information can be measured based on how its value changes with changes in different attributes of information such as improve accuracy, greater frequency of collection or other characteristics of the data product itself. The value of information also depends on the value of the resultant output in the market. That is, the aggregate value of the resources or activities that are managed, monitored, or regulated (Macaulay, 2006). In other words, the willingness to pay for weather information relevant to crop production depends in part on the value of the output. Willingness to pay for or demand for weather information is therefore a derived demand.

How much it will cost decision makers to use the information to make decisions and the price of the next-best substitute for the information are factors that also play a part in determining the value of information.

Generally, there is positive a relationship between value of information and the decision maker's level of uncertainty and what is at stake as an outcome of their decision. The larger the level of uncertainty and the larger the outcome of their decision, the more they will be willing to pay for information and hence the larger the value of information, all things being equal.

A decision maker usually has his/her own subjective probabilities about the quality of weather information. Thus, these values also depend on the person who is making use of the weather information. The value of information is zero when the subjective probability is at zero or one, since at these extremes, the farmer for example is already certain in his mind about the weather, for example whether it is going to rain or not. The implication for the value of information from this approach according to Macaulay are that information is without value when there are no costs associated with making the wrong decision and when there are no actions that can be taken in light of the information.

In a related development (Hilton, 1981) specifies four general determinants of the value of information as follows; (a) the structure of the decision set, (b) the structure of the decision environment (the manager, technology, environment and relative preference for outcome), (c) the manager's initial beliefs about the distribution of the stochastic variables in the decision environment, and (d) the characteristics of the information system (timeliness, accuracy and relevance). Though most studies focused on the accuracy of the system, others characteristics are also important to decision makers. These characteristics include; (a) timing of the forecast (lead time), (b) predictive accuracy, (c) the number of future periods forecast at a given point in time, (d) specificity, that is how many separate values or categories a given parameter can assume, (e) spatial resolution (the potential divergence between regional weather and weather outcomes for a specific location within the region), (f) the weather parameters to be forecast and (g) time span covered by a given forecast (for example, year, month or week).

Furthermore, the value of weather information could be affected by such programs as crop insurance, disaster assistance, fixed and counter cyclical payments, and commodity loans, among others. Cabrera et al (2007) in a study of value of climate information in North Florida concluded that farm programs substantially impacted the value of weather information. Specifically, the study points out that commodity loan and crop insurance programs reduce farm income variability and risk level of the enterprises. As a result, the inclusion of commodity loan and crop insurance programs tends to reduce the overall value of weather information, though the value could vary considerably depending on the risk aversion level of the farmer.

### 2.5 Value of Weather Information in Efficient Water Management

Agricultural production is virtually impossible without the use of water resources (rainfall and irrigation). Irrigated agriculture is estimated to provide 40% of worldwide food supplies and despite the fact that water use by non agricultural sectors continue to increase, irrigation continues to be the main water user on a global scale (Muralidharan et al., 2009). Irrigation has been identified as an important risk management tool in agricultural production. Irrigation is therefore, needed to reduce the risk associated with agricultural production and increase food production. At the same time, there is an increasing pressure to use water more efficiently in irrigated agricultural production.

The development and use of simulation tools to model crop production using weather information to take advantage of available rainfall and to schedule irrigation more efficiently is gaining popularity among researchers. For instance, Harman (2004) used a crop simulation model linked to a utility function to evaluate the economic benefits of modifying cropping practices based on seasonal rainfall expectations. The study found the potential economic benefits of tailoring dry land cotton production practices to seasonal rainfall expectations to be from $17 to $21 million per year for the Texas High Plains.

In a related study, Gowing et al. (2000) studied real-time scheduling of supplemental irrigation using short-term weather information and an optimizing decision model. The approach is demonstrated for potatoes grown in eastern England under conditions that represent wet, dry and average years. The results of the study suggest that the model used can provide definite advantages in terms of practical on-farm water management. Specifically, the results show that applying the model to wet years would result in cost and water saving from unnecessary irrigation, resulting in increased profit and efficiencies of irrigation water use. In average and dry years, the benefit of the approach would derive from improved efficiency in the use of limited water supply. Generally, the irrigation schedules developed without weather information applied the highest amount of water in all seasons compared to irrigation scheduling that is developed using weather information

In addition, Wilks and Wolfe (1997) analyzed the economic value of weather information for lettuce irrigation in central New York State using a stochastic dynamic programming algorithm. The results suggest that irrigation is quite valuable, with the economic value of irrigation (scheduled according to a conventional, non-optimal rule) vs. no irrigation estimated at approximately $4,000 to $5,000 per hectare per year for lettuce. Optimal use of weather information to schedule irrigations is estimated to provide additional value of approximately $1,000 per hectare per year, much of which is derived from avoiding crop damage due to excessive soil moisture.

Furthermore, Fox et al. (1998) developed a framework based on a mean-variance model to characterize the value of precipitation forecast information to winter wheat producers in the province of Ontario, Canada. This theoretical framework was applied to precipitation forecast data from the Windsor and the London weather offices for the crop years of 1994 and 1995. The results reveals that the estimates of the value of precipitation forecast information averaged $100.00 (CDN)/ha per year for winter wheat.

### 2.6 Economic Valuation of Weather Information

In many countries around the world, weather information is provided and subsidized by their governments. Estimation of the economic value of weather information is therefore an important way to help justify public investment into technologies that are needed to provide the weather information. Different researchers have approached the estimation of the economic value of weather information differently. Some of these approaches are based on the decision theory to simulate ideal weather responses (Federico et al., 2005)

Using the decision theory, Federico et al. (2005) simulated maize yield in the pampas region with the Ceres-maize model (DSSAT v3.5). The data required for this simulation included daily weather series, soil parameters and initial soil conditions, crop genetic coefficients, and a description of selected crop management. The daily weather variables (max and min temperature, precipitation and solar radiation) were synthetically generated using the stochastic weather generator. Net returns were then calculated by multiplying the simulated yields by a constant output price and subtracting fixed and variable cost. Fixed cost included cost of seeds, fertilizer, herbicides and labor while variable cost included cost of harvesting and marketing. To derive an initial estimate of the value of seasonal forecast, Federico et al. (2005) compared the management combination that maximized simulated average profits for each El Niño-Southern Oscillation (ENSO) phase with the management selected for neutral years with the assumption that management selected for neutral ENSO years is a representation of the preferred management in the absence of any weather information. Federico and others also reasoned that actual decisions frequently deviated from those of typical economic models, a second estimate of forecast value was therefore estimated by comparing the results for census managements selected for each extreme ENSO phase and the management selected for neutral years. This is an alternative and complementary approach and relies on observed or elicited decision, where the emphasis is on how weather forecasts information are actually interpreted and used, rather than ideal responses (Stern and Easterling; Stewart et al., 1997; Stewart et al., 2004).

Victor et al., (2006) also use the decision theory to evaluate the value of weather information by integrating weather, agronomic, economic and policy components in a farm decision model. The agronomic component simulated crop yield by ENSO phases using the longest historical daily weather available (Max and min temperatures, precipitation, radiation) for the study area. The economic component constituted the generation of synthetic prices to match with the simulated yields crop yields that were generated by the agronomic component of the study. Production cost for the crops used (peanut, cotton and maize) were also estimated within the economic framework. The whole farm model was then evaluated using a stochastic non-linear whole farm model to study the role of weather information in decision making and to estimate the value of the weather information. The study was also interested in finding out the effect of government policy on the value of weather information, hence the commodity loan program (CLP) and the crop insurance program (CIP) were introduced in the model to examine the direction of influence of these programs on the value of weather information, if there was any. Crop simulation models are useful in that they allow decision makers to assess the outcome of a wide range of decision alternatives under different weather scenarios.

In a similar manner Jones et al. (2000) indicated that in light of the high cost of long-term field experiments and the long delay before results are available for a sufficient range of weather conditions, crop simulation is the only feasible way to examine the interaction between weather variability, management decisions, and crop yields. Jones et al., (2000) therefore combined crop simulation models and economic decision models to evaluate the potential benefits of tailoring crop production decisions to ENSO phases in Tifton Georgia.

Other researchers have also used the decision model and crop simulation to estimate the value of weather information (Wilks and Wolfe, 1998; Mjelde et al., 1999; Meza and Wilks, 2003; Amissah-Arthur, 2005; Sonka et al., 1987; Fraisse et al., 2006). The decision theory and crop simulation models therefore seems to be a popular choice among researchers and an approach that is increasingly being used by researchers interested in estimating the economic value of weather information.

Other approaches other than the decision theory and crop simulation models have also been used to value weather information. For example, Rollings et al. (2003) use the willingness-to-pay to assess the economic value of weather forecast information in Canada. Other methods that have also been used include; the game theory (lave, 1963 and Anderson, 1979), the Bayesian expected utility maximization (Baquet et al., 1976; Katz et al., 1982; Wilks and Murphy, 1985), the benefit-cost ratio (Mason, 1966), the Marshallian surplus (Bradford and Kelejian, 1978 and Antonovitz and Roe, 1984) and the Bayesian expected cost minimization (Stewart et al., 1984 and Katz et al., 1982). The hedonic analyses have also been used to estimate the value of weather information.

### 2.7 Value of Weather Information for the Agricultural Sector

There are many economic sectors that use weather information on seasonal or long-term basis to make different kinds of decisions. The value of weather forecast may vary from one sector of the economy to the other. Within the agricultural sector, the value of weather information is found to differ from one study to another. The difference in value is in part explained by the different methodological approaches used by different studies to arrive at these values. The values could also vary depending on whether seasonal or long-term weather is being analyzed or whether perfect or imperfect weather information is the subject of concern. Houston et al., (2004) provides a comprehensive summary of values of weather information from numerous studies on agriculture and other sectors of the economy. This summary is presented in Table 2.1 and 2.2.

**Table 2.1: Agricultural Value of Long-Term Weather Information**

| Type of Information | Value of Weather Information | Source |
|---|---|---|
| ENSO predictions | Imperfect: $297-$329 million/yr<br>Perfect: $400 million/yr from US agriculture. | Solow et al. (1998) |
| ENSO early warning system | Imperfect: $20-31 million/yr<br>Perfect: $59-79 million/yr from 5 important agricultural states in Mexico. | Adams et al. (2003) |
| ENSO predictions | Imperfect: $168 million/yr<br>Perfect: $254 million/yr from Southeast U.S. agricultural region. | Adams et al. (1995) |

Source: Houston et al., (2004)

**Table 2.1 Continued**

| Type of Information | Value of Weather Information | Source |
|---|---|---|
| Changes in ENSO frequency and strength | $482-$592 million per year<br>From global agriculture's use of an ENSO monitoring and early warning system. | Chen et al. (2002) |
| ENSO predictions | Imperfect: $507-$959/yr million<br>Perfect: $1,768 million/yr from US agriculture. | Chen et al. (2002) |
| Southern African seasonal forecasts | Imperfect: $178 million/year<br>Perfect: $0.72 billion/year. | Harrison and Graham (2001) |
| Precipitation, temperature, and radiation forecasts | Imperfect $0-$102/ha-yr from Texas sorghum producers. | Hill et al. (1999) |
| Precipitation, temperature, and radiation forecasts | Imperfect: $0-11/ha-yr<br>Perfect:$10-57/ha-yr from planning fertilizer applications on US and Canadian wheat fields. | Hill et al. (2000) |
| Precipitation and temperature forecasts | Imperfect: $-159-$5/section-yr<br>Perfect:$-49-129/section-yr from livestock ranchers in Texas. | Jochec et al. (2001) |
| Precipitation and temperature forecasts | Imperfect: $848-$2,276/yr<br>Perfect: $1,314-$2,800/yr derived from wool producers in Victoria Australia. | Bowman et al. (1995) |
| Precipitation, temperature, and radiation forecasts | Perfect: $1.4-$3.2 billion over 10 years from making fertilizer application decisions in the Corn Belt region. | Mjelde and Penson (2000) |

Source: Houston et al., (2004)

**Table 2.1 Continued**

| Type of Information | Value of Weather Information | Source |
|---|---|---|
| Precipitation forecasts | Imperfect: $1,170-14,520/farm<br>Perfect: $19,900/farm from crop type, nitrogen application, Federal Farm Program participation, and crop insurance decisions. | Mjelde et al. (1996) |
| Precipitation forecasts | Imperfect: $11/ha-yr<br>perfect: $19/ha-yr derived from implementing wheat harvest strategies such as early harvesting, drying, and contract harvesting. | Abawi et al. (1995) |
| Precipitation forecasts | Imperfect: $1.2-2.3/acre from fertilizer application level, planting date and seeding rate decisions. | Mjelde et al. (1997) |

Source: Houston et al., (2004)

**Table 2.2 Agricultural Value of Short-Term Weather Information**

| Type of Information | Value of Weather Information | Source |
|---|---|---|
| Precipitation forecast | Imperfect forecast:<br>-$4.5 to +$27/ha-yr<br>Perfect forecast: $3-$55/ha-yr Alfalfa dry hay production in Canada. | Fox et al. 1999b |
| Precipitation forecast | Imperfect forecast:<br>-$116 to +$276/ha-yr<br>Perfect forecast: $0-$276/ha-yr Winter wheat production in Canada. | Fox et al. 1999a |
| Precipitation and frost timing | Imperfect: 20% increase in profit for wheat producers in Australia<br>Perfect: 15% of value of perfect forecasts is achieved by present Forecasts. | Hammer et al. (1996) |

Source: Houston et al., (2004)

**Table 2.2 Continued**

| Type of Information | Value of Weather Information | Source |
|---|---|---|
| Frost forecast | Perfect forecast:<br>$6,210/hectare/yr for apple orchards.<br>$3,781/hectare/yr for pear orchards.<br>$2,076/hectare/yr for peach orchards. | Katz et al. (1982) |
| Frost forecast | Imperfect forecast: $2,642/ha-yr for pear orchards.<br>Perfect forecast: $4,203/ha-yr for pear orchards. | Baquet et al. (1976) |
| Temperature forecasts | Imperfect: $0.38-$1.09/dollar of insurance premium. | Lou et al. (1994)* |
| Precipitation, temperature, and wind forecasts | Imperfect forecast: $379,248/yr for cotton producers in Australia. | Anaman and Lellyett (1996) |
| Precipitation and temperature forecasts | Imperfect forecast: $1040-$1156/ha-yr for lettuce irrigation timing in a humid US climate. | Wilks and Wolfe (1998) |
| Precipitation, temperature, and evaporation forecasts | Perfect forecast: $105/ha/yr for alfalfa. | Wilks et al. (1993) |
| Improved satellite imagery and sounder which improve short-term (3-hr) temperature forecasts | $9 million/year derived from improvements in frost mitigation. | NOAA (2002) |
| Improved satellite imagery and sounder which improve evapotranspiration estimates | $33 million/year derived from improved irrigation efficiency. | NOAA (2002) |

Source: Houston et al., (2004)

# CHAPTER 3

# METHODOLOGY

## 3.1 Introduction

This chapter describes the methodology developed and used to accomplish the objectives of this thesis. The methodology is divided into three main sections. The first section involves the use of the Decision Support System for Agro-technological Transfer (DSSAT) crop model to simulate crop yield and irrigation water use at selected locations and on selected soils. The second section of the methodology uses an expected utility model, specifically the Constant Relative Risk Aversion (CRRA) utility function to identify the optimal irrigation threshold and planting date for selected crops. The third section of the methodology uses Thiessen polygon analysis in ArcGIS to spatially identify the nearest neighbors of a reference Georgia AEMN weather station and estimate the number of irrigated acres of selected crops on selected soils that are within the sphere of influence of the reference weather station. This makes it possible to apply Kriging and Zonal Statistics, also in ArcGIS, to assess the net revenue lost for losing the reference weather station, forcing farmers within the sphere of influence of the reference weather station to use weather information from different neighboring Georgia AEMN weather stations to make optimal production decisions.

## 3.2 DSSAT Crop Simulations

An approach that is increasingly being used to assess the agricultural value of weather information is the use of DSSAT to simulate crop production (Amissah, 2005). DSSAT has been in use for more than 15 years by researchers in over 100 countries around the world (DSSAT Software). DSSAT is a computer software package that combines soil, crop and weather data into standard formats for access by crop models and application programs (DSSAT Software). DSSAT allows the user to ask "what if" questions and makes it possible to predict crop yield, resource use, and environmental impact as a function of weather and soil data, genetics, and crop management options specified by the researcher. It also allows the user to simulate multiple-year outcomes of crop management strategies for different crops at any location in the world in minutes (provided site-specific data are available). This is important because it eliminates the high cost and long-term field experiments and the long delay before results are ready for any analysis (Jones et al., 2000).

Site-specific minimum weather data set required to run DSSAT are daily weather (maximum and minimum temperature, rainfall and solar radiation). In addition, data on the physical, chemical and morphological soil properties such as surface slope, soil color, permeability and soil drainage are utilized. Furthermore, crop management options data specified by the user are required. These management data include information on planting date, dates when soil conditions were measured prior to planting, planting density, row spacing, planting depth, crop variety, irrigation and fertilizer practices (DSSAT Software).

Although predicted crop yield is the popular and most used output, DSSAT crop simulations produces a variety of outputs including; anthesis date, maturity date, harvest date, irrigation water used, number of irrigation applications, total precipitation received, nutrient uptake, nutrients leached out and byproducts among many others.

This thesis uses the seasonal analysis application in DSSAT (4.5) which allows multiple-year crop simulations to predict the yield and irrigation water used. Ten years of weather data are used to simulate yield of corn, cotton, peanut and soybean at ten different irrigation thresholds on two soils - the Tifton Loamy Sand (TLS) and Norfolk Loamy Sand (NLS). The different irrigation thresholds are discussed in detail under model specification in chapter four.

### 3.3 Determination of Optimal Crop Production Strategy

It is possible to identify from the results of a DSSAT crop simulation which crop management combination produces the highest crop yield. Crop yield alone, however, is not sufficient for determining an optimal crop production strategy. Hence the need for an economic optimization model that takes into account several parameters in identifying the optimal crop production strategy for a given crop.

The Constant Relative Risk Aversion (CRRA) utility function is widely used by researchers to identify the optimal crop production strategy that maximizes expected utility (Messina et al., 1999; Jones et al., 2000; Lin, 2008). This thesis utilizes the CRRA utility function to identify the crop production strategy (irrigation threshold and planting date) mix that maximizes expected utility based on given costs and prices, risk preferences, and crop yield simulated for each set of weather years in Southwestern Georgia. The functional form of the CRRA utility function used is parameterized as:

$$Utility(U) = \frac{NR^{(1-risk)}}{1-risk} \tag{3.1}$$

Where *NR* is the expected net returns to the decision maker, *risk* is the relative risk aversion coefficient. The estimation of expected utility for a given crop production strategy mix is based on the distribution of yield of each crop predicted by the DSSAT crop simulation models. Simulations are run over ten years of daily weather for each crop and we assume that all years are equally likely to occur. It is also assumed that the decision makers (farmers) allocate land among cropping enterprises in a way that maximizes expected utility. Net returns (NR) is estimated via equation 3.2 below.

$$NR = TR - TVC \qquad 3.2$$

TR is gross receipts or total revenue and TVC is total variable cost of the producer. Expected utility is estimated over all years for each planting date and irrigation threshold. The combination of planting date and irrigation threshold that yields the greatest expected utility is then identified. This is captured in equation 3.3.

$$E\left[U_{P,I}\right] = \frac{\sum_{t} U_{t,P,I}}{10} \qquad (3.3)$$

Where *P* and *I* are planting date and irrigation respectively, *U* is the expected utility at a given planting date and irrigation management over time *t*, where *t* = (1, 2,……..10).

The optimal combination of planting date and irrigation threshold identified in this expected utility framework is specific to the reference weather station, which is the location where weather data were collected.

The optimal planting dates and irrigation thresholds identified for the reference weather station are applied to the weather information of other relevant Georgia AEMN weather stations to simulate crop production. From this simulation, the discrete irrigation events (amount of water applied and the time of application) are obtained and applied back to the weather data of the reference weather station and yields, costs and expected net revenues estimated for each of the crops under consideration. The expected net revenues are estimated at this stage are subtracted from the expected net revenues estimated from the initial simulations specific to the reference weather station. The difference between these revenues (lost revenues) represents a change in expected welfare of producers. Measurement of the expected welfare change of the producer is further explained under section 3.4

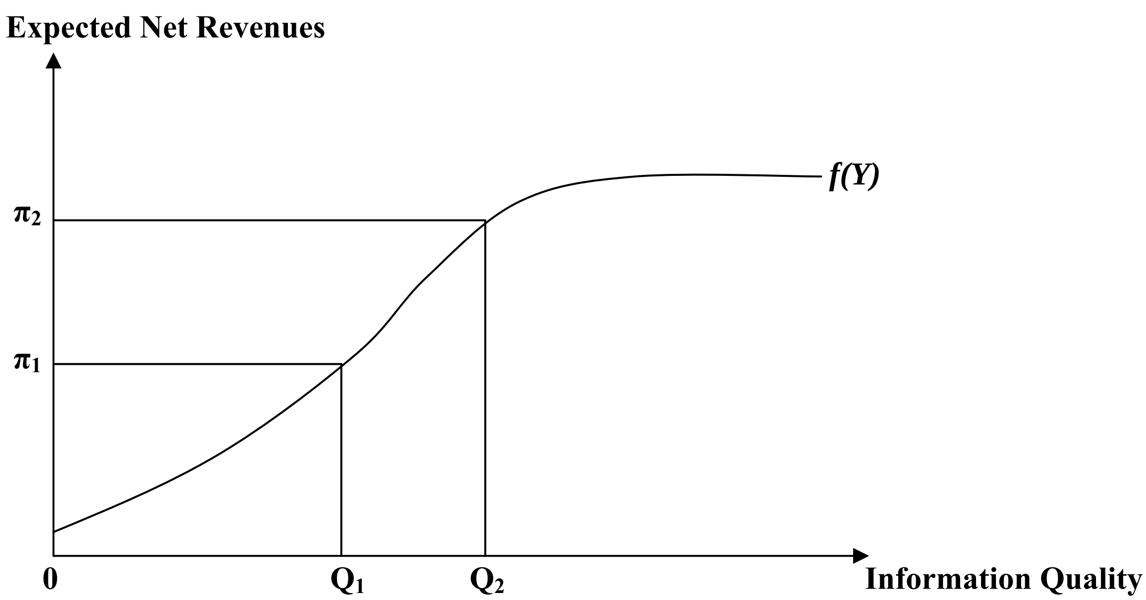
**3.4 Measuring Expected Welfare Changes**

The present study uses an expected utility framework to select an optimal production strategy, consisting of an irrigation threshold and planting date, for each crop using weather data from the reference weather station (the Camilla AEMN weather station). Implementing the optimal production strategy generates actual yields, revenues, costs, water use, and profits for a given set of weather conditions. Implementing the production strategy under weather conditions for multiple years generates expectations for these variables. The values these variables take on, however, are dependent not only on weather conditions, but also on the quality of information about actual weather conditions.

This study uses the proximity of a field to a weather station as a proxy for the quality of weather information. The farther a field is from the site at which the weather information is collected, the lower the expected quality of that information. As a result, producers are more likely to implement the optimal production strategy in a sub-optimal manner as information quality diminishes. When producers are forced to use information from weather stations farther away from their fields, the expected net revenues generated by the optimal production strategy are hypothesized to fall. Figure 3.1 illustrates the hypothesized relationship between expected net revenues and the quality of information.

The change in expected welfare from the loss of a weather station is measured as the change in expected net revenues from producers utilizing lower quality information to implement the optimal production strategy. This is represented by the vertical distance $\pi_1$ $\pi_2$

**Figure 3.1** Measure of Expected Welfare Changes




In this study, two crop production scenarios were considered. In the first scenario, optimal irrigation thresholds and planting dates were developed for peanut, cotton, corn and soybean using weather data from a referenced weather station (the Camilla AEMN weather station). These optimal strategies were used to simulate crop yield in Camilla. The quality of the weather information from the reference weather station is represented by $Q_2$ and the corresponding expected net revenue is $\pi_2$ as show on figure 3.1. In the second scenario, it was assumed that if the referenced weather station is closed down for any reason, producers at Camilla will implement these optimal production strategies based on the weather data of the nearest AEMN weather station. We hypothesized that weather information from these other stations will be lower in quality and therefore result in lower expected net revenue. The Lower quality weather information is represented by $Q_1$ and the associated lower expected net revenue is also represented by $\pi_1$ as shown on figure 3.1. Thus the change in expected net revenue (producer welfare change) is the difference between $\pi_2$ and $\pi_1$.

### 3.5 Spatial Analysis

The first step in the spatial analysis involves the creation of Thiessen polygons also known as proximal polygons around the selected weather stations in the study area. The Thiessen polygons have a unique property that each polygon contains only one input point (weather station) and that any location within a polygon is closer to its associated point than to the point of any other polygon (ESRI Software). The Thiessen polygons are created first with all selected weather stations included and then re-created without the reference weather station. The two layers are then overlaid on top of each other to create a "union polygon". The creation of the union polygon makes it possible to determine the sphere of influence of each weather station. This is important because it allows the estimation of the number of irrigated acres of selected crops for selected soils within the sphere of influence of each weather station.

The second step in the spatial analysis uses the Kriging technique, also in ArcGIS, to create an interpolated surface across the study area (the union polygon). Kriging is an advanced geostatistical procedure in which the surrounding measured values are weighted to derive predicted values for unmeasured locations. In other words Kriging generates an estimated surface from a scattered set of points. Kriging is unique among the interpolation methods in that it provides an easy method for characterizing the variance, or the precision, of prediction (ESRI Software). The lost revenues from losing the reference weather station, relative to the other selected weather stations as described under the section 3.2, are used as the input for the Kriging exercise.

The final step under the spatial analysis applies Zonal Statistics to calculate the average interpolated value per hectare from the interpolated surface created through Kriging. Zonal Statistics is a spatial analysis tool that writes a statistical summary of the values in a raster layer that falls within the bounds of each zonal polygon (that is, minimum, maximum, mean, standard deviation and count) and report the results to a table (ESRI Software).

**Figure 3.2** Diagrammatic Presentation of the Decision Process

**Step 1**
Use DSSAT crop models to simulate crop yield for selected planting dates and irrigation thresholds over a number of years for selected crops on selected soils at the location where weather data were collected (reference weather station). This is the first simulation.

**Step 2**
Use an economic optimization model (The Constant Relative Risk Aversion (CRRA) utility function) to identify the combination of planting date and irrigation threshold that maximizes expected utility over the years simulated at the reference weather station. This is referred to as the optimal strategy for the reference weather station.

**Step 3**
For each of the other selected neighboring weather stations to the reference station, simulate crop production to identify discrete irrigation events (amount of water applied and date of application), using the optimal strategy for the reference weather station from step 2 and the historic weather data from the neighboring weather stations.

**Step 4**
Simulate yields for each year using the discrete irrigation events from step 3 and weather data from the reference weather station.

**Step 5**
Estimate expected net revenues based on the predicted crop yield in step 1 and step 4 and calculate the difference between those two net revenues (the difference is the lost in revenue from losing the reference weather station, and forcing farmers to use weather data from neighboring weather stations to make optimal irrigation decisions).

**Step 6**
Use the Thiessen polygon technique to create Thiessen polygons for all selected weather stations and another one without the reference weather station. Overlay the two Thiessen polygons to show which weather stations constitute the nearest neighbor of the reference station (this is called the union polygon).

**Step 7**
Use Kriging to create an interpolated surface for the union polygon created in step 6 with the expected net revenue lost estimated in step 5 as the input data.

**Step 8**
Use Zonal Statistics to calculate the average value of the interpolated surface created in step 7 for each polygon in the Union polygon.

This in effect, generates an estimate of the net revenue lost for using the optimal strategy for the reference weather station, but implementing that strategy based on the weather information from the neighboring weather stations.

# CHAPTER 4

# MODEL SPECIFICATION

## 4.1 Introduction

This chapter describes the specific management practices, soil and weather data specified in the DSSAT crop simulations for corn, cotton, peanut, and soybean at the Georgia AEMN weather station at Camilla in Mitchell County. The specification of the Constant Relative Risk Aversion (CRRA) utility function and the economic data used to identify the combination of optimal irrigation and planting date are also discussed. Finally, the chapter describes how Thiessen polygons, Kriging, and Zonal Statistics are used in the framework of spatial analysis to estimate the net revenue lost for losing the Georgia AEMN weather station at Camilla.

## 4.2 Crop Simulations

As shown on the study area map, seven Georgia AEMN weather stations were selected for the present study. These weather stations are located at Arlington, Attapulgus, Camilla, Dawson, Tifton, Plains and Fort Valley. Three different sets of crop simulations were carried out. The first set of crop simulations were performed on the weather data of the Georgia AEMN weather station at Camilla (the reference weather station), using DSSAT to simulate crop yield for a range of planting and irrigation thresholds for corn, cotton, peanut, and soybeans. These simulations were done on two soils, the Norfolk Loamy Sand (NLS) and Tifton Loamy Sand (TLS). Site-specific weather data used to run the DSSAT crop model are daily weather (maximum and minimum temperature, rainfall and solar radiation). In addition, crop management data are specified for each crop simulated. The crop management data set varies from one crop to another but is fixed across all years for each crop. The crop management data specified includes crop cultivar choice, planting population, planting date, irrigation and fertilizer applications.

Given the differences in resource endowment as well as differences in risk tolerance among farmers, different farmers are expected to plant their crops on different days within the planting window during the growing season. As a result, crop yield is expected to vary from one farmer to another. It is against this background that different planting dates and other crop management decision variables were examined through crop simulations to determine the optimal combination of planting dates and irrigation thresholds for the four crops considered. The specifications of the different crop management combinations set up in DSSAT are discussed for each crop in the following sections.

### 4.3 Crop Management Data for Peanut Simulation

Georgia is the number one producer of peanut in the United States, producing almost half of the entire peanut produced in the country. A number of peanut varieties are available to Georgia farmers for planting. The Georgia Green, however, is a popular Peanut cultivar in Georgia and in the study area and therefore selected for the DSSAT peanut crop simulations. Georgia Green is a new runner-type cultivar that was released in 1995 by the University of Georgia peanut breeding program. Georgia Green is a very productive cultivar and also has a good stability across many environments. It also produces a significantly higher percentage of Total Sound Mature Kernels (TSMK). The cultivar has also shown good resistance to tomato spotted wilt virus and other peanut diseases and pests (Beasley et al, 2008).

The normal planting window for Georgia peanuts is April 15 - May 20, with a few South Georgia counties being able to plant slightly earlier. In all areas some plantings may be made in late May. These planting periods for Georgia Peanut are based on the recommendations of the UGA Cooperative Extension Services. Based on this recommended planting window, five planting dates were selected for the Peanut simulations. The planting dates are April 10, April 20, April 30, May 10, and May 20.

In addition, ten automatic irrigation thresholds are specified for each of the five planting dates stated above. The automatic irrigation in DSSAT was set up to irrigate the top 30 cm of the soil any time the available soil moisture to plants falls to 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90%. The last irrigation threshold is the no irrigation and means that the crop is simulated under rain fed condition. This wide range of irrigation thresholds were specified to increase the chance of identifying the most efficient irrigation threshold.

As show on table 4.1 below, 11kg/ha of Diammonium phosphate is applied once on the date of planting for each of the five planting dates. Planting method is dry seed and plants are distributed in rows. Row spacing and planting depths are 31 and 4 cm respectively. Simulations are based on plant population of $12.9/m^2$. These specifications are based on recommendations by peanut extension specialists (Beasley et al, 2008).

Ten years of weather data (1997 to 2006) are used to run the simulations. Thus, for each planting date there are 100 DSSAT runs. That is (one planting date, ten automatic irrigations and ten weather years). There are therefore, 500 DSSAT runs for the five planting dates. Simulations are done using the Tifton Loamy Sand and Norfolk Loamy Sand.

**Table 4.1 Crop Management Data for Peanut Production**

| Planting date | Peanut cultivar | Irrigation thresholds | Fertilizer Application | | Soil type | Planting Method | Planting Distribution | Row Spacing (cm) | Planting Depth (cm) | Plant population / $m^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Type | Amount /Time | | | | | | |
| 04/10 | Georgia green | Rain fed, 10%,20%,30%, 40%,50%,60%, 70%, 80%,90% | Diammonium phosphate | 11kg/ha on 04/10 | NLS<br>TLS | Dry seed | Row | 31 | 4 | 12.9 |
| 04/20 | Georgia green | Rain fed, 10%,20%,30%, 40%,50%,60%, 70%, 80%,90% | Diammonium phosphate | 11kg/ha on 04/20 | NLS<br>TLS | Dry seed | Row | 31 | 4 | 12.9 |
| 04/30 | Georgia green | Rain fed, 10%,20%,30%, 40%,50%,60%, 70%, 80%,90% | Diammonium phosphate | 11kg/ha on 04/30 | NLS<br>TLS | Dry seed | Row | 31 | 4 | 12.9 |
| 05/10 | Georgia green | Rain fed, 10%,20%,30%, 40%,50%,60%, 70%, 80%,90% | Diammonium phosphate | 11kg/ha on 05/10 | NLS<br>TLS | Dry seed | Row | 31 | 4 | 12.9 |
| 05/20 | Georgia green | Rain fed, 10%,20%,30%, 40%,50%,60%, 70%, 80%,90% | Diammonium phosphate | 11kg/ha on 05/20 | NLS<br>TLS | Dry seed | Row | 31 | 4 | 12.9 |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

## 4.4 Crop Management Data for Corn Simulation

Like Peanut, many different cultivars of corn are available each year for Georgia corn growers to plant. Differences exist among cultivars in yield potential, maturity, disease resistance, grain quality and adaptability to different geographic areas of the state. Choosing the right cultivar for any production system is important since large genetic differences exist for the many traits of yield. The PIO31G98 Corn cultivar was select because of its wide use in the study area.

Depending on the location, planting dates for corn may range from early March in South Georgia to mid-May in north Georgia. The recommendation by Lee Dewey, Extension grain agronomist, is that if soil temperatures are $55^0$F and higher, and projections are for a warming trend, then corn planting can proceed. Seven planting dates were selected within the early March to mid-May planting window for the DSSAT corn simulations. These planting dates were March 1, March 15, and March 30. The rest are April 15, April 30, May, 15 and May 30.

For each planting date, ten automatic irrigation thresholds were set up in DSSAT for Corn simulation. This means that for each planting date, DSSAT will simulate corn production 100 times at ten different irrigation thresholds. These automatic irrigation thresholds include the 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90% available soil moisture to plants. The tenth irrigation threshold is the no irrigation (rain fed).

The other recommended management practices specified for Corn are shown on table 4.2. Urea (a nitrogenous fertilizer) is applied twice for each planting date. The first dose of 70kg/ha is applied on the day of planting and second dose of 90kg/ha is applied one month after the planting date. Plants are distributed in rows and planted as dry seed. Row spacing is 61 cm and planting depth is 7 cm. Simulations are based on a population of 7.2 plants/$m^2$, the recommended rate for irrigated Corn. Simulations are done on two soils, Tifton Loamy Sand and Norfolk Loamy Sand.

**Table 4.2 Crop Management Data for Corn Production**

| Planting date | Corn Cultivar | Irrigation thresholds | Fertilizer Application | | Soil type | Planting Method | Planting Distribution | Row Spacing (cm) | Planting Depth (cm) | Plant population / $m^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Type | Amount /Time | | | | | | |
| 03/01 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 03/01 90kg/ha on 03/30 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |
| 03/15 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 03/15 90kg/ha on 04/15 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |
| 03/30 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 03/30 90kg/ha on 04/30 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |
| 04/15 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 04/15 90kg/ha on 05/15 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |
| 04/30 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 04/30 90kg/ha on 05/30 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |
| 05/15 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 05/15 90kg/ha on 06/15 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |
| 05/30 | PIO31G98 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Urea | 70kg/ha on 05/30 90kg/ha on 06/30 | NLS TLS | Dry seed | Row | 61 | 7 | 7.2 |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

### 4.5 Crop Management Data for Soybean Simulation

The DSSAT crop simulations for soybean were run over five planting dates. The specified planting dates are May 10, May 20, May 30, June 10 and June 20. These planting dates were selected to fall within the recommended soybean planting window for Georgia. According to the UGA Cooperative Extension Services, the optimum period for planting soybean in Georgia is from May 10 to June 10, but planting can begin as early as May 1 if soils are warm (>70$^{o}$F) and tall-growing MG VI or VII varieties were used. Planting period can also be extended as late as June 30 if adapted tall growing late maturing varieties are used.

The MG VII is one of the recommended varieties of soybeans for Georgia by the UGA Cooperative Extension Services and therefore, selected for the DSSAT soybean simulations. Top soybean yields are generally obtained with row spacing of 20 to 30 inches (Woodruff et al., 2008). In line with this recommended spacing, row spacing of 60 cm was specified in DSSAT for soybean simulations. Similar to corn and peanut, ten automatic irrigation thresholds were set up in DSSAT for each of the five planting dates selected for soybean simulation. A total of 70kg/ha of ammonium phosphate was applied on date of planting. Soybean simulations were based on a population 20 plants/m$^2$. Other recommended practices are show on table 4.3

**Table 4.3 Crop Management Data for Soybean Production**

| Planting date | Soybeans Cultivar | Irrigation thresholds | Fertilizer Application | | Soil type | Planting Method | Planting Distribution | Row Spacing (cm) | Planting Depth (cm) | Plant population / $m^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Type | Amount /Time | | | | | | |
| 05/10 | MG VII | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Diammonium Phosphate | 70kg/ha on 05/10 | NLS<br>TLS | Dry seed | Row | 60 | 3 | 20 |
| 05/20 | MG VII | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Diammonium Phosphate | 70kg/ha on 05/20 | NLS<br>TLS | Dry seed | Row | 60 | 3 | 20 |
| 05/30 | MG VII | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Diammonium Phosphate | 70kg/ha on 06/30 | NLS<br>TLS | Dry seed | Row | 60 | 3 | 20 |
| 06/10 | MG VII | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Diammonium Phosphate | 70kg/ha on 06/10 | NLS<br>TLS | Dry seed | Row | 60 | 3 | 20 |
| 06/20 | MG VII | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Diammonium Phosphate | 70kg/ha on 06/20 | NLS<br>TLS | Dry seed | Row | 60 | 3 | 20 |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

### 4.6 Crop Management Data for Cotton Simulation

Choosing the variety to plant is one of the most important steps in producing a cotton crop. Cotton producers not only choose a variety based on genetic performance but also on pest management traits. The DP 555 BG/RR variety has been successful in recent seasons and will no doubt be widely planted in 2009 (UGA Cooperative Extension Service). Based on this assessment, the DP 555 was selected for cotton simulations.

The best planting window for cotton varies from year to year. Soil temperature is an important consideration for planting. Generally, planting can safely proceed when the 10.2 cm soil temperatures reach 18.3 $^{o}$C for 3 days and warming conditions are projected over the next several days. Planting in late April and early May has shown advantages in South Georgia (UGA Cooperative Extension Service). Five planting dates were selected to cover the recommended April-May planting window for Cotton in South Georgia. The plating dates include; April 1, April 15, April 30, May 15 and May 30.

Like corn, peanut and soybean, the DSSAT simulations for cotton were run over ten automatic irrigation thresholds for each of the five planting dates. These irrigation thresholds as usual include the 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and the no irrigation threshold.

Ammonium Nitrate fertilizer is applied in three dozes of 20kg/ha for each planting date. Planting method is dry seed and plants are distributed in rows. Row spacing is specified at 90 cm and planting depth is 4 cm. The DSSAT cotton simulation is based on a population of 14 plants/m$^2$. These recommended management practices for cotton are outlined in table 4.4 below.

**Table 4.4 Crop Management Data for Cotton Production**

| Planting date | Cotton Cultivar | Irrigation thresholds | Fertilizer Application | | Soil type | Planting Method | Planting Distribution | Row Spacing (cm) | Planting Depth (cm) | Plant population / $m^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Type | Amount /Time | | | | | | |
| 04/01 | DP 555 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Ammonium Nitrate | 20kg/ha on 04/01<br>20kg/ha on 04/24<br>20kg/ha on 05/24 | NLS<br>TLS | Dry seed | Row | 90 | 4 | 14 |
| 04/15 | DP 555 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Ammonium Nitrate | 20kg/ha on 04/15<br>20kg/ha on 05/06<br>20kg/ha on 06/06 | NLS<br>TLS | Dry seed | Row | 90 | 4 | 14 |
| 04/30 | DP 555 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Ammonium Nitrate | 20kg/ha on 04/30<br>20kg/ha on 05/21<br>20kg/ha on 06/21 | NLS<br>TLS | Dry seed | Row | 90 | 4 | 14 |
| 05/15 | DP 555 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Ammonium Nitrate | 20kg/ha on 05/15<br>20kg/ha on 06/05<br>20kg/ha on 07/05 | NLS<br>TLS | Dry seed | Row | 90 | 4 | 14 |
| 05/30 | DP 555 | Rain fed,10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% | Ammonium Nitrate | 20kg/ha on 05/30<br>20kg/ha on 06/21<br>20kg/ha on 07/21 | NLS<br>TLS | Dry seed | Row | 90 | 4 | 14 |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

## 4.7 Determination of Optimal Irrigation Thresholds and Planting Dates

The optimal combination of irrigation thresholds and planting dates for each crop are identified in an expected utility framework. The data used to determine the optimal irrigation thresholds and planting dates included average crop yield data, fertilizer cost, water cost, water application cost and other production variable costs. These data are described in detail under the data section later in this chapter. The first step in identifying the optimal combination of irrigation threshold and planting date for each crop is the estimation of expected net revenues. Expected net revenues are estimated via the following equation 4.1.

$$NR_i^t = TR_i^t - TVC_i^t \tag{4.1}$$

Where $NR_i^t$ = Net revenue for crop *i* in year *t*

$TR_i^t$ = *Total revenue from producing* crop *i* in year *t*

$TVC_i^t$ = *Total variable costs of producing* crop *i* in year *t*

Total revenue is the product of average crop price and average crop yield simulated from DSSAT crop simulation models. The composition of total variable costs is discussed under economic data. The expected net revenues estimated from equation 4.1 and the risk aversion level of the producer are used to calculate expected utility through the Constant Relative Risk Aversion (CRRA) Utility Function. The (CRRA) Utility Function is specified as follows.

$$Utility \quad (U) = \frac{NR^{(1-risk)}}{1 - risk} \tag{4.2}$$

Where *NR* is the expected net revenue and *risk* is the risk aversion coefficient. Producers are classified into two risk aversion levels –moderately risk aversion with risk equal 1.1 and a significant risk aversion with a relative risk aversion coefficient of 2.5. The risk aversion coefficients and the expected net revenues are then plugged into equation 4.2 to calculate the expected utility for each irrigation threshold across all planting dates. Finally, the average expected utility is calculated for each planting date to identify the combination of planting dates and irrigation thresholds that yield the highest average expected utility.

### 4.8 Estimating the Net Revenue Lost for Losing the Camilla AEMN Weather Station

The net revenue lost for losing the Camilla Georgia AEMN weather station is estimated through a combination of crop simulations and spatial analysis. The first step involves the use of DSSAT to simulate crop yield, cost and expected net revenues using weather data from the Camilla weather station. From this initial crop simulation, the optimal planting dates and irrigation thresholds are identified for each crop in an expected utility framework as described above. These optimal planting dates and irrigation thresholds are specific to the Camilla weather station. The second step involves the application of the optimal planting dates and irrigation thresholds to the weather data of the other selected Georgia AEMN weather stations (Arlington, Attapulgus, Dawson, Tifton, Plains, and Fort Valley) to simulate crop production. From this second simulation, the discrete irrigation events (amount of water applied and the time of application) are obtained and applied back to the weather data of the Camilla weather station and yield simulated for each of the crops under consideration. The expected net revenues estimated at this stage are subtracted from the expected net revenues estimated from the initial simulations specific to Camilla weather station. The difference between these revenues (lost revenues) is calculated and used as input data for the spatial analysis. We assumed that in the event of losing the Camilla weather station, farmers who used to depend on the Camilla station's weather data, will use weather data from their nearest neighbors. The Thiessen polygon application in ArcGIS is used to determine which stations constitute the nearest neighbors of the Camilla station. The Thiessen polygons are drawn with and without the Camilla weather station (reference station) and the two layers are overlaid on top of each other to show the sub polygons within the Camilla polygon and the weather stations they are nearest to. The various polygons are shown below.

**Figure 4.1: Thiessen Polygons with all Selected Weather Stations**

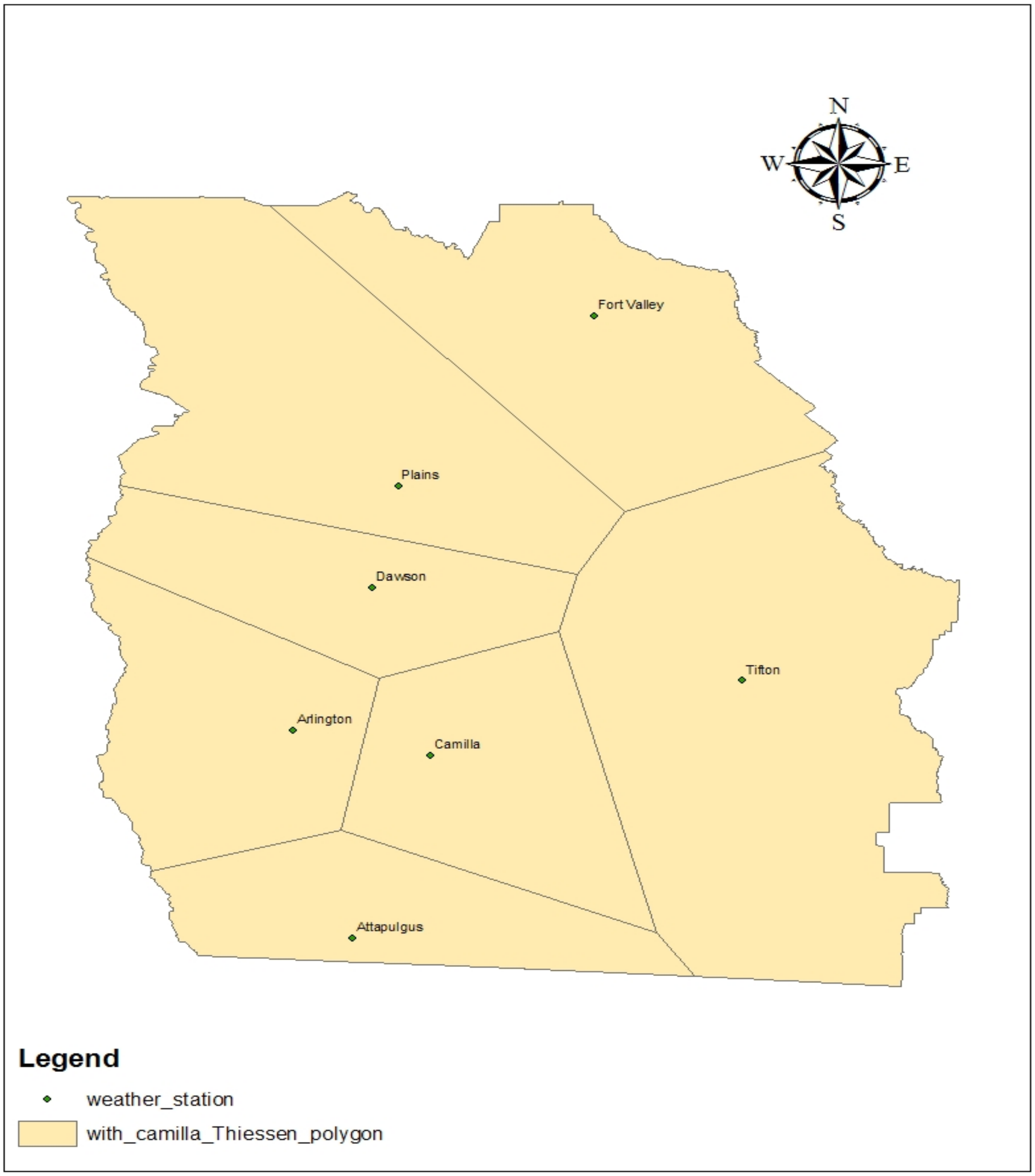


**Figure 4.2: Thiessen Polygons without the Camilla Station**

**Figure 4.3: Thiessen Polygons Showing an Overlay of the with and without Camilla**

As shown on figure 4.3, the overlay of the with and without Camilla polygons shows the sub polygons within the Camilla polygon and which stations these sub polygon are nearest to. In the event that the Camilla station is no more, producers located within the Camilla (A) sub-polygon will use weather information from Arlington, Camilla (B) will turn to the Tifton station for weather data, while Camilla(C) and Camilla (D) will use weather information from Attapulgus and Dawson respectively.

The lost revenues are used as input in the spatial analysis framework through kriging to create an interpolated surface across figure 4.3. The average interpolated value is calculated for Camilla (A), Camilla (B), Camilla (C) and Camilla (D) using zonal statistics. To estimate the net revenue lost for losing the Camilla weather station, the average interpolated values for Camilla (A), Camilla (B), Camilla (C) and Camilla (D) are subtracted from the corresponding lost revenues at the weather stations at Arlington, Attapulgus, Tifton, and Dawson respectively. The difference represent the net revenue lost for losing the Camilla station and forcing producers to implement the Camilla optimal strategy using weather data from Arlington, Attapulgus, Tifton, and Dawson.

**4.9 Data**

**4.10 Soil Data**

Norfolk Loamy Sand and Tifton Loamy Sand are common soil types in Georgia and the top two common soils in Mitchell County where the Camilla Georgia AEMN weather station is located. The soil data is obtained from the Southeast Climate Consortium Database. This database provides soil type information at the county level for counties in Georgia, Florida and Alabama. This database is available via the web at (http://www.agroclimate.org/tools/yieldRisk).

Furthermore, the USDA National Resources Conservation Services custom soil resource report provides data on actual acreage and proportional extent of soils for each County in Georgia. This database is also available at (http://www.mo15.nrcs.usda.gov/states/ga.html). The number of acres of NLS and TLS for all counties within the study area were obtained from this source.

### 4.11 Economic Data

The economic data used for this study include output prices and variable production input cost data for peanut, corn, cotton and soybean. Average output prices for peanut, corn, cotton and soybean were obtained from the UGA Center for Agribusiness and Economic Development. These prices are available through the web at http://georgiastats.uga/sasweb/cgi-bin/broker.
All prices were converted to average price/ton for unit consistency using appropriate conversion factors.

**Table 4.5** 2008 Average Prices for Peanut, Corn, Cotton and Soybean

| **Crop** | **Price** |
|---|---|
| Corn | $ 0.24/lb |
| Cotton | $ 4.75/bu |
| Peanut | $ 0.685/lb |
| Soybean | $ 8.77/bu |

**Source: UGA Center for Agribusiness and Economic Development**

All variable costs except for fertilizer and irrigation costs were obtained from the 2008 South Georgia Crop Enterprise Estimates. Fertilizer prices used for this study are 2008 average US fertilizer prices. The fertilizer price data comes from the National Agricultural Statistics Service of the USDA. These prices are documented and can be accessed from the USDA website at http://www.ers.usda.gov/Data/fertilizeruse/.

**Table 4.6 2008 Average USA Fertilizer Prices**

| **Fertilizer** | **Price** |
|---|---|
| Urea | $ 552/ton |
| Diammonium Phosphate | $ 850/ton |
| Ammonium Nitrate | $ 509/ton |

Source: National Agricultural Statistics Service of the USDA.

Irrigation cost is assumed to consist of two parts: water cost (water price) and water application cost. Because water is not a market good, an explicit water price is not available in Georgia (Mullen et al., 2009). As a result, farm-level water pumping cost is used to approximate water price. In this study, water price is set to $ 0.1953/ha $mm^{-1}$. This is calculated from the water costs estimate of $ 19.53/1000 $m^3$ by Mullen et al (2009).

We approximate water application cost by the labor cost of irrigation water application. The hours of labor required depends on the type of irrigation system been used. This study assumes the irrigation system used is the non-towable center pivot irrigation system. The estimated labor hours required to run this type of irrigation system is two hour per application (Hogan et al., 2007). Labor costs consist of the hourly wage rate times the number of labor hour required. The average of 2008 agricultural wage rate for the Southeast is $ 9/hour (Agricultural Statistics Board, NASS, USDA). Thus the approximate water application cost is set to $ 18 per application. Other variable costs are show on table 4.6 below. These variable costs are costs per acre and thus were converted to costs per hectare.

**Table 4.7** 2008 Variable Production Costs

| **Variable Costs** | **Crops** | | | |
|---|---|---|---|---|
| | **Cotton** | **Peanut** | **Corn** | **Soybean** |
| Seed | 65 | 98 | 60 | 35 |
| Cover Crop Seed | 17 | 17 | 17 | 17 |
| BWEP | 2.5 | - | - | - |
| Chemicals | 88 | 196 | 27 | 47 |
| Scouting | 7.5 | - | - | - |
| Fuel and Lube | 44 | 53 | 21 | 19 |
| Repairs and Maintenance | 22 | 28 | 10 | 9 |
| Labor | 19 | 24 | 9 | 8 |
| Insurance | 13 | 17 | 20 | 14 |
| Drying and Cleaning | - | 40 | 57 | - |
| Interest on Operating Capital | 23 | 25 | 24 | 12 |
| Marketing and Fees | - | 15 | - | - |
| **Total Variable Cost** | **300** | **512** | **243** | **161** |

Source: 2008 South Georgia Crop Enterprise Estimates (UGA Cooperative Extension)

### 4.12 Weather Data

Site-specific weather data used to run the DSSAT crop model are daily weather (maximum and minimum temperature, rainfall and solar radiation) collected at the selected Georgia AEMN weather station. The weather data were obtained from the University of Georgia's Department of Biological and Agricultural Engineering (www.georgiaweather.net). Graphs of average monthly precipitation, maximum and minimum temperature and solar radiation for all the selected weather stations are documented in the appendix section. (Appendix C).

# CHAPTER 5

# RESULTS

## 5.1 Optimal Irrigation Thresholds and Planting Dates

Farmers plant their crops on different dates during the planting season for the same crop. In other words, there is no particular day of the year when all farmers of a particular crop plant their crops. The period of time within which sowing of a crop can be done is referred to as the planting window and this varies from one crop to another. In the same way, differences in soil type, amount of rainfall received as well as the crop that is being planted influences the amount of irrigation water to apply. Thus the first step was to identify the optimal planting date and irrigation threshold for corn, cotton, soybean, and peanut at the Camilla weather station.

The results of the optimal irrigation thresholds and planting dates that maximizes expected net returns to corn, cotton, soybean, and peanut at Camilla are presented in table 5.1. The results show different optimal planting dates and irrigation thresholds across the different crops and soils. The optimal planting date and irrigation threshold for corn planted on Norfolk Loamy Sand (NLS) at the Camilla AEMN weather station is May 15 and 50% automatic irrigation. The optimal mix for corn grown on TLS is May 30 and 40% automatic irrigation. At this optimal mix, the average expected water used is 173 and 185 mm/ha for TLS and NLS respectively. The results also show that soybean produces the best expected net returns when planted on May 10 on both NLS and TLS. The corresponding optimal irrigation threshold for soybean grown on NLS and TLS is 50% automatic irrigation for both soils.

Furthermore, the optimal planting date and irrigation threshold for cotton is April 15 for TLS and, April 1 for NLS. The optimal irrigation is 40% automatic irrigation for both soils.

Optimal planting date for Peanut is April 30 on NLS and May 20 on TLS and the corresponding optimal irrigation threshold is 60% and 70% automatic irrigation respectively. In terms of crop yield, NLS appears to produce the highest yield across planting dates and irrigation thresholds, except for soybean where TLS produces the highest crop yield. The results of the optimal strategies as reported in table 5.1 is based on the risk coefficient of 1.1. However, the results remain the same for the risk coefficient of 2.5 except for soybean (TLS) and corn (NLS). The optimal planting date for soybean (TLS) at this risk level is May 20 and the optimal irrigation is 40% automatic irrigation. That of corn (NLS) is May 30 and 40% irrigation

**Table 5.1 Optimal Irrigation Thresholds and Planting Dates at Camilla**

| Crop | Soil Type | Optimal Irrigation Threshold (%) | Optimal Planting Date | Ave. yield (kg/ha) | Expected net revenue ($/ha) | Expected water used (mm/ha) |
|---|---|---|---|---|---|---|
| Cotton | TLS | 40 | 4/15 | 3425 | 4168 | 221 |
| Cotton | NLS | 40 | 4/01 | 3646 | 4404 | 317 |
| Peanut | TLS | 70 | 5/20 | 3660 | 496 | 158 |
| Peanut | NLS | 60 | 4/30 | 5828 | 1433 | 258 |
| Corn | TLS | 40 | 5/30 | 7719 | 557 | 173 |
| Corn | NLS | 50 | 5/15 | 7963 | 592 | 185 |
| Soybean | TLS | 50 | 5/10 | 3720 | 345 | 315 |
| Soybean | NLS | 50 | 5/10 | 3610 | 397 | 295 |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

The difference in yield between the two soils could be due to differences in soil fertility and other physical and chemical soil properties that support plant growth. It also appears that, except for corn, early planting is more advantageous than late planting as the optimal planting dates for peanut, soybean and cotton are associated with the early planting dates in the planting window. The difference between the optimal planting dates for peanut on NLS and TLS are particularly wide and may not make sense agronomically. However, within the framework of the utility function used for this study, such choices make sense because the optimal planting dates were found to be associated with options that had the highest net revenue and the lowest standard deviation. This assessment holds true for both peanut on TLS and NLS. These summary statistics are available in the appendix section (Appendix D)

### 5.2 Effects for Imposing Optimal Irrigation from other Station on the Camilla Station

We hypothesized that implementing the Camilla optimal strategies based on the weather information from other AEMN weather will result in crop yield decline and some lost of revenue. To verify this hypothesizes, the optimal planting dates and irrigation thresholds developed based on Camilla's weather and presented on table 5.1 was applied to the weather data from the other stations (Arlington, Attapulgus, Dawson, Fort Valley, Plains and Tifton) to simulate crop yield. Net revenues are then estimated based on this yield and the yield obtainable when Camilla's own weather is used to simulate yield at Camilla and the difference in net revenue estimated.

When producers at Camilla implement their optimal strategy using the weather data from neighboring AEMN weather stations, they lose yield and revenue. The lost revenue numbers are showcased in table 5.2. For instance if a producer at Camilla implements the Camilla optimal strategy based on the weather data from Arlington to produce peanut at Camilla, net revenue will decline by $65/ha and $51/ha respectively for NLS and TLS. Similarly, if the optimal strategy is implemented based on Tifton's weather information to produce peanut at Camilla, the producer's net revenue goes down by $154/ha and $208ha for NLS and TLS respectively. The same explanation hold true for the rest of table 5.2.

**Table 5.2 Change in Net Revenue ($/ha)**

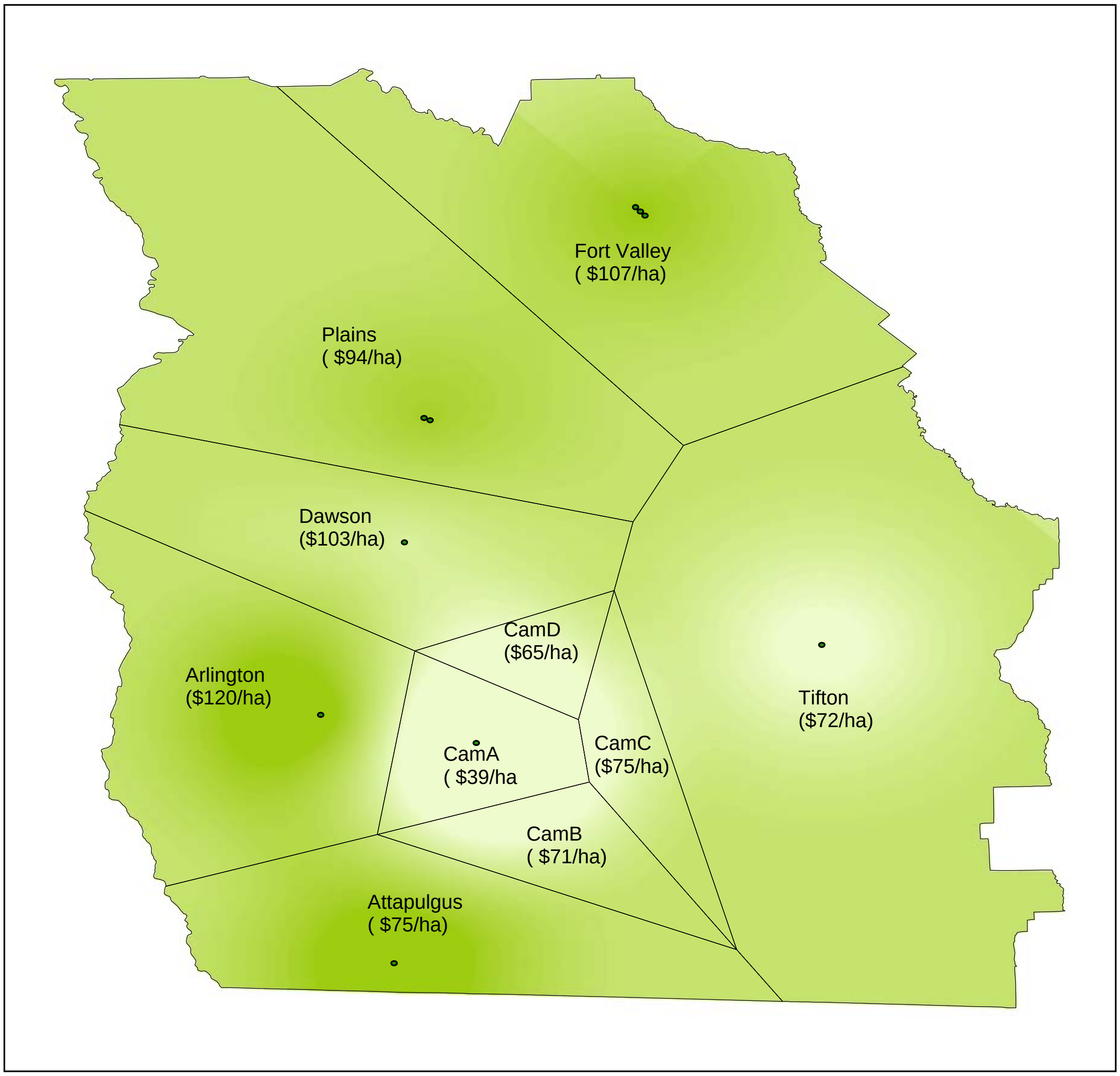
| Weather Stations | Peanut (NLS) | Peanut (TLS) | Soybean (NLS) | Soybean (TLS) | Corn (NLS) | Corn (TLS) | Cotton (NLS) | Cotton (TLS) |
|---|---|---|---|---|---|---|---|---|
| Arlington | -63 | -51 | -157 | -178 | -53 | -120 | -64 | -61 |
| Attapulgus | -63 | -98 | -186 | -184 | -63 | -75 | -47 | -69 |
| Dawson | -129 | -2 | -190 | -129 | -28 | -103 | -48 | -79 |
| Fort Valley | -297 | -8 | -157 | -150 | -100 | -107 | -69 | -67 |
| Plains | -84 | -89 | -140 | -155 | -28 | -94 | -94 | -95 |
| Tifton | -154 | -208 | -168 | -132 | -52 | -72 | -75 | -92 |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

### 5.3 Changes in Net Revenue from Losing the Camilla Weather Station

One of the objectives of this thesis is to estimate the revenue lost for losing the Camilla weather station so that farmers who used to depend on it to develop optimal irrigation threshold and planting date will now have to use neighboring weather stations to make their optimal production decisions. This objective was achieved with the use of GIS techniques (kriging and zonal statistics). The input data for this exercise is the lost revenues presented on table 5.2 above. The kriging technique uses the lost revenues to create an interpolated surface across the study area and zonal statistics estimates the mean interpolated value for each sub-polygon. In calculating the revenue lost for losing the Camilla weather station for each crop, the four sub-polygons (CamA, CamB, CamC and CamD) in the Camilla polygon and their closest neighbor (Arlington, Attapulgus, Tifton, and Dawson) are used (see figure 5.1 below). The dollar value for CamA, CamB, CamC and CamD as shown on figure 5.1 represents the average interpolated value per hectare for each of these sub-polygons. On the other hand, the dollar values for the other polygons on figure 5.1 are the lost revenues when those stations weather data are used to implement optimal strategies for Camilla (change in net revenues from table 5.2)

**Figure 5.1 Kriging Results for Corn TLS**




The results of the net revenue lost from losing the Camilla station for corn simulated on TLS is presented in table 5.3. Column (2) shows the change in net revenue (net revenue lost) for corn simulated on TLS at Camilla, if Arlington, Attapulgus, Tifton or Dawson's weather data is used to implement the optimal strategy for Camilla. Column (4) represents the average interpolated value for the Camilla sub polygons. Thus, the actual revenue lost from losing Camilla and depending on Arlington, Attapulgus, Tifton or Dawson is represented by column (5), which is the difference between column (2) and column (4). As can be seen on figure 5.1, the sub polygons within the Camilla polygon (CamA, CamB, CamC and CamD) are of different sizes and the weighted average approach is used to account for these differences in area. Column (6), therefore, represents the proportion of each sub Camilla polygon and column (7) which is the product of (5) and (6) is the weighted average revenue lost from losing the Camilla weather station.

**Table 5.3 Results of the Net Revenue Lost from Losing Camilla (Corn TLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -120 | camA | -39 | -81 | 0.31 | -25 |
| Attapulgus | -75 | camB | -71 | -4 | 0.29 | -1 |
| Tifton | -72 | camC | -75 | +3 | 0.24 | +1 |
| Dawson | -103 | camD | -65 | -38 | 0.16 | -6 |
| **Total** | | | | | | **$-31/ha** |

The positive number in column (7) for camC is interpreted to mean that producers of irrigated corn in camC are actually better off implementing the Camilla optimal strategy using Tifton's weather data instead of Camilla which they are closest to. This is an unexpected result and could be due to topological effects in the landscape which was not taken into consideration by this thesis. The net effect, however, is negative as shown by the total of column (7) and means that the total net revenue lost from losing the Camilla AEMN weather station and depending on Arlington, Attapulgus, Tifton and Dawson is $ 31/ha for irrigated corn grown on TLS.

Similar interpolated maps like figure 5.1 were created through kriging for cotton, peanut and soybean on NLS and TLS. These maps are available at the index section (Appendix A). The net revenue lost from losing Camilla and depending on Arlington, Attapulgus, Tifton and Dawson weather to produce cotton, peanut and soybean at Camilla were estimated in exactly the same manner as corn on table 5.3 above. The results are presented in tables 5.4 to 5.10.

**Table 5.4 Results of the Net Revenue Lost from Losing Camilla (Corn NLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -53 | camA | -15 | -38 | 0.31 | -12 |
| Attapulgus | -63 | camB | -31 | -32 | 0.29 | -9 |
| Tifton | -52 | camC | -26 | -26 | 0.24 | -6 |
| Dawson | -28 | camD | -17 | -11 | 0.16 | -2 |
| **Total** | | | | | | **$-29/ha** |

**Table 5.5 Results of the Net Revenue Lost from Losing Camilla (Peanut NLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -63 | camA | -25 | -38 | 0.31 | -12 |
| Attapulgus | -63 | camB | -44 | -19 | 0.29 | -6 |
| Tifton | -154 | camC | -67 | -87 | 0.24 | -21 |
| Dawson | -129 | camD | -68 | -61 | 0.16 | -10 |
| **Total** | | | | | | **$-49/ha** |

**Table 5.6 Results of the Net Revenue Lost from Losing Camilla (Peanut TLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -51 | camA | -23 | -28 | 0.31 | -9 |
| Attapulgus | -98 | camB | -64 | -34 | 0.29 | -10 |
| Tifton | -208 | camC | -81 | -127 | 0.24 | -30 |
| Dawson | -2 | camD | -42 | +40 | 0.16 | +6 |
| **Total** | | | | | | **$-43/ha** |

**Table 5.7 Results of the Net Revenue Lost from Losing Camilla (Cotton NLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -64 | camA | -21 | -43 | 0.31 | -13.33 |
| Attapulgus | -47 | camB | -42 | -5 | 0.29 | -1.45 |
| Tifton | -75 | camC | -46 | -29 | 0.24 | -6.96 |
| Dawson | -48 | camD | -33 | -15 | 0.16 | -2.4 |
| **Total** | | | | | | **$-24/ha** |

**Table 5.8 Results of the Net Revenue Lost from Losing Camilla (Cotton TLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -61 | camA | -21 | -40 | 0.31 | -12 |
| Attapulgus | -69 | camB | -43 | -26 | 0.29 | -8 |
| Tifton | -92 | camC | -47 | -45 | 0.24 | -11 |
| Dawson | -79 | camD | -39 | -40 | 0.16 | -6 |
| **Total** | | | | | | **$-37/ha** |

**Table 5.9 Results of the Net Revenue Lost from Losing Camilla (Soybean NLS)**

| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -157 | camA | -60 | -97 | 0.31 | -30 |
| Attapulgus | -186 | camB | -120 | -66 | 0.29 | -19 |
| Tifton | -168 | camC | -125 | -43 | 0.24 | -10 |
| Dawson | -190 | camD | -106 | -84 | 0.16 | -13 |
| **Total** | | | | | | **$-72/ha** |

**Table 5.10 Results of the Net Revenue Lost from Losing Camilla (Soybean TLS)**

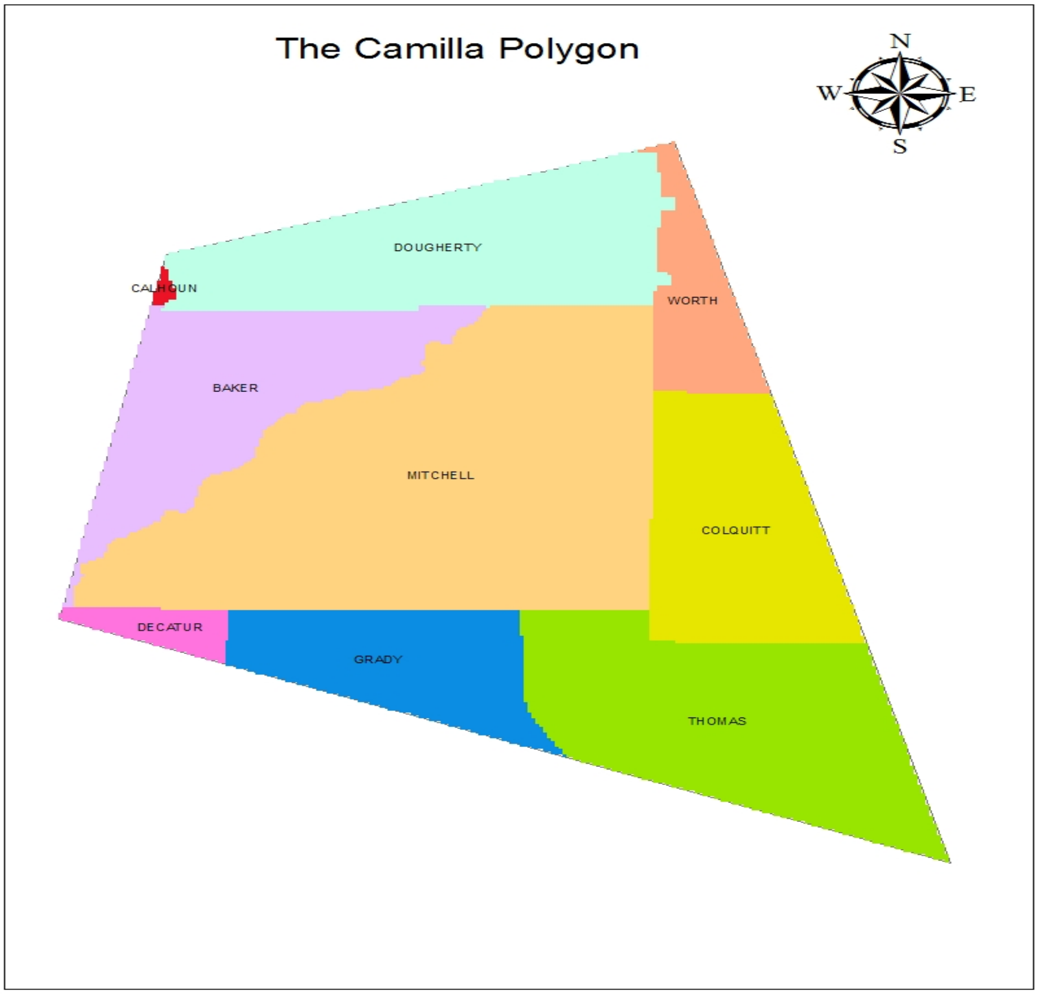
| Polygon | Change in net revenue ($/ha) | Camilla sub-Polygons (CSP) | Average interpolated value for (CSP) ($/ha) | Lost net revenue (LNR) ($/ha) | Proportion of (CSP) area | Weighted (LNR) ($/ha) |
|---|---|---|---|---|---|---|
| Arlington | -178 | camA | -61 | -117 | 0.31 | -36 |
| Attapulgus | -184 | camB | -115 | -69 | 0.29 | -20 |
| Tifton | -132 | camC | -121 | -11 | 0.24 | -3 |
| Dawson | -129 | camD | -101 | -28 | 0.16 | -4 |
| **Total** | | | | | | **$-63/ha** |

**Table 5.11 Summary of Net Revenue Lost**

| Crop/Soil | Net Revenue Lost ($/ha) |
|---|---|
| Corn (NLS) | -29 |
| Corn (TLS) | -31 |
| Peanut (NLS) | -49 |
| Peanut (TLS) | -43 |
| Cotton (NLS) | -24 |
| Cotton (TLS) | -37 |
| Soybean (NLS) | -72 |
| Soybean (TLS) | -63 |

Table 5.11 above gives a summary of the net revenue lost from losing the Camilla weather station for all four crops. This is used to estimate the total net revenue lost for losing the Camilla station for irrigated peanut, corn, soybean and cotton within the Camilla polygon. Figure 5.2 is the entire Camilla polygon showing the portions of the counties surrounding Mitchell County that are found within it. Information on the total land area for each of these counties as well as the land area of the portions of each county that is within the Camilla polygon was used to determine the percentage of each county that is within the Camilla Polygon.

**Figure 5.2 The Camilla Polygon**




Information on total acres under crops, the total number of irrigated acres for all crops as well as for peanut, corn, soybean and cotton within the Camilla polygon, together with the net revenue lost summary information on table 5.11 and the land area of those counties forming the Camilla polygon were used to estimate the total net revenue lost from losing the Camilla station. The total net revenue lost estimation are presented on table 5.12 for corn NLS and TLS. The nine counties that form the Camilla polygon as shown on figure 5.2 above are listed. The proportions of the land area of each county within the Camilla polygon are also estimated and total irrigated corn acres on NLS and TLS in the Camilla polygon were estimated based on these proportions. Tables showing the detailed estimation of the total irrigated NLS and TLS within the Camilla Polygon are documented in the appendix section of this thesis (Appendix B). The total net revenue lost for irrigated corn on NLS is simply the product of the total irrigated corn hectares on NLS for each county and the per hectare net revenue lost from losing the Camilla station for corn NLS (estimated on table 5.4). Thus, the total net revenue lost from losing the Camilla station for irrigated corn on NLS is $74,482 and that of corn TLS is $140,844 (Total of table 5.12).

**Table 5.12 Total Net Revenue Lost for Losing Camilla (Corn NLS and TLS)**

| County | Proportion of county in Camilla polygon | Total irrigated corn hectares on NLS in the Camilla Polygon | Total irrigated corn hectares on TLS in the Camilla Polygon | Total net revenue lost for irrigated cotton on NLS | Total net revenue lost for irrigated cotton on TLS |
|---|---|---|---|---|---|
| Baker | 0.55 | 159.41 | 126.98 | -4623 | -3936 |
| Calhoun | 0.01 | 9.39 | 8.39 | -272 | -260 |
| Colquitt | 0.32 | 316.39 | 38.61 | -9175 | -1197 |
| Decatur | 0.04 | 6.12 | 15.92 | -177 | -494 |
| Dougherty | 0.67 | 80.78 | 373.69 | -2343 | -11584 |
| Grady | 0.27 | 43.55 | 339.68 | -1263 | -10530 |
| Mitchell | 1.00 | 1911.47 | 2511.94 | -55433 | -77870 |
| Thomas | 0.46 | 38.21 | 940.32 | -1108 | -29150 |
| Worth | 0.12 | 3.03 | 187.84 | -88 | -5823 |
| **Total** | | | | **$-74,482** | **$-140,844** |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

The estimation of the total net revenue lost for losing the Camilla station for the other crops are done in the same way as corn NLS and TLS above and are presented in the following tables

**Table 5.13 Total Net Revenue Lost for Losing Camilla (Cotton NLS and TLS)**

| County | Proportion of county in Camilla polygon | Total irrigated cotton hectares on NLS in the Camilla Polygon | Total irrigated cotton hectares on TLS in the Camilla Polygon | Total net revenue lost for irrigated cotton on NLS | Total net revenue lost for irrigated cotton on TLS |
|---|---|---|---|---|---|
| Baker | 0.55 | 174.18 | 138.74 | -4180 | -5133 |
| Calhoun | 0.01 | 10.99 | 9.83 | -264 | -364 |
| Colquitt | 0.32 | 1772.37 | 216.31 | -42537 | -8003 |
| Decatur | 0.04 | 23.24 | 60.39 | -558 | -2234 |
| Dougherty | 0.67 | 56.15 | 259.79 | -1348 | -9612 |
| Grady | 0.27 | 19.25 | 150.13 | -462 | -5555 |
| Mitchell | 1.00 | 2371.84 | 3116.93 | -56924 | -115326 |
| Thomas | 0.46 | 16.08 | 395.66 | -386 | -14639 |
| Worth | 0.12 | 10.36 | 640.65 | -249 | -23704 |
| **Total** | | | | **$-106,908** | **$-184,570** |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

**Table 5.14 Total Net Revenue Lost for Losing Camilla (Peanut NLS and TLS)**

| County | Proportion of county in Camilla polygon | Total irrigated peanut hectares on NLS in the Camilla Polygon | Total irrigated peanut hectares on TLS in the Camilla Polygon | Total net revenue lost for irrigated peanut on NLS | Total net revenue lost for irrigated peanut on TLS |
|---|---|---|---|---|---|
| Baker | 0.55 | 165.47 | 131.81 | -8108 | -5667 |
| Calhoun | 0.01 | 5.23 | 4.68 | -256 | -201 |
| Colquitt | 0.32 | 698.23 | 85.22 | -34213 | -3664 |
| Decatur | 0.04 | 15.71 | 40.83 | -770 | -1756 |
| Dougherty | 0.67 | 42.84 | 198.20 | -2099 | -8523 |
| Grady | 0.27 | 7.39 | 57.64 | -362 | -2479 |
| Mitchell | 1.00 | 1716.98 | 2256.35 | -84132 | -97023 |
| Thomas | 0.46 | 7.64 | 188.10 | -374 | -8088 |
| Worth | 0.12 | 7.22 | 446.63 | -354 | -19205 |
| **Total** | | | | **$-130,668** | **$-146,606** |

**Table 5.15 Total Net Revenue Lost for Losing Camilla (Soybean NLS and TLS)**

| County | Proportion of county in Camilla polygon | Total irrigated soybean hectares on NLS in the Camilla Polygon | Total irrigated soybean hectares on TLS in the Camilla Polygon | Total net revenue lost for irrigated peanut on NLS | Total net revenue lost for irrigated peanut on TLS |
|---|---|---|---|---|---|
| Baker | 0.55 | 24.66 | 19.64 | -1776 | -1237 |
| Calhoun | 0.01 | 0.57 | 0.51 | -41 | -32 |
| Colquitt | 0.32 | 86.89 | 10.61 | -6256 | -668 |
| Decatur | 0.04 | 5.93 | 15.39 | -427 | -970 |
| Dougherty | 0.67 | 5.06 | 23.41 | -364 | -1475 |
| Grady | 0.27 | 1.49 | 11.69 | -107 | -736 |
| Mitchell | 1.00 | 51.12 | 67.18 | -3681 | -4232 |
| Thomas | 0.46 | 20.64 | 508.03 | -1486 | -32006 |
| Worth | 0.12 | 1.99 | 123.61 | -143 | -7787 |
| **Total** | | | | **$-14,281** | **$-49,143** |

**TLS and NLS are Tifton Loamy Sand and Norfolk Loamy Sand respectively**

From the results presented on the tables above, it is now possible to estimate the total net revenue lost for losing the Camilla AEMN weather station for irrigated corn, cotton, peanut and soybean. From the results obtained, net revenue lost for irrigated corn on NLS and TLS within the Camilla polygon is $74,482 and $140,844 respectively if the Camilla weather station is eliminated. On the other hand, net revenue will decline by $130,668 and $146,606 for irrigated peanut on NLS and TLS respectively if the Camilla station is eliminated. Similarly, the loss in net revenue for irrigated cotton on NLS is $106,908 and $184,570 for irrigated cotton on TLS for losing the Camilla weather station. Finally, net revenues will decline by $14,281 and $49,143 for irrigated soybean on NLS and TLS respectively in the event that the Camilla station is terminated. Thus, the total net revenue lost for losing the  Camilla station is estimated at $847,502 for irrigated corn, cotton, soybean and peanut.

# CHAPTER 6

# SUMMARY AND CONCLUSIONS

## 6.1 Summary

Many agricultural activities are affected negatively by unfavorable weather events. In fact, the agricultural sector is said to be the most weather dependent of all human activity. Thus, the day to day variation in weather conditions presents a major source of risk and uncertainty to the agricultural sector, especially field crops. Farmers largely do not have control over what weather conditions they get in any given growing season and also do not know with certainty what weather conditions to expect on their fields. As a result, many farmers make their production decisions based on their general understanding of weather pattern for their region. This uncertainty most often than not, results in conservative strategies that sacrifice some productivity to reduce the risk of production losses.

There has been significant progress in the generation and dissemination of weather information over the past years. However, the potential for farmers to benefit from this progress depends on their ability and willingness to adopt farming operations to the weather information, timing and accuracy of the weather information and the effectiveness of the communication process. Many resourceful farmers are capable of adjusting their management decisions to take advantage of expected favorable conditions or reduce unwanted impact if they have reliable information of the weather into the season. Fortunately, it is now possible with the use of DSSAT to model crop production at specific locations to provide farmers with the tools that they need to make important production decisions.

The National Weather Service is the primary supplier of short-term weather information for the citizens of the State of Georgia. However, the weather information generated by the National Weather Service is not representative of weather date needed for agricultural and environmental applications. This is largely because the detail weather information collected by the National Weather Service are around airport and large cities and are therefore influenced by runways and large concrete building. Because of these concerns, the College of Agriculture and Environmental Sciences of the University of Georgia in 1991 established the Georgia Automated Environmental Monitoring Network (Georgia AEMN) weather stations to collect reliable weather data and other environmental variables for agriculture and other related applications. The weather information generated from these stations is made available to the public through the web at www.georgiaweather.net. Many individual farmers, utility companies, businesses, researchers, the government and non governmental agencies have benefited in different ways from the weather information provided by the network. The network also contributed significantly to the planning and overall success of the 1996 Olympic Games held in Atlanta Georgia.

A lot of research work has been done on valuing weather information. However, the results of these studies have generated a wide range of values. This is partly because of the differences in methodological approaches used by the different research efforts. In addition, the weather product being value and the scope of the valuation could also differ from one research to another. The use of DSSAT to model crop production, however, is becoming more popular among research valuing weather and climate information.

This thesis estimated the value of a Georgia AEMN weather station for irrigated cotton, corn, peanut and soybean by evaluating the net revenue lost for losing the Georgia AEMN weather station at Camilla. DSSAT is employed to simulate crop yield for the four crops considered. A planting window consisting of a number of planting dates were specified for each crop and ten different levels of automatic irrigation specified for the simulations. The average crop yield for each planting date and irrigation threshold, together with the average prices of these crops and the total variable cost were used to estimate expected net revenues. The expected net revenues and two different levels of risk aversion coefficients were run through a constant utility function to determine the optimal planting date and irrigation threshold at Camilla for each crop using Camilla's weather information. This initial optimal planting date and irrigation threshold developed based on Camilla's weather were applied to the weather information of other selected Georgia AEMN weather stations (Arlington, Attapulgus, Dawson, Tifton, Fort Valley and Plains) to simulate crop yield. The discrete irrigation events were then obtained and applied back to Camilla's weather to simulated yields of all the crops considered. The difference between the average yields for the two scenarios represents the change in yield for implementing the Camilla's strategy using weather data from other stations. Expected net revenue changes were also estimated and used in GIS through Kriging to created interpolated surfaces across the study area. Zonal statistics also in GIS was used to estimate the average interpolated value to determine that actual net revenue lost for losing the Camilla station for all crops considered.

The results of this research indicate that the optimal planting date and irrigation for corn on Norfolk Loamy Sand (NLS) at Camilla is May 15 at 50% automatic irrigation. That of corn on Tifton Loamy Sand (TLS) is May 30 at 40% irrigation. Soybean is May 10 at 50% irrigation for both NLS and TLS. The optimal mix for cotton is April 15 for NLS and April 1for TLS. Optimal irrigation threshold, however, is 40% for both soils. Peanut does best when planted on April 30 for NLS and May 20 for TLS. Optimal irrigation threshold is 60% for NLS and 70% for

TLS. These optimal strategies are based on the risk aversion coefficient of 1.1. However, the results remains the same for the aversion coefficient of 2.5 except for corn NLS and soybean NLS. Finally, the total net revenue lost for losing the Camilla station for irrigated corn, cotton, peanut and soybean on NLS and TLS is estimated at $ 847,502 per year.

**6.2 Conclusions and Implications**

A number of conclusions can be drawn from the results of this research. First of all the results shows that the optimal planting date and irrigation thresholds are different for different crops and even different for the same crop planted on different soils. This is an important observation and implies that farmers do not have to assume that an optimal decision mix that works well for one crop will necessarily apply to another crop even if the two crops are planted under similar conditions. It is recommended that farmers consult with their county or district extension agents to get expert advice on the best management practices to adopt for the crops they intend to produce.

Secondly, the results points to an important conclusion about using the weather data of other weather stations to implement the optimal crop production strategies developed based on the weather data of the Camilla. The results present overwhelming evidence that using other weather stations data to implementing the Camilla optimal strategy will lead to losses in crop yield and eventually reduce expected net revenue. This implies that installing and maintaining weather stations like the Georgia AEMN at recommended intervals across agricultural production sites is ideal. It is therefore recommended that all existing Georgia AEMN weather stations be kept and new ones added where they are needed, if possible.

Furthermore, the results reveal that the Georgia AEMN weather stations are highly valuable. The estimated net revenue lost for losing the Camilla station alone for irrigated corn, cotton, peanut and soybean producers is $ 847,502 per year. This estimated net revenue lost is a conservative and a snap shot estimate of a particular time period. The estimated net revenue lost could be much higher if changes in irrigation permits leads to more irrigated acres and if other high value crops were included in the analysis. Changes in crop prices and crop production costs will also affect the result. We can, therefore, conclude that the Georgia AEMN weather stations contribute significantly to the agricultural sector and for that matter the general economy of the State of Georgia. As a result, every effort should be made to provide the needed funding to support all existing Georgia AEMN weather stations and if possible provide extra funds to purchase and install new stations where they may be needed.

### 6.3 Limitations and Suggestion for Future Research

This research estimated the value of site specific weather information generated by a Georgia AEMN weather station. This was done by estimating the net revenue lost for losing the Camilla Georgia AEMN weather station and forcing producers of irrigated corn, cotton, soybean and peanut within the sphere of influence of the Camilla station, to use weather data from neighboring weather stations to make optimal irrigation decisions. It is important to note that the analysis of this study is conditioned on some assumptions.

First of all, the sphere of influence of the Georgia AEMN Camilla weather station (the Camilla polygon in figure 5.2) was determined by using the Thiessen polygon approach in ArcGIS to draw Thiessen polygons around the selected Georgia AEMN weather stations. The size and shape of the Camilla polygon could change depending on which weather stations around the Camilla station are selected. In reality, the sphere of influence of the Georgia AEMN Camilla weather station could be much smaller or much larger than what the Thiessen polygons suggest. Thus, future research should determine the sphere of influence of any referenced weather station by using some meteorological measure.

Secondly, we estimated the total number of irrigated hectares of corn, cotton, peanut and soybean in the Camilla polygon by assuming that Tifton Loamy Sand and Norfolk Loamy Sand as well as irrigated crops within the Camilla polygon are evenly distributed. Realistically, soils and irrigated crops may not necessarily be evenly distributed. To mitigate for this limitation, future research should conduct a soil and irrigation survey in the study area to determine the actual number of irrigated crops of interested.

Thirdly, although this study uses corn, cotton, peanut and soybean in analyzing the value of weather information from the Camilla station, many more crops are produced in the study area and could be use in the analysis. It is, therefore, suggested that future research efforts should be directed at using other crops to estimate the value of weather information from the Camilla station. This will give an important indication as to how the value of weather information changes or otherwise with different crops.

Finally, the methodology developed by this study is universal and can be applied to any crop that is simulated by DSSAT or other simulation software and any location in the world where the required site specific data are available. Applying the methodology of this research in other states and other countries will provide a broader perspective on the value of weather information.

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**APPENDICES**

## APPENDIX A: Kriging Results

**Figure A.1 Kriging Results for Corn NLS**

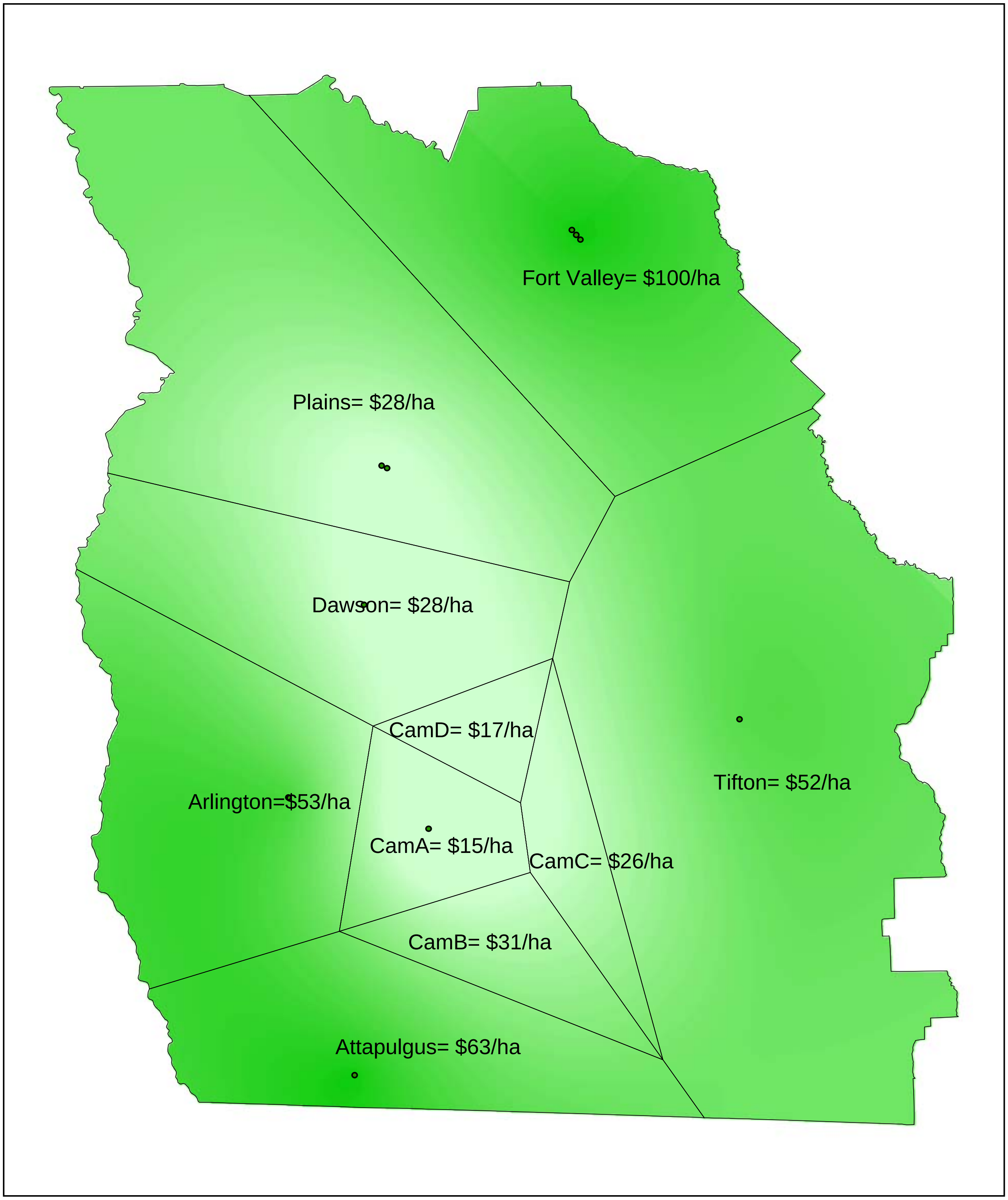


**Figure A.2 Kriging Results for Peanut TLS**

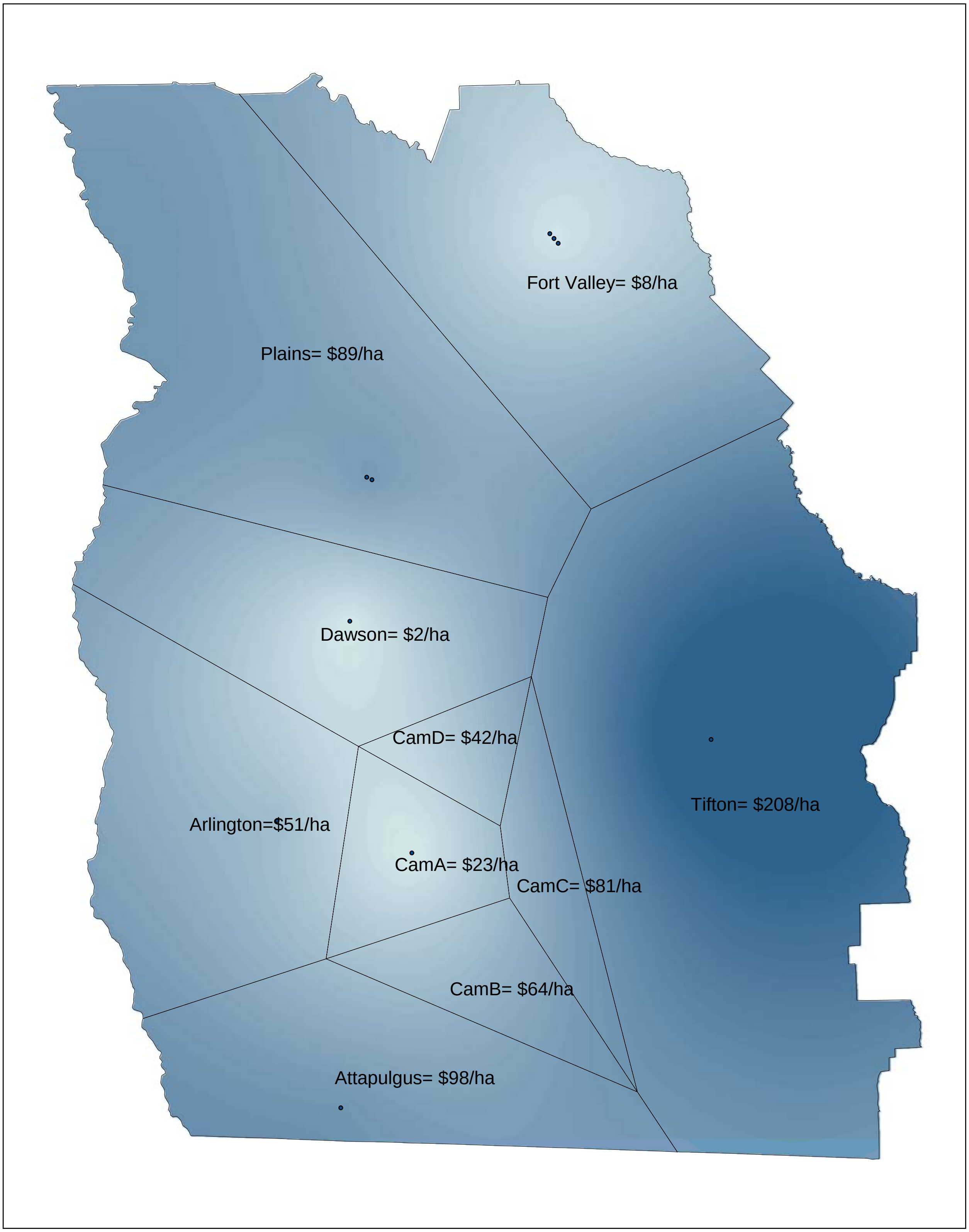


**Figure A.3 Kriging Results for Peanut NLS**

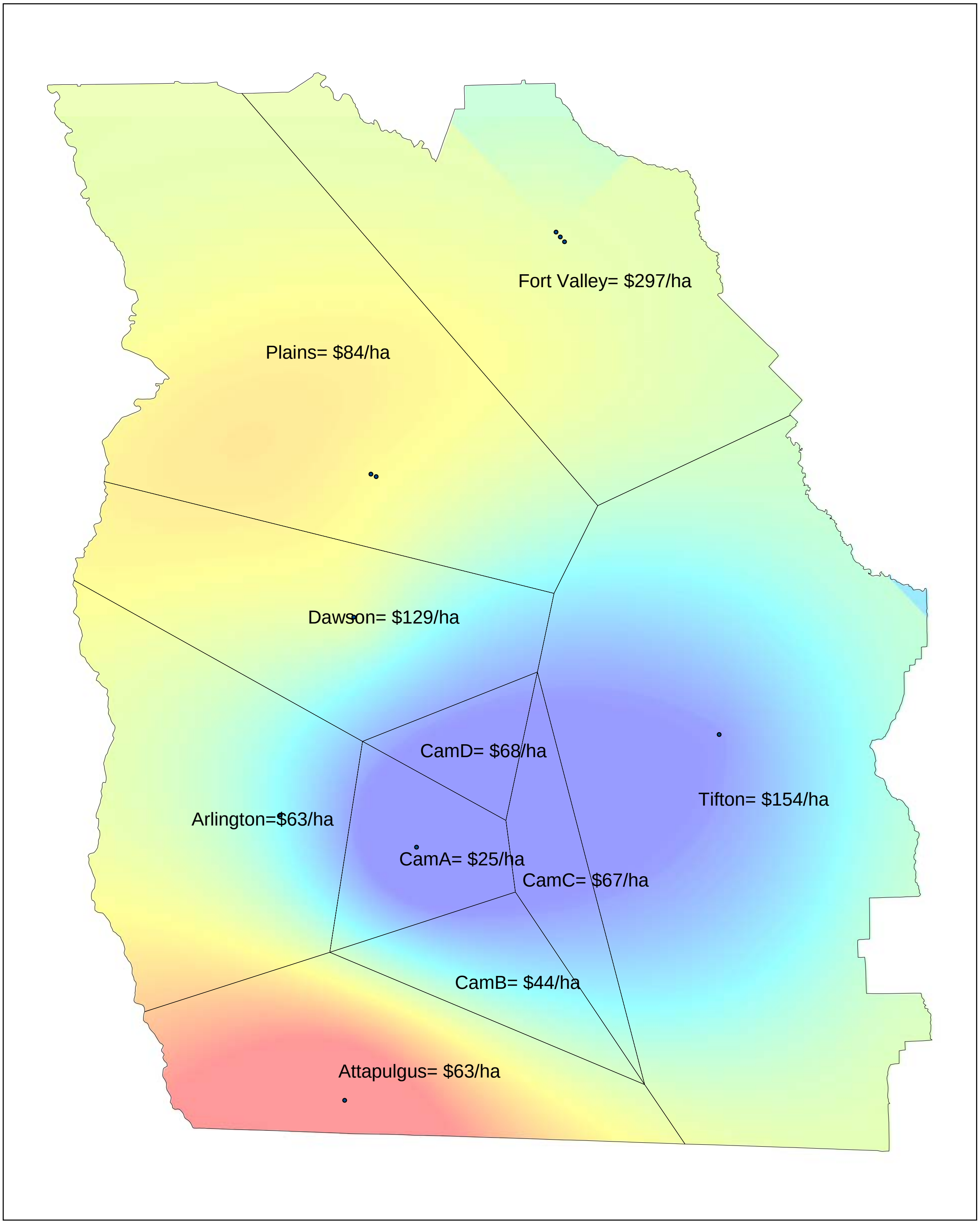


**Figure A.4 Kriging Results for Cotton TLS**

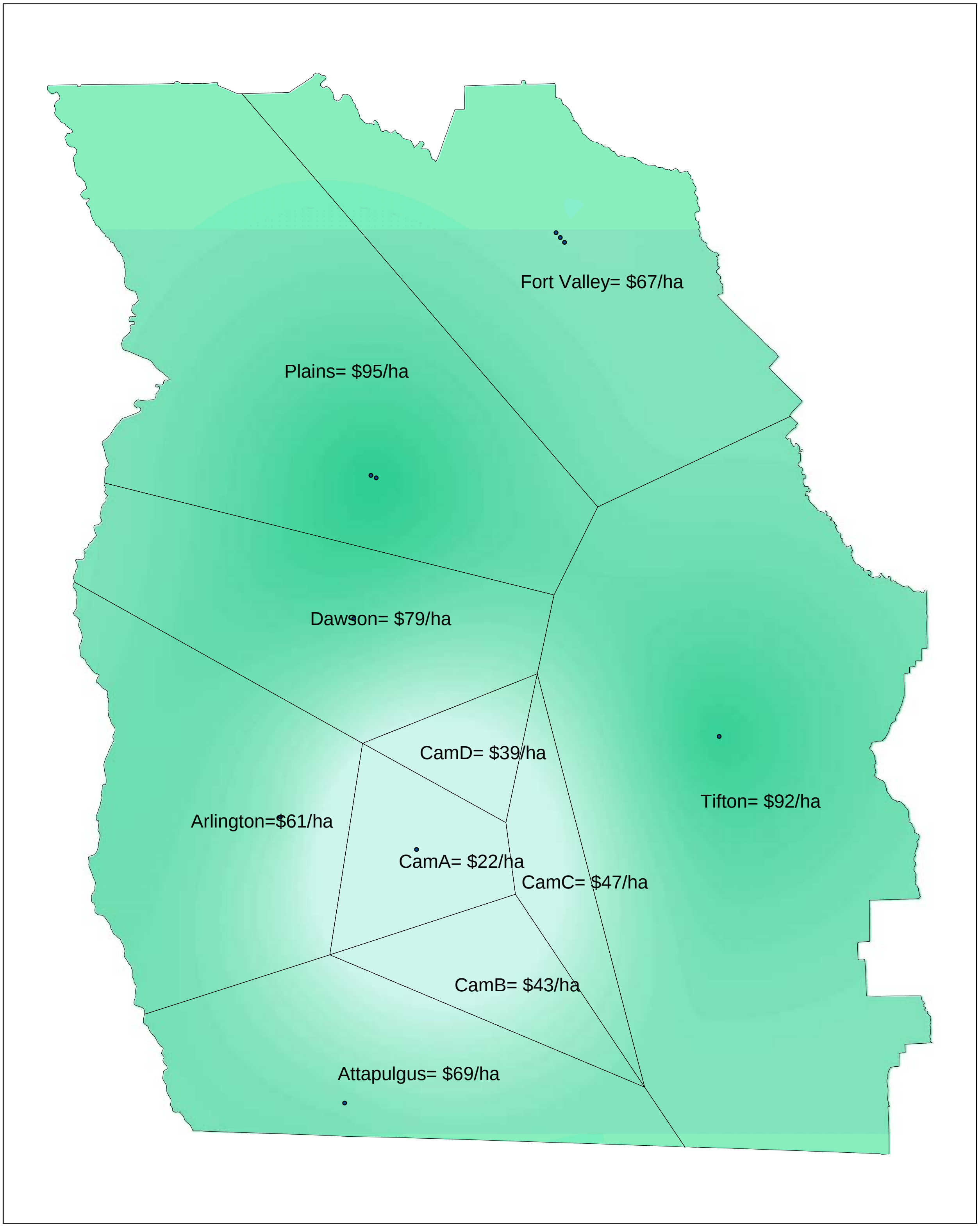


**Figure A.5 Kriging Results for Cotton NLS**

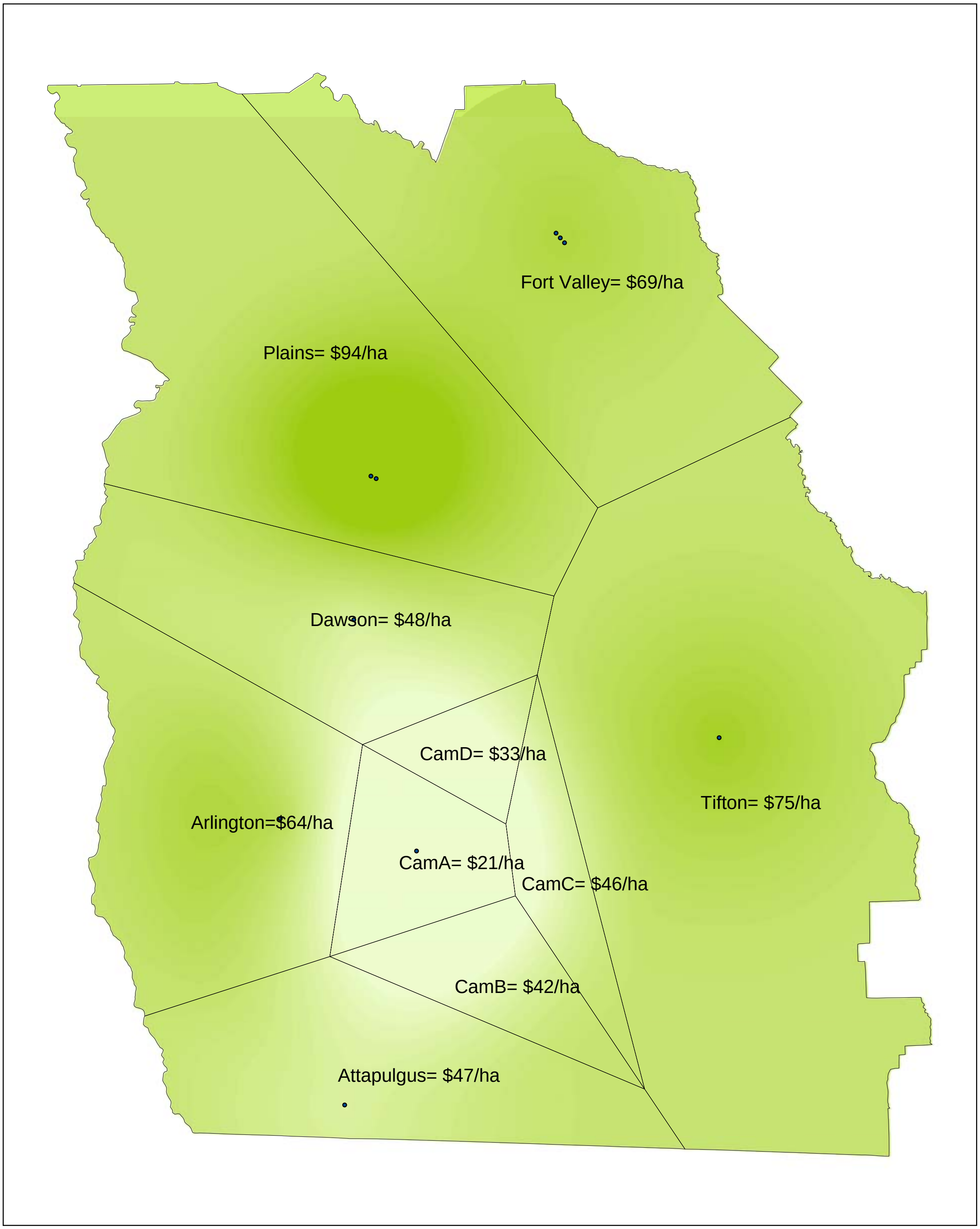


**Figure A.6 Kriging Results for Soybeans TLS**

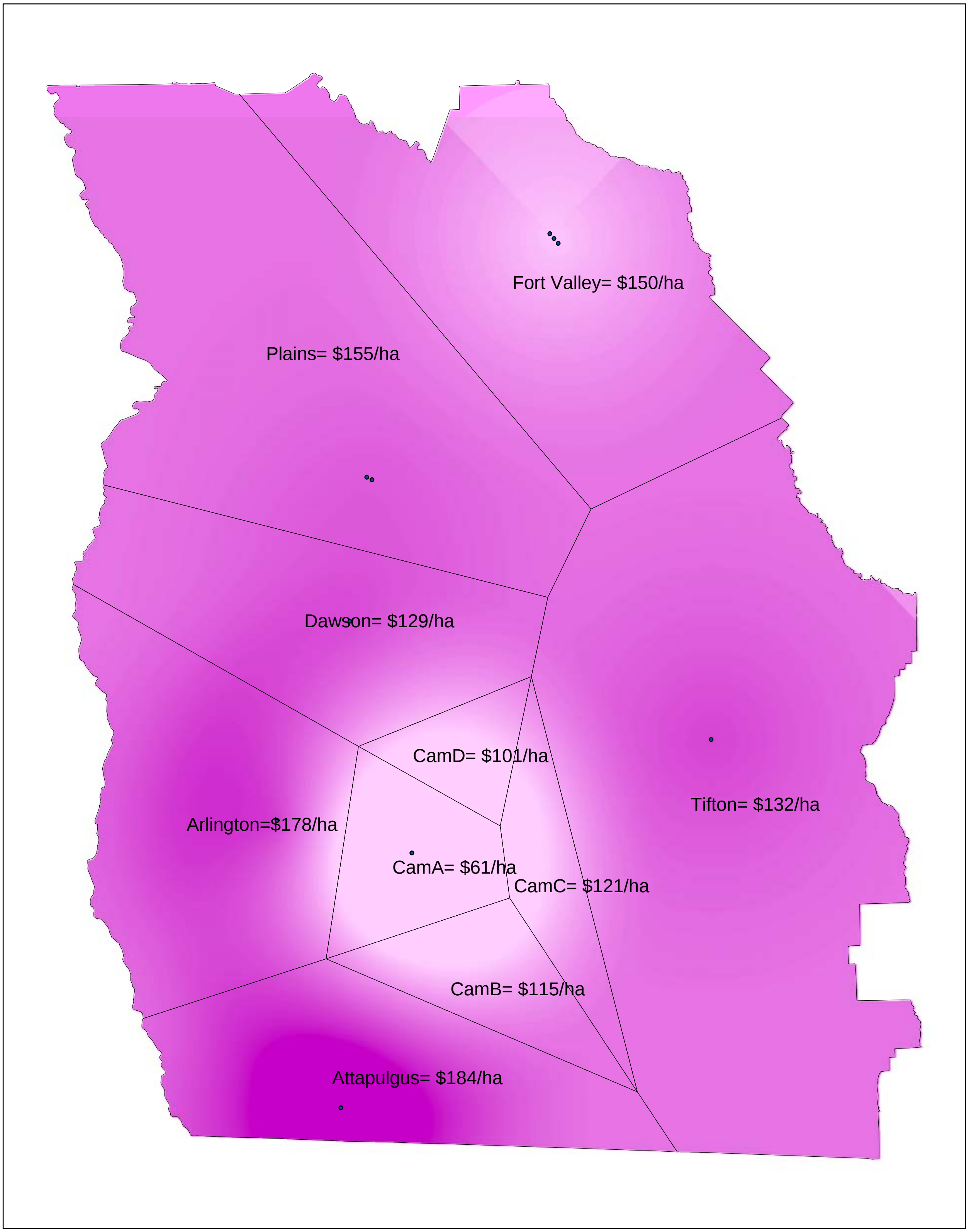
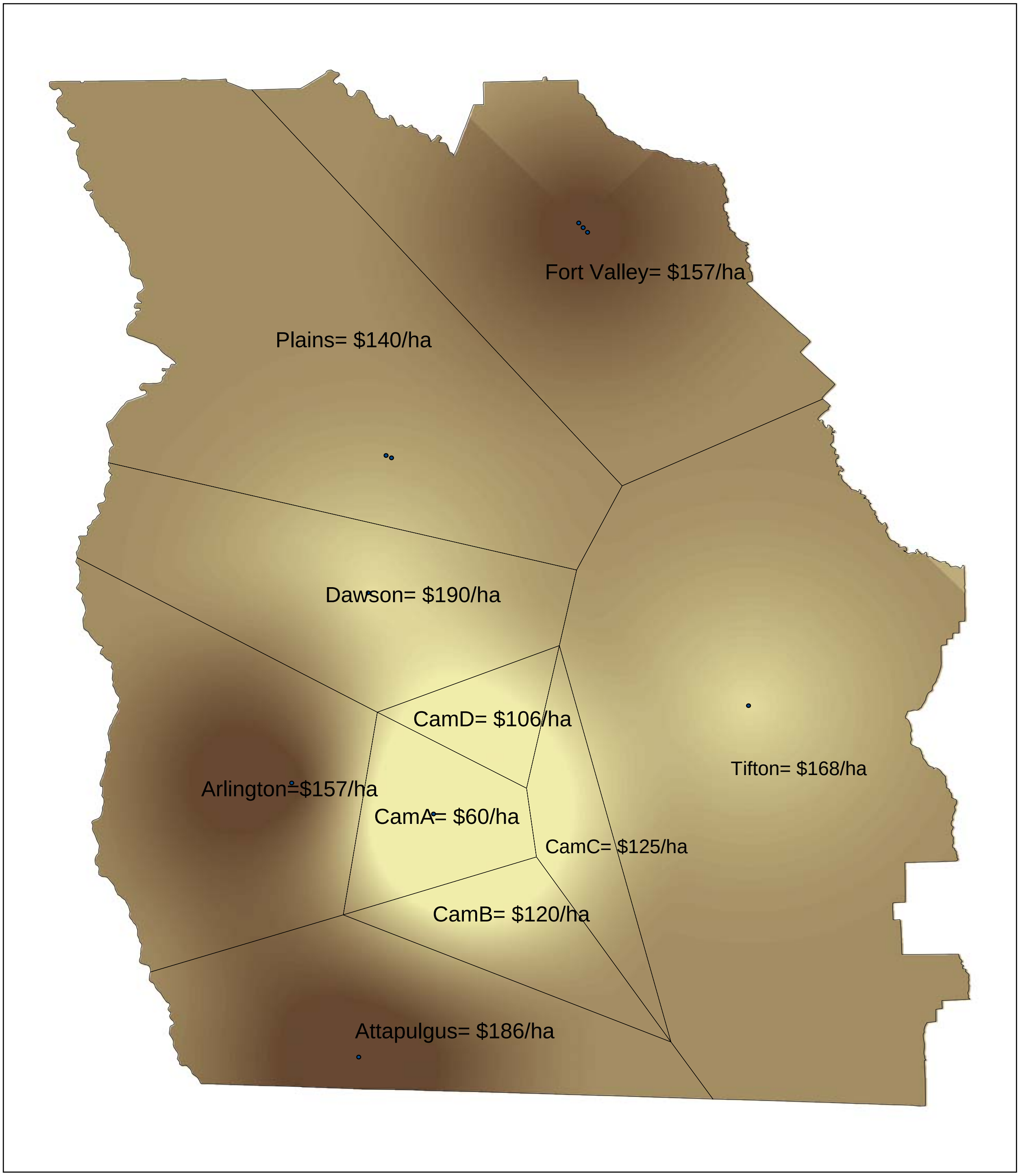


**Figure A.7 Kriging Results for Soybeans NLS**



## APPENDIX B: Detailed Estimation of Irrigated Hectares of TLS and NLS in Camilla Polygon

**Table: B.1 Total Hectares of Irrigated NLS under Corn in Camilla Polygon**

| County | Total number of NLS hectares in County | Percentage of County in Camilla polygon | Total number of NLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated NLS hectares in Camilla polygon | Percentage of irrigated corn hectares in County | **Irrigated corn hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 2312.45 | 0.55 | 1271.85 | 0.43 | 542.43 | 0.29 | **159.41** |
| Calhoun | 6412 | 0.01 | 64.12 | 0.45 | 29.03 | 0.32 | **9.39** |
| Colquitt | 37866.72 | 0.32 | 12117.35 | 0.38 | 4659.26 | 0.07 | **316.39** |
| Decatur | 3155.84 | 0.04 | 126.23 | 0.45 | 56.82 | 0.11 | **6.12** |
| Dougherty | 1248.4 | 0.67 | 836.43 | 0.46 | 385.26 | 0.21 | **80.78** |
| Grady | 3230 | 0.27 | 872.1 | 0.14 | 124.11 | 0.35 | **43.55** |
| Mitchell | 19436 | 1.00 | 19436 | 0.38 | 7318.45 | 0.26 | **1911.47** |
| Thomas | 1357.85 | 0.46 | 624.61 | 0.13 | 82.93 | 0.46 | **38.21** |
| worth | 740 | 0.12 | 88.8 | 0.27 | 24.13 | 0.13 | **3.03** |

**Table: B.2 Total Hectares of Irrigated TLS under Corn in Camilla Polygon**

| County | Total number of NLS hectares in County | Percentage of County in Camilla polygon | Total number of NLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated NLS hectares in Camilla polygon | Percentage of irrigated corn hectares in County | **Irrigated corn hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 1842 | 0.55 | 1013.1 | 0.43 | 432.07 | 0.29 | **126.98** |
| Calhoun | 5732 | 0.01 | 57.32 | 0.45 | 25.95 | 0.32 | **8.39** |
| Colquitt | 4621.45 | 0.32 | 1478.86 | 0.38 | 568.64 | 0.07 | **38.61** |
| Decatur | 8201.6 | 0.04 | 328.06 | 0.45 | 147.67 | 0.11 | **15.92** |
| Dougherty | 5775.84 | 0.67 | 3869.81 | 0.46 | 1782.42 | 0.21 | **373.69** |
| Grady | 25193.2 | 0.27 | 6802.17 | 0.14 | 968.04 | 0.35 | **339.68** |
| Mitchell | 25541.6 | 1 | 25541.6 | 0.38 | 9617.46 | 0.26 | **2511.94** |
| Thomas | 33419.4 | 0.46 | 15372.9 | 0.13 | 2041.1 | 0.46 | **940.32** |
| worth | 45766 | 0.12 | 5491.92 | 0.27 | 1492.59 | 0.13 | **187.84** |

**Table: B.3 Total Hectares of Irrigated NLS under Cotton in Camilla Polygon**

| County | Total number of NLS hectares in County | Percentage of County in Camilla polygon | Total number of NLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated NLS hectares in Camilla polygon | Percentage of irrigated cotton hectares in County | **Irrigated cotton hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 2312.45 | 0.55 | 1271.85 | 0.43 | 542.43 | 0.32 | **174.18** |
| Calhoun | 6412 | 0.01 | 64.12 | 0.45 | 29.03 | 0.38 | **10.99** |
| Colquitt | 37866.72 | 0.32 | 12117.35 | 0.38 | 4659.26 | 0.38 | **1772.37** |
| Decatur | 3155.84 | 0.04 | 126.23 | 0.45 | 56.82 | 0.41 | **23.24** |
| Dougherty | 1248.4 | 0.67 | 836.43 | 0.46 | 385.26 | 0.15 | **56.15** |
| Grady | 3230 | 0.27 | 872.1 | 0.14 | 124.11 | 0.16 | **19.25** |
| Mitchell | 19436 | 1.00 | 19436 | 0.38 | 7318.45 | 0.32 | **2371.84** |
| Thomas | 1357.85 | 0.46 | 624.61 | 0.13 | 82.93 | 0.19 | **16.08** |
| worth | 740 | 0.12 | 88.8 | 0.27 | 24.13 | 0.43 | **10.36** |

**Table: B.4 Total Hectares of Irrigated TLS under Cotton in Camilla Polygon**

| County | Total number of TLS hectares in County | Percentage of County in Camilla polygon | Total number of TLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated TLS hectares in Camilla polygon | Percentage of irrigated cotton hectares in County | **Irrigated cotton hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 1842 | 0.55 | 1013.1 | 0.43 | 432.07 | 0.32 | **138.74** |
| Calhoun | 5732 | 0.01 | 57.32 | 0.45 | 25.95 | 0.38 | **9.83** |
| Colquitt | 4621.45 | 0.32 | 1478.87 | 0.38 | 568.64 | 0.38 | **216.31** |
| Decatur | 8201.6 | 0.04 | 328.06 | 0.45 | 147.67 | 0.41 | **60.39** |
| Dougherty | 5775.84 | 0.67 | 3869.81 | 0.46 | 1782.42 | 0.15 | **259.79** |
| Grady | 25193.24 | 0.27 | 6802.17 | 0.14 | 968.04 | 0.16 | **150.13** |
| Mitchell | 25541.6 | 1.00 | 25541.6 | 0.38 | 9617.46 | 0.32 | **3116.93** |
| Thomas | 33419.37 | 0.46 | 15372.91 | 0.13 | 2041.1 | 0.19 | **395.66** |
| worth | 45766 | 0.12 | 5491.92 | 0.27 | 1492.59 | 0.43 | **640.65** |

**Table: B.5 Total Hectares of Irrigated NLS under Peanut in Camilla Polygon**

| County | Total number of NLS hectares in County | Percentage of County in Camilla polygon | Total number of NLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated NLS hectares in Camilla polygon | Percentage of irrigated peanut hectares in County | **Irrigated peanut hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 2312.45 | 0.55 | 1271.85 | 0.43 | 542.43 | 0.31 | **165.47** |
| Calhoun | 6412 | 0.01 | 64.12 | 0.45 | 29.03 | 0.18 | **5.23** |
| Colquitt | 37866.72 | 0.32 | 12117.35 | 0.38 | 4659.26 | 0.15 | **698.23** |
| Decatur | 3155.84 | 0.04 | 126.23 | 0.45 | 56.82 | 0.28 | **15.71** |
| Dougherty | 1248.4 | 0.67 | 836.43 | 0.46 | 385.26 | 0.11 | **42.84** |
| Grady | 3230 | 0.27 | 872.1 | 0.14 | 124.11 | 0.06 | **7.39** |
| Mitchell | 19436 | 1 | 19436 | 0.38 | 7318.45 | 0.23 | **1716.98** |
| Thomas | 1357.85 | 0.46 | 624.61 | 0.13 | 82.93 | 0.09 | **7.64** |
| worth | 740 | 0.12 | 88.8 | 0.27 | 24.13 | 0.30 | **7.22** |

**Table: B.6 Total Hectares of Irrigated TLS under Peanut in Camilla Polygon**

| County | Total number of TLS hectares in County | Percentage of County in Camilla polygon | Total number of TLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated TLS hectares in Camilla polygon | Percentage of irrigated peanut hectares in County | **Irrigated peanut hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 1842 | 0.55 | 1013.1 | 0.43 | 432.07 | 0.31 | **131.81** |
| Calhoun | 5732 | 0.01 | 57.32 | 0.45 | 25.95 | 0.18 | **4.68** |
| Colquitt | 4621.45 | 0.32 | 1478.86 | 0.38 | 568.64 | 0.15 | **85.22** |
| Decatur | 8201.6 | 0.04 | 328.06 | 0.45 | 147.67 | 0.28 | **40.83** |
| Dougherty | 5775.84 | 0.67 | 3869.81 | 0.46 | 1782.42 | 0.11 | **198.20** |
| Grady | 25193.24 | 0.27 | 6802.17 | 0.14 | 968.04 | 0.10 | **57.64** |
| Mitchell | 25541.6 | 1 | 25541.6 | 0.38 | 9617.46 | 0.23 | **2256.35** |
| Thomas | 33419.37 | 0.46 | 15372.91 | 0.13 | 2041.10 | 0.09 | **188.10** |
| worth | 45766 | 0.12 | 5491.92 | 0.27 | 1492.59 | 0.30 | **446.63** |

**Table: B.7 Total Hectares of Irrigated NLS under Soybean in Camilla Polygon**

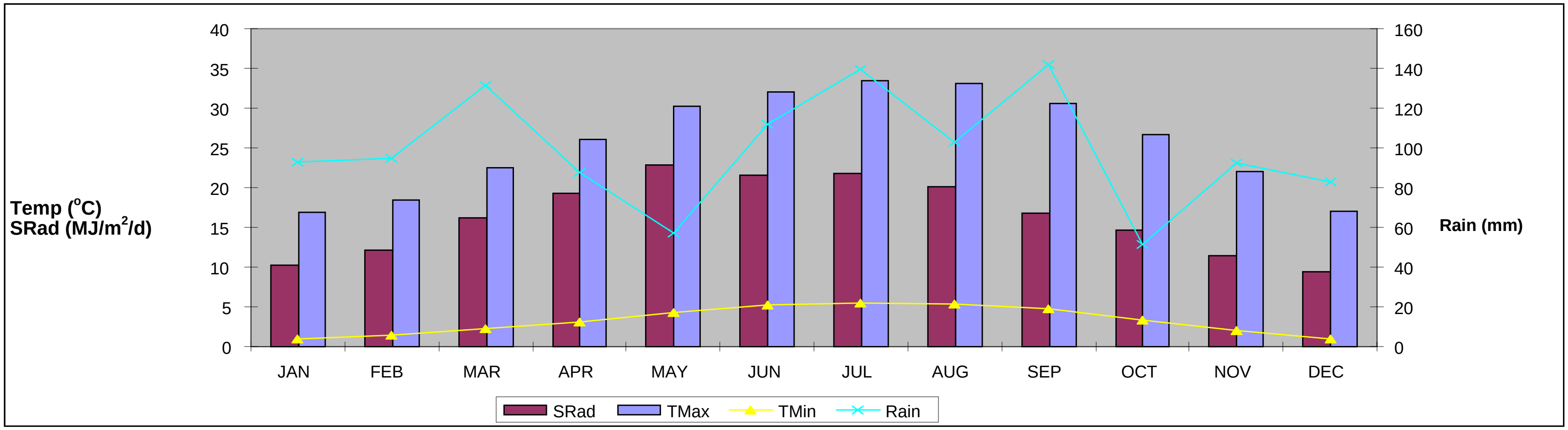
| County | Total number of NLS hectares in County | Percentage of County in Camilla polygon | Total number of NLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated NLS hectares in Camilla polygon | Percentage of irrigated soybeans hectares in County | **Irrigated soybeans hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 2312.45 | 0.55 | 1271.85 | 0.43 | 542.43 | 0.05 | **24.66** |
| Calhoun | 6412 | 0.01 | 64.12 | 0.45 | 29.03 | 0.20 | **0.57** |
| Colquitt | 37866.72 | 0.32 | 12117.35 | 0.38 | 4659.26 | 0.02 | **86.89** |
| Decatur | 3155.84 | 0.04 | 126.23 | 0.45 | 56.82 | 0.10 | **5.93** |
| Dougherty | 1248.4 | 0.67 | 836.43 | 0.46 | 385.26 | 0.01 | **5.06** |
| Grady | 3230 | 0.27 | 872.1 | 0.14 | 124.11 | 0.01 | **1.49** |
| Mitchell | 19436 | 1 | 19436 | 0.38 | 7318.45 | 0.01 | **51.12** |
| Thomas | 1357.85 | 0.46 | 624.61 | 0.13 | 82.93 | 0.25 | **20.64** |
| worth | 740 | 0.12 | 88.8 | 0.27 | 24.13 | 0.08 | **1.99** |

**Table: B.8 Total Hectares of Irrigated TLS under Soybean in Camilla Polygon**

| County | Total number of TLS hectares in County | Percentage of County in Camilla polygon | Total number of TLS hectares in Camilla polygon | Percentage of harvested irrigated hectares for all crops in county | Irrigated TLS hectares in Camilla polygon | Percentage of irrigated soybeans hectares in County | **Irrigated soybeans hectares in Camilla polygon** |
|---|---|---|---|---|---|---|---|
| Baker | 1842 | 0.55 | 1013.1 | 0.43 | 432.07 | 0.01 | **19.64** |
| Calhoun | 5732 | 0.01 | 57.32 | 0.45 | 25.95 | 0.02 | **0.51** |
| Colquitt | 4621.45 | 0.32 | 1478.86 | 0.38 | 568.64 | 0.019 | **10.61** |
| Decatur | 8201.6 | 0.04 | 328.06 | 0.45 | 147.67 | 0.10 | **15.39** |
| Dougherty | 5775.84 | 0.67 | 3869.81 | 0.46 | 1782.42 | 0.013 | **23.41** |
| Grady | 25193.24 | 0.27 | 6802.17 | 0.14 | 968.036 | 0.012 | **11.69** |
| Mitchell | 25541.6 | 1 | 25541.6 | 0.38 | 9617.46 | 0.01 | **67.18** |
| Thomas | 33419.37 | 0.46 | 15372.91 | 0.13 | 2041.09 | 0.25 | **508.03** |
| worth | 45766 | 0.12 | 5491.92 | 0.27 | 1492.59 | 0.08 | **123.61** |

## APPENDIX C: Graphs of Monthly Averages of Rain, Solar Radiations and Temperature

### Table: C.1 Graph of Monthly Averages for Camilla




### Table: C.2 Graph of Monthly Averages for Dawson

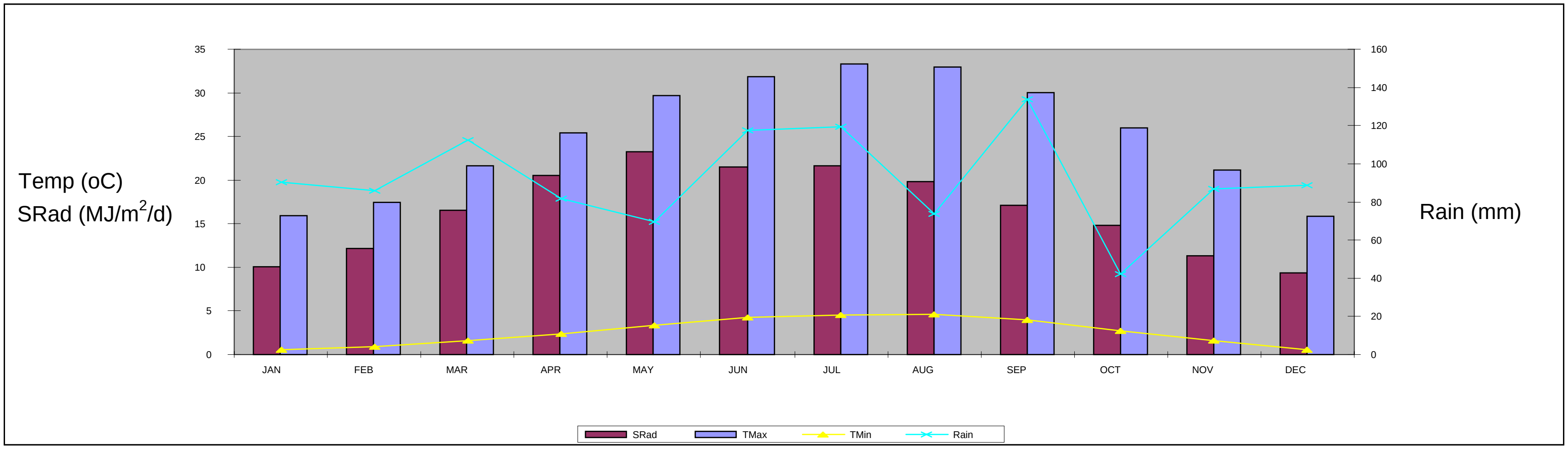


Table: C.3 Graph of Monthly Averages for Arlington

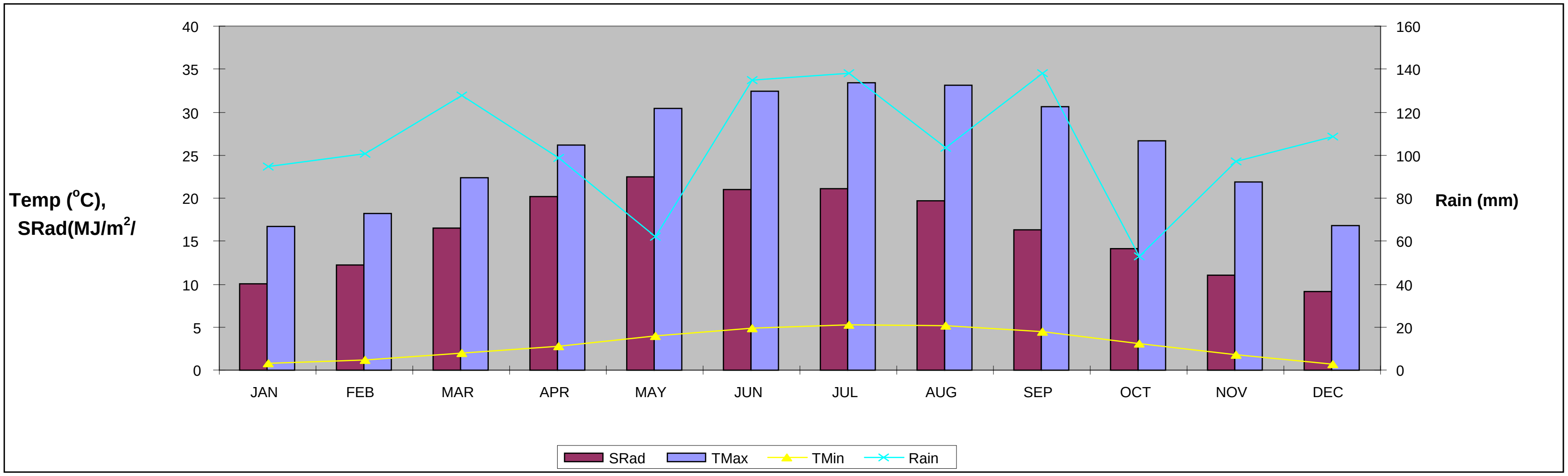



Table: C.4 Graph of Monthly Averages for Attapulgus

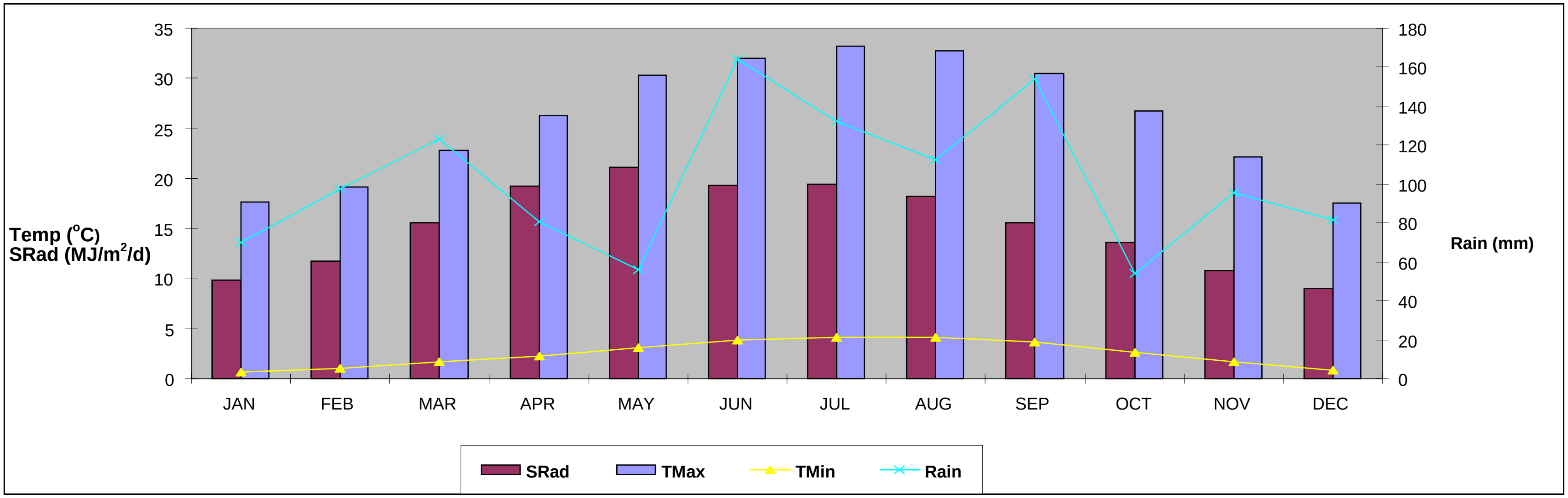


Table: C.5 Graph of Monthly Averages for Fort Valley

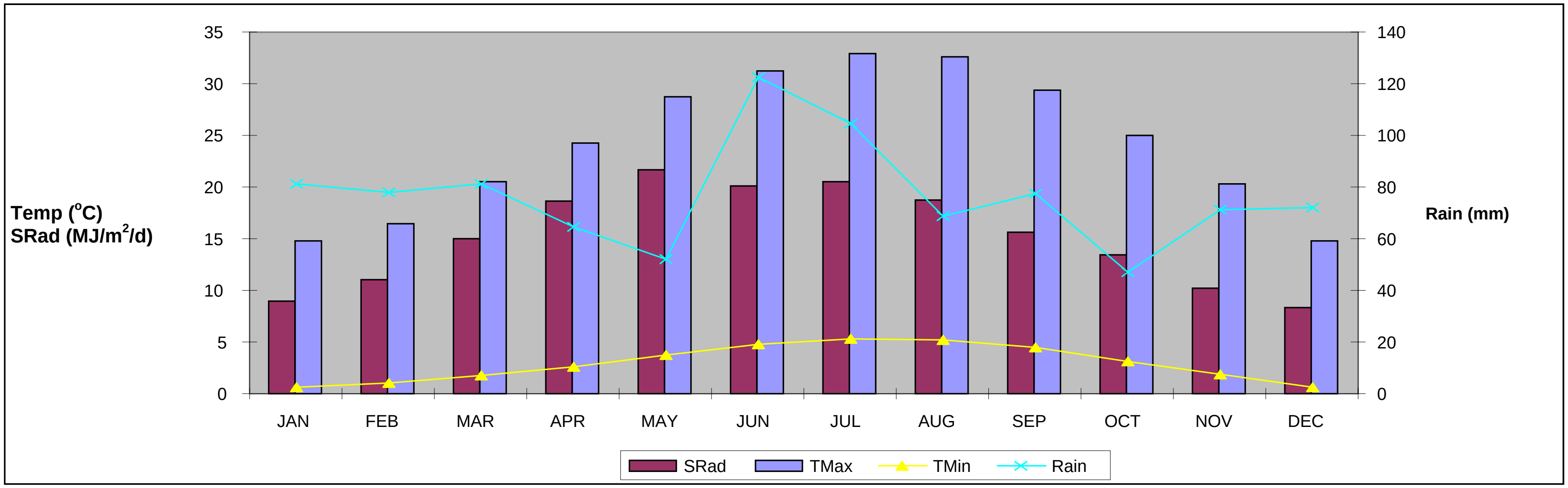



Table: C.6 Graph of Monthly Averages for Plains

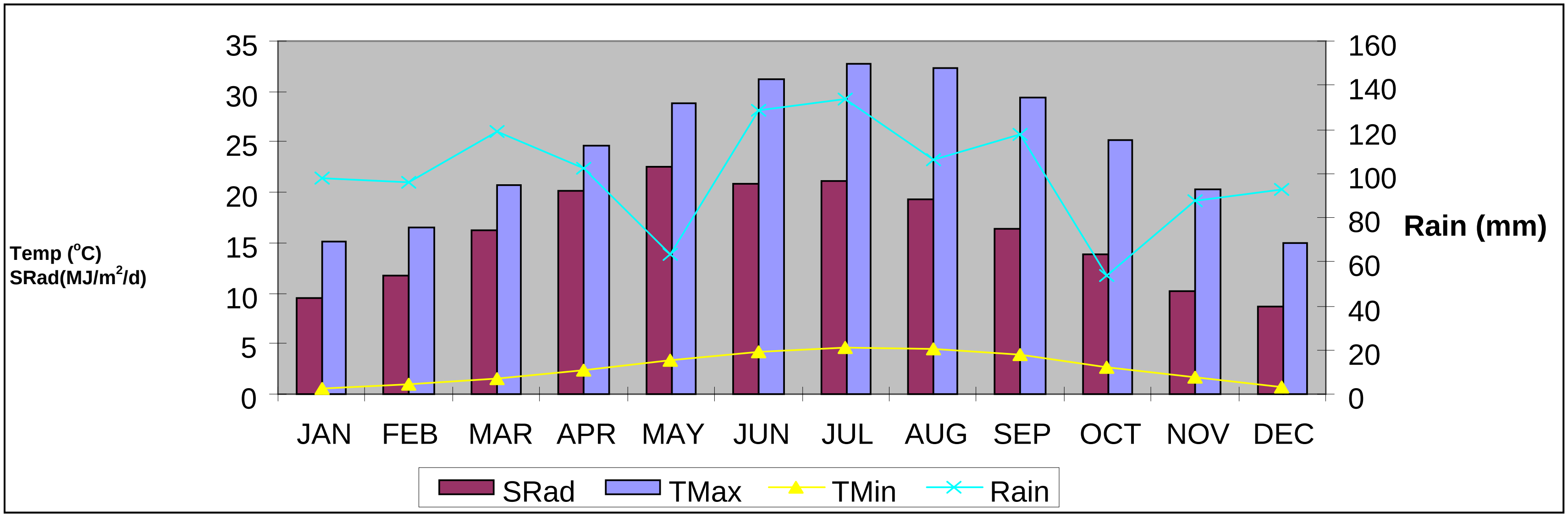
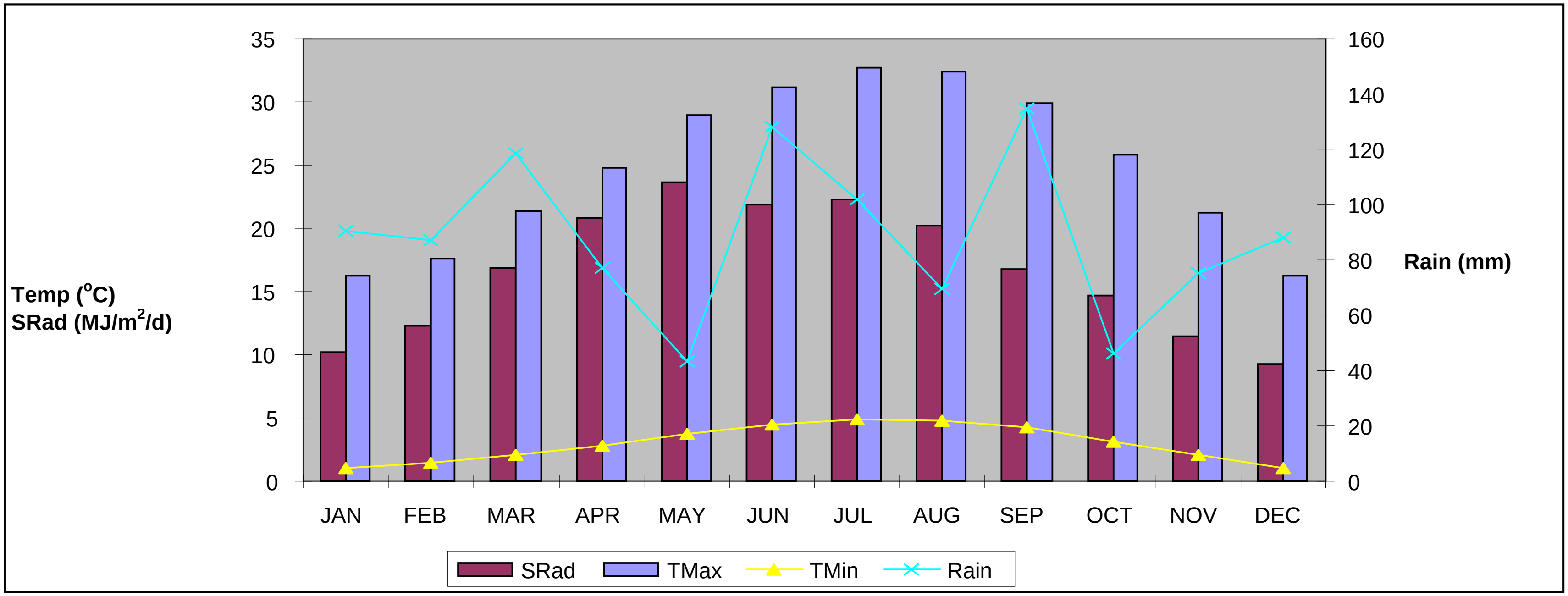


**Table: C.7 Graph of Monthly Averages for Tifton**



## APPENDIX D: Summary Statistics for Yield, Expected Net Revenue and Expected Water Use

| Crop | Soil Type | Optimal irrigation threshold (%) | Optimal planting date | Ave. yield (kg/ha) | Standard deviation of yield | Expected net revenue ($/ha) | Standard deviation of net revenue | Expected water used (mm/ha) | Standard deviation of water used |
|---|---|---|---|---|---|---|---|---|---|
| Cotton | TLS | 40 | 4/15 | 3425 | 204 | 4168 | 300 | 221 | 53 |
| Cotton | NLS | 40 | 4/01 | 3646 | 185 | 4404 | 249 | 317 | 93 |
| Peanut | TLS | 70 | 5/20 | 3660 | 339 | 496 | 215 | 158 | 40 |
| Peanut | NLS | 60 | 4/30 | 5828 | 449 | 1433 | 295 | 258 | 86 |
| Corn | TLS | 40 | 5/30 | 7719 | 523 | 557 | 109 | 173 | 47 |
| Corn | NLS | 50 | 5/15 | 7963 | 790 | 592 | 171 | 185 | 66 |
| Soybean | TLS | 50 | 5/10 | 3720 | 313 | 345 | 142 | 315 | 52 |
| Soybean | NLS | 50 | 5/10 | 3610 | 339 | 397 | 137 | 295 | 50 |