BEST MANAGEMENT PRACTICE DEVELOPMENT WITH THE CERES-MAIZE MODEL FOR SWEET CORN PRODUCTION IN NORTH FLORIDA

By

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A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2008

To my parents, brother, and the teachers who taught me at different stages in my life

ACKNOWLEDGMENTS

I believe my most important achievement in the past four years was learning how to do academic research and how to cooperate with other people. I recognized that this crucial improvement in my life is owed to the contributions of many people.

First and foremost, I am greatly indebted to my supervisor, Dr. Michael D. Dukes, for his insightful guidance, continuous encouragement, and unselfish support in my research over the past more than four years. His thoughtful coaching with all aspects of my research was a guarantee of the success of this endeavor. His enthusiasm and preciseness have left an everlasting impression on me. I will never forget how he never even neglected a tiny typo when he was revising my writing. Without his help, it would not have been possible for me to complete this research.

I would like to express sincere appreciation to Dr. Wendy Graham and Dr. James Jones for their insightful and invaluable advice on resolving all kinds of technical problems in my research. I will never forget their sacrifices, spending their valuable time to meet with me many times. Their enthusiasm for research and pursuit for excellence will be an example to me forever. Without their combined supervision of each step throughout the model simulation, this study would not have been possible.

I am grateful to Dr. Jasmeet Judge for her help in the field experiment and advice in model simulation, to Dr. George Hochmuth for his advice in sweet corn BMP development, and to Dr. Michael Annable for his advice in nitrogen movement. I deeply benefited from their suggestions and advice on a multitude of perspectives regarding my research.

I would like to thank Dawn Lucas and Dr. Donald Graetz for their help in laboratory experiments. Dawn helped me analyze thousands of soil and water samples. I am thankful they

let me occupy their laboratory for my experiment at least three weeks in every summer from 2004 to 2006.

Special thanks go to Danny Burch, staff of the Agricultural and Biological Engineering (ABE) Department, and people in the Plant Science Research and Education Unit, University of Florida. Without their help, the burdensome field work would not have been completed. I would also like to thank the undergraduate students (Steve, Clay, Frank, Habtu, Sanjiv, Patrick, Thi, David, etc.). They helped me conduct the field and laboratory experiments. Now they are my good friends. I am also grateful to several officemates for their friendship and encouragement, and faculty, staff and students in the ABE Department for the harmonious academic environment.

Finally I particularly appreciate my parents and younger brother for their unconditional love, understanding, patience and encouragement. I love and miss them.

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August 2008

Chair: Michael D. Dukes
Major: Agricultural and Biological Engineering

Increasing nitrogen loads within the Suwannee River Basin of North Florida has become a major concern. Nitrogen fertilizer application in field crop production is proved to be the most import nitrogen contribution in this region. Florida ranks highest in the nation in the production and value of fresh market sweet corn. Thus it is necessary to develop research based nitrogen best management practices (N-BMPs) to reduce nitrogen leaching while keeping an acceptable yield in sweet corn production.

This study is an attempt to utilize the CERES-Maize mode of the Decision Support System for Agrotechnology Transfer (DSSAT) model as a platform to develop potential BMPs for sweet corn production in North Florida.

The results show that the non-restricted and restricted one-at-a-time (OAT) method can be used to conduct global sensitivity analysis for the CERES-Maize so as to select the most influential parameters for model calibration. The generalized likelihood uncertainty estimation (GLUE) method was proved to be a powerful tool for model parameter estimation, since the uncertainties in model input parameters were significantly reduced after GLUE was used to

estimate the model input parameters. The uncertainties in model outputs were reduced correspondingly.

The comparison between the model simulated and field observed results of the seven treatments in a field plot experiment of sweet corn in 2006, shows that the model did a good job in predicting dry yield and phenology dates.

The results of BMP development with the calibrated CERES-Maize model show that if the growers could apply both irrigation water and nitrogen fertilizer more frequently but with smaller amounts in each application, this would result in an acceptable yield and a lower level of nitrogen leaching. The results showed a total nitrogen amount between 196 and 224 kg N ha^{-1} would be enough for sweet corn production in North Florida, which confirmed that the recommendation nitrogen amount (224 kg N ha^{-1}) by Institute of Food and Agricultural Sciences （IFAS）, Univerisity of Florida, was reasonable.

The results of uncertainty analysis of the CERES-Maize model for sweet corn simulation show that the weather was the dominant uncertainty contributor. This was because after two rounds of GLUE parameter estimation procedure, the uncertainties existing in input parameters were minimized.

CHAPTER 1
INTRODUCTION

1.1 Study Background

1.1.1 Nitrate Pollution in North Florida

Increasing nitrogen loads within the Suwannee River Basin of North Florida has recently become a major concern. According to the "Surface Water Quality and Biological Annual Report 2003" (Suwannee River Water Management District, 2004), in 2003, 4,165 metric tons of nitrate-nitrogen and 1,733 metric tons of phosphorus were transported to the Gulf of Mexico by the Aucilla, Econfina, Fenholloway, Suwannee, and Waccasassa Rivers. The Suwannee River Basin alone accounted for 4,069 metric tons of nitrate nitrogen and 1,476 metric tons of total phosphorus.

In 1995, a study was conducted to determine how springs and other ground-water inflow affect the quantity and quality of water in the Suwannee River (Pittman et al., 1997). They studied a 53-km stretch of the Suwannee River from Dowling Park, Fla., to Branford, Fla. Water samples for nitrate concentrations (dissolved nitrite plus nitrate as nitrogen) and discharge data were collected at 11 springs and 3 river sites during the 3-day period in July 1995 during base flow in the river. They found that nitrate (NO_3^{-1}) loads increased downstream from 2,300 to 6,000 kg day^{-1}, an increase of 160% in the study reach, and that 54% of nitrate load increase was supplied by the groundwater inflow. Eighty-nine percent of the nitrate load increase occurred in the lower two-thirds of the stretch. Ham and Hatzell (1996) found that nitrate concentration in Suwannee River increased at a rate of 0.02 mg L^{-1} per year over a twenty-year period from 1971 to 1991, with an average concentration for the 20-year period of 0.5 mg L^{-1}.

Leaching of nitrate nitrogen is economically and environmentally undesirable (Katyal et al., 1985; Poss and Saragoni, 1992; Theocharopoulos et al., 1993). Nitrate that leaches below the

crop root zone represents the loss of a valuable plant nutrient, and hence, increases agricultural costs. If nitrate enters groundwater supplies, it can also impose risks to both human health and the environment. Consumption by humans and animals through drinking water with high nitrate levels has been associated with several health problems. The most serious is methemoglobinemia or blue baby syndrome (O_2 deficiency in blood) in infants. High nitrate concentrations in drinking water are detrimental to the health of infants especially during the first 6 months of life. Additionally, groundwater with high nitrate levels that discharge into sensitive surface waters can contribute to long-term eutrophication of these water bodies (Asadi, et al., 2002). For this reason, the US Environmental Protection Agency (EPA) has set a maximum contaminant level requiring the nitrate-nitrogen concentration not exceed 10 mg N L^{-1} and the nitrite-nitrogen concentration not exceed 1 mg N L^{-1} in public water supplies (U.S. Dept. Health, Education, and Welfare, 1962).

Nitrates leached into the groundwater of Suwannee River Basin are believed to come from several sources including animal wastes, chemical fertilizer, industrial, and domestic sewage. The Middle Suwannee River Basin, which includes Lafayette and Suwannee counties, has hundreds of residential and commercial septic systems in rural areas, about 300 row crop and vegetable farms, 44 dairies with more than 25,000 animals and 150 poultry operations with more than 38 million birds. Suwannee County is the leading poultry production area in Florid (Woods, 2005). According to the report by Katz et al. (1999), in Suwannee County, the relative contribution of N from fertilizers increased from about 23% in 1955 to more than 60% in 1980. During 1955-1995, the contribution of estimated N inputs from animal wastes (poultry, dairy and beef cows, and swine) ranged from about 21 to 42% of the total estimated N inputs. It is obvious that N fertilizer is the most important N contributor in this region.

1.1.2 Sweet Corn Production in Florida

Florida ranks highest in the nation in the production and value of fresh market sweet corn (*Zea mays L.*), typically accounting for approximately 25% of both national sweet corn production and of U.S. cash receipts for fresh sales (FASS, 2002; USDA-NASS, 1997, 1999a).

Sweet corn has typically ranked as one of Florida's five most valuable vegetable crops. During the 2000-01 production seasons, sweet corn was the second ranked vegetable crop in terms of acreage and fifth ranked in total value. Harvested acreage for sweet corn represented 14.9% of the state's total vegetable acreage during that season, while production value represented 8% of the total production value of all Florida vegetables (FASS, 2002). Average yield ranged from approximately 8,200 kg ha^{-1} fresh sweet corn yield in 1969-1970, to 16,400 kg ha^{-1} in 2000-2001 (FASS 2001, 2002).

The principal fresh sweet corn production region in Florida is the Everglades area (Palm Beach County), which during the 1999-2000 season produced 63% of the state crop. The southeastern/southwestern area (Miami-Dade, Collier, and Hendry Counties) were responsible for 25% of the state's production. The west/north area (Suwannee and Jackson Counties) accounted for about 7% of the sweet corn production. Sweet corn was also grown in the central area around Lake Apopka, but this region only produced about 5% of the crop since the muck soils in this area have been taken out of production (FASS, 2001).

Table 1-1 shows the harvested acreage of sweet corn in Florida in 1997 and 2002 (USDA-NASS, 1998, 2002). It can be seen that in 1997 there were 413 sweet corn producing farms in Florida, with a total planted area of 17,791 ha. In 2002, number of farms decreased to 340, while the total planted area decreased to15,768 ha. In both years, the large farms, especially the ones that were greater than 200 ha consisted of the most part of total area.

Table 1-2 shows the applications of chemical nitrogen fertilizer in Florida from 1992 to 2006 (USDA-NASS, 1993, 1995, 1999b, 2003, 2006). In 1998 and 2002, all sweet corn acreage in Florida received nitrogen applications totaling 1.83 and 2.61million kg, respectively. Between 1992 and 2006, from 81 to 100 % of sweet corn acreage in Florida received an average of 2.0 to 10.0 applications of nitrogen seasonally. An average range of 46 to 62 kg N ha^{-1} had been used at each application, with a statewide annual total N application ranging from 1.64 to 5.48 million kg. It should be noticed that in 2006 though only 86% of total planted area received nitrogen fertilizer, the total number of N applications increased dramatically to 10 times a season. Consequently, the N rate per crop year in 2006 increased to 475 kg ha^{-1}, which was almost 3 times as that of 2002. The total applied chemical nitrogen fertilizer to sweet corn also doubled from 2002 to 2006.

Adequate water is especially important in sweet corn production during periods of silking and tasseling and of ear development (Hochmuth et al., 1996). Most of Florida's sweet corn is grown under irrigation. In 1997, 53% of farms and 71% of sweet corn acreage was irrigated (USDA-NASS, 1998). About 92% of sweet corn growers in Florida surveyed in 1993 reported that they checked soil moisture and plant need to determine irrigation needs, while 8% used an established schedule modified to meet plant needs. Furthermore, only 8% were using a mechanical system to monitor soil moisture, and of those not using a mechanical system, 30% considered it too expensive, 30% reported not knowing of a good and inexpensive system, 30% cited limited water supply, and 10% said that lack of time prevented them from adopting a mechanical system (Larson et al., 1999).

1.1.3 Total Maximum Daily Loads and Best Management Practice

In 1972, Congress passed the Clean Water Act (CWA) which set forth federal requirements for identification of polluted or impaired water bodies. These rules were passed

down to the states by the U.S. Environmental Protection Agency (EPA), which requires states to establish a prioritized list of impaired water bodies and to develop estimated loads that the water bodies could receive of each pollutant while meeting water quality standards (DeBusk, 2001).

These estimated loads determined for each water body are called Total Maximum Daily Loads (TMDLs). TMDLs are defined as the maximum amount of a pollutant that a water body can receive and still meet the water quality standards as established by the 1972 Clean Water Act. Section 303(d) of the act requires states to submit lists of surface waters that do not meet applicable water quality standards and to establish TMDLs for these waters on a prioritized schedule.

In response to state TMDL requirements, the Florida Watershed Restoration Act (FWRA) was passed in 1999. This act established the Florida Department of Environmental Protection (FDEP) as the lead agency in coordinating the implementation of the TMDL allocation through water quality protection programs. These programs include non-regulatory and incentive-based programs, including best management practices (BMPs), cost sharing, waste minimization, pollution prevention, and public education. This act also required the Florida Department of Agriculture and Consumer Services (FDACS) to develop and adopt rules pursuant to suitable interim measures, best management practices, or other measures necessary to achieve the level of pollution reduction established by the FDEP for agricultural pollutant sources. These practices and measures may be implemented by those parties responsible for agricultural pollutant sources and the department, the water management districts, and the FDACS shall assist with implementation (Florida Statutes, s.403.067, 1999).

The FDEP also should develop TMDL calculations for each water body or water body segment according to the priority ranking and schedule unless the impairment of such waters is

due solely to activities other than point and non-point sources of pollution. When a water body is identified as impaired and a TMDL is established, pollutant loads are divided among the different stakeholders (agriculture and urban). Hence, the TMDL shall include establishment of reasonable and equitable allocations of the total maximum daily load between or among point and non-point sources that will alone, or in conjunction with other management and restoration activities, and achieve water quality standards for the pollutant causing impairment. The allocations may establish the maximum amount of the water pollutant that may be discharged or released into the water body or water body segment in combination with other discharges or releases. Allocations may also be made to individual basins and sources or as a whole to all basins and sources or categories of sources of inflow to the water body or water body segments (Florida Statutes, s.403.067, 1999).

Normally, each stakeholder would implement a set of management practices that are expected to reduce its contribution to meet its designated load. These practices are commonly referred to as BMPs and can be defined as a practice or combination of practices determined by the coordinating agencies, based on research, field-testing, and expert review, to be the most effective and practicable on-location means, including economical and technological considerations, for improving water quality in agricultural and urban discharges. Although some water bodies do not have designated TMDLs as of yet, and therefore do not legally require BMPs, many agricultural BMP manuals are being developed. FDEP, FDACS, and the Institute of Food and Agricultural Science (IFAS) at the University of Florida have partnered with local agencies and stakeholders to develop BMP manuals (Migliaccio and Boman, 2006).

The primary benefit for growers implementing agricultural BMPs (even without a designated TMDL) is that if a BMP program is in place, an agricultural producer is considered to

be operating under a presumption of compliance with water quality standards. This protects the farmer from liabilities to the state when water quality standards are not met (IFAS-UF, 2006).

According to the "Water Quality/Quantity Best Management Practices for Florida Vegetable and Agronomic Crops" (FDACS, 2005), all farming operations using this BMP manual shall reasonably attempt to implement the recommended BMPs in order to establish a baseline set of BMPs to ensure a reduction in pollutant loading to impaired receiving waters. Depending on the farm's site specific conditions, all of these baseline BMPs need not be implemented. Only BMPs applicable for a particular location and production system should be implemented. This Tier-1 or first level of BMP protection also includes many of the practices that are identified as "essential" under USDA-NRCS conservation planning procedures. Irrigation scheduling and optimum fertilizer management are two of the proposed set of minimum BMPs that are suggested to be implemented.

1.1.4 Best Management Practices for Sweet Corn Production

In this research, focus was on the most common cultural practices that directly affect the N cycle, N fertilization and irrigation. Fertilization is the cultural practice that can directly influence the N cycle in the root zone of sweet corn. Fertilization affects not only plant uptake, but also mineralization, nitrification, denitrification, and ammonia volatilization (Cockx and Simonne, 2003). Mineralization will not be significant in sandy soil due to the low organic matter content, but will be significant in organic soils. However, approximately 50% of total N-fertilizer applied can be taken up by the crop (Bundy and Andradki, 2005), i.e. about 50% of the total applied N-fertilizer would be lost by leaching, volatilization, denitrification, etc.

Irrigation is another important factor. Florida is among the wettest states in the U.S. with most areas receiving an average of 1,270 mm of rain annually (Black, 2003). However, rainfall

distribution is not adequate for vegetable production and irrigation must be used since rainfall is always unevenly distributed in time and space (Cockx and Simonne, 2003).

Irrigation scheduling is used to apply the proper amount of water to a crop at the proper time. The characteristics of the irrigation system, crop needs, soil properties, and atmospheric conditions must all be considered to properly schedule irrigations. Poor timing or insufficient water application can result in crop stress and reduced yields from inappropriate amounts of available water and/or nutrients. Excessive water applications may reduce yield and quality, are a waste of water, and increase the risk of nutrient leaching (Maynard and Olson, 2001).

Irrigation must be scheduled according to water availability and crop need. Irrigation scheduling requires knowing when to irrigate and how much water to apply. When to irrigate can be determined from plant or soil indicators or water balance techniques. How much water to apply can be based on soil water measurements or water balance techniques (Fangmeier etc., 2006).

Monitoring soil status always means checking soil water tension (SWT). SWT represents the magnitude of the suction (negative pressure) the plant roots have to create to free soil water from the attraction of the soil, and move it into root cells. The dryer the soil, the higher the suction needed, hence, the higher SWT. SWT can be measured in the field with moisture sensors or tensiometers (Olson and Simonne, 2005).

Crop water requirement information is needed when establishing a soil water budget to forecast irrigation events. The sum of the water lost from the soil surface (evaporation) and water used by plants (transpiration) is called evaportranspiration (ET). There are many factors that affect the rate of ET, including plant species, weather factors, and the amount and quality of water available to the plant. Generally, reference ET (ET_0) is determined for use as a base level.

Crop water use (ET_C) is related to ET_0 by a crop coefficient (K_C) that is the ratio of ET_C to ET_0 (Irrigation Association, 2001).

Water usage also varies with soil dryness. Plants can remove water more easily from a wet soil. To account for this, a concept called readily available water (RAW) has been developed (Keller and Bliesner, 1990). It defines the amount of water that is more easily remove by the plant. Another associated term, maximum allowable depletion (MAD) relates RAW with available water (AW), which is the water that can be stored in soil and be available for growing crops. Usually, the value of MAD is given for a particular plant and the RAW is then computed with equation EAW=AW×MAD. The MAD values can be expressed as percentage and usually range from 0.4 to 0.6 (Rochester, 1995).

BMPs are specific cultural practices that aim at reducing the loads of specific compounds while increasing or maintaining economical yields (Simonne and Hochmuth, 2003). The implementation of BMPs may be a key factor in reducing the consequences of alterations of the N cycle in sweet corn fields. Implementation of BMPs at the farm level is a key to maintaining the quality and the quantity of ground and surface water.

Li and Yost (2000) stated that the application rates, timing, and method of both N fertilization and irrigation are important tools that determine and control the fate and behavior of N in soil-plant systems. For example, multiple applications with small amounts of fertilizer (e.g. split application) usually enhance plant uptake and reduce potential nitrate leaching, although increasing costs.

Waskom (1994) summarized BMPs for nitrogen fertilization for crops such as corn, sugar beet, and beans as follows:

(1) Time application of N fertilizer to coincide as closely as possible to the period of maximum crop uptake;

(2) Use sidedress or in-season fertilizer application for at least 40% of the total N applied to irrigated spring planted crops or fields with severe leaching hazard;

(3) Apply N fertilizer where it can be most efficiently taken up by the crop:
   a) Ridge banded fertilizer used in conjunction with alternate row furrow irrigation can reduce downward movement of N;
   b) Multiple, small applications of N through sprinkler irrigation systems can increase fertilizer efficiency and reduce total N fertilizer application;
   c) Fertilizers applied on irrigated fields with high surface loss potential should be subsurface banded or incorporated immediately after application;
   d) Nitrogen applied in irrigation water should be metered with an appropriate device that is properly calibrated. Due to the increased possibility of leaching or runoff, N fertilizer through conventional flood or furrow irrigation system is strongly discouraged.

(4) The following recommendations apply to cropland fields where the leaching potential is moderate to severe:
   a) Follow alfalfa or other legumes with high N use crops (such as small grains, sugar beets, or corn) that efficiently use N fixed by the legume;
   b) Follow shallow-rooted crops with low N use efficiency in the rotation by a deep-rooted, high N use crop that scavenges excess N (such as corn, sugar beets, or alfalfa). Analyze subsoil samples for residual nitrate to determine carryover credit to the subsequent crop.

Bauder and Waskom (2003) summarized the BMPs for corn in Colorado. The BMPs include: (1) use sidedress or in-season fertilizer application for at least 40% of the total N applied to irrigated crops with sandy soils; (2) use fall planted cover crops such as rye or triticale to scavenge excess N left in the soil after poor crop; (3) mix and store N fertilizer at least 30 m (100 feet) away from wells or any water supply; (4) if applying manure, incorporate manure as soon as possible after application to minimize volatilization losses, reduce odor, and prevent runoff, and (5) apply only enough irrigation water to fill the effective crop root zone.

Hochmuth (2000) recommended the nitrogen management practices for vegetable production in Florida as follows: (1) knowing the crop nutrient requirement (CNR) for N and targeting this amount for total crop N fertilization; (2) setting realistic yield goals; (3) using polyethylene mulch, where practical, to protect N from leaching; (4) selecting controlled-release

N fertilizers when practical and economical; (5) calibrating fertilizer applicators accurately and making adjustments to equipment so that the correct amount of N is applied in the correct position of the root zone or production bed, near the root system; (6) applying N at periods during the growing season when crop N uptake is most active; (7) using fertigation where possible to "spoon-feed" N to crops during the season; (8) managing irrigation water properly to avoid leaching and to keep water and N in the root zone; and (9) using tissue-testing or petiole sap testing to monitor crop-N status and to determine adjustments needed in the N-fertilization program. In addition, he also suggested 224 kg N ha^{-1} as nitrogen recommendations for sweet corn production on sandy mineral soils in Florida.

In the "Vegetable Production Guide for Florida 2003-2004", Olson and Simonne (2005) suggested that 20% to 25% of N should be applied at planting, then sidedress band the remaining N in one or two applications during the early part of growth cycle. After midseason, N can be applied through center pivot irrigation systems at rates of 11 to 22 kg N ha^{-1} in several applications.

1.1.5 Best Management Practice Development

Best management practices related with irrigation and N fertilizer application have been developed with field plot experiments. For example, a study was conducted in an acid-sulfate soil in the central region of Thailand, in 1999 and 2000 to assess the influence of different rates of N fertigation on corn yield and nitrate leaching. The corn varieties planted in the two years were super sweet corn Agro variety (*Zea mays L.*) and the Suwan 3851 single-cross hybrid (*Zea mays L.*), respectively. The nitrogen source was urea and there were four N fertigation treatments that included 0 (control), 100, 150 and 200 kg N ha^{-1}, each having three replications arranged in a randomized complete block design (RCBD). Soil was irrigated to field capacity at 50% available soil moisture depletion regime throughout the season. The average maximum corn

grain yield of 3,520 kg ha^{-1} was obtained at 200 kg N ha^{-1} in 1999 and 5,420 kg ha^{-1} was obtained at 150 kg N ha^{-1} in 2000. But the statistical analysis did not show any significant differences in grain yield between N200 and N150 treatments in either year. The nitrate leaching was calculated from the equation $LN = DPR \times C$, where DPR was the water drainage, and C was nitrate nitrogen concentration in soil water measured by a soil water sampler. The results of leaching calculation showed that the highest leaching values were obtained in N200 treatments in both years with 23 and 5.3 kg N ha^{-1} in 1999 and 2000, respectively. The lowest yield of 0.55 and 0.98 t ha^{-1} were obtained at 0 kg N ha^{-1} in 1999 and 2000, respectively (Asadi et al., 2002).

Sweet corn fertilization research has been conducted in Florida for more than thirty years. During the 35-year period from 1962 to 1996 yields have increased. Sustained high yields can be expected with fertilization practices designed to supply crop nutrient requirements (Volk, 1962; Robertson, 1962; Rudert and Locascio, 1979; Hochmuth et al., 1992; Hochmuth, 1994; White et al., 1996).

Hochmuth and Cordasco (2000) summarized the field research of nitrogen fertilizer application in sweet corn production that occur on the mineral soils of the north, west, southwest, and central regions of Florida. Of the fifteen summarized experiments, fourteen resulted in optimum yields with N rates at or below the nitrogen fertilizer application rate of 168 kg N ha^{-1}. However, additional studies are needed to evaluate yield responses to nitrogen rates above 168 kg N ha^{-1}. Plants fertilized with 190, 381 or 526 kg N ha^{-1} on marl and rockland soils resulted in yields equivalent to those fertilized with 168 kg N ha^{-1}. Split N application increased yield 14% in a 1962 experiment compared to yields from plants fertilized in a single application (Volk, 1962). The remaining experiments were fertilized with the split method, recommended for un-mulched crops where leaching and fertilizer burn might occur with the single application method.

Nitrogen recovery was improved when fertilizer was banded in the root zone to one side or to both sides of the plant row. In some experiments, the length of ear blank-tip area decreased with N rates from 0 to 168 kg N ha^{-1}, yield of cull ears decreased, and yield of fancy and No. 1 grade ears increased with168 kg N ha^{-1} compared to yields with lower N treatments.

However, development and certification of site-specific guidelines for optimal timing, water, and nitrogen requirements requires extensive and expensive field experiments. Since it is impossible to test all the interactions between the amount of water and nitrogen during the seasons, use of simulation models can greatly facilitate the evaluation of different production practices and/or environments and thereby streamline the decision-making process (Rinaldi et al., 2007). Several examples of using crop models to test different practices for different crops are summarized as follows.

Paz et al. (1999) stated that past efforts to correlate yield from small field plots to soil type, elevation, fertility, and other factors had been only partially successful for characterizing spatial variability in corn yield. Furthermore, methods to determine optimum nitrogen rate in grids across fields depended upon the ability to accurately predict yield variability and corn response to nitrogen. They developed a technique to use the CERES-Maize crop growth model to characterize corn (*Zea mays L.*) yield variability. The model was calibrated using 3 years of data from 224 grids in a 16 ha field near Boone, IA. The model gave excellent predictions of yield trend along transects in the field, explaining approximately 57% of the yield variability. Once the model was calibrated for each grid cell, optimum nitrogen rate to maximize net return was computed for each location using 22 years of historical weather data.

The model for potato growth (LINTUL-NPOTATO) was used to explore N uptake, tuber yield and residual soil mineral N (RSMN) of a potato crop (*Solanum tuberosum L.*) for 30 years

of historical weather data, as influenced by: (1) the time of slurry application; (2) cultivar maturity; (3) the N/P ratio of the manure; and (4) historical N use. Results indicated that a spring-applied slurry is to be preferred over an autumn-applied slurry in order to avoid over-winter N losses. Patterns of N uptake suggest that organic N with a large proportion of mineral N and applied shortly after emergence, could improve potato yields in organic farming (Van Delden et al, 2003).

Rinaldi et al. (2007) used the CROPGRO model to predict the growth of processing potato (*Lycopersicon esculentum Mill.*) in Southern Italy. One data set of 2002 was used to calibrate the model, while three independent data sets were used to validate the model. Subsequently this model was combined with 53 years of local historical weather data and it was used as a research tool to evaluate the benefits, risks and costs of 23 different interactive irrigation and/or N-management scenarios. Irrigation water was applied (1) on reported dates with 3 and 5 days intervals and application rates of 15 and 25 mm or (2) with automatic irrigation initiated at residual soil moisture levels in the upper 30 cm of the soil profile of 25, 50, or 75%. Three amount levels of N application (100, 200 and 300 kg ha^{-1} as ammonium nitrate) were considered. Based on simulation results it is concluded that irrigation scenario with low amount but with frequent applications ("3-day 15 mm" scenario) resulted in high value of irrigation water use efficiency; frequent irrigation applications combined with low N rates reduced crop stress and represented the best scenario from both a production and environmental point of view (low N leaching).

Thorp et al. (2006) used the CERES-Maize crop growth model to study the corn (*Zea mays L.*) yield response and the nitrogen (N) dynamics of a cornfield in central Iowa, USA. The model was calibrated to minimize error between simulated and measured yield over five growing

seasons. Model simulations were then completed for 13 spring-applied N rates in each of 100 grid cells with varying soil properties. For each N rate and grid cell, simulations were repeated for 37 years of historical weather information collected near the study site. Model runs provided the crop yield and unused N in the soil at harvest for all combinations of N rate, grid cell, and weather year. The overall goal of this work was to develop a methodology for directly contrasting the production and environmental concerns of N management in agricultural systems. In this way, N management plans can be designed to achieve a proper balance between production and environmental goals.

1.2 Objectives

The current project is an attempt to utilize the CERES-Maize model of the Decision Support System for Agrotechnology Transfer (DSSAT) model to develop potential N-BMPs for sweet corn production in North Florida. The objectives include:

- Study on the response of sweet corn yield quantity and quality to different irrigation and nitrogen application levels;
- Study of the nitrogen fate and balance in sweet corn production;
- Global sensitivity analysis of the CERES-Maize model;
- Application of the generalized likelihood uncertainty estimation (GLUE) method in parameter estimation of the CERES-Maize model;
- Utilization of the CERES-Maize model to develop potential N-BMPs for sweet corn production;
- Uncertainty analysis for the developed potential BMPs both under weather and input parameter uncertainties.

1.3 Dissertation Outline

This current research both involves field experimentation and crop model simulation. The main purpose of field experiments is to provide necessary data for model simulations such as

sensitivity analysis, model calibration, and model verification. At the same time, field experiments also provide enough materials to study the response of sweet corn yield to different nitrogen fertilizer and irrigation levels and the fate of fertilizer nitrogen in sweet corn production. The model simulation is the core part of the research. The main research structure could be shown in Figure 1-1.

In general, Chapter 2 of this dissertation will present a sensitivity analysis of the crop model, in which the behavior of the crop model is investigated and the most sensitive input parameters are selected for calibration. In Chapter 3, the generalized likelihood uncertainty estimation (GLUE) parameter estimation process will be described as a procedure for model calibration. Chapter 4 will compare the model outputs and field observations in a procedure of model verification. In Chapter 5, the procedures of BMP development will be discussed, where some potential BMPs will be selected with the calibrated model. In Chapter 6 uncertainty analysis will be conducted for the selected potential BMPs. Finally in the last chapter (Chapter 7), some research conclusions and suggestions about future work will be provided.

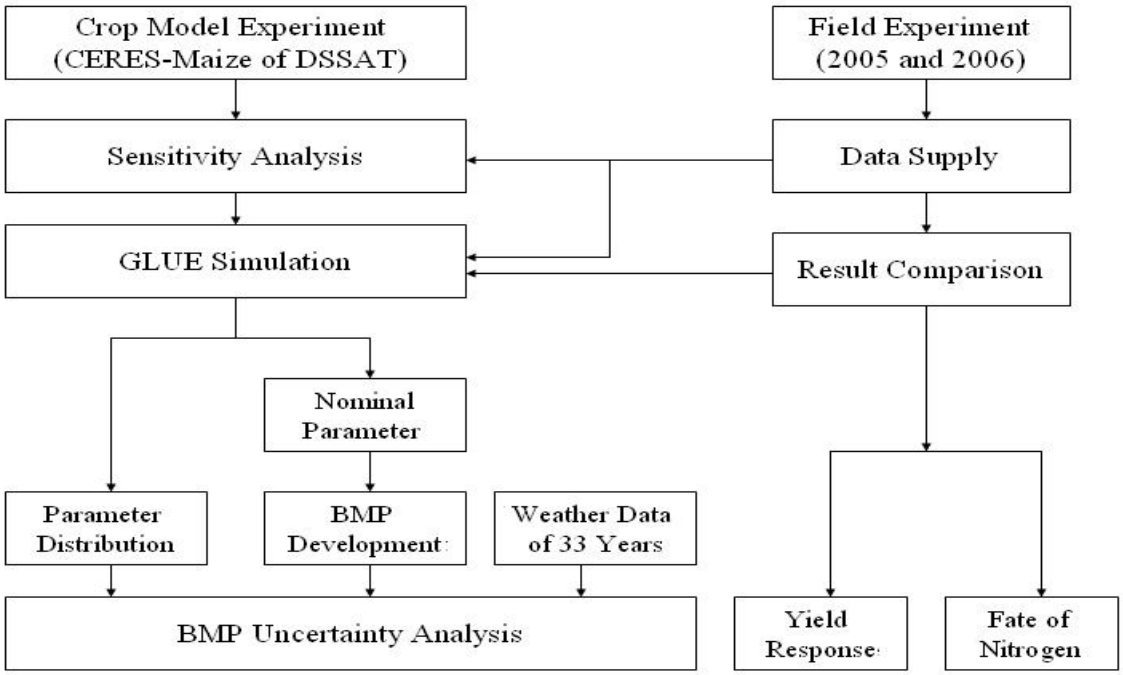


Figure 1-1. Diagram of research structure

Table 1-1. Sweet corn harvested for sale in Florida in 2002 and 1997 (USDA-NASS, 1998, 2002)

Level	2002		1997	
	Farms	Area (ha.)	Farms	Area (ha.)
0-2 ha.	225	114	268	132
2-20 ha.	73	403	94	436
20-100 ha.	15	872	12	616
100-200 ha.	13	2,010	14	1,824
More than 200 ha	14	12,368	25	14,708
Total	340	15,768	413	17,791

Table 1-2. Nitrogen fertilizer application for sweet corn in Florida (USDA-NASS, 1993, 1995, 1999b, 2003, 2006)

Year	Planted Area	Area Applied	Applications	Rate per Application	Rate per Crop Year	Total Applied
	ha.	%	Number	kg ha^{-1}	kg ha^{-1}	kg
1992	20,800	81	3.0	46	137	2,300,000
1994	17,200	90	2.3	47	106	1,648,000
1998	16,800	100	2.0	54	109	1,831,000
2002	16,400	100	2.5	62	159	2,606,000
2006	13,400	86	10.0	47	475	5,480,000

CHAPTER 2
GLOBAL SENSITIVITY ANALYSIS OF CERES-MAIZE MODEL WITH ONE-AT-A-TIME METHOD

2.1 Introduction

2.1.1 Sensitivity Analysis

A crop model has been described as a "quantitative scheme for predicting the growth, development and yield of a crop, given a set of genotype coefficients and relevant environmental variables" (Monteith, 1996). A crop model is the result of a long and complex construction process, involving data at multiple states for understanding basic process, elaborating model structure, estimating parameters and evaluating prediction quality. However, there is a need to study the model on its own, with an emphasis on its behavior rather than its coherence with a given data set. This is where sensitivity analysis becomes useful for the modeler and model user (Monod et al., 2006).

The sensitivity analysis determines how sensitive the output of a crop model is, with respect to the elements of the model which are subject to uncertainty or variability. This is useful as a guiding tool when the model is under development as well as to understand model behavior when it is used for prediction or for decision support. For dynamic models, sensitivity analysis is closely related to the study of error propagation, i.e. the influence that the lack of precision on model input will have on the output.

Because sensitivity analysis usually relies on simulations, it is also closely related to the methods associated with computer experiments. A computer experiment is a set of simulation runs designed in order to efficiently explore the model responses when the input varies within given ranges (Sacks et al., 1989; Welch et al., 1992). The goals in computer experiments identified by Koehler and Owen (1996) include optimization of the model response, visualization

of the model behavior, approximation by a simpler model or estimation of the average, variance, or probability of the response to exceed some threshold.

Within a given model, model equations, parameters and input variables are all subject to variability or uncertainty. The following 3 reasons make it an inevitably necessary step to do sensitivity analysis before any model simulation.

First, choices have to be made regarding the model structure and on the functional relationships between input variables and output variables. These choices may sometimes be quite subjective and it is not always clear what their consequences will be. For example, Martinez et al. (2001) performed a sensitivity analysis to determine the effects of the number of soil layers on the output of a land surface-atmosphere model. For spatial models, there was frequently a need to evaluate how the scale chosen for input variables affects the precision of the model output (see e.g. Salvador et al., 2001).

Second, parameter values result from estimation procedures or sometimes from bibliographic reviews or expert opinion. Their precision is however limited by the variability and possible lack of adequacy of the available data. Some parameters may also naturally vary. The uncertainty and natural variability of parameters are the central point of many sensitivity analyses. Barlund and Tattari (2001), for example, studied the influence of model parameters on the predictions of field-scale phosphorus losses, in order to get better insight into the management model ICECREAM. Ruget et al. (2002) performed sensitivity analysis on parameters of the crop simulation model STICS, in order to determine the main parameters that need to be estimated precisely.

Third, additional and major sources of variability in a model output are the input variables. Lack of precision when measuring or estimating input variables need to be quantified when

making predictions from a model or when using it for decision support. Rahn et al. (2001) compared contrasted input scenarios for HRI WELL-N model on crop fertilizer requirements through a sensitivity analysis. They identified the main factors that need to be measured precisely to provide robust recommendations on fertilization. Contrasted settings of the input variables were used for performing sensitivity analyses assuming different scenarios by Dubus and Brown (2002).

As shown by the examples above, sensitivity analysis may have various objectives, such as: (1) to check that the model output behaves as expected when the input varies; (2) to identify which parameters have a small or a large influence on the output; (3) to identify which parameters need to be estimated more accurately; (4) to detect and quantify interaction effects between parameters, between input variables, or between parameters and input variables; (5) to determine possible simplification of the model; and (6) to identify input variables which need to be measured with maximum accuracy (Monod et al., 2006). Some of these objectives have close links with other methods associated with modeling, like model construction, parameter estimation or model use for decision support.

2.1.2. Local Sensitivity Analysis

Local sensitivity analysis is based on the local derivatives of a model output $\widehat{Y} = f(Z)$ with respect to a single input factor Z, which indicates how fast the output increases or decreases locally around given values of Z. The derivatives can sometimes be calculated analytically, but they are usually calculated numerically for complex models. Problems may arise if the derivative of the model does not exist at some points. In addition, the derivatives may depend strongly on the Z value (Monod et al., 2006).

The local (first-order) sensitivity coefficient $S_i^{local}(Z_k)$ is defined as the partial derivative of the output variable $\widehat{Y}$ with respect factor Z_i, calculated at the scenario Z_k:

$$S_i^{local}(Z_k) = \frac{\partial f(Z)}{\partial Z_i} \tag{2-1}$$

This criterion is equivalent to the slope of the calculated model output in the parameter space, and $S_i^{local}(Z_k)$ criterion is an absolute measure of sensitivity, which depends on the scales or measurement units of $\widehat{Y}$ and Z_i. A standardized version, called the relative sensitivity, is defined by following equation (Monod et al., 2006):

$$S_{ir}^{local}(Z_k) = \frac{\partial f(Z)}{\partial Z_i} \times \frac{Z_{k,i}}{f(Z_k)} \tag{2-2}$$

Local sensitivity analysis can be used to study the role of some parameters or input variables in the model. But this method is less useful than global sensitivity when the purpose of the analysis it to study the effect of uncertainty of several factors on model outputs.

2.1.3 Global Sensitivity Analysis

In global sensitivity analysis, the output variability is evaluated for input factors varying within their entire domains. This provides a more realistic and comprehensive view of the model behavior.

There are several methods for global sensitivity analysis, such as the one-at-a-time (OAT) method (Morris, 1991), factorial design and analysis of variance (Monod et al., 2006), intensive sampling and variance-based method (Monod et al., 2006), and the Fourier amplitude sensitivity test (FAST) method (Chan et al., 2000). The OAT method is more straightforward and less complicated in application compared to the other methods mentioned above.

The objective of this research is to conduct global sensitivity analysis for the CERES-Maize model with the one-at-a-time (OAT) method so as to: (1) determine the sensitivity of the model outputs (dry matter yield, kg ha^{-1} and cumulative nitrogen leaching, kg N ha^{-1}) with respect to changes in soil and genotype input parameters, and (2) identify the most influential input parameters that need to be calibrated in future research.

2.2 Materials and Methods

2.2.1. Model Description

2.2.1.1 CERES-Maize model

The crop model CERES-Maize, used for this research is embedded in the Decision Support System for Agrotechnology Transfer (DSSAT) software (Jones et al., 2003), version 4.0. To run the model, several input files must be compiled that contain information about the experiment site, soil, climate and genotype (Tsuji et al., 1994).

At the heart of the DSSAT revisions is a cropping system model (DSSAT-CSM), which incorporates all crops as modules using a single soil model (Jones et al., 2003). The CERES-Maize, Wheat and Barley models were modified for integration into the modular DSSAT-CSM. For these CERES models, the plant life cycle is divided into several phases, which are similar among the crops. Rate of development is governed by thermal time, or growing degree days (GDD), which is computed based on the daily maximum and minimum temperatures. The GDD required to progress from one growth stage to another are either defined as a user input, or are computed internally based on user inputs and assumptions about duration of intermediate stages. The genotype coefficients for the DSSAT CERES-Maize, Wheat and Barley models are listed in Table 2-1.

Daily plant growth is computed by converting daily intercepted photosynthetically active radiation (PAR) into plant dry matter using a crop-specific radiation use efficiency parameter.

Light interception is computed as a function LAI, plant population, and row spacing. The amount of new dry matter available for growth each day may also be modified by the most limiting of water or nitrogen stress, and temperature, and is sensitive to atmospheric CO_2 concentration. Above ground biomass has priority for carbohydrate, and at the end of each day, carbohydrate not used for above ground biomass is allocated to roots. Roots must receive, however, a specified state-dependent minimum of the daily carbohydrate available for growth. Leaf area is converted into new leaf weight using empirical functions (Jones et al., 2003).

Kernel numbers per plant are computed during flowering based on the cultivar's genotype potential, canopy weight, average rate of carbohydrate accumulation during flowering, and temperature, water and nitrogen stresses. Potential kernel number is a user-defined input for specific cultivars. Once the beginning of grain fill is reached, the model computes daily grain growth rate based on a user-specified cultivar input defined as the potential kernel growth rate (mg $kernel^{-1}d^{-1}$). Daily growth rate is modified by temperature and assimilate availability. If the daily pool of carbon is insufficient to allow growth at the potential rate, a fraction of carbon can be remobilized from the vegetative to reproductive sinks each day. Kernels are allowed to grow until physiological maturity is reached. If the plant runs out of resources, however, growth is terminated prior to physiological maturity. Likewise, if the grain growth rate is reduced below a threshold value for several days, growth is also terminated (Jones and Kiniry, 1986; Ritchie and Otter, 1985; Ritchie et al., 1998).

2.2.1.2 Soil water sub-module

The soil water balance model developed for CERES-Wheat by Ritchie and Otter, (1985) was adapted for use by all of the DSSAT v3.5 crop models (Jones, et al, 2003). This one-dimensional model computes the daily changes in soil water content by soil layer due to infiltration of rainfall and irrigation, vertical drainage, unsaturated flow, soil evaporation, and

root water uptake processes. The model uses a “tipping bucket” approach for computing soil water drainage when a layer’s water content is above a drained upper limit parameter, or field capacity. Upward unsaturated flow is also computed using a conservative estimate of the soil water diffusivity and differences in volumetric soil water content of adjacent layers (Ritchie, 1998).

Soil water infiltration during a day is computed by subtracting surface runoff from rainfall that occurs on that day. The SCS (Soil Conservation Services) method is used to partition rainfall into runoff and infiltration, based on a “curve number” that attempts to account for texture, slope, and tillage. When irrigation is applied, the amount applied is added to the amount of rainfall for the day to compute infiltration and runoff. Drainage of liquid water through the profile is first calculated based on an overall soil drainage parameter assumed to be constant with depth. The amount of water passing through any layer is then compared with the saturated hydraulic conductivity of that layer, if this parameter is provided. If the saturated hydraulic conductivity of any layer is less than computed vertical drainage through that layer, actual drainage is limited to the conductivity value, and water accumulates above the layer. This feature allows the model to simulate poorly drained soils and perched water tables. For example, a soil may have a layer with very low or no drainage at the bottom of the profile. Vertical drainage from the profile would not occur or it would be very low, limited by the saturated hydraulic conductivity value of the bottom layer (Jones et al., 2003).

Evaporation of water from the soil surface and root water uptake (transpiration) from each layer are computed in the soil-plant-atmosphere model (SPAM) with the Priestley-Taylor equation (Priestly and Taylor, 1972) and communicated to this soil water balance module. Each

day, the soil water content of each layer is updated by adding or subtracting daily flows of water to or from the layer due to each process (Jones et al., 2003).

2.2.1.3 Soil nitrogen sub-module

The nitrogen balance model simulates the processes of organic matter turnover with the associated mineralization and/or immobilization of nitrogen, nitrification, denitrification, hydrolysis of urea, ammonia volatilization, N plant uptake and translocation to the different organs during crop cycle. Transport of nitrate occurs at the same rate as the flow of water (Booltink et al., 1996).

The CERES N model of the DSSAT model has two forms, one for upland cereal crops and one for flooded soil rice cropping systems. Both versions simulate the turnover of soil organic matter and the decay of crop residues with the associated mineralization and/or immobilization of N. Nitrification of ammonium and N losses associated with denitrification are estimated by both models. The lowland version adds to this a floodwater chemistry routine which simulates the fluxes of ammonia N and urea between floodwater and soil, and calculates ammonia and volatilization losses. Both models incorporate a plant N component that simulates N uptake and distribution within the plant and remobilization during grain filling and plant growth responses to plant N status. The models are closely coupled with the CERES water balance and crop growth routines (Tsuji et al., 1998).

Since the soil nitrogen model used within the DSSAT is intrinsically linked to the water balance model, those parameters used by the water balance model that define ranges of soil water availability, soil drainage and deep percolation characteristics and layer depth increments are also required by the N model. The inputs for the soil water balance model are described by Ritchie and Otter (1985). The N model itself requires input data that describe the initial amount of mineral N present in the soil profile and information that will enable the estimation of how

much N will be mineralized from soil organic matter, the potassium chloride extractable nitrate and ammonium present in each of the layers. The soil bulk density is used in the calculations of concentrations of N from mass (Tsuji et al., 1998).

2.2.2 Non-restricted OAT Method

The most intuitive method to conduct a sensitivity analysis is to vary one factor at a time, while the other factors are fixed at their nominal values. The relationship between the values z_i of factor Z_i and the responses $f(z_{0,1},...z_{0,i-1}, z_i, z_{0,i+1}...z_{0,S})$ determines an OAT response profile, where S is the total number of parameters. In practice, each input factor Z_i takes k equispaced values from $z_{\min,i}$ to $z_{\max,i}$, with an increment of $\delta = \frac{z_{\max,i} - z_{\min,i}}{(k-1)}$. The model responses $f(z_{0,1},...z_{0,i-1}, z_i, z_{0,i+1}...z_{0,S})$ are then calculated for each of the k discretized values of Z_i (Monod et al., 2006). The main idea of non-restricted OAT method can also be briefly shown in Figure 2-1.

In Figure 2-1, the space of possible values of parameter Z_i from the minimum to the maximum value could be divided and represented as a $1 \times k$ matrix, where k is the dimension of the space. Other parameters were assigned with their nominal value, which were the mean values derived from DSSAT model database in current research. In the example shown in Figure 2-1, the first element or the minimum value of the matrix was selected as the model input parameter.

The model is run with the discretized values of Z_i and the relevant outputs are recorded. After trying all of the available values of Z_i in its discretized space, the process is repeated for other input parameters. When the value of Z_i varies, all other parameters keep their norminal

values. If the number of sensitivity parameters is not too large, graphical representations are the best way to summarize the response profiles.

The number of k must be chosen carefully when the model is non-linear and particularly when it is non-monotonic. Provided the value of k is odd, the number of model simulations to calculate all profiles is equal to $s(k-1)+1$. When k is small and the model is non-linear, the non-linear effects, as well as maxima or minima, may be undetected, which may lead to under-estimating sensitivity indices such as the index of Bauer and Hamby (1991). However, when k is too large, the computing time may become very long if there are many input factors and the model is complex.

However, the non-restricted OAT method does not provide any information about covariance and interaction between the input parameters, which might also contribute to uncertainty in predictions. When only selecting parameters just according to the response profiles, some important parameters might be missed. To compensate for the drawback mentioned above, a correlation coefficient matrix was established for the genotype and soil parameters concerned to assist in parameter selection.

2.2.3 Normalization of Input Parameters

The results of global sensitivity analysis with non-restricted OAT method can be shown as response curves of outputs concerned to input parameters. However, input parameters always have different units and ranges. It is difficult to present all of the response curves in one figure when under such different ranges and units. If a common range is used for all parameters, the presentation could be simplified.

The simplification could be done by normalizing the levels of the factors so that they vary between -1 and +1 or between 0 and 1. Normalized values z_i^C of an input factor Z_i can easily be

calculated from the un-normalized values through the following relationships (Monod et al., 2006):

$$z_i^C = \frac{z_i - (z_{\max(i)} + z_{\min(i)})/2}{(z_{\max(i)} - z_{\min(i)})/2} \tag{2-3}$$

or

$$z_i^C = \frac{z_i - z_{\min(i)}}{(z_{\max(i)} - z_{\min(i)})} \tag{2-4}$$

In this research, with Equation (2-3), the response curves of dry matter yield and cumulative nitrogen leaching to the genotype and soil parameters in their whole domains were represented.

2.2.4 Restricted OAT Method

Unfortunately, the non-restricted OAT method does not tell model users anything about the sensitivity contribution by the interactions between input parameters, since this method holds other parameters fixed at their nominal values while only changing one factor. This problem can be solved by the restricted OAT method, which was exploited by Morris (1991).

The main idea of the Morris restricted OAT method can be briefly explained by Figure 2-2. The space of each parameter is divided into k equal sections, shown as a $k \times 1$ matrix. For all of the s factors, a $k \times s$ matrix is constructed. It was assumed the input paremeters were independent. One value is then randomly picked up for each parameter from its own space. The s randomly picked values of relevant parameters construct a possible parameter scenario. Then the model can be run with this established scenario to calculate the elementary effect or local sensitivities for each of the parameters by just changing one parameter while keeping other parameters fixed at their nominal values of this specific scenario. After this scenario, another randomly

established scenario can be used to repeat the same process until sufficient local sensitivity values are available for each parameter.

The random selection of parameter values to construct a scenario can be realized with the method below. First, a $1 \times s$ matrix of random integers is generated. Each element of the integer matrix follows a uniform distribution of [1, k]. Then use these random integers as addresses to select values for the parameters from their individual spaces. For example (as shown in Figure 2-2), the first element of the integer matrix, R1, is 2. Then the second element of the space of Z_1 is selected as the nominal value for Z_1 in the scenario. The same process is repeated for other parameters to construct the scenario. It is obvious that more scenarios were constructed, more reliable the results would be. However, the running time should also be considered, because tens of thousands of model runs were required. In this research, 2,000 scenarios were constructed finally.

Morris defined the elementary effect of the *i*th input factor for a given scenario $Z_0 = (z_{0,1},...z_{0,i-1}, z_{0,i}, z_{0,i+1}...z_{0,S})$ as:

$$d_i(Z_0) = \frac{f(z_{0,1},...z_{0,i-1}, z_{0,i} + \Delta, z_{0,i+1}...z_{0,S}) - f(z_{0,1},...z_{0,i-1}, z_{0,i}, z_{0,i+1}...z_{0,S})}{\Delta} \qquad (2-5)$$

where $z_{0,i} + \Delta$ is a perturbed value of $z_{0,i}$, and Δ is a predetermined multiple of $1/(k-1)$.

The number of parameter scenarios depends on the reliability of the result of sensitivity analysis and the time of model running. In theory, more scenarios are tested, more reliable the sensitivity analysis result. However, if too many scenarios and parameters are involved, it will require huge number of model running, which will be very time consuming and delay future work. In this research, 2,000 scenarios were constructed.

After calculating $d_i(Z_0)$ for sufficient scenarios, the resulting distribution of the elementary effects of the *i*th factor is then characterized by its mean and variance. A high mean indicates a factor with an important influence on the output. A high variance indicates either a factor interacting with another factor or a factor whose effect is non-linear.

2.2.5 One-at-a-time (OAT) Method for CERES-Maize Model

In the current research, all of the soil and genotype input parameters of the CERES-Maize model were investigated both with the non-restricted and restricted OAT method to identify the most influential parameters for future model calibration. The six genotype input parameters of the model are listed in Table 2-1. The nine soil parameters include the following: soil water saturation (SSAT), drained lower limit (SLLL), drained upper limit (SDUL), bulk density (SBDM), soil albedo (SALB), evaporation limit (SLU1), runoff curve number (SLRO), drainage rate (SLDP), and fertility factor (SLPF). See Appendix A for details about the definitions and units of these parameters.

This procedure provides useful information for the model developers, e.g. which input parameters need more accurate measurement or calculation. The outputs of concern are dry matter ear yield (kg ha^{-1}) and cumulative nitrogen leaching (kg ha^{-1}), since they are the two main factors in potential best management practices (BMPs) development in this study (Chapter 5).

The main procedures of global sensitivity analysis of the CERES-Maize model with the restricted OAT method in this study are outlined here. First, the sampling spaces for each of the six genotype and nine soil parameters were established according to the values available in the DSSAT model database. For each parameter, the range between the minimum and maximum value was divided into 100 equal sections, with an increment of $\delta = (Z_{\max} - Z_{\min})/(100-1)$. These 100 values were saved as a vector. The same process was repeated for other parameters.

However, for SLLL, SDUL and SSAT, the scenarios of SLLL>SDUL or SDUL>SSAT were avoided since they could cause the model to stop running. For example, if SLLL>SDUL, it means the soil available water (SDUL-SLLL) would be negative, which conflicts with the basic physical principles. Therefore the minimum value of SLLL is set as its own minimum value, but the maximum value is set as the minimum value of SDUL. In the same way, the minimum value of SSAT is set as the maximum value of SDUL.

Next, 15 random integer numbers following a uniform distribution of [1,100] were generated, since there were a total of 15 genotype and soil parameters under investigation. These 15 random integers were assigned to each of the 15 parameters as the addresses for selecting values from their individual matrix space. The 15 selected numbers from the spaces of input parameters constructed a scenario of parameter set to run the model.

Third, the values of the scenario were used to change corresponding values in the soil and genotype files and replace their original files in the correct installation directory of DSSAT model. As the model was run, outputs were saved.

Fourth, a perturbation was given to the ith parameter, for example a 5% increment from the initial value. The perturbation value should not be too large. Otherwise the result will fail to approximate the definition of local sensitivity (Equation 2-1 and 2-2). It also should be not too small. Otherwise some of the model outputs, especially nitrogen leaching, will not change when only under a very small perturbation of the input parameters. In this research, it was found that 5% was a good choice for perturbation after comparing the results under a perturbation of 3%, 5%, 10%, and 20%. Thus, a new parameter vector was generated. The values in this new parameter vector were used to change the genotype or soil file again. The model was then rerun and the process was repeated. Equation (2-5) was used to calculate the elementary effect of

ith parameter under this specific scenario. The same procedure was repeated to calculate the elementary effects for all of the input parameters under this specific input parameter scenario.

Fifth, the elementary effects for the parameters under other randomly established scenarios were calculated, as well as the mean and variance values of the elementary effects for each parameter. Since the values of elementary effects might be either positive or negative, indicating a parameter may increase the output in some places or decrease the output in other places when the value of the parameter increases, the mean values alone might be misleading. For example, a parameter that simultaneously has large positive and negative values of elementary effect might have a very low mean value of elementary effect. Therefore in the current research, the mean and variance of the absolute values of the elementary effects were calculated.

Finally, the mean and variance of the absolute values of the elementary effects of each parameter were compared to determine which parameters have greater influences on the output.

The global sensitivity analysis with the restricted OAT method was conducted with Matlab program (Appendix B for more detailed codes). A total of 2,000 scenarios were randomly generated, and hence $2000 \times (15 + 2) = 34{,}000$ model runs were conducted.

The main procedures of non-restricted OAT method were similar to those of restricted OAT method. However, the number of model runs was smaller. As described above, since the domain of each input parameter was evenly separated into 100 sections and 15 input soil and genotype parameters were investigated, thus only $100 \times 15 = 1{,}500$ model runs were required.

In the current research, both the restricted and non-restricted OAT method were used to conduct global sensitivity analyses for the dry matter yield and nitrogen leaching responding to input parameters. However, for the restricted OAT method, the sensitivity analyses were conducted separately for the genotype and soil parameters. It means when doing sensitivity

analysis for the genotype parameters, the soil parameters were fixed at their nominal values, and vice versa. This is because the genotype and soil parameters are two completely different kinds of input parameters. Thus it was assumed that the influence of interaction or correlation between them on the results of sensitivity analysis would be neglectable.

2.2.6 Field Experiment

When doing sensitivity analysis, except for the soil and genotype input parameters, additional information, such as planting date, harvest, irrigation, and, potassium application, nitrogen fertilizer application etc., was required as fundamental inputs to run the model. This information was obtained from the field experiment in this study.

The field experiments were conducted at the Plant Science Research and Education Unit, the University of Florida in the spring of 2005. The unit is located in Pine Acres (29.4094^{o}N, 82.1777^{o}W, 20.746 meters above sea level), Marion County, Florida, U.S. (Judge et al., 2005). There were two experiment field identified as Block1 and Plots. The variety of sweet corn planted was Saturn SH2.

Finally, field management information obtained in Block1 in 2005 was used as fundamental inputs for model testing. Weather data, including daily solar radiation, maximum temperature, minimum temperature, and rainfall, were also required as the necessary driving force for model testing. In this study, these data were obtained from the weather database of the Florida Automated Weather Network (FAWN) in 2005 at the Citra, where the unit is located. See Chapter 3 for more information about the field experiment in Block1.

2.3 Results and Discussion

2.3.1 Non-restricted OAT Results

2.3.1.1 Response profiles

Drawing response profiles is often useful, at least in preliminary stages. The response profiles of dry matter yield to genotype and soil parameters are shown in Figure 2-3 and 2-4 below, while the response profiles for nitrogen leaching are shown in Figure 2-5 and 2-6 for the results of global sensitivity analysis with the non-restricted OAT method. Please be noticed these figures do not represent any actual growth scenario of sweet corn, because the nominal values of the input parameters were set as the mean values of them, which were derived from the DSSAT database.

From these four figures it can be seen that genotypes P1, P5, PHINT and soil parameters SLLL, SDUL and SLPF had strong influences on yield, while soil parameters SLLL, SDUL, SLDR and SLRO had strong influences on nitrogen leaching. For example, when P1 is the mean value, the predicted dry yield was about 8,400 kg ha^{-1}. Then the predicted dry yield decreased to about 6,200 kg ha^{-1} when P1 decreased to its minimum value, with a decrement of 26%. And it increased to almost 11,800 kg ha^{-1} when P1 increased to its maximum value, with an increment of 40%. However, for the genotype parameters (P2, G2, and G3) and soil parameters (SLDR, SLRO and SBDM etc.), the predicted dry yields were almost kept at the same values as about 8,400 kg ha^{-1}. These simulated dry yields were much higher than the field plot experiment results (Chapter 4), since the model was not calibrated yet. The genotype parameters did not describe the genetic characteristics of the real corn in the experiment.

Similar results were observed for nitrogen leaching. For example, the amount of nitrogen leaching decreased from 220 kg N ha^{-1} to about 40 kg N ha^{-1} , when the value of SDUL increased from its minimum value (0.145 to 0.374 cm^3/cm^3) to the mean value,. And the amount of

nitrogen leaching increased from 40 kg N ha^{-1} to about 190 kg N ha^{-1}, when the value of SLLL decreased from its mean value to the maximum value. However, the amounts of predicted nitrogen leaching under other soil parameters were all approximately 40 kg N ha^{-1} with minimal changes due to input parameter changes.

Those parameters that showed high influence on model outputs when their values changed should be considered with priority when select parameters for future model calibration with the generalized likelihood uncertainty estimation (GLUE) method (Chapter 3). However, these figures do not provide information about covariance and interaction between parameters, which might also contribute to uncertainty in predictions. When only selecting parameters just according to the response profiles, some important parameters might be missed.

2.3.1.2 Correlation coefficient matrix

As described in Section 2.2.2 and 2.3.1.1, the non-restricted OAT method did not provide any information about the covariance of the input parameters. Some important parameters probably will be missed if not considering the influence of covariance between the input parameters. Thus, a correlation coefficient matrix was established to assist in influential parameter selection.

In the current research, the parameter values in the database of the DSSAT model were used to calculate the covariance values between each pair of the parameters. It was assumed that there was no covariance between cultivar and soil parameters since they are completely different kinds of parameters.

The calculated results were used to establish a correlation coefficient matrix as shown in Table 2-2, where it can be observed that soil parameters SLLL, SDUL and SSAT are highly correlated to each other.

2.3.1.3 Influential parameter selection based on non-restricted OAT method

Based on the response profiles of input genotype and soil parameters to dry matter yield and cumulative and the correlation coefficient matrix, the influential input parameters either to dry matter yield or nitrogen leaching could be selected for further calibration.

The criteria of selection were listed in Table 2-3. According to the criteria, if a parameter was highly sensitive, it was selected. If a parameter was not very sensitive, but it had a high correlation with a highly sensitive one, it was also selected. For example, from Figure 2-3, it is easy to see that P1, P5, and PHIN were the most sensitive genotype parameter to dry matter yield, since the response curves of them have the steepest slope. Thus P1, P5, and PHIN were selected. In Figure 2-4 soil parameter SLLL, SDUL, and SLPF showed the highest sensitivity to dry matter yield, so they were also selected.

Similarly, in Figure 2-5, P1, P5, and PHIN were the most sensitive genotype parameters to cumulative nitrogen leaching, though the sensitivities were much lower than the influential soil parameters. In Figure 2-6, more soil parameters showed significant influence on nitrogen leaching, including SLLL, SDUL, SLDR, SLRO. These parameters were also selected.

For these four figures, it can be seen that soil parameter SSAT only showed a little bit sensitivity to dry matter yield and nitrogen leaching. However, SSAT had a very high correlation with the sensitive soil parameter SLLL and SDUL. As shown in Table 2-2, the covariance coefficients between SSAT and SLLL and between SSAT and SDUL, were 0.576 and 0.647 respectively. To consider the probable sensitivity contribution by the covariance, soil parameter SSAT was also selected. Thus, in the end, totally nine parameters selected based on the non-restricted OAT method and the correlation coefficient matrix were listed in Table 2-4.

In general, one more parameter SSAT was selected than only considering the response curves but not considering the covariance.

2.3.2 Influential Parameter Selection Based on Restricted OAT Method

As described in Section 2.2.4 that the results of the restricted OAT method were presented as absolute elementary effect values, which have no units. The mean values and standard deviations of the elementary effect values of the input parameters were calculated. If an input parameter has a high mean value, e.g. greater than 1.0, it means the parameter is sensitive to the output concerned. If the parameter has a high value of standard deviation, it means the parameter is non-linear or highly correlated with other parameters.

The mean values and standard deviations of the elementary elements of the genotype parameters corresponding to predicted dry matter yield and cumulative nitrogen leaching, which are the two main factors for BMP development, are summarized in Table 2-5. It can be seen that P1 was the most sensitive factor for dry matter yield, with P5 and PHINT following.

PHINT had a large value of variance for dry matter yield, which implies that the response curve of PHINT to dry yield may be nonlinear, for example, existing plateau or threshold regions. Actually from Figure 2-3, it can be seen that the response curve of dry matter yield to PHINT was dentate. P5 and PHINT are also sensitive to nitrogen leaching, comparing with other parameters. Therefore P1, P5 and PHINT should be selected when doing model calibration.

Table 2-6 shows the results of global sensitivity analysis with the restricted OAT method of soil parameters corresponding to dry matter yield and nitrogen leaching. Most soil parameters have little influence on yield, except for SLPF, SLLL and SDUL. This is true because SLPF is the fertility factor that reflects the influence of micronutrients such as copper and zinc. SDUL is the soil water holding capacity, while SLLL is the soil permanent wilting point. These two parameters determine the soil available water (SAW) in the soil profile, which is always defined as the difference between SDUL and SLLL. If the value of SAW is small, the corn may suffer from water stress when the amount of irrigation is fixed, thus reducing yield.

SLLL, SDUL, and SLRO have strong influence on nitrogen leaching. Nitrogen leaching is accompanied by water movement in soil profile, with more water infiltrating into soil profile, more nitrogen will be leached. When the value of SDUL is lower, less water can be held by soil, and more nitrogen will be leached. SLRO is the soil runoff curve number, which influences water runoff on soil surface. If less water was lost by runoff, more would be lost by infiltration and more nitrogen would be leached consequently.

Though the mean and variance of elementary elements to nitrogen leaching of SLDR were lower than SLLL, SDUL, and SLRO, the values were still considerable (0.88 and 8.28) as shown in Table 2-6. From Figure 2-6, it can also be seen that SLDR was sensitive to nitrogen leaching. And the SLDR represents the soil drainage coefficient, while soil drainage will definitely influence soil water movement and final nitrogen leaching. Thus, SLDR was also selected. Considering both the influence on yield and nitrogen leaching, SLDR, SLRO, SLPF, SLLL, and SDUL should be selected.

In general, genotype parameter of P1, P5 and PHINT and the soil parameter of SLDR, SLRO, SLPF, SLLL, and SDUL should be selected based on the results of restricted OAT method (Table 2-7).

If comparing the selected parameters listed in Table 2-4 and 2-7, it is interesting to that the two methods almost share the same results, except for parameter SSAT. Since SSAT was so highly correlated with other sensitive parameters such as SLLL and SDUL, this parameter should be selected. Finally, the input parameters listed in Table 2-4 were used for future research in GLUE simulation.

2.4 Summary and conclusions

In this research, the non-restricted and restricted OAT methods were used to conduct global sensitivity analysis for the CERES-Maize model. The outputs of concern were dry matter

yield and accumulative nitrogen leaching, because they are the two main factors for BMP development in this study (Chapter 5). Some conclusions were drawn as follows.

Genotypes parameters P1, P5, PHINT and soil parameters SDUL, SLLL and SLPF have strong influence on dry matter yield. The mean values of absolute elementary effect of P1, P5 and PHINT to dry yield were 14.50, 2.14, and 1.95, while other genetic parameters all have a mean value less than 1.0. This means that genotype parameters P1, P5, and PHINT had 2 to 14 times more influence on dry matter yield than the other genotype parameters. The mean values of absolute elementary effect of SDUL, SLLL, and SLPF were 4.46, 2.07, and 1.56, while the values of other soil parameter are all less than 1.0.

Genetic parameters P5 and PHINT and soil parameters SDUL, SLLL, and SLRO have strong influence on nitrogen leaching. The mean values of absolute elementary effect of P5 and PHINT to nitrogen leaching were 1.61 and 2.19, while other genotype parameters all have a mean value less than 1.0. This means that genotype parameters P5 and PHINT had 1.6 to about 2 times more influence on dry matter yield than the other genotype parameters. The mean values of absolute elementary effect of SDUL, SLLL, and SLRO to nitrogen leaching were 7.63, 4.51, and 2.65, while other soil parameters all have a mean value less than 1.0.

Soil parameters SLLL, SDUL and SSAT were highly correlated to each other. The covariance coefficient between SLLL and SDUL was 0.935, while the coefficient between SLLL and SSAT, SDUL and SSAT were 0.576 and 0.647.

Nine parameters were selected for future model calibration with GLUE method (Chapter 3). They were P1, P5, PHINT, SLDR, SLRO, SLPF, SLLL, SDUL and SSAT. Genotype parameters P1, P5, and PHINT and soil parameters SLLL, SDUL, SLDR and SLRO were selected because they have highest mean values of absolute elementary effect corresponding to either dry yield or

nitrogen leaching. The soil parameter SSAT was selected because it was highly correlated with sensitive parameters SDUL and SLLL. Though the mean and variance of elementary elements to nitrogen leaching of SLDR were lower than SLLL, SDUL, and SLRO, the values were still considerable, much greater than other rest soil parameters. And the SLDR represents the soil drainage coefficient, while soil drainage will definitely influence soil water movement and final nitrogen leaching. Thus, SLDR was also selected.

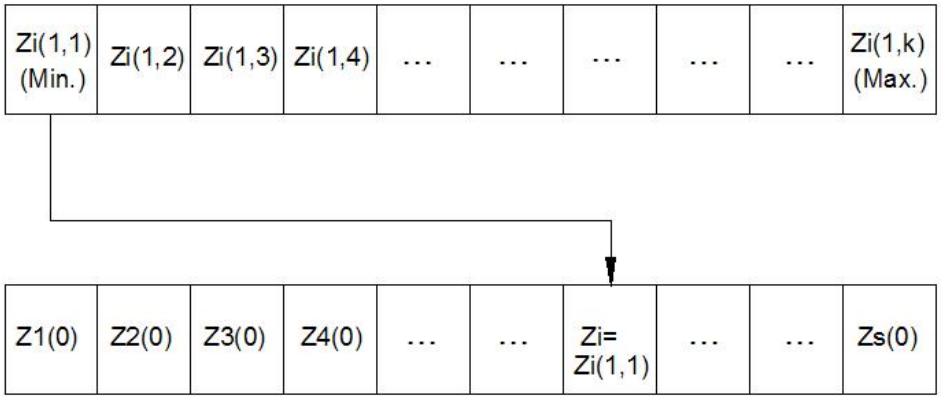


Figure 2-1. Scheme of non-restricted OAT method. Zi is the *i*th input parameter. Zs(0) represents the nominal value of input parameter Zs.

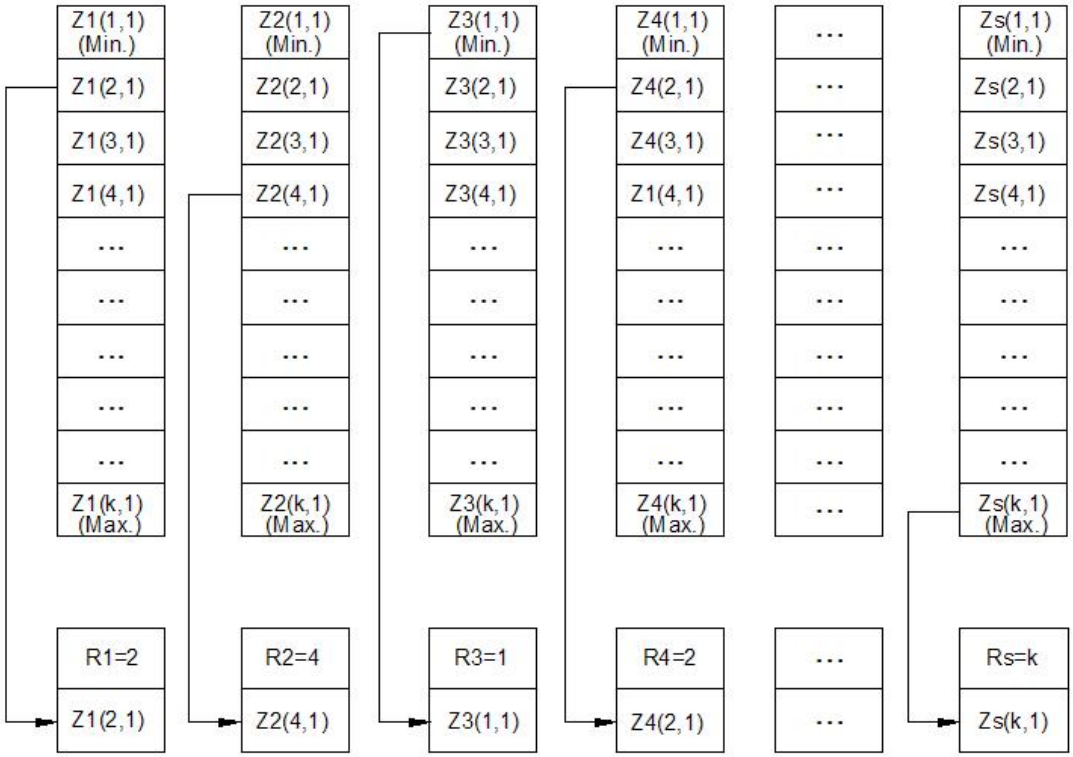


Figure 2-2. Scheme of restricted OAT method. Z is an input parameter. Zs(k,1) represents the value of the element (k,1) of the space matrix of input parameter Zs. R is the random integer following uniform distribution and used as address for nominal value selection in the domain of the input parameter.

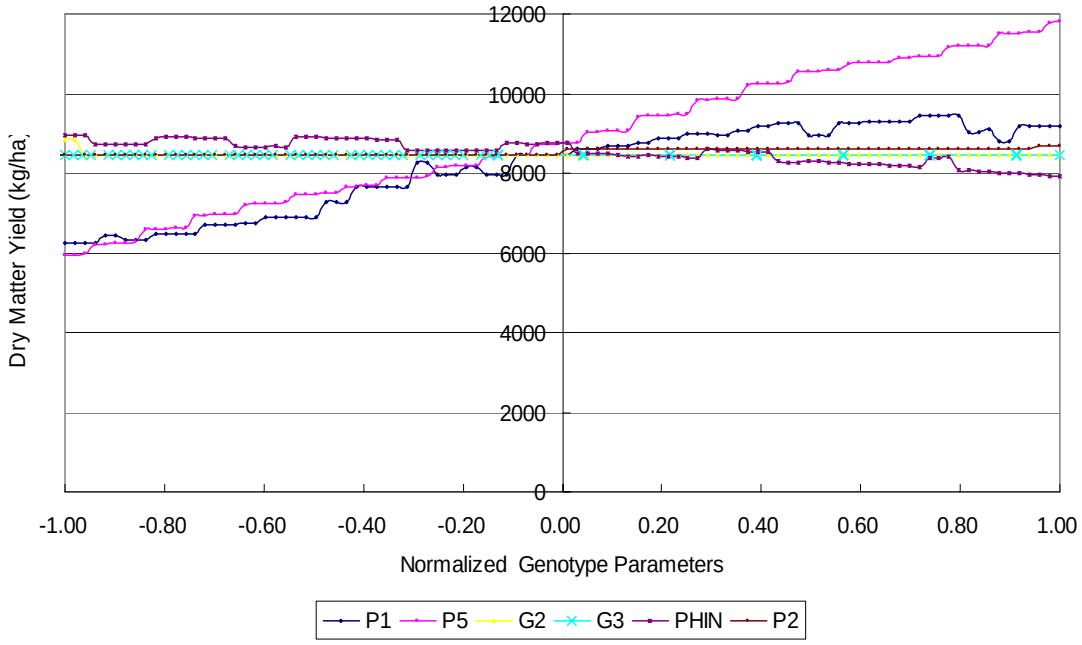


Figure 2-3. Response profiles of sweet corn yield to six normalized genotype parameters

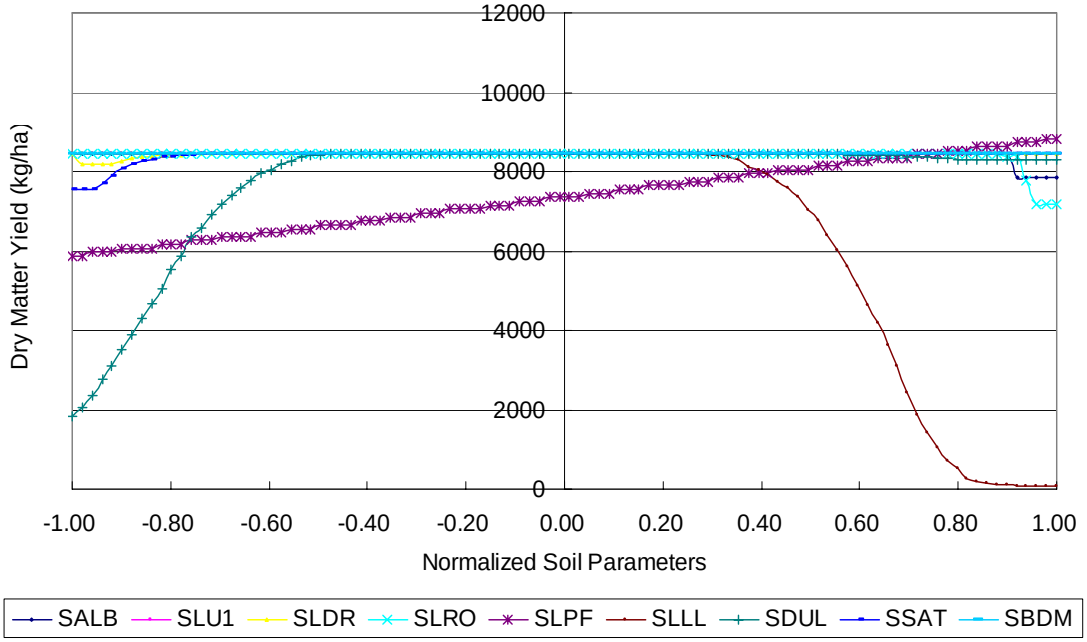


Figure 2-4. Response profiles of sweet corn yield to nine normalized soil parameters

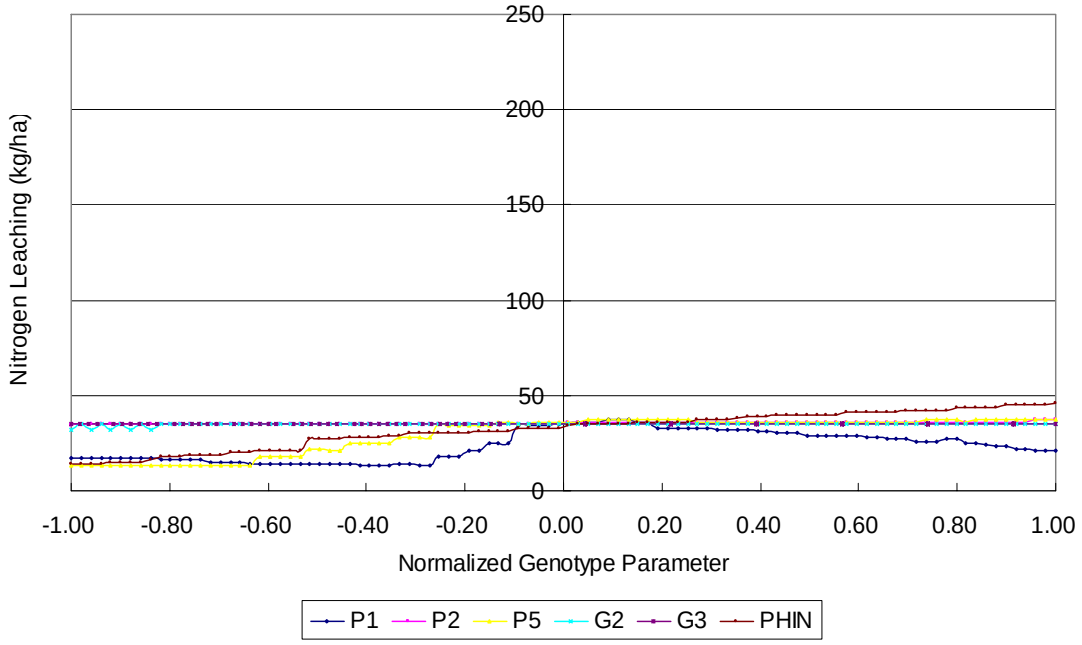


Figure 2-5. Response profiles for the nitrogen leaching to six normalized genotype parameters

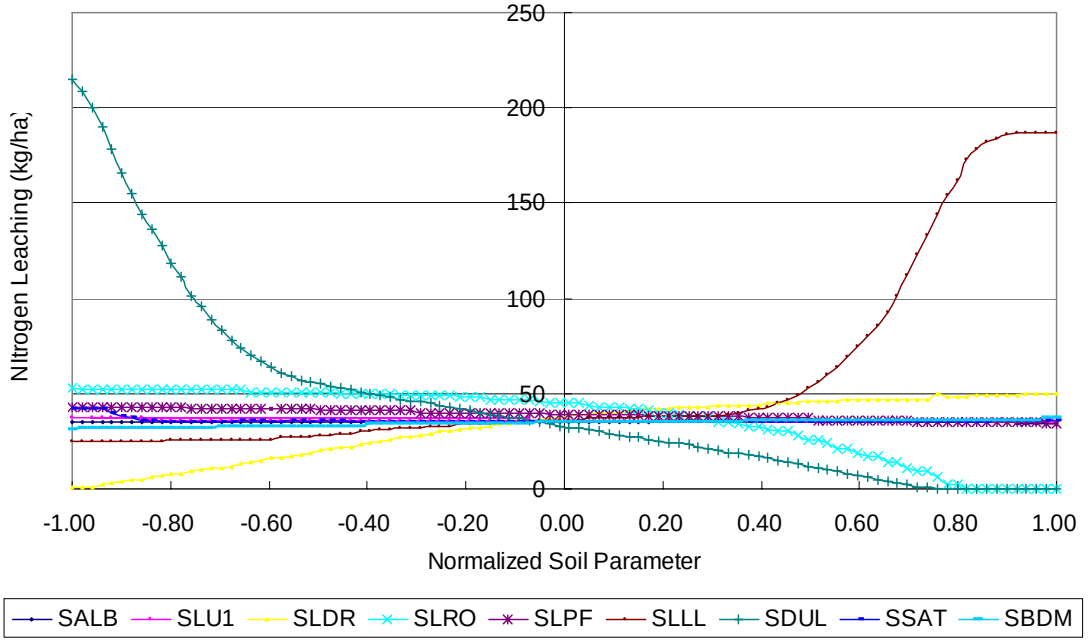


Figure 2-6. Response profiles for the nitrogen leaching to nine normalized soil parameters

Table 2-1. Genotype coefficient for the DSSAT CERES-Maize model

No.	Parameter	Definition
1	P1	Degree days (base 8℃) from emergence to end of juvenile phase
2	P2	Photoperiod sensitivity coefficient (0-1.0)
3	P5	Degree days (base 8℃) from silking to physiological maturity
4	G2	Potential kernel number
5	G3	Potential kernel growth rate mg/(kernel d)
6	PHINT	Degree days required for a leaf tip to emerge (phyllochron interval) (℃ d)

Table 2-2. Covariance coefficient matrix of genotype and soil parameters of the DSSAT model

	P1	P2	P5	G2	G3	PHINT	SALB	SLU1	SLDR	SLRO	SLPF	SLLL	SDUL	SSAT	SBDM
P1	1.000	0.359	0.354	-0.276	-0.135	0.227	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P2	0.359	1.000	-0.078	-0.270	0.059	0.337	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P5	0.354	-0.078	1.000	-0.189	-0.453	0.141	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
G2	-0.276	-0.270	-0.189	1.000	0.183	-0.029	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
G3	-0.135	0.059	-0.453	0.183	1.000	-0.031	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PHINT	0.227	0.337	0.141	-0.029	-0.031	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SALB	0.000	0.000	0.000	0.000	0.000	0.000	1.000	-0.314	0.268	-0.063	-0.203	-0.482	-0.557	-0.439	0.063
SLU1	0.000	0.000	0.000	0.000	0.000	0.000	-0.314	1.000	0.044	0.485	0.119	0.275	0.323	0.312	-0.171
SLDR	0.000	0.000	0.000	0.000	0.000	0.000	0.268	0.044	1.000	-0.153	-0.082	-0.187	-0.156	-0.271	0.026
SLRO	0.000	0.000	0.000	0.000	0.000	0.000	-0.063	0.485	-0.153	1.000	-0.015	0.242	0.273	0.238	-0.019
SLPF	0.000	0.000	0.000	0.000	0.000	0.000	-0.203	0.119	-0.082	-0.015	1.000	0.156	0.194	0.224	-0.119
SLLL	0.000	0.000	0.000	0.000	0.000	0.000	-0.482	0.275	-0.187	0.242	0.156	1.000	0.935	0.576	-0.328
SDUL	0.000	0.000	0.000	0.000	0.000	0.000	-0.557	0.323	-0.156	0.273	0.194	0.935	1.000	0.647	-0.352
SSAT	0.000	0.000	0.000	0.000	0.000	0.000	-0.439	0.312	-0.271	0.238	0.224	0.576	0.647	1.000	-0.471
SBDM	0.000	0.000	0.000	0.000	0.000	0.000	0.063	-0.171	0.026	-0.019	-0.119	-0.328	-0.352	-0.471	1.000

Table 2-3. Criteria for input parameter determination[a]

	High Correlation	Low Correlation	No Correlation
High Sensitivity	+	+	+
Low Sensitivity	+	-	-
No Sensitivity	-	-	-

[a] +=Accepted, -=Rejected; High Sensitivity=High relative sensitivity;
High Correlation =High correlation coefficient to high sensitive parameters, defined as greater than 0.5 in this research.

Table 2-4. Selected parameters for GLUE simulation based on the non-restricted OAT method and covariance coefficient matrix[a]

Parameter	P1	P5	PHINT	SLPF	SLDR	SLRO	SDUL	SLLL	SSAT
	℃d	℃d	℃d	-	-	-	cm^3/cm^3	cm^3/cm^3	cm^3/cm^3
Value	225.10	763.60	41.20	0.96	0.46	73.00	0.25	0.13	0.38

[a] ℃d means degree day.

Table 2-5. Mean and variance of absolute elementary effects of genotype parameters

Parameter	Unit	Dry Yield		Nitrogen Leaching	
		Mean	Variance	Mean	Variance
P1	℃d	1.71	4.14	0.67	4.15
P2	-	0.22	3.68	0.19	2.18
P5	℃d	2.15	19.14	1.61	13.54
G2	-	0.73	20.29	0.84	10.88
G3	$mg\ day^{-1}$	0.96	20.92	0.85	10.67
PHINT	℃d	1.96	25.56	2.20	11.80

Table 2-6. Mean and variance of absolute elementary effects of soil parameters

Parameter	Unit	Dry Yield		Nitrogen Leaching	
		Mean	Variance	Mean	Variance
SALB	-	0.03	0.01	0.22	3.05
SLU1	-	0.06	0.09	0.24	3.11
SLDR	-	0.36	1.61	0.88	8.28
SLRO	-	0.26	2.19	2.65	30.11
SLPF	-	1.56	2.74	0.25	2.16
SLLL	m^3/m^3	2.07	18.92	4.51	35.82
SDUL	m^3/m^3	4.46	333.58	7.63	36.26
SSAT	m^3/m^3	0.12	0.55	0.34	4.04
SBDM	g/cm^3	0.00	0.00	0.00	0.00

Table 2-7. Selected parameters for model calibration based on the restricted OAT method

Parameter	P1	P5	PHINT	SLPF	SLDR	SLRO	SDUL	SLLL
	℃d	℃d	℃d	-	-	-	cm^3/cm^3	cm^3/cm^3
Value	225.10	763.60	41.20	0.96	0.46	73.00	0.25	0.13

CHAPTER 3
PARAMETER ESTIMATION FOR CERES-MAIZE MODEL WITH THE GLUE METHOD

3.1 Introduction

3.1.1 Parameter Estimation

Proper estimation of model parameters is required for ensuring accurate model predictions and good model based decision rules (Makowski et al., 2002). If a crop model was considered as an equation system, the parameters could be considered as the unknowns and the observed data could be considered as the constants. The process of model parameter estimation could be considered as the process of solving the equation system. Since crop models usually have many parameters, there are often more parameters than the number of observations and the number of equations is smaller than the number of the unknowns. Thus, it is generally numerically impossible to estimate all the parameters of the crop models. On the other hand, crop models are based on equations that describe the processes involved in crop growth and development, and generally there is limited information about these processes in model application. For example, information might be needed about the thermal time to flowering, which can only come from controlled environmental experiments, or information about maximum rate of root elongation from specific experiments on this aspect of crop growth. Thus the problem of parameter estimation for crop models is not a straightforward regression problem. Rather the problem is using both field data and information about growth and development to estimate model parameters (Makowski et al., 2006).

The objective of parameter estimation is to determine the values or range of values of model parameters. A parameter is a numerical value that is not a measured or observed input variable (Makowski et al., 2006). The same quantity may or may not be a parameter depending on circumstances. For example, initial soil mineral nitrogen may be measured, in which case it is

an input variable. In other cases it may not be measured, in which case it is a parameter that has to be estimated.

It is useful to distinguish two approaches of parameter estimation, the frequentist and the Bayesian. The frequentist uses estimation methods to approximate the true parameter values θ by using only a sample of data. For the frequentist, parameters are not random variables but are fixed. Prior information on parameter values are not taken into account. Different types of frequentist methods (maximum likelihood, least squares, etc) were developed in the 1920s and 1930s by R.A. Fisher, J. Neyman, and E. Pearson notably (Makowski et al., 2006). The application of a frequentist method to a particular dataset gives a point estimate of the model parameters and the function that relates point estimates to datasets is called an estimator (Makowski et al., 2006).

The Bayesian method estimates parameters from two different types of information, a sample of data (like the frequentist) and prior information about parameter values. The result of the application of a Bayesian method is a probability distribution of parameter values. All Bayesian methods proceed in two steps. The first step is to define a parameter probability distribution based on literature or expert knowledge. This distribution is called prior parameter distribution and reflects the initial state of knowledge about parameter values. The prior distribution can be, for example, a uniform distribution with lower and upper bounds derived form expert knowledge or a normal distribution. The second step consists in calculating a new parameter probability distribution from both the prior distribution and the available data, such as observed crop yields, soil moisture, and biomass nutrient concentration etc. This new distribution, called posterior distribution, is computed by using the Bayes theorem. The posterior distribution can be used in different ways. Point estimates of parameters can be taken as the expected value

or, alternatively, the mode of the posterior distribution. The posterior parameter distribution can also be used for generating the probability distribution of the model outputs, for instance, the distribution of yield (Makowski et al., 2006).

Bayesian methods are becoming increasingly popular for estimating parameters for complex mathematical models (e.g. Campbell et al., 1999), because this approach provides a coherent framework for dealing with uncertainty. This is also due to the increase in the speed of computer calculation and the recent development of new algorithms (Malakoff, 1999).

The principle is to start with a prior probability distribution of the model parameters whose density is noted $P(\theta)$. This prior distribution describes our belief about the parameter values before we observe the set of measurements Y. In practice, $P(\theta)$ is based on past studies, expert knowledge, and literature. The Bayesian methods then tell us how to update this belief about θ using the measurements Y to give the posterior parameter density $P(\theta \mid Y)$ (density of θ based on the data Y). What we now believe about θ is captured in $P(\theta \mid Y)$.

The posterior parameter distribution is given by Bayesian theorem, as shown in following Equation (3-1):

$$P(\theta \mid Y) = \frac{P(Y \mid \theta) \cdot P(\theta)}{P(Y)} \qquad (3\text{-}1)$$

where Y is the vector of measurements, θ is the parameter, $P(\theta)$ is the prior distribution of the parameter, $P(\theta \mid Y)$ is the posterior distribution of parameter based on measurement Y, $P(\mathrm{Y})$ is a constant of proportionality determined by the requirement that the integral of $P(\theta \mid Y)$ over the parameter space equals 1, and $P(Y \mid \theta)$ is a likelihood function of Y under prior distribution of θ. The likelihood is the probability of the data Y given the parameter θ. Its value is determined from the probability distribution of the errors between modeled and observed data. It is readily seen

that both the prior distribution and the new data affect the posterior parameter distribution (Makowski et al., 2002).

The Bayesian method has several advantages: (1) a parameter can be estimated from different types of information (data, literature, expert knowledge); (2) the posterior probability distribution can be used to implement uncertainty analysis methods; and (3) the posterior probability distribution can be used for optimizing decisions in face of uncertainty.

3.1.2 GLUE Method

Due to the complexity of agronomic models (non-linearity and a large number of parameters), it is almost impossible to directly calculate analytically the posterior parameter distribution. However, the growing power of computers and the development of new methods of numerical calculation make the Bayesian approach accessible even with complex models (Campbell et al, 1999; Franks, et al., 1998; Harmon and Challenor, 1997; Malakoff, 1999).

One increasingly popular method is the Generalized Likelihood Uncertainty Estimation method (GLUE) (Beven and Binley, 1992; Franks et al., 1998; Shulz et al., 1999). The principle of this method is to discretize the parameter space by generating a large number of parameter values from the prior distribution. Likelihood values are then calculated at each parameter value with likelihood functions and measurements. Weights or probabilities are calculated with the Bayesian equation. Finally, posterior distribution of the parameter was estimated with the weights.

The GLUE method is based on the equifinality concept. In the study of Beven and Freer (2001), it is argued that, given current levels of understanding and measurement technologies, it may be endemic to mechanistic modeling of complex environmental systems that there are many different model structures and many different parameter sets within a chosen model structure that may be behavioral or acceptable in reproducing the observed behavior of the system. Indeed, to

focus attention on a rejection of the concept of the optimal model in favor of multiple possibilities for producing simulations that are acceptable simulators in some sense, this idea has been called equifinality (Beven, 1993).

One implication of rejecting the concept of a single optimal parameter set and accepting the concept of equifinality is that the uncertainty associated with the use of a model in prediction might be wide, since if there are several different acceptable model structures or many acceptable parameter sets scattered throughout the parameter space, all of which are consistent in some sense with the calibration data (Beven and Freer, 2001).

This appears to lead quite naturally to a form of Bayesian averaging of parameter sets and predictions, in which prior distributions of parameters are assessed in terms of some likelihood measure relative to the observations and a posterior distribution is calculated that can then be used in prediction. This is the basis of the GLUE methodology proposed by Beven and Binley (1992).

The principle of the GLUE methodology (Beven and Binley, 1992) is to approximate the posterior parameter distribution $P(\theta \mid Y)$ by a discrete probability distribution (θ_i, p_i), $i = 1,..., N$, $\sum_{i=1}^{N} p_i = 1$, where p_i is the probability associated with the parameter vector θ_i, and N is the total number of available parameter vectors. The procedure of this method was described in the paper of Makowski (2002).

The objective of this current research is to use the GLUE method to estimate the genotype and soil parameters of the CERES-Maize component of the DSSAT model under sweet corn (*Zea mays L.*) production in North Florida.

3.2 Method and Materials

3.2.1 Field Experiment

In this study, field experiments were necessary to conduct the GLUE simulation. First, the CERES-Maize model needs fundamental input data for model run, such as weather data, planting date, irrigation depths and timing, nitrogen fertilizer application rates and timing, and other management information. Second six kinds of field observation data, such as yield, anthesis date, maturity date, corn leaf N concentration, soil moisture, and soil nitrate concentration, were required to compare the simulated and measured outputs so as to calculate the likelihood values.

The sweet corn field experiments were conducted at the Plant Science Research and Education Unit, the University of Florida in the spring of 2005 and 2006. The unit is located near Citra (29.4094^{o}N, 82.1777^{o}W, 20.746 meters above sea level), Marion County, Florida. The experiment field was identified as Block1 and the variety of sweet corn planted was Saturn SH2.

In this study, the data collected in the experiment field Block 1 (Figure 3-1) were used for the GLUE process for model parameter estimation. In Block 1, there were only two treatments each year, the high-nitrogen-level treatment and the low-nitrogen-level treatment, while the irrigation level was the same. The size of Block 1 was about 9.0 acres and divided in half for these two treatments.

The soil of the experiment field is coarse and is mapped as Lake Sand, Candler Variant, Tavares Variant, and Millhopper Variant 1 etc., which mainly belong to Quartzipsamments (Entisol). Soil characterization was done for 24 sites at 3 depths of 0-15 cm, 15-30 cm, and 30-60 cm. The samples were analyzed at the Soil and Water Science Department of the University of Florida.The permanent wilting point (PWP) was measured as the soil moisture at a soil pressure of 15.3 bar, field capacity (FC) as the soil moisture at 0.1 bar, and soil saturation as the soil moisture at 0bar. In this study, the small soil core method was used to measure the values of

PWP and FC (Klute, 1986). This method requires soil sampler and core rings for obtaining undisturbed soil cores, pressure plate apparatus or similar device, moisture cans, balance, drying oven, and spatula etc. The procedures of soil core analysis can be found in "Methods of Soil Analysis Part 1: Physical and Mineralogical Methods" (Klute, 1986). The main measured properties of the soil at the experiment site are summarized in Table 3-1.

The nitrogen fertilizer used in the experiment was a composite of several nitrogen compounds. The total nitrogen mass concentration was about 32%, including 7.9% nitrate nitrogen, 7.9% ammoniacal nitrogen, and 16.2% urea nitrogen. The density of the fertilizer solution was 1.294 kg L^{-1}, while the concentration of nitrogen in this solution was 0.414 kg N L^{-1}.

In the field experiments of 2005 and 2006, soil and biomass samplings were conducted to evaluate the nitrogen status in soil profile and corn tissue. Yield sampling was conducted at harvest to determine the final yield of each treatment.

Soil sampling was roughly at biweekly intervals during the growth season according to sampling positions in the field map (Figure 3-1). Soil samples were collected in each of the eight locations (W1 through W4, E1 through E4 as described in Figure 3-1) at 4 depths of 0-15 cm, 15-30 cm, 30-60 cm, and 60-90 cm. The samples were analyzed at the Department of Soil and Water Science University of Florida for KCL extractable nitrate and ammonium concentrations and moisture content as well.

Gravimetric soil moisture content was determined by calculating the ratio of mass of water to that of the dry soil. The mass of water is the difference between wet soil sample and the dry soil sample. Traditionally, the most frequently used definition for a dry soil is the mass of a soil sample after it has come to constant weight in an oven at a temperature between 100 and 110 ^{o}C. Then the gravimetric soil moisture content (θ_{dw}) can be converted to the volumetric soil moisture

content (θ_{vb}) by use of the formula of $\theta_{vb} = (\rho_b / \rho_w)\theta_{dw}$, where ρ_b is the bulk density of the soil, and ρ_w is the density of water (Klute, 1986).

The analysis of soil nitrate and ammonium concentration included two main procedures: (1) extraction of exchangeable ammonium, nitrate; and (2) determination of nitrate and ammonium concentration with colorimetric method (Page et al, 1982).

The procedure of extraction is described as follows. Place 3 g of soil in a wide-mouth bottle, and add 30 ml of 1M KCl. Stopper the bottle, and shake it on a mechanical shaker for 1 hour. Allow the soil-KCl suspension to settle until the supernatant liquid is clear (usually about 30 min). Then use a vacuum filter with a pore size of 0.45 μm to filter the solution.

Nitrate and ammonium concentrations were measured by colorimetric methods. The special apparatus required for nitrate concentration determination was Rapid Flow Analyzer (RFA), ALPKEM 300 Series (OI Corporation, College Station, TX). The apparatus for ammonium concentration determination was Technicon Industrial Method AA II (Technicon Instrument Corporation, Tarrytown, NY).

Biomass sampling was conducted at the eight locations close to the soil sampling. The sampling frequency was also once every two weeks. In each sampling, a whole plant that had an average height in the sampling area was collected. The sample was then processed and analyzed in the lab. The analysis of the plant samples included measurement of the moisture and total Kjeldahl nitrogen (TKN) of different plant parts. Each plant was divided into leaves, stems, husks, cobs, and kernels, then weighed wet. Plant roots were not considered here, because of the negligible amount of nitrogen in the roots (Albert, 2002).

Fresh mass of each biomass sample was measured first. Then the samples were dried in the oven for 48 years at a constant temperature of 60 ^{o}C for 48 hours. The dry mass of each sample was measure. Then the biomass moisture was calculated.

The Kjeldahl procedures generally employed for determination of total N involve two steps: (1) digestion of the sample to convert organic N to NH_4^+-N, and (2) determination of NH_4^+-N in the digest. The digestion is usually performed by heating the sample with H_2SO_4 containing substances that promote oxidation of organic matter and conversion of organic N to NH_4^+-N. The substances generally favored are salts such as K_2SO_4 or Na_2SO_4, which increase the temperature of digestion, and catalysts such as Hg, Cu, or Se, which increase the rate of oxidation of organic matter by H_2SO_4 (Page et al, 1982). In this study, the substances were K_2SO_4 and $CuSO_4$. The determination of NH_4^+-N in the digest was conducted with colorimetric method in the Analytical Research Laboratory (ARL), Institute of Food and Agricultural Sciences, the University of Florida.

Yield sampling was conducted at the end of the experiment season at a sweet corn physiological maturity. This date was about 70 to 80 days after planting. Ears in a sampling zone, which consisted of a 6.1 m (20 feet) section of two rows near each of the eight sampling location, were completely collected whether the kernels were fully filled or not. The total plant numbers in this zone were also counted. Then the collected ears were weighed and classified into three classes, US #1, US #2, and Cull according to the USDA sweet corn classification standards (USDA, 1962).

The dates and methods of planting, tillage, irrigation, fertigation, pesticide and herbicide application, and harvest were collected. Some critical dates for sweet corn growth, such as tasseling, silking, physiological maturity, were also recorded. They were important management

data. These data were primarily obtained from in situ observations made by the managers of the farm.

3.2.2 Main Procedure of GLUE

In general the main procedures of the parameter estimation with the GLUE method are as follows:

- Select the input parameters for estimation with the GLUE method;
- Determine the prior distributions of the selected input parameters;
- Determine the number of model runs, N ;
- Randomly generate N vectors θ_i , $i = 1,..., N$, from the prior parameter distribution $P(\theta)$;
- Run the model N times with the N generated parameter vectors θ_i ;
- Calculate the likelihood values $P(Y \mid \theta_i)$, associated with the different generated parameter vectors θ_i ;
- Calculate the probability p_i with $p_i = \dfrac{P(Y \mid \theta_i) \cdot P(\theta_i)}{\sum_{j=1}^{N} P(Y \mid \theta_i) \cdot P(\theta_i)}$;
- Use the pairs (θ_i, p_i), $i = 1,..., N$, to determine various characteristics of the posterior distribution, such as mean, variance, and covariance of the input parameters.

3.2.3 Selection of Input Parameters

Complex dynamic crop models include many parameters. For example, the STICS model (Brisson et al., 1998) includes more than 200 parameters. This problem is often called over-parameterization. And in many crop models, it is impossible to estimate simultaneously all the parameters because several parameters are unidentifiable due to the structure of the model equations. Lack of identifiability occurs when several sets of parameters lead to the same model prediction (Makowski et al., 2006).

A common practice is to select a subset of parameters, to estimate those parameters from measurement data, and to set the others equal to predefined values. The implementation of this approach requires one to decide which among all the parameters will be adjusted to the data and to choose a method for estimating the values of the selected parameters. Four methods are proposed for selecting parameters by Makowski et al. (2006) as follows: (1) selection based on literature, (2) selection to avoid identifiability problems, (3) sensitivity analysis, and (4)statistical choice of parameters to estimate.

In the current research, the sensitivity analysis method was used to select input parameters. The principle method is to calculate a sensitivity index for each parameter and to select parameters with high sensitivity index values. This method allows modelers to identify the parameters that have a strong influence on the model output variables of interest. Only these parameters will be estimated with the measured data and others are fixed to values provided by the literature.

In Chapter 2, the restricted and non-restricted one-at-a-time (OAT) methods were used to conduct global sensitivity of the input parameters (including soil and genotype parameters) to model outputs (dry matter yield, kg ha^{-1} and accumulative nitrogen leaching, kg ha^{-1}). These two methods gave similar results of parameter selection. The selected parameters are specified in Table 3-2.

3.2.4 Prior Distribution

In this current research, the parameter values in the database of the DSSAT model were used to derive the prior distribution of input parameters. The form of distribution and the statistical properties, such as the mean value, variance, maximum, minimum values of each parameter were calculated with the available parameter values.

The normal distribution was considered as the first choice, because it is the most common distribution. In addition, the statistical parameters, mean value (μ) and variance (σ^2), are easy to obtain. To determine whether the selected parameters follow normal distributions, a normality test was conducted. The Jarque-Bera test (Judge et al, 1982) was used in this research. This test evaluates the hypothesis the random variable x has a normal distribution with unspecified mean and variance, against the alternative that x does not have a normal distribution.

3.2.5 Model Run with Generated Parameter Vectors

According to the results of normality test mentioned in Section 3.2.4, a multivariate normal distribution was assigned to all selected parameters except for SLPF. SLPF was assigned a uniform distribution of [0.7, 1.0].

A Matlab program titled "mvnrnd.m" (See Appendix C) was used to generate random parameter vectors. The function R = MVNRND (MU, SIGMA, CASES) returns a matrix of random numbers chosen from the multivariate normal distribution with mean vector, MU, and covariance matrix, SIGMA. Here CASES is the number of rows in R, or the number of the generated parameter sets. SIGMA is a square positive definite matrix with size equal to the length of MU. Table 3-2 and 3-3 show the mean vector and covariance matrix of the prior distribution of the selected parameters to run the function above. The mean vector and covariance matrix were all obtained by calculating the mean values, variances, and covarriance of the available parameter values in the database of DSSAT model.

For layered parameters, such as SLLL, SDUL, and SSAT, random values for each layer had to be assigned. There are two ways to resolve this problem. First, each layer of a layered parameter could be considered as an individual input parameter with individual random numbers

generated. However, this method would make the covariance matrix very large and difficult to handle.

The second method reasonably assumes that there exist perfect correlations among the soil layers. Then for each generated random number for layer 1 of an input parameter, there exists a perturbation defined as follows:

$$\varepsilon_i = \frac{x1_i - \mu 1}{\sigma 1} \qquad (3\text{-}2)$$

Where $x1_i$ is the ith generated random number for a soil property for layer 1, $\mu 1$ and $\sigma 1$ are the mean and standard deviation of the soil property of layer 1. Then for the soil property of layer 2, the ith random number, $x2_i$ can be calculated with equation (3-3).

$$x2_i = \mu 2 + \varepsilon_i \cdot \sigma 2 \qquad (3\text{-}3)$$

where $\mu 2$ is the mean value, while $\sigma 2$ is the standard deviation of the soil property of layer 2. The same approach was used to calculate the input values for layer 3, layer 4, layer 5 etc. In this current research, the soil profile was divided into five layers, as follows: 0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, and 60-90 cm.

With the method above, the values of the 5 layers of SLLL, SDUL and SSAT can be generated with their own different perturbation values.

Then the model was run with these parameter vectors and the following outputs were recorded: dry yield (HWAH, kg ha^{-1}), anthesis date (ADAT, days after planting), maturity date (MDAT, days after planting), cumulative nitrogen leaching (NLCM, kg ha^{-1}), soil nitrate nitrogen of four layers (mg g^{-1}), soil moisture of four layers (%) and leaf total nitrogen content (%).

3.2.6 Determination of Number of Model Runs

Determining an acceptable number of model runs is very important. Enough simulations must be conducted to guarantee reliable statistical characteristics of the model input parameters and the model outputs, but the amount of time needs to be considered at the same time. In theory, more simulations were conducted, more reliable the statistical properties of the model outputs.

When enough simulations have been carried out, the means or standard deviations of the generated parameter values and model outputs should all converge to constants. This occurs when the means and standard deviations cease to change as the number of model runs continues to increase. These criteria were used to determine the minimum number of model runs for this research.

However, it should be noticed that the minimum number of model runs mentioned here is not something to guarantee the reliability of the posterior distribution in the GLUE process for parameter estimation, but only something to guarantee the reliability of model input parameters and model outputs when starting the process. The number of model runs for a reliable posterior distribution will depend on the range and distribution of the prior distribution, and the number of observations involved. Generally, if the range of the prior distribution is wide, more model runs will be required to increase the occurrence probability of the optimal parameter sets in the smaller range that is more close to the actual values of the parameters. And if more observations are involved in the GLUE process, more model runs will also be required because the occurrence probability of the parameter sets that can optimize all observations will decrease.

3.2.7 Likelihood Function and Likelihood Value

3.2.7.1 Available likelihood functions

Based on the simulation and measurement results, the likelihood values of each parameter vector θ_i were calculated with a selected likelihood function. As with any calibration procedure,

the GLUE methodology requires the definition of some measure of goodness-of-fit, in this case the likelihood measure, in comparing observations and predictions of the model. The likelihood measure or the likelihood function must have some specific characteristics. It should be zero for all simulations that are considered to exhibit behavior dissimilar to the system under study, and it should increase monotonically as the similarity in behavior increases (Beven and Binley, 1992).

Several likelihood functions have previously been used in GLUE simulations by different people. Some examples are introduced below:

(1) Likelihood function based on auto-correlated Gaussian error model (Romanowicz et al., 1996):

$$L[Y_T \mid \Theta, \Phi, X_T] = (2\pi\sigma^2)^{-\frac{\tau}{2}} \cdot (1-\alpha^2)^{\frac{1}{2}} \cdot \exp\left[-(1/2\sigma^2)\left\{(1-\alpha^2)\cdot(\varepsilon_1-\mu)^2 + \sum_{t=2}^{\tau}\left(\varepsilon_t - \mu - \alpha(\varepsilon_{t-1}-\mu)^2\right)\right\}\right] \tag{3-4}$$

where $\Phi = (\mu, \sigma, \alpha)$ is the parameter vector; μ, σ, α represent the coefficients of the likelihood function; X_T is model input; Θ is the input parameter set; Y_T is model output; σ^2 is the variance of model prediction error; μ is the mean of model prediction error; ε_t is the model prediction error at different time steps; and τ is the number of time steps in the simulation.

(2) Likelihood function based on inverse error variance with shaping factor N (Beven and Binley., 1992):

$$L[M(\Theta \mid X_{T,} O_T)] = (\sigma_\varepsilon^2)^{-N} \tag{3-5}$$

where $M(\Theta \mid X_{T,} O_T)$ indicates the *ith* model structure, conditioned on input X_T and observation O_T; σ_ε^2 is the model prediction error variance; and N is shaping factor.

(3) Likelihood function based on Nash and Sutcliffe efficiency criterion with shaping factor N (Freer et al., 1996):

$$L\left[M\left(\Theta \mid X_{T,}O_T\right)\right] = \left(1 - \frac{\sigma_\varepsilon^2}{\sigma_0^2}\right)^N \text{ for } \sigma_\varepsilon^2 < \sigma_0^2 \tag{3-6}$$

where $M(\Theta \mid X_{T,}O_T)$ indicates the *ith* model structure, conditioned on input X_T and observation O_T; σ_ε^2 is the model prediction error variance; σ_o^2 is the observation variance; and N is shaping factor.

(4) Likelihood function based on exponential transformation of error variance with shaping factor N (Freer et al., 1996):

$$L\left[M\left(\Theta \mid X_{T,}O_T\right)\right] = \exp\left(-N\sigma_\varepsilon^2\right) \tag{3-7}$$

where $M(\Theta \mid X_{T,}O_T)$ indicates the *ith* model structure, conditioned on input X_T and observation O_T; σ_ε^2 is the model prediction error variance; and N is shaping factor.

(5) Likelihood function based on minimum mean square error (MSE) (Wang et al., 2005):

$$L\left[\theta_i \mid O\right] = \exp\left(-\frac{MSE_i}{\min(MSE)}\right), \ (i = 1,2,3...N) \tag{3-8}$$

where θ_i is the *ith* parameter vector; O is the measured or observed value; MSE_i is the mean square model prediction error for the *ith* parameter set; $\min(MSE)$ is the minimum value of MSE_i; and N is the number of parameter vectors for equation.

(6) Maximum likelihood function (Makowski et al., 2006):

$$L\left[\theta \mid O\right] = \prod_{i=1}^{M} \frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}} \exp\left(-\frac{\left(O_i - P_i(\theta)\right)^2}{2\sigma_o^{\ 2}}\right) \tag{3-9}$$

where θ is the parameter vector; O is the measured or observed value; σ_o^2 is the variance of the observations; O_i is the measured or observed value for model simulation scenario i; P_i is the corresponding value calculated by the model; and M is the number of observations.

The model prediction error was calculated with following equation:

$$\varepsilon = O - P \tag{3-10}$$

In this research, considering the normal distribution of the selected input parameters except for SLPF and the availability of observations, another available likelihood function was defined (Personal communication with Dr. Shrikant Jagtap, Department of Agricultural and Biological Engineering, the University of Florida):

$$L(\theta_i \mid O) = \exp\left(-\frac{MSE_i}{2\sigma_o^{\ 2}}\right),\ (i = 1,2,3...N) \tag{3-11}$$

$$MSE_i = \frac{1}{M}\sum_{j=1}^{M}\left(P(\theta_i) - O_j\right)^2 \tag{3-12}$$

where θ_i is the ith parameter set; MSE_i is the mean square model prediction error for the ith parameter set; σ_o^2 is the variance of observations; N is the number of parameter vectors; M is the number of observation replicates; $P(\theta_i)$ is the single predicted value with input parameter set θ_i; and O_j is jth the replicate value of the observation.

The likelihood function (Equation 3-11) was derived from the commonly used maximum likelihood function (Equation 3-9). Since the observation variance σ_o^2 was the same for the different replicates of an observation, equation (3-9) can be rearranged as such:

$$L[\theta \mid O] = \prod_{i=1}^{M}\frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}}\exp\left(-\frac{(O_i - P_i(\theta))^2}{2\sigma_o^{\ 2}}\right) = \left(\frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}}\right)^M \prod_{i=1}^{M}\exp\left(-\frac{(O_i - P_i(\theta))^2}{2\sigma_o^{\ 2}}\right) \tag{3-13}$$

$$L[\theta \mid O] = \left(\frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}}\right)^M \prod_{i=1}^{M}\exp\left(-\frac{(O_i - P_i(\theta))^2}{2\sigma_o^{\ 2}}\right) = \left(\frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}}\right)^M \exp\left(-\frac{\sum_{i=1}^{M}(O_i - P_i(\theta))^2}{2\sigma_o^{\ 2}}\right) \tag{3-14}$$

$$L[\theta \mid O] = \left(\frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}} \right)^M \exp\left(-\frac{\sum_{i=1}^{M} (O_i - P_i(\theta))^2}{2\sigma_o^{\ 2} \cdot M} \cdot M \right) = \left(\frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}} \right)^M \exp\left(-\frac{MSE}{2\sigma_o^{\ 2}} \cdot M \right) \tag{3-15}$$

If want to find the parameter vector θ that can maximize this rearranged maximum likelihood function (Equation 3-15), it is equivalent to find the same parameter vector θ to maximize the following equation (3-16), since the variance of observation σ_o^2 and number of replicates of the observation M , were constants for each model run. Thus the likelihood function shown in Equation 3-19 can be simplified to the likelihood function shown in Equation 3-16.

$$L(\theta \mid O) = \exp\left(-\frac{MSE}{2\sigma_o^{\ 2}} \right) \tag{3-16}$$

Equation (3-16) was the likelihood function for one parameter vector θ. When this equation was used for every parameter vector, θ_i, then:

$$L(\theta_i \mid O) = exp\left(-\frac{MSE_i}{2\sigma_o^{\ 2}} \right), \ (i = 1,2,3...N) \tag{3-17}$$

Equation (3-17) became the likelihood function previously defined in equation (3-11). The procedure above shows how the likelihood function (Equation 3-11) was derived. This likelihood function can also be considered as a variant of Equation 3-8, by replacing the $\min(MSE)$ with $2\sigma_o^{\ 2}$. When the real value of σ_o^2 is unknown, then $\min(MSE)$ is used as an estimation for the observation variance. But when the value of σ_o^2 is available, it is better to use it directly (Personal communication with Dr. James Jones, department of Agricultural and Biological Engineering, the University of Florida).

The last likelihood function is (Personal communication with Dr. Wendy Graham, Department of Agricultural and Biological Engineering, the University of Florida):

$$L[\theta_i \mid O] = \frac{1}{\sqrt{2\pi\sigma_o^{\ 2}}} \cdot \exp\left(-\frac{\left(\overline{O} - P(\theta_i)\right)^2}{2\sigma_o^{\ 2}} \right) \tag{3-18}$$

$$\overline{O} = \frac{1}{M}\sum_{j=1}^{M} O_j \tag{3-19}$$

where $\overline{O}$ is the mean value of all replications of the observation. This likelihood function is a variant of (3-9), which used the mean value of the observations instead of calculating the product of several observations.

In this research, there were six observations from three types of field experiment results. The first type was an integrated observation, which means there was only one observation value in the entire crop growth season, such as yield at maturity (kg ha^{-1}), anthesis date (days after planting), and maturity date (days after planting). The second type was temporal variant observations, which had several observation values at different days during the growth season, such as leaf nitrogen concentration (%). The third type was both temporal and spatial variant observations, which have different observation values in different soil layers and on different days, such as soil nitrate content (mg g^{-1}) and soil volumetric moisture content (%) in four soil layers.

A method of combining the individual likelihood values was required, for the general case of multiple sites or types of observations contributing to an overall likelihood weight for each simulation. There are also a number of different methods for doing this. Examples of likelihood measure combination equations (before renormalization) are listed below:

(1) Bayes' multiplication (e.g. Beven and Binley, 1992; Romanowicz et al., 1994, 1996):

$$L[M(\Theta_i)] \propto L_0[M(\Theta_i)] \cdot L_1[M(\Theta_{1i} \mid Y_1, O_1)] \tag{3-20}$$

where $M(\Theta_{1i} \mid Y_{1,} O_1)$ indicates the ith model simulation results, conditioned on a new value Θ_{1i} of parameter Θ_i, input data Y_1, and observation O_1; $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ is the likelihood value of $M(\Theta_{1i} \mid Y_{1,} O_1)$; $L_0[M(\Theta_i)]$ is the prior likelihood value of model prediction conditioned on parameter Θ_i. The posterior likelihood value of parameter Θ_i $L[M(\Theta_i)]$, was defined proportional to the production of the $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ and $L_0[M(\Theta_i)]$.

(2) Weighted addition (e.g. Zak et al., 1997):

$$L[M(\Theta_i)] \propto \omega_0 L_0[M(\Theta_i)] + \omega_1 L_1[M(\Theta_{1i} \mid Y_{1,} O_1)] \tag{3-21}$$

where ϖ_0 and ϖ_1 are weighting coefficients for different periods or different variables; $M(\Theta_{1i} \mid Y_{1,} O_1)$ indicates the ith model simulation results, conditioned on a new value Θ_{1i} of parameter Θ_i, input data Y_1, and observation O_1; $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ is the likelihood value of $M(\Theta_{1i} \mid Y_{1,} O_1)$; $L_0[M(\Theta_i)]$ is the prior likelihood value of model prediction conditioned on parameter Θ_i. The posterior likelihood value of parameter Θ_i $L[M(\Theta_i)]$, was defined proportional to the weighted sum of the $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$, and $L_0[M(\Theta_i)]$.

(3) Fuzzy union, fuzzy intersection, weighted fuzzy combination (e.g. Aronica et al., 1997):

$$L[M(\Theta_i)] \propto Min[L_0[M(\Theta_i)], L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]] \tag{3-22}$$

$$L[M(\Theta_i)] \propto Max[L_0[M(\Theta_i)], L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]] \tag{3-23}$$

$$L[M(\Theta_i)] \propto \varpi_0 Min[L_0[M(\Theta_i)], L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]] + \varpi_1 Max[L_0[M(\Theta_i)], L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]] \tag{3-24}$$

where ϖ_0 and ϖ_1 are weighting coefficients for different periods or different variables; $M(\Theta_{1i} \mid Y_{1,} O_1)$ indicates the ith model simulation results, conditioned on a new value Θ_{1i} of

parameter Θ_i, input data Y_1, and observation O_1; $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ is the likelihood value of $M(\Theta_{1i} \mid Y_{1,} O_1)$; $L_0[M(\Theta_i)]$ is the prior likelihood value of model prediction conditioned on parameter Θ_i. In Equation (3-22), the posterior likelihood value of parameter Θ_i $L[M(\Theta_i)]$, was defined proportional to the minimum value among $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ and $L_0[M(\Theta_i)]$. In Equation (3-23), $L[M(\Theta_i)]$, was defined proportional to the maximum value among $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ and $L_0[M(\Theta_i)]$. And in Equation (3-24), $L[M(\Theta_i)]$, was defined proportional to the weighted sum of minimum and maximum value among $L_1[M(\Theta_{1i} \mid Y_{1,} O_1)]$ and $L_0[M(\Theta_i)]$.

(4) Aggregated function suggested by Wang et al. (2005):

$$L_{combined} = \left[\sum_{k=1}^{K} W_i \cdot L(\theta_i \mid O_k)^2 \right]^{1/2}$$

$$\sum_{k=1}^{K} W_i = 1 \tag{3-25}$$

where $L_{combined}$ is the combined likelihood value of parameter vector θ_i; $L(\theta_i \mid O_k)$ is the likelihood value derived from observation O_k; K is the number of observation types; and W_i is the weight of the likelihood value. The total sum of W_i should equal 1.

3.2.7.2 Selection of likelihood function and method of likelihood value combination

From the descriptions above, it can be seen that many likelihood functions and methods of likelihood value combination exist. However, to determine the best one that can reduce the parameter uncertainties most significantly and give the best outputs, likelihood functions and likelihood combination methods were investigated.

As discussed in Section 3.2.2, the input parameters follow a multivariate normal distribution. So it is reasonable to choose the likelihood functions that are derived from normal

distribution. In addition, the availability of observation data should also be considered. Hence, four types of likelihood functions were chosen and investigated with the same model outputs. The four likelihood functions, identified as L1 (Equation 3-9), L2 (Equation 3-18), L3 (Equation 3-8) and L4 (Equation 3-11), are as follows:

$$L[\theta_i \mid O] = \prod_{j=1}^{M} \frac{1}{\sqrt{2\pi\sigma_o^{\,2}}} \exp\left(-\frac{\left(O_j - P(\theta_i)\right)^2}{2\sigma_o^{\,2}} \right), (i = 1,2,3...N) \tag{L1}$$

$$L[\theta_i \mid O] = \frac{1}{\sqrt{2\pi\sigma_o^{\,2}}} \cdot \exp\left(-\frac{\left(\overline{O} - P(\theta_i)\right)^2}{2\sigma_o^{\,2}} \right), \ (i = 1,2,3...N) \tag{L2}$$

$$L[\theta_i \mid O] = \exp\left(-\frac{MSE_i}{\min(MSE)} \right), (i = 1,2,3...N) \tag{L3}$$

$$L(\theta_i \mid O) = \exp\left(-\frac{MSE_i}{2\sigma_o^{\,2}} \right), \ (i = 1,2,3...N) \tag{L4}$$

where θ_i is the ith parameter set; $P(\theta_i)$ is the model output under parameter set θ_i; O is the observation; O_j is the jth replicate of O; σ_o^2 is the variance of observations; $\overline{O}$ is the mean value of the observation replicates; MSE_i is the mean square model prediction error for the ith parameter set; $\min(MSE)$ is the minimum value of MSE_i; N is the number of parameter sets; and M is the number of observation replicates.

Another factor is the method of likelihood value combination that integrates the likelihood values derived from different observations (dry matter yield, anthesis date, maturity date, leaf TKN concentration, soil nitrate concentration, and soil volumetric moisture) together. Three types of methods, identified as C1, C2 and C3 respectively, were investigated:

$$L_{combined} = \frac{\sum_{i=1}^{K} L_i\left[M\left(\Theta \mid Y, O\right)\right]}{K} \tag{C1}$$

$$L_{combined} = \prod_{i=1}^{K} L_i\left[M\left(\Theta \mid Y, O\right)\right] \tag{C2}$$

$$L_{combined} = \left[\sum_{i=1}^{K} \frac{1}{\mathrm{K}} \cdot L_i\left[M\left(\Theta \mid Y, O\right)\right]^2\right]^{1/2} \tag{C3}$$

where $L_{combined}$ is the combined likelihood value; $M\left(\Theta \mid Y, O\right)$ indicates the model simulation results, conditioned on parameter Θ, input data Y, and observation O; $L_i\left[M\left(\Theta \mid Y, O\right)\right]$ is the likelihood value calculated from different observations; and K is the number of observation types.

Equation (C1) is a special case of the combination function (3-21), where the weighting coefficients of all terms were equally set as $1/K$. Equation (C2) is the same as the combination function (3-20). Equation (C3) is a special case of combination function (3-25), where the weighting coefficients were all set as $1/K$. In each equation, K is the total number of likelihood values derived from different observations.

As described previously, there were three types of observations in this study. For the integrated observation, K is just the number of observation types. For example, if only consider the dry matter yield, anthesis date, and maturity date, the value of K was three since only three kinds of integrate observations were considered.

However, for temporally variant observation, such as leaf nitrogen concentration, there were five observations at five different dates during the growth season. It is necessary to calculate some kind of combined likelihood value of for leaf nitrogen concentration first with the methods described above before combining it with other likelihood values. In this case, the value

of K equals five, the number of observations in the growth season. The both temporally and spatially variant observations, such as soil nitrate concentration and water concentration, could also be handled to calculate some combined likelihood values first.

After each of the six types of observations has an individual likelihood value, the final combined likelihood value can be calculated with the methods described above.

3.2.7.3 Comparison of distributions of input parameters

A 4×3 complete factorial (four likelihood functions and three methods of likelihood combination) experiment design was used to find the best likelihood function and method of likelihood value combination that can most significantly reduce the uncertainties in parameter distributions and model outputs, where the likelihood function was considered as one factor, while the method for likelihood value combination was another factor.

The best likelihood function and method of likelihood value combination should be the ones that would have the lowest uncertainties or variances in the posterior distributions of model input parameters.

3.2.7.4 Comparison of distributions of outputs

After comparing the uncertainties in the posterior distributions of model input parameters, it was also necessary to compare the uncertainties in model outputs, because it was believed that the best likelihood function and method of likelihood value combination could be the ones that can produce outputs that are closest to observation data.

In this study, the mean values and standard deviations of different model outputs such as yield, anthesis date, maturity date, and accumulative nitrogen leaching, which were obtained from different posterior distributions derived from different likelihood functions and methods of likelihood combination, were compared to the measured values in field experiment.

3.2.8 Estimation of Posterior Distribution

With the calculated likelihood values, the value of probability p_i was calculated with following equation:

$$p(\theta_i) = \frac{L(\theta_i \mid O)}{\sum_{i=1}^{N} L(\theta_i \mid O)} \tag{3-26}$$

In this study, all of the generated random parameter sets were involved when calculating the probability. No parameter sets were truncated according to their combined likelihood values.

In some literature, the probability p_i is also called likelihood weight (Wang et al., 2005). There are many pairs $(\theta_i, p_i \mid i = 1,..., N)$ available, which describe the posterior distribution of θ and then can be used to estimate expected value for each of the selected parameters. In addition, the variance and covariance among parameters can be determined, with the following equation:

$$\hat{\mu}_{post} = \sum_{i=1}^{N} p(\theta_i) \cdot \theta_i \tag{3-27}$$

$$\hat{\sigma}^2{}_{post} = \sum_{i=1}^{N} p(\theta_i) \cdot (\theta_i - \hat{\mu}_{post})^2 \tag{3-28}$$

$$Cov(X, Y) = \sum_{i=1}^{N} p(\theta_i) \cdot (X_i - \hat{\mu}_{X-post}) \cdot (Y_i - \hat{\mu}_{Y-post}) \tag{3-29}$$

where $\hat{\mu}_{post}$, $\hat{\sigma}^2{}_{post}$, and $Cov(X, Y)$ are the estimated mean value, variance, and covariance between two parameters of posterior distribution. These three estimated statistical values will help to reconstruct a new prior distribution for future research.

3.2.9 GLUE Simulation

Two rounds of GLUE process for model parameter estimation were conducted respectively with the input variables (weather and field management) and observation data of field experiments in Block 1 in the spring of 2005 and 2006.

In the first round of GLUE, the first posterior distribution of parameters was derived from the calculated N pairs $(\theta_i, p_i \mid i = 1,..., N)$, where θ_i is the ith parameter set, p_i is the calculated probability of the ith parameter set, conditioned on the observation O. Then this first posterior distribution was used as the new prior distribution for the second round of GLUE. Then a second posterior distribution was obtained. This second posterior distribution was used for model verification, development of best management practices, and uncertainty analysis in the rest part of the dissertation.

The procedures of random number generation, model running, and result saving were all automatically realized with Matlab programs (see Appendix C for details). The calculation of likelihood values and derivation of posterior distribution were conducted with spreadsheets of Microsoft Excel.

3.2.10 GLUE Verification

Though the soil and genotype parameters could be estimated with the GLUE method, the reliability and accuracy of this method might still be suspect if without direct comparison between the estimated parameter values and the really measured parameter values. Estimated values of some soil parameters, such as SLLL, SDUL and SSAT, were compared with the field measured ones to see whether they were correctly calibrated. However, for some parameters, especially the genotype parameters, there was no experiment designed in this study to obtain their measured values. To obtain more confidence in the GLUE method, in the selected

likelihood function, and in the method of likelihood value combination, a verification procedure was conducted.

The steps of this verification procedure were as follows: (1) select a parameter set in the second round of GLUE that gave the highest likelihood value; (2) run the model with this selected parameter set under the field experiment condition in Block 1 in 2005 , and record the outputs; (3) use the variances of the observations (dry matter yield, anthesis date, maturity date, corn leaf N concentration, soil moisture, and soil nitrate concentration) as variances and their corresponding model outputs as mean values, to generate four replicates for each observation; (4) conduct first-round GLUE with the generated replications of different observations, using the prior distribution derived from DSSAT database; (5) run the model with this selected parameter set under the conditions of 2006, and also make a record of the outputs; (6) repeat GLUE with the first-round posterior distribution as the prior distribution; (7) compare the second-round posterior distribution with the initially-selected parameter set (Personal communication with Dr. Wendy Graham and James Jones, Department of Agricultural and Biological Engineering, the University of Florida).

If the second-round posterior distribution could approach the initial parameter set very well, which means the mean value of posterior distribution should be very close to the initial parameter set, and the variance or uncertainty of the posterior distribution should be reduced to a small level.Then it can be concluded that the GLUE method and the selected likelihood function are reliable for input parameter estimation. It was assumed in this procedure that the observations followed a normal distribution with given means and variances.

3.2.11 Expected Values of Posterior Distribution

In this study, the GLUE estimation was used for model calibration. The calibrated model was used as a computer platform to explore different combinations of nitrogen fertilizer levels

and irrigation levels for sweet corn production in North Florida. Some of these combinations were selected as potential BMPs (See Chapter 5). The selected potential BMPs were then tested for their uncertainties caused both by weather uncertainties and parameter uncertainties (See Chapter 6).

When exploring many possible treatments to find some potential BMPs, a nominal parameter set is needed to carry out pre-selections of the BMPs. In other words, the prediction uncertainties caused by input parameter uncertainties were temporarily neglected. Since a second posterior distribution was already available after two rounds of GLUE estimations in this study, it was reasonable to use the expectations of the distribution as the nominal values to run the model. The expectations of the selected parameters were obtained with following equation:

$$E(\theta) = \sum_{i=1}^{N} p(\theta_i) \times \theta_i \tag{3-30}$$

3.3 Results and Discussion

3.3.1 Results of Prior Distribution

Table 3-4 shows the results of normality test with the Jarque-Bera method for the selected parameters. It can be seen that parameter SLDR, SLLL, SDUL, and SSAT all followed a normal distribution under a significance level of 0.05. For parameter P1 and P5, though they failed to strictly follow a normal distribution under a significance level of 0.05, they had larger p-values, which means if they could follow a normal distribution if under a lower significance level, for example 0.01. At the same time the covariance between the parameters were also considered, it is reasonable to select some kind of distribution that can represent covariance. The multivariate normal distribution would be a good choice. So parameter PHINT and SLRO were also assigned a normal distribution.

SLPF completely failed to follow a normal distribution. It is a parameter that represents the influence of micronutrients such as zinc (Zn) and copper (Cu). Its values were always set as 1 when its actual value is unknown. In this research, a uniform distribution of [0.7, 1.0] was assigned for SLPF, where 0.7 and 1.0 were the minimum and maximum of SLPF, respectively.

Thus, finally except for SLPF, a multivariate normal distribution was used as the prior distribution for the selected input parameters.

3.3.2 Results of Number of Model Runs

Enough number of model runs should be carried out to guarantee the statistical properties of the input parameters, in other words, to guarantee the prior distribution. Thus, the stability of the generated random values of the selected input parameters was tested to determine the number of model runs. Each of the selected input parameters was tested. For convenience, only P1 was used as an example for the genotype parameters. The results were shown in Figure 3-2 and 3-3.

Figure 3-2 shows the response curve of mean value of different numbers of generated values of P1 vs. number of model runs or parameter sets, while Figure 3-3 shows the response curve of standard deviations of P1 vs. number of model runs. From these figures, it can found that after about 1,000 randomly generated values of P1, the mean values of generated P1 would reach a constant of 225, which was the mean value of P1 in the prior distribution (225.10). The standard deviation of generated P1distribution did not reach a constant of 68 until about 2,000 model runs, which is comparable to real value of standard deviation of 67.5.

The soil parameter SLRO was also used as a representative for the test of generated soil parameter stability. Figures 3-4 and 3-5 show that the minimum reliable number of model runs should be about 2,000, since additional parameters sets yielded little change in the values of mean and standard deviation of SLRO.

Thus, it can be concluded that at least 2,000 randomly generated parameter sets or model runs could guarantee the parameters follow the prior distribution.

Next, the stability of statistical properties of model outputs was tested. Figures 3-6 through 3-9 show the mean values and standard deviations of predicted yields (kg ha^{-1}) and nitrogen leaching (kg ha^{-1}) under different numbers of model runs with generated random parameter sets.

From the four figures above, it can be seen that after about 3,000 model runs, the four statistics all reached constant values. However, before 3,000, most notably before 1,000 runs, values varied dramatically. It could be concluded that at least 3,000 simulations should be conducted to generate reliable results. Thus, the number of 3,000 model runs was chosen since this value satisfied both input and output stability. However, it should be noticed that the minimum number of model runs mentioned here is not something to guarantee the reliability of the posterior distribution in the GLUE process for parameter estimation, but only something to guarantee the reliability of model input parameters and model outputs when starting the process.

3.3.3 Results of Likelihood Function and Method of Likelihood Value Combination

3.3.3.1 Comparison of distributions of input parameters

From Table 3-5, it can be seen that under any of the likelihood functions, L1, L2, L3 or L4, the way to combine the likelihood values derived from different observations had a very strong influence on the corresponding posterior distributions, since they influenced the standard deviations of the posterior distributions to varying degrees.

For the combination methods of C1 and C3, the standard deviations or the uncertainties of most input parameters did not decrease, and even increased in some cases. For example, under L1 the standard deviation of P1 became 112.31 under C1 and 112.01 under C2, but the standard deviation of P1 in the prior distribution was only 67.83. Similar trend occurred for P5, PHINT, etc. Thus, likelihood combination methods C1 and C3 failed as a tool to reduce the parameter

uncertainties. This is because these two methods were not strict enough to eliminate some parameter sets that simultaneously have extremely good predictions for some outputs and poor predictions for the others. For example, one parameter set had gained a likelihood value of 0.9 in predicting the dry matter yield, but only 0.0001 in predicting the maturity date, which means this parameter set did a very good job in predicting the dry matter yield, but a poor job in predicting the maturity date.Then under C1 and C3, the combined likelihood values would be 0.450 and 0.636, respectively. This parameter set might be selected when deriving the posterior distributions of the input parameters, since the combined likelihood values were considerable. However, under C2 the combined likelihood value would only be 0.00009, which was very small and would probably be neglected when deriving the posterior distribution. If this parameter set was selected, the ranges of the parameters that control corn yield might be refined, but the ranges of the parameters that control maturity date might be coarser at the same time because more poor parameter values were selected when contructing the posterior distribution. Finally, the uncertainties of the input parameters could not be reduced.

Under C2, the results were much better than under C1 and C3. The standard deviations of almost every selected parameter decreased. This method, which is defined as a factorial product, had the most powerful ability to eliminate unsatisfactory parameter sets as mentioned above. Thus in future research, C2 was used as the standard method to combine different likelihood values. Under C2, there was no great difference among the posterior distributions derived from L1, L2, L3 and L4, especially between L1 and L2, L3 and L4. For example, the mean value of the prior distribution of P1 was 225.10. Then it changed to 144.49, 142.12, 166.20, and 166.45 under L1, L2, L3 and L4, respectively. The results were not surprising since the forms of the likelihood function of L1 and L2 were similar, as were L3 and L4. The standard deviation of the

prior distribution of P1 was 67.83. Then it decreased to 23.39, 12.98, 38.04, and 37.49 under L1, L2, L3 and L4 respectively. It can be seen that likelihood function L2 had the lowest value of standard deviation or lowest uncertainty in the posterior distribution. However, this result may be a little bit misleading, becaue L2 used the average observation $\overline{O}$ instead of the replicates of the observation, in other words, this likelihood function under-represent the uncertainties in observations.

In general, it might be concluded that the likelihood functions did not have dramatic influence on the posterior distributions for the same method of likelihood value combination, if the functions were reasonably defined and close to each other.

3.3.3.2 Comparison of distributions of model outputs

As shown in Table 3-5, there was some difference between the results from L2 and L3, especially for genotype parameters P1 and P5. For example, the mean value of P1 under L1 and L2 was 144.49 and 142.12, which were close to each other. However, it was 166.20 and 166.45 under L3 and L4, which was higher than L1 and L2. The same situation can be seen for P5.

These differences could heavily influence the length of growth stages and the dry matter yield at last. Therefore when the best method of likelihood value combination, C2, was determined, it was still necessary to find the likelihood function that was most efficient in the GLUE procedure.

The model was run 3,000 times in a second round with the input parameter distributions determined by L1C2, L2C2, L3C2 and L4C2 (Table 3-5). Then the outputs were compared with the observed values to determine which likelihood function should be selected. The outputs are listed in Table 3-6. To quantify the agreement between the outputs derived from different

likelihood functions and observations of field experiment, a measure called absolute relative error (ARE) was defined as follows:

$$ARE = \frac{|Y - Y'|}{Y} \tag{3-35}$$

where Y is the measured value, and Y' is the model predicted value.

From Table 3-6, it is easy to see that L1C2 most precisely matched the observations, especially in yield. The input parameter distribution of L2C2 over-predicted the yield, but had the lowest mean value of nitrogen leaching of 73.32 kg ha^{-1}. For example, the ARE value of yield of L2C2 compared with measured value is 0.15, which was higher than L1C2, L3C2, and L4C2. No ARE value is available for nitrogen leaching, since there was no direct measurement for it in this study.

However, the input parameter distribution of L3C2 and L4C2 underestimated the yield with an ARE value of 0.03 and 0.05, but over-predicted the anthesis date and maturity date with a substantial ARE value of 0.24. Therefore, it can be concluded that the L1C2 (likelihood function 1 and likelihood value combination 2) should give the best results in the process of parameter estimation with the GLUE method. Actually this is really the most theoretical approach. However it was also obvious that L1C2 overestimated the anthesis date (about 5 days longer) and maturity date (about 8 days longer).

The prior distribution was derived from the database of the DSSAT model. The range and uncertainty in the prior distribution were very large. The occurrence probability of behavioral parameter sets that were very close to the actual values was low. And six types of observations were involved in the GLUE process, among which some were temporally and spatially variant. Thus, it required the GLUE method to optimize multiple objectives simultaneously, which also decreased the occurrence probability of behavioral parameter sets. In the first round of GLUE

estimation, the generated parameter sets were widely distributed. Most generated parameter sets failed to have a considerable likelihood value. Only about 10 parameter sets, which had considerable likelihood values, were finally selected to construct the posterior distributions. Other parameter sets were automatically eliminated by the GLUE process.

However, it seems ten parameter sets were not very enough to construct the posterior distribution. There were two possible ways to compensate this drawback. The first way was to increase the number of model runs. For example, if the number of model runs could be increased to ten times of the initial one, the number of behavioral parameter sets might also increase to ten times. However, this method would also greatly increase the model running time. Another method was to conduct a second round of GLUE process. After the first round of GLUE, the range and variance of the posterior distribution of the input parameters would be decreased, the occurrence probability of behavioral parameter sets with the new distributions would be increased significantly. Consequently, the second posterior distribution would be more smooth and precise. In this research, the second method was used.

In the second round of GLUE process, the first posterior distribution was used as the new prior distribution. The observations of field experiment in 2006 in Block 1 were used to construct the second posterior distributions. From this point on, the default strategy of likelihood function and likelihood value combination will be L1C2. L1 is the likelihood function 1 as shown in Equation (3-9), which is directly derived from the density function of normal distribution. C2 is the method 2 of likelihood combination, which is based on Bayes' multiplication.

3.3.4 Distributions of Selected Parameters

Table 3-7 shows the statistical properties of the prior, the first, and the second posterior distributions of the input parameters after two rounds of GLUE simulation using likelihood function of L1 and method of likelihood combination of C2. By comparison, it can be seen that

the initial mean values of the selected parameters changed. The ranges defined by the minimum and maximum values also became narrower. The values of standard deviations decreased, which means the uncertainties of the input parameters were decreased dramatically. For example, the initial mean value of genotype parameter of P1 was 225.10. It changed to 144.49 and then to 99.17 in the two rounds of GLUE simulation. The initial range was [110.00, 450.00], then the range of first posterior distribution narrowed to [136.93, 216.80], and the range of second posterior distribution continuously narrowed to [77.68, 118.22]. The standard deviation of P1 for the prior, first posterior and second posterior distributions was 67.83, 23.39, and 8.22, respectively. Similar changes could also be found in other parameters, either in genotype or soil.

The measured mean values in field experiment and estimated mean values with the GLUE method of the soil parameters are given in Table 3-8. Interestingly, the mean values of estimated and measured soil parameters were pretty close to each other. For example, the mean value of calibrated SDUL in the second posterior distribution was 0.104 cm^3/ cm^3, while the mean value of measure SDUL was 0.110 cm^3/ cm^3. The error was only about 0.006 cm^3/ cm^3. Similar results were observed in SLLL and SSAT.

In general, the uncertainties of the selected 9 input parameters were dramatically decreased after two rounds of GLUE estimations.

3.3.5 PDF Plot of Selected Parameters

The prior distribution, first and second posterior distribution of the selected input parameters were plotted with their histograms to show the changes of their ranges and distribution forms (Figure 3-10 to 3-18).

From these figures, the ranges and distributions of the selected input parameters during the two rounds of GLUE can be estimated. In the first round of GLUE, most of the distributions did not follow a normal distribution. This was because very few qualified parameter sets were

selected under a very restrictive likelihood function. But in the second round of GLUE, most of the distributions tended to follow a normal distribution. This result occurred because the ranges of the new prior distributions were heavily narrowed. More acceptable parameter sets that could give good outputs were generated and selected finally to smooth the final distributions became smoother.

3.3.6 Distributions of Outputs

The four figures below (Figures 3-19 to 3-22) show the distributions of the predicted yields (dry matter, kg ha^{-1}), anthesis dates (days after planting), maturity dates (days after planting), and accumulative nitrogen leaching (NLCM, kg ha^{-1}), respectively. Red curves in the figures are the fitted normal distribution curves. These figures show the trend that after two rounds of GLUE estimation, the uncertainties of predicted outputs, such as yields, anthesis date, maturity date, and nitrogen leaching, were also reduced. The uncertainties of the input parameters were significantly reduced since the mean values shifted toward the field measured values (especially for soil parameters), and standard deviations were noticeably reduced. Consequently, the uncertainties in outputs also decreased. For example, under the second posterior distribution, the mean value of the predicted dry matter yield was near 3,000 kg ha^{-1}, which approximated the measured yield of sweet corn production in North Florida (See Chapter 4 for information on sweet corn yield). For anthesis dates and maturity dates, most parameter sets gave a prediction of 55 and 80 days after planting, respectively. These values were also equal to observations in the field experiment of 2006. In general, the output uncertainties were dramatically reduced after two round of GLUE simulation, which strengthened the confidence in the model behavior and to use the posterior distributions of the selected input parameters for future research.

3.3.7 Joint Distribution between Yield and Nitrogen Leaching

Yield and nitrogen leaching were two main concerns in this study to develop potential best management practices (BMPs) (see Chapter 5). Therefore it was necessary to know how these two correlated to each other. A 3-D plot of the joint distribution between yield and nitrogen leaching was developed. Figures 3-23, 3-24 and 3-25 show the 3-D plots under prior, first posterior and second posterior distribution of the selected input parameters, respectively.

In Figure 3-23, the predicted yields spread out in a very wide range with a mean value of close to 6,000 kg ha^{-1}, which was much greater than the observed values. For nitrogen leaching, the values mainly focused around 0 to 20 kg N ha^{-1}. They were also far from the estimated values of nitrogen leaching in field plot experiment in 2006, which were 90 to 170 kg N ha^{-1} (Table 4-16 in Chapter 4).

In Figures 3-24 and 3-25, the ranges of yield and nitrogen leaching narrowed, meaning the uncertainties of these two outputs decreased. Finally, yields were around 3,000 kg ha^{-1}, which were more close to the measured values in field experiment (Table 4-16 in Chapter 4). And the values of nitrogen leaching were mainly between 50 to 100 kg ha^{-1}. Though they were still less than the estimated nitrogen leaching amouts in field plot experiment, they became more close to the estimated values. See Chapter 4 for more information about sweet corn yield and nitrogen leaching.

3.3.8 GLUE Verification

Though the GLUE procedure did a good job in soil parameter estimation because the estimated SLLL, SDUL and SSAT values were close to measured values (Table 3-8), the accuracy of the estimated genotype parameters may not have been accurate. For example, genotype parameter P1 still had a coefficient of variation of 0.083. However, there was no experiment designed in this study to directly measure those genotype parameters. To obtain more

confidence in the GLUE method and more confidence in the likelihood function (L1) and the method of likelihood value combination (C2), a verification procedure was conducted.

The selected parameter set was shown in Table 3-9. Four replicates for each observation were generated with a normal distribution. The mean value of the normal distribution was the model output derived from this selected parameter set. The variance of the normal distribution was the variance of observation.

Since the leaf nitrogen content, soil nitrate and moisture content were both temporally and/or spatially variant, it is inconvenient to list them all here. Therefore only the generated yields, anthesis dates (ADAT), and maturity dates (MDAT), were specified in Table 3-10.

The results of input parameters of the GLUE verification were summarized in Table 3-11. It can be seen that after two rounds of GLUE, the uncertainties of the selected parameters continuously decreased. All mean values gradually approached the measured values listed in Table 3-9, and all standard deviations decreased gradually. The mean values, especially for the selected parameters in the second-round GLUE, were similar to the generated replicates.

For example, the initial mean value of P1 in the prior distribution was 225.1. Then it became 140.4 after the first-round GLUE simulation and 97.3 after the second-round GLUE simulation. The value of 97.3 was close to the initially selected value of P1 (95.1). The value of absolute relative error was only about 2.3%. The highest value of RAE occurred in soil parameter SLDR, which was about 8.1%.

In general, the results were acceptable because it was impossible to make the estimated values of parameters completely converge to the selected ones, since error always existed in the observations. This confirmed that the GLUE method was efficient in parameter estimation. After

a strict GLUE process, the mean values of the posterior distributions of the sensitive parameters approached the actual values, if those values can be measured.

Table 3-12 summarizes the single values for the integrated observations in the growth season, the yield, anthesis date, and maturity date in the GLUE verification. After two rounds of GLUE, the uncertainties of the model outputs all decreased. For example, the value of standard deviation of predicted yields decreased from 2173 to 268. The same change can be observed in predicted anthesis date (ADAT) and maturity date (MDAT). All mean values gradually approached the measured values (last column of Table 3-12), and all standard deviations gradually decreased. The values of CV all decreased to a very low level. For example, the value of CV of predicted yields decreased from 0.316 under the prior distribution to about 0.077 under the second posterior distribution.

The mean values of the predicted anthesis dates and maturity dates after two rounds of GLUE simulation were especially close to the means of the observation values. The values of RAE were almost 0. The results again confirmed the validity of the GLUE method.

3.3.9 Result of Expected Values of Posterior Distribution

After two rounds of GLUE estimations in this study, a second posterior distribution was available. Then the expectations of the distribution were calculated with Equation (3-29) to act as nominal parameter set for future study. The results are listed in Table 3-13.

3.4 Conclusions

In this study, the generalized likelihood uncertainty estimation (GLUE) method was used to estimate the genotype and soil parameters of the CERES-Maize model of DSSAT. Two years of field experiment data (2005 and 2006) in Block 1 were used in a two-round GLUE process of parameter estimation. In the first round of GLUE, the prior distribution was obtained from the database of DSSAT. The model was run with data of 2005 and the prior distribution. The first

posterior distribution was derived. Then in the second round of GLUE, the first posterior distribution was used as the new prior distribution. The model was run with data of 2006 and the new prior distribution. Then the second posterior distribution was obtained.

It was found that all of the selected input parameters (P1, P5, PHINT, SLDR, SLRO, SDUL, SLLL, and SSAT) can approximate to or follow a normal distribution, except for SLPF, which was because SLPF was set as 1 when the actual value of it was unknown.

It was necessary to know the number of model runs that must be conducted so as to guarantee the reliability of model inputs and outputs. Finally it was found that at least 3,000 random parameter sets should be generated and 3,000 model runs should be conducted. It should be noticed that 3,000 is not the number of model runs to get enough behavioral parameter sets to construct the posterior distribution.

Though many likelihood functions and methods of likelihood value combination had been suggested in the literatures, it was found that the likelihood functions and methods of likelihood value combination could have a very strong influence on the posterior distributions. The likelihood function L1 (Equation L1), which is based on the probability density function of normal distribution, and method of combination C2 (Equation C2), which is based on multiplication, was the best choice for this study.

After two rounds of GLUE simulations, the uncertainty in input parameters and model outputs were substantially reduced. For example, the standard deviation of P1 for the prior, first posterior and second posterior distributions were 67.83, 23.39, and 8.22, respectively. Similar trends occurred for other input parameters. In comparison, the mean values of estimated and measured soil parameters were very close to each other. The mean value of calibrated SDUL in the second posterior distribution was 0.104 cm^3/ cm^3, while the mean value of measure SDUL

was 0.110 cm^3/ cm^3. The error was only about 0.006 cm^3/ cm^3. Similar results were observed in SLLL and SSAT with an error of -0.009 and 0.014 cm^3/ cm^3, respectively.

To guarantee the reliability of the GLUE method, a process of GLUE verification was conducted. The verification involved selecting a parameter set, running model with the parameter set, generating new replicates for the corresponding outputs, conducting two rounds of GLUE simulation, and comparing the selected parameter set with the second posterior distribution According to the results, it can be seen that after two rounds of GLUE, the uncertainties of the model outputs all decreased, and all mean values gradually approached the selected true values. For example, the value of initially selected P1 was 95.1, while the mean value of the second posterior distribution of P1 was 97.3, with an error only of 2.2. Similar trends occurred for other input parameters. The expectations of the posterior distributions should be used as the nominal values to continue future research in the development of best management practices.

In general the results of this study confirmed that the GLUE method was a powerful tool to estimate the model input parameters, and strengthened the model users' confidence in their research.

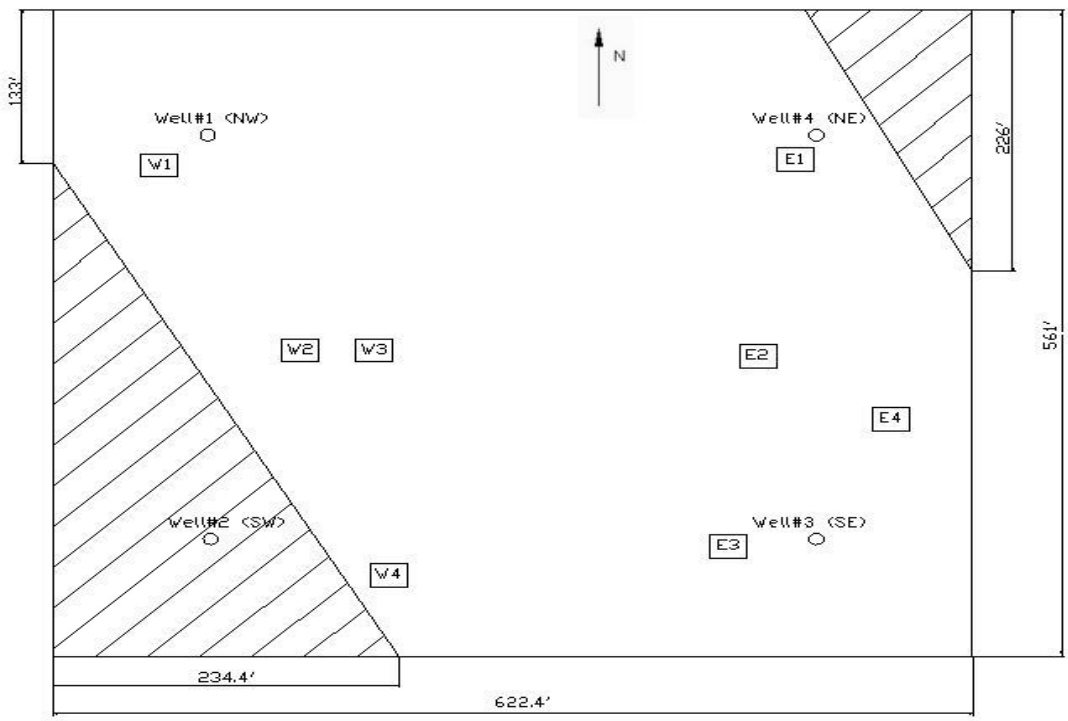


Figure 3-1. Diagram of Block 1 of field experiment. Symbols of E1 to E4 represent the four soil and plant sampling sites on the east part, while W1 to W4 represent the west part. Symbols of Well #1to Well #4 represent the four minitoring wells for groundwater.

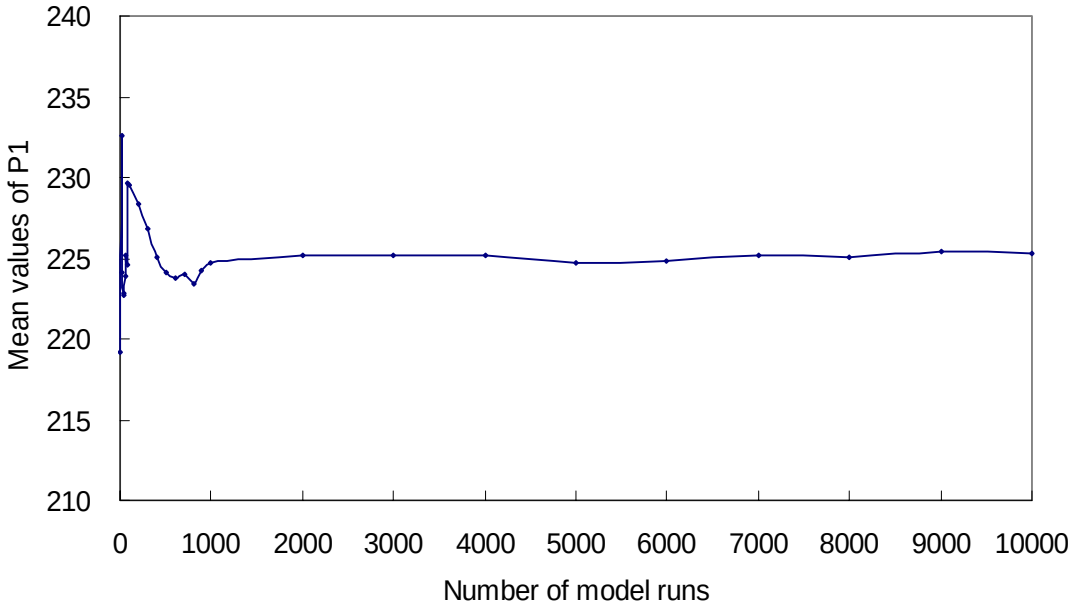


Figure 3-2. Influence of number of model runs on mean values of P1

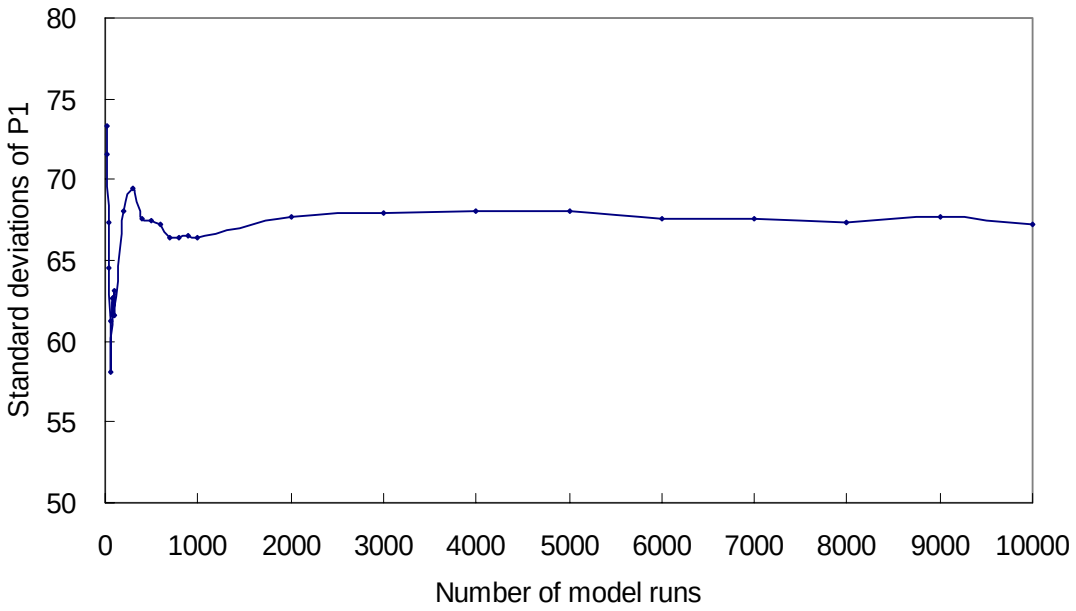


Figure 3-3. Influence of number of model runs on standard deviations of P1

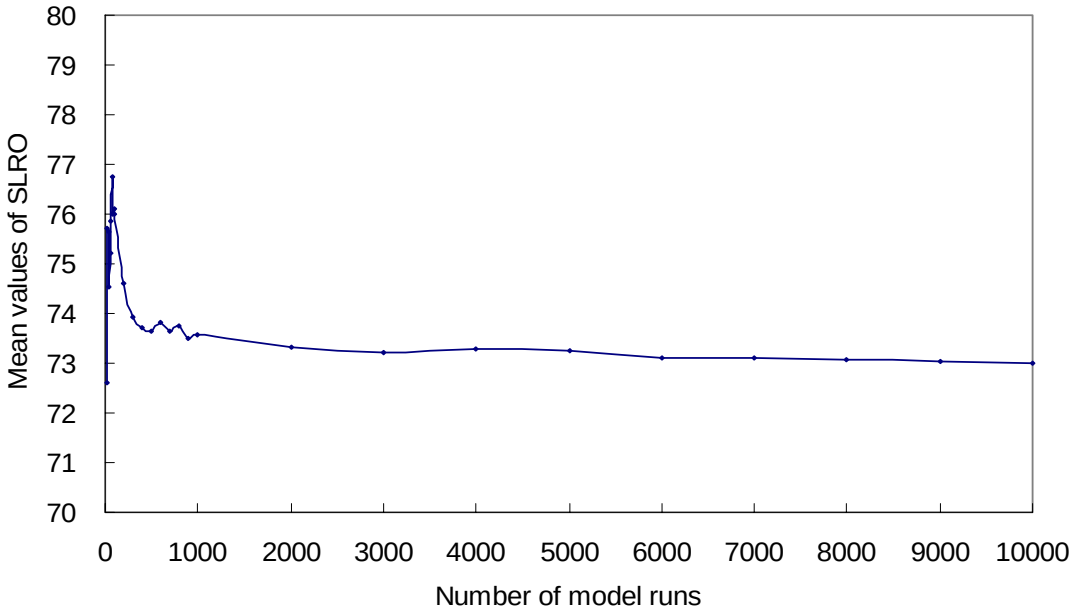


Figure 3-4. Influence of number of model runs on mean values of SLRO

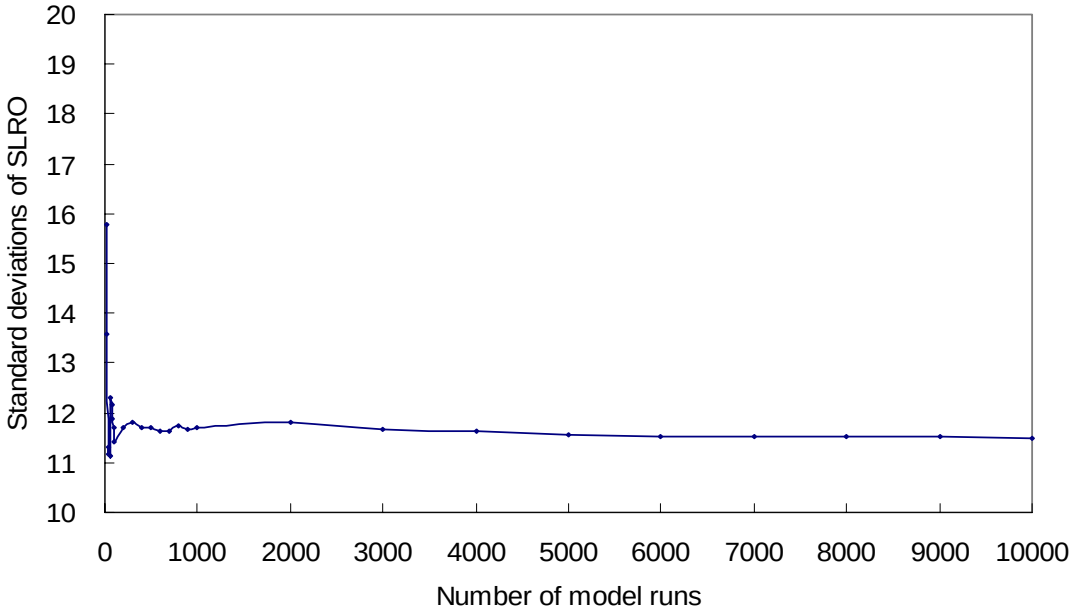


Figure 3-5. Influence of number of model runs on standard deviations of SLRO

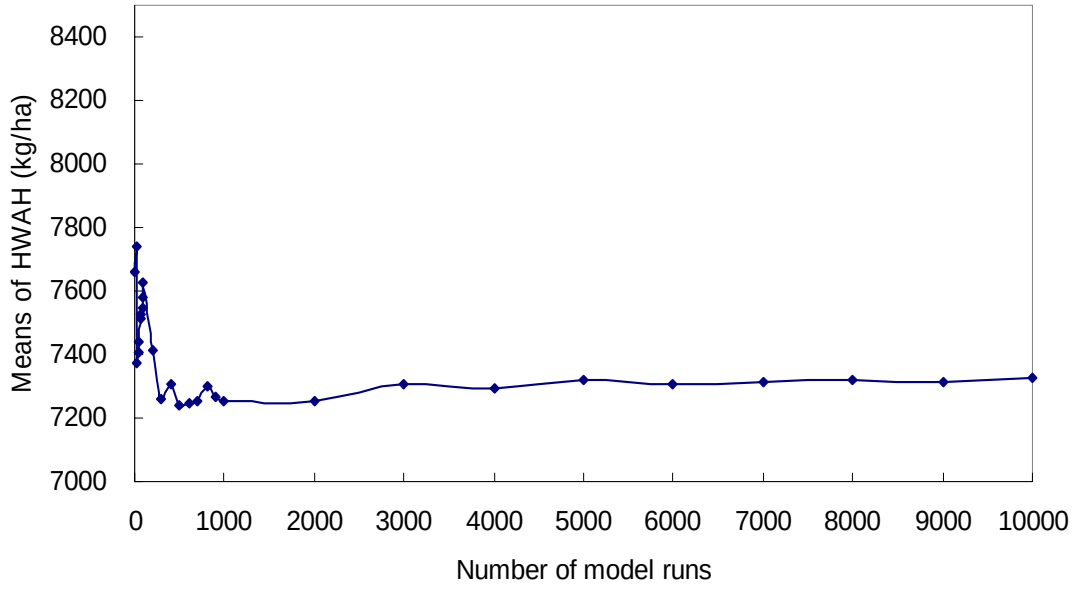


Figure 3-6. Influence of number of model runs on mean values of simulated dry yields

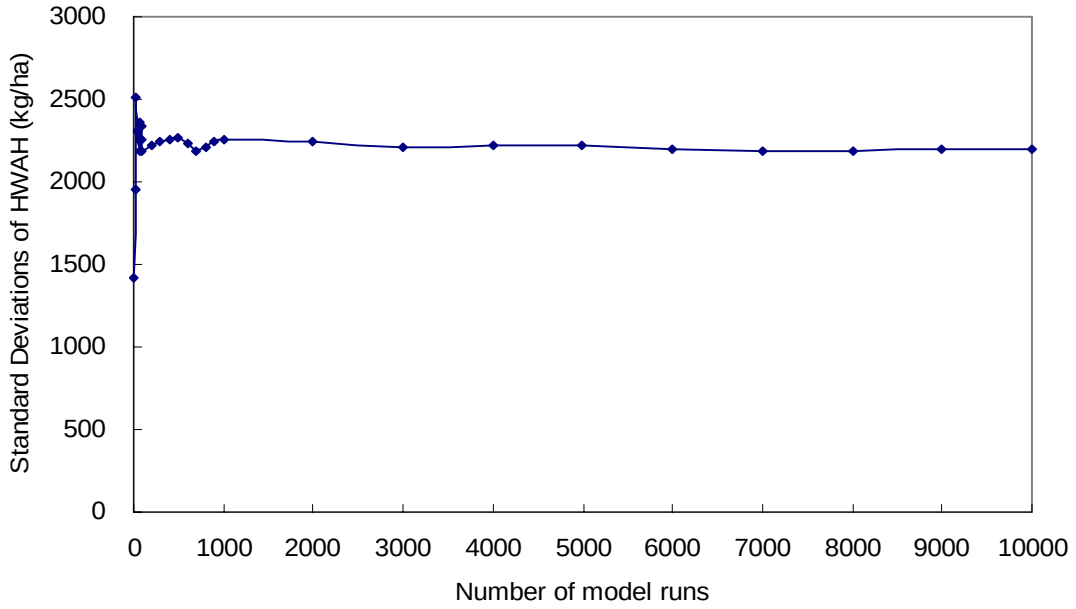


Figure 3-7. Influence of number of model runs on standard deviations of simulated dry yields

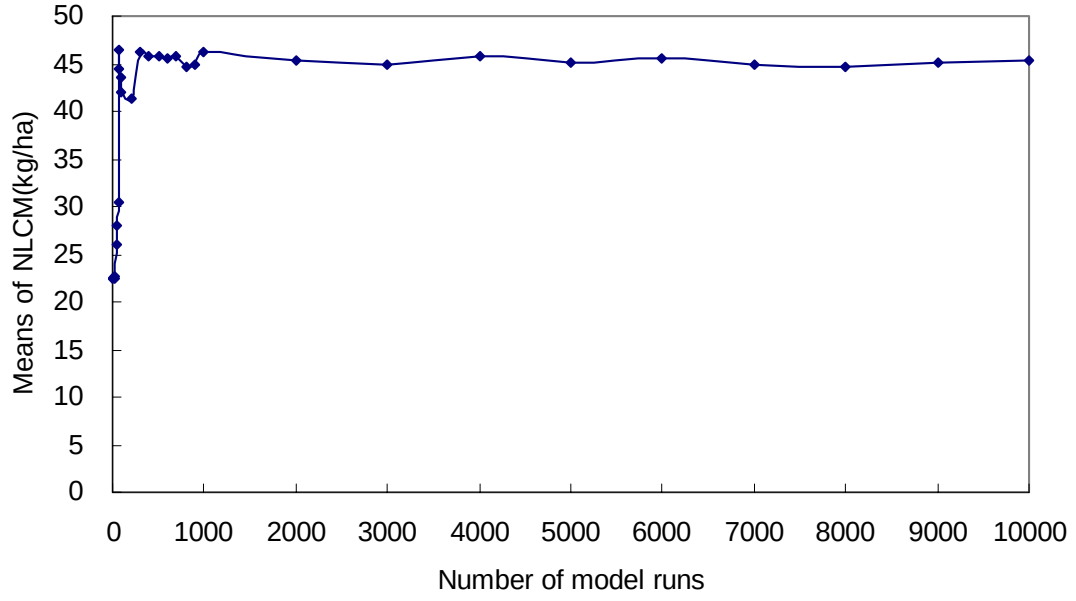


Figure 3-8. Influence of number of model runs on mean values of simulated nitrogen leaching

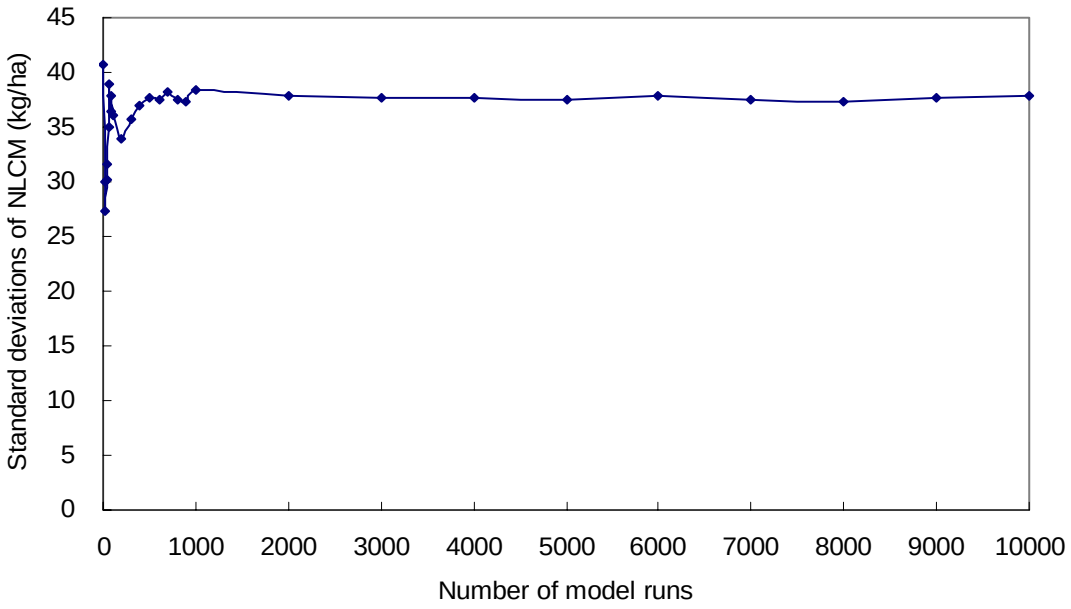


Figure 3-9. Influence of number of model runs on standard deviations of simulated nitrogen leaching

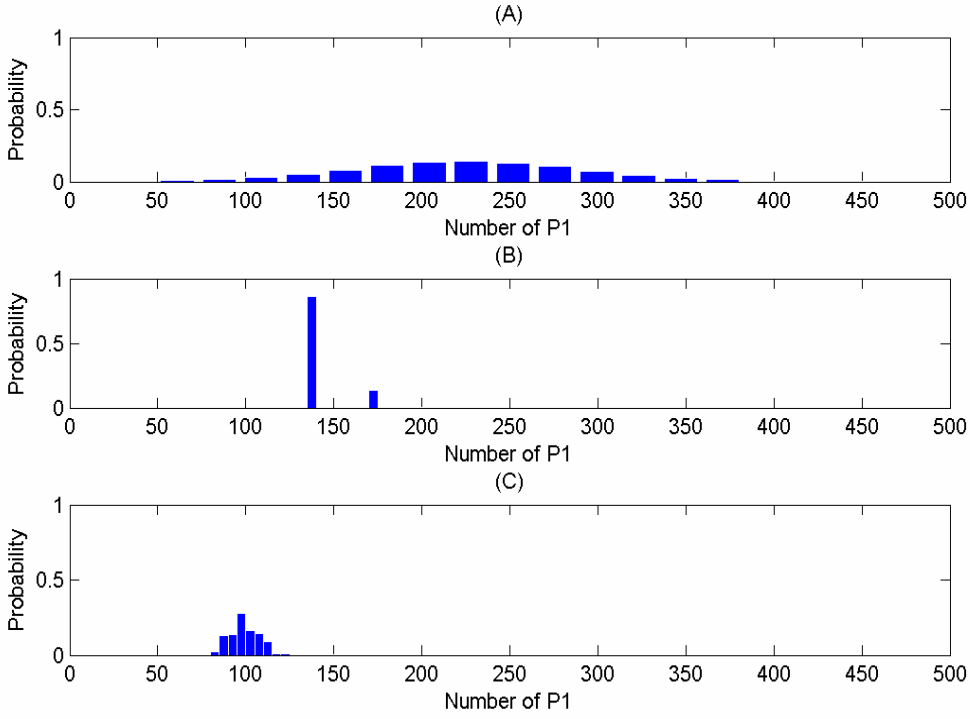


Figure 3-10. Parametre P1: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

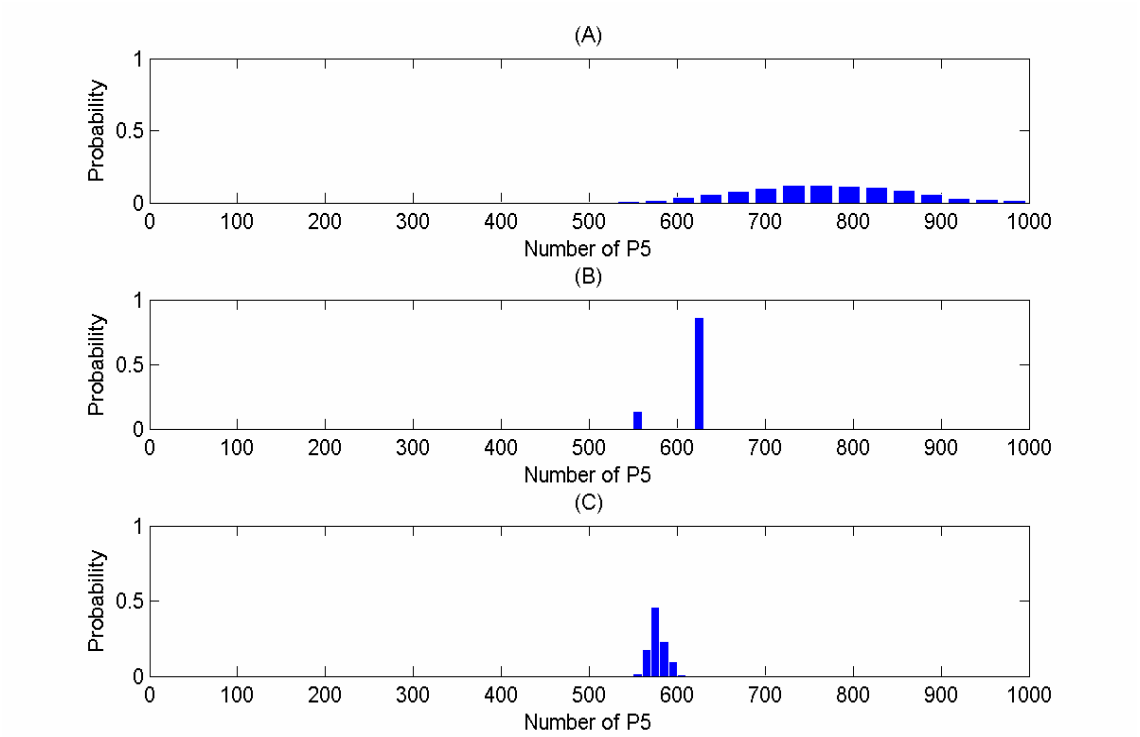


Figure 3-11. Parametre P5: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

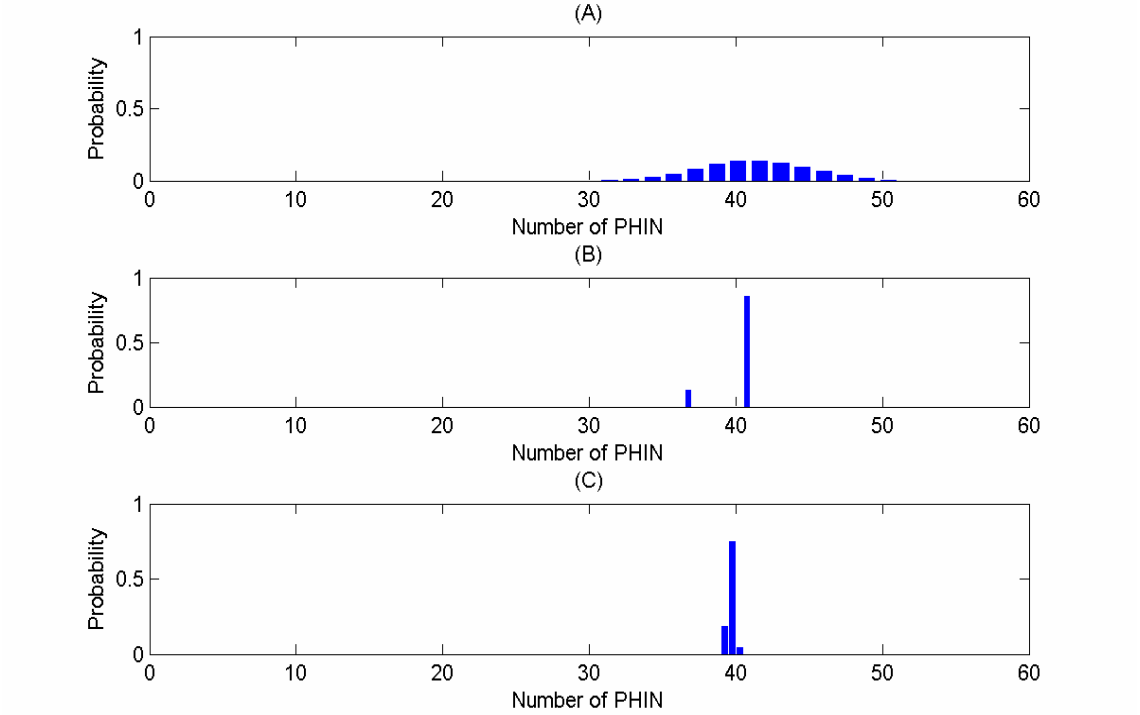


Figure 3-12. Parametre PHINT: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

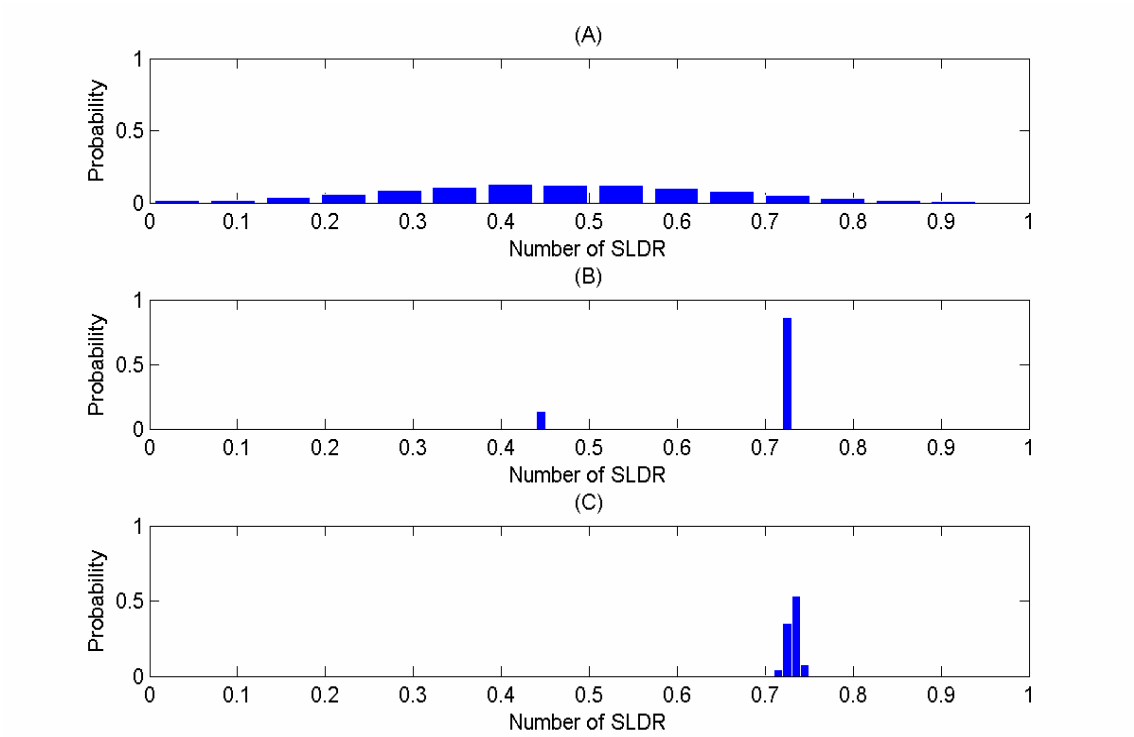


Figure 3-13. Parametre SLDR: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

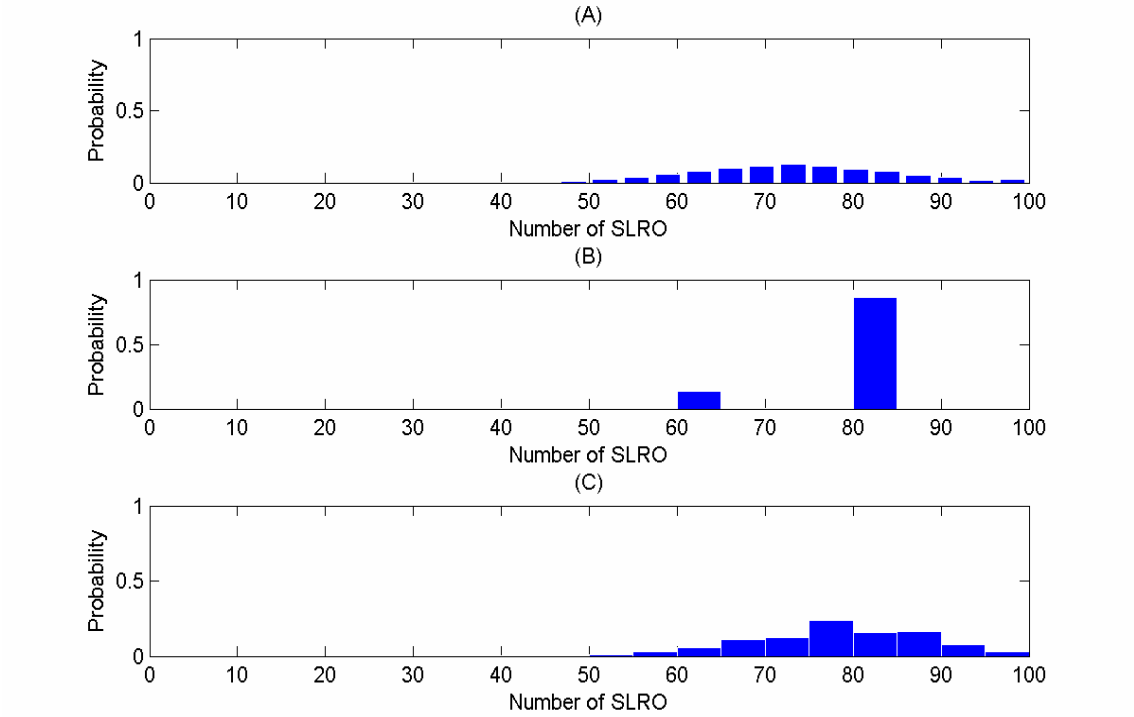


Figure 3-14. Parametre SLRO: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

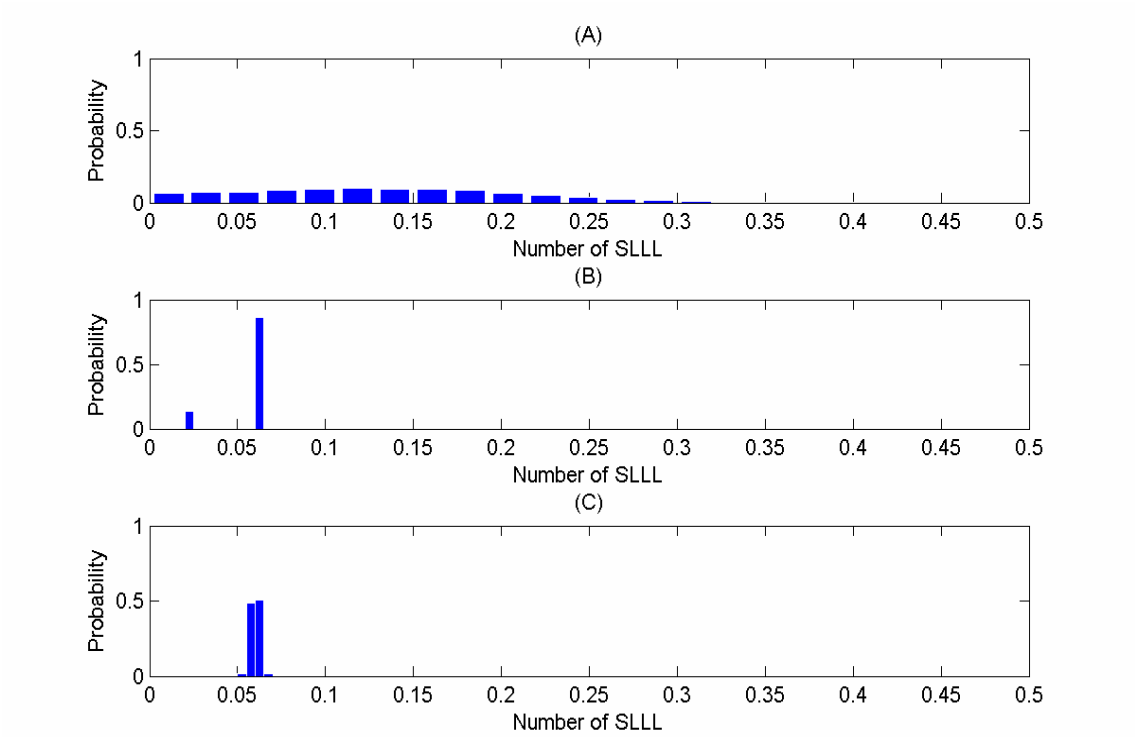


Figure 3-15. Parametre SLLL: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

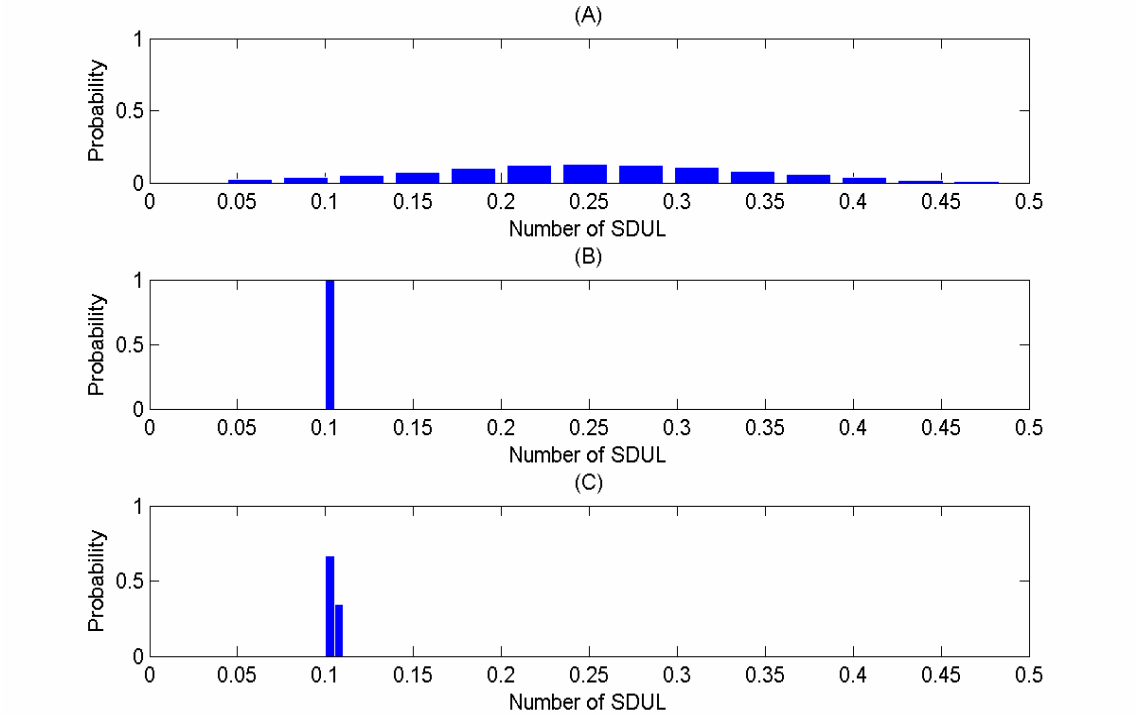


Figure 3-16. Parametre SDUL: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

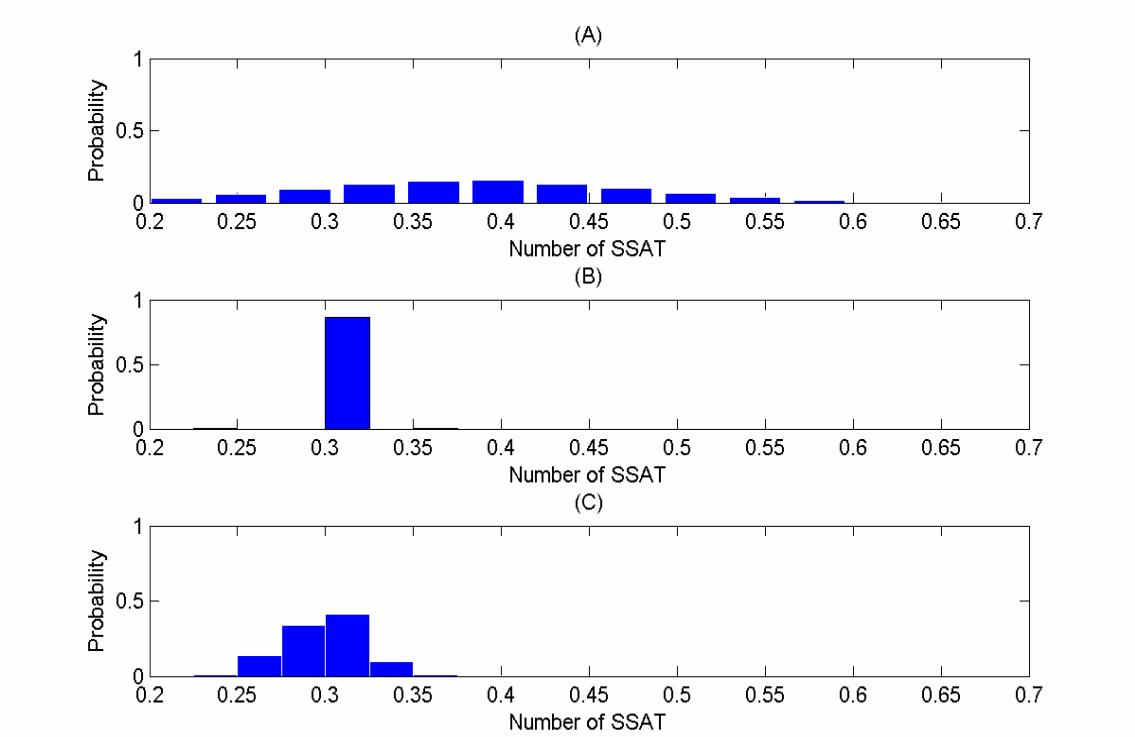


Figure 3-17. Parametre SSAT: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

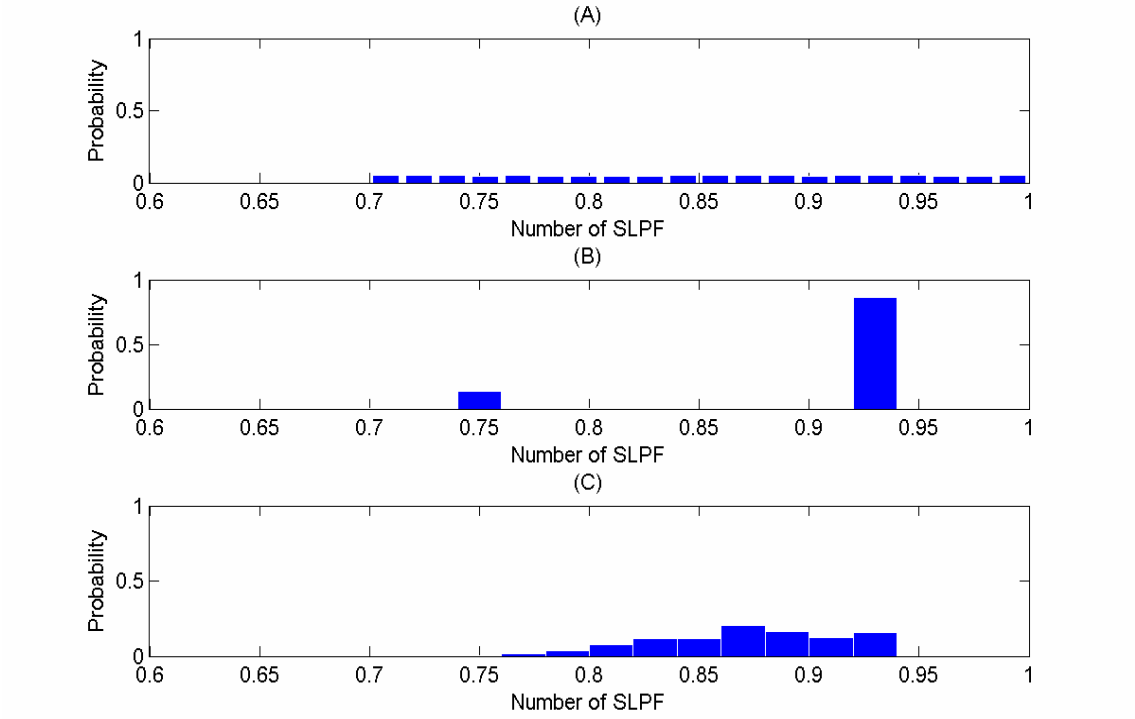


Figure 3-18. Parametre SLPF: probability distribution under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

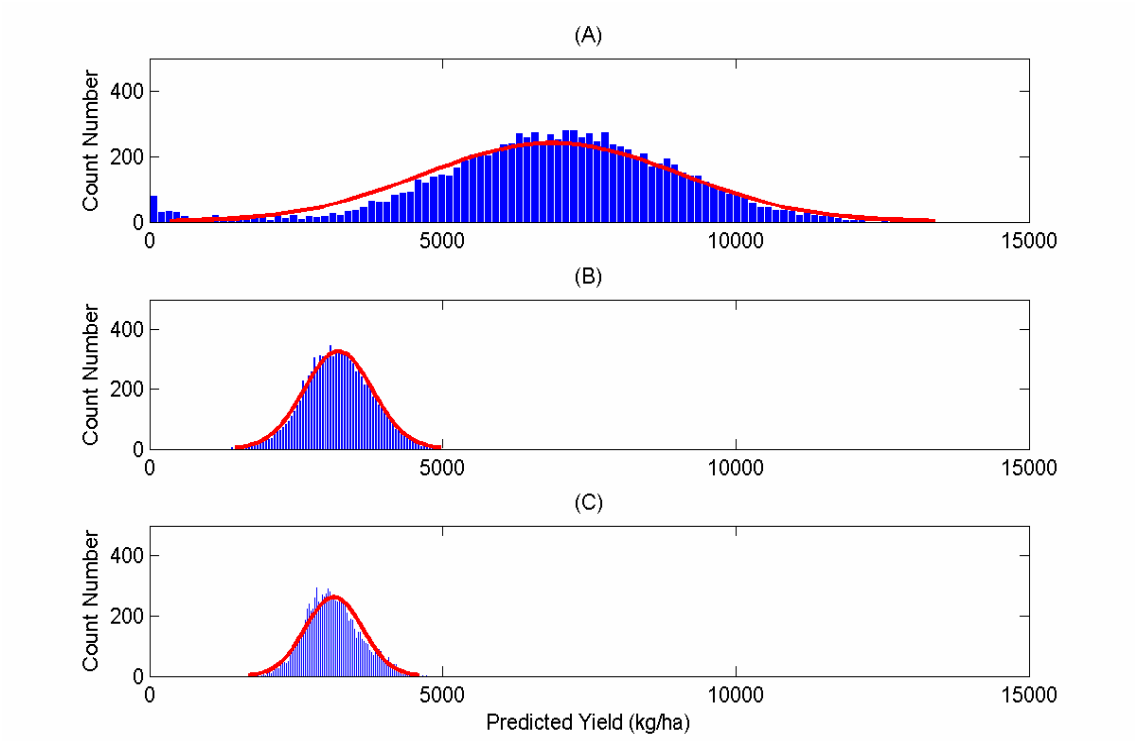


Figure 3-19. Histogram of predicted dry matter yields under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

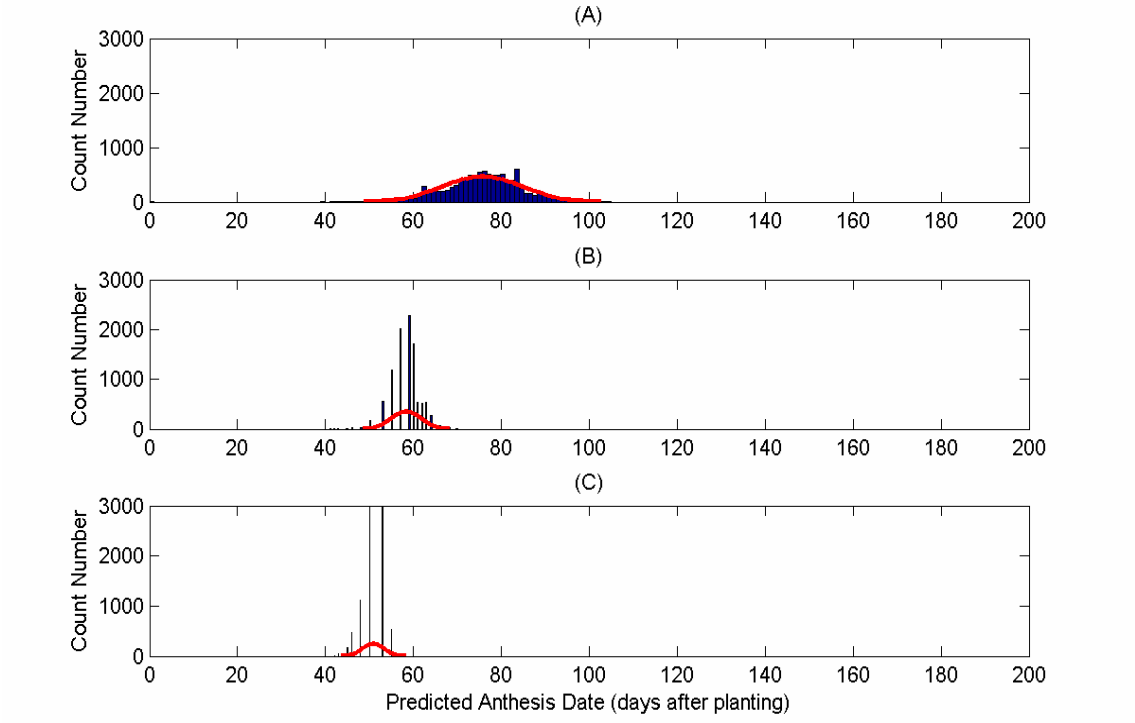


Figure 3-20. Histogram of predicted anthesis dates under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

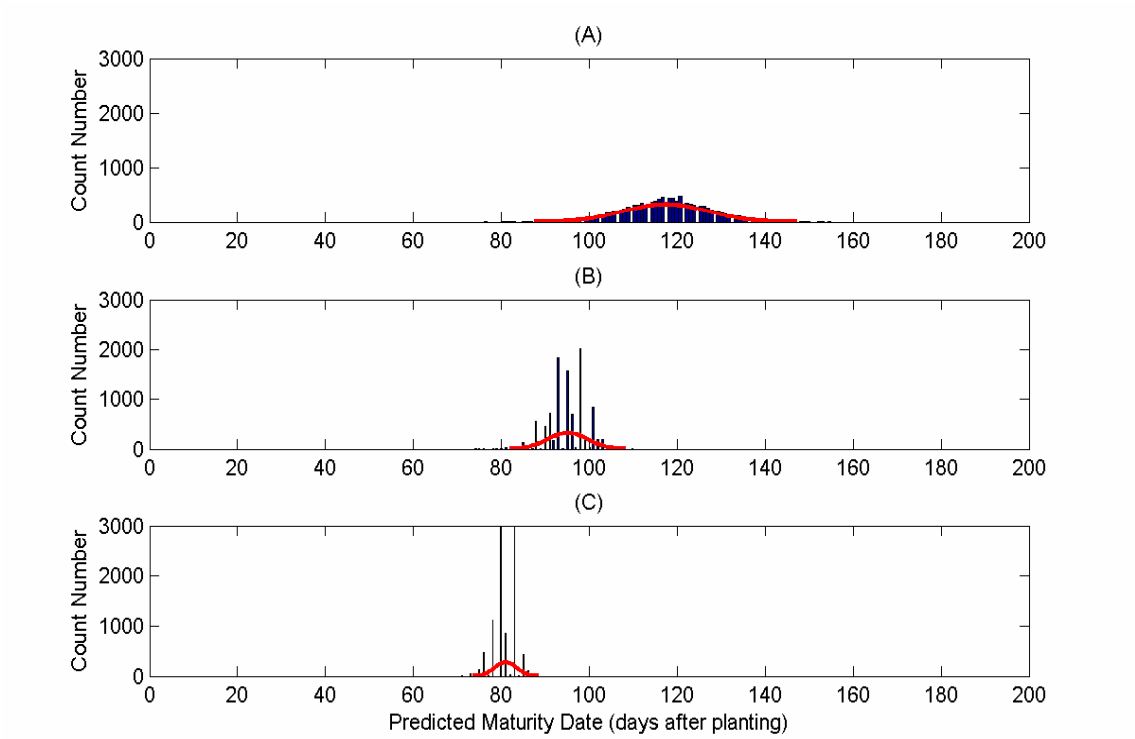


Figure 3-21. Histogram of predicted maturity dates under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

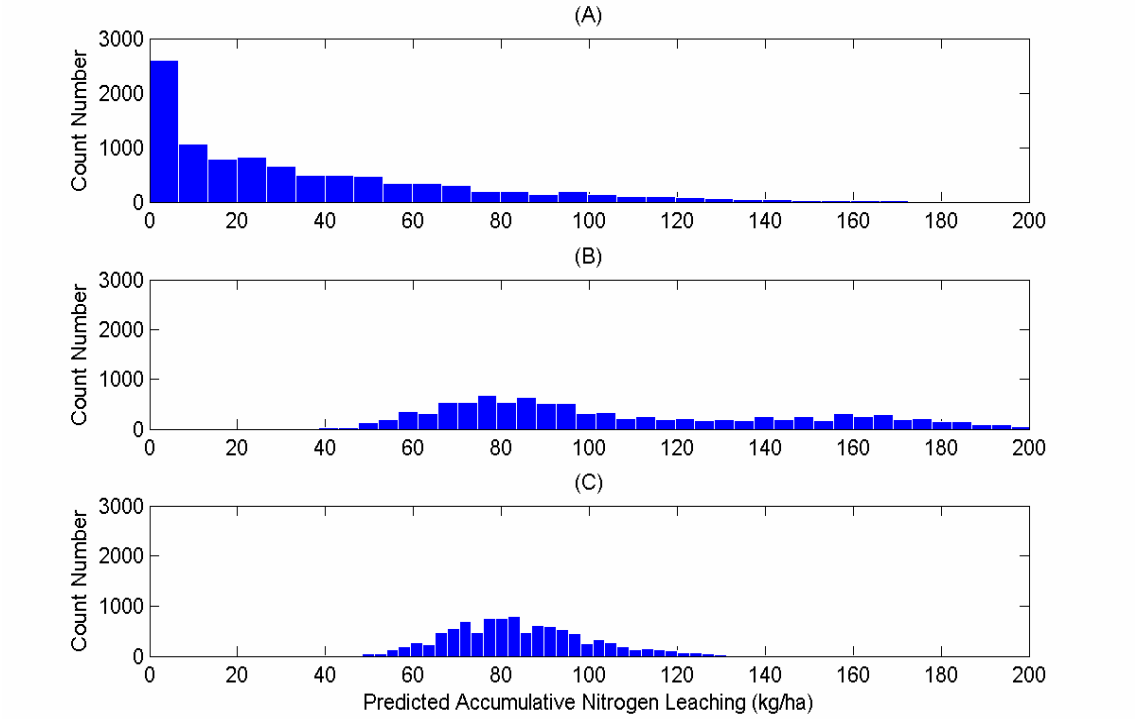


Figure 3-22. Histogram of predicted cumulative nitrogen leaching under (A) prior distribution; (B) first posterior distribution, and (C) second posterior distributions

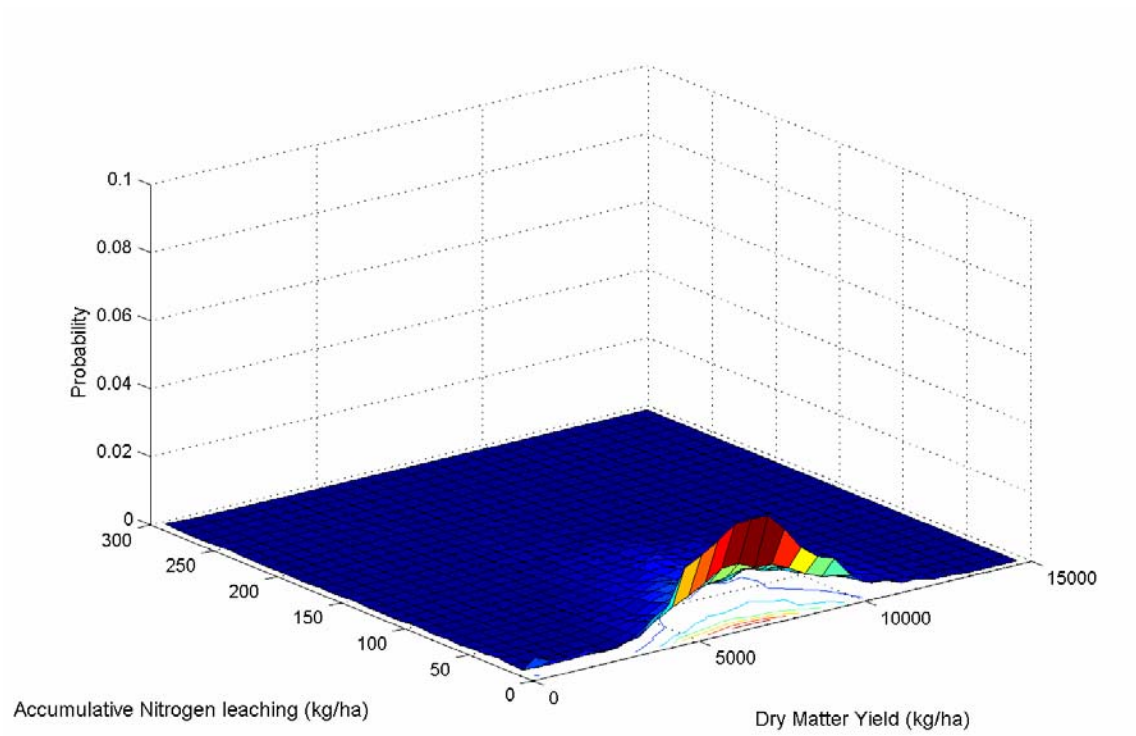


Figure 3-23. Joint distribution between yield and nitrogen leaching under prior distribution of input parameters

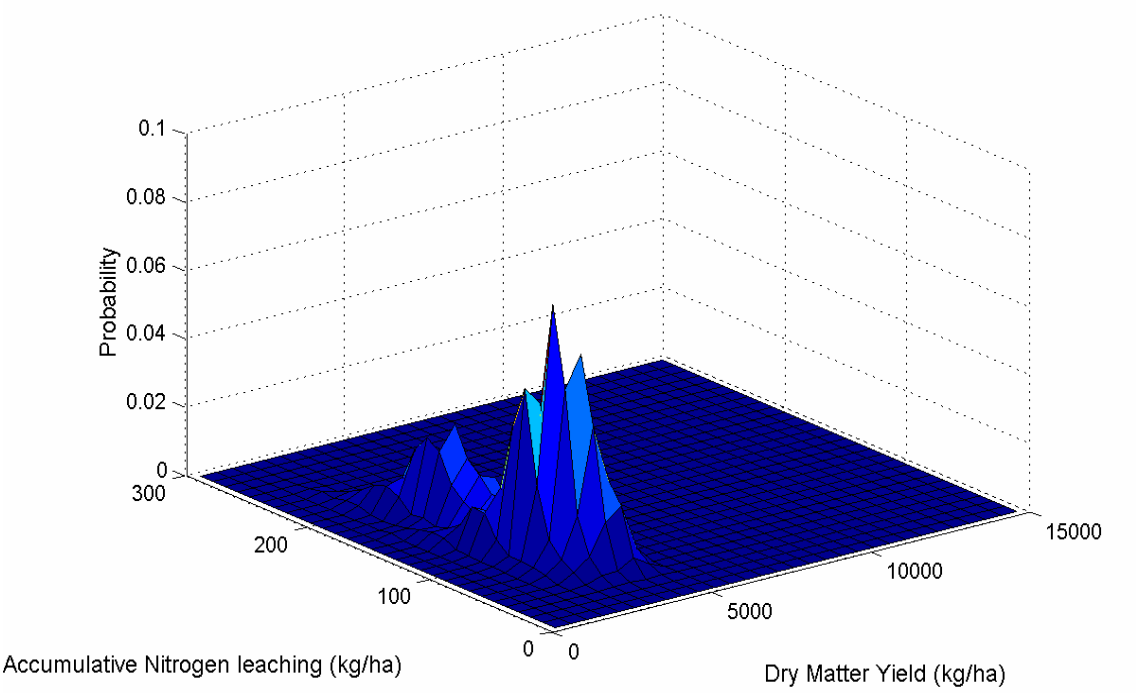


Figure 3-24. Joint distribution between yield and nitrogen leaching under the first posterior distribution of input parameters

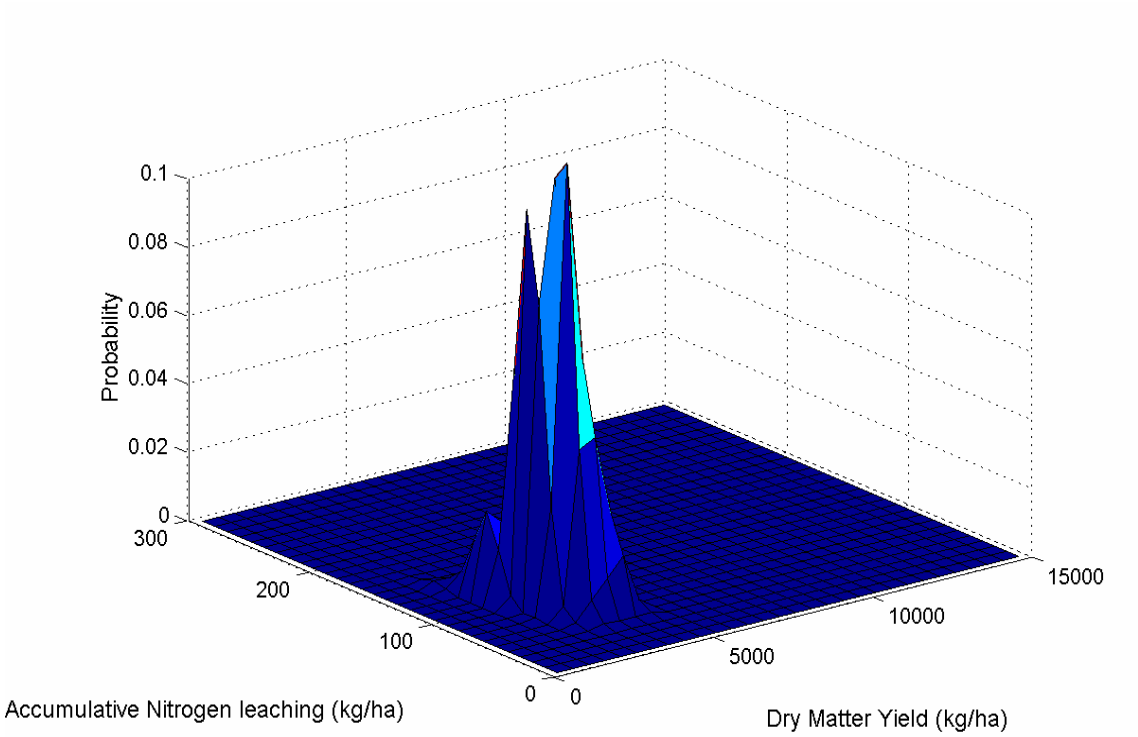


Figure 3-25. Joint distribution between yield and nitrogen leaching under the second posterior distribution of input parameters

Table 3-1. Average soil physical properties of the experiment site (from 24 sampling locations)

Depth (cm)	Texture	Clay (%)	Silt (%)	Sand (%)	Bulk Density (g/cm^3)	PWP (cm^3/cm^3)	FC (cm^3/cm^3)	Saturation (cm^3/cm^3)
15	Sandy soil	2.75	1.92	95.33	1.67	0.051	0.110	0.313
30	Sandy soil	2.56	2.35	95.08	1.69	0.061	0.117	0.317
60	Sandy soil	2.36	1.76	95.88	1.67	0.077	0.118	0.357

Table 3-2. Selected parameters for GLUE method due to sensitivity analysis of predicted dry matter yield and accumulative nitrogen leaching (See Chapter 2 for details)[a]

Parameter	P1 ℃d	P5 ℃d	PHINT ℃d	SLPF -	SLDR -	SLRO -	SDUL cm^3/cm^3	SLLL cm^3/cm^3	SSAT cm^3/cm^3
Value	225.10	763.60	41.20	0.96	0.46	73.00	0.25	0.13	0.38

[a] ℃d means degree day.

Table 3-3. Covariance matrix of the prior distribution

	P1	P5	PHINT	SLDR	SLRO	SDUL	SLLL	SSAT
P1	4561.712	2373.905	61.862	0.00	0.000	0.000	0.000	0.000
P5	2373.905	9679.386	55.854	0.000	0.000	0.000	0.000	0.000
PHINT	61.862	55.854	15.975	0.000	0.000	0.000	0.000	0.000
SLDR	0.000	0.000	0.000	0.036	-0.339	-0.003	-0.003	-0.005
SLRO	0.000	0.000	0.000	-0.339	132.383	0.314	0.236	0.259
SDUL	0.000	0.000	0.000	-0.003	0.314	0.010	0.008	0.006
SDLL	0.000	0.000	0.000	-0.003	0.236	0.008	0.007	0.005
SSAT	0.000	0.000	0.000	-0.005	0.259	0.006	0.005	0.009

Table 3-4. Results of Jarque-Bera test of the input parameters [a b]

Parameter	H	p-value	JBSTAT	CV
P1	1	0.012	8.862	5.992
P5	1	0.014	8.566	5.992
PHINT	1	1.398e-004	17.751	5.992
SLDR	0	0.079	5.083	5.992
SLRO	1	0.001	13.153	5.992
SLPF	1	0.000	9.733e+003	5.992
SLLL	0	0.080	5.063	5.992
SDUL	0	0.248	2.786	5.992
SSAT	0	0.083	5.576	5.992

[a] H=1: reject the hypothesis that x has a normal distribution; while H=0: accept the hypothesis.

[b] CV is the critical value, and JBSTAT is the constructed statistic in the Jarque-Bera test. If JBSTAT>CV, then H=1, while JBSTAT<CV, then H=0, at a significance level α =0.05.

Table 3-5. Mean values and standard deviations (STDEV) of first-round posterior distributions derived from different likelihood functions and likelihood combinations[a]

	Prior Distribution		Under C1		Under C2		Under C3	
	Mean	STDEV	Mean	STDEV	Mean	STDEV	Mean	STDEV
Under L1								
P1	225.10	67.83	176.90	112.31	144.49	23.39	178.34	112.01
P5	763.60	98.80	698.38	120.07	630.78	27.68	700.44	119.00
PHINT	41.17	4.01	41.38	4.78	40.77	0.57	41.46	4.75
SLDR	0.46	0.19	0.52	0.22	0.73	0.01	0.52	0.22
SLRO	73.00	11.56	72.33	11.00	77.40	10.63	72.31	11.02
SDUL	0.26	0.10	0.19	0.10	0.10	0.00	0.19	0.10
SLLL	0.14	0.08	0.11	0.07	0.06	0.00	0.11	0.07
SSAT	0.39	0.09	0.33	0.11	0.30	0.02	0.33	0.11
SLPF	0.96	0.11	0.83	0.09	0.92	0.04	0.83	0.09
Under L2								
	Prior Distribution		Under C1		Under C2		Under C3	
	Mean	STDEV	Mean	STDEV	Mean	STDEV	Mean	STDEV
P1	225.10	67.83	178.45	105.42	142.12	12.98	181.11	104.62
P5	763.60	98.80	700.20	124.40	611.96	24.67	704.36	122.21
PHINT	41.17	4.01	40.75	4.47	40.06	1.32	40.88	4.44
SLDR	0.46	0.19	0.52	0.23	0.69	0.10	0.53	0.23
SLRO	73.00	11.56	71.27	11.56	78.24	6.48	71.21	11.60
SDUL	0.26	0.10	0.20	0.11	0.10	0.00	0.20	0.11
SLLL	0.14	0.08	0.11	0.08	0.06	0.01	0.11	0.08
SSAT	0.39	0.09	0.32	0.11	0.28	0.06	0.32	0.11
SLPF	0.96	0.11	0.83	0.09	0.91	0.06	0.83	0.09
Under L3								
	Prior Distribution		Under C1		Under C2		Under C3	
	Mean	STDEV	Mean	STDEV	Mean	STDEV	Mean	STDEV
P1	225.10	67.83	176.72	110.12	166.20	38.04	178.95	109.72
P5	763.60	98.80	698.61	121.44	653.98	47.55	701.90	119.85
PHINT	41.17	4.01	41.23	4.78	41.20	1.13	41.34	4.75
SLDR	0.46	0.19	0.52	0.22	0.73	0.04	0.52	0.22
SLRO	73.00	11.56	72.23	11.09	67.50	17.29	72.21	11.12
SDUL	0.26	0.10	0.19	0.11	0.11	0.00	0.19	0.11
SLLL	0.14	0.08	0.11	0.08	0.06	0.01	0.11	0.07
SSAT	0.39	0.09	0.33	0.11	0.28	0.04	0.33	0.11
SLPF	0.96	0.11	0.83	0.09	0.88	0.07	0.83	0.09
Under L4								
	Prior Distribution		Under C1		Under C2		Under C3	
	Mean	STDEV	Mean	STDEV	Mean	STDEV	Mean	STDEV
P1	225.10	67.83	75.31	40.52	166.45	37.49	75.94	41.25
P5	763.60	98.80	663.15	98.37	650.43	50.16	669.97	97.07
PHINT	41.17	4.01	37.71	4.22	41.06	1.36	37.80	4.23
SLDR	0.46	0.19	0.45	0.19	0.72	0.07	0.45	0.19
SLRO	73.00	11.56	72.77	10.80	67.39	17.01	72.69	10.84
SDUL	0.26	0.10	0.25	0.10	0.11	0.00	0.25	0.10
SLLL	0.14	0.08	0.13	0.08	0.06	0.01	0.13	0.08
SSAT	0.39	0.09	0.37	0.10	0.27	0.05	0.37	0.10
SLPF	0.96	0.11	0.85	0.08	0.87	0.07	0.85	0.08

[a] "Under L1" means deriving posterior distribution with the likelihood function L1, "Under C1"means deriving posterior distribution under the method of likelihood value combination C1, and so on and so forth.

Table 3-6. Mean values and standard deviations (STDEV) of model outputs derived from first-round posterior distributions[ab]

	Outputs	Yield	Anthesis Date	Maturity Date	Nitrogen Leaching
	Unit	kg ha^{-1}	Days	Days	kg ha^{-1}
L1C2	Mean	3217.20	55.35	88.09	110.88
	ARE	0.01	0.09	0.11	-
	STDEV	582.94	3.26	4.39	42.07
L2C2	Mean	3724.53	57.94	93.52	73.32
	ARE	0.15	0.14	0.18	-
	STDEV	1473.95	1.33	0.83	56.09
L3C2	Mean	3148.53	60.92	98.59	138.14
	ARE	0.03	0.20	0.24	-
	STDEV	1162.27	5.28	6.98	63.32
L4C2	Mean	3080.4	61.05	98.4	137.67
	ARE	0.05	0.20	0.24	-
	STDEV	1386.31	5.18	6.93	73.14
Measured	Mean	3234.79	50.75	79.5	-
	STDEV	120.9	2.22	3.7	-

[a] ARE is the absolute relative error, which is defined as ARE=|Y-Y'|/Y, where Y is the measured value and Y' is the predicted value of model output.

[a] Signal '-' means no absolute relative error was available since there was no direct measurement of nitrogen leaching in this study.

Table 3-7. Fundamental statistical properties of prior, first posterior and second posterior distributions derived from L1C2

	Min	Max	Mean	Standard Deviation	CV
			Prior		
P1	110.000	450.000	225.096	67.826	30.1%
P5	580.000	1000.000	763.595	98.800	12.9%
PHINT	30.000	50.000	41.175	4.014	9.8%
SLDR	0.000	1.000	0.463	0.192	41.4%
SLRO	30.000	95.000	72.995	11.561	15.8%
SDUL	0.086	0.470	0.263	0.100	37.9%
SLLL	0.020	0.351	0.138	0.084	61.1%
SSAT	0.230	0.700	0.388	0.094	24.2%
SLPF	0.700	1.000	0.962	0.114	11.9%
			First Posterior		
	Min	Max	Mean	Standard Deviation	CV
P1	136.926	216.797	144.492	23.387	16.2%
P5	550.355	716.360	630.781	27.684	4.4%
PHINT	36.777	42.524	40.772	0.567	1.4%
SLDR	0.443	0.750	0.731	0.006	0.9%
SLRO	44.543	80.836	77.398	10.627	13.7%
SDUL	0.102	0.109	0.104	0.002	1.7%
SLLL	0.023	0.070	0.062	0.003	4.4%
SSAT	0.141	0.305	0.298	0.021	7.2%
SLPF	0.759	0.933	0.919	0.042	4.6%
			Second posterior		
	Min	Max	Mean	Standard Deviation	CV
P1	77.676	182.175	99.169	8.217	8.3%
P5	553.141	676.212	577.201	9.746	1.7%
PHINT	39.162	41.712	39.676	0.202	0.5%
SLDR	0.708	0.752	0.732	0.006	0.9%
SLRO	41.492	99.850	78.143	9.660	12.4%
SDUL	0.097	0.109	0.104	0.002	1.6%
SLLL	0.053	0.068	0.060	0.002	4.0%
SSAT	0.235	0.362	0.300	0.021	7.0%
SLPF	0.760	0.932	0.872	0.041	4.7%

Table 3-8. Measured and estimated mean values of soil properties of the field experiment site

	SLLL (cm^3/cm^3)		SDUL (cm^3/cm^3)		SSAT (cm^3/cm^3)	
	Measured	Estimated	Measured	Estimated	Measured	Estimated
Mean	0.051	0.060	0.110	0.104	0.314	0.300
STDEV	0.031	0.002	0.044	0.002	0.070	0.021
CV	60.8%	3.3%	40.0%	1.9%	22.3%	7.0%

Table 3-9. Selected parameter set for GLUE verification[a]

Parameter	P1	P5	PHINT	SLDR	SLRO	SDUL	SLLL	SSAT	SLPF
	℃d	℃d	℃d	-	-	cm^3/cm^3	cm^3/cm^3	cm^3/cm^3	-
Value	95.1191	572.0396	39.5679	0.7392	89.4470	0.1037	0.0604	0.3190	0.9312

[a] ℃d means degree day.

Table 3-10. Generated duplicates of observations for GLUE verification

2005	Measured		Generated Replication			
Observation	Mean	STDEV	1	2	3	4
Yield	3451	59	3046	3100	3385	3686
ADAT	55	3	60	50	56	50
MDAT	85	4	87	82	84	84
2006	Measured		Generated Replication			
Observation	Mean	STDEV	1	2	3	4
Yield	3206	121	3170	3052	3236	3360
ADAT	50	2	49	51	50	51
MDAT	85	4	87	80	88	82

Table 3-11. Means and standard deviations of the selected parameters in GLUE verification[a]

	Prior Distribution			First-round GLUE			Second-round GLUE			Selected	ARE
	Mean	STDEV	CV	Mean	STDEV	CV	Mean	STDEV	CV		
P1	225.096	67.826	0.301	140.43	10.689	0.076	97.334	1.929	0.02	95.119	2.3%
P5	763.595	98.8	0.129	617.347	24.137	0.039	566.077	2.279	0.004	572.04	1.0%
PHINT	41.175	4.014	0.097	40.375	1.416	0.035	38.723	0.498	0.013	39.568	2.1%
SLDR	0.463	0.192	0.414	0.707	0.082	0.116	0.799	0.033	0.041	0.739	8.1%
SLRO	72.995	11.561	0.158	78.879	5.905	0.075	85.258	1.061	0.012	89.447	4.7%
SDUL	0.263	0.1	0.379	0.103	0.001	0.006	0.104	0.001	0.005	0.104	0.0%
SLLL	0.138	0.084	0.611	0.057	0.011	0.188	0.057	0.002	0.03	0.06	5.0%
SSAT	0.388	0.094	0.242	0.292	0.047	0.16	0.322	0.014	0.042	0.319	0.9%
SLPF	0.962	0.114	0.119	0.915	0.052	0.057	0.91	0.004	0.004	0.931	2.3%

[a] ARE was the absolute relative error between the selected values and the estimated values of the parameters after two rounds of GLUE process; "Selected" means the parameter set was selected from the behavioral parameter sets in the second round of GLUE process; the selected parameter set was used as the "true" value in GLUE verification.

Table 3-12. Means and standard deviations of model outputs in GLUE verification

		Prior	First Posterior	Second Posterior	Measured in 2006
Yield	MEAN	6867	3442	3471	3206
	STDEV	2173	1396	268	121
	CV	0.316	0.406	0.077	0.038
	RAE	114.2%	7.4%	8.3%	-
ADAT	MEAN	76	58	50	50
	STDEV	9	3	0	2
	CV	0.118	0.059	0.009	0.044
	RAE	52.0%	16.0%	0.0%	-
MDAT	MEAN	117	94	85	85
	STDEV	10	4	0	4
	CV	0.084	0.048	0.005	0.044
	RAE	37.6%	10.6%	0.0%	-

Table 3-13. Expectation values of second posterior distribution of selected parameters[a]

Parameter	P1	P5	PHINT	SLDR	SLRO	SDUL	SLLL	SSAT	SLPF
	℃d	℃d	℃d	-	-	cm^3/cm^3	cm^3/cm^3	cm^3/cm^3	-
Expectation	99.17	577.20	39.68	0.73	78.14	0.10	0.06	0.30	0.87

[a] ℃d means degree day.

CHAPTER 4
FIELD PLOT EXPERIMENT OF SWEET CORN AND SIMULATION WITH CALIBRATED CERES-MAIZE MODEL

4.1 Introduction

Leaching of nitrate nitrogen is economically and environmentally undesirable (Asadi, et al., 2002). Due to the large acreage of sweet corn planted and the relative large amount of N fertilizer application to this crop, something must be done to control this situation. A proactive, incentive-based program of developing crop specific Best management practices (BMPs) in Florida began in 1994 as a result of an amendment to the Florida Fertilizer Law approved by the state legislature (Alva et al., 2005). This amendment authorized the Florida Department of Agriculture and Consumer Services (DACS) to develop research based crop specific N-BMPs.

The U.S. Environmental Protection Agency (EPA) defines a BMP as "methods, measures or practices selected by an agency to meet its non-point source control needs" (Code of Federal Regulations, 1994). BMPs generally refer to practices determined to be the most effective practical means for preventing or reducing the amount of pollution generated by non-point sources to a level compatible with quality goals (Center et al., 1996).

Bottcher et al. (1995) defined the specific BMP for Florida, where the environmental impact and economics of the farming operations were maintained as fairly important. In their definition, the BMPs were those on-farm activities designed to reduce nutrient losses in drainage waters to an environmentally acceptable level, while simultaneously maintaining an economically viable farming operation for the grower. Practices that have a high potential for negatively impacting the financial profitability of a farm should not, therefore, be considered BMPs. In the case where the economic cost of implementing certain BMPs puts an excessive financial burden on the farmer, such practices should be considered as BMPs only if external funds are available to return an acceptable level of profitability to the farm (Bottcher et al., 1995).

Research, concentrating on finding the optimum N rate and N placement method for sweet corn production, has been conducted in several experiments in Florida, some of those were in Gainesville by Rudert and Locascio in 1976 and 1977 (Rudert and Locascio, 1979), in Quincy, North Florida Research and Education Center, in 1990 (Rhoads, 1990), and at the Suwannee Valley Agricultural Research and Education Center near Live Oak (Hochmuth and Donley, 1992; Kidder et al., 1989). All of the experiments provided information about how much N fertilizer should be used to optimize sweet corn yield. But there were some limitations to these experiments. First, some of the experiments only concentrated on N fertilizer itself and excluded irrigation, which can simultaneously influence nitrogen leaching and corn yield. Second, most of the experiments failed to explain the effects of N fertilizer and irrigation on ear quality characteristics, such as ear grade according to their lengths and diameters.

The fate and budget of nitrogen in the agricultural systems of sweet corn in Florida is also an important issue and should receive much attention for both the agricultural and the environmental aspect if research based BMPs are to be developed. The N budget or balance is often evaluated by comparing various N inputs and outputs in soil-crop systems by considering changes of soil mineral N (Sogbedji et al., 2000). Research on the N balance that takes into account mineralization and inorganic N in soils can provide more detailed information on the N cycles and losses by integrating soil N process into the total N budgets (Liu et al., 2003). There are limitations to the calculation of the N balance, however, because it is difficult to measure each component of the N budget accurately in relation to soil processes (Jarvis, 1996; Sogbedji et al., 2000).

With the development of computer technology, crop models have become a strong tool for exploration of possible management strategies in crop production. A crop model has been

described as a "quantitative scheme for predicting the growth, development and yield of a crop, given a set of genetic coefficients and relevant environmental variables" (Monteith, 1996). Models are not perfect, and can at best only represent a current understanding of biological systems; yet they do highlight the areas where information and understanding are lacking (Boote et al., 1996). With these caveats, crop models can be used to predict crop growth, development and yield as a function of soil, climate, weather, and crop management conditions (Ghaffari et al., 2001). The CERES-Maize corn growth and yield model (Jones and Kiniry, 1986; Tsuji et al., 1994) in the Decision Support System for Agrotechnology Transfer (DSSAT) model, V4.0, is a popular crop model. This crop model can be used to simulate field experiments. Then the reliability of the model can be evaluated according to the results of comparison between the simulated results and observed results.

The objectives of this research were the following: (1) explore the response of yield quantity and quality of sweet corn to different irrigation and fertilization levels; (2) study the fate of nitrogen fertilizer in sweet corn production; and (3) simulate the field plot treatments with CERES-Maize mode of DSSAT model and compare the outputs with observations so as to evaluate the model.

4.2 Material and Methods

4.2.1 Experiment Site and Design

A field plot experiment was conducted in the spring of 2006 at the Plant Science Research and Education Unit, the University of Florida. The unit is located in Pine Acres (29.4094^{o}N, 82.1777^{o}W, 20.746 meters above sea level), Marion County, Florida, U.S. (Judge et al., 2005).

The soil of the experiment field is very sandy. It consists of Lake Sand, Candler Variant, Tavares Variant, and Millhopper Variant 1 etc, which mainly belong to Quartzipsamments (Entisol). Soil samples were collected at 24 sites at 3 depths of 0-15 cm, 15-30 cm, and 30-60 cm.

The samples were sent to the lab of the Soil and Water Science Department of the University of Florida and analyzed for physical properties. The permanent wilting point (PWP) was measured as the soil moisture at a soil pressure of 15.3 bar, field capacity (FC) as the soil moisture at 0.1 bar, and soil saturation as the soil moisture at 0 bar. The main measured properties of the soil at the experiment site are summarized in Table 4-1.

The plot experiment was designed as a two-factor split-plot experiment, since fertilizer and irrigation rates, which simultaneously affect nitrogen leaching and corn yield, were tested. This experiment consisted of two irrigation levels and three rates of N fertilizer application. The two irrigation levels were I_0 and $1.5 \times I_0$, where I_0 is the irrigation schedule based on daily water balance in soil profile. They were identified as I1 and I2 respectively. Three fertilizer application levels were 185, 247 and 309 kg N ha^{-1}, which were identified as F1, F2 and F3. Subsequently, there were six combination treatments as F1I1, F2I1, F3I1, F1I2, F2I2, and F3I2 (Figure 4-1).

As shown in Figure 4-1, there were 4 blocks. In each block, a single replicate of a complete factorial experiment by irrigation and nitrogen levels was included. However, the treatment combinations within a block were not completely randomized. Each block in the design was divided into two whole plots (I1 and I2). Then each whole plot was divided into three subplots or split-plots (F1, F2 and F3). So irrigation levels were considered as main treatments, with fertilizer levels as subplot treatment. Four blocks resulted in four replications for each of the six treatment combinations.

To estimate the growth and yield of sweet corn under extreme conditions, some extra treatments were also arranged as controls in this study. A non-irrigated, I0, and zero nitrogen fertilizer level, F0, were added to the experimental design. The additional treatments were derived using F0 and I0 along with other nitrogen and irrigation levels. These treatments were

F1I0, F2I0, F3I0, and F0I1. Treatment F0I1 had 3 replicates, which were arranged in a single column. However the combinations, F1I0, F2I0, and F3I0, were not replicated (Figure 4-1). Since these treatments were not randomly arranged in the field or did not have enough replicates to meet the statistical requirement of a successful field experiment, only the results from the first eight columns (Figure 4-1, from left to right) of field were used for statistical analysis, while the results from the rest two columns were only treated as a reference. Other aspects of fertility (such as the application of phosphorus (P), potassium (K), and micronutrient) and management (such as planting, harvesting, and pest control) were the same across all the treatments.

Each plot consisted of eight rows of sweet corn (*Zea mays L.,* Saturn SH2) corn with a row spacing of 76 cm. The plot length was 15.2 m. The planting date was March 14, 2006, or Julian day 73. The corn was planted at a depth of 3.8 cm with a planting population density of 59,000 plants ha^{-1} (24,000 plan ac^{-1}).

Weather data was extremely important for production management, especially for irrigation scheduling. The values of daily reference evapotranspiration (ET_0) and precipitation were used to schedule the timing and depth of irrigation events. Daily weather data, including daily ET_0, rainfall, minimum temperature, and maximum temperature for Pine Acres was directly obtained from the weather database of the Florida Automated Weather Network (FAWN) at the Citra site where Pine Acres is located. The methodology of reference evapotranspiration adopted by FAWN was described in Section 4.2.3.

4.2.2 Nitrogen Fertilizer Application

Growers typically apply fertilizer through the sprinkler irrigation system, such as the center pivot system or linear move irrigation system. However, in this experiment the experiment design made it difficult to apply fertilizer via the linear move irrigation system. First, the length of a span of the system was more than 40 m, while the width of each experiment plot was only

15.2 m. One span could almost cover the three plots in each column (Figure 4-1). However, different rates of nitrogen fertilizer were required for the three plots as the experiment design, while one span could only apply one rate. Second, the linear system was cumbersome to control, making accurate application of fertilizer difficult on small plots. Thus, the nitrogen fertilizer was applied into the field through a drip tape system instead in this research to simulate the sprinkler. Nitrogen fertilizer was also applied as solution with high application uniformity, which could guarantee the experiment results would not be impacted.

As shown in Figure 4-1, there were twenty seven sub-main lines conveying fertilizer solution and water to each fertigated plot. These twenty seven sub-main lines were connected to three main lines. When applying fertigation, nitrogen fertilizer solution was injected with an injection pump into the drip tape system through the injection hole. The injection pump used in this experiment was an Easy-Load II MASTERFLEX peristaltic pump (Cole-Parmer Instrument Company, Vernon Hills, Illinois).

The nitrogen fertilizer used in the experiment was a composite of several nitrogen compounds. The total nitrogen mass was about 32% of the solution, including 7.9% nitrate nitrogen, 7.9% ammoniacal nitrogen, and 16.2% urea nitrogen. The concentration of total fertilizer solution was 1.29 kg L^{-1}, while the concentration of nitrogen in this solution was 0.41 kg N L^{-1}.

When arranging the drip tapes between each row, fertigation uniformity was considered. The uniformity mainly depends on the number of drip tapes between rows. A model simulation was conducted with the HYDRUS-2D computer program to decide how many drip tapes were needed to obtain adequate uniformity. The dimension of simulation profile was 76×50 cm, where 76 cm is the row width and 50 cm is the soil profile depth. Each emitter of a drip tape was

represented as a point with a constant pressure of 0 bar and placed at the top of the profile. Initial soil pressure was set as 0.2 bar. The bottom of the profile was set as free drainage. Figure 4-2 shows the simulated soil moisture in the soil profile after 30 minutes with one, two, three, and four drip tapes, respectively between rows. The different blue colors from light to dark represent different soil moisture from higher to lower.

In this research, the low quarter distribution uniformity (DU_{lq}) value as defined in Equation (4-1), were used to quantify the uniformity between the various numbers of drip tapes. The calculated DU_{lq} values for four different numbers of drip tapes at three depths of D1 (10cm), D2 (20cm), and D3 (30cm) at a time of 30 minutes are listed in Table 4-2.

$$DU_{lq} = \frac{Average\_Minimum\_25\%}{Average\_Total} \times 100\% \tag{4-1}$$

where $Average\_Minimum\_25\%$ is the average of lower 25% of soil water contents, and $Average\_Total$ is the average of total soil water contents. The values of soil water contents at different locations were provided as outputs of HYDRUS-2D.

The uniformities at the depth of D3 were all 1.00, which means the water applied did not reach this layer, yet. The water moisture at deep layers was assumed homogeneous. For layer D1 and D2, it can be found that with four drip tapes, highest fertigation uniformity could be obtain ed. These four drip tapes were evenly fixed in each of the row interval.

The final arrangement of drip tapes in each row interval was shown as Figure 4-3. Four drip tapes were evenly fixed in the interval to guarantee the uniformity of fertigation. For example, as shown in Table 4-1, the DU_{lq} at D1 (10cm) at 30 minutes was only 0.42 with only two drip tapes, while it increased to 0.97 with four drip tapes. There were seven inter-row areas in each plot. However, only the central five row intervals were arranged with drip tapes since the

outer two rows were border rows. See Appendix D for the photos of fertigation system, corn growth, and sampling in field experiment.

The final N fertilizer application schedules in 2006 are given in Table 4-3. The middle fertilizer level (F2) was about 10% higher than the nitrogen fertilizer level recommended by Institute of Food and Agricultural Sciences (IFAS), which is about 224 kg N ha^{-1} (Hochmuth, 2000). F1 was 75% of F2, while F3 was 125% of F2. The first N application was carried out during planting, while all other applications were applied in weekly applications beginning three weeks after planting with an injection pump.

4.2.3 Irrigation Scheduling

In this experiment, the irrigation schedule was prepared with the water balance for the soil profile. This schedule was defined as the standard irrigation for this study. The water content in the effective root zone was estimated by using following dynamic water balance equation:

$$\mathrm{WC_t} = \mathrm{WC_{t\text{-}1}} + IRR + RAIN - ET_C - (DP + RO) \tag{4-2}$$

where
$\mathrm{WC_t}$= Soil water content today, mm
$\mathrm{WC_{t\text{-}1}}$= Soil water content yesterday, mm
IRR= Irrigation depth since yesterday, mm
RAIN= Rain since yesterday, mm
$\mathrm{ET_C}$ = Crop ET, mm
DP= Deep percolation, mm
RO=Runoff, mm

Supposing there is no water wasted in each irrigation event, i.e. there is no DP or RO, and IRR and RAIN are all known. Hence, the irrigation level, $\mathrm{WC_t}$ - $\mathrm{WC_{t\text{-}1}}$, is a function of $\mathrm{ET_C}$:

$$\mathrm{ET_C} = \mathrm{ET_0} \times K_C \times K_S \tag{4-3}$$

The reference crop ET or reference ET, denoted as $\mathrm{ET_0}$, is the evapotranspiration from the reference surface. The reference surface is a hypothetical grass reference crop with an assumed

crop height of 0.12 m, a fixed surface resistance of 70 s m-1 and an albedo of 0.23 (Allen et al., 1998).

Equation 4-3 adjusts ET_0 by the crop coefficient (K_C) and the stress coefficient (K_S). In practice, the K_S was set as 1 for this project due to the well-watered nature of the crop. The daily ET_0 and rainfall values were obtained from Florida Automated Weather Network (FAWN).

In the FAWN system, the daily ET_0 values were calculate using the IFAS Penman method (Jones et al., 1984). The working Penman equation is give by following equation:

$$ET_p = \frac{\frac{\Delta}{\Delta+\gamma}\left[(1-\alpha)R_s - \sigma T^4\left(0.56-0.08\sqrt{e_d}\right)\left(1.42\frac{R_s}{R_{so}}-0.42\right)\right]}{\lambda} + \frac{\gamma}{\Delta+\gamma}\left[0.263\times(0.5+0.0062u_2)\times(e_a-e_d)\right] \quad (4\text{-}4)$$

where

ET_p =daily potential evapotranspiration, mm day^{-1}

R_s =total incoming solar radiation, cal cm^{-2} day^{-1}

R_{so} =total daily cloudless sky radiation, cal cm^{-2} day^{-1}

T =average air temperature in K

e_a =vapor pressure of air=$(e_{\max}+e_{\min})/2$, mb

$e_{\max}$ =maximum vapor pressure of air during a day, mb

$e_{\min}$ = minimum vapor pressure of air during a day, mb

e_d =vapor pressure at dew point temperature (T_d), mb

u_2 =wind speed at a height of 2m, km day^{-1}

Δ =slope of saturated vapor pressure curve of air, mb ^{o}C^{-1}

γ =psychrometric constant, 0.66 mb ^{o}C^{-1}

λ =latent heat of vaporization of water=(59.59-0.055T_{avg}), cal cm^{-2} mm^{-1}

$T_{avg}=(T_{\max}+T_{\min})/2$, ^{o}C

$T_{\max}$ =maximum daily temperature, ^{o}C

$T_{\min}$ =minimum daily temperature, ^{o}C

The crop coefficient of sweet corn depends on the growth stages. The following crop coefficients (Table 4-4) recommended by Bauder and Waskom (2003), were used to determined

ET_C used by sweet corn for various stages of development. Similar information can also be found in the "Vegetable Production Guide for Florida" (Olson and Simonne, 2005).

4.2.4 Soil, Biomass, and Yield Sampling

In the field experiments soil and biomass samplings were done to evaluate the nitrogen status in soil profile and corn tissue. Finally yield sampling was conducted to evaluate the yield. The sampling position in each plot was shown in Figure 4-4.

Soil Sampling was conducted approximately biweekly during the growth season. Soil samples were collected in each of the plots at 4 depths of 0-15 cm, 15-30 cm, 30-60 cm, and 60-90 cm. The samples were analyzed at the Department of Soil and Water Science University of Florida for KCL extractable nitrate, ammonium concentrations, and moisture content.

Gravimetric soil moisture content is determined by calculating the ratio of mass of water to that of the wet soil. The mass of water is calculated by subtracting the mass of dry soil sample from the mass of the wet one. Traditionally, the most frequently used definition for a dry soil is the mass of a soil sample after it has come to constant weight in an oven at a temperature between 100 and 110 ^{o}C. Then the gravimetric soil moisture content (θ_{dw}) can be converted to the volumetric soil moisture content (θ_{vb}) by use of the formula of $\theta_{vb} = (\rho_b / \rho_w)\theta_{dw}$, where ρ_b is the bulk density of the soil, and ρ_w is the density of water (Klute, 1986).

The analysis of extractable nitrate and ammonium included two main procedures: (1) extraction of exchangeable ammonium, nitrate; and (2) determination of nitrate and ammonium concentration with colorimetric method (Page et al, 1982).

The procedure of extraction is described as follows. Place 3 g of soil in a wide-mouth bottle, and add 30 ml of 1M KCl. Stopper the bottle, and shake it on a mechanical shaker for 1

hour. Allow the soil-KCl suspension to settle until the supernatant liquid is clear (usually about 30 min). Then use a vacuum filter with a pore size of 0.45 μm to filter the solution.

Nitrate and ammonium concentrations were measured by colorimetric methods. The special apparatus required for nitrate concentration determination was Rapid Flow Analyzer (RFA), ALPKEM 300 Series (OI Corporation, College Station, TX). The apparatus for ammonium concentration determination was Technicon Industrial Method AA II (Technicon Instrument Corporation, Tarrytown, NY).

Biomass sampling was performed near the soil sampling locations. The sampling frequency was once every two weeks. When sampling, the collected crop plants were stored in a cooler on ice for transport. Then the samples were stored in the freezer with a temperature around 0 ℃ before processing.

A whole plant that had an average height in the plot was collected and divided into leaves, stems, husks, cobs, and kernels for fresh weight and dry weight determination. The analysis of the plant samples included measurement of the moisture and total Kjeldahl nitrogen (TKN) of different plant parts. Plant roots were not considered in this project, because of the negligible amount of nitrogen in the roots (Albert, 2002).

Fresh mass of each biomass sample was measured first. Then the samples were dried in the oven for 48 years at a constant temperature of 60 ^{o}C for 48 hours. The dry mass of each sample was measure. Then the biomass moisture was calculated.

The Kjeldahl procedures generally employed for determination of total N involve two steps: (1) digestion of the sample to convert organic N to NH_4^+-N, and (2) determination of NH_4^+-N in the digest. The digestion is usually performed by heating the sample with H_2SO_4 containing substances that promote oxidation of organic matter and conversion of organic N to

NH_4^+-N. The substances generally favored are salts such as K_2SO_4 or Na_2SO_4, which increase the temperature of digestion, and catalysts such as Hg, Cu, or Se, which increase the rate of oxidation of organic matter by H_2SO_4 (Page et al, 1982). In this study, the substances were K_2SO_4 and $CuSO_4$. The determination of NH_4^+-N in the digest was conducted with colorimetric method in the Analytical Research Laboratory (ARL), Institute of Food and Agricultural Sciences, the University of Florida.

Yield sampling was conducted at the end of the experiment season, at the time of physiological maturation of sweet corn, 70 to 80 days after planting. Ears in a sampling zone, which consisted of a 6.1-meter (20 feet) section of the 2 center rows of each sampling site, were completely collected whether the kernels were fully filled or not. The total plant numbers in this zone were also counted. Then the collected ears were weighed and classified into three classes, US #1, US #2, and Cull according to the classification standard of USDA on the quality of sweet corn (USDA, 1962).

4.2.5 CERES-Maize Model Simulation

The CERES-Maize model of DSSAT (Jones et al., 2003) was calibrated with the generalized likelihood uncertainty estimation (GLUE) method (see Chapter 3 for details). In this method, the second posterior distributions of the selected sensitive input parameters were used (Table 4-5). See Appendix A for the definition and units of the parameters in the table.

Genotype parameters P1, P5, and PHINT described the genetic properties of the sweet corn planted. Their values could be obtained through controlled experiment. However, there was no experiment designed in this study to directly measure those genotype parameters. So a GLUE verification procedure was conducted in Chapter 3 to guarantee the accuracy of these genotype parameters (See Section 3.3.8 Chapter 3 for details).

The values of some soil parameters were measured in the experiment site (Table 4-1). If compared the measured and estimated mean values of soil parameter SLLL, SDUL, and SSAT (Table 4-6), it can be found that the mean values of estimated and measured soil parameters were pretty close to each other. For example, the mean value of calibrated SDUL in the second posterior distribution was 0.104 cm^3/ cm^3, while the mean value of measure SDUL was 0.110 cm^3/ cm^3. The error was only about 0.006 cm^3/ cm^3. Similar results were observed in SLLL and SSAT.

In general, the uncertainties of the selected 9 input parameters were dramatically decreased after two rounds of GLUE estimations. The second posterior distributions (Table 4-5) can be used to simulate the real field experiment of sweet corn, since the output uncertainties were reduced after GLUE simulations (see Chapter 3 for details). In this research, the new mean value vector and covariance matrix derived from the second round of GLUE process were used to generate random parameters.

In this study, the seven treatments (F0I1, F1I1, F2I1, F3I1, F1I2, F2I2, and F3I2) mentioned in Section 4.2.1 were run with the CERES-Maize model under the weather and management conditions of field plot experiment in 2006. For each treatment, 3,000 simulations were conducted with 3,000 different parameter sets that were randomly generated by the posterior distributions. Then the results were recorded and the mean and variance of yield, anthesis date, maturity date, and accumulative nitrogen leaching of each treatment were calculated.

4.3 Results and Discussion

4.3.1 Quantity of Sweet Corn Yield

Quantity of sweet corn yield was defined as the fresh mass of the ears collected in a unit area in this study. A complete ear included husks, kernels, and cob. The total weight of US #1 and US #2 yield was defined as marketable yield.

As described in Section 4.2.1, the field experiment was designed as a split-plot experiment. An ANOVA analysis was performed to determine treatment effects on yield quantity with SAS program (SAS Inst. Inc., 1996). The results of ANOVA were specified in Table 4-7. See Appendix E for detailed SAS program.

It can be found in Table 4-7 that irrigation levels (P=0.1068) and interactions between irrigation and nitrogen fertilizer (P=0.7434) were not significant. However nitrogen fertilizer levels showed significance influence on yield quantity of sweet corn. A similar ANOVA analysis was also performed for marketable yields, which showed the interaction was also not significant.

The irrigation and nitrogen treatment effects on total yield and marketable yield are shown in Table 4-8. It can be found that whether for total yield or marketable yield, irrigation level did not show significant influence, though the average total yield increased from 18,618 kg ha^{-1} to 20,091 kg ha^{-1}, and marketable yield increased from 16,681 kg ha^{-1} to 18,431 kg ha^{-1}.

However, nitrogen level showed significant influence on both total yield and marketable yield. There was a significant difference between the total or marketable yields under F1 and F2, which means when increasing the nitrogen application from 185 to 247 kg ha^{-1}, the yields were increased significantly. But, there was not a significant difference between F2 and F3, thus increasing nitrogen fertilizer beyond 247 kg N ha^{-1} did not significantly increase yield.

Figure 4-5 and 4-6 show the difference of total and market fresh yields between the different nitrogen fertilizer levels under individual irrigation level I1 and I2. The same trend as described above can be found from these figures.

For all of the histograms in this current publication, the upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

4.3.2 Quality of Sweet Corn Yield

According to the USDA (1962), "U.S. No.1" consists of ears of sweet corn of similar color characteristics that are fresh and free from damage by freezing, cross pollination, denting, worms, birds, fermentation, smut or other disease or other means. Each ear must have at least an average of 10.2 cm of the cob covered with undamaged kernels, in addition to any good kernels that would necessarily be lost in the usual method of trimming to remove damaged kernels. "U.S. No.2" shall also meet the same color characteristics as "U.S. No.1", but each ear must have at least an average of 7.6 cm of the cob covered with kernels. "Culls" consists of ears of sweet corn that fail to meet the requirement of "U.S. No.2" grade.

As for yield quantity, ANOVA analyses were also conducted for total corn ears, US #1 ears, US #2 ears and culls harvested per hectare. For convenience, only the ANOVA results of total ears per hectare were listed in Table 4-9.

It is easy to find that at a significance level of 0.05, no factor whether irrigation level, or nitrogen level, or interaction between irrigation and nitrogen treatments, had a significant influence on the total ears numbers of sweet corn harvest on a unit acreage of field. Actually, this is reasonable, because the number of ears that can show up in a field should be mainly controlled by the genetic properties of corn, rather than by field management.

In the results of ANOVA of US #1, US #2, and cull, interactions between irrigation and nitrogen treatment also did not show significant influence. Thus, the effects of irrigation and nitrogen levels on yield quality were listed in Table 4-10.

From Table 4-10, it can be seen that irrigation level did not significantly influence yield quality though the number of US #1 per unit acreage increased a bit from I1 to I2. Fertilizer level did not show significant influence on the number of US #2 and cull per unit acreage, either. However, as it was expected, nitrogen level showed significant influence on the number of US #1 per unit acreage. From F1 to F2, the total number of US #1 ears increased from 42,764 ears ha^{-1} to 52,612 ears ha^{-1}, which was an increment of almost 10,000 ears ha^{-1}, i.e. the nitrogen level improved the yield quality significantly. There was no significant difference between the US #1 ears under F2 and F3, which means the stimulus of nitrogen fertilizer on yield quality will be limited after a special point of nitrogen application.

Figures about the influence of irrigation levels and nitrogen fertilize levels on yield quality were drawn as well to visualize the trend of quality improvement. Figure 4-7 and 4-8 show the number of ears under different nitrogen fertilizer levels, respectively under I1 and I2. Figure 4-9, 4-10 and 4-11 show the number of ears under different irrigation levels, respectively under F1, F2 and F3. In these figures, the data of the control plots were also presented for reference, however they were not used in ANOVA or Duncan's multiple range test.

Interestingly, it can be found in Figure 4-7 that when there was no nitrogen applied, even though there was irrigation, the harvest ears were all "culls", which could not be sold in the market. In Figures 4-9 to 4-11, it can also be found that when no irrigation was applied, the yield quality was greatly deteriorated. Though there were ears available, most or all of them were

"Culls". Thus, it can be concluded that both adequate irrigation and nitrogen fertilizer are necessary to guarantee both yield quantity and quality.

These figures also show that the number limit of "total ears" of a unit area was about 110,000 ears ha^{-1}. The ear number limit of "U.S. No. 1" of a unit area was about 60,500 ears ha^{-1}. The ear number limit of "U.S. No. 2" of a unit area was about 28,000 ears ha^{-1}. There was no obvious ear number limit for "Culls".

4.3.3 Nitrogen Balance Estimation

In this current research, the equation used by Meisinger and Randall (1991) to calculate long-term potentially leachable total nitrogen, N_{pl} was used as the fundamental equation to estimate nitrogen leaching in the field experiment. The equation is:

$$N_{pl} = N_{input} - N_{output} - \Delta N_{st} \tag{4-5}$$

where N_{input} and N_{output} are N entering and leaving the field between the top of the crop canopy and the bottom of the soil sampling zone (90cm below the soil surface) respectively, and ΔN_{st} is the change in N storage. N_{pl} was used as the budget-derived estimation of nitrogen loading to groundwater during a crop growth season.

The components of the right side of Equation (4-5) were investigated before using the equation to estimate the potential nitrogen leaching in sweet corn production.

4.3.3.1 Nitrogen input

There were four possible nitrogen sources in the corn production system. The first was the N fertilizer applied (Table 4-3), which was the largest nitrogen source. The second source was the initial organic or inorganic nitrogen already present in the soil profile. This could be determined by the results of initial soil nitrogen sampling. The third source was the corn seeds, because there was organic N present in them as protein, amino acids, and nucleic acids.

According to the research of Meisinger and Randall (1991), the seed of sweet corn could supply an N input of 0.3 kg N ha^{-1}. The forth source was the N from atmospheric deposition. Small portions of atmospheric N_2 could return to the soil in rainfall or through the effects of lightning. An estimated 10^{13} g per year of N_2 could be fixed and transformed in ammonia by lighting in the world. According to the research of Li et al. (2002), the annual atmospheric N deposition rate in Florida was about 11 kg N ha^{-1} $year^{-1}$. Since the whole growth season of sweet corn in north Florida was only about 70 to 80 days, about one fifth of a year, the atmospheric N deposition in the experiments could be estimated as about one fifth of the annual deposition, which was about 2.4 kg N ha^{-1}.

The fifth source was the N dissolved in irrigation water. Near the plot experiment site, four wells were developed to monitor the nitrate and ammonium concentration in the groundwater. Thus the nitrogen concentration data collected from these wells during the experiment could be a good reference to estimate the nitrogen concentration for irrigation water. The average N-NO_3 concentration was about 3.65 mg L^{-1}, while the average N-NH_4 concentration was about 0.22 mg L^{-1}. The depth of irrigation level I1 was about 21.0 cm, while the depth of I2 was about 27.8 cm. Thus, the total nitrogen contained in irrigation water of I1 and I2 were about 8.1 and 10.8 kg N ha^{-1}, respectively. See Appendix F for the details about changes of nitrate and ammonium concentrations in these monitoring wells.

The last possible N source could be the N that was biochemically fixed in the soil by specialized micro-organisms including bacteria, actinomycetes, and cyanobacteria. This process is called nitrogen fixation. It occurs in plants that harbor nitrogen-fixing bacteria within their root nodules (Cockx and Simonne, 2003). The best-studied example of N fixation is the association between legumes and bacteria in the genus rhizobium. The main legume crops commercially

grown in Florida are peanuts, snap bean and pink-eyed and black-eyed pea (Cockx and Simonne, 2003). But in this current research, the field was kept fallow before experiment and no legume was planted during experiment. Thus this N source was considered negligible when establishing the N balance.

4.3.3.2 Nitrogen output

The nitrogen output of the corn production system includes several components. The most important N output was the N in corn tissues. This part of N could be estimated with the TKN concentration of corn tissues, the weight of corn biomass and plant density at harvest. See Appendix G for more information about the TKN concentration of leaves and stems of sweet corn during the growth season.

The second N output was the final inorganic nitrogen in the soil profile, or the final residual N, which was determined by analyzing the nitrate and ammonium concentrations in the initial and final soil samples. The N stored in the 90-cm top soil profile at the first soil sampling conducted at planting was defined as the initial N storage. The N stored in the 90-cm top soil profile at the last soil sampling conducted at harvest was defined as the final N storage. Then the net N residual in the 90-cm top soil profile was defined as the difference between the final N storage and initial N storage. See Appendix H for more information about the nitrate and ammonium nitrogen concentrations in soil profile during the growth season.

Another possible N output was the gaseous loss. It includes several physical and chemical processes, such as volatilization of ammonia and denitrification of nitrate from farmland. Since instruments were not installed during field experiments to measure the gaseous loss caused by volatilization and denitrification, an estimation based on literatures was performed. According to Liu et al. (2003), the miscellaneous gaseous N loss was about 4-7% of the total N fertilizer application as urea in maize production. In this research, the total nitrogen mass was about 32%

of the solution, including 7.9% nitrate nitrogen, 7.9% ammoniacal nitrogen, and 16.2% urea nitrogen. The urea nitrogen covers more than half of the total nitrogen. The nitrate nitrogen and ammoniacal nitrogen can also be lost through denitrification and NH_3 volatilization. Thus, the gaseous loss in this experiment was estimated as 6% of total N fertilizer applied.

4.3.3.3 Nitrogen balance

Based on the data and assumptions mentioned above, N balance was established with Equation (4-5) for the sweet corn experiments in 2006. Table 4-11 shows the N balance of a replicate in Block 1 of the treatment F1I1 in 2006. Similar procedures were also conducted for all of the replicates of other 5 treatments, F2I1, F3I, F1I2, F2I2 and F3I2. The final estimated amounts of potential N leaching of the seven treatments were summarized in Table 4-12.

Then an ANONA analysis was conducted to analyze the influence of irrigation level, fertilizer level, and their interaction on nitrogen leaching. The result is summarized in Table 4-13. From Table 4-13, it can be found that under the confidence level of 0.05, both irrigation and nitrogen fertilizer levels showed significant influence on nitrogen leaching, especially the nitrogen fertilizer levels. This confirmed that common assumption that more water applied, more nitrogen will be leached, and more nitrogen fertilizer applied, more nitrogen will be leached as well.

Since the interaction does not show significant influence on nitrogen leaching, the average nitrogen leaching amounts estimated from N balance under different irrigation and N fertilizer levels were summarized in Table 4-14. From the results in Table 4-14, the increase of nitrogen leaching caused by the increasing irrigation water and nitrogen fertilizer application was more obvious. Under I1, the average potential nitrogen leaching was 150.26 ka ha^{-1}, then it increased to 167.00 ka ha^{-1} when under I2. The average amount of potential nitrogen leaching was 124.17,

146.89, and 204.83 ka ha^{-1} respectively when under F1, F2, and F3. The increment was higher than under different irrigation levels.

4.3.4 Comparison between Model Simulations and Field Observations

4.3.4.1 Comparison between dry matter yields

The seven treatments (F0I1, F1I1, F2I1, F3I1, F1I2, F2I2, and F3I2) that were investigated in field plot experiment were also simulated with the CERES-Maize model under the weather and management conditions of the field plot experiment in 2006. The model simulation results were recorded and the mean and variance of yield, anthesis date, maturity date, and accumulative nitrogen leaching of each treatment were calculated.

Table 4-15 shows the simulations and measurements of dry yields of the seven treatments. The simulated results were relatively close to the measured results for all treatments except for F0I1 and F1I2. The absolute relative errors (ARE) between the measured and simulated yields were all near or less than 10% except for treatment F0I1 and F1I2. The simulated mean dry matter yield of treatment F2I1 was 3023 kg ha^{-1}., while the measured one was 2902 kg ha^{-1}. The difference was only about 100 kg ha^{-1}, or 4% of the measured yield.

However, for treatment F0I1 and F1I2, the simulated yields were higher than the measured results. For F0I1, there was some nitrogen contributed by senesced organic matter and soil nitrogen (nitrate and ammonium) in the soil profile in the initial conditions of the CERES-Maize model. For example, the model assumed the nitrogen from dead organic matter was 7 kg N ha^{-1}. The initial nitrate-N and ammonium-N concentration was 0.1 g N Mg^{-1} and 0.5 g N Mg^{-1}, which was equal to about 1.3 and 6.7 kg N ha^{-1}. And there was also a starter N application of 15 kg N ha^{-1} at planting. Thus, the available N for sweet corn growth was about 30 kg N ha^{-1} even when there was no additional nitrogen fertilizer application. The model probably underestimated the influence of N stress on corn yield and finally had a higher dry matter yield than the field

experiment. However, for F1I2, the source of difference is not clearly known. Probably it was due to the uncertainties in initial soil N and organic matter condition.

It can also be seen that the measured yields had relatively higher values of standard deviations compared to the simulated values. This is because the observed yields suffered many kinds of uncertainties and non-uniformity in weather and management, while the CERES-Maize model just assumed these factors were homogeneous throughout the area.

4.3.4.2 Comparison between phenology dates

The simulated and observed anthesis and maturity dates of sweet corn were summarized in Table 4-16. The observed the anthesis and maturity dates for different treatments were the same. So the standard deviations of them were just set as zero and not listed. It were found that the calibrated model performed very well in predicting these important phenology dates. This is true because the model was just calibrated with the data collected from a similar field experiment near the plots with the same corn genotype, nitrogen fertilizer, soil, etc.

4.3.4.3 Comparison between potential nitrogen leaching

Before comparing the simulated and estimated, it was necessary to check the N balance in the model simulation. The main N input of model simulation included: inorganic N applied (identified as NICM in DSSAT) or nitrogen fertilizer, initial nitrate-N in soil profile, initial ammonium-N in soil profile, and nitrogen from senesced plant matter. In this research, the nitrogen fertilizer application amounts (NICM) for each application were listed in Table 4-3. The initial nitrate-N and ammonium-N concentration was 0.1 g N Mg^{-1} and 0.5 g N Mg^{-1}, which equal to about 1.3 and 6.7 kg N ha^{-1}.The nitrogen obtained from dead organic matter was calculated as 7 kg N ha^{-1} by the model. The main N output of model simulation included three main components: nitrogen uptake during season (NUCM), nitrogen leached during the season (NLCM), and inorganic N at maturity in soil (NIAM).

In this research, treatment F1I1 was used as an example to show the nitrogen balance in the simulation of sweet corn growth with the CERES-Maize model. The result was shown in Table 4-17. It can be seen that when under F1I1, about 94 kg N ha^{-1} from the total application of 184 kg N ha^{-1} was utilized by sweet corn biomass. The N utilization efficiency was about 51%. The amount of nitrogen leaching during the season was about 32 kg N ha^{-1}, while the amount of inorganic nitrogen at maturity in soil was 73 kg N ha^{-1}.

Similar balance calculations were also conducted for other six treatments (F2I1, F3I1, F1I2, F2I2, F3I2, and F0I1). Since the amount of nitrogen leaching was concerned in this research, the amounts of NLCM and NIAM were summarized in Table 4-18. It can be seen that NLCM only covered a part of the N output except for NUCM. A significant part of N output was calculated as NIAM in soil profile. NLCM represented the nitrogen that had already been leached into groundwater, while NIAM represented the inorganic nitrogen (nitrate and ammonium) that was still in the soil profile at corn maturity. Thus if we only consider NCLM as the value of potential nitrogen leaching in this research, it might be unrepresentative and misleading. The NIAM also would be subject to leaching after harvest due to rainfall. From a long-term point of view, the total potential N leaching should be the sum of NLCM and NIAM.

A comparison was conducted between the simulated and estimated potential nitrogen leaching in Table 4-19. It can be seen that the for treatment F1I1, F2I2, and F3I2, the results were close since they all had a value of absolute relative error (ARE) less than 10%. However, for treatment F0I1, F2I1, F3I1, and I1I2, the difference was greater, since all values of ARE were all greater than 20%. This difference was probably caused by the uncertainties in the process of estimation of nitrogen leaching in field experiment since many components in the nitrogen balance were not directly measured and just obtained from literature or other source. For

example, in the estimation of nitrogen leaching for treatment F1I1, the sum of nitrogen input by corn seed, atmospheric deposition, and irrigation water was about 10.8 kg N ha^{-1}, which was only about 5.8% of the input as nitrogen fertilizer (185 kg N ha^{-1}). It is obvious that nitrogen fertilizer contributed the main nitrogen input. The amount of nitrogen fertilizer applied was measured and reliable. The uncertainty contribution by corn seed, atmospheric deposition, and irrigation water should be insignificant. However, for nitrogen output, the amount of plant utilization, net soil nitrogen residue, and gaseous loss, was 51.4, -15.9, and 11.1 kg N ha^{-1}, respectively. The estimation of gaseous loss might contribute some uncertainty when determining nitrogen output. The value of net soil nitrogen residual was negative, which means some of the initial soil N residue was used by the plant. The inaccuracy in soil nitrogen concentration measurement could also contribute some uncertainty. The biomass TKN of each plot was estimated with only one average plant, so uncertainty was inevitable. In general, the uncertainties in nitrogen output could weaken the reliability of the estimation of nitrogen leaching in this study. If all of the uncertainties in the process of estimation were considered, the difference between the simulated and estimated potential nitrogen leaching would not be surprising and unacceptable. Thus to obtain more confidence on the value of nitrogen leaching, a direct measurement should be conducted, for example, with lysimeter.

It should also be noticed that if comparing the NLCM in model simulation (Table 4-18) with the estimated potential nitrogen leaching (Table 4-12), the difference would be large and hard to interpret. And under F0I1 when there was no nitrogen applied, there was still some nitrogen leaching, which was due to the initial inorganic N in soil profile and N from dead plant matter.

In general, there was a little higher difference between the simulated and estimated potential nitrogen leaching for some treatments. The calibrated CERES-Maize model did a pretty good job at predicting the growth and influence of management on yields of sweet corn. It could be a good tool to help explore some potential optimal management practices for sweet corn production in North Florida.

4.4 Conclusions

Sweet corn is a very important economic crop in Florida. Nitrogen fertilizer applications and irrigation levels had dramatic effects on sweet corn quantity and quality. Field plot experiment and model simulation with the CERES-Maize model were conducted in North Florida in 2006 to explore the relationships among them. Several conclusions could be drawn as follows.

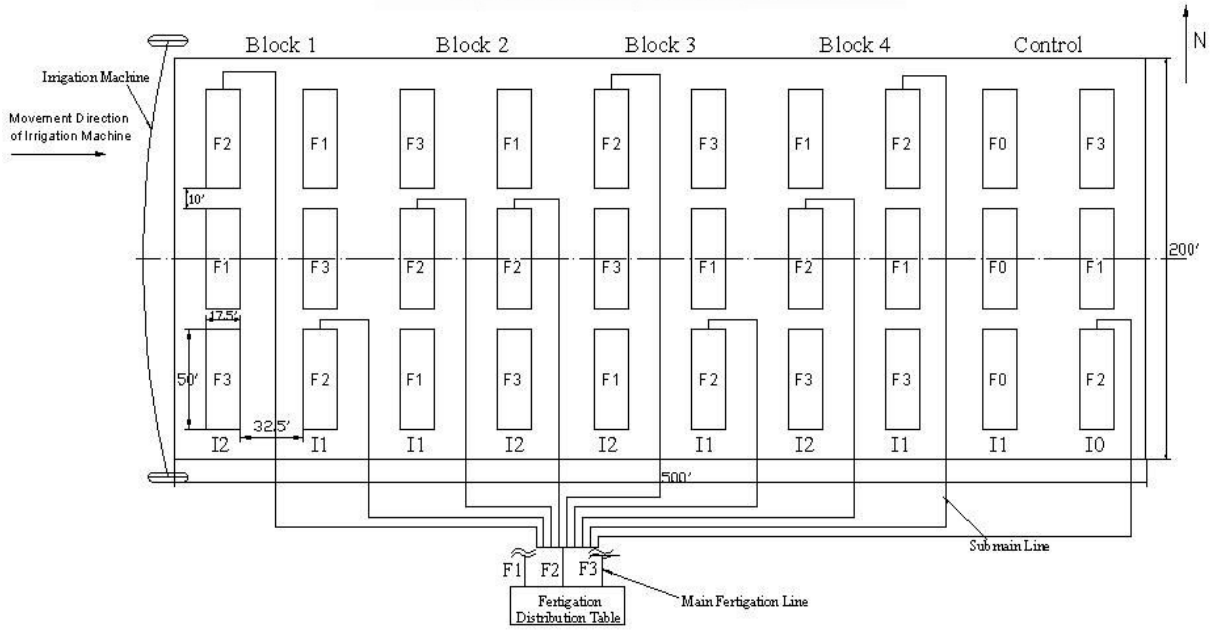
N fertilizer level was significant in improving both fresh total yield and fresh marketable yield, while irrigation level and interaction between N fertilizer level and irrigation level was not significant. N fertilizer level was not significant in increasing total ears, or US #2, or cull ears per unit area, but significant in improving the number of US #1 ears. Irrigation level and the interaction between irrigation and N fertilizer did not show any significance for yield quality.

The results show that 247 kg N ha^{-1} was adequate to guarantee the yield quantity and quality in sweet corn production. More nitrogen application, e.g. 309 kg N ha^{-1}, did not significantly improve yield quantity and quality. Irrigation level I1, which was based on daily ET_0, could guarantee the yield quantity and quality, since irrigation level I2 (1.5×I1) did not significantly improve yield quantity and quality.

According to the results of ANOVA of nitrogen leaching estimated from nitrogen balance, both irrigation and nitrogen fertilizer levels showed significant influence on nitrogen leaching. This confirmed that common assumption that more water applied, more nitrogen will be leached, and more nitrogen fertilizer applied, more nitrogen will be leached as well. However, the interaction does not show significant influence on nitrogen leaching.

After comparing the simulated and observed dry matter yields, anthesis dates and maturity dates, and estimated nitrogen leaching of the seven treatments in field plot experiment of sweet corn in 2006, it shows that the model did a good job in predicting dry yield and phenology dates. There was a little larger difference between the simulated and estimated amount of potential nitrogen leaching for some treatments. This is probably mainly because of the uncertainties in the process of estimation of potential N leaching in field plot experiment. Thus the results were not surprising or unacceptable.

In general, the calibrated CERES-Maize model did a very good job at predicting the growth and influence of management on yields of sweet corn. It can be a good tool to help explore some potential optimal management practices for sweet corn production in North Florida.



Notes:
1. Totally 30 plots, including factorial experiment 2I x 3F x 4Block=24 plots, and 6 control plots.
2. I1=irrigation based on daily ET value, I2=1.5*I1, and I0=no irrigation.
3. F1=fertilizer level 1, F2=fertilizer level 2, F3=fertilizer level 3, while fertilizer levels randomized in each irrigation plots.
4. F0=no fertilizer application.
5. The layout pattern of submain lines of F1 and F3 is as sams as F2.

Figure 4-1. Experiment plot arrangement layout

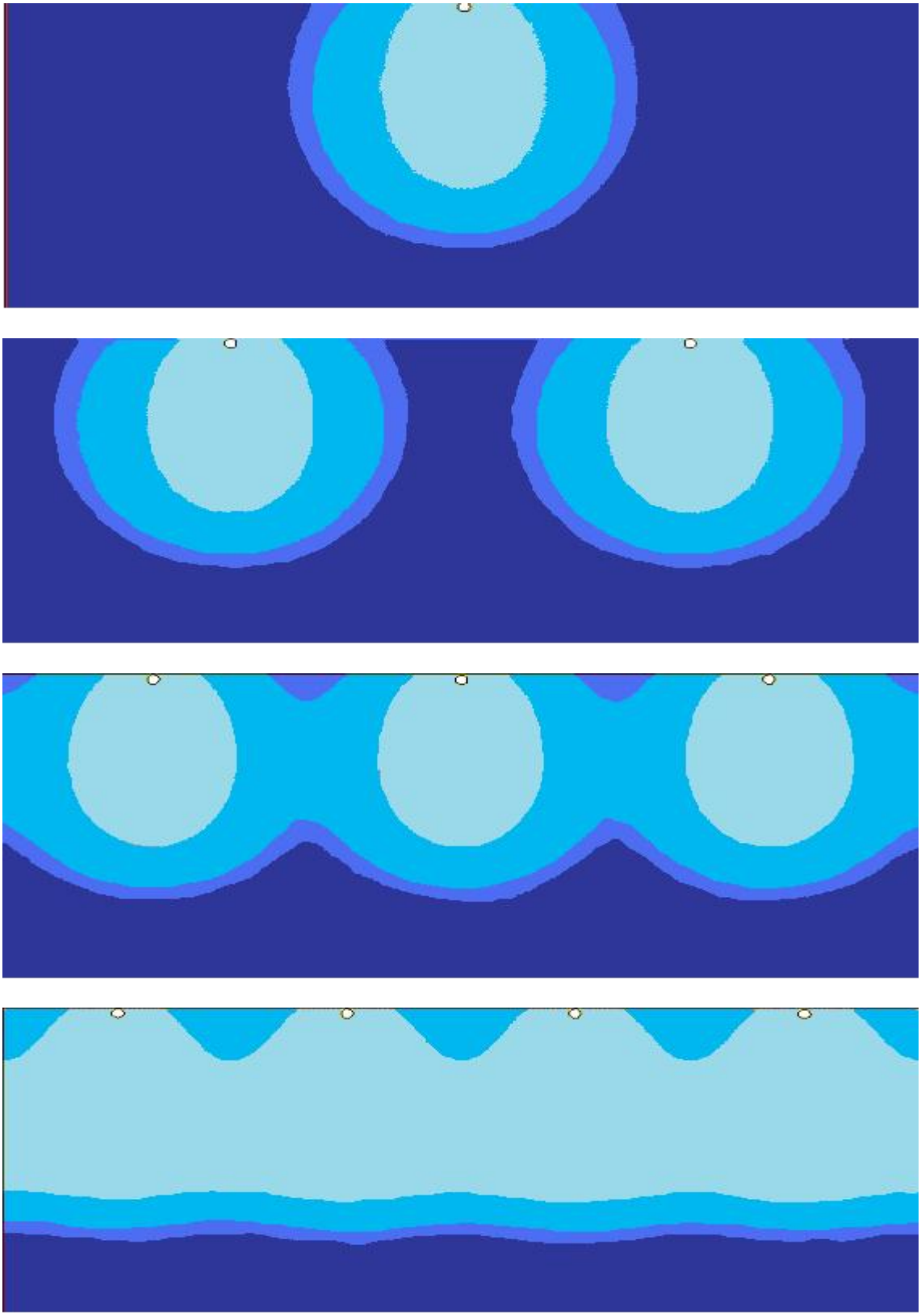


Figure 4-2. Soil moisture at t=30 minutes with 1, 2, 3 and 4 drip tapes. The different blue colors from light to dark represent different soil moistures from higher to lower.

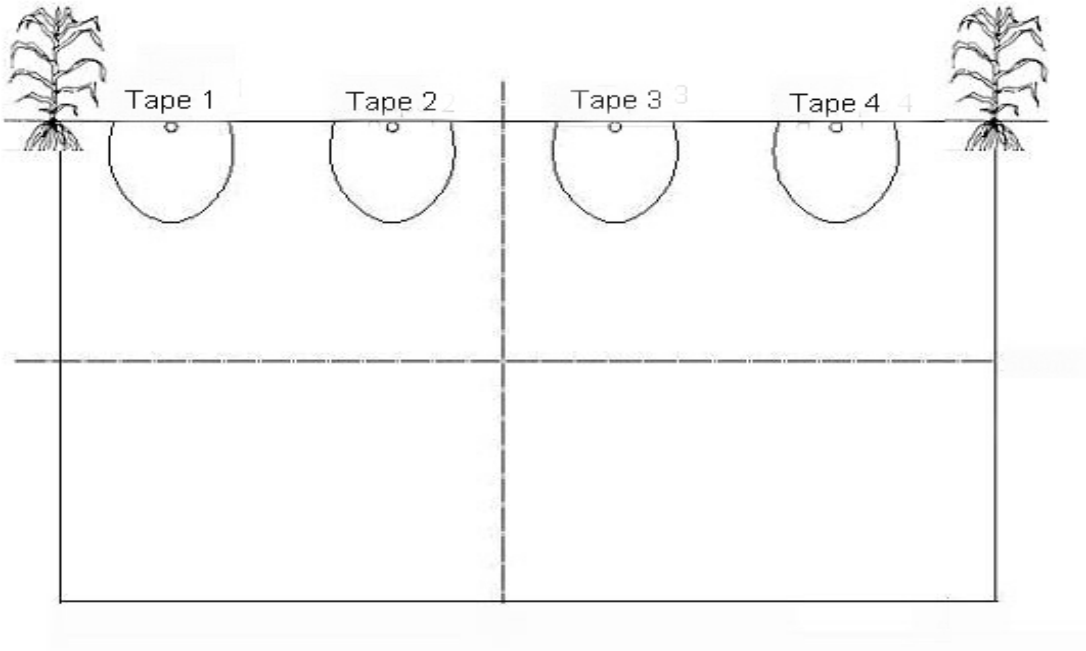


Figure 4-3. Drip tape arrangement in each row interval

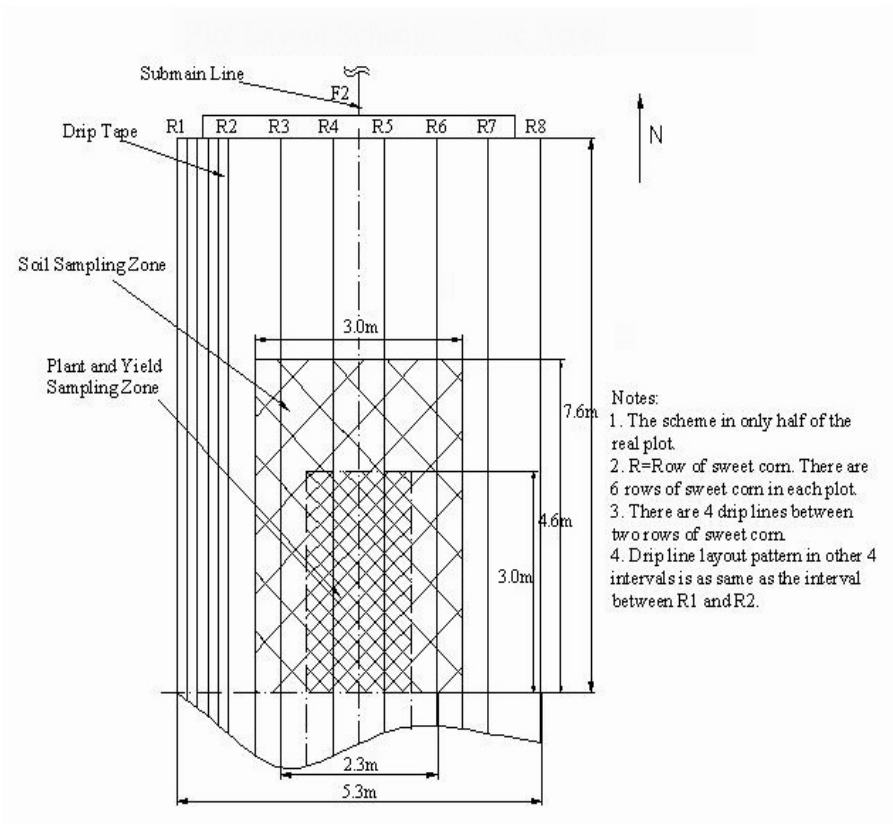


Figure 4-4. Drip tape arrangement and sampling zone in each plot

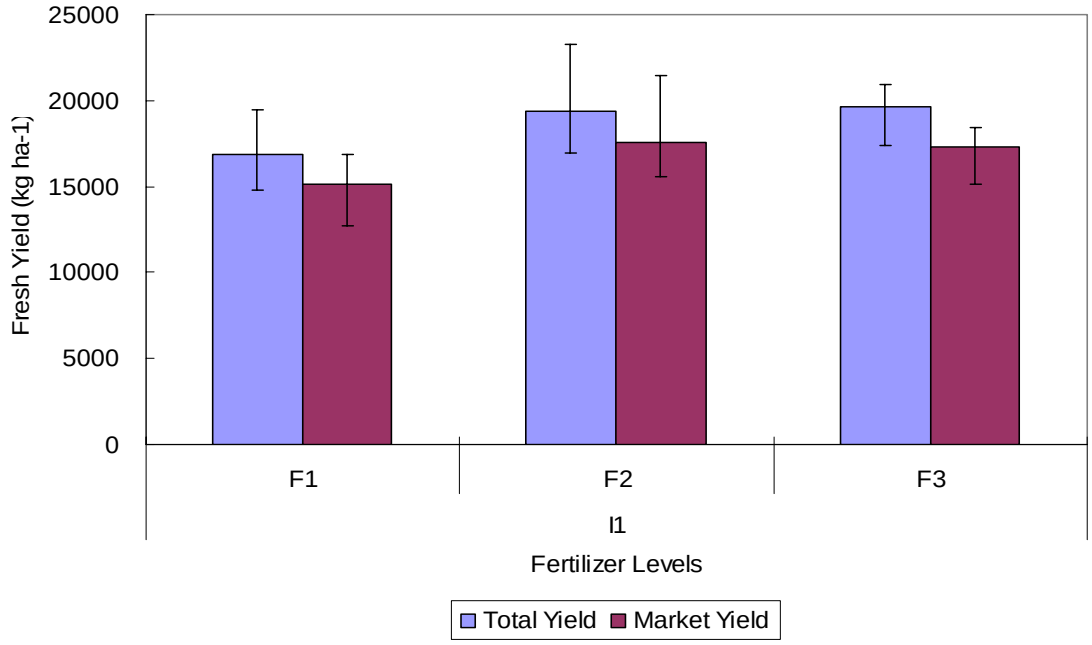


Figure 4-5. Fresh yield under different N fertilizer levels under I1. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

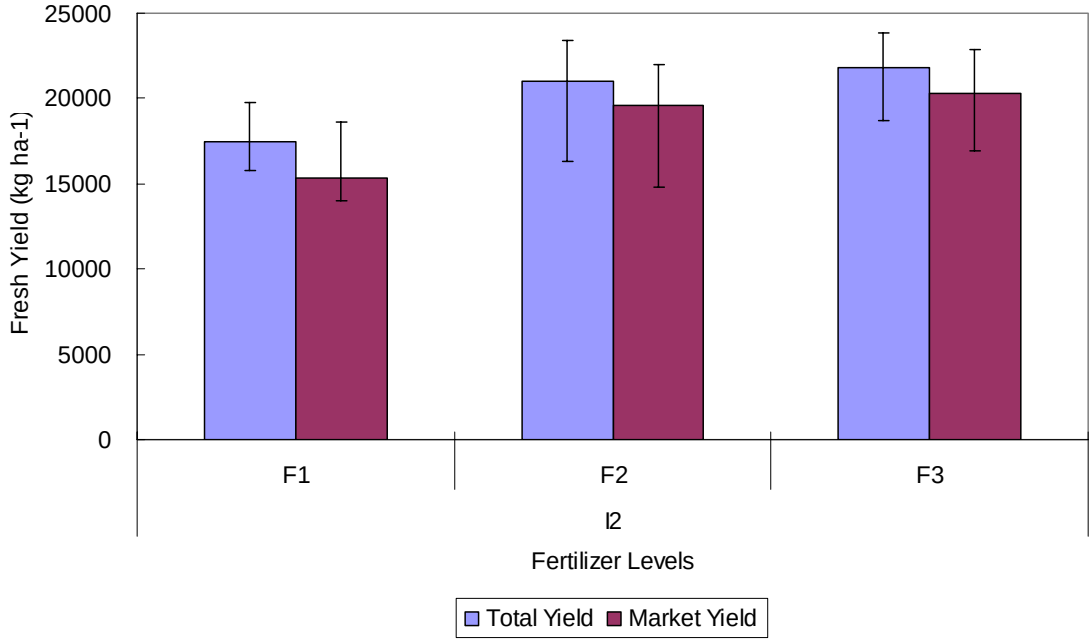


Figure 4-6. Yield under different N fertilizer levels under I2. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

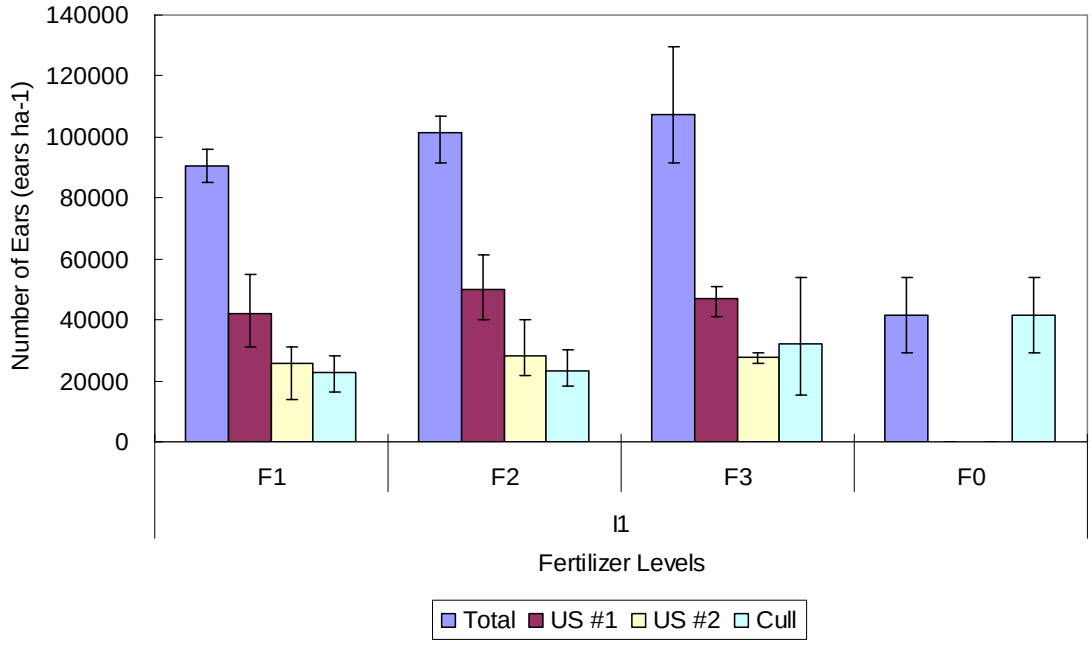


Figure 4-7. Number of ears per unit area under different N fertilizer levels under I1. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

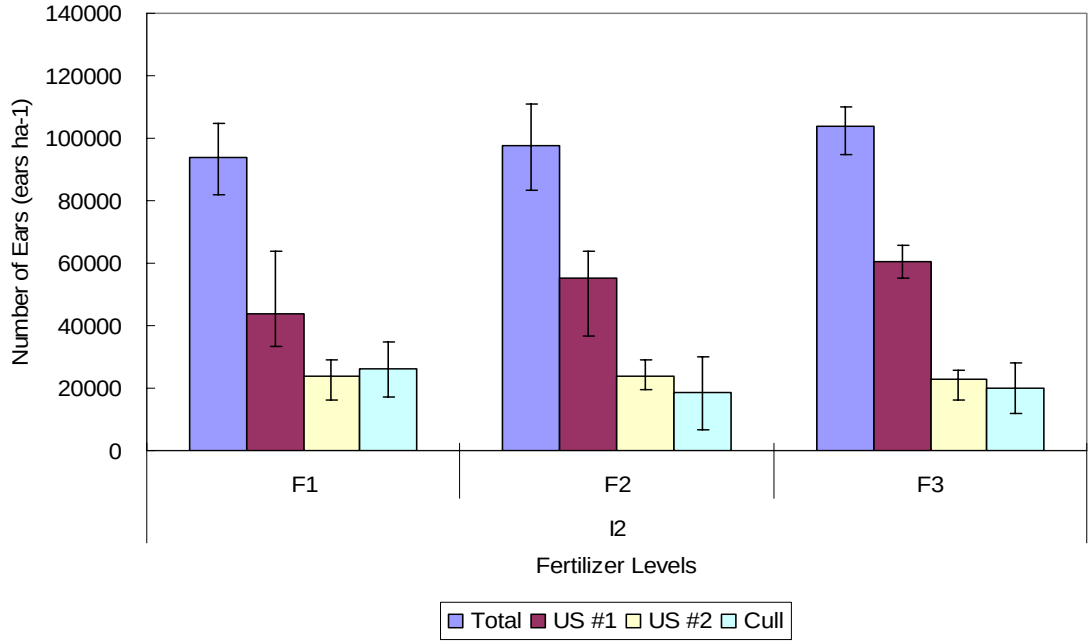


Figure 4-8. Number of ears per unit area under different N fertilizer levels under I2. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

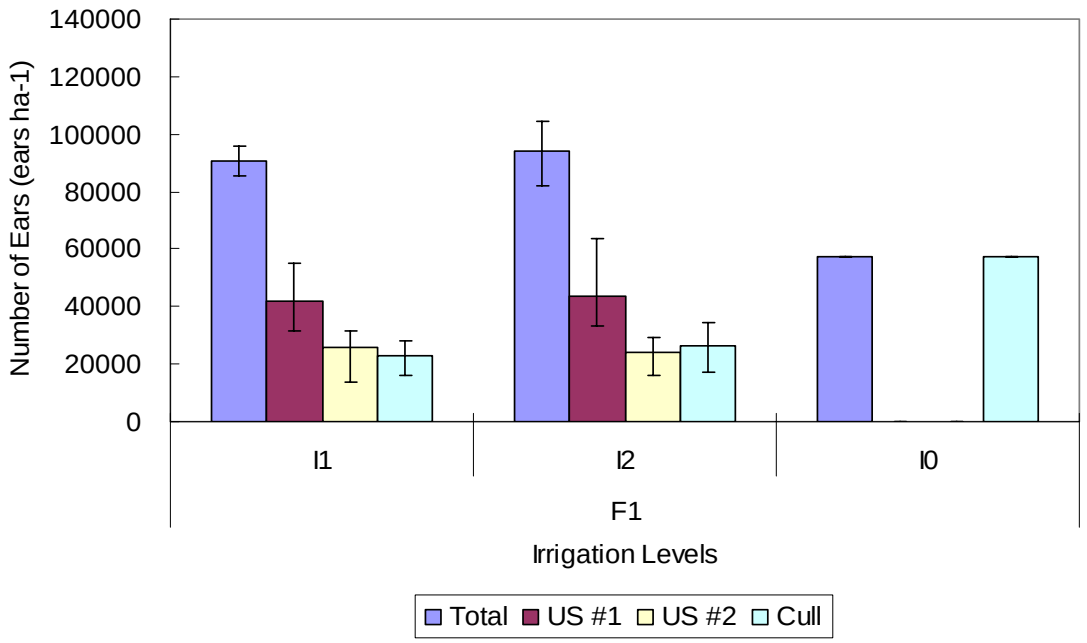


Figure 4-9. Number of ears per unit area under different irrigation levels under F1. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

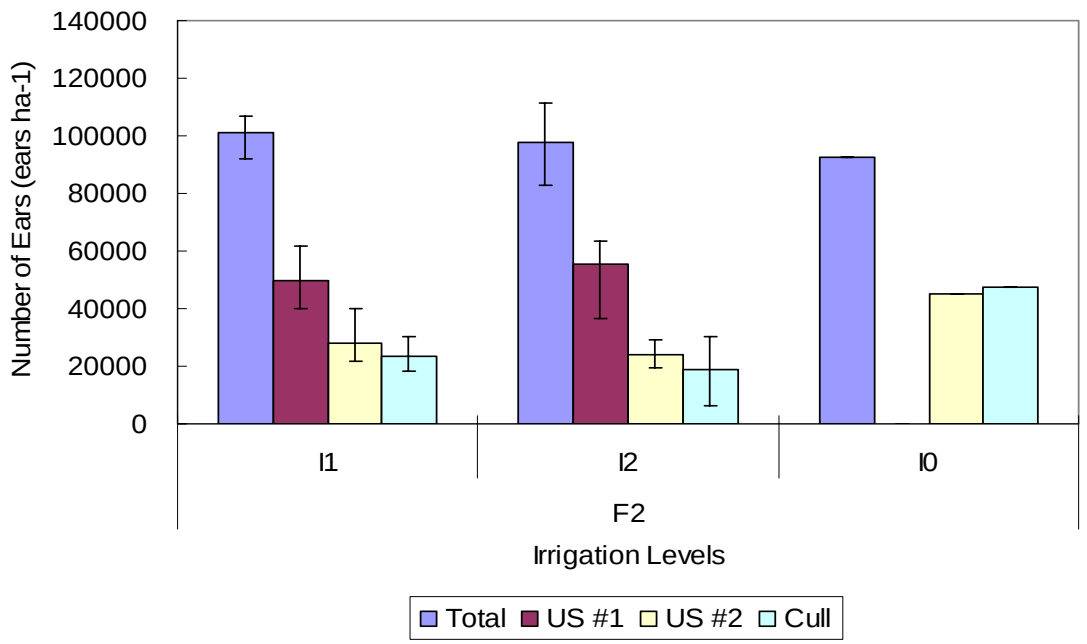


Figure 4-10. Number of ears per unit area under different irrigation levels under F2. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

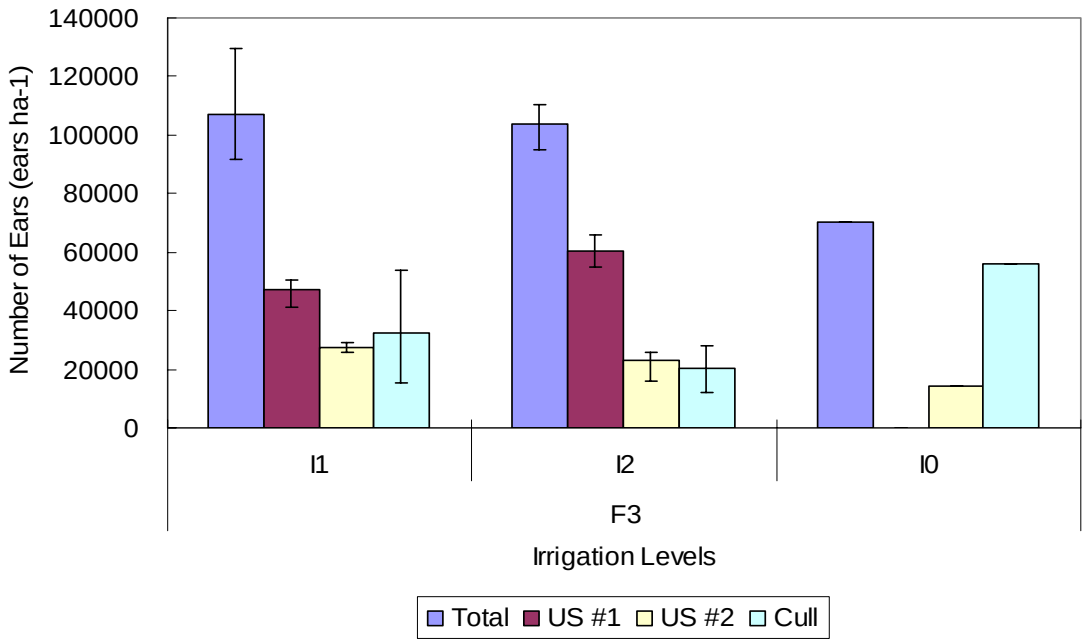


Figure 4-11. Number of ears per unit area under different irrigation levels under F3. The upper error bar shows the maximum value of the four duplicates of the treatment, while the lower error bar shows the minimum one.

Table 4-1. Soil properties of the experiment site

Depth (cm)	Texture	Clay (%)	Silt (%)	Sand (%)	Bulk Density (g/cm^3)	PWP (cm^3/cm^3)	FC (cm^3/cm^3)	Saturation (cm^3/cm^3)
0-15	Sandy soil	2.75	1.92	95.33	1.67	0.051	0.110	0.313
15-30	Sandy soil	2.56	2.35	95.08	1.69	0.061	0.117	0.317
30-60	Sandy soil	2.36	1.76	95.88	1.67	0.077	0.118	0.357

Table 4-2. DU_{lq} values of 4 different numbers of drip tapes at 3 depths at t=30min

Depth	1 Drip Tape	2 Drip Tapes	3 Drip Tapes	4 Drip Tapes
D1 (10cm)	0.58	0.42	0.82	0.97
D2 (20cm)	0.65	0.51	0.55	0.99
D3 (30cm)	1.00	1.00	1.00	1.00

Table 4-3. Fertigation schedules of field plot experiment in 2006

Date	F1 (kg N ha^{-1})	F2 (kg N ha^{-1})	F3 (kg N ha^{-1})
3/14/06	15	15	15
4/7/06	27	41	55
4/12/06	21	28	35
4/19/06	21	28	35
4/26/06	21	28	35
5/3/06	21	28	35
5/10/06	21	28	35
5/17/06	21	28	35
5/24/06	17	23	29
Total	185	247	309

Table 4-4. Crop coefficients of sweet corn at different stages of development

Growth Stage	Time (weeks after planting)	KC
1	Planting-2	0.15
2	3-4	0.30
3	5-6	0.50
4	7-8	0.65
5	9-10	1.00
6	11-Harvest	0.90

Table 4-5. Second posterior distribution of the selected parameters

Parameter	Unit	Min	Max	Mean	Standard Deviation	CV
P1	℃d	77.6758	182.1748	99.1689	8.2169	0.0829
P5	℃d	553.1408	676.2120	577.2011	9.7462	0.0169
PHINT	℃d	39.1615	41.7123	39.6760	0.2021	0.0051
SLDR	-	0.7079	0.7521	0.7316	0.0063	0.0086
SLRO	-	41.4916	99.8501	78.1428	9.6603	0.1236
SDUL	cm^3/cm^3	0.0970	0.1093	0.1044	0.0016	0.0155
SLLL	cm^3/cm^3	0.0526	0.0684	0.0601	0.0024	0.0401
SSAT	cm^3/cm^3	0.2352	0.3624	0.3002	0.0209	0.0695
SLPF	-	0.7595	0.9322	0.8720	0.0414	0.0474

Table 4-6. Measured and estimated mean values of soil properties of the field experiment site

	SLLL (cm^3/ cm^3)		SDUL (cm^3/ cm^3)		SSAT (cm^3/ cm^3)	
	Measured	Estimated	Measured	Estimated	Measured	Estimated
Mean	0.051	0.060	0.110	0.104	0.314	0.300
STDEV	0.031	0.002	0.044	0.002	0.07	0.021

Table 4-7. ANOVA results of total yield of sweet corn

Source of Variance	Degrees of Freedom	Sum of Squares	F Value	P-Value	CV
Block	3	41846554.24	3.26	0.0596	
Irrigation (I)	1	13012402.31	3.04	0.1068	
Irrigation Error	3	5059041.81	0.39	0.7597	
Nitrogen (N)	2	57707644.3	6.74	0.0109	
I x N [a]	2	2602660.19	0.3	0.7434	
Error	12	51375030.4			
Total	23	171603333.2			10.69

[a] Interaction between irrigation and nitrogen fertilizer treatments.

Table 4-8. Irrigation and nitrogen treatment effects on yield quantity

	Total Yield (kg ha^{-1})	Marketable Yield (kg ha^{-1})
Irrigation Level		
I1	18,618 a [a]	16,681 a
I2	20,091 a	18,431 a
Nitrogen Level		
F1	17,182 B [b]	15,255 B
F2	20,181 A	18,584 A
F3	20,701 A	18,828 A
I x N Interaction	NS	NS
CV	10.69	11.56

NS: non-significant.
[a] Means with columns followed by the same lowercase letters are not significantly different ($p \leq 0.05$) according to t-test;
[b] Means with columns followed by the same uppercase letters are not significantly different ($p \leq 0.05$) according to Duncan's multiple range test.

Table 4-9. ANOVA results of total ears of sweet corn

Source of Variance	Degrees of Freedom	Sum of Squares	F Value	P-Value	CV
Block	3	665639481.3	1.78	0.2041	
Irrigation (I)	1	9511908.6	0.08	0.7869	
Irrigation Error	3	9511908.6	0.03	0.9942	
Nitrogen (N)	2	686895685.2	2.76	0.1034	
I x N [a]	2	60662682.4	0.24	0.7876	
Error	12	1494146132			
Total	23	2926367798			11.27

[a] Interaction between irrigation and nitrogen fertilizer treatments.

Table 4-10. Irrigation and nitrogen treatment effects on yield quality

	Total Ears (ears ha^{-1})	US #1 (ears ha^{-1})	US #2 (ears ha^{-1})	Cull (ears ha^{-1})
Irrigation Level				
I1	99,648 a [a]	46,317 a	27,160 a	26,171 a
I2	98,389 a	53,152 a	23,563 a	21,674 a
Nitrogen Level				
F1	92,274 B [b]	42,764 B	24,957 A	21,674 A
F2	99,423 AB	52,612 A	25,901 A	20,910 A
F3	105,359 A	53,826 A	25,227 A	26,306 A
I x N Interaction	NS	NS	NS	NS
CV	11.27	16.10	23.73	34.25

NS: non-significant.

[a] Means with columns followed by the same lowercase letters are not significantly different ($p \leq 0.05$) according to t-test;

[b] Means with columns followed by the same uppercase letters are not significantly different ($p \leq 0.05$) according to Duncan's multiple range test.

Table 4-11. Nitrogen budget of a replicate of treatment F1I1 in Block 1 of the plot experiment

Component	Item	Part	Value	Unit
Input	N Fertilizer		184.94	kg ha^{-1}
	Seed		0.3	kg ha^{-1}
	Atmospheric Deposition		2.41	kg ha^{-1}
	Irrigation Water Nitrate		7.66	kg ha^{-1}
	Irrigation Water Ammonium		0.45	kg ha^{-1}
Net Residual	Soil Nitrate	0-15cm	-0.88	kg ha^{-1}
		15-30cm	-1.76	kg ha^{-1}
		30-60cm	0.50	kg ha^{-1}
		60-90cm	-0.34	kg ha^{-1}
		Subtotal	-2.47	kg ha^{-1}
	Soil Ammonium	0-15cm	-5.27	kg ha^{-1}
		15-30cm	-4.41	kg ha^{-1}
		30-60cm	-9.23	kg ha^{-1}
		60-90cm	5.46	kg ha^{-1}
		Subtotal	-13.46	kg ha^{-1}
	Gaseous Loss	Volatilization and denitrification	11.10	kg ha^{-1}
Output	Plant Uptake	Cobs	5.14	kg ha^{-1}
		Husks	2.47	kg ha^{-1}
		Kernels	28.37	kg ha^{-1}
		Leaves	12.94	kg ha^{-1}
		Stems	2.51	kg ha^{-1}
		Subtotal	51.42	kg ha^{-1}
Potential Leaching			149.17	kg ha^{-1}

Table 4-12. Estimated nitrogen leaching of seven treatment in field plot experiment

Treatment	Mean (kg ha^{-1})	STDEV (kg ha^{-1})
F0I1	17.28	7.11
F1I1	115.15	17.89
F2I1	139.97	19.11
F3I1	195.65	15.26
F1I2	133.18	23.15
F2I2	153.81	15.38
F3I2	214.01	13.20

Table 4-13. ANOVA results of nitrogen leaching estimated from N balance

Source of Variance	Degrees of Freedom	Sum of Squares	F Value	P-Value	CV
Block	3	1013.03103	1.03	0.4145	
Irrigation (I)	1	1681.80989	5.12	0.0429	
Irrigation Error	3	643.05542	0.65	0.5962	
Nitrogen (N)	2	27681.78488	42.17	<.0001	
I x N [a]	2	25.42077	0.04	0.9621	
Error	12	3938.75866			
Total	23	34983.86065			11.42

[a] Interaction between irrigation and nitrogen fertilizer treatments.

Table 4-14. Irrigation and nitrogen treatment effects on cumulative nitrogen leaching estimated from N balance

	Accumulative nitrogen leaching (kg ha^{-1})
Irrigation Level	
I1	150.26 b [a]
I2	167.00 a
Nitrogen Level	
F1	124.17 C [b]
F2	146.89 B
F3	204.83 A
I x N Interaction	NS
CV	22.57

NS: non-significant.

[a] Means with columns followed by the same lowercase letters are not significantly different ($p \leq 0.05$) according to t-test;

[b] Means with columns followed by the same uppercase letters are not significantly different ($p \leq 0.05$) according to Duncan's multiple range test.

Table 4-15. Simulated and measured dry yields in field plot experiment in 2006

Treatment	Simulated (kg ha^{-1})			Measured (kg ha^{-1})			
	Mean	STDEV	CV	Mean	STDEV	CV	ARE[a]
F0I1	1438	679	47%	152	33	21%	846%
F1I1	2843	664	23%	2533	276	11%	12%
F2I1	3023	655	22%	2902	389	13%	4%
F3I1	3024	655	22%	2943	220	7%	3%
F1I2	3377	933	28%	2621	231	9%	29%
F2I2	3419	949	28%	3152	463	15%	8%
F3I2	3447	960	28%	3268	324	10%	5%

[a] ARE is the absolute relative error, defined as ARE=|Y-Y'|/Y, where Y is the measured value and Y' is the predicted value of model output.

Table 4-16. Simulated and measured anthesis and maturity dates in field plot experiment

Treatment	Anthesis Date			Maturity Date		
	Simulated		Observed	Simulated		Observed
	Mean	STDEV		Mean	STDEV	
F0I1	51	1	51	81	2	80
F1I1	51	1	51	81	2	80
F2I1	51	1	51	81	2	80
F3I1	51	1	51	81	2	80
F1I2	51	1	51	81	2	80
F2I2	51	1	51	81	2	80
F3I2	51	1	51	81	2	80

Table 4-17. Nitrogen balance of model simulation of treatment F1I1

Component	Item	Value	Unit
Input	Inorganic N Applied or N Fertilizer (UNIM)	184	kg ha^{-1}
	Initial Soil Nitrate-N	1.3	kg ha^{-1}
	Initial Soil Ammonium-N	6.7	kg ha^{-1}
	N from Senesced Plant Matter	7	kg ha^{-1}
	Subtotal	**199**	kg ha^{-1}
Output	N Uptake during Season (NUCM)	94	kg ha^{-1}
	N Leached during Season (NLCM)	32	kg ha^{-1}
	Inorganic N at Maturity (NIAM)	73	kg ha^{-1}
	Subtotal	**199**	kg ha^{-1}
Potential N Leaching	NLCM+NIAM	**115**	kg ha^{-1}

Table 4-18. Simulated potential nitrogen leaching of the seven treatment in field plot experiment

Treatment	N Leached during Season (NLCM) kg ha $^{-1}$	Inorganic N at Maturity (NIAM) kg ha $^{-1}$	Potential N Leaching (NLCM+NIAM) kg ha $^{-1}$	
	Mean	Mean	Mean	STDEV
F0I1	9.04	11.92	20.96	2.11
F1I1	31.95	73.21	105.16	9.93
F2I1	32.58	144.81	177.39	9.74
F3I1	33.12	206.14	239.27	9.69
F1I2	55.48	47.13	102.61	15.72
F2I2	66.23	97.42	163.64	15.86
F3I2	76.48	148.36	224.85	16.04

Table 4-19. Simulated and estimated accumulative nitrogen leaching in field plot experiment

Treatment	Simulated (kg ha^{-1})			Estimated (kg ha^{-1})			ARE[a]
	Mean	STDEV	CV	Mean	STDEV	CV	
F0I1	20.96	2.11	10%	17.28	7.11	41%	21%
F1I1	105.16	9.93	9%	115.15	17.89	20%	9%
F2I1	177.39	9.74	5%	139.97	19.11	11%	27%
F3I1	239.27	9.69	4%	195.65	15.26	7%	22%
F1I2	102.61	15.72	15%	133.18	23.15	13%	23%
F2I2	163.64	15.86	10%	153.81	15.38	12%	6%
F3I2	224.85	16.04	7%	214.01	13.20	7%	5%

[a] ARE is the absolute relative error, defined as ARE=|Y-Y'|/Y, where Y is the measured value and Y' is the predicted value of model output.

CHAPTER 5
BEST MANAGEMENT PRACTICE DEVELOPMENT WITH CERES-MAIZE MODEL FOR SWEET CORN PRODUCTION IN NORTH FLORIDA

5.1 Introduction

Best management practices (BMPs) are specific cultural practices that are aimed at reducing the loads of specific compounds while increasing or maintaining economical yields (Simonne and Hochmuth, 2003). The implementation of BMPs may be key in reducing the consequences of alterations of the N cycle in sweet corn fields. Implementation of BMPs at the farm level is a key to maintaining the quality and the quantity of ground and surface water (Simonne and Hochmuth, 2003).

The planned BMPs related with irrigation and N fertilizer application could be obtained with traditional field plot experiments. But development and certification of site-specific guidelines for optimal timing and water and nitrogen requirements requires extensive and expensive field experiments. Since it is impossible to test all the interactions between the amount of water and nitrogen during the seasons, use of simulation models can greatly facilitate the evaluation of different production practices and/or environments and thereby streamline the decision-making process (Rinaldi et al., 2007).

Due to the important roles of nitrogen application and irrigation in sweet corn production in Florida, these two factors were studied to obtain relevant potential BMPs for sweet corn production in North Florida. For irrigation, the focus was on irrigation rate and timing. The rate was mainly dependent on the water balance in the relevant soil profile. The timing of irrigation could be determined both by water balance or soil moisture status. For nitrogen fertilizer, the two factors were total application amount and application split. The nitrogen application split was the number of times that N fertilizer was applied, while the application amount was how much fertilizer was applied in each application.

Previous BMP development depended on sampling experiments. Some initial traditional efforts to study yield variability of crops have focused on taking static measurements of soil, management, or plant properties and regressing these values against grid level yields (Jones et al., 1989; Cambardella et al., 1996; Khakural et al., 1996; Sudduth et al., 1996). However, these efforts have proven to be illusive in determining causes of yield variability. The reason for this is because crop yield is influenced by temporal interactions of management, soil properties, and environment. Traditional analytical techniques, which regress static measurements against yield do not account for temporal interactions of stress on crop growth and yield (Paz, et al., 1999). In addition, experiment time and cost should also be considered.

With the development of computer technology, crop models fall into our eyesight as a strong tool for exploration of possible BMPs for crop production. A crop model has been described as a "quantitative scheme for predicting the growth, development and yield of a crop, given a set of genetic coefficients and relevant environmental variables" (Monteith, 1996). Models are not perfect, and can at best only represent a current understanding of biological systems; yet they do highlight where information and understanding are lacking (Boote et al., 1996). With these caveats, crop models can be used to predict crop growth, development and yield as a function of soil, climate, weather, and crop management conditions (Ghaffari et al., 2001). The CERES-Maize corn growth and yield model (Jones and Kiniry, 1986; Tsuji et al., 1994) in the Decision Support System for Agrotechnology Transfer (DSSAT) model, V4.0, is a popular crop model.

This current research demonstrates the use of the CERES-Maize model to develop some potential BMPs for sweet corn (*Zea mays L.*) production on sandy soil in North Florida. The objective was to select management combinations of different irrigation and nitrogen fertilizer

levels that can simultaneously obtain acceptable yield and lower nitrogen leaching as potential BMPs for future study.

5.2 Materials and Methodology

5.2.1 Experiment Site

In this study, a field experiment was necessary. First field data such as yield, anthesis date, maturity date, corn leaf N concentration, soil moisture, and soil nitrate concentration, were required for model calibration with the generalized likelihood uncertainty estimation (GLUE) method. Second some information such as planting date, corn population density, planting depth, micro nutrient application, pest control etc., were required data to run the model.

The field experiments of sweet corn were conducted at the Plant Science Research and Education Unit, the University of Florida in the spring of 2005 and 2006. The unit is located near Citra (29.4094^{o}N, 82.1777^{o}W, 20.746 meters above sea level), Marion County, Florida. The experiment field was identified as Block1. The variety of sweet corn planted was Saturn SH2 (Judge et al., 2005).

In this study, the data collected in the experiment field identified as Block 1 (Figure 3-1 in Chapter 3) were used for the GLUE simulation. In Block 1, there were only two treatments each year, the high-nitrogen-level treatment and the low-nitrogen-level treatment, while the irrigation level was the same. The size of Block 1 was about 9.0 acres and divided into two even parts for these two treatments.

The nitrogen fertilizer used in the experiment was a composite solution of several nitrogen compounds. The total nitrogen mass concentration was about 32%, including 7.9% nitrate nitrogen, 7.9% ammoniacal nitrogen, and 16.2% urea nitrogen. The concentration of total fertilizer solution was 1.294 kg L^{-1}, while the concentration of nitrogen in this solution was 0.414 kg N L^{-1}. When applying fertigation, nitrogen fertilizer solution was injected with an injection

pump into the drip tape system through the injection hole. The injection pump used in this experiment was an Easy-Load II MASTERFLEX pump (Cole-Parmer Instrument Company, Vernon Hills, Illinois).

A total of 230 kg N ha^{-1} was applied in the East Half with a starter application of 15 kg N ha^{-1}, while the rest was applied in eight even application. And 335 kg N ha^{-1} was applied in the West Half in the same way as in the East Half. Other practices including irrigation were the same for the two parts.

Since model input parameter calibration had already been done with the GLUE method in Chapter 3, only the necessary information collected in the experiment of 2006 was used as input for model running.

5.2.2 Crop Model Calibration

The crop model CERES-Maize used in this study is embedded in the Decision Support System for Agrotechnology Transfer (DSSAT) software (Jones et al., 2003), version 4.0. It was used to simulate the growth of sweet corn to find potential BMPs.

First, the model was calibrated. In this study, both the genetic parameters of the sweet corn variety and the soil parameters were estimated through the generalized likelihood uncertainty estimation (GLUE) method (See Chapter 3 for details about GLUE method and procedures).

In contrast to the commonly used methods of model calibration, the GLUE method provided a posterior distribution of the input parameters rather than a unique parameter set that can optimize all of the observations and relevant predictions. This study is a pre-selection of potential BMPs for sweet corn production, which means the uncertainties in predictions caused by uncertainties of input parameter should be temporarily neglected so as to reduce the number of model runs and facilitate the study. Thus, the expectation values of the most sensitive input

parameters (Table 5-1) derived in Chapter 3 were used as the nominal parameter set to conduct BMP simulations.

5.2.3 BMP Simulations

In this study, common cultural practices such as planting, weed management, disease management, micro nutrient application, and harvest etc., were used for sweet corn production in North Florida. More information is available in the "Vegetable Production Guide for Florida 2003-2004" (Olson and Simonne, 2005).

However, the focus of this study was on the cultural practices that most directly affect the nitrogen cycle and yield of sweet corn production according to the definition of nitrogen BMP in this study. So the computer experiment was designed mainly considering irrigation and N fertilizer application.

Generally, the procedures of the BMP development consisted of the following steps: (1) model simulation with different irrigation strategies; (2) model simulation with different irrigation strategies; (3) model simulation with different irrigation and N fertilizer combinations; and (4) identification of potential BMPs.

The irrigation events were scheduled with two methods. First, irrigation water was applied automatically with specific irrigation depths that were derived from soil properties when 10, 20, 30, 40, 50, 60, 70, 80 and 90% of the maximum available water (MAW) in the upper 50 cm of the soil profile was remaining, i.e. from 90 to 10% of the MAW was depleted. The DSSAT model requires model users to provide the irrigation depth and remaining MAW. The soil profile depth was set as 50 cm because more than 70% of sweet corn roots are concentrated in the top two feet of soil (Bauder and Waskom, 2003).

To determine the irrigation depth in each irrigation event, the irrigation scheduling method based on maximum allowable depletion (MAD) of the total available soil water (ASW) was applied (Panda, 2004).

The ASW was taken as the difference between root zone water storage at field capacity (FC) and permanent wilting point (PWP). Since soil is always inhomogeneous and can be treated as layered medium, the value of ASW of a layered soil profile can be calculated with Equation (5-1):

$$ASW = \sum_{i}^{N} \left(FC_i - PWP_i \right) \times RZ_i \tag{5-1}$$

where RZ_i is the root zone depth of ith soil layer. N is the number of soil layers.

The soil of the experiment field is very sandy. It consists of Lake Sand, Candler Variant, Tavares Variant, and Millhopper Variant 1 etc. Soil experiment was conducted at 24 sites at 3 depths of 0-15 cm, 15-30 cm, and 30-60 cm. Then the samples were sent to the lab of the Soil and Water Science Department of the University of Florida. According to the definitions, the permanent wilting point (PWP) was measured as the soil moisture at a soil pressure of 15.3 bar, field capacity (FC) as the soil moisture at 0.1 bar, and soil saturation as the soil moisture at 0 bar. The main measured properties of the soil at the experiment site are summarized in Table 5-2.

According to the FC and PWP values in Table 5-2, the 50 cm soil profile could be separated into 3 layers: 0-15 cm, 15-30 cm, 30-50 cm. The calculated ASW value was 25 mm as shown in Table 5-3.

The MAD is the maximum amount of depletion that can occur without stress to the plant. Hence, the readily available water (RAW) is:

$$RAW = MAD \times ASW = MAD \times \sum_{i}^{N} \left(FC_i - PWP_i \right) \times RZ_i \tag{5-3}$$

If the MAD value is 50%, it simply means, before half of the available water in the root zone is depleted (either was evaporated, transpired, or has transpired or has traveled outside of the root zone), supplemental irrigation is added to "refill" the reservoir. Allowing the depletion amount to drop down below 50% can lead to plant stress for some plant material and once a plant has reached PWP, no amount of water can be applied for recovery.

If an irrigation event was triggered at a threshold of 40% of the MAW remaining in the soil profile in the DSSAT model, it equals to a MAD value of 60%, which means 60% of the ASW could be used by sweet corn without stress. A supplementary irrigation should be triggered to compensate this MAD. The necessary irrigation depth should equal to the value of RAW.

All of the irrigation depths could be calculated with the same method. With this scheduling method, there were a total of 9 possible irrigation scenarios, identified as $I1$ to $I9$ (Table 5-4).

In addition, a set of irrigation schedules based on fixed days and depths were also tested. In each schedule, irrigation water was applied with a fixed irrigation depth for 1 time (Wednesday), 2 times (Tuesday and Friday), or 3 times (Monday, Wednesday and Friday) every week during the growth season. This type schedule was meant to represent typical sweet corn grower practices. As mentioned in Table 5-3, the value of ASW was about 25 mm. If the precipitation depth in each irrigation event was higher than 25 mm, deep percolation and runoff would happen. Thus, the fixed irrigation depths here were set as 20, 40, 60, 80 and 100% of the ASW value, which were 5, 10, 15, 20 and 25 mm. Hence, there were $5 \times 3 = 15$ possible irrigation scenarios both considering irrigation times and irrigation depth, identified as $I10$ to $I24$ (Table 5-5).

The irrigation schedule based on water balance in soil profile was not considered, because this schedule is dependent on daily rainfall and ET values, which would change year to year. In this study, any irrigation schedule was run with the measured weather data of 33 years (1958-

1990). It is hard to automatically set the irrigation events for each year. And at the same time, values of reference ET were also not available.

When doing irrigation simulations, the N application schedule was fixed as the one of East Half of Block 1 in 2006 (See Section 5.2.1 for details), where a total of about 230 kg N ha^{-1} was applied in eight applications. The initial values of soil volumetric moisture for each layer were all set as 8.6%. The initial nitrate-N and ammonium-N concentration was 0.1 g N Mg^{-1} and 0.5 g N Mg^{-1}, which equal to about 1.3 and 6.7 kg N ha^{-1}.The previous crop was set as cotton since it was planted in Blcok 1 in the end of 2005 before sweet corn. The values of root weight, nodule weight, and residue nitrogen and phosphorus, were all set as zero.

For nitrogen fertilizer, three factors should be considered. First is the total amount fertilizer nitrogen. Totally 21 nitrogen fertilizer levels were simulated. They were the amounts from 0 kg N ha^{-1} to 561 kg N ha^{-1} with increments of 28 kg N ha^{-1} (0 lb N $acre^{-1}$ to 500 lb N $acre^{-1}$ with increments of 25 lb N $acre^{-1}$). Among these levels, 224 kg N ha^{-1} (200 lb N $acre^{-1}$), is recommended by Institute of Food and Agricultural Sciences (IFAS), University of Florida (Hochmuth, 2000). This level was defined as the standard nitrogen level for this research. Other levels were derived from this recommended level. These N levels were identified as $N1$ to $N21$.

The second factor is when to apply the given amount of fertilizer nitrogen. Since inorganic nitrogen is not stable in soil and becomes less available for crop uptake over time, application time is important. Corn absorbs the majority of its nitrogen during rapid growth between 8-leaf and dough growth stages (Bauder and Waskom, 2003). If nitrogen is insufficient during this period, yield loss will occur. Application of nitrogen immediately before or during this period will result in higher uptake by the crop and less nitrate lost to leaching or transformations to unavailable forms. An application schedule that applies a small amount of nitrogen early in the

season (pre-plant or starter) followed by later, in-season applications of higher amounts of nitrogen is ideal. This schedule takes care of the small, but important, early season nitrogen needs and maximizes uptake by applying nitrogen during the rapid growth and nitrogen requirement period, i.e. the nitrogen application should coincide with corn nutrient demand.

In this study, the growth season of sweet corn in North Florida was defined as three main growth stages: small plant stage, large plant stage, and ear development stage as recommended by the "Vegetable Production Guide for Florida 2003-2004" (Olson and Simonne, 2005). The small plant stage roughly includes the first 4 weeks after planting, or from planting to 12 leaves fully emerged. The large plant stage roughly includes week 5 to 7, or from 12 leaves to 20 leaves fully emerged (tasseling/silking). The remaining 4 weeks (from tasseling to maturity) can be considered as the ear development stage. These 3 stages will be used to determine the amounts of N fertilizer applied at different time periods during the whole growth season.

A nitrogen split was defined as the quotient between the amount of nitrogen applied in each stage and the total N amount except for the starter N fertilizer. This factor was considered and tested to find the optimal time of nitrogen fertilizer application so that the time of N application could coincide with the nitrogen need of sweet corn plant. Finally, 30 kinds of N split could be set up as shown in Table 5-6. For example, "1:0:0" means apply all of given amount N except for the 15 kg N ha^{-1} as starter (see Section 5.2.1) during the small leaf stage and nothing for the later periods. These splits were identified as $S1$ to $S30$. Based on the real nitrogen application schedule in field experiment, the split of "0:1/2:1/2" was defined as the standard split.

The third factor is how much N fertilizer should be applied in each fertigation event. For example, 224 kg N ha^{-1} was applied with a split of 0:1/4:3/4, which means 56 kg N ha^{-1} was applied in the large leaf stage, while 168 kg N ha^{-1} was applied in the ear development stage. The

168 kg N ha^{-1} could be applied just in one event in week 8, or two events in week 7 and 9. It is obvious that frequent application with small amount could be a good choice, because less nitrogen would be leached. But the cost will also increase when the number of application increased. To determine the optimal N fertilizer application in each event, "application amount" should be considered.

In this study, 20 kinds of "application amount" ranging from 5 to 100 kg N ha^{-1} with a step 5 kg N ha^{-1} were investigated. All these kinds of "application amount" were identified as $A1$ to $A20$. And the "application amount" of 40 kg N ha^{-1} was set as the standard, because it was close tot the "application amount" in field experiment.

When doing N simulations, the irrigation schedule was set to the actual field experiment in 2006, which was set up according to daily ET value and water balance in the top soil profile. When doing single factor (such as total amount, split or application amount) analysis for N application, the other factors were set at their defined standard levels. The initial values of soil volumetric moisture for each layer were all set as 8.6%. The initial nitrate-N and ammonium-N concentration was 0.1 g N Mg^{-1} and 0.5 g N Mg^{-1}. The previous crop was set as cotton. The values of root weight, nodule weight, and residue nitrogen and phosphorus, were all set as zero.

For each of the irrigation and nitrogen fertilizer treatment, the model was run under 33 years (1958-1990) of historical weather data at Gainesville, FL, the USA, which is about 32 km from the experiment site of this study. These weather data were provided by the McNair Bostick Simulation Lab of the Department of Agricultural and Biological Engineering, the University of Florida. Then the average values of the dry yield and nitrogen leaching over these 33 years were used to show their responses to different management strategies. In this way, the uncertainties of simulation results caused by climate variability were considered. In another words, the potential

BMPs selected could be considered applicable in weather conditions represented by the simulated time period.

5.2.4 Determination of Acceptable Yield

It is necessary to know the acceptable yield when determining the potential BMPs from the combination scenarios of irrigation and N fertilizer practices. The acceptable yield in this study was defined as the lowest yield that would be accepted by farmers. If the simulated yield was below the acceptable yield, the strategy of irrigation and N fertilizer application was considered as failure. Since there was no established "acceptable yield" for sweet corn production in Florida found in the literature, an estimate had to be made according to currently existing sources.

One possible way is the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA). USDA proposed reports on "Florida: Acreage, yield, production, and value of Florida vegetables, melons, potatoes, blueberries, and strawberries" every year. In these reports, important information about sweet corn production in Florida could be found, such as total planted and harvested acreage, yield, price and total value etc. Table 5-6 summarizes the information about sweet corn production from 1998-2007 (USDA NASS, 2007).

From Table 5-7, it can be seen that the average fresh yield of sweet corn in the past 9 years in Florida was 16,939 kg ha^{-1} (15,111 lb $acre^{-1}$). The average moisture of fresh ears of sweet corn obtained from field experiment was as high as 84.0%, so the average dry yield was about 2,418 kg ha^{-1}. The highest marketable fresh yield in the field experiment of this study with sufficient N and water application could be 20,346 kg ha^{-1}, and a corresponding dry matter yield of 3,255 kg ha^{-1}, which was almost 800 kg ha^{-1} greater than the average dry matter yield obtained from the statistics.

Another way to estimate the acceptable yield of sweet corn production in Florida is to survey the results of related experiments conducted in Florida or southern United States.

In the study of yield, ear characteristics, and consumer acceptance of selected white sweet corn varieties by Simonne et al. (1999), they summarized the yields of 10 varieties of white sweet corn planted in Clanton, Ala., in 1995 and 1996 (Table 5-8). No information about N fertilizer application was provided. The data in Table 5-7 shows the yield is strongly dependent on sweet corn variety. For "Even Sweeter", the yield could be as high as 14,726 kg ha^{-1}, but for "Rising Star", it is only 8,291 kg ha^{-1}, less than 60% of "Even Sweeter".

Mullins et al. (1999) studied the response of selected sweet corn cultivars to nitrogen fertilization at Springfield, Tenn., in 1993, 1994 and 1995. Their results are shown in Table 5-9. It can be seen that N fertilizer rate, cultivar, and year (climate) all had some kind of influence on sweet corn yields. In general the yields in their experiment were lower than the ones listed in Table 5-6.

Rangarajan et al. (2002) conducted research at Eden Valley and Freeville, NY, from 1998 to 2001. They concentrated on the in-row spacing and cultivar on sweet corn yield. The yields of sweet corn in their experiment are summarized in Table 5-10. The yields shown in this table are close to those listed in Table 5-7. It also shows that in-row spacing did not have a strong influence on yield.

Shuler (2002) studied the effect of within-row plant spacing on sweet corn grown on muck soil at Belle Glade, Florida in spring and fall 2001. In his research, 4 within-row spacing treatments of 0.15, 0.18, 0.20 or 0.23 meters (6, 7, 8 and 9 inches), and 5 varieties were used. Unfortunately, there was no information available about N fertilizer applications, either. The yields obtained in his research are shown in Table 5-11.

Hochmuth and Cordasco (2000) summarized the field experiments conducted in Florida from 1961 to 1997 to evaluate the sweet corn yield responses to varying rates of fertilizers. The

yields are shown in Table 5-12. The average fresh yield in the experiments summarized in Table 5-12 was only 15,596 kg ha^{-1}. It was only a little bit higher than the average fresh yield (15,111 kg ha^{-1}) specified in Table 5-6 from the Florida Agricultural Statistics.

From the research summarized above, it can be found that sweet corn yield was influenced by many factors, such as location, variety, within-row spacing, N fertilizer level, etc. In many cases, the average fresh yields were lower than 20,000 kg ha^{-1}. The results specified in Table 5-11 could be a good reference, since the research site was in south Florida and research time period was in 2001, which were all comparable to the site and time of this current research. The average fresh yield in Table 5-10 was 20,251 kg ha^{-1}. This average yield is close to the results in field experiments in this study, where the average yield was about 20,000 ka ha^{-1} (see Chapter 4 for details).

Finally, the fresh yield of 21,000 kg ha^{-1} and corresponding dry yield of 3,400 kg ha^{-1} at average ear moisture of 84.0% were selected as a good estimation for the acceptable yield for this study.

5.3 Results and Discussion

5.3.1 Effects of Irrigation

First, the response of sweet corn yield (dry matter, kg ha^{-1}) and accumulative nitrogen leaching (kg ha^{-1}) to different irrigation strategies were investigated. As mentioned in Section 5.2.3, the first 9 irrigation strategies identified as $I1$ to $I9$ (Table 5-4), were designed as automatic irrigation with specific depths triggered by remaining available soil water refill the soil profile with a depth of 50 cm.

Figure 5-1 and 5-2 show the response curves of yield and nitrogen leaching to different remaining ASW moistures. In Figure 5-1, it can be seen that if the irrigation event was triggered at a threshold of 70% ASW remained (or a MAD of 30%) with a precipitation depth of 7.5 mm

(Table 5-4), the predicted dry yield arrived its maximum value as 3,867 kg ha^{-1}. If an irrigation event was triggered at a very low level of remaining ASW, e.g. 10%, then there would be long interval between two irrigation events. Corn growth would suffer from water stress, and yield would be reduced significantly to less than 1,000 kg ha^{-1}, which is only about one third of the acceptable dry matter yield mentioned in Section 5.2.4. Under a threshold of 20%, 30%, 40%, or 50% remaining ASW (or a MAD of 80%, 70%, 60%, or 50%), there appeared to be water stress since the yields were all below 3,000 kg ha^{-1}.

When the irrigation event was triggered at higher levels of remaining ASW, e.g. 80% and 90% (or a MAD of 20% and 10%), it meant more frequent irrigations with very small depth of irrigation (5.0 and 2.5 mm respectively). The predicted dry material yield would decrease a little bit, which might be caused by more nitrogen leaching and less nitrogen available for plant uptake.

Figure 5-2 shows an obvious trend of increasing of nitrogen leaching if irrigation events were more frequent. For example, if the irrigation event of 22.5 mm was triggered when remaining ASW was10%, the accumulative nitrogen leaching (NLCM) value was approximately 32 kg ha^{-1}. But it could be as high as almost 120kg ha^{-1}, if the event was triggered with a threshold of 80% or 90% remaining ASW (or a MAD of 20% or 10%) and a precipitation depth of 5 or 2.5 mm.

Considering the yield and nitrogen leaching, it was observed that a threshold of a MAD value of 40 or 30% with a precipitation depth of 10 or 7.5 mm would be a good choice for irrigation scheduling, since they result in a higher yield though they failed to obtain the lowest nitrogen leaching level. This conclusion could be confirmed by the values of MAD provided by James et al. (1982), where the MAD value of sweet corn was 50%.

Haman and Smajstrla (1997) mentioned that Florida's sandy soils are well known for their inability to hold water. Very little water is stored in the root zone. A general rule for vegetable irrigation is to provide irrigation before 50% of this water is used in order to avoid plant stress, which means a MAD value of 50%. They also pointed out that if possible, 33% depletion should be used for scheduling drip irrigation, which requires frequent (once or more per day) and short water applications. Thus, a MAD value of 40% or 30% in this study should be reasonable.

In addition, if irrigating at a low MAD value such as 10%, it requires a low irrigation depth (2.5 mm). These depths probably can not match the lower irrigation depth limit of the linear or center pivot irrigation systems, which are usually used by farmers in North Florida for crop irrigation. At the same time, the frequency of irrigation events will also be very high, probably less than 24 hours. However, it might not be practical for a center pivot system, because it could take more than 24 hours for a 400-meter system to finish an irrigation circle (Keller and Bliesner, 1990).

Next, the irrigation strategies designed as automatic irrigation on fixed days with specific depth were investigated (Figure 5-3 and 5-4). When enough water was applied, e.g. 2 or 3 irrigations per week with a depth of 15, 20, or 25 mm, the yield didn't increase, and in some cases decreased. There was no significant difference between the yields of 2 and 3 irrigations a week when irrigation depths were 15, 20 and 25 mm, but yield could be significantly reduced when there was just 1-irrigation a week due to water stress.

The assumption that when more water is applied more nitrogen is leached was confirmed by Figure 5-4. For example, at 2 or 3 irrigation events a week with a depth of 25 mm, the simulated nitrogen leaching could be about 150 kg ha^{-1}, while the real nitrogen application was only about 230 kg ha^{-1}, indicating more than 65% of the applied nitrogen was leached.

Evaluating the amounts of yield and nitrogen leaching, it is apparent that two-irrigations a week with a precipitation depth of 15 mm, or three-irrigations a week with a precipitation depth of 10 mm would achieve a relatively higher level of yield and lower nitrogen leaching. Compared with the irrigation schedules with a MAD value of 30% or 40%, these two fixed-date-and-depth methods share the similar predicted dry matter yield (3,500 to 40,000 kg ha^{-1}) and amount of nitrogen leaching (80 to 100 kg ha^{-1}).

Finally based on the criterion of higher yield and lower nitrogen leaching, six irrigation strategies (Table 5-13) were selected as the optimal ones for future combination simulations. Among these irrigation schedules, Irrigation 2, 3, 5 and 6 had close predicted dry matter yield and amount of nitrogen leaching as mentioned above. While Irrigation 1 had a lower yield (about 2,500 kg ha^{-1}) and lower nitrogen leaching (about 65 kg ha^{-1}), and Irrigation 4 had a similar dry matter yield (about 3,700 kg ha^{-1}) and a higher amount of nitrogen leaching (about 120 kg ha^{-1}).

5.3.2 Effects of Nitrogen Fertilizer

5.3.2.1 Total nitrogen fertilizer amount

Total amount of fertilizer nitrogen required for sweet corn production was a core issue in developing research-based N BMPs. The recommended nitrogen amount by the Institute of Food and Agricultural Sciences (IFAS), University of Florida (Hochmuth, 2000) was 224 kg N ha^{-1} (200 lb N ac^{-1}). What are the implications if this recommendation is reduced? How will the yield and accumulative nitrogen leaching change with different nitrogen fertilizer levels? It will be necessary to explore the influence of total N amount first.

As mentioned in Section 5.2.3, when doing nitrogen simulations, the irrigation strategy was the actual one of Block 1 in 2006, which was scheduled according to the daily ET value. The accumulated irrigation amount and rainfall data in 2006 are shown in Figure 5-5.

Figure 5-6 and 5-7 show the response curves of yield and nitrogen leaching to different nitrogen fertilizer levels. The irrigation strategy was the actual field experiment in Block 1 in 2006. Here the nitrogen fertilizer was applied with a split of 0:1/2:1/2 (nothing in the small leaf stage, 1/2 of total nitrogen except for the starter N fertilizer in the larger leaf stage, and 1/2 in the ear development stage) and 40 kg N ha^{-1} for "application amount", A starter nitrogen application of 17 kg N ha^{-1} was set for all of the simulations.

The two curves in these two figures (Figure 5-6 and 5-7) confirmed the fact as more nitrogen is applied, more will be leached. After 196 kg N ha^{-1} or 175 lb N $acre^{-1}$ (red star in Figure 5-6 and 5-7) , the yield increment caused by added N fertilizer decreased and finally approached zero, where the predicted dry matter yield was near 3,400 kg ha^{-1}. At the same time, nitrogen leaching kept steadily increased when more nitrogen was applied. For example, the amount of nitrogen leaching increased from 82 to 266 kg N ha^{-1} when nitrogen application level increased from 196 to 561 kg N ha^{-1}. When the fertilizer level was zero, there was still some yield and nitrogen leaching (Figure 5-6 and 5-7). This is because the model assumed the nitrogen from dead organic matter was 7 kg N ha^{-1}. The initial nitrate-N and ammonium-N concentration was 0.1 g N Mg^{-1} and 0.5 g N Mg^{-1}, which equal to about 1.3 and 6.7 kg N ha^{-1}. And there was alos a starter N application of 15 kg N ha^{-1} at planting. In other words, there was some nitrogen available except for N fertilizer application.

It seemed 168 kg N ha^{-1} (green star in Figure 5-6 and 5-7) would be enough for sweet corn growth and produce comparably less nitrogen leaching. However, the model simulation assumed the fertilizer application efficiency as 1.0, which means no nitrogen was wasted. It is not true in actual production. The efficiency must be less than 1.0. Thus, the actual amount of nitrogen fertilizer should be greater than 168 kg N ha^{-1}.

To explore other possible N fertilizer strategies, 6 nitrogen amounts, as 140, 168, 196, 224, 252 and 280 kg N ha^{-1} (or 125, 150, 175, 200, 225 and 250 lb N $acre^{-1}$), were selected as optimal total amounts for future combination simulations.

5.3.2.2 Nitrogen fertilizer split

The whole growth season of sweet corn could be divided into three stages, the small leaf stage, large leaf stage, and ear development stage. Nitrogen can arbitrarily be applied during the growth season, but the best way is to make nitrogen application coincide with the N requirement of sweet corn.

As shown in Table 5-6, 30 splits identified as $S1$ to $S30$ were simulated. The top-10 splits that have the highest yields or lowest nitrogen leaching amounts are summarized in Table 5-14. The results in Table 5-14 show that nitrogen fertilizer split did not show a significance influence on yield if there was application of N during the small leaf stage or large leaf stage, since the predicted dry matter yields were all about 3,400 ka ha^{-1}. However, splitting N applications showed a significant influence on N leaching. The best splits were “0:1/4:3/4”, “0:1/3:2/3”, because these fertigation schedules could best coincide the nitrogen need of sweet corn growth, especially from tasseling to maturity.

The results showed that 3 splits S3, S4 and S5 (0-1/4-3/4, 0-1/3-2/3, 0-1/2-1/2) all rank in top-10 either in yield or nitrogen leaching. High yield and low nitrogen leaching was the objective of this research for BMP. Therefore, these 3 splits were selected as optimal ones for combination simulations.

5.3.2.3 Amount of nitrogen fertilizer in each application

The amount of each N fertilizer application determines how many times the total N fertilizer would be applied into the field. As mentioned in Section 5.2.3, 20 different kinds of

"application amount" ranging from 5 to 100 kg N ha^{-1} with a step 5 kg N ha^{-1} were simulated in this study. These "application amount" were identified as $A1$ to $A20$.

In Figure 5-8, the response curve of yield to "application amount" shows that if the application of the total nitrogen fertilizer was less then 70 kg N ha^{-1} in each event (red stars in Figure 5-8 and 5-9), the yield would stay almost the same. In Figure 5-9, the response curve of nitrogen leaching to splits was not a straight line. Lowest nitrogen leaching would be obtained when applying just 5 or 10 kg N ha^{-1} in each fertigation event. The main trend showed that the accumulative N leaching would increase with the increasing of "application amount" (Figure 5-9).

However, too little N fertilizer applied in application amount could result in too many fertigation events, which would increase production cost. It seems 30, 40 or 50 kg N ha^{-1} could be the best "application amount", if the production cost was considered in addition to yield and nitrogen leaching. Finally, these three kinds of "application amount" were selected as optimal ones for future combination simulations.

After the single factor analysis above, the main factors for best N fertilizer management strategies were selected (Table 5-15). The first factor was the total N amount. Six different N fertilizer levels ranged from 140 to 280 kg N ha^{-1} were selected. The second factor was the nitrogen application split strategy. Three kinds of split were selected since they were believed to coincide with the nitrogen need of sweet corn growth. And three kinds of N application amount were selected both considering nitrogen leaching and labor cost.

Thus for a complete factorial experiment design to test all of the possible combinations, these three selected factors could result in $6 \times 3 \times 3 = 54$ kinds of fertilizer application strategies

among which the optimal one of N fertilizer was assumed to exist. These N fertilizer strategies would also be combined with the selected irrigation strategies to look for the potential BMPs.

5.3.3 Selection of Potential BMPs

As mentioned in previous sections, there is a total of 6 irrigation strategies (Table 5-13) and 54 N fertilizer strategies (Table 5-15). So there will be $6 \times 54 = 324$ possible management scenarios. AS mentioned in Section 5.2.3, all of these scenarios were simulated under the 33-year continuous historical weather conditions (1958-1990) of Gainesville.

All of the combination treatments that had a simulated yield (HWAH, kg ha^{-1}) above the acceptable yield, 3,400 kg ha^{-1} (Section 5.2.4) were selected. Then these selected treatments were ranked according to their nitrogen leaching values (NLCM, kg ha^{-1}). Table 5-16 specifies the top 20 of these treatments that had the lowest NLCM values.

For irrigation strategies, it seemed that 5.0 mm irrigation triggered by a MAD of 20% and 7.5 mm irrigation at a MAD of 30% would be the best irrigation strategies. Actually this also confirmed the assumption that frequent irrigation with small amount of water could reduce nitrogen leaching due to the less water loss by deep percolation. In practice, this requires the linear or center pivot irrigation systems continuously running round by round with a high speed and low irrigation depth. Actually, this is what the farmers usually do in sweet corn production especially from tasseling to maturity.

For N fertilizer, the ranking shows that the optimal total amount of nitrogen application was 196 kg N ha^{-1} or 224 kg N ha^{-1}. The splits were dominantly the ones of “0:1/4:3/4” and “0:1/3:2/3”. Only one combination with a split of “0:1/2:1/2” fell in the top-20 combinations selected. It seemed 30, 40 or 50 kg N ha^{-1} all could be the best “application amount”. There were 10 combinations that had an “application amount” of 30 kg N ha^{-1} in the top-20 combinations.

This confirmed another assumption that frequent application of N fertilizer with small amount could reduce nitrogen leaching.

In general from the combination simulation results, it could be concluded that if growers can apply both irrigation water and N fertilizer in more frequent applications but with smaller amounts in each event, it will result in an acceptable yield and a lower level of nitrogen leaching. But this requires farmers to run their irrigation and fertigation system more often, which could increase the production cost due to the increase of labor, electricity, etc.

Finally, considering the yield, nitrogen leaching and operation cost, the following six combination treatments (Table 5-17) were selected as potential BMPs for future study. For example, for potential BMP1 it means an irrigation of 5.0 mm should be started when the MAD value was 20%. Totally 196 kg N ha^{-1} should be applied. Except for a starter application of 15 kg N ha^{-1}, nothing should be applied during the small leaf stage, 1/4 of the total N during the large leaf stage, and 3/4 during the fruit development stage. In each N application, only 30 kg N ha^{-1} should be applied.

These selected potential BMPs will be used to conduct uncertainty analysis both under input variable and weather variations in following research in Chapter 6.

5.3.4 Evaluation and Implementation of Potential BMPs

By definition, BMPs are practices or combination of practices determined by the coordinating agencies, based on research, field-testing, and expert review, to be the most effective and practicable on-location means, including economic and technological considerations, for improving water quality in agricultural and urban discharges. BMPs are typically implemented as a “BMP treatment train” that includes a combination of nonstructural and structural practices that have been determined to be effective for reducing or preventing pollution. BMPs must be: technically feasible, economically viable, and socially acceptable.

For the six developed potential BMPs listed in Table 5-17, they had a total nitrogen application amount of 196 or 224 kg N ha^{-1} (175 or 200 lb. N $ac.^{-1}$), which was lower or equal to the recommended nitrogen level of 200 lb. N $ac.^{-1}$ by IFAS, the Univerisity of Florida (Hochmuth, 2000). The crop model simulation results confirmed that the recommendation of IFAS is correct. In actual production, farmers always apply more nitrogen than the recommended value to guarantee their yields. For example, in the EPA319 demonstration project (Hochmuth, 2003) in Suwannee Farms, O'Brien, FL, total nitrogen application was 302 kg N ha^{-1}, which was almost 50% higher than the recommended N application amount. Thus, it can be concluded that if the developed potential BMPs could be implemented in reality, more nitrogen fertilizer would be saved and consequently less nitrogen would be leached.

However, it should be noticed that even if these potential BMPs were adopted, it does not mean the groundwater quality will be definitely protected. For example, the nitrate-N standard for drinking water is 10 mg N L^{-1} (U.S. Dept. Health, Education, and Welfare, 1962). The total rainfall and irrigation water depth was 64.0 mm and 270.5 mm respectively, in the field experiment of Block 1 in 2006. If it is designed to make the solution concentration of nitrogen leaching equal to or less than 10 mg N L^{-1}, only about 33.5 kg N ha^{-1} was allowed for leaching. From Table 5-16, it can be seen that no potential treatment could approach this standard because the simulated average nitrogen leaching in season (NLCM) were all greater than 34 kg N ha^{-1}. And considering the inorganic N left in soil profile (NIAM), which was subject to leaching in a long term, the potential nitrogen leaching would be even higher. In this case, these potential BMPs probably would not be real BMPs any more, since they failed to definitely prevent nitrogen pollution.

Thus, it can be concluded that the nitrogen pollution is almost inevitable when planting sweet corn on the sandy soils in North Florida. However, the developed potential BMPs could significantly reduce the amount of actual nitrogen fertilizer application and consequently improve the pollution.

Ultimately, the developed potential BMPs need to be incorporated into actual farm production. To fully integrate these developed potential BMPs into a meaningful farm production plan requires an on-farm assessment and a quality assurance program. For on-farm assessment, all growers should perform an environmental assessment of their crop production operations, which will aid in identifying which BMPs should be considered to achieve the greatest economic and environmental benefit. Having a viable quality assurance program is very important to ensure that BMP implementation is occurring on track. The quality assurance program also serves to build overall program credibility and further provides assurance that BMPs are constructed or installed as designed (Florida Department of Agriculture and Consumer Services, 2005).

Thus, the simulation of potential BMPs with the CERES-Maize model is just a first step in BMP development for sweet corn production. If want to make these "potential BMPs" to be "real BMPs", more works such as education, assessment, and quality assurance have to be done in the future.

5.4 Summary and Conclusions

In this study, the CERES-Maize module of the DSSAT model was utilized as a platform to develop BMPs for sweet corn production in North Florida. The model was calibrated with the GLUE method. The expectation values of the posterior distributions of the input parameters were used as the nominal parameter set to conduct the simulations. Each treatment was simulated under 33 years' historical weather data.

A total of 24 irrigation treatments, 21 nitrogen fertilizer levels, 30 nitrogen splits, and 20 kinds of application amount were simulated. Finally six potential BMPs were selected according to their dry matter yields and amounts of nitrogen leaching. Some conclusions were drawn as follows.

Irrigation frequency and amount had strong influence on corn yield. For example, if the irrigation event was triggered by lower remaining available soil moisture (such as 10% and 20%), which means a longer interval between two irrigation events, the yield would be significantly reduced to less than 1,000 kg ha^{-1} due to water stress, which is only about one third of the acceptable dry matter yield.

The trend of increasing nitrogen leaching was obvious if irrigation events were more frequent and more water was applied in each event. For example, at 2 or 3 irrigation events a week with a depth of 25 mm, the simulated nitrogen leaching could be about 150 kg ha^{-1}, while the real nitrogen application was only about 230 kg ha^{-1}, indicating more than 65% of the applied nitrogen was leached.

More nitrogen applied resulted in more being leached. After 168 kg N ha^{-1}, the yield increment caused by increasing of N fertilizer approached zero, where the predicted dry matter yield was near 3,400 kg ha^{-1}. At the same time, nitrogen leaching kept steadily increased when more nitrogen was applied. For example, the amount of nitrogen leaching increased from 82 to 266 kg N ha^{-1} when nitrogen application level increased from 196 to 561 kg N ha^{-1}.

Nitrogen fertilizer split did not show a significant influence on yield if there was application of N during the small leaf stage or large leaf stage. However, splitting N applications showed a significant influence on N leaching. Except for a starter N application of 15 kg N ha^{-1} ,

the best splits were 0:1/4:3/4 and 0:1/3:2/3, because these fertigation schedules could best coincide the nitrogen need of sweet corn growth, especially from tasseling to maturity.

A small "application amount" could not increase yield very much if it was less than 70 kg N ha^{-1}, but it could decrease N leaching. However, too little N fertilizer applied in application amount could result in too many fertigation events, which would increase production cost. It seems 30, 40 or 50 kg N ha^{-1} could be the best "application amount", if the production cost was considered in addition to yield and nitrogen leaching.

If grower could apply both irrigation water and nitrogen fertilizer more frequently but with smaller amounts in each application, this would result in an acceptable yield and a lower level of nitrogen leaching.

The nitrogen pollution is almost inevitable when planting sweet corn on the sandy soils in North Florida. However, the potential BMPs could significantly reduce the amount of actual nitrogen fertilizer application and consequently improve the pollution. The simulation of potential BMPs with the CERES-Maize model is just a step in BMP development for sweet corn production. If want to make these "potential BMPs" to be "real BMPs", more works such as education, assessment, and quality assurance have to be done.

The CERES-Maize model verified itself as a powerful tool to develop practical strategies for agricultural production. It provided a convenient and economical way to obtain useful information on the interactions between crop, soil, weather and field management strategies.

However, the current model still has some disadvantages. First, the current CERES-maize model can only predict the yield quantity, but not the quality. According to the classification standard of USDA, sweet corn can be classified into (USDA, 1962) three levels, US #1, US #2 and Cull. The sum of US #1 and US #2 is the marketable yield. The current model could not do

such classification. For example, in the prediction results, even when there was completely no nitrogen application, there was still some level of yield, near 500 kg ha^{-1}. However, from field production experience in this region, when there is no nitrogen, the quality will be all culls with no marketable yield (see yield quality results in Chapter 4 for reference).

Second, no model is perfect. Uncertainty always exists in the prediction results. If the uncertainty is too great, the simulation results will be misleading. For example, the model was only run with a set of nominal values of input parameters. What will be the response of the selected BMPs under the uncertainties of input parameters and weather uncertainty? To answer this question, the selected BMPs must be investigated for their output uncertainties caused by weather and input parameter uncertainties. This will be the main topic of Chapter 6.

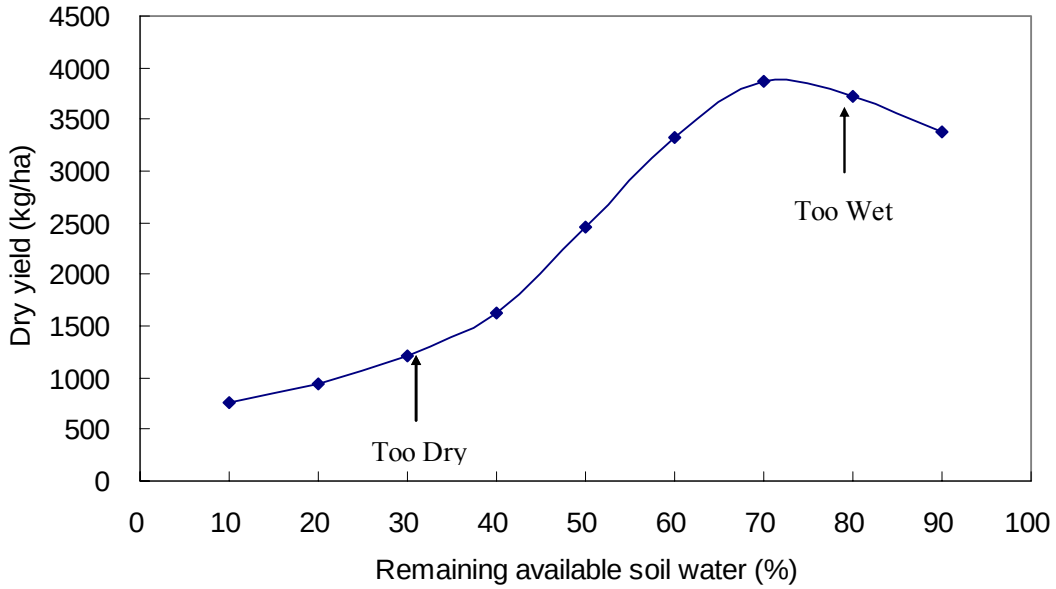


Figure 5-1. Response curves of yield to different remaining ASW

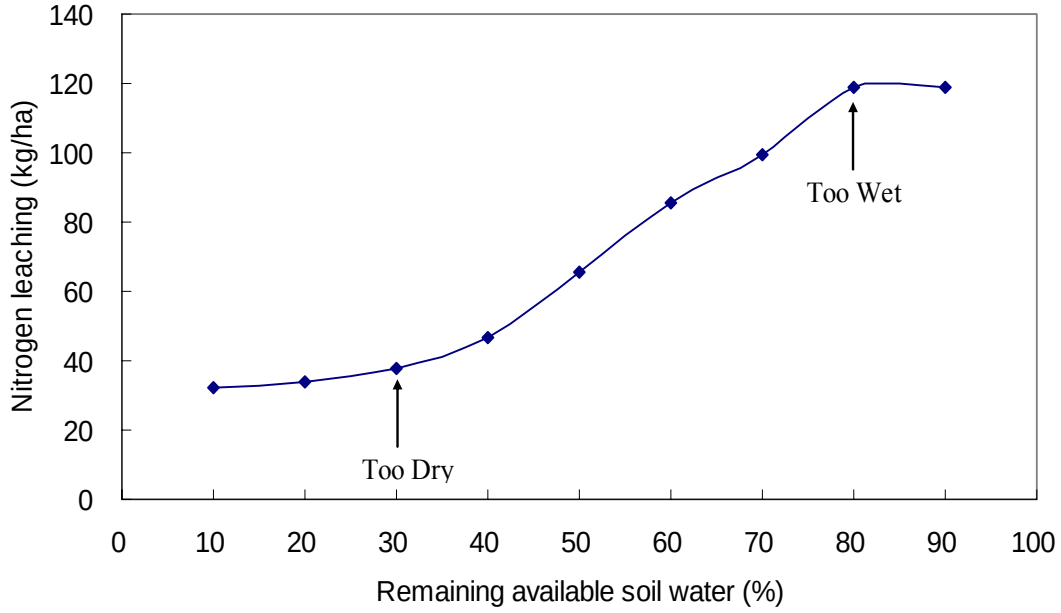


Figure 5-2. Response curves of nitrogen leaching to different remaining ASW

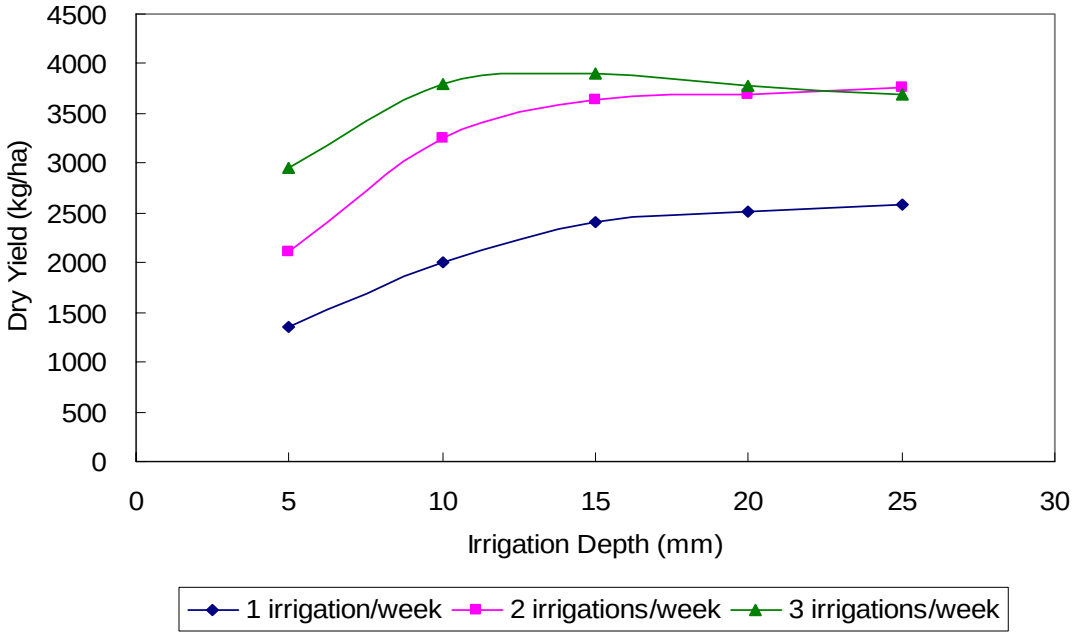


Figure 5-3. Response curves of yield to different irrigation depths

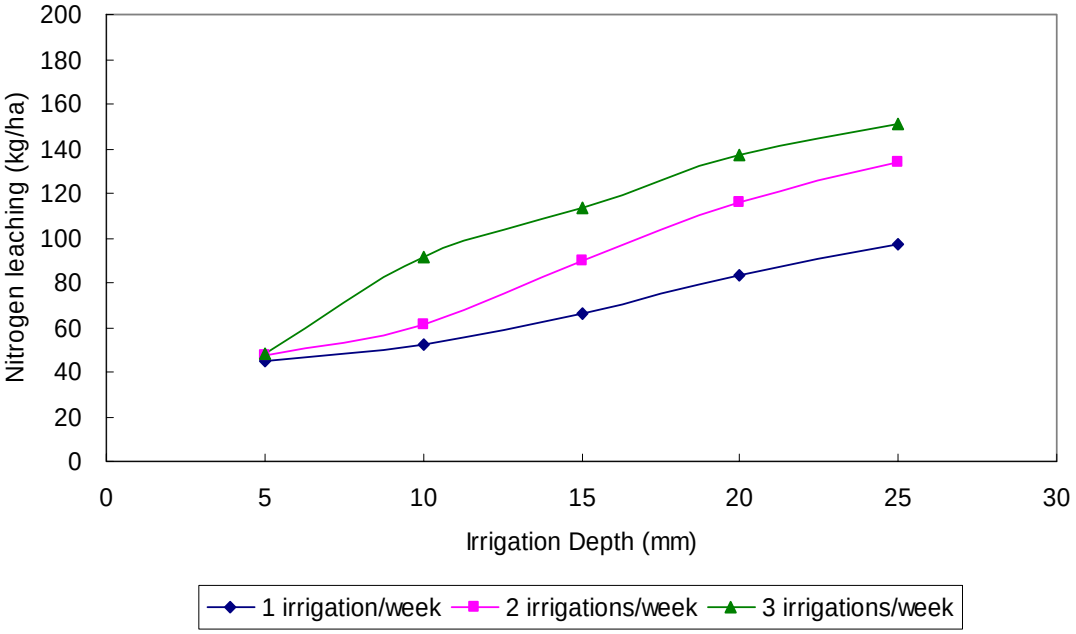


Figure 5-4. Response curves of nitrogen leaching to different irrigation depths

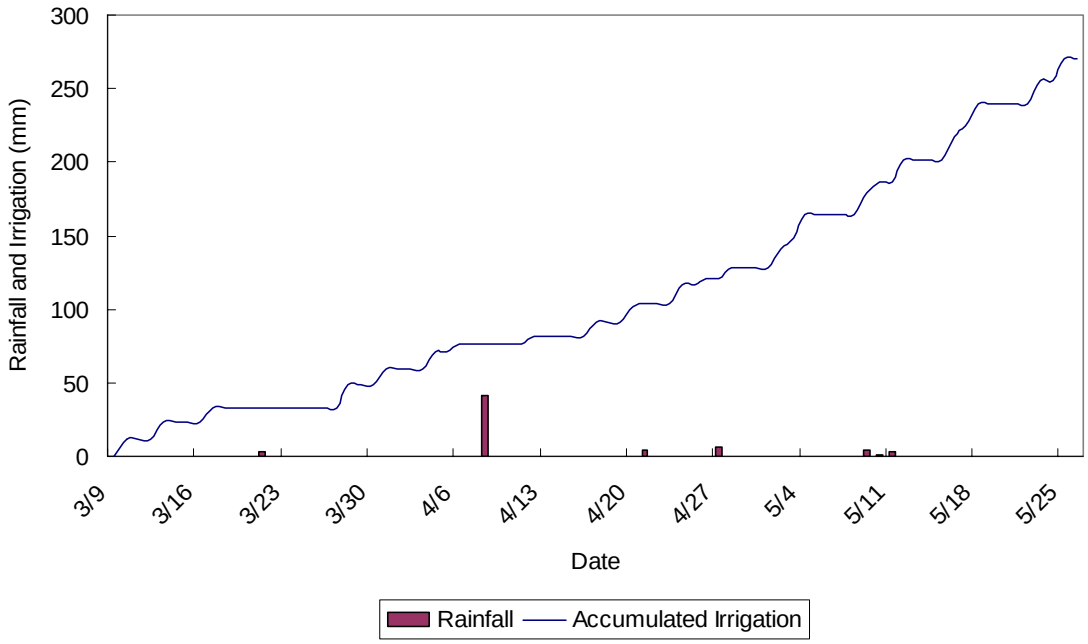


Figure 5-5. Rainfall and accumulated irrigations in East Half of Block1 in 2006

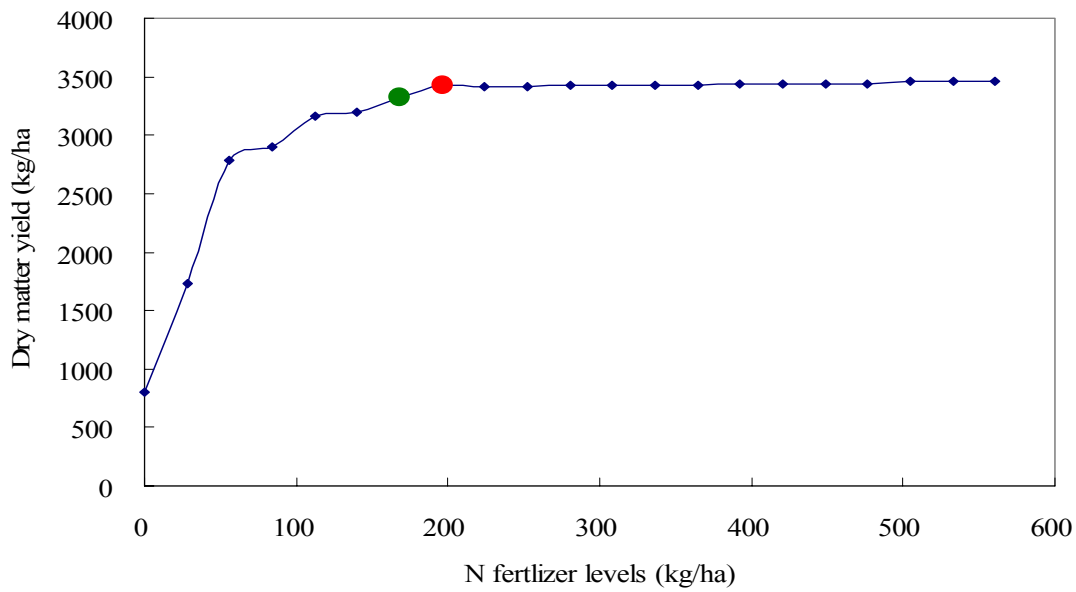


Figure 5-6. Response curves of yield to different N fertilizer levels. Green dot indicates the nitrogen fertilizer level of 168 kg N ha^{-1}, while red dot indicates the nitrogen fertilizer level of 196 kg N ha^{-1}.

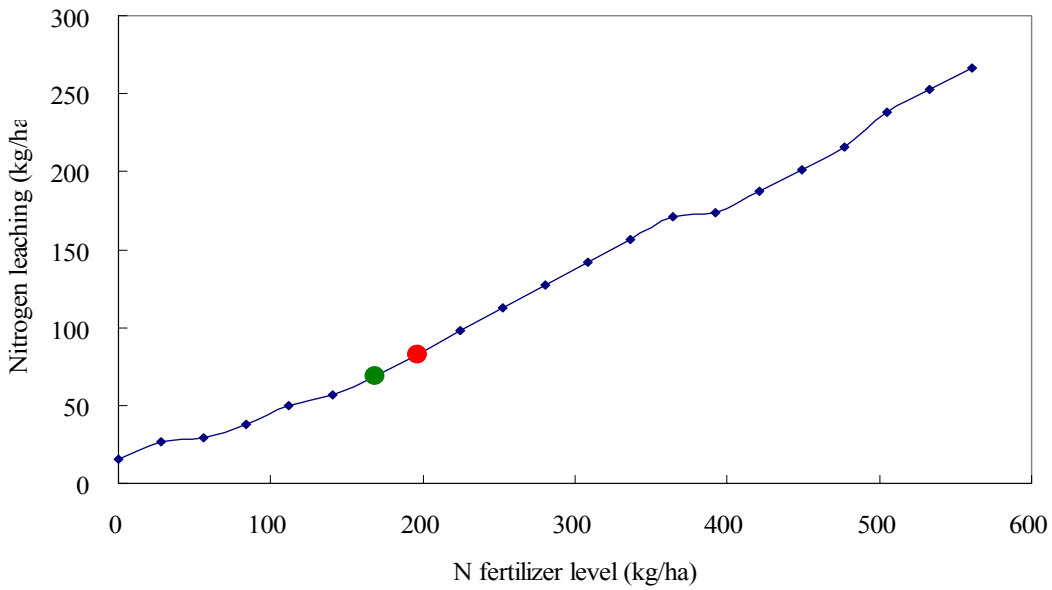


Figure 5-7. Response curves of nitrogen leaching to different N fertilizer levels. Green dot indicates the nitrogen fertilizer level of 168 kg N ha^{-1}, while red dot indicates the nitrogen fertilizer level of 196 kg N ha^{-1}.

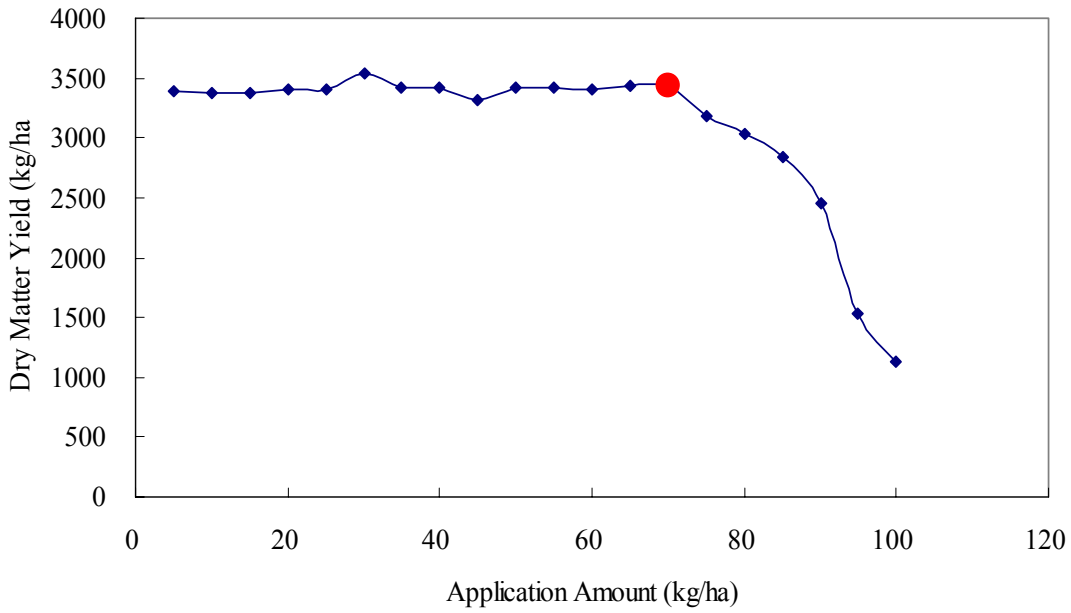


Figure 5-8. Dry yield vs. different N fertilizer application amount. Red dot indicates the "application amount" of 70 kg N ha^{-1} in each event.

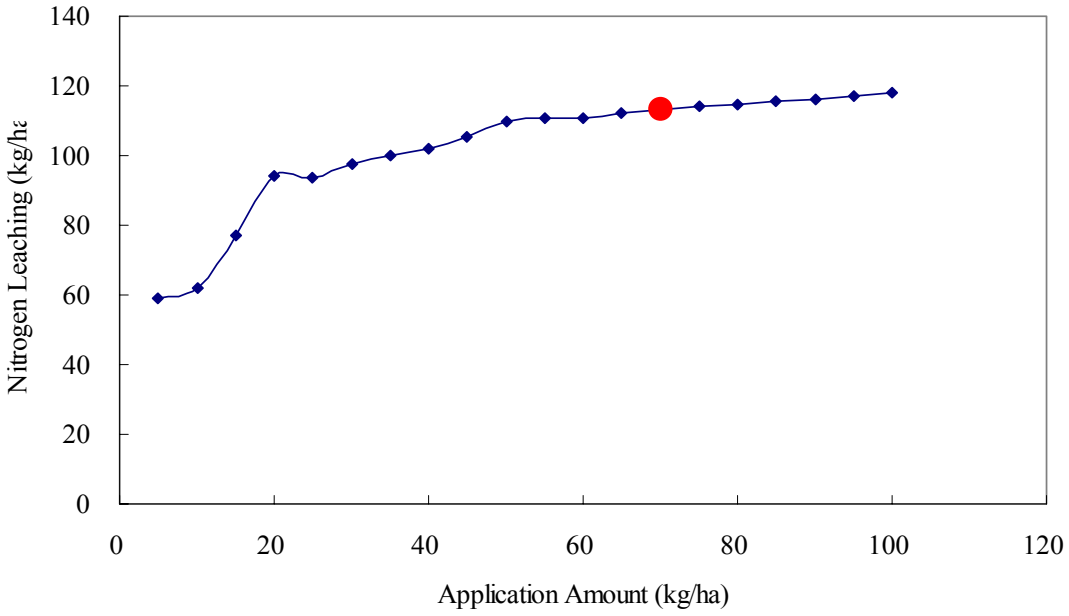


Figure 5-9. Nitrogen leaching vs. different N fertilizer application amount. Red dot indicates the "application amount" of 70 kg N ha^{-1} in each event.

Table 5-1. Expectation values of second posterior distribution of selected parameters[a]

Parameter	P1 ℃d	P5 ℃d	PHINT ℃d	SLDR -	SLRO -	SDUL cm^3/cm^3	SLLL cm^3/cm^3	SSAT cm^3/cm^3	SLPF -
Expectation	99.17	577.20	39.68	0.73	78.14	0.10	0.06	0.30	0.87

[a] ℃d means degree day.

Table 5-2. Soil properties of the experiment site

Depth (cm)	Texture	Clay (%)	Silt (%)	Sand (%)	Bulk Density (g/cm^3)	PWP (cm^3/cm^3)	FC (cm^3/cm^3)	Saturation (cm^3/cm^3)
0-15	Sandy soil	2.75	1.92	95.33	1.67	0.051	0.110	0.313
15-30	Sandy soil	2.56	2.35	95.08	1.69	0.061	0.117	0.317
30-60	Sandy soil	2.36	1.76	95.88	1.67	0.077	0.118	0.357

Table 5-3. Calculation of total available soil water (ASW) in the soil profile

Layer (cm)	FC	PWP	Soil Depth (mm)	ASW (mm)
0-15	0.110	0.051	150.0	8.7
15-30	0.117	0.061	150.0	8.4
30-50	0.118	0.077	200.0	8.3
Sum	-	-	-	25.4

Table 5-4. Irrigation treatments based on different MAD values

Treatment	MAD	ASW (mm)	Irrigation Depth (mm)
I1	90%	25.0	22.5
I2	80%	25.0	20.0
I3	70%	25.0	17.5
I4	60%	25.0	15.0
I5	50%	25.0	12.5
I6	40%	25.0	10.0
I7	30%	25.0	7.5
I8	20%	25.0	5.0
I9	10%	25.0	2.5

Table 5-5. Nitrogen splits used in BMP simulation

Treatment	Number of Irrgiation per week	Irrigation Day	Irrigation Depth (mm)
I10	1	Wednesday	5
I11	2	Monday and Thursday	5
I12	3	Monday, Wednesday, and Friday	5
I13	1	Wednesday	10
I14	2	Monday and Thursday	10
I15	3	Monday, Wednesday, and Friday	10
I16	1	Wednesday	15
I17	2	Monday and Thursday	15
I18	3	Monday, Wednesday, and Friday	15
I19	1	Wednesday	20
I20	2	Monday and Thursday	20
I21	3	Monday, Wednesday, and Friday	20
I22	1	Wednesday	25
I23	2	Monday and Thursday	25
I24	3	Monday, Wednesday, and Friday	25

Table 5-6. Nitrogen splits used in single factor simulation

No.	Split	Description	No.	Split	Description	No.	Split	Description
1	S1	0-0-1 [a]	11	S11	1/5-1/5-3/5	21	S21	1/3-2/3-0
2	S2	0-1/5-4/5	12	S12	1/5-2/5-2/5	22	S22	1/2-0-1/2
3	S3	0-1/4-3/4	13	S13	1/5-3/5-1/5	23	S23	1/2-1/2-0
4	S4	0-1/3-2/3	14	S14	1/5-4/5-0	24	S24	2/3-0-1/3
5	S5	0-1/2-1/2	15	S15	1/4-0-3/4	25	S25	2/3-1/3-0
6	S6	0-2/3-1/3	16	S16	1/4-1/4-2/4	26	S26	3/4-0-1/4
7	S7	0-3/4-1/4	17	S17	1/4-2/4-1/4	27	S27	3/4-1/4-0
8	S8	0-4/5-1/5	18	S18	1/4-3/4-0	28	S28	4/5-0-1/5
9	S9	0-1-0	19	S19	1/3-0-2/3	29	S29	4/5-1/5-0
10	S10	1/5-0-4/5	20	S20	1/3-1/3-1/3	30	S30	1-0-0

[a] "0-0-1" means nothing was applied in the small leaf stage, nothing in the large leaf stage, and all nitrogen in the fruit development stage except for a starter N application of 15 kg N ha^{-1}.

Table 5-7. Acreage, yield, production, and value of Florida sweet corn 1998-2006 (USDANASS, 2007)

Year	Acreage (acres) Planted	Harvested	Yield (lb acre^{-1})	Production (million lb.)
1998	41600	40300	14500	584.4
1999	39200	37800	14000	529.2
2000	40900	37400	15000	561
2001	40200	37900	14000	530.6
2002	41600	40800	14000	571.2
2003	39400	38800	14500	562.6
2004	38900	38700	15500	599.9
2005	35100	33600	16000	537.6
2006	33000	26300	18500	486.6
Average	38878	36844	15111	551.456

Table 5-8. Fresh yields of selected white sweet corn varieties in Clanton Ala. 1995-1996 (Simonne et al. 1999)

No.	Year	Place	Cultivar	Yield (kg ha^{-1})
1	1995-19967	Clanton, Ala.	Even Sweeter	14,726
2	1995-19967	Clanton, Ala.	Treasure	14,264
3	1995-19967	Clanton, Ala.	Snow White	12,400
4	1995-19967	Clanton, Ala.	Snow Belle	11,432
5	1995-19967	Clanton, Ala.	Fantasia	11,342
6	1995-19967	Clanton, Ala.	Starshine	10,495
7	1995-19967	Clanton, Ala.	Silver Queen	9,180
8	1995-19967	Clanton, Ala.	FMX 413	8,925
9	1995-19967	Clanton, Ala.	Silverado	8,675
10	1995-19967	Clanton, Ala.	Rising Star	8,291

Table 5-9. Fresh yields of sweet corn experiment in Springfield Tenn. 1993-1995 (Mullins et al., 1999)

Parameter	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
N rate (lb/acre)	0	0	2.50	5,600
	50	56	3.10	6,944
	100	112	3.6	8,064
	150	168	3.7	8,288
Cultivar				
Silver Queen	100	112	3.2	7,168
Incredible	100	112	4	8,960
Chanllenger	100	112	2.5	5,600
Year				
1993	100	112	2.9	6,496
1994	100	112	4.1	9,184
1995	100	112	2.7	6,048

Table 5-10. Fresh yields of sweet corn experiment in Eden Valley and Freeville, NY, 1998-2001 (Rangarajan et al., 2002)

Place	In-row spacing (inches)	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
		1998			
Eden Valley, NY	7	120	134.4	8.30	18,592
	8	120	134.4	8.00	17,920
	9	120	134.4	7.00	15,680
		1999			
Place	In-row spacing (inches)	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
Freeville, NY	7	100	112	8.30	18,592
	8	100	112	7.90	17,696
	9	100	112	7.10	15,904
	Cultivar	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
	Sweet Symphony	100	112	7.50	16,800
	Temptation	100	112	7.00	15,680
		2000			
Place	In-row spacing (inches)	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
Freeville, NY	6	120	134.4	6.50	14,560
	8	120	134.4	6.50	14,560
	Cultivar	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
	Temptation	120	134.4	7.10	15,904
	Sweet Symphony	120	134.4	6.10	13,664
	Seneca Spring	121	135.52	6.30	14,112
		2001			
Place	In-row spacing (inches)	N (lb acre^{-1})	N (kg ha^{-1})	Yield (tons acre^{-1})	Yield (kg ha^{-1})
Freeville, NY	6	120	134.4	6.50	14,560
	8	120	134.4	6.30	14,112
	Cultivar	N (lb/acre)	N (kg/ha)	Yield (tons/acre)	Yield (kg/ha)
	Temptation	120	134.4	6.70	15,008
	Sweet Symphony	120	134.4	6.90	15,456
	Seneca Spring	121	135.52	5.70	12,768

Table 5-11. Fresh yields of sweet corn experiment in Belle Glade, Florida, in spring of 2001 (Shuler, 2002)

Variety	Spacing (inches)	Yield (42 lb crt^{-1})	Yield (kg ha^{-1})
A&C '945'			
	9	364	17,123
	8	391	18,393
	7	304	14,300
	6	424	19,945
Rogers '9686'			
	9	468	22,015
	8	441	20,745
	7	497	23,379
	6	478	22,485
A&C 'Summer Sweet 8102 BC'			
	9	384	18,063
	8	422	19,851
	7	466	21,921
	6	527	24,790
Average			
	9	405	19,051
	8	418	19,663
	7	449	21,121
	6	476	22,391
'945'	-	391	18,393
'9686'	-	471	22,156
'8102'	-	449	21,121

Table 5-12. Summary of sweet corn yield in field experiments conducted in Florida (Hochmuth and Cordasco, 2000)

No.	Year	Location	N Rate (kg ha^{-1})	Yield (kg ha^{-1})	Source
1	1961, 1962	Gainesville, FL	125	11,252	Volk, 1962
2	1961, 1962	Gainesville, FL	168	14,360	Robertson, 1962
3	1976, 1977	Gainesville, FL	224	14,595	Rudert and Locascio, 1979
4	1991	Live Oak, FL	168	15,537	Hochmuth et al., 1992
5	1993	Gainesville, FL	168	17,279	Hochmuth, 1994
6	1996	Sanford, FL	252	15,349	White et al., 1996
7	1997	Gainesville, FL	168	21,375	Hochmuth, 1997a
8	1997	Gainesville, FL	168	15,019	Hochmuth, 1997b

Table 5-13. Selected irrigation strategies

No.	Title	Description
1	Irrigation 1	12.5 mm with a MAD of 50%
2	Irrigation 2	10.0 mm with a MAD of 40%
3	Irrigation 3	7.5 mm with a MAD of 30%
4	Irrigation 4	5.0 mm with a MAD of 20%
5	Irrigation 5	2 irrigation per week with a depth of 15 mm
6	Irrigation 6	3 irrigation per week with a depth of 10 mm

Table 5-14. Ranking of dry yield (HWAH) and nitrogen leaching (NLCM) under different N fertilizer application splits

HWAH Ranking			NLCM Ranking		
Split	Description	HWAH (kg ha^{-1})	Split	Description	NLCM (kg ha^{-1})
S12	1/5-2/5-2/5	3499	S4	0-1/3-2/3	80
S19	1/3-0-2/3	3494	S1	0-0-1	82
S4	0-1/3-2/3	3453	S2	0-1/5-4/5	84
S5	0-1/2-1/2	3447	S10	1/5-0-4/5	84
S20	1/3-1/3-1/3	3432	S3	0-1/4-3/4	87
S6	0-2/3-1/3	3429	S15	1/4-0-3/4	87
S3	0-1/4-3/4	3414	S5	0-1/2-1/2	88
S16	1/4-1/4-2/4	3406	S19	1/3-0-2/3	91
S11	1/5-1/5-3/5	3403	S11	1/5-1/5-3/5	94
S17	1/4-2/4-1/4	3376	S12	1/5-2/5-2/5	101

Table 5-15. Selected factors of N fertilizer application strategies

Total Amount		Split		Application amount	
Title	Description	Title	Description	Title	Description
N Fertilizer 1	140 kg N ha^{-1}	Split 1	0:1/4:3/4	Application amount 1	30 kg N ha^{-1}
N Fertilizer 2	168 kg N ha^{-1}	Split 2	0:1/3:2/3	Application amount 2	40 kg N ha^{-1}
N Fertilizer 3	196 kg N ha^{-1}	Split 3	0:1/2:1/2	Application amount 3	50 kg N ha^{-1}
N Fertilizer 4	212 kg N ha^{-1}				
N Fertilizer 5	252 kg N ha^{-1}				
N Fertilizer 6	280 kg N ha^{-1}				

Table 5-16. Ranking of average nitrogen leaching (NLCM) of combination management over 33 years (1958-1990)

No.	Irrigation	Total Nitrogen kg N ha^{-1}	Nitrogen Split	Application Amount kg N ha^{-1}	HWAH Mean kg N ha^{-1}	HWAH STDEV kg N ha^{-1}	NLCM Mean kg N ha^{-1}	NLCM STDEV kg N ha^{-1}	Percent of Leaching
1	5.0 mm-MAD 20%	196	0-1/4-3/4	30	3495	887	35	24	18%
2	7.5 mm-MAD 30%	196	0-1/4-3/4	30	3515	667	37	26	19%
3	5.0 mm-MAD 20%	196	0-1/4-3/4	40	3549	875	37	25	19%
4	5.0 mm-MAD 20%	196	0-1/3-2/3	30	3511	893	37	25	19%
5	5.0 mm-MAD 20%	196	0-1/4-3/4	50	3548	869	38	26	19%
6	5.0 mm-MAD 20%	196	0-1/3-2/3	40	3544	900	38	26	19%
7	5.0 mm-MAD 20%	196	0-1/4-3/4	40	3532	725	38	27	19%
8	5.0 mm-MAD 20%	224	0-1/4-3/4	30	3511	890	39	28	17%
9	7.5 mm-MAD 30%	196	0-1/3-2/3	30	3513	663	39	26	20%
10	7.5 mm-MAD 30%	196	0-1/4-3/4	50	3550	752	40	27	20%
11	7.5 mm-MAD 30%	196	0-1/3-2/3	40	3516	699	40	27	20%
12	7.5 mm-MAD 30%	224	0-1/4-3/4	30	3516	666	40	29	18%
13	10.0 mm-MAD 60%	196	0-1/4-3/4	30	3506	769	40	26	20%
14	5.0 mm-MAD20%	196	0-1/3-2/3	50	3556	888	41	27	21%
15	5.0 mm-MAD20%	224	0-1/4-3/4	40	3555	902	41	30	18%
16	5.0 mm-MAD20%	224	0-1/3-2/3	30	3524	899	41	29	18%
17	10.0 mm-MAD 60%	196	0-1/4-3/4	40	3589	829	42	27	21%
18	5.0 mm-MAD20%	196	0-1/2-1/2	30	3540	898	42	27	21%
19	10.0 mm-MAD 60%	196	0-1/3-2/3	30	3499	765	42	27	21%
20	7.5 mm-MAD 30%	196	0-1/3-2/3	50	3498	708	42	28	21%

Table 5-17. Selected potential BMPs for sweet corn production

No.	Irrigation	Nitrogen Level kg N ha^{-1}	Nitrogen Split	Application amount kg N ha^{-1}
1	5.0 mm-MAD 20%	196	0-1/4-3/4	30
2	5.0 mm-MAD 20%	196	0-1/3-2/3	30
3	7.5 mm-MAD 30%	196	0-1/4-3/4	40
4	7.5 mm-MAD 30%	196	0-1/3-2/3	30
5	5.0 mm-MAD 20%	224	0-1/4-3/4	30
6	7.5 mm-MAD 30%	224	0-1/4-3/4	30

CHAPTER 6
UNCERTAINTY ANALYSIS OF POTENTIAL SWEET CORN BMPS UNDER WEATHER AND INPUT PARAMETER VARIABILITY

6.1 Introduction

Techniques of system analysis and crop growth modeling are increasingly being used in agriculture for estimating production potential, agro-technology transfer, designing plant types, strategic and tactical decisions, and setting research priorities (Teng & Penning de Vries, 1992; Penning de Vries & Teng, 1993). Dynamic process based models simulate daily increase in crop growth through a number of processes such as photosynthesis, dry matter partitioning, crop development and transpiration as affected by soil and weather factors and crop management (Aggarwal, 1995).

However, uncertainties in model outputs always exist. Models can at best only represent a current understanding of biological systems; yet they do highlight where information and understanding are lacking (Boote et al., 1996). This is because models are all simplified representations of reality. Even if the structures of the model equations are perfect, there will be errors in model output due to inaccuracies both in the initial conditions and in the values of model parameters and forcing functions (Pei and Wang, 2003). In other words, uncertainty in model prediction is unavoidable. Clarification of the inherent uncertainties and quantification of uncertainties in modeling results is thus critical for improving model prediction methods and identifying effective management strategies (Van Straten and Keesman, 1991). Linkov and Burmistrov (2005) defined uncertainty of models as following three broad categories: (1) Parameter uncertainty—uncertainty in the value of input parameters in a model; (2) Model uncertainty—uncertainty about a model structure (i.e., the relevance of simplifying assumptions and mathematical equations); (3) Scenario uncertainty—uncertainty regarding missing or incomplete information to fully define the system under study.

Much of the uncertainty in model outputs can be ascribed to incomplete information on input values relating to crop, soil and weather factors, and agronomic management date required to run the model (Burrough, 1989; Richter & Sondgerdth, 1990). Crop parameter values could be significantly uncertain due to imperfect knowledge of those caused by random errors related to size and number of observations and systematic errors related to bias in the experimental, measurement, observation and calibration procedures. In addition, crop input parameters may exhibit spatial and temporal variability. Recognizing model parameter variability, biologists generally report model simulation results with standard deviations or standard errors that describe variation associated with the measured variable (Aggarwal, 1995).

Soil parameters required by the crop models have also shown spatial and temporal variation and might have considerable measurement errors. These inputs are often estimated, e.g. using Geographical Information Systems (Richardson, 1984; Nix, 1987). The stochastic nature of many soil parameters are expected to result in uncertainty of the outputs of crop models (Aggarwal, 1995).

The weather during the growing season affects growth and development through accumulative dynamic growth, and the final value of crop characteristics of interest, e.g. grain yield (Lawless and Semenov, 2005). Weather has been shown to have a strong influence on the most suitable crop type and to a certain extent the most suitable cultivar at a given site (Jagtap et al., 2002).

Heinmann et al. (2002) showed that the accuracy of rainfall observations was critical for the simulation of crop yield and that the variability of simulated estimates was directly correlated to the accuracy of model inputs. Xie et al. (2003) evaluated the importance of input variables on the yield estimates made for maize and sorghum by the ALMANAC model. They concluded that,

in a dry land environment, rainfall and then solar radiation were the most important of the meteorological variables for non-irrigated crops.

Solar radiation is a key variable since it is used, amongst other things, as part of the estimation of evapotranspiration (ET) and biomass accumulation. Bellocchi et al. (2003) tested the impacts of three air-temperature-based methods for estimating solar radiation data on the estimates of reference crop ET and subsequent determination of above ground biomass at 20 locations worldwide. The results showed that each source had different levels of performance, in terms of yield estimates, with each geographical location and season patterns.

In previous research, the CERES-Maize model of the DSSAT model (Jones et al., 2003) was used to develop nitrogen (N) best management practices (BMPs) for sweet corn *(Zea mays L.)* production on the sandy soil in North Florida (see Chapter 5 details). Six management combinations of different irrigation and N fertilizer application strategies were selected as potential BMPs. The CERES-Maize model requires soil parameters, genotype parameters, and four kinds of climatic parameters as follows: daily rainfall, minimum daily temperature, maximum daily temperature, and daily solar radiation. As discussed above, these potential BMPs inevitably suffered from the uncertainties caused by these input parameters, since all of them were selected with a set of nominal input parameters. Will these selected potential BMPs work under other possible weather conditions, especially some extreme climate situations? What will be the variance of the relevant model outputs? To answer these questions, an uncertainty analysis of model outputs should be done.

The main objective of this research was to quantify the total uncertainties in simulated dry matter yields (HWAH, kg ha^{-1}) and accumulative nitrogen leaching (NLCM, kg ha^{-1}) of the six

selected potential BMPs when simulating them with the CERES-Maize model. Two sources of uncertainties were concerned: the input parameters (genotype and soil) and the weather data.

In addition, a similar simulation was also conducted for one real field management strategy with the CERES-Maize model so as to compare the difference between the potential BMPs and the real management practice.

6.2 Materials and Methods

6.2.1 Field Experiment and Weather Data

Except for the information about irrigation and nitrogen fertilizer application provided by the selected potential BMPs (see Chapter 5 for details), some additional management information was required by the CERES-Maize model as fundamental inputs to conduct simulations. These inputs include planting date, planting population density, planting depth, micro nutrient application, and harvest date etc.

In this study, this kind of fundamental information was obtained from the field experiment in Block 1 in the spring of 2006 at the Plant Science Research and Education Unit, the University of Florida. The unit is located in Pine Acres (29.4094^{o}N, 82.1777^{o}W, 20.746 meters above sea level), Marion County, Florida, U.S. (Judge et al., 2005). See Chapter 3 and 5 for details about the field experiment in Block 1.

The climate in Florida is subtropical and is characterized by long, warm summers and mild winters. However, there are large variations between locations and from year to year. For example, average annual rainfall (1971-2000) is 1,448 mm at DeLand, 1295 mm at Sanford, and 1270 mm at Ocala. Most of the rainfall occurs in June-September, with some months having as much as 510 mm of rainfall. About 70-75 percent of the rainfall commonly returns to the atmosphere as evapotranspiration (Sumner, 1996; Knowles, 1996).

A complete weather data set, which included precipitation, maximum temperature, minimum temperature, and solar radiation for model simulations, was not available for Citra, FL, where the experiment site is located. In the absence of site-specific data for his specific experiment field, a model user has several choices of weather data source: (1) historical weather data from nearby alternative weather stations; (2) artificial data from stochastic weather generators e.g. LARS-WG (Barrow and Semenov, 1995), ClimGen (Stockle et al., 2001).

In this study, 33 years (1958-1990) of historical weather data at Gainesville, FL, the USA, which is about 32 km from the experiment site of this research, were chosen as the nearest complete weather data. These measured weather data were provided by the McNair Bostick Simulation Lab of the Department of Agricultural and Biological Engineering, the University of Florida.

6.2.2 Uncertainty of Input Parameters

In previous research, the generalized likelihood uncertainty estimation (GLUE) method was used to calibrate the CERES-Maize model of the DSSAT model (see Chapter 3 for details). In contrast to the commonly used methods of model calibration, the GLUE method gives a distribution of the input parameters rather than a unique parameter set that can optimize all of the observations and relevant predictions. Thus, the calibrated model still contains uncertainty caused by input parameters, but the degree of uncertainty is significantly reduced by the GLUE simulations.

The reduced uncertainty of the input parameters of soil and genotype can be presented by their variance and mean value as shown in Table 6-1. The distribution of the selected parameter is a multivariate normal distribution, except for parameter SLPF, which was assigned a uniform distribution.

6.2.3 Selected Potential BMPs

Six potential BMPs were selected in previous research (Table 6-2, See Chapter 5 for details). The details of each BMP were explained as follows. For example, in BMP1 irrigation "5.0 mm-MAD 20%" meant that a 5.0 mm-irrigation was triggered by a value of maximum amount of depletion (MAD) of 20% in the top 50 cm soil profile, i.e. 80% of the available soil water (ASW) was remaining in that spoil profile. The ASW was defined as the water between water holding capacity and permanent wilting point of the soil.

Nitrogen amount is the total fertilizer N applied in each growth season of sweet corn. Nitrogen split determines how much of the total N fertilizer should be applied during the small leaf stage, large leaf stage, and ear development stage, respectively. Application amount is how much N fertilizer should be applied into the field in each fertilization event.

6.2.4 A Grower Practice of N Fertilizer and Irrigation Management

It is necessary to compare these potential BMPs with the actual N fertilizer and irrigation management strategies utilized by sweet corn growers for their simulated dry matter yield (kg ha^{-1}) and accumulative amount of nitrogen leaching (kg ha^{-1}), so as to determine whether these potential BMPs have advantages in decreasing N leaching and maintaining an acceptable yield.

An example of N fertilizer and irrigation program was borrowed from the 2003 sweet corn crop in an EPA319 demonstration project (Hochmuth, 2003). The project was conducted in Suwannee Farms, O'Brien, FL, which is about 150 km from Pine Acres, the field experiment site of this study. Most of the soil at Suwannee Farms is considered a Blanton Fine Sand or a Penney Fine Sand according to the Suwannee County Soil Survey. Both of these soils are very similar, and for practical purposes can be considered the same for nutrient and irrigation management.

The IFAS nitrogen fertilizer recommendation for sweet corn is 224 kg N ha^{-1}, allowing for an additional 34 kg N ha^{-1} for a leaching rain. However, in the "EPA319 project", total nitrogen application of 302 kg N ha^{-1} was targeted.

Liquid nitrogen sources that can be injected through the irrigation system were recommended and could greatly improve nutrient efficiency of placement and utilization. Applications through the irrigation system should traditionally target 11 to 22 kg N ha^{-1}, however in the "EPA319 project", the goal was to maintain applications for approximate 45 kg N ha^{-1} per fertigation event. The detailed information about the N management is specified in Table 6-3.

When reducing total nitrogen rates from a production program, irrigation management becomes critical, and will become the major factor that keeps the nutrient management program on track. Nitrogen is easily leached, especially on the sandy soils common to much of Florida (Hochmuth and Hanlon, 2000).

The following irrigation recommendations (Table 6-4) are designed to provide adequate moisture for the crop while minimizing leaching potential of nitrates. These recommendations are also dependent on a highly efficient irrigation system that can apply specific irrigation amounts. The guide is designed without consideration of rainfall. Any sufficient moisture contribution from rainfall should replace the irrigation recommendation suggested for that day or time period. Actual irrigation amounts should be increased or decreased depending on actual weather conditions and crop growth rate.

This actual grower practice of nitrogen fertilizer and irrigation management was simulated with the CERES-Maize model under the same fundamental inputs derived from the field experiment in Block 1, Citra, FL. The model was run with the same input parameter distribution

obtained in Chapter 3 and the weather data described in Section 6.2.1. Then the uncertainties in the predicted dry yield and nitrogen leaching were analyzed.

Finally the results of uncertainty analysis were compared with the six selected potential BMPs mentioned above in order to make sure that the selected potential BMPs could actually reduce nitrogen leaching amount while maintaining an acceptable yield.

6.2.5 Monte Carlo Simulation

Several methods have been used to account for uncertainty, such as Kalman filtering (Peter, 1979; Ahsam and O'Connor, 1994), first-order analysis (FOA) (Chaubey et al., 1999; Haan and Skaggs, 2003a, 2003b), Monte Carlo simulation (MCS) (Hession et al., 1996; Haan and Skaggs, 2003a, 2003b; Ogle et al., 2003), Latin hypercube sampling (LHS) (Pebesman and Heuvelink, 1999), and generalized likelihood uncertainty estimation (GLUE) (Beven and Binley, 1992; Beven, 1993). Among these methods, the Monte Carlo method is a "brute-force" approach to estimate the probability density function of output variables from the probability density functions of input variables (Hanna et al., 1997). It is the most commonly used non-structured method. The Monte Carlo technique generates an estimate of the overall uncertainty in the predictions due to all the uncertainties in the input parameters, regardless of interactions and quantity of parameters (Macdonald and Strachan, 2001).

In Monte Carlo simulations, the input parameters are described by probability distributions, and a single set of input data is randomly generated based on the distributions. This single data set is run through the model and an output data set is obtained. The results of the run are stored and a new set of input data is generated. Multiple simulations, typically thousands, are carried out until the results of a new run do not affect the probability distribution of the output variable. The number of simulations depends on the number and variability of input parameters, and the required confidence in the output probability distribution (Graettinger and Dowding, 2001).

A Monte Carlo simulation was carried out for the six selected potential BMPs and one actual management practice (described in Section 6.2.3 and 6.2.4), under the uncertainties of input parameters and weather. The main procedure were as follows: (1) generate 1,000 random parameter sets according to the statistical properties specified in Table 1; (2) run the model for the six potential BMPs and the actual grower practice with these 1,000 parameter sets under 33 years' (1958-1990) measured weather data and record the relevant outputs, so 231,000 simulations were performed; and (3) process the output files and plot the results with the software Matlab.

6.3 Results and Discussion

6.3.1 BMP Comparison

The mean values and standard deviations of simulated sweet corn dry yield and nitrogen leaching amounts were summarized for three uncertainty scenarios: under only parameter uncertainties, under only weather uncertainties, and under both parameter and weather uncertainties (Table 6-5). When only considering parameter uncertainties, the weather condition was fixed as 1958, since it is the first yield of simulation. When only considering weather uncertainties, the parameter set was set as the nominal set, which was derived from the second-round posterior distribution of GLUE simulation (Table 6-1).

To tell which pairs of outputs of the treatments are different, so as to determine which one was more suitable, a one-way analysis of variance (ANOVA) was conducted for the scenarios of under only parameter uncertainty, under only weather uncertainty, and under both parameter and weather uncertainties (Table 6-5).

When under only parameter uncertainty, the six potential BMPs and the actual grower practice show some difference in predicting dry matter yield and amount of nitrogen leaching. The actual grower practice has the highest value of nitrogen leaching and a moderate dry yield.

However, for the scenarios of under only weather uncertainty and under both parameter and weather uncertainties, the actual grower practice shows a significant difference in nitrogen leaching, much higher than the six potential BMPs, while there is no difference among the BMPs. For dry yield, all the BMPs and actual grower practice show no great difference, i.e. they give the similar yields.

It can be seen in Table 6-5 that the weather was the dominant uncertainty contributor. This was because after two rounds of GLUE simulation, the uncertainties existing in input parameters were minimized (see Chapter 3 for details). However, the uncertainties of climate could not be reduced artificially. Hence, when simulating the selected BMPs both with respect to parameter and weather uncertainties, weather contributed the most part of uncertainties in model outputs.

When both considering weather and parameter influences, the predicted means of dry matter yield per treatment ranged from about 3,310 kg ha^{-1} to 3,505 kg ha^{-1}. The values of coefficient of variation (CV) of the predicted yields only using the generated weather data were all in the range of 25%. For predicted cumulative nitrogen leaching, the predicted mean values per treatment ranged from about 30 to 76 kg ha^{-1}. The values of CV were all in the range of 80%, more than three times the variability of predicted dry matter yields.

It could be concluded that weather variability could cause higher uncertainty in model outputs of nitrogen leaching than in yields. This was because nitrogen leaching was more sensitive to weather conditions (especially rainfall), than yield.

According to the ANOVA result, it can also be concluded that the real case that applied 270 lb N $acre^{-1}$ could not increase yield, but could increase nitrogen leaching significantly, i.e. the selected potential BMPs did a better job in reducing nitrogen leaching while obtaining an acceptable yield. For realistic production, it seems that BMP3 and BMP4 could be good choices

since they had the highest yields and relatively higher reliability. In BMP3 and BMP4, 196 kg N ha^{-1} (175 lb N $acre^{-1}$) was required, but this amount of nitrogen fertilizer was obtained based on the assumption that the fertilizer application efficiency was 1.0. Actually this efficiency could be not obtained due to irrigation uniformity, crop canopy interception, and effects of wind. So in realistic production, an extra increment should be considered, for example a 10% increase. This result supports the IFAS (Institute of Food and Agricultural Sciences of the University Of Florida) recommendation of N fertilizer for sweet corn production, which is 224 kg N ha^{-1} (200 lb N $acre^{-1}$) (Hochmuth, 2000).

6.3.2 Output Uncertainty Plot

The distributions of the predicted annual dry corn yields for each treatment over the 33-year simulation period are shown in Figure 6-1, while the distributions of the predicted average annual accumulative nitrogen leaching for each BMP treatment are shown in Figure 6-2.

These figures visualize the uncertainties of model output when both considering uncertainties in input parameters (genotype and soil) and weather data. In each figure, each predicted corn yield or nitrogen leaching of one year was an average over 1,000 different simulations with 1,000 different sets of randomly generated input parameters were used. The 90% confidence interval (CI) estimated from the 5% and 95% quantiles of the cumulative distribution function (CDF) were used as the uncertainty limits of the predictions (Haan and Skaggs, 2003; Sabbagh and Fox, 1999).

From Figure 6-1, it can be seen that the distributions of the predicted dry yields under the six potential BMPs and the actual grower practice all approximately follow a normal distribution, especially for BMP3, BMP4, and BMP6. The 90% CI range of dry yield for BMP1, BMP2, BMP5, and actual grower practice is 1,500 kg ha^{-1} (from about 2,800 to 4,300 kg ha^{-1}). For

BMP3, BMP4, and BMP6, the value of 90% CI range of dry yield is also 1,500 kg ha^{-1}, but changes from about 2,800 to 4,300 kg ha^{-1}.

The values of 50% quantile of the seven practices are all between 3,300 and 3,400 ka ha^{-1}, which is a little bit higher than the measured dry yield in field experiment in this study (Table 4-15 in Chapter 4), science there was no water stress under these BMPs.

From Figure 6-2, it can be seen that the distributions of the predicted amounts of nitrogen leaching under the six potential BMPs and the actual grower practice all fail to follow a normal distribution. All of the distributions skew to the left side. Thus, it is better to find another kind of distribution to describe the predicted nitrogen leaching in the DSSAT model.

The 90% CI range of nitrogen leaching during the season for the six selected potential BMPs is wide, more than 70 kg N ha^{-1} (from about 10 to 80 kg ha^{-1}). The 50% quantile is all around 30 kg N ha^{-1}. The predicted mean values (Table 6-5) of these BMPs were much lower than the estimated ones in field experiment (Table 4-19 in Chapter 4). This is because the predicted nitrogen leaching here was only the nitrogen completely leached during season, which did not include the organic nitrogen left in the soil after maturity. If considering the sum of nitrogen leaching during the season and inorganic nitrogen in soil profile in model prediction as the potential nitrogen leaching, the predicted and estimated amounts of potential nitrogen leaching would be much closer (See Chapter 4 details).

The 90% CI range of nitrogen leaching for the actual grower practice is much wider, more than 120 kg N ha^{-1} (from about 10 to 130 kg ha^{-1}). The 50% quantile is around 55 kg N ha^{-1}. The mean value nitrogen leaching of grower practice (Table 6-5) is also much lower than the measured values (Table 4-19 in Chapter 4) due to the same reason mentioned above. However, the result can also support the assumption that when more nitrogen is applied, more will be

leached, i.e. the selected BMPs can reduce nitrogen leaching compared with the actual grower practice.

6.3.3 Output Uncertainty over Time Range of 1958-1990

It is necessary to show how the corn yield and nitrogen leaching changed in the simulation years, since it could give model users an idea of what level the yield and nitrogen would change if a special BMP strategy was used across in a range of actual weather conditions. For convenience, only the selected BMP1 was chosen as an example. It is sure that the similar analysis can be conducted for other selected BMPs and the actual grower practices. Figure 6-3 shows the simulated 10% and 90% confidence limits of the average yearly corn yields for the study period for treatment BMP1, while Figure 6-4 shows similar information of the average yearly nitrogen leaching.

From Figure 6-3, it can be seen that the average yields ranged between 2,500 kg ha^{-1} and 4,500 kg ha^{-1}, considering both the weather and input parameter uncertainties. Cumulative nitrogen leaching ranged between 10 and 90 kg N ha^{-1} (Figure 6-4). There exist great differences among the amounts of cumulative nitrogen leaching in different years. For example, the nitrogen leaching amount could be as high as about 90 kg N ha^{-1} in 1959, but it decreased to 40 kg N ha^{-1} in 1960 and 1961. A 50 kg N ha^{-1} difference exists between these continuous years.

The variations in the curves in Figure 6-4 can be explained by the uncertainties in weather conditions. For example, in Figure 6-4, there are two obvious peaks in nitrogen leaching in 1959 and 1984. The respective cumulative rainfall in the growth season of sweet corn (90 days after planting date of March 8th) in 1959 and 1984 was 591 and 341 mm. In 1964 and 1981, when there was the lowest amount of nitrogen leaching, the respective cumulative rainfall was 193 and 130 mm. These dry year cumulative rainfall amounts were only about one third of those in 1959 and 1984. For other years (e.g. 1971 and 1980), the cumulative rainfall was between 210 and 310

mm. These curves confirmed the sensitivity of nitrogen leaching to weather conditions, especially rainfall.

However, the yield variations shown in Figure 6-3 were difficult to explain with a single factor. The collective influence includes temporal variations of temperature, solar radiation, and rainfall. For example, in 1987 the predicted yield was low (less than 2,500 kg ha^{-1}). One reason was probably because of the low temperature in the early growth season. The average maximum and minimum temperature in the first 2 weeks of the growth season of 1987 was about 23.2 ℃ and 9.1 ℃, respectively, but the corresponding temperatures in 1986 was about 26.1 ℃ and 12.5 ℃, i.e. 3 ℃ higher than 1987. The cold weather could inevitably retard or harm the corn seedlings, and finally reduce the yield. And the accumulated rainfall in growth season was about 324.2 mm that year, which resulted in a large amount of nitrogen leached and unavailable for corn consumption.

6.4 Summary and Conclusions

Outputs of crop models may be uncertain depending on the range of uncertainty of the input parameters (genotype and soil) and weather data. However, crop models still remained important in applications related to estimation of production potentials, strategic and tactical decisions and agricultural technology transfer, since they are efficient, quantitative tools for the integration of complex and dynamic interactions of crops with climatic, soil, and agronomic environments.

In this study, six selected potential best management practices and a real N fertilizer application and irrigation management case were investigated for uncertainties of yield and accumulative nitrogen leaching caused by weather and input parameter uncertainty. Some conclusions were drawn as follows.

The weather was the dominant uncertainty contributor to model outputs such as dry matter yield and nitrogen leaching during season, which was because after two rounds of GLUE simulation, the uncertainties existing in input parameters were minimized (see Chapter 3 for details). However, the uncertainties of climate could not be reduced artificially.

Weather variability could cause higher uncertainty in model outputs of nitrogen leaching than in yields. This is because nitrogen leaching was more sensitive to weather conditions (especially rainfall), than yield.

After comparison, the selected BMP3 (an irrigation of 7.5 mm with a MAD value of 30%, a total of 196 kg N ha^{-1} with a split of 0-1/4-3/4 and an application amount of 40 kg N ha^{-1}) and BMP4 (an irrigation of 7.5 mm with a MAD value of 30%, a total of 196 kg N ha^{-1} with a split of 0-1/3-2/3 and an application amount of 30 kg N ha^{-1}) could be good choices for real sweet corn production, compared with other BMPs and the actual grower practice.

The simulation results support the recommendation of IFAS about N fertilizer for sweet corn production, which is 224 kg N ha^{-1} (200 lb N $acre^{-1}$) if fertilizer application efficiency was considered.

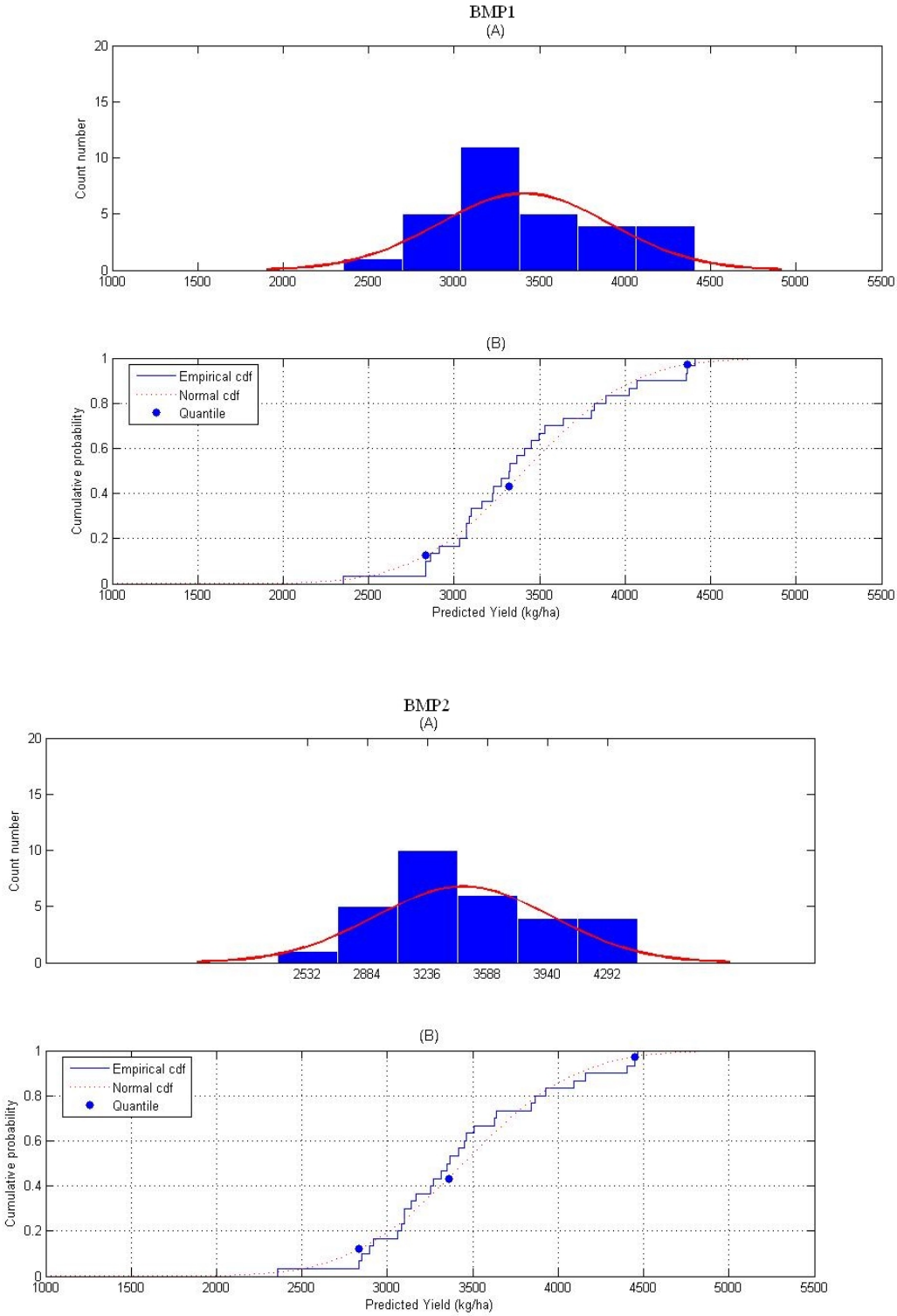


Figure 6-1. Histogram (A) and cumulative distribution (B) of predicted average annual dry yield of the six selected potential BMPs and the actual grower practice both under weather and input parameter uncertainty. The red curve in each histogram is the fitted normal distribution curve. The 5%, 50% and 95% quantiles are shown as dots in (B).

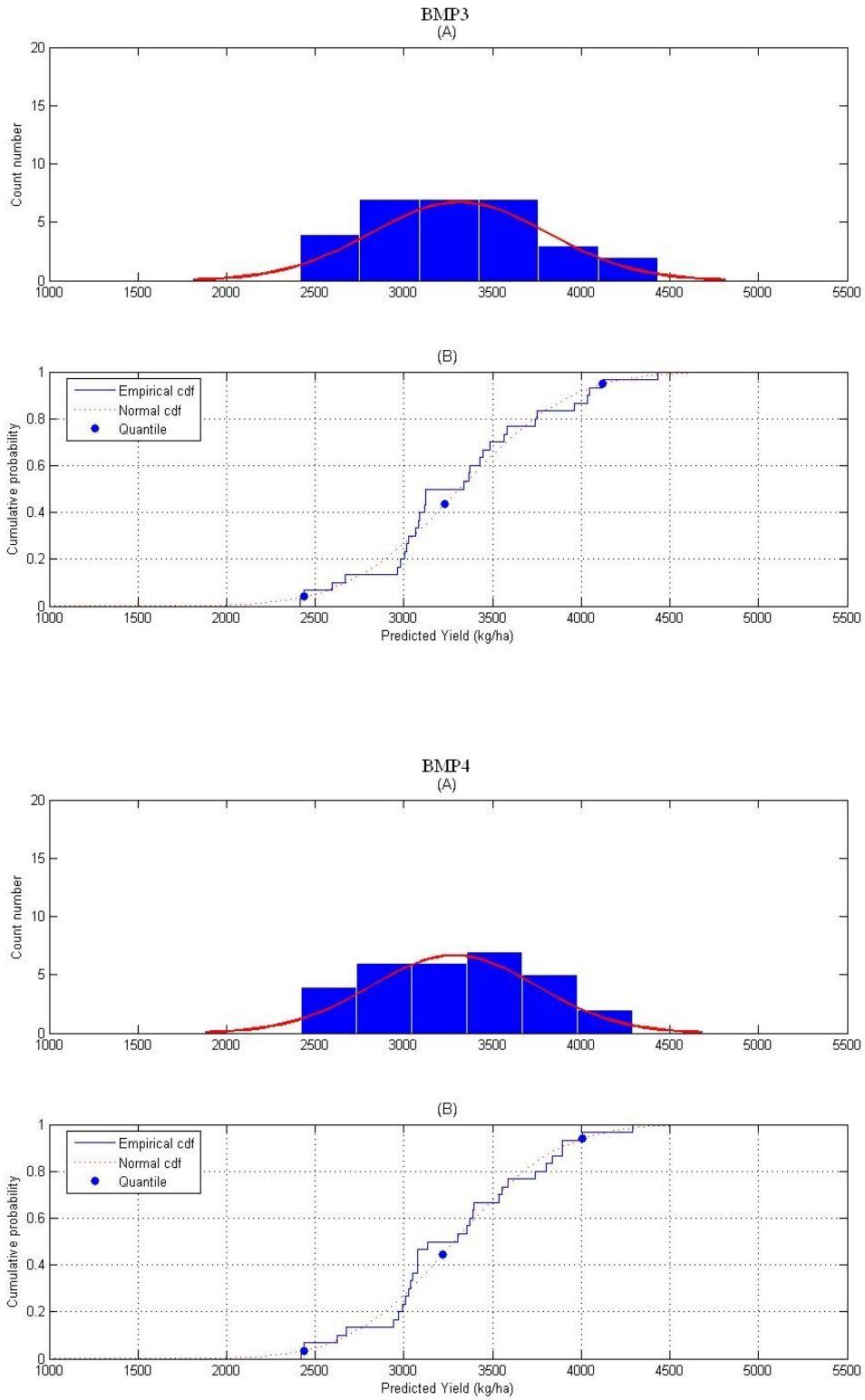


Figure 6-1. Continued

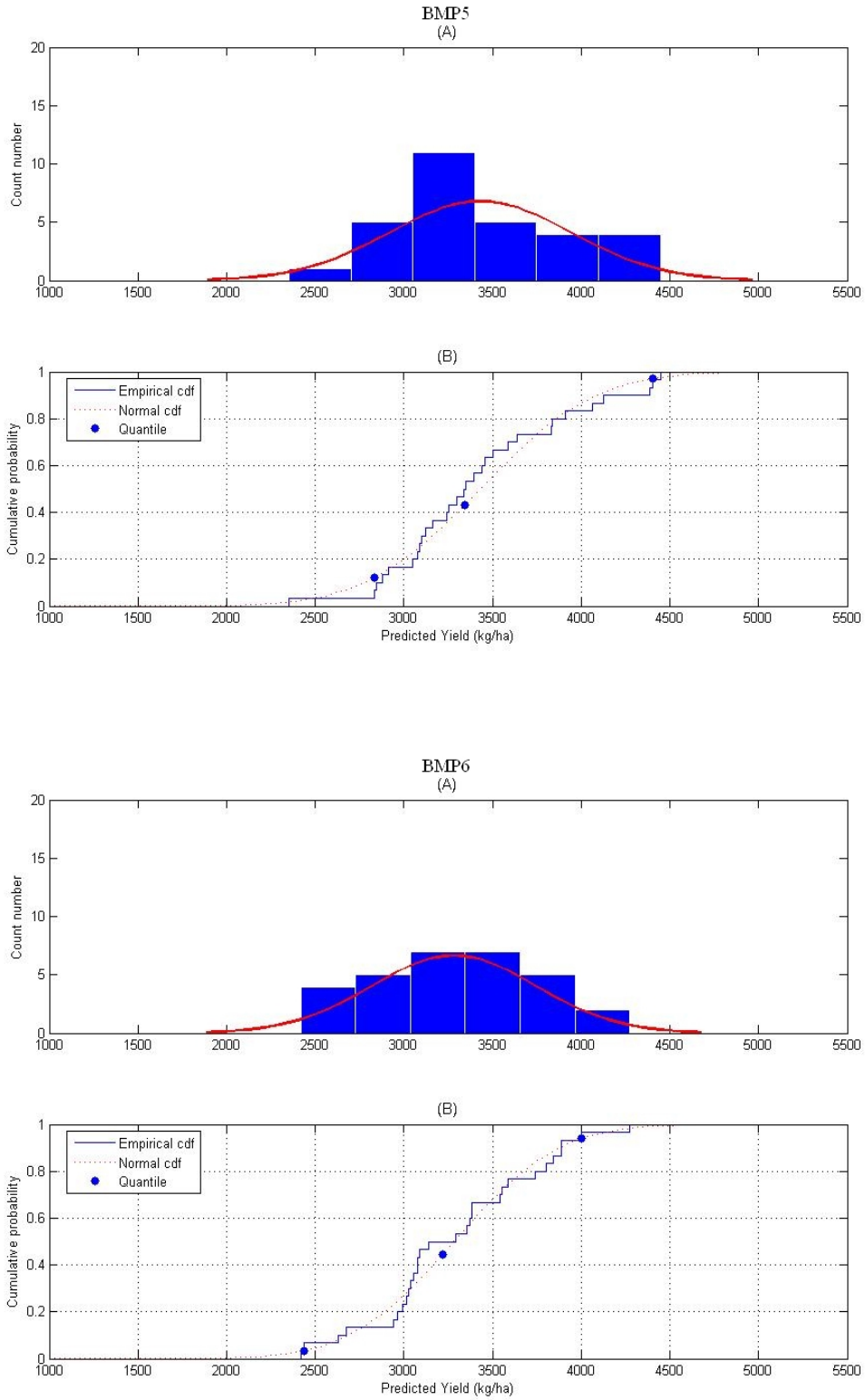


Figure 6-1. Continued

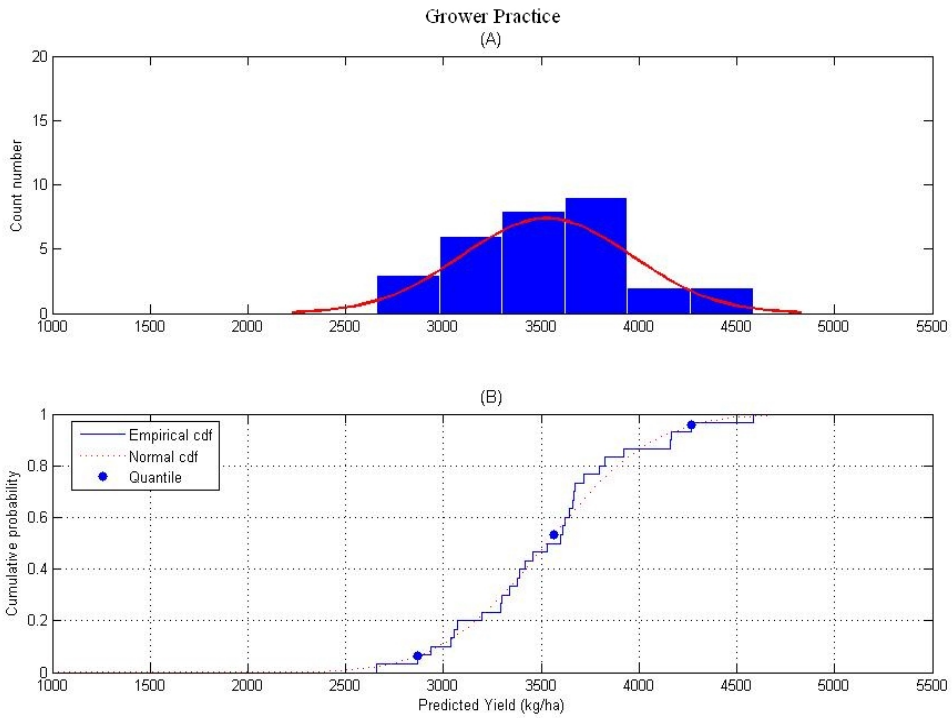


Figure 6-1. Continued

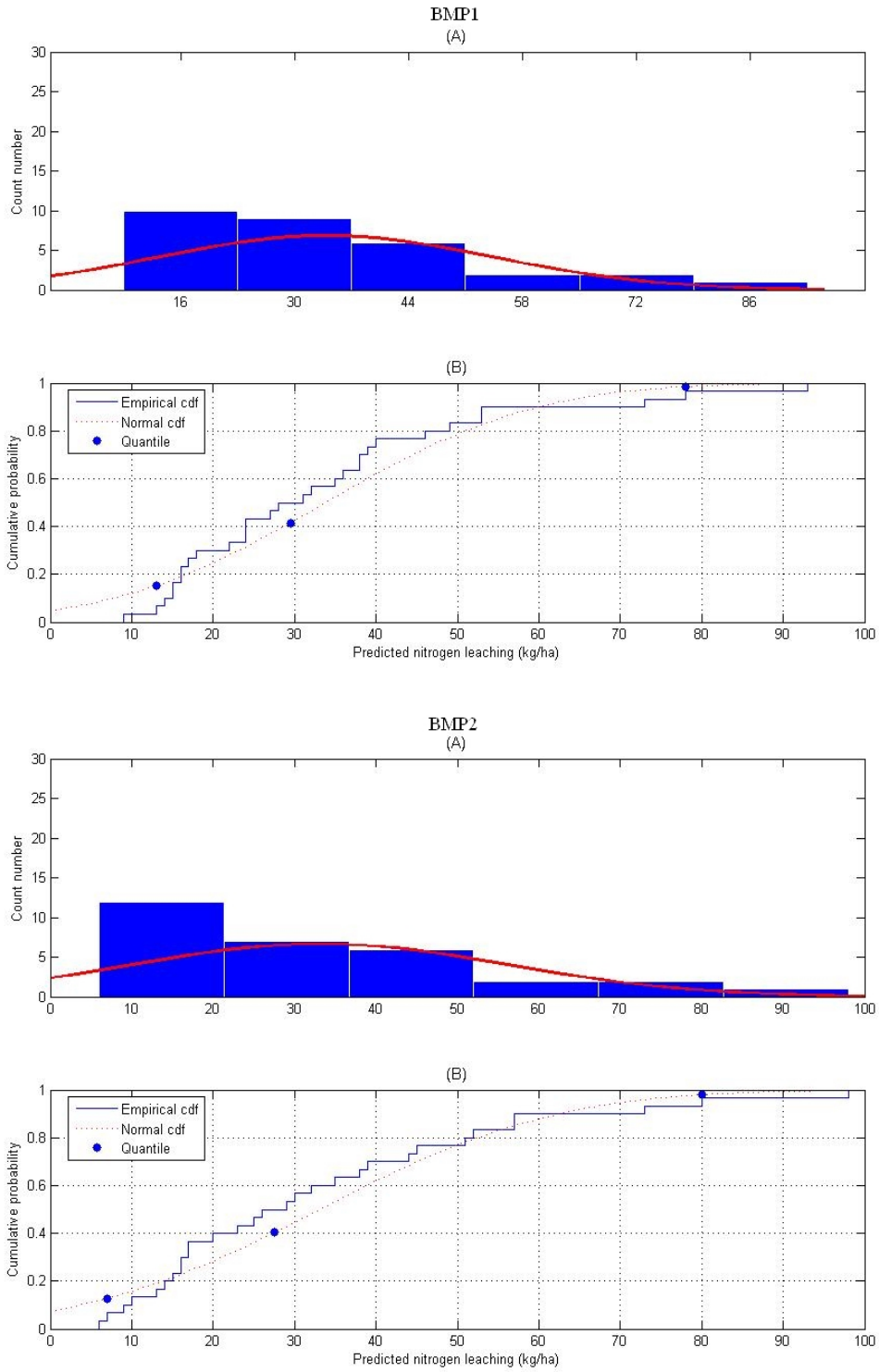
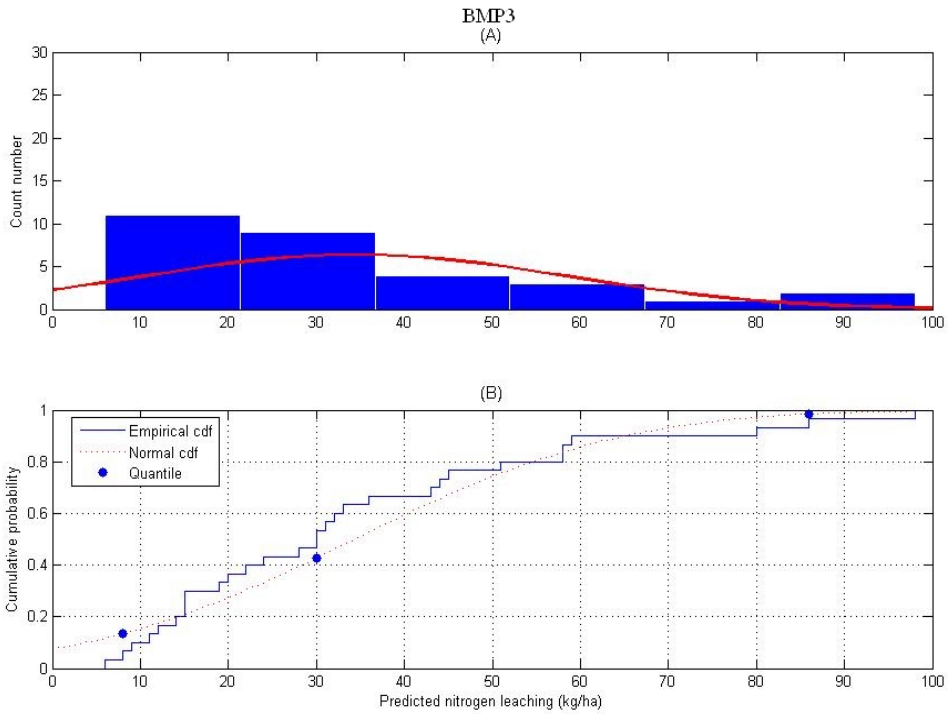


Figure 6-2. Histogram (A) and cumulative distribution (B) of predicted average annual nitrogen leaching (NLCM) of the six selected potential BMPs and the actual grower practice both under weather and input parameter uncertainty. The red curve in each histogram is the fitted normal distribution curve. The 5%, 50% and 95% quantiles are shown as dots in (B).



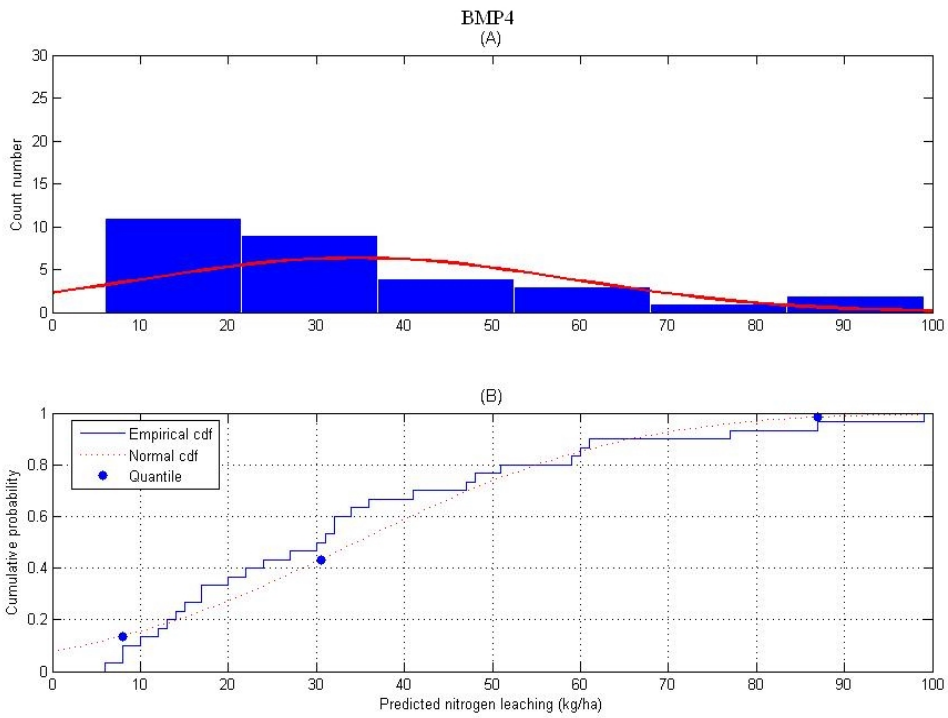
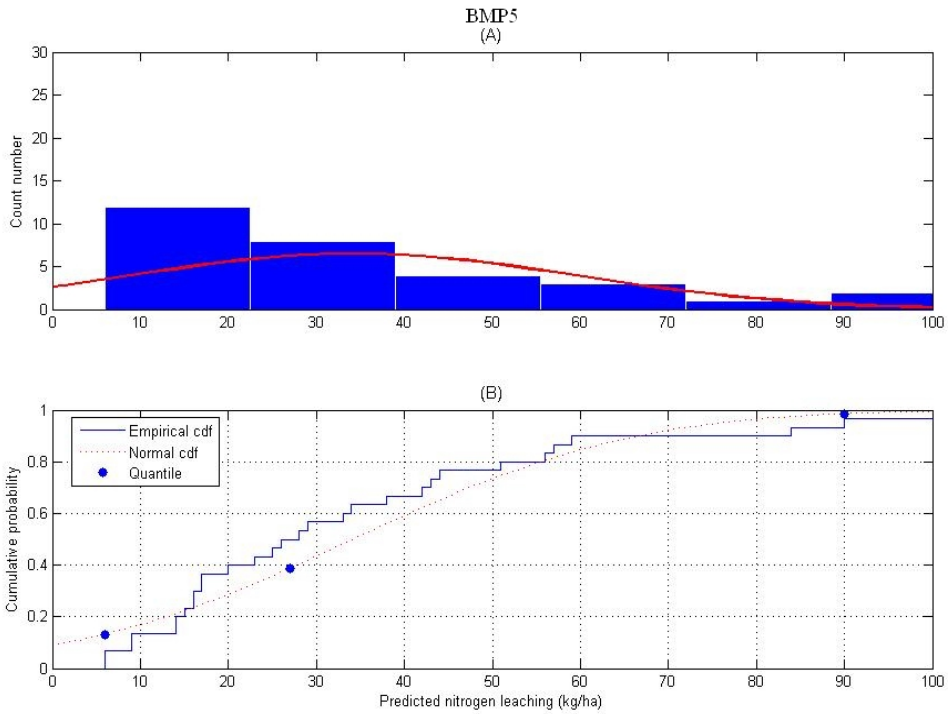


Figure 6-2. Continued



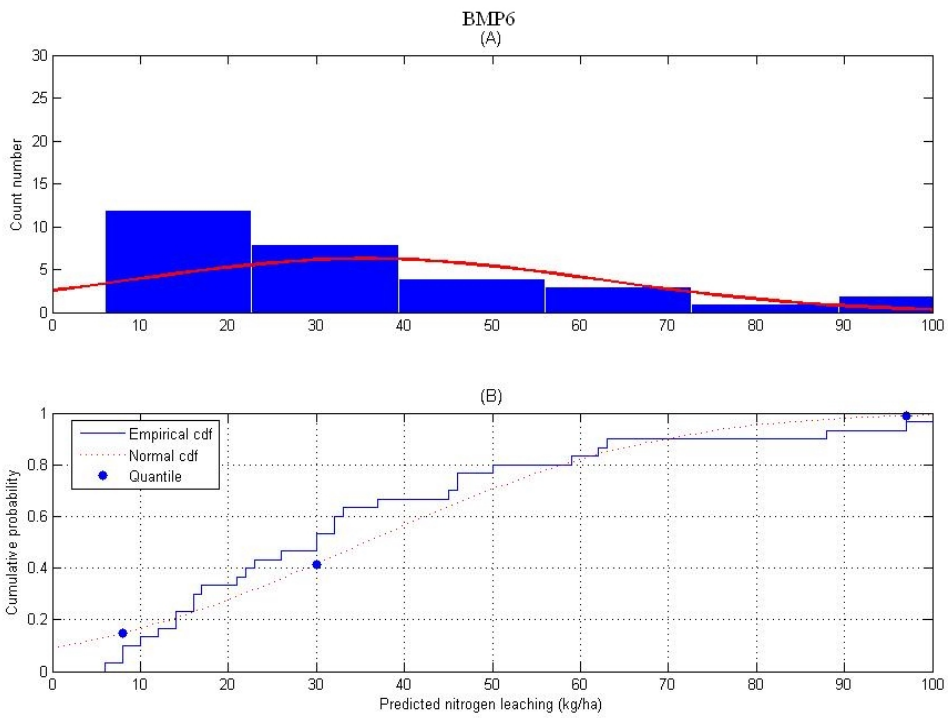


Figure 6-2. Continued

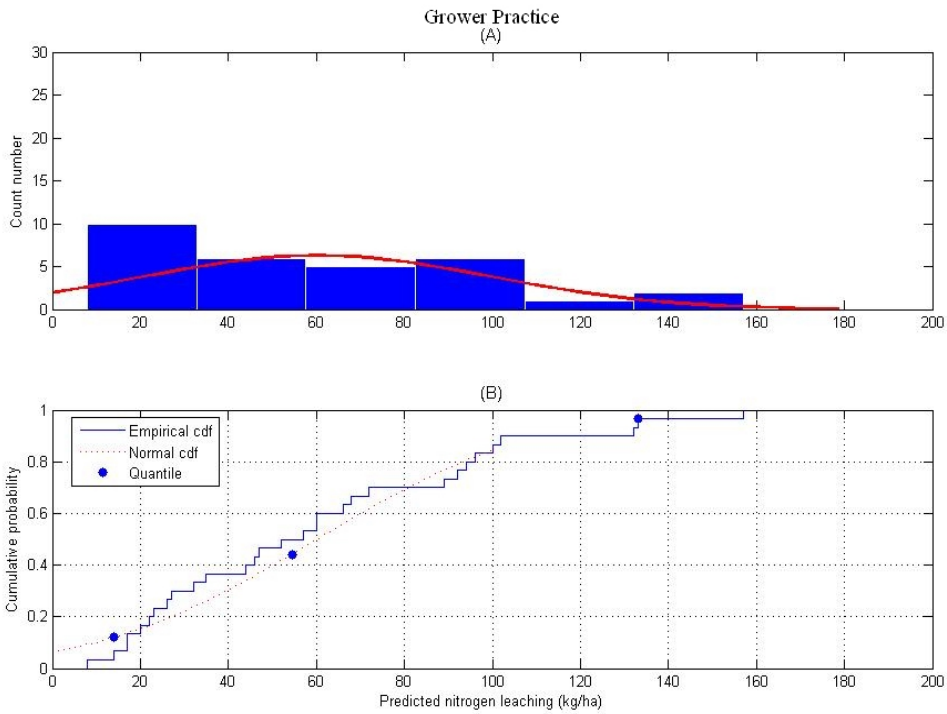


Figure 6-2. Continued

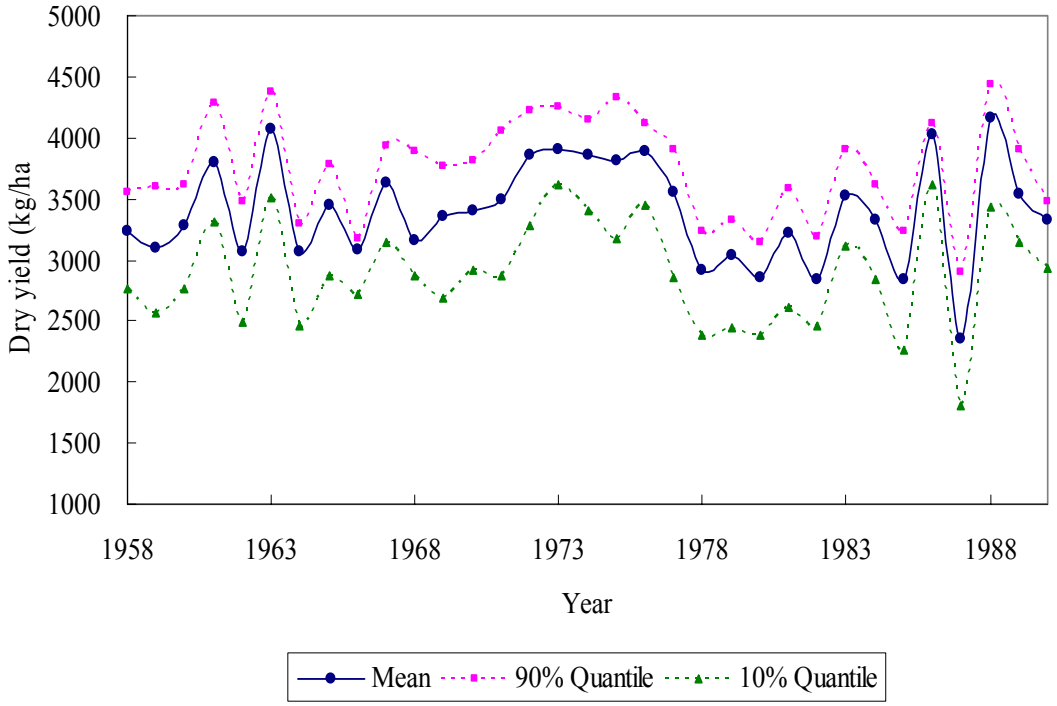


Figure 6-3. Simulated 10% and 90% confidence limits of average annual yields of BMP1 both under weather and input parameter uncertainty

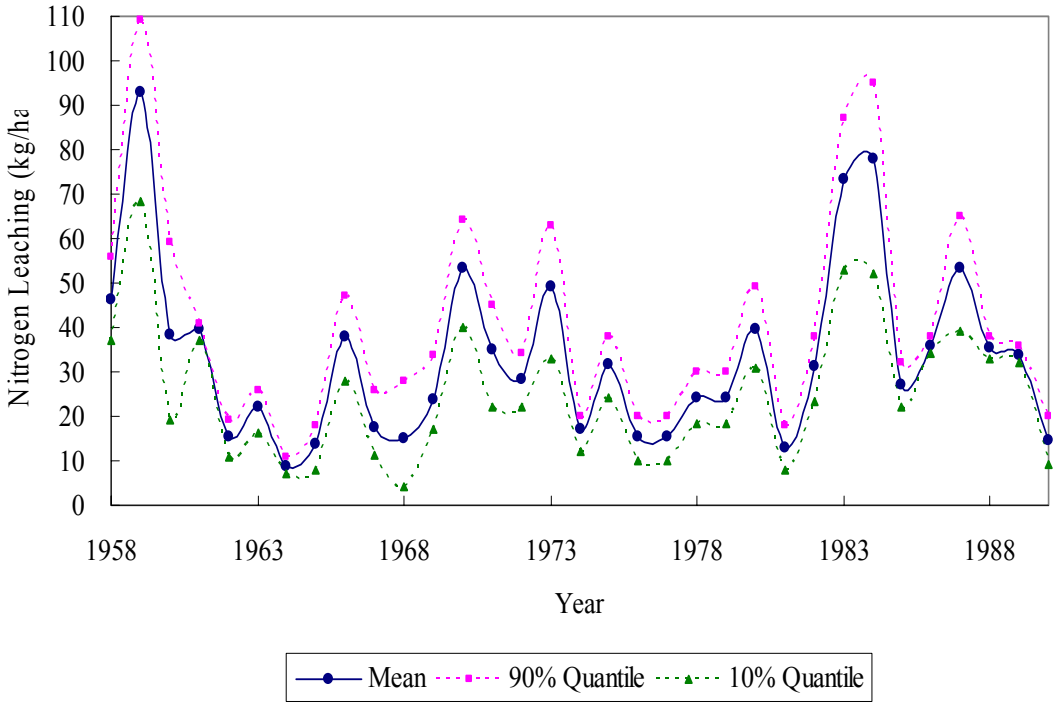


Figure 6-4. Simulated 10% and 90% confidence limits of average annual nitrogen leaching of BMP1 both under weather and input parameter uncertainty

Table 6-1. Second posterior distribution of the selected parameters (from Chapter 3)

Parameter	Unit	Min	Max	Mean	Standard Deviation	CV
P1	℃d	77.676	182.175	99.169	8.217	8.3%
P5	℃d	553.141	676.212	577.201	9.746	1.7%
PHINT	℃d	39.162	41.712	39.676	0.202	0.5%
SLDR	-	0.708	0.752	0.732	0.006	0.9%
SLRO	-	41.492	99.850	78.143	9.660	12.4%
SDUL	cm^3/cm^3	0.097	0.109	0.104	0.002	1.6%
SLLL	cm^3/cm^3	0.053	0.068	0.060	0.002	4.0%
SSAT	cm^3/cm^3	0.235	0.362	0.300	0.021	7.0%
SLPF	-	0.760	0.932	0.872	0.041	4.7%

Table 6-2. Six selected potential BMPs for sweet corn production (from Chapter 5)

BMP	Irrigation	Nitrogen Amount (kg N ha^{-1})	Nitrogen Split	Application Amount (kg N ha^{-1})
BMP1	5.0 mm-MAD 20%	196	0-1/4-3/4	30
BMP2	5.0 mm-MAD 20%	196	0-1/3-2/3	30
BMP3	7.5 mm-MAD 30%	196	0-1/4-3/4	40
BMP4	7.5 mm-MAD 30%	196	0-1/3-2/3	30
BMP5	5.0 mm-MAD 20%	224	0-1/4-3/4	30
BMP6	7.5 mm-MAD 30%	224	0-1/4-3/4	30

Table 6-3. N fertilizer management in the "EPA319 Project"

No.	Time	Management Description
1	Pre-plant	Nitrogen based fertilizers should not be broadcast to the soil surface before planting. This will be highly susceptible to leaching.
2	Planting	Traditional applications of nitrogen at planting are approximately 17 kg N ha^{-1} (15 lb N $acre^{-1}$). However applications of 34 kg N ha^{-1} (30 lb N $acre^{-1}$) are acceptable.
3	Approximately 21 days after planting (DAP)	By now the root system is developing rapidly and an application of approximately 18 kg (40 lbs) nitrogen can be banded beside the corn plants. The bands should be applied approximately 5 to 10 cm (2 to 4 inches) to the side of the corn row. It is recommended that this application be applied as a dry granular or liquid nitrogen solution. If applying liquid, applying approximately 5 to 10 cm (2 to 4 inches) below the soil sources will help reduce volatilization. Nitrogen applications made through irrigation is not recommended, as the small plants do not yet have sufficient roots to utilize broadcast nitrogen efficiently.
4	Approximately 36 DAP	Nitrogen applications made through the irrigation systems can now improve nitrogen use efficiency if accompanied by appropriate irrigation. Applications of approximate 45 kg N ha^{-1} (40 lb N $acre^{-1}$) per application can be made on weekly basis. Approximate nitrogen management should target between 3 and 5 of these applications during the season. In this project, it is targeting a maximum of 5 applications made through the irrigation system applying approximately 45 kg N ha^{-1} each.
5	Within 1 week from harvest	Nitrogen applications made during the final week of ear development and maturity are not beneficial.

Table 6-4. Irrigation management in the "EPA319 Project"

No.	Time	Management Description
1	Pre-plant Herbicides	Herbicides applied pre-plant that have a 'water-in' requirement should receive no more than 0.64 cm (0.25 inches), even on a very dry soil. An irrigation of this amount may wet the soil to a depth of at least 4 inches and may penetrate much deeper, depending on current soil moisture levels.
2	Pre-plant	To facilitate planting, the soil should be moist enough to allow proper seed placement. Apply no more than 0.51 cm (0.20 inches) if rainfall has not provided sufficient moisture.
3	Post Plant	A light application of approximate 0.39 cm (0.15 inches) immediately after planting will allow the soil surface to 'crust'. This will help retain soil moisture as the seeds begin to germinate and grow.
4	Pre-emergence	As the seeds germinate and growth begins, water requirements are very small, and soil moisture levels within the root zone may remain adequate for some time. Soil moisture should be checked 2 or 3 times per week. Irrigation during this period usually applies 'surface moisture' to prevent the soil surface from drying out excessively and reducing wind erosion. These applications should apply a minimum amount.
5	Post-emergence Approx. 10 to 18 DAP	As the plants emerge, and photosynthesis begins, water use increases gradually with plant size. Irrigation during this period should be scheduled every 3 or 4th day, with rates of 0.38 to 0.64 cm (0.15 to 0.25 inches) per application. (Example: 0.38 cm at 10 DAP, 0.51 cm at 14 DAP, and 0.64 cm at 18 DAP.) Soil moisture should be checked every other day, if not daily.
6	19-38 DAP	The sweet corn plants are growing rapidly and water use is increasing accordingly. Irrigation events should be scheduled every 2nd or 3rd day, applying 0.64 to o.76 cm (0.25 to 0.30 inches) per application. Soil moisture should be checked daily.
7	39-48 DAP	Irrigation should now be applied daily to meet the daily water uptake by the sweet corn. During this period, water use is still increasing, but is averaging just below 0.51 cm per day. With a highly efficient irrigation system, applications of 0.51 to 0.64 cm (0.20 to 0.25 inches) per day should be adequate to keep up with the crop requirements.
8	49-58 DAP	Irrigation should be increased to around 0.64 to 0.69 cm (0.25 to 0.27 inches) per day.
9	59 DAP through Harvest	Irrigation should be approximately 0.76 to 0.84 cm (0.30 to 0.33 inches) per day.

Table 6-5. Mean and standard deviation (STDEV) of simulated corn dry yield and nitrogen leaching both under different uncertainty scenarios [a]

Treatment	Dry Yield (kg ha^{-1})			Nitrogen leaching (kg ha^{-1})		
	Mean	STDEV	CV	Mean	STDEV	CV
Under parameter uncertainties						
BMP1	3230 a	491	15.2%	48 c	9	18.6%
BMP2	3268 a	497	15.2%	52 b	10	18.6%
BMP3	3064 b	454	14.8%	51 bc	9	17.2%
BMP4	2993 b	451	15.1%	51 bc	9	18.0%
BMP5	3252 a	495	15.2%	51 bc	9	17.9%
BMP6	2991 b	449	15.0%	50 c	8	16.9%
Grower Practice	3059 b	513	14.0%	101 a	22	22.4%
Under weather uncertainties						
BMP1	3495 a	903	25.8%	35 b	24	68.3%
BMP2	3511 a	908	25.9%	37 b	25	67.8%
BMP3	3532 a	737	20.9%	38 b	27	68.9%
BMP4	3513 a	674	19.2%	39 b	26	67.7%
BMP5	3511 a	905	25.8%	39 b	28	72.0%
BMP6	3516 a	677	19.3%	40 b	29	72.8%
Grower Practice	3186 a	801	25.1%	77 a	50	64.3%
Under both parameter set and weather uncertainties						
BMP1	3396 a	900	25.9%	33 b	25	75.7%
BMP2	3505 a	912	26.0%	30 b	25	81.9%
BMP3	3334 a	822	24.7%	32 b	26	82.0%
BMP4	3309 a	794	24.0%	32 b	26	82.7%
BMP5	3491 a	907	26.0%	31 b	27	86.2%
BMP6	3308 a	891	26.9%	33 b	28	86.8%
Grower Practice	3482 a	813	23.4%	76 a	48	87.2%

[a] Values within columns followed by the same lower case letters were not significantly different at a 5% level, according to the Tukey's Studentized Range (HSD) test.

CHAPTER 7
CONCLUSIONS AND FUTURE WORK

7.1 Summary and Research Contributions

Increasing nitrogen loads within the Suwannee River Basin of North Florida and other areas has become a major concern. Leaching of nitrogen is economically and environmentally undesirable. Nitrogen fertilizer application in field crop production is believed to be the most import nitrogen contribution in this region. Something must be done to improve this situation.

Florida ranks highest in the nation in the production and value of fresh market sweet corn, typically accounting for approximately 25% of both national sweet corn production and of U.S. cash receipts for fresh sales. Thus it is necessary to develop research based nitrogen best management practices (N-BMPs) to reduce nitrogen leaching while keeping an acceptable yield in sweet corn production.

Crop models are becoming attractive for BMP development because field plot experiments have spatial and temporal limitations, and are expensive and time-consuming. This study utilized the CERES-Maize mode of the Decision Support System for Agrotechnology Transfer (DSSAT) model as a platform to develop potential BMPs for sweet corn production in North Florida. The research involved both field experiments and crop model simulations.

The main contributions of this research to the fields of crop modeling and land and water resource engineering include follows:

(1) It is the first time to use the non-restricted and restricted one-at-a-time (OAT) method for global sensitivity analysis for the CERES-Maize model of DSSAT. These methods were proved to be effective tool to investigate the behavior of the model and to select influential parameters for calibration.

(2) The generalized likelihood uncertainty estimation (GLUE) as a method for model parameter estimation was used for hydrological models before. This is the first time the method was successfully used in a crop model (CERES-Maize model). The results showed that this method could significantly reduce the uncertainties in model input parameters and consequently reduce the

uncertainties in model outputs. This research also tested the influence of different likelihood functions and method of likelihood combination on GLUE results. It also tried a procedure of GLUE verification to prove that GLUE is a valid method. In general, this research has provided a paradigm for model parameter estimation with the Bayesian method.

(3) It is the first time to use the calibrated CERES-Maize model as a computer platform to conduct crop model experiments to explore potential best management practices (BMPs) for nitrogen management.

(4) Uncertainty analysis was conducted for the selected potential BMPs, which showed the different contributions of input parameters and weather conditions to model output uncertainties. It will provide information for model users how large the output uncertainty will be when using the model.

7.2 Conclusions

7.2.1 Global Sensitivity Analysis of CERES-Maize Model with One-at-a-time (OAT) Method

In this research, global sensitivity analysis was used as a tool to select the most influential input parameters for model calibration. Both non-restricted and restricted OAT methods were used to conduct global sensitivity analysis for the CERES-Maize model. Some conclusions were drawn as follows.

First, genotype parameters P1 (degree days from emergence to end of juvenile phase), P5 (degree days from silking to physiological maturity), PHINT (degree days required for a leaf tip to emerge) and soil parameters SDUL (soil drained upper limit), SLLL (soil drained lower limit) and SLPF (soil fertility factor) have a strong influence on dry matter yield. Second, genetic parameters P5 and PHINT and soil parameters SDUL, SLLL, and SLRO (soil runoff curve number) have strong influence on nitrogen leaching. Third, soil parameters SLLL, SDUL and SSAT (soil saturation) were highly correlated with each other.

Finally, nine parameters were selected for future model calibration with generalized likelihood uncertainty estimation (GLUE) method (Chapter 3). They were P1, P5, PHINT, SLDR (soil drainage rate), SLRO, SLPF, SLLL, SDUL and SSAT.

7.2.2 Parameter Estimation for CERES-Maize Model with GLUE Method

In this part of research, the GLUE method was used to estimate the influential genotype and soil parameters, which were selected in global sensitivity analysis of the CERES-Maize model. Some conclusions were drawn as follows.

According to the normality test with the Jarque-Bera method, it was found that all of the selected parameters are close to or follow a normal distribution, except for SLPF. To determine the number of model runs, it was found that at least 3,000 random parameter sets should be generated and 3,000 model runs should be completed to guarantee reliable model simulation results. To determine the best likelihood function and method of likelihood value combination for this study, it was found that the likelihood functions and methods of likelihood value combination could have very strong influence on the posterior distributions. The likelihood function L1 (Equation L1 in Chapter 3) and method of combination C2 (Equation C2 in chapter 3) was the best choice, since the combination L1C2 had the lowest relative error, 0.01 for dry matter yield, 0.09 for anthesis date, and 0.11 for maturity date (see Table 3-6 for details).

After two rounds of GLUE simulations, the uncertainty in input parameters and model outputs were substantially reduced. For example, the value of standard deviation of input parameter P1 for the prior, first posterior and second posterior distributions changed from 67.83 to 23.39, and to 8.22, respectively. For anthesis dates and maturity dates, the predictions were 55 and 80 days after planting after two rounds of GLUE simulation, which were very close to the real field observations 51 and 80, respectively (see Table 3-6 for details).

The mean values of estimated and measured soil parameters were very close to each other. For example, the mean value of calibrated SDUL in the second posterior distribution was 0.104 cm^3/ cm^3, while the mean value of measure SDUL was 0.110 cm^3/ cm^3. The error was only about 0.006 cm^3/ cm^3. Similar results were observed in SLLL and SSAT.

According to the results of GLUE verification, it can be seen that after two rounds of GLUE, the uncertainties of the model outputs all decreased, and all mean values gradually approached the selected true values. The expectations of the posterior distributions were used as the nominal values to continue future research in the development of best management practices.

In general, the results of this study confirmed that the GLUE method was a powerful tool to estimate the model input parameters.

7.2.3 Field Plot Experiment of Sweet Corn and Simulation with Calibrated CERES-Maize Model

A field plot experiment was conducted at the Plant Science Research and Education Unit, the University of Florida in the spring of 2006 to explore the influence of fertilizer applications and irrigation levels on sweet corn quantity and quality. The nitrogen fertilizer and irrigation treatments in field plot experiment were also simulated with the CERES-Maize model with the expectation values of the posterior distributions of the selected influential parameters as the nominal values. Thus, this part of research could be considered as a procedure of model verification. Several conclusions were drawn.

Increasing nitrogen fertilizer from 185 to 247 kg N ha^{-1} significantly increased both fresh total yield and marketable yield. Increasing irrigation rate from I1 (irrigation level based on daily ET value and soil profile water balance) to I2 (1.5 times of I1), was not significant for fresh total yield or for fresh marketable yield. The increase in N fertilizer rate was not significant in increasing total ears, US #2, or cull ears per unit area, but increased the number of US #1 ears.

Both irrigation and nitrogen fertilizer levels showed significant influence on nitrogen leaching. When irrigation level increased from I1 to I2, the average amount of estimated nitrogen leaching increased from 150 to 167 kg N ha^{-1}. When nitrogen fertilizer level increased from 247 to 309 kg N ha^{-1}, the average amount of nitrogen leaching increased from 124 to 205 kg N ha^{-1}.

See Table 4-13 for details. This confirmed the common assumption that more water applied, more nitrogen will be leached, and more nitrogen fertilizer applied, more nitrogen will be leached as well.

After comparing the simulated and observed dry matter yields, anthesis dates and maturity dates, and estimated nitrogen leaching of the seven treatments in field plot experiment of sweet corn in 2006, it appears that the model did a good job in predicting dry yield and phenology dates. From Table 4-15, it can be seen that the relative errors between the measured and simulated yields were all near or less than 10% except for treatment F0I1 and F1I2. From Table 4-16, it can be seen that the measured and simulated anthesis dates were that same, while there was only one day difference in the maturity dates.

However there was a great difference if comparing the simulated nitrogen leaching during season and the estimated potential nitrogen leaching. This is because the model calculated a significant part of nitrogen output in the system as inorganic nitrogen left in the soil profile after maturity. Thus, it is reasonable to use the sum of nitrogen leaching during the season and the inorganic nitrogen left in soil profile after maturity as the potential nitrogen leaching in prediction. If compare the predicted and measured potential nitrogen leaching (as shown in Table 4-19 in Chapter 4), the difference would be small, though there was still some uncertainties due to the procedure of nitrogen leaching estimation.

7.2.4 Best Management Practices Development with CERES-Maize Model for Sweet Corn Production in North Florida

In this study, the CERES-Maize module was utilized as a platform to develop BMPs for sweet corn production in North Florida. The expectation values of the posterior distributions of the input parameters derived in GLUE simulation were used as the nominal parameter set to

conduct the simulations. Each irrigation, nitrogen, or irrigation and nitrogen combination treatment was simulated using 33 years of historical weather data for North Florida.

Irrigation frequency and amount significantly influenced corn yield. For example, when apply water with a maximum allowable depletion (MAD) value of 10%, corn growth would suffer from water stress, and yield would be reduced significantly to less than 1,000 kg ha^{-1}.

Second, the trend of increasing nitrogen leaching was obvious if irrigation events were more frequent and more water was applied in each event. For example, if the irrigation event of 22.5 mm was triggered with a MAD value of 90%, the nitrogen leaching amount was approximately 32 kg ha^{-1}. But it could be as high as almost 120kg ha^{-1}, if the event was triggered with a threshold of a MAD of 20% or 10% and a precipitation depth of 5 or 2.5 mm.

Third, more nitrogen applied resulted in more being leached. For example, the amount of nitrogen leaching increased from 82 to 266 kg N ha^{-1} when nitrogen application level increased from 196 to 561 kg N ha^{-1}.

Fourth, nitrogen fertilizer split did not show a significance influence on yield if there was application of N during the small leaf stage or large leaf stage. However, splitting N applications showed a significant influence on N leaching. The best splits were 0:1/4:3/4 (nothing in the small leaf stage, 1/4 of the total nitrogen except for the starter nitrogen in large leaf stage, and 3/4 in the ear development stage) and 0:1/3:2/3 (nothing in the small leaf stage, 1/3 of the total nitrogen except for the starter nitrogen in large leaf stage, and 2/3 in the ear development stage), because these fertigation schedules could best meet the nitrogen need of sweet corn growth, especially from tasseling to maturity. A small "application amount" could not increase yield very much if it was less than 70 kg N ha^{-1}, but it could decrease N leaching from 110 kg N ha^{-1} to about 60 kg N ha^{-1} when the value of "application amount" decreased from 70 kg N ha^{-1} to 10 kg N ha^{-1}.

However, it seems 30, 40 or 50 kg N ha^{-1} could be good choices of "application amount", if the production cost was considered in addition to yield and nitrogen leaching.

Finally, if growers could apply both irrigation water and nitrogen fertilizer more frequently but with smaller amounts in each application, this would result in an acceptable yield and a lower level of nitrogen leaching.

7.2.5 Uncertainty Analysis of Potential Sweet Corn BMPs under Weather and Input Parameter Variability

In this study, six selected potential best management practices obtained in BMP development (Chapter 5) and an actual N fertilizer application and irrigation management case were investigated for uncertainties of yield and accumulative nitrogen leaching caused by weather and input parameter uncertainty.

The weather was the dominant uncertainty contributor. This was because after two rounds of GLUE simulation, the uncertainties existing in input parameters were minimized (see Chapter 3 for details). However, the uncertainties of climate could not be reduced artificially.

Second, weather variability could cause higher uncertainty in model outputs of nitrogen leaching than in yields. This is because nitrogen leaching was more sensitive to weather conditions (especially rainfall), than yield.

Third, after comparison, the selected BMP3 (an irrigation of 7.5 mm with a value of maximum allowable depletion (MAD) of 30%, a total of 196 kg N ha^{-1} with a split of 0-1/4-3/4 and an application amount of 40 kg N ha^{-1}) and BMP4 (an irrigation of 7.5 mm with a MAD value of 30%, a total of 196 kg N ha^{-1} with a split of 0-1/3-2/3 and an application amount of 30 kg N ha^{-1}) could be good choices for real sweet corn production, compared with other BMPs (BMP1, BMP2, BMP5, and BMP6) and the actual grower practice in the EPA319 demonstration project.

Finally, the simulation results supported the recommendation of IFAS about N fertilizer for sweet corn production, which is 224 kg N ha^{-1} (200 lb N $acre^{-1}$) if fertilizer application efficiency is considered.

7.3 Future Work

The CERES-Maize model verified itself as a powerful tool to develop strategies for agricultural production. It provided a convenient and economical way to obtain useful information on the interactions between crop, soil, weather and field management strategies. This study provided a useful paradigm of model sensitivity analysis, model calibration with GLUE method, and BMP development. However, the current research still has some disadvantages, requiring future work.

First, the current CERES-maize model can only predict the yield quantity, but not the quality. According to the USDA sweet corn quality classification standard, the cobs of sweet corn can be separated into three levels, US #1, US #2 and Cull. The US #1 and US #2 can be sold in the market. Their sum is called the marketable yield. The current model can not make such classification, and as such it would be a good research topic to add the quality component into the current crop model.

Second, this research only focused on timing and amount of N fertilizer application, but it did not consider other factors such as N fertilizer types (such as ammonia, nitrate, urea etc.), N fertilizer application method (banding on surface, banding beneath surface, broadcast and incorporated, or broadcast and not incorporated), and controlled release N fertilizer. These factors all can influence N fertilizer use efficiency and leaching.

Third, this study only investigated potential N-based BMPs. The BMPs addressing phosphorus, crop rotation, cover crop, and intercrop could all be simulated with the properly calibrated crop model.

Fourth, this research did not integrate economic analysis of the developed BMPs. This could strongly influence the adoption of these BMPs by growers. If a BMP is too expensive, though it could decrease the N leaching significantly, it may not be adopted by growers. How to balance the economic and social benefits would be an important topic.

Fifth, as described in Section 7.2.3 there was a great difference if comparing the simulated nitrogen leaching during season (NLCM) and the estimated potential nitrogen leaching. This is because the model calculated a significant part of nitrogen output in the system as inorganic nitrogen left in the soil profile after maturity (NIAM). According to the results of nitrogen leaching estimation in field experiment, it seems the model allocated too much nitrogen to NIAM. Thus, in the future, it is also necessary to find the correct ratio between NLCM and NIAM in model nitrogen prediction. This will be a good topic to improve model performance.

APPENDIX A
INPUT AND OUTPUT PARAMETERS OF CERES-MAIZE MODEL IN DSSAT

Symbol	Definition	Unit	Values based upon
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8℃) during which the plant is not responsive to changes in photoperiod.	degree days above a base temperature of 8℃	DSSAT Database
P2	Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours).	-	DSSAT Database
P5	Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8℃).	degree days above a base temperature of 8℃	DSSAT Database
G2	Maximum possible number of kernels per plant.		DSSAT Database
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions.	mg day^{-1}	DSSAT Database
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	degree days	DSSAT Database
SLLL	Drained lower limit	m^3/m^3	DSSAT Database
SDUL	Drained upper limit	m^3/m^3	DSSAT Database
SSAT	Soil saturation water content	m^3/m^3	DSSAT Database
SBDM	Soil bulk density	g/cm^3	DSSAT Database
SALB	Soil albedo	-	DSSAT Database
SLU1	Soil evaporation limit	-	DSSAT Database
SLRO	Soil runoff curve number	-	DSSAT Database
SLDP	Soil drainage rate	-	DSSAT Database
SLPF	Growth reduction/ Fertility factor	-	DSSAT Database
HWAH	Dry matter at maturity	kg ha^{-1}	Simulation
NLCM	Cumulative nitrogen leaching	kg ha^{-1}	Simulation

APPENDIX B
MATLAB CODE FOR GLOBAL SENSITIVITY ANALYSIS WITH THE RESTRICTED OAT METHOD

B.1 Main Function

```
%%Main program to do soil and genotype parameter sensitivity analysis at the same time

n='Please input N to determine the numbers of simulations,N*100';
disp('')
disp(n)
n=input('N=');
Num=n;

system('copy C:\MATLAB7\work\Sensitivity\MZCER040_Plate.cul
C:\DSSAT4\Genotype\MZCER040.cul');%%Fix the genotyoe file first
SoilSensitivityAnalysis(Num);

system('copy C:\MATLAB7\work\Sensitivity\soil_Plate.sol C:\DSSAT4\Soil\soil.sol');%%Fix the soil file first
GenoSensitivityAnalysis(Num);
```

B.2 Sensitivity Analysis of Genotype Parameter

```
function GenoSensitivityAnalysis(N)

Num=N;

ResultRZero=zeros(0,2);
ResultRP1Zero=zeros(0,2);
ResultRP2Zero=zeros(0,2);
ResultRP5Zero=zeros(0,2);
ResultRG2Zero=zeros(0,2);
ResultRG3Zero=zeros(0,2);
ResultRPHINTZero=zeros(0,2);

for i=1:1:Num

   addpath C:\MATLAB7\work\Sensitivity;
   [R,RP1,RP2,RP5,RG2,RG3,RPHINT]=GenoParameterSpace;

%     SoilChange;%%Change soil file

   GenoChange(R);%%Change genotype file with a set of norminal value
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummaryGeno.txt');
   [Result]=GenoSummaryProcess2005;
   ResultRZero=[ResultRZero;Result];

   GenoChange(RP1);%%Change genotype file with a set of norminal value but increase P1 by 5%
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummaryGeno.txt');
   [Result]=GenoSummaryProcess2005;
```

```
    ResultRP1Zero=[ResultRP1Zero;Result];

    GenoChange(RP2);%%Change genotype file with a set of norminal value but increase P2 by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummaryGeno.txt');
    [Result]=GenoSummaryProcess2005;
    ResultRP2Zero=[ResultRP2Zero;Result];

    GenoChange(RP5);%%Change genotype file with a set of norminal value but increase P5 by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummaryGeno.txt');
    [Result]=GenoSummaryProcess2005;
    ResultRP5Zero=[ResultRP5Zero;Result];

    GenoChange(RG2);%%Change genotype file with a set of norminal value but increase G2 by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummaryGeno.txt');
    [Result]=GenoSummaryProcess2005;
    ResultRG2Zero=[ResultRG2Zero;Result];

    GenoChange(RG3);%%Change genotype file with a set of norminal value but increase G3 by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummaryGeno.txt');
    [Result]=GenoSummaryProcess2005;
    ResultRG3Zero=[ResultRG3Zero;Result];

    GenoChange(RPHINT);%%Change genotype file with a set of norminal value but increase PHINT by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummaryGeno.txt');
    [Result]=GenoSummaryProcess2005;
    ResultRPHINTZero=[ResultRPHINTZero;Result];

end

ResultRZero;
ResultRP1Zero;
ResultRP2Zero;
ResultRP5Zero;
ResultRG2Zero;
ResultRG3Zero;
ResultRPHINTZero;

P1Change=ResultRP1Zero-ResultRZero;
P2Change=ResultRP2Zero-ResultRZero;
P5Change=ResultRP5Zero-ResultRZero;
G2Change=ResultRG2Zero-ResultRZero;
G3Change=ResultRG3Zero-ResultRZero;
PHINTChange=ResultRPHINTZero-ResultRZero;

dP1=P1Change./ResultRZero/0.05;%%Elementary effect of P1
dP2=P2Change./ResultRZero/0.05;%%Elementary effect of P2
dP5=P5Change./ResultRZero/0.05;%%Elementary effect of P5
dG2=G2Change./ResultRZero/0.05;%%Elementary effect of G2
```

```
dG3=G3Change./ResultRZero/0.05;%%Elementary effect of G3
dPHINT=PHINTChange./ResultRZero/0.05;%%Elementary effect of PHINT

dP1mean_Yield=mean(dP1(:,1));
dP1variance_Yield=var(dP1(:,1));
dP1mean_NLCM=mean(dP1(:,2));
dP1variance_NLCM=var(dP1(:,2));%%Mean and variance of elementary effect of P1 for HWAH and NLCM

dP2mean_Yield=mean(dP2(:,1));
dP2variance_Yield=var(dP2(:,1));
dP2mean_NLCM=mean(dP2(:,2));
dP2variance_NLCM=var(dP2(:,2));%%Mean and variance of elementary effect of P2 for HWAH and NLCM

dP5mean_Yield=mean(dP5(:,1));
dP5variance_Yield=var(dP5(:,1));
dP5mean_NLCM=mean(dP5(:,2));
dP5variance_NLCM=var(dP5(:,2));%%Mean and variance of elementary effect of P5 for HWAH and NLCM

dG2mean_Yield=mean(dG2(:,1));
dG2variance_Yield=var(dG2(:,1));
dG2mean_NLCM=mean(dG2(:,2));
dG2variance_NLCM=var(dG2(:,2));%%Mean and variance of elementary effect of G2 for HWAH and NLCM

dG3mean_Yield=mean(dG3(:,1));
dG3variance_Yield=var(dG3(:,1));
dG3mean_NLCM=mean(dG3(:,2));
dG3variance_NLCM=var(dG3(:,2));%%Mean and variance of elementary effect of G3 for HWAH and NLCM

dPHINTmean_Yield=mean(dPHINT(:,1));
dPHINTvariance_Yield=var(dPHINT(:,1));
dPHINTmean_NLCM=mean(dPHINT(:,2));
dPHINTvariance_NLCM=var(dPHINT(:,2));%%Mean and variance of elementary effect of PHINT for
HWAH and NLCM


dSetGeno=[dP1,dP2,dP5,dG2,dG3,dPHINT];

fid_new=fopen('C:\MATLAB7\work\Sensitivity\dSetGeno.txt','w+');
for i=1:Num
fprintf(fid_new,'%10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f
%10.9f\n',...
      dSetGeno(i,1),dSetGeno(i,2),dSetGeno(i,3),dSetGeno(i,4),dSetGeno(i,5),dSetGeno(i,6),...
      dSetGeno(i,7),dSetGeno(i,8),dSetGeno(i,9),dSetGeno(i,10),dSetGeno(i,11),dSetGeno(i,12));
end
fclose(fid_new);%%Make a txt file for the elementary effect values for each parameter
```

B.3 Genotype File Change

```
%%Modify Genotype File

function GenoChange(R)

%R=[1,2,3,4,5,6]
```

```
LinePara1=47;
fid_MZCER040=fopen('MZCER040_Plate.cul','r');
fid_new=fopen('C:\DSSAT4\Genotype\MZCER040.cul','w+');

for i=1:50
line=fgetl(fid_MZCER040);
if ~ischar(line), break, end

%%For P1, P2, P5, G2 and G3 and PHIN
if i==LinePara1
   line1=line(1:31);
   line2=line(32:36);
   line3=line(37:38);
   line4=line(39:43);
   line5=line(44);
   line6=line(45:49);
   line7=line(50);
   line8=line(51:55);
   line9=line(56:57);
   line10=line(58:60);
   line11=line(61:62);
   line12=line(63:66);
   line13=line(67:end);%%Devide the each line of genotype file into 13 sections

   line2str=num2str(R(1,1),'%5.1f');%%P1
   line4str=num2str(R(1,2),'%5.1f');%%P2
   line6str=num2str(R(1,3),'%4.1f');%%P5
   line8str=num2str(R(1,4),'%4.1f');%%G2
   line10str=num2str(R(1,5),'%4.1f');%%G3
   line12str=num2str(R(1,6),'%4.1f');%%PHINT

   NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9 line10str line11 line12str line13];
   fprintf(fid_new,'%s\n',NewLine);

else
 fprintf(fid_new,'%s\n',line);
end
end

fclose(fid_MZCER040);
fclose(fid_new);
```

B.4 Genotype Parameter Space

```
%%Generate the paramter space for each parameter, then do sampling from
%%these spaces to form a series of nominal scenarios

function [R,RP1,RP2,RP5,RG2,RG3,RPHINT]=GenoParameterSpace

N=100;% Section Number for every parameter

P1Min=5;
```

```
P1Max=450;
DeltaP1=P1Max-P1Min;
P1Space=[P1Min:(1/(N-1))*DeltaP1:P1Max];%Generation of sampling space of P1

P2Min=0;
P2Max=2;
DeltaP2=P2Max-P2Min;
P2Space=[P2Min:(1/(N-1))*DeltaP2:P2Max];%Generation of sampling space of P2

P5Min=580;
P5Max=990;
DeltaP5=P5Max-P5Min;
P5Space=[P5Min:(1/(N-1))*DeltaP5:P5Max];%Generation of sampling space of P5

G2Min=248;
G2Max=990;
DeltaG2=G2Max-G2Min;
G2Space=[G2Min:(1/(N-1))*DeltaG2:G2Max];%Generation of sampling space of G2

G3Min=5;
G3Max=16.5;
DeltaG3=G3Max-G3Min;
G3Space=[G3Min:(1/(N-1))*DeltaG3:G3Max];%Generation of sampling space of G3

PHINTMin=30;
PHINTMax=50;
DeltaPHINT=PHINTMax-PHINTMin;
PHINTSpace=[PHINTMin:(1/(N-1))*DeltaPHINT:PHINTMax];%Generation of sampling space of PHIN

Random = unifrnd(1,100,[1 6]);%Generate the random number as the subscript of each parameter...
%selected from its own space

IntRandom=int16(Random);

R=[P1Space(IntRandom(1,1)),P2Space(IntRandom(1,2)),P5Space(IntRandom(1,3)),...
   G2Space(IntRandom(1,4)),G3Space(IntRandom(1,5)),PHINTSpace(IntRandom(1,6))];%One sapling of
parameter...
%%set


Incre=0.05;  %Degree of increment

IncreP1=[P1Space(IntRandom(1,1))*Incre, 0, 0, 0, 0, 0];
RP1=R+IncreP1;%%Increment of P1

IncreP2=[0, P2Space(IntRandom(1,2))*Incre, 0, 0, 0, 0];
RP2=R+IncreP2;%%Increment of P2

IncreP5=[0, 0, P5Space(IntRandom(1,3))*Incre, 0, 0, 0];
RP5=R+IncreP5;%%Increment of P5

IncreG2=[0, 0, 0, G2Space(IntRandom(1,4))*Incre, 0, 0];
RG2=R+IncreG2;%%Increment of G2
```

```
IncreG3=[0, 0, 0, 0, G3Space(IntRandom(1,5))*Incre, 0];
RG3=R+IncreG3;%%Increment of G3

IncrePHINT=[0, 0, 0, 0, 0, PHINTSpace(IntRandom(1,6))*Incre];
RPHINT=R+IncrePHINT;%%Increment of PHINT
```

B.5 Processing Sensitivity Analysis Results of Genotype Parameter

```
%%Processing the Sensitivity simulation results, selecting the data needed

function [Result]=GenoSummaryProcess2005

N=5;

%%%%To get the values of anthesis days, maturity days, yield and nitrogen
%%%%leaching.

fid_Summary=fopen('C:\DSSAT4\Maize\Output\SummaryGeno.txt','r');

LinePara1=5;

for i=1:(N+2)
line=fgetl(fid_Summary);
if ~ischar(line), break, end

if i==LinePara1
   line1=line(1:66);
   line2=line(67:73);
   line3=line(74);
   line4=line(75:81);
   line5=line(82);
   line6=line(83:89);
   line7=line(90:110);
   line8=line(111:115);
   line9=line(116:219);
   line10=line(220:222);
   line11=line(223:end);

   PDAT=str2num(line2);%%Planting date
   ADAT=str2num(line4);%%Anthesis date
   MDAT=str2num(line6);%%Maturity date
   HWAH=str2num(line8);%%Yield
   NLCM=str2num(line10);%%Nitrogen leaching

%    Result=[PDAT,ADAT,MDAT,HWAH,NLCM];
   Result=[HWAH,NLCM];
end
end

fclose(fid_Summary);
```

B.6 Sensitivity Analysis of Soil Parameter

```
function SoilSensitivityAnalysis(N)

Num=N;

ResultRZero=zeros(0,2);
ResultRSALBZero=zeros(0,2);%%Storage for the results of SALB 1
ResultRSLU1Zero=zeros(0,2);%%Storage for the results of SLU1 2
ResultRSLDRZero=zeros(0,2);%%Storage for the results of SLDR 3
ResultRSLROZero=zeros(0,2);%%Storage for the results of SLRO 4
ResultRSLPFZero=zeros(0,2);%%Storage for the results of SLPF 5
ResultRSLLLZero=zeros(0,2);%%Storage for the results of SLLL 6
ResultRSDULZero=zeros(0,2);%%Storage for the results of SDUL 7
ResultRSSATZero=zeros(0,2);%%Storage for the results of SDUL 8
ResultRSBDMZero=zeros(0,2);%%Storage for the results of SDUL 9

for i=1:1:Num

   addpath C:\MATLAB7\work\Sensitivity;
   [R, RSALB, RSLU1, RSLDR, RSLRO, RSLPF, RSLLL, RSDUL, RSSAT, RSBDM]=SoilParameterSpace;

%     SoilChange;%%Change soil file

   SoilChange(R);%%Change soil file with a set of norminal value
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummarySoil.txt');
   [Result]=SoilSummaryProcess2005;
   ResultRZero=[ResultRZero;Result];

   SoilChange(RSALB);%%Change soil file with a set of norminal value but increase SALB by 5%
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummarySoil.txt');
   [Result]=SoilSummaryProcess2005;
   ResultRSALBZero=[ResultRSALBZero;Result];

   SoilChange(RSLU1);%%Change soil file with a set of norminal value but increase SLU1 by 5%
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummarySoil.txt');
   [Result]=SoilSummaryProcess2005;
   ResultRSLU1Zero=[ResultRSLU1Zero;Result];

   SoilChange(RSLDR);%%Change soil file with a set of norminal value but increase SLDR by 5%
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummarySoil.txt');
   [Result]=SoilSummaryProcess2005;
   ResultRSLDRZero=[ResultRSLDRZero;Result];

   SoilChange(RSLRO);%%Change soil file with a set of norminal value but increase SLRO by 5%
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy summary.out Output\SummarySoil.txt');
   [Result]=SoilSummaryProcess2005;
   ResultRSLROZero=[ResultRSLROZero;Result];
```

```
    SoilChange(RSLPF);%%Change soil file with a set of norminal value but increase SLPF by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummarySoil.txt');
    [Result]=SoilSummaryProcess2005;
    ResultRSLPFZero=[ResultRSLPFZero;Result];

    SoilChange(RSLLL);%%Change soil file with a set of norminal value but increase SLLL by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummarySoil.txt');
    [Result]=SoilSummaryProcess2005;
    ResultRSLLLZero=[ResultRSLLLZero;Result];

    SoilChange(RSDUL);%%Change soil file with a set of norminal value but increase SDUL by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummarySoil.txt');
    [Result]=SoilSummaryProcess2005;
    ResultRSDULZero=[ResultRSDULZero;Result];

    SoilChange(RSSAT);%%Change soil file with a set of norminal value but increase SSAT by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummarySoil.txt');
    [Result]=SoilSummaryProcess2005;
    ResultRSSATZero=[ResultRSSATZero;Result];

    SoilChange(RSBDM);%%Change soil file with a set of norminal value but increase SBDM by 5%
    system('..\DSCSM040.EXE B D4Batch.DV4');
    system('copy summary.out Output\SummarySoil.txt');
    [Result]=SoilSummaryProcess2005;
    ResultRSBDMZero=[ResultRSBDMZero;Result];


end

ResultRZero;
ResultRSALBZero;%%Storage for the results of SALB 1
ResultRSLU1Zero;%%Storage for the results of SLU1 2
ResultRSLDRZero;%%Storage for the results of SLDR 3
ResultRSLROZero;%%Storage for the results of SLRO 4
ResultRSLPFZero;%%Storage for the results of SLPF 5
ResultRSLLLZero;%%Storage for the results of SLLL 6
ResultRSDULZero;%%Storage for the results of SDUL 7
ResultRSSATZero;%%Storage for the results of SDUL 8
ResultRSBDMZero;%%Storage for the results of SDUL 9

SALBChange=ResultRSALBZero-ResultRZero;
SLU1Change=ResultRSLU1Zero-ResultRZero;
SLDRChange=ResultRSLDRZero-ResultRZero;
SLROChange=ResultRSLROZero-ResultRZero;
SLPFChange=ResultRSLPFZero-ResultRZero;
SLLLChange=ResultRSLLLZero-ResultRZero;
SDULChange=ResultRSDULZero-ResultRZero;
SSATChange=ResultRSSATZero-ResultRZero;
```

```
SBDMChange=ResultRSBDMZero-ResultRZero;

dSALB=SALBChange./ResultRZero/0.05;%%Elementary effect of SALB
dSLU1=SLU1Change./ResultRZero/0.05;%%Elementary effect of SLU1
dSLDR=SLDRChange./ResultRZero/0.05;%%Elementary effect of SLDR
dSLRO=SLROChange./ResultRZero/0.05;%%Elementary effect of SLRO
dSLPF=SLPFChange./ResultRZero/0.05;%%Elementary effect of SLPF
dSLLL=SLLLChange./ResultRZero/0.05;%%Elementary effect of SLLL
dSDUL=SDULChange./ResultRZero/0.05;%%Elementary effect of SDUL
dSSAT=SSATChange./ResultRZero/0.05;%%Elementary effect of SSAT
dSBDM=SBDMChange./ResultRZero/0.05;%%Elementary effect of SBDM

dSALBmean_Yield=mean(dSALB(:,1));
dSALBvariance_Yield=var(dSALB(:,1));
dSALBmean_NLCM=mean(dSALB(:,2));
dSALBvariance_NLCM=var(dSALB(:,2));%%Mean and variance of elementary effect of SALB for HWAH
and NLCM

dSLU1mean_Yield=mean(dSLU1(:,1));
dSLU1variance_Yield=var(dSLU1(:,1));
dSLU1mean_NLCM=mean(dSLU1(:,2));
dSLU1variance_NLCM=var(dSLU1(:,2));%%Mean and variance of elementary effect of SLU1 for HWAH
and NLCM

dSLDRmean_Yield=mean(dSLDR(:,1));
dSLDRvariance_Yield=var(dSLDR(:,1));
dSLDRmean_NLCM=mean(dSLDR(:,2));
dSLDRvariance_NLCM=var(dSLDR(:,2));%%Mean and variance of elementary effect of SLDR for HWAH
and NLCM

dSLROmean_Yield=mean(dSLRO(:,1));
dSLROvariance_Yield=var(dSLRO(:,1));
dSLROmean_NLCM=mean(dSLRO(:,2));
dSLROvariance_NLCM=var(dSLRO(:,2));%%Mean and variance of elementary effect of SLRO for HWAH
and NLCM

dSLPFmean_Yield=mean(dSLPF(:,1));
dSLPFvariance_Yield=var(dSLPF(:,1));
dSLPFmean_NLCM=mean(dSLPF(:,2));
dSLPFvariance_NLCM=var(dSLPF(:,2));%%Mean and variance of elementary effect of SLPF for HWAH and
NLCM

dSLLLmean_Yield=mean(dSLLL(:,1));
dSLLLvariance_Yield=var(dSLLL(:,1));
dSLLLmean_NLCM=mean(dSLLL(:,2));
dSLLLvariance_NLCM=var(dSLLL(:,2));%%Mean and variance of elementary effect of SLLL for HWAH
and NLCM

dSDULmean_Yield=mean(dSDUL(:,1));
dSDULvariance_Yield=var(dSDUL(:,1));
dSDULmean_NLCM=mean(dSDUL(:,2));
dSDULvariance_NLCM=var(dSDUL(:,2));%%Mean and variance of elementary effect of SDUL for HWAH
and NLCM
```

```
dSSATmean_Yield=mean(dSSAT(:,1));
dSSATvariance_Yield=var(dSSAT(:,1));
dSSATmean_NLCM=mean(dSSAT(:,2));
dSSATvariance_NLCM=var(dSSAT(:,2));%%Mean and variance of elementary effect of SSAT for HWAH
and NLCM

dSBDMmean_Yield=mean(dSBDM(:,1));
dSBDMvariance_Yield=var(dSBDM(:,1));
dSBDMmean_NLCM=mean(dSBDM(:,2));
dSBDMvariance_NLCM=var(dSBDM(:,2));%%Mean and variance of elementary effect of SBDM for HWAH
and NLCM


dSetSoil=[dSALB, dSLU1, dSLDR, dSLRO, dSLPF, dSLLL, dSDUL, dSSAT, dSBDM];

fid_new=fopen('C:\MATLAB7\work\Sensitivity\dSetSoil.txt','w+');
for i=1:Num
fprintf(fid_new,'%10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f
%10.9f %10.9f  %10.9f %10.9f %10.9f %10.9f\n',...
      dSetSoil(i,1),dSetSoil(i,2),dSetSoil(i,3),dSetSoil(i,4),dSetSoil(i,5),dSetSoil(i,6),...
      dSetSoil(i,7),dSetSoil(i,8),dSetSoil(i,9),dSetSoil(i,10),dSetSoil(i,11),dSetSoil(i,12),...
      dSetSoil(i,13),dSetSoil(i,14),dSetSoil(i,15),dSetSoil(i,16),dSetSoil(i,17),dSetSoil(i,18));
end
fclose(fid_new);%%Make a txt file for the elementary effect values for each parameter
```

B.7 Soil File Change

```
%%Modify Soil File

function SoilChange(R)

LinePara1=60;
LinePara2=62;
fid_soil=fopen('soil_Plate.sol','r');
fid_new=fopen('C:\DSSAT4\Soil\soil.sol','w+');

for i=1:70
line=fgetl(fid_soil);
if ~ischar(line), break, end

%%For SALB, SLU1, SLDR SLRO and SLPF
if i==LinePara1
   line1=line(1:8);
   line2=line(9:12);
   line3=line(13:15);
   line4=line(16:18);
   line5=line(19:20);
   line6=line(21:24);
   line7=line(25:26);
   line8=line(27:30);
   line9=line(31:32);
   line10=line(33:36);
```

```
    line11=line(37:38);
    line12=line(39:42);
    line13=line(243:end);

    line2str=num2str(R(1,1),'%4.2f');
    line4str=num2str(R(1,2),'%3.1f');
    line6str=num2str(R(1,3),'%4.2f');
    line8str=num2str(R(1,4),'%4.1f');
    line12str=num2str(R(1,5),'%4.2f');

    NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9 line10 line11 line12str line13];
    fprintf(fid_new,'%s\n',NewLine);

%%Generate the values of SLLL, SDUL, SSAT and SBDM for other 4 layers according to the random value
of the first layer
ParaSLLL=R(1,6);
MeanSLLL=[0.12979 0.13355 0.13740 0.14300 0.14471];
StdevSLLL=[0.08797 0.08901 0.09332 0.10033 0.10152];
PertSLLL=(ParaSLLL-MeanSLLL(1))/StdevSLLL(1);

ParaSDUL=R(1,7);
MeanSDUL=[0.25205 0.25550 0.25824 0.25836 0.25716];
StdevSDUL=[0.10966 0.11195 0.11560 0.12133 0.12151];
PertSDUL=(ParaSDUL-MeanSDUL(1))/StdevSDUL(1);

ParaSSAT=R(1,8);
MeanSSAT=[0.37986 0.37619 0.37831 0.37816 0.37383];
StdevSSAT=[0.09691 0.09334 0.09803 0.09329 0.09050];
PertSSAT=(ParaSSAT-MeanSSAT(1))/StdevSSAT(1);

ParaSBDM=R(1,9);
MeanSBDM=[1.327068966      1.352068966      1.370344828      1.382241379      1.393448276];
StdevSBDM=[0.213196299      0.215103065      0.212660387      0.217957368      0.227569552];
PertSBDM=(ParaSSAT-MeanSBDM(1))/StdevSBDM(1);
%%Mean, STDEV and perturbation of each layer

    for j=1:5
        Para2SLLL(j,1)=MeanSLLL(j)+PertSLLL*StdevSLLL(j);
        Para2SDUL(j,1)=MeanSDUL(j)+PertSDUL*StdevSDUL(j);
        Para2SSAT(j,1)=MeanSSAT(j)+PertSSAT*StdevSSAT(j);
        Para2SBDM(j,1)=MeanSBDM(j)+PertSBDM*StdevSBDM(j);

        if Para2SLLL(j,1)==0
            Para2SLLL(j,1)=Para2SLLL(j,1)+0.001;
            Para2SDUL(j,1)=Para2SDUL(j,1)+0.002;
            Para2SSAT(j,1)=Para2SSAT(j,1)+0.003;
        end

        if Para2SLLL(j,1)==Para2SDUL(j,1)
            Para2SDUL(j,1)=Para2SDUL(j,1)+0.001;
            Para2SSAT(j,1)=Para2SSAT(j,1)+0.002;
        end
```

```
        if Para2SDUL(j,1)==Para2SSAT(j,1)
            Para2SSAT(j,1)=Para2SSAT(j,1)+0.001;
        end
    end

    Para2=ones(5,4);%% Define the parameter matrix 5X3, for SLLL, SDUL, SSAT and SBDM

    Para2Temp(:,:)=[Para2SLLL(:,1) Para2SDUL(:,1) Para2SSAT(:,1) Para2SBDM(:,1)];
    Para2(:,:)=abs(Para2Temp(:,:));
    B=sort(Para2(:,:),2);
    Para2(:,:)=B;%%% Adjust the values of SLLL, SDUL and SSAT

%%For Layer 1 of SLLL SDUL and SSAT
elseif i==LinePara2
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:44);
    line8=line(45:48);
    line9=line(49:end);

    line2str=num2str(Para2(1,1)+0.001,'%5.3f');
    line4str=num2str(Para2(1,2)+0.002,'%5.3f');
    line6str=num2str(Para2(1,3)+0.003,'%5.3f');
    line8str=num2str(Para2(1,4),'%4.2f');

    NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9];
    fprintf(fid_new,'%s\n',NewLine);

%%For Layer 2 of SLLL SDUL and SSAT
elseif i==LinePara2+1
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:44);
    line8=line(45:48);
    line9=line(49:end);

    line2str=num2str(Para2(2,1)+0.001,'%5.3f');
    line4str=num2str(Para2(2,2)+0.002,'%5.3f');
    line6str=num2str(Para2(2,3)+0.003,'%5.3f');
    line8str=num2str(Para2(2,4),'%4.2f');

    NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9];
    fprintf(fid_new,'%s\n',NewLine);

%%For Layer 3 of SLLL SDUL and SSAT
```

```
elseif i==LinePara2+2
   line1=line(1:13);
   line2=line(14:18);
   line3=line(19);
   line4=line(20:24);
   line5=line(25);
   line6=line(26:30);
   line7=line(31:44);
   line8=line(45:48);
   line9=line(49:end);

   line2str=num2str(Para2(3,1)+0.001,'%5.3f');
   line4str=num2str(Para2(3,2)+0.002,'%5.3f');
   line6str=num2str(Para2(3,3)+0.003,'%5.3f');
   line8str=num2str(Para2(3,4),'%4.2f');

   NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9];
   fprintf(fid_new,'%s\n',NewLine);

%%For Layer 4 of SLLL SDUL and SSAT
elseif i==LinePara2+3
   line1=line(1:13);
   line2=line(14:18);
   line3=line(19);
   line4=line(20:24);
   line5=line(25);
   line6=line(26:30);
   line7=line(31:44);
   line8=line(45:48);
   line9=line(49:end);

   line2str=num2str(Para2(4,1)+0.001,'%5.3f');
   line4str=num2str(Para2(4,2)+0.002,'%5.3f');
   line6str=num2str(Para2(4,3)+0.003,'%5.3f');
   line8str=num2str(Para2(4,4),'%4.2f');

   NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9];
   fprintf(fid_new,'%s\n',NewLine);

%%For Layer 5 of SLLL SDUL and SSAT
elseif i==LinePara2+4
   line1=line(1:13);
   line2=line(14:18);
   line3=line(19);
   line4=line(20:24);
   line5=line(25);
   line6=line(26:30);
   line7=line(31:44);
   line8=line(45:48);
   line9=line(49:end);

   line2str=num2str(Para2(4,1)+0.001,'%5.3f');
   line4str=num2str(Para2(4,2)+0.002,'%5.3f');
```

```
    line6str=num2str(Para2(4,3)+0.003,'%5.3f');
    line8str=num2str(Para2(4,4),'%4.2f');

    NewLine=[line1 line2str line3 line4str line5 line6str line7 line8str line9];
    fprintf(fid_new,'%s\n',NewLine);

else
 fprintf(fid_new,'%s\n',line);
end
end

fclose(fid_soil);
fclose(fid_new);
```

B.8 Soil Parameter Space

```
%%Generate the paramter space for each parameter, then do sampling from
%%these spaces to form a series of nominal scenarios

function  [R, RSALB, RSLU1, RSLDR, RSLRO, RSLPF, RSLLL, RSDUL, RSSAT,
RSBDM]=SoilParameterSpace

N=100;% Section Number for every parameter

SALBMin=0.07;
SALBMax=0.18;
DeltaSALB=SALBMax-SALBMin;
SALBSpace=[SALBMin:(1/(N-1))*DeltaSALB:SALBMax];%Generation of sampling space of SALB

SLU1Min=2;
SLU1Max=12.7;
DeltaSLU1=SLU1Max-SLU1Min;
SLU1Space=[SLU1Min:(1/(N-1))*DeltaSLU1:SLU1Max];%Generation of sampling space of SLU1

SLDRMin=0;
SLDRMax=1;
DeltaSLDR=SLDRMax-SLDRMin;
SLDRSpace=[SLDRMin:(1/(N-1))*DeltaSLDR:SLDRMax];%Generation of sampling space of SLDR

SLROMin=30;
SLROMax=95;
DeltaSLRO=SLROMax-SLROMin;
SLROSpace=[SLROMin:(1/(N-1))*DeltaSLRO:SLROMax];%Generation of sampling space of SLRO

SLPFMin=0.7;
SLPFMax=1;
DeltaSLPF=SLPFMax-SLPFMin;
SLPFSpace=[SLPFMin:(1/(N-1))*DeltaSLPF:SLPFMax];%Generation of sampling space of SLPF

SLLLMin=0.02;
SLLLMax=0.252;
DeltaSLLL=SLLLMax-SLLLMin;
SLLLSpace=[SLLLMin:(1/(N-1))*DeltaSLLL:SLLLMax];%Generation of sampling space of SLLL
```

```
SDULMin=0.253;
SDULMax=0.374;
DeltaSDUL=SDULMax-SDULMin;
SDULSpace=[SDULMin:(1/(N-1))*DeltaSDUL:SDULMax];%Generation of sampling space of SDUL

SSATMin=0.375;
SSATMax=0.7;
DeltaSSAT=SSATMax-SSATMin;
SSATSpace=[SSATMin:(1/(N-1))*DeltaSSAT:SSATMax];%Generation of sampling space of SSAT

SBDMMin=0.7;
SBDMMax=1.66;
DeltaSBDM=SBDMMax-SBDMMin;
SBDMSpace=[SBDMMin:(1/(N-1))*DeltaSBDM:SBDMMax];%Generation of sampling space of BDM

Random = unifrnd(1,100,[1 9]);%Generate the random number as the subscript of each parameter...
%selected from its own space

IntRandom=int16(Random);

R=[SALBSpace(IntRandom(1,1)),SLU1Space(IntRandom(1,2)),SLDRSpace(IntRandom(1,3)),...
   SLROSpace(IntRandom(1,4)),SLPFSpace(IntRandom(1,5)),SLLLSpace(IntRandom(1,6)),...
   SDULSpace(IntRandom(1,7)),SSATSpace(IntRandom(1,8)),SBDMSpace(IntRandom(1,9))];%One sapling
of parameter...
%%set


Incre=0.05;  %Degree of increment

IncreSALB=[SALBSpace(IntRandom(1,1))*Incre, 0, 0, 0, 0, 0, 0, 0, 0];
RSALB=R+IncreSALB;%%Increment of SALB

IncreSLU1=[0, SLU1Space(IntRandom(1,2))*Incre, 0, 0, 0, 0, 0, 0, 0];
RSLU1=R+IncreSLU1;%%Increment of SLU1

IncreSLDR=[0, 0, SLDRSpace(IntRandom(1,3))*Incre, 0, 0, 0, 0, 0, 0];
RSLDR=R+IncreSLDR;%%Increment of SLDR

IncreSLRO=[0, 0, 0, SLROSpace(IntRandom(1,4))*Incre, 0, 0, 0, 0, 0];
RSLRO=R+IncreSLRO;%%Increment of SLRO

IncreSLPF=[0, 0, 0, 0, SLPFSpace(IntRandom(1,5))*Incre, 0, 0, 0, 0];
RSLPF=R+IncreSLPF;%%Increment of SLPF

IncreSLLL=[0, 0, 0, 0, 0, SLLLSpace(IntRandom(1,6))*Incre, 0, 0, 0];
RSLLL=R+IncreSLLL;%%Increment of SLLL

IncreSDUL=[0, 0, 0, 0, 0, 0, SDULSpace(IntRandom(1,7))*Incre, 0, 0];
RSDUL=R+IncreSDUL;%%Increment of SDUL

IncreSSAT=[0, 0, 0, 0, 0, 0, 0, SSATSpace(IntRandom(1,8))*Incre, 0];
RSSAT=R+IncreSSAT;%%Increment of SSAT
```

```
IncreSBDM=[0, 0, 0, 0, 0, 0, 0, 0, SBDMSpace(IntRandom(1,9))*Incre];
RSBDM=R+IncreSBDM;%%Increment of SBDM
```

B.9 Processing Sensitivity Analysis Results of Soil Parameter

```
%%Processing the Sensitivity simulation results, selecting the data needed
function [Result]=SoilSummaryProcess2005

N=5;
%%%%To get the values of anthesis days, maturity days, yield and nitrogen
%%%%leaching.

fid_Summary=fopen('C:\DSSAT4\Maize\Output\SummarySoil.txt','r');

LinePara1=5;

for i=1:(N+2)
line=fgetl(fid_Summary);
if ~ischar(line), break, end

if i==LinePara1
   line1=line(1:66);
   line2=line(67:73);
   line3=line(74);
   line4=line(75:81);
   line5=line(82);
   line6=line(83:89);
   line7=line(90:110);
   line8=line(111:115);
   line9=line(116:219);
   line10=line(220:222);
   line11=line(223:end);

   PDAT=str2num(line2);%%Planting date
   ADAT=str2num(line4);%%Anthesis date
   MDAT=str2num(line6);%%Maturity date
   HWAH=str2num(line8);%%Yield
   NLCM=str2num(line10);%%Nitrogen leaching

%     Result=[PDAT,ADAT,MDAT,HWAH,NLCM];
   Result=[HWAH,NLCM];
end
end

fclose(fid_Summary);
```

APPENDIX C
MATLAB CODE FOR GLUE PROCESS

C.1 Main Function

```
%GLUE simulations, totally Num*100 times

n='Please input N to determine the numbers of simulations,N*100';
disp('')
disp(n)
n=input('N=');
Num=n

RG(Num);
Para1Zero=zeros(0,3);
Para2Zero=zeros(0,3);
Para3Zero=zeros(0,3);

for i=1:1:Num

   fprintf('This is the %gth batch of simulation.\n',i);

   addpath C:\MATLAB7\work\Soil;
   [Para1,Para2,Para3]=ParaSetup(i);

   Para2(1,:,:);
   for m=1:100
      for n=1:3
         Para22(m,n)=Para2(1,n,m);
      end
   end

   Para1Zero=[Para1Zero;Para1];
   Para2Zero=[Para2Zero;Para22];
   Para3Zero=[Para3Zero;Para3];%%Collect generated parameter sets

   SoilChange;%%Change soil file
   GenoChange;%%Change genotype file

   %addpath C:\DSSAT4\Maize
   system('..\DSCSM040.EXE B D4Batch.DV4');
   system('copy Output\summary_output.txt+summary.out Output\summary_output.txt');
   system('copy Output\PlantN_output.txt+PlantN.out Output\PlantN_output.txt');
   system('copy Output\SoilN_output.txt+SoilN.out Output\SoilN_output.txt');
end
ParaSet=[Para3Zero,Para1Zero,Para2Zero];

fid_new=fopen('C:\MATLAB7\work\Soil\Paraset.txt','w+');
for i=1:Num*100
fprintf(fid_new,'%10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f\n',...
      ParaSet(i,1),ParaSet(i,2),ParaSet(i,3),ParaSet(i,4),ParaSet(i,5),ParaSet(i,6),...
      ParaSet(i,7),ParaSet(i,8),ParaSet(i,9));
end
```

```
fclose(fid_new);%%Make a txt file for the generated parameter sets
```

C.2 Generation of Random Numbers

```
% Random number generator. This is the function to generate the random numbers that follow an assumed
% multivariate normal distribution.

% n='Please input the lines of random numbers';
% disp('')
% disp(n)
% n=input('N=');
% N=n

function RG(Num)
N=100*Num;

% %Prior
% A=[4561.71   2373.91        61.86    0        0        0        0        0;
% 2373.91      9679.39        55.85    0        0        0        0        0;
% 61.86        55.85    15.97    0        0        0        0        0;
% 0      0        0        0.0364   -0.3392 -0.0030 -0.0030 -0.0049;
% 0      0        0        -0.3392 132.3833        0.3141   0.2355   0.2587;
% 0      0        0        -0.0030 0.3141   0.0098   0.0078   0.0061;
% 0      0        0        -0.0030 0.2355   0.0078   0.0070   0.0046;
% 0      0        0        -0.0049 0.2587   0.0061   0.0046   0.0088
% ];
%
% B=[225.10     763.60   41.20    0.460    73.000   0.252    0.130    0.380];

%%First Posterior
% A=[372.9828  -229.3543       -21.7743        0        0        0        0        0;
% -229.3543    2597.0686       -29.9287        0        0        0        0        0;
% -21.7743     -29.9287        11.4105         0        0        0        0        0;
% 0      0        0        0.0256   -1.0992 0.0032   0.0016   -0.0035;
% 0      0        0        -1.0992 79.6101         -0.0985 -0.0499 0.1952;
% 0      0        0        0.0032   -0.0985 0.0016   0.0015   0.0003;
% 0      0        0        0.0016   -0.0499 0.0015   0.0026   -0.0012;
% 0      0        0        -0.0035 0.1952   0.0003   -0.0012 0.0045 ;
% ];
%
% B=[59.7269   520.0481        36.3871         0.4441   71.6747         0.2321   0.1369   0.3806];

%%Second Posterior
A=[25.0172     -1.5125 -7.5566 0        0        0        0        0;
-1.5125 1121.8859       -21.2470        0        0        0        0        0;
-7.5566 -21.2470        8.9119   0        0        0        0        0;
0        0        0        0.0205   -0.8059 0.0027   0.0013   -0.0021;
0        0        0        -0.8059 69.3364         -0.0923 -0.0374 0.0855;
0        0        0        0.0027   -0.0923 0.0011   0.0008   0.0003;
0        0        0        0.0013   -0.0374 0.0008   0.0012   -0.0005;
0        0        0        -0.0021 0.0855   0.0003   -0.0005 0.0025;
];
```

```
B=[68.3377        524.2715          36.5520            0.4665   70.8025            0.2299   0.1252   0.3868];

R=mvnrnd(B,A,N);

%First Posterior
% min=0.8238;
% max=0.9797;
% SLPF=unifrnd(min,max,N,1)

%Second Posterior
min=0.8239;
max=0.9791;
SLPF=unifrnd(min,max,N,1);

format long
R=abs(R);
SLPF;

fid_new=fopen('C:\MATLAB7\work\Soil\Randoms.txt','w+');
for i=1:N
fprintf(fid_new,'%10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f %10.9f\n',...
      R(i,1),R(i,2),R(i,3),R(i,4),R(i,5),R(i,6),R(i,7),R(i,8),SLPF(i));
end
fclose(fid_new);
```

C.3 Function "mvnrnd"

```
function r = mvnrnd(mu,sigma,cases);
%MVNRND Random matrices from the multivariate normal distribution.
%    R = MVNRND(MU,SIGMA,CASES) returns a matrix of random numbers
%    chosen from the multivariate normal distribution with mean vector,
%    MU, and covariance matrix, SIGMA. CASES is the number of rows in R.
%
%    SIGMA is a square positive definite matrix with size equal to
%    the length of MU

%    B.A. Jones 7-6-94 % Copyright(c) 1993-95 by The MathWorks, Inc.


[m1 n1] = size(mu);
c = max([m1 n1]);
if m1 .* n1 ~= c
  error('Mu must be a vector.');
end

[m n] = size(sigma);
if m ~= n
  error('Sigma must be square');
end

if m ~= c
  error('The length of mu must equal the number of rows in sigma.');
end
```

```
[T p] = chol(sigma);
if p ~= 0
  error('Sigma must be a positive definite matrix.');
end


if m1 == c
  mu = mu';
end

mu = mu(ones(cases,1),:);

r = randn(cases,c) * T + mu;
```

C.4 Parameter Setup for Genotype and Soil

```
%Processing the generated random numbers to genotype and soil

function [Para1,Para2,Para3]=ParaSetup(i)

B=load('C:\MATLAB7\work\Soil\Randoms.txt');

A=B((i-1)*100+1:i*100,:);

J=find(A(:,5)>=100);
A(J,5)=99;%%Change the runoff curve number that is greater than 100 to 99.

Para1=[A(:,4) A(:,5) A(:,9)];

ParaSLLL=[A(:,7)];
ParaSDUL=[A(:,6)];
ParaSSAT=[A(:,8)];

MeanSLLL=[0.12979 0.13355 0.13740 0.14300 0.14471];
StdevSLLL=[0.08797 0.08901 0.09332 0.10033 0.10152];
PertSLLL=(ParaSLLL-MeanSLLL(1))/StdevSLLL(1);

MeanSDUL=[0.25205 0.25550 0.25824 0.25836 0.25716];
StdevSDUL=[0.10966 0.11195 0.11560 0.12133 0.12151];
PertSDUL=(ParaSDUL-MeanSDUL(1))/StdevSDUL(1);

MeanSSAT=[0.37986 0.37619 0.37831 0.37816 0.37383];
StdevSSAT=[0.09691 0.09334 0.09803 0.09329 0.09050];
PertSSAT=(ParaSSAT-MeanSSAT(1))/StdevSSAT(1);

for i=1:100
   for j=1:5
      Para2SLLL(j,i)=MeanSLLL(j)+PertSLLL(i)*StdevSLLL(j);
      Para2SDUL(j,i)=MeanSDUL(j)+PertSDUL(i)*StdevSDUL(j);
      Para2SSAT(j,i)=MeanSSAT(j)+PertSSAT(i)*StdevSSAT(j);

      if Para2SLLL(j,i)==0
```

```
        Para2SLLL(j,i)=Para2SLLL(j,i)+0.001;
        Para2SDUL(j,i)=Para2SDUL(j,i)+0.002;
        Para2SSAT(j,i)=Para2SSAT(j,i)+0.003;
      end

      if Para2SLLL(j,i)==Para2SDUL(j,i)
        Para2SDUL(j,i)=Para2SDUL(j,i)+0.001;
        Para2SSAT(j,i)=Para2SSAT(j,i)+0.002;
      end

      if Para2SDUL(j,i)==Para2SSAT(j,i)
        Para2SSAT(j,i)=Para2SSAT(j,i)+0.001;
      end
    end
end

Para2=ones(5,3,100);

for i=1:100
    Para2Temp(:,:,i)=[Para2SLLL(:,i) Para2SDUL(:,i) Para2SSAT(:,i)];
    Para2(:,:,i)=abs(Para2Temp(:,:,i));
    B=sort(Para2(:,:,i),2);
    Para2(:,:,i)=B;
end

%%Genotype
I=find(A(:,2)>=1000);%%Change the P5 value that is greater than 1000 to 990.
A(I,2)=990;
Para3=[A(:,1) A(:,2) A(:,3)];

save parameter Para1 Para2 Para3;
```

C.5 Change of Soil File

```
%%Modify Soil File

function SoilChange
load parameter;
LinePara1=60:13:1347;
LinePara2=LinePara1+2;
fid_soil=fopen('soil_Plate.sol','r');
fid_new=fopen('C:\DSSAT4\Soil\soil.sol','w+');
k=1;
for i=1:2000
line=fgetl(fid_soil);
if ~ischar(line), break, end

%%For SLDR SLRO and SLPF
if k<=100 & i==LinePara1(k)
    line1=line(1:20);
    line2=line(21:24);
    line3=line(25:26);
    line4=line(27:30);
```

```
    line5=line(31:38);
    line6=line(39:42);
    line7=line(43:end);
    line2str=num2str(Para1(k,1),'%4.2f');
    line4str=num2str(Para1(k,2),'%4.1f');
    line6str=num2str(Para1(k,3),'%4.2f');
    NewLine=[line1 line2str line3 line4str line5 line6str line7];
    fprintf(fid_new,'%s\n',NewLine);


%%For Layer 1 of SLLL SDUL and SSAT
elseif k<=100 & i==LinePara2(k)
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:end);

    line2str=num2str(Para2(1,1,k)+0.001,'%5.3f');
    line4str=num2str(Para2(1,2,k)+0.002,'%5.3f');
    line6str=num2str(Para2(1,3,k)+0.003,'%5.3f');
    NewLine=[line1 line2str line3 line4str line5 line6str line7];
    fprintf(fid_new,'%s\n',NewLine);

%%For Layer 2 of SLLL SDUL and SSAT
elseif k<=100 & i==LinePara2(k)+1
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:end);

    line2str=num2str(Para2(2,1,k)+0.001,'%5.3f');
    line4str=num2str(Para2(2,2,k)+0.002,'%5.3f');
    line6str=num2str(Para2(2,3,k)+0.003,'%5.3f');
    NewLine=[line1 line2str line3 line4str line5 line6str line7];
    fprintf(fid_new,'%s\n',NewLine);

%%For Layer 3 of SLLL SDUL and SSAT
elseif k<=100 & i==LinePara2(k)+2
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:end);

    line2str=num2str(Para2(3,1,k)+0.001,'%5.3f');
```

```
    line4str=num2str(Para2(3,2,k)+0.002,'%5.3f');
    line6str=num2str(Para2(3,3,k)+0.003,'%5.3f');
    NewLine=[line1 line2str line3 line4str line5 line6str line7];
    fprintf(fid_new,'%s\n',NewLine);

%%For Layer 4 of SLLL SDUL and SSAT
elseif k<=100 & i==LinePara2(k)+3
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:end);

    line2str=num2str(Para2(4,1,k)+0.001,'%5.3f');
    line4str=num2str(Para2(4,2,k)+0.002,'%5.3f');
    line6str=num2str(Para2(4,3,k)+0.003,'%5.3f');
    NewLine=[line1 line2str line3 line4str line5 line6str line7];
    fprintf(fid_new,'%s\n',NewLine);

%%For Layer 5 of SLLL SDUL and SSAT
elseif k<=100 & i==LinePara2(k)+4
    line1=line(1:13);
    line2=line(14:18);
    line3=line(19);
    line4=line(20:24);
    line5=line(25);
    line6=line(26:30);
    line7=line(31:end);

    line2str=num2str(Para2(5,1,k)+0.001,'%5.3f');
    line4str=num2str(Para2(5,2,k)+0.002,'%5.3f');
    line6str=num2str(Para2(5,3,k)+0.003,'%5.3f');
    NewLine=[line1 line2str line3 line4str line5 line6str line7];
    fprintf(fid_new,'%s\n',NewLine);

    k=k+1;
else
 fprintf(fid_new,'%s\n',line);
end
end

fclose(fid_soil);
fclose(fid_new);
```

C.6 Change of Genotype File

```
%%Modify Genotype File

function GenoChange
load parameter;
LinePara1=47:1:146;
```

```
fid_MZCER040=fopen('MZCER040_Plate.cul','r');
fid_new=fopen('C:\DSSAT4\Genotype\MZCER040.cul','w+');
k=1;
for i=1:200
line=fgetl(fid_MZCER040);
if ~ischar(line), break, end

%%For P1, P5 and PHIN
if k<=100 & i==LinePara1(k)
   line1=line(1:31);
   line2=line(32:36);
   line3=line(37:44);
   line4=line(45:49);
   line5=line(50:62);
   line6=line(63:66);
   line7=line(67:end);
   line2str=num2str(Para3(k,1),'%5.1f');
   line4str=num2str(Para3(k,2),'%5.1f');
   line6str=num2str(Para3(k,3),'%4.1f');
   NewLine=[line1 line2str line3 line4str line5 line6str line7];
   fprintf(fid_new,'%s\n',NewLine);

   k=k+1;%%Next Line
else
 fprintf(fid_new,'%s\n',line);
end
end

fclose(fid_MZCER040);
fclose(fid_new);
```

C.7 Summary Output Processing

```
%%Processing the GLUE simulation results, selecting the data needed

N=10400;

%%%%To get the values of anthesis days, maturity days, yield and nitrogen
%%%%leaching.

fid_Summary=fopen('C:\DSSAT4\Maize\Output\Summary_Output.txt','r');
fid_new=fopen('C:\DSSAT4\Maize\Output\Summary.txt','w+');

k=1;%%Subscriot of Line Matrix

for i=1:(N+5)
line=fgetl(fid_Summary);
if ~ischar(line), break, end

if length(line)==283
  if line(67:73)=='2005068'
    line1=line(1:66);
    line2=line(67:73);
```

```
    line3=line(74);
    line4=line(75:81);
    line5=line(82);
    line6=line(83:89);
    line7=line(90:110);
    line8=line(111:115);
    line9=line(116:219);
    line10=line(220:222);
    line11=line(223:end);

    PDAT=line2;%%Planting date
    ADAT=num2str(line4);%%Anthesis date
    MDAT=line6;%%Maturity date
    HWAH=line8;%%Yield
    NLCM=line10;%%Nitrogen leaching

    NewLine=[PDAT,' ',ADAT,' ',MDAT,' ',HWAH,' ',NLCM];
    fprintf(fid_new,'%s\n',NewLine);
  end
end
end

fclose(fid_Summary);
fclose(fid_new);
```

C.8 Plant Nitrogen Output Processing

```
%%Processing the GLUE simulation results, selecting the data needed

N=1300000;

%%%%To get the values of anthesis days, maturity days, yield and nitrogen
%%%%leaching.

fid_PlantN=fopen('C:\DSSAT4\Maize\Output\PlantN_Output.txt','r');

LN90=zeros(0,1);
LN97=zeros(0,1);
LN112=zeros(0,1);
LN126=zeros(0,1);
LN136=zeros(0,1);
LN140=zeros(0,1);
LN147=zeros(0,1);
LN153=zeros(0,1);%%Empty matrix for leaf nitogen concentration at different days


for i=1:(N+5)
line=fgetl(fid_PlantN);
if ~ischar(line), break, end

if length(line)==114
    if line(2:5)=='2005'
```

```
    line1=line(1);
    line2=line(2:5);
    line3=line(6);
    line4=line(7:9);
    line5=line(10:87);
    line6=line(88:91);
    line7=line(91:end);

    YearStr=line2;%%Planting year as string
    DayStr=line4;%%Sampling day as string
    LNStr=line6;%%Maturity date as string

    Yea=str2num(YearStr);%%Planting year as number
    Day=str2num(DayStr);%%Sampling day as number
    LN=str2num(LNStr);%%Leaf nitrogen concentration

    if Day==90
       LN90=[LN90;LN];
    else if Day==97
          LN97=[LN97;LN];
       else if Day==112
             LN112=[LN112;LN];
          else if Day==126
                LN126=[LN126;LN];
             else if Day==136
                   LN136=[LN136;LN];
                else if Day==140
                      LN140=[LN140;LN];
                   else if Day==147
                         LN147=[LN147;LN];
                      else if Day==153
                            LN153=[LN153;LN];
                         end
                      end
                   end
                end
             end
          end
       end
    end

    end

end
end

% fid_new=fopen('C:\DSSAT4\Maize\Output\PlantN.txt','w+');
fid_new1=fopen('C:\DSSAT4\Maize\Output\PlantN90.txt','w+');
fid_new2=fopen('C:\DSSAT4\Maize\Output\PlantN97.txt','w+');
fid_new3=fopen('C:\DSSAT4\Maize\Output\PlantN112.txt','w+');
fid_new4=fopen('C:\DSSAT4\Maize\Output\PlantN126.txt','w+');
fid_new5=fopen('C:\DSSAT4\Maize\Output\PlantN136.txt','w+');
fid_new6=fopen('C:\DSSAT4\Maize\Output\PlantN140.txt','w+');
```

```
fid_new7=fopen('C:\DSSAT4\Maize\Output\PlantN147.txt','w+');
fid_new8=fopen('C:\DSSAT4\Maize\Output\PlantN153.txt','w+');

for i=1:length(LN90)
% fprintf(fid_new,'%4.1f %4.1f %4.1f %4.1f %4.1f %4.1f %4.1f %4.1f\n',...
%        LN90,LN97,LN112,LN126,LN136,LN140,LN147,LN153);
fprintf(fid_new1,'%4.1f\n',LN90(i,1));
end

for i=1:length(LN97)
fprintf(fid_new2,'%4.1f\n',LN97(i,1));
end

for i=1:length(LN112)
fprintf(fid_new3,'%4.1f\n',LN112(i,1));
end

for i=1:length(LN126)
fprintf(fid_new4,'%4.1f\n',LN126(i,1));
end

for i=1:length(LN136)
fprintf(fid_new5,'%4.1f\n',LN136(i,1));
end

for i=1:length(LN140)
fprintf(fid_new6,'%4.1f\n',LN140(i,1));
end

for i=1:length(LN147)
fprintf(fid_new7,'%4.1f\n',LN147(i,1));
end

for i=1:length(LN153)
fprintf(fid_new8,'%4.1f\n',LN153(i,1));
end

fclose(fid_new1);
fclose(fid_new2);
fclose(fid_new3);
fclose(fid_new4);
fclose(fid_new5);
fclose(fid_new6);
fclose(fid_new7);
fclose(fid_new8);
%%Make a txt file for the generated parameter sets


fclose(fid_PlantN);
% fclose(fid_PlantN);
```

C.9 Soil Nitrogen Output Processing

```
%%Processing the GLUE simulation results, selecting the data needed

N=1300000;

%%%%To get the values of anthesis days, maturity days, yield and nitrogen
%%%%leaching.

fid_SoilN=fopen('C:\DSSAT4\Maize\Output\SoilN_Output.txt','r');

SN90=zeros(0,4);
SN97=zeros(0,4);
SN112=zeros(0,4);
SN126=zeros(0,4);
SN136=zeros(0,4);
SN140=zeros(0,4);
SN147=zeros(0,4);
SN153=zeros(0,4);%%Empty matrix for soil nitogen concentration at different days in four layers


for i=1:N
line=fgetl(fid_SoilN);
if ~ischar(line), break, end

if length(line)==224
   if line(2:5)=='2005'
   line1=line(1:6);
   line2=line(7:9);
   line3=line(10:70);
   line4=line(71:76);
   line5=line(77:82);
   line6=line(83:88);
   line7=line(89:94);
   line8=line(95:100);
   line9=line(101:end);

   DayStr=line2;%%Sampling day as string
   L1Str=line4;%%Soil NItrogen in Layer 1 as string
   L2Str=line5;%%Soil NItrogen in Layer 2 as string
   L3Str=line6;%%Soil NItrogen in Layer 3 as string
   L4Str=line8;%%Soil NItrogen in Layer 4 as string

   Day=str2num(DayStr);%%Sampling day as number
   L1=str2num(L1Str);%%Soil NItrogen in Layer 1 as number
   L2=str2num(L2Str);%%Soil NItrogen in Layer 2 as number
   L3=str2num(L3Str);%%Soil NItrogen in Layer 3 as number
   L4=str2num(L4Str);%%Soil NItrogen in Layer 4 as number
   SN=[L1,L2,L3,L4];

   if Day==90
      SN90=[SN90;SN];
   else if Day==97
```

```
            SN97=[SN97;SN];
        else if Day==112
                SN112=[SN112;SN];
            else if Day==126
                    SN126=[SN126;SN];
                else if Day==136
                        SN136=[SN136;SN];
                    else if Day==140
                            SN140=[SN140;SN];
                        else if Day==147
                                SN147=[SN147;SN];
                            else if Day==153
                                    SN153=[SN153;SN];
                                end
                            end
                        end
                    end
                end
            end
        end
    end

    end

end
end

fid_new1=fopen('C:\DSSAT4\Maize\Output\SoilN90.txt','w+');
fid_new2=fopen('C:\DSSAT4\Maize\Output\SoilN97.txt','w+');
fid_new3=fopen('C:\DSSAT4\Maize\Output\SoilN112.txt','w+');
fid_new4=fopen('C:\DSSAT4\Maize\Output\SoilN126.txt','w+');
fid_new5=fopen('C:\DSSAT4\Maize\Output\SoilN136.txt','w+');
fid_new6=fopen('C:\DSSAT4\Maize\Output\SoilN140.txt','w+');
fid_new7=fopen('C:\DSSAT4\Maize\Output\SoilN147.txt','w+');
fid_new8=fopen('C:\DSSAT4\Maize\Output\SoilN153.txt','w+');

for i=1:length(SN90)
fprintf(fid_new1,'%5.1f %5.1f %5.1f %5.1f\n',SN90(i,:));
end

for i=1:length(SN97)
fprintf(fid_new2,'%5.1f %5.1f %5.1f %5.1f\n',SN97(i,:));
end

for i=1:length(SN112)
fprintf(fid_new3,'%5.1f %5.1f %5.1f %5.1f\n',SN112(i,:));
end

for i=1:length(SN126)
fprintf(fid_new4,'%5.1f %5.1f %5.1f %5.1f\n',SN126(i,:));
end

for i=1:length(SN136)
```

```
fprintf(fid_new5,'%5.1f %5.1f %5.1f %5.1f\n',SN136(i,:));
end

for i=1:length(SN140)
fprintf(fid_new6,'%5.1f %5.1f %5.1f %5.1f\n',SN140(i,:));
end

for i=1:length(SN147)
fprintf(fid_new7,'%5.1f %5.1f %5.1f %5.1f\n',SN147(i,:));
end

for i=1:length(SN153)
fprintf(fid_new8,'%5.1f %5.1f %5.1f %5.1f\n',SN153(i,:));
end

fclose(fid_new1);
fclose(fid_new2);
fclose(fid_new3);
fclose(fid_new4);
fclose(fid_new5);
fclose(fid_new6);
fclose(fid_new7);
fclose(fid_new8);
%%Make a txt file for the soil nitrogen in 4 different layer on different
%%days

fclose(fid_SoilN);
```

C.10 Parameter PDF Plot

```
%%%%%%%Plot histograms for the selected parameters

%%%%%%%%%%Histograms of P1%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (1)
break_point=[0:25:500];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,1),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of P1');
ylabel('Probability');
title('\fontsize{11}PDF of P1 under prior distribution')%%PDF of P1.
axis([break_point(1)  break_point(l)  0  1.0]);
```

```
subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,1);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of P1');
ylabel('Probability');
title('\fontsize{11}PDF of P1 under first posterior distribution')%%PDF of P1.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,1);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of P1');
ylabel('Probability');
title('\fontsize{11}PDF of P1 under second posterior distribution')%%PDF of P1.
```

```
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of P5%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (2)
break_point=[0:50:1000];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,2),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of P5');
ylabel('Probability');
title('\fontsize{11}PDF of P5 under prior distribution')%%PDF of P5.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,2);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of P5');
ylabel('Probability');
title('\fontsize{11}PDF of P5 under first posterior distribution')%%PDF of P5.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
```

```
x=C(:,2);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of P5');
ylabel('Probability');
title('\fontsize{11}PDF of P5 under second posterior distribution')%%PDF of P5.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%%Histograms of PHIN%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (3)
break_point=[0:3:60];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,3),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of PHIN');
ylabel('Probability');
title('\fontsize{11}PDF of PHIN under prior distribution')%%PDF of PHIN.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,3);
n=B(:,10);
```

```
m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of PHIN');
ylabel('Probability');
title('\fontsize{11}PDF of PHIN under first posterior distribution')%%PDF of PHIN.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,3);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of PHIN');
ylabel('Probability');
title('\fontsize{11}PDF of PHIN under second posterior distribution')%%PDF of PHIN.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of SLDR%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (4)
break_point=[0:0.05:1];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,4),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLDR');
ylabel('Probability');
title('\fontsize{11}PDF of SLDR under prior distribution')%%PDF of SLDR.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,4);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
   I=find(x>=break_point(i) & x<=break_point(i+1));
   Pp_group=n(I);
   P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLDR');
ylabel('Probability');
title('\fontsize{11}PDF of SLDR under first posterior distribution')%%PDF of SLDR.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,4);
n=C(:,10);

m=length(n);
```

```
a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
   I=find(x>=break_point(i) & x<=break_point(i+1));
   Pp_group=n(I);
   P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLDR');
ylabel('Probability');
title('\fontsize{11}PDF of SLDR under second posterior distribution')%%PDF of SLDR.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of SLRO%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (5)
break_point=[0:5:100];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,5),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLRO');
ylabel('Probability');
title('\fontsize{11}PDF of SLRO under prior distribution')%%PDF of SLRO.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,5);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
```

```
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
   I=find(x>=break_point(i) & x<=break_point(i+1));
   Pp_group=n(I);
   P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLRO');
ylabel('Probability');
title('\fontsize{11}PDF of SLRO under first posterior distribution')%%PDF of SLRO.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,5);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
   I=find(x>=break_point(i) & x<=break_point(i+1));
   Pp_group=n(I);
   P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLRO');
ylabel('Probability');
title('\fontsize{11}PDF of SLRO under second posterior distribution')%%PDF of SLRO.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of SDUL%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');
```

```
figure (6)
break_point=[0:0.025:0.5];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,6),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SDUL');
ylabel('Probability');
title('\fontsize{11}PDF of SDUL under prior distribution')%%PDF of SDUL.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,6);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
   I=find(x>=break_point(i) & x<=break_point(i+1));
   Pp_group=n(I);
   P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SDUL');
ylabel('Probability');
title('\fontsize{11}PDF of SDUL under first posterior distribution')%%PDF of SDUL.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,6);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;
```

```
middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SDUL');
ylabel('Probability');
title('\fontsize{11}PDF of SDUL under second posterior distribution')%%PDF of SDUL.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of SLLL%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (7)
break_point=[0:0.025:0.5];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,7),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLLL');
ylabel('Probability');
title('\fontsize{11}PDF of SLLL under prior distribution')%%PDF of SLLL.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,7);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
```

```
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLLL');
ylabel('Probability');
title('\fontsize{11}PDF of SLLL under first posterior distribution')%%PDF of SLLL.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,7);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLLL');
ylabel('Probability');
title('\fontsize{11}PDF of SLLL under second posterior distribution')%%PDF of SLLL.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of SSAT%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (8)
break_point=[0.2:0.025:0.7];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
```

```
[n,x]=hist(A(:,8),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SSAT');
ylabel('Probability');
title('\fontsize{11}PDF of SSAT under prior distribution')%%PDF of SSAT.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,8);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SSAT');
ylabel('Probability');
title('\fontsize{11}PDF of SSAT under first posterior distribution')%%PDF of SSAT.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,8);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
```

```
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SSAT');
ylabel('Probability');
title('\fontsize{11}PDF of SSAT under second posterior distribution')%%PDF of SSAT.
axis([break_point(1)  break_point(l)  0  1.0]);


%%%%%%%%%%Histograms of SLPF%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
A=load('Histogram_Prior.txt');
B=load('Histogram_First_Posterior.txt');
C=load('Histogram_Second_Posterior.txt');

figure (9)
break_point=[0.6:0.02:1.0];
l=length(break_point);

subplot(3,1,1);%%Histogram under prior distribution
[n,x]=hist(A(:,9),20);
bar(x,n/10000);

h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLPF');
ylabel('Probability');
title('\fontsize{11}PDF of SLPF under prior distribution')%%PDF of SLPF.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,2);%%Histogram under first posterior distribution
x=B(:,9);
n=B(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end
```

```
bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLPF');
ylabel('Probability');
title('\fontsize{11}PDF of SLPF under first posterior distribution')%%PDF of SLPF.
axis([break_point(1)  break_point(l)  0  1.0]);

subplot(3,1,3);%%Histogram under second posterior distribution
x=C(:,9);
n=C(:,10);

m=length(n);

a=(break_point(1)+break_point(2))/2;
%%l=length(break_point);
b=break_point(2)-break_point(1);
c=(break_point(l-1)+break_point(l))/2;

middle_point=[a:b:c];

for i=1:length(break_point)-1
  I=find(x>=break_point(i) & x<=break_point(i+1));
  Pp_group=n(I);
  P_group(i)=sum(Pp_group);
end

bar(middle_point,P_group,1,'b');
h=findobj(gca,'Type','patch');
set(h,'FaceColor','blue','EdgeColor','w')
xlabel('Number of SLPF');
ylabel('Probability');
title('\fontsize{11}PDF of SLPF under second posterior distribution')%%PDF of SLPF.
axis([break_point(1)  break_point(l)  0  1.0]);
```

C.11 3-D Plot of Joint Distribution of Yield and Nitrogen Leaching

```
clear;
%%Yield and nitrogen leaching joint distribution under prior distribution
%%of input parameters
A=load('Joint_Prior.txt');

figure (1)

Yield=A(:,1);
NLCM=A(:,2);%%Get the data of yield and nitrogen leaching (NLCM)
Num_Data=length(Yield);%%Get the number of total data

break_point1=[0:500:15000];
L1=length(break_point1);%%Set the grid vector for yield

break_point2=[0:10:300];
L2=length(break_point2);%%Set the grid vector for NLCM
```

```
a1=(break_point1(1)+break_point1(2))/2;
b1=break_point1(2)-break_point1(1);
c1=(break_point1(L1-1)+break_point1(L1))/2;
middle_point1=[a1:b1:c1];%%Set the midddle point vector for yield

a2=(break_point2(1)+break_point2(2))/2;
b2=break_point2(2)-break_point2(1);
c2=(break_point2(L2-1)+break_point2(L2))/2;
middle_point2=[a2:b2:c2];%%Set the midddle point vector for NLCM


I=zeros(0,1);

for i=1:L1-1
  I1=find(Yield>=break_point1(i) & Yield<break_point1(i+1));

  for j=1:L2-1
     I2=find(NLCM>=break_point2(j) & NLCM<break_point2(j+1));

     for m=1:length(I1)
        for n=1:length(I2)
           if (I1(m)==I2(n))
              I=[I;I2(n)];
           end
        end
     end

     count(j,i)=length(I);
     I=zeros(0,1);

  end

end

middle_point1=[a1:b1:c1];
middle_point2=[a2:b2:c2];
count; %% Use these three things to plot the joint distribution between yield and nitrogen leaching

[X,Y]=meshgrid(middle_point1,middle_point2);
Z=count/Num_Data;
surfc(X,Y,Z)

xlabel('Yield (kg/ha)');
ylabel('Nitrogen leaching (NLCM, kg/ha)');
Zlabel('Probability');
title('\fontsize{11}Joint Distribution between yield and NLCM under prior distribution of parameter')%%PDF
of P1.
axis([0 15000  0 300  0 0.2]);

clear;
%%Yield and nitrogen leaching joint distribution under first posterior distribution
%%of input parameters
```

```
A=load('Joint_First_Posterior.txt');

figure (2)

Yield=A(:,1);
NLCM=A(:,2);%%Get the data of yield and nitrogen leaching (NLCM)
Num_Data=length(Yield);%%Get the number of total data

break_point1=[0:500:15000];
L1=length(break_point1);%%Set the grid vector for yield

break_point2=[0:10:300];
L2=length(break_point2);%%Set the grid vector for NLCM

a1=(break_point1(1)+break_point1(2))/2;
b1=break_point1(2)-break_point1(1);
c1=(break_point1(L1-1)+break_point1(L1))/2;
middle_point1=[a1:b1:c1];%%Set the midddle point vector for yield

a2=(break_point2(1)+break_point2(2))/2;
b2=break_point2(2)-break_point2(1);
c2=(break_point2(L2-1)+break_point2(L2))/2;
middle_point2=[a2:b2:c2];%%Set the midddle point vector for NLCM


I=zeros(0,1);

for i=1:L1-1
  I1=find(Yield>=break_point1(i) & Yield<break_point1(i+1));

  for j=1:L2-1
     I2=find(NLCM>=break_point2(j) & NLCM<break_point2(j+1));

     for m=1:length(I1)
        for n=1:length(I2)
           if (I1(m)==I2(n))
              I=[I;I2(n)];
           end
        end
     end

     count(j,i)=length(I);
     I=zeros(0,1);

  end

end

middle_point1=[a1:b1:c1];
middle_point2=[a2:b2:c2];
count; %% Use these three things to plot the joint distribution between yield and nitrogen leaching

[X,Y]=meshgrid(middle_point1,middle_point2);
```

```
Z=count/Num_Data;
surfc(X,Y,Z)

xlabel('Yield (kg/ha)');
ylabel('Nitrogen leaching (NLCM, kg/ha)');
Zlabel('Probability');
title('\fontsize{11}Joint Distribution between yield and NLCM under first posterior distribution of
parameter')%%PDF of P1.
axis([0 15000  0 300  0 0.2]);

clear;
%%Yield and nitrogen leaching joint distribution under second posterior distribution
%%of input parameters

A=load('Joint_Second_Posterior.txt');

figure (3)

Yield=A(:,1);
NLCM=A(:,2);%%Get the data of yield and nitrogen leaching (NLCM)
Num_Data=length(Yield);%%Get the number of total data

break_point1=[0:500:15000];
L1=length(break_point1);%%Set the grid vector for yield

break_point2=[0:10:300];
L2=length(break_point2);%%Set the grid vector for NLCM

a1=(break_point1(1)+break_point1(2))/2;
b1=break_point1(2)-break_point1(1);
c1=(break_point1(L1-1)+break_point1(L1))/2;
middle_point1=[a1:b1:c1];%%Set the midddle point vector for yield

a2=(break_point2(1)+break_point2(2))/2;
b2=break_point2(2)-break_point2(1);
c2=(break_point2(L2-1)+break_point2(L2))/2;
middle_point2=[a2:b2:c2];%%Set the midddle point vector for NLCM


I=zeros(0,1);

for i=1:L1-1
  I1=find(Yield>=break_point1(i) & Yield<break_point1(i+1));

  for j=1:L2-1
     I2=find(NLCM>=break_point2(j) & NLCM<break_point2(j+1));

     for m=1:length(I1)
        for n=1:length(I2)
           if (I1(m)==I2(n))
              I=[I;I2(n)];
           end
        end
```

```
        end

        count(j,i)=length(I);
        I=zeros(0,1);

    end

end

middle_point1=[a1:b1:c1];
middle_point2=[a2:b2:c2];
count; %% Use these three things to plot the joint distribution between yield and nitrogen leaching

[X,Y]=meshgrid(middle_point1,middle_point2);
Z=count/Num_Data;
surfc(X,Y,Z)

xlabel('Yield (kg/ha)');
ylabel('Nitrogen leaching (NLCM, kg/ha)');
Zlabel('Probability');
title('\fontsize{11}Joint Distribution between yield and NLCM under second posterior distribution of
parameter')%%PDF of P1.
axis([0 15000  0 300  0 0.2]);
```

APPENDIX D
PICTUES OF FIELD EXPERIMENT

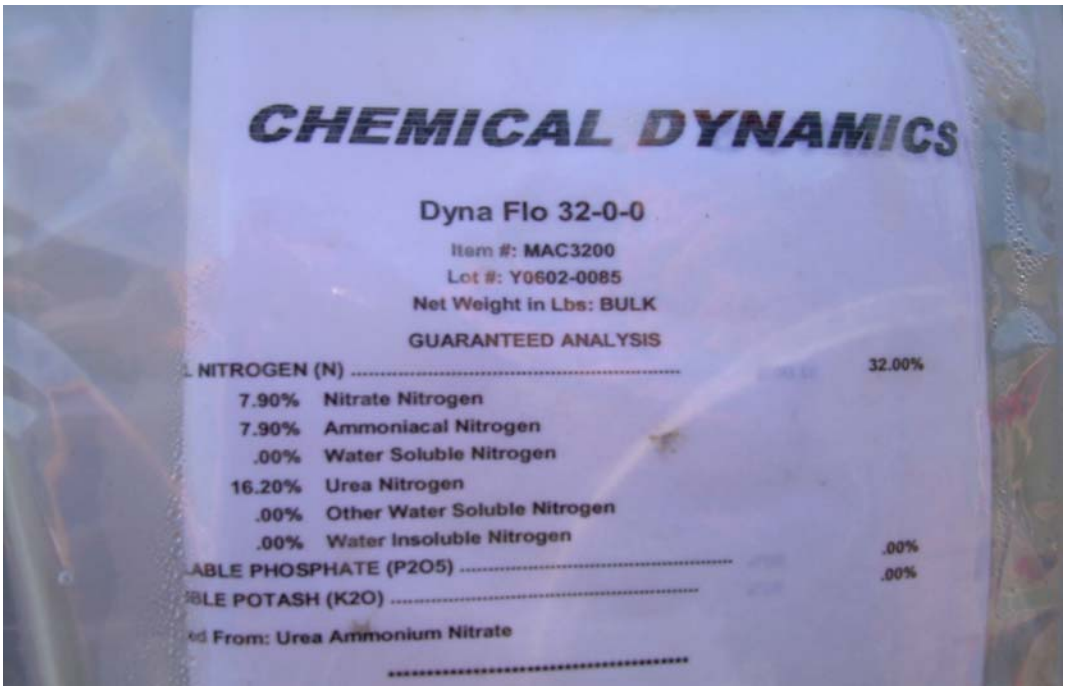


Figure D-1. Components of nitrogen fertilizer solution

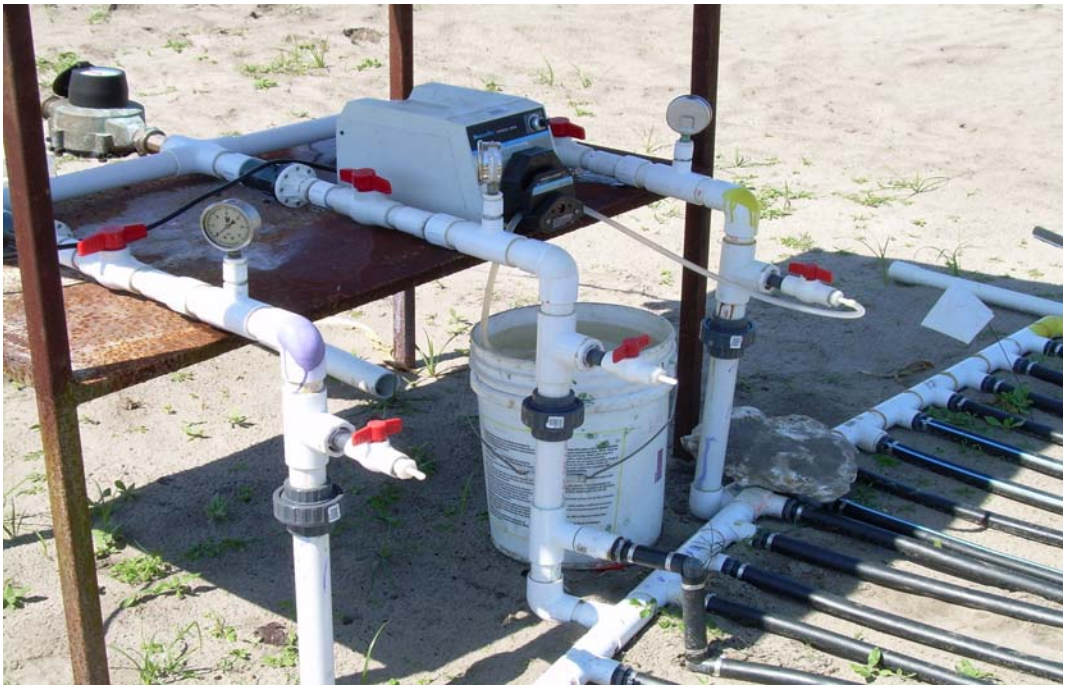


Figure D-2. Fertigation control table

Figure D-3. Fertigation system installation

Figure D-4. Main fertigation lines, injection holes, peristaltic pump, and solution bucket

Figure D-5. Sub-main fertigation lines

Figure D-6. Drip tapes and sub-main fertigation line

Figure D-7. Drip tape distribution in one row

Figure D-8. Irrigation with the linear move irrigation system

Figure D-9. Sweet corn planting

Figure D-10. Sweet corn emergence

Figure D-11. Comparison between no-nirogen-applied plot (near) and nitrogen-applied plot (far)

Figure D-12. Sweet corn tasseling

Figure D-13. Sweet corn maturity

Figure D-14. Sweet corn harvest

Figure D-15. Plant sampling

Figure D-16. Soil sampling

Figure D-17. Yield sampling

Figure D-18. Yield weighing

Figure D-19. Yield grading

Figure D-20. Research partner

APPENDIX E
SAS CODE FOR ANOVA OF YIELD QUANTITY AND QUALITY

```
proc import
datafile='C:\Jianqiang He\PhD Study\PhD Research\SAS Data Analysis\Yield Analysis of Plots\Yields of
      Plots in 2006.xls'
out=Yield DBMS=excel2000 REPLACE;
SHEET="Yield";
Getnames=yes;
run;
proc print data=Yield;
run;

proc anova data=Yield;
class Block I N;
 model TotalYield= Block I Block*I N I*N;
     test h=I e=Block*I;
MEANS I|N/DUNCAN;
run;

proc anova data=Yield;
class Block I N;
 model MarketYield= Block I Block*I N I*N;
     test h=I e=Block*I;
MEANS I|N/DUNCAN;
run;

proc anova data=Yield;
class Block I N;
 model TotalEar= Block I Block*I N I*N;
     test h=I e=Block*I;
MEANS I|N/DUNCAN;
run;

proc anova data=Yield;
class Block I N;
 model US1= Block I Block*I N I*N;
     test h=I e=Block*I;
MEANS I|N/DUNCAN;
run;

proc anova data=Yield;
class Block I N;
 model US2= Block I Block*I N I*N;
     test h=I e=Block*I;
MEANS I|N/DUNCAN;
run;

proc anova data=Yield;
class Block I N;
```

```
 model Cull= Block I Block*I N I*N;
    test h=I e=Block*I;
MEANS I|N/DUNCAN;
run;
```

APPENDIX F
NITRATE AND AMMONIUM CONCENTRATIONS IN MONITORING WELLS IN BLOCK1 IN THE PLANT SCIENCE RESEARCH AND EDUCATION UNIT UNIVERSITY OF FLORIDA

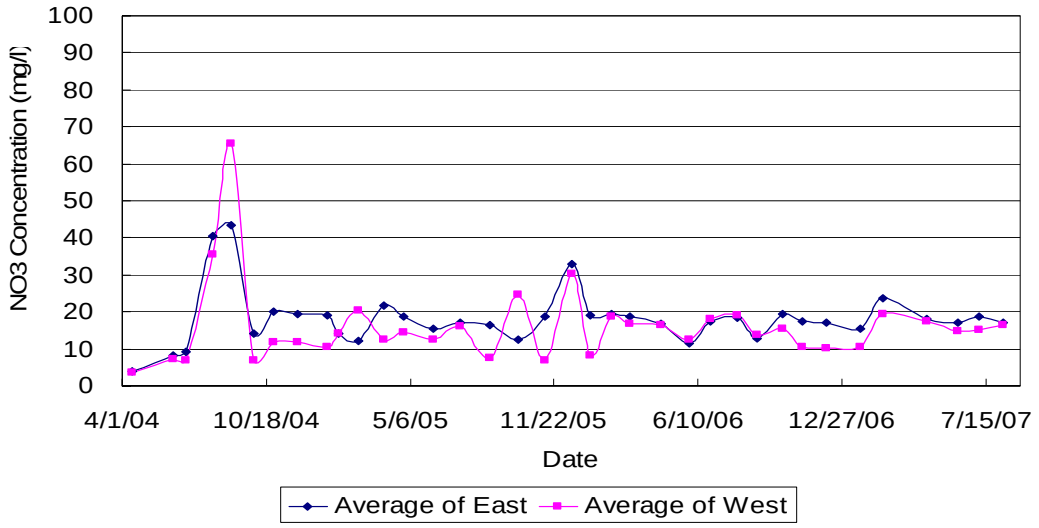


Figure F-1. Average nitrate concentration in the monitoring wells on the west part and east part of Block 1

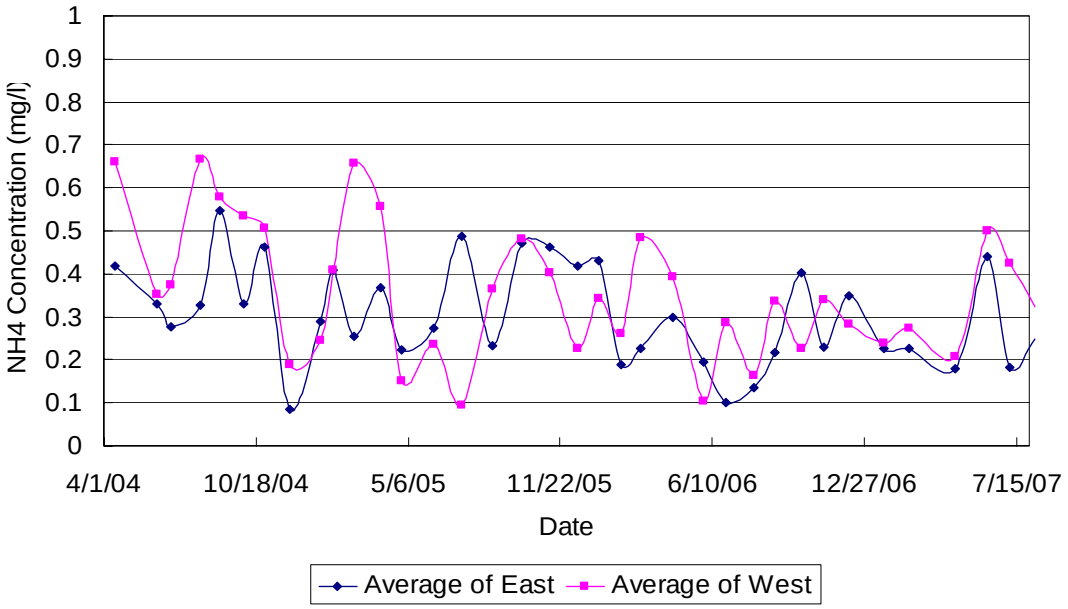


Figure F-2. Average ammonium concentration in the monitoring wells on the west part and east part of Block 1

APPENDIX G
TOTAL KJELDAHL NITROGEN CONCENTRATION OF LEAVES AND STEMS OF SWEET CORN IN FIELD EXPERIMENT IN PLOTS IN 2006

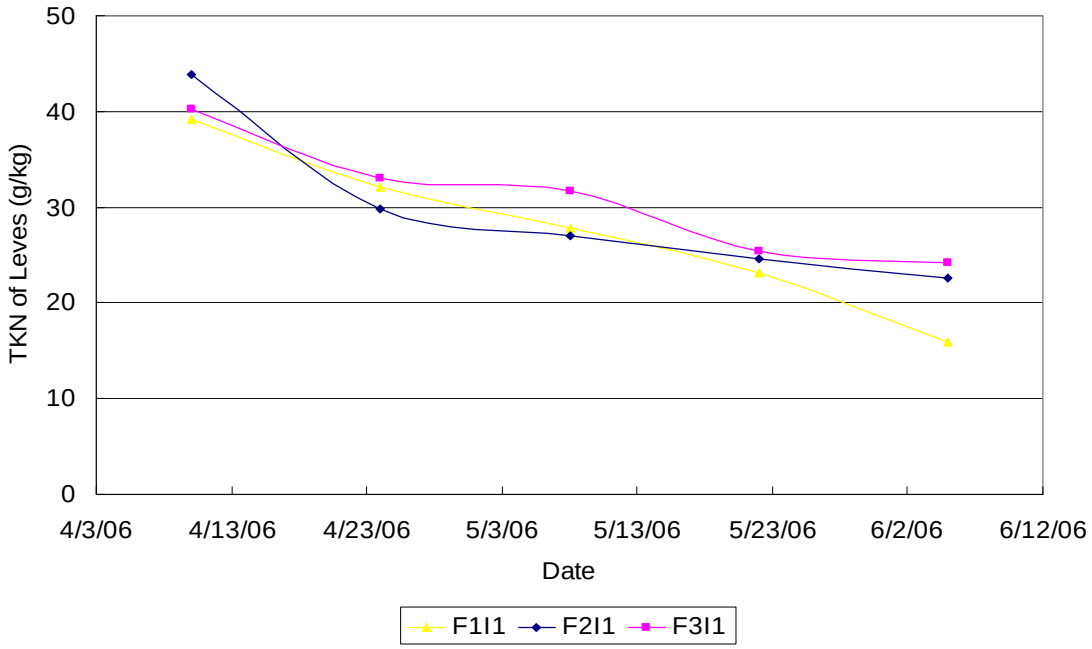


Figure G-1. Average total Kjeldahl nitrogen (TKN) concentration of leaves of sweet corn under irrigation level I1

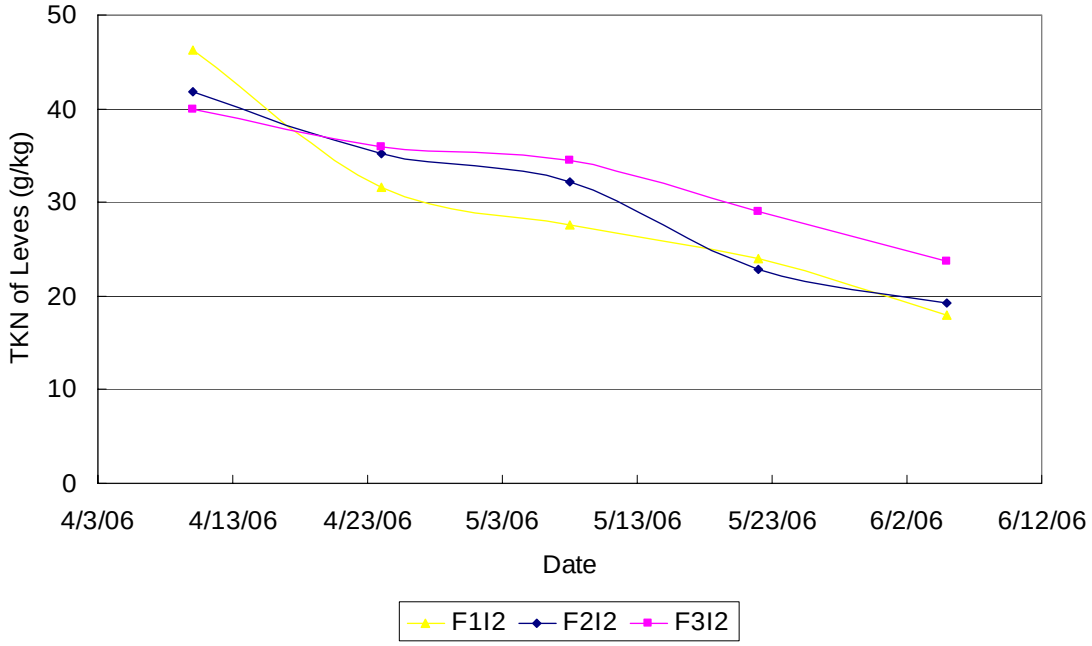


Figure G-2. Average total Kjeldahl nitrogen (TKN) concentration of leaves of sweet corn under irrigation level I2

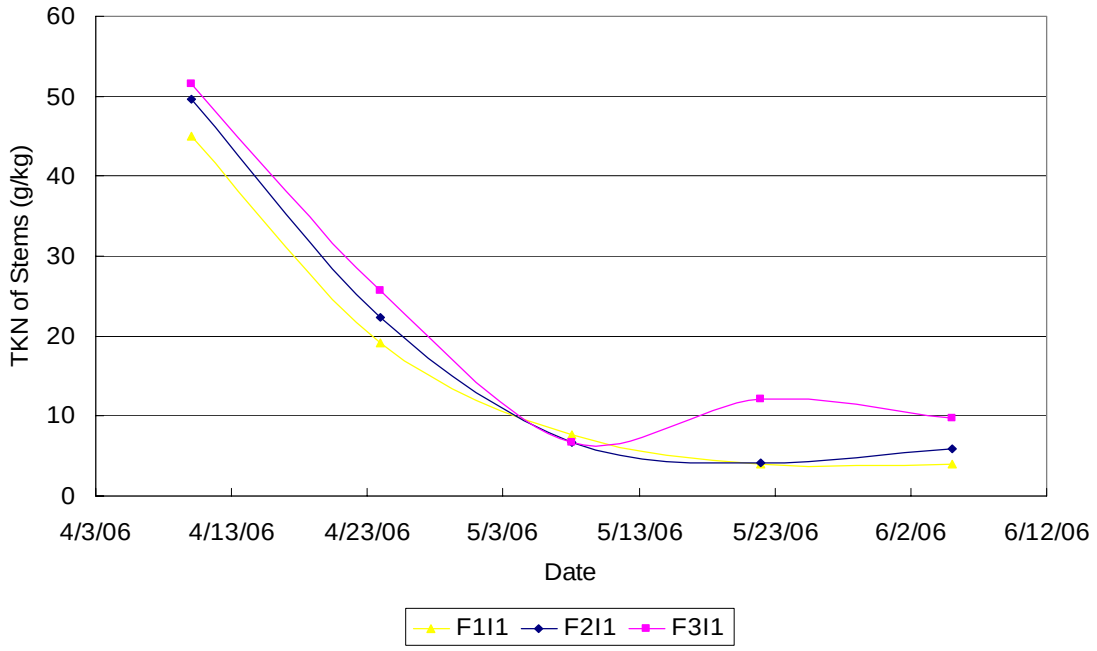


Figure G-3. Average total Kjeldahl nitrogen (TKN) concentration of stems of sweet corn under irrigation level I1

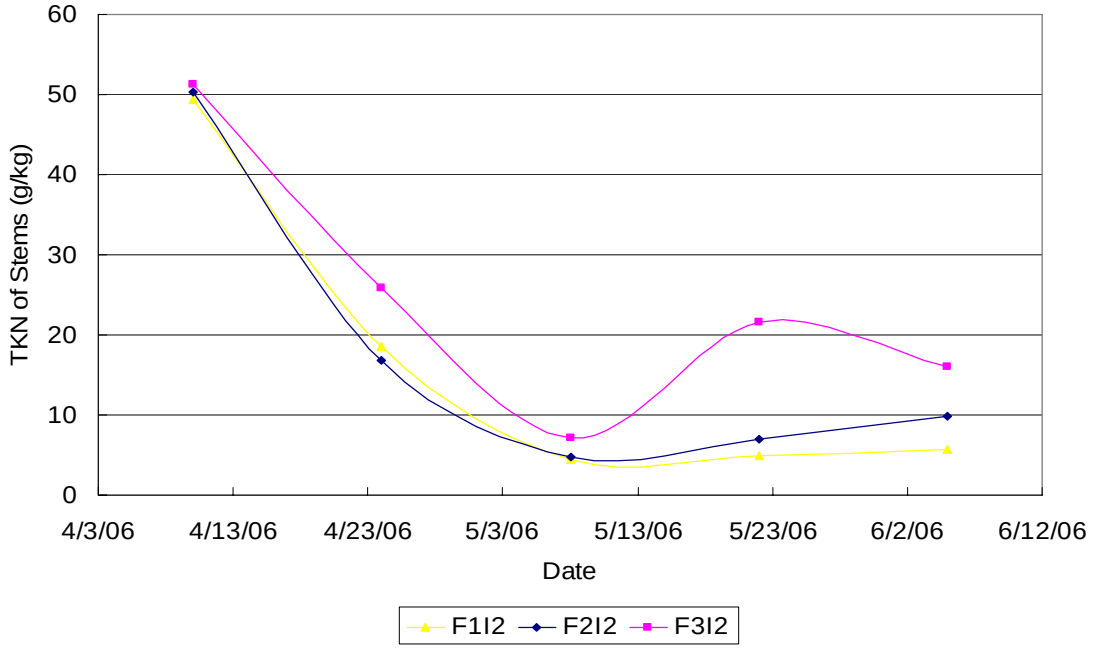


Figure G-4. Average total Kjeldahl nitrogen (TKN) concentration of stems of sweet corn under irrigation level I2

APPENDIX H
NITRATE AND AMMONIUM NITROGEN CONCENTRATION OF SOIL IN FIELD EXPERIMENT OF SWEET CORN IN PLOTS IN 2006

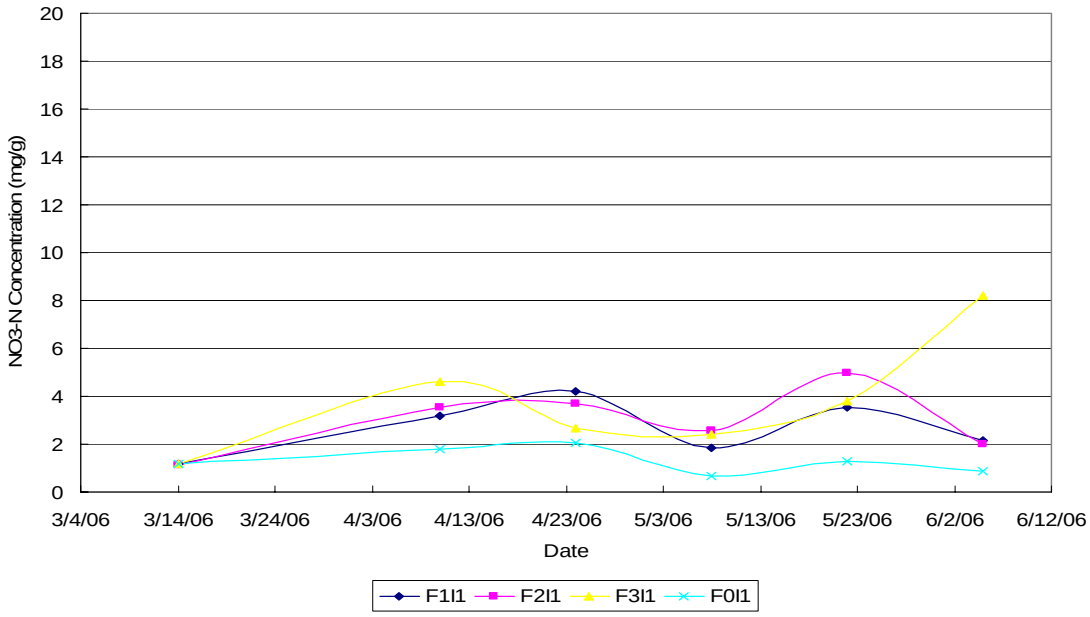


Figure H-1. Average nitrate nitrogen concentration of soil at layer 1 (0-15 cm) under irrigation level I1

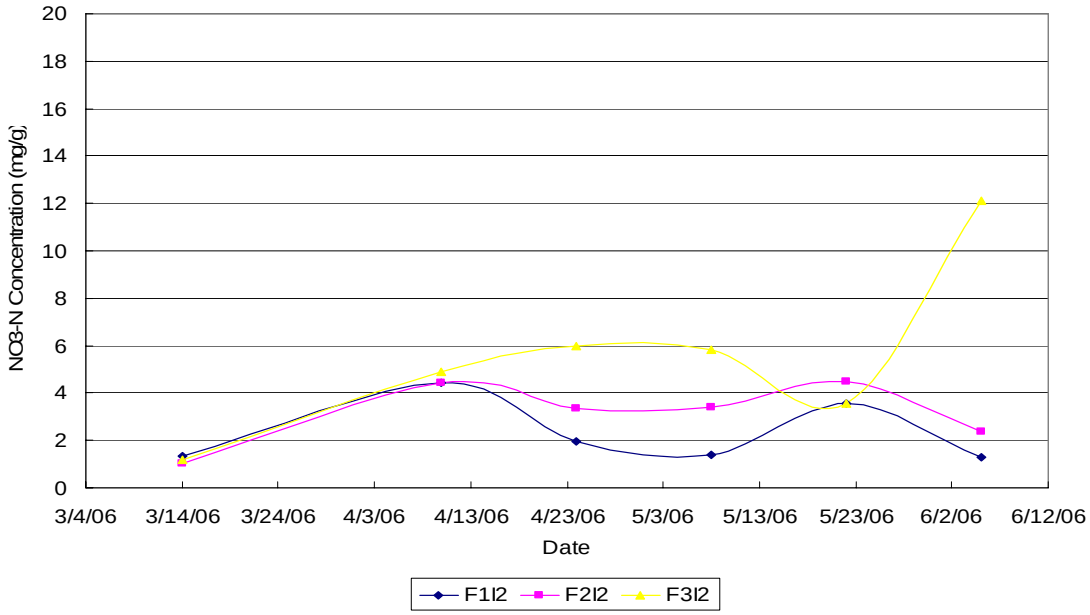


Figure H-2. Average nitrate nitrogen concentration of soil at layer 1 (0-15 cm) under irrigation level I2

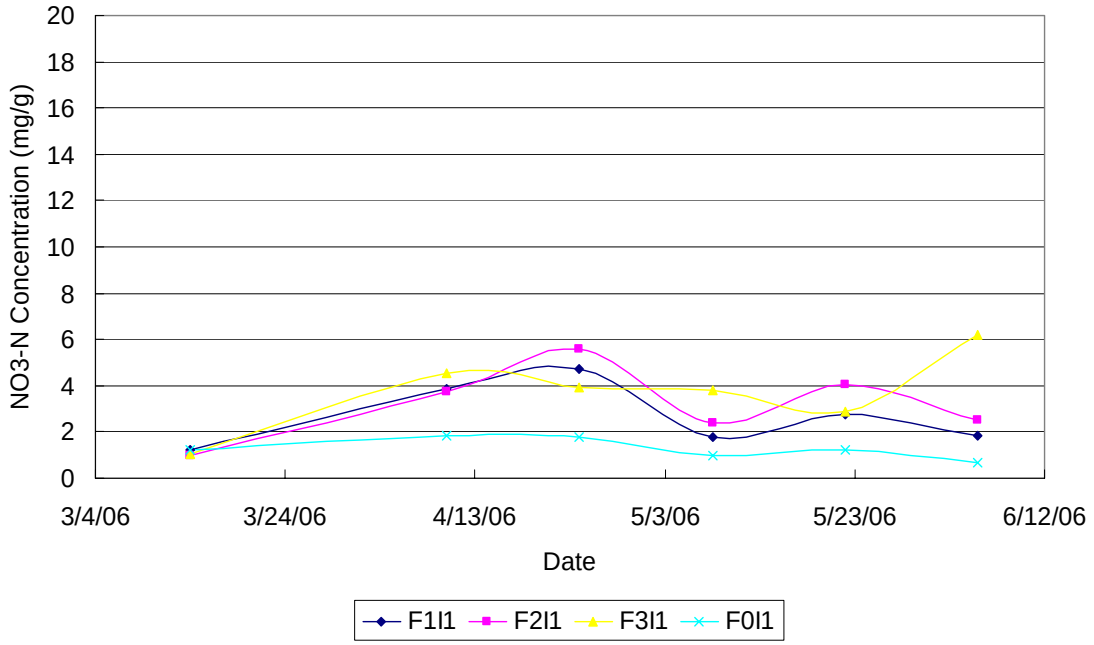


Figure H-3. Average nitrate nitrogen concentration of soil at layer 2 (15-30 cm) under irrigation level I1

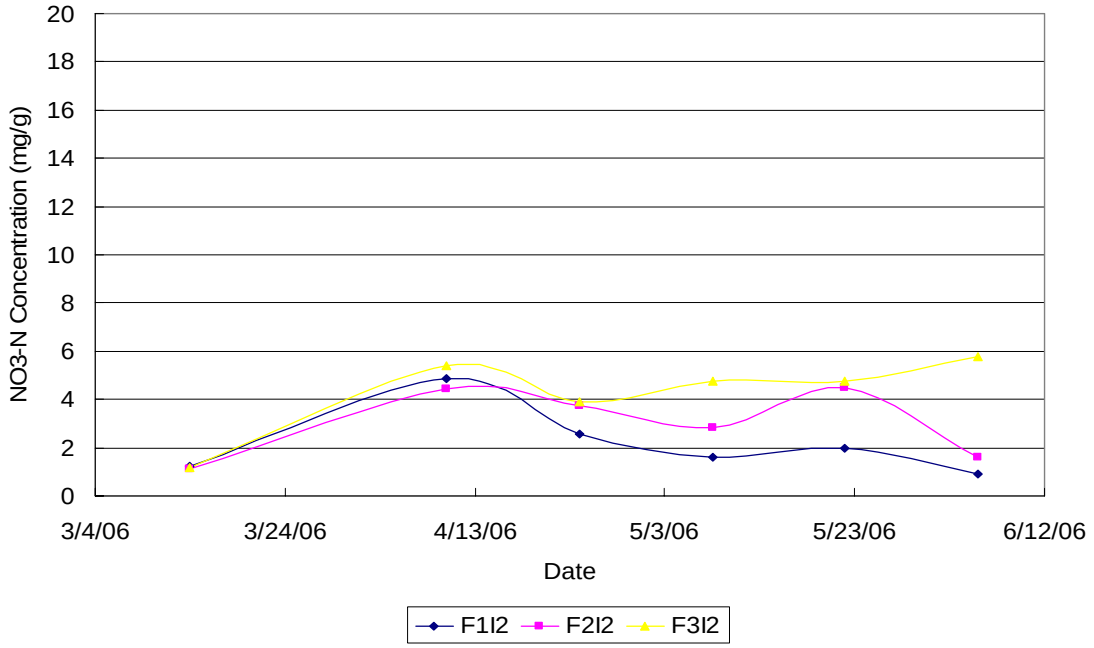


Figure H-4. Average nitrate nitrogen concentration of soil at layer 2 (15-30 cm) under irrigation level I2

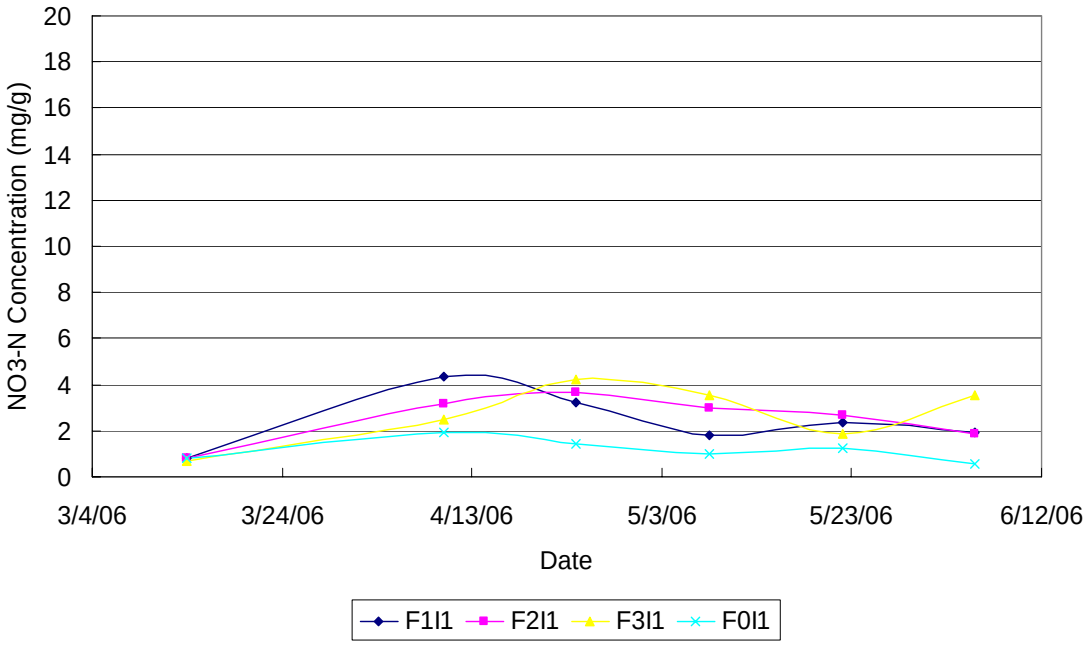


Figure H-5. Average nitrate nitrogen concentration of soil at layer 3 (30-60 cm) under irrigation level I1

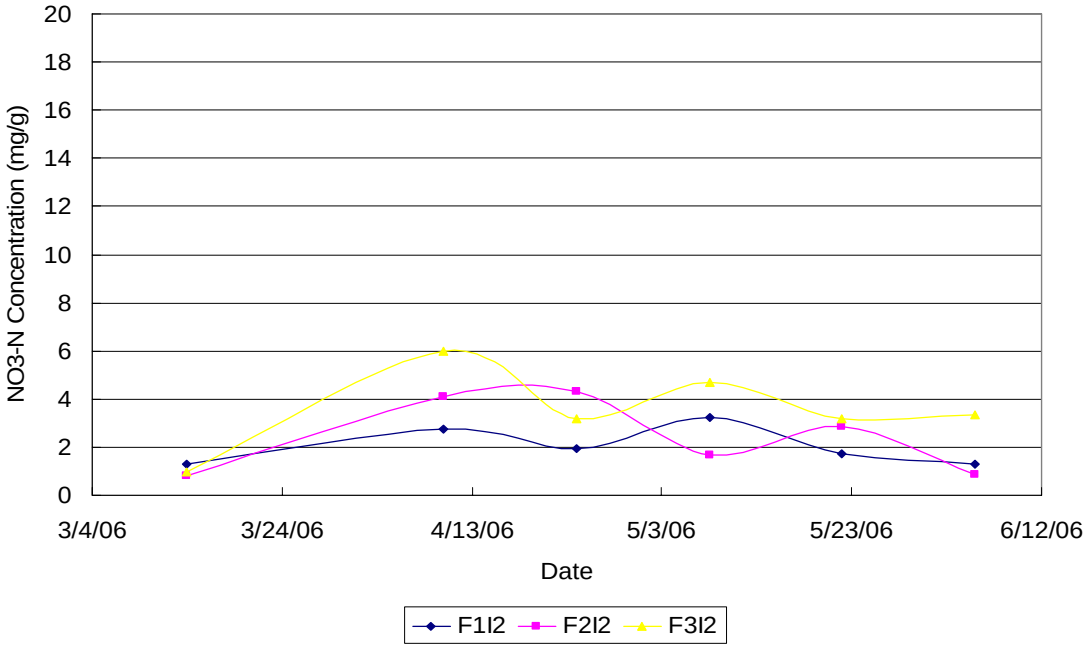


Figure H-6. Average nitrate nitrogen concentration of soil at layer 3 (30-60 cm) under irrigation level I2

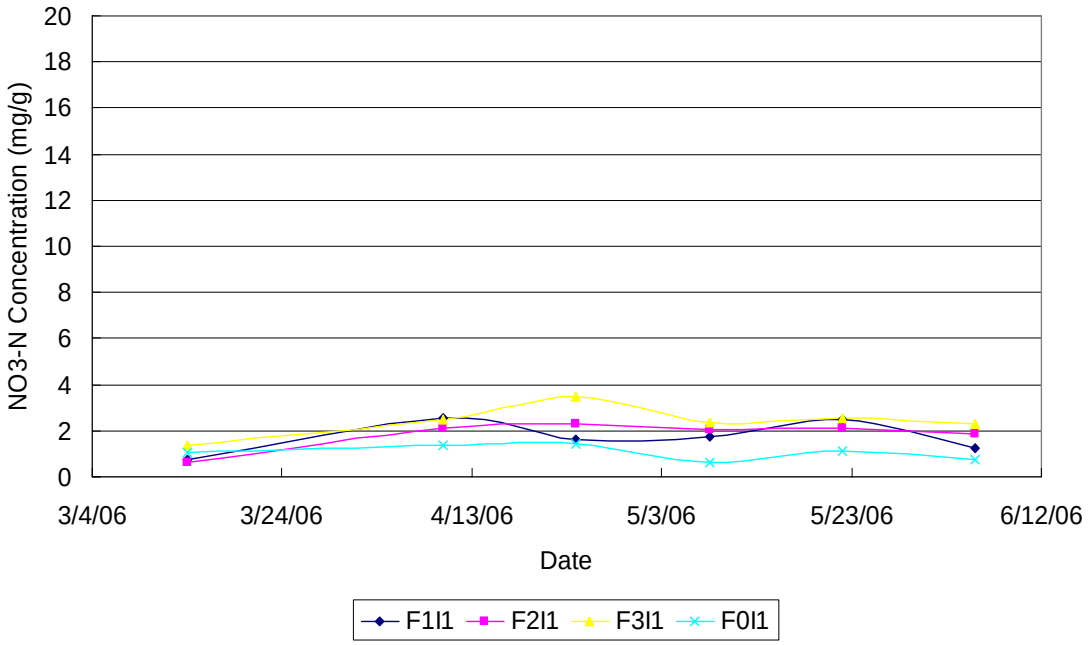


Figure H-7. Average nitrate nitrogen concentration of soil at layer 4 (60-90 cm) under irrigation level I1

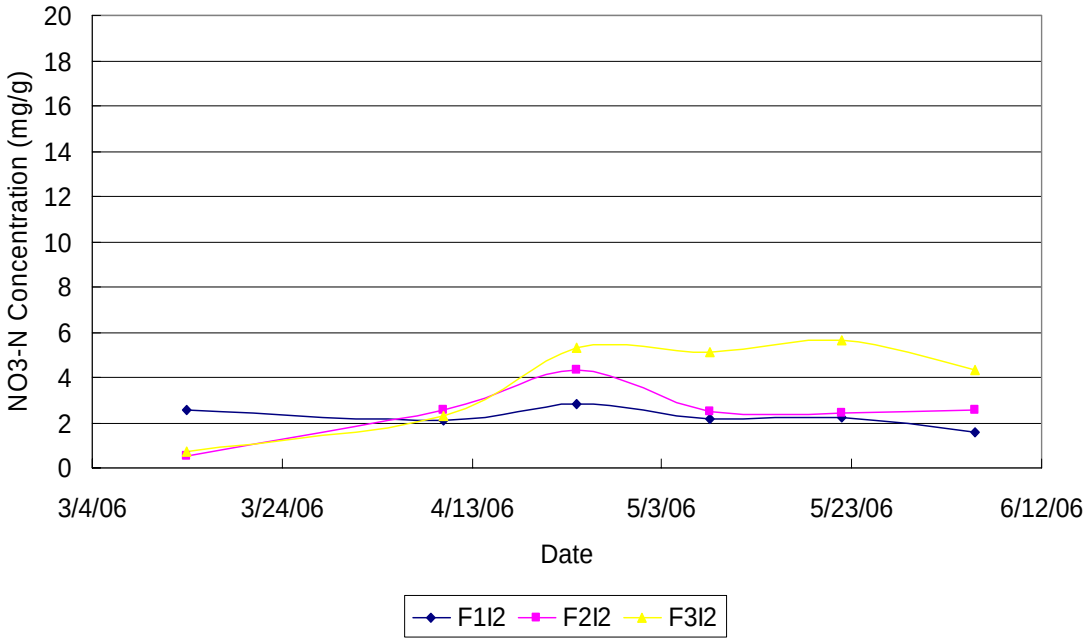


Figure H-8. Average nitrate nitrogen concentration of soil at layer 4 (60-90 cm) under irrigation level I2

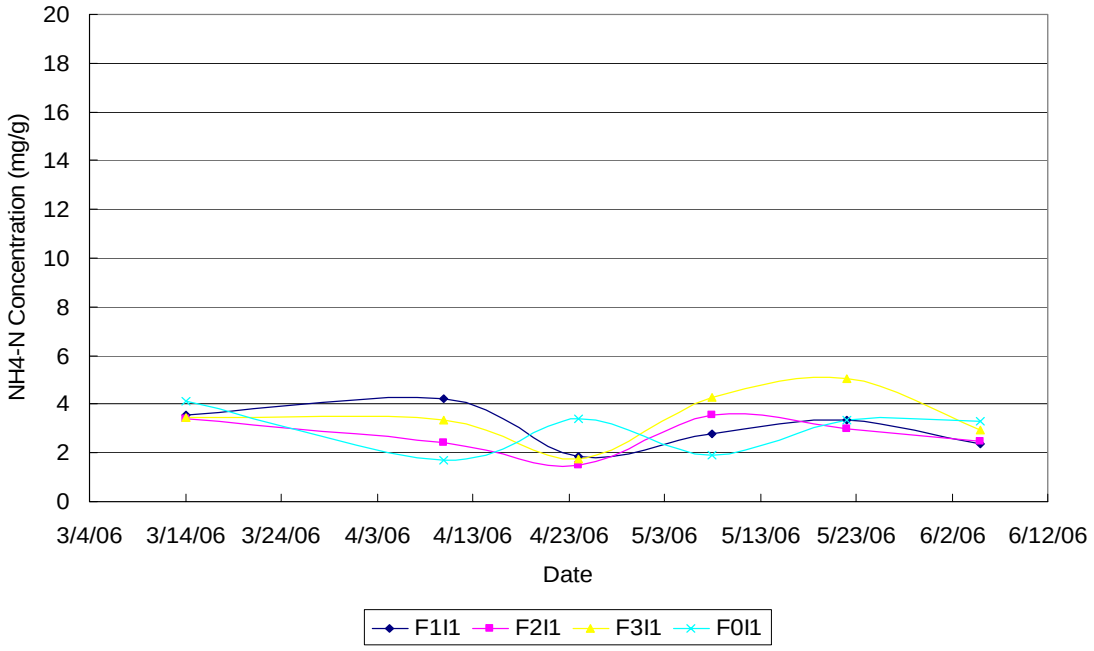


Figure H-9. Average ammonium nitrogen concentration of soil at layer 1 (0-15 cm) under irrigation level I1

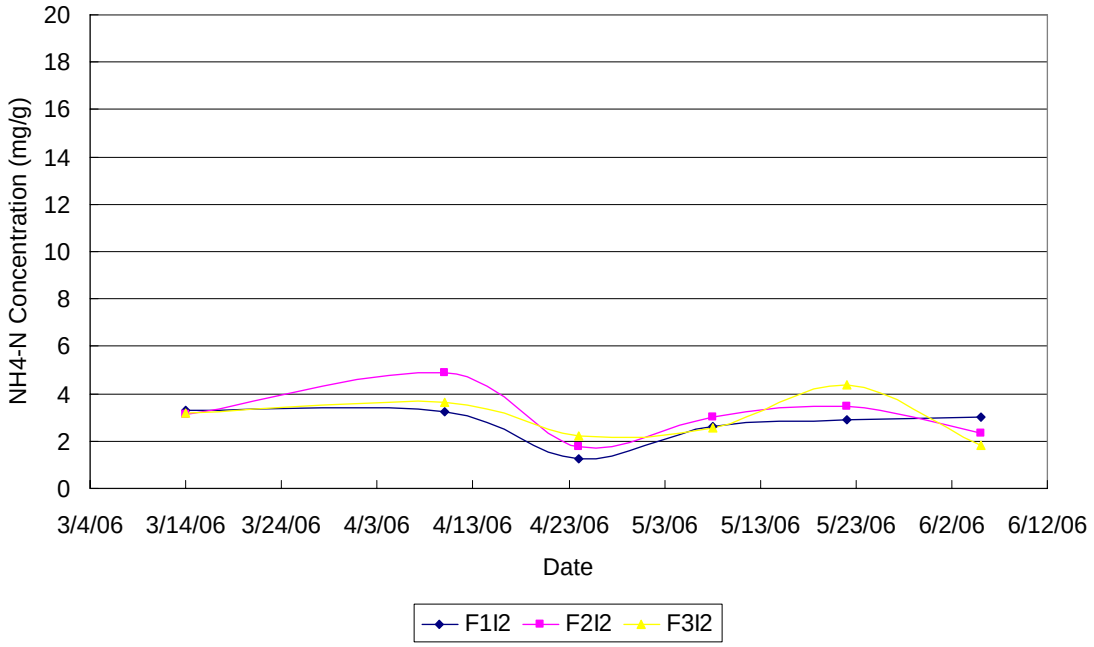


Figure H-10. Average ammonium nitrogen concentration of soil at layer 1 (0-15 cm) under irrigation level I2

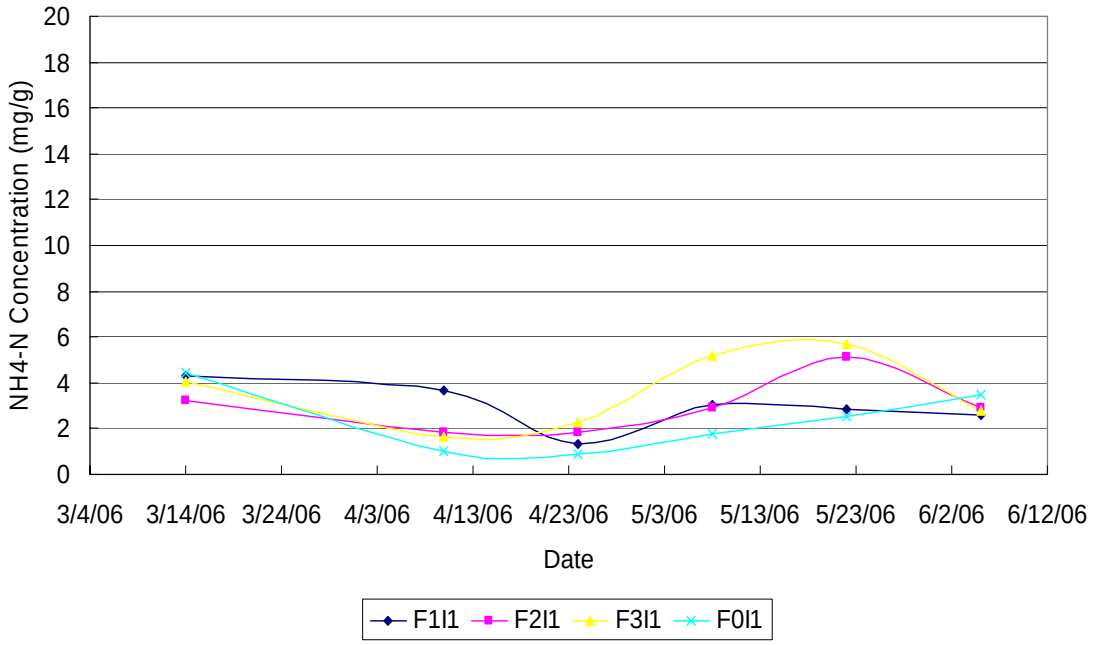


Figure H-11. Average ammonium nitrogen concentration of soil at layer 2 (15-30 cm) under irrigation level I1

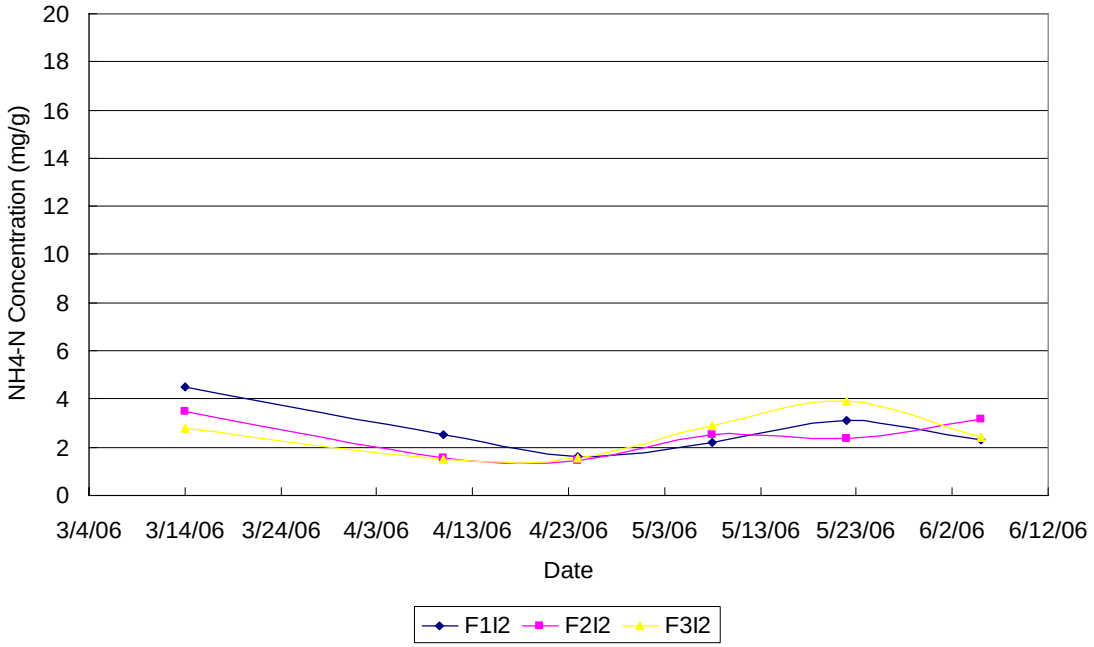


Figure H-12. Average ammonium nitrogen concentration of soil at layer 2 (15-30 cm) under irrigation level I2

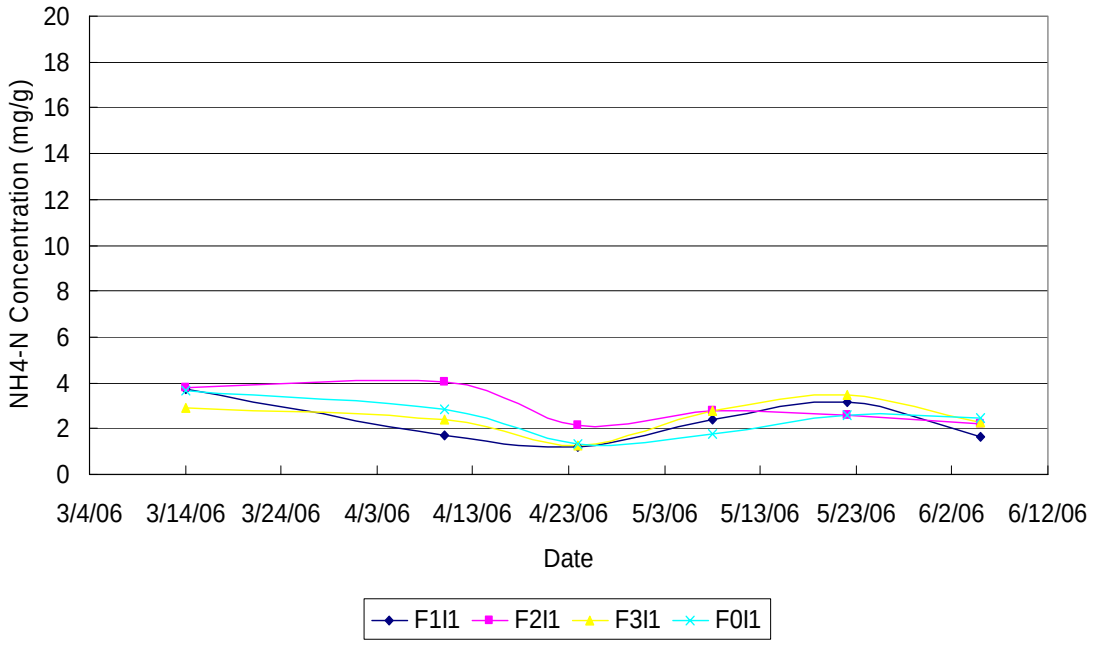


Figure H-13. Average ammonium nitrogen concentration of soil at layer 3 (30-60 cm) under irrigation level I1

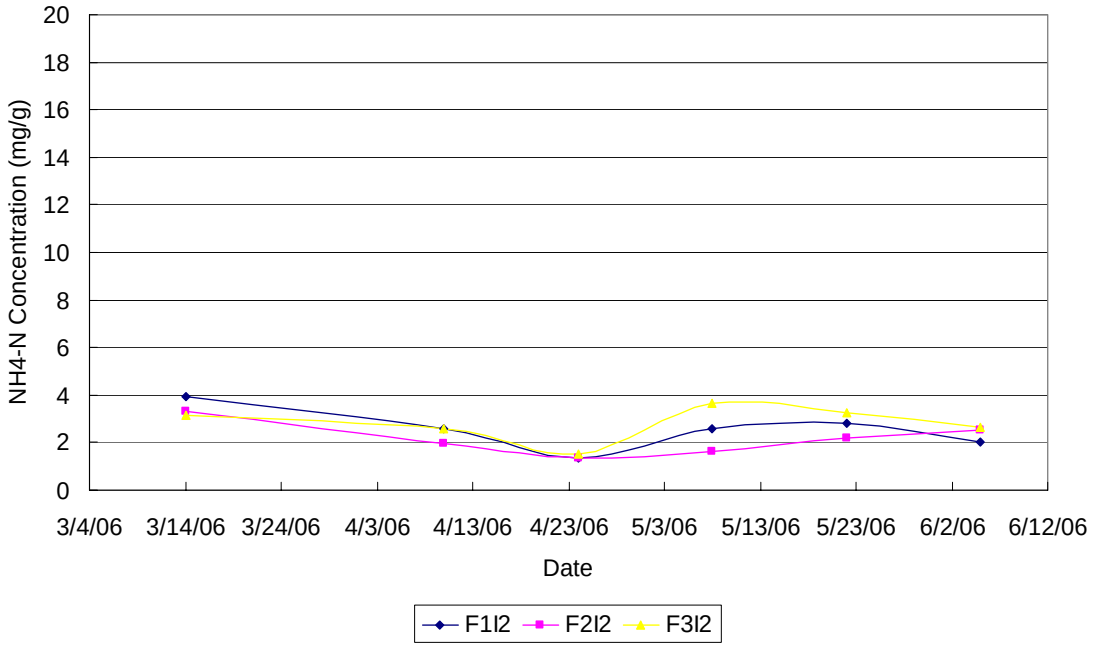


Figure H-14. Average ammonium nitrogen concentration of soil at layer 3 (30-60 cm) under irrigation level I2

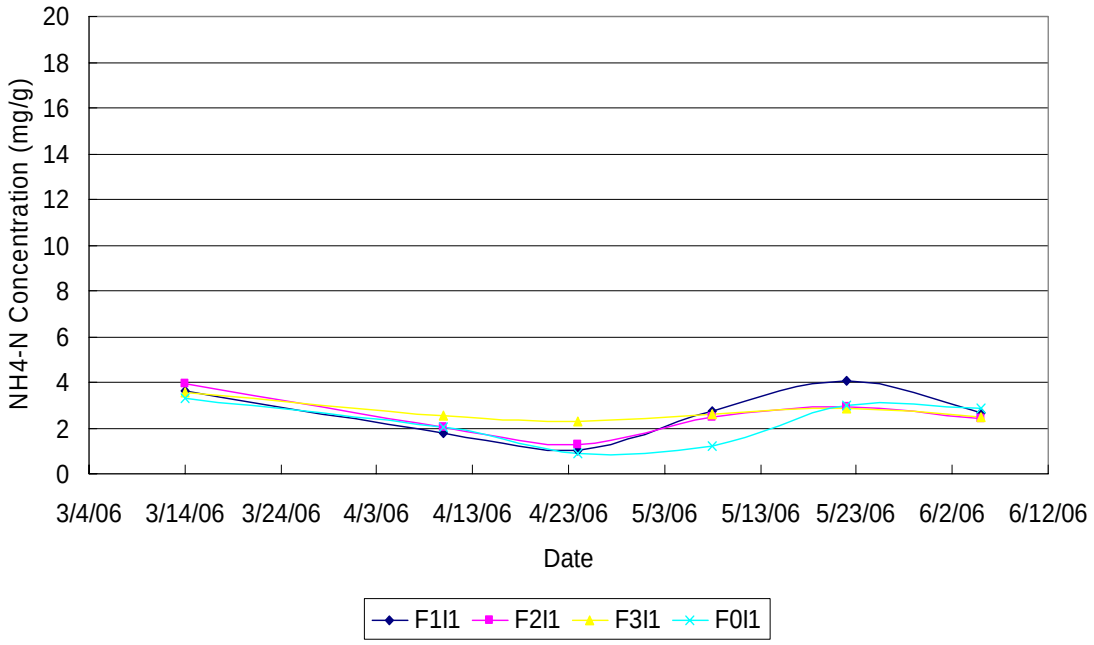


Figure H-15. Average ammonium nitrogen concentration of soil at layer 4 (60-90 cm) under irrigation level I1

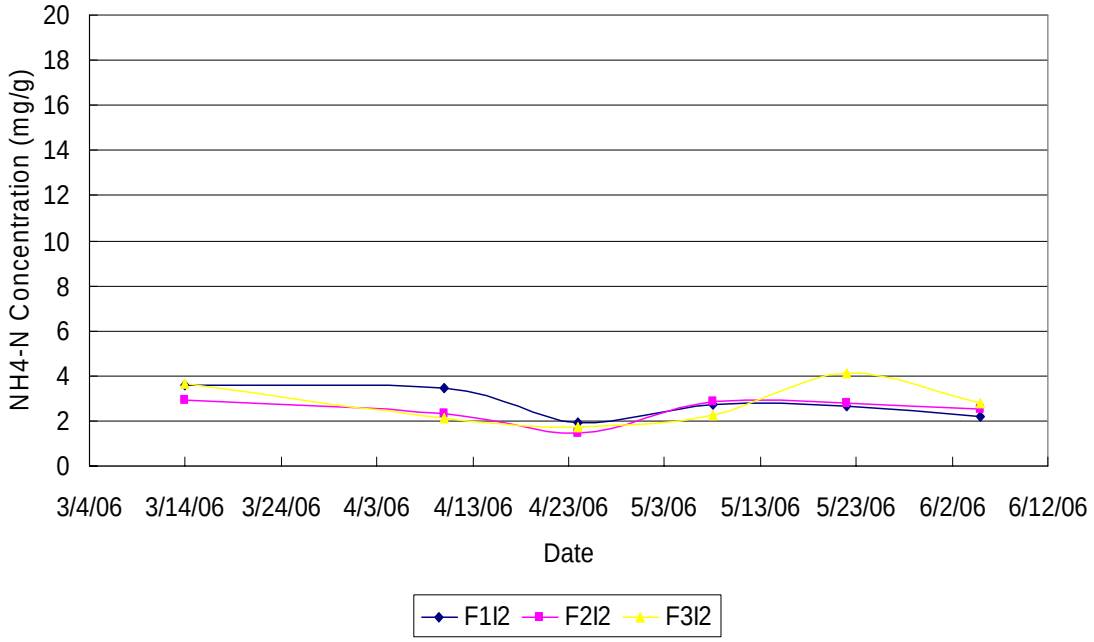


Figure H-16. Average ammonium nitrogen concentration of soil at layer 4 (60-90 cm) under irrigation level I2

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