DISSERTATION

EVALUATION AND IMPROVEMENT OF CERES-MAIZE EVAPOTRANSPIRATION SIMULATIONS UNDER FULL AND LIMITED IRRIGATION TREATMENTS IN NORTHERN COLORADO

Submitted by

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ABSTRACT

EVALUATION AND IMPROVEMENT OF CERES-MAIZE EVAPOTRANSPIRATION SIMULATIONS UNDER FULL AND LIMITED IRRIGATION TREATMENTS IN NORTHERN COLORADO

Population growth in urbanizing areas such as the Front Range of Colorado has led to increased pressure to transfer water from agriculture to municipalities. In some cases, farmers may remain agriculturally productive while practicing "limited or deficit irrigation," where substantial yields may be obtained with reduced water applications during the non-water sensitive growth stages. Savings in crop evapotranspiration (ET) could then be leased to municipalities or other entities as desired. This dissertation examined the benefit of limited irrigation in comparison with full irrigation in the northern Front Range of Colorado, in both an on-field context and in a crop modeling context. Because of Colorado water law the quantification of ET is especially important, as ET is considered a consumptive use of the crop and therefore can be transferred between entities. The overall goal was to improve understanding of both field and model maize yield response to limited water supplies, accurately simulate this management scenario with a crop growth model, and evaluate and improve model simulation of ET. This goal was achieved in the context of three studies that are included in this dissertation. First, the CERES-Maize corn growth model was calibrated and evaluated for full and limited irrigation of corn; the model generally simulated many aspects of crop growth, including yield, leaf area index, leaf growth, and phenology. The model performed better overall for the full irrigation treatment than the limited irrigation treatment. The model underestimated treatment differences in cumulative ET between treatments, simulating too little ET under full irrigation (-7.2% relative error over three years) and too much ET under limited irrigation (12.7% relative error over the same three years). Second, a global sensitivity analysis was performed on genotype and soil hydraulic parameters in addition to radiation use efficiency, using full and limited irrigation treatments and two global sensitivity analysis methods (Morris and Sobol'). Outputs evaluated included phenological stages, leaf growth, leaf area index, yield, and ET. The model showed similar sensitivities between treatments in regard to phenology and leaf expansion. However, leaf area index, yield, and ET were primarily sensitive to genotype parameters under full irrigation, but under limited irrigation showed increased sensitivity to soil hydraulic parameters. Results from both sensitivity analysis methods were highly correlated. Finally, the model processes that govern major aspects of the water balance, particularly the calculation of potential ET and the partitioning of this value into potential soil evaporation and potential plant transpiration, were evaluated and improved. A new equation for the crop coefficient as a function of LAI was added to better represent the ET demand based on plant canopy. This new formula, as well as a new coefficient determining ET partitioning, were evaluated using five years of management and weather data, and both irrigation treatments. Under full irrigation

simulated yield was unchanged compared to previous simulations, while ET and water use efficiency (WUE) were simulated closer to observations. Under limited irrigation, ET and WUE simulations were improved, with RMSD reduced from 80.9 mm to 49.9 mm for ET and from 5.97 kg/ha-mm to 2.86 kg/ha-mm for WUE. While this model change is a significant improvement in regard to the estimation of ET under water stress, it is further recommended that future model changes attempt to incorporate physiological response to stress, such as stomatal conductance or canopy temperature, to better represent plant response to water stress.

ACKNOWLEDGEMENTS

Taking on the task of graduate school is never an easy decision to make, and it is difficult to imagine such a task without the support of others. I have been very fortunate throughout this process to have a long list of people that I get to thank.

Thanks first to Dr. Amy Kaleita of Iowa State University and Dr. Kelly Thorp of the USDA-ARS in Maricopa, AZ, for serving as my respective advisor and colleague while pursing my M.S. at Iowa State. Both encouraged me to pursue a doctorate, and their advice along the way has been indispensable.

I am very grateful to the members of my graduate committee, all of which have been a pleasure to work with, which include Dr. Luis Garcia, Dr. Allan Andales, Dr. Mazdak Arabi, Dr. Jim Ascough II, and Dr. Neil Hansen. The flexibility allowed by this group of men has given me a unique multidisciplinary opportunity: to earn a degree in the Civil Engineering Department while working for the Soil and Crop Sciences Department. This is not a situation that occurs often, and I am happy that it worked out so well. I have been given great amounts of advice from all of these men, especially Allan, Jim, and Neil, and I thank them all for helping shape my career at CSU. I am also extremely grateful toward Allan and Neil for continuing to fund me while I traveled home to help my mother battle cancer, your generosity allowed me to focus my energy on my family when it could have easily been somewhere else. Thanks also to Dr. Terry Podmore, who first met with me seven years ago when I was first interested in grad school, and who I still consult for career advice. Also thanks to Dr. Ramchand Oad for allowing me to serve as a teaching assistant for his soil and water engineering course for the last two years.

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Throughout this experience I have crossed paths and collaborated with many other researchers and organizations which I feel deserve recognition. These include the Agricultural Systems Research Unit and the Water Management Research Unit (WRMU) of the USDA-ARS. I have learned a great deal from scientists in both of these units, and look forward to working with them more in the future. Thanks also to Decagon Devices Inc. for the award of the G.A. Harris Fellowship, which gave me the opportunity to work with the WMRU, as well as Regenesis Management and others at CSU, in a collaborative effort to learn more about quantifying evapotranspiration in limited irrigation (a study separate from this dissertation). This fellowship was the catalyst which introduced me to a project that I believe shows great promise, and I look forward to continuing to work in this area. I owe special thanks to Dr. Tom Trout for funding me through my final summer as a student and for considering me as an asset to his unit, where I will start the next stage of my career.

Thanks to my parents and my family for their support, encouragement, and understanding as to why I have been so busy these past three years. My family background has been an imperative contribution to this graduate degree: I may be part of a dying generation of kids to grow up on an irrigation ditch with a shovel in hand. I am especially grateful to my father Randy DeJonge and my stepfather Dave Olsen for teaching me how to irrigate and work hard, among many other life lessons. Obviously this background has lended itself toward a career in irrigation, and although it is not the traditional career I am grateful. I hope that through the rest of my career I can make scientific contributions that will help farmers like you. Most importantly, thanks to my wife Katy for having the faith to follow me here to CSU, and for the sacrifices she has made, for I know they have not been easy. Our first three years of marriage have been the best of my life thus far, and I look forward to many more.

While graduate school is not easy, it is neither cheap. Many thanks to Regenesis Management, USCID, the Irrigation Foundation, the Whitney Borland family, the CSU Water Center, the SSSA, and Decagon Instruments for their assistance in scholarships, travel, and other networking opportunities. Your support for higher education does not go unnoticed.

Finally, a random short list of those who will likely never read this but deserve recognition for keeping my sanity throughout this process: my neighbors at 1717 and

friends throughout Fort Collins who distract me, my dogs who love me no matter what, and the inventors of coffee and beer.

Alice: Would you tell me, please, which way I ought to go from here?

The Cat: That depends a good deal on where you want to get to.

Alice: I don't much care where.

The Cat: Then it doesn't much matter which way you go.

Alice: ... so long as I get somewhere.

The Cat: Oh, you're sure to do that, if only you walk long enough.

-Lewis Carroll

DEDICATION

For Katy: my wife, companion, and inspiration.

It doesn't much matter which way I go, as long as I do it with you.

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CHAPTER 1. INTRODUCTION

This dissertation examines the use of the CERES-Maize crop model to simulate irrigation treatments of corn in northeast Colorado. Specifically, this study explores modeling scenarios that will help producers plan for future water allocation, as well as improve overall knowledge and ability to effectively simulate the interaction of yield and available water under stressed conditions.

1.1 SOCIAL AND ECONOMIC NEED

1.1.1 Population Growth

Garrett Hardin's famous (1968) essay, "The Tragedy of the Commons," warns society of the overuse of resources in a world increasing in resource needs. One quote from the essay warns that "A finite world can support only a finite population . . ." These concerns can be transferred on global and local scales in terms of various resources, including available fresh water, which is under increasing pressure worldwide. Because irrigated agriculture is the largest user of fresh water, its importance is paramount, especially in a world with an increasing population.

Some estimates say that by 2025, the world demand for fresh water may be approaching the limits of readily accessible supplies (Postel, 1999). In terms of agricultural production, water is typically considered the most limiting factor, and the

United Nations' Food and Agriculture Organization (FAO) says that on at least a third of the world's fields today, "water rather than land is the binding constraint" on production (Pearce, 2006). While water availability for agriculture is of extreme importance, world populations are growing as well. According to the U.S. Census Bureau (2010), the world population is projected to grow from 6 billion in 1999 to 9 billion by 2044, an increase of 50% in approximately 45 years (Figure 1-1). This increasing world population will create a demand for more food and agricultural products, while simultaneously adding need for municipal use. If estimates such as Postel's (1999) hold true, agricultural producers will simply need to learn how to make more food with less water.

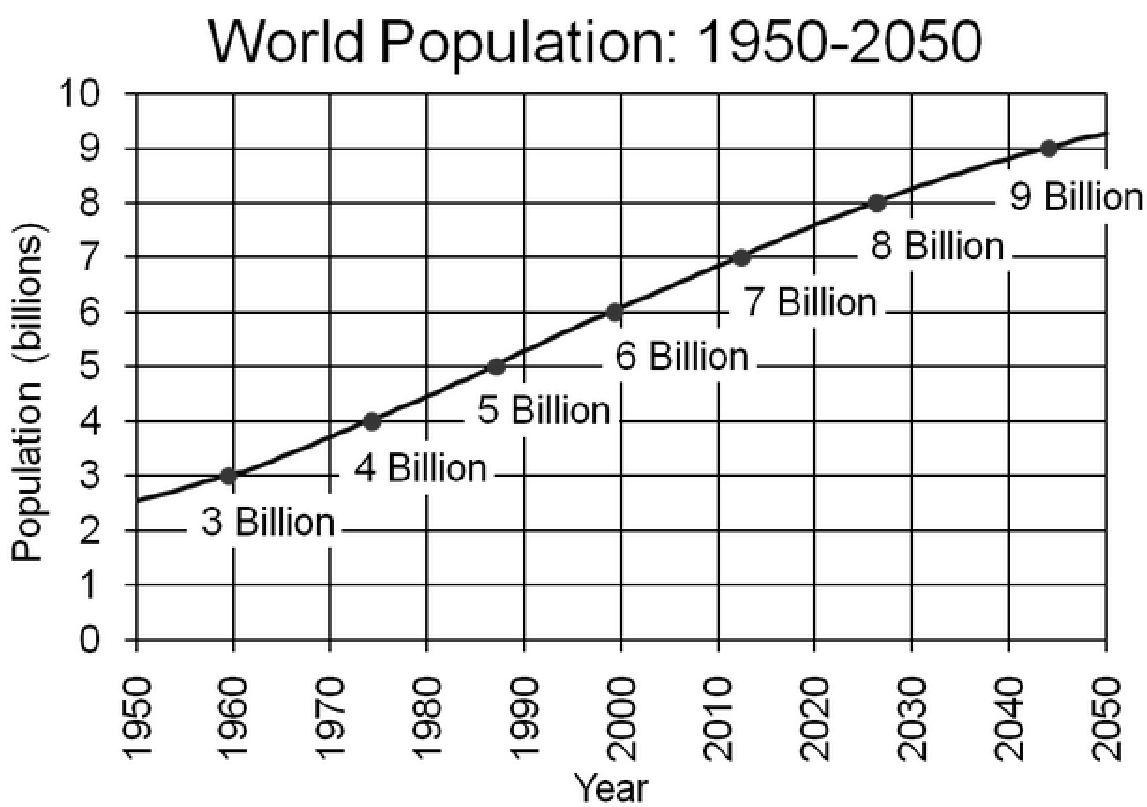

Figure 1-1. Projected world population (U.S. Census Bureau, 2010).

Irrigated agriculture is of tremendous importance to the food supply of the United States and the world. Most of the agricultural production in the semiarid regions of the world is a direct result of irrigation: of the entire agricultural land use in the world, irrigation is used on about 20% of the area but provides 40% of the production (Ahuja et al., 2008). While these areas depend on agricultural irrigation to provide for food requirements, several factors such as increasing population, urbanization, and environmental awareness are leading to a new demand for water resources. Reallocation of available water resources is occurring more frequently, and many questions regarding long-term water sustainability remain unanswered (Johansson et al., 2002). For example, in many cases growing urban populations are purchasing water, thereby leaving less available for agriculture. Unsurprisingly, the slogan "more crop per drop" is becoming increasingly prevalent in regard to global water sustainability (Farahani et al., 2007). In the preface to the recent text "Response of Crops to Limited Water," Ahuja et al. (2008) ask two important questions: 1) "How can irrigated agriculture sustain productivity and meet the growing need for food and fiber with reduced water available for irrigation?" and 2) "What research knowledge and technologies are needed to accomplish this sustainability?" These are questions this body of work makes strides to answer.

In the state of Colorado (Figure 1-2), agricultural uses currently account for more than 85% of the water diverted and consumed, and agricultural users hold most of the senior water rights (CDM, 2007). Just as is occurring with the global population, several areas of the United States, including the Front Range of Colorado, are observing large urban population growth despite limited availability of water resources. For example, population in the South Platte River basin is expected to increase by 65% from 2000 to 2030 (CDM, 2007). A recent trend to deal with this large municipal growth has been for cities to purchase water rights from farmers. CDM (2007) predicts that nearly 54,000 irrigated hectares will be lost by 2030, a 37% loss from 2000. In many cases this transfer involves all water rights and often the land, leading to dry-up of large areas and detrimental ecological and socio-economic consequences for rural communities (Pritchett et al., 2008).

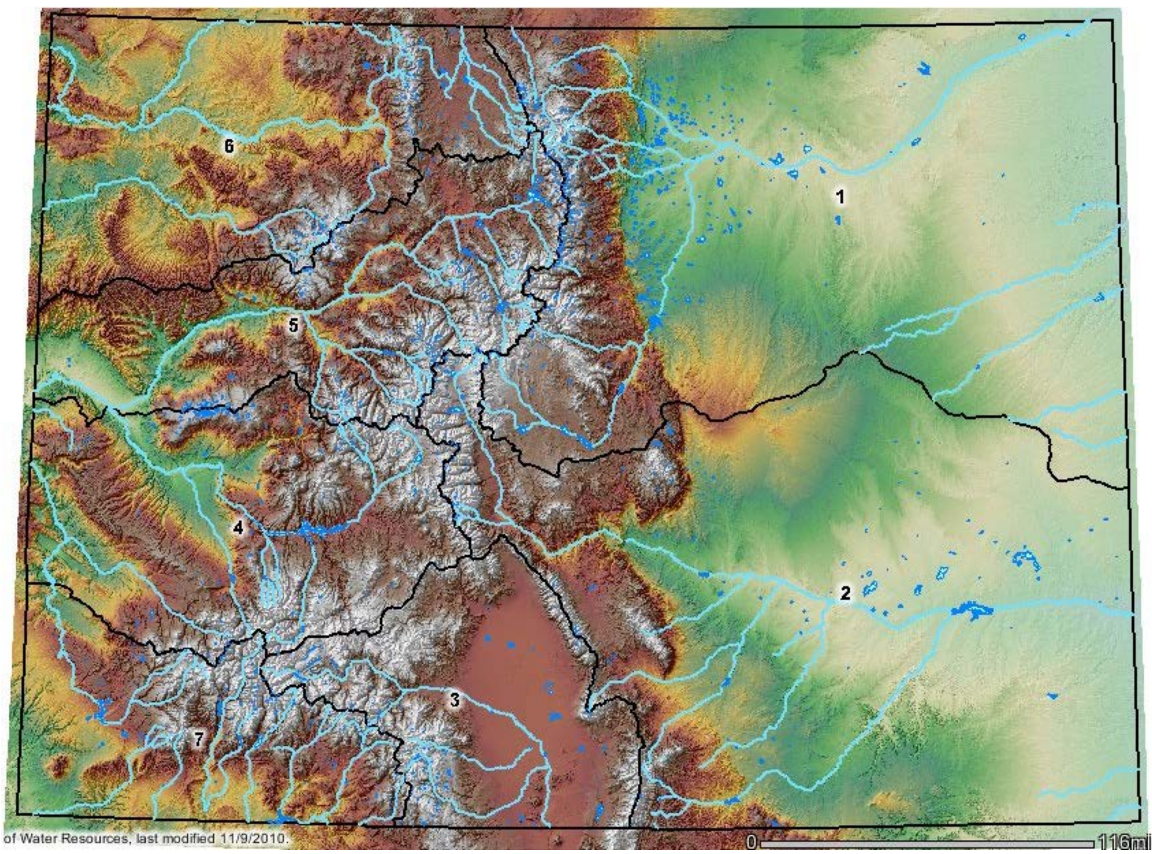

Figure 1-2. State of Colorado and watersheds contained within, including (1) South Platte and Republican, (2) Arkansas, (3) Rio Grande, and (4-7) Colorado (Colorado Division of Water Resources, 2011).

This "buy and dry" trend obviously troubles farmers and smaller communities that depend on agriculture to fuel their economies, not to mention potential environmental impacts of leaving land fallow. Colorado's South Platte River Basin (Figure 1-3) had approximately 730,700 acres of irrigated cropland in 1992, 40% of the total cropland in the basin (Smith et al., 1996). In the South Platte basin, an irrigated acre generates nearly $700 of economic activity (Pritchett et al., 2008), so potential losses due to water rights transfer are substantial, notably in sparsely populated rural areas. Other negative effects can include decreased land values because of limited alternative land uses, greater potential for soil erosion, and unreliability of dryland cropping practices because of limited and variable natural precipitation and climate (Sutherland and Knapp, 1988). As opposed to permanent transfers, a survey within the South Platte basin showed that over 60% of farmers are willing to participate in a water *lease* for the right price (Pritchett et al., 2008). If such leases were to occur, farmers will need to *manage* and *allocate* their remaining water supplies to maximize profits, not to mention *quantify* water use for legal transfer of unused water.

1.1.2 Limited Irrigation Economics

English et al. (2002) argue that a fundamental change in irrigation management is destined for the future as water supplies become more limited. Farmers typically irrigate in an effort to maximize yields, under the assumption that the maximum yield will result in the maximum profit. This relationship, shown in Figure 1-4, typically has a linear increase in yield with applied water, but later turns curvilinear and then downward. The peak of this curve is the maximum yield, obtained by water application at the $\mathbf{W_m}$ level

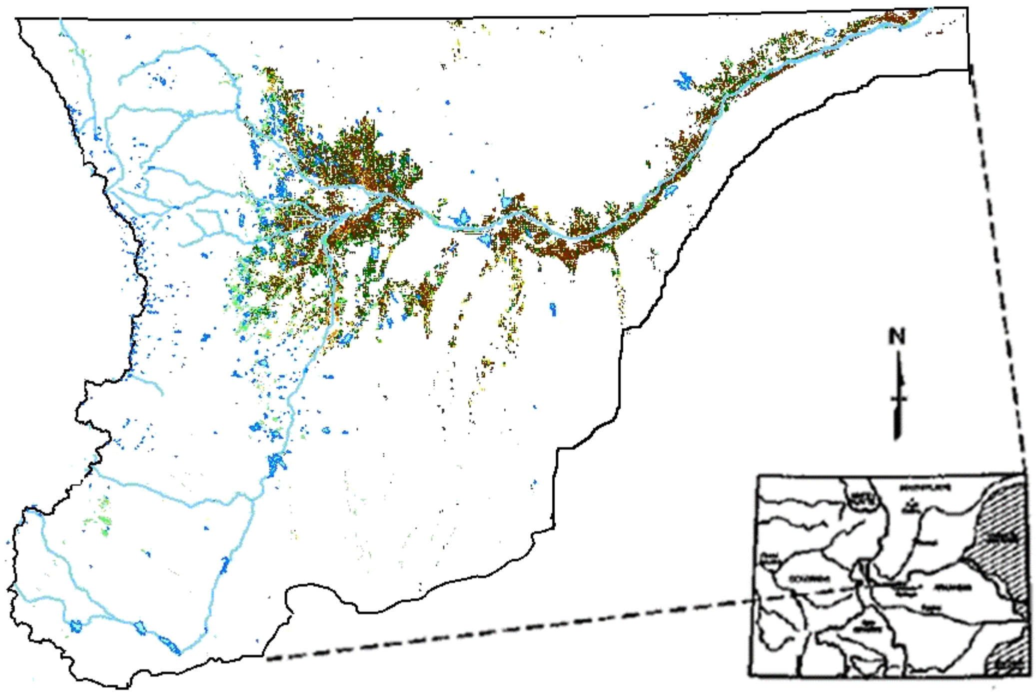

Figure 1-3. Colorado's South Platte River basin, water features, and irrigated areas (Colorado Division of Water Resources, 2011 and Smith et al., 1996).

indicated in the figure. It is also important to note that while crop yield functions are commonly based on ET, it is important to consider the function in regards to applied water, as that is the input that irrigators have control over (English et al., 2002). While commonly practiced by farmers, striving simply for maximum yield is a simplistic approach that does not weigh the profits gained by increased yield with the losses resulting from input costs such as fertilizer, fuel, labor, and water. Crop prices and input costs are highly variable with market conditions, but a general relationship when considering the inputs in an attempt to maximize profits can be determined and is shown in Figure 1-5 (English et al., 2002; Mannocchi and Mecarelli, 1994). With fixed prices of inputs, increasing applied water typically has a linear increase in yield. The maximum net profit results from the largest gap between revenues and costs.

With irrigated crops, two water availability scenarios normally occur (Mannocchi and Mecarelli, 1994): 1) available water resources are sufficient to guarantee irrigation with minimal risk of inadequate supply (Figure 1-4); and 2) water resources are insufficient to guarantee an adequate water supply for a fully irrigated crop (Figure 1-5). Where water supply is adequate, profit maximization methods are fairly simple. However, when supply is limited, the question of profit potential becomes much more complicated. Payero et al. (2009) note that when water availability is limited, it is very important to know how to time irrigations in order to optimize yields, water use efficiency (WUE), and eventually profits. English et al. (2002) define several functions that describe how to maximize profits under varying water availability scenarios. To maximize the net income when water is the limiting resource, as is often the case in Northern Colorado, the farmer tries to maximize the total income, *I(w)*:

$$I(w) = [p_c y(w) - c(w)]A \qquad (1\text{-}1)$$

where p_c is the price paid for the crop ($/Mg), *y(w)* is the crop yield function where *y* indicates yield per unit of land (Mg/ha) and *w* is the depth of applied water (mm), *c(w)* represents production costs as a function of applied water ($/mm), and *A* indicates the irrigated area (ha).

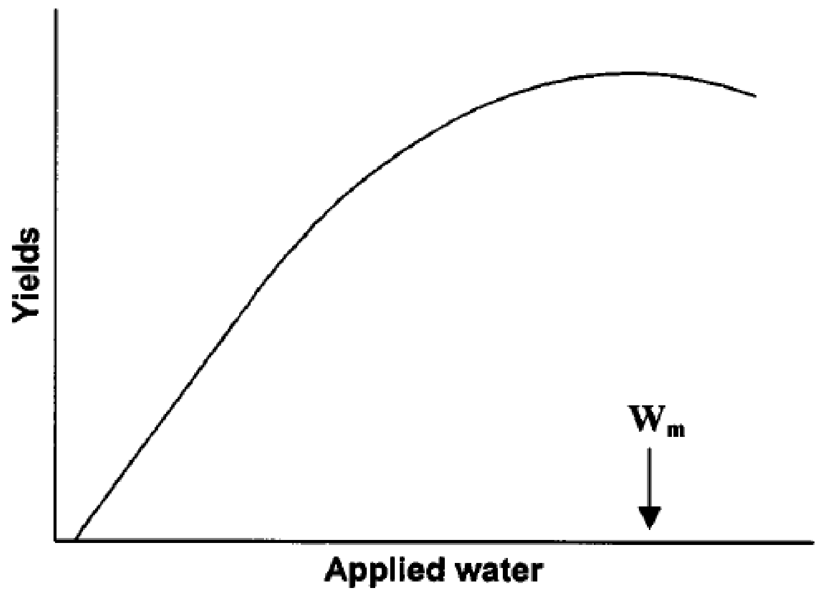

Figure 1-4. General relationship between applied water and crop yield (English et al., 2002).

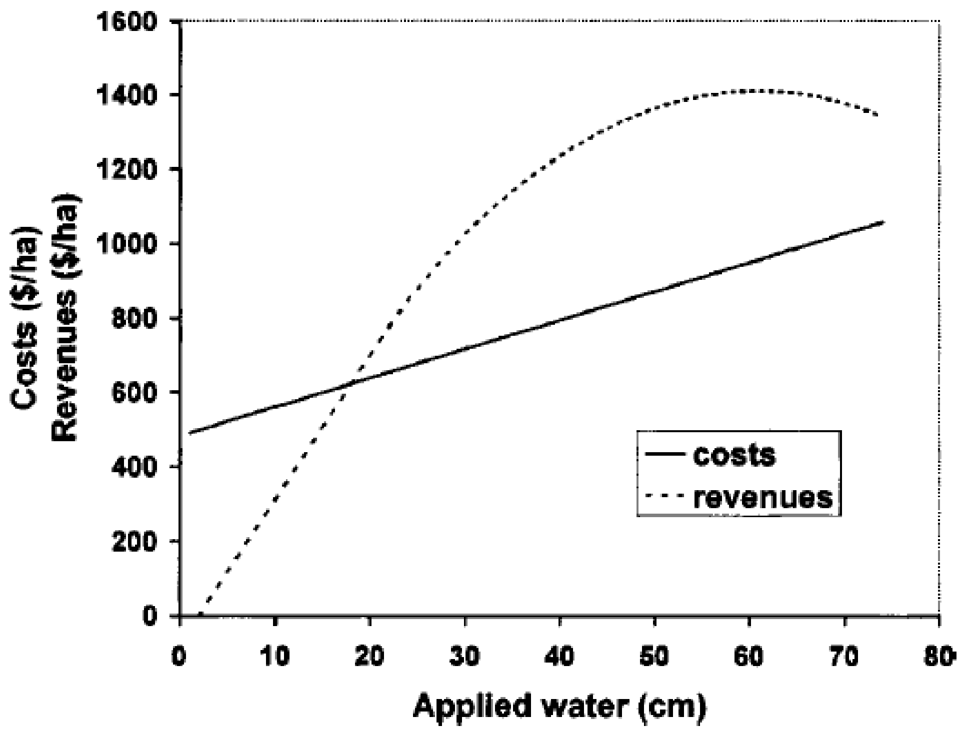

Figure 1-5. Costs and revenue as a function of applied water (English et al., 2002).

While Eqn. 1-1 from English et al. (2002) certainly describes the relationship for maximizing yield based on associated costs, it does not consider what happens if the water becomes a commodity itself. If irrigators have the option to sell or lease a *portion* of their available water at a certain market price, the function described in Eqn. 1 is changed to:

$$I(w) = [p_c y(w_i) - c(w_i) + p_w w_{ni}]A \qquad (1\text{-}2)$$

where w_i is the water used for irrigation (mm), w_{ni} is the water leased (mm), and p_w is the price paid for water leased ($/ha-mm). In such a case, w_i and w_{ni} would add up to the total allocation given to the irrigator's water right.

In some cases, such as is outlined for the State of Colorado in the following section, the amount of water that can be considered for income resides not in the water applied but in the consumptive use (CU) of the actual crop, or the crop ET. For many crops, the effect of deficient ET on crop yield may depend on the plant growth stage during which the water deficit or stress occurs (Kirda and Kanber, 1999). In this case, the above economic functions for income based on reduced irrigation becomes dependent also on the crop water production function, or the crop yield response to reduced ET, which may vary based on the growth stage and extent of stress. Thus, it is extremely important to understand and quantify both yield and ET under limited irrigation scenarios. For example, the function described in Eqn. 1-2 now becomes:

$$I(w, ET) = [p_c y(ET_i) - c(w_i) + p_w w_{ni}]A \qquad (1\text{-}3)$$

where ET_i is the evapotranspiration or consumptive use of the crop. In this case, w_{ni} is the difference between ET under full irrigation and ET_i, and obviously this makes the quantification of profit potential much more complex than the simple relationship described in Eqn. 1-1.

1.1.3 Colorado Water Law and Water Rights Transfers

American water law doctrines typically fall into two categories: riparian rights and prior appropriation rights. Under the riparian doctrine, equal rights of water use are given to owners of land adjacent to a body of water. On the other hand, the more arid 18 states west of the 98th meridian (Figure 1-6 shows annual rainfall and the 100th Meridian), including Colorado, typically use the prior appropriation doctrine for water law and allocation (Sutherland and Knapp, 1988).

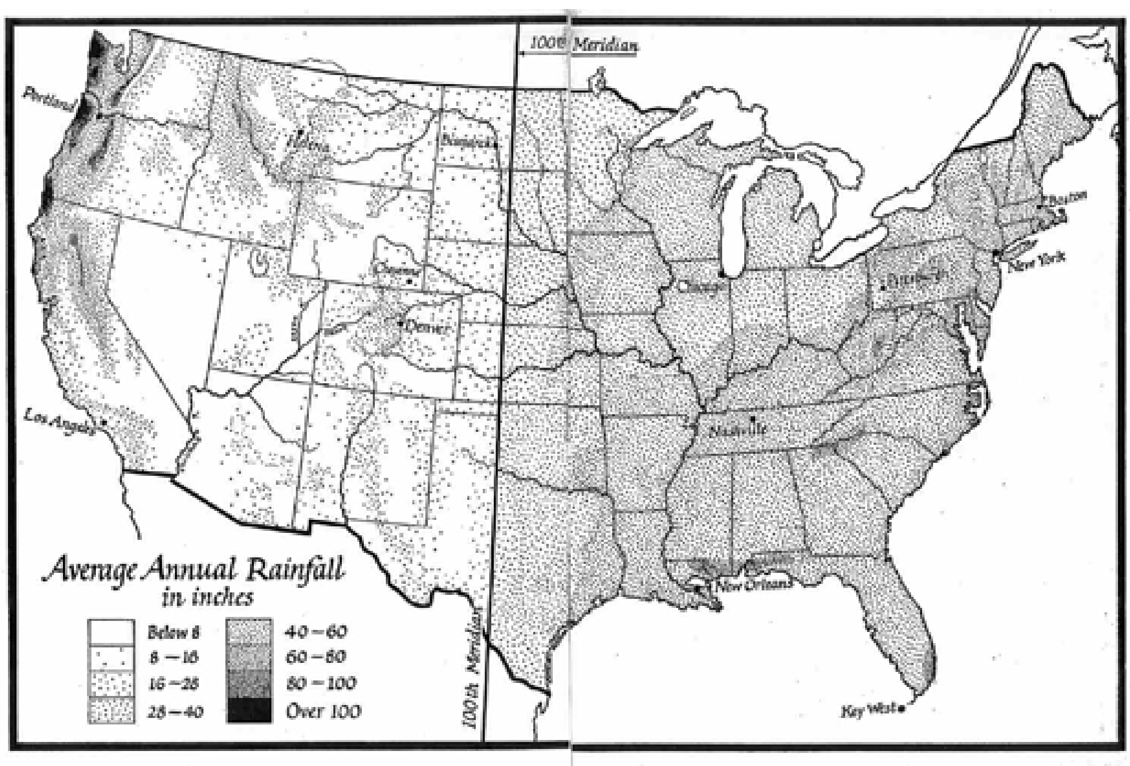

Figure 1-6. Continental U.S. rainfall and 100th meridian.

In the state of Colorado, the prior appropriation system of water allocation was originally developed within mining camps, where the first person to occupy a work site established a legal claim to the mining rights on that site. Likewise, prioritization of water use was granted to the first person to put the water from the stream to a productive use. In limited water scenarios, senior (oldest) appropriations claimed priority, and junior appropriations could possibly be denied use. To establish a water right in Colorado, the water must be used for a beneficial purpose including but not limited to municipal, domestic, industrial, recreational, environmental, or agricultural purposes. Prior appropriation also employs the "use it or lose it" principle, where the water right will be abandoned if not put to beneficial use over ten years (Smith et al., 1996).

The consumptive use (CU) portion of a water right is defined as water that is no longer within a stream or aquifer system after it has been applied to beneficial use; in other words, used by crops through plant transpiration and evaporation. Multiple uses of water within a basin are often possible through beneficial use of return flows; however, water quality degradation can become an issue with this practice. Wide-scale conservation practices designed to increase diversion efficiencies have the potential to reduce the magnitude of return flows. *Only the amount of water considered as CU can be transferred.* Because it is difficult, costly, and time-consuming to determine the CU with complete accuracy, engineering estimates are typically used based on historical irrigation methods and hydrologic conditions (Smith et al., 1996). In some cases, CU may also include non-beneficial losses such as evaporation from canal and ditches (Sutherland and Knapp, 1988).

Water rights in Colorado can be transferred or changed, but are subject to certain restrictions imposed by the water courts and the State Engineer's office. Water right transfers can be temporary or permanent, and can involve changes in use, timing, amount, and location of either diversion or use. Because water right changes cannot have a detrimental impact on other vested or decreed water rights, it is necessary to maintain stream conditions that were present at the time other vested water rights were established, hence return flow conservation. In alluvial watershed basins, incentives to improve practices that decrease CU or result in saved water are somewhat limited unless the water conserved can be used to extend supplies of an existing water right. Additionally, incentives for adopting deficit or limited irrigation practices are lacking, mainly because of barriers to transfer a portion of the historic CU. One alternative is dry-year option contracts where farmers will be paid to fallow land when supplies are short; however, this takes the land completely out of production (Smith et al., 1996). Some researchers note that eventual changes in water law are likely as irrigators find increased pressure to use their irrigation water more economically (English et al., 2002; Smith et al., 1996). This research explores yield potential and consumptive use in the context of limited irrigation, which are the economic drivers of importance as water rights transfers face potential change.

1.2 LIMITED IRRIGATION FIELD STUDIES

When considering limited irrigation management, it is important to consider the effects of water stress timing and severity. Water stress, sometimes referred to as "water deficit stress," is a condition where plant cells and tissues have less than full turgor because of transpiration demand in excess of root water uptake. This condition typically adversely affects the growth and development processes of the crop, subsequently limiting overall productivity or yield (Saseendran et al., 2008b). Water stress has been found to delay several growth components of maize, including flowering and maturity (Farre and Faci, 2009), as well as tassel initiation, silking, and leaf appearance and area (Abrecht and Carberry, 1993).

Some earlier literature typically considered deficit irrigation as a reduction of irrigation amount or frequency, and looked less at the effect of irrigation timing and allocation. For example, in an early study of deficit irrigation, Stockle and James (1989) found that large soil water holding capacity, high soil water contents at planting, and deep root exploration were important for successful implementation of deficit irrigation. However, they did little to look into the effect of irrigation timing in regard to deficit irrigation, a subject that has seen increased focus in recent literature. Other earlier studies were aware of the importance of irrigation timing, for example Doorenbos and Kassam (1979) reported that maize is relatively tolerant to water deficits imposed during the vegetative and ripening periods. Barrett and Skogerboe (1978) found that withholding irrigation during vegetative growth reduced yields by 13%, while withholding irrigation during reproductive growth reduced yields by 30%. Gilley et al. (1980) found no yield reduction when stressing corn only during the vegetative stages, but significant reductions when stressing during the reproductive stages. Even fifty years ago, researchers found that moisture stress prior to silking reduced yield by 25%, at silking by 50%, and after silking by 21% (Denmead and Shaw, 1960).

More recently, Norwood (2000) tested treatments of zero, one, two, and three irrigations on corn in Garden City, KS over three years, and concluded that corn can obtain adequate yields with one or more irrigations, therefore under restricted water availability, limited irrigation would be preferred over a dryland alternative. Payero et al. (2009) found that irrigation timing can play a considerable role on crop ET and the proportion of crop ET to potential ET; also, this effect is variable with seasonal differences such as rainfall and initial soil water conditions. In their study, irrigations applied near North Platte, NE in July had the greatest positive effect on crop yield since they resulted in less water stress during the critical reproductive growth stages, and suggested that flexibility in irrigation scheduling should be adopted instead of using fixed timing strategies. In the case of limited water, Payero et al. (2009) suggest focusing irrigation applications on late season (from dent to maturity) for the least risk of significant yield reduction. Also, in an earlier study, Payero et al. (2006) found good linear relationships between yield and irrigation water applied, but found no beneficial increase in Water Use Efficiency (WUE) due to deficit irrigation.

Çakir (2004) found that 66% to 93% of corn yield could be lost because of prolonged water stress during tasseling and ear formation stages, and that a single irrigation omission during sensitive growth stages could cause up to 40% grain yield loss. Farre and Faci (2009) evaluated two field experiments of corn in northeast Spain where they divided the growing season into three phases: vegetative, flowering, and grain filling. They found that Irrigation Water Use Efficiency (IWUE) was higher in treatments fully irrigated around flowering, showing flowering as the most sensitive stage to water deficit. Similarly, Mansouri-Far et al. (2010) evaluated the effects of water stress during vegetative, reproductive, and both vegetative and reproductive stages, finding that the highest IWUE when water deficit occurred at the vegetative stage, and limited irrigation imposed during the reproductive stage proved significant. They also reported a linear relationship between yield and irrigation water, and noted that the slopes of these lines were different between nitrogen treatments. Klocke et al. (2004) compared fully irrigated corn with irrigation initiated at pollination and water allotted (150 mm) management strategies on farm-scale sprinkler irrigated plots, finding that the late initiated and water allocated plots had respective yields of 93% and 84% of the fully irrigated yield. Schneekloth et al. (1991) developed relationships between crop water use and grain yield of continuous corn in west-central Nebraska, finding that limited irrigated corn yielded 81% of the fully irrigated corn. Other experiments have found similar results where irrigation is deemed extremely important in the reproductive stages (Igbadun et al., 2008; Ko and Piccinni, 2009; Payero et al., 2009).

Payero et al. (2009) gives a comprehensive list of studies regarding the effect of stress timing and crop yield. Some have developed mathematical models. However, others suggest that corn yield is simply a linear function of seasonal ET or transpiration. Farahani et al. (2007) suggests that increased efforts are needed to understand water-stressed crops, especially in terms of the Penman-Monteith equation (Allen et al., 1998). One field study of furrow irrigation with limited water (Schneekloth et al., 2006) concludes that "Irrigation management strategies, which reduce irrigation during the vegetative growth stages, can reduce applied water with little or no yield reduction." This is the general idea of limited irrigation management. However, more research is needed as *to what degree* these yields may be reduced based on specific *timing* and *amount*. Such specific relationships will be highly distributed because of seasonal variability, and are likely site-specific (Igbadun et al., 2008; Katerji et al., 2010).

1.3 CROP MODELS

1.3.1 Introduction

As mentioned in Section 1.1, past focus on irrigated agriculture has primarily been on maximizing yields. For example, the FAO defines crop water requirements in terms of production potential (Doorenbos and Pruitt, 1992). English et al. (2002) suggest that future evaluations of production potential will require combinations of crop production models and operations research, as well as planning for some optimal degree of crop stress. They go on to say that "well-established rules of thumb will become obsolete as economic considerations are explicitly addressed, and formulation of new, fixed guidelines will be difficult at best." Other authors agree that accurate model simulations of water stressed conditions are necessary (Ahuja et al., 2006; Ma et al., 2007; Saseendran et al., 2008b). Even twenty-five years ago, Heermann (1985) noted: "Managers will, in the future, use yield models to implement management strategies for limited available water." Ma et al. (2007) note that while applications of models cannot fully replace field studies, they do help researchers understand the interactions of various components and extend results beyond experimental sites and years. They list several factors that models can evaluate and field studies cannot, including climate impact, risk and probability analysis, optimization of management, and others.

Crop models have proven to be valuable tools that can significantly shorten the experimental process needed to evaluate and improve cropping systems under various management strategies, especially using long-term multiyear weather datasets (López-Cedrón et al., 2008). Researchers suggest that increased understanding of crop model response is required to be more effective in knowledge transfer (Ma et al., 2007). Additionally, many authors suggest modelers need to increase understanding of soil water and various plant growth and development processes under water stressed conditions, especially in terms of transpiration, photosynthesis, carbon allocation, canopy temperature, and LAI for production (Ahuja et al., 2006; Saseendran et al., 2008b). Crop system models can be an effective way to evaluate some of these outputs.

One crop model that has been widely used is the DSSAT (Decision Support System for Agrotechnology Transfer) family of models (Hoogenboom et al., 2010; Hoogenboom et al., 2004; Jones et al., 2003; Ritchie et al., 1998; Tsuji et al., 1994). This system contains two crop specific plant growth models (CERES and CROPGRO). The Cropping System Model (CSM) is the core crop simulation model of the DSSAT (Hoogenboom et al., 2004; Jones et al., 2003). The CERES-Maize model is a subset of the DSSAT models to simulate corn growth. The CERES-Maize crop model used in this dissertation is discussed in detail in later sections, but below are a few examples of crop model calibration philosophies and other crop simulation models used in regard to water stress and limited water supplies.

1.3.2 Calibration Techniques

Calibration and validation of crop models is typically performed by adjusting input parameters and comparing output parameters simulated by the model with values observed in the field. Common model input parameters in crop models can include: soil physical parameters (texture, organic matter content, bulk density, porosity), soil hydrologic parameters (soil water retention curve, or volumetric water content as a function of soil matric pressure or suction), hydraulic conductivity as a function of water content, potential ET estimation methods, crop growth parameters, environmental stress factors, among others (Ahuja and Ma, 2002). Common evaluation parameters for comparison are yield, leaf area index (LAI), biomass, volumetric water content at various soil layers, among others.

Ahuja and Ma (2002) give four current approaches to model parameterization: (1) estimating measured values when available; (2) estimating values from available properties based on established empirical relationships; (3) using values from established databases of measured or estimated values; and (4) calibrating or refining parameter values by comparing model results with observed data. They also note a disconnect between modelers (who require large amounts of data) and field researchers (who are expected to supply much of this data), and suggest continuing collaborations between the two groups for increased knowledge of cropping systems and potential (Ma et al., 2007; Ma et al., 2002). Ma et al. (2002) suggest that when simulated and observed values in crop production disagree, discrepancies may be due to: (1) inaccurate soil water and nutrient simulation; (2) lack of model sensitivity to plant environmental stresses; (3) unrecorded damage from natural disasters, extreme weather events, pests, diseases, and weeds; (4) variability in field measurements; and (5) lack of accuracy in model parameters or process simulation. Ahuja and Ma (2002) make special note of the difficulties in parameterizing models to field datasets that are both spatially and temporally variable. They suggest averaging parameters (lumped parameters), use of probability distributions for the parameters (stochastic simulation), or running the model separately for various parts of the field (distributed simulation). Because of the various difficulties, agricultural system models are usually parameterized by trial-and-error or iterative processes.

Boote (1999) suggests calibrating models to a non-stressed condition. Many irrigation studies calibrate the model to a fully irrigated, non-stressed treatment (Castrignano et al., 1998; Ma et al., 2002; Panda et al., 2004; Saseendran et al., 2008a). Some irrigation studies (Ma et al., 2002; Saseendran et al., 2005) assume unlimited nitrogen conditions in order to eliminate the question of nitrogen stress. However, results of some of these studies suggest nitrogen stress may have been present (Ma et al., 2002). A few studies have calibrated based on the most stressed treatments (Ma et al., 2003). As more recent studies have emphasized management of crops under stressed conditions, some authors are suggesting increased understanding and development of accurate simulations of water stress on various plant growth and development processes (Saseendran et al., 2008b). Most current crop models use a simple stress factor to quantify the effect of water stress, typically based on a ratio of observed ET to potential (unstressed) ET (Hanson, 2000).

1.3.3 Modeling Under Limited Water Supplies

In a given region, fully irrigated yields are fairly stable and easy to estimate; however, yield under dryland and deficit irrigation can vary considerably, especially in arid and semiarid climates (Payero et al., 2009). Because irrigation is a supplemental (or artificial) method of increasing soil moisture, it can be controlled at the farm level. Taking this degree of control in combination with the natural stochastic processes, dependent on the weather, there remains a large degree of uncertainty in regard to yield as a function of available water resources for irrigation (Mannocchi and Mecarelli, 1994). Also, uncertainties due to spatial and temporal variability make field studies costly and time-consuming to perform, especially in the context of output probability. However, numerical crop models have the capability of quickly evaluating numerous years of variable weather input without costly field experiments (DeJonge et al., 2007). Likewise, crop yields can be highly variable spatially, often due to soils, but can also be evaluated rather quickly using crop models and have even been used in the context of precision agriculture (DeJonge et al., 2007; Thorp et al., 2008).

Vazifedoust et al. (2008) calibrated and validated the Soil Water Atmosphere Plant (SWAP) model for fodder maize in Iran, and used this model to evaluate water production functions in terms of limited irrigation water supply. They found that deficit irrigation scheduling can increase water production (the ratio of yield and total applied irrigation) by a factor of 1.5. Katerji et al. (2010) used the STICS model to evaluate corn yield and WUE based on three varying inputs: a 25-year dataset, soil type, and water supply. They determined that the soil water holding capacity plays an important part in deficit irrigation and water stress, and noted that the reproductive stage is particularly sensitive to water deficit. Ma et al. (2002) tested RZWQM for water stress responses of corn grown under various limited irrigation treatments. They calibrated the model based on the most stressed treatment. Results showed fair prediction of treatments; however, the model did correctly simulate the relative increase in yield with irrigation amount. RZWQM was also used as a management tool to predict the impact of irrigation and fertilization practices on corn yield in Uzbekistan (Stulina et al., 2005).

Some authors have found that the CERES-Maize model does not adequately simulate productivity under water scarcity, mainly attributed to poor leaf surface simulation and the water stress functions (Nouna et al., 2000). In a later study (Nouna et al., 2003), these authors added new modules addressing these supposed shortcomings. They found their new stress function showed less severity than the original CERES-Maize model, indicating that original stress functions are too severe. López-Cedrón et al., (2008) evaluated CERES-Maize 4.0 for rainfed and irrigated treatments with the intent to improve the model's ability to predict biomass and yield under water-limited conditions where the model had previously given good predications under irrigated conditions. They found that the default model adequately predicts irrigated treatments but under predicts rainfed treatments, partly because the Priestley-Taylor ET method tends to overestimate the actual ET of the crop, therefore predicts too early and severe water deficit. They found that the FAO-56 method is a better predictor of ET. Lizaso et al. (2005) created a leaf-level canopy assimilation model for CERES-Maize in order to improve model accuracy under stress; this model subsequently could simulate leaf-level processes such as hail or mechanical damage.

1.4 OBJECTIVES

This research project evaluated comparisons of full and limited irrigation treatments of corn in the northern Front Range of Colorado. Both field experiments and numerical modeling approaches (using the CERES-Maize crop growth model) were used in an effort to increase understanding of corn response to limited irrigation water, especially in regard to yield, ET, and vegetative growth, as well as increased knowledge of CERES-Maize model response to these conditions.

The overall objective of this research project was to gain knowledge about potential yield and water savings benefits of limited irrigation management of corn in comparison with full irrigation using crop modeling approaches, and potential for model improvement regarding simulation of corn under water stress. Specific objectives were to:

1) Calibrate and evaluate the CERES-Maize crop growth model for full and limited irrigation conditions and statistically determine the model's ability to differentiate irrigation treatments in terms of ET, crop growth, and yield.
2) Evaluate corn yield, ET, vegetative growth, and phenological timing sensitivity to model inputs, as well as differences in sensitivity between full and limited irrigation

treatments, using the calibrated CERES-Maize crop growth model and global sensitivity analysis procedures.

3) Review CERES-Maize model processes determining water balance and ET, and enhance model code to improve overall simulation of ET and WUE under limited irrigation management.

1.5 HYPOTHESIS

It has been demonstrated in the literature that the CERES-Maize crop model generally performs well under fully irrigated conditions but not as well under water stress. The model is also typically calibrated based on non-stressed observations. The hypothesis for this study was as follows:

The CERES-Maize crop model can be calibrated and validated using full and limited irrigation field experiments, and statistical analyses comparing experimental data to model ET, yield, and LAI output responses can quantify the potential for model improvement. Additionally, as suggested by Ma et al. (2002), both input parameter variability and model stress component structure have the possibility to change CERES-Maize output responses and can be analyzed and quantified. The evaluation of these processes can lead to increased understanding of model response to water stress and provide opportunity for improvement upon CERES-Maize modeling techniques and/or processes under water stress.

1.6 DISSERTATION ORGANIZATION

Previous sections of this document outline the need for further research regarding the modeling of maize response to limited irrigation resources. The remainder of the dissertation is organized into three individual papers covering separate but relevant topics regarding irrigation and crop modeling. The first is a study in which the CERES-Maize crop growth model was calibrated and validated for full and limited irrigation, in which the results were statistically compared to field observations. This paper was published in the *Transactions of the ASABE* in April of 2011. The second paper used two global sensitivity analysis procedures to analyze the effects of input variability on phenological crop development, LAI, yield, and ET, noting that these sensitivities differ between irrigation treatments. This paper has been submitted and is under review for publication in *Ecological Modelling*. The final paper explored changes to the model structure regarding calculation of a crop coefficient for potential ET and partitioning of potential ET into potential transpiration and soil evaporation. A new equation to determine a crop coefficient for ET demand as a function of LAI was added to the model, improving ET estimation under limited irrigation. This paper is intended for publication in *Agricultural Water Management* or another relevant journal. Furthermore, Appendix A of this dissertation demonstrates the use of the revised model in the context of water production functions under limited irrigation management.

The logic of these three papers is outlined more specifically in Figure 1-7. The principal intent was to increase and transfer knowledge regarding limited irrigation of corn and crop model response. The calibration, validation, and statistical evaluation study (Chapter 2) was conducted prior to the other two studies whose objectives were shaped on the result that the CERES-Maize model performed much better in non-stressed conditions than under water stress. The two subsequent papers involved global sensitivity analysis of model output responses to input parameters (Chapter 3) and improvement of model processes governing ET estimation under water stress (Chapter 4).

1.7 DATA AVAILABILITY AND SCOPE

This research project was based on several field studies of irrigated agriculture; most of these are complete datasets, but some are still in progress. All datasets used in models are complete; for example the dataset used to calibrate and validate the CERES-Maize model included data from 2006 through 2008; 2009 and 2010 field trial management were added to the previous years' data as inputs for the global sensitivity analysis and evaluation of model stress and ET demand processes. Climate was an important variable in regard to this study, and is highly variable in both space and time. To narrow the scope of this project, irrigation studies included were considered site-specific or at least region-specific to the northern Front Range of Colorado.

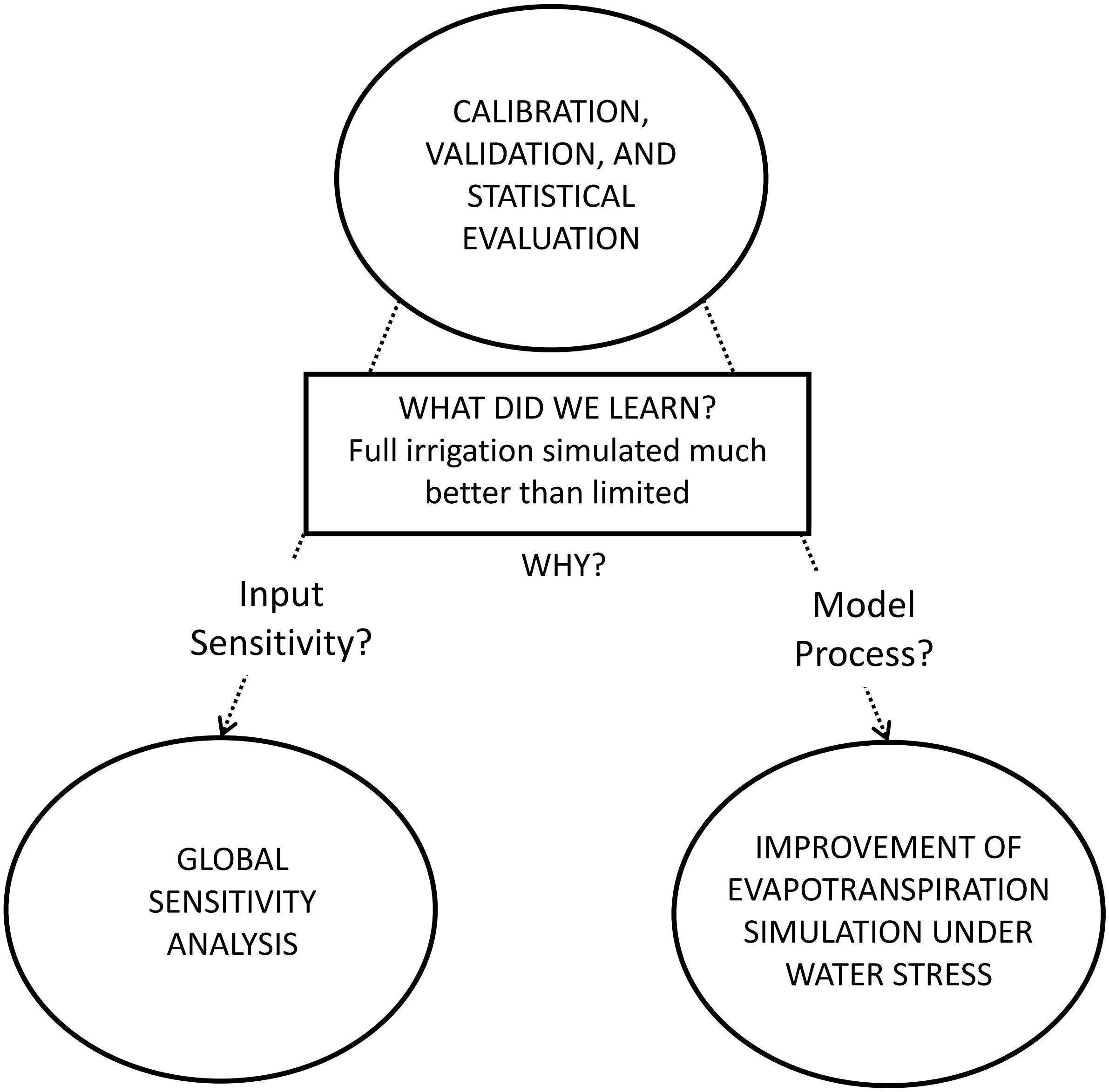

Figure 1-7. Dissertation papers and logic flow for dissertation, regarding three studies using the CERES-Maize model to evaluate full and limited irrigation treatments.

1.8 EXTERNAL BENEFITS OF RESEARCH

It is expected that this body of research will be of benefit to many in the agricultural and research communities. For field experimentalists, this research provides a first look at a much larger ongoing project involved in quantifying consumptive use and yield potential with limited irrigation supplies. For modelers (especially users of CERES-Maize), it brings attention to potential parameterization and/or model process improvements regarding the simulation of stressed crops (i.e., ET demand), a management objective the original model has difficulty replicating. It should also be of interest to modelers in general as it shows an example of global sensitivity analysis procedures, a more robust and thorough procedure than local sensitivity procedures that are more commonly used. Finally this research attempts to link simulation and field experiments of limited irrigation agriculture, a process that will only become more relevant as the world population increases. It is the hope that the lessons learned as part of this research will be used by other scientists for accurate simulations under water-limited management, thus providing individual producers with simpler methods to optimize their water management and increase farm income.

CHAPTER 2. MODELING OF FULL AND LIMITED IRRIGATION SCENARIOS FOR CORN IN A SEMIARID ENVIRONMENT

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2.1 INTRODUCTION

In several areas of the U.S., including the Front Range of Colorado, large urban population growth is occurring despite limited availability of water resources. Agricultural uses currently account for more than 85% of the total water consumed in Colorado, and agricultural users hold most of the senior water rights (CDM, 2007). Furthermore, population in the South Platte River basin of northeast Colorado is expected to increase by 65% from 2000 to 2030 (CDM, 2007). To deal with large municipal growth, cities have purchased water rights from farmers. In many cases, this transfer involves all water rights and often the land, leading to dry-up of large areas and adverse ecological and socio-economic consequences for rural communities (Colorado Water, 2010). CDM (2007) predicts that nearly 37% of the irrigated area in the South Platte River basin (54,000 ha) will be lost between 2000 and 2030. In addition to potential economic losses to farmers and smaller communities that depend on agriculture, this loss could cause negative environmental impacts from leaving land fallow, such as erosion by wind, weed invasion, lack of management (Skidmore et al., 1979), and soil carbon loss (Paustian et al., 1997). Current Colorado water law is based on the prior appropriation system of water allocation, the main components of which place high emphasis on return flow conservation and quantification of consumptive use or evapotranspiration (ET) (Colorado Water, 2010; Smith et al., 1996). Current water rights transfers allow only for complete transfer of consumptive use, but some researchers note that changes in water law are likely as irrigators find increased pressure to use their water more economically (Smith et al., 1996; English et al., 2002). English et al. (2002) suggest that a fundamental change is necessary in the way that producers approach irrigation management. They propose that irrigated agriculture adopt a new paradigm based on the maximization of net benefits, instead of simply the biological objective of maximizing yields.

One example of this proposed change is limited irrigation of crops. Limited irrigation practices incorporate water management under restricted water application and minimize water stress during critical crop growth stages in order to maximize yields (Schneekloth et al., 2009). Older field studies have addressed maize response to growth-timing of irrigation (e.g., Barrett and Skogerboe, 1978; Doorenbos and Kassam, 1979; Gilley et al., 1980). More recent studies have supported this idea, e.g., Klocke et al. (2004) achieved 93% of fully irrigated corn yield using 76% of the water applied. In a separate study, Klocke et al. (2007) achieved limited irrigation yields of 80% to 90% of fully irrigated yields while using about half the applied water compared to full irrigation. More recent studies regarding the importance of growth-stage directed irrigation timing include Payero et al. (2006), Igbadun et al. (2008), Farre and Faci (2009), Ko and Piccinni (2009), Payero et al. (2009), and Mansouri-Far et al. (2010).

Accurate crop simulation models, such as those found in the Decision Support System for Agrotechnology Transfer (DSSAT v4.0), can play a role in assessing the costs and benefits of limited irrigation and the interactions of timing and amount of irrigation (Hoogenboom et al., 2004). The DSSAT Cropping System Model (CSM)-CERES-Maize model (Jones and Kiniry, 1986; Ritchie et al., 1998; Jones et al., 2003) has been widely used to assess cropping and management strategies for corn (both rainfed and irrigated) for well over two decades. Adapted versions of CERES-Maize were successfully used in Kenya to simulate dry land and irrigated maize grain yields for plant populations of 1 to 9 plants m^{-2} (Keating et al., 1988). Kiniry et al. (1997) and Kiniry and Bockholt (1998) both evaluated CERES-Maize yield response to rainfed climate, with simulated grain yields within 5% and 10% of measured grain yields, respectively. More recent studies have evaluated crop models specifically in terms of limited water availability. Cabelguenne et al. (1995) used the EPIC model to simulate limited irrigation of maize in southwestern France, finding that simulated results agreed with known effects of drought stress during critical growth periods. Vazifedoust et al. (2008) used the Soil Water Atmosphere Plant (SWAP) model for fodder maize in Iran to evaluate water production functions in terms of limited irrigation water supply. They found that deficit irrigation scheduling can increase water production (the ratio of yield and total applied irrigation) by a factor of 1.5. Katerji et al. (2010) used the Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS) model to evaluate corn yield and WUE for varying inputs including soil type and water supply. They determined that soil water holding capacity played an important part in deficit irrigation and water stress, and noted that the plant reproductive growth stage was particularly sensitive to water deficit. Ma et al. (2002) evaluated the Root Zone Water Quality Model (RZWQM) for water stress responses of corn grown under various limited irrigation treatments and concluded that the model correctly simulated relative increase in yield with irrigation amount.

Recent studies using CERES-Maize have raised concerns about model accuracy in water-limited scenarios. For example, Xie et al. (2001) found that simulated vegetative growth and kernel weight were extremely sensitive to growth stress. Additionally, López-Cedrón et al. (2008) evaluated CERES-Maize for rainfed and irrigated treatments with the intent to improve model ability in predicting biomass and yield under water-limited conditions. They found that the model adequately predicted yield from irrigated treatments but underpredicted yield from rainfed treatments. Other researchers have found that CERES-Maize overestimated the effects of water stress on vegetative growth and subsequently adjusted the stress functions and improved simulation results (Nouna et al., 2000; Mastrorilli et al., 2003). Recent studies have emphasized management of crops under stressed conditions, with some researchers suggesting a need for increased understanding and development of accurate simulations of water stress on various growth and development processes (e.g., Saseendran et al., 2008b). Limited water resources and increasing pumping costs have caused farmers in Colorado to consider limited irrigation as an alternative to full irrigation practices. Alternatively, farmers may consider either a reduction in planted area or schedule irrigation events so that plants do not encounter stress during sensitive growth stages. For example, Saseendran et al. (2008a) simulated various water allocations and irrigation amounts in northeastern Colorado using CERES-Maize and found that split irrigation applications of 20% of the total water applied during vegetative growth stages and 80% of the total water applied during reproductive growth stages obtained the highest yield for a given irrigation allocation (ranging from 100 to 700 mm of total irrigation).

Additional research is needed to assess the effects of limited irrigation practices on corn grain yield and ET. While there is a need for controlled field research, valuable information can come from modeling studies of limited irrigation practices because models such as CERES-Maize can evaluate several alternatives much more quickly and efficiently than experimental research. However, literature containing detailed statistical evaluations of CERES-Maize for yield and ET is sparse, especially with respect to limited irrigation. Therefore, the objective of this study was to statistically determine the ability of CERES-Maize to accurately differentiate between full and limited irrigation treatments in northeastern Colorado in terms of grain yield, leaf area index (LAI), leaf number, ET, water use efficiency (WUE), and irrigation use efficiency (IUE). The study utilizes an integrated experimental design and modeling approach whereby the tested CERES-Maize model can be used in future studies to guide irrigation management decisions, e.g., defining yield-ET and yield-irrigation relationships for varying irrigation amounts as well as maximizing economic return with limited water resources.

2.2 MATERIALS AND METHODS

2.2.1 Field Experiment

This study compares output responses from the CERES-Maize crop growth model with results from an on-going field experiment of limited irrigation cropping systems near Fort Collins, Colorado (40° 39' 19" N, 104° 59' 52" W). Two irrigation treatments of continuous corn (the dominant irrigated crop in northeast Colorado) were studied during the 2006 through 2008 growing seasons: full irrigation (ET requirement supplied throughout the season) and limited irrigation (no irrigation before the V12 reproductive stage unless necessary for emergence, and then full irrigation afterwards). There were four replications of each treatment, arranged in a randomized complete block design. Each plot consisted of 12 rows spaced 76 cm apart, with a row length of 26 m. All data were taken from the middle four rows, with the outer eight rows serving as buffers to minimize boundary effects from adjacent treatments. Irrigation water was applied through a linear-move sprinkler system. Both treatments were monitored for crop growth (total leaf number, LAI, crop height, and biomass), crop development (phenology stages), soil water content (SWC), ET by water balance, and final grain yield.

2.2.2 Model Input Data and Calculation of Evapotranspiration

An on-site weather station (station FTC03; 40° 39' 09" N, 105° 00' 00" W; elevation 1557.5 m) within the Colorado Agricultural Meteorological Network (CoAgMet, http://ccc.atmos.colostate.edu/~coagmet/) continually recorded daily precipitation, solar radiation, minimum and maximum temperature, vapor pressure (which was converted to dew point temperature), and wind run. A tornado struck near the field site in Windsor, Colorado, on 22 May 2008, causing damage to the weather station. Missing data from 20 May through 16 June 2008, as well as any other missing weather data, were replaced by data from the Wellington, Colorado, station (station WLT01; 40° 40' 34" N, 104° 59' 49" W; elevation 1567.9 m) approximately 2 km north of the FTC03 station.

The soil at the study site is a Fort Collins Loam (fine-loamy, mixed, superactive, mesic Aridic Haplustalf). When possible, field capacity and permanent wilting point were estimated from respective high and low field observations of gravimetric SWC, as Ritchie (1998) suggests, using field observations of these values for DSSAT model parameterization. Additionally, samples taken from two plots were used for all bulk density measurements and any missing field capacity and permanent wilting point values (based on pressure plate analysis). Saturated hydraulic conductivity was estimated from soil texture, field capacity, and permanent wilting point values using the Rosetta version 1.2 pedotransfer function model (Schaap et al., 2001). Soil characteristics were assumed uniform across all plots and are shown in Table 2-1.

Management and yield data, as well as other experimental observations, were available from 2006 through 2008 (Table 2-2). However, the most intensive data collection occurred in 2008, which included weekly gravimetric soil water (to a depth of 40 cm) and neutron moisture meter (NMM) measurements, and LAI based on length and width measurements of each leaf taken by hand. On 14 August 2008, a hailstorm occurred at the study site, significantly reducing yields. Final 2008 crop yields were

Table 2-1. Soil properties at the Fort Collins limited irrigation experimental site.

Depth from Surface (mm)	Wilting Point (mm^3 mm^{-3})	Field Capacity (mm^3 mm^{-3})	Saturation (mm^3 mm^{-3})	Available Water (mm)	Sat. Hyd. Cond. (mm d^{-1})	Bulk Density (g cm^{-3})	Sand (%)	Clay (%)	Initial NH_4 (g N per Mg soil)	Initial NO_3 (g N per Mg soil)
0 - 150	0.100	0.320	0.461	33.0	200	1.28	37.4	31.0	8.8	17.6
150 - 300	0.150	0.280	0.461	19.5	345	1.25	37.4	31.0	6.0	15.1
300 - 450	0.150	0.325	0.461	26.2	79	1.46	36.0	31.0	3.4	11.3
450 - 600	0.179	0.262	0.466	12.5	273	1.34	34.2	31.2	3.4	11.3
600 - 900	0.169	0.400	0.445	69.3	66	1.38	40.3	31.7	1.3	6.3
900 - 1200	0.160	0.420	0.425	78.0	40	1.45	48.6	27.1	0.4	3.5
1200 - 1500	0.180	0.400	0.419	66.0	39	1.47	46.4	29.2	0.4	3.5
1500 - 1780	0.180	0.420	0.429	67.2	39	1.44	44.4	30.4	0.4	3.5

Table 2-2. Experimental management data and grain yield.

	2006		2007		2008	
	Limited Irrigation	Full Irrigation	Limited Irrigation	Full Irrigation	Limited Irrigation	Full Irrigation
Hybrid	Garst 8827	Garst 8827	Garst 8827	Garst 8827	Pioneer 38P	Pioneer 38P
Planting date	10 May	10 May	10 May	8 May	30 April	30 April
Planting population (seeds m^{-2})	5.9	7.9	5.9	8.0	7.9	7.9
Nitrogen application date(s) (kg ha^{-1})	29 June (67)	29 June (157)	27 June (67)	27 June (157)	30 April (52), 23 June (157)	30 April (52), 23 June (191)
Anthesis date	Not collected	Not collected	3 August	27 July	30 July	30 July
Average yield (kg ha^{-1})	8916	11107	7576	10891	10451	10863
Harvest date	4 November	4 November	14 November	14 November	19 November	19 November

Note: 2008 yields measured and adjusted based on LAI reductions at the growth stage when hail damage occurred (Vorst, 1993).

measured and adjusted to levels if hail damage had not occurred, based on LAI reductions and the growth stage (Vorst, 1993).

Soil water content was measured on a weekly basis, typically the day before irrigations occurred. Soil water content was measured at each plot by NMM in 30 cm intervals to a depth of 180 cm (although data were sparse at depths below 1 m). NMM measurements used two separate calibrations for the top 30 cm and all depths below 30 cm. Initial SWC conditions in all years were determined by NMM and used as initial conditions for CERES-Maize modeling. Assuming an effective root zone of 1 m, the total SWC in the top 1.0 m of soil was used in the analyses. Calculations were restricted to the top 1.0 m of soil because NMM observations were sparse at deeper depths, observed SWC differences below 1.0 m were minimal (e.g., ET calculated using deeper observations was less than 5% higher than when calculated for the top 1.0 m), and observed root density dropped off dramatically after 60 cm depth (N. Hansen, personal communication, 18 October 2010). Total leaf number per plant was sampled in 2007. This was done by counting open leaves on ten representative plants per plot. LAI was taken by non-destructive sampling in 2008. Two representative plants were selected in each plot, and subsequent samples were done on the same exact plants. Length and width of each leaf was measured, and the sum of all these areas was multiplied by 0.74 to estimate the total leaf area (Kang et al., 2003). LAI was estimated by dividing total leaf area by the average ground area per plant, based on observed plant population. Both field experiments and simulations had sufficient available nitrogen (N) to assume negligible N stress. Soil N samples were taken on 21 May 2007 only (13 days after planting). These values were assumed to represent initial N conditions for all treatments in the three years modeled by CERES-Maize (Table 2-1). Additional N was applied during planting in 2008 and in mid-season for all years (Table 2-2).

Irrigation was applied by a linear-move sprinkler system, generally at a weekly interval, and irrigations were applied equally to each replication for the desired treatment. Irrigation amounts were determined by crop need and supported by potential ET estimates from the on-site weather station. Because of flow limitations on the linear sprinkler, irrigations occurred over a two-day period, with the southernmost two replicates being irrigated the first day and the remainder being irrigated the following day. No runoff was observed in irrigations, as application rates did not exceed infiltration capacity and the field had negligible slope. Irrigation schedules for all treatments between 2006 and 2008 are given in

.

Irrigation management for a fully irrigated crop typically ensures that the crop experiences no water stress during any stage of growth. Where limited irrigation differs is not only in the total amount irrigated, but also in the timing. Limited irrigation for corn may allow some visually observable (e.g., wilting and discoloring of leaves) stress of the crop during the vegetative stages but avoids stress during the reproductive stages, which are the most water-sensitive (Nielsen et al., 1996). In all three years, irrigation was applied early in the season to all treatments to encourage germination and avoid total loss of the crop. Additionally, some irrigations were applied late in the vegetative stage to ensure no stress at the beginning of the reproductive stage (i.e., irrigations on 19 and 25 July in 2007). This management strategy dictates that limited irrigation should closely

Table 2-3. Irrigation schedule and amount for both full and limited irrigation treatments (2006-2008).

		Irrigation Amount (mm)	
Year	Date	Limited	Full
2006	18 May	--	38.1
	1 June	38.1	0.0
	15 June	--	38.1
	22 June	--	38.1
	3 July	--	76.2
	13 July	--	50.8
	21 July	50.8	50.8
	27 July	55.9	55.9
	3 August	38.1	38.1
	10 August	--	38.1
	18 August	38.1	38.1
	24 August	38.1	38.1
	Total	259.1	500.4
2007	25 May	38.1	38.1
	20 June	44.5	44.5
	28 June	--	50.8
	11 July	--	50.8
	19 July	50.8	50.8
	25 July	38.1	38.1
	16 August	38.1	38.1
	23 August	--	25.4
	29 August	--	25.4
	Total	209.6	362.0
2008	11 May	38.1	38.1
	4 June	38.1	38.1
	12 June	--	25.4
	26 June	--	38.1
	3 July	--	38.1
	10 July	--	38.1
	17 July	--	38.1
	24 July	38.1	38.1
	31 July	38.1	38.1
	7 August	25.4	25.4
	Total	177.8	355.6

match full irrigation beginning at (or slightly before) the anthesis date and continuing through the rest of the reproductive phase (Figure 2-1).

Observed ET values were calculated using a water balance for the top 1.0 m of soil:

$$ET = P + I - RO \pm \Delta SW \qquad (2\text{-}1)$$

where ET is evapotranspiration (mm), P is precipitation (mm), I is irrigation (mm), RO is runoff (mm), and ΔSW is the change in SWC in the soil profile (mm). Runoff was calculated by the SCS curve number method (SCS, 1972) and was insignificant in both observations and simulations. Drainage, or deep percolation below the effective 1.0 m root zone, was assumed to be zero, as all NMM measurements below this zone were less than field capacity. Cumulative observed ET was calculated weekly based on days that soil water content was measured. Daily cumulative potential ET values for a fully irrigated crop were also calculated using the Penman-Monteith model and input data from the on-site weather station (Allen et al., 1998).

Water use efficiency (WUE, kg ha^{-1} mm^{-1}) was calculated as:

$$WUE = \frac{Y}{ET} \qquad (2\text{-}2)$$

where Y is grain dry mass yield (kg ha^{-1}), and ET is cumulative evapotranspiration (mm). Because ET is calculated based on water balance, this method is analogous to the "benchmark" WUE calculated by Howell (2001). ET values typically provided in the literature indicate seasonal or total water use. However, because of data limitations, both

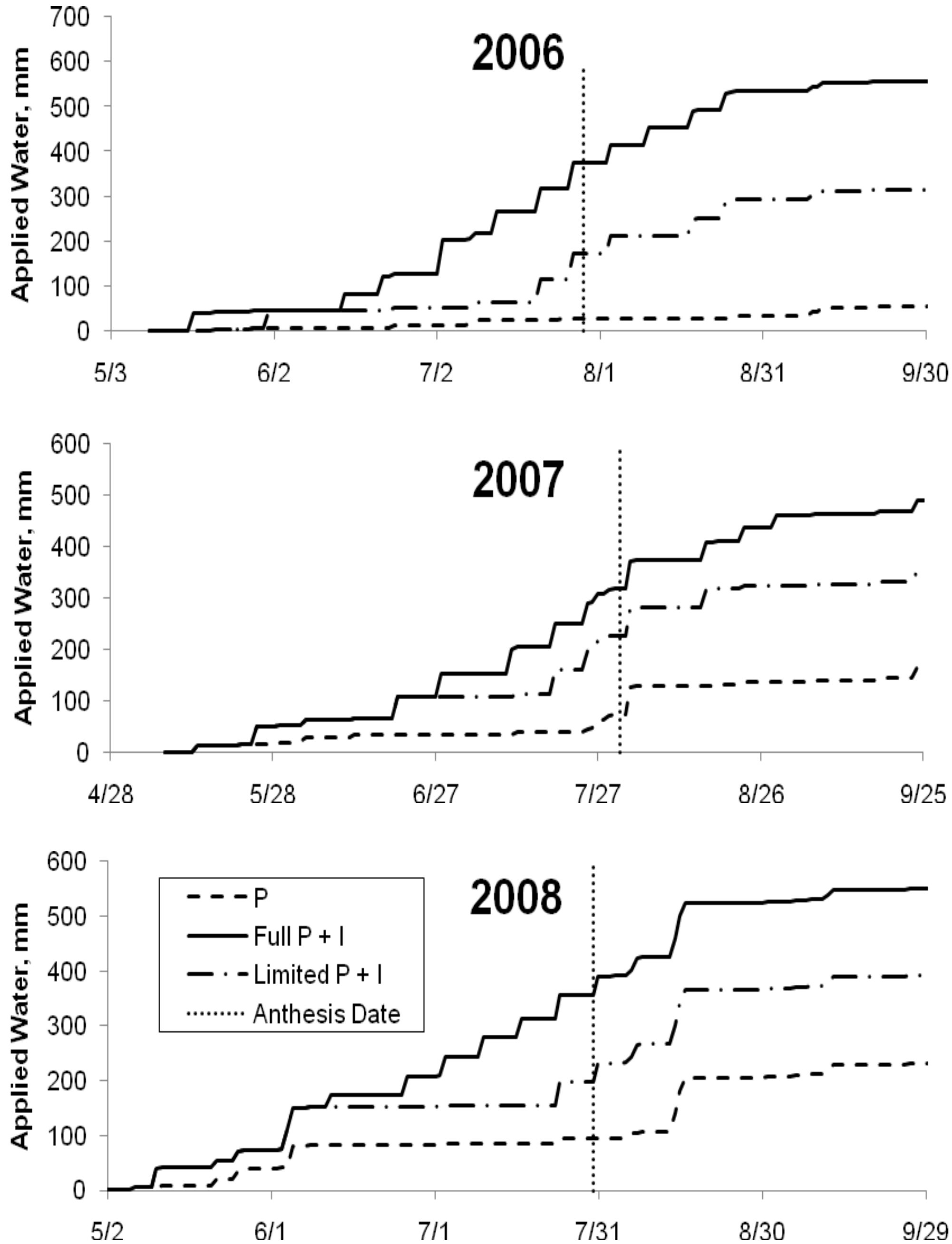

Figure 2-1. Cumulative precipitation (P) and total water applied as precipitation and irrigation (P + I), for both limited and full irrigation treatments, 2006-2008.

observed and simulated values for WUE were calculated using cumulative ET values based on the latest SWC observation for each season (ranging from 27 August to 30 September). Because cumulative ET for each growing season was evaluated using different lengths of growth time, treatment comparisons can only be made within individual years but not across years. Additionally, irrigation use efficiency (IUE, kg ha^{-1} mm^{-1}) was calculated as:

$$IUE = \frac{Y}{TI} \tag{2-3}$$

where TI is total seasonal irrigation (mm). This is similar to the method suggested by Bos (1985), but in this case the yield component is the total grain yield and not yield improvement above dryland only yield.

2.2.3 Model Description

CERES-Maize is a process-oriented corn growth model that simulates the following: biomass accumulation based on light interception; partitioning of accumulated biomass to leaves, stems, roots, and grain; environmental stresses; soil water balance; soil N transformations and uptake; and crop growth and development including phenological states, biomass production, and yield. Required model inputs include soil characteristics, daily weather, cultivar parameters, fertilizer applications, irrigations, planting date, plant population, and other management practices. This model is available as part of the DSSAT v4.0 suite of crop models designed to estimate production, resource use, and risks associated with crop production practices (Tsuji et al., 1994; Jones et al., 1998; Jones et al., 2003). A complete description of the model can be found in Ritchie et al.

(1998). Four discrete functions of simulated leaf-tip number are used for predicting plant canopy leaf area in CERES-Maize (Jones and Kiniry, 1986). The calculated canopy leaf area is subjected to senescence coupled with plant development. Calculated senescence rate is modified to account for population and leaf-shading effects. In addition, deficits of N and water accelerate senescence. Final LAI is calculated from the canopy leaf area balance available each day as a function of plant population.

To facilitate use of a minimum data set, CERES-Maize uses a simple water balance algorithm following a layered soil and a "tipping-bucket" approach to calculate yield reductions related to water stress (Ritchie, 1998). The USDA curve number technique (SCS, 1972) is used to calculate runoff and infiltration amounts resulting from rain and irrigation. The FAO-56 Penman-Monteith method (Allen et al., 1998), available as an option in DSSAT, was used to calculate crop ET. This method requires daily solar radiation, minimum and maximum temperature, daily average dew point temperature, and wind speed. These inputs are used in combination with energy balance and mass transfer to calculate reference crop ET. CERES-Maize partitions the potential ET into potential soil evaporation and potential plant transpiration, and actual soil evaporation and plant transpiration rates depend on the soil water availability to meet the potential values (López-Cedrón et al., 2008). In CERES-Maize, crop development rates are calculated based only on temperature and photoperiod (Ritchie et al., 1998). Biomass partitioned to grain in CERES-Maize can be affected by daily minimum temperature (Singh, 1985). Soil organic matter in CERES-Maize consists of fast-decaying "fresh organic matter" and slowly decaying "soil humus fraction." Volatilization loss of N is not simulated for dryland conditions (Godwin and Singh, 1998). N uptake is simulated based on the crop N demand and potential N uptake rate, as described by Godwin and Singh (1998).

2.2.4 Model Calibration

Data taken from the 2007 growing season were used for calibration. Six cultivar coefficients (Table 2-4) were adjusted to match observed growth. First, coefficients P1 and P2 were adjusted to match the anthesis date observed in the field experiments (Boote, 1999), and P5 was matched to the growing degree day units for the hybrids planted in this study (Pioneer, 2008). Next, the PHINT coefficient (phylochron interval, or thermal time between successive leaf tip appearances) was adjusted to match the number of total leaves for each plant throughout the vegetative phase in 2007. Reproductive growth parameters G2 and G3 were also adjusted to closely match yield. Cultivar parameter values were within reasonable limits compared to those found in the literature and also within maize cultivar input files distributed with the DSSAT v4.0 software. Finally, the soil root growth weighting factor ($0 \leq SRGF \leq 1$) was adjusted for each soil layer to find a reasonable root growth distribution (similar to the approach used by Ma et al., 2002, and Saseendran et al., 2008a), as well as adequately simulating SWC and cumulative ET.

Using the calibrated model from the 2007 season, the same parameters were used to simulate the 2006 and 2008 growing seasons. Data available from these seasons were used to statistically evaluate the accuracy of the CERES-Maize model's ability to differentiate between the model response to the full and limited irrigation treatments. These datasets included grain yield, LAI, SWC, and ET estimates.

Table 2-4. Cultivar growth coefficients and soil root growth weighting factor calibrated for CERES-Maize.

Parameter	Description	Units	Value(s)
P1	Thermal time from seedling emergence to the end of juvenile phase during which the plants are not responsive to changes in photoperiod.	degree-days	265
P2	Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development is at maximum rate, which is considered to be 12.5 h.	days	0.4
P5	Thermal time from silking to physiological maturity.	degree-days	589
PHINT	Phylochron interval.	degree-days	45
G2	Maximum possible number of kernels per plant.	unitless	908
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions.	mg d^{-1}	10.0
SRGF	Soil root growth weighting factor for top five soil layers from the surface downward (Table 2-1).	unitless	1, 1, 0.61, 0.22, 0.12

2.2.5 Model Statistical Evaluation

Four statistical evaluation criteria were used to evaluate the CERES-Maize model. The criteria are quantitative statistics that measure the agreement between simulated and observed values and include the Nash-Sutcliffe efficiency (E_{NS}; Nash and Sutcliffe, 1970), root mean square deviation (RMSD), normalized objective function (NOF), and relative error (RE). The E_{NS}, RMSD, NOF, and RE statistics are defined as follows:

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \tag{2-4}$$

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{2-5}$$

$$\text{NOF} = \frac{\text{RMSD}}{\overline{O}} \tag{2-6}$$

$$\text{RE} = \frac{(\overline{P} - \overline{O})}{\overline{O}} * 100 \qquad (2\text{-}7)$$

where O_i is the observed value, P_i is the CERES-Maize predicted value, n is the total number of observations, $\overline{P}$ is the mean of all predicted values, and $\overline{O}$ is the mean of all observed values. E_{NS} indicates how well the plot of observed versus simulated values fits a 1:1 line. The value of E_{NS} in Eqn. 2-4 may range from $-\infty$ to 1.0, with 1.0 representing a perfect fit of the data. The normalized objective function (NOF) in Eqn. 2-6 is based on the root mean square deviation (RMSD), which shows the average deviation between predicted and observed values, regardless of sign. The NOF should be interpreted as a relative value to compare model performance of simulating different data sets. NOF = 0 indicates a perfect fit between experimental data and simulated results; NOF < 1 may be interpreted as a simulation error of less than 1 standard deviation around the experimental mean. RE is a measure of the average tendency of the simulated values to be larger or smaller than the observed values. The optimal RE value is 0.0; a positive value indicates a model bias toward overestimation, whereas a negative value indicates a model bias toward underestimation.

2.3 RESULTS AND DISCUSSION

2.3.1 Model Calibration

For the 2007 calibration data, CERES-Maize indicated an anthesis date of 2 August for both treatments, while field observations showed that fully irrigated corn had an anthesis date around 27 July, and limited irrigation corn had an anthesis date around 3

August (Table 2-2). Vegetative growth in terms of total leaves per plant was adequately simulated (Figure 2-2). Total leaf number had an E_{NS} value of 0.949 for the full irrigation treatment and 0.900 for the limited treatment, indicating excellent agreement in both cases (Table 2-5). Limited irrigation corn was planted two days later than full irrigation corn; this was entirely the cause for the differences in the simulated treatments but only partially the cause for the difference between observed treatments. The CERES-Maize model simulates leaf number strictly as a function of thermal time and the PHINT parameter (Table 2-4) and does not take into account any treatment differences, such as water or nutrient stress. Toward the end of the vegetative growth phase, the model overestimated the leaves per plant for limited irrigation (the last four simulations compared were the only ones outside of one standard deviation of the mean and RE = 7.3% despite all earlier simulations being very close to observed). Peak total leaf number on the anthesis date (27 July) was overestimated for both treatments, although the error was greater for limited irrigation.

The model performed well in simulating yield for the two irrigation treatments in 2007 (Table 2-6). Observed values for full and limited irrigation yield in 2007 had very little variability, with mean yields ±1 standard deviation of 10,891 ±856 kg ha^{-1} and 7,576 ±917 kg ha^{-1}, respectively. Simulated full and limited irrigation yields were 9,925 and 8,164 kg ha^{-1}, respectively, which gives a good representation of the differences between treatments. Observations of total 1.0 m soil water content (SWC) in 2007 (Table 2-6) were slightly underestimated by CERES-Maize for full irrigation (RE = -2.7%) but were underestimated more in the limited irrigation treatment (RE = -13.7%). Cumulative

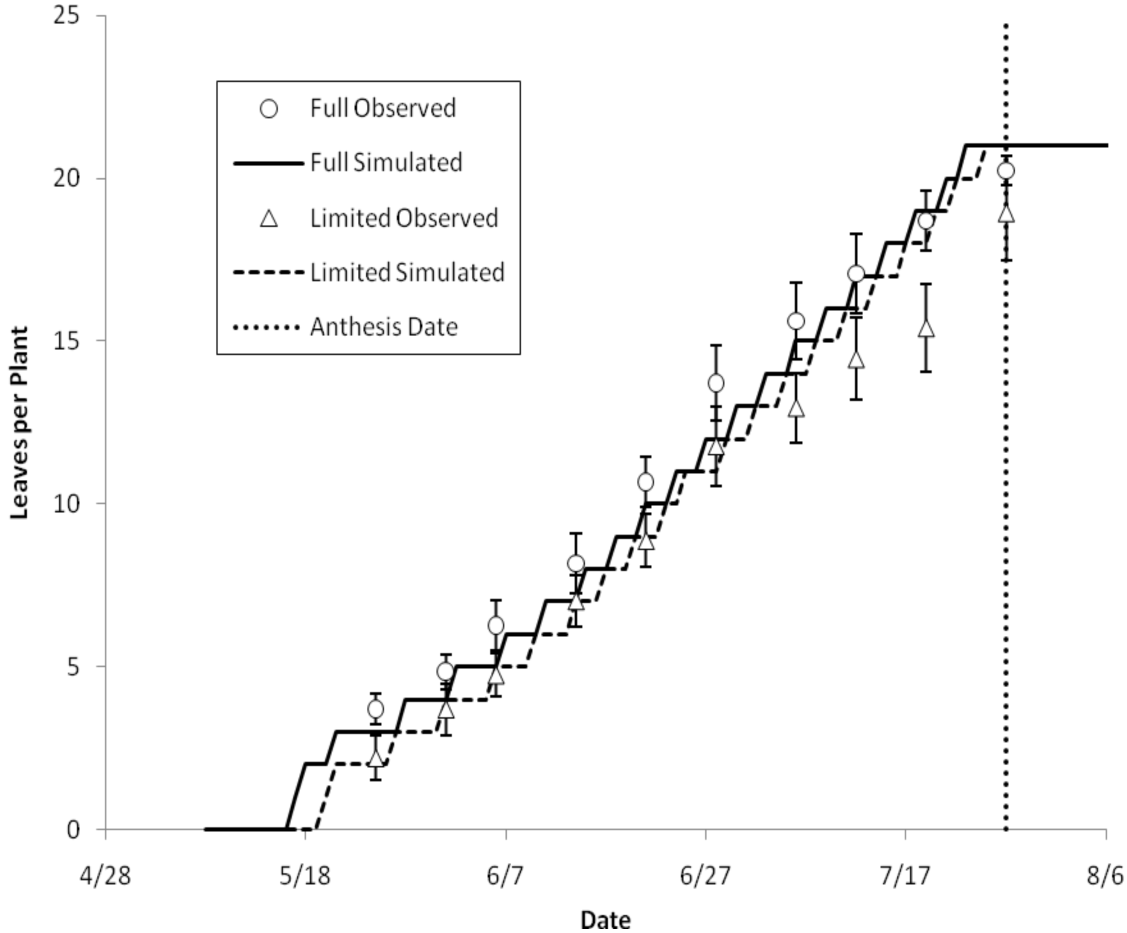

Figure 2-2. Total observed and simulated leaves per plant in 2007 for the full and limited irrigation treatments. Error bars on observed data indicate one standard deviation from the mean. Planting date was 8 May for full irrigation and 10 May for limited irrigation.

evapotranspiration (ET) (Table 2-6) had high model efficiency for both treatments (E_{NS} = 0.947 for full irrigation and 0.805 for limited irrigation). The model slightly underestimated cumulative ET for the full irrigation treatment, while limited irrigation was slightly overestimated (RE = -5.9% and 4.0%, respectively).

Table 2-5. CERES-Maize statistical evaluation criteria for total leaf number (2007 calibration) and leaf area index (2008 evaluation).

	Total Leaf Number		Leaf Area Index	
Statistics[a]	Full	Limited	Full	Limited
N	390	370	70	70
$\overline{P}$	11.51	11.22	2.59	1.79
$\overline{O}$	12.12	10.46	2.25	1.56
E_{NS}	0.949	0.900	0.896	0.666
RMSD	1.284	1.663	0.691	0.841
NOF	0.106	0.159	0.307	0.537
RE (%)	-5.0	7.3	15.1	14.5

[a] N = number of observations, $\overline{P}$ = predicted mean, $\overline{O}$ = observed mean, E_{NS} = Nash-Sutcliffe efficiency, RMSD = root mean square deviation, NOF = normalized objective function, and RE = relative error.

In 2007, water use efficiency (WUE) showed little difference between treatments for both mean observed (full WUE = 24.2 kg ha^{-1} mm^{-1}, limited WUE = 23.7 kg ha^{-1} mm^{-1}) and simulated (full WUE = 22.0 kg ha^{-1} mm^{-1}, limited WUE = 20.5 kg ha^{-1} mm^{-1}) values, and for both treatments simulated WUE was less than observed. Irrigation use efficiency (IUE) for the full irrigation treatment had a mean observed value of 30.1 kg ha^{-1} mm^{-1}, while CERES-Maize simulated 27.4 kg ha^{-1} mm^{-1}. Limited irrigation showed a notable increase in IUE, with 36.1 kg ha^{-1} mm^{-1} for mean observed and 38.9 kg ha^{-1} mm^{-1} for simulated IUE.

2.3.2 Model Evaluation

Using model parameters calibrated with 2007 data, the CERES-Maize model was evaluated using 2006 and 2008 data. The model accurately simulated leaf area index (LAI) for 2008 (Table 2-5 and Figure 2-3), although the model performed better in the full irrigation treatment than in the limited irrigation treatment (full E_{NS} = 0.896, limited

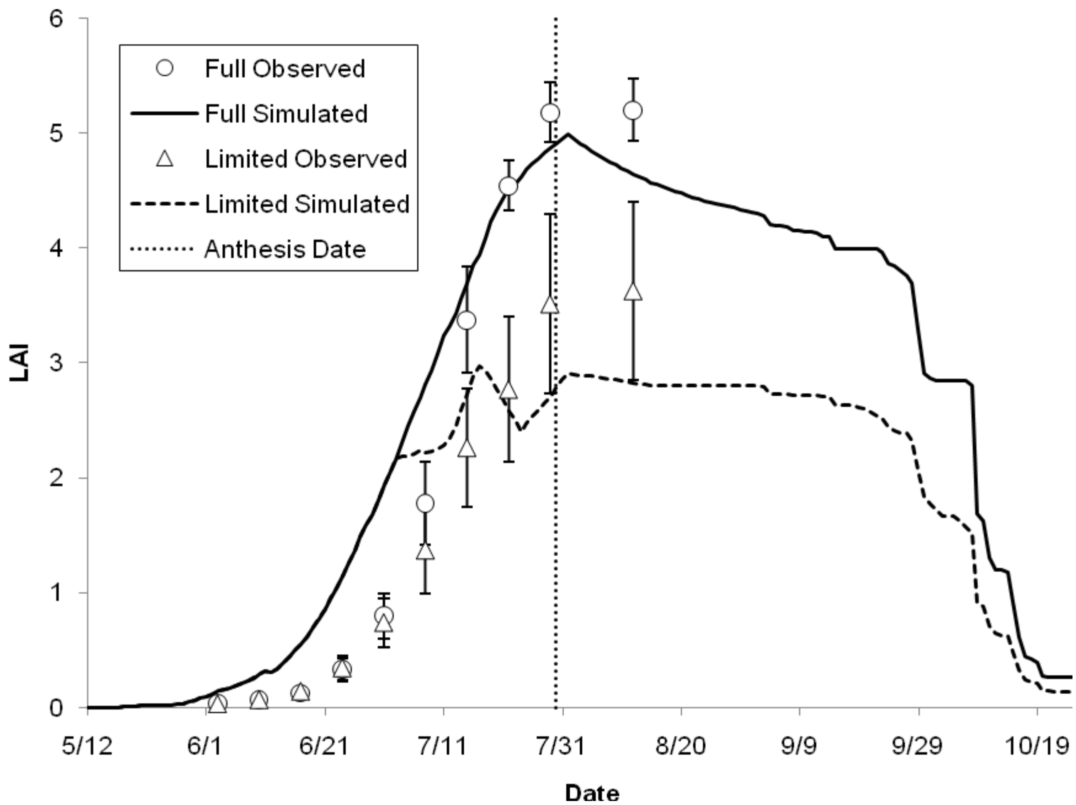

Figure 2-3. Leaf area index (LAI) in 2008 for both irrigation treatments. Error bars on observed data indicate one standard deviation from the mean.

E_{NS} = 0.666). It is interesting to note that observed LAI values are delayed approximately ten days relative to simulated LAI in both treatments. The observed lag in LAI development was likely due to a tornado that occurred in nearby Windsor, Colorado, on 22 May 2008. While the corn did not show any direct visible damage as a result of the tornado, field observations indicated that the corn remained stunted for nearly two weeks, delaying the observed vegetative growth. In both irrigation treatments, CERES-Maize statistically overestimated LAI over the entire season (full irrigation RE = 15.1%, limited irrigation RE = 14.5%); however, the model underestimated LAI during the reproductive stage only. In the limited irrigation treatment the underestimation was greater, indicating that the model was simulating too much LAI reduction due to water stress during the late vegetative and early reproductive stages. López-Cedrón et al. (2008) observed similar trends of growth reduction in terms of biomass when comparing irrigated and rainfed treatments. Additionally, Castrignano et al. (1998) found that CERES-Maize performed well under ideal conditions but underpredicted biomass and LAI when subjected to salinity stress. Results from Xie et al. (2001) indicate that simulated LAI and kernel weight appeared to be overly sensitive to drought stress. Nouna et al. (2000) found that LAI under water stress was underestimated by CERES-Maize and suggested that functions describing leaf growth and soil water deficit be adjusted. A later study by Mastrorilli et al. (2003) simultaneously adjusted the leaf growth and soil water deficit functions in CERES Maize v 3.0 and found that simulation results were significantly improved. The above examples indicate that CERES-Maize water stress factors may have too great of an effect on simulated plant growth, and that the model could benefit from further evaluation under water-stressed conditions.

Similar to other yield studies using CERES-Maize (e.g., Saseendran et al., 2008a), simulated yields were in agreement with observations for 2006 and 2008 (Table 2-6). Simulated yield for 2006 full irrigation and 2008 limited irrigation nearly matched mean observed values (RE = 2.8% and -0.8%, respectively), whereas yield was overestimated for full irrigation in 2008 (RE = 18.5%) and underestimated for limited irrigation in 2006 (RE = -16.0%). Observed treatment differences in yield for 2008 were minimal (412 kg ha^{-1}) and could be partially due to 2008 being the only year with no difference in planting

Table 2-6. CERES-Maize statistical evaluation criteria for soil water content (SWC), evapotranspiration (ET), and grain yield. Results for 2007 are model calibration; results for 2006 and 2008 are model evaluation.

		2006		2007		2008		All Years	
		Full	Limited	Full	Limited	Full	Limited	Full	Limited
Total 1.0 m	N	50	46	44	44	72	72	166	162
SWC (mm)	$\overline{P}$	257	205	317	266	289	236	287	235
	$\overline{O}$	253	232	326	309	313	296	298	281
	RMSD (mm)	55	62	44	72	32	71	43	69
	NOF	0.217	0.268	0.134	0.234	0.102	0.239	0.144	0.245
	RE (%)	1.6	-11.7	-2.7	-13.7	-7.8	-20.3	-3.9	-16.3
Cumulative	N	50	46	44	44	72	72	166	162
ET (mm)	$\overline{P}$	294	198	189	163	265	215	254	196
	$\overline{O}$	297	174	200	157	286	184	273	174
	E_{NS}	0.751	0.759	0.947	0.805	0.977	0.884	0.966	0.835
	RMSD (mm)	96	55	37	54	31	44	61	50
	NOF	0.323	0.313	0.186	0.343	0.110	0.241	0.222	0.289
	RE (%)	-1.0	13.5	-5.9	4.0	-7.4	16.7	-7.2	12.7
Yield	N	4	4	4	4	4	4	12	12
(kg ha^{-1})	$\overline{P}$	11421	7491	9925	8164	12872	10371	11406	8675
	$\overline{O}$	11107	8916	10891	7575	10863	10451	10954	8981
	RMSD (kg ha^{-1})	2321	2633	1218	989	2591	2001	2128	1992
	NOF	0.209	0.295	0.112	0.131	0.239	0.191	0.194	0.222
	RE (%)	2.8	-16.0	-8.9	7.8	18.5	-0.8	4.1	-3.4

[a] N = number of observations, $\overline{P}$ = predicted mean, $\overline{O}$ = observed mean, E_{NS} = Nash-Sutcliffe efficiency, RMSD = root mean square deviation, NOF = normalized objective function, and RE = relative error.

population. However, as previously mentioned, a late-season hailstorm hindered the ability to obtain completely accurate yield estimates, so caution should be exercised when considering yield results from this year.

In 2006, total 1.0 m SWC (Table 2-6) was simulated more effectively for full irrigation (NOF = 0.217, RE = 1.6%) than for limited irrigation (NOF = 0.268, RE = -11.7%). Overall, the model underestimated SWC under limited irrigation. In 2008, similar results were found for full irrigation (NOF = 0.102, RE = -7.8%) and limited irrigation (NOF = 0.239, RE = -20.3%). These results for total 1.0 m SWC were consistent with overestimations of cumulative ET under limited irrigation (Table 2-6). In 2006, results were fairly similar between treatments (i.e., full E_{NS} = 0.751 and limited E_{NS} = 0.759), but limited ET was overestimated (RE = 13.5%) along with the underestimation of total 1.0 m SWC. A similar trend in results occurred in 2008, with simulated full irrigation having excellent agreement with observed values (E_{NS} = 0.977).

Both 2006 and 2008 showed higher values of mean observed WUE for limited irrigation (27.9 kg ha^{-1} mm^{-1} in 2006 and 24.6 kg ha^{-1} mm^{-1} in 2008) in comparison with full irrigation (18.1 kg ha^{-1} mm^{-1} in 2006 and 12.9 kg ha^{-1} mm^{-1} in 2008). However, the model simulated minimal differences in WUE between treatments for both years. For observed data and CERES-Maize simulations, IUE increased in both 2006 (full observed mean = 22.2 kg ha^{-1} mm^{-1}, full simulated = 22.8 kg ha^{-1} mm^{-1}, limited observed mean = 34.4 kg ha^{-1} mm^{-1}, and limited simulated = 28.9 kg ha^{-1} mm^{-1}) and 2008 (full observed mean = 30.5 kg ha^{-1} mm^{-1}, full simulated = 36.2 kg ha^{-1} mm^{-1}, limited observed mean = 59.0 kg ha^{-1} mm^{-1}, and limited simulated = 58.6 kg ha^{-1} mm^{-1}) when comparing limited to full irrigation.

2.3.3 Summary of All Years

Regarding vegetative growth, no direct comparisons could be made between years due to data availability. The yield observations for 2006 and 2008 (evaluation) were much more scattered than in 2007 (calibration), as indicated by larger standard deviations from the mean and smaller RMSD and NOF statistics in both 2007 treatments (Table 2-6 and Figure 2-4). Although yields in general were correctly simulated by CERES-Maize, the model had a slight tendency to overestimate high observed yields and underestimate low observed yields, a trend noted by other studies (e.g., Xie et al., 2001; Panda et al., 2004; López-Cedrón et al., 2008). Dogan et al. (2006) reported the opposite trend; however, this study had very poor correlation between simulated and observed yield values (R^2 = 0.16).

Past studies have shown good agreement between CERES-Maize simulated and observed SWC (e.g., Panda et al., 2004; Saseendran et al., 2008a), but detailed statistical evaluation criteria for soil water are rarely presented. In this study, total 1.0 m SWC on a weekly basis was not simulated as well as other CERES-Maize output response variables (Table 2-6). For example, all values of E_{NS} for total 1.0 m SWC were negative (data not shown), indicating that on days sampled the mean of all observations would be a better predictor than the predicted value (Legates and McCabe, 1999). However, this interpretation is not representative of the entire SWC, as data collection immediately

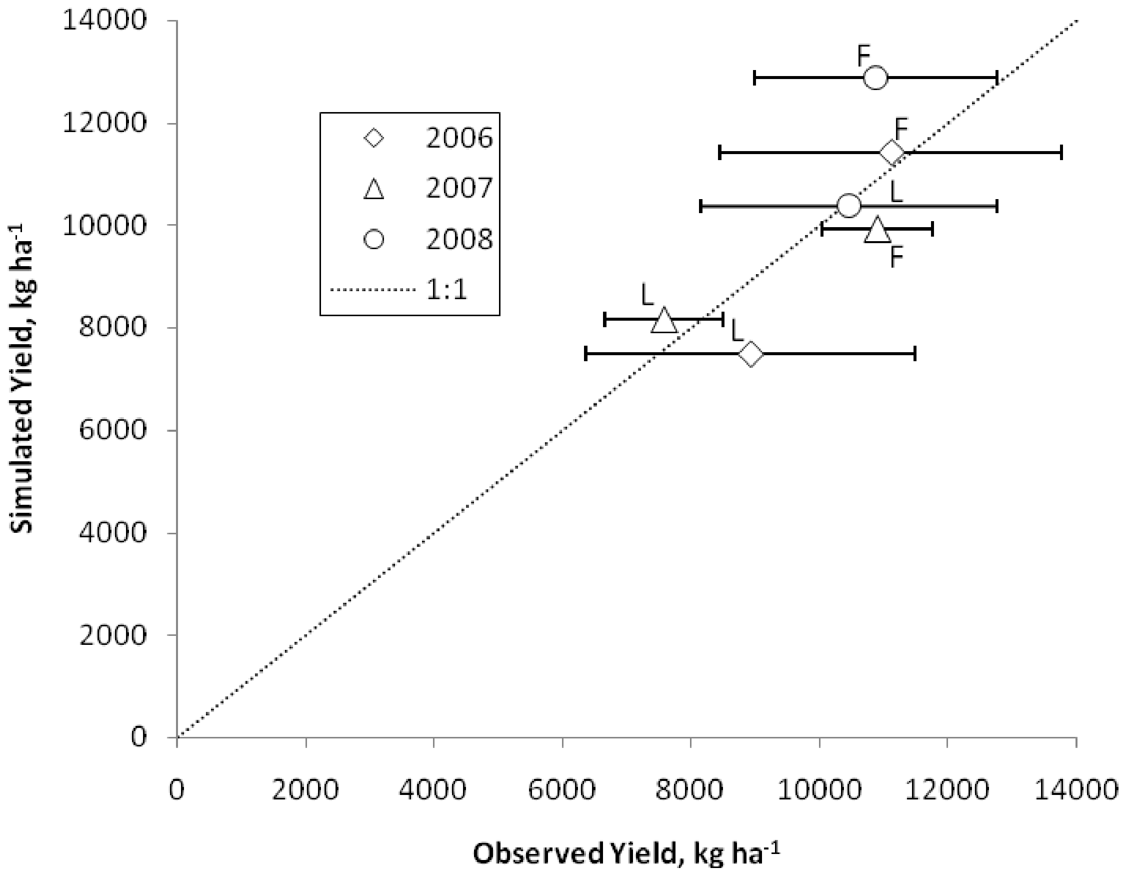

Figure 2-4. Simulated and observed mean yield for full (F) and limited (L) treatments (2006-2008). Error bars on observed data indicate one standard deviation from the mean. Results for 2007 are model calibration; results for 2006 and 2008 are model evaluation.

following irrigation was avoided to circumvent compaction issues in the soils, thereby limiting the ability to determine model accuracy following wetting. Again, CERES-Maize performed better (for all statistical evaluation criteria) in predicting total 1.0 m SWC for the full irrigation treatment than for limited irrigation , but across all years the comparisons to observed values were reasonable (RE = -3.9% for full irrigation and -16.3% for limited). A recent study by Soler et al. (2007) found good agreement between simulated and observed soil water content, where all NOF values were < 0.15. For this study, NOF was 0.144 for full irrigation and 0.245 for limited irrigation over the three years considered. The CERES-Maize model underestimated total 1.0 m SWC in all years and treatments except full irrigation in 2006. On average, full irrigation total 1.0 m SWC was underestimated by 11 mm, and limited irrigation total 1.0 m SWC was underestimated by 46 mm (Table 2-6). Regarding the mean difference between treatments, observed total 1.0 m SWC was 17 mm higher for full irrigation than for limited, while CERES-Maize predicted a much larger difference of 52 mm.

Despite the variability of the total 1.0 m SWC simulations, the overall SWC trends were simulated correctly. Calculated from the water balance (eq. 2-1), simulated and observed ET is the direct result of the SWC trends (Figure 2-5). It is important to note that potential ET (PET) predictions (also included in Figure 2-5) can only be compared with the full irrigation treatment, as PET calculations are based on a non-stressed (non-water-limiting) crop using data collected by the on-site weather station. ET statistics in Table 2-6 were calculated using weekly observations derived from water balance. The model performed much better in simulating cumulative ET than in simulating total 1.0 m SWC, with all values of E_{NS} greater than 0.75. Simulated cumulative ET was most accurate in 2008 (full E_{NS} = 0.977, limited E_{NS} = 0.884), which was also the year with the best simulation of total 1.0 m SWC, as indicated by the RMSD evaluation statistic. Simulated cumulative ET was least accurate in 2006 (full E_{NS} = 0.751, limited E_{NS} = 0.759). In 2006 and 2007, the observed results were somewhat scattered, a likely result of less reliable SWC data for these years. Fully irrigated ET

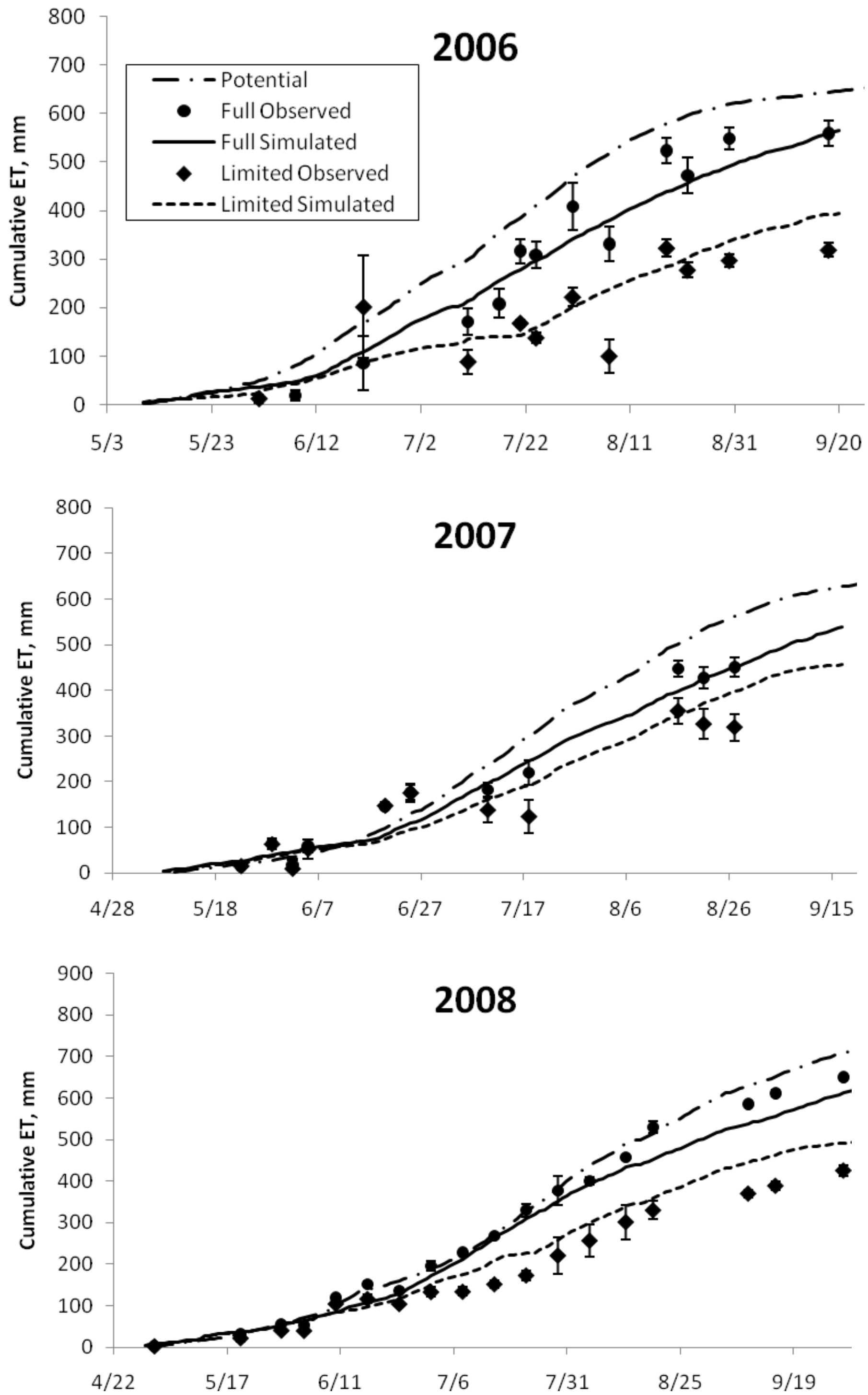

Figure 2-5. Cumulative evapotranspiration (ET) for 2006-2008.

Error bars on observed data indicate one standard deviation from the mean.

simulations followed the PET predictions closely, tracked very close to observed values through July, and were slightly underpredicted afterward (38 mm less by 30 September). Likewise, Dogan et al. (2006) found that CERES-Maize-simulated ET was significantly less than that found by the KanSched program, which was used to schedule irrigations in their study. Conversely, CERES-Maize had a tendency to overpredict limited irrigation cumulative ET, especially toward the end of the growing season. After 1 July, simulations for limited irrigation cumulative ET were an average of 20.1% higher than observed values. Overall, the model tracked observed values of cumulative ET well. However, as cumulative ET was underestimated for full irrigation and overestimated for limited irrigation, the differences in cumulative ET between these two treatments will likely be underestimated by the CERES-Maize model.

In 2006 and 2008, limited irrigation resulted in a significant increase in observed WUE (kg ha^{-1} mm^{-1}; Figure 2-6). This difference was not apparent in 2007, most likely because 2007 was the driest year of the three and saw a larger drop in yield from full irrigation to limited irrigation. Because these WUE values are based on cumulative ET (mm) values taken at different points of the growing season for each year, comparisons should only be made between treatments within a year and not between years. CERES-Maize did not predict any significant differences in WUE in any year. This is possibly due to the model's tendency to underpredict full irrigation ET and overpredict limited irrigation ET. Because these biased estimates of ET are used to determine simulated WUE, the difference between treatments is lost. Other researchers have concluded that models such as CERES-Maize are adequate for simulating yield and ET, but not their

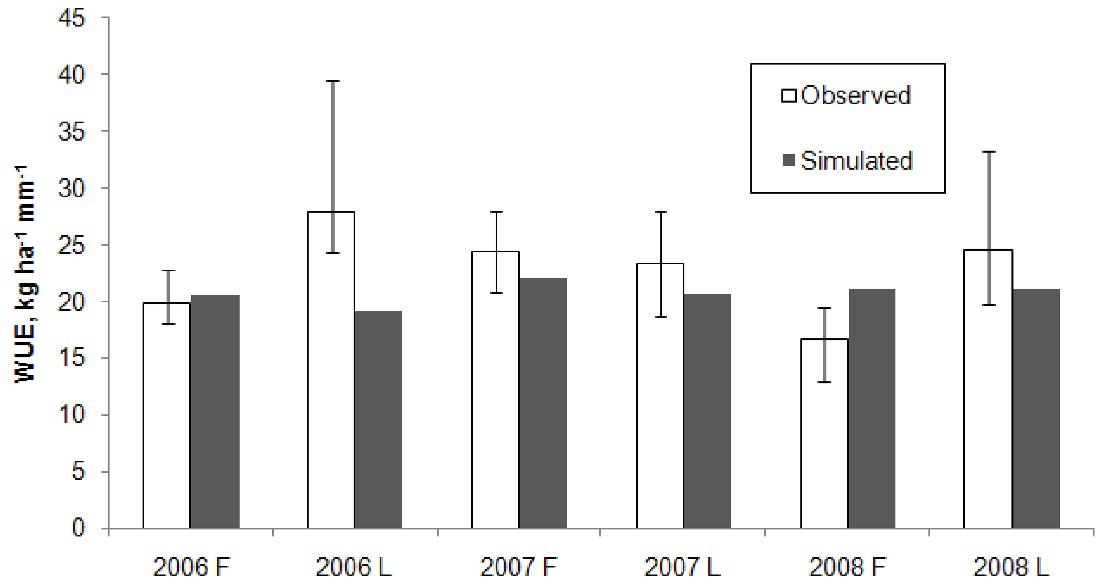

Figure 2-6. Water use efficiency (WUE) for all treatments and years. F indicates full irrigation, and L indicates limited irrigation. Error bars indicate maximum and minimum observed values.

interaction. For example, Evett and Tolk (2009) suggested that crop models correctly simulate WUE under well-watered conditions but tend to poorly predict WUE under conditions of water stress.

The other method used to compare both water use and yield among treatments is IUE (Figure 2-7). Figure 2-7 is advantageous because simultaneous comparisons can be made including treatments and years, whereas in Figure 2-6 comparisons can only be made between treatments in the same year. A power curve was fit to the IUE (kg ha^{-1} mm^{-1}) versus total irrigation (mm) observed dataset. The CERES-Maize simulations predicted nearly the same exact trend as the observed values, with a somewhat higher R^2 of 0.72 (regression line not shown). The decaying curve in Figure 2-7 shows that the most yield benefit from irrigation comes at smaller amounts, i.e., IUE decreases as irrigation is increased. While increased irrigation amounts certainly increase yields to a point of maximum potential (ignoring excess water stress), this is not a linear trend (Figure 2-7). When water is limited, net income can be maximized by decreasing the irrigation amount (English et al., 2002); therefore, it is desirable to explore yield potential with less irrigation. Saseendran et al. (2008a) compared simulated grain yield with irrigation amount over various irrigation allocations and amounts. They showed a similar increase in yield potential with irrigation, with a plateau in yields as irrigation totaled near 400 mm, while simulating N stress. While it is impossible to predict rainfall amounts and timing, Figure 2-7 can be helpful in determining expected site-specific yields based on the available irrigation amount (assuming that the producer would follow a limited irrigation management scheme similar to that shown in this article).

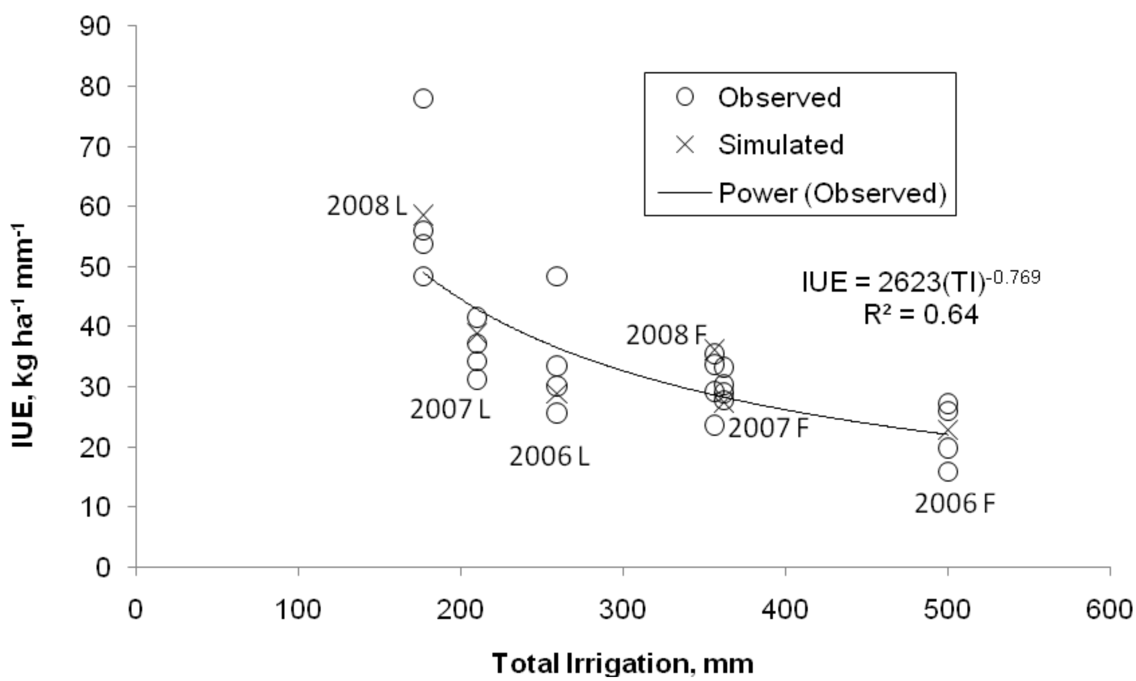

Figure 2-7. Irrigation use efficiency (IUE) as a function of total irrigation (TI) for all treatments and years. Regression line and formulas shown for observed values.

2.4 SUMMARY AND CONCLUSION

The CERES-Maize model, calibrated using 2007 data and evaluated using 2006 and 2008 data, correctly simulated trends in treatment differences between full and limited irrigation as observed in the field experiment. Overall, the model performed better for the full irrigation treatment than for the limited irrigation treatment for nearly every statistical evaluation criterion. Simulated model grain yield, leaf area index (LAI), and leaf number generally agreed with observed values. Corn anthesis date, generally accepted as the transition between vegetative and reproductive growth stages, was predicted within four days of observed values for all years. Crop growth measurements of total leaf number and LAI had high values of accuracy, although observed LAI values in 2008 were possibly shifted in time due to a nearby tornado that occurred in the early vegetative stage. Total leaf number for limited irrigation was overestimated in the late season, due to leaf number being strictly a function of thermal time. LAI in the reproductive stage was underestimated in both treatments.

Total 1.0 m soil water content (SWC) was slightly underestimated overall, although this trend was much more prevalent in the limited irrigation treatment. Limited irrigation total 1.0 m SWC was fairly consistent in simulation error between the three years, whereas total 1.0 m SWC simulations for the full irrigation treatment improved dramatically in the last year of the experiment. While neutron moisture meter measurements are an accurate method of indirectly obtaining soil moisture content and calculating total SWC, this method is time consuming and was limited in this experiment in that measurements could not be taken within several days of irrigation without causing compaction. Experiments of similar design may benefit from alternative soil moisture monitoring methods that can log at more frequent intervals (including during and immediately following irrigation and precipitation events), especially if the accuracy of such measurement methods can be improved and made less sensitive to outside factors such as temperature and salinity.

While the weekly simulations of total 1.0 m SWC showed marginal success, the overall trends in SWC variability proved to be adequate when comparing simulated cumulative evapotranspiration (ET) with observed values found by water balance. Cumulative ET had a high correlation between simulated and observed values; however, the full irrigation treatment showed a tendency to underpredict ET (especially toward the end of the season), while the limited treatment overpredicted ET. This trend could prove problematic in using CERES-Maize to quantify treatment differences in ET, as the potential water savings as a result would be underestimated as compared to field-observed savings. Water use efficiency (WUE) showed significant treatment differences in observed values for 2006 and 2008, but no significant difference in 2007 due to this being the driest year evaluated. There were no treatment differences in simulated WUE because simulated ET was underestimated for the full irrigation treatment and overestimated for the limited irrigation treatment. Because these errors caused the overall ET difference between treatments to be underestimated, the calculation negated any treatment differences in WUE. Observed irrigation use efficiency (IUE) as a function of seasonal irrigation amount showed a decaying trend, indicating that the most benefit from irrigation occurred at low seasonal irrigation totals. CERES-Maize nearly perfectly agreed with the observed IUE trend. This relationship could be particularly interesting in the study of sensitivity and uncertainty analysis, exploring yield and ET effects of stress based on varying crop growth parameters as well as soil water and growth properties.

Overall, this study serves as an example of integrating a full and limited irrigation field experiment with agronomic modeling. Observed data indicate that limited irrigation has the potential to increase WUE; however, the inability of CERES-Maize to accurately simulate response to crop water stress hinders its capacity to consistently simulate end functions of irrigation treatments, such as WUE in stressed crops. Crop models typically are a combination of mechanistic and empirical components; while crop stresses are indicated based on mechanistic or agronomic relationships, the functions to determine degree of reduction from stress are nearly always empirical (Brisson et al., 2006). By introducing a treatment effect that is highly dependent on water stress, especially during the reproductive growth stages, the model would not be expected to perform as well as in an unstressed situation. Further modeling studies focusing on water stress functions and ET methods, such as those by Ahuja et al. (2008) and López-Cedrón et al. (2008), are needed. Improved crop models that can accurately quantify crop ET under various levels of water stress can be useful tools in maximizing net benefits from irrigation with limited water supplies.

CHAPTER 3. GLOBAL SENSITIVITY ANALYSIS OF A DYNAMIC AGROECOSYSTEM MODEL UNDER DIFFERENT IRRIGATION TREATMENTS

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3.1 INTRODUCTION

Water availability issues, combined with population growth and the uncertainty of climate change have created significant challenges for water resources scientists (Anderson-Wilk, 2008). English et al. (2002) argue that a fundamental paradigm shift in agroecosystem irrigation management is inevitable as water supplies become more limited, as farmers will manage irrigation to maximize net benefits instead of simply the biological objective of maximizing yields. Limited water resources and increasing pumping costs have recently caused farmers in Colorado, USA to consider limited irrigation as an alternative to full irrigation practices. Alternatively, farmers may consider either a reduction in planted area or schedule irrigation events so that plants do not encounter stress during sensitive growth stages. Thus, in many irrigated areas such as the Colorado Front Range, studies (e.g., DeJonge et al., 2011) are increasingly exploring benefits of limited or deficit irrigation of water-intensive crops such as corn (*Zea mays*

L.). Limited irrigation practices incorporate water management under restricted water application, and minimize water stress during critical crop growth stages in order to maximize yields (Schneekloth et al., 2009).

Crop simulation models can play an important role in assessing the costs and benefits of limited irrigation and the interactions of timing and amount of irrigation water applications. The Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM)-CERES-Maize model (Hoogenboom et al., 2004; Jones and Kiniry, 1986; Jones et al., 2003; Ritchie et al., 1998) has been widely used to assess cropping and management strategies for both rainfed and irrigated corn. For example, Xie et al. (2001) found that simulated vegetative growth and kernel weight are extremely sensitive to drought stress. A group of researchers found that CERES-Maize overestimated the effects of water stress on vegetative growth, and subsequently adjusted the stress functions and improved simulation results (Mastrorilli et al., 2003; Nouna et al., 2000). Saseendran et al. (2008b) simulated various water allocations and irrigation amounts in northeastern Colorado using CERES-Maize, and found that split irrigation applications of 20% of the total water applied during vegetative growth stages and 80% of the total water applied during reproductive growth stages obtained the highest yield for a given irrigation allocation (ranging from 100 to 700 mm of total irrigation). López-Cedrón et al. (2008) evaluated CERES-Maize for rainfed and irrigated treatments with the intent to improve the model’s ability to predict biomass and yield under water-limited conditions (where the model had previously given good predictions under irrigated conditions). They found that the model adequately predicted irrigated treatments but underpredicted rainfed treatments. Most recently, DeJonge et al. (2011) provided a detailed statistical comparison of CERES-Maize with a field experiment consisting of full and limited irrigation treatments in northern Colorado, finding that the model performed better in the non-stressed (full irrigation) treatment than in the stressed (limited irrigation) treatment. Additionally, they found the model estimated yield adequately but overestimated ET for full irrigation and underestimated ET for limited irrigation.

The CERES-Maize crop model described above is a complex nonlinear dynamic system that simulates outputs such as crop yield as a function of various inputs, including plant cultivar, soil hydraulic parameters, and irrigation timing/amount. It contains a large number of input parameters which are commonly estimated based on field experiments or determined through model calibration and/or parameterization. Accurate estimation of values for important CERES-Maize input parameters is imperative as the accuracy of model outputs is a direct outcome. Therefore, it is desirable to conduct a sensitivity analysis (SA) as a component of further CERES-Maize evaluation to determine which model input parameters require the most certainty. Saltelli et al. (2004) defined SA as "the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input." The aim of SA is to determine how sensitive the output of a model is with respect to the elements of the model which are subject to uncertainty or variability. SA methods are typically classified as local (i.e., derivative-based) or global (Saltelli et al., 2008). When the purpose of the SA is to study the effects of several input parameters on the model output responses, local SA (e.g., one-factor-at-a-time or OAT) is less useful than global sensitivity analysis

(GSA) where the output variability is evaluated while the input factors vary in their individual uncertainty domains (Monod et al., 2006). GSA methods, such as Morris (1991), Fourier Amplitude Sensitivity Test (FAST, Saltelli et al., 1999), and Sobol' (1993) can determine not only sensitivity to individual factors, but sensitivity to interactions between factors as well. The Morris (1991) method is a OAT "screening method" that is a computationally efficient means of identifying sensitive parameters, but is ultimately considered global because it attempts to explore the majority of the parameter space (Saltelli et al., 2004). Variance-based methods such as FAST and Sobol' are commonly accepted methods of GSA that explore the entire parameter space but are more efficient than complete factorial design (Saltelli et al., 2000a).

Very little SA literature exists for crop models that concentrates specifically on the methodology, particularly sensitivity differences between treatments and/or GSA methods. Ma et al. (2000) performed a SA on the RZWQM for a manured corn field in eastern Colorado. Four groups of model input parameters (saturated hydraulic conductivity, organic matter/nitrogen (N) cycling, plant growth, and irrigation water/manure application rates) were selected with plant N uptake, silage yield, and nitrate leaching as outputs evaluated. Latin Hypercube Sampling (LHS) was used to randomly choose parameters from various probability distributions and the resulting model parameter sets were analyzed using linear regression analysis. Crop yield output response was found to be most sensitive to plant growth input parameters and manure application rates. Makowski et al. (2005) explored using SA methods to reduce the number of field experiments performed for estimating genetic parameters by determining key cultivar parameters whose uncertainty most affects AZODYN winter wheat model outputs. They used a winding stairs method and an extended FAST (eFAST) method, finding that only five genetic parameters out of thirteen explored have a significant influence on simulated yield and grain protein content. Pathak et al. (2007) evaluated the DSSAT-CROPGRO cotton model in terms of the most sensitive crop growth parameters for predicting development and yield under irrigated and rainfed conditions. They used both local and global SA methods to evaluate the model and found that the factorial design GSA method was beneficial with regard to defining interactions among parameters, but suggested the method was more computationally expensive than desired. Varella et al. (2010) used the eFAST GSA method to evaluate the ability of the STICS model to accurately evaluate outputs based on varying soil input factors. The results showed that a few soil parameters (e.g., clay content, organic N content, and soil water content at field capacity) were accessible by inverse parameter estimation using observations of yield at harvest, leaf area index, and N absorbed by the plant at various dates. However, the quality of parameter estimation largely depended on several factors, in particular the climate of the observed year and the type of soil at depth (Varella et al., 2010). The rice model WARM (Water Accounting Rice Model) was recently evaluated to determine the effect of site and climate on model sensitivity in Europe using the Morris and Sobol' SA methods (Confalonieri et al., 2010). Radiation use efficiency, optimum temperature, and leaf area index at emergence were found to be the most sensitive model input parameters.

Very few examples in the literature focus directly on SA for CERES-Maize input parameters, especially in regard to irrigation management in semi-arid regions. St'astná and Zalud (1999) performed a local SA on the CERES-Maize and MACROS (Modules for an Annual CROp Simulation) models, adjusting wilting point, saturated soil water content, and field capacity from -6 to 6% of their nominal values to evaluate changes in yield and LAI. They found a linear dependence of LAI on all three parameters, and negligible influence on yield. Bert et al. (2007) studied the sensitivity of maize yield predictions in Argentina to uncertainty in several soil-related parameters (e.g., soil N and water content at sowing, soil organic matter content, and soil infiltration curve number) as well as solar radiation was conducted using a combination of mathematical (local) and graphical SA approaches. They found that CERES-Maize showed more sensitivity to solar radiation than for soil parameters, and that some parameters (e.g., soil curve number and soil water content at sowing) exhibited non-linear responses. He (2008) performed a restricted OAT (Morris) SA on CERES-Maize cultivar and soil input parameters, evaluating corn yield and N leaching output responses. It was determined that thermal time from emergence to end of juvenile phase, thermal time from silking to physiological maturity, phyllochron interval, soil lower limit, soil drained upper limit, and soil fertility factor model input parameters all have a strong influence on crop yield, and the soil lower limit, soil drained upper limit, soil drainage rate, and runoff curve number have a strong influence on N leaching. Although He (2008) evaluated sensitive soil and cultivar parameters for the CERES-Maize model, the study was conducted in Florida, USA with very sandy soils and high rainfall (average 1320 mm annual).

The above CERES-Maize SA studies do not quantify higher-order interactions between variables, a likely issue in such a robust model. Additionally, most studies in any context of GSA explore overall sensitivity of the model in general, without looking for sensitivity differences between treatments as we would expect in this case. Therefore, a detailed GSA in regard to potential CERES-Maize input parameter sensitivity differences between irrigation treatments would be extremely beneficial to modelers who wish to use the model in dryland, semi-arid, or other similar management regimes with limited water resources. Improved knowledge of model sensitivity to various inputs will assist new users of the model with calibration based on these parameters, similar to methods described in Ma et al. (2011). Increased understanding in regard to CERES-Maize input parameter sensitivity and response to water-stressed treatments may also be valuable to users of the new RZWQM2, which has been coupled with the DSSAT plant growth modules (Ma et al., 2007; Ma et al., 2006). Campolongo et al. (2007) suggested that the Morris screening method is underutilized in the context of SA and can be used to simplify more robust methods such as Sobol' (1993). Finally, there are a limited number of direct comparisons between the Morris and Sobol' methods in the literature. Assessment of these approaches in the context of this study should provide new insight to crop modelers in regard to computational expense and results for each approach.

Previous attempts to simulate the difference in irrigation treatments with the CERES-Maize crop growth model have indicated that the model responds more accurately in regard to yield, ET, and vegetative growth under full irrigation with no water stress, as compared to limited irrigation under water stress during the vegetative growth stage (DeJonge et al., 2011). Therefore, in this study focus is placed on evaluating model input properties that should have a large effect on both water availability and crop response to water under full and limited irrigation (e.g., soil hydraulic and phenological growth properties). The overall objectives of this study are to determine and rank the global sensitivity of CERES-Maize v4.5 physiological timing, growth, yield, and ET output responses to soil hydraulic and phenological growth model inputs using both qualitative (Morris) and quantitative (Sobol') SA approaches. Specifically, this study aims to identify and quantify a well-defined group of sensitive CERES-Maize input parameters for full and limited irrigation treatments in regard to output responses including anthesis date, maturity date, leaf number per stem, maximum leaf area index, crop yield, and cumulative evapotranspiration. The Morris screening and Sobol' SA methods will be used to compare between the full and limited irrigation treatments, using the DeJonge et al. (2011) parameterized model setup as the baseline. It is hoped that the resulting SA will lead to a justifiable increased focus on improved estimation of sensitive input parameters for CERES-Maize, as well as guidance to potential model improvements under water-stressed conditions.

3.2 MATERIALS AND METHODS

3.2.1 Site and Experiment Description

In a prior study, the CERES-Maize crop growth model was calibrated and validated based on a multi-replicate field research plot near Fort Collins, Colorado (40°39'19" N, 104°59'52" W) from 2006 to 2008; details can be found in DeJonge et al.

(2011). The soil at the study site is a Fort Collins Loam (fine-loamy, mixed, superactive, mesic Aridic Haplustalf). Two irrigation treatments of continuous corn (the dominant irrigated crop in northeast Colorado) were studied during the 2006 through 2010 growing seasons: full irrigation (ET requirement supplied throughout the season) and limited irrigation (no irrigation before the V12 reproductive stage unless necessary for emergence, then full irrigation afterwards). In all years, less significant early irrigations were required by all treatments to encourage germination and avoid total loss of crop. There were four replications of each treatment, arranged in a randomized complete block design. Each plot consisted of 12 rows spaced 76 cm apart, with a row length of 26 m. All data were taken from the middle four rows, with the outer eight rows serving as buffers to minimize boundary effects from adjacent treatments. Both treatments were monitored weekly for crop growth (total leaf number, LAI, crop height, and biomass), crop development (phenology stages), soil water content (SWC), ET by water balance, and final grain yield. Irrigation water was applied by a linear move sprinkler system, generally at a weekly interval. Irrigation amounts were determined by crop need and supported by potential ET estimates from the onsite weather station (station FTC03; 40°39'09" N, 105°00'00" W; elevation 1557.5 m) within the Colorado Agricultural Meteorological Network (CoAgMet, http://ccc.atmos.colostate.edu/~coagmet/). Daily precipitation, solar radiation, minimum and maximum temperature, vapor pressure (which was converted to dew point temperature), and wind run were continually recorded, and any missing weather data were replaced by data from the Wellington, CO station (station WLT01; 40°40'34" N, 104°59'49" W; elevation1567.9 m) approximately two km to the north of the FTC03 station.

It was assumed that CERES-Maize sensitivity responses would differ between the full and limited irrigation treatments. Therefore, for each input parameter set, the model was evaluated for both treatments over the five years (2006-2010) management and weather data were fully available (for a total of ten runs per input set). Additionally, simulated inputs (namely irrigation timing and amount) were set to exactly match field management. This was done to ensure that model output response sensitivity was a result of parameter uncertainty and not necessarily varying irrigation schedule and amounts. In all years and treatments, adequate N was applied to avoid N stress.

3.2.2 CERES-Maize Model Description

Crop simulations models such as those found in the Decision Support System for Agrotechnology Transfer (DSSAT v4.5) can play a role in assessing the costs and benefits of limited irrigation and the interactions of timing and amount of irrigation water applications (Hoogenboom et al., 2010; Jones et al., 2003). The DSSAT Cropping System Model (CSM) CERES-Maize is available as part of the DSSAT suite of crop models designed to estimate production, resource use, and risks associated with crop production practices (Jones and Kiniry, 1986; Ritchie et al., 1998). It has been widely used to assess cropping and management strategies for corn (both rainfed and irrigated) for well over two decades. CERES-Maize is a process-oriented corn growth model that simulates the following: biomass accumulation based on light interception; partitioning of accumulated biomass to leaves, stems, roots, and grain; environmental stresses; and crop growth and development including phenological states, biomass production, and yield. Additionally, the CSM contains modules for soil water balance as well as soil N transformations and uptake, which are used for other crop modules in addition to CERES-Maize. Required model inputs include soil characteristics, daily weather, cultivar parameters, fertilizer applications, irrigations, planting date, plant population, and other management practices. Four discrete functions of simulated leaf-tip number are used for predicting plant canopy leaf area in CERES-Maize (Jones and Kiniry, 1986). The calculated canopy leaf area is subjected to senescence coupled with plant development. Calculated senescence rate is modified to account for population and leaf-shading effects. Also, deficits of N and water accelerate senescence. Final LAI is calculated from the canopy leaf area balance available each day as a function of plant population.

To facilitate use of a minimum data set, the CSM uses a simple water balance algorithm following a layered soil and a “tipping-bucket” approach to calculate yield reductions related to water stress (Ritchie, 1998). The USDA curve number technique (SCS, 1972) is used to calculate runoff and infiltration amounts resulting from rain and irrigation. The Priestley-Taylor (1972) and FAO-56 Penman-Monteith method (Allen, 1998) are available as options in DSSAT to calculate crop ET; the latter was used in this study. This method requires daily solar radiation, minimum and maximum temperature, daily average dew point temperature, and wind speed; these inputs are used in combination with energy balance and mass transfer to calculate reference crop ET. CERES-Maize partitions the potential ET into potential soil evaporation and potential plant transpiration, and actual soil evaporation and plant transpiration rates depend on the soil water availability to meet the potential values (López-Cedrón et al., 2008). Water stress is generally determined as the comparison between potential transpiration (demand) and potential root water uptake (plant extractable soil water) (Saseendran et al., 2008a). In well-watered conditions, potential root water uptake exceeds potential transpiration. As the soil dries, potential root water uptake decreases, thus introducing stress into the simulated crop.

Because it is relevant to the study, it is important to understand how yield and biomass production is determined in CERES-Maize. In CERES-Maize, crop development rates are calculated based only on temperature and photoperiod (Ritchie et al., 1998). Biomass partitioned to grain in CERES-Maize can be affected by daily minimum temperature (Singh, 1985). Soil organic matter in CERES-Maize consists of fast-decaying "fresh organic matter" and slowly decaying "soil humus fraction." Volatilization loss of N is not simulated for dryland conditions (Godwin and Singh, 1998). N uptake is simulated based on the crop N demand and potential N. In terms of crop yield, number of grains per plant is a function of the potential number of kernels per plant and the average crop growth rate (g/plant) from silking to the beginning of grain filling. The model assumes one ear of corn per plant, however if the number of kernels per plant is significantly smaller than the potential number of kernels, the model creates some barren plants. Ear growth rate (g/ear/day) is increased by daily thermal time but can be decreased by water or N stress. The effective grain filling period is based on the thermal time from silking to maturity, and during this period leaf senescence increases, whereas ears, stalks, and roots are the only active growing tissues. Daily grain growth rate is a function of temperature, grains per plant, potential kernel growth rate, and soil moisture effect on growth (Ritchie et al., 1998).

3.2.3 Sensitivity Analysis Input Parameters and Output Responses

CERES-Maize input parameters were selected that are relevant in regard to their ability to affect crop growth timing and magnitude, yield, and ET (Table 3-1). These mainly include crop cultivar parameters typically used in model calibration and soil hydraulic parameters (i.e., DeJonge et al., 2011; Fraisse et al., 2001; He, 2008). Random values for each parameter were determined assuming a uniform distribution between the lower and upper bounds (Table 3-1). Maize cultivar parameters P1, P2, P5, G2, G3, and PHINT (Table 3-1) were used as calibration parameters in DeJonge et al. (2011). Many of these same parameters were previously used in the He (2008) Morris SA study, but they were evaluated separately from soil hydraulic parameters because it was assumed that these groups of parameters were independent. However, in this study all parameters are evaluated simultaneously as it is assumed that interactions between soil hydraulic parameters are possible in the context of water-stressed conditions. Additionally, some model growth components are based strictly on thermal time and have no influence from stress, i.e., as indicated by total leaf count in DeJonge et al. (2011) showing no decrease in simulated successive leaf tip appearances. It is therefore important to identify in this context which cultivar parameters have no stress effects to growth and subsequent yield and ET. In addition to the cultivar parameters, the ecotype parameter (i.e., a type of parameter meant to be specific to the species or subspecies at hand) for radiation use efficiency (RUE, g dry matter per MJ photosynthetically active radiation, PAR) was evaluated for sensitivity. In DSSAT versions 4.0 and above, RUE is set to 4.2 g MJ^{-1} PAR (Hoogenboom et al., 2010), but Lindquist et al. (2005) suggest maize simulation models such as CERES-Maize that rely on RUE for biomass accumulation should use RUE of 3.8 g MJ^{-1} absorbed PAR for non-stressed crops. Additionally, Stöckle et al. (2008) indicate that RUE has a dramatic daily fluctuation in response to weather variability. While CERES-Maize model developers do not recommend using RUE as a calibration parameter (Ma et al., 2011; K. Boote, personal communication), there is some discrepancy as to what the baseline value should be. Instead of adjusting RUE, Ma et al. (2011) suggest using the soil fertility factor (SLPF) to adjust the conversion rate from solar radiation to biomass, and this input was evaluated in addition to RUE as an input in this study. Cultivar and ecotype upper and lower bounds were generally determined by the range of values used in prior studies as indicated by the DSSAT v4.5 software (Hoogenboom et al., 2010). CERES-Maize output responses (Table 1) were selected based on potential effects from water stress, and were statistically evaluated in the DeJonge et al. (2011) study. Growth stage timing outputs include anthesis day and maturity day after planting (ADAY and MDAY, respectively), crop growth outputs include total leaf number per stem and maximum leaf area index (LNS and LAIX, respectively), and the most important evaluation outputs for limited irrigation management: crop yield (YIELD) and cumulative evapotranspiration (ETC).

The soil was assumed to be the same texture as used in DeJonge et al. (2011), determined as a Fort Collins loam (fine-loamy, mixed, superactive, mesic Aridic

Haplustalf) by the NRCS Web Soil Survey (http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx), with a typical profile of loam from 0 to 18 cm, loam or clay loam from 18 to 56 cm, and loam, silt loam, or fine sandy loam from 56 to 152 cm. In order to test parameter uncertainty (and avoid error from input uncertainty), the soil was assumed to be a loam or clay loam throughout the profile (Table 3-1). To simplify analysis, the nine separate soil layers were determined simultaneously and assumed to be homogeneous throughout all layers. From the soil surface, these layers are at depths of 0-5, 5-15, 30-45, 45-60, 600-90, 900-120, 120-150, and 150-178 cm. Upper and lower bounds for soil lower limit (SLLL), soil drained upper limit (SDUL), saturation (SSAT), and saturated hydraulic conductivity (SSKS) were taken from Schwab et al. (1993) as typical values for loam or clay loam (Table 3-1). By limiting the analysis to loam and clay loam soil types, the upper and lower bounds applied ensure that SLLL < SDUL < SSAT, as would be expected mathematically. Upper and lower bounds for bulk density (SBDM) were found in the DSSAT input files for recommendations based on soil classification (Hoogenboom et al., 2010).

3.2.4 Sensitivity Analysis Methods

In general, sensitivity analysis (SA) is the study of how the variation of the output of a model can be apportioned to different sources of variation or input (Saltelli et al., 2000a). Sensitivity analyses are typically classified as either local sensitivity analysis or global sensitivity analysis (GSA) (Saltelli et al., 2000a). Local SA examines the local response of model output responses by varying input parameters one at a time while holding other parameters at fixed values. GSA characterizes methods that possess two

Table 3-1. CERES-Maize sensitivity analysis input parameters and output responses.

Name	Definition	Unit	Lower bound	Upper bound
Input parameters				
P1	Thermal time from emergence to end of juvenile	degree-day	130	350
P2	Development delay factor	day	0	0.8
P5	Thermal time from silking to physiological maturity	degree-day	600	950
G2	Maximum possible kernels per plant	kernel	450	950
G3	Kernel filling rate under optimum conditions	mg day^{-1}	5.0	10.5
PHINT	Phylochron interval	degree-day	35	75
RUE	Radiation use efficiency	g MJ^{-1}	2	5
SLPF	Soil fertility factor	-	0.7	1.0
SLU1	Evaporation limit	cm	5	12
SLDR	Drainage rate	day^{-1}	0	1
SLRO	Runoff curve number	-	60	95
SLLL	Soil lower limit, or wilting point	mm^3 mm^{-3}	0.11	0.20
SDUL	Drained upper limit, or field capacity	mm^3 mm^{-3}	0.25	0.42
SSAT	Saturation	mm^3 mm^{-3}	0.43	0.51
SSKS	Saturated hydraulic conductivity, macropore	cm h^{-1}	0.3	2.0
SBDM	Bulk density	g cm^{-3}	1.24	1.50
Output responses				
ADAY	Anthesis day	day		
MDAY	Maturity day after planting	day		
LNS	Total leaf number per stem			
LAIX	Maximum leaf area index			
YIELD	Crop yield	kg ha^{-1}		
ETC	Cumulative evapotranspiration	mm		

basic properties (Saltelli et al., 2000a): (i) multiple parameters are varied simultaneously, and (ii) sensitivity is measured over the entire range of each input factor. When dealing with a nonlinear model and input factors that are affected by uncertainties of varying magnitude, a GSA approach is the more robust option. Thus, more studies currently are using GSA techniques instead of local SA. Most of the global SA methods are variance-based, for example the global sensitivity index is presented by the contribution of each input factor to the total variance of the model output. Methods for GSA are typically decomposed into four steps: (1) definition of the inputs and their distribution; (2) generation of a sample of input values; (3) evaluation of the model output for each sample set of inputs; and (4) estimation of the effect of each input on the model output (Tong, 2010). To perform the last step, two main approaches are used: a model approximation (e.g., linear regression) or a direct decomposition of the output variance; the latter is typically considered more advantageous in nonlinear models. The following paragraphs briefly describe two common GSA methods which are used in this study, the Morris screening method and the method of Sobol'.

Morris (1991) proposed an experimental plan to determine which input factors have important effects on an output using individually randomized one-factor-at-a-time (OAT) designs, also referred to as "elementary effects." The method is well-suited for cases with a large number of input factors and/or expensive computation, and is often considered a good compromise between accuracy and efficiency (Campolongo et al., 2007). The main idea behind the Morris screening method is to discriminate, at low sample size, among effects which are (a) non-influential or negligible, (b) linearly influential and additive, and (c) non-linearly influential or influential by interactions with other factors (Campolongo et al., 2007; Saltelli et al., 2004; Saltelli et al., 1999). For each input, two sensitivity measures are computed: μ^*, which assesses the overall influence of the factor on the output, and σ, which estimates the ensemble of the factor's higher order effects, i.e., non-linear and/or due to interactions with other factors (Campolongo et al., 2007). While considered a GSA method because it covers the entire space over which the factors may vary, the experimental part of the method is composed of individually randomized OAT experiments (Saltelli et al., 2004). Morris suggests evaluating a graphical representation of σ vs. μ^* to determine the most important factors. One of the main advantages of the Morris method is the low computational cost, especially in comparison with other screening methods such as fractional factorial designs. However, the sensitivity measures are typically considered qualitative (i.e., ranking significant input factors) but not necessarily quantitative in regard to the degree of significance. Quantitative methods, such as the variance-based method of Sobol' discussed next, give precise calculations of output variance but are also more computationally expensive (Saltelli et al., 2004).

The Sobol' (1993) GSA method computes an ANOVA-based decomposition of the output variance, where both main effects and interaction terms can be computed (Saltelli et al., 2000a). The Sobol' sensitivity index represents the fraction of the total variance that is due to any individual factor or combination of factors. Additionally, the method of Sobol' is able to estimate the total sensitivity index ST_i, defined as the sum of all effects (including first-order and higher-order) involving the input factor of interest

(Saltelli et al., 2000b). With k quantitative input factors, the decomposition of the variance var($\hat{Y}$) generalizes to:

$$\mathrm{var}\big(\hat{Y}\big) = \sum_{i=1}^{k} D_i + \sum_{1\le i<j\le k} D_{ij} + \ \dots + D_{1,2,\dots,k} \qquad \text{(3-1)}$$

where D_1 is the variability associated with the main effect of input factor x_1, D_2 is the variability associated with the main effect of x_2, and D_{12} is the variability associated with the interaction between x_1 and x_2, and so on. This technique is very similar to the analysis of variance (ANOVA), except that var($\hat{Y}$) represents the variability of $\hat{Y}$ in terms of the overall uncertainty of the input factors, including irregular and non-linear effects (Monod et al., 2006). The sensitivity indices are derived from the above equation by dividing individual importance measures by the total variability var($\hat{Y}$):

$$S_i = \frac{D_i}{\mathrm{var}(\hat{Y})} \qquad \text{(3-2)}$$

$$S_{ij} = \frac{D_{ij}}{\mathrm{var}(\hat{Y})} \qquad \text{(3-3)}$$

and so on, where S_i is called the first order sensitivity index for factor x_i, measuring the main effect of x_i on the output [or the fractional contribution of x_i to the variance of $f(x)$]. S_{ij} is called the second-order sensitivity index which measures the interaction effect of the two inputs x_i and x_j, without considering the sum of the individual effects (Saltelli et al., 2000b). A useful property of these sensitivity indices is that all of the possible first-order sensitivity index terms sum to one:

$$\sum_{i=1}^{k} S_i + \sum_{1\le i<j\le k} S_{ij} + \ \dots + S_{1,2,\dots,k} = 1 \qquad \text{(3-4)}$$

The total sensitivity index (ST_i) can be defined as the sum of all the sensitivity indices involving the factor in question. For example, in a three-factor model, the three total effect terms for ST_i are:

$$ST_1 = S_1 + S_{12} + S_{13} + S_{123}$$
$$ST_2 = S_2 + S_{12} + S_{23} + S_{123} \quad (3\text{-}5)$$
$$ST_3 = S_3 + S_{13} + S_{23} + S_{123}$$

where each S_i is simply the fraction of the variance of that value to the total variance of the model, as previously defined. Although the sum of the individual effect terms will add to one, the sum of all the ST_i values is typically larger than one because interactions are counted multiple times.

GSA input samples were generated with SimLab (2010), and evaluation of CERES-Maize model input sets was automated with SimLab and MATLAB (Mathworks, 2010). Morris SA was executed by sampling r = 10 elementary effects (i.e., individualized OAT comparisons per factor) and k = 16 input factors for a total experiment cost (as suggested by Morris, 1990) of r*(k+1) = 170 model input sets. Sobol' was computed with 2000 input sets, consistent with other examples with similar number of input parameters (Saltelli et al., 2000a). Each input set was run for both full and limited irrigation treatments, using observed management data from five years (2006-2010).

3.3 RESULTS

3.3.1 Morris Screening Method

Results for the Morris SA are shown in both graphical (Figure 3-1) and tabular (Table 3-2) form. Morris (1991) suggested that only factors with relatively high values of μ^* and σ are considered important. As mentioned in the previous section, high values for μ^* indicate large overall sensitivity to the input parameter, whereas a high value for σ indicates interaction or non-linear effects associated with the input parameter. ADAY was most sensitive to P1, a trend that was typical for every output response except YIELD and ETC (Table 3-2). In order of decreasing μ^* (i.e., decreasing sensitivity), PHINT was the next highest, with slightly higher σ than P1 indicating more interaction. ADAY was less sensitive to P2 than PHINT, but σ for these inputs was nearly the same as P1. For these three input parameters, there was little difference between treatments (Figure 3-1). There was minor sensitivity to the soil parameters SLLL and SDUL (due to higher standard deviations) for the limited irrigation treatment, but very low μ^* values (indicating low overall influence). Another phenological timing output, MDAY was similar to ADAY in that it was most sensitive to P1, with the full irrigation treatment having a slightly higher μ^* (Figure 3-1). This trend is logical, as changes to ADAY will naturally cause changes to MDAY, although their sensitivity to inputs was not identical because of thermal growth accumulations after ADAY. P5 and PHINT were the next most influential inputs with sensitivity to P2 very low.

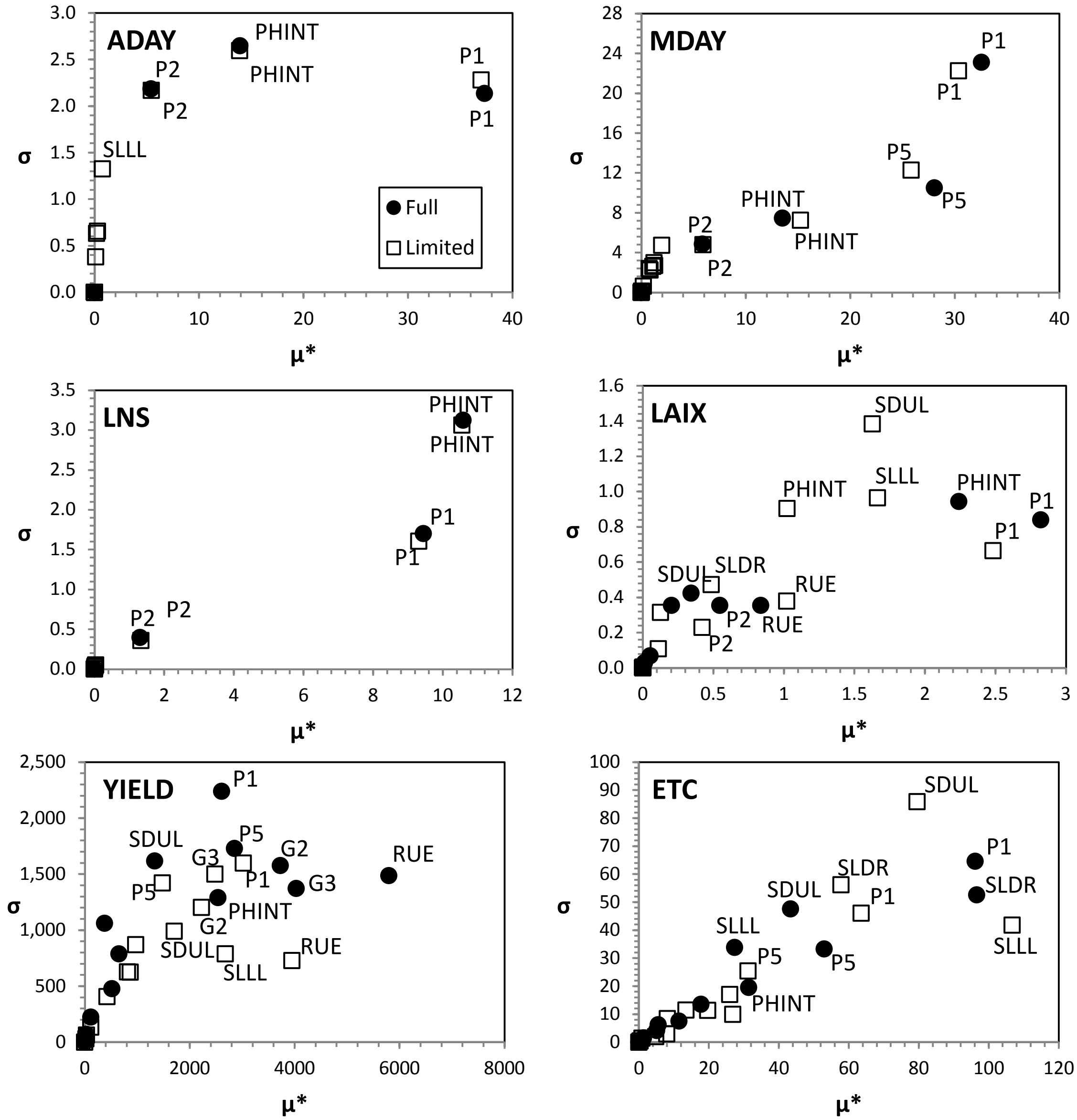

Figure 3-1. Morris sensitivity analysis results shown in graphical form for all CERES-Maize output responses of interest. Filled circles indicate full irrigation treatment, open squares indicate limited irrigation treatment. Labels of the most important factors are shown.

Table 3-2. Morris sensitivity analysis rankings for both full and limited treatments and all CERES-Maize output responses evaluated, in decreasing order of importance based on Morris μ* (1 = most important input for the given output).

Treatment	Output response	Input parameters [a]										
		P1	P2	P5	G2	G3	PHINT	RUE	SLDR	SLRO	SLLL	SDUL
Full	ADAY	1	3	--[b]	--	--	2	--	--	--	--	--
	MDAY	1	4	2	--	--	3	--	--	--	--	--
	LNS	2	3	--	--	--	1	--	--	--	--	--
	LAIX	1	4	--	--	--	2	3	--	--	--	5
	YIELD	5	--	4	3	2	6	1	--	--	8	7
	ETC	2	7	3	--	--	5	8	1	--	6	4
Limited	ADAY	1	3	--	--	--	2	--	--	--	--	--
	MDAY	1	4	2	--	--	3	--	--	--	--	--
	LNS	2	3	--	--	--	1	--	--	--	--	--
	LAIX	1	7	--	--	--	4	5	6	--	2	3
	YIELD	2	11	7	5	4	10	1	9	8	3	6
	ETC	3	9	5	--	--	6	8	4	7	1	2

[a] Input parameters SLPF, SLU1, SSAT, SSKS, and SBDM had no significant influence on any output responses and were omitted from the rankings.

[b] "- -" = no significant influence based on Morris μ* less than 10% of the maximum μ* for the output response in question).

Both LNS and LAIX are vegetative growth outputs which should be sensitive to phenological inputs but also to water stress. LNS was mostly sensitive to PHINT and P1, with little difference between irrigation treatments (Figure 3-1). There was a limited amount of sensitivity to P2 as well for LNS. On the other hand, for the two treatments there was a large difference between sensitive input parameters for LAIX. For both treatments, P1 was the most influential input considering μ^* but the sensitivity was higher for full irrigation than for limited irrigation. PHINT was also a highly influential input for both treatments, again with much higher sensitivity for full irrigation than for limited irrigation. However, the soil input parameters SLLL and SDUL were highly influential for limited irrigation with μ^* values greater than the value for PHINT. RUE also had some effect on LAIX for both treatments (Figure 3-1).

YIELD was most sensitive to RUE for both treatments (Table 3-2), although it had a higher $\mu^*$and σ for full irrigation (mainly because fully irrigated yield naturally has higher values with more variance expected than for limited irrigation yield). For full irrigation, the next five highest influential parameters were all cultivar coefficients (G3, G2, P5, P1, PHINT). Although these cultivar parameters were also sensitive for limited irrigation, sensitivity to the soil parameter SLLL was much higher for the full irrigation treatment and should be considered equally influential. In addition, YIELD was also sensitive to the soil parameter SDUL for both treatments. ETC was most sensitive to SLDR and P1 for full irrigation, followed by P5, SDUL, PHINT, and SLLL (Table 3-2). Several of these parameters were sensitive for limited irrigation; however the order of sensitivity was much different: SLLL was the most influential input parameter, followed by SDUL, P1, SLDR, and P5. This indicates that when water is limited the cumulative ET is very responsive to the water holding capacity and the drainage from the deepest layer.

As suggested by prior literature (i.e., DeJonge et al., 2011), phenological timing and total leaf count are not responsive to lack of available water, as shown by little treatment difference between sensitivity of any input parameter in ADAY, MDAY, and LNS (Figure 3-1). Conversely, there was a large contrast in sensitive inputs between treatments for the LAIX, YIELD, and ETC output responses, with much greater sensitivity to soil hydraulic parameters in limited irrigation (Figure 3-1).

3.3.2 Sobol' Variance-Based Method

Because Morris is often used as a "screening" method to eliminate insensitive parameters, the Sobol' analysis used default values for input parameters SLPF, SLU1, SSAT, SSKS, and SBDM, as they indicated no influence on CERES-Maize output responses of interest for the Morris method. The Sobol' total sensitivity index (ST_i) results (Figure 3-2, Table 3-3 and Table 3-4) were very similar the Morris μ* ranking results (Figure 3-1 and Table 3-2). First-order sensitivities were typically very close to the ST_i for output responses typically sensitive to two or three input parameters (i.e., ADAY, LNS, and LAIX for full irrigation), but yielded many more interactions when the output response was sensitive to three or more parameters (i.e., LAIX for limited irrigation, YIELD, and ETC). Interactions can easily be identified by a large difference between ST_i and S_i in Figure 3-2 or a large interaction number as found in Table 3-3 or

Table 3-4. A ranking of sensitive parameters in decreasing order of ST_i is also displayed (Table 3-5).

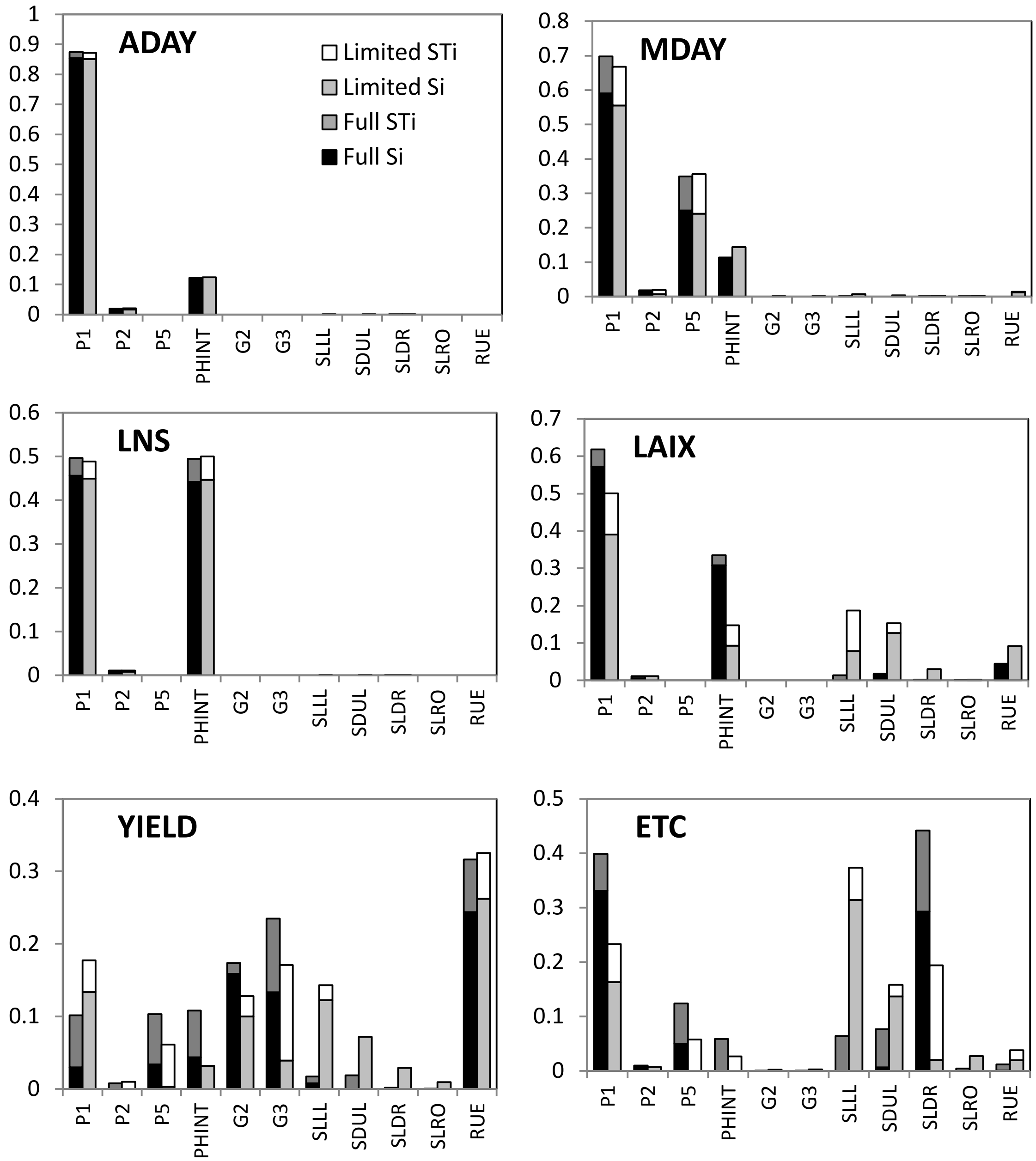

Figure 3-2. Sobol' total sensitivity (ST_i), and 1st order sensitivity (S_i) indices for CERES-Maize output responses ADAY, MDAY, LNS, LAIX, YIELD, and ETC. Model input parameters are those found sensitive by the Morris screening method.

Table 3-3. Sobol' total sensitivity (ST_i), 1st order sensitivity (S_i), and interaction (difference between ST_i and S_i) for both full and limited treatments and CERES-Maize output responses for ADAY, MDAY, and LNS.

			Input parameters										
Output Response	Treatment	Order	P1	P2	P5	PHINT	G2	G3	SLLL	SDUL	SLDR	SLRO	RUE
ADAY	Full	Total	0.87	0.02	- -[a]	0.12	- -	- -	- -	- -	- -	- -	- -
		1st	0.85	0.02	- -	0.12	- -	- -	- -	- -	- -	- -	- -
		Interaction	0.02	- -	- -	- -	- -	- -	- -	- -	- -	- -	- -
	Limited	Total	0.87	0.02	- -	0.12	- -	- -	- -	- -	- -	- -	- -
		1st	0.85	0.02	- -	0.12	- -	- -	- -	- -	- -	- -	- -
		Interaction	0.02	- -	- -	- -	- -	- -	- -	- -	- -	- -	- -
MDAY	Full	Total	0.70	0.02	0.35	0.11	- -	- -	- -	- -	- -	- -	- -
		1st	0.59	0.01	0.25	0.11	- -	- -	- -	- -	- -	- -	- -
		Interaction	0.11	0.01	0.10	- -	- -	- -	- -	- -	- -	- -	- -
	Limited	Total	0.67	0.02	0.36	0.14	- -	- -	- -	- -	- -	- -	0.01
		1st	0.56	- -	0.24	0.14	- -	- -	- -	- -	- -	- -	0.01
		Interaction	0.11	0.02	0.12	- -	- -	- -	- -	- -	- -	- -	- -
LNS	Full	Total	0.50	0.01	- -	0.49	- -	- -	- -	- -	- -	- -	- -
		1st	0.46	- -	- -	0.44	- -	- -	- -	- -	- -	- -	- -
		Interaction	0.04	0.01	- -	0.05	- -	- -	- -	- -	- -	- -	- -
	Limited	Total	0.49	0.01	- -	0.50	- -	- -	- -	- -	- -	- -	- -
		1st	0.45	- -	- -	0.45	- -	- -	- -	- -	- -	- -	- -
		Interaction	0.04	0.01	- -	0.05	- -	- -	- -	- -	- -	- -	- -

[a] "- -" indicates values < 0.01

Table 3-4. Sobol' total sensitivity (ST_i), 1st order sensitivity (S_i), and interaction (difference between ST_i and S_i) for both full and limited treatments and CERES-Maize output responses for LAIX, YIELD, and ETC.

Output Response	Treatment	Order	Input parameters										
			P1	P2	P5	PHINT	G2	G3	SLLL	SDUL	SLDR	SLRO	RUE
LAIX	Full	Total	0.62	0.01	- -[a]	0.33	- -	- -	0.01	0.02	- -	- -	0.04
		1st	0.57	- -	- -	0.31	- -	- -	- -	0.01	- -	- -	0.04
		Interaction	0.05	0.01	- -	0.02	- -	- -	0.01	0.01	- -	- -	- -
	Limited	Total	0.50	0.01	- -	0.15	- -	- -	0.19	0.15	0.03	- -	0.09
		1st	0.39	0.01	- -	0.09	- -	- -	0.08	0.13	0.03	- -	0.09
		Interaction	0.11	- -	- -	0.06	- -	- -	0.11	0.02	- -	- -	- -
YIELD	Full	Total	0.10	- -	0.10	0.11	0.17	0.23	0.02	0.02	- -	- -	0.32
		1st	0.03	- -	0.03	0.04	0.16	0.13	- -	- -	- -	- -	0.24
		Interaction	0.07	- -	0.07	0.07	0.01	0.10	0.02	0.02	- -	- -	0.08
	Limited	Total	0.18	- -	0.06	0.03	0.13	0.17	0.14	0.07	0.03	- -	0.33
		1st	0.13	- -	- -	0.03	0.10	0.04	0.12	0.07	0.03	- -	0.26
		Interaction	0.05	- -	0.06	- -	0.03	0.13	0.02	- -	- -	- -	0.07
ETC	Full	Total	0.40	- -	0.12	0.06	- -	- -	0.06	0.08	0.44	- -	0.01
		1st	0.33	- -	0.05	- -	- -	- -	- -	- -	0.29	- -	- -
		Interaction	0.07	- -	0.07	0.06	- -	- -	0.06	0.08	0.15	- -	0.01
	Limited	Total	0.23	- -	0.06	0.03	- -	- -	0.37	0.16	0.19	0.03	0.04
		1st	0.16	- -	- -	- -	- -	- -	0.31	0.14	0.02	0.03	0.02
		Interaction	0.07	- -	0.06	0.03	- -	- -	0.06	0.02	0.17	- -	0.02

[a] "--" indicates values < 0.01

Table 3-5. Sensitive CERES-Maize input parameters, in order of decreasing total Sobol' sensitivity (ST_i), for both full and limited treatments and all CERES-Maize output responses evaluated.

Output response	Treatment	Sensitive input parameters [a]
ADAY	Full	P1, PHINT
	Limited	P1, PHINT
MDAY	Full	P1, P5, PHINT
	Limited	P1, P5, PHINT
LNS	Full	P1, PHINT
	Limited	PHINT, P1
LAIX	Full	P1, PHINT, RUE
	Limited	P1, SLLL, SDUL, PHINT, RUE
YIELD	Full	RUE, G3, G2, PHINT, P5, P1
	Limited	RUE, P1, G3, SLLL, G2, SDUL, P5
ETC	Full	SLDR, P1, P5, SDUL, SLLL, PHINT
	Limited	SLLL, P1, SLDR, SDUL, P5

[a] All sensitive input parameters have ST_i greater than 0.05.

The CERES-Maize output response ADAY was highly sensitive to P1 and slightly sensitive to PHINT (Table 3-3) with minimal interactions between the input parameters. MDAY was also very sensitive to P1 (followed by P5 and PHINT, respectively), with slight interactions between input parameters P1 and P5. LNS was primarily sensitive to P1 and PHINT, again with small interactions between the two inputs. There were minimal differences between full and limited irrigation treatments for the ADAY, MDAY, and LNS output responses, considering both ST_i and S_i values. LAIX was the most sensitive to P1 and PHINT for full irrigation, but for limited irrigation exhibited significant sensitivity to soil parameters SLLL and SDUL as well as RUE. For full irrigation, there were very small interactions between the two sensitive input parameters for LAIX; however, there were larger interactions between P1, SLLL, and PHINT (Table 3-3). YIELD was the most sensitive to RUE for both treatments, followed by cultivar parameters typically used in calibration, although for limited irrigation YIELD was much more sensitive to soil parameters SLLL and SDUL. First-order sensitivity was highest in full irrigation to RUE, G2, then G3; however for limited irrigation this was RUE, P1, SLLL, and G2. For YIELD, G3 had the largest amount of interaction, for both treatments. For full irrigation, ETC was primarily sensitive to P1 and SLDR, and slightly sensitive to P5, with interactions involved in all three inputs. For limited irrigation, ETC was the most sensitive to SLLL followed by P1, SLDR, and SDUL, with larger interactions for SLDR and P1 as well. Furthermore, ETC sensitivity to SLDR showed the highest interaction of all the CERES-Maize input parameters across both treatments.

3.3.3 Comparison Between Morris and Sobol' GSA Methods

Because the Sobol' ST_i results so closely replicated the order and magnitude of the Morris μ^* results (taking into account the entire sensitivity of the output to each input parameter), a direct comparison was made for each output response and treatment by calculating the correlation (r) between Sobol' ST_i and Morris μ^* (Table 3-6). Comparisons were made using only inputs evaluated in both GSA methods, so inputs with negligible sensitivity as found by the Morris screening method were eliminated from this comparison. All comparisons yielded r values greater than 0.928, indicating a very high correlation between the two GSA methods used.

Table 3-6. Correlation (r) comparisons between the Sobol' method total sensitivity index (ST_i) and the Morris method μ*.

	Treatment	
Output response	Full irrigation	Limited irrigation
ADAY	0.969	0.970
MDAY	0.943	0.950
LNS	0.960	0.928
LAIX	0.995	0.995
YIELD	0.980	0.969
ETC	0.962	0.954

3.4 DISCUSSION

Because the Morris μ* and Sobol' ST_i results had such a high correlation, the remainder of this paper will refer to the sensitivity of a parameter in a general sense rather than in specific terms of SA method (i.e., Morris or Sobol'). It is important to consider that the results for Morris were found with 170 runs and a simpler algorithm than the more complicated Sobol' algorithm which required 2000 runs. In this study, the Morris and Sobol' methods served equally well in terms of not only ranking the input parameters, but also in quantifying relative total sensitivity of the input parameters. Similar results were found by Compolongo et al. (2007) when assessing the sensitivity of a chemical reaction model for dimethylsulphide (DMS). As the Morris method is less computationally expensive, it may be preferred over the Sobol' method for many types of SA studies. However, caution must be used in this approach as interactions and nonlinearity are difficult to distinguish based on Morris screening results alone (Saltelli et al., 2000a). For example, in a previous study Campolongo and Saltelli (1997) performed both Morris and Sobol' analyses using the GMSK model to simulate the oceanic production of DMS, evaluating 34 factors, and found that the Pearson correlation coefficient (r) between the Morris and Sobol' methods was 0.66, a much lower value than consistently found in this study. Campolongo and Saltelli (1997) go on to suggest a procedure matching accuracy and cost that would include a Morris analysis followed by a Sobol' analysis on a subset of selected inputs, just as was conducted in this study. However, simple linear correlations between the two methods were very high in our case. Confalonieri et al. (2010) used both the Morris and Sobol' methods to evaluate the effects of location and climate on the rice model WARM, but did not make the direct correlative comparisons performed herein. They echoed Campolongo and Saltelli (1997), noting that the Morris method is a suitable technique for a first screening of parameters, thus reducing computational efforts needed for Sobol'.

CERES-Maize output responses ADAY, MDAY, and LNS had no notable difference between treatments, indicating that anthesis and maturity timing, as well as successive leaf tip appearances, are insensitive to the effects of water stress. This is contradictory to observed field responses, for example Farre and Faci (2006) observed delays in maize flowering and maturity due to water stress, and DeJonge et al. (2011) observed differences in total leaf count using the same field experiment as this study. Abrecht and Carberry (1993) observed delayed leaf tip emergence, tassel emergence, silking, and onset of grain filling due to varying amounts of water stress. For the CERES-Maize LAIX, YIELD, and ETC output responses, water holding capacity was an extremely important factor in regard to sensitivity under limited irrigation, as the sensitivity is highly dependent upon the water management objectives. For full irrigation, none of the model output responses evaluated in this study exhibited significant sensitivity to the soil parameters SLLL or SDUL. However, under limited irrigation, these input parameters were very important in terms of total sensitivity, especially SLLL which was the most sensitive input parameter for both LAIX and ETC (Table 4). This indicates that much more attention is required in estimating SLLL and SDUL for limited irrigation simulations than for full irrigation simulations, especially SLLL as it a main limiting factor for leaf area growth, crop yield, and ET (Table 3-4). Interactions are also important to consider, for example in LAIX under limited irrigation SLLL has a large interaction (0.09) with P1 and PHINT. SLDR was also an influetial input in regard to ETC under limited irrigation, as increased drainage out of the soil profile limits the model's ability to meet ET demand, and also had a large interaction with other parameters (0.17). Where these interactions exist, all parameters should be considered simultaneously instead of one at a time, and this GSA study illustrates this importance.

Ma et al. (2011) describe a systematic calibration of cultivar parameters for DSSAT models, in which they suggest calibrating these inputs based on phenology first, followed by biomass, LAI, and yield. As this GSA study shows, the calibration method described by Ma et al. (2011) may be appropriate in a study that observes no water stress. However, the difference in input sensitivity in regard to limited irrigation treatments found in this study provides a unique opportunity to perform a systematic calibration of datasets for water stressed conditions, such as those used in DeJonge et al. (2011), and could provide guidance for other DSSAT modelers to improve calibrations under limited water conditions. Such a calibration would be roughly based on the method described by Ma et al. (2011) by calibrating or parameterizing individual output responses to observed values based on which influential inputs can be solved for the most easily. However, this new calibration method would also acknowledge the strong influence that water holding capacity has on outputs such as LAI and yield. In this study, no output response was overly sensitive to P2 so the recommended default value for this parameter could likely be used. PHINT also was not an overly sensitive parameter in this study, but could be estimated based on observations of successive leaf tip appearances and growing degree days. Once PHINT is known, P1 can then be estimated by matching ADAY for both treatments and LNS for full irrigation only (as we know that limited irrigation, the model will not correctly predict observed leaf number). With P1 and PHINT known, only P5 is left to estimate to fit MDAY. At this point, LAIX (and leaf area index throughout the season, for that matter) should match closely for full irrigation. Soil hydraulic parameters SLLL and SDUL can then be estimated within acceptable levels for the known soil type, and should help closely match leaf area index for the limited irrigation treatment. Ma et al. (2011) recommend using SLPF to improve simulations, but this study found all relevant outputs to be insensitive to changes in SLPF. While RUE has not traditionally been documented in past studies as a calibration parameter, this study suggests it could be evaluated within reasonable ranges. RUE can also be used to make smaller adjustments to LAIX, as it provides some sensitivity without interactions, and obviously has a high influence on YIELD. Finally, YIELD can be fitted by finding values for G2 and G3, whereas ETC can be fitted by defining SLDR. Without full testing, it is impossible to speculate if such a systematic method of calibration would be worthwhile, but it is certainly worth considering in future studies as another extension of this GSA.

3.5 SUMMARY AND CONCLUSIONS

Two types of SA were performed on full and limited irrigation treatments of corn using the CERES-Maize growth model and five years of observed irrigation schedules and weather. Outputs evaluated included growth timing of anthesis date and maturity, total leaf number per stem, maximum leaf area index, crop yield, and cumulative evapotranspiration. Inputs, which were systematically varied throughout acceptable value intervals, included crop cultivar parameters, soil hydrologic parameters, and radiation use efficiency. The Morris SA method was used to eliminate completely insensitive parameters prior to performing the more computationally intensive Sobol' method. In this experiment, results comparing Morris mean and Sobol' total sensitivity index showed very high correlation between the two (Table 3-6), indicating that in this case the computationally cheaper Morris method could have been used as the sole indicator of input sensitivity. For the full irrigation treatment, outputs were mostly sensitive to crop cultivar parameters. This is unsurprising, as the model has been known to perform best in non-water stressed environments and these parameters are typically used for calibration (DeJonge et al., 2011). However, in the limited irrigation treatment outputs for leaf area index, yield, and evapotranspiration were highly influenced by inputs SLLL and SDUL (which define water holding capacity). Evapotranspiration was also highly sensitive to drainage rate (SLDR) in both treatments, and crop yield was most sensitive to radiation use efficiency (RUE) in both treatments. For both treatments, anthesis date and maturity date were not sensitive to soil hydraulic parameters and had the same sensitivity between treatments, unsurprising as in CERES-Maize these outputs are strictly a function of thermal time and have no reaction to available water. However, there were no differences in sensitivity between treatments for leaf number per stem, a trend expected based on the DeJonge et al. (2011) results.

It is a well-known fact that identifying influential model parameters, in a specific arena of application, is of primary importance for all types of models, in this case the agroecosystem (and specifically crop) modeling community. This is true for aiding not only efficacious parameterization and calibration, but also for model development and enhancement itself. This study shows that as prediction problems related to water availability in agriculture become more complex, our analysis techniques need to evolve and progress to better represent and quantify how crop growth models behave under water limited environments. Although this study focused on parameter sensitivity, a future study should focus on CERES-Maize sensitivity to water stress and how those functions are calculated. The ability to better quantify crop development delay under water stress is a potential model improvement. The current version of CERES-Maize shows no phenological timing or growth response (in the form of total leaf count) to water stress, as these outputs are strictly functions of thermal time (DeJonge et al., 2011). Saseendran et al. (2008a) review several examples of observed maize phenology delay due to water stress, and emphasize that crop models that simulate water stress should emphasize these effects. One possibility for future improvement of CERES-Maize would be to adopt an approach similar to the APSIM (Agricultural Production Systems Simulator) v 5.0 generic plant module. For example, between the stages of emergence and flowering, the calculated daily thermal time in APSIM is scaled back by water and N stresses, causing delayed phenology under stress (Saseendran et al., 2008a). It is also notable that DeJonge et al. (2011) reported underestimation of LAI under limited irrigation while ET was overestimated. To obtain a full understanding of contributors to these output biases, an evaluation of the water stress sub-procedures is suggested to supplement this GSA study.

Finally, the linkage between sensitivity analysis and model parameterization/calibration is not always well-defined or readily apparent for the casual or even advanced crop modeler. As real-world management paradigms change, for example limited irrigation of crops, the models that are used to simulate these management changes will need to adjust appropriately. For example, formerly suggested calibration methods for non-stressed crops may not be adequate in cases that include, or even focus on, water stress. Therefore, a basic methodology for a systematic calibration of CERES-Maize, based on sensitivity indices for the two irrigation treatments, is proposed for future evaluation.

CHAPTER 4. IMPROVING EVAPOTRANSPIRATION SIMULATIONS IN THE CERES-MAIZE MODEL UNDER LIMITED IRRIGATION

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4.1 INTRODUCTION

4.1.1 Limited Irrigation

Water availability issues, combined with population growth and the uncertainty of climate change have created significant challenges for water resources scientists (Anderson-Wilk, 2008). English et al. (2002) argue that a fundamental paradigm shift in agroecosystem irrigation management is inevitable as water supplies become more limited, as farmers will manage irrigation to maximize net benefits instead of simply the biological objective of maximizing yields. Limited water resources and increasing pumping costs have recently caused farmers in Colorado, USA to consider limited irrigation as an alternative to full irrigation practices. Obviously, yield potential is very important in regard to the economic optimization required for such management, but crop evapotranspiration (ET) also must be considered and quantified as the potential for Colorado water rights transfer depends on "consumptive use" or ET (Smith et al., 1996). Alternatively, farmers may consider either a reduction in planted area or schedule irrigation events so that plants do not encounter stress during sensitive growth stages. Thus, in many irrigated areas such as the Colorado Front Range, studies are increasingly exploring benefits of limited or deficit irrigation of water-intensive crops such as corn (DeJonge et al., 2011).

Limited irrigation practices incorporate water management under restricted water application, and minimize water stress during critical crop growth stages in order to maximize yields (Schneekloth et al., 2009). Previous field studies have addressed corn (*Zea mays* L.) response to growth-timing of irrigation (Barrett and Skogerboe, 1978; Doorenbos and Kassam, 1979; Gilley et al., 1980). More recent studies have supported this idea, for example, Klocke et al. (2004) achieved 93% of fully irrigated corn yield using 76% of the water applied and Klocke et al. (2007) achieved limited irrigation yields of 80% to 90% of fully irrigated yields while using about half the applied water for full irrigation. Several recent studies also emphasize the importance of growth-stage timed irrigation timing (Farre and Faci, 2009; Igbadun et al., 2008; Ko and Piccinni, 2009; Mansouri-Far et al., 2010; Payero et al., 2006; Payero et al., 2009).

4.1.2 CERES-Maize Stress Response

Water stress, sometimes referred to as water deficit stress, is a physiological condition where plants have less than full turgor because the transpiration demand exceeds root water uptake. Water stress can adversely affect growth and development processes of the crop or plant, often limiting productivity (Saseendran et al., 2008a). While many cropping system models have recently been used in regard to water stress, they could benefit from increased understanding especially in regard to transpiration, photosynthesis, carbon allocation, canopy temperature, and water use efficiency (Ahuja et al., 2006). Sasseendran et al. (2008a) give a detailed review of water stress simulations using several crop models, including the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM) (Hoogenboom et al., 2004; Jones and Kiniry, 1986; Jones et al., 2003; Ritchie et al., 1998).

As part of the DSSAT system, the CERES-Maize model has been widely used to assess cropping and management strategies for corn (both rainfed and irrigated). For example, Xie et al. (2001) found that simulated vegetative growth and kernel weight were extremely sensitive to drought stress. A group of researchers found that CERES-Maize v3.0 overestimated the effects of water stress on vegetative growth, and subsequently adjusted the stress functions to be based on pre-dawn leaf water potential, and improved simulation results (Mastrorilli et al., 2003; Nouna et al., 2000).

Saseendran et al. (2008b) simulated various water allocations and irrigation amounts in northeastern Colorado using CERES-Maize, and found that split irrigation applications of 20% of the total water applied during vegetative growth stages and 80% of the total water applied during reproductive growth stages obtained the highest yield for a given irrigation allocation, ranging from 100 to 700 mm of total irrigation. López-Cedrón et al. (2008) evaluated CERES-Maize for rainfed and irrigated treatments with the intent to improve the model's ability to predict biomass and yield under water-limited conditions (where the model had previously given good predictions under irrigated conditions). They found that the model adequately predicted irrigated treatments but underpredicted rainfed treatments.

Most recently, DeJonge et al. (2011) provided a detailed statistical comparison of CERES-Maize with a field experiment consisting of full and limited irrigation treatments in northern Colorado, finding that the model performed better in the non-stressed (full irrigation) treatment than in the stressed (limited irrigation) treatment. More specifically, they found that the CERES-Maize model estimated yield adequately but slightly underestimated ET for full irrigation and overestimates ET for limited irrigation. These two findings contradict each other, as lower leaf area should cause decreased photosynthesis, thus decreased ET instead of increased ET as the model found, indicating that model simulations under stress may not only need improvement, but need better linkage between leaf area and ET as well. A global sensitivity analysis was performed on CERES-Maize using these same datasets plus two additional years of management data, and found that the limited irrigation treatment was very sensitive to inputs affecting the soil's available water capacity (Chapter 3 of this dissertation).

4.1.3 Objectives

The CERES-Maize crop model has been shown to perform adequately in regard to irrigation management that meets crop ET demands. However, the model shows some difficulty in simulating processes affected by water stress, such as rainfed treatments (López-Cedrón et al., 2008) or limited irrigation treatments (DeJonge et al., 2011). In the context of crop water production functions, it is imperative that the model adequately simulate both yield and ET in terms of limited irrigation. DeJonge et al. (2011) showed that the CERES-Maize v4.0 model slightly underestimated ET under full irrigation and overestimated ET under limited irrigation, while simultaneously underestimating LAI under limited irrigation. This is unsurprising, as the DSSAT simulation of plant transpiration is not directly coupled with energy balance or stomatal behavior (Sasseendran et al., 2008b). The overall objective of this study is to identify, evaluate, and improve crop model processes that affect crop yield, ET, and LAI under both non-stressed and stressed conditions. Specifically, this study explores crop simulations of full and limited irrigation treatments by:

1) Evaluating local sensitivity of maximum crop coefficient (EORATIO) values greater than 1.0 , as well as alternative values for the extinction coefficient (KEP) that partitions potential soil evaporation and transpiration, in terms of yield, cumulative ET, and maximum LAI.
2) Creating and statistically evaluating a new function that determines the crop coefficient for potential ET (K_{C_LAI}) based on LAI, therefore determining ET demand as a function of vegetative growth.

4.2 METHODS

4.2.1 Field Experiment

In a prior study, the CERES-Maize crop growth model was calibrated and validated based on a multireplicate field research plot near Fort Collins, Colorado

(40°39'19" N, 104°59'52" W) from 2006 to 2008; details for 2006 to 2008 can be found in DeJonge et al. (2011). Two irrigation treatments of continuous corn (the dominant irrigated crop in northeast Colorado) were studied during the 2006 through 2010 growing seasons: full irrigation (ET requirement supplied throughout the season) and limited irrigation (no irrigation before the V12 reproductive stage unless necessary for emergence, then full irrigation afterwards). In all years, less significant early irrigations were required by all treatments to encourage germination and avoid total loss of crop. Irrigations were applied by a linear move sprinkler system, generally at a weekly interval. Irrigation amounts were determined by crop need and supported by potential ET estimates from the onsite weather station. An on-site weather station (station FTC03; 40°39'09" N, 105°00'00" W; elevation 1557.5 m) within the Colorado Agricultural Meteorological Network (CoAgMet, http://ccc.atmos.colostate.edu/~coagmet/) continually recorded daily precipitation, solar radiation, minimum and maximum temperature, vapor pressure (which was converted to dew point temperature), and wind run. Any missing weather data were replaced by data from the Wellington, CO station (station WLT01; 40°40’34” N, 104°59’49” W; elevation1567.9 m) approximately two km to the north of the FTC03 station.

4.2.2 CERES-Maize model

Crop simulation models, such as those found in the Decision Support System for Agrotechnology Transfer (DSSAT v4.5), can play a role in assessing the costs and benefits of limited irrigation and the interactions of timing and amount of irrigation water applications (Hoogenboom et al., 2010; Jones et al., 2003). The DSSAT Cropping System Model (CSM) CERES-Maize is available as part of the DSSAT suite of crop models designed to estimate production, resource use, and risks associated with crop production practices (Jones and Kiniry, 1986; Ritchie et al., 1998). It has been widely used to assess cropping and management strategies for corn (both rainfed and irrigated) for well over two decades. CERES-Maize is a process-oriented corn growth model that simulates the following: biomass accumulation based on light interception; partitioning of accumulated biomass to leaves, stems, roots, and grain; environmental stresses; soil water balance; soil N transformations and uptake; and crop growth and development including phenological states, biomass production, and yield. CERES-Maize requires various inputs: soil (texture, field capacity, permanent wilting point, saturation, saturated hydraulic conductivity, bulk density, soil root growth factor), daily weather (minimum and maximum temperature, solar radiation, dew point temperature, wind run, rainfall), management (planting date, tillage, N applications, irrigation, planting population), initial conditions (volumetric soil water content, N content), and phenological growth parameters specific to the hybrid or cultivar used. Many inputs are accessible through model input files but are not recommended to be changed except for special cases (Ma et al., 2011). CERES-Maize simulates detailed plant growth, including phenological development, growth of leaves, stems, and roots, biomass accumulation, soil N transformation and uptake, and crop growth and development (Jones and Kiniry, 1986). Four discrete functions of simulated leaf-tip number are used for predicting plant canopy leaf area in CERES-Maize (Jones and Kiniry, 1986). The calculated canopy leaf area is subjected to senescence coupled with plant development. Calculated senescence rate is modified to account for population and leaf-shading effects. Also, deficits of N and water accelerate senescence. Final LAI is calculated from the canopy leaf area balance available each day as a function of plant population. CERES-Maize does not simulate crop height (Ma et al., 2002).

In CERES–Maize, crop development rates are calculated based only on temperature and photoperiod (Ritchie et al., 1998). Biomass partitioned to grain in CERES-Maize can be affected by daily minimum temperature (Singh, 1985). Soil organic matter in CERES-Maize consists of fast-decaying “fresh organic matter” and slowly decaying “soil humus fraction.” N uptake is simulated based on the crop N demand and potential N. In terms of crop yield, number of grains per plant is a function of the potential number of kernels per plant (G2) and the average crop growth rate (g/plant) from silking to the beginning of grain filling. The model assumes one ear of corn per plant, however if the number of kernels per plant is significantly smaller than the potential number of kernels, the model creates some barren plants. Ear growth rate (g/ear/day) is increased by daily thermal time but can be decreased by water or N stress. The effective grain filling period is based on the thermal time from silking to maturity (P5), and during this period leaf senescence increases, whereas ears, stalks, and roots are the only active growing tissues. Daily grain growth rate is a function of temperature, grains per plant, potential kernel growth rate (G3), and soil moisture effect on growth (Ritchie et al., 1998).

4.2.3 CERES-Maize Evapotranspiration and Water Balance

The daily soil-water balance in all DSSAT models, including CERES-Maize, uses the Ritchie (1985; 1998) one-dimensional "tipping bucket" approach, which simulates soil water flow and root water uptake for each individual user-defined soil layer (maximum 10 layers). Because soils are typically heterogeneous with depth, soil properties at several layers are desired. For each layer it is required to know soil water contents (on a volumetric basis) for the lower limit of plant water availability or wilting point (SLLL), the limit where capillary forces are greater than gravity forces known as the drained upper limit or field capacity (SDUL), and for field saturation or porosity (SSAT). Ritchie recommends SLLL and SDUL should be found in the field instead of lab measurements based on disturbed samples. For each layer, initial soil water content is required, typically found by observed values at planting. The root weighting factor (SRGF) is required for each layer, where a maximum value of 1 indicates a soil most hospitable to root growth and a minimum value of 0 indicates the soil is inhospitable to root growth. Low values for SRGF can be used to simulate restricted root growth in layers with poor physical or chemical properties. Infiltration is assumed to be rainfall plus irrigation minus runoff, calculated by the curve number method (SCS, 1972). Soil water redistribution within the soil is described in more detail in Ritchie (1998), and is a function of the water contents in neighboring layers and the distance between subsequent layers. Additional information regarding simulation of water balance and water stress components can be found both in Saseendran et al. (2008a) and ICASA (2008).

For CERES-Maize as implemented in DSSAT v4.5, the overall logic of ET and water stress calculation is shown in Figure 4-1. Potential evapotranspiration (ETo) was calculated in earlier versions of the model using the Priestley-Taylor (1972) method whose inputs are solar radiation and minimum and maximum temperature. Current versions of the DSSAT model can also use the FAO-56 Penman-Monteith method which requires additional wind and humidity data (Allen, 1998).

The FAO-56 method computes reference crop ET (ETo) based on a non-stressed 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:

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \gamma \frac{900}{T+273} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34\,U_2)} \quad (4\text{-}1)$$

where ETo is the hypothetical reference crop ET rate in mm d^{-1}, R_n the net radiation flux density at the surface, G the sensible heat flux density from the surface to the soil, γ the psychrometric constant, T is mean air temperature in ^{o}C, U_2 is wind speed in m s^{-1} at 2 m above the ground (relative humidity and dew point are also assumed to be measured at this height), e_s is mean saturated vapor pressure in kPa computed as the mean vapor pressure as calculated at the daily minimum and maximum temperature, e_a the actual

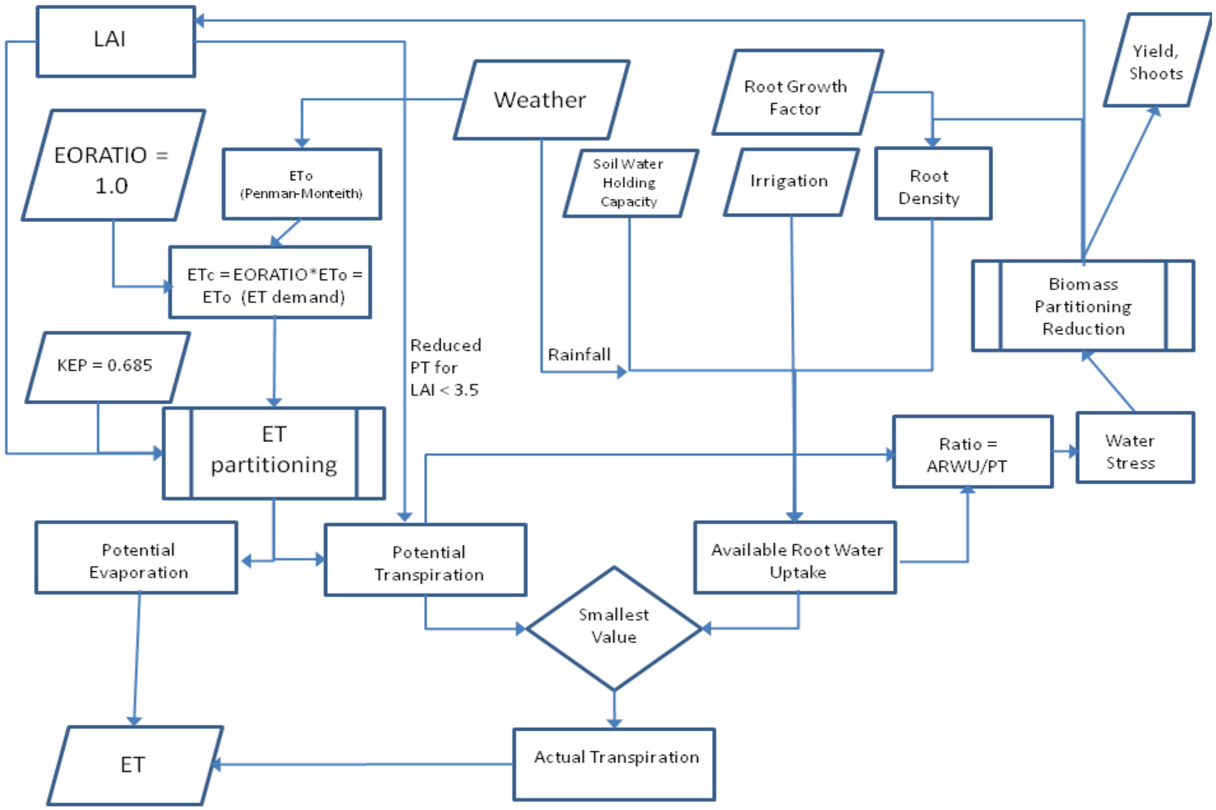

Figure 4-1. Logic of current ET calculation in CERES-Maize model.

vapor pressure of the air in kPa, and Δ the slope of the saturation vapor pressure versus temperature curve (Allen et al., 1998).

Potential crop ET (E0) is calculated from:

$$E0 = K_{c\_LAI} * ET_o \tag{4-2}$$

where K_{C_LAI} is the crop coefficient. In the context of this study, it is important to understand that K_{C_LAI} is not necessarily the same as a crop coefficient in the traditional sense as described by Allen et al. (1998). While it is true that the crop coefficient K_{C_LAI} is multiplied by a reference ET, the resulting value denotes ET *demand*, not necessarily actual ET. CERES-Maize model code employs the following formula for calculation of K_{C_LAI}:

$$K_{c\_LAI} = 1.0 + (EORATIO - 1.0) * \frac{LAI}{6.0} \tag{4-3}$$

where LAI is leaf area index and EORATIO is defined as the ratio of increase in ETc with increase in LAI, up to LAI of 6.0 (Sau et al., 2004). This formula ensures that K_{C_LAI} varies daily between 1.0 and EORATIO. Values of EORATIO less than 1 should not be used, as it would actually decrease the ET based on increased LAI. Despite this functionality, the current version of CERES-Maize sets the value of EORATIO equal to 1, ensuring that K_{C_LAI} is not dynamic and remains at 1.0 for the entire simulation. Allen et al. (1998) note that close-spaced plants with tall canopy heights may have mid-season ET greater than the reference ET, and suggests Kc of up to 1.2 for a non-stressed maize crop. This option has been evaluated in a couple of cases. For example, López-Cedrón et al. (2008) used the FAO-56 option with EORATIO (maximum K_{C_LAI}) of 1.0 and 1.1 (in addition to the Priestley-Taylor method) to simulate rainfed and irrigated maize biomass and yield, finding that EORATIO greater than 1.0 proved to be too stressful on rainfed biomass and yield. Sau et al. (2004) evaluated EORATIO values ranging from 1.0 to 1.2 on faba beans and noted in many cases these increases improved predictions.

E0 is partitioned into potential plant evaporation or transpiration (EPo) and potential soil evaporation (EPs), where

$$EP_o = E0 * (1 - \exp(-KEP * LAI)) \quad (4\text{-}4)$$

$$ES_O = E0 - EP_O \quad (4\text{-}5)$$

where KEP is defined as an energy extinction coefficient of the canopy for total solar irradiance used for partitioning E0 to EPo and ESo. The default value for KEP is currently set at 0.685, but López-Cedrón et al. (2008) found that a value of 0.50 improved predictions of biomass and grain yield, when using both the Priestley-Taylor and FAO-56 ET methods. Sau et al. (2004) used the default value for KEP of 0.85, and recommended lowering this to a value closer to 0.5.

Soil-limited root water uptake (EPr) is calculated based on the effective root zone of the crop and the available water within that root zone. The actual plant water uptake (EP) is found as the smaller of EPr and EPo. In other words, if the potential plant evaporation (transpiration) can be supplied by the soil water, then this demand is met. It is important to remember that in the current version of CERES-Maize, EPo is based on a non-stressed full canopy crop, even when the crop itself may be in the vegetative growth stage with less actual ET demand. Cases where demand would not be met can include during these beginning growth stages (where the root water uptake will be minimal) and during water shortage, where the ET demand will not be met.

Two stress factors are based on the ratio of EPr to EPo. Under well-watered conditions, potential root water uptake is greater than potential transpiration and this ratio is greater than one. As soil dries because of root water uptake, EPr is reduced. Eventually a threshold is reached where the turgor stress factor (TURFAC, Equation 4-6 and Figure 4-2) is triggered, limiting expansive growth which is considered more sensitive to drought stress than other growth and development processes (Saseendran et al., 2008a). In the current version of the model, this is calculated as:

$$TURFAC = \frac{EP_r}{RWUEP1 * EP_o} \tag{4-6}$$

where RWUEP1 is a species-specific parameter that is currently set to 1.5 for all DSSAT crops. When potential transpiration demand exceeds the potential root water uptake, a second stress factor affecting photosynthesis (SWFAC, Figure 4-2) is activated, where

$$SWFAC = \frac{EP_r}{EP_o} \tag{4-7}$$

Both stress factors are bounded by values of 0 and 1. For both stress factors, values of 1 indicate that no stress is imposed on photosynthesis or expansion processes. Values between 0 and 1 will impose stresses on the crop, with lower values indicating more stress.

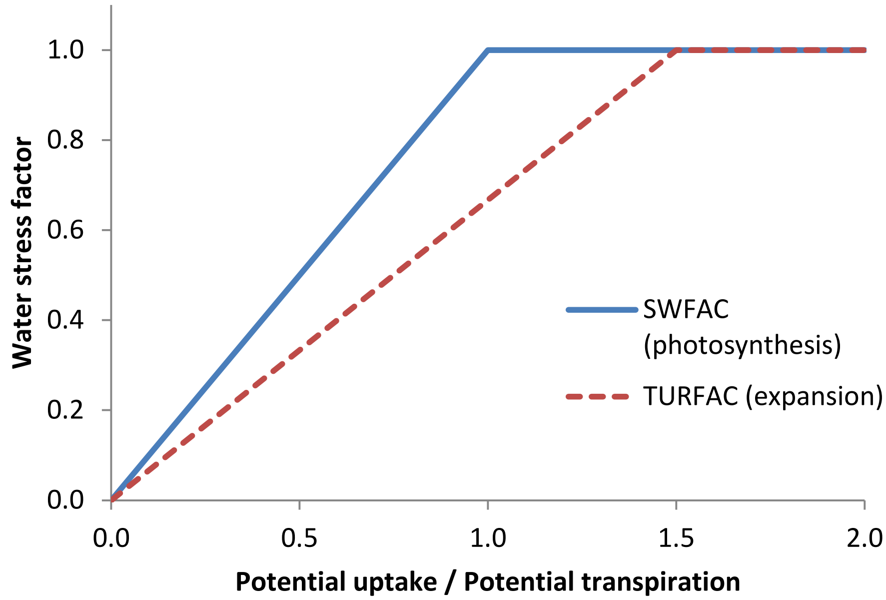

Figure 4-2. Water stress factors used in DSSAT models (Ritchie, 1998 via Saseendran et al., 2008b).

4.2.4 Local Sensitivity of EORATIO and KEP

The two main model parameters and processes that are initially explored are the maximum Kc for FAO-56 Penman-Monteith potential ET (E0) and the KEP value partitioning EPo and EPr based on LAI. These values were individually changed from baseline (default) values to evaluate local sensitivity of change in the parameters. Five years of management data (2006-2010) were used with the two irrigation treatments to simulate the model output variability, and treatments were separated in the analysis. Outputs evaluated included yield at maturity (kg/ha), maximum seasonal LAI, and cumulative ET (mm). Mean and standard deviation of outputs for each treatment were calculated, as well as the overall change (%) from the mean values using the baseline model. In the case of KEP, this process was made possible by adjusting default values in input files. In the case of EORATIO, new variables were created in input files and the model code was changed to allow application of this new function.

As suggested by Allen et al. (1998), the crop coefficient (Kc) can be as high as 1.2 for midseason corn. The CERES-Maize model has been coded to allow for a maximum K_{C_LAI} higher than 1 as a function of increased LAI (Eqn. 4-3), thus allowing for potential ET greater than the reference ET. However, as mentioned above, this option has been hard-coded into the model to only allow the K_{C_LAI} value to be set at 1. The DSSAT code was modified to allow a maximum K_{C_LAI} value (as set by EORATIO) to be initialized in the maize species input file. EORATIO values of 1.1, 1.2, and 1.3 were compared with the baseline value of 1.0. While EORATIO of 1.3 may give higher than expected K_{C_LAI} values, maximum observed LAI in Colorado is typically not much higher than 5.0 (e.g.., DeJonge et al., 2011), which using Eqn. 4-3 would give K_{C_LAI} of 1.25.

Values of KEP were varied to evaluate the effects of varying partitioning to potential transpiration and potential soil evaporation based on leaf area index (Eqn. 4-4). These values have been changed in previous literature, for example, Sau et al. (2004) used a KEP value of 0.85 with DSSAT v3.5 and López-Cedrón et al. (2008) used a value of 0.685 with DSSAT v4.0. Both authors recommended lowering the KEP value to 0.5 for better simulation of biomass and yield and López-Cedrón et al. (2008) evaluated KEP of 0.5 in rainfed maize. However, no analysis of the direct effect of changing these values on ET or LAI was made in either study. For the purposes of this study, KEP was evaluated for the default value (0.685) and several other values (0.605, 0.524, and 0.444) (Figure 4-3).

4.2.5 New Crop Coefficient Calculation

In order to potentially improve the simulation of ET, it is desirable to replace Eqn. 4-3 with a new estimation of crop coefficient (K_{C_LAI}, the ratio of potential crop ET to reference ET) that more reasonably estimates the ET demand as a function of LAI. A few past studies show this direct relationship between the traditional crop coefficient (Kc) and LAI (Figure 4-4). All of these studies used lysimeters to determine ET, and are all for corn with the exception of Duchemin et al. (2006) which was wheat. These relationships generally had R^2 between 0.72 and 0.86, and the first leg of the Kang et al. (2003) relationship had R^2 of 0.95. These graphs all share commonalities, for example the graphs typically start with Kc between 0 and 0.4 for LAI = 0, and increase in a linear or exponential decay fashion until approximately LAI = 3, where Kc is between 0.8 and 1.1. At this point the trend levels off with small increases in Kc for any increase in LAI. Examples were cited in several of these papers that ET demand does not increase much as LAI increases above 3, as this LAI level nears maximum intercepted net radiation.

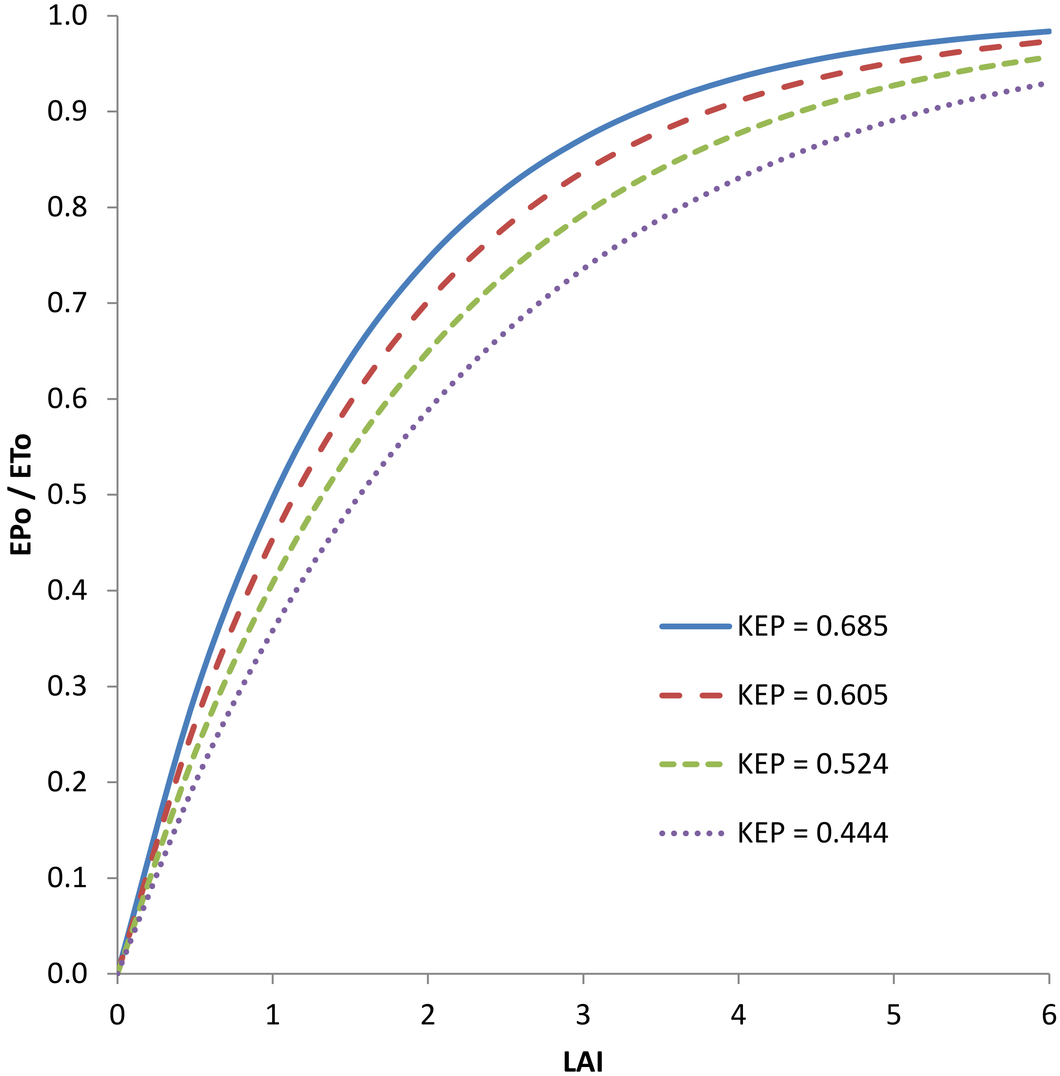

Figure 4-3. Partitioning of potential plant transpiration as a fraction of potential ET, based on LAI, for varying KEP values.

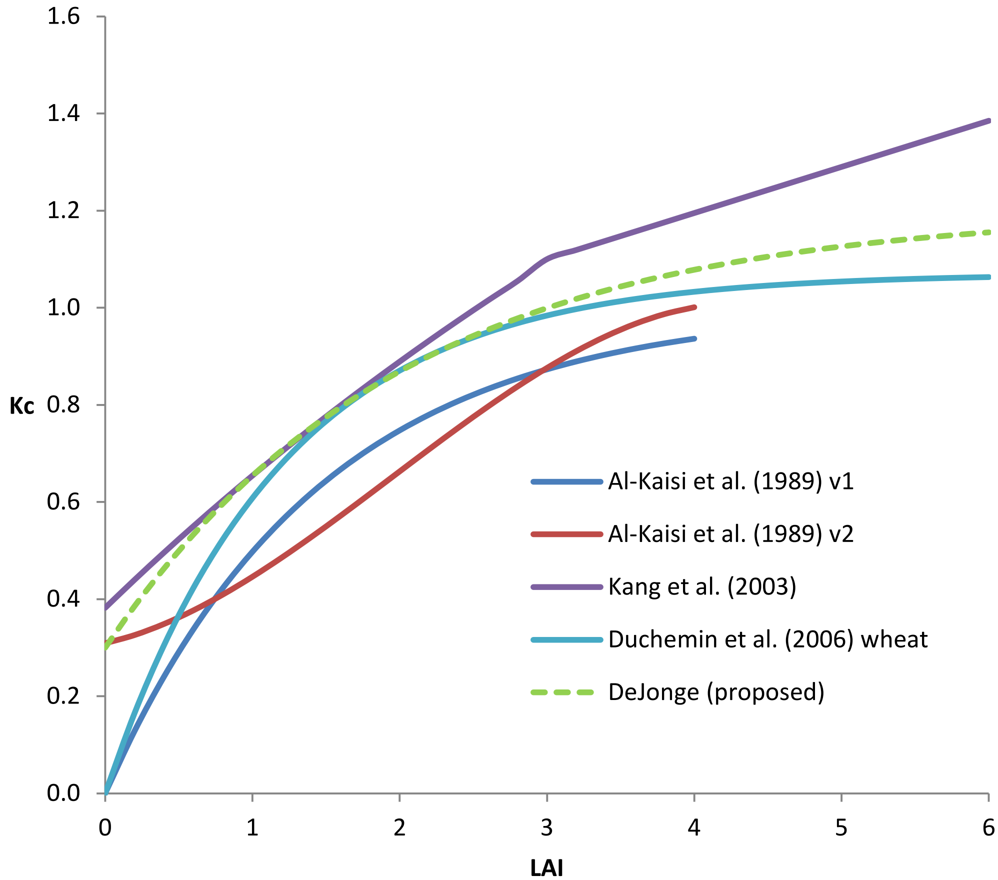

Figure 4-4. Crop coefficient (Kc) versus leaf area index (LAI) relationships found in literature, and newly proposed function for this study.

For the purposes of improving the CERES-Maize crop growth model, it is desirable to link the factors governing interception of solar radiation (i.e., LAI) with those governing ET demand (i.e., K_{C_LAI}) to provide for a more physically-based representation of the ET process. Based on production functions used in previous literature (Figure 4-4), the following exponential decay function is proposed and evaluated:

$$K_{c\_LAI} = K_{cmin} + (K_{cmax} - K_{cmin})(1 - \exp(-SK_c * LAI)) \qquad (4\text{-}8)$$

where K_{cmin} is the minimum crop coefficient or K_c at LAI=0, K_{cmax} is the maximum crop coefficient at high LAI, and SK_c is a shaping parameter that determines the shape of the K_c vs. LAI curve. The three unknown terms other than LAI in this function were added to the model code as parameters in a new input file. FAO-56 (Allen, 1998) includes several examples of K_{cmin} and K_{cmax} for various crops. Recommended values for these parameters for corn are $0 \leq K_{cmin} \leq 0.4$, $0.9 \leq K_{cmax} \leq 1.2$, and $0.5 \leq SK_c \leq 1.0$.
Both irrigation treatments were evaluated using 2006-2010 data after replacing Eqn. 4-3 with Eqn. 4-8. Values for K_{cmin} and K_{cmax} were set at 0.3 and 1.2, respectively, based on typical values expected for corn (Allen, 1998). This will ensure an early-season K_{C_LAI} near 0.3 before the canopy grows significantly, as well as K_{C_LAI} well above 1 with higher LAI. Additionally, SK_c was set to 0.5 to closely match values used in previous literature (Figure 4-4) and KEP was set to 0.5 to follow recommendations by Sau et al. (2004). Model changes are shown in red in Figure 4-5.

4.2.6 Statistical Evaluation

Yield, cumulative ET, and water use efficiency (WUE, yield divided by cumulative ET) were evaluated using the original model (static Kc value) and the new model (dynamic K_{C_LAI} function), and comparing with observed values. These values

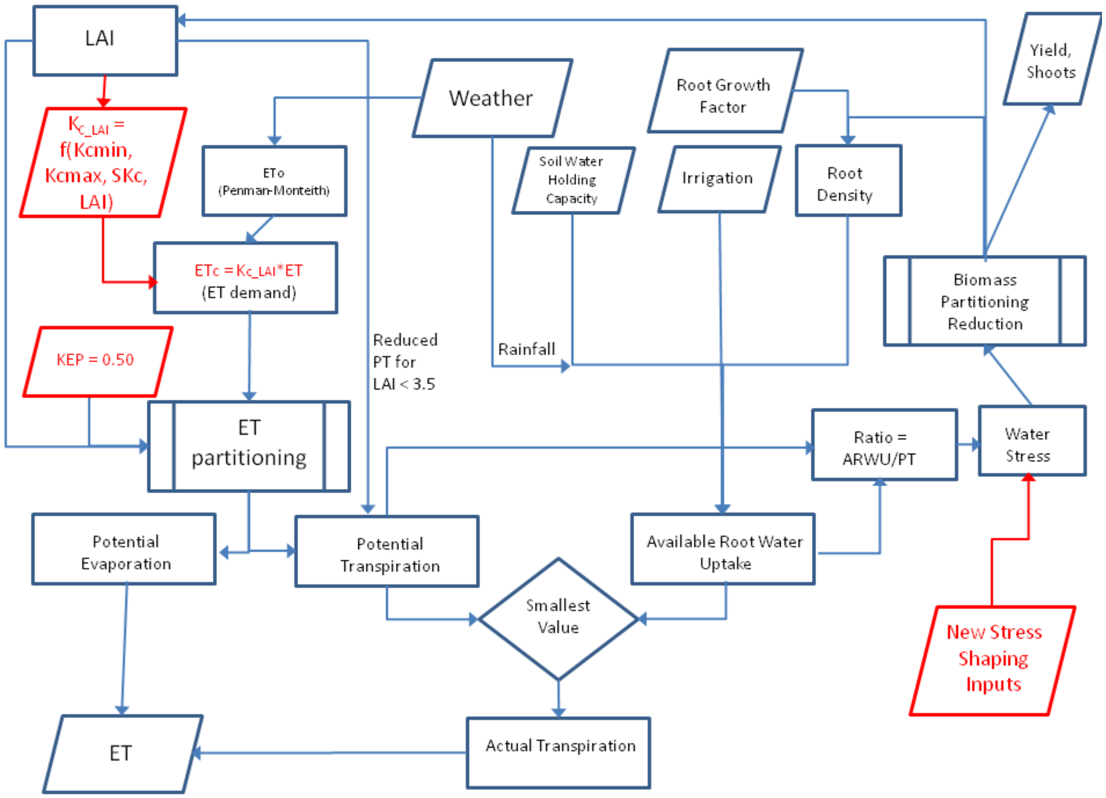

Figure 4-5. Logic of ET calculation in CERES-Maize model with model changes (in red).

were also evaluated using the root mean square deviation (RMSD), normalized objective function (NOF), and relative error (RE):

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{n}\left(O_i - P_i\right)^2}{n}} \tag{4-9}$$

$$\mathrm{NOF} = \frac{\mathrm{RMSD}}{\overline{O}} \tag{4-10}$$

$$\mathrm{RE} = \frac{(\overline{P} - \overline{O})}{\overline{O}} * 100 \tag{4-11}$$

where O_i is the observed value, P_i is the CERES-Maize predicted value, n is the total number of observations, $\overline{P}$ is the mean of all predicted values, and $\overline{O}$ is the mean of all observed values. Smaller values of RMSD among the same data type indicate better performance of the model. The NOF should be interpreted as a relative value to compare model performance of simulating different data sets. RMSD or NOF = 0 indicate perfect fit between experimental data and simulated results; NOF < 1 may be interpreted as a simulation error of less than one standard deviation around the experimental mean. RE is a measure of the average tendency of the simulated values to be larger or smaller than the observed values. The optimal RE value is 0.0; a positive value indicates a model bias toward overestimation, whereas a negative value indicates a model bias toward underestimation.

4.3 RESULTS AND DISCUSSION

4.3.1 Local Sensitivity of EORATIO and KEP

As expected, increasing EORATIO increased cumulative ET for the full irrigation treatment (Figure 4-6). Cumulative ET was increased 4.6% by changing EORATIO to 1.1, and increased 8.0% by changing EORATIO to 1.2. Increasing EORATIO to 1.3 produced a smaller incremental change in cumulative ET (10.1% higher than baseline). Because ET increased for this treatment, the water in the soil profile was less than in the baseline model, so a small amount of water stress was introduced that slightly decreased yield (e.g., 1.9% decrease in yield with EORATIO of 1.2) but had an even smaller effect on LAI (only a 0.8% reduction with EORATIO of 1.3). DeJonge et al. (2011) showed that cumulative ET under full irrigation was generally underpredicted, with a relative error of -7.2% for the three years evaluated. As Allen et al. (1998) note that a maximum Kc value of 1.2 for unstressed, full canopy corn is typical, it is conceivable that this value would improve simulations of ET for fully irrigated corn.

As the limited irrigation treatment is not expected to reach full ET throughout the season, changes in EORATIO did not have a significant impact on ET, with only a 0.7% increase in cumulative ET for EORATIO of 1.3 (Figure 4-6). However, due to the processes used to partition ET and calculate water stress, increases in EORATIO introduced significant decreases in both yield and LAI. For example, with EORATIO of 1.2, yield decreased 17.2% and LAI decreased 5.8%. By allowing for a higher K_{C_LAI}, Eqn. 4-2 calculates a higher E0 (ET demand, or potential ET). When E0 is partitioned based on Eqns. 4-4 and 4-5, this in turn produces a higher potential transpiration (EPo).

Although the overall ET rate changes little, more of ET is partitioned into crop water needs so Eqns. 4-6 and 4-7 will introduce more stress into the model, thus decreasing yield and leaf expansion. By definition, Eqn. 4-5 limits the K_{C_LAI} to values greater than 1, which in turn simulates excessive demand for a crop with less than full canopy. Eqn. 4-8 is an attempt to remedy this issue.

Values of KEP, the extinction coefficient for partitioning E0 into EPo and EPr, were varied from the baseline of 0.685 to lower values of 0.605, 0.524, and 0.444. Both Sau et al. (2004) and López-Cedrón et al. (2008) recommend lowering KEP to around 0.5. Effects on full irrigation were minimal (Figure 4-7) as expected. Since full irrigation management meets the ET demand of the crop, no stress was invoked, causing no change from baseline for yield or maximum LAI. Because shifting KEP downward changes the partitioning (Figure 4-3), a smaller amount of transpiration is apportioned to ET. However, because full irrigation has such high LAI, the differences between KEP values was minimal (for example a 1.9% decrease by changing KEP from 0.685 to 0.444).

There was minimal response in ET (< 0.5%) to changes in KEP for the limited irrigation treatment (Figure 4-7). On the other hand, there were substantial increases in yield and LAI due to decreases in KEP. As KEP is reduced (Figure 4-3), partitioning of E0 results in lower potential transpiration (EPo). Because this demand is more easily met, the ratio of EPr/EPo will be higher and water stress functions (Eqns. 4-6 and 4-7) will be less severe, thus allowing for less yield and LAI reduction. For example,

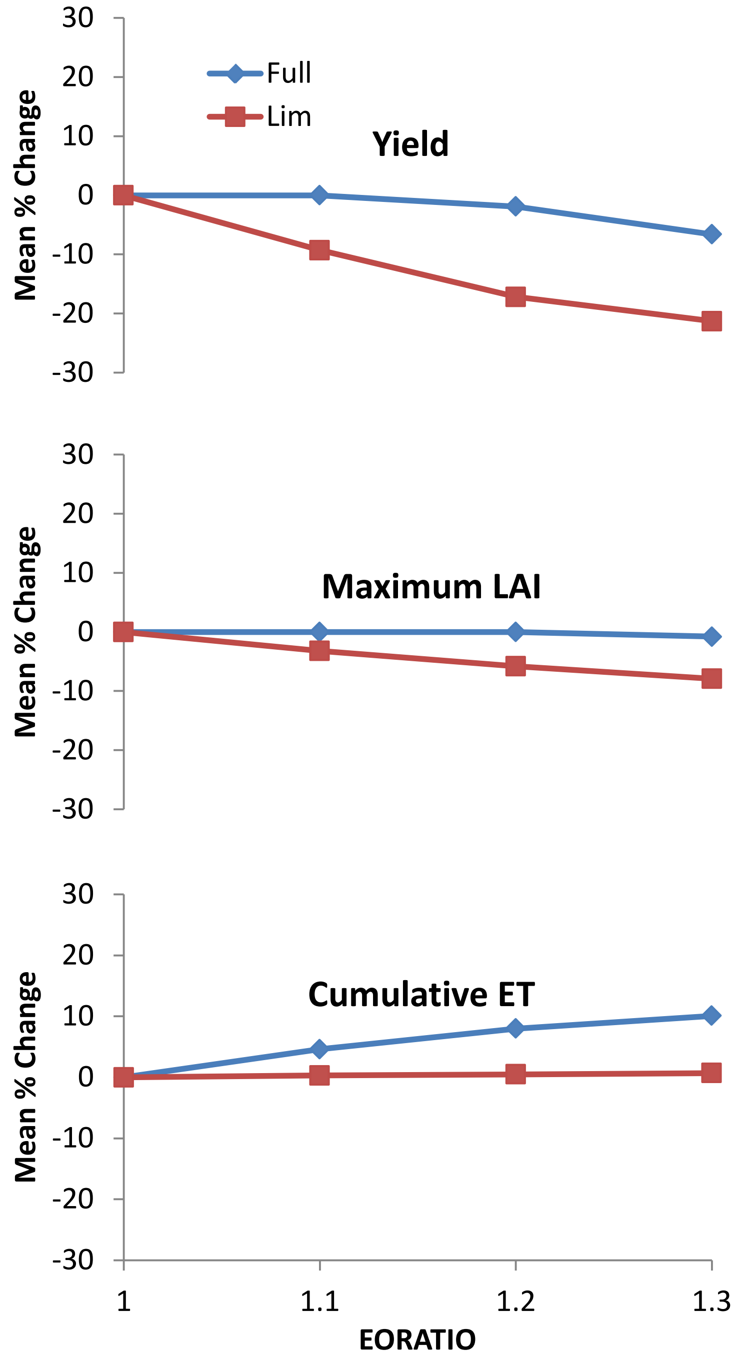

Figure 4-6. Local sensitivity of yield, maximum LAI, and cumulative ET to changes in EORATIO, for full and limited irrigation treatments. Vertical axis indicates change in output (%) from baseline (EORATIO = 1.0) averaged over five years simulated.

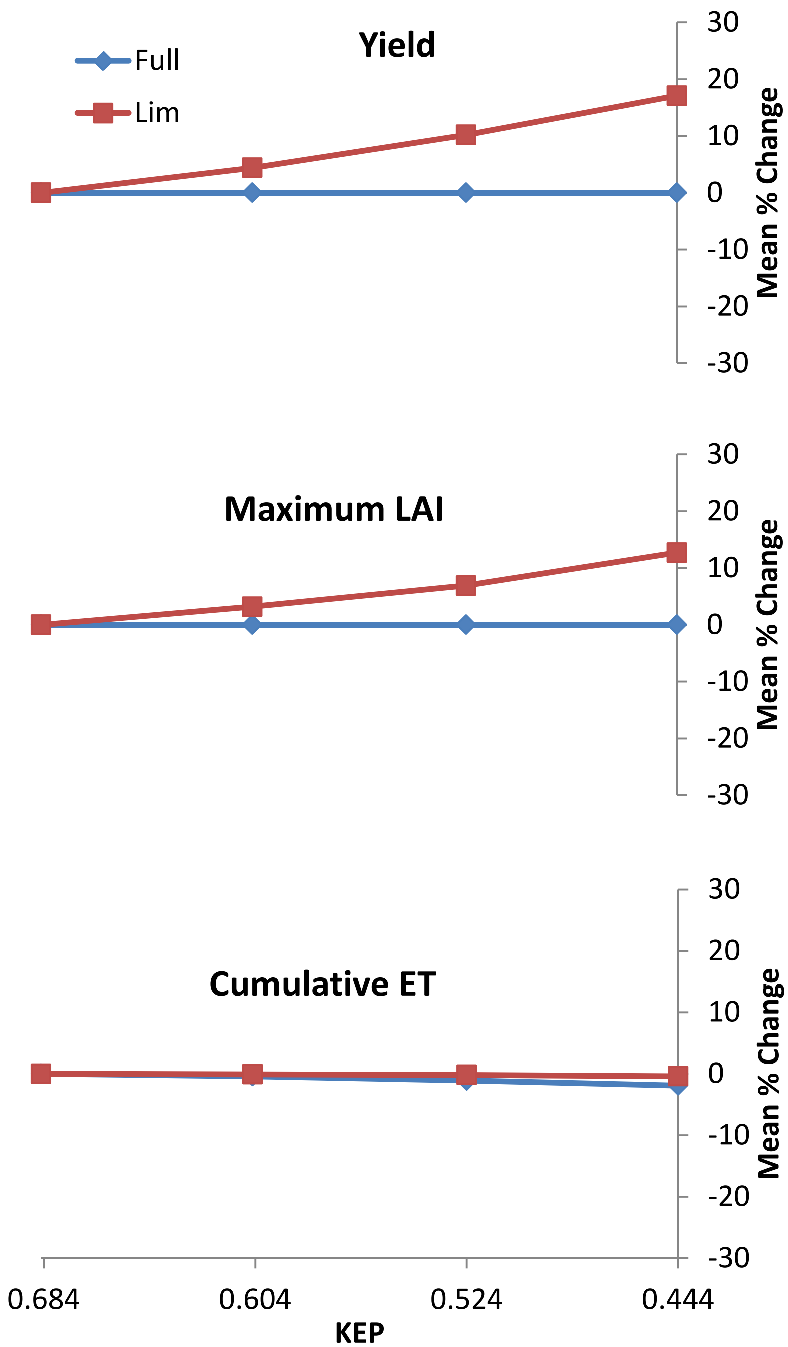

Figure 4-7. Local sensitivity of yield, maximum LAI, and cumulative ET to changes in KEP, for full and limited irrigation treatments. Vertical axis indicates change in output (%) from baseline (KEP = 0.685) averaged over five years simulated.

changing KEP from 0.685 to 0.524 resulted in a 10.2% increase in yield and a 6.9% increase in maximum LAI.

4.3.2 Kc as a Function of LAI

By using values of Kcmin = 0.3, Kcmax = 1.2, and SKc = 0.5, Eqn. 4-8 can be simplified to:

$$K_c = 0.3 + (1.2 - 0.3)(1 - \exp(-0.5 * LAI)) \tag{4-11}$$

Additionally, KEP was changed from 0.685 to 0.5 (Eqns. 4-4 and 4-5).

Full irrigation treatment data from year 2008 is used in Figure 4-8 to show the functionality of the new equation. The previous method to calculate K_{C_LAI} had the value hard-coded at 1.0 for the entire growing season, and even by changing EORATIO would still be greater than 1.0 at all times (Eqn. 4-3). The new equation allows for a dynamic K_{C_LAI} as a function of leaf canopy, as shown in Figure 4-4. Beginning at planting, the K_{C_LAI} for both irrigation treatments is near K_{cmin} or 0.3 for several weeks (Figure 4-8). A typical Kc curve from FAO-56 (Allen, 1998) was shown for comparison purposes (dashed line). It is encouraging to see that the new K_{C_LAI} curve for the full irrigation, nonstressed treatment, follows extremely closely through most of the growing season. In the full irrigation treatment, the crop is irrigated to meet ET demand, which as can been seen in this figure meets non-stressed values proposed by FAO-56.

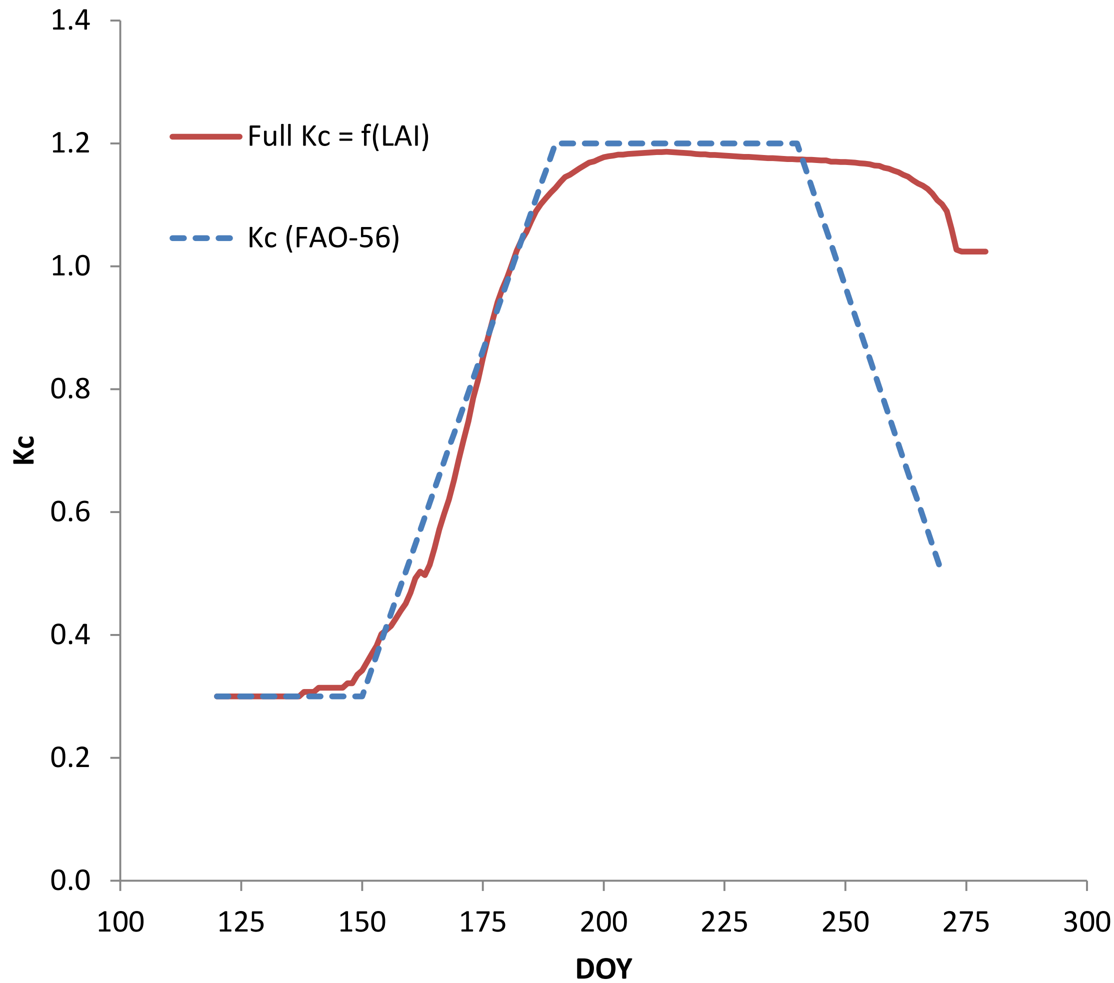

Figure 4-8. Crop coefficient curve for potential ET in full irrigation treatment (2008) as a function of LAI, found by Eqn. 4-11. For comparison purposes, a crop coefficient curve from FAO-56 is also shown (Allen, 1998).

Additionally, the 2008 dataset was used to show the daily ET simulation ratio, or ratio of simulated ET under limited irrigation to simulated ET under full irrigation (Figure 4-9). In both original and new versions of the model, the ET ratio is near 1 toward the beginning of the season because the only difference between treatments at this point is the initial soil water, which has very little difference. When the ratio goes less than 1, this is the beginning of the differences in irrigation treatments, or when the limited irrigation treatment is given less irrigation water. In both treatments this ratio is reduced further, to around 0.2 as the water deficit under limited irrigation increases. Up to this point, both versions of the model behave in an acceptable manner. However, near late July, the beginning of the reproductive growth, both treatments are given large amounts of water to meet ET demand. In the original version of the model, the ET demand was generally the same in both treatments because K_{C_LAI} was always 1.0, so the ratio was near 1 during this time of high watering. However, it is unreasonable to believe that a crop with reduced LAI (limited irrigation) would have the similar ET as that of a crop with full canopy (full irrigation). With this model improvement, the new dynamic K_{C_LAI} model simulates the ratio of limited irrigation ET to full irrigation ET at a maximum of about 0.85 during this reproductive stage, and often below 0.85. This trend shows one example of how overall ET simulation is improved under water stress.

Original and new versions of the model were run for all years from 2006 through 2010, with both full and limited irrigation treatments. Simulated yield

(Figure 4-10), cumulative ET (Figure 4-11), and WUE (Figure 4-12) were compared against original values; yearly values for each of these outputs are also shown in Table 4-1. Additionally, statistical comparisons of both model versions were performed against observed data (Table 4-2).

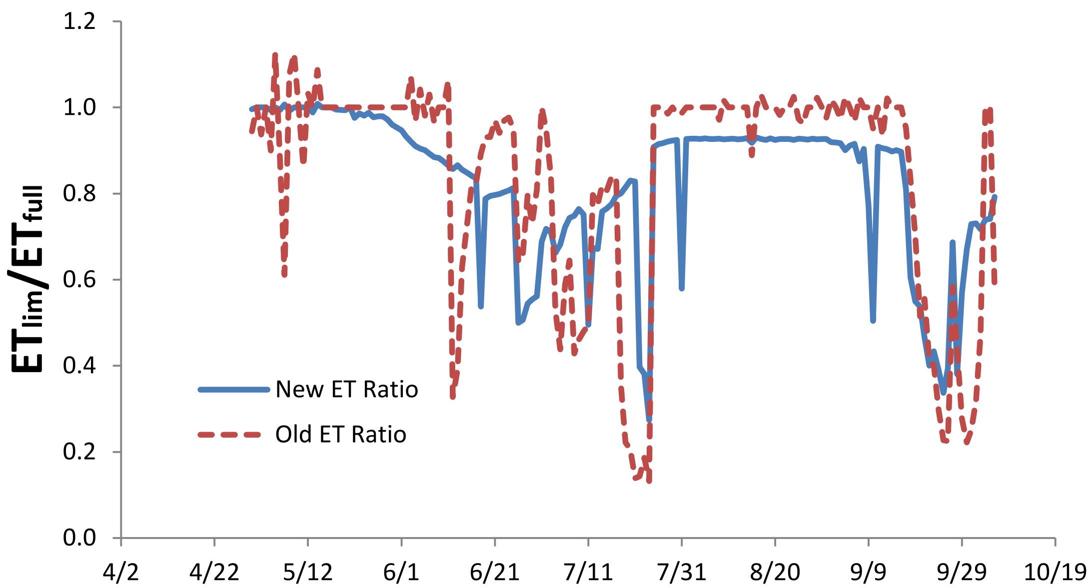

Figure 4-9. Ratio of 2008 simulated ET under limited irrigation to simulated ET under full irrigation, for original and new versions of model.

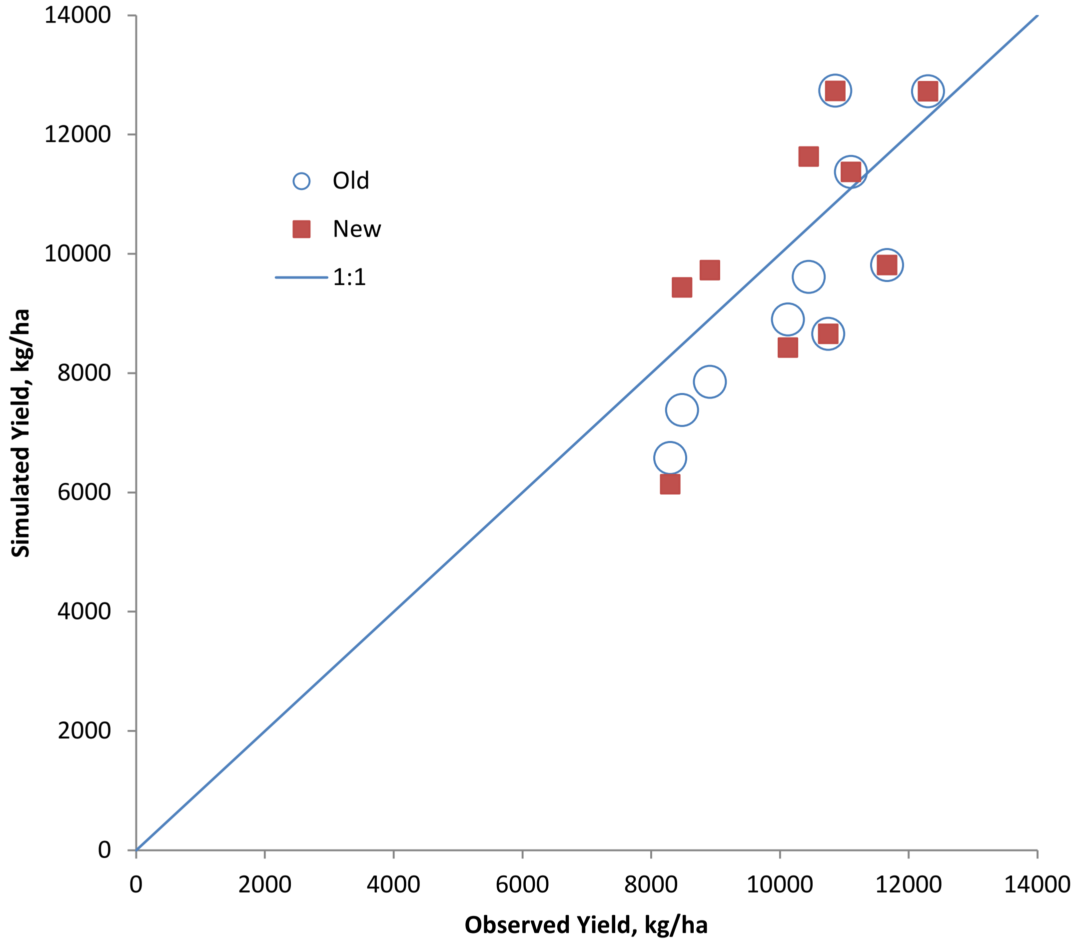

Figure 4-10. Simulated vs. observed yield for the original and new model.

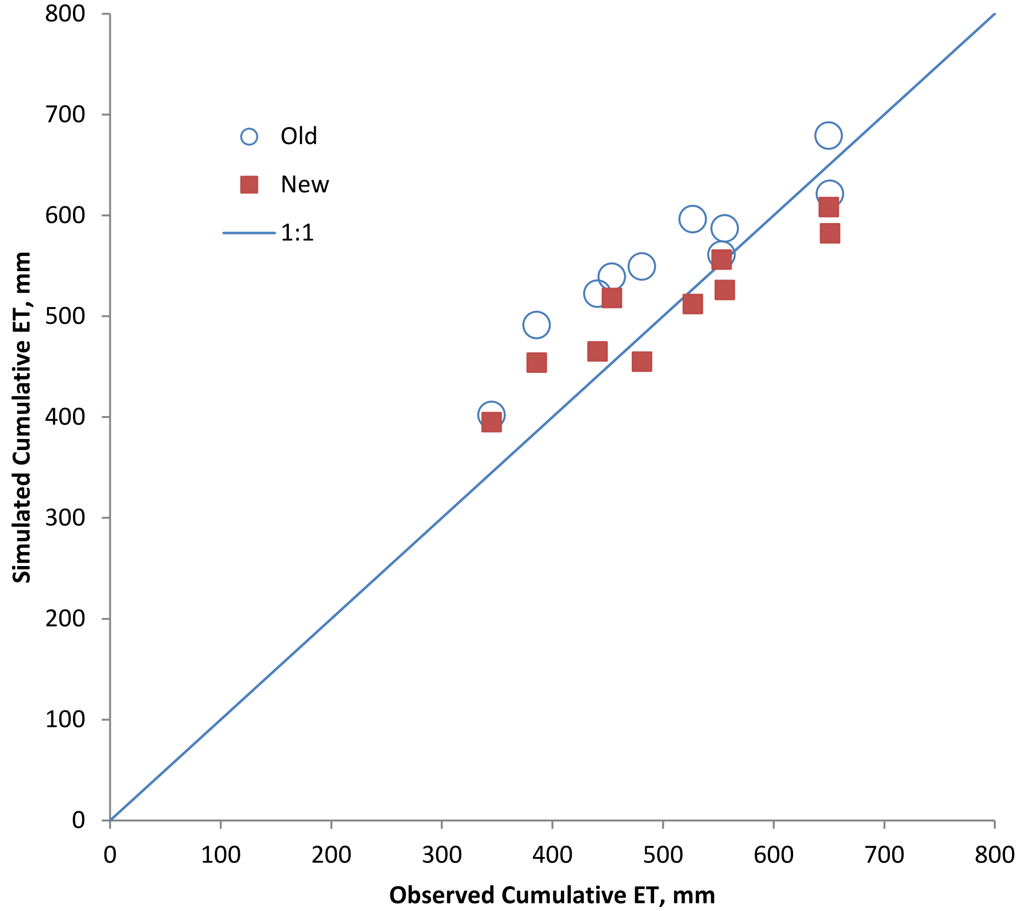

Figure 4-11. Simulated vs. observed cumulative evapotranspriation (ET) for the original and new model.

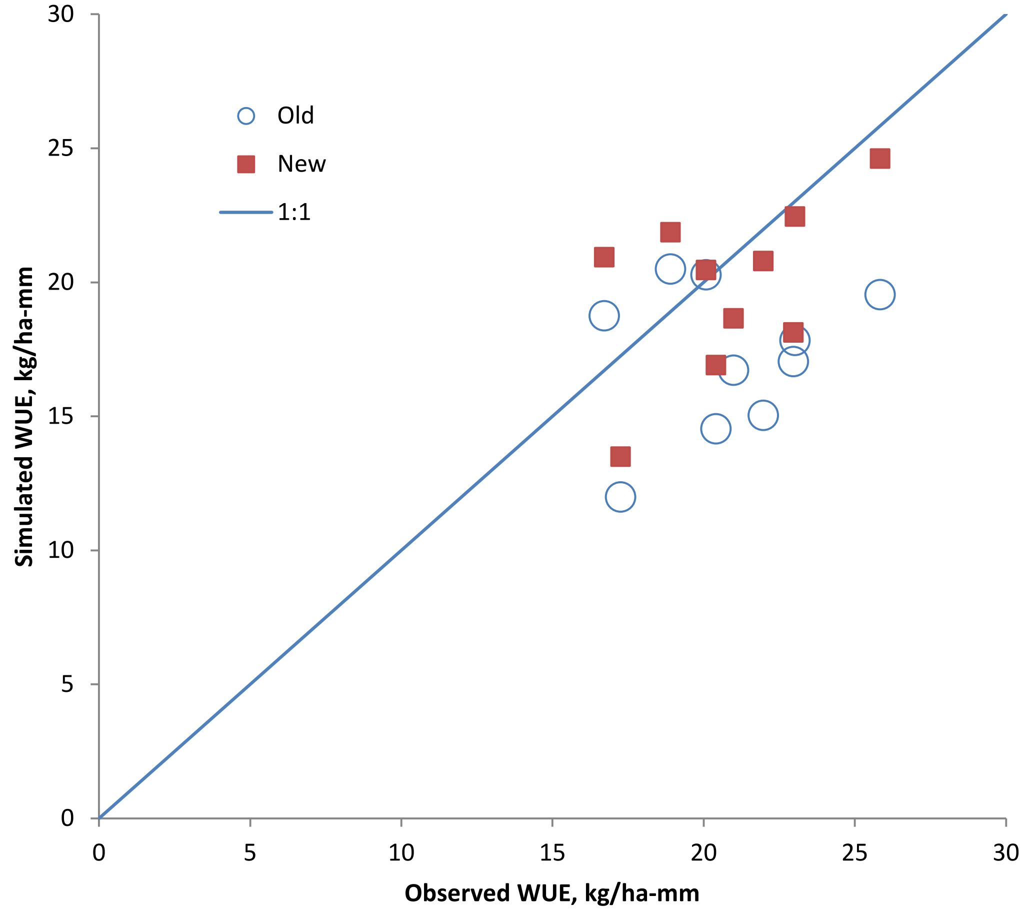

Figure 4-12. Simulated vs. observed water use efficiency (WUE, yield divided by cumulative ET) for the original and new model.

Table 4-1. Observed (Obs.) and simulated (Sim.) results for yield, ET, and WUE, using both original and new versions of the model.

		Yield, kg/ha			Cumulative ET, mm			Water Use Efficiency, kg/ha-mm		
Treatment	Year	Obs.	Old Sim.	New Sim.	Obs.	Old Sim.	New Sim.	Obs.	Old Sim.	New Sim.
Full	2006	11107	11373	11373	553	561	556	20.1	20.3	20.5
	2007	11670	9810	9810	556	587	526	21.0	16.7	18.7
	2008	10863	12733	12727	650	679	608	16.7	18.8	20.9
	2009	10755	8659	8659	527	596	512	20.4	14.5	16.9
	2010	12307	12724	12723	651	621	582	18.9	20.5	21.9
	Mean	11340	11060	11058	587	609	557	19.4	18.2	19.8
Limited	2006	8916	7851	9723	345	402	395	25.8	19.5	24.6
	2007	8484	7378	9436	386	491	454	22.0	15.0	20.8
	2008	10451	9611	11628	454	539	518	23.0	17.8	22.4
	2009	8301	6577	6136	481	549	455	17.3	12.0	13.5
	2010	10129	8896	8426	441	522	465	23.0	17.0	18.1
	Mean	9256	8063	9070	421	501	457	22.2	16.3	19.9

Table 4-2. RMSD and NOF for original and new model simulations, both irrigation treatments, and outputs of yield, ET, and WUE.

Statistic (unit)	Treatment	Yield, kg/ha		Cumulative ET, mm		WUE, kg/ha-mm	
		Old	New	Old	New	Old	New
RMSD (output unit)	Full	1523	1521	38.8	39.1	3.45	2.98
	Limited	1229	1451	80.9	49.9	5.97	2.86
NOF (unitless)	Full	0.134	0.134	0.066	0.067	0.178	0.153
	Limited	0.133	0.157	0.192	0.119	0.269	0.129
RE (%)	Full	-2.47	-2.49	3.64	-5.21	-6.53	1.76
	Limited	-12.90	-2.01	18.79	8.54	-26.70	-10.46

Before evaluating all of the years as a whole, it is important to note that simulated yield was much lower than the observed yield for both treatments in 2009, as compared with the other years (Table 4-1). This occurred for several reasons, the first being that planting occurred later than any other year evaluated (DOY 133, or May 13). Other years were planted between DOY 121 (April 30 in 2008, a leap year) and DOY 130 (May 10 in 2006 and 2007). Because of this delay, the simulation for 2009 was already predisposed to transition into subsequent growth periods later in the calendar year. Additionally, 2009 was the coolest year of the five, with the coldest average temperatures for several months of the growing season. Because growth stage advances in CERES-Maize are based strictly on thermal time, the simulated grain filling stage occurred much later than in normal years. Finally, in late September and early October the temperatures became very cold and the model halted further accumulation of grain biomass. Efforts were made to alter default temperature parameters governing grain growth, but no significant changes were obtained. It is also worth noting that 2009 yield observations were estimated based on bird damage.

Simulated yield barely changed under full irrigation, with the mean simulated yield over the five years differing by only 2 kg/ha (Table 4-1), lending very little statistical difference between the models (Table 4-2). Simulated yields under limited irrigation generally increased with the model change, with mean yield increasing by 1,007 kg/ha. Statistically, yield under limited irrigation had a slightly higher RMSD under the new model as compared with the original model, however RE improved from -12.9% to -2.0%. Both versions of the model simulated higher limited irrigation yields in 2006, 2007, and 2008 while simulating slightly lower yields in 2009 and 2010.

It is interesting to note the differences in WUE averaged among the years (Table 4-1). Observations indicated that WUE under limited irrigation (22.2 kg/ha-mm) was higher than under full irrigation (19.4 kg/ha-mm). Using the new model to predict WUE under full irrigation, the value is very close to observation (19.8 kg/ha-mm). However, despite statistically improved simulation of WUE under limited irrigation, the model fails to note the observed increase in WUE for this treatment, with simulated WUE of 19.9 kg/ha-mm being nearly the same as under full irrigation. If increased WUE is possible under limited irrigation management, as the observations from this study suggest, future efforts should be made to further improve both yield and ET simulation under such irrigation management.

Simulated ET under full irrigation was previously slightly overestimated on average (mean of 587 mm observed and 609 simulated, RE = 3.6%), whereas the new model now slightly underestimates ET (simulated mean of 557 mm, RE = -5.2%). Statistically, when including 2009 data, there was little difference in simulated ET under full irrigation (RMSD of 38.8 mm for the original model, and 39.1 mm for the new model). However, there were significant improvements in ET estimation for the limited irrigation treatment as mean simulated ET was lowered from 501 mm to 457 mm. This was still higher than the observed (421 mm) but much improved statistically (RMSD of 80.9 mm for the original model and 49.9 mm for the new model). Furthermore, RE was reduced from 18.8% to 8.5%).

When including 2009 data, WUE (yield divided by cumulative ET) was slightly improved for full irrigation (RMSD decreased from 3.45 to 2.98 kg/ha-mm, RE changed from -6.5% to 1.8%) and significantly improved for limited irrigation (RMSD decreased from 5.97 to 2.86 kg/ha-mm, RE changed from -26.7% to -10.5%). Both irrigation treatments had similar RMSD values under the new model, an overall improvement over the original model where the RMSD was much higher for limited irrigation than for full irrigation.

The NOF statistic is convenient because it divides the RMSD by the mean observation, thus normalizing the value so it can be compared between data types. For full irrigation, there were no differences in yield while ET and WUE performed not quite as well as in the original model. Of the three outputs, Table 4-2 shows that cumulative ET under full irrigation had the lowest NOF (0.066), indicating that it was the best predicted overall, followed by yield (0.134) and WUE (0.153). The NOF for limited irrigation in the original model was the lowest for ET (0.119), followed by WUE (0.129) and yield (0.133). However, ET and WUE were dramatically improved, even indicating that WUE under limited irrigation (NOF = 0.110) is now predicted slightly better than under full irrigation (NOF = 0.148).

4.4 SUMMARY AND CONCLUSIONS

Previous efforts to use the CERES-Maize crop model under water stress have provided unsatisfactory results. A previous study (DeJonge et al., 2011) indicated that cumulative ET under limited irrigation treatments was significantly overestimated, a trend that could be very problematic if the model is used to determine consumptive use as defined by Colorado water rights laws. An effort was made in this study to evaluate and improve ET simulation under water stress while not detrimentally affecting other model processes.

The CERES-Maize crop model yield, LAI, and cumulative ET local sensitivity was evaluated using both full and limited irrigation treatments, using data available from years 2006 through 2010. This sensitivity analysis was performed in an effort to quantify potential changes in the maximum crop coefficient (EORATIO) to determine ET demand, as well as the KEP parameter that determines partitioning of ET demand into potential soil evaporation and potential plant transpiration as a function of LAI. Results showed that under full irrigation, increasing EORATIO could increase predicted cumulative ET, but under limited irrigation increasing K_{C_LAI} led to significantly decreased predicted yield and vegetative growth with no change in ET. Changes to KEP essentially had no effect on full irrigation (as ET demand was met regardless of partitioning), but decreasing KEP allowed for higher predicted yield and leaf growth under limited irrigation. It is recommended to change the default value of KEP from 0.685 to 0.5, also suggested by López-Cedrón et al. (2008) and Sau et al. (2004).

In the previous version of the model, ET demand was determined by multiplying reference crop ET by a crop coefficient of 1.0 (or higher, with changes to model code). While this method has worked well in the past, few studies have emphasized ET accumulation under water stress, in which case this method is unreasonable. Because a stressed crop has a smaller leaf area than a full canopy crop, the ET demand and subsequent actual ET will be less. Therefore, a new equation was proposed that calculates a dynamic crop coefficient as a function of LAI, which changes daily throughout the simulation. The dynamic equation results in a crop coefficient relationship that very closely correlates to that suggested by FAO-56 (Allen, 1998) under full irrigation. Previously, ET under the stressed crop would equal ET under the nonstressed crop if additional water was applied during the reproductive stage; now ET during the reproductive stage is limited based on plant canopy so ET under limited irrigation will be less than under full irrigation once stress has been applied. This new model change vastly improved ET estimation under limited irrigation, thereby significantly improving WUE estimation under limited irrigation as well. WUE under full irrigation was also improved with this model change.

As the addition of this new K_{C_LAI} function and changing of KEP created more accurate simulations of yield and ET overall, it is recommended to continue work with this new combination of parameters. While not an easy proposition, the ability of

CERES-Maize and other DSSAT models to further improve crop response prediction to limited water, especially in regard to ET, could be again strengthened by working toward more physically and physiologically-based model processes. Such model enhancements could be based on stomatal conductance and other parameters that are inputs to physically-based ET models. Increased multidisciplinary collaboration between model programmers, field experimentalists, and plant physiologists will be necessary to carry out such an endeavor.

CHAPTER 5. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

As irrigation management paradigms evolve, it is expected that limited irrigation (where the crop is intentionally stressed during non-critical vegetative growth stages to reduce ET) may become a more viable option. Because of Colorado water law, quantification of ET is a tremendously important factor in water rights transfer, and is a necessity when considering limited irrigation practices. Although crop models show tremendous computational potential in evaluating various management objectives in terms of risk and uncertainty analysis, the CERES-Maize crop growth model has traditionally been calibrated based on non-stressed conditions and has difficulty accurately simulating stressed crops. The research presented herein was an effort to determine how well the CERES-Maize model simulated stressed crops (especially in terms of yield, ET, and LAI), and to evaluate the influence of both input parameters and model processes on the outputs of interest.

The first study provided a statistical analysis comparing full and limited irrigation treatments, and quantified the ability of CERES-Maize outputs to match field observations of ET, crop growth, and yield. While yield and full irrigation LAI simulation was generally acceptable, the model underestimated LAI and overestimated ET under limited irrigation, and also underestimated ET under full irrigation. This discovery caused further concern, especially in regard to the model's ability to simulate ET under stress, and led to the other two papers in this dissertation.

Next, a global sensitivity analysis was conducted on the two irrigation treatments, using both the Morris and Sobol' sensitivity methods. Global sensitivity analysis is more robust than local sensitivity analysis in that, instead of varying one parameter at a time around baseline values, it simultaneously evaluates multiple input parameters through the entire possible parameter input space and can identify interactions between inputs. The same outputs were evaluated as in the previous paper, and both sensitivity methods gave results that were highly correlated. Growth processes that define phenological development and successive leaf tip appearances showed no difference in sensitivity between treatments, expected because these processes are strictly based on thermal time and are unaffected in the model by water stress. Yield, maximum LAI, and cumulative ET all were mostly sensitive in the full irrigation treatment to cultivar parameters that are recommended for use in calibration. However, in limited irrigation these three outputs became increasingly sensitive to inputs affecting water holding capacity, suggesting that these parameters may be important for calibration as well when evaluating stressed crops.

Finally, the model processes that govern major aspects of the water balance, particularly the calculation of potential ET and the partitioning of this value into potential soil evaporation and potential plant transpiration, were evaluated and improved. Instead of the potential ET being a result of a default crop coefficient of 1.0 times the reference ET, a new function for the crop coefficient as a function of LAI was added to better represent the ET demand based on plant canopy. This new equation, as well as a new coefficient determining ET partitioning, were evaluated using five years of management and weather data, and both irrigation treatments. Under full irrigation estimates of yield and ET changed slightly, so that while mean yield and ET were generally unchanged, WUE were simulated closer to observations. Under limited irrigation, ET simulations were significantly improved, creating vastly improved estimation of WUE. Although WUE under limited irrigation is now simulated much closer to observations, observed WUE under limited irrigation showed an increase over full irrigation WUE while the simulations did not. Therefore, there is further potential for model improvements regarding simulation of yield and ET under limited irrigation. With these new improvements it is intended to further examine trends of the model to predict water production curves under various forms of limited irrigation management. Preliminary results of this study are included in Appendix A of this dissertation.

The general conclusion of this body of work is that the original CERES-Maize model functions that simulate ET are inadequate in regard to water stressed conditions, an issue that has been addressed in this dissertation. It is recommended that model developers consider inclusion of the new equation to determine crop coefficient as a function of LAI in CERES-Maize and all other DSSAT models, as this model improvement will likely create more accurate ET simulation of other crops under water stress. While this model improvement is a large step forward, it is also suggested that ET simulation could be further improved by adding modules that consider physiological responses to stress, such as control of stomatal conductance or effects of canopy temperature, to better simulate plant response to limited irrigation management as described in this dissertation. Such a model improvement would likely be the result of a multidisciplinary collaboration between crop modelers, field experimentalists, and plant physiologists.

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APPENDIX A. APPLICATION OF NEW MODEL FOR WATER PRODUCTION FUNCTIONS

A.1. BACKGROUND

Chapter 4 of this dissertation improved model simulation of evapotranspiration (ET) under water stress, more closely matching observations from field experiments. It is desirable to use this new model to predict water production functions (WPFs), or the relationship between yield and ET, using various forms of limited irrigation management. While a thorough evaluation of these relationships is beyond the scope of this dissertation, a preliminary modeling exercise was conducted to illustrate the potential utility of the model and is detailed in this appendix. This demonstration used the calibrated, validated, and improved model to evaluate potential for improved water use efficiency (WUE) under various methods of limited irrigation management.

The objectives of this effort were 1) to evaluate WPF for various alternate limited irrigation management scenarios and to define a WPF for these types of management and 2) to evaluate various levels of water stress during vegetative growth stages from limited irrigation management to see if the newly simulated yield and ET values differ from the WPF found in the earlier objective.

A.2. METHODS

To evaluate the irrigation scenarios mentioned above, the new model was run using the irrigation treatments from the field experiment (full and limited irrigation), along with three other theoretical treatments (Table A-1). All scenarios were run using observed input data from 2006 through 2010, except that the theoretical irrigation treatments were modifications of the observed irrigation data. In the new irrigation treatments, irrigation timing was based on the full and limited irrigation treatments, in that irrigation occurred only on the same dates as for the observed treatments, but the irrigation quantities varied toward a specific objective.

In order to further evaluate the effectiveness of the limited irrigation management treatments as applied in these studies and to test the model using climate scenarios outside of those used in the model parameterization, an additional comparison was made, creating virtual limited irrigation experiments with varying levels of stress. Five years of historical weather data were used, from 2001 to 2005, using the onsite CoAgMet weather database for weather inputs (FTC03, any missing data was replaced by the nearby FTC01 Fort Collins station). All precipitation data was deleted and replaced with a weekly "artificial" water application. During the vegetative stage, these applications varied from 2.5, 5, 7.5, 10, and 20 mm per week. During the reproductive and maturity stages, these weekly water applications were set at 50 mm to ensure a full water profile. All other initial conditions and management inputs were taken from the previous simulations of the 2008 full irrigation, including planting day of year, nitrogen applications, initial water conditions, etc.

Table A-1. Observed and hypothetical irrigation treatments explored with new model.

Treatment	Description	Goal
Full (observed)	Irrigation applied to meet ET demand throughout the season	Achieve maximum yield, zero stress throughout season
Limited (observed)	During vegetative stage, irrigations only applied to establish stand. Full irrigation during reproductive stage	Intentionally stress crop during vegetative stage but minimize stress after reproductive stage
50% full (hypothetical)	Irrigation events on same days as full irrigation, but 50% of full	Reduced irrigation amount with no change in irrigation timing
Full Anthesis Only (hypothetical)	Same as 50% full treatment, but full irrigation amounts are within a week of anthesis date	Reduced irrigation amount with no stress during sensitive reproductive stage
Stress Anthesis Only (hypothetical)	Same as full irrigation treatment, but zero irrigation is applied within a week of anthesis date	Maximum stress during sensitive reproductive stage with no irrigation reduction otherwise

A.3. RESULTS

The new model was applied to the two observed irrigation treatments, as well as three new hypothetical irrigation treatments (Table A-1), and yield was shown as a function of ET (Figure A-1). As discussed in Chapter 4, the model poorly matched 2009 data in any treatment because of abnormally cold weather conditions and this data was, therefore, omitted from this analysis. Full irrigation, as expected, has both high yield and high ET, whereas limited irrigation has lower values for both outputs overall. The full irrigation, Full Anthesis Only, Stress Anthesis Only, and 50% Full treatments all appear to form a linear relationship (best fit line shown has R^2 of 0.901). However, the limited irrigation treatment as shown in this figure is distinctly different from this relationship in three out of four years, indicating that the model predicts higher yield for given values of ET when stress occurs at the vegetative growth stage only.

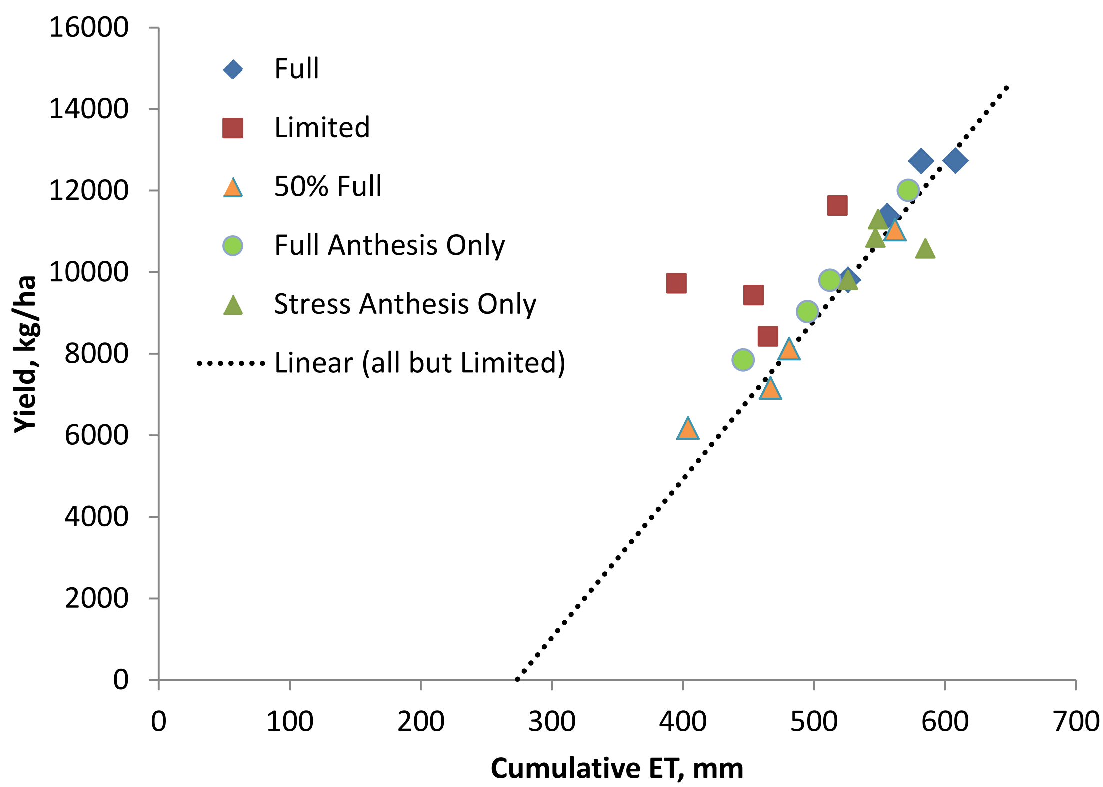

Figure A-1. Model-predicted water production functions for two observed irrigation management treatments and three hypothetical treatments.

Because the limited irrigation treatment shows values above the linear yield ET fit, further model simulations were performed using variations of limited irrigation management. To ensure that simulations were not biased to the years used in calibration and validation, weather inputs from 2001 to 2005 were used. To control the crop response to water inputs, precipitation data was erased and replaced with a hypothetical precipitation schedule that would ensure water management similar to the limited irrigation treatment, in that there is water stress applied during the vegetative growth stage but no stress in the reproductive stage. A weekly precipitation schedule was applied, with 2.5, 5, 7.5, 10, and 20 mm each week during the vegetative stress stage (for a total of 11 weeks from planting), and ET demand fully met during the reproductive stage with 50 mm each week.

Individual values for yield and cumulative ET are plotted for each treatment (Figure A-2), along with the best fit line from Figure A-1 that represents the linear water production function assumed for other types of management. On average the 20 mm treatment, which essentially represents a full irrigation simulation because there is minimal stress applied, lands very near the line of the water production function. Under this limited irrigation management strategy, however, the CERES-Maize model predicts that significant savings in ET can occur with minimal losses to yield. As each treatment applies less water, there is a slight drop in yield; however ET is reduced relatively more, creating points that are above the linear water production function curve. One can visualize the potential for separate ET-yield relationships for the individual irrigation treatments (save for the 2005 year that has higher ET than the others). As less irrigation is applied to the vegetative growth stage, the potential ET-yield relationships appear to shift more to the left (less ET while retaining high yields). WUE (Figure A-3) is also shown, indicating that treatments with less water applied during the vegetative stage have a higher WUE as well.

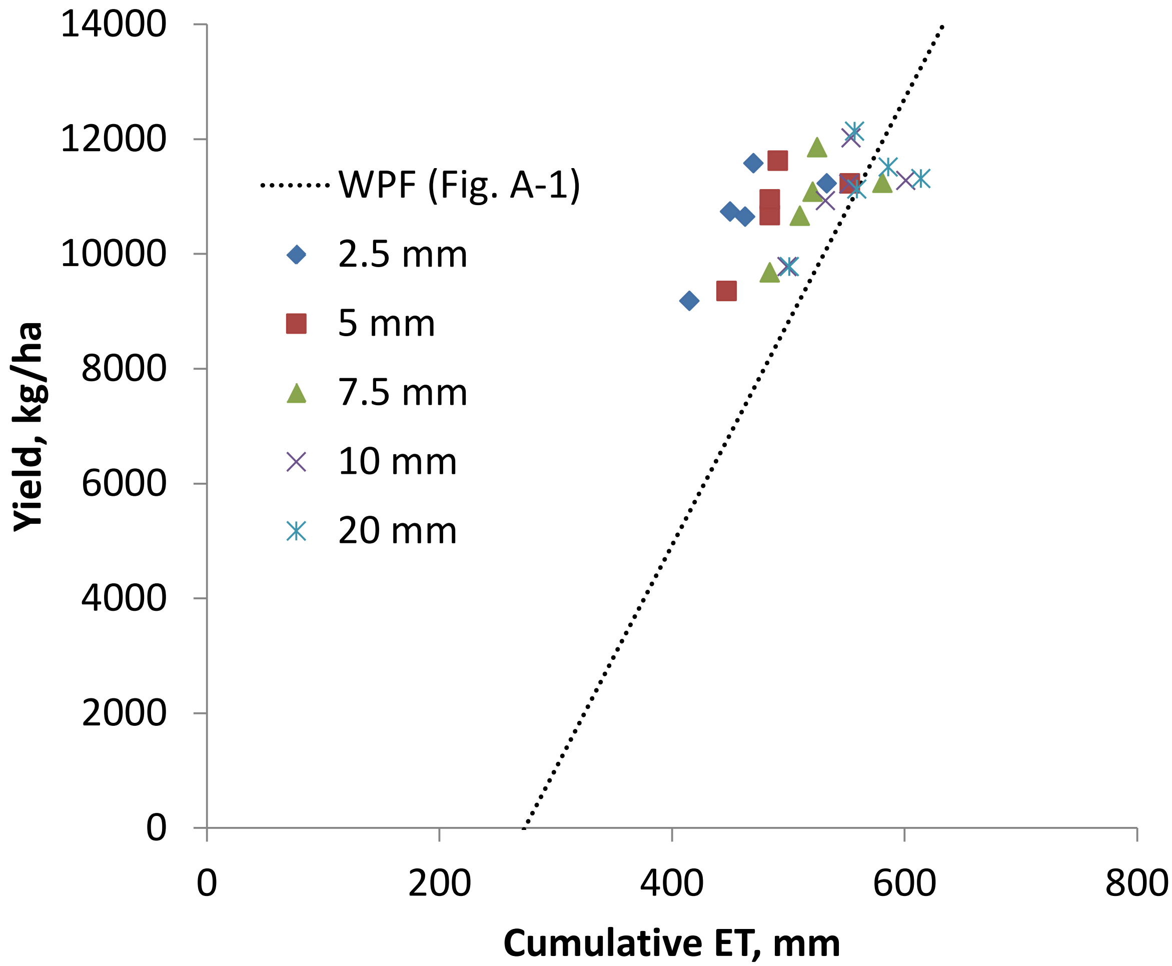

Figure A-2. WPF simulations using hypothetical limited irrigation treatments. Dotted line taken from WPF line defined by Figure A-1. Treatment name in legend indicates weekly irrigation amount during the vegetative stage (mm). No water stress occurred during the reproductive stage for any treatment.

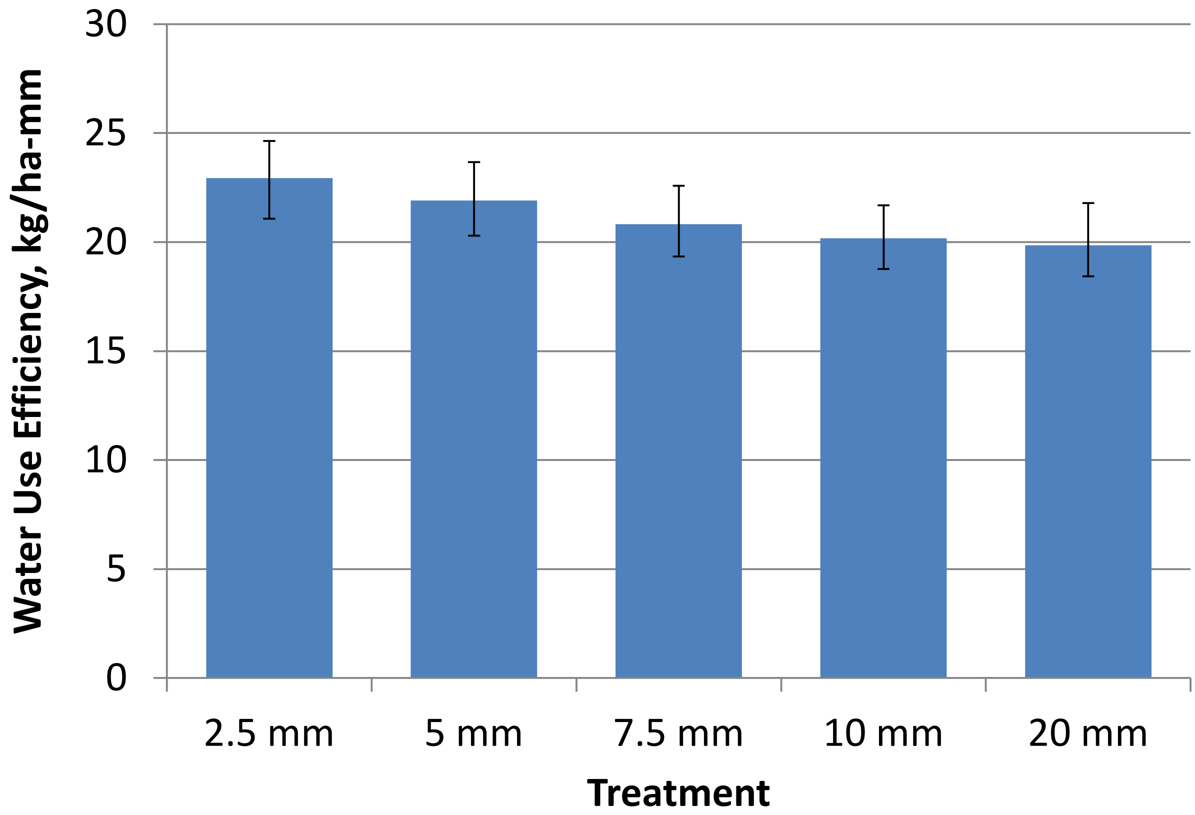

Figure A-3. Mean simulated water use efficiency (yield divided by cumulative ET) for varying treatments, indicating weekly precipitation amount during the vegetative growth stage. Error bars indicate minimum and maximum values from the five years simulated.

A.4. DISCUSSION

The results of these simulations indicate that the new CERES-Maize crop model predicts that higher WUE of corn can be obtained through limited irrigation management where the crop is water stressed during the vegetative growth stage, and where there is no stress during or following anthesis. It seems, as indicated by Figure A-2, that the water production function may be parallel to what is considered a typical water production function for full irrigation management or otherwise, but has the potential to have the same yield for smaller amounts of ET (i.e., WPF may shift upward).

Field studies, as shown in DeJonge et al. (2011) indicate there may indeed be physiological potential to increase WUE through limited irrigation management. While the model was calibrated, validated, and improved to better simulate limited irrigation management as outlined in this dissertation, it was important to evaluate potential outcomes with new weather datasets as shown in this appendix. The results suggest that limited irrigation may have a role in improving crop WUE. The results further suggest that development of crops with higher potential water productivity should consider separately the effects of water stress during vegetative and reproductive growth stages. As knowledge about water stress improves, especially in terms of physiologic responses, these outcomes should be incorporated into new versions of this model and others.

It is also likely that increases in WUE as described here may not be attainable in every year under limited irrigation management, as there is inherent variability and randomness in precipitation and other weather patterns that will ultimately dictate the final yield and ET. For example, in a season with a wet spring and little potential to apply water stress during the vegetative stage, there may not be the opportunity to save ET during the early growth stages. It may be desirable to compare a more controlled physiological experiment to the model using a rainout shelter and/or greenhouse tests.