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Using the CERES-Maize Model to Create a Geographically Explicit Grid Based Estimate of Corn Yield Under Climate Change Scenarios

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USING THE CERES-MAIZE MODEL TO CREATE A GEOGRAPHICALLY EXPLICIT GRID BASED ESTIMATE OF CORN YIELD UNDER CLIMATE CHANGE SCENARIOS

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ABSTRACT

The CERES-Maize model was evaluated in its capacity to predict both regional maize yield and water use within the United States Department of Agriculture (USDA) Economic Research Service (ERS) Region 1 between the years 1997-2007. A grid based, geospatially explicit method was developed to express the various rainfed and irrigated maize cultivars grown across the region. Overall, the calibrated model compared well for both physiological and yield parameters, producing significant linear relationships ($p<0.05$) between observed and predicted values for days to anthesis, days to maturity, and total yield under both rainfed and irrigated conditions. The validation results also produced strong correlations for days to anthesis and total yield; however days to maturity did not compare as well ($R^2<0.5$). After the calibration and validation process, regional estimates of evapotranspiration and irrigation for eastern Nebraska and South Dakota were produced. The results were comparable to previous studies in the region.

The calibrated and validated CERES-Maize model was used to predict potential evapotranspiration and yield under three IPCC weather scenarios for the year 2050 to evaluate crop production under climate change. Regional evapotranspiration was predicted to increase for both rainfed and irrigated maize; however, declines were predicted in rainfed evapotranspiration for the states of Indiana and Ohio. Regional maize yields were predicted to increase under both rainfed and irrigation conditions compared to the baseline (1997-2007) conditions. Despite the increases in overall maize yield projected across the region as a whole, large declines were observed in certain areas such as Illinois, Indiana, and Ohio under rainfed conditions and South Dakota under irrigated conditions. Overall irrigation demands declined in Nebraska and South Dakota. The results suggest that maize production could improve under climate change scenarios, and shifts in production to western locations could maximize production in 2050.

This thesis is approved for recommendation

to the Graduate Council.

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DEDICATIONS

Regressions are like women. You never understand them fully. When you *think* you do, the next model is entirely different.

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CHAPTER 1 - INTRODUCTION

The agricultural sector faces serious challenges from a variety of issues in the near future. Current population estimates indicate that the human population will surpass 9 billion by 2050 (United Nations, 2011). The consequences of this expansion become more ominous when one considers that over 1 billion went hungry and undernourished worldwide in 2009 (Paoletti, Gomiero, & Pimentel, 2011). With so many people already lacking adequate food resources, some experts have argued that humans will need to increase food production between 70–100% to meet the future needs (Godfray, et al., 2010). This places agriculture center stage in a battle between a rapidly growing human population and Earth's carrying capacity. Agriculture will face many challenges never before seen by food producers.

With a growing human population and an increased demand for food, the natural presumption would be to increase the number of acres planted. Unfortunately, this may not be possible as the human population may be reaching the limits of arable land. In the year 1700, the human population reached roughly 650 million. At this time, the amount of arable land in production was roughly 220,000 hectares. During the next 260 years, the human population grew to 3 billion, and the amount of arable land in production kept pace and increased to roughly 1,100,000 hectares. Since 1961, the human population has increased over 114%, from 3.081 billion to 6.593 billion in 2006. During the same time, arable land only increased 10.1%. This statistic implies that, while in the past there may have been room to expand cropland to meet demand, this will be less of the case in the future (The Land Commoditites Global Agriculture & Farmland Investment Report, 2009). In addition, while there will not be enough land to increase crop production, current available arable land will also be limited by future land use changes.

Arable land is likely to see only minor increases in the future, as any expansion will be countered by urbanization, salinization, and desertification (Fedoroff, et al., 2010). This puts a major growth constraint on agriculture as farmers cannot simply continue the traditional strategy of increasing planted areas to increase production.

Without major increases in available land, agriculture will need to increase the productivity of existing land. Since the 1930s, agricultural yields in the US have increased drastically. This increase is a result of many factors including hybrid cultivars, increased fertilizers use, the development of mechanical operations, and recent advances in genetic engineering technology (Karlen, Archer, Liska, & Meyer, 2012). During this time, crop yields, especially corn, have had a distinct linear trend with yields increasing each year since the 1930s (Egli, 2008). These trends may continue, at least in the short term, due to improvement in genetically modified varieties. Whether technologic advances can continue to sustain these growth trends long term, however, is currently unclear. In some parts of the world, yield plateaus have developed including rice in the Republic of Korea and China, wheat in northwest Europe and India, and maize in China (Cassman, Grassini, & Wart, 2011). The author also speculates that even irrigated maize yields in the US have begun to plateau, although a few more years of data are needed to confirm this trend. Regardless, this is a very troublesome statistic, as crop yield plateaus are occurring in some of the world's most productive systems. Maximizing productivity will become an even more vital goal in the near future, and can only be achieved through efficient management of agricultural inputs. This is especially true for the United States most valuable crop: maize.

US MAIZE

Based on 2003 data, the FAO estimated that 40% the world's maize production was grown in the United States (Karlen, Archer, Liska, & Meyer, 2012). To put the magnitude of US maize production in perspective, maize for grain was the US's largest field crop in 2007, including 347,760 farms, 86,248,542 total acres planted, and 12,738,519,330 bushels harvested. Of the planted acreage, 13,156,769 were irrigated, making maize the most irrigated crop in the US (NASS U. , 2007). Maize's importance in the US economy makes its management a top priority. One of the greatest concerns in the near future will be the ability of the United States to not only sustain maize production at current levels, but continue to maximum maize yields while maintaining agricultural integrity.

WATER CONSUMPTION

The increased demand for agricultural output will put a major strain on production and agricultural input resources. This is especially true for one of agriculture's most important inputs, water. Freshwater is a finite resource that varies enormously in time and space. Increased agricultural demand coupled with a growing population will put pressure on water resources. In order to meet the acute freshwater challenges facing humans in the next fifty years, substantial reductions in agricultural water use will have to be made (Mekonnen & Hoekstra, 2010). This fact has led to the development of several studies concerning water consumption, and the concept of "water footprints" which started under the calculation of national water footprints and their subsequent trade around the globe (Hoekstra & Hung, 2002). This concept has since evolved and now encompasses many different aspects including the water footprint of products, consumers or groups of consumers, geographically delineated areas, nations, catchments and/or river basins, administrative units, or businesses (Hoekstra, Chapagain, Aldaya, & Mekonnen, 2011). The water footprint of a crop consists of three major components: green, blue, and grey water. The green water footprint comprises the water used that is derived directly from rainwater. Blue water footprints are made up of the water consumed from surface or ground water storage resources. Grey water footprints are defined as the volume of freshwater that is required to assimilate the load of pollutants based on natural background concentrations and existing ambient water quality standards (Hoekstra, Chapagain, Aldaya, & Mekonnen, 2011). Knowing the geospatial extent of blue and green water withdrawals can lead to better management of the agricultural systems in which they are grown. Unfortunately, few studies have attempted to define blue and green water use in the United States in a grid-based manner, and instead have focused on analysis at the global level.

Several studies have attempted to define global trends in water consumption. Early attempts at water footprinting were made by Hoekstra and Hung (2002) who looked at the water consumption of different nations. This early study did not distinguish between blue and green water use. Several later studies expanded on the blue and green water consumption of crops. Rost et al. (2008) used the dynamic global vegetation and water balance model (LPJmL) to estimate the agricultural blue and green water consumption of eleven major crop categories at a spatial resolution of 30' arc minute s. Siebert and Doll (2010) used the global crop water model (GCWM) to estimate the blue and green water consumption of 24 crops using a grid based approach at a spatial resolution of 5 arc minutes. Liu and Yang (2010) used a GIS-based version of EPIC (GEPIC) to estimate the blue and green water consumption of 20 crops across the globe at a spatial resolution of 30 arc minutes. Finally, Mekonnen and Hoekstra (2011) used the

CROPWAT model to estimate the blue and green water consumption of 20 crops at a 5 arc minute resolution.

While these articles have been essential to the understanding of global water consumption and virtual water trade between countries, all of them use nationwide assumptions for crop management that do not make them specific enough for use within any one nation for better crop management. It is for this reason that a United States specific grid-based approach is needed to determine better crop water management and provide a more specific insight to water scarcity issues. This type of study can help meet the challenges of future population growth and reduced freshwater resources, all in the face of climate change.

CLIMATE CHANGE

Defining water consumption of current agricultural production is of great importance in minimizing water consumption within in a product supply chain, or in the determination of water scarcity, but it greatest utility may be in determining future water demands to aid decision makers in policy preparation. Climate change, and its consequent impacts on water availability, may be agriculture's greatest antagonist. The potential effects of climate change were witnessed in Europe during the summer of 2003. During this time, a heat wave ran through Europe and killed an estimated 30,000 to 50,000 people. Summer temperatures averaged 3.5°C higher than that of the average for the last century and resulted in a 20-36% decline in yields of grains and fruits. If current projections are accurate, the temperatures witnessed in 2003 will become the average by 2050 (Fedoroff, et al., 2010). Coupled with increases in average temperature, drastic changes in weather patterns that result in droughts could amplify water scarcity across the globe.

In order to maintain high agricultural yields, any potential decreases in rainwater availability will need to be met with increased irrigation inputs.

Irrigation is in part responsible for the rapid increases in agricultural yields and outputs over the past few decades and remains one of the most critical inputs for farming (Rosegrant, Ringler, & Zhu, 2009). In the United States, agriculture accounts for 80% of the national consumptive water use and for over 90% of water use in many western States (Salazar, et al., 2012). Furthermore, agriculture accounts for roughly 70% of global freshwater consumption (Koehler, 2008). In addition, 53% of cereal production growth during 2000-2050 is expected to be met from irrigated agriculture (Rosegrant, Ringler, & Zhu, 2009). With irrigation playing such a great role in agriculture both now and in the near future, especially in the US, it will be important to model to in order to both predict and maximize water use efficiency for future crop lands.

MODELING STUDIES

A handful of studies have attempted to predict the influence climate will have on aspects of US agricultural production. Alexandrov and Hoogenboom (2000) conducted an assessment of the potential impacts climate change can have on agriculture. The authors examined the potential yields of several crops including maize, winter wheat, soybeans, and peanuts in the Southeastern US. The modeling strategy included using four general circulation models to create inputs to represent weather conditions for the 2020s. Two CO_2 fertilization scenarios were evaluated including current concentration and a doubling situation. Under current CO_2 concentrations, crop yield across all crops decreased within the entire study area. In relation to maize, yield decreased during the 2020s due to a decreased growing season and decreased precipitation during the early phenological stages of development. Under the CO_2 doubling scenario, maize and wheat yield decreased. Increased CO_2 concentrations had no significant impact on growth, development, or yield contrary to what is expected of a C_4 crop. The authors suggested several adaptation strategies including earlier sowing dates, changing hybrid varieties, and increasing fertilizer inputs in mitigate yield reductions.

Another major study concerning the impacts of climate change on agricultural productivity and irrigation supply in the US was conducted by a National Assessment Synthesis Team mandated by the government in 1990 (Izaurralde, Rosenberg, Brown, & Thomson, 2003). The authors looked at possible climate-change impacts on crop yields, yield variability, incidence of various stress factors on yield and on evapotranspiration and national crop production in the conterminous US. The authors also detail the impacts of climate change on US water resources. Climate data were obtained from the National Center for Atmospheric Research and were the results from the Hadley Center Model (HadCM2) general circulation model (GCM) for the period 1994-2100. A watershed approach was used along with representative farms to characterize soil-climate conditions prevailing in each of the 4-digit Hydrological Unit Area (HUA) basins. In addition, the EPIC model was used to simulate grain yield of corn, wheat, soybean, and alfalfa. In relation to maize, projections indicate the yields will decrease 45% below current levels, but somewhat recover by 2095 due to CO_2 fertilization in the Mountain West, Northern and Southern Plains. The Corn Belt, Great Lakes, and Northeast regions will see yield increases due to lower incidence of low-temperature extremes. The authors also indicated irrigation requirements for maize will decrease due to suppressed transpiration.

While the aforementioned studies provided a great deal of insight as to the potential consequences of climate change on agricultural production in the US, they failed to provide output data that could be useful for other types of studies such as water footprinting or scarcity indexing. A high resolution, grid based approach is needed that could simulate present and future levels of both the yield and water demands, as well as provide a geospatially explicit expression of water use that could be used to inform management decisions. It is for this reason the author decided to undertake this research project.

MODEL SELECTION

The criteria for model selection was that it be scaled to the regional level as well as allow for a multitude of agricultural inputs from different sources. The model had to be sensitive to climate, and therefore have high spatial resolution with regards to the impact of temperature and water on growth stages and yield. The model had to be sensitive to geographic characteristics, including soil type, day length, and seasonal temperatures. Several physical process models were considered for the study including the Lund-Potsdam-Jena managed Land model, the Global Crop Water Model, the Environmental Policy Integrated Climate model, CROPWAT, and the CERES-Maize model.

LPJmL

The Lund-Potsdam-Jena managed Land (LPJmL) model is a dynamic global vegetation and water balance model that predicts the establishment, growth and productivity of the world's major natural and agricultural plant types, and the associated carbon and water fluxes as well as their spatiotemporal variations in response to climate conditions and human interactions such as irrigation on a daily time step (Rost, et al., 2008). The model has been developed recently and uses a grid-based approach at a 0.5 degree resolution. Water use is based on crop evapotranspiration potential and lacks the ability to implement specific crop management practices as focuses more on land use definitions.

GCWM

The Global Crop Water Model (GCWM) was developed to simulate crop water use in rainfed and irrigated agriculture. The model uses a spatial resolution of 5 arc minutes and considers 26 crop classes (Siebert & Doll, 2010). Crop water use is predicted with a soil water balance routine in combination with evapotranspiration values calculated using FAO methodology. The FAO methods rely on reference evapotranspiration values and apply a reduction coefficient to calculate actual evapotranspiration for different cropping classes (Allen, Pereira, Raes, & Smith, 1998). The FAO method has been used in a number of studies to predict crop water requirements, but lacks the ability to implement specific cropping practices. The GCWM also does not allow for specific crop management to be incorporated into the model.

GEPIC

The Environmental Policy Integrated Climate (EPIC) model was developed by the USDA-ARS and TAES. The model operates on a daily time step to simulate major soil-crop-atmospheric process. Potential crop yield is simulated based on the interception of solar radiation, crop parameters, leaf area index (LAI) and harvest index (HI). Crop growth is decreased by stresses caused by water, nutrient deficiencies, extreme temperatures, and poor soil conditions. The model was adapted to run within an ArcGIS interface, hereby known as GEPIC (Liu, Williams, Zehnder, & Yang, 2007). The model is very comprehensive and incorporates parameters for production practices and runoff volumes. Evapotranspiration can be calculated a number of ways including the Hargreaves, Penman, Priestley-Taylor, Penman-Monteith, and

Baier-Robertson methods. Irrigated areas are defined according to a digital global map of irrigated areas generated by the Center for Environmental Systems Research. Irrigated volumes are calculated by dividing the irrigation water use provided by AQUASTAT by total irrigation area in individual countries.

CROPWAT

CROPWAT is a decision support system developed by the Land and Water Development Division of FAO. The model uses FAO evapotranspiration equations to calculate reference evapotranspiration, crop water requirements and irrigation requirements in order to develop irrigation schedules under various management conditions and water supply levels. CROPWAT uses the Penman-Monteith method for determining reference crop evapotranspiration and the development of irrigation practices are based on a daily soil-moisture balance (Feng, Liu, & Zhang, 2007). The model utilizes a global network of weather stations to represent climate data and cannot use grid based inputs for analysis without extensive data alteration.

CERES-Maize

The CERES-Maize model was developed by Jones and Kiniry (1986). Over the years, the model has been improved through several updates and is now included in the software package DSSAT-CSM, the Decision Support System for Agrotechnology Transfer – Crop Simulation Model (Jones, et al., 2003; Hoogenboom, et al., 2004). The CERES-Maize crop model is a dynamic simulation model that operates on a daily time step to predict crop growth in response to weather, soil, and management strategies. The model simulates phenologicaldevelopment, biomass accumulation and partition, and yield in a variety of environments and scenarios. The model can use different approaches to simulate evapotranspiration including the Priestley-Taylor and the Penman-Montieth method. Irrigation can either be scheduled or applied automatically using user specified conditions.

MODEL COMPARISON

A weighted objects table was used to determine which model would be used for the study. Potential models were evaluated in five categories, including ability to be scaled for a regional analysis, ability to be applied for climate change scenarios, ability to perform in a US cropping environment, ability to allow comprehensive management inputs for future studies, and ability to use high resolution gridded input and produce gridded outputs. Weights were assigned according to the relative importance to the study (Table 1). The models LPJmL and GCWM were developed for global applications and thus rely on national level inputs making them inappropriate for a regional analysis. In addition, they do not allow for detailed managed input. The CROPWAT model uses a comprehensive database of weather stations. However, using these stations becomes difficult when particular areas within a region are not covered or have multiple potential representative stations and scored low in utilizing gridded inputs and outputs. Both the GEPIC and CERES-Maize models scored highly for this application. Between the two, CERES-Maize was the more vetted of the two, and was chosen for the study.

GOALS AND OBJECTIVES

The goals of this research were to determine if the CSM-CERES-Maize could be used to quantify yield over a large geographic area, to quantify the impacts of water scarcity on corn yield, and to predict corn yield under future climate scenarios. This research could assist both farmers and policy makers with expectations for future yield losses under climate change and improve water resource management decisions in order to mitigate potential yield losses. The main objectives of the research included:

1) Develop a crop model calibration approach for use in regional studies with limited input data to predict maize yield.
2) Develop a crop model capable of assessing regional water use; more specifically, the blue versus green water use based on yield information.
3) Use the calibrated model outputs under future scenarios to determine the impacts of climate change on maize yield, and the volume of water required to mitigate any adverse yield effects that are scalable to the entire United States.

HYPOTHESIS

A set of hypotheses were constructed to evaluate the model's ability to predict the phenological development of maize and its subsequent yield at the regional level, which are the key characteristics of the predictive utility of the model. Furthermore, additional hypotheses were constructed to assess the potential impacts of climate change on current US maize production. The following hypotheses were tested in this project:

Modeling Hypothesis 1

H_0: The CERES-Maize model cannot predict the number of days in the development period from planting to anthesis with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

H_A: The CERES-Maize model can predict the number of days in the development period from planting to anthesis with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is significantly different from zero (probability greater than 0.95 (α=0.05)).

Modeling Hypothesis 2

H_0: The CERES-Maize model cannot predict the number of days in the development period from planting to maturity with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

H_A: The CERES-Maize model can predict the number of days in the development period from planting to maturity with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is significantly different from zero (probability greater than 0.95 (α=0.05)).

Modeling Hypothesis 3

H_0: The CERES-Maize model cannot predict maize yields with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

H_A: The CERES-Maize model can predict maize yields with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is significantly different from zero (probability greater than 0.95 (α=0.05)).

Projective Hypothesis 1

H_0: Mean regional maize yield will not be significantly different from current levels (mean yields from 1997 to 2007) under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

H_A: Mean regional maize yield will be significantly different from current levels (mean yields from 1997 to 2007) under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

Projective Hypothesis 2

H_0: Mean regional maize green water use will not be significantly different from current levels (mean yields from 1997 to 2007) under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

H_A: Mean regional maize green water use will be significantly different from current levels (mean yields from 1997 to 2007) under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

Projective Hypothesis 3

H_0: Mean regional maize blue water use will not be significantly different from current levels (mean yields from 1997 to 2007) under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

H_A: Mean regional maize blue water use will be significantly different from current levels (mean yields from 1997 to 2007) under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

TABLES

Table 1. Weighted objectives used for model determination for analyzing climate change impacts on US corn production.

		Model				
Category	***Weight***	**LPJmL**	**GCWM**	**GEPIC**	**CROPWAT**	**CERES-Maize**
Regional Adaptability	*25*	6	6	9	7	9
Climate Change	*15*	7	6	8	7	9
US Environment	*30*	6	6	9	6	10
Management Input	*15*	1	1	7	6	9
Gridded Input/Output	*15*	6	8	8	3	8
Total	*100*	26	27	41	29	45

FIGURES

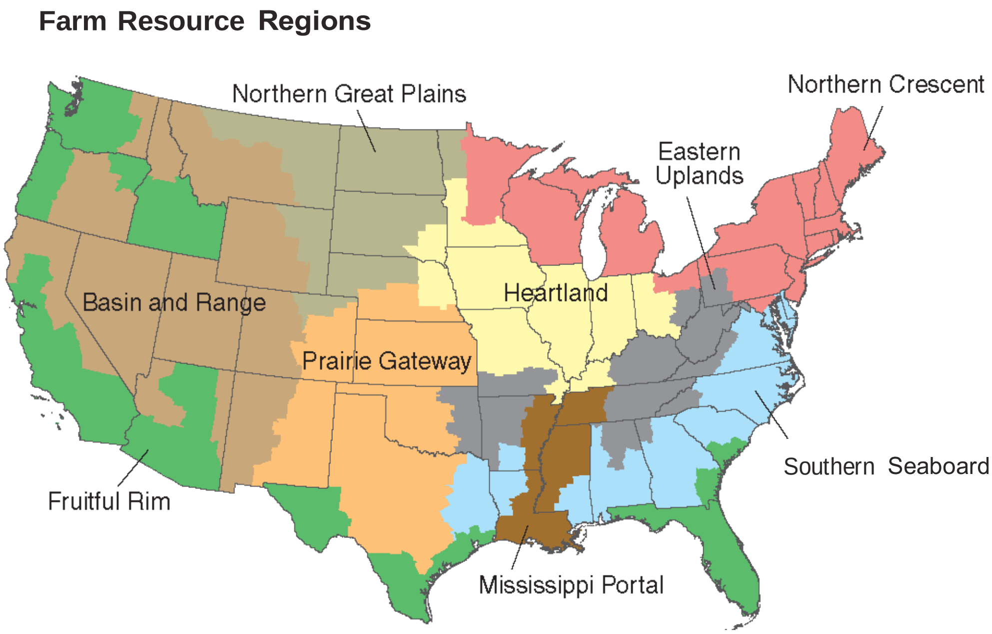

Figure 1. The USDA Economic Research Service (ERS) farm resource regions (Modified from (Hoppe & Banker, July 2010)

CHAPTER 2 - LITERATURE REVIEW

Crop modeling is an extensive process that takes into account a multitude of different environmental variables as well as human decisions to predict some aspect of crop production, usually yield. A modeler must understand the system that is to be modeled, and develop a process capable of producing the desired results. The following literature review of the current practices for modeling maize production represents the state of practice in crop modelining at regional scales. This review includes both calibration and validation procedures for regional maize modeling, and explores how the models can be used for climate change applications.

MAIZE MODELING

Corn production relies on many complex interactions to determine crop growth and yield, including management strategies (cultivar selection and cultivation techniques), soil properties (topography and initial conditions), and weather patterns. Most crop models were developed to assist farmers with management decisions at the farm level, where an assumption of homogeneity across a plot is often employed. However, policy decisions are rarely implemented at the farm level and decision makers need information at broader spatial scales where the homogenous environment assumption of does not hold (Hansen & Jones, 2000). To evaluate crop production at the regional level, crop models must be used to assess management strategies capable of increasing yields and reducing irrigation. These models allow researchers to understand the relationships between management strategies and crop response, without having to do it in the field.

In relation to model type, there are several varieties to consider. However, process oriented models are better equipped than regression models to extrapolate beyond the range of current climatic conditions because crop responses to varying temperature, humidity, soil moisture, and irradiance can be established through calibration at the leaf and whole plant levels in controlled climates. The whole plant response can then be evaluated in terms of the causal plant physiological processes such as photosynthesis, respiration, transpiration and translocation (Brown & Rosenberg, 1999). Furthermore, crop simulation models have the potential to for accurately simulate crop growth over a wide range of conditions with little or no adjustment for individual locations. Models can also generate forecasts of regional yields before harvest (Hodges, Botner, Sakamota, & Haug, 1987). The model should accurately simulate plant physiological processes, allow for the complex management inputs, and deliver estimated outputs in a comprehensive manner.

CERES-MAIZE MODEL

The CERES-Maize model was developed by Jones and Kiniry (1986). The model represents one of the most vetted and established maize models currently available. Over the years, the model has been improved through several updates and is now included in the software package DSSAT-CSM, the Decision Support System for Agrotechnology Transfer – Crop Simulation Model (Jones, et al., 2003; Hoogenboom, et al., 2004). The CERES-Maize crop model is a dynamic simulation model that operates on a daily time step to predict crop growth in response to weather, soil, and management strategies. The model simulates phenological development, biomass accumulation and partition, and yield in a variety of environments and scenarios.

The CERES-Maize model relies on user supplied inputs to simulate maize development. Obtaining the necessary cropping information can be a great challenge, especially when one considers cultivar type. The CERES-Maize model uses six phenological coefficients to describe cultivar specific development in response to photoperiod and temperature (Table 2). Plant life in the model is divided into several phases in which maize development, and the transition from one phase to the next, is governed by growing degree days (GDD). The GDD required to progress to the next phase are defined by the user (P1, P2, and P5), or are computed internally. The number of GDD occurring on a calendar day is a function of a triangular or trapezoidal function based on a base temperature (8°C for CERES-Maize), one optimum temperature, and a maximum temperature at which growth no longer occurs. Only temperature and day length affect GDD accumulation; drought and nutrient stress have no effect (Jones, et al., 2003).

Since its beginning, the CERES-Maize model has been tested in a variety of environments, including the United States Corn Belt. A few of the studies outside the United States include: Argentina (Ferreyra, et al., 2001), Australia (Carberry, Muchow, & McCown, 1989), Brazil (Liu W. T., 1989) (Soler, Sentelhas, & Hoogenboom, 2007), China (Binder, et al., 2008) (Xiong, Holman, Conway, Lin, & Li, 2008), Italy (Nouna, Katerji, & Mastrorilli, 2000) (Nouna, Katerji, & Mastrorilli, 2003), Kenya (Wafula, 1995), Nigeria (Jagtap, Abamu, & Kling, 1999), Portugal (Braga, Cardoso, & Coelho, 2008), Spain (Lopez-Cedron, Boote, Ruiz-Nogueira, & Sau, 2005), South Africa (Pisani, 1987), and Thailand (Asadi & Clemente, 2003). The extensive validation of the CERES-Maize model over a myriad of environments makes it an excellent choice for simulating crop production and subsequent water use in the Corn Belt.

In the 2005 study, Lopez-Cedron compared three versions of the CERES-Maize model to examine the possible differences between model predictions. Three CERES-Maize versions were compared, including CERES-2003, the official DSSAT V3.5 release or CERES-3.5, and DSSAT V4.0 of CERES-Maize, in a relative cool Spanish environment using field datasets between the years 1998 and 2002. The authors found that the CERES-Maize 4.0 simulated maize biomass and grain yield more accurately than the other versions. The principal reasons for this was that the new temperature functions, radiation use efficiency (RUE), and grain growth, implemented in the V4.0 model were less sensitive too temperature variations.

MODEL CALIBRATION PROCEDURES

It is necessary to calibrate the model to observed data prior to evaluating the utility of the model for applications. There exist two lines of reasoning associated with model calibration. The first involves using a trial and error approach, where genetic coefficients and/or soil parameter values are selected and used to simulate corn growth. The simulated corn growth is then compared to observed production values. With each new simulation, the coefficients or parameters are evaluated based on goodness fit to the observed dataset. New combinations of coefficients are based on the results of previous simulations and will continue to be refined until a calibrated dataset is found that reduces error when compared with the observed dataset to within an acceptable range. The second method involves using a more structured approach through optimization procedures. Optimum genetic coefficients were selected across a range of possible values using a grid search procedure. This was repeated until the physiological growth periods (days to anthesis and maturity) and corn yields matched the observed values within an acceptable error boundary. Both procedures have been implemented with success and have been documented in the current literature, as identified in the following literature review.

Programs have been developed to assist in the calibration process of the CERES-Maize model. One such model is Genetic Coefficient Calculator, GENCALC (Hunt, et al., 1993), which was developed to estimate genetic coefficients for a genotype iteratively by running the

CERES-Maize model with approximate coefficients and comparing the model outputs to actual data. The process is repeated until an optimum set of genetic coefficients is selected that result in simulated yield and physiological growth periods that most closely match observed values

GENCALC was compared with another program, Uniform Covering by Probabilistic Region (UCPR), based on their ability to estimate two phenological parameters; degree days from emergence to end of juvenile phase and photoperiod sensitivity (Roman-Paoli, Welch, & Vanderlip, 2000). UCPR has an advantage over GENCALC in that it provides both parameter estimates and a joint confidence region for the parameters. To evaluate program performance, the model output for dates to silking and maturity was compared to observed values for four hybrid cultivars grown in Rossville, Kansas during the 1995 season, producing several conclusions. When comparing both models predictive capability, based on observed versus predicted plots, the regressions produced intercepts that were significantly greater than 0 and slopes that were less than 1. Both models overpredicted early silking dates and underpredicted silking dates that occurred later in the season. The authors concluded that based on the ability of the UCPR method to produce realistic joint confidence regions along with better point estimates, it was the superior of the two methods. One downside to the UCPR method was long processing times that were are not associated with the GENCALC method.

Asadi and Clemente (2003) used the CERES-Maize model to investigate nitrate leaching, nitrogen uptake, corn yield, and soil moisture content in an acid sulfate soil in Thailand. The calibration procedure used in the study involved using a trial and error approach. Genetic coefficients describing maize phenological development were adjusted until there was a match between observed and simulated silking and maturity dates. Once a proper fit was realized, coefficients describing maize yield were optimized until simulated values for grain yield, weight, and number matched the observed values. The authors found a good fit between simulated and observed values for grain yield, with an R^2 value of 0.9726 for the years 1990 and 2000.

In a 1989 Brazilian study, Liu et al. calibrated the CERES-Maize model genetic coefficients for a hybrid cultivar grown in a tropical climate. Input data were obtained from field trials performed at Sete Lagoas and included maize grain yield, phenological cycle, plant population density, sowing depth, photoperiod sensitivity, dates of sowing, silking and physiological maturity. Observed soil data included drained upper limit, lower limit of plant-extractable soil water, saturated soil water content by volume, upper limit of Stage 1 soil evaporation and soil rooting depth. The calibration procedure involved a trial and error approach in which maize phenological coefficients were adjusted until the model estimates were in close agreement with observed values. Calibration was considered a success when maize grain yield was within 2% of observed values.

Yang et al., (2009), evaluated the CERES-Maize model under North Carolina growing conditions. The authors focused on calibrating the genetic coefficients using field performance trials under non-limiting nitrogen conditions. Four genetic coefficients and two soil parameters were used to calibrate for the 53 corn hybrids included in the study. Parameters were optimized by of minimizing root mean squared error between observed and simulated values. Estimation errors for coefficients used to describe anthesis and maturity dates were in line with results from other studies. The authors' simulated yields were plotted against observed values, and the data was linearly regressed. The results indicated that the simulated values were close to observed yields, with a linear regression slope of 0.98 and a coefficient of determination of 0.99.

REGIONAL MODELING WITH THE CERES-MAIZE MODEL

One of the earliest regional applications of the CERES-Maize model was the regional study conducted by Hodges et al. (1987) over the United States Corn Belt. Calibration of the model for each location involved defining five genetic coefficients for a cultivar in a particular location. Typically this process involves planting the cultivar over several dates and locations and measuring the leaf number, tasselling date, maturity date, grain number, and grain weight (Hodges, Botner, Sakamota, & Haug, 1987). However, for regional applications this approach is not possible as a broad study area can encompass dozens, or even hundreds, of different cultivars. Hodges et al. used an approach that tried to represent much of the crop variety within the study region. Data for the study originated from crop reporting districts or states and included average yield and dates for planting, tasselling, maturity (Hodges, Botner, Sakamota, & Haug, 1987). The calibration of the model involved making initial estimates of the five coefficients and iteratively changing the coefficients until the error between simulated and observed values was reduced at 51 different weather stations throughout the Corn Belt for 1982. The CERES-Maize model demonstrated success in estimating production for the Corn Belt from 1983 through 1985.

Jagtap and Jones (2002) used a grid based approach to model soybean yield and production in Georgia using the CROPGRO-soybean model. CROPGRO-soybean is a similar model to CERES-Maize as it uses crop growth on a daily time step in response to soil, weather, and management conditions, and is part of the DSSAT program. Inputs for weather and soil characteristics were pulled from the VEMAP database. To capture the regional variability of management inputs, including cultivars and cultivation practices, data was collected from published agricultural censuses, extension publications, and expert knowledge. Nine combinations of management inputs, including three commonly grown varieties, three planting windows, and two soil profiles, were used to capture the regional variability of the study area. Historical yields were used for calibration and were based on county level NASS data. The yields (from 1974-1990) were aggregated to 0.5 degree grids using an area weighted approach. Finally, a yield bias correction was used to reduce bias and systemic errors between observed and simulated yields. The model proved to be successful and was able to predict soybean production with 70% precision.

CERES-Maize has also been used to predict crop yield of within season maize under rainfed conditions in Delaware, USA (Quiring & Legates, 2008). Accurate commodity forecasts such as these can be a great tool for agricultural industries to improve risk management and decision making at the regional scale. The authors used a gridded approach to modeling, and the calibration of the model involved the use of field trial reports for three counties in Delaware to describe management inputs. Genetic coefficients were derived using the 'grid search approach' developed by Mavromatis et al. (2001, 2002). The authors found that the CERES-Maize model could be used to accurately simulate regional corn yields in Delaware; however, the model systematically overestimated yield since it did not account for disease outbreaks, pest, or effects of extreme weather. With the addition of a bias adjustment, the model was able to predict final yields with less than 1% error.

CLIMATE CHANGE CROP MODELING

Much of the current research on regional crop modeling has come in response to efforts to prepare for climate change. One such study was conducted by Southworth et al. (2000). The authors looked at current and future maize production in the Great Lakes region. Calibration of the model included first dividing the study region into 10 agricultural areas based on climate, soils, land use, and agricultural practices. Farms were chosen in each area to represent the regional growing conditions. Current parameters were selected from the VEMAP database. Future climate scenarios were derived from the Hadley Center model, HadCM2. After running the model for future scenarios, yields both increased and decreased across the region. Yields in the southern most states generally decreased as a result of maximum temperatures becoming too high. Yields in Northern States typically increased as a result of a longer growing season. The authors concluded that the long-season maize currently grown in the regions will have increased yields under future climate scenarios (Southworth, et al., 2000).

In a 1999 study, Mearns et al. compared the CERES crop models to the EPIC crop models in relation to climate change in the Great Plains region of the US. The purpose of the study was to determine if the two commonly used crop models responded differently to two climate change scenarios, one at a high resolution scale (RegCM) and one at a low resolution scale (GCM). Differences in crop model responses could be attributed to the different methods that each model uses to calculate temperature and moisture stress. In relation to water stress, CERES calculates a water stress factor (SWDF1) that is defined as the ratio of total root water uptake to plant evaporative demand. Plant evapotranspiration was determined using the Priestly-Taylor method which uses temperature and solar radiation as inputs. This is in contrast with EPIC, where the water stress factor (SW) is a function of the ratio of water use to the potential evaporation and leaf area index (LAI). The Penman-Monteith method was used to calculate potential evapotranspiration (PET) within EPIC, which accounts for humidity and wind effects. These differences resulted in EPIC responses being determined more by aggregate stress during the crop’s lifecycle whereas stress occurring during the grain fill period in CERES was the major determinant. The authors were quick to point out that neither model was particularly better suited than the other for regional agricultural production modeling.

In the 2007 study, Xiong et al. modeled potential maize production at the regional scale under climate change scenarios. The authors used a grid based approach to model maize production in mainland China. Calibration of the model involved defining genetic coefficients for five different cultivars using data from 1990-1997 conducted at four agricultural experimental stations located across China. Once calibrated, the cultivars were used in each grid along with future climate data obtained from PRECIS. At the field level, simulated values were in agreement with observed values and resulted in an R^2 of 0.99. However, once these cultivars were modeled at the regional level, the correlation between simulated and observed maize yields dropped considerably, resulting in a R^2 of 0.243. At the regional level, the model tended to overestimate low yield level grids and underestimate high yield level grids.

Kapetanaki and Rosenzweig (1996) looked at applying the CERES-Maize model to evaluate the impacts of climate change on maize yields in Northern Greece and to estimate possible mitigation alternatives. The calibration involved modeling growth at three sites across Greece. A previously developed cultivar definition, Pioneer 3183, was used to initially describe the varieties grown within the study areas. The cultivar coefficients describing yield were then altered to obtain a better fit between simulated and observed values for each of the study locations. Simulated values compared well with observed values with R^2 values of 0.76, 0.55, and 0.60 at Karditsa, Naoussa, and Xanthi respectively.

In a more recent study, Salazar et al. (2012) used the CERES-Maize model to estimate maize water use in Georgia. Five of the top producing counties for maize in the state were used for model evaluation.   Irrigation management included applying a fixed amount, 25 mm, at a 60% automatic irrigation threshold. The selected application technology included the center pivot with an irrigation efficiency of 75%. The results were in agreement with observed values for irrigation volumes, resulting in an R^2 equal to 0.79 after a linear regression of predicted and observed values (Salazar, et al., 2012).

The potential for improved yield with irrigation were echoed in the 2007 study conducted by DeJonge et al. The authors used the CERES-Maize model, in coordination with Apollo, a shell program, to evaluate the potential yield improvements in an Iowa cornfield on a spatial and temporal basis (DeJonge, Kaleita, & Thorp, 2007). A 20.25 ha test field was divided into 100 even grid cells and five years of management data were used for model calibration. The calibration procedure involved minimizing the root mean square error (RSME) between observed values and simulated values for each grid cell.   Calibration variables included the effective tile drainage rate and saturated hydraulic conductivity of the deep impermeable layer of the soil profiles. Once the soil profiles were calibrated, three irrigation scenarios were investigated, including no irrigation, scheduled uniform irrigation of reported dates, and precision irrigation that automatically applies a fixed amount when required. The model was used to simulate corn growth over a 28 year period. Simulated yields were improved with irrigation for both scenarios; however, precision irrigation showed lower overall yields than scheduled uniform irrigation.

MODEL VALIDATION

Calibrated models must be evaluated to determine their predictive or analytical utility using datasets independent of the calibration data. Validation is typically conducted using data from years that were not used for calibration of the model. In the Hodges et al. (1987) study, the years 1983 (drought year), 1984, 1985 were used for validation after calibrating for 1982. Final production estimates compared well to the data reported by NASS, with estimates being 92, 97, 98, and 101% of observed values for the year 1982, 1983, 1984, and 1985, respectively. Jagtap and Jones (2002) used years 1974-1990 for calibration of the model and used the year 1991-1995 for validation.

Common tools used for evaluation include the coefficient of determination (R^2), root mean squared error of prediction (RMSEP), and Nash-Sutcliffe model efficiency (E). The coefficient of determination measures how well a model, in crop modeling a linear model is most often used, approximates real data points. A perfect regression would result in a 1:1 slope with a y-intercept of zero. Deviation from this regression allow modelers to determine whether the calibrated model is over-predicting, or under-predicting, or both. In the Kapetanaki and Rosenweig (1996), coefficients of determination between 0.55 – 0.76 were deemed acceptable for climate change impact studies. Root mean squared error of prediction is another tool commonly used to check model performance and can be calculated using Eq. 1 (Thorp, Batchelor, Paz, Kaleita, & DeJonge, 2007),

$$\mathrm{RMSEP_i} = \left(\frac{1}{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}}\left(\mathrm{Ym_{i,j}} - \mathrm{Ys_{i,j}}\right)^2\right)^{0.5}$$

Eq. 1

where *Ym i,j* is the measured yield value for the *i* th grid cell in the *j* th of the *n* growing seasons, and *Ys i,-j* is the simulated yield value in the *i* th grid cell obtained using the optimum parameters from a calibration with the *j* th growing seasons used for validation. The RMSE represents a measure of overall deviation between observed and simulated values, that is, a synthetic indicator of the absolute model uncertainty (Heng, Hsiao, Evett, Howell, & Steduto, 2009). Thrope et al. (2007) found that increasing the number of years used for calibration, decreased RMSEP in the study area. RMSEP can be used to assess model performance both temporally and spatially. The Nash-Sutcliffe coefficient represents the overall deviation between observed and simulated values depart from the overall deviation between observed values and their mean values. With the Nash-Sutcliffe, one can assess how well the model performs over the whole simulation span, including both high and low simulated values. Considering RMSE does not distinguish between large deviations between simulated and observed values occurring in some parts of a simulation and small deviations occurring in other parts of a simulation, the Nash-Sutcliffe can aid the modeler is assessing overall model efficiency. The coefficient E is unitless and expands a range of -∞ to 1, with better efficiency values approaching the value 1 (Heng, Hsiao, Evett, Howell, & Steduto, 2009).

MANAGEMENT

Evaluating the utility of a calibrated and validated model to predict growth under different climate scenarios or management strategies for a particular environment, such as sustainable cultivation practices or irrigation strategies, requires characterizing the probable conditions under which those management strategies would be developed. This approach can provide corn producers and policy decision makers guidance in managing a maize crop to minimize cultivation inputs and maximize outputs, key sustainability criteria.

In 1997, Iglesias and Minguez evaluated the impacts of climate change on yields and water use of two crops, maize and wheat, in response to elevated CO_2 concentrations in Spanish cropping systems. Spain represents a semiarid Mediterranean climate where water availability is the predominant limiting factor to summer grain growth. Five study sites were selected in the main cereal growing regions for the study. Irrigation management for all sites included 100% efficiency of the automatic irrigation using a 1 m irrigation management depth. Automatic application was used when the available water was 50% of soil water capacity and soil water for each layer was re-initialized to 100% capacity at the start of each growing season (Iglesias & Minguez, 1997). GCM results were used to define future climate conditions. Simulated maize yield as well as evapotranspiration decreased in all future scenarios. Due to decreases in evapotranspiration, irrigation demands also decreased. The authors looked at two major adaptive strategies to alleviate the effects of climate change, including planting maize sooner to avoid water stressed periods, and planting a secondary crop with a short growth cycle to be sown after barley crops. Early sowing dates increased yield for cultivars grown under climate change conditions, but did not completely offset decreases in some regions. Short season maize reduced water demand since the maximum crop water requirements coincided with lower temperatures and higher precipitation, although yield was still reduced compared to traditional varieties.

Popova and Kercheva (2004) evaluated the long term impact of different irrigation rates and the timing of fertilizer applications on water stress indicators in a water scarce region of Bulgaria. The CERES-Maize model was used to simulate soil-play system interactions. Four irrigation strategies were considered including no irrigation (rainfed), automatic irrigation when water content fell below 75% of field capacity, automatic irrigation when water content fell below 85% of field capacity, and a drainage controlling scenario based on 75-80% of the required irrigation depth. Each irrigation treatment was simulated with three N-application scenarios including one with a single fertilizer application in the spring (200 kg ha^{-1} N), one with partial equal application at sowing and just before the period of maximum crop uptake and one-third of the total rate at sowing and two-thirds in the middle of the development stage. All irrigation scenarios improved N-uptake efficiency, mitigated drought, and significantly reduced yield and N-uptake variability. The most efficient scenario was a combination of drainage-controlling irrigation, where 75-80% of the required irrigation depth was applied during the most sensitive phases of growth and development, which reduced irrigation water demand by 95 mm yr^{-1}. The authors recommended an N-rate of 200 kg ha^{-1} N under drainage-controlling irrigation to satisfy water demands and diminish N-leaching (Popova & Kercheva, 2004).

Meza et al. (2008) examined the impacts of climate change on maize production in Chile and explored the possibility of a doubling cropping system as a mitigation strategy. Climate change predictions estimate changes in rainfall intensity that will reduce cloud cover and increase shortwave radiation and photosynthetically active radiation. The combination of these factors allows for a longer growing season. Two possible alternatives exist including utilizing longer season varieties or implementing a double cropping season. The authors compared these two options using future climate scenarios that were derived from the HadCM3 model. Doubling cropping produced better results than adaptation alternatives based on agronomic decisions with the ability to mitigate the economic impacts of climate change or even generate additional monetary return if climate change is less severe (Meza, Silva, & Vigil, 2008). However, adoption of a double cropping system could become a global change driver, as nutrient and water demands will increase.

The authors of another study, Saseendran et al. (2008), attempted to determine optimum location specific management strategies to maximize water use efficiency (WUE). The study site was located in Akron, Colorado, which has a semiarid environment and is prone to low precipitation and high temperatures. The objectives of the project included calibrating and validating the CERES-Maize model to evaluate irrigation scenarios in order to optimize WUE and limited irrigation scenarios between vegetative and reproductive growth stages. The authors found that when less than 100 mm of water was available for irrigation, maximum yields and WUE were obtained when 40% of the irrigation was applied during the vegetative stage and 60% was supplied during the reproductive stage, or with a 50:50 split. However, when more than 100 mm of water was available for irrigation, yield was maximized when 20% of irrigation was supplied during the vegetative stage and 80% was supplied during the reproductive stage. Also, yields were maximized when irrigation was delayed until the available soil water was depleted to 80% of its maximum threshold in the top 0.45 m zone. The authors contend that the methodology used in the study could be adapted to other regions for irrigation recommendations with a balanced set of region specific data.

CHAPTER 3 - CALIBRATING AND VALIDATING THE CERES-MAIZE MODEL FOR SIMULATING YIELD AND WATER USE UNDER NON-LIMITING NUTRIENT CONDITIONS IN THE HEARTLAND REGION

INTRODUCTION

Process oriented crop growth models can be a valuable tool for assessing and predicting cropping responses to changes in the environment. This makes them quite useful in studies pertaining to agricultural water use and the potential impacts of climate change. One such model is the CERES-Maize model developed by Jones and Kiniry (1986) (Hoogenboom, et al., 2004), which represents one of the most vetted and established models currently in use. The CERES-Maize crop model is a dynamic simulation model that operates on a daily time step to predict crop growth in response to weather, soil, and management strategies. Since its inception, the CERES-Maize model has been tested in a variety of growth environments, including the United States Corn Belt as well as many other countries around the world, making it an excellent choice for studies related to yield and water use.

Before the CERES-Maize model can be used in simulating cropping responses, it must first be calibrated and validated for the area of interest. The calibration process usually revolves around setting the correct management profile with fixed climate and soil parameters. In relation to management, correctly defining the crop variety is essential. The CERES-Maize model uses six genetic coefficients to describe maize varieties. For regional studies, genetic coefficients are typically determined at the field scale and then applied to the region of interest. For example, Xiong et al. (2007) calibrated the CERES-Maize model using field trial data from experimental plots across China. Once validated, the cultivars were applied over a large region in China.

Southworth et al. (2000) used representative farms located in the Great Lakes region to characterize maize production for large subregions around the Great Lakes for climate change studies. Quiring and Legates (2008) used field crop trails to calibrate a region specific cultivar definition for use in in-season maize forecasting in Delaware. All of these studies have enjoyed relative success at the regional scale, but were all unified under the assumption of regional homogeneity within the region, or subregion.

Maize production in the US employs the use of numerous different management strategies as well as location specific cultivar varieties. Collecting this type of data at a high resolution would be impractical given the large size of the study area. However, recent studies have shown the CERES-Maize model to be effective in predicting, with the use of a limited amount of input data, the anthesis and maturity dates, and total yield of corn production (Yang, Wilkerson, Buol, Bowman, & Heiniger, 2009). Given the recent success of the CERES-Maize in a North Carolina environment with limited input data, there exists potential for the use of the CERES-Maize in larger regional applications in coordination with national crop production databases containing information on silking rates, maturity rates, and yield, such as the National Agricultural Statistics Service (NASS).

The goal of this project was to create a cropping model capable of estimating maize water use and potential future impacts due to climate change. The following objectives were created to accomplish this goal: (i) develop a crop model calibration approach for use in regional studies with limited input data to predict maize yield, and (ii) develop a crop model capable of assessing regional water use; more specifically, the blue versus green water use based on yield information. To test the model's predictive ability, a set of hypotheses were also constructed:

- Determine the ability of the CERES-Maize model to predict physiological anthesis of maize on a regional scale. The hypothesis to be tested (H_{01}) was that the CERES-Maize model could not predict the number of days in the development period from planting to anthesis with a Coefficient of Determination (R^2) > 0.5, and a regression of the observed versus predicted plot would result in a slope that was not significantly different from zero (probability greater than 0.95 (α=0.05)).
- Determine the ability of the CERES-Maize model to predict physiological maturity of maize on a regional scale. The hypothesis to be tested (H_{02}) was that the CERES-Maize model could not predict the number of days in the development period from planting to maturity with a Coefficient of Determination (R^2) > 0.5, and a regression of the observed versus predicted plot would result in a slope that was not significantly different from zero (probability greater than 0.95 (α=0.05)).
- Determine the ability of the CERES-Maize model to predict maize yield on a regional scale. The hypothesis to be tested (H_{03}) was that the CERES-Maize model could not predict maize yields with a Coefficient of Determination (R^2) > 0.5, and a regression of the observed versus predicted plot would result in a slope that was not significantly different from zero (probability greater than 0.95 (α=0.05)).

METHODOLOGY

Study Area

For the purposes of this study, the Farm Resource Region 1 (36.042°N to 46.625°N and 99.292°W to 82.125°W), also known as the ”Heartland” Region, was chosen the as the study area (Figure 1). The ERS regions encompass geographic specialization in the production of U.S.

farm commodities and are derived from four major sources including the older farm production region classifications, a cluster analysis of U.S. farm characteristics (Sommer & Hines, 1991), the USDA Land Resource Region, and the National Agricultural Statistics Service (NASS) Crop Reporting Districts. The Heartland accounts for roughly 70% of total US corn production on a bushel basis (Foreman, 2006). The Heartland region was chosen for this study because it represents not only one of the largest areas of maize production regions in the U.S., but in the entire world.

Model Geographic Architecture

The performance of the CERES-Maize model was examined under the ERS “Heartland” region environment. This region encompasses the majority of maize production in the US and represents one of the most productive systems on the planet. Considering the large size and the multitude of different cropping practices employed within the region, a MATrix LABoratory Program (MATLAB) algorithm was created to facilitate the use of a variety of data inputs at various spatial scales within a grid based approach. The overall approach was to first estimate a specific soil profile within the International Soil Reference and Information Centre (ISRIC) World Inventory of Soil Emission Potentials (WISE) database for each grid cell, and then determine an appropriate genetic coefficient profile based on NASS supplied dates for anthesis and physiological maturity and yield. All values were determined based on minimizing root mean squared error (RSME) during the calibration stage. The ability of the calibrated model to simulate yield and phenological stage development was then evaluated over three years.

Initial attempts to model regional maize in the US were undertaken with MATLAB on one desktop computer. This strategy resulted in long processing times (upwards of two weeks) for calibration and validation. In order to develop a high resolution model, an alternative method of computing was needed. The second phase of the project involved implementing the MATLAB model at the University of Arkansas's High Performance Computing Center (AHPCC). With the use of the AHPCC's super computer, calibration times were greatly reduced, allowing the author to run over 10 million different simulations.

Model Inputs

The CERES-Maize model simulates maize physiology in response to management, soil, and climate interactions. Unfortunately these data are hardly uniform in their spatial and temporal coverage. The following describes the selected data sources for climate, soil, and US maize management inputs.

Weather Inputs

Weather inputs were obtained from the NASA Agroclimatology Archive, one component of NASA's POWER (Prediction of Worldwide Energy Resource) project. POWER was created to allow access to data derived from NASA's Surface Meteorological and Solar Energy (SSE) project for those interested in the design of renewable energy systems. The Agroclimatology archive was developed with agricultural Decision Supports Systems (DSS) in mind and provides easy download of historical data for specific site locations. The parameters contained in this dataset are based on solar radiation data derived from satellite observations and meteorological data from the Goddard Earth Observing System assimilation model. The archive is globally comprehensive at 1° resolution, with dates ranging from July 1983 to near present time, although data after January 1, 2008 are derived from different sources and are not directly comparable to earlier data. Parameters selected from this archive include daily estimates of insolation on a horizontal surface (MJ m^{-2}), daily mean, maximum, and minimum temperatures at 2m above ground surface (°C), and precipitation (mm) (NASA POWER Team, 2010).

Soil Inputs

Soil inputs were derived from the ISRIC-WISE soils database. The WISE 1.1 database is a globally comprehensive dataset at 5 min resolution, one of the highest resolutions available. The data were created using the FAO-Unesco Soil Map of the World (DSMW) and soil profile estimates are derived from ISRIC's global WISE soil profile database (Batjes, 2006). The WISE 1.1 database contains 4382 globally distributed soil profiles, sampled from 123 different countries, which are georeferenced and classified according to the 1974 and revised 1988 FAO distribution system. Soil profiles were assigned according to the FAO classification within the ERS region (Figure 2). The ISRIC-WISE soil database files were converted to DSSAT compatible formats by Romero et al. (2012). This study corrected faulty soil profile data and filled in missing values with best estimates. These updated files were used in this study.

Management Inputs

Crop production is the result of complex inputs by farmers. Regionally yield variability is a consequence of the variability of planted cultivars, management practices including planting date, density, depth, and row spacing, as well as the skill of the farmers (Jagtap & Jones, 2002). These factors can change both spatially and temporally. To capture this variability, management values were obtained from a variety of different sources at the highest spatial resolution available. To describe planting density, state averages were obtained from email communication with a NASS corn expert (Anthony Prillaman, May 2011). The values described plant population per acre and were converted to plants per m^2 for use within CERES-Maize. The data was pulled from NASS's 10 Objective Yield states, of which three states within the study region were not a part of the system until 2004 (Kansas, Missouri, and South Dakota). To supplement for the missing values, an average of the planting densities between years 2004–2007 was used. Kentucky was not part of the 10 Object Yield states program and thus, no information on planting densities were given. To supplement for the area grown in Kentucky, a single average of the neighboring states densities, including Missouri and Illinois, was used. To describe the major maize phenological stages, data for maize progress throughout the season was obtained through the NASS Quick Stats program (NASS, 2011). Information of planting, emergence, silking, maturity, and harvesting dates were later used for calibration.

ERS Yield Data

Maize yield data for the study area between the years 1997-2007 were obtained from the USDA's National Agricultural Statistics Service (NASS, 2011). The data was obtained at the county level. For most counties in the study area, no distinction was made between rainfed and irrigated maize and, was instead classified as "Total for Crop." With no distinction being made, this value was used for both irrigated and rainfed scenarios. Nebraska and South Dakota however, did report different yield values between rainfed and irrigated operations, which were both used for evaluation within their respective categories. Consequently, Nebraska and South Dakota make up the majority of irrigated land use in the study area.

Before the yield data could be used for calibration and validation, it had to be normalized for the time period of interest. Simulated and observed yields between the years 1997 and 2007 are not directly comparable, as the simulated yields assume a constant level of technology throughout the test period. CERES-Maize is incapable of accounting yield gains due to improved technology, such as improved fertilizer use, better pest management, improved seeds and so forth. The result of these factors is a low frequency trend within the dataset. To account for this trend, a linear trend analysis was performed to isolate technological gains from higher frequency weather variability trends (Jagtap & Jones, 2002). Using a simple linear expression, comparing maize yield versus time, county yield for each year were recomputed by adding the yield gain due to technology changes between production year and the last year of the test date, 2007, to the observed difference between observed yields and detrended yields for the year of interest.

Determining Calibration versus Validation Years

With only 11 years available for calibration and validation, a difficult decision had to be made as to which years would be used for calibration and which would be used for validation. Using the general principal that calibration datasets should use at least an equal amount of data compared to validation datasets, initial calibration procedures involved setting all odd years as calibration years and all even years as validation years. This resulted in six years used for calibration and five for validation. Unfortunately, this resulted in an unacceptablly high level of modeling error. To improve the validation results, a second method was developed.

Considering the primary goal of this project was to predict water use, years were ranked according to water availability. To determine water availability for each growing season, the Crop Moisture Index (CMI) was used. The CMI is the sum of plant evapotranspiration and total moisture excess. The evapotranspiration anomaly is weighted to make it comparable in space and time. The CMI is negative when the potential moisture demand exceeds available moisture supplies. Conversely, if moisture exceeds demand, the index becomes positive (NOAA, 2011). The CMI was obtained for each of the National Oceanic and Atmospheric Administration

(NOAA) climate divisions. On average, each US state was comprised of roughly nine climate regions. CMI values were distributed to each county that made up the region.

To determine which values were used for calibration and which were used for validation, county yields were ranked according to the CMI. To develop the best results possible, the model needed to be able to predict yields under both dry and wet conditions. At the same time, more calibration years were needed when compared to earlier attempts. To satisfy both constraints, years two, six, and ten were used for validation while the rest were used for calibration. This allowed for the second driest and wettest years during the evaluation period, ranks two and ten respectively, to be used to verify the calibration in addition to a relative normal year, rank six.

Calibration Procedure

The calibration procedure involved using a grid based approach at the highest spatial resolution the data could support. Soil data represented the highest resolution dataset at a 5 min resolution, so this became the computational resolution for the project. Other input data were disaggregated to the 5 min level for analysis.

Selecting Soil Profiles

The first step in the calibration procedure was to choose the correct soil profile characteristics for each grid cell. The ISRIC-WISE soil database used a high-resolution gridded map to classify each soil group. However, within each group, data on the specific vertical soil profiles for each grid cell were not distinguished. Instead, several profiles for each group were provided without geospatial reference. In total, there were 22 different types of soil groups within the study area (

Table ***3***). Without any other means as to determine which profile belonged to each grid cell, a stratified calibration had to be performed. To do this, a proxy cultivar definition was used. The genetic coefficients across the study region, including P1, P2, and P5, were set to values expressed in Jones and Kiniry 1986. The yield coefficients were set to that of the generic medium season variety provided in the DSSAT genotype database. With the proxy cultivars established, the optimum soil profile was determined for each grid cell based on rainfed yield. The minimization of root mean squared error was the objective function used for selection:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2}$$

where S_i represents simulated yield, O_i represents observed yield, and n is the number of grid-years selected for calibration. Once the soil profile that was the best predictor of yield was determined, the genetic coefficients used to describe each grid cell were calibrated.

Estimating Phenological Parameters P1, P2, and P5

The next step was to better define the phenological coefficients used to describe the growth phases with CERES-Maize. During these simulations, the yield coefficients, G2 and G3, were set to the generic medium season values described within the DSSAT genotype database. Much to the same effect as determining the optimum soil profile based on yield, the phenological coefficients were optimized using the RMSE equation. First, P1 was adjusted until the 75% silking value, found in the CERES-Maize *summary.out* file, matched the reported state value obtained from NASS. Following the best identified P1 coefficient, P2 was adjusted until a better match for the 75% silking date could be found using RMSE. Finally, P5 was adjusted until the simulated maturity date matched the calculated state value.   This procedure was carried out for both rainfed and irrigated scenarios.

Estimating Genetic Coefficients G2 and G3

Once the phenological coefficients were determined, the yield coefficients were optimized. G2 and G3 were optimized at the same time in a coupled procedure. Again, the most predictive combination of G2 and G3 was selected based on the minimization of RMSE. Once the best genetic profile was calibrated, the profiles were validated over dry, normal, and wet conditions. This procedure was carried out for both rainfed and irrigated scenarios.

Validation Procedure

To validate the cultivar profiles, three years were left out of the eleven year cropping period. The three years were selected based on a Palmer Drought Index Score.   Each of the eleven years was ranked according to the Palmer Drought Index within each grid cell. The years ranked 2, 6, and 10 were used for validation. Within each grid cell, the year ranked 2 was considered a dry year, the year ranked 6 was considered a normal year, and the year ranked 10 was considered a wet year. This allowed for model validation over a wide range of environmental condition in relation to climate.   To assess the predictive ability of the model, the coefficient of determination (R^2) and the Nash Sutcliffe coefficient were used.

Green versus Blue Water Use

To estimate the amount of green, rainfed, and blue water, irrigated, consumed within the region, the calibration processes described above were repeated, keeping the same soil profiles, with the model’s automatic irrigation setting turned on. Only Nebraska and South Dakota were considered for irrigation calibration as these two states were the only two to specify irrigated yields. Irrigation management included irrigating when the total soil moisture content fell below 45% until the moisture returned to 100% of maximum. Irrigation was assumed to be supplied via sprinkler system. This management strategy represents a common technique to prevent water stress within the region.

RESULTS AND DISCUSSION

Calibration

The calibration procedure worked well in most areas of the study region. Areas that represented medium range yields matched most closely with observed values. However, areas that represented low and high yields showed larger deviation from observed values. Green and blue water use was also estimated for the study area and compared well with the regional results from other global studies.

Rainfed Phenological Coefficient Calibration

The average simulated anthesis date for the rainfed maize in the region was 81 days after planting, with a maximum of 85 days and a minimum of 77 days after planting. Estimated P1 values ranged from 135 to 360 degree days with an average of 278. Estimated P2 values ranged from 0.0 to 0.8 with an average of 0.41. The RMSE for simulated anthesis ranged from 1.2 to 5.7 days, with an average 3.1 days for the calibrated grid cells within the region. Estimation errors related to anthesis appeared reasonable and close to other studies (Yang, Wilkerson, Buol, Bowman, & Heiniger, 2009). A regression analysis, as well as a regional Nash-Sutcliffe coefficient, was calculated to determine how well the predicted values compared to observed anthesis values at the county level. A linear regression was used and coefficient of determination determined for the region. The regression produced a slope of 0.999 with an R^2 of 0.942 and was found to be significantly different from zero ($p < 0.05$) (Figure 3). The Nash-Sutcliffe coefficient for the region over the eight year calibration period was 0.934.

Values for calibration of maturity produced similar results. The average simulated maturity date for the region was 132 days after planting, with a maximum of 179 days and a minimum of 95 days after planting. Estimated P5 values ranged from 490 to 1,000 degree days, with an average of 776. The sum of RMSE for both anthesis and maturity ranged from 3 to 20.1 days, with an average of 7.2 days. A linear regression analysis was also conducted to test the model's ability to predict maturity dates. The linear regression produced a slope of 0.885 with an R^2 of 0.943. The regression slope was found to be significantly different from zero ($p < 0.05$) (Figure 4). The regional Nash-Sutcliffe coefficient was 0.924.

Irrigated Phenological Coefficient Calibration

The average simulated anthesis for irrigated maize in the region was 81.2 days after planting, with a maximum of 101 and a minimum of 69.9. Estimated P1 values ranged from 185 to 310 growing degree days with an average of 261. Estimated P2 values ranged from 0.25 to 0.8, with an average of 0.46. Average RMSE anthesis for the irrigated region was 4.26 days, with a maximum of 5.37 and a minimum of 2.29 days. A linear regression of the simulated anthesis date vs. the observed anthesis for the irrigated counties produced a slope of 1.09 and an R^2 of 0.975. The regression slope was found to be significantly different from zero ($p < 0.05$) (Figure 5). The Nash Sutcliffe for the region was 0.946.

Simulated maturity values also compared well with the observed dataset. Average simulated maturity was 134.9 days after planting with a maximum of 179.1 and a minimum of 110.5 days after planting. Estimated P5 values ranged from 500 to 830, with an average of 681. The sum of both irrigated anthesis and maturity averaged 10.1 days after planting, with a maximum of 13.7 and a minimum of 5.21. A linear regression analysis was also conducted to test the model's ability to predict maturity dates. The linear regression of the predicted vs. observed data produced a slope of 1.319 with an R^2 of 0.781. The regression slope was found to be significantly different from zero ($p < 0.05$) (Figure 6). The regional Nash-Sutcliffe coefficient was -0.487.

Rainfed Yield Coefficients Calibration

The results for the calibrated yield coefficients were more highly variable than the calibration results from the phenological coefficients. Simulated rainfed yields averaged 9,513 kg ha^{-1}, with a maximum of 17,059 and a minimum of 3,093 kg ha^{-1}. The RMSE for yield ranged from 359 to 3,149 kg ha^{-1}, and averaged 1,530 kg ha^{-1} (Figure 7). The RMSE as a percentage of average observed yield over the calibration period ranged from 5.0% to 68% and averaged 16.6%. Estimated G2 values ranged from 50 to 1600 kernels per plant with an average of 374. Estimated G3 values ranged from 0.5 to 19 mg d^{-1} with an average of 13. Although the RMSE as a percentage of average observed yield was in good agreement with values seen in the literature, the high values (upwards of 68%) are not common in the published modeling world (Jones & Kiniry, 1986; Hoogenboom, et al., 2004). Despite the high error in some locations, simulated yields across the region were in good agreement with reported values produced a coefficient of determination of 0.927 and a slope of 0.892 with a slope significantly different from zero ($p < 0.05$) (Figure 8).

Out of the 534 counties that covered the study area, 40 had RMSE as a percentage of observed yield above 25% throughout the calibration period. The locations with the high errors within were located across the study area including central Nebraska, southern South Dakota, and across Missouri. Some of the highest relative RMSE values (> 35%) corresponded to the lowest average county yields (< 6,500 kg ha^{-1}). The calibrated yield coefficients for these counties were also the lowest within the calibration range, with 50 kernels per plant with a fill rate of 0.5 mg d^{-1}. Even with the unrealistically low yield coefficients, the model was unable to replicate low yield counties. Possible causes of such great yield drift could be due to planting density not being representative of rainfed maize growth in these states. Planting densities can vary greatly under rainfed conditions. For example, Grassini et al. (2009) suggested that plant populations vary between 32,000 and 78,000 individuals per ha^{-1} along a west to east gradient in Nebraska. Plant population used in the study varied from 56,000 to 60,000 individuals per ha^{-1}, in Nebraska, and may not be broad enough to accurately predict rainfed maize production. Other potential reasons for the model over predicting very low yields in the region was the fact that the CERES-Maize model did not incorporate yield losses due to pests or disease. These two factors can have a large impact on maize yields, but in the model's current state, coupled with a lack of data, it is unable to factor in these losses.

Irrigated Yield Coefficients

For irrigated maize grown in Nebraska and South Dakota, the model produced yield values similar to the NASS reported values. Rainfed yields averaged 9,885 kg ha^{-1}, with a maximum of 15,709 and a minimum of 5,335 kg ha^{-1}. The RMSE ranged from 904 to 3,124 kg ha^{-1}, and averaged 1650 kg ha^{-1}. The RMSE as a percentage of average observed yield over the calibration period ranged from 8.2% to 40%, with an average of 18.1% (Figure 9). Estimated G2 values ranged from 50 to 1050 kernels per plant. Estimated G3 values ranged from 3 to 19 mg d^{-1}. Much to the same effect as during the calibration under rainfed conditions, high errors were observed in the study area. Planting densities were a likely contributing factor, much to the same effect as during the rainfed calibration. Large geospatial discrepancies were also observed in the results. Nebraska calibrated well under irrigated conditions, unlike South Dakota which produced the highest errors. It is currently unclear as to why corn grown in the northern latitudes produced larger simulation errors. Despite the high error in some locations, simulated yields across the region were in good agreement with reported values producing a coefficient of determination of 0.688 and a slope of 0.624 with a slope significantly different from zero ($p < 0.05$) (Figure 10). The model consistently under predicted yields for production elements greater than 9000 kg ha^{-1}, and slightly overpredicted yields for elements less than 9000 kg ha^{-1}. The regional Nash Sutcliffe coefficient was 0.982.

The calibration procedure produced results that compared well to observed values in the calibration dataset. For anthesis, both rainfed and irrigated maize R^2 values were over 0.9 and the Nash Sutcliffe coefficients between 0 and 1. Maturity dates also compared well, producing values in the same range with the exception of the Nash Sutcliffe coefficient for irrigated maize. This indicates that the simulated variance was greater than the observed variance within the calibration dataset. Final yields also compared well, producing a Coefficient of Determination > 0.6 and Nash Sutcliffe coefficients between 0 and 1. Results could be improved with the addition of a geospatially explicit database of planting densities at the county level across the region.

Validation

To determine the predictive ability of the model, the calibrated coefficients were compared to values within the 1997-2007 dataset that were withheld during calibration. The validation dataset was comprised of one wet, one normal, and one dry year. The following describes the model's predictive ability across a broad range of climate conditions.

Calibrated rainfed maize compared well with respect to anthesis and yield across the study region. However, the model was less successful when predicting maturity. Anthesis dates compared well to the observed values, with a linear regression producing a slope of 0.926 and an R^2 of 0.644 with a slope significantly different from zero ($p < 0.05$) (Figure 11). The regional Nash Sutcliffe was 0.521. Maturity validation did not produce the same level of predictive ability as shown by the anthesis validation. The observed versus predicted regression produced a slope of 0.811 and an R^2 of 0.407. The regression slope was found to be significantly different from zero ($p < 0.05$) (Figure 12). The regional Nash Sutcliffe coefficient was -0.011. Finally, yields compared well over the validation dataset, producing a linear regression slope of 0.847 and an R^2 of 0.672. The regression slope was found to be significantly different from zero ($p < 0.05$) (Figure 13). The Nash Sutcliffe for regional yields was 0.611.

The calibrated cultivar coefficients for irrigated maize produced simulation results with similar trends compared to the rainfed cultivars. Simulated anthesis did not achieve the same level of success when compared to rainfed validation, producing a linear regression slope of 1.487 and an R^2 of 0.741 that was significantly different from zero ($p < 0.05$) (Figure 14). The anthesis Nash Sutcliffe coefficient was -0.015. Maturity also did not compare well, producing a linear slope of 0.951 and an R^2 of 0.192, although a significant nonzero trend was found (p

=0.0012) (Figure 15). The Nash Sutcliffe related to maturity was -4.30. Finally, despite the poor performance predicting physiological coefficients, yields compared well. An observed versus predicted plot produced a slope of 0.673 and an R^2 of 0.743 that was significantly different from zero ($p < 0.05$) (Figure 16). The regional Nash Sutcliffe coefficient was 0.636.

Overall, the validation was able to predict both rainfed and irrigated maize yield with reasonable accuracy. The physiological parameters were not replicated with the same consistency. The modeling technique predicted anthesis well for rainfed maize; however, irrigated anthesis was consistently under predicted. Maturity was predicted poorly for both rainfed and irrigated maize. The lack of predictive ability related to physiological parameters, while still able to predict yield, could be attributed to the scale difference between the physiological parameters, anthesis and maturity, and yield. Each of the physiological parameters was supplied at the state level, contrary to yields, which were obtained at the county level. More research is needed to determine if higher resolution physiological data could improve simulation results.

Statistical Interpretation

Using conventional statistical procedures, the model results showed significant trends ($p<0.05$) in relation to the slope of each of the regressions of observed versus predicted plots being non-zero. However, this particular statistic did not fully describe how well the model performed. After the initial analysis, two additional statistics were considered, including whether the y-intercepts were significantly different from zero and whether the slope of the regressions were significantly different from one (Table 4). When the regressions were evaluated to determine whether the y-intercepts were significantly different from zero, most of the plots showed significant differences from zero ($p<0.05$) with the regressions for calibrated, rainfed anthesis and validated, irrigated maturity being the expectations. This indicates that the model includes bias in most cases, and consistently over predicts lower values for anthesis, maturity, and yield, especially when one considers hypothetical minimum values around the origin.

When the slope of regressions was evaluated on whether the slopes were significantly different from one, none of the regressions showed any significance, indicating the null hypothesis that slope =1 could not be rejected. Combining these statistics with the previous one, one can deduce that the model can predict significant non-zero correlations in anthesis, maturity, and yield in which the null hypothesis that slope = 1 cannot be rejected. With most of the y-intercepts being significantly different from zero, the regressions were shown to be inherently inaccurate, especially around the origin, where a theoretical regression for an observed versus predicted plot would lie. However, given that no dependent variable values of zero were used during calibration, the y-intercept falls out of the calibration range and its relevance may be of less importance when compared to the slope of the regression lines. The results indicate that the model predicted well within the calibration range, however drift could occur if the results were extrapolated out toward hypothetical minimums.

It should also be noted that forcing the regressions through the origin were considered for the analysis. However, after careful consideration, it was concluded that such an act could result in a poorly fit model, and give a misleading estimate of slope. Allowing the model to include a y-intercept value, and testing the significance of the y-intercept being non-zero was deemed a better alternative (Gbur, personal communication, 2013).

Water Use

In addition to predicting development and yield, the model was also evaluated on its ability to predict water use. Specifically, green water use, or evapotranspiration derived from rainwater, was predicted across the region. Blue water use, or evapotranspiration derived from irrigation, was calculated for counties within Nebraska and South Dakota. The water use values compared well to other studies conducted in the region.

Output from the model runs provided information as to the evapotranspiration, green water demand of the maize production. Average evapotranspiration for rainfed calibrated cultivars over the study period ranged from 453 to 893 mm yr^{-1}, with an average of 696 mm yr^{-1}. Higher ET values were estimated in Iowa, Nebraska, central Illinois, and northern Missouri (Figure 17).

Evapotranspiration and irrigation volumes were also calculated for irrigated maize in both Nebraska and South Dakota. Total evapotranspiration ranged from 631 to 867 mm yr^{-1}, with an average of 744 mm yr^{-1}. Total irrigation volumes ranged from 0 to 338 mm yr^{-1}, with a average irrigation volume of 132 mm yr-1 (Figure 18). The number of irrigation applications was also calculated. Throughout the region, averages of 4.2 applications were applied throughout the growing season, to a maximum of 10 and a minimum of 0 (Figure 19). Finally, evapotranspiration from rainwater averaged 612 mm yr^{-1}, with a minimum of 354 and maximum of 760 mm yr^{-1} (Figure 20).

Predicted water use compared well to other studies in the Corn Belt. Grassini et al. (2009), found that evapotranspiration for rainfed maize ranged from 200 mm to 600 mm over the growing season and ranged from 400 mm to 900 mm for irrigated maize in the Western Corn Belt.

CONCLUSIONS

The goal of this project was to calibrate the CERES-Maize model across a large geographic region using a modified interface. The following objectives were met to accomplish this goal: (i) develop a crop model calibration approach for use in regional studies with limited input data to predict maize yield, (ii) develop a crop model framework capable of assessing blue versus green regional water use based on yield information. To test the model's predictive ability, several hypotheses were tested.

> H_{01}: The CERES-Maize model cannot predict the number of days in the development period from planting to anthesis with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

The CERES-Maize model was evaluated on its ability to predict physiological anthesis for rainfed and irrigated cultivares. For both calibration and validation, and for both rainfed and irrigated maize, the CERES-Maize model compared well to the observed datasets, producing R^2 > 0.5 and a trend that was significantly different from zero ($p < 0.05$). In addition, the slope of the regression line could not be proven to be significantly different from one ($p<0.05$). Therefore, the null hypothesis was rejected, indicating the model could predict anthesis with reasonable accuracy.

H_{02}: The CERES-Maize model cannot predict the number of days in the development period from planting to maturity with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

While the CERES-Maize Model proved it could predict anthesis in regional applications, the same could not be said for rainfed and irrigated maturity. During the calibration step, both rainfed and irrigated maize compared well to the observed datasets. However, during validation, rainfed maize produced an R^2 of 0.407 and irrigated maize produced an R^2 of 0.192, although the slopes of both regression lines were significantly different from zero ($p < 0.05$). Also, the slope of the regression could not be proven to be significantly different from one. Given the low predictive ability of the model for maturity, we failed to reject the null hypothesis.

H_{03}: The CERES-Maize model cannot predict maize yields with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

For calibration and validation, both rainfed and irrigated maize yield produced good results. Validated rainfed maize produced an R^2 of 0.672 and irrigated maize produced and R^2 of 0.743 both of which were found to be significantly different from zero. To the same extent as anthesis, and maturity, the slope of the regression line could not be proven to be significantly different from one ($p>0.05$). Considering both situations yielded $R^2 > 0.5$, the null hypothesis was rejected. It should be noted that despite the relative success at predicting yields, the calibrated coefficients consistently drifted past realistic ranges.

The calibration procedure described above performed well in many aspects of the modeling process. For both rainfed and irrigated maize, good coefficients of determination as well as Nash Sutcliffe coefficients were observed over the calibration dataset. Physiological coefficients also fell within realistic ranges. However, calibrated yield coefficients for rainfed maize did not, with the highest and lowest values for G2 and G3 often being found to be the best predictors of yield. For maize grown in ERS 1, G2 values should fall between 450 – 1,000 kernels per plant, and G3 values should fall between 4 – 10 mg d^{-1} (Jones & Kiniry, 1986). Large yields often resulted in G2 values of 1,600 kernels per plant and low yields resulted in values of 50 kernels per plant. This represents a major limitation to the model, as realistic coefficients could not be produced. Yield coefficients for irrigated maize did produce results that were more in line with coefficients seen in the literature.

Currently, the modeling procedure described above has shown potential, but could be improved for future studies. The calibration stage produced adequate agreement between simulated and measured anthesis, maturity, and yield values as indicated by the coefficient of determination. However, these results were not replicated during the validation stage given the much lower coefficient of determination values for anthesis and maturity. Considering the physiological parameters were calibrated with the coarsest of input, the modeling process could be improved with higher resolution physiological data. Green and blue water use was also estimated and the results seem to be in line with other studies that have been produced at the global scale.

TABLES

Table 2. CERES-Maize genetic coefficient definitions (Hoogenboom, et al., 2004).

Symbol	Definition
P1	Thermal time from emergence to end of juvenile phase (degree days)
P2	Development delay for each hour increase in photoperiod above longest photoperiod at which development rate is maximum (days)
P5	Thermal time from silking to physiological maturity (degree days)
G2	Maximum number of kernels per plant
G3	Kernel fill rate during linear fill stage under optimal conditions (mg d-1)
PHINIT	Phylochron interval; thermal time between successive leaf tip appearances (degree days)

Table 3. WISE 1.1 soil types and number of profiles found in the ERS1.

Soil ID	Soil Name	Number of Profiles
AF	Ferric Acrisol	47
AO	Haplic Acrisol	89
BD	Dystric Cambisol	64
BE	Eutric Cambisol	99
CH	Haplic Chernozem	13
CK	Calcic Chernozem	23
CL	Luvic Chernozem	7
DE	Eutric Podzoluvisol	5
GD	Dystric Gleysol	44
GE	Eutric Gleysol	79
GM	Mollic Gleysol	31
HG	Gleyic Phaeozem	15
HH	Haplic Phaeozem	49
HL	Luvic Phaeozem	84
KH	Haplic Kastanozem	8
KK	Calcic Kastanozem	18
KL	Luvic Kastanozem	2
LC	Chromic Luvisol	91
LG	Gleyic Luvisol	41
LO	Haplic Luvisol	113
RE	Eutric Regosol	29
WE	Eutric Planosol	26

Table 4. Regression results from both the calibration and validation runs for three null hypotheses: whether the y-intercept was equal to zero, the slope of the regression was equal to zero, and the slope of the regression was equal to one.

Parameter			**Regression Results (p-value)**		
			H_0:y-intercept=0	**H_0:slope=0**	**H_0:slope=1**
Anthesis					
	Rain				
		Calibration	0.894	<0.05	1.000
		Validation	0.0138	<0.05	0.973
	Irrigated				
		Calibration	<0.05	<0.05	0.848
		Validation	<0.05	<0.05	0.762
Maturity					
	Rain				
		Calibration	<0.05	<0.05	0.913
		Validation	<0.05	<0.05	0.971
	Irrigated				
		Calibration	<0.05	<0.05	0.789
		Validation	0.934	0.0012	0.993
Yield					
	Rain				
		Calibration	<0.05	<0.05	1.000
		Validation	<0.05	<0.05	0.999
	Irrigated				
		Calibration	<0.05	<0.05	1.000
		Validation	<0.05	<0.05	1.000

FIGURES

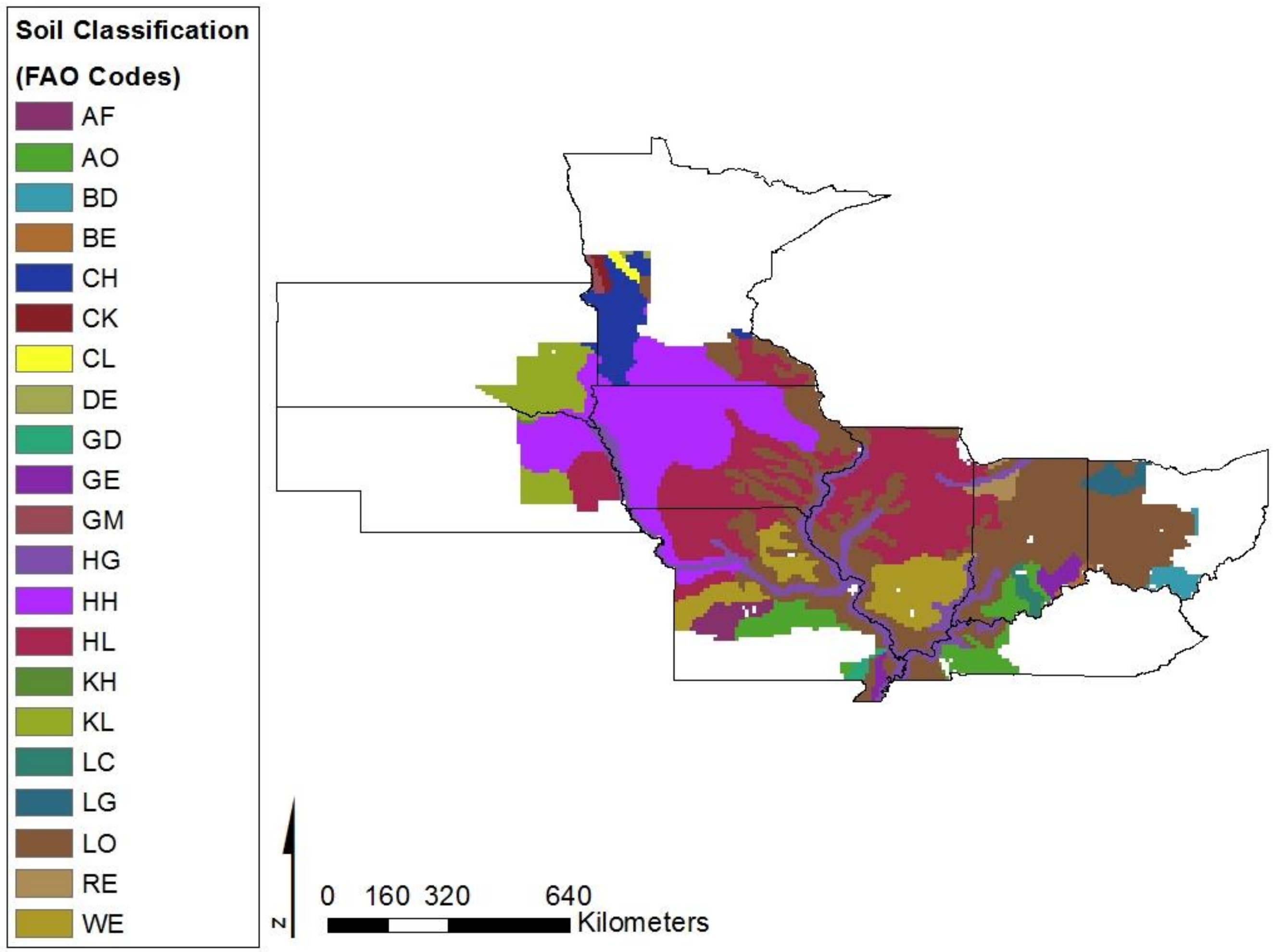

Figure 2. Soil classification within ERS1 according to the FAO-Unesco Soil Map of the World (DSMW).

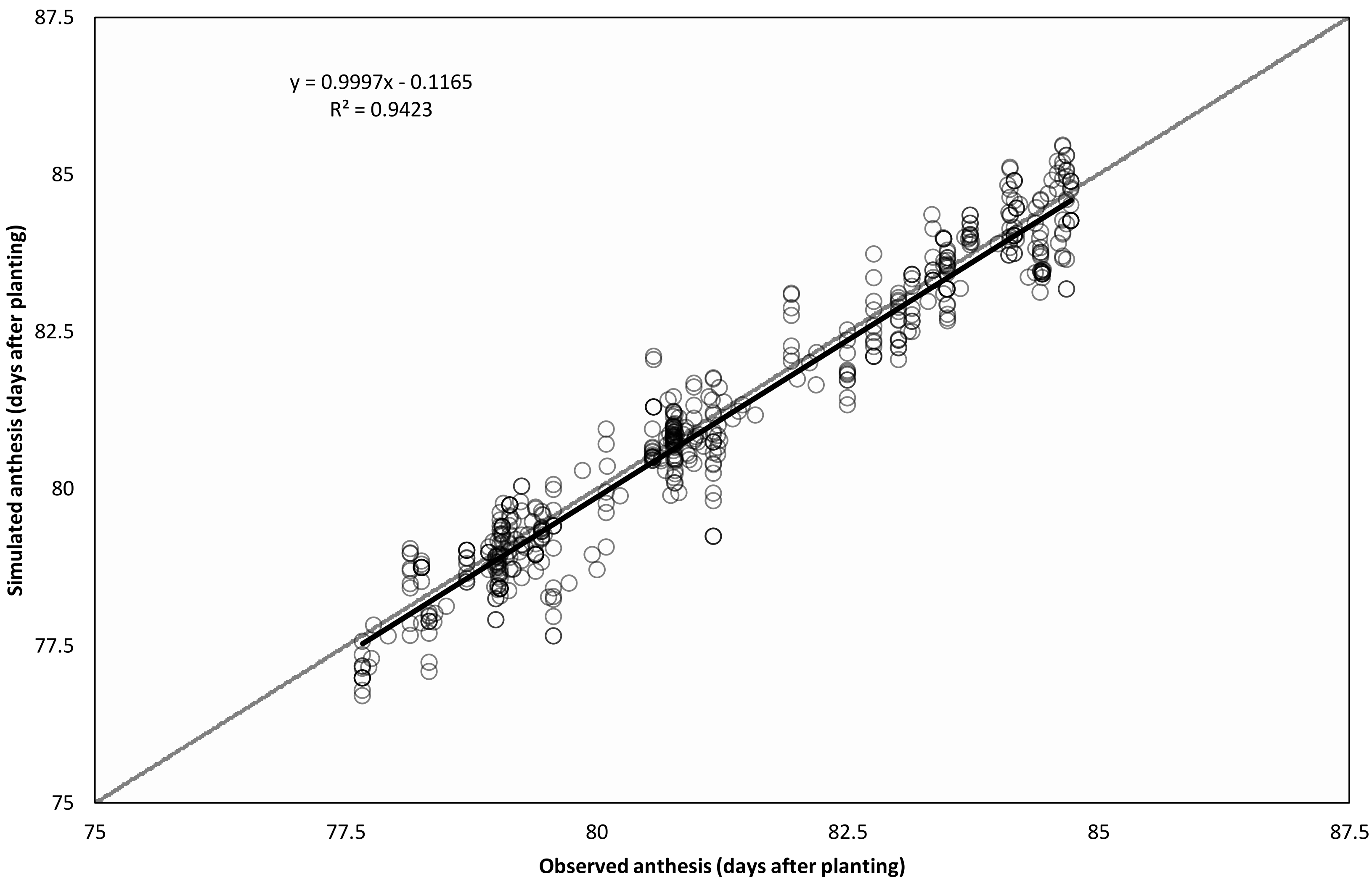

Figure 3. Rainfed calibration results for simulated vs. measured days from planting to rainfed anthesis for all grid cells in the eight year calibration dataset.

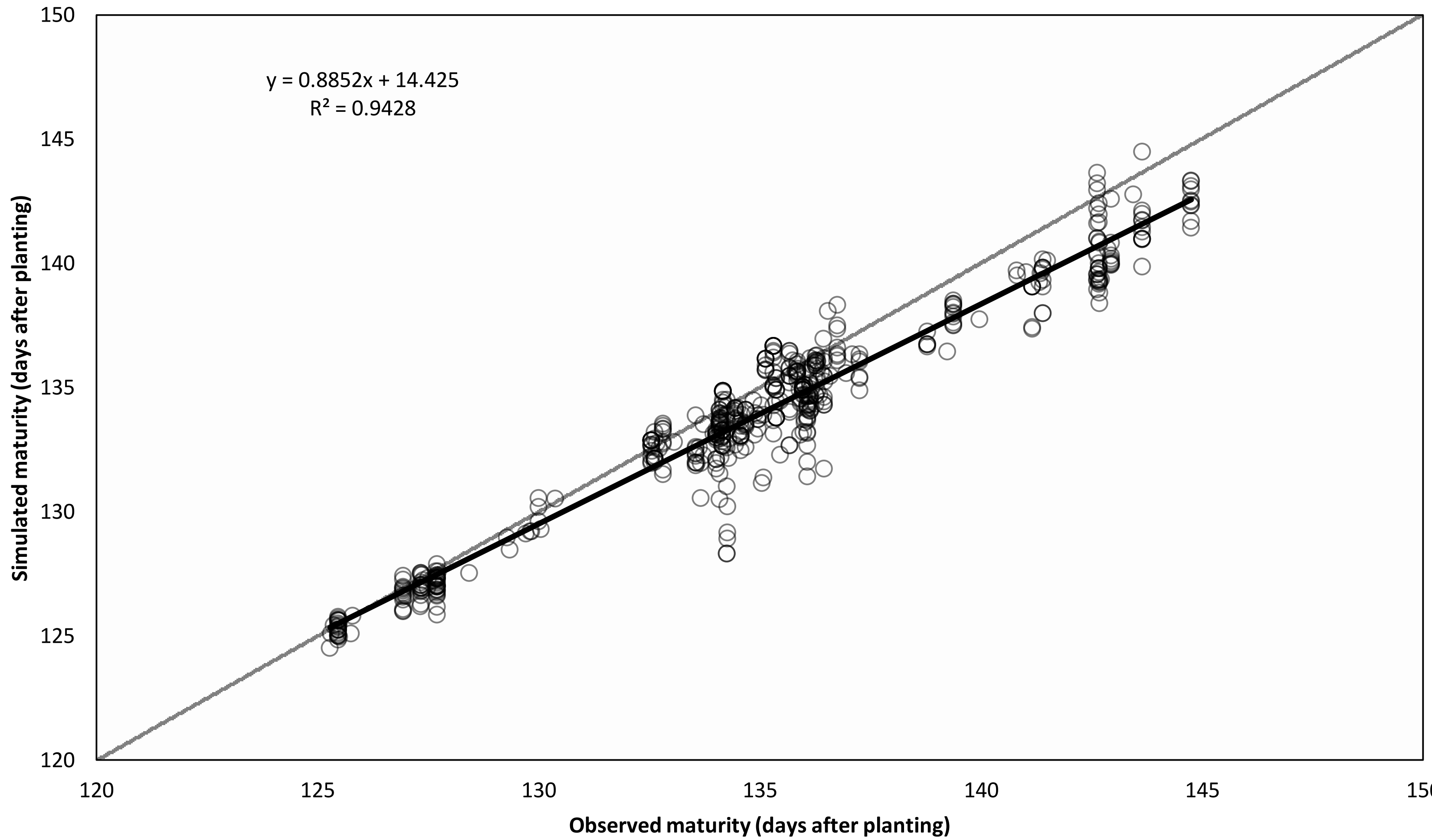

Figure 4. Rainfed calibration results for simulated vs. measured days from planting to rainfed maturity for all grid cells in the eight year calibration dataset.

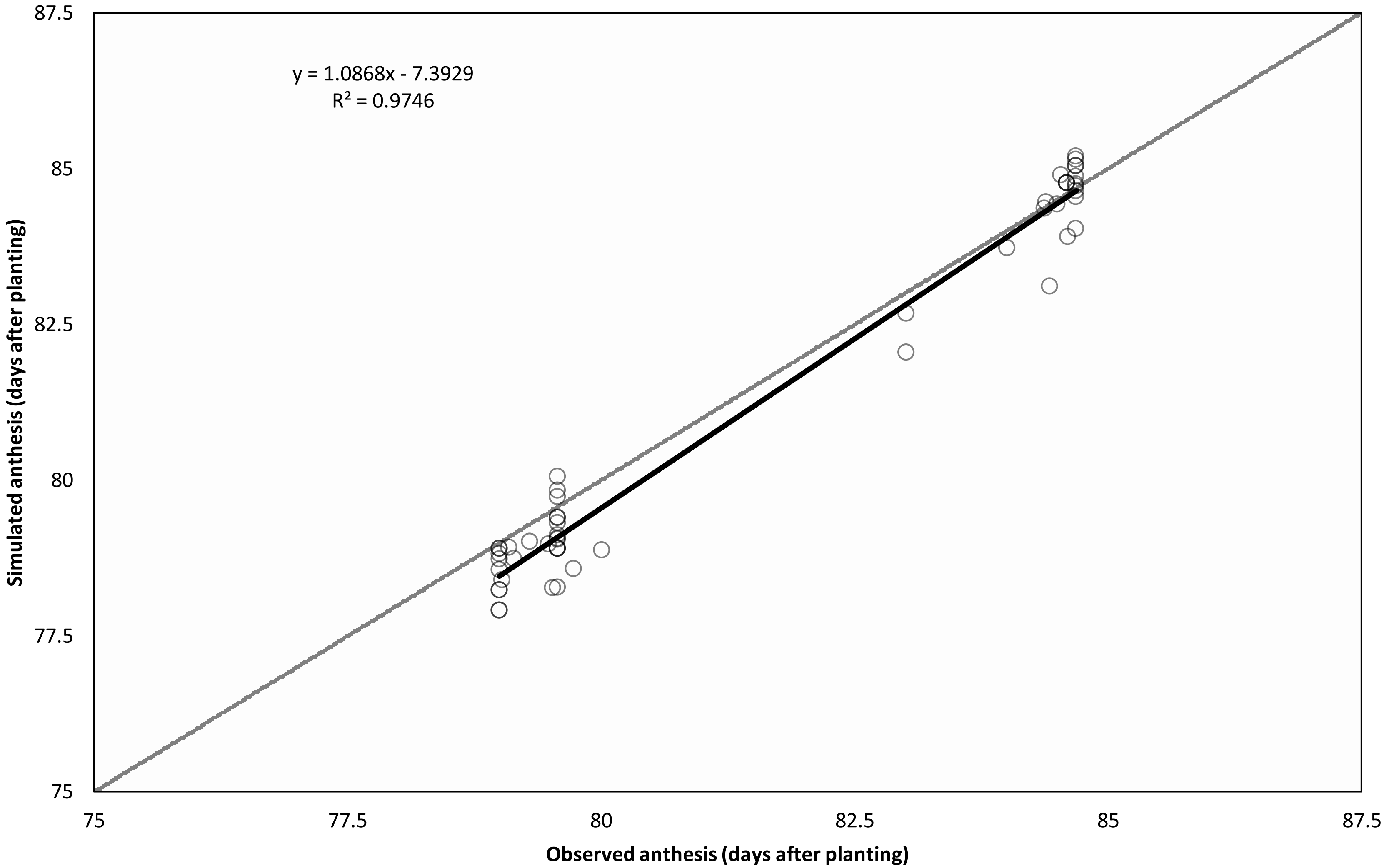

Figure 5. Irrigated calibration results for simulated vs. measured days from planting to anthesis for all grid cells in the eight year calibration dataset.

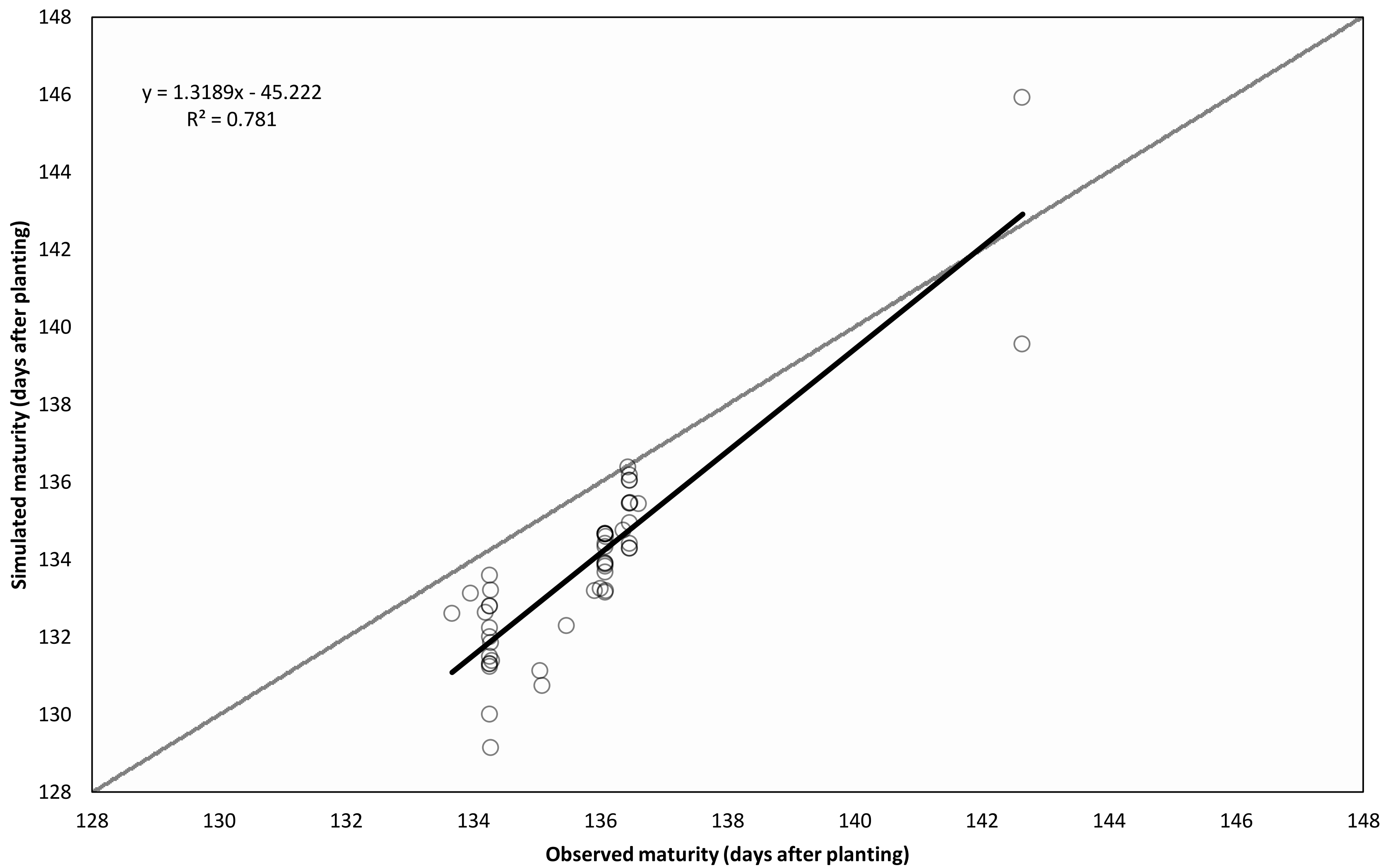

Figure 6. Irrigated calibration results for simulated vs. measured days from planting to maturity for all grid cells in the eight year calibration dataset.

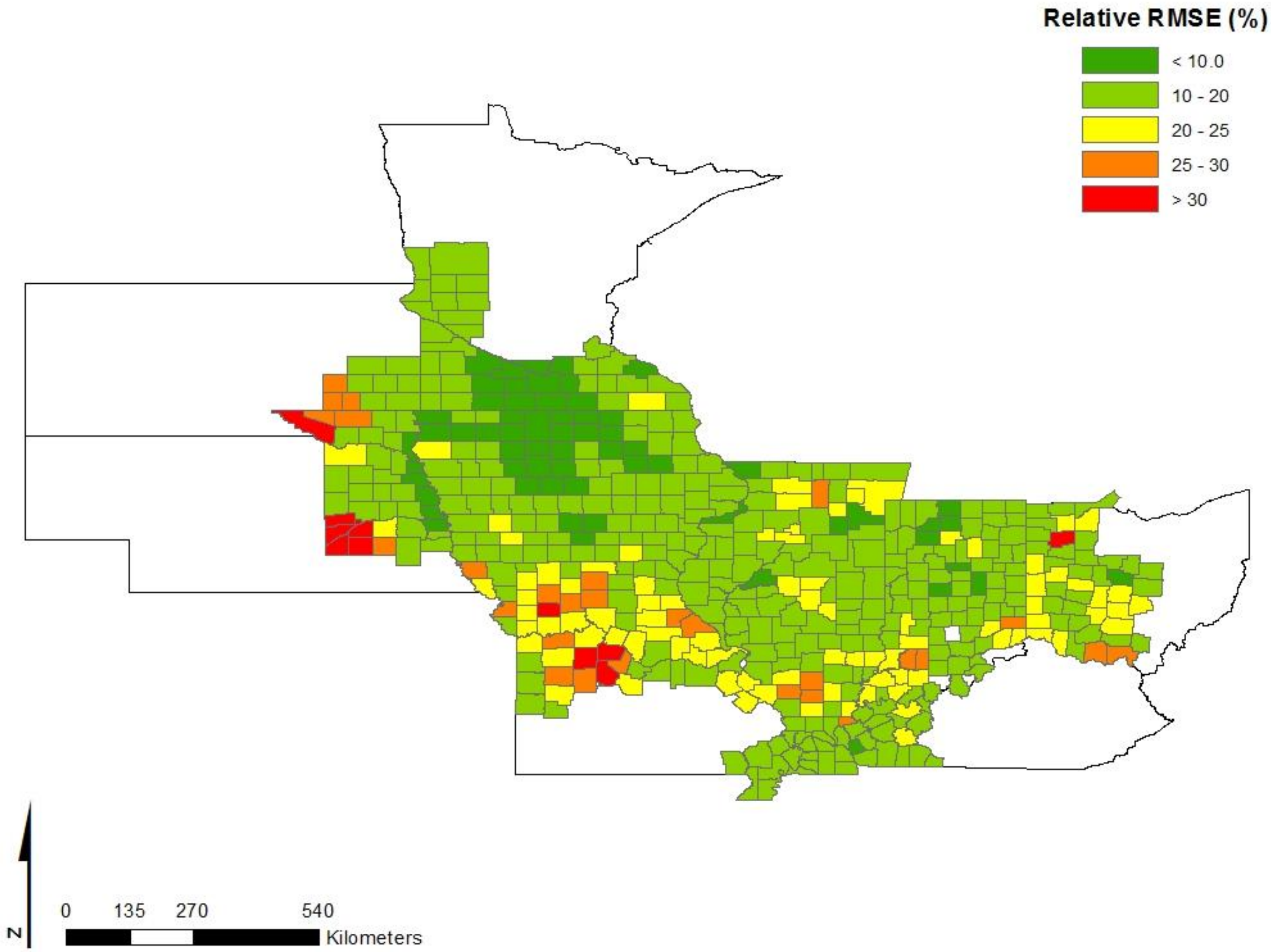

Figure 7. Spatial distribution of relative RMSE in ERS1 of rainfed maize yield for the calibration dataset.

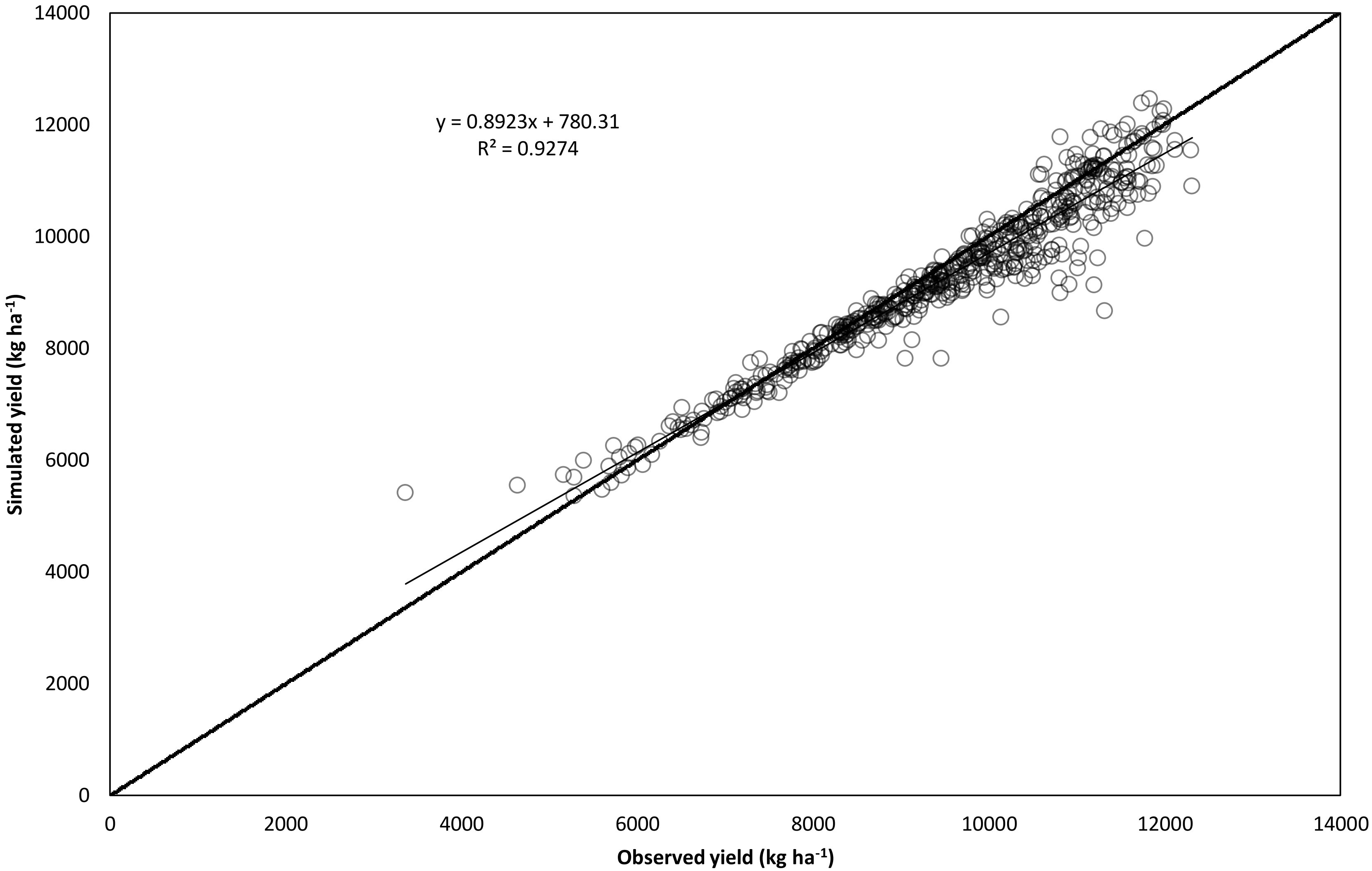

Figure 8. Rainfed calibration results for simulated versus measured mean yields for all grid cells over the eight year calibration period.

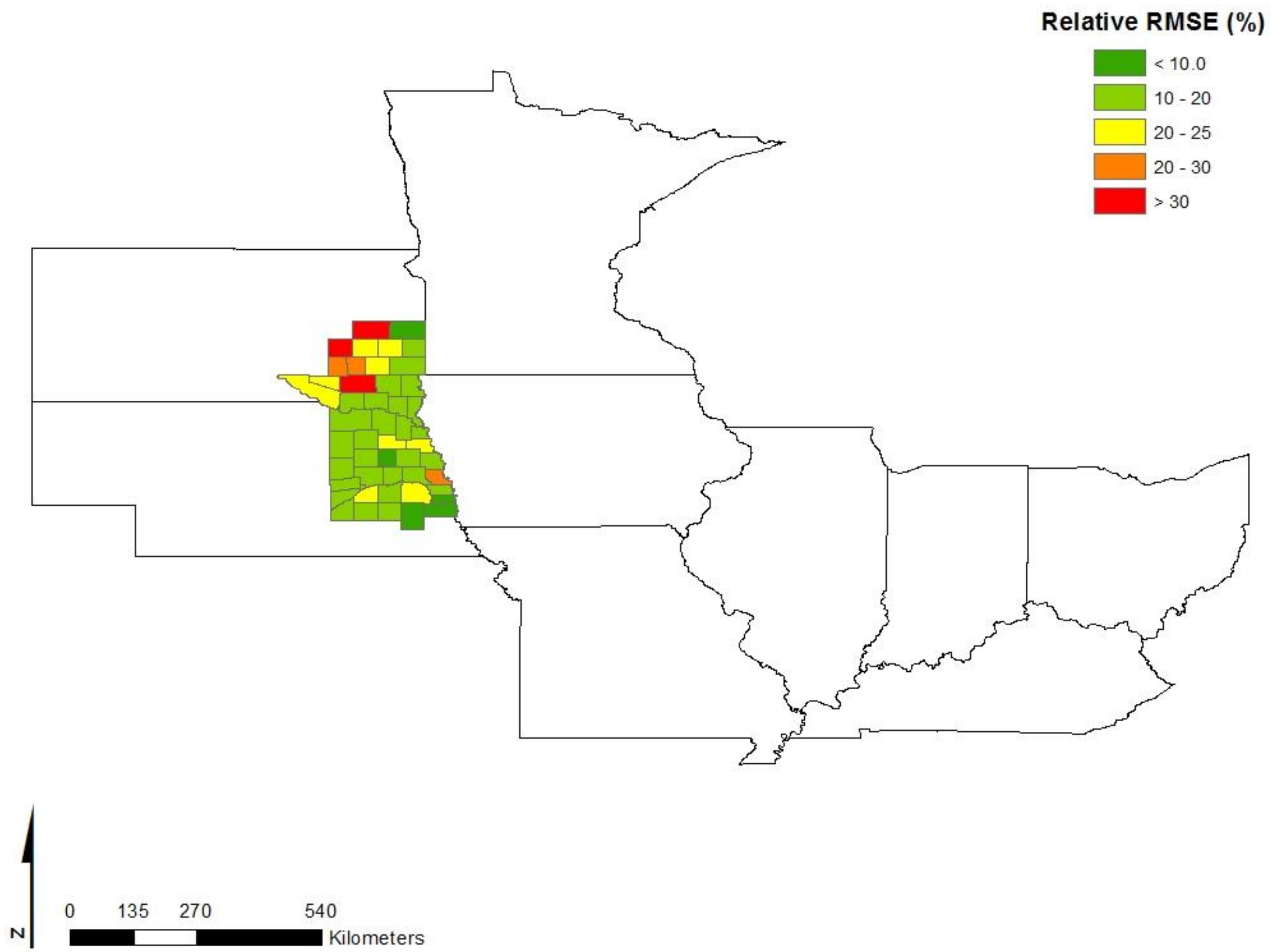

Figure 9. Spatial distribution of relative RMSE in ERS1 for irrigated maize for the calibration dataset.

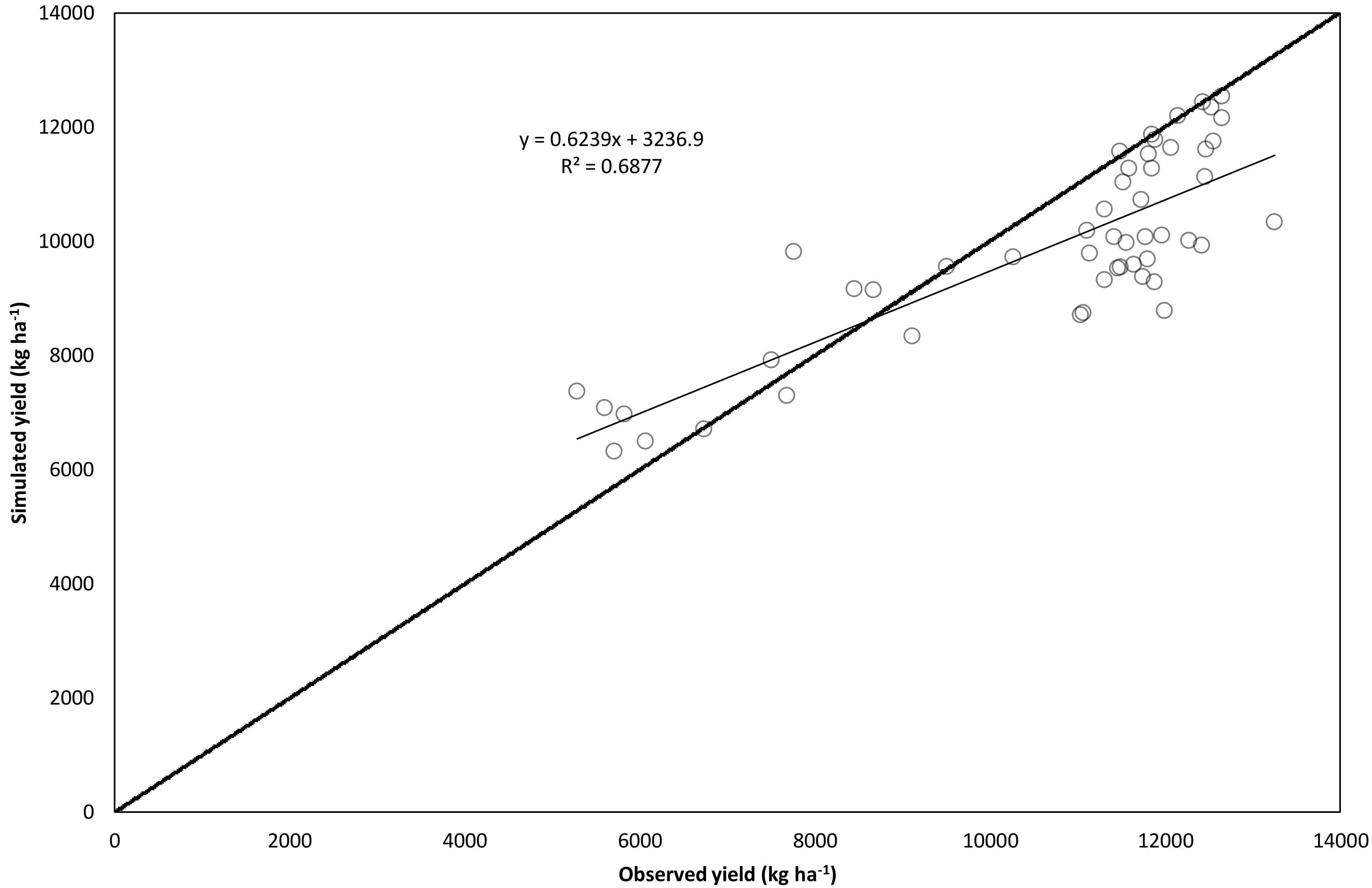

Figure 10. Irrigated calibration results for simulated versus measured mean yields for all grid cells over the eight year calibration dataset.

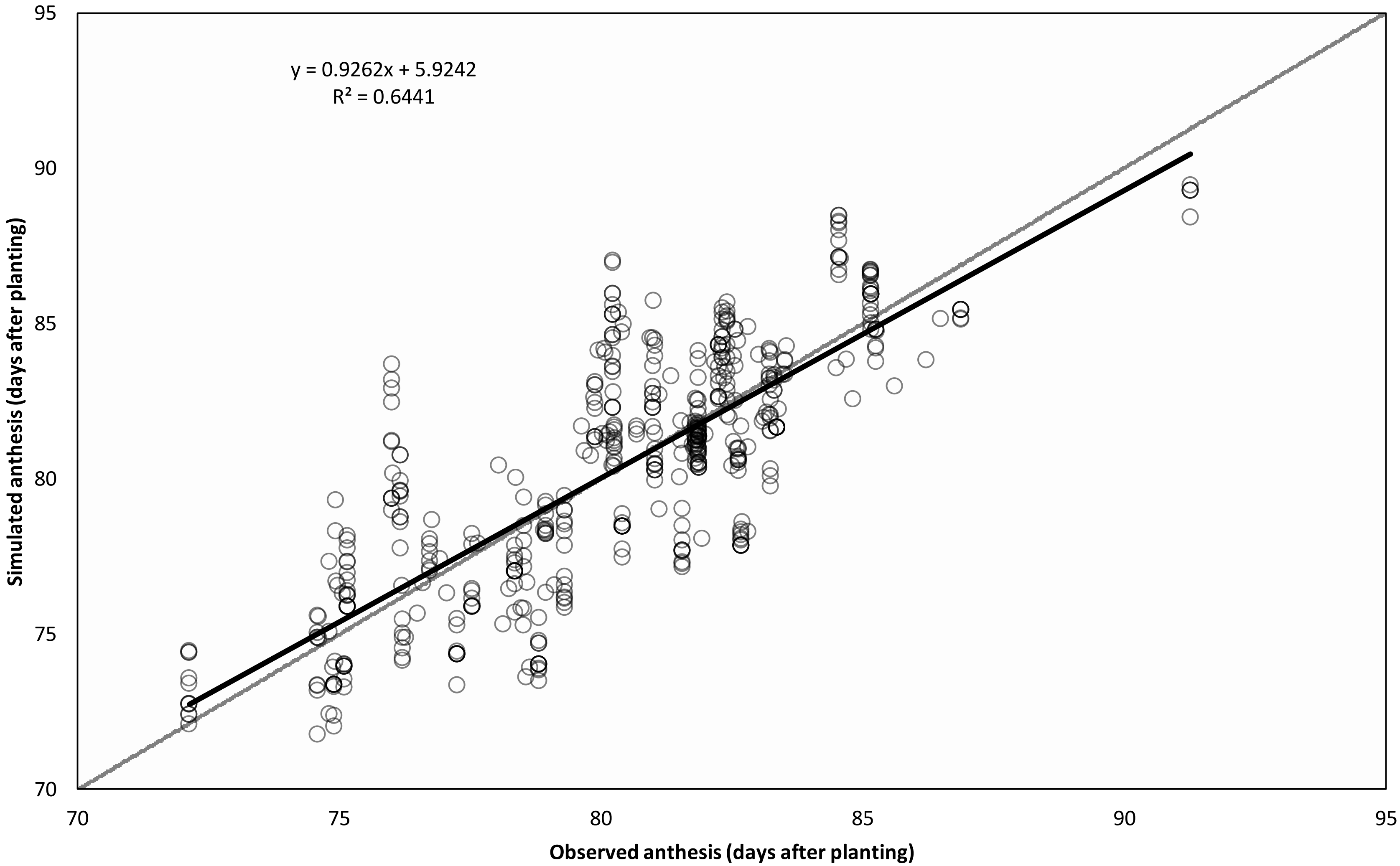

Figure 11. Rainfed validation results for simulated versus measured mean anthesis for all grid cells over the three year validation dataset.

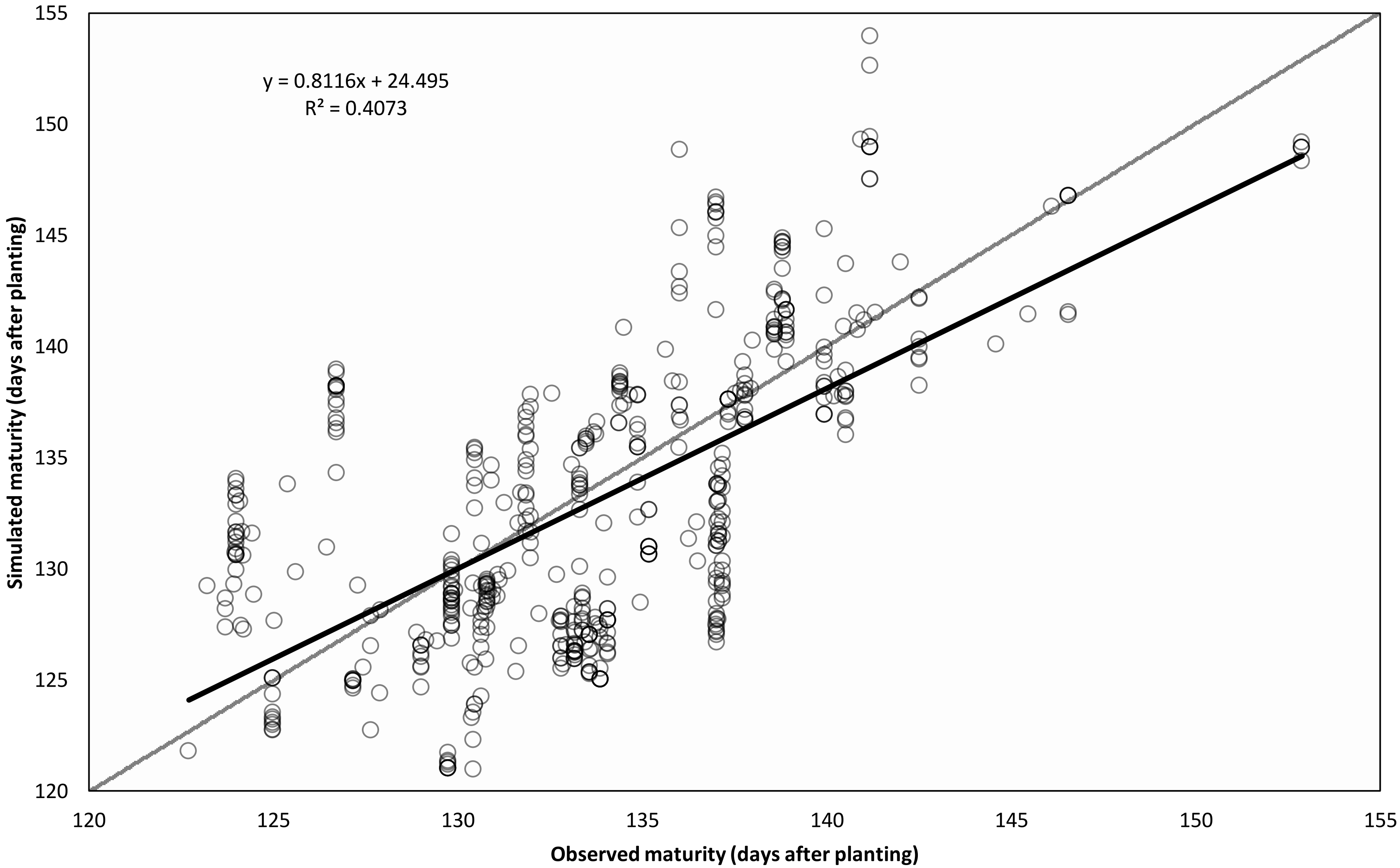

Figure 12. Rainfed validation results for simulated versus measured mean maturity for all grid cells over the three year validation dataset.

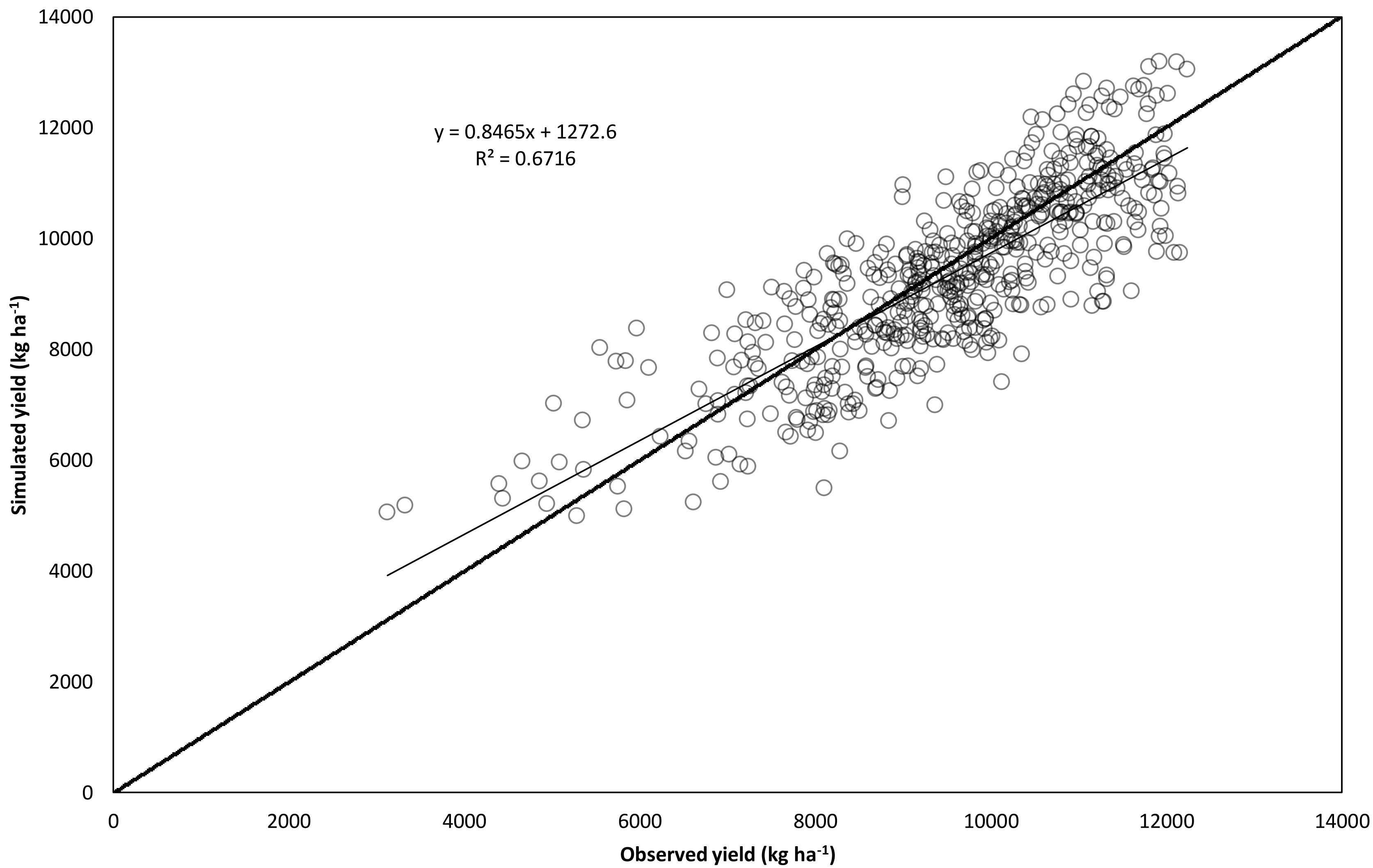

Figure 13. Rainfed validation results for simulated versus measured mean yield for all grid cells over the three year validation dataset.

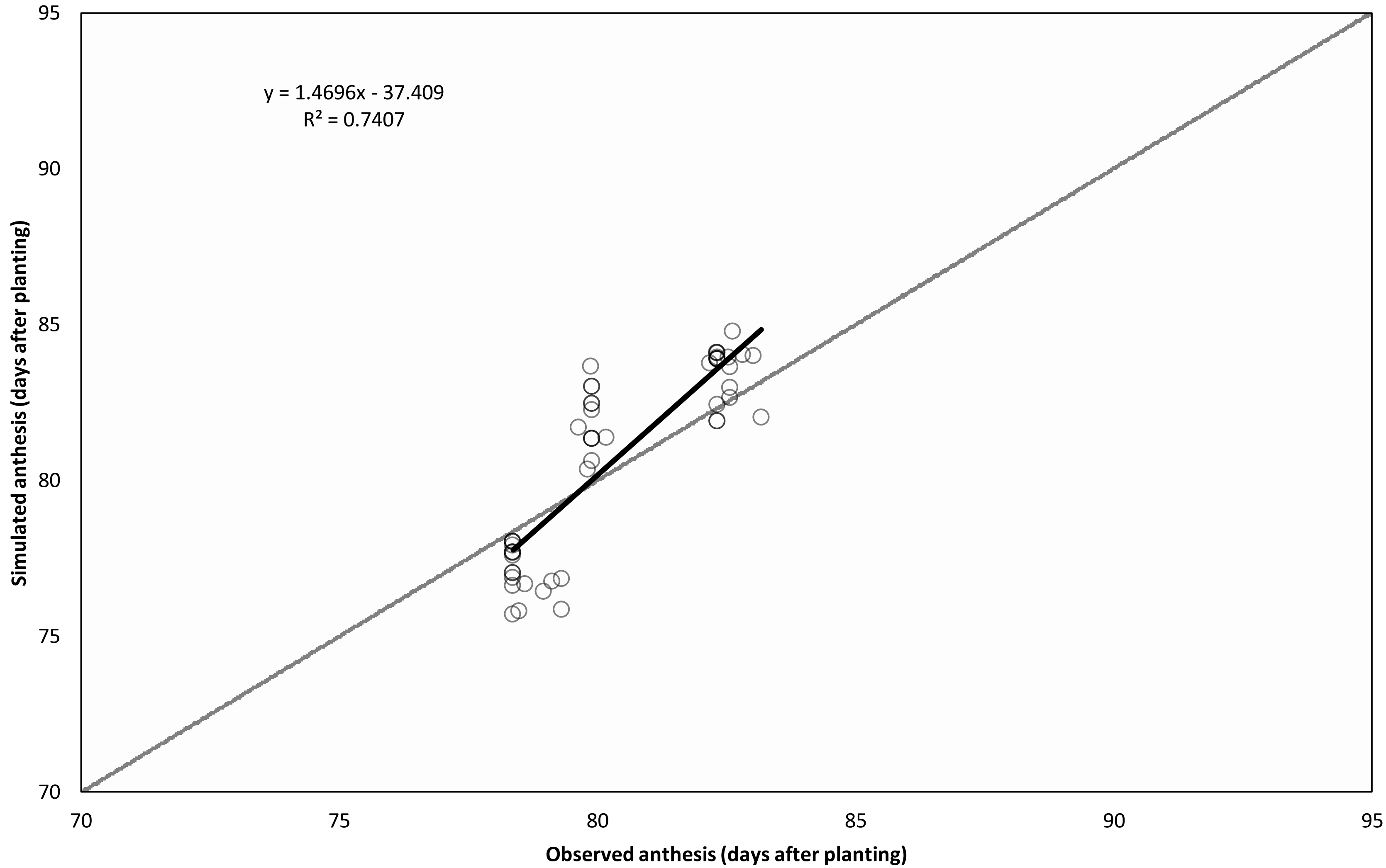

Figure 14. Irrigated validation results for simulated versus measured mean anthesis for all grid cells over the three year validation dataset.

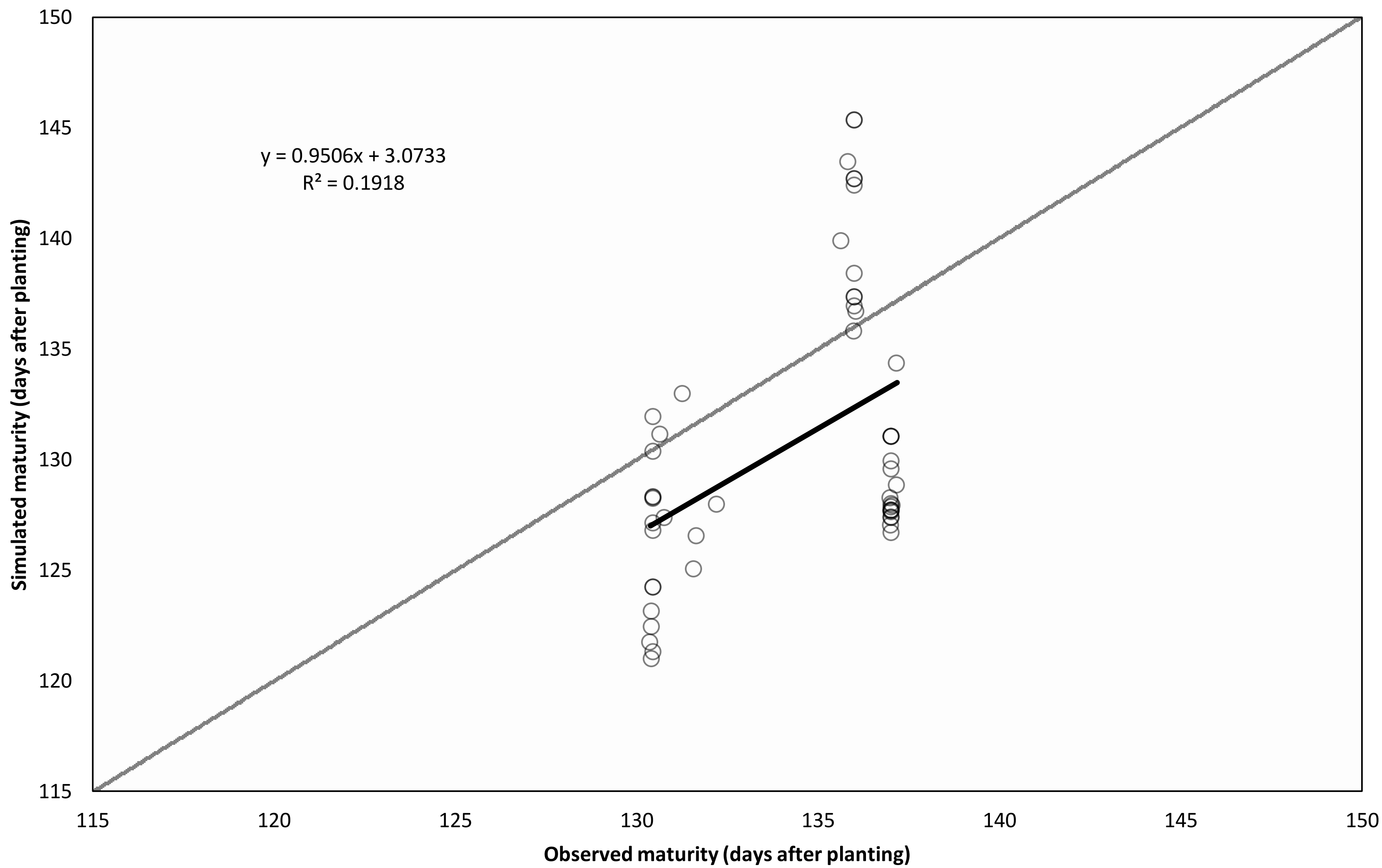

Figure 15. Irrigated validation results for simulated versus measured mean maturity for all grid cells over the three year validation dataset.

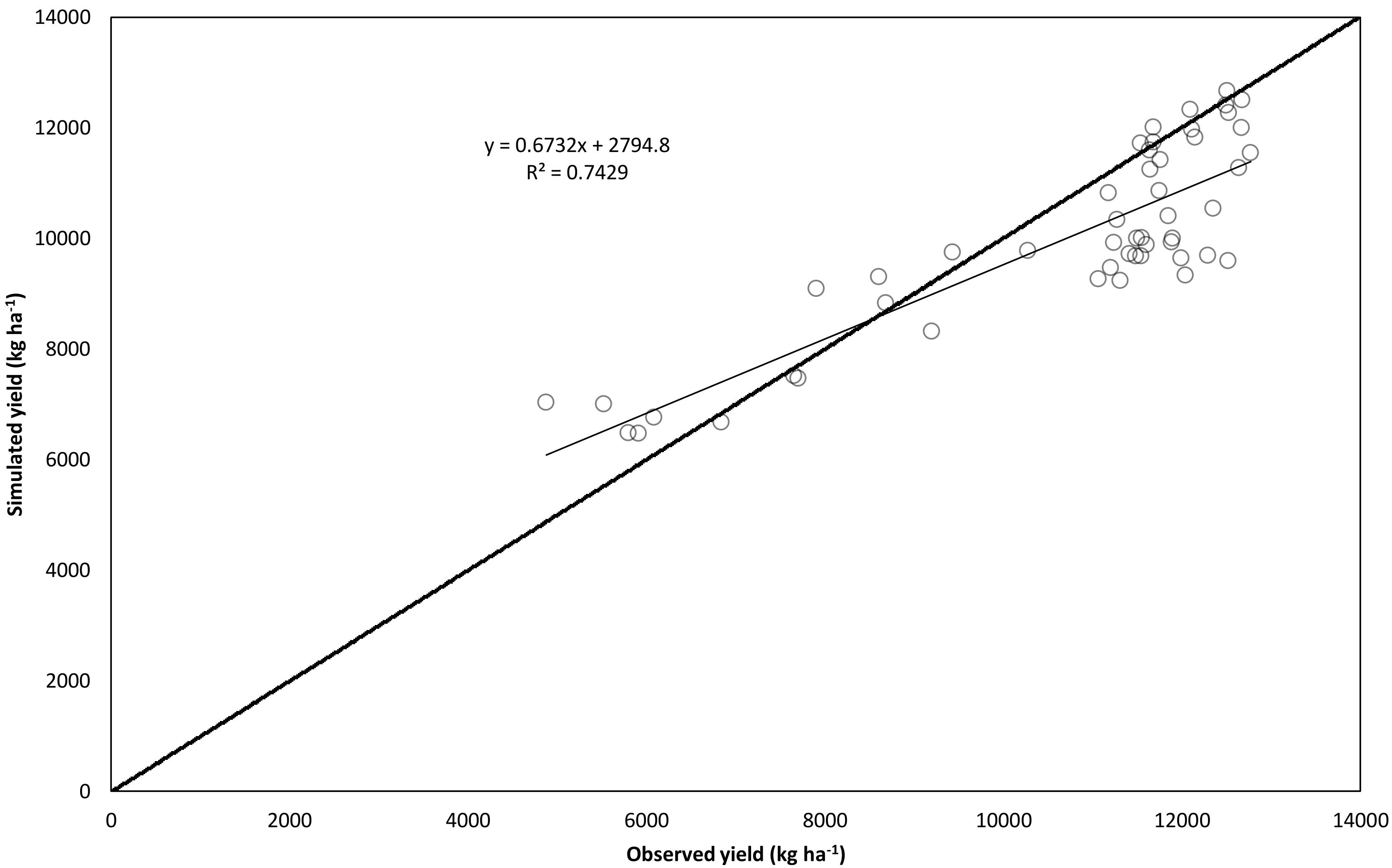

Figure 16. Irrigated validation results for simulated versus measured mean yield for all grid cells over the three year validation dataset.

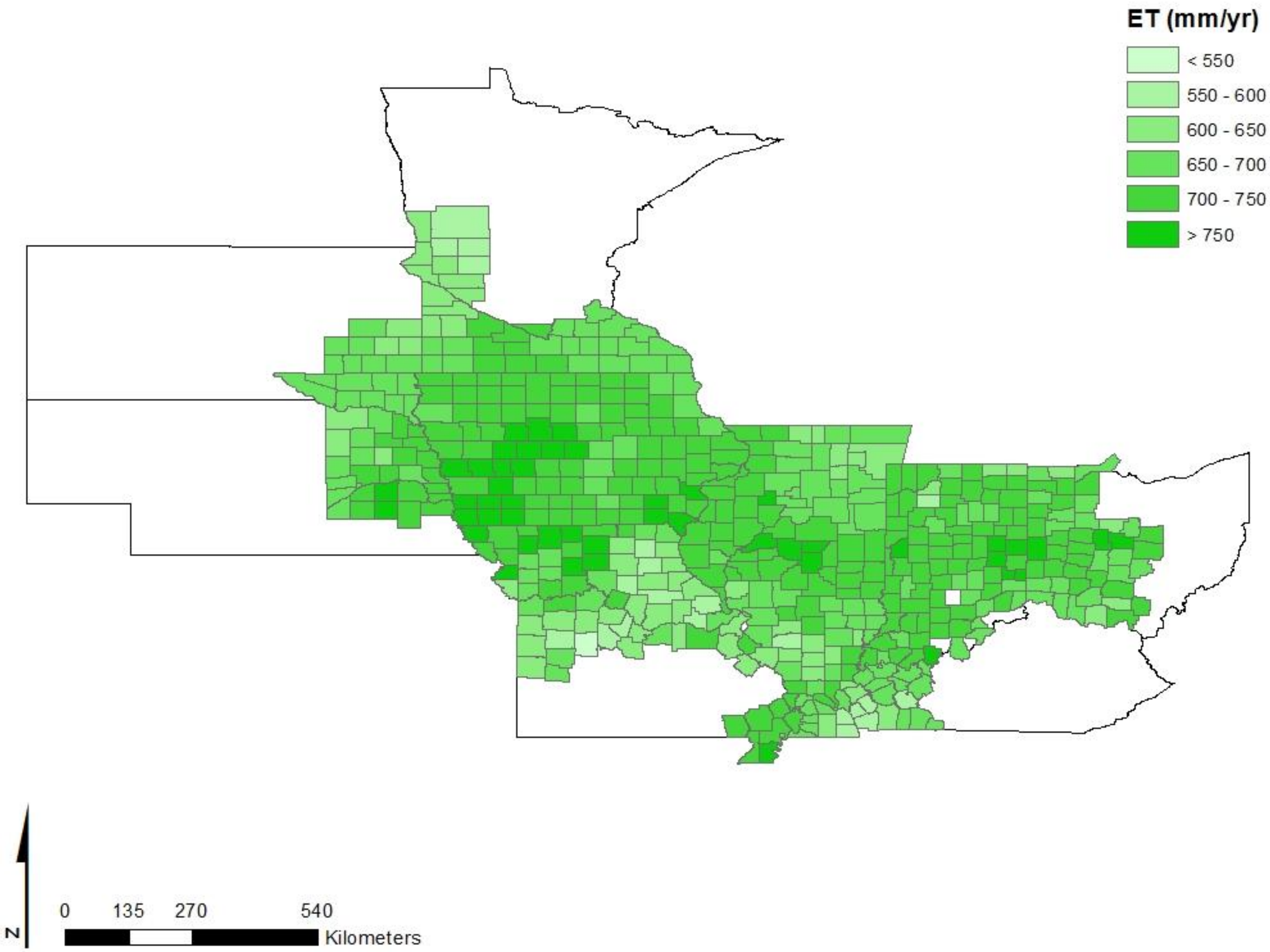

Figure 17. Average evapotranspiration of rainfed maize grown during the 11 year study period for ESR 1.

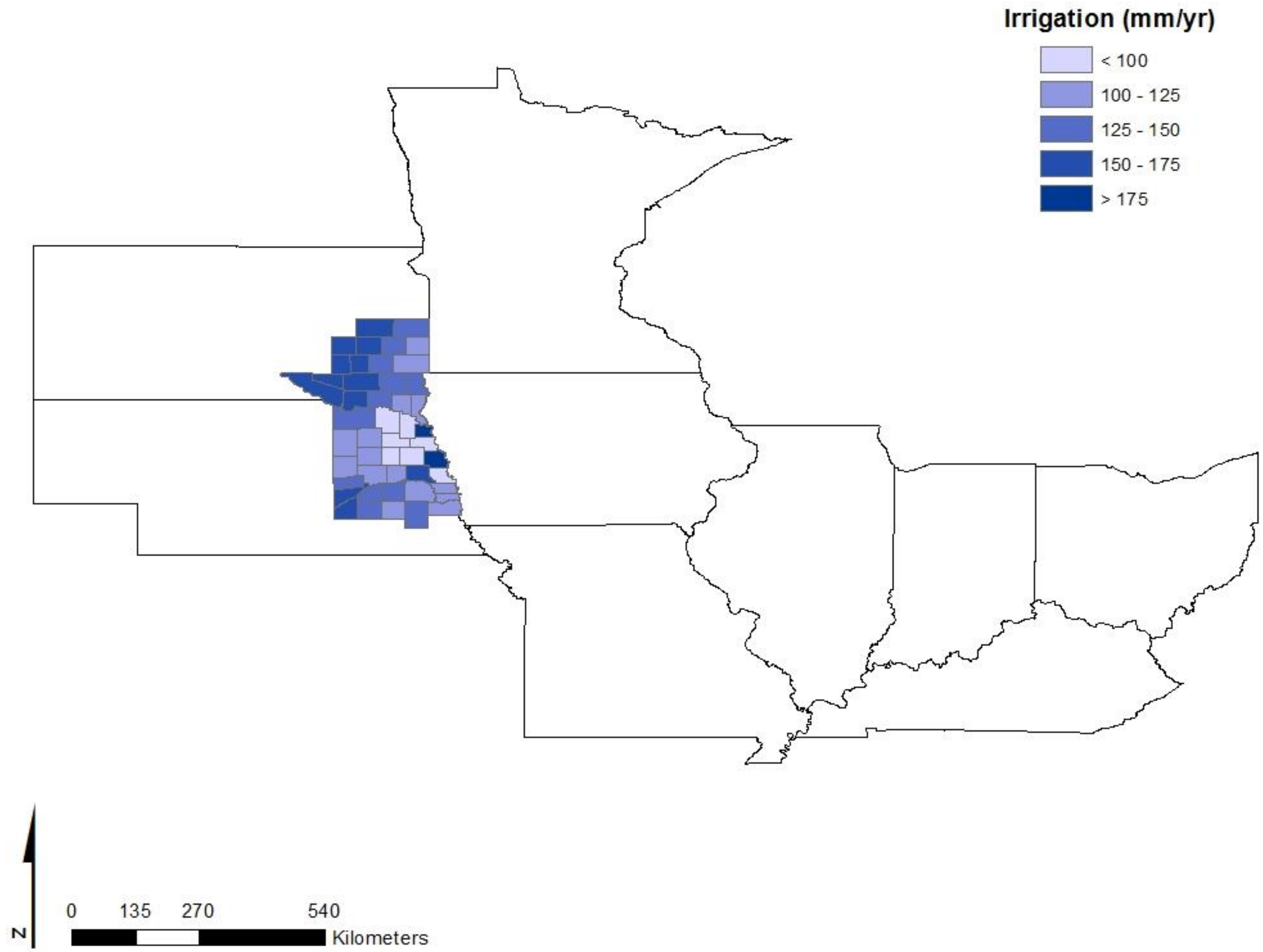

Figure 18. Average irrigation volumes during the 11 year study period for irrigated maize grown in ESR 1.

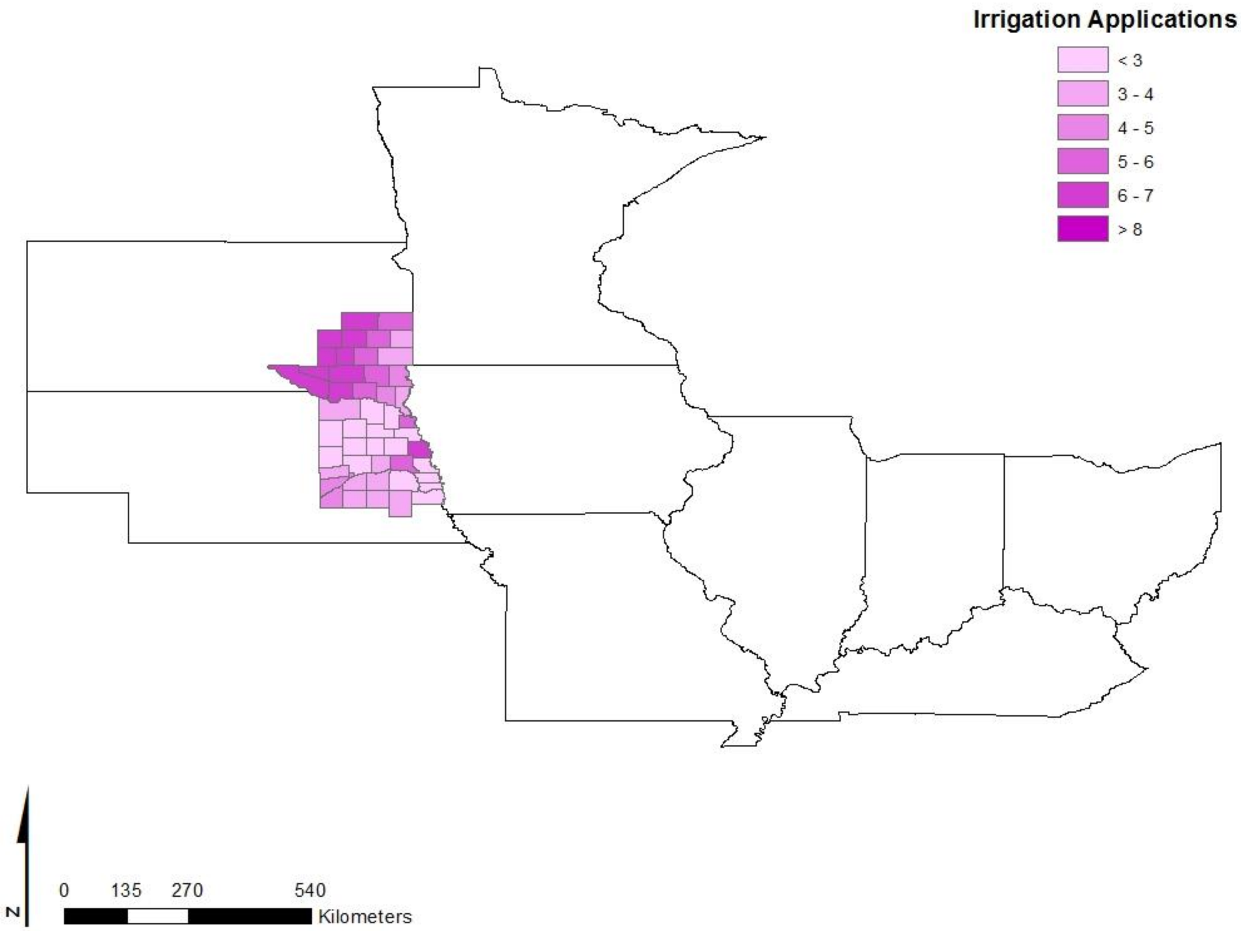

Figure 19. Average number of irrigation applications applied under an automatic setting during the 11 year study period for irrigated maize

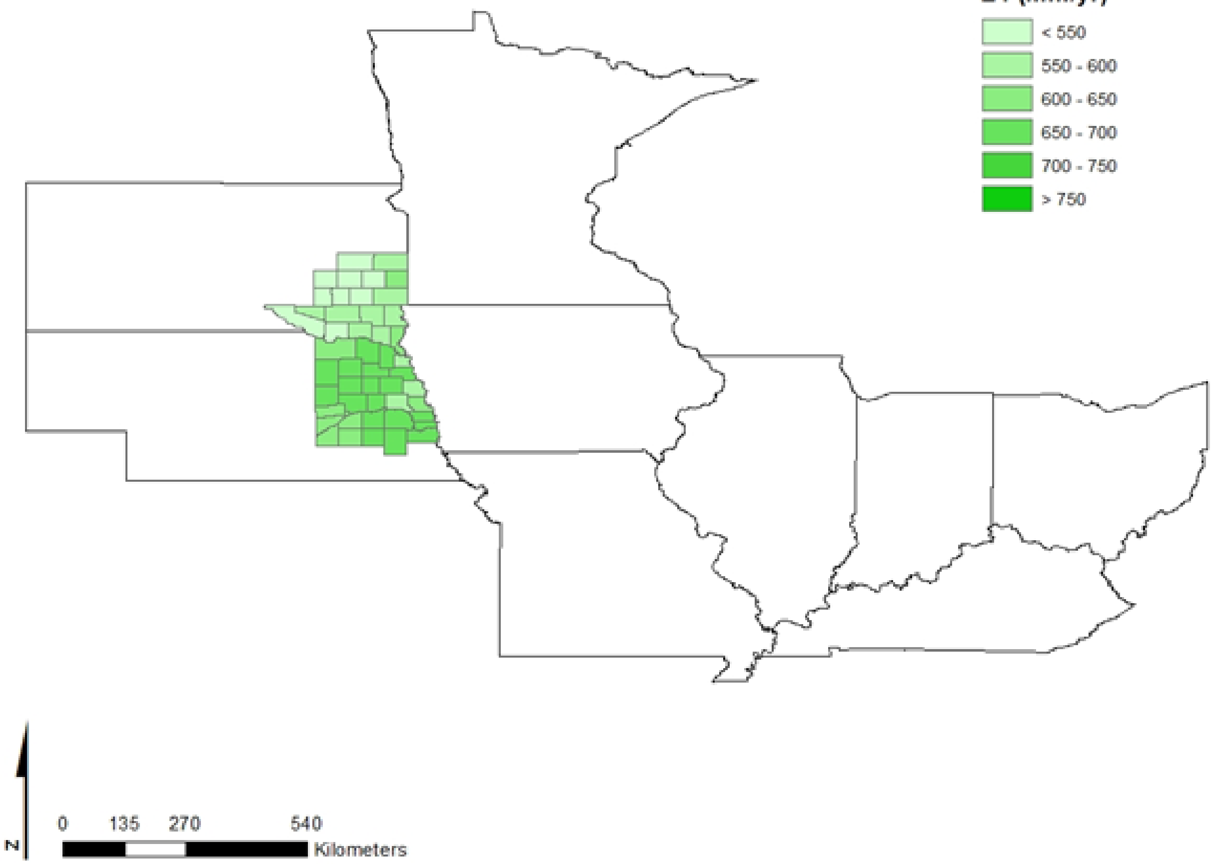

Figure 20. Average evapotranspiration of irrigated maize grown during the 11 year period for ESR 1.

CHAPTER 4 - MAIZE YIELD AND WATER USE UNDER CLIMATE CHANGE SCENARIOS

INTRODUCTION

The impacts of climate change from greenhouse gas emissions include near-surface warming on terrestrial ecosystems, which is likely to have significant effects on the earth's hydrologic cycle (Barnett, Adam, & Lettenmaier, 2005). Potential changes in the distribution and intensity of precipitation could increase the local impacts of water scarcity (Farre & Faci, 2006). This trend would have dire consequences for global agriculture, which is one of the largest consumers of the world's freshwater, and can account for up to 70-80% of the total diverted water usage in arid and semi-arid regions (Fereres & Soriano, 2007). In addition to the potential for local changes in water distribution due to climate change, water demands are predicted to increase sharply in the coming decades (Farre & Faci, 2006). As the human population increases, and more people gain access to water and sewer treatment facilities, regional water withdrawals will increase dramatically. While the actual amount of water on the planet will not decrease as a result of climate change (in fact, changes in global water volumes only occur on geologic time scales), the quality and available quantity of water will be lessened as the trend of global water withdrawal increases (Oki & Kanae, 2006). This could result in an increase in regional water scarcity, which would be impactful for agricultural production (Fereres & Soriano, 2007).

To date, much research has been done to predict the potential impacts of climate change on the hydrologic cycle. The intensification of the water cycle could result in local water deficits and an increase in the intensity and frequency of weather events such as droughts, hurricanes, and floods (Huntington, 2006). The impact of these phenomena can be devastating for agriculture. Short-term spikes in temperature can significantly decrease productivity. Studies have shown that even one to two days of extreme temperatures during a critical growth stage can be damaging to agricultural operations. In addition to the sensitivity of crops to sudden increases in temperature, historically, periods of abnormally low precipitation have resulted in the most dramatic reductions in crop productivity (Gornall, et al., 2010). Decreasing local precipitation, combined with water requirements for other human activities, can lead to significant deficits in the amount of water available for irrigation (Vorosmarty, Green, Salisbury, & Lammers, 2000).

The competition for water resources between different sectors is likely to become more evident as climate change progresses. This has raised concerns about the potential for security risks stemming from a decrease in potable water and potential decreases in crop production due to a lack of water for irrigation (Scheffran & Battaglini, 2011). Given the potential threats that climate change poses to agricultural operations, it is important for researchers and individuals working in the industry to consider future irrigation scenarios under water scarce conditions. It is likely that in the future deficit irrigation will become the norm in agricultural production (Farre & Faci, 2006; Fereres & Soriano, 2007).

The objective of this study was to apply the calibrated CERES-Maize model described in Chapter 3 under predicted 2050 weather scenarios to determine the potential impacts of climate change on maize yield, and volume of water required to mitigate any adverse yield effect that is scalable to the entire United States. To test whether predicted future climate patterns will have an impact on maize production in the US, a set of hypothesis were constructed:

- Determine the impact that climate change will have on maize yields in 2050 on a regional scale. The hypothesis to be tested (H_{04}) was that mean regional maize yield would not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).
- Determine the impact climate change will have on maize green water use on a regional scale. The hypothesis to be tested (H_{05}) was that mean regional maize green water use would not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).
- Determine the impact climate change will have on maize blue water use on a regional scale. The hypothesis to be tested (H_{06}) was that mean regional maize blue water use would not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

METHODOLOGY

Using the previously calibrated cultivars for both rainfed and irrigated maize in ESR 1, the maize yield and water use response to climate change was investigated. The CERES-Maize model was used in conjunction with climatic outputs for future Global Circulation Models (GCMs) to compare to current baseline crop production in the US. To represent baseline crop production, current estimates for crop management, such as planting density, planting and harvesting dates, were used. Output for future climatic conditions was provided by the MarkSim^{TM} DSSAT weather file generator (Jones, Thornton, & Heink, 2011). The overall approach involved combining current crop management with weather simulations using a grid based approach, and then aggregating all the results to the county level for comparison to baseline conditions. Changes in anthesis, maturity, yield, and water use were calculated.

Climate Data

Future climatic data were provided by the MarkSim^{TM} DSSAT weather file generator. Climate parameters were compared to baseline conditions, or the 11 years used for the calibration and validation of the CERES-Maize model, over the growing season for ERS 1. Major increases in both temperature and solar radiation were predicted. Maximum temperature increased between 8 – 10 % through all scenarios. For minimum temperature, the ECHam5 model predicted major increases ranging from 400 to 550%. Solar radiation increases ranged from 13.5 – 15.2%. Contrary to the increases in temperatures and solar radiation, precipitation decreases were predicted and ranged between 6.4 – 8.8% between the different scenarios (Table 5).

The fifth generation of the atmospheric general circulation model (ECHAM5) developed by the Max Planck Institute for Meteorology was used to generate weather data for the climate change analysis. General atmospheric circulation models are designed to generate climate data based on the foundational physical conservation laws such as the conservation of mass, energy, and angular momentum. The ECHAM model is broken down vertically into 19 discrete levels, with pressure being defined at the interface between each layer. The model variables include temperature, specific humidity, cloud water mixing ratio, vorticity, divergence, and the logarithm of surface pressure.

The interface for the ECHAM5 model allows the user to choose one of three IPCC greenhouse gas emissions scenarios: low emissions (**B1**), medium emissions (**A1b**), and high emissions (**A2**). The latitudes and longitudes for approximately 270 grid zones were input into the model, which then calculated daily maximum, minimum, and average temperature, solar radiation, and depth of precipitation at each location for a one-year period. These values represent a 10-year average centering around the year 2050.

RESULTS AND DISCUSSION

Future Physiological Development

Across all scenarios, climate change had a significant impact on physiological development of rainfed maize in the ERS 1. Rainfed anthesis occurred sooner across all counties through all scenarios (Table 6). Scenario **A1b** produced the largest acceleration in anthesis on average, with anthesis occurring 13.9% percent sooner. Scenarios **A2** and **B1** resulted in anthesis occurring 12.4% and 11.2% percent sooner on average, respectively. The largest shift to earlier anthesis dates were in Minnesota, Illinois, and Ohio for all three climate scenarios.

Rainfed maturity also showed similar trends when compared to anthesis. On average, maturity occurred earlier across all counties, through all scenarios (Table 7). As with anthesis, scenario **A1b** produced the largest shift in maturity dates, with a maximum shift of 31% occurring in Minnesota and an average decline in the number of days to maturity of 17.5% across the region. Scenarios **A2** and **B1** produced maximal declines of 28.4% and 27.0% and average declines of 15.3% and 13.9% respectively. The largest declines occurred in Minnesota, South Dakota, and Illinois.

Similar to rainfed maize, irrigated maize reached anthesis much sooner than when compared to baseline conditions. Under all future scenarios, irrigated maize reached anthesis sooner, throughout all counties (Table 8). Scenario **A1b** produced the largest decrease in the amount of time to reach anthesis on average, with anthesis occurring 15.8% percent sooner. Scenarios **A2** and **B1** resulted in anthesis occurring 13.4% and 12.0% percent sooner on average, respectively. Generally, maize grown in Nebraska had the fewest number of days to anthesis.

Irrigated maturity also underwent large decreases in maturity dates, similar to what was observed with the rainfed cultivars. Again, all counties under all three scenarios achieved maturity significantly sooner than compared to baseline conditions (Table 9). Under the **A1b** scenario maturity occurred 14.0% sooner on average. The other scenarios, **A2** and **B1**, reached maturity 20.3% and 18.9% sooner on average respectively. Counties in South Dakota consistently matured faster than counties in Nebraska, with a maximum maturity of occurring 29.1% sooner when compared to the baseline.

Impacts on Yield

Predicted impact of climate change on yield across all scenarios was much more variable than predicted change in physiological characteristics. Rainfed regional yield showed an average 4.61% increase under the **A1b** scenario, 2.41% under the **A2** scenario, and 4.06% under the **B1** scenario compared to baseline conditions (Table 10). The earlier physiological development across several areas corresponded to large increases in maize yields (Figure 21). Rainfed cultivars in both Nebraska and South Dakota consistently averaged over 50% more production through all scenarios, with counties in Nebraska topping out at 155% in the **B1** scenario. Model predictions of eastern production regions did not result in increased productivity. Simulated yields in Ohio, Illinois, Missouri, and Minnesota predicted large declines in yields. The largest declines in yield occurred in the counties of Illinois and Ohio through all scenarios with an upwards of approximately 30%.

Predicted irrigated yield was highly varied when current irrigated cultivars were grown under climate change scenarios. Both large gains as well as large declines in yield were observed over the irrigated portion of the study region, although the regional average increased by 6.15% under the **Alb** scenario, and 11.0% and 13.2% under the **A2** and **B1** scenarios respectively compared to the baseline. The **A1b** scenario however, did not significantly vary when compared to baseline conditions (p=0.156), in contrast to the other scenarios (Table 11). The largest decreases occurred in South Dakota, with certain counties experiencing a decline of approximately 40%. Contrary to counties in South Dakota, certain counties in Nebraska had the highest yield gains, with one county more than doubling yield output (Figure 22).

With changes in crop productivity predicted under climate change scenarios, farmers will seek to mitigate losses to keep maize production profitable. One possible way to achieve this may be for regional maize production to transition to Iowa and Nebraska and away from the eastern states in the region. Both of these areas achieved the greatest gains. Another possible solution may be to utilize a double cropping rotation. Given the predicted increases in solar radiation, in addition to warmer average temperatures, farmers may be able to plant to multiple maize crops in one season. Other authors have suggested that this may be a viable mitigation solution (Meza et al. 2008). Maize yields in both Indiana and Ohio could benefit from a double rotation, although more research in needed on the topic.

Changes in Water Use

Rainfed maize increased evapotranspiration rates under future climate scenarios. On average, evapotranspiration increased 6.72% under the **A1b** scenario, 5.72% under the **A2** scenario, and 4.67% under the **B1** scenario (Table 12). Although the average ET rates did increase throughout the region as a whole, several areas experienced major declines in the ET while others increased dramatically (Figure 24). Evapotranspiration decreased by the largest percentage in counties in Ohio, with a decrease of upwards of 15% across all scenarios. Counties in South Dakota and Indiana also showed predicted decreases in ET. Large increases in ET were also seen in Kentucky, with a maximum of roughly 33% across all scenarios. Counties in Nebraska and Indiana also showed that ET increased by up to 17%.

Evapotranspiration under irrigated maize generally increased across the observation region to the same degree as rainfed maize. Overall, average evapotranspiration increased 8.33% under the **A1b** scenario, 10.5% under the **A2** scenario, and 7.42% under the **B1** scenario (Table 13). Declines in ET were consistently observed in South Dakota, with decreases as much as 6.1% being observed (Figure 25). Similar to the rainfed situation, scenario **A2** did not produce substantial declines in ET. Scenario **B1** did see declines with an upwards of 4.34% in Nebraska.

Irrigation volumes applied to irrigated maize generally declined across the irrigated portion of the study region. Overall, irrigation declined 34.6% under the **A1b** scenario, 51.4% under the **A2** scenario, and 52.0% under the **B1** scenario (Table 14). Few increases were seen under the **A1b** scenario, occurring in southern Nebraska (Figure 26). No increases were observed under the other two scenarios. One county in Nebraska actually required no irrigation under any of the scenarios. Large declines, upwards of 75% were observed in both states.

Subsequently, the number of irrigation applications also significantly declined (Table 15). South Dakota consistently required the largest number of application through all scenarios (Figure 27).

Additional Water Applications to Rainfed Maize

To evaluate the potential for irrigation to reduce water stress in rainfed maize, an automatic irrigation management was applied to rainfed cultivars to test whether additional water applications would mediate any yield declines, and to what extent water was required. Across the region, minimal gains were observed with the addition of irrigation (Figure 23). On average under the **A1b** scenario, yields increased by 1.09%, under the **A2** scenario yields increased 3.22%, and under the **B1** scenario, yields increased 1.43% compared to the non-irrigated rainfed results (Figure 23). In addition, several counties did not require any additional irrigation. Under the **A1b**, **A2**, and **B1** scenarios, 57, 88, and 46 counties respectively required no additional irrigation. If irrigation was applied, the average irrigation volume was 108 mm yr^{-1} for the **A1b** scenario, 107 mm yr^{-1} under the **A2** scenario, and 104 mm yr^{-1} with an average of roughly 3 applications required for all scenarios. Areas in Illinois, Indiana, and Ohio observed the largest increases in rainfed maize yields with irrigation, with an upwards of 40% improvement. Inexplicably, certain counties did show decreased yields with the addition of irrigation. These areas were in the same states that witnessed the vast gains in yield with added irrigation.

Irrigating the rainfed cultivars increased ET in most areas. On average, applying irrigation for water stress alleviation increased ET by 6.27% under the **A1b** scenario, 5.97% under the **A2** scenario, and 5.87% under the **B1** scenario (Table 12). Applying irrigation actually decreased ET in certain counties in Ohio under the **A1b** scenario, yet ET increased under the other scenarios in the same counties. The reason for this phenomenon is currently unknown.

Few declines were observed under the **A2** scenario with only 9 decreasing ET across 5 different states. The **B1** scenario did produce consistent declines in counties of Ohio, and Indiana; however the largest decline was only around 4%. Across the region, irrigation volumes averaged 108 mm yr^{-1} for both the **A1b** scenario and **A2** scenario, and 103 mm yr^{-1} under the **B1** scenario (Figure 29). Average application rates were approximately 3 applications over the growing season for all scenarios (Figure 30).

Interpretation of Results

Certain aspects of the model were consistent with the current literature on maize production under climate change scenarios. Both the anthesis and maturity dates occurred sooner when compared to baseline averages, and maize yields drastically fluctuated across the region, which agrees with other studies (Southworth, et al., 2000). However, the water use results were not consistent with expected results, especially when irrigation was applied to rainfed maize. The most drastic difference was the fact that additional water supplied to rainfed maize, through irrigation, did little to improve yields. This prediction is most likely a direct result of increased high temperatures during the growing that were above the optimal range. After 35°C, any temperature increase detracts from the maize growth rate (Jones, et al., 2003). The effects of temperature stress most likely outweighed any declines in water stress.

This phenomenon could also explain why the **A1b** scenario resulted in the largest simulated yields and evapotranspiration rates under rainfed conditions. For both rainfed yield and evapotranspiration, the **Alb** scenario, or medium emissions scenario, outperformed the **B1** scenario, or low emission scenario. This is to be expected as higher temperatures would typically lead to higher metabolic rates in the corn plants. However, declines in yields and evapotranspiration occurred under the **A2** scenario relative to the medium emission scenario. It is likely that the higher temperatures occurring under the **A2** scenario consistently surpassed the threshold, having a detrimental effect on growth and causing a physiological response to conserve water and decrease evapotranspiration with increased temperature.

Despite the lack of increased yield with additional water under rainfed conditions, the rainfed maize used a large amount of irrigation water relative to the volumes used by irrigated corn. Certain areas in the southern portion of the study region required more than 20 irrigation applications over the growing season and used up to 800 mm of water. One must remember that irrigation was applied not necessarily when the crop was stressed; rather when the soil reached a critical threshold, 45% moisture content. The soil profiles found in the southern latitudes, which differ from profiles found in the north, east and west, could have become drier more quickly. Higher evapotranspiration rates caused by increased temperatures coupled with less precipitation could have reduced the water in the soil at faster rates, causing the large irrigation demand. Finally, irrigated maize used less water under the climate change scenarios. This could be attributed to the shortening of the growing season. More research is needed in these areas before any conclusive determination can be made with regards to maize water use and climate change.

CONCLUSIONS

Overall, the model predicted several future trends for maize production. Rainfed maize was projected to have both increases and decreases in yields across the region. Areas most negatively affected by changing climate were Illinois, Ohio, Northern Missouri, Southern Indiana and Southern Minnesota. Despite these large decreases in maize yields, other areas drastically increased production. Counties in central Iowa, Nebraska, and Southern South Dakota produced large increases in maize output across all scenarios. Unlike rainfed maize, irrigated maize did relatively well under all future scenarios, with yields generally increased upwards of 12%. However, large declines were observed in the South Dakota area.

H_{04}: Mean regional maize yield will not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

One of the major points of emphasis of this study was to predict whether the US's largest food crop would suffer under future climates. Overall regional yields increased across all scenarios for rainfed maize ($p < 0.05$), thus rejecting the null hypothesis. In relation to irrigated maize, maize yields increased significantly in the **A2** and **B1** scenarios, while the **A1b** scenario did not increase significantly ($p = 0.156$). Despite this, large declines were observed in certain parts of the study area, indicating that future production in certain major producing areas will still need to adapt to future climates.

H_{05}: Mean regional maize green water use will not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

Similar to yields, ET increased across the region for all scenarios for both rainfed and irrigated maize ($p < 0.05$). This happened despite large decreases in precipitation. The null hypothesis was rejected. Despite these decreases in precipitation, a faster growth induced from warmer temperature could have increase ET rates across the region.

H_{06}: Mean regional maize blue water use will not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

Under the future scenarios, applied irrigation volumes decreased across all scenarios ($p < 0.05$). Considering, the major decline in irrigation applications and volumes, the null hypothesis was rejected. This was most likely a result of the significantly shortened growing season.

To supplement any negative effects caused by water stress, rainfed maize was supplied irrigation to measure any improvements in yield addition water could supply. To the surprise of the author, addition water did little to improve yields across the region. Yields did improve in certain counties, such as in Ohio, Missouri, and Southern Illinois. Unfortunately, additional water was not enough to overcome yield declines due to temperature stress. The region also demanded large amounts of irrigation, especially in the south. This could be a result of the different soil profiles found in the southern latitude, coupled with higher evapotranspiration rates that might dry the soil faster. It should also be noted that the cultivars found in the rainfed region were not calibrated for irrigated conditions, which could also affect the results.   More research is needed to predict irrigation demands in current rainfed region of the US, although this paper suggests temperature extremes will play a larger role in maize production compared to water stress.

Using the calibrated model, regional increases in yield and ET were observed for both rainfed and irrigated maize. However, the overall regional determination masks the fact that while large increases were seen in certain portions of the study area, large decreases were also observed. Areas in Ohio, Illinois, Missouri, and Minnesota witnessed declines in yields of approximately 30%. For these areas, mitigation strategies, such as the double cropping rotation suggested by Meza et al. (2008), could help to alleviate yield losses in the future.   Also, considering the fact that heat stress was more prevalent than water stress, the exploration into the cultivation of heat tolerant maize may also be an important endeavor for protecting the US food resources.

TABLES

Table 5. Comparison of ECHam5 climate scenario mean maximum, minimum, average temperature, precipitation, and solar radiation to NASA Power baseline condition over the growing season for ERS 1.

Scenario	Tmax (°C)	Tmin (°C)	Tave (°C)	Precipitation (mm)	Solar Radiation (MJ m^{-2})
Baseline	35.9	0.72	20.3	896	19.4
A1b	+10.0%	+553%	+15.7%	-8.8%	+15.2%
A2	+8.4%	+402%	+13.2%	-6.4%	+13.5%
B1	+8.2%	+504%	+12.4%	-8.0%	+14.0%

Table 6. Difference in rainfed anthesis dates (days after planting) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	$\pm\sigma$	p-value ($\alpha = 0.05$)
Baseline	535	81.1	2.08	
2050 A1b	535	69.7	2.76	<0.05
2050 A2	535	70.9	2.79	<0.05
2050 B1	535	71.9	2.99	<0.05

Table 7. Difference in rainfed maturity dates (days after planting) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	$\pm\sigma$	p-value ($\alpha = 0.05$)
Baseline	535	134.6	4.51	
2050 A1b	535	110.7	6.41	<0.05
2050 A2	535	113.8	6.08	<0.05
2050 B1	535	115.7	5.91	<0.05

Table 8. Difference in irrigated anthesis dates (days after planting) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Baseline	52	84.9	6.62	
2050 A1b	52	71.5	5.99	<0.05
2050 A2	52	73.5	6.01	<0.05
2050 B1	52	74.7	6.49	<0.05

Table 9. Difference in irrigated maturity dates (days after planting) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates that the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Baseline	52	135.4	1.88	
2050 A1b	52	102.9	4.59	<0.05
2050 A2	52	107.8	4.36	<0.05
2050 B1	52	109.9	4.13	<0.05

Table 10. Difference in rainfed yields (kg ha^{-1}) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates the observed means are significantly different when compared to the baseline.

	Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Rainfed	**Baseline**	535	9520	1535	
	2050 A1b	535	9905	2301	<0.05
	2050 A2	535	9691	2214	0.0196
	2050 B1	535	9844	2170	<0.05
With Irrigation	**Baseline**	535	9520	1535	
	2050 A1b	535	9966	2125	<0.05
	2050 A2	535	9964	2066	<0.05
	2050 B1	535	9957	2077	<0.05

Table 11. Difference in irrigated yields (kg ha^{-1}) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Baseline	52	9897	1310	
2050 A1b	52	10387	2279	0.156
2050 A2	52	10871	2383	0.011
2050 B1	52	11068	1941	<0.05

Table 12. Difference in rainfed evapotranspiration (mm yr^{-1}) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates that the observed means are significantly different when compared to the baseline.

	Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Rainfed	**Baseline**	535	696	47.4	
	2050 A1b	535	743	63.8	<0.05
	2050 A2	535	736	59.2	<0.05
	2050 B1	535	728	53.9	<0.05
With Irrigation	**Baseline**	535	696	47.4	
	2050 A1b	535	785	65	<0.05
	2050 A2	535	776	58.2	<0.05
	2050 B1	535	768	61.3	<0.05

Table 13. Difference in irrigated evapotranspiration (mm yr^{-1}) for each of the 2050 climate scenarios compared to baseline conditions. A p-value of <0.05 indicates that the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Baseline	52	669	53.9	
2050 A1b	52	732	53.8	<0.05
2050 A2	52	728	50.5	<0.05
2050 B1	52	714	53.9	<0.05

Table 14. Difference in irrigation volumes (mm yr^{-1}) for each of the 2050 climate scenarios compared to baseline conditions for irrigated maize. A p-value of <0.05 indicates that the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Baseline	52	131.9	30.2	
2050 A1b	52	74.6	34.7	<0.05
2050 A2	52	54.7	27.9	<0.05
2050 B1	52	53.5	25.6	<0.05

Table 15. Difference in irrigation application events (mm yr^{-1}) for each of the 2050 climate scenarios compared to baseline conditions for irrigated maize. A p-value of <0.05 indicates that the observed means are significantly different when compared to the baseline.

Scenario	n	$\bar{x}$	± σ	p-value (α = 0.05)
Baseline	52	4.25	1.59	
2050 A1b	52	2.27	1.28	<0.05
2050 A2	52	1.7	1.09	<0.05
2050 B1	52	1.62	0.857	<0.05

FIGURES

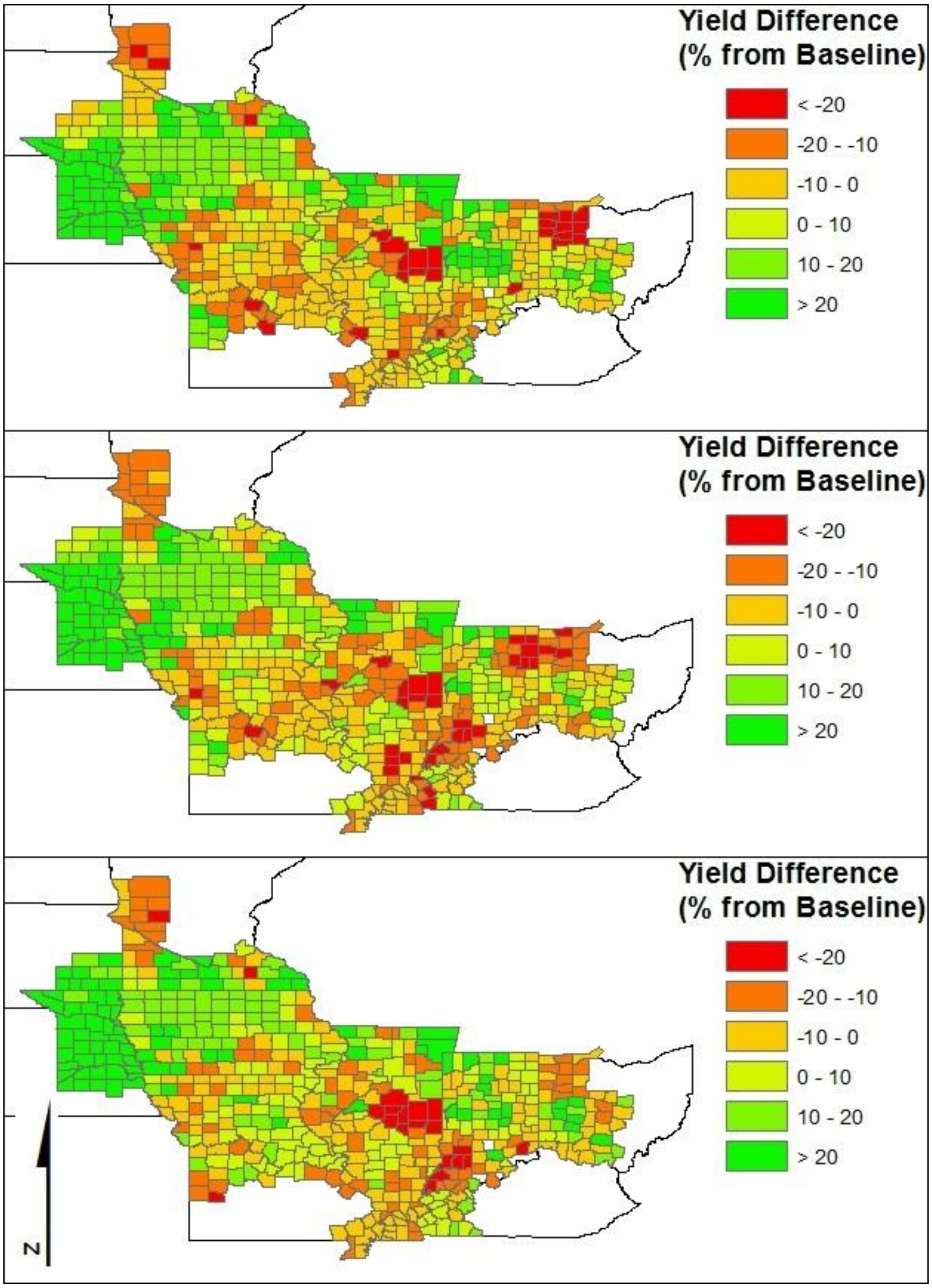

Figure 21. Relative rainfed maize yields under climate change scenarios for 2050 compared to baseline averages (1997-2007). The top figure represents the ***A1b*** *scenario, middle figure represents the* ***A2*** *scenario, and the bottom figure represents the* ***B1*** *scenario.*

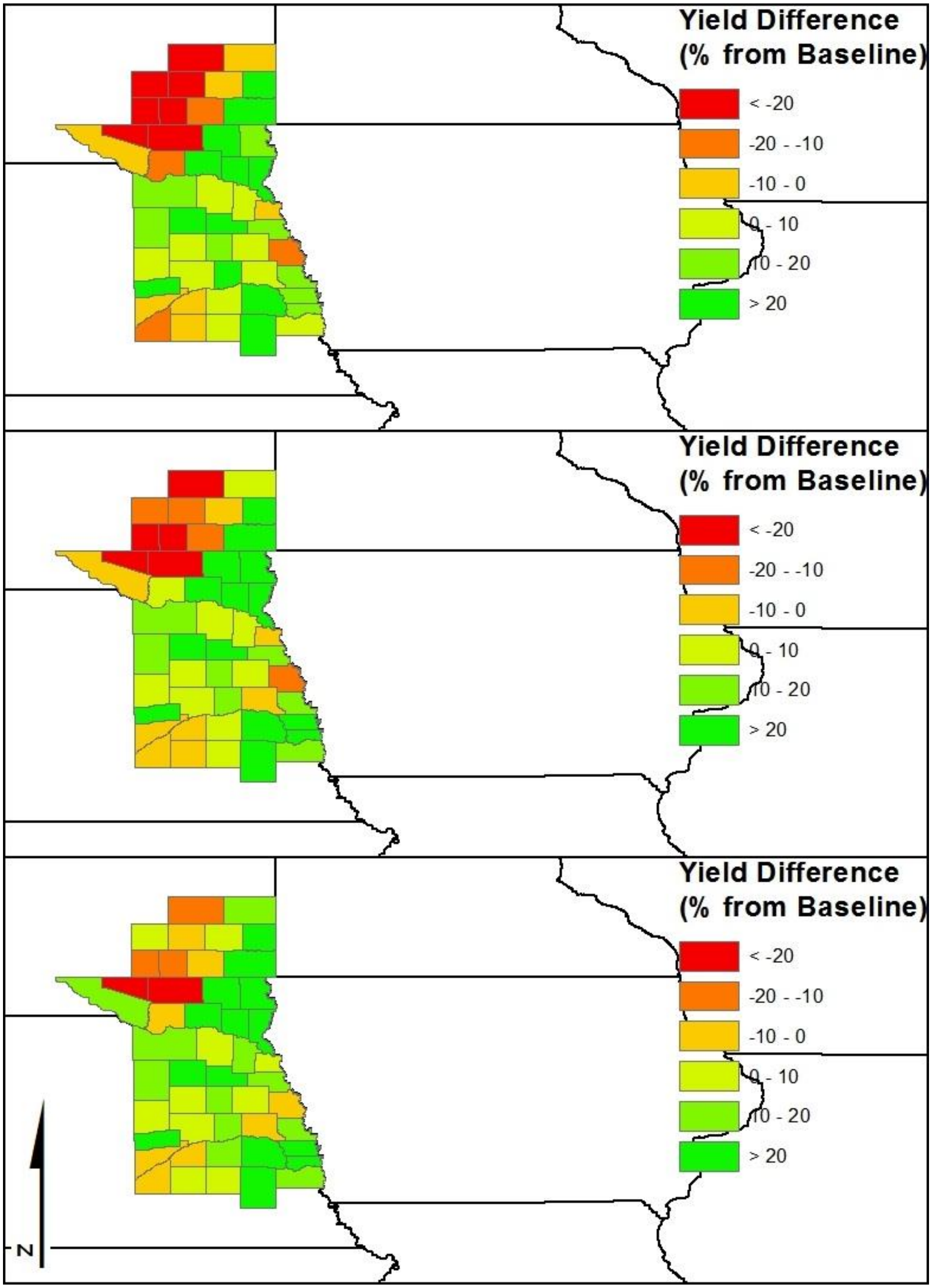

*Figure 22. Relative irrigated maize yields under climate change scenarios for 2050 compared to baseline averages (1997-2007). The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario.*

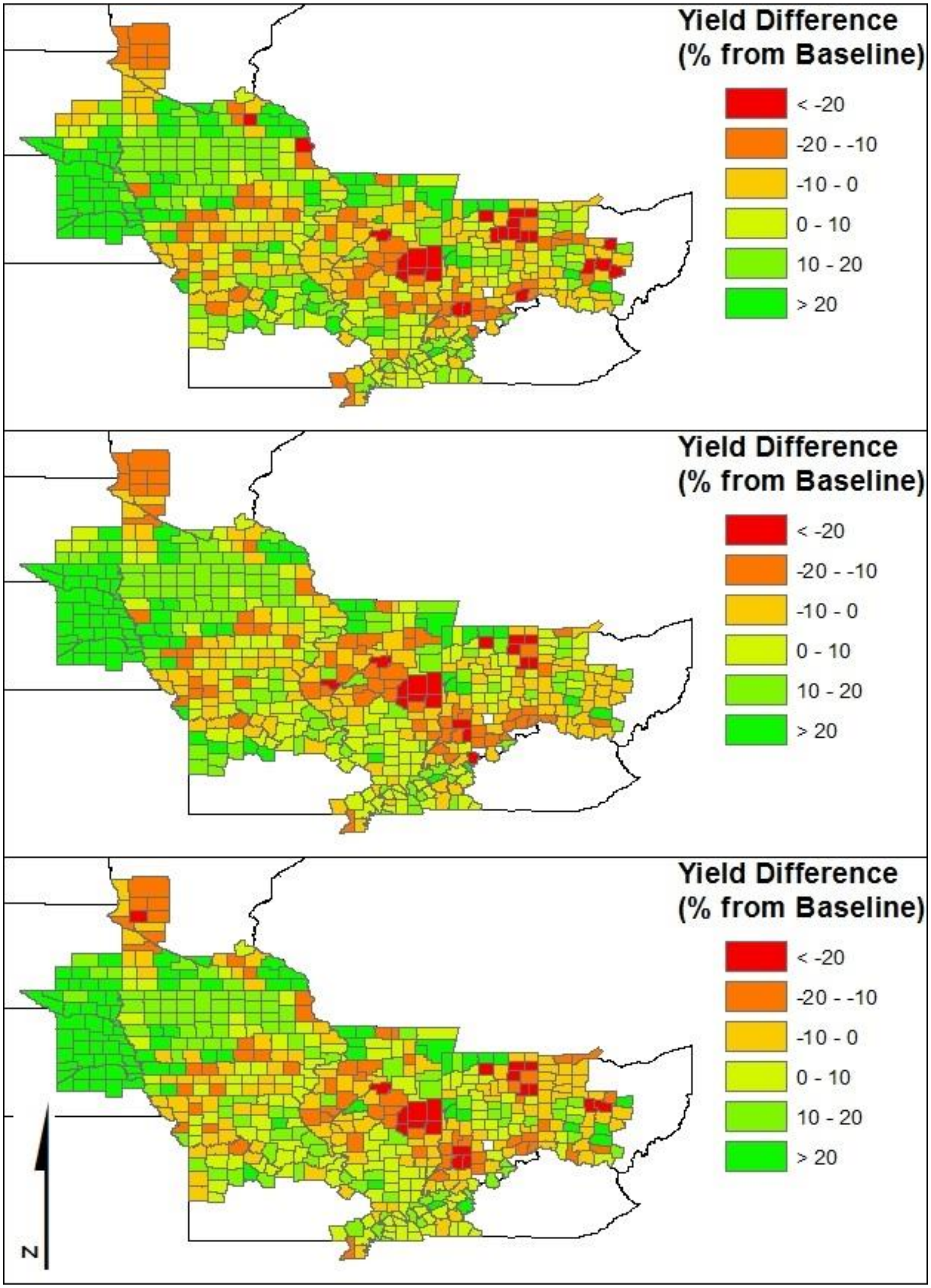

*Figure 23. Relative rainfed maize yields under climate change scenarios for 2050 with irrigation compared to baseline averages (1997-2007). The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario.*

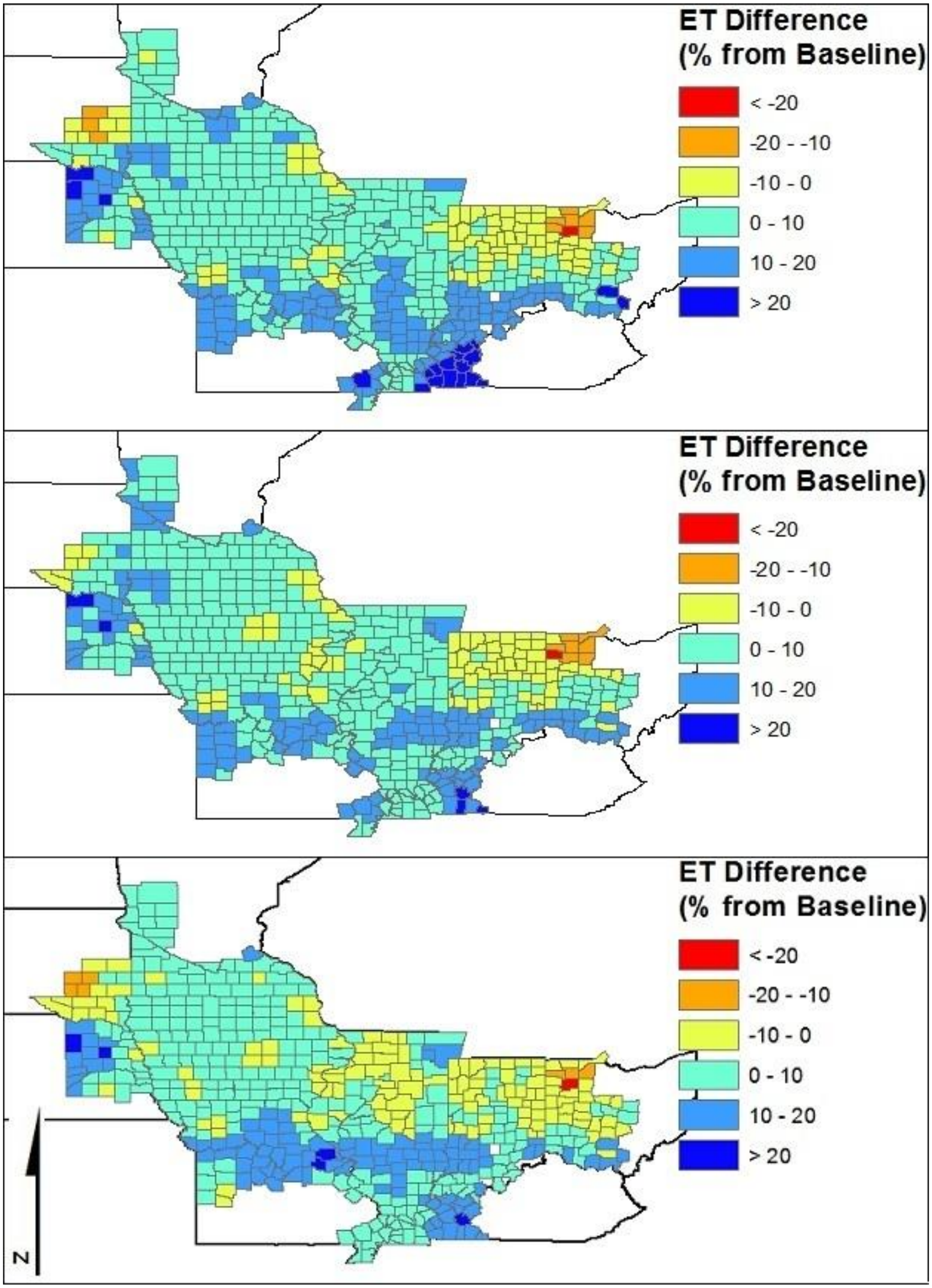

*Figure 24. Relative rainfed maize evapotranspiration under climate change scenarios for 2050 compared to baseline averages (1997-2007). The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario.*

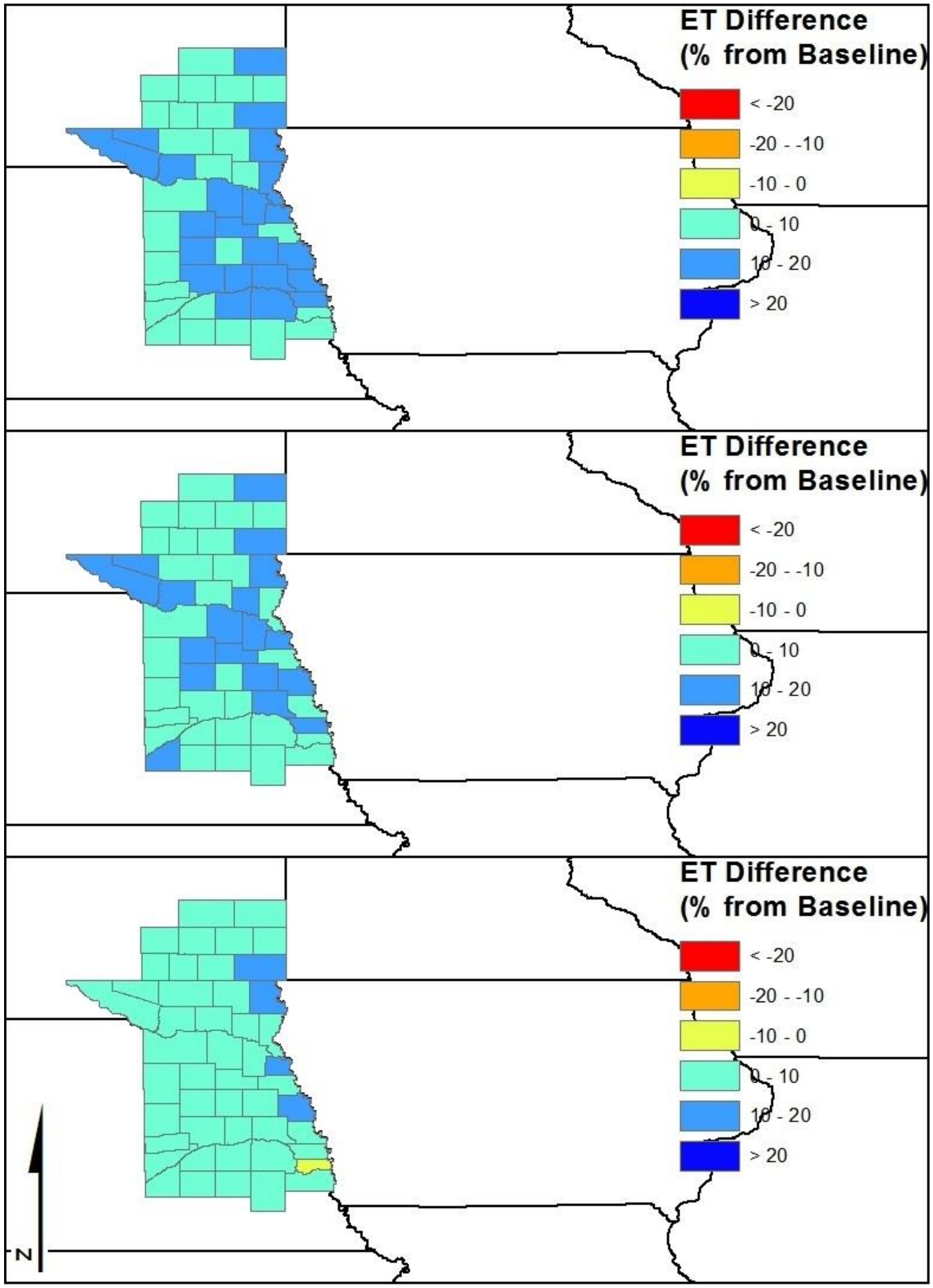

*Figure 25.Relative irrigated maize evapotranspiration under climate change scenarios for 2050 compared to baseline averages (1997-2007). The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario.*

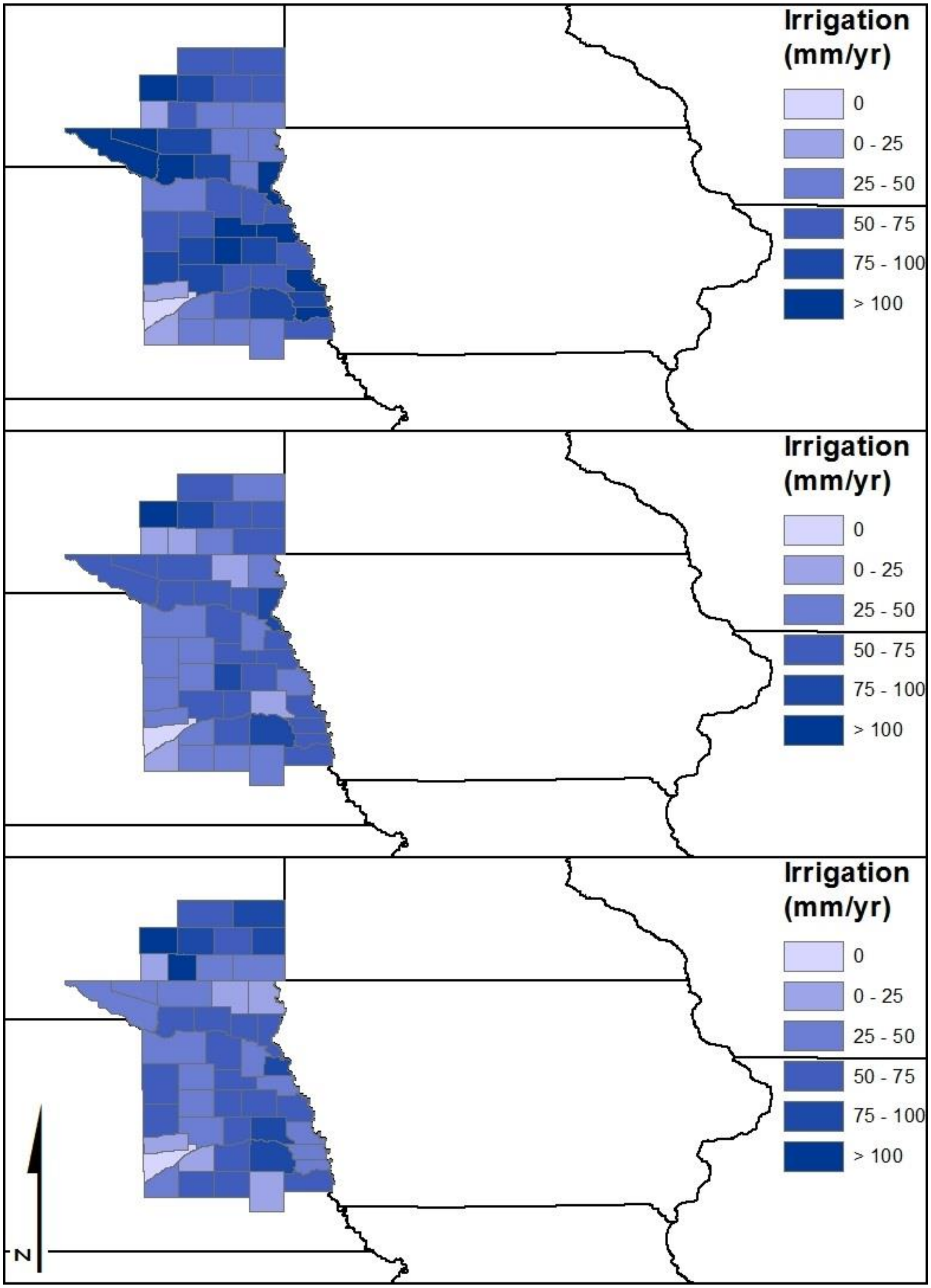

*Figure 26. Amount of irrigated maize irrigation under climate change scenarios for 2050. The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario.*

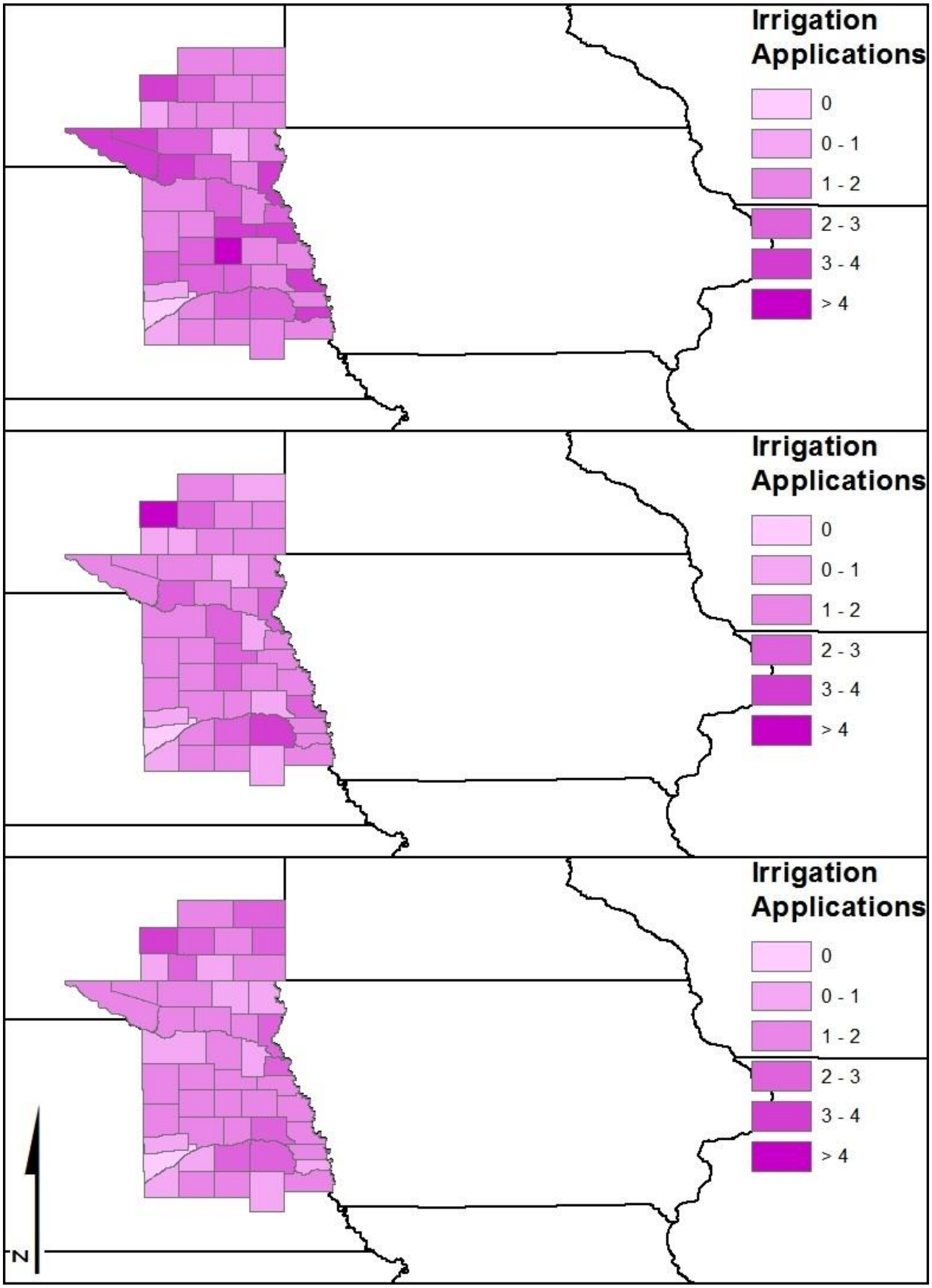

*Figure 27. Number of irrigated maize irrigation applications under climate change scenarios for 2050. The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario.*

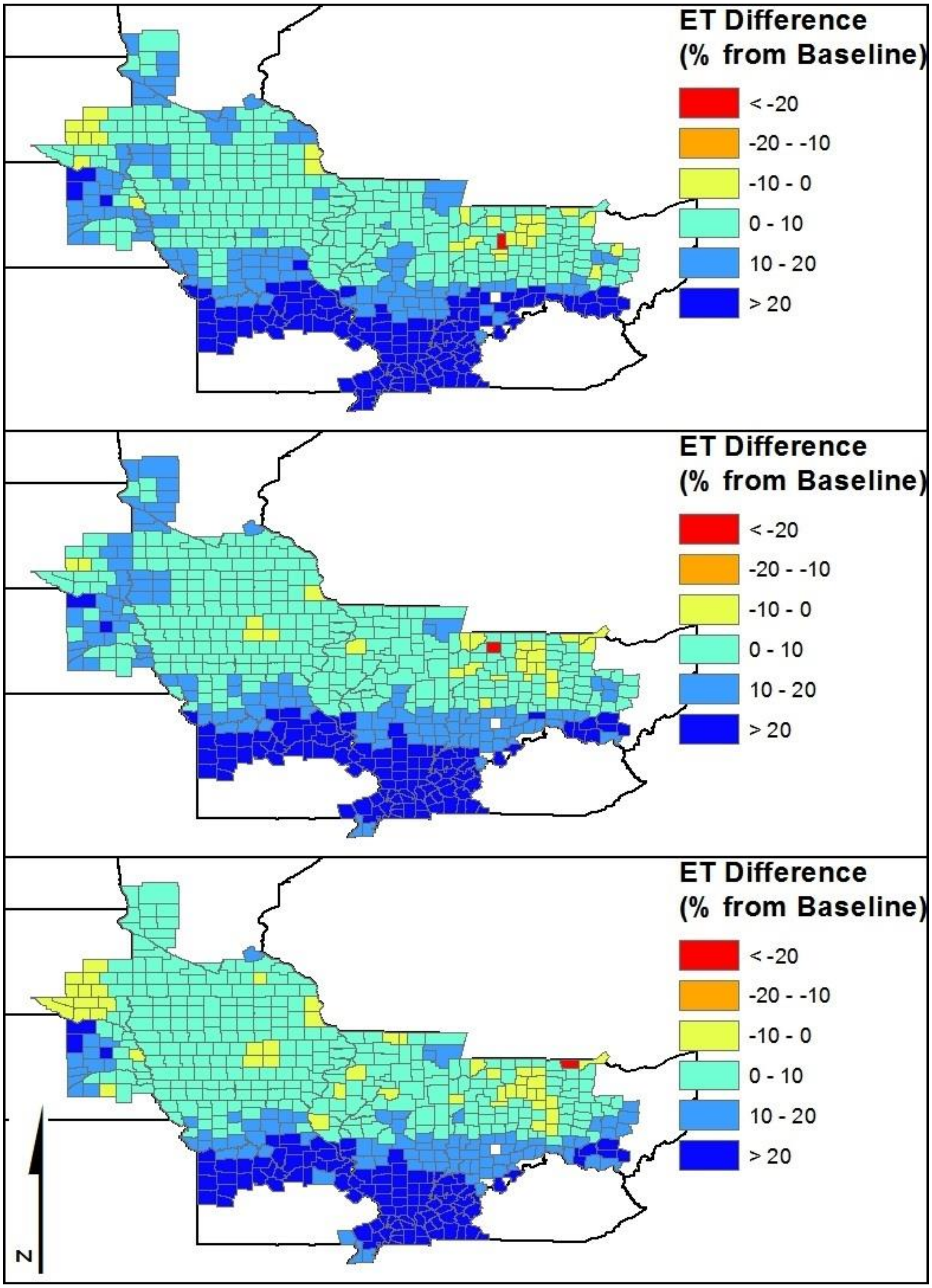

*Figure 28. Relative rainfed maize evapotranspiration under climate change scenarios for 2050 with irrigation compared to baseline averages (1997-2007). The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario*

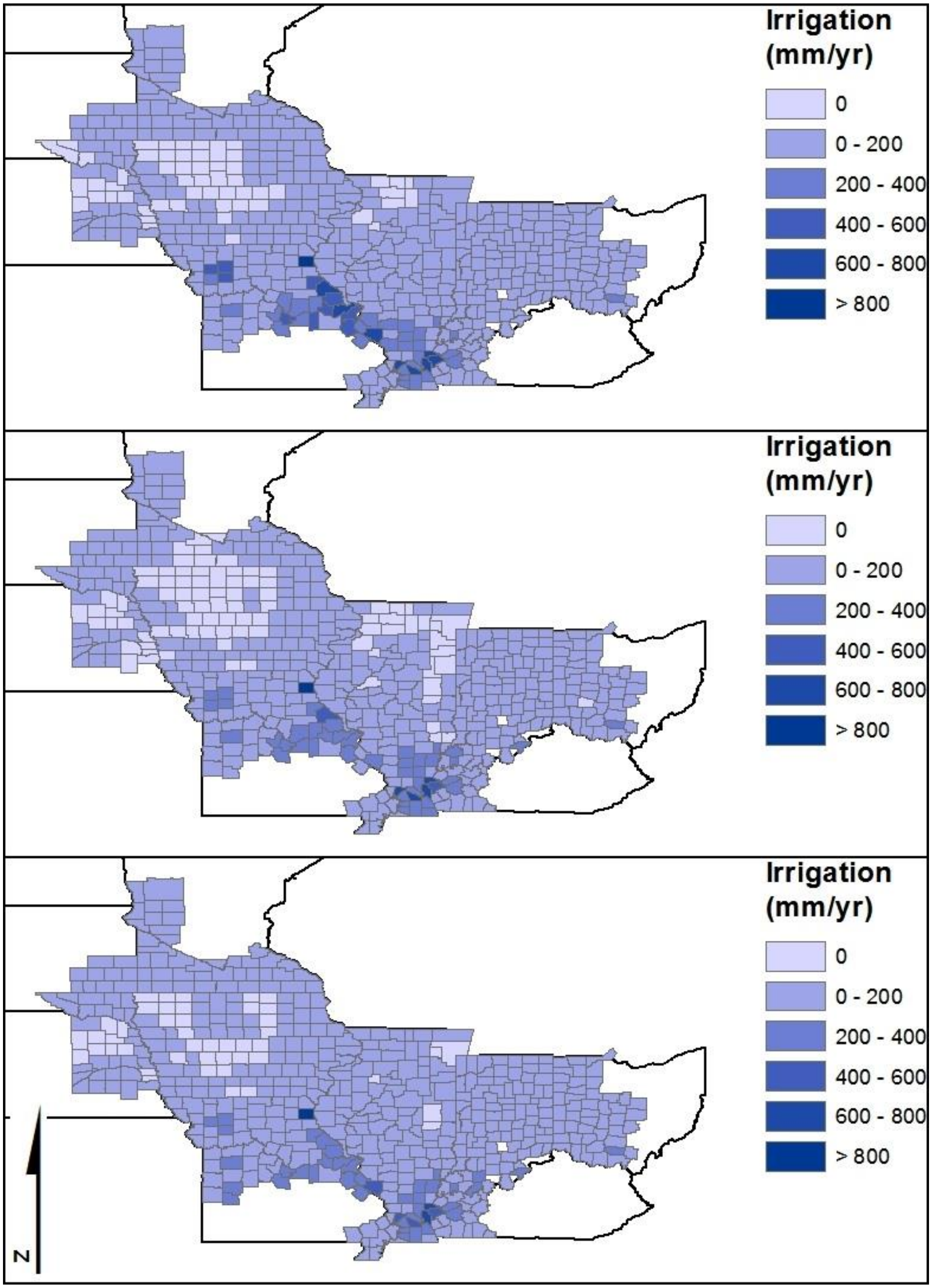

*Figure 29. Amount of irrigation applied to rainfed maize with automatic management under climate change scenarios for 2050. The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario*

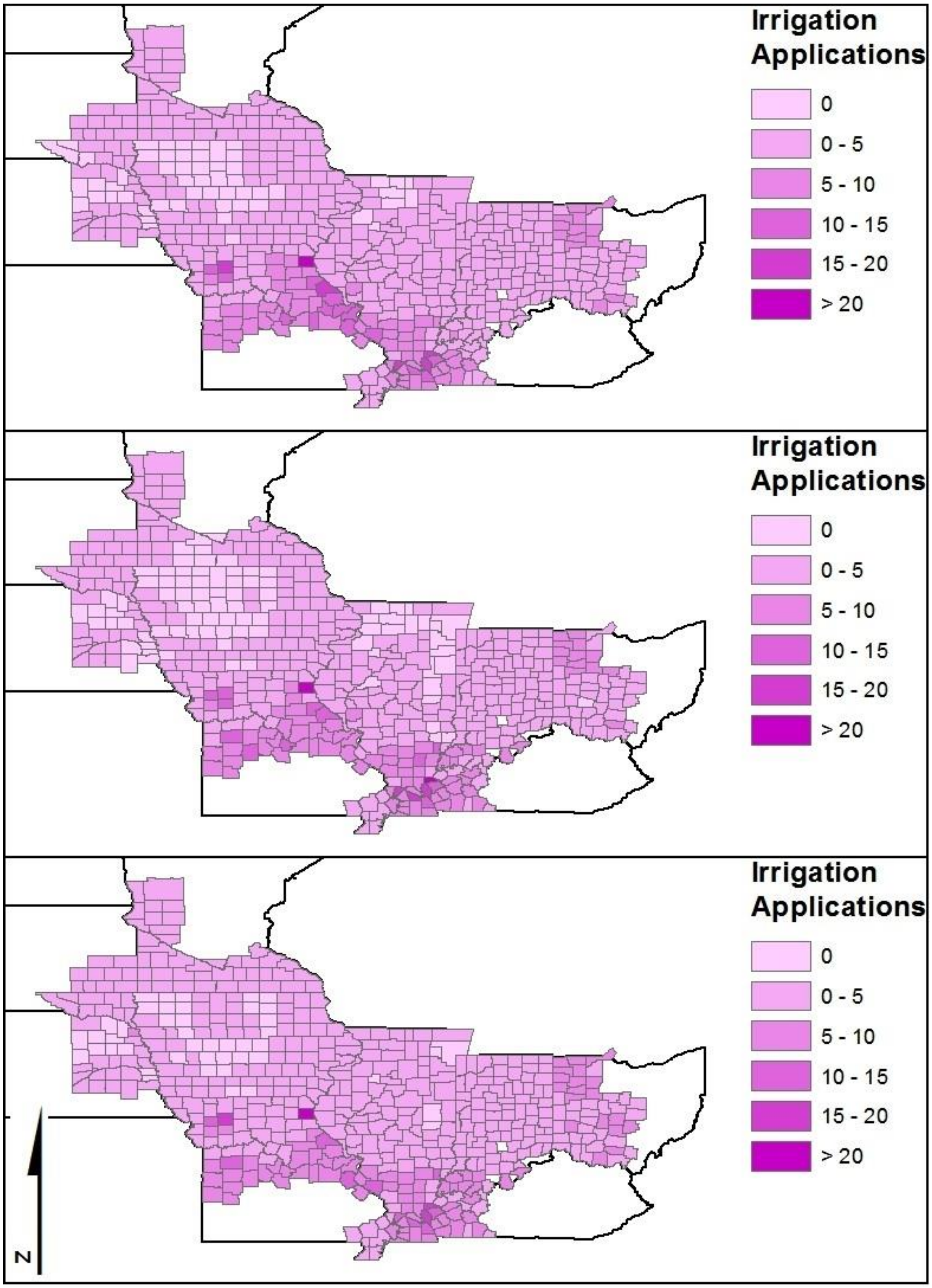

*Figure 30. Number of irrigation applications applied to rainfed maize with automatic management under climate change scenarios for 2050. The top figure represents the **A1b** scenario, middle figure represents the **A2** scenario, and the bottom figure represents the **B1** scenario*

CHAPTER 5 – CONCLUSIONS AND RECOMMENDATIONS

The goal of this project was to implement the CERES-Maize model to predict the impact of climate change on corn growth. The following objectives were created to accomplish this goal: (i) develop a crop model calibration approach for use in regional studies with limited input data to predict maize yield, (ii) develop a crop model capable of assessing regional water use; more specifically, the blue versus green water use based on yield information, (iii) use the calibrated model outputs under future scenarios to determine the impacts of climate change on maize yield, and volume of water required to mitigate any adverse yield effect that is scalable to the entire United States. These objectives were evaluated by testing the following hypothesis:

> H_{01}: The CERES-Maize model cannot predict the number of days in the development period from planting to anthesis with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

The CERES-Maize model was evaluated on its ability to predict physiological anthesis for rainfed and irrigated cultivars. For both calibration and validation, and for both rainfed and irrigated maize, the CERES-Maize model compared well to the observed datasets, producing R^2 > 0.5 and a slope that was significantly different from zero ($p < 0.05$). In addition, it could not be concluded that the slope of the regression line was significantly different from one ($p > 0.05$). Therefore, the null hypothesis was rejected, indicating the model could predict anthesis with reasonable accuracy.

> H_{02}: The CERES-Maize model cannot predict the number of days in the development period from planting to maturity with a Coefficient of Determination (R^2) > 0.5. A

regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

While the CERES-Maize Model was able to predict anthesis in regional applications, the same could not be said for rainfed and irrigated maturity. During the calibration step, both rainfed and irrigated maize compared well to the observed datasets. However, during validation, rainfed maize produced an R^2 of 0.407 and irrigated maize produced an R^2 of 0.192, although the slopes of both regressions were significantly different from zero ($p < 0.05$). Also, the slope of the regression could not be proven to be significantly different from one. Given the low predictive ability of the model for maturity, we failed to reject the null hypothesis.

H_{03}: The CERES-Maize model cannot predict maize yields with a Coefficient of Determination (R^2) > 0.5. A regression of the observed versus predicted plot will result in a slope that is not significantly different from zero (probability greater than 0.95 (α=0.05)).

For calibration and validation, both rainfed and irrigated maize produced good results. Validated rainfed maize produced an R^2 of 0.672 and irrigated maize produced and R^2 of 0.743, with slopes significantly different from zero ($p < 0.05$) for both conditions. To the same extent as anthesis, and maturity, the slope of the regression line could not be proven to be significantly different from one ($p > 0.05$). Considering both situations yielded $R^2 > 0.5$, the null hypothesis was rejected. It should be noted that despite the relative success at predicting yields, the calibrated yield coefficients consistently drifted past realistic ranges.

H_{04}: Mean regional maize yield will not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

One of the major points of emphasis of this study was to predict whether the US's largest food crops would suffer under future climates. Overall regional yields increased across all scenarios for rainfed maize ($p < 0.05$ from paired two sample t-test), thus rejecting the null hypothesis. In relation to irrigated maize, maize yields increased significantly in the **A2** and **B1** scenarios, with the exception of the **A1b** scenario ($p = 0.156$). Despite this, large declines were observed in certain parts of the study area, indicating that future production in certain major producing areas will still need to adapt to future climates.

H_{05}: Mean regional maize green water use will not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

Similar to yields, ET increased across the region for all scenarios for both rainfed and irrigated maize ($p < 0.05$). This happened despite large decreases in participation. One possible explanation for this occurrence is the higher temperatures experienced during the growing season. The higher temperatures likely increased the metabolic rates, thus increasing ET. However, the highest temperature experienced during the **A2** scenario likely begin a downward trend in productivity due to surpassing a temperature threshold. Considering the results, the null hypothesis was rejected.

H_{06}: Mean regional maize blue water use will not be significantly different from current levels under future 2050 climate conditions (probability greater than 0.95 (α=0.05)).

Under the future scenarios, applied irrigation volumes decreased across all scenarios ($p < 0.05$) when compared to current levels. This was most likely a result of the significantly reduced growing season. One interesting outcome of the research was the consequence of applying irrigation to rainfed maize. The model predicted rainfed maize would require excessively large amounts of irrigation with minimal yield gains. Considering, the significant decline in irrigation applications and volumes, the null hypothesis was rejected.

RECOMMENDATIONS

Given the results of the study, the CERES-Maize Model showed promise in regional applications with geospatially explicit data inputs. However, there is still much room for improvement with the calibration, validation, and application process.

Crop Modeling

The overall modeling process could be improved in a variety of ways. One of the easiest would be the inclusion of more calibration and validation data. In theory, more data for both calibration and validation should improve results. At the regional scale, this can be hard to come by. The US has one of the most comprehensive agricultural archives (complements of NASS) in the world. Using the techniques described above could prove difficult if replicated in other regions. In addition, using data from too large a time scale could result in inaccurate results, as many crop models do not take in account technology. Also, data on other parameters could be beneficial, such yield losses caused be pests and disease. Neither of these parameters was accounted for in the model, which could be the cause of the models inability to predict lower yield values in certain areas.

Data Resolution

Another means to improve the model would call for higher resolution inputs. Many of the inputs for this study were disaggregated from larger scales. If high resolution data was available, better estimates could be produced. The following describes the difficulty observed with the different input data from the study.

- Climate Data – The climate data provided by NASA provided an easy to use dataset at a high temporal resolution (daily), but at a low spatial resolution. Other datasets exist at a much higher spatial resolution, but only provide monthly estimates. Weather generators must be used with these datasets. High resolution climate data used in conjunction with a weather generator have shown success. Directly comparing the two different types of data might be of benefit as to which is the better predictor of yield and water use.
- Soils Data – The IRSIC-WISE DSSAT ready soil dataset provided over 4000 soil profiles for use in crop modeling studies. Unfortunately, the soils were georeferenced according a FAO soil map from the 1970s. While the soil map was at a 5 min resolution, the only link between the soil profiles and the spatial distribution was the soil classification name, which covered expansive areas of land. With only knowing soil type and not the specific profile location, and preliminary calibration had to be preform to determine the best profile fit according to yield. Knowing which soil profile was representative of each grid could improve the modeling process.
- Management Data – Some of the major potential sources of error in the study could have come from the coarse resolution of the management inputs. Crop progress, used to calibrate P1 and P5, were entered at the state level. The same is true for the planting densities. County level estimates for these values could greatly improve model performance.
- Green vs. Blue Water Use – Another source of error in this study was the yield classification supplied by NASS. Most of the states do not report the difference in yield

between rainfed and irrigation maize; only Nebraska and South Dakota provided information on this distinction. Coincidentally, these two states represent the largest consumers of irrigated water. However, the calibration process could be greatly enhanced if the yield difference for all counties could be estimated.

Climate Scenarios

Finally for future climate simulations, a Monte Carlo analysis would help the better define expected ranges for each of the different scenarios, and thus help to mitigate the risk associated with cropping in the future. The MarkSIM future weather simulator allowed for multiple simulations of a given climate scenario, and allowed for different seed values to be used to initial each simulation. Allowing the simulator to run hundreds or even thousands of different simulation for a scenario could offer better insight to the weather patterns of the future. This option was not explored due to time limits. Higher resolution climate scenarios would also aid in producing better estimates.

WORKS CITED

Alexandrov, V. A., & Hoogenboom, G. (2000). Vulnerability and adaptation assessments of agricultural crop under climate change in the Southeastern USA. *Theoretical and Applied Climatology, 67*, 45-63.

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration - Guidelines for computing crop water requirements.* Rome: FAO.

Asadi, M. E., & Clemente, R. S. (2003). Evaluation of CERES-Maize of DSSAT model to simulate nitrate leaching, yield and soil moisture content under tropical conditions. *Food, Agriculture & Environment, 1*(3&4), 270-276.

Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature, 438,* 303-309.

Batjes, N. H. (2006). *ISRIC-WISE dervied soil properties on a 5 by 5 arc-minutes global grid (version 1.0).* Wageningen: ISRIC-World Soil Information.

Binder, J., Graeff, S., Link, J., Claupein, W., Liu, M., Dai, M., & Wang, P. (2008). Model-Based Approach to Quantify Production Potentials of Summer Maize adn Spring Maize in the North China Plain. *Agronomy Journal, 100,* 862-873.

Braga, R. P., Cardoso, M. J., & Coelho, J. P. (2008). Crop model based decision support for maize (Zea mays L.) silage production in Portugal. *European Journal of Agronomy, 28,* 224-233.

Brown, R. A., & Rosenberg, N. J. (1999). Climate change impacts on the potential productivity of corn and winter wheat in their primary United States growing regions. *Climate Change, 41*, 73-107.

Carberry, P. S., Muchow, R. C., & McCown, R. L. (1989). Testing the CERES-Maize Simulation Model in a Semi-Arid Tropical Environment. *Field Crops Research, 20*, 297-315.

Cassman, K. G., Grassini, P., & Wart, J. (2011). Crop Yield Potential, Yield Trends, and Global Food Security in a Changing Climate. In D. Hillel, & C. Rosenzweig (Eds.), *Handbook of Climate Change and Agroecosystems: Impacts, Adaptation, and Mitigation* (Vol. 1, pp. 37-51). London, UK: Imperial College Press.

DeJonge, K. C., Kaleita, A. L., & Thorp, K. R. (2007). Simulating the effects of spatially variable irrigation on corn yields, costs, and revenue in Iowa. *Agricultural Water Management, 92,* 99-109.

Egli, D. B. (2008). Comparison of Corn and Soybean Yields in the United States: Historical Trends and Future Propects. *Agronomy Journal, 100*, S79-S88.

Farre, I., & Faci, J. M. (2006). Comparative response of maize (Zea mays L.) and sorghum (Sorghum bicolor L. Moench) to deficit irrigation in a Mediterranean environment. *Agricultural Water Management, 83*, 135-143.

Fedoroff, N. V., Battisti, D. S., Beachy, R. N., Cooper, P. M., Fischhoff, D. A., Hodges, C. N., . . . Zhu, J.-K. (2010). Radically Rethinking Agriculture for the 21st Century. *Science, 327*, 833-834.

Feng, Z., Liu, D., & Zhang, Y. (2007). Water requirements and irrigation scheduling of spring maize using GIS and CropWat model in Beijing-Tianjin-Hebei region. *Chinese Geographcial Science, 17*(1), 056-063.

Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany, 58*(2), 147-159.

Ferreyra, R. A., Podesta, G. P., Messina, C. D., Letson, D., Dardanelli, J., Guevara, E., & Meira, S. (2001). A linked-modeling framework to estimate maize production risk assoicated with ENSO-related climate variability in Argentina. *Agriculture and Forest Meteorology, 107*, 177-192.

Foreman, L. (2006). *Characteristics and Production Costs of U.S. Corn Farms, 2001.* United States Department of Agriculture, Economic Research Service. Retrieved from http://www.ers.usda.gov/publications/eib7/eib7.pdf

Godfray, H. C., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., . . . Toulmin, C. (2010). Food Security: The Challenge of Feeding 9 Billion People. *Science, 327*, 812-818.

Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., & Wiltshire, A. (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society, 365*, 2973-2989.

Grassini, P., Yang, H., & Cassman, K. G. (2009). Limit to maize productivity in Western Corn Belt: A simulation analysis for fully irrigated and rainfed conditions. *Agricultural and Forest Meteorology, 149*(8), 1254-1265.

Hansen, J. W., & Jones, J. W. (2000). Scaling-up crop models for climate variablity applications. *Agricultural Systems, 65*, 43-72.

Heng, L. K., Hsiao, T., Evett, S., Howell, T., & Steduto, P. (2009). Validating the FAO AquaCrop Model for irrigated and water deficient field maize. *Agronomy Journal, 101*(3), 488-498.

Hodges, T., Botner, D., Sakamota, C., & Haug, J. H. (1987). Using the CERES-Maize Model to Estimate Production for the U.S. Cornbelt. *Agricultural and Forest Meteorology, 40*, 293-303.

Hoekstra, A. Y., & Hung, P. Q. (2002). *Virtual Water Trade: A Quantification of Vrtual Water Flows between Nations in relation to International Crop Trade.* Delft, The Netherlands: UNESCO-IHE.

Hoekstra, A. Y., Chapagain, A. K., Aldaya, M. M., & Mekonnen, M. M. (2011). *The Water Footprint Assessment Manual.* Washington DC, USA: Earthscan.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Batchelor, W. D., Hunt, L. A., . . . Tsuji, G. Y. (2004). Decision Support System for Agrotechnology Transfer Version 4.0 [CD-ROM]. Honolulu: University of Hawaii.

Hoppe, R. A., & Banker, D. E. (July 2010). *Structure and Finances of U.S. Farms: Family Farm Report, 2010 Edition.* U.S. Department of Agriculture, Economic Research Service. Retrieved from http://www.ers.usda.gov./Publications/EIB66/EIB66.pdf

Hunt, L. A., Pararajasingham, S., Jones, J. W., Hoogenboom, G., Imamura, D. T., & Ogoshi, R. M. (1993). GENCALC: Software to Facilitate the Use of Crop Models for Analyzing Field Experiments. *Agronomy Journal, 85*, 1090-1094.

Huntington, T. G. (2006). Evidence for intensification of the global water cycle: Review and synethesis. *Journal of Hydrology, 319*, 83-95.

Iglesias, A., & Minguez, M. I. (1997). Modelling crop-climate interactions in Spain: vulnerability and adaptation of different agricultural systems to climate change. *Mitigation and Adaptation Strategies for Global Change, 1*, 273-288.

Izaurralde, R. C., Rosenberg, N. J., Brown, R. A., & Thomson, A. M. (2003). Integrated assessment of Hadley Center (HadCM2) climate-change impacts on agricultural productivity and irrigation water supply in the conterminous United States Part II. Regional agricultural production in 2030 and 2095. *Agricultural and Forest Meteorology, 117*, 97-122.

Jagtap, S. S., & Jones, J. W. (2002). Adaptation and evaluation of the CROPGRO-soybean model to predict regional yield and production. *Agriculture, Ecosystems and Environment, 93*, 73-85.

Jagtap, S. S., Abamu, F. J., & Kling, J. G. (1999). Long-term assessment of nitrogen and variety technologies on attainable maize yields in Nigeria using CERES-maize. *Agricultural Systems, 60*, 77-86.

Jones, C. A., & Kiniry, J. R. (1986). *CERES-Maize, a simulation model of maize growth and development.* College Station: Texas A&M University Press.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., . . . Richie, J. T. (2003, January). The DSSAT cropping system model. *European Journal of Agronomy, 18*(3-4), 235-265.

Jones, P. G., Thornton, P. K., & Heink, J. (2011). *Generating characteristic daily weather data using downscaled climate model data from the IPCC's Fourth Assessment.* Retrieved from https://hc.box.net/shared/f2gk053td8

Karlen, D. L., Archer, D., Liska, A., & Meyer, S. (2012). *Energy Issues Affecting Corn/Soybean Systems: Challenges for Sustainable Production.* Ames, Iowa: CAST.

Koehler, A. (2008). Water use in LCA: managing the planet's freshwater resources. *International Journal of Life Cycle Assessment, 13*(6), 451-455.

Leakey, A. D., Uribelarrea, M., Ainsworth, E. A., Naidu, S. L., Rogers, A., Ort, D. R., & Long, S. P. (2006). Photosynthesis, Productivity, and Yield of Maize Are Not Affected by Open-Air Elevation of CO2 Concentration in the Absence of Drought. *Plant Physiology, 140*, 779-790.

Liu, J., & Yang, H. (2010). Spatially explict assessment of global consumptive water uses in cropland: Green and blue water. *Journal of Hydrology, 384*(3-4), 187-197.

Liu, J., Williams, J. R., Zehnder, A. J., & Yang, H. (2007). GEPIC - modelling wheat yield and crop water productivity with high resolution on a global scale. *Agricultural Systems, 94*(2), 478-493.

Liu, W. T. (1989). Application of CERES-Maize Model to yield prediction of a Brazilian maize hybrid. *Agricultural and Forest Meteorolgy, 45*(3-4), 299-312.

Lopez-Cedron, F. X., Boote, K. J., Ruiz-Nogueira, B., & Sau, F. (2005). Testing CERES-Maize versions to estimate maize production in a cool environment. *European Journal of Agronomy, 23*(1), 89-102.

Mavromatis, T., Boote, K. J., Jones, J. W., Irmak, A., Shinde, D., & Hoogenboom, G. (2001). Developing Genetic Coefficients for Crop Simulation Models with Data from Crop Performace Trials. *Crop Science, 41*, 40-51.

Mavromatis, T., Boote, K. J., Jones, J. W., Wilkerson, G. G., & Hoogenboom, G. (2002). Repeatability of Model Genetic Coefficients Derived from Soybean Performace Trials across Different States. *Crop Science, 42*, 76-89.

Mearns, L. O., Mavromatis, T., & Tsvetsinskaya, E. (1999). Comparative responses of EPIC and CERES crop models to high and low spatial resolution climate change scenarios. *Journal of Geophysical Research, 104*(D6), 6623-6646.

Mekonnen, M. M., & Hoekstra, A. Y. (2010). A global and high-resolution assessment of the green, blue and grey water footprint of wheat. *Hydrology and Earth System Sciences, 14*, 1259-1276.

Mekonnen, M. M., & Hoekstra, A. Y. (2011). The green, blue and grey water footprint of crops and derived crop products. *15*, 1577-1600.

Meza, F. J., Silva, D., & Vigil, H. (2008). Climate change impacts on irrigated maize in Mediterranean climates: Evaluation of double cropping as an emerging adaptation alternative. *Agricultural Systems*, *98*, 21-30.

NASA POWER Team. (2010). *Surface meteorology and solar energy (SSE) release 6.0 methodology VERSION 2.4.1.* NASA POWER Agroclimatology. Retrieved from http://power.larc.nasa.gov

NASS. (2011). *Quick Stats 2.0*. Retrieved from http://quickstats.nass.usda.gov/

NASS, U. (2007). *Census of Agriculture.* Retrieved from http://www.agcensus.usda.gov/Publications/2007/Full_Report/

NOAA. (2011). *Palmer Drought Severity & Crop Moisture Indices*. Retrieved from http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/palmer_drought/

Nouna, B. B., Katerji, N., & Mastrorilli, M. (2000). Using the CERES-Maize model in a semi-arid Mediterranea evironment. Evaluation of model performance. *European Journal of Agronomy, 13*, 309-322.

Nouna, B. B., Katerji, N., & Mastrorilli, M. (2003, May). Using the CERES-Maize model in a semi-arid Mediterranean environment. New modelling of leaf area and water stress functions. *European Journal of Agronomy, 19*(2), 115-123.

Oki, T., & Kanae, S. (2006). Global Hydrological Cycles and World Water Resources. *Science, 313*, 1068-1072.

Paoletti, M. G., Gomiero, T., & Pimentel, D. (2011). Introduction to the Special Issue: Towards a More Sustainable Agriculture. *Critical Reviews in Plant Sciences, 30*, 2-5.

Pisani, A. L. (1987). The CERES-MAIZE model as a potential tool for drought assessment in South Africa. *Water SA*, *13*(3), 159-164.

Popova, Z., & Kercheva, M. (2004). Integreated strategies for maize irrigation and fertilization under water scarcity and environmental pressure in Bulgaria. *Irrigation and Drainage, 53*, 105-113.

Prillaman, A. (2011, May 12). (R. Johnston, Interviewer)

Quiring, S. M., & Legates, D. R. (2008, June). Application of CERES-Maize for within-season prediction of rainfed corn yields in Delaware, USA. *Agricutural and Forest Meteorology, 148*(6-7), 964-975.

Roman-Paoli, E., Welch, S. M., & Vanderlip, R. L. (2000). Comparing genetic coefficient estimation methods using the CERES-Maize model. *Agricultural Systems, 65*, 29-41.

Romero, C. C., Hoogenboom, G., Baigorria, G. A., Koo, J., Gijsman, A. J., & Wood, S. (2012). Reanalysis of a global soil database for crop and environmental modeling. *Environmental Modelling & Software, 35*, 163-170.

Rosegrant, M. W., Ringler, C., & Zhu, T. (2009). Water for Agriculture: Maintaining Food Security under Growing Scarcity. *Annual Review of Environment and Resources, 34*, 205-222.

Rost, S., Geren, D., Bondeau, A., Lucht, W., Rohwer, J., & Schaphoff, S. (2008). Agricultural green and blue water consumption and its influence on the global wate system. *Water Resources Research, 44*, W09405.

Salazar, M. R., Hook, J. E., Garcia y Garcia, A., Paz, J. O., Chaves, B., & Hoogenboom, G. (2012). Estimating irrigation water use for maizee in the Southeastern USA: A modelling approach. *Agriculutral Water Management, 107*, 104-111.

Saseendran, S. A., Ahuja, L. R., Nielsen, D. C., Trout, T. J., & Ma, L. (2008). Use of crop simulation models to evaluate limited irrigation management options for corn in a semiarid environment. *Water Resources Research*, W00E02.

Scheffran, J., & Battaglini, A. (2011). Climate and conflicts: the security risks of global warming. *Reg Environ Change, 11*(Suppl 1), S27-S39.

Siebert, S., & Doll, P. (2010). Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation. *Journal of Hydrology, 384*, 198-217.

Soler, C. M., Sentelhas, P. C., & Hoogenboom, G. (2007). Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. *European Journal of Agronomy, 27*(2-4), 165-1777.

Sommer, J. E., & Hines, F. K. (1991). *Diversity in U.S. Agriculture: A New Delineation by Farming Characteristics.* ERS, USDA.

Southworth, J., Randolph, J. C., Habeck, M., Doering, O. C., Pfeifer, R. A., Rao, D. G., & Johnston, J. J. (2000). Consequences of future climate change and changing climate variability on maize yields in the midwestern United States. *Agriculture, Ecosystems and Environment, 82*, 139-158.

The Land Commoditites Global Agriculture & Farmland Investment Report. (2009). Baar, Switzerland: Land Commodities Asset Management AG. From http://www.landcommodities.com

Thorp, K. R., Batchelor, W. D., Paz, J. O., Kaleita, A. L., & DeJonge, K. C. (2007). Using cross-validation to evaluate CERES-Maize yield simulations within a decision support system for precesion agriculture. *Transactions of the ASABE, 50*(4), 1467-1479.

United Nations, D. o. (2011). *World Populaiton Prospects: The 2010 Revision, Highlights and Adavance Tables.*

USDA. (2008). *Farm and Ranch Irrigation Survey.* United States Department of Agriculture.

Vorosmarty, C. J., Green, P., Salisbury, J., & Lammers, R. B. (2000). Global water resources: vulnerability from climate change and population growth. *Science, 289*, 284-288.

Wafula, B. M. (1995). Applications of Crop Simulation in Agricultural Extension and Research in Kenya. *Agricultural Systems, 49*, 399-412.

Xiong, W., Holman, I., Conway, D., Lin, E., & Li, Y. (2008). A crop model cross calibration for use in regional climate impacts studies. *Ecological Modelling, 213*, 365-380.

Xiong, W., Matthews, R., Holman, I., Lin, E., & Xu, Y. (2007). Modelling China's potential maize production at regional scale under climate change. *Climate Change, 85*, 433-451.

Yang, Z., Wilkerson, G. G., Buol, G. S., Bowman, D. T., & Heiniger, R. W. (2009). Estimating Genetic Coefficients for the CSM-CERES-Maize Model in North Carolina Environments. *Agronomy Journal, 101*, 1276-1285.