

CROP PRODUCTION AND FUTURE CLIMATE CHANGE IN
A HIGH LATITUDE REGION: A CASE STUDY FOR THE UPPER GREAT LAKES
REGION OF THE UNITED STATES

By

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ABSTRACT

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Agriculture is particularly susceptible to climate change, as inferred from large historical variations in crop production in response to past climate variability. The major goal of this dissertation is to evaluate the spatial variability of the impacts of projected future climate change on crop production in a high latitude region. Corn and soybean production in the Upper Great Lakes Region (UGLR) of the United States, encompassing the states of Michigan, Wisconsin and Minnesota, serves as the case study. The CERES-Maize and CROPGRO-Soybean models included in the *Decision Support System for Agrotechnology Transfer* (DSSAT) were employed to simulate county-level crop production for current and future time slices.

A first step in the analysis was to assign individual counties to nearby climate stations, as climate data (e.g., temperature and precipitation) are primary drivers for the DSSAT simulations. A climate regionalization procedure was applied to group climate stations from the United States Historical Climate Network into subregions with similar characteristics of the annual cycle of temperature and precipitation. Representative stations were chosen from each climate region, and counties were assigned to the closest representative station. The regionalization ensured that the spatial gradients of temperature and precipitation across the UGLR were captured in the analysis.

Daily solar radiation, also an important variable for the DSSAT simulation but one which is infrequently recorded, was calculated using a mechanistic solar radiation model parameterized at a central site within the study area for which concurrent observations of solar radiation,

temperature and precipitation were available. This model was selected after systematically evaluating the sensitivity of simulated corn and soybean yield to different solar radiation sources.

Climate change projections for a mid century (2041-2070) time slice were derived from eight combinations of regional climate models and global climate models released by the North American Climate Change Assessment Program. The impact assessment revealed that by the mid century, assuming the current CO₂ level, corn and soybean yield for the northern part of the region likely will increase due to more favorable growing season conditions than at present; whereas, a slight decrease in yield due to shorter time to maturity may occur in the southern part of the UGLR, which is currently a major crop production region. However, under elevated CO₂ concentrations, the number of counties with a projected decrease in yield is smaller due to the positive impacts of higher CO₂ levels, particularly for soybean production.

As the DSSAT simulations do not capture the effects of pest and disease infestations or economic factors on crop yield, a prototype interdisciplinary model for corn yield was developed using an asymmetric production function to integrate the DSSAT simulated yields with economic determinants (i.e., costs of pesticides, machinery, labor and fertilizer) to estimate observed county-level yield. The interdisciplinary model was shown to be a viable alternative to classical yield functions, and this model framework merits future study and refinement.

In general, this study suggests that more favorable growing conditions by the mid century will benefit the northern UGLR where some areas may produce relatively high corn and soybean yields especially under elevated CO₂ concentrations. Despite a potentially small reduction in crop yields, current crop production in the southern UGLR will remain large, partially due to the positive impact of elevated CO₂ concentrations.

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CHAPTER 1.

Background and Research Objectives

1.1. *Background*

Recent studies (e.g., Gilland, 2002; Jaggard et al., 2010; Tilman et al., 2011) raise as a serious challenge the ability of global food supply to meet the demand for food consumption in 2050, as human population is expected to increase to about nine billion. Climate change, including changes in the mean climatic state and changes in variability, intensifies the challenge of future world food supply (Rosenzweig and Parry, 1994; Schmidhuber and Tubiello, 2007). Globally, climate change likely will adversely impact crop productivity in low latitude countries, whereas high latitude countries may benefit (Cline, 2007; Parry et al., 2005). The adverse impacts of climate change are also projected to increase the risk of hunger in developing countries (Parry et al., 2005; Schmidhuber and Tubiello, 2007).

Given the perspective of climate change as a global threat to human livelihood (Barnett, 2010; Wilby et al., 2009), the estimated potential benefits of climate change to crop productivity in high latitude regions is an interesting subject. Potential benefits are expected because increased precipitation in high latitude regions (IPCC, 2007) may offset greater evapotranspiration arising from future higher temperatures, leading to more favorable conditions for crop production such as in the high latitude regions of North America (Fischer et al., 2005). However, this generalization needs further exploration as the impacts of climate change on crop productivity in high latitude regions likely is regionally and even locally specific (e.g., Brassard and Singh, 2008; Southworth et al., 2002; Southworth et al., 2000). Regional variations in climate change impacts are anticipated because changes in temperature and precipitation will

vary spatially, as illustrated by the impact of recent (1976-2006) climate trends on county-level corn and soybean yield in Wisconsin of the United States (Kucharik and Serbin, 2008).

This study will evaluate spatial variability of future climate change impacts on county-level corn and soybean production in counties located within the Upper Great Lakes Region of the United States, encompassing the states of Michigan, Wisconsin and Minnesota. Corn and soybean, the two most commonly grown crops in the region (Hatfield, 2012; Niyogi and Mishra, 2013), were chosen to represent the two major crop types, i.e., C4 (corn) and C3 (soybean), which are expected to respond differently to climate change (Mera et al., 2006). Although agricultural production is considered a major economic contributor for the region, the spatial detail of potential future climate change impacts on crop production rarely has been studied for the region.

Previous studies for the study area (Andresen et al., 2000; Southworth et al., 2002; 2000) selected a few representative locations to evaluate the potential impact of future climate change on corn and soybean production. Ten sites (Southworth et al., 2000) and nine sites (Southworth et al., 2002), located across the states of Indiana, Illinois, Ohio, Michigan, and Wisconsin, were selected to evaluate the consequences of projected climate change for a future period (2050-2059) relative to the baseline period (1961-1990) on corn and soybean yields. Southworth et al. (2000) found specifically for locations in Michigan and Wisconsin, that future climate change may have either a positive or negative impact on grain yield of long and medium season corn varieties, depending on the location within these two states and/or climate scenarios; whereas, the projected impact was negative for a short season corn variety for all locations and climate scenarios. For example, simulated corn yields of long-season variety in the Michigan Thumb and eastern Wisconsin were projected to increase up to 50% and 40%, respectively, regardless of

climate scenario. In contrast, grain yields of long season variety for south-central Michigan and southwest Wisconsin were projected to change from 20% to -20% and 20% to -10%, respectively, with the differences in sign corresponding to different climate scenarios. In these two locations, the short season variety was projected to decrease by up to 30% and 50%.

Furthermore, Southworth et al. (2002) found that future climate change is likely to boost soybean yields, especially for late-maturing soybean cultivars. They estimated that the yield of late-maturing soybean cultivars may increase up to 120% in south-central Michigan and the Michigan Thumb region. For mid-maturing cultivars, yields were projected to increase by 5% or decrease by 25% in southwestern Wisconsin, depending on climate scenarios; whereas, soybean productivity in eastern Wisconsin, south-central Michigan, and the Michigan Thumb were projected to increase by up to 60%. The largest increase in yields for the early maturing cultivar were expected in south-central Michigan where yields could possibly increase up to 120%. Overall, the increase in yields for late-maturing variety was expected to be greater than that for early maturing cultivars across the study locations (Southworth et al., 2002).

However, an assessment specifically for the UGLR gives somewhat different projections compared to those for the wider Midwest region. Andresen et al. (2000) did not project a future decrease in corn and soybean yields for the ULGR region; rather, they reported that yields in the period of 2000-2099 for 13 locations within the UGLR are likely to significantly increase compared to yields for historical records (1896-1996). This increase was attributed to the positive impacts of CO₂ enrichment on crop yield, particularly for soybean (Andresen et al., 2000). A similar carbon fertilization effect was also found by Southworth et al. (2002).

Although, the conclusions drawn from the above studies may be appropriate for estimating the impacts of climate change at particular locations, generalizing the conclusions

across the region could be problematic, thus further exploration is needed to identify areas with decreasing or increasing crop production under future climate change and elevated atmospheric CO₂ concentrations. In addition, the limited locations employed in the previous analyses also prevent the use of their results to explore potential latitudinal shifts of major crop production regions to the north that is frequently highlighted by national-scale impact studies for the United States (e.g., Thomson et al., 2005; Tubiello et al., 2002).

A major challenge of regional climate change impact assessments at the county level, the scale chosen in this study, is data availability. Ecophysiological models, commonly known as crop models (White and Hoogenboom, 2011), often have been employed for climate change impact assessments in recent decades as reviewed by White et al. (2011a), require extensive data inputs (e.g., climate data, soil information and farming practices) for the model simulations. Unfortunately, the required data inputs are not available for each county in the UGLR. Specifically for climate data, daily solar radiation, one of the main climate variables which is needed for crop model simulations, is infrequently recorded compared to temperature and precipitation (Liu and Scott, 2001).

Crop models are regularly employed in climate change impact assessments because they are able to simulate the non-linear interactions among plants, environment and farming practices at a specific location (Hoogenboom et al., 2004; Meinke et al., 2001). However, crop models generally poorly simulate the impacts of weeds and pest and disease infestations (Soussana et al., 2010; Tubiello et al., 2002), and can not capture the contribution of economic determinants to yield variability (Kaufmann and Snell, 1997; Vera-Diaz et al., 2008). The inclusion of economic stressors has been recommended by the climate impact research community (Challinor et al., 2009), recognizing the contribution of economic factors to yield variability (Cabas et al., 2010;

Kaufmann and Snell, 1997). Socio-economic conditions can influence farmers' decisions in managing their land and selecting farming practices (de Koeijer et al., 1999). Guan et al. (2006) assert that economic factors such as capital and labor can create favorable growing conditions for crop production.

A potential approach proposed to overcome the limitation of crop models is to develop yield models that combine the outputs of crop models and economic determinants (i.e., 'a hybrid model'), such as the model proposed by Kaufmann and Snell (1997). This hybrid model, referred by Kaufmann and Shell as a "*interdisciplinary model*", offers an advantage over the direct use of crop models by capturing, at least in part, the influence of socio-economic drivers on crop yield fluctuations. In comparison to traditional empirical yield models (e.g., Almaraz et al., 2008; Cabas et al., 2010; Tannura et al., 2008), the interdisciplinary model better captures non-linear interactions between weather variables, environmental conditions and crop growth processes, which are often oversimplified in empirical yield models (Challinor et al., 2009; Soussana et al., 2010). A recent application is the development by Vera-Diaz et al. (2008) of an interdisciplinary model for soybean yield that combines simulated yields from a crop simulation model, geographic location (i.e., latitude and longitude) and economic variables (i.e., credit, transports costs) to explain soybean yield variability in the Brazilian Amazon.

Yet, none of the earlier interdisciplinary models include economic determinants associated with chemicals to control pest and diseases, capital, and labor. A recent study conducted by Guan et al. (2006) proposed an empirical yield model based on an asymmetric framework to distinguish the impacts of growth inputs (i.e., land, seed, environmental factors) and facilitating inputs (i.e., pesticides, capital and labor) on attainable and actual yield (vanIttersum and Rabbinge, 1997), respectively. Unfortunately, the utilization of dummy

variables to reflect environmental conditions (e.g., soil and climate) limits the application of the model for climate change assessments. However, the model structure proposed by Guan et al. (2006) can provide an alternative framework for the development of a new type of interdisciplinary model. A crop model can be used to simulate crop yields (i.e., attainable yield) based on agricultural growth inputs and agronomic practices (i.e. cultivar, row and spacing, and planting dates), and economic determinants are used to adjust simulated yields in order to obtain estimated yields (i.e., actual yield).

The recent release of future climate projections for the mid century (2041-2070) from an ensemble of regional climate models (RCMs) driven by several global climate models (GCMs), included in the North American Regional Climate Change Assessment Program (Mearns et al., 2009), offers an opportunity to utilize higher resolution climate model outputs for the development of climate change scenarios. Many studies (e.g., Frei et al., 2003; Kim et al., 2008; Kjellstrom et al., 2010) argued that the finer resolution of RCMs offers an advantage in simulating details of regional climate compared to the corresponding lateral boundary condition. Furthermore, the extensive effort of downscaling outputs of several GCMs to a regional scale using multiple RCMs, known as dynamical downscaling (Fowler et al., 2007), is rarely applied for regional climate change impact assessments because dynamical downscaling is computationally expensive (Fowler et al., 2007; Wilby and Wigley, 1997).

This dissertation attempts to address the above challenges to better understand the spatial variation of future climate change impacts on crop production in high latitude regions by using the Upper Great Lakes Region of the United States as a case study. This study offers a methodology to prepare required data for crop model simulation at the county-level. Additionally, alternative daily solar radiation sources are assessed to choose appropriate daily

solar radiation estimates as inputs for crop model simulations. Climate change scenarios derived from the NARCCAP datasets are employed to evaluate the potential regional impacts of projected climate change for the mid century on crop production in the study region. An interdisciplinary model for corn yield is developed to explore the contribution of economic determinants to explain the deviation between simulated and observed yields.

The outcomes of this research contribute to the enhancement of methods for conducting regional climate change assessments, especially at the county scale. The impact assessment conducted for the study region also enhances our understanding of the spatial variation of future climate change impacts on crop production in high latitude regions. The relatively detailed spatial analysis of the potential impacts allows potential latitudinal shifts of crop production region under exposure of future climate change to be examined. The interdisciplinary model provides an alternative approach for evaluating the possible consequences of combining climate and economic exposures to crop yield variability. Finally, the outcomes of this research will help decision makers in the region to devise agricultural management strategies for climate change adaptation.

1.2. *Research Objectives*

The main goal of this dissertation is to evaluate the spatial variability of future climate change impacts on corn and soybean production in the Upper Great Lakes Region (UGLR) of the United States. Specifically, the first goal is to develop an objectively-defined climate regionalization for the region that is proposed to prepare climate data for crop model simulations at the county scale. The second goal is to evaluate the sensitivity of simulated corn and soybean yields to different daily solar radiation estimates in order to choose appropriate daily solar

radiation estimates for crop model simulations employed for climate change impact assessments. The third goal is to identify the spatial distribution of future climate impacts on corn and soybean production over the UGLR. The fourth goal is to develop an interdisciplinary model for corn yield that can be employed for regional climate change assessments. This dissertation addresses each objective in separate chapters. The objectives and methods will be explained in more detail in each chapter.

1.3. Study Region

The UGLR is comprised of the states of Michigan, Wisconsin and Minnesota (Safir et al., 2008). This region is located in the United States (US) Midwest (Pryor and Barthelmie, 2013), which is considered the ‘main heartland’ of agriculture in the US (Figure 1-1). Corn and soybean, the crops selected for this study, are considered the two major agricultural commodities in the region (Hatfield, 2012; Niyogi and Mishra, 2013).

The major growing areas of corn and soybean are located mostly in the southern part of the UGLR (Safir et al., 2008). County averages of corn and soybean yield from 1942 to 2008 are larger in the southern part of the region (Figure 1-2). In these areas, the variability of corn and soybean yields is also highest. Corn and soybean yields in each of the three states display a positive trend since 1942 (Figure 1-3). Corn yield in Minnesota increased about 108 kg/ha per year; whereas, in Michigan and Wisconsin, yield increased about 91 kg/ha per year. Trends of soybean yields for Wisconsin, Minnesota and Michigan were 31.5, 29.7, and 26.5 kg/ha per year, respectively. Improvements in agricultural management and technology and favorable weather over the period are considered the key factors contributing to increased corn and soybean yields in the region (Andresen et al., 2001; Tannura et al., 2008).

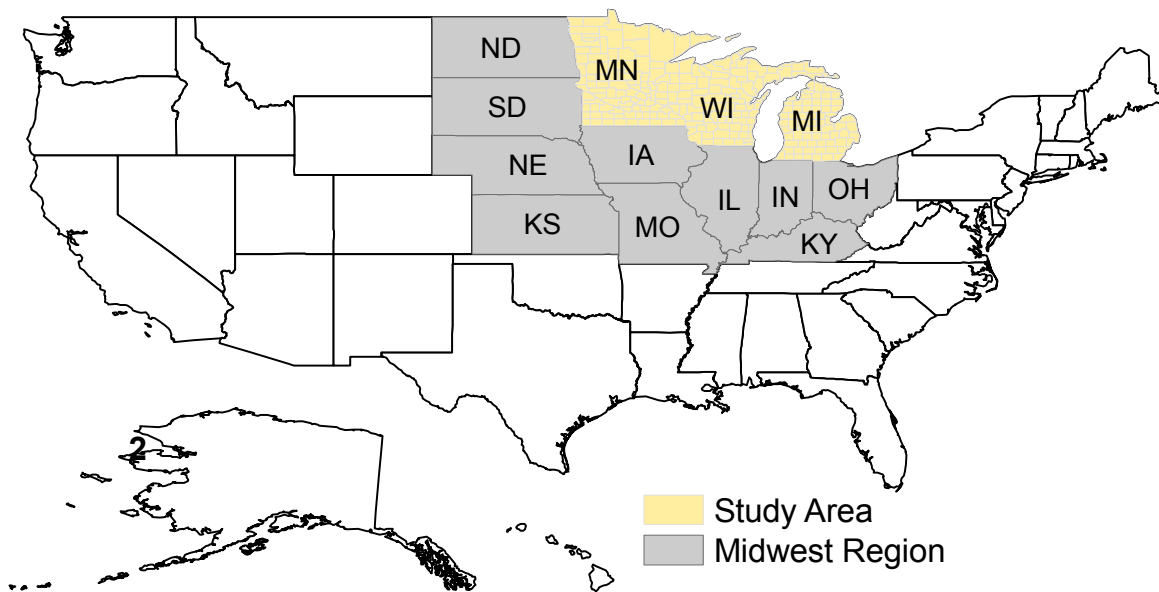


Figure 1-1. The study area within the Midwest region of the United States. [“For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this dissertation.”]

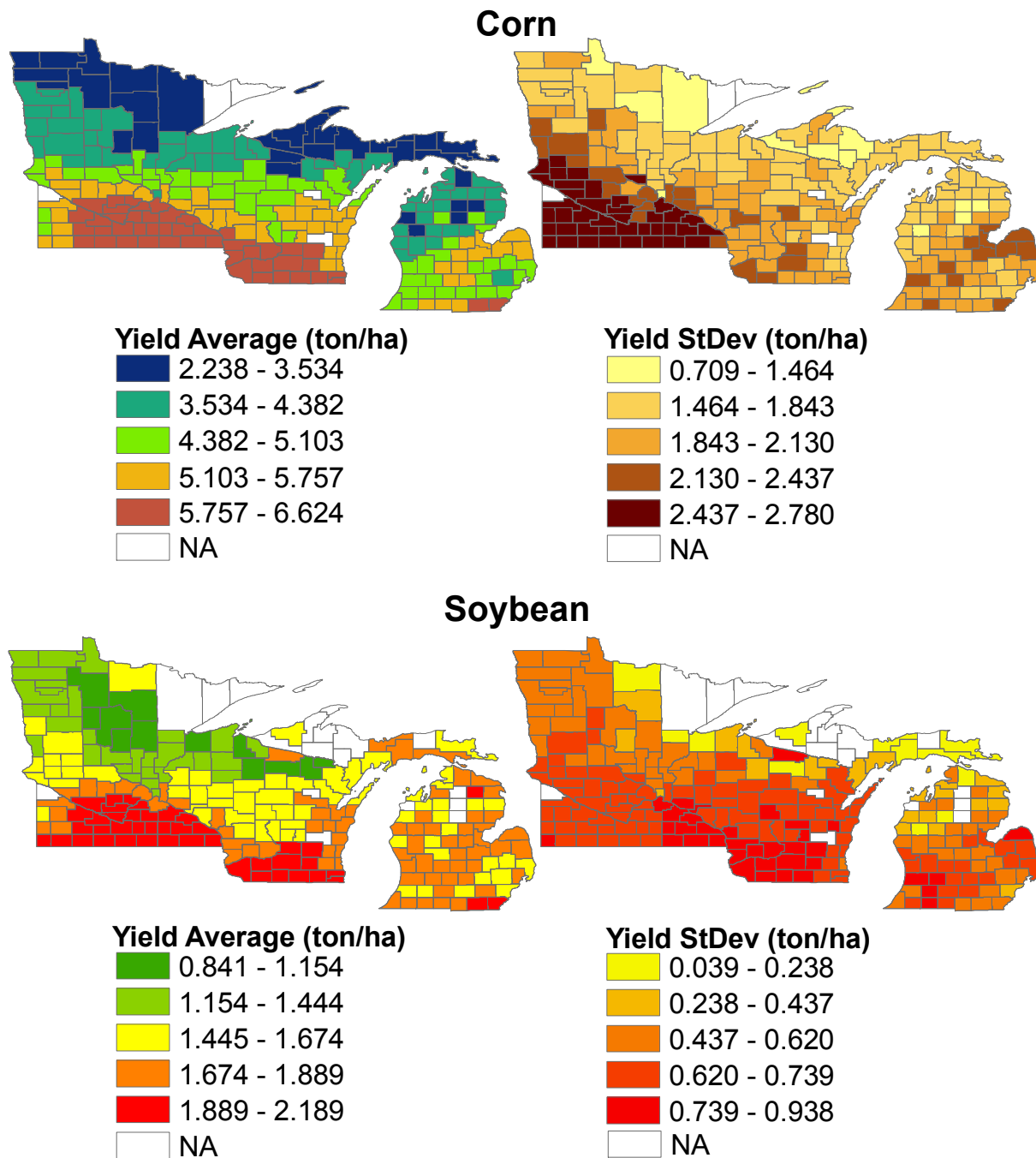


Figure 1-2. Average and standard deviation of corn (top figures) and soybean (bottom figures) yields over the UGLR from 1942 to 2008. Data source: National Agriculture Statistics Service - United States Department of Agriculture (NASS-USDA, 2011)

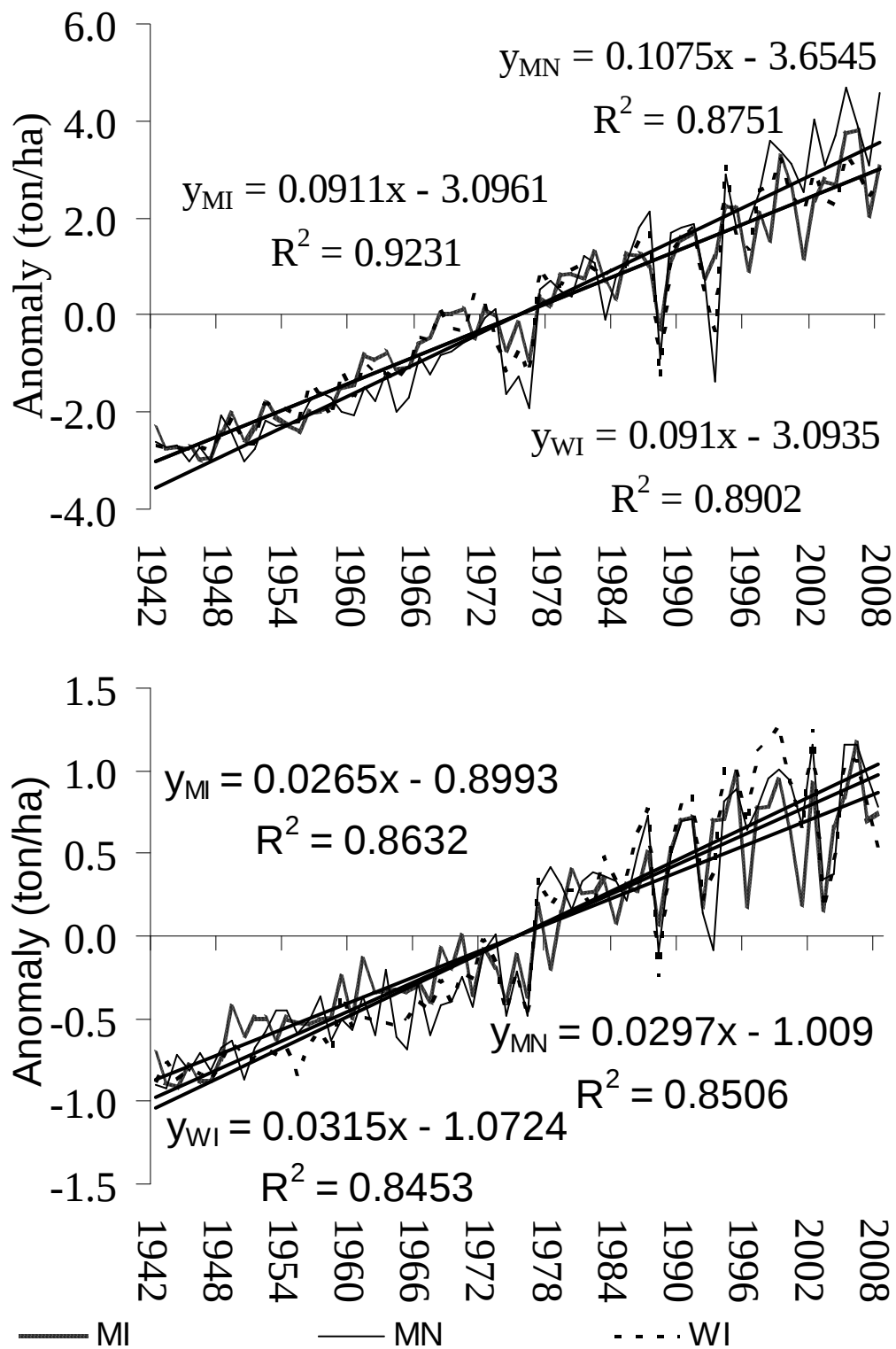


Figure 1-3. Trends of corn (top) and soybean (bottom) yields in the UGLR from 1942 to 2008.

1.4. Dissertation Structure

This dissertation is divided into six chapters. The first chapter (Chapter 1) provides a background of the research, the research objectives, and the study region.

Chapter 2 discusses the climate regionalization of the study region. Climate stations included in the United States Historical Climate Networks (USHCN) for the UGLR and neighboring states were grouped using a combination of principal component analysis (PCA) and non-hierarchical (kmeans) clustering method. Euclidian allocation and distance was employed to create clustering boundaries and assign a specific climate group to counties, respectively.

Chapter 3 evaluates the sensitivity of crop models to six different daily solar radiation estimations, i.e., point-based estimates (empirical, dynamical, and weather generator), and gridded datasets (NASA-POWER, NARR, and NARCCAP). Statistical analyses, e.g., t-test, mean absolute error (MAE), root means square error (RMSE), correlation coefficient (r)/coefficient determination (R^2), and mean squared deviation (MSD), were applied to assess the performance of the alternative radiation sources and their impacts on corn and soybean yields.

Chapter 4 elaborates the spatial variation of future climate impacts on corn and soybean production across counties in the UGLR. Representative climate stations were selected and assigned to each county by considering the climate groups for the UGLR (Chapter 2). Soil parameters for each county were obtained from the STATGO database. Farming practices were set at the rainfed condition with multiple planting windows to optimally start planting crop across the UGLR counties. Climate change projections of precipitation, maximum and minimum temperature were derived from eight RCM-gcm combinations available from the NARCCAP database.

Chapter 5 discusses the development of an interdisciplinary model for county-level corn yield in the UGLR. This model was developed by relating the ratio of observed to simulated corn yield (predictand) with economic data (predictors) at the county level. Observed corn yields were detrended in order to be comparable with simulated yields. Economic data (i.e., total costs of chemical, machinery, labor and fertilizer) for the model development were obtained from the agricultural census for 1997, 2002, and 2007 and adjusted using a corresponding price index for each economic variable. The model parameters were estimated using nonlinear least square (NLS) estimator. The contribution of each economic variable to the dependent variable was evaluated using elasticity analysis.

Chapter 6 summarizes findings from Chapter 2 to Chapter 5. Implications of the research outcomes and their contribution to enhancing knowledge about regional climate change impacts also are discussed.

CHAPTER 2.

Selection of Climate Information for Regional Climate Change Assessments using Regionalization Techniques: a Case Study for the Upper Great Lakes Region, USA

In collaboration with

Julie A. Winkler

2.1. Introduction

The impacts of climate change, such as those for crop production, are regionally (e.g., Cline, 2007; Motha and Baier, 2005) and even locally (e.g., Goldblum, 2009; Kucharik and Serbin, 2008) specific. Consequently, most climate change assessments are conducted at the regional scale (Carter *et al.*, 2007). A common approach in regional-scale assessment studies is to select a modest number of locations that hopefully capture within-region spatial variations of the current climate and potential climate change impacts (e.g., Brassard and Singh, 2008; Southworth *et al.*, 2002; Southworth *et al.*, 2000). This approach is in part dictated by the need for fine-scale climate scenarios for regional climate change assessments. As pointed out by Winkler *et al.* (2011), climate scenario development, which typically consists of homogeneity testing of historical time series of climate observations, application of models (dynamic and/or empirical) to “downscale” coarse resolution output from global climate models to the regional or local scale, and extensive evaluation of the downscaled variables, is time consuming and resource intensive and often a “road block” for an impact assessment. Thus, for many assessment studies, developing scenarios for a large number of locations within a region may not be an option (Winkler *et al.*, 2002).

When selecting locations for an assessment, previous studies typically have considered the length of the historical time series or the perceived representativeness of climate stations within a region (e.g., Almaraz et al., 2008; Andresen et al., 2000). A concern of the first selection criterion is that the stations with the longest records may not adequately capture the spatial variability of climate across the study area, whereas the second criterion requires that the size of the subregion for which a station is representative be clarified and that the characteristics used to evaluate representativeness be specified. These concerns illustrate the need for innovative approaches for selecting climate stations for climate change assessments.

We propose and demonstrate that an objectively-defined climate regionalization can be useful when selecting the number and location of representative stations with the goal of capturing the spatial variability of a region's climate. Furthermore, the proposed approach provides an indication of the needed resources for climate scenario development. For the illustrative application described below, a combination of principal component analysis (PCA) and hierarchical and non-hierarchical clustering techniques is employed to group climate stations from the United States Historical Climatology Network (Menne *et al.*, 2009) in the Upper Great Lakes region (UGLR) of the United States. The regionalization is based on mean monthly maximum and minimum temperature and precipitation. These three climate variables were chosen so that the regionalization would be applicable to a wide range of assessments, although the choice of climate variables for a particular application should be dependent on the assessment goals. The regionalization was performed separately for three different periods, 1971-2000, 1941-1970, and 1911-1940 to investigate the sensitivity of the climate groups to the choice of time period for which the regionalization is conducted. To help visualize the spatial variability in climate, cluster boundaries were defined using Euclidean allocation (ESRI, 2008). In addition,

Euclidian distance was employed to link the cluster regions and site specific information from representative climate stations for each region with aggregated datasets (e.g., agricultural, biological, social-economic) at the United States county level (USDA-NASS, 2007). The regionalization and linkages to political units provide a starting point and framework for further assessment activities, including climate scenario development, incorporation of additional datasets and multiple aggregation levels into an assessment, and the use and development of decision-making models.

2.2. Data Methods

2.2.1. Climate Data

Record length and the quality of climate observations are critical considerations in a climate regionalization. For this reason, climate observations from the United States Historical Climatology Network (USHCN) ver. 2.0 (Menne *et al.*, 2009) were used. Each station within this network is generally considered to have a relatively long time series and the highest quality temperature and precipitation observations (Menne *et al.*, 2009) compared to other stations within the United States Cooperative Observer Program (COOP) Network (Daly *et al.*, 2007). This research utilized 180 climate stations distributed over the study area (Michigan, Wisconsin and Minnesota) and neighboring states (Figure 2-1). Stations from neighboring states were included to minimize edge effects that can reduce the accuracy of clustering results (e.g., DeGaetano, 1996; DeGaetano, 2001; Fovell and Fovell, 1993; Stooksbury and Michaels, 1991). Monthly mean maximum and minimum temperature adjusted for time of observation bias and other inhomogeneities and total monthly precipitation were extracted from the USHCN database for the period 1911-2000. The monthly time series were used to calculate climatic normals for the three 30-year time periods, 1971-2000, 1941-1970, and 1911-1940. Temperature and

precipitation were selected for analysis as they are the two most commonly utilized variables for climate regionalization (e.g., Bunkers et al., 1996; DeGaetano, 2001; Fovell and Fovell, 1993).

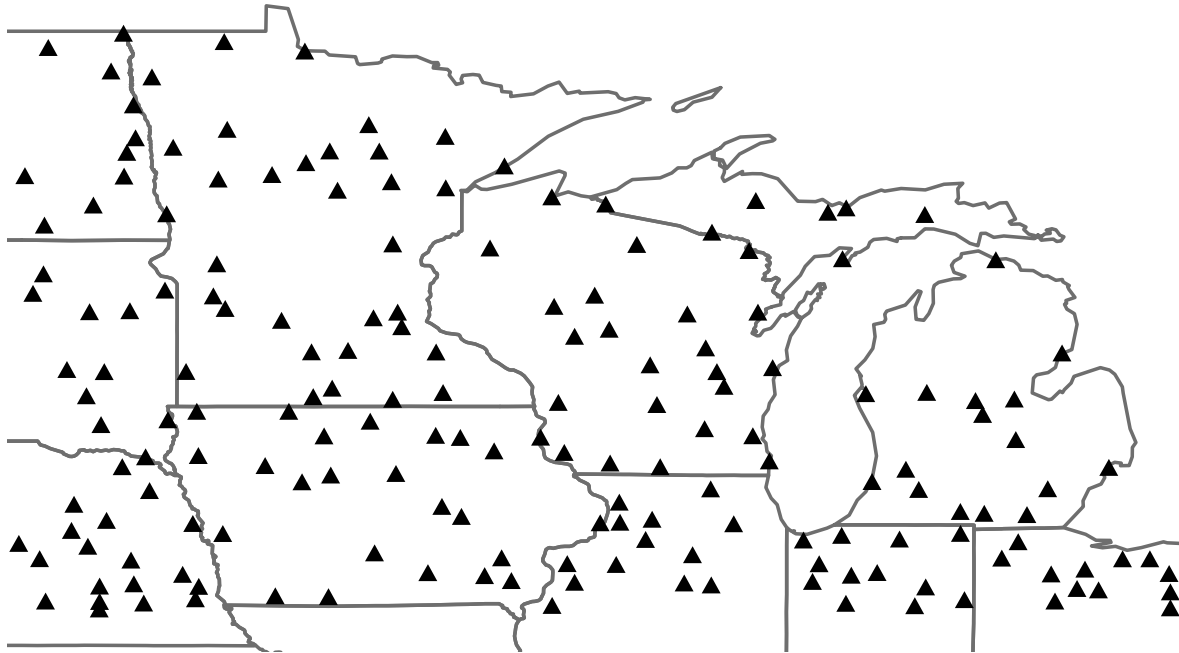


Figure 2-1. Distribution of the USHCN climate stations used in the climate regionalization. The UGLR study area is defined as the states of Minnesota, Wisconsin, and Michigan.

2.2.2. Regionalization Procedures

A combination of PCA and a two step clustering process (hierarchical and non-hierarchical clustering) was used for the climate regionalization. These techniques have been widely applied to understand the structure of climate datasets, as summarized by Jolliffe and Philipp (2010). The climate regionalization was initially performed for the period 1971-2000 (Figure 2-2). Separate regionalizations were conducted for two earlier periods, 1941-1970 and 1911-1940, although for comparison the number of clusters initially obtained for the 1971-2000 period was held constant for all three regionalizations. The latest period is preferable as a reference, under the assumption it exhibits the current climatic conditions for the region.



Figure 2-2. Time periods used for the climate regionalization.

PCA was used to reduce data dimensionality (Kalkstein *et al.*, 1987) and to remove multicollinearity among variables (Bohm *et al.*, 2001). The 30-year monthly maximum and minimum temperature and precipitation averages were initially standardized to zero mean and unit variance to remove the influence of different physical units on the PCA performance (Fovell and Fovell, 1993; e.g., Stooksbury and Michaels, 1991; Wilks, 1995). The PCA was then applied to the correlation matrix calculated from the 36 climate variables (columns) and 180 locations (rows). A Varimax orthogonal rotation (Kaiser, 1959), which has been widely employed in climate research (e.g., Bohm *et al.*, 2001; Dommenges and Latif, 2002; Fovell and Fovell, 1993; Richman, 1986), was applied to simplify interpretation. Only rotated components with at least one loading >0.5 were retained for the cluster analysis following Guentchev and Winkler (2010), resulting in four retained components explaining approximately 93% of the variation.

A two-step clustering process was utilized to take advantage of the strengths of both hierarchical and non-hierarchical clustering. Hierarchical clustering was used to provide an estimate of the possible number of clusters in a dataset. The k-means partitioning technique, a non-hierarchical method, was used to assign objects to clusters. Unlike traditional hierarchical clustering, k-means analysis permits the reassignment of objects until a convergent criterion is achieved, but requires that the initial number of clusters be specified at the beginning of the

clustering process (Dezfuli, 2011; Jolliffe and Philipp, 2010; Rhee et al., 2008; Stooksbury and Michaels, 1991). For the hierarchical clustering, the scores of the rotated components were grouped into different clusters using Euclidian distance as the similarity measurement and various linkage functions (McQuitty, median, average, single, complete, centroid, and Ward), all of which are regularly used for climate regionalization (e.g., Bunkers et al., 1996; Fovell and Fovell, 1993; Kalkstein et al., 1987; Stooksbury and Michaels, 1991). The component scores were not standardized preceding the cluster analysis, as such standardization may cause the distances between observations to be unrealistic (Johnson, 1998). The number of candidate clusters was evaluated using the Sarle Cubic Clustering Criterion (CCC) (SAS Institute Inc., 2004), Pseudo-F and Pseudo-t2 statistics (Fovell and Fovell, 1993), and distances between clusters (Fovell and Fovell, 1993; Wilks, 1995). Candidate numbers of clusters were chosen by searching for a breakpoint in the plots of these indices by merger level. Two breakpoints were selected for each criterion to provide a range of possible clusters for input to the k-means analysis.

The non-hierarchical k-means cluster analysis was then performed using each candidate number of clusters obtained from the hierarchical clustering. A drift option was specified to update the cluster seeds during the partitioning processes to allow for adjustments of the seeds every time an observation was reassigned (SAS Institute Inc., 2004). The final number of clusters was determined based on Beale's Pseudo-F criterion (Johnson, 1998) and a graphical evaluation of the sum of squares of the within cluster distances. Beale's Pseudo-F was calculated from the intracluster sum of squares and compared to critical values of the F-distribution to assess whether a solution with additional clusters offers a significant improvement over a solution with a smaller number of clusters.

To help depict the spatial distribution of climate groups across the study region, cluster boundaries were defined objectively using Euclidian allocation, available in ArcGIS (ESRI, 2008). The Euclidean allocation method is preferable over other interpolation techniques when the data being interpolated (in this case cluster membership) are nominal rather than interval/ratio measurements. The feature class of cluster memberships for the climate stations was converted to a raster grid of approximate size of 1 km². For cells without climate stations, the Euclidean distance to the closest source cell (i.e., cell with a climate station) was calculated and the cluster membership of the source cell was assigned to the cell without a climate station. In effect, the “edges” of the raster cells falling in different clusters form the climate region boundaries, although the boundaries were identified within ArcGIS by converting the “filled in” raster grid to polygons. Euclidean distance was also used to assign cluster regions to counties. In this case, the Euclidean distance of all surrounding climate stations to the centroid of each county was calculated, and the county was assigned to the climate cluster of the nearest climate station.

2.3. Results

2.3.1. Climate regionalization for 1971-2000

The hierarchical clustering analyses resulted in a wide range of possible number of clusters as input for the k-means non-hierarchical clustering. As shown in Table 1, the number of clusters considered were 4-17, 21, 24, 26-28, 33, 35-37, 41-42, 45-46, 51, 59, and 67. The final number of clusters was determined based on Beale’s Pseudo-F criterion (Johnson, 1998) and a graphical evaluation of the first and second breakpoints of the sum of squares of the within

cluster distances. Beale's Pseudo-F, suggested a 7 cluster solution, whereas either 7 or 21 clusters was suggested by the graphical evaluation (Figure 2-3).

The climate regionalization patterns are generally similar for the 7 and 21 cluster solutions (Figure 2-4). The 21-cluster solution captures more local characteristics, as indicated by the larger number, but smaller in size, clusters, especially in the lake-modified areas surrounding the Great Lakes and along the study area borders. The latter may be a reflection of "edge effects" on the analysis, in spite of the use of climate stations outside of the UGLR in the cluster analysis. The 7-cluster solution suggests that there is greater spatial variability in regional climate in Michigan and eastern Wisconsin where several non-contiguous clusters are evident. Both solutions suggest a small number of large, broad climate regions extending from northwest Minnesota to central Wisconsin. The discussion below focuses on the 7-cluster solution, given the overall similarity of the solutions and the Beale's Pseudo-F test result that the 21-cluster solution is not a statistically significant improvement over the 7-cluster solution.

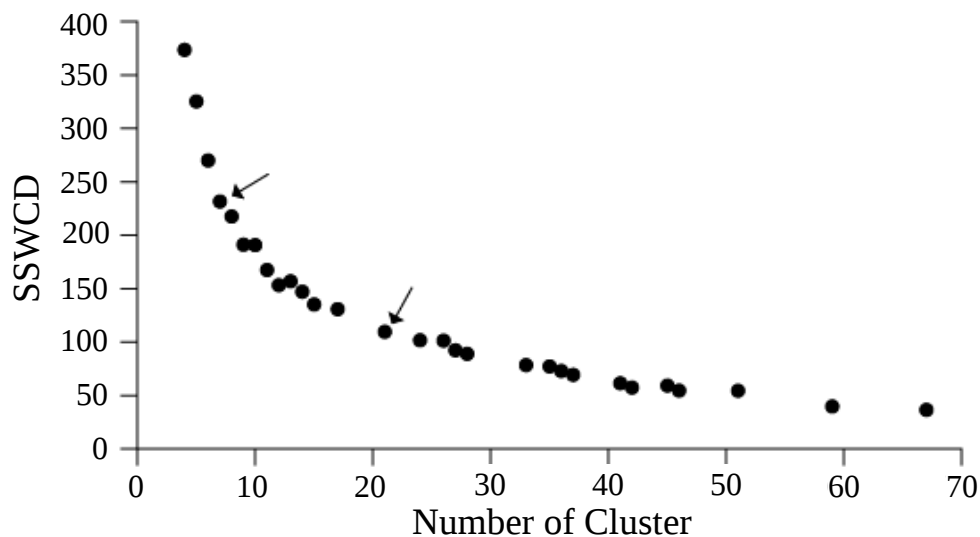


Figure 2-3. Determination of the number of clusters based on graphical evaluation of the slope of the relationship between the sum of squares of within cluster distances (SSWCD) and the number of clusters. The two arrows indicate the 7 and 21 cluster solutions.

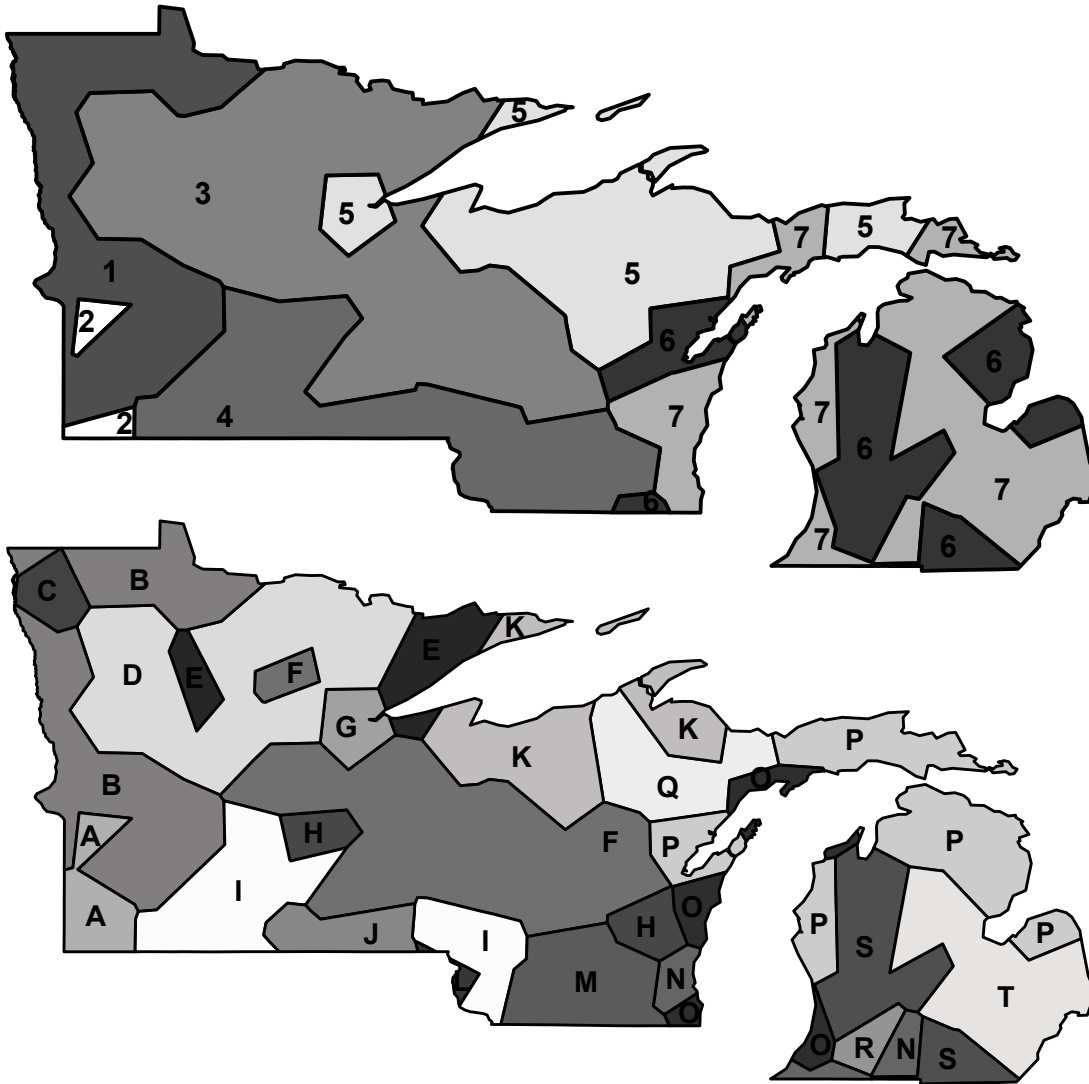


Figure 2-4. The seven (top) and twenty one (bottom) cluster solutions. The climate regions for the 7-cluster solution have arbitrarily been assigned numbers for reference in the text. For the 21-cluster solution, each region is assigned a letter to help readers distinguish between clusters and more easily identify non-contiguous clusters.

2.3.2. Differences between the climate regions

The differences between the climate regions were evaluated through a comparison of the deviations of the mean monthly precipitation and maximum and minimum temperature for each climate region from the average calculated across all climate regions, referred to as the UGLR

average. Starting with precipitation, western Minnesota (labeled Cluster 1 in Figure 2-4) is drier throughout the year compared to the other climate regions (Figure 2-5). In contrast, mean precipitation for Cluster 4 extending from southern Minnesota to south central Wisconsin is above the UGLR average for almost all months of the year. Wintertime precipitation is higher compared to other regions in non-contiguous Clusters 7 and 6, both located in Michigan and eastern Wisconsin, whereas spring and early summer precipitation is lower than the regional average. The seasonal variations are largest for Cluster 7. Distinct seasonality is evident in the deviation of mean monthly precipitation for Clusters 2, 3, and 5. For Cluster 2, a relatively small non-contiguous region in southwestern Minnesota, mean monthly precipitation is below the UGLR average for all months except May. In contrast, a positive deviation in autumn precipitation is evident for Cluster 5, located in lake effect precipitation-influenced regions of northeastern Minnesota, northern Wisconsin, and the Upper Peninsula of Michigan. For Cluster 3, extending from central Minnesota to central Wisconsin, mean monthly precipitation is above the UGLR average from June to October but below the large-scale average for the remainder of the year.

Distinct differences are also seen between clusters in terms of mean monthly maximum and minimum temperature. Small, non-contiguous Cluster 2 in western Minnesota has a relatively higher mean maximum temperature compared to the other climate regions, although minimum temperature is warmer than that of other regions only in summer. From winter through early spring, the highest mean minimum temperatures in the study area are found in Cluster 6 in eastern Wisconsin and Michigan. Cluster 5 in northern Wisconsin and Michigan's Upper Peninsula has lower maximum and minimum temperatures during most of the year compared to the other climate regions with the exception of winter when temperatures are lower

in Clusters 1 and 3 found in Minnesota. In Cluster 7, a lake-modified region, mean maximum temperature is above the UGLR average from November-February but below the large-scale average for the remainder of the year. This pattern differs from that seen for Cluster 6, another lake-modified region, where monthly mean maximum temperatures are either similar to or warmer than the UGLR average throughout the year. Average minimum temperatures for Cluster 2 are above the UGLR average for all months, and are generally similar to the mean temperatures observed in Cluster 6. Cluster 4 is unique in that mean monthly maximum and minimum temperature are close to the UGLR averages throughout the year.

2.3.3. Changes in climate regions with time

The application of cluster analysis to the other time periods shows substantial changes in the climate regions between the early- (1911-1940) and mid- (1941-1970) century time periods, whereas the cluster pattern for the mid-century period is similar to that for the late-century (1971-2000) period (Figure 2-6). Notable differences with time in the climate regions are found in the Lower Peninsula of Michigan, which was grouped into a single contiguous cluster for the early time period rather than the fragmented non-contiguous clusters seen for the later time periods. Substantial differences are also found in Minnesota. With time the large climate region seen in western Minnesota in the early time period retreats westward, whereas in northeastern Minnesota and northern Wisconsin, the climate regions coalesce during the mid-century time period into a fairly large region. This larger region is separated again during the late-century time period into two broad regions, one in northeastern and western Wisconsin and the other in northern Wisconsin.

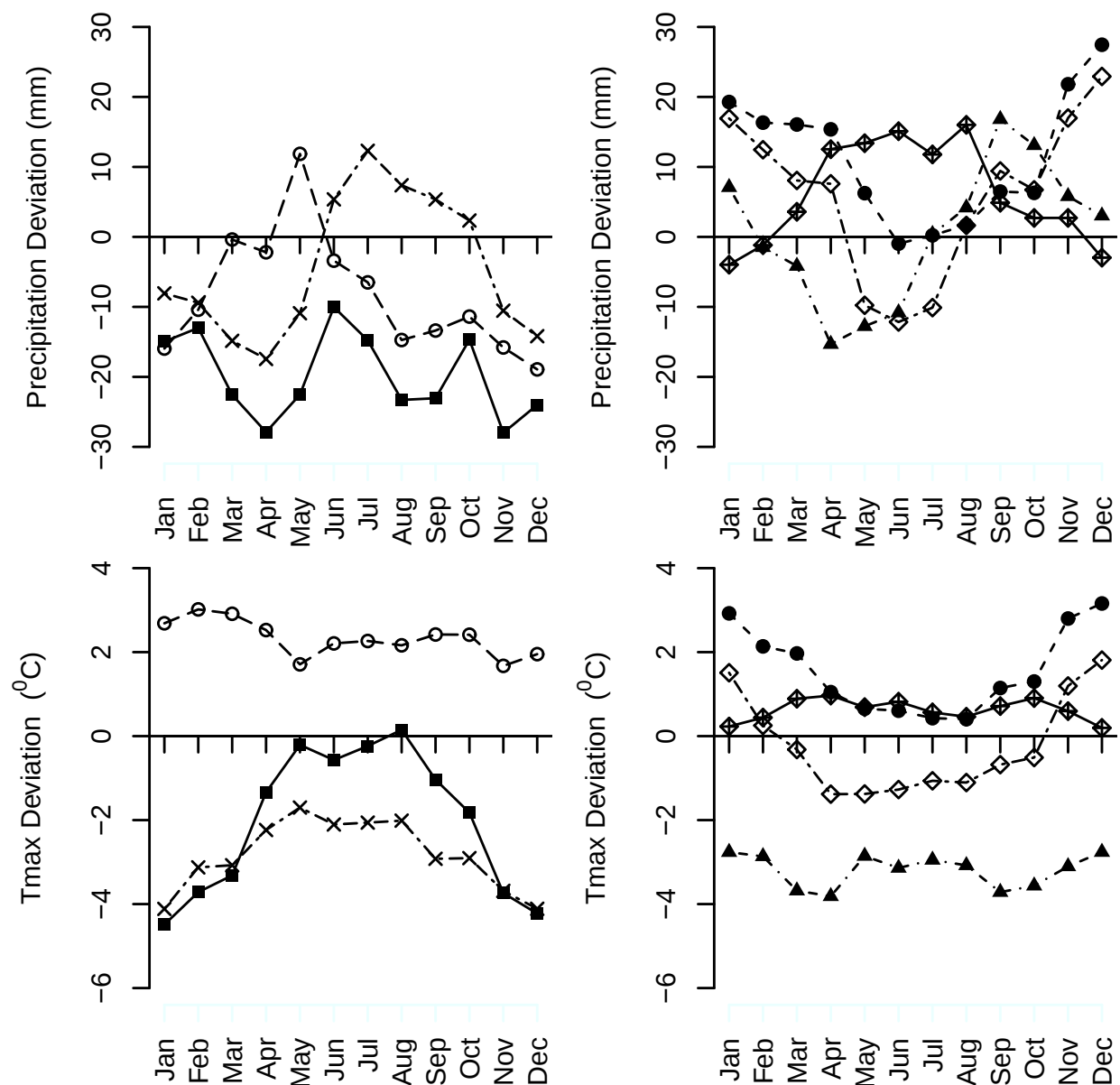
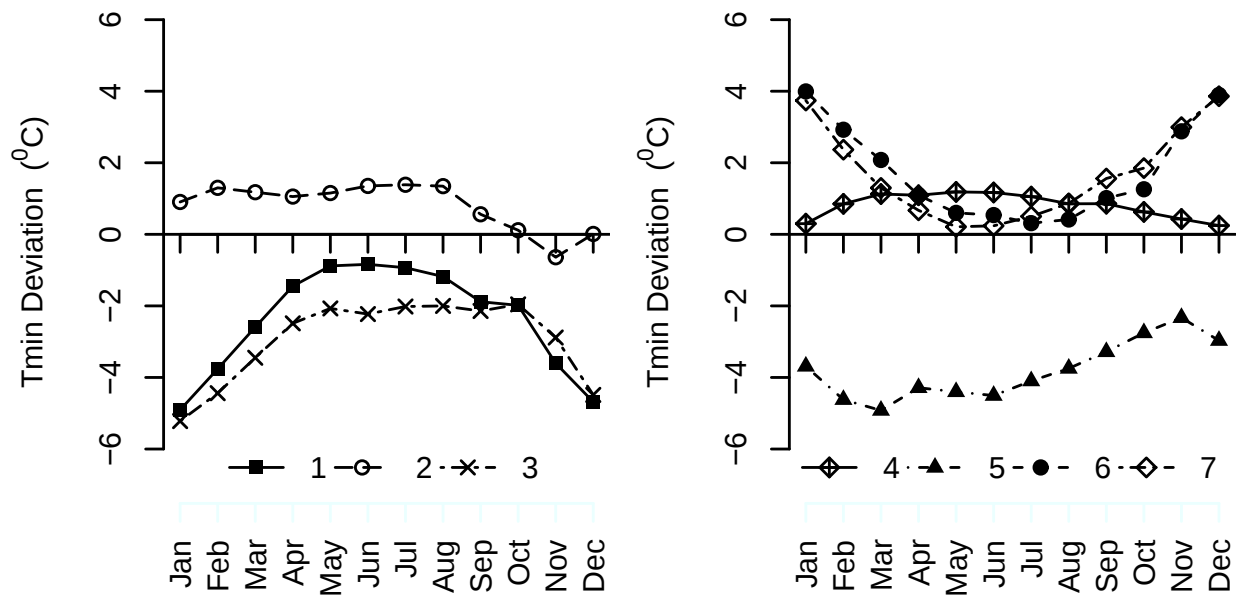


Figure 2-5. Deviation of mean monthly precipitation (top), maximum temperature (Tmax, center), and minimum temperature (Tmin, bottom) for each climate region from the average for the study area. The line symbols refer to cluster number; see Figure 2-4 for location of each cluster. Climate regions 1, 2, and 3 are displayed in the left-hand panels, and climate regions 4, 5, 6, and 7 are shown in the right-hand panels.

Figure 2-5. (cont'd)



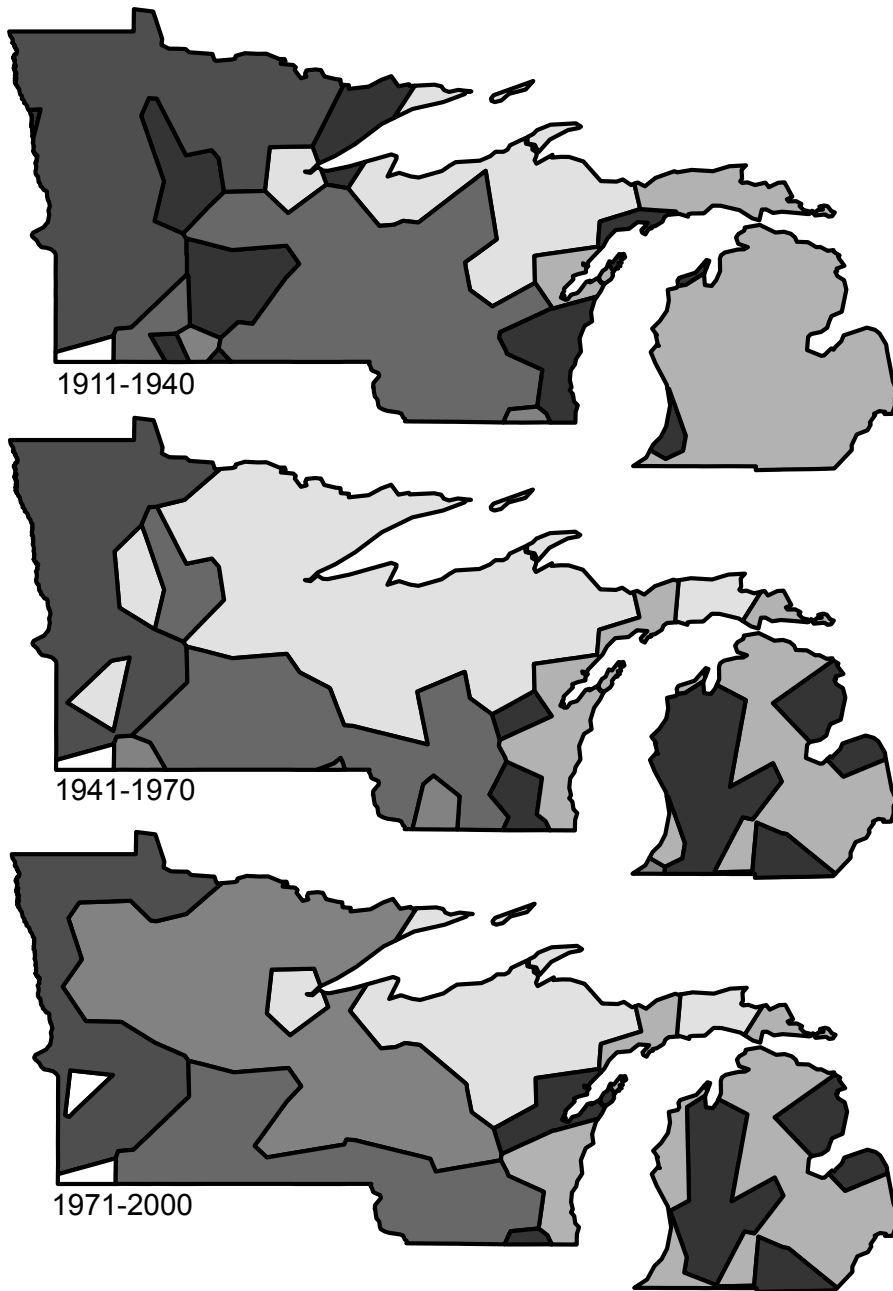


Figure 2-6. Application of a seven cluster solution for three periods, 1911-1940 (top), 1941-1970 (middle), and 1971-2000 (bottom).

2.3.4. Assignment of political units to climatic regions and selection of representative climate stations

One of our goals was to link climate observations with other variables required for climate change impact studies that are available at different spatial scales and aggregation levels. For this purpose, we assigned counties to climate group memberships based on the Euclidean distance between the county centroid and the nearest climate station (Figure 2-7). This assignment offers an alternative to link climate information from a climate station with other datasets such as economic data which are available at the county level.

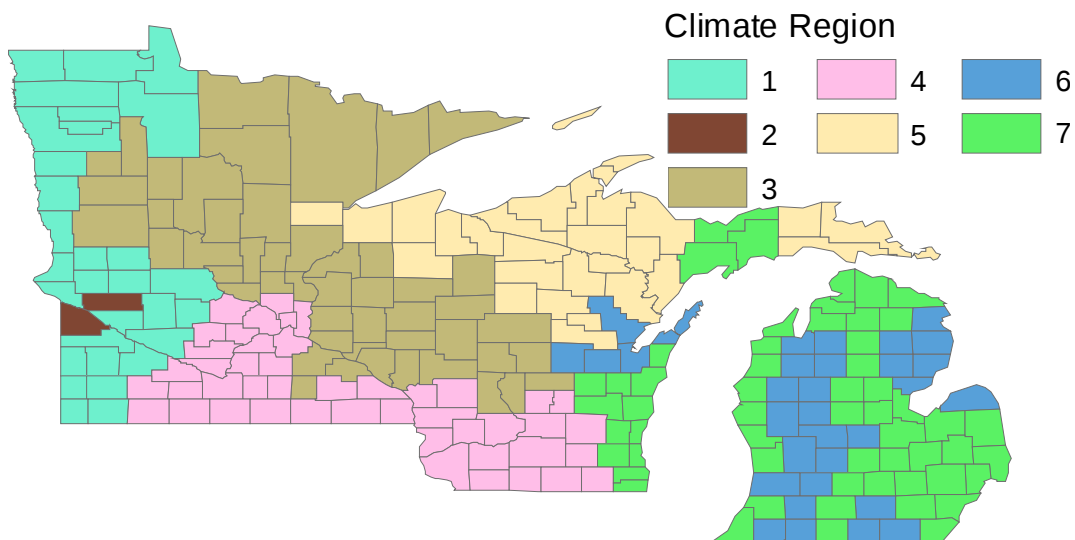


Figure 2-7. Assignment of counties in the study area to climate clusters.

Furthermore, as discussed in the introduction, a key motivation of the climate regionalization was to assist in selecting a small number of representative climate stations for a climate impact assessment. For this example, two climate stations were selected for each cluster that was contiguous in space, and one station was selected in each of the separate areas for those climate clusters that are non-contiguous, with preference given to stations that were close to the midpoints of each region (Figure 2-8). The underlying consideration in our choice of

representative stations was uniform spatial coverage across the study area; however, the number of representative stations per cluster and considerations in their selection should be influenced by the intended application.

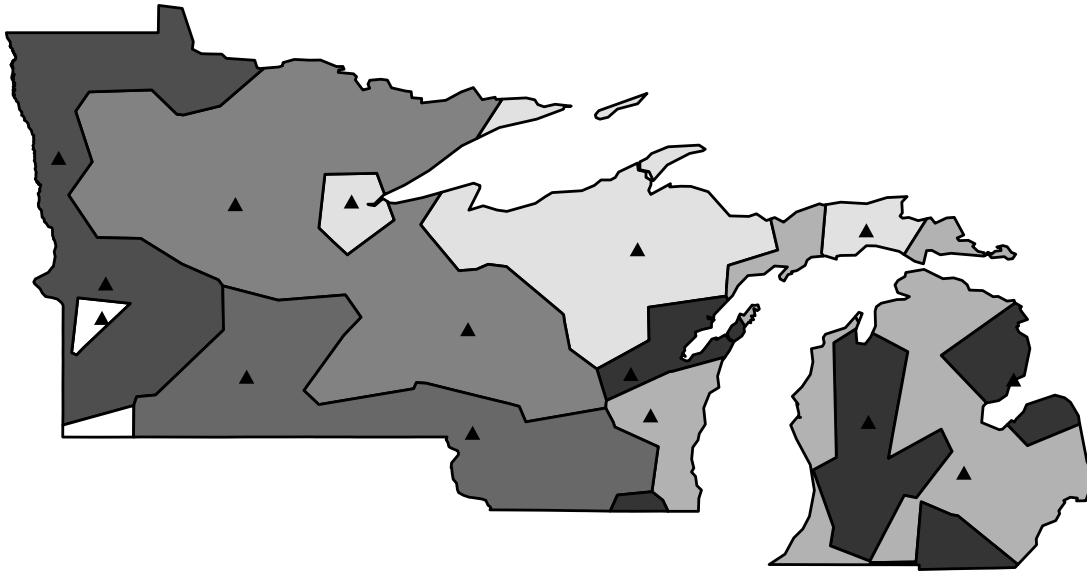


Figure 2-8. The representative climate stations selected for each climate cluster.

2.4. Discussion

In the discussion below, we consider several issues related to the application of the procedures described above; namely, considerations when interpreting climate regions and boundaries, the interpretation of non-contiguous climate regions, fluctuations in climate regions with time, and potential contributions of the proposed methods for climate change studies.

2.4.1. Interpretation of climate regions and boundaries

For any application, care must be taken to not over interpret objectively-defined climate regions and boundaries. Although the combined approach of PCA and hierarchical and non-hierarchical clustering used here has been widely employed in previous regionalizations (e.g., Gong and Richman, 1995; Stooksbury and Michaels, 1991; Winkler, 1992), alternative

classification approaches exist and may result in differing results particularly if the clusters are not well nucleated (Everitt, 1980). Additionally, several previous analyses (e.g. Alijani et al., 2008; Briggs and Lemin Jr, 1992; DeGaetano, 1996) have combined methods for summarizing climate observations, such as PCA, with spatial interpolation techniques to define climate boundaries rather than delineating boundaries based on cluster membership as was used here. Whatever the method used, the ensuing regionalization will be influenced by the initial density of the climate stations, and users must take this into account for any application. A relatively coarse station network was employed for the UGLR regionalization presented here. This was a reasonable choice given that an intended initial application is an assessment of climate impacts on corn and soybean production; both crops are broadly grown across the region. Other applications may require that a denser network of climate observations is used. Euclidian allocation within ArcGIS is a unique approach for delineating climate region boundaries and provides a convenient means for visualizing climate groups. However, it does not take into account abrupt climate gradients such as those observed in areas of complex terrain and that are not captured by the climate station density. Alternative means of delineating cluster boundaries should be considered in these situations.

2.4.2. *Non-contiguous climate regions*

Several of the UGLR climate regions shown above are not spatially contiguous. Similar segmentation of climate regions was found in earlier studies that grouped climate stations in the southeastern United States (Stooksbury and Michaels, 1991), the state of Maine in the United States (Briggs and Lemin Jr, 1992), central and eastern North America (Gong and Richman, 1995), and the northeastern United States (DeGaetano, 1996). Several previous authors have considered non-contiguous climate regions an artifact of aggregation error or observation biases,

under the assumption that near objects should have stronger correlations than distant objects. Although k-mean clustering is generally considered better in retaining spatial coherency than hierarchical clustering (Gong and Richman, 1995), Whitfield *et al.* (2002) proposed that k-means clustering results are sensitive to the temporal aggregation level of the climate variables and found that decreasing the temporal aggregation increased, particularly for precipitation, the proportion of near climate stations that were clustered into the same climate group. Assignment of geographically-close climate stations into different climate regions may also be due to differences in local site characteristics (e.g., exposure) or observational biases (e.g., time of observation bias) (Briggs and Lemin Jr, 1992). On the other hand, several authors have argued that spatial contiguity is not a requirement for creating climatologically homogeneous regions (e.g., Fovell and Fovell, 1993) and found that nearby climate stations may exhibit different precipitation or temperature patterns (Yeh *et al.*, 2000). Furthermore, regional climatic conditions are generally controlled by three basic forcings, i.e., latitude, elevation or topography, and distance to water bodies (e.g. DeGaetano, 1996; Rhee *et al.*, 2008), and non-contiguous climate regions can reflect spatial variations in these forces.

For the UGLR climate regionalization, we did not force the solution into coterminous regions in contrast to several earlier regionalizations (e.g. Stooksbury and Michaels, 1991; Yeh *et al.*, 2000), but rather allowed for the segmentation of climate regions. One consideration in this decision was our use of climate observations from the USHCN ver. 2.0 database in the regionalization. Most of the USHCN stations are located in rural areas, and the monthly mean maximum and minimum temperatures (but not precipitation) are adjusted for time of observation bias (Menne *et al.*, 2009). Although this dataset is still imperfect, its use does reduce the contribution of observational bias to the segmentation of climate regions. The primary

consideration, however, was that most of the non-contiguous climate regions appeared along the lake-modified zones of Michigan and eastern Wisconsin are likely due to the influence of the lakes on local climate. Similar segmentation of climate groups located along lake zones was observed by DeGaetano (1996) in a climate regionalization for the northeastern United States.

2.4.3. *Temporal changes in regionalization patterns*

An interesting finding was the substantial changes in the climate regionalization between the 1911-1940 and 1941-1970 periods. Differences in the extent and location of the climate regions were more modest between 1941-1970 and 1971-2000. These changes may in part result from heterogeneities in the time series of temperature and precipitation observations. Alternatively, the changes in the climate regionalization may reflect spatial differences in climatic trends. In this case, the spatial distributions of climate groups may be useful for detecting climate change in the region (Jacobeit, 2010) and can provide an alternative to traditional trend analysis at individual stations (Pielke *et al.*, 2000). Considerable further analysis is needed to better understand the reasons behind the differences in regionalization between the three time periods for the UGLR. We suspect, however, that these changes are partly due to climatic trends. The UGLR lies at the northern edge of the Midwest “warming hole” (Kunkel *et al.*, 2006), with a cooling trend reported in southern portion of the UGLR and a warming trend in the northern portion (Strode, 2003). These differences in trends may contribute to the observed changes with time in the climate clusters.

2.4.4. *Potential contributions of climate regionalization to impact studies*

One advantage of objective regionalization techniques is that they avoid the use of political boundaries to define climate regions such as what is done for National Weather Service

(NWS) climate divisions (Guttman and Quayle, 1996). Although frequently used, NWS climate divisions may not be relevant for summarizing regional climate conditions (DeGaetano, 2001) for climate impact studies. In fact, Guttman and Quayle (1996) acknowledge that climate division boundaries, which are delineated based on drainage basins in the western states and crop reporting districts that generally overlap with county boundaries in the eastern states, often do not have a direct relation to climate. Heterogeneous climate conditions may exist within climatic divisions that can cause difficulties when using climate data from the divisions for climate applications (Rhee *et al.*, 2008). Additionally, objective climate regionalization provides more flexibility compared to pre-defined climate regions such as the NWS climate divisions, as climate regions can be defined in terms of the climate variables of interest to a specific application. Although, the climate variables employed for the UGLR regionalization shown here are commonly-used mean monthly temperature and precipitation, climate regions can be defined based on any number of derived parameters such as heat accumulation units, the frequency of days above or below threshold temperatures, precipitation rates, or the timing of critical events (e.g., date of spring freeze). For example, Shinker (2010) included the ratio of monthly-to-annual precipitation to identify regions with similar annual cycles of precipitation occurrence in the western United States.

A primary contribution of regionalization approaches to climate impact studies is that they can provide an understanding of what climate type is presented by an individual station (Pielke *et al.*, 2002). Thus, they are useful in selecting the number and location of climate stations to include in an impact assessment and help to ensure that regional climate variations across the study area are captured. The selection of a limited number of representative climate stations is helpful for reducing the workload preparing the inputs needed for climate change

assessments including the development of fine-scale climate scenarios. Additionally, a climate regionalization can assist in the evaluation of regional climate model (RCM) simulations such that the RCM performance is evaluated for the different climate types within a study area. The selection of representative stations can also assist in the formulation of bias correction functions that are commonly applied to RCM outputs (e.g., Rivington et al., 2008a) before they are used for climate applications. Formulating bias corrections for all stations within a region is time consuming, and, depending on the RCM grid resolution, climate observations are usually not available for all RCM grid cells. In this situation, RCM grid cells can be related to a climate group so that the bias correction developed for that group (i.e., for a representative station of the group) can be applied to those cells for which climate observations do not exist.

As demonstrated above, climate regionalization can also be used to help link different datasets that are required for climate change assessments but that have varying spatial resolutions and aggregation levels. The linkage can be performed by overlying the climate regionalization with the aggregated data, for example county-level socio-economic information, or by assigning the nearest climate group to an aggregation unit based on Euclidian distance or some other measure. Using the first approach, a particular aggregation unit may overlap two or more climate groups. The second approach, which was chosen in this study, is useful to uniquely link the aggregated information to a climate region. For the application above, we focused on linking information at the United States county-level to the climate regions. Rhee *et al.* (2008) also suggest the use of a county as an aggregation unit because county-level analysis is very useful for planning and management strategies and many datasets, particularly economic data .that are useful for decision making, are available at this level.

2.5. Conclusions

This study attempted to demonstrate, employing the Upper Great Lakes region (UGLR) of the United States as an example, the usefulness of climate regionalization for impact assessments, specifically for the selection of representative climate stations for a region and to assign those stations to different aggregation levels. Using a combination of principal components analysis and clustering methods, the UGLR, encompassing Michigan, Wisconsin and Minnesota, was grouped into seven climate regions based on average monthly precipitation and maximum and minimum temperature. The seven cluster solution is able to distinguish spatial variability of climatic conditions over the study area, as indicated by the different annual variations of the climate variables for each cluster. Euclidian allocation, which is readily available in the widely used ArcGIS software, was employed to define cluster boundaries.

Application of the regionalization procedures to three different 30-year time periods indicates that the greatest changes in the distribution of the climate types occurred between the early (1911-1940) and mid (1941-1970) century, and that the climate patterns were relatively similar for the mid and late (1971-2000) century. This alteration of cluster memberships can be employed to provide insights into regional climate change.

The climate regionalization for the late century time period was used to select representative climate stations for future analysis and to link the climate observations with county-level aggregated datasets. The value of selecting the representative stations based on a climate regionalization is that the number of climate stations needed for the assessment, is substantially reduced, but at the same time the spatial variability in climate is represented in the analysis. The results of this study are useful for climate change studies within the ULGR region, and the methods are applicable for other regions.

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CHAPTER 3.

Traditional versus Modern Approaches of Estimating Daily Solar Radiation for Input to Crop Process Models

In collaboration with

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3.1. Introduction

Crop simulation models are useful for estimating crop biophysical processes under different environmental conditions, including climate variability and change, as well as simulating the potential impacts of changes in agricultural management practices on yields. Daily solar radiation, which is used in conjunction with precipitation and air temperature, is considered a critical input to crop models for estimating evapotranspiration, water stress, plant biomass production, and yield (Hoogenboom, 2000; Jones et al., 2003). However, the availability of solar radiation observations is a major concern for crop model applications, as this variable is infrequently measured compared to temperature and precipitation (Liu and Scott, 2001).

In the United States, solar radiation measurements are not included in the observations taken by the two primary national *in situ* observing networks (i.e., the Automated Surface Observing System (ASOS) and the Cooperative Observer Program (COOP)). Solar radiation is observed by the recently-established Climate Reference Network (CRN). However, in addition to the short period in operation, this network consists of only 114 stations (Leduc et al., 2009), most of which are located outside of primary agricultural regions. Additional radiation

measurements are taken by specialized networks, such as those maintained by universities and agricultural extension services, but coverage is non-uniform and quality control standards vary. To illustrate the dearth of radiation measurements in the United States, Wilcox et al. (2007) reported that of about 1445 meteorological stations archived in the National Solar Radiation Database (NSRDB), only 40 stations measured solar radiation. The coarse spatial resolution of daily solar radiation observations (when available) is also a concern as estimating radiation from surrounding, but often distant, stations may not be appropriate (e.g., Hunt et al., 1998; Rivington et al., 2006).

Given these challenges, a number of alternative approaches have been developed to estimate daily solar radiation at a location. In general, daily solar radiation has been estimated using stochastic, mechanistic, or empirical methods. Of these, stochastic methods have been employed more frequently, especially for assessments of climate impacts on crop production (e.g., Apipattanavis et al., 2010; Kilsby et al., 2007) and possible adaptation options (e.g., Luo et al., 2009; Meza and Silva, 2009). Stochastic methods include the use of weather generators such as WGEN (Richardson and Wright, 1984) and SIMMETEO (Geng et al., 1986) to generate multiple daily time series. The stochastically-generated series attempt to mimic the statistical characteristics of a long-term time series of solar radiation at a particular site (Garcia and Hoogenboom, 2005; Woli and Paz, 2012) rather than the value for a particular day. Typically, the estimated daily solar radiation total is selected randomly from a distribution conditioned on a sequence of wet and dry days. The representation of the day-to-day interrelationships between solar radiation and observed values of other weather variables (e.g. temperature) is a concern, particularly as preserving the interactions among weather variables is important for crop models (Rivington et al., 2005).

In contrast, mechanistic and empirical approaches provide greater synchrony between estimated daily solar radiation and observed daily values of other weather variables. Mechanistic models predict site-specific daily incoming solar radiation (S) from daily extra-terrestrial radiation (S_0) at a location and other observations for that day such as sunshine duration (e.g., Yang et al., 2006), temperature (Bristow and Campbell, 1984; Weiss et al., 2001) and/or a combination of temperature and precipitation (Hunt et al., 1998; Thornton et al., 2000; Thornton and Running, 1999). S_0 is calculated based on latitude, day of year, solar angle and solar constant (Hunt et al., 1998; Liu and Scott, 2001). On the other hand, empirical models use regression techniques to estimate solar radiation at a location from daily weather variables, such as precipitation and temperature (e.g., Ball et al., 2004). Ideally, mechanistic and empirical models should be parameterized for an individual location, which limits their application for locations without solar radiation observations (Abraha and Savage, 2008). Liu and Scott (2001) argue that these models can be applied to locations with a similar regional climate as the site for which the models were initially developed, but defining “similar” climates can be challenging particularly for areas with large topographic variations.

As the different methods for estimating solar radiation can introduce biases that may significantly impact the outcomes of crop models (Nonhebel, 1994; Weiss et al., 2001), a number of previous studies have evaluated the sensitivity of crop model simulations to generated solar radiation from weather generators (e.g., Cooter and Dhakhwa, 1996; Garcia et al., 2008) and mechanistic models (e.g., Abraha and Savage, 2008; Trnka et al., 2007). Cooter and Dhakhwa (1996) found that interannual variability of crop yields is relatively sensitive to different sources of generated solar radiation, even though the long-term average of crop yield is not. In line with this finding, concern has been raised on utilizing generated solar radiation when forecasting

seasonal yields (Trnka et al., 2007). The sensitivity of crop model outputs (e.g., evapotranspiration and total biomass) to generated versus observed solar radiation also appears to vary from location to location (Abraha and Savage, 2008). Although generated solar radiation is still considered by many researchers to be a viable option for crop model applications when observed solar radiation is unavailable (Cooter and Dhakhwa, 1996; Garcia et al., 2008), further research is needed to explore other possible sources of daily solar radiation and evaluate associated potential biases.

Recently available alternative sources of daily solar radiation time series include “reanalysis” datasets that blend output from atmospheric models with observations, simulations from regional climate models, and satellite estimations. Two potential sources of daily solar radiation estimates for North America are the fine scale (32 km) North American Regional Reanalysis (NARR) datasets (Mesinger et al., 2006), available from 1979 to present, and the 50 km resolution regional climate model simulations from the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al., 2009), available for 1979-2004. Additionally, the National Aeronautical and Space Agency (NASA) Prediction of Worldwide Energy Resource (POWER) database (Stackhouse, 2006), which was developed with agricultural uses in mind, provides daily averaged values of daily solar radiation at a spatial resolution of one degree latitude/longitude for the period 1983 to present based on satellite estimations. Implementation of these alternative datasets for crop model applications would provide a substantial advantage over mechanistic or empirical approaches as no further model development or parameterization is required, and, unlike stochastic approaches, the interrelationships with observed daily weather variables are maintained. The NARCCAP simulations have an additional advantage in that projections of daily solar radiation for a future period (2041-2070) are also

available, facilitating analyses of potential climate change impacts and adaptation options. However, in spite of the potential utility of these alternative datasets, only a few studies have assessed the potential biases in the radiation estimates obtained from the POWER dataset and their impact on crop simulations (e.g., Bai et al., 2011; White et al., 2008; White et al., 2011b), and potential biases remain largely unaddressed for the radiation estimates from NARR and NARCCAP.

The objectives of this study are to 1) compare observed solar radiation to estimated daily solar radiation from stochastic, empirical, and mechanistic models (traditional approaches), and the POWER, NARR, and NARCCAP datasets (modern approaches), and 2) assess the sensitivity of simulated grain yield of maize and soybean to the different sources of daily solar radiation inputs. The inclusion of the NARR and NARCCAP gridded datasets distinguishes this study from recent work that investigated the impacts of solar radiation estimates obtained from stochastic, mechanistic and empirical models (e.g., Abraha and Savage, 2008; Garcia et al., 2008) and satellite estimates (e.g., Bai et al., 2011; White et al., 2011b) on crop model applications. The analysis was performed for Hancock, Wisconsin, located within an agricultural region in the Upper Great Lakes region of the United States. Maize and soybean were selected because they are the two most widely grown crops in the region (Hatfield, 2012) and more importantly represent the two major crop types, namely C4 (maize) and C3 (soybean) plants. Each type has different light saturation thresholds and photosynthesis mechanisms which can cause them to respond differently to solar radiation as discussed by Garcia et al. (2008).

3.2. *Materials and Methods*

3.2.1. *Climate Observations and Study Period*

Daily solar radiation observations for the evaluation of the different radiation estimates along with the temperature and precipitation measurements used as input to the stochastic, empirical and mechanistic models were obtained from the Wisconsin Automated Weather Network (WAWN) station at Hancock, Wisconsin (Figure 3-1). This station was selected because of its 1) relatively long period of record (1985 to present) and 2) geographic proximity to a station (Necedah, Wisconsin) within the Climate Reference Network (CRN). Observations from the CRN station were used to evaluate the quality of the solar radiation measurements at Hancock, assuming that little difference should exist in the radiation time series given the similar elevation and climate of the two locations. The equality of the means of the radiation time series was assessed for the overlapping period of 1 October 2004 to 31 December 2010 using both unpaired t-tests (assuming unequal variance) and paired t-tests. The two-sample F-test was used to test for equality of variances, and Pearson's correlation coefficient was calculated to measure the association between the radiation observations at the two stations. Means and variances of the solar radiation time series were not significantly different at the 95% probability level and the two time series were highly (0.97) correlated. These analyses suggest that the solar radiation observations recorded at the Hancock WAWN station are consistent with those from the CRN reference station.

The study period was constrained by the period of overlap for the different radiation estimates and observations from 1985 to 2000. Unfortunately, there were numerous missing observations for the Hancock WAWN station prior to 1989 so that we further evaluated data availability from 1990-2000. Within this period, a large number of missing observations

occurred at the Hancock WAWN in 1991, 1999 and 2000 with 184, 100, and 84 missing days, respectively, when at least one climate variable (i.e., radiation, temperature, precipitation) was missing. These years were removed, and, as a result, only 1990 and 1992-1998 were included in the analysis for a total of eight years. Although relatively short, an eight-year period was also used in a recent evaluation of the performance of several mechanistic models and a variation of WGEN to estimate daily solar radiation for the southeastern United States (Woli and Paz, 2012).

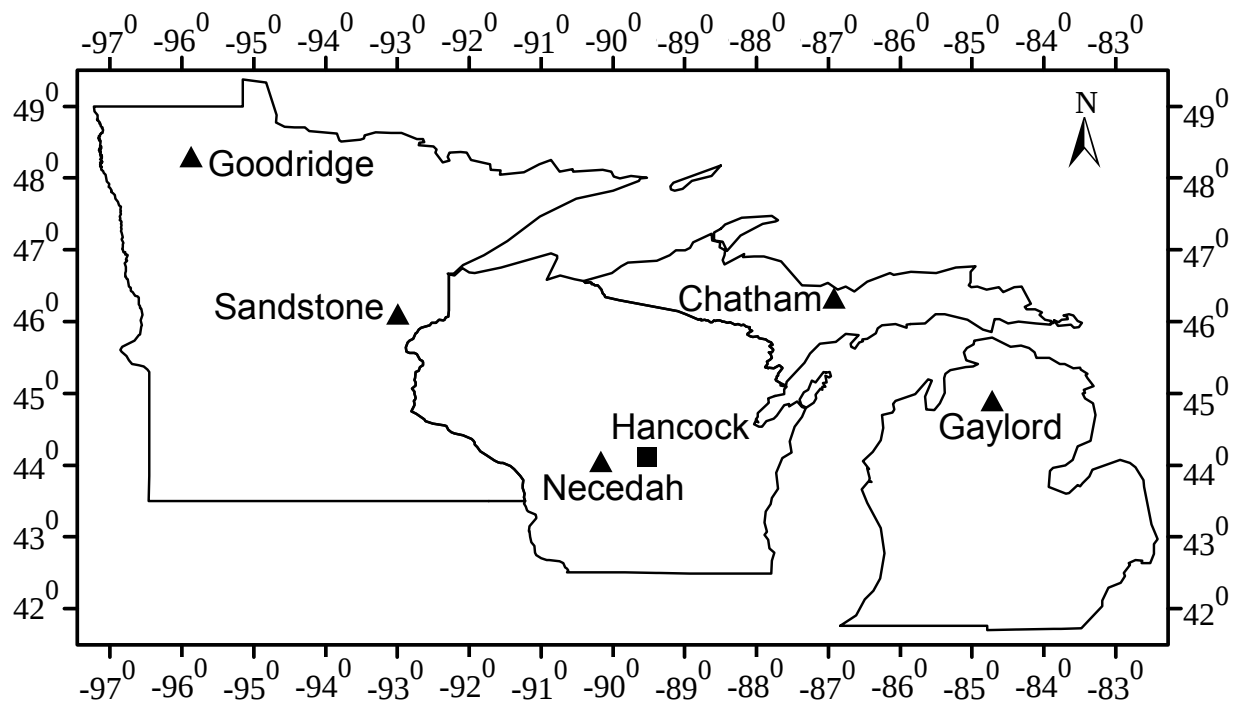


Figure 3-1. Location of the Hancock WAWN station and of the Necedah CRN station used to evaluate the quality of the solar radiation time series at Hancock. The additional CRN climate stations in Michigan and Minnesota were used for a sensitivity analysis of the coefficients of the mechanistic and empirical models.

The limited number of missing precipitation and temperature observations that occurred in 1990 and 1992-1998 were filled in with observations from the United States Historical Climate Network (USHCN) Hancock station (Menne et al., 2009). The missing daily solar radiation observations were filled in with daily averages of the non-missing observations. For the development of the empirical and mechanistic models, measurements for the eight-year study period were divided into two groups. Data from 1990, 1992, 1994, and 1997 were used for model calibration, and the remaining data were saved for model validation. Four additional CRN climate stations (Goodridge, Minnesota; Sandstone, Minnesota; Chatham, Michigan; Gaylord, Michigan) were employed to evaluate the sensitivity of the coefficients of the mechanistic and empirical models.

3.2.2. *Daily Solar Radiation Estimates*

Daily solar radiation is defined here as the daily mean downward shortwave radiation flux. Estimated daily solar radiation was obtained from six different sources, namely a stochastic weather generator, a mechanistic model, an empirical equation, POWER, NARR, and NARCCAP. All daily solar radiation estimates were converted to mega-joule per meter squared ($\text{MJ m}^{-2} \text{ day}^{-1}$) for comparison and for input to the crop simulation model.

(a) *Stochastic Generation*

Solar radiation was stochastically generated using a weather data management program included in DSSAT called “Weatherman” (Pickering et al., 1994). As noted by Mavromatis and Hansen (2001), Weatherman is a variant of the well-known WGEN (Richardson and Wright, 1984) weather generator. In Weatherman, all underlying model parameters are estimated on a monthly basis. Daily values of the model parameters are calculated internally using linear

interpolation to preserve the monthly means. The major advance over WGEN is that Weatherman replaces coefficients of variation with standard deviations to stabilize model estimations when temperatures are close to zero Celsius (Mavromatis and Hansen, 2001). Solar radiation is generated separately for wet and dry days (Mavromatis and Hansen, 2001; Soltani and Hoogenboom, 2003). For this analysis, Weatherman was parameterized using observed precipitation and maximum and minimum temperature data from the Hancock station for the 8-year analysis period. Observed daily solar radiation was not included in the parameterization, as our intent is to evaluate the sensitivity of crop models to generated solar radiation when observed daily solar radiation is unavailable for a location. Using the parameterized Weatherman, we generated daily series of precipitation, maximum and minimum temperature, and solar radiation. However, only the generated solar radiation was used in the following analyses; daily temperature and precipitation for input to the crop process models were obtained directly from the Hancock observations, following (e.g., Andresen et al., 2001; Carbone et al., 2003).

(b) Empirical Model

The regression equation developed by Ball et al. (2004) to estimate daily incoming solar radiation at Keiser, Arkansas, United States, was recalibrated for the Hancock station. The Ball et al. model employs a General Linear Model in the form:

$$R_s = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_{12} X_{12} \quad \text{Eq. 3-1}$$

where, R_s is daily solar radiation ($\text{MJ m}^{-2} \text{day}^{-1}$); β_0 and $\beta_{1...12}$ are intercept and regression coefficients, respectively; X_1 and X_5 are precipitation (mm) and precipitation squared; X_2 and X_6 are maximum temperature ($^{\circ}\text{C}$) and maximum temperature squared; X_3 and X_7 are minimum temperature ($^{\circ}\text{C}$) and minimum temperature squared; X_4 and X_8 are day of year and

day of year squared. The interaction terms are X_9 (precipitation x minimum temperature), X_{10} (maximum temperature x minimum temperature), X_{11} (precipitation x maximum temperature) and X_{12} (maximum temperature x day of year). Comparison of the radiation estimates when the model developed for the calibration period (1990, 1992, 1994, 1997) was applied to the validation period (1993, 1995, 1996, 1998) indicated that model performed similarly for both periods (correlations between simulated and observed daily radiation of 0.87 and 0.89 for the calibration and validation periods, respectively).

The transferability of the empirical model was assessed by applying the model to estimate daily solar radiation at other CRN climate stations within the states of Michigan and Wisconsin (Figure 3-1) and comparing the estimated radiation values with observations. The time periods for which precipitation, temperature and solar radiation observations are available vary for each location (Table 3-1). Days with missing observations were excluded from the sensitivity analysis.

(c) *Mechanistic Model*

A number of mathematical models, which we label here as “mechanistic models”, have been developed to estimate solar radiation based on the fraction of extraterrestrial radiation (S_0) reaching to the ground. This fraction is estimated as a function of the atmospheric transmissivity (Ball et al., 2004; Donatelli et al., 2003; Spitters et al., 1986), which can be modeled based on temperature and precipitation (Liu and Scott, 2001). Of the numerous mechanistic models available (e.g., Bristow and Campbell, 1984; Hunt et al., 1998; Thornton et al., 2000; Thornton and Running, 1999), those that utilize a combination of precipitation and temperature as inputs

generally are considered to be preferable to those using only temperature or only precipitation (Hunt et al., 1998; Liu and Scott, 2001; Woli and Paz, 2012).

For this study, the Hunt et al. (1998) radiation model was used to estimate daily solar radiation at the Hancock WAWN station. This model was chosen as it was developed for Ontario, Canada, which has a relatively similar climate to our study location. Daily solar radiation was estimated by:

$$S = a_0 S_0 (t_{\max} - t_{\min})^{0.5} + a_1 t_{\max} + a_2 P + a_3 P^2 + a_4 \quad \text{Eq.3-2}$$

where S is daily solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$); a_0, a_1, a_2, a_3, a_4 are the coefficients; S_0 is the daily extraterrestrial solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$), $t_{\max}$ and $t_{\min}$ are maximum and minimum daily temperatures ($^{\circ}\text{C}$); and P is daily precipitation (mm). The model uses equations previously defined by Spitters et al. (1986) to estimate daily solar radiation at the top of atmosphere (S_0):

$$S_0 = S_{sc} [1 + 0.033 \cos(360t_d / 365)] \sin \beta \quad \text{Eq.3-3}$$

where, S_0 is extra-terrestrial irradiance ($\text{J m}^{-2} \text{ s}^{-1}$); S_{sc} is the solar constant $1370 \text{ J m}^{-2} \text{ s}^{-1}$, the cosine term is the yearly course of the distance between the earth and sun expressed in degrees, t_d is the day since 1 January, and $\sin \beta$, the sine of the elevation of the sun above the horizon, is defined as:

$$\sin \beta = \sin \lambda \sin \delta + \cos \lambda \cos \delta \cos[15(t_h - 12)] \quad \text{Eq.3-4}$$

where, λ is latitude of the site, t_h is hour of the day (solar time), and δ is the solar declination for the day of year, measured in degrees and estimated by:

$$\sin \delta = -\sin(23.45) \cos[360(t_d + 10) / 365] \quad \text{Eq.3-5}$$

The daily value of S_0 is calculated by integrating the extra-terrestrial irradiance from sunrise till sunset:

$$D = 12 + (24/180) \arcsin(\tan \lambda - \tan \delta) \quad \text{Eq.3-6}$$

where, D is day length.

The Hunt model performed equally well for both the calibration and validation periods with correlations between simulated and observed solar radiation of 0.87 for the calibration period and 0.89 for the validation period. As for the empirical model, the mechanistic model parameterized for Hancock was applied to estimate daily solar radiation at the other CRN stations (Table 3-1) to assess the sensitivity and transferability of the model to other locations within the study region.

Table 3-1. Geographic location and analysis period for the CRN stations located in the states of Michigan and Minnesota

Station	State	Latitude	Longitude	Elevation	Period of Analysis	Distance ^b
Chatham	MI	46.33	-86.92	267 m	11/10/2004-12/31/2010	320 km
Gaylord	MI	44.91	-84.72	441 m	09/19/2007-12/31/2010	392 km
Goodridge	MN	48.31	-95.87	351 m	08/20/2003-12/31/2010	675 km
Sandstone	MN	46.11	-92.99	354 m	06/22/2007-12/31/2010	351 km

^b Distance from to the Hancock station.

(d) POWER

As noted above, satellite estimates of surface incoming solar radiation were obtained from the NASA POWER database (Stackhouse, 2006), available at <http://power.larc.nasa.gov/>. Daily solar radiation in this database was inferred using the Pinker and Laszlo (1992) radiative transfer model in conjunction with water vapor amounts from the Goddard Earth Observing System Data Assimilation System version 4 (NASA, 2011). Measurements from the

International Satellite Cloud Climatology and parameters from the NASA/Global Energy and Water Cycle Experiment were used as inputs to the radiative transfer model. Please refer to the methodological summary provided by NASA (2011) for more detailed information on the derivation of the radiation estimates. The daily series of incoming radiation was extracted from the POWER archive for the 1° latitude/longitude grid point nearest the Hancock station.

(e) NARR and NARCCAP

The NARR dataset was obtained from the NOAA Earth Systems Laboratory (<http://www.esrl.noaa.gov/psd/>). Three-hourly values of downward solar radiation flux were extracted for the NARR grid point closest to the Hancock WAWN station and then averaged to estimate daily solar radiation. The daily averages were calculated based on local time, using the 3-hourly values from 0900 UTC of the current day to 0600 UTC of the next day.

The NARCCAP dataset was accessed through the Earth System Grid gateway at the National Center for Atmospheric Research (<http://www.earthsystemgrid.org/home.htm>). NARCCAP simulations from four regional climate models -- CRCM (*Canadian Regional Climate Model*), ECP2 (*Experimental Climate Prediction Center/Regional Spectral Model*), HRM3 (*Hadley Regional Model 3*), and WRFG (*Weather Research & Forecasting Model*) -- were included in the analysis. All simulations employed coarse-scale ($2.5^{\circ} \times 2.5^{\circ}$) NCEP/NCAR reanalysis fields (Kalnay et al., 1996) as lateral boundary conditions. For each model, the eight 3-hourly values of surface downwelling shortwave radiation from 0900-0600 UTC were averaged for the grid point closest to Hancock to obtain estimates of daily solar radiation.

3.2.3. Crop Yield Simulations

Decision Support System for Agrotechnology Transfer (DSSAT) version 4.5 was used to simulate grain yields of maize and soybean at the Hancock site. DSSAT is a compilation of simulation programs that model biophysical interactions among weather, soil, crops and farming management (Jones et al., 2003). The programs allow a cropping system to respond dynamically to changes in plant biology, farming management and environment. DSSAT has been widely used around the world to explore the consequences of environmental changes and differing farming practices on crop growth and development (e.g., Hartkamp et al., 2004; O'Neal et al., 2005; Thorp et al., 2008; Vucetic, 2011). This simulation package also has been applied to specifically assess the effects of generated solar radiation on crop evapotranspiration and yields (e.g., Garcia et al., 2008). DSSAT's capabilities and performances have been widely reviewed (e.g., Mera et al., 2006; Southworth et al., 2002; Southworth et al., 2000).

Two modules of the DSSAT package, CROPGRO-Soybean and CERES-Maize, were used in this study. Each module uniquely calculates the conversion of incoming radiation to plant biomass through different photosynthetic processes. As summarized by Jones et al. (2003), the CROPGRO module utilizes leaf-level photosynthesis, while the CERES family of models employs radiation use efficiency. Consequently, the response of each module, as reflected in crop yields, to different sources of solar radiation is expected to vary.

DSSAT requires that users supply cropping management options such as crop variety, row spacing and planting date. This study generally adopted the cropping management options utilized by Andresen et al. (2001), who investigated weather impacts on maize, soybean, and alfalfa production in the Upper Great Lakes Region from 1895 to 1996 (Table 3-2) and common farming practices applied in the region (Hoeft et al., 2000). Following Andresen et al., irrigation

was not used and soil fertility was set as non-limiting. These choices focus the investigation only on the sensitivity of the crop model outputs to solar radiation estimates.

Table 3-2. Farming management for the DSSAT simulation

Management Rules	Soybean	Maize
Plant populations	20 plants per m ²	8 plants per m ²
Cultivar	Generic Group 2	Short-season cultivar - Base temperature: 8 °C - Thermal time for juvenile phenological stages (P1): 200 degree days - Thermal time from silking to maturity (P2): 685 degree days
Planting dates*	Automatically after May 1	Automatically after May 22
Harvest	At physiological maturity	

*Determined automatically based on soil temperature in the top of 10 cm ≥ 10 °C.

Soil information for Hancock was obtained from the STATGO database published by NRCS-USDA (Soil Survey Staff, 2010). Detailed soil physical properties needed for running DSSAT were calculated using SBuild, a supporting package designed to create or modify soil information to meet DSSAT requirements (Uryasev et al., 2003). Model simulations for the two crops were run independently, and no rotation between the two crops was permitted. Simulated grain yields at the time of maturity were saved for further analysis.

3.2.4. Evaluation Methods

Estimated daily solar radiation from the different sources was compared to observed daily solar radiation using the coefficient of determination (R^2) and root mean square error (RMSE), both of which have been widely used in previous studies (e.g., Ball et al., 2004; Hunt et al., 1998; Liu and Scott, 2001). Similar to Rivington et al. (2005), we also calculated the daily bias

(b_i) between the daily radiation estimates (Se_i) and observations (So_i), averaged over the study period:

$$b_i = Se_i - So_i \quad \text{Eq.3-7}$$

$$Se_i = \frac{1}{n} \sum_{j=1}^n Se_{ji} \quad \text{and} \quad So_i = \frac{1}{n} \sum_{j=1}^n So_{ji} \quad \text{Eq.3-8}$$

where i is day, j is year, and n is the number of years. Additionally, the paired t-test assuming unequal variance was used to test for significant differences in mean daily radiation by month, and the F-test was used for evaluating equality of variance by month.

The differences in crop yields obtained from estimated and observed daily solar radiation as inputs were initially evaluated using scatter plots of the yields for the study period. Following Garcia et al. (2008), further evaluation was conducted using the mean squared deviation (MSD) as defined by Kobayashi and Salam (2000). MSD is composed of three parts, namely squared bias (SB), squared difference between standard deviation (SDSD) and the lack of correlation weighted by the standard deviation (LCS). These measures were explicitly developed for comparing output from crop process models and have fewer underlying assumptions compared to commonly-used evaluation methods (Kobayashi and Salam, 2000). SD is a traditional measure of bias, whereas SDSD provides an indication, for this application, of how well the yield estimates obtained from estimated daily solar radiation represent the magnitude of the annual fluctuations of the yield estimates obtained using observed solar radiation, and LSC provides an indication of how well the pattern of the annual fluctuations is captured. The mathematical forms of MSD, SB, SDSD, and LCS are:

$$MSD = SB + SDSD + LCS \quad \text{Eq.3-9}$$

$$SB = (\bar{x} - \bar{y})^2 \quad \text{Eq.3-10}$$

$$SDSD = (SDx - SDy)^2 \quad \text{Eq.3-11}$$

$$LCS = 2(SDx)(SDy)(1 - r) \quad \text{Eq.3-12}$$

$$SDx = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{Eq.3-13}$$

$$SDy = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2} \quad \text{Eq.3-14}$$

where $\bar{x}$ and $\bar{y}$ are the means of crop yields obtained from the generated (x_i) and observed (y_i) daily solar radiation, i is 1, 2, 3 up to the length of study period (n), SDx and SDy are the standard deviations for crop yields simulated using estimated and observed solar radiation, respectively. The MSD analyses were supplemented with more conventional evaluation methods including paired t-test for equality of means, F-test for equality of variances, and correlation analysis.

3.3. Results

3.3.1. Solar Radiation

Daily averages of observed and estimated solar radiation for the 8-year analysis period indicate that the radiation estimations capture the annual cycle relatively well (Figure 3-2). The large degree of day-to-day variability in the observed daily means and the estimated values from some of the radiation sources, particularly during spring and summer, may partly be a reflection of the short study period and the highly variable cloud cover at this time of year.

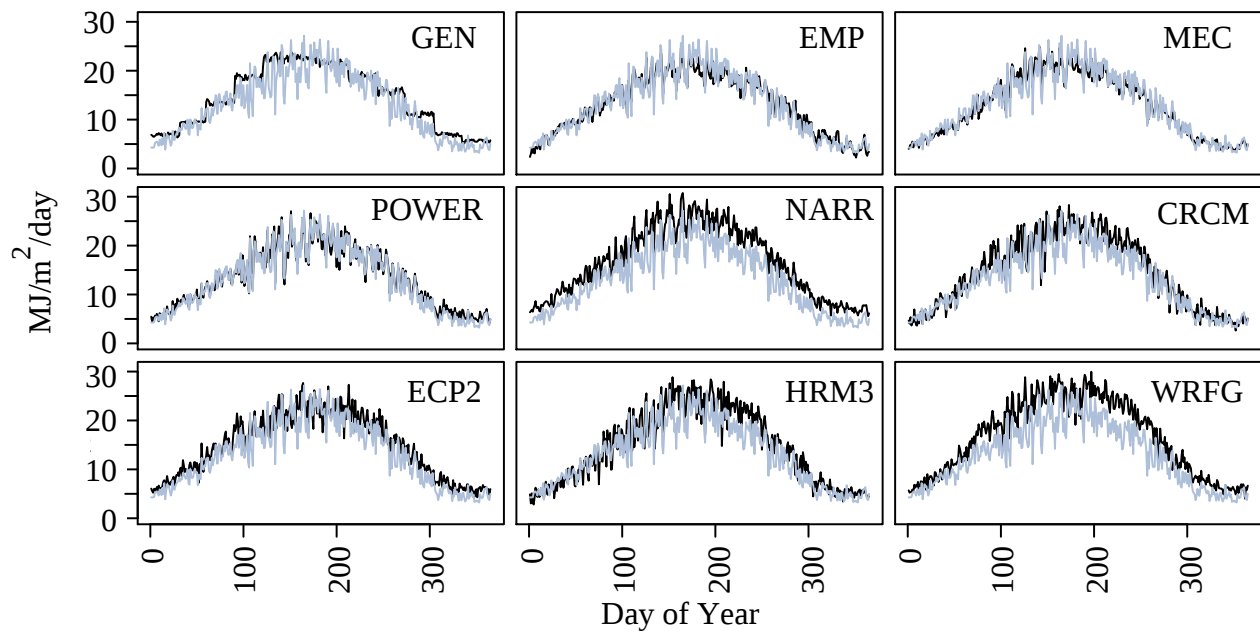


Figure 3-2. Daily averages of estimated (black line) and observed (grey line) solar radiation at Hancock-Wisconsin for the 8-year study period for the weather generator (GEN), empirical (EMP) and mechanistic (MEC) models, POWER, NARR, and the NARCCAP (CRCM, ECP2, HRM3, and WRFG) regional climate models.

Seasonal variations in daily bias are seen for the majority of the radiation estimates, although the biases should be interpreted carefully given the short (eight year) study period over which they were calculated. Solar radiation estimates obtained from the weather generator display substantial positive biases in spring and fall, but negative biases during summer (Figure 3-3). In contrast, the magnitude of the average daily bias is relatively small for radiation estimates obtained from the empirical and mechanistic models and especially for the POWER estimates, although, in general, daily bias tends to be positive in mid to late spring and negative in summer. Modest positive biases are seen for almost all days for the radiation estimates obtained from NARR. For the four NARCCAP models (i.e., CRCM, ECP2, HRM3, and

WRFG), substantial fluctuations in daily biases are observed, with particularly large positive biases found from early spring to late summer, similar to the pattern seen for the weather generator.

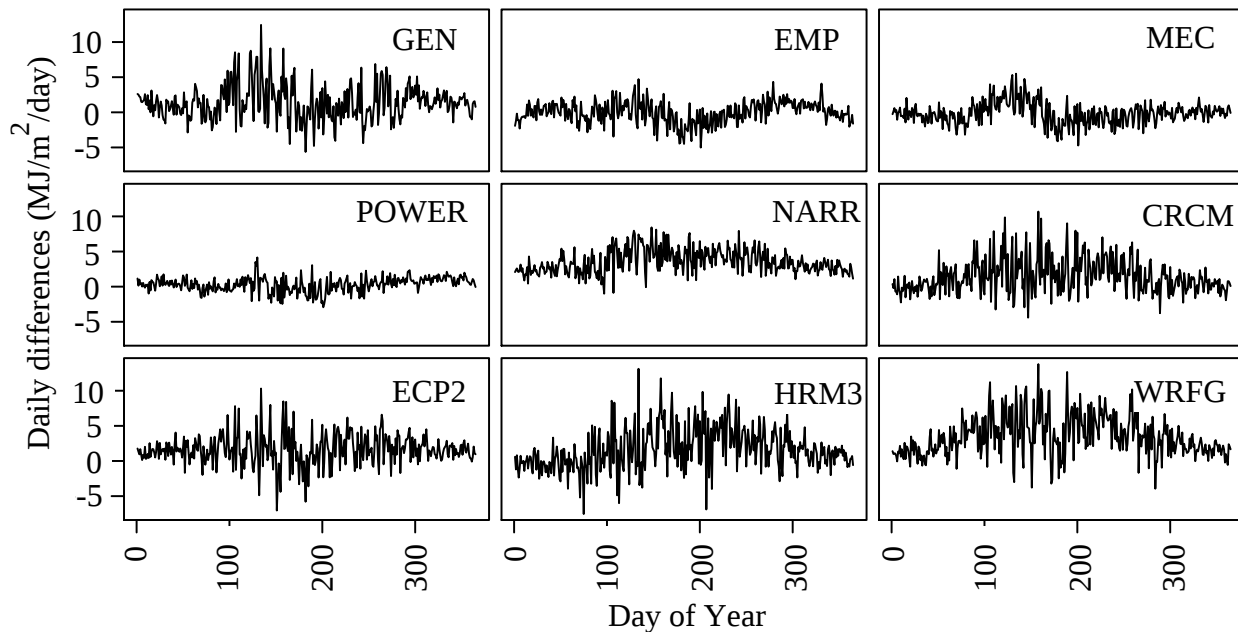


Figure 3-3. Average daily bias for the solar radiation estimates. See Fig. 2 for definition of the abbreviations.

Further evaluation based on RMSE and coefficient of determination (R^2) suggests that several of the daily solar radiation sources (i.e., POWER, the empirical and mechanical models, and NARR) perform better than the commonly-used weather generator (Figure 3-4). However, daily solar radiation from the weather generator agrees better with daily observations than estimates obtained from the regional climate models, with the exception of the CRCM simulations which have a higher R^2 although also a higher RMSE. It is important to note that while most of the estimation techniques considered attempt to preserve day-to-day relationships between observed and solar radiation, the weather generator instead imitates the statistical

structure of a long time series of radiation (Apipattanavis et al., 2010; Castellvi and Stockle, 2001; Garcia and Hoogenboom, 2005; White et al., 2011b), and mimics the observed daily totals only indirectly through sequences of wet and dry days.

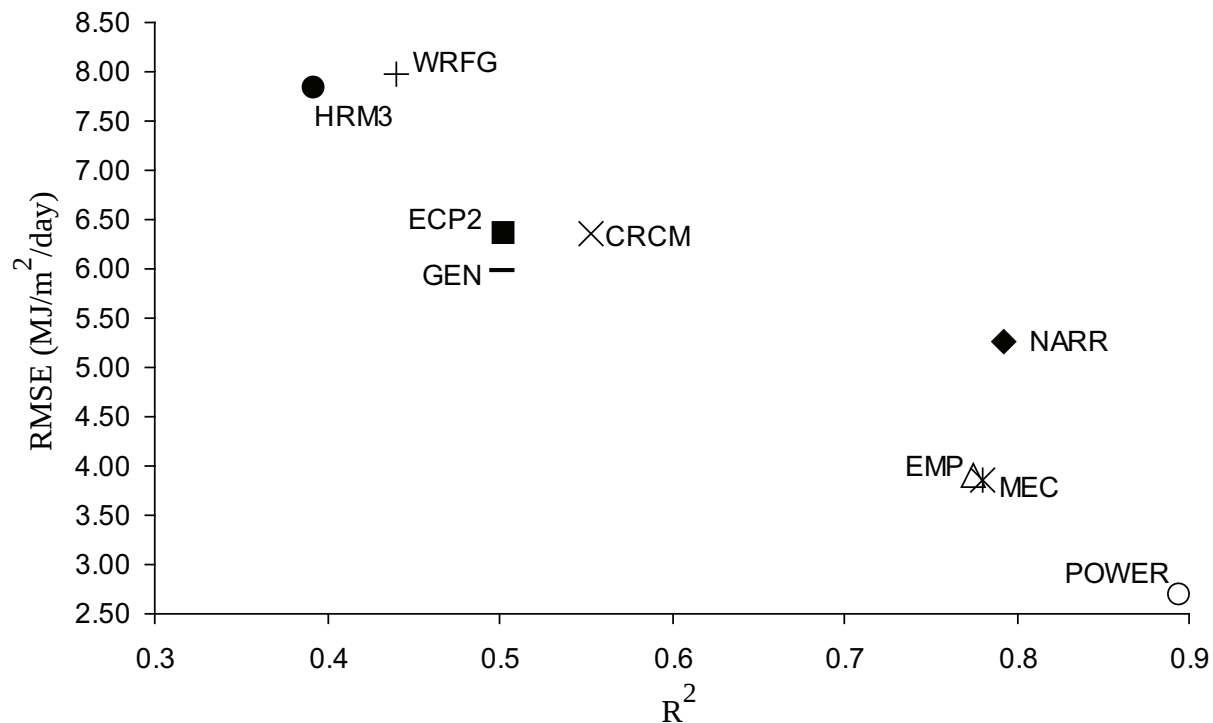


Figure 3-4. Root mean squared error (RMSE) and the correlation with observed daily solar radiation for the solar radiation estimates. See Fig. 2 for definition of abbreviations.

Mean daily solar radiation by month differs significantly from observed solar radiation for most radiation sources, based on paired t-tests (Table 3-3). [Note that a 99 percent probability level was used to assess significance, given the relative larger number of values and thus the greater likelihood that small differences in the mean are statistically, but not necessarily physically, significant.] Some exceptions are the insignificant differences found for approximately the first half of the year for the empirical model and POWER estimates and in the second half of the year for the mechanistic model. The largest differences in monthly mean daily

radiation are seen for the NARR and NARCCAP WRF estimates, which exceed 20 percent in almost all months, whereas the differences are smallest (<10 percent for most months) for the mechanistic and empirical models and the POWER estimates. All four of the NARCCAP models better capture the monthly variance compared to the other radiation sources, as seen in the insignificant results of the F-test for equality of variance. The variance is particularly poorly captured by the weather generator and mechanistic and empirical models.

The mechanistic model parameterized at Hancock performs well at the CRN locations in Michigan (Chatham and Gaylord) and Minnesota (Goodridge and Sandstone), as indicated by the relatively high R^2 (above 0.79) and low RMSE (3.68 to 4.2 MJ/m²/day), although model performance is weaker at Chatham compared to the other locations (Figure 3-5). Model performance not strongly associated with the distance between the station and the location where the model was parameterized. For example, Goodridge, which is located farthest from Hancock (~675 km), has lower RMSE and higher R^2 values (i.e., the “best” performance) compared to the other stations. On the other hand, the highest RMSE and lowest R^2 values are found for Chatham, which is located closest (~320 km) to Hancock. Validation of the empirical model parameterized at Hancock indicates that it also performs well at the other four locations. RMSE and R^2 range from 4 to 4.6 MJ/m²/day and 0.74 to 0.79, respectively. Model performance is again weakest at Chatham, although the performance at Goodridge is relatively poor in contrast to the mechanistic model which performed well at Goodridge (Figure 3-5).

Table 3-3. Percent difference by month in the mean and standard deviation of daily solar radiation for the different radiation sources compared to observed radiation at Hancock, Wisconsin.

Month	GEN	EMP	MEC	POWER	NARR	CRCM	ECP2	HRM3	WRFG
<i>Difference in monthly mean daily solar radiation (percent)</i>									
Jan	19.0	-3.7	-1.6	8.0	39.2	-3.7	21.5	-4.9	22.0
Feb	6.1	5.6	-6.5	4.7	30.8	6.2	17.6	-3.8	19.9
Mar	4.1	-2.2	-6.6	-1.0	20.4	10.1	11.3	-3.0	26.7
Apr	17.0	2.0	6.2	0.9	22.6	14.3	13.3	10.1	28.0
May	18.9	2.9	10.1	2.4	27.9	10.6	8.9	10.8	25.7
Jun	6.3	-5.0	-2.1	-1.4	21.0	12.3	5.8	16.5	21.2
Jul	1.1	-8.4	-6.0	-3.4	19.9	11.5	3.7	12.7	21.7
Aug	4.9	-3.6	-4.9	0.3	25.3	16.5	13.8	22.7	31.5
Sep	10.9	4.1	-3.3	3.7	29.1	13.0	16.3	19.5	30.1
Oct	16.8	14.0	-2.3	8.2	33.2	5.1	20.1	20.7	28.2
Nov	33.3	21.3	2.5	21.7	54.9	11.4	32.2	20.7	43.6
Dec	24.4	-9.5	0.6	21.2	55.9	3.0	31.0	13.4	32.6
<i>Difference in monthly standard deviation of daily solar radiation (percent)</i>									
Jan	-72.8	9.7	-25.9	8.0	-14.7	13.6	-12.5	12.7	12.5
Feb	-84.3	-28.5	-33.3	4.7	-21.1	14.4	-13.5	14.0	3.3
Mar	-81.8	-34.4	-34.7	-1.0	-11.9	13.5	-10.3	20.0	-1.3
Apr	-78.4	-37.3	-36.2	0.9	-14.1	-1.6	-15.5	8.7	-4.2
May	-76.3	-34.4	-36.0	2.4	-13.4	4.0	-10.7	15.8	-5.7
Jun	-77.7	-31.8	-33.1	-1.4	-15.0	-4.1	-10.3	-0.5	1.3
Jul	-84.9	-35.1	-38.8	-3.4	-16.1	2.7	-6.4	11.0	3.6
Aug	-77.0	-23.8	-30.0	0.3	-17.5	-6.9	-4.6	-7.8	-9.8
Sep	-77.4	-20.5	-33.9	3.7	-16.9	-5.7	-9.8	2.9	-11.3
Oct	-73.0	-1.6	-28.5	8.2	-11.1	1.1	-8.3	7.9	0.2
Nov	-78.2	2.3	-37.9	21.7	-14.7	10.2	-8.1	11.7	8.8
Dec	-58.4	38.5	-29.4	21.2	-21.3	14.2	-16.5	5.9	10.9

**Bolded values indicate significant differences at the 99 percent probability level based on a paired t-test (assuming unequal variance) for equality of means or a F-test for equality of variance.

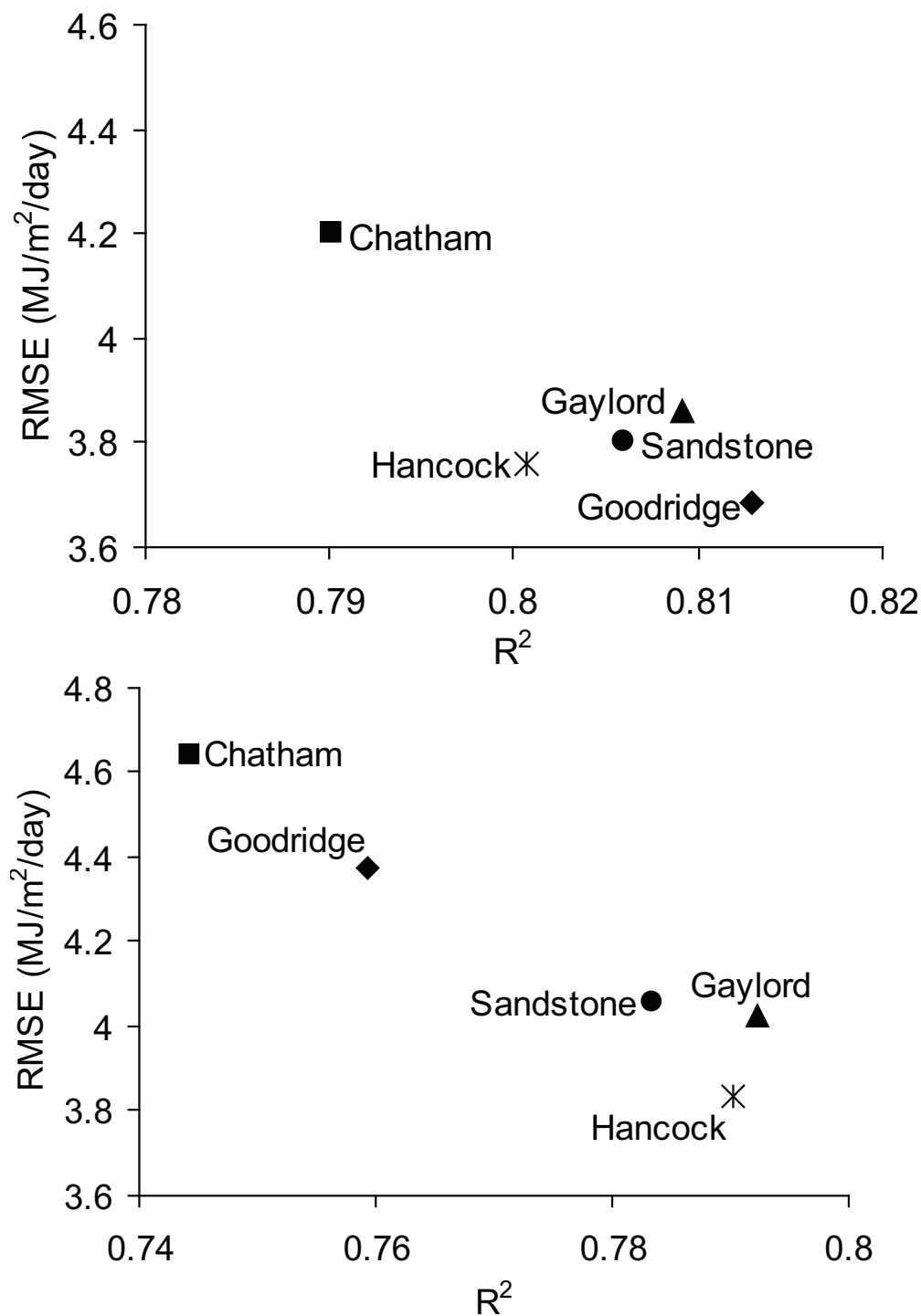


Figure 3-5. Evaluation of the performance of the mechanistic (left) and empirical (right) models parameterized at Hancock when applied to four Climate Reference Network stations in Minnesota (Sandstone and Goodrich) and Michigan (Chatham and Gaylord) based on root mean square error (RMSE) and coefficient of determination (R^2)

3.3.2. Crop Yields

Comparison of maize yields simulated using daily observed and estimated solar radiation as input to CERES-Maize indicates a close agreement between the simulated yields (Figure 3-6). Small differences exist between the radiation sources, although in general the correspondence between the yields simulated using observed and estimated solar radiation is greatest for lower (less than 4000 kg/ha) yields, whereas at higher yields the simulated values when using estimated radiation are somewhat larger than those obtained using observed radiation for most (but not all) radiation estimates.

Yield deviations are also small for soybean, although the pattern of overestimation and underestimation varies from that observed for maize (Figure 3-7). For the three traditional radiation sources (weather generator, empirical and mechanistic models), soybean yield obtained using estimated radiation is larger than that obtained using observed radiation at yields >1000 kg/ha, although close agreement is observed for smaller yields. In contrast, yields simulated using estimated radiation from NARR and three of the NARCCAP models (CRCM, HRM3, WRFG) somewhat underestimate the yields simulated from observed radiation. Good agreement is observed between the yield simulations using estimated and observed radiation when the POWER and NARCCAP ECP2 sources of daily solar radiation are employed.

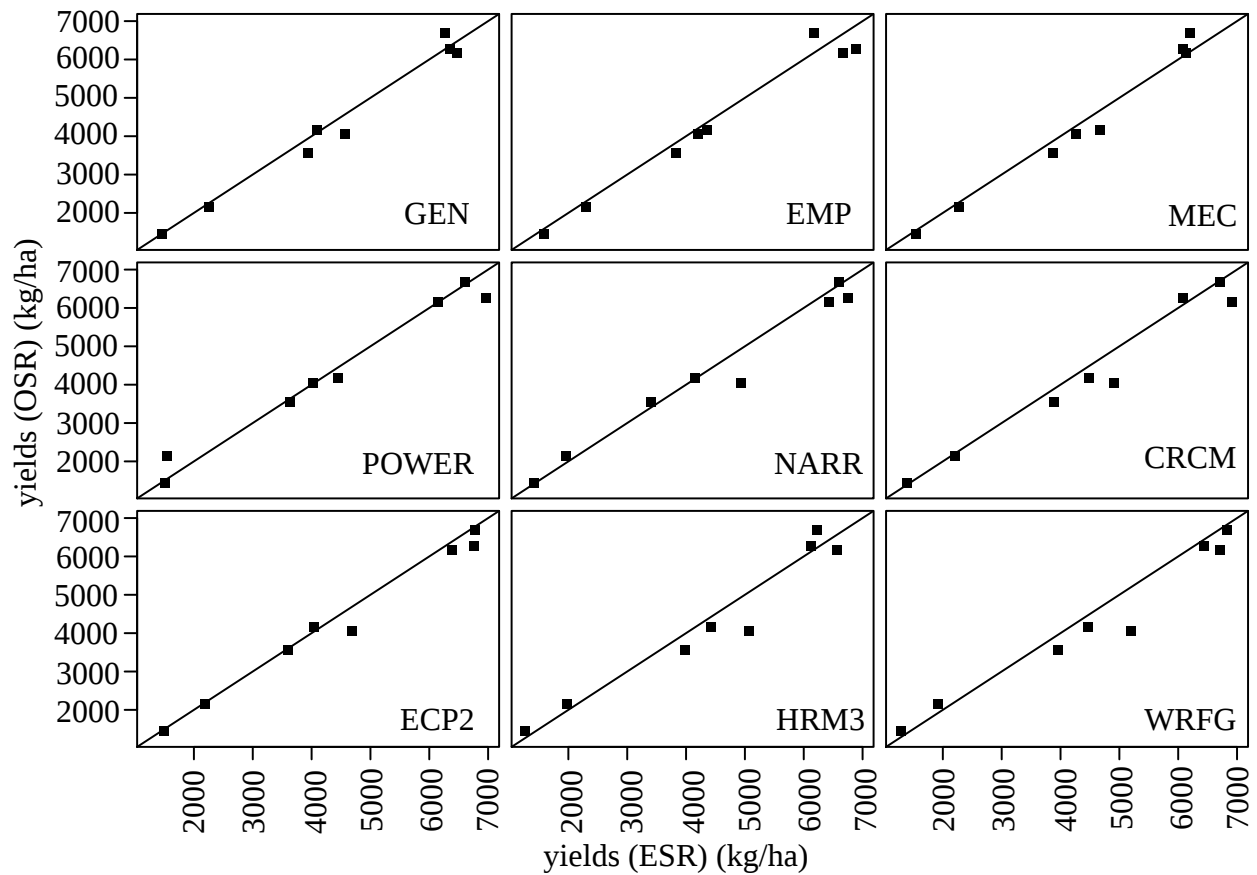


Figure 3-6. Maize yields for the eight-year analysis period simulated using daily solar radiation observations and estimates as input to CERES-Maize. OSR and ESR refer to observed and estimated solar radiation, respectively.

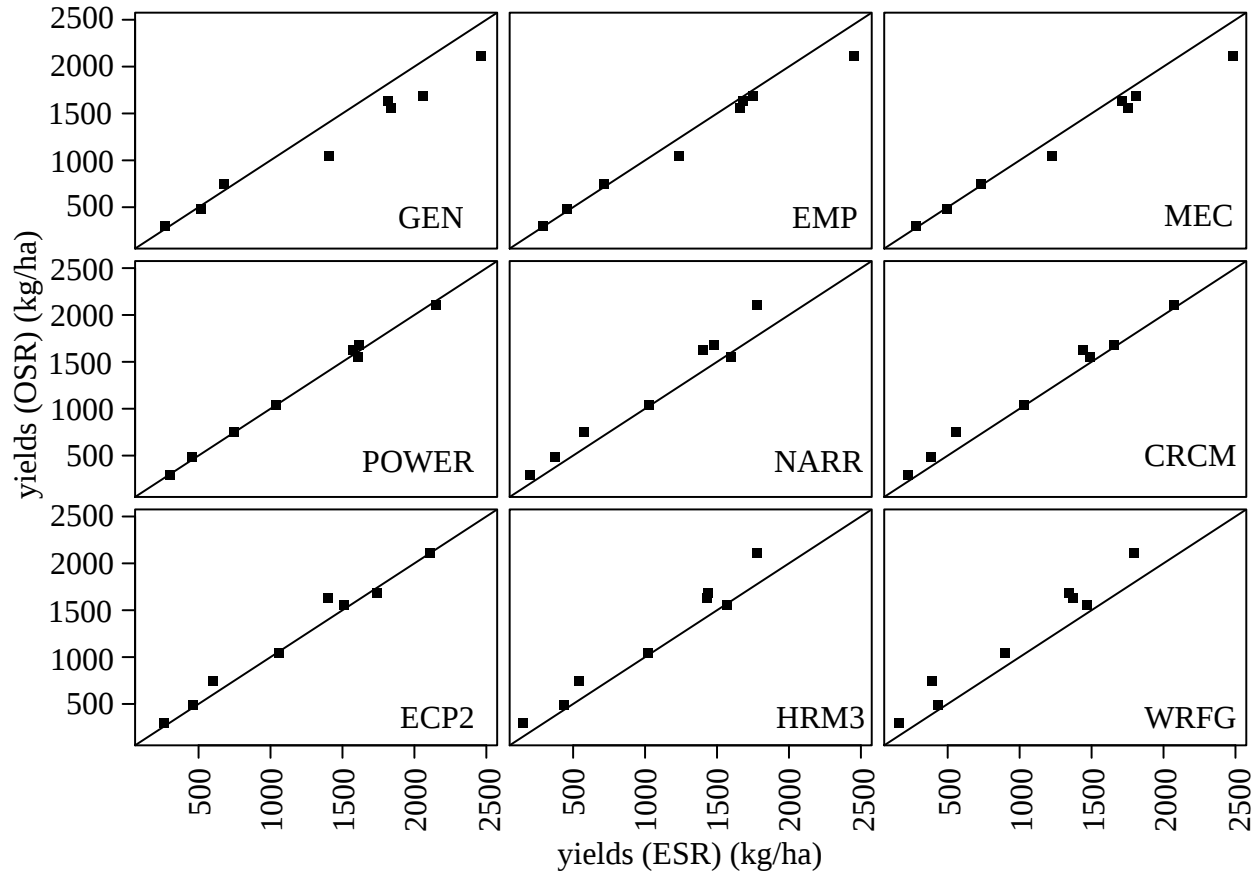


Figure 3-7. Soybean yields for the eight-year analysis period simulated using daily solar radiation observations and estimates as input to CROPGRO-Soybean. OSR and ESR refer to observed and estimated solar radiation, respectively.

For maize yield, mean squared deviation (MSD) is smallest when radiation estimates obtained from the mechanistic model, weather generator, and NARCCAP EPC2 regional climate model were used as input to CERES-Maize and largest for the other three NARCCAP models (i.e., WRFG, CRCM, HRM3) (Figure 3-8). Separation of MSD into its components indicates that the lack of correlation weighted by the standard deviation (LCS) is the largest contributor to the MSD values for all radiation estimation techniques, and that, with the exception of the maize yields obtained using the mechanistic model and NARR radiation estimates, squared difference

between standard deviation (SDSD) is the least contributor to MSD. Squared bias (SB) of the simulated maize yields is small for all but two of the radiation estimates (i.e., NARCCAP CRCM and WRFG). The relatively large LCS values suggest that the simulated maize yields using the radiation estimates do not have the same pattern of variation across the 8-year study period compared to the simulated yields obtained using observed radiation as input. In contrast, the low SDSD values indicate that the magnitude of the yield fluctuations is similar whether estimated or observed solar radiation serves as input to the CERES-MAIZE process model. The small SB values for most of the radiation estimates suggest that the means are similar for the simulated yields obtained using estimated and observed radiation.

The distribution of MSD for soybean yield across the different radiation sources is not consistent with that seen for maize yields (Figure 3-8). The smallest MSD values are observed for soybean yields obtained using the POWER and the NARCCAP ECP2 and CRCM radiation estimates, followed by the empirical and mechanistic models. The largest MSD values are observed for soybean yields simulated using solar radiation from the weather generator and NARCCAP WRFG model. SDSD provides the least contribution to MSD for most radiation estimates, with the exception of the mechanistic model and weather generator, indicating that the fluctuations in soybean yield across the study period are similar whether estimated or observed radiation estimates are used as input. However, in contrast to what was observed for maize yield, squared bias (SB) is the largest contributor to MSD for all sources of radiation estimates except for NARCCAP ECP2 for which the contribution from LCS is larger. This finding suggests that the mean of the soybean yields obtained using the different sources differs from the mean soybean yield simulated using observed daily radiation.

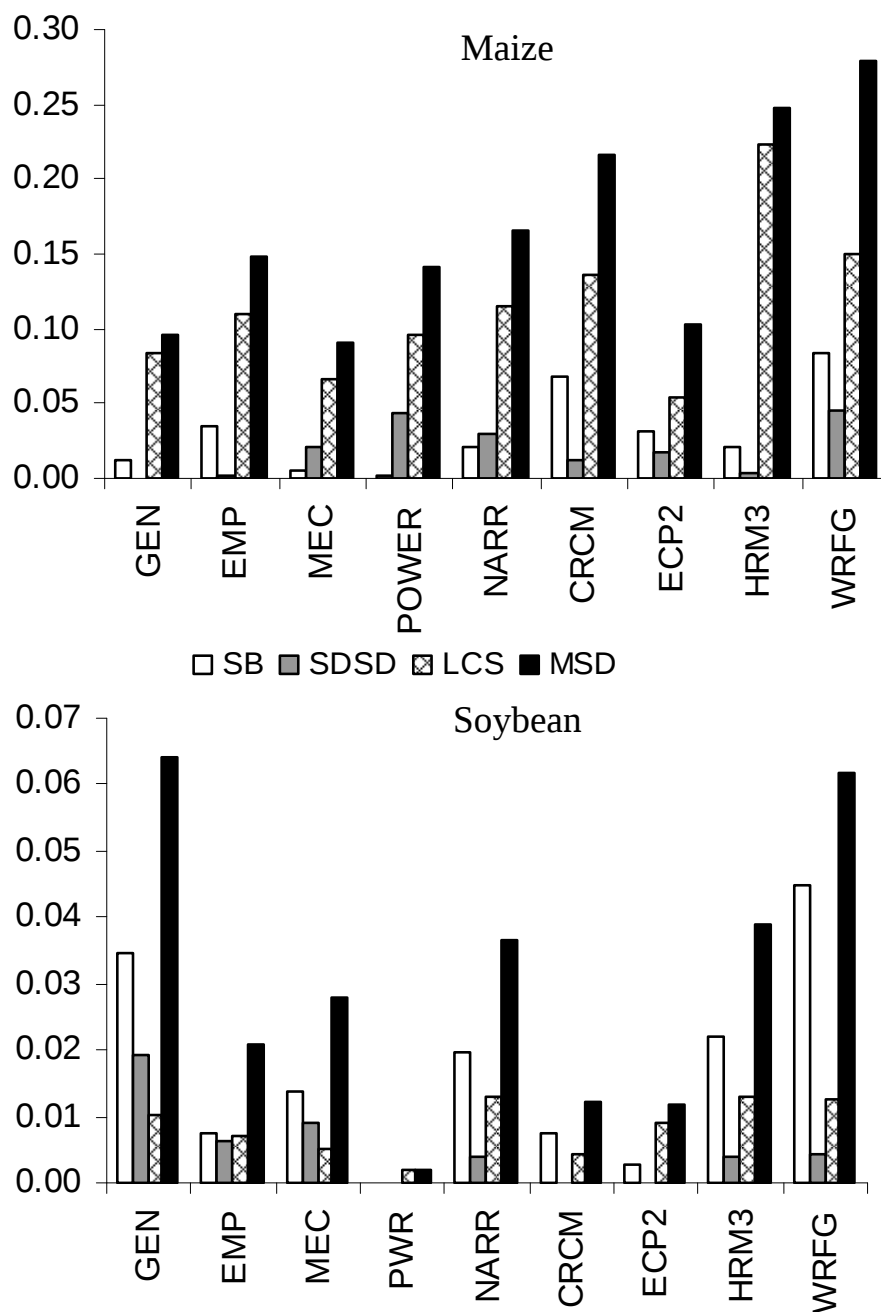


Figure 3-8. Mean squared deviation (MSD), squared bias (SB), squared difference between standard deviation (SDSD) and the lack of correlation weighted by the standard deviation (LCS) for maize (left) and soybean (right) yield simulated using daily solar radiation estimates compared to yield simulations using radiation observations. Please note the difference in the vertical axes for the two plots. See text for definition of SB, SDSD, LCS, and MSD.

Paired tests indicate that, for all the radiation sources, the differences between maize yields obtained using estimated versus observed daily solar radiation are insignificant (two-tailed probability of 95%), in line with the interpretation above of the small values of the SD component of the MSD statistic (Table 3-4). Percent deviations in mean maize yield range from slightly over 1 percent for the POWER radiation estimates to approximately 7 percent for the NARCCAP WRFG estimates. Similarly, the insignificant results for the F-test of equality of variances for all radiation estimates agree with the interpretation of the SDSD component that the magnitude of the yield fluctuations over the 8-year study period is similar. For all radiation sources, the standard deviation of maize yield differs by less than 10 percent from that obtained using observed daily solar radiation. On the other hand, correlations between the simulated maize yields from estimated and observed radiation are high (>0.90) for all radiation sources, even though the LCS component suggests that the yields do not have the same pattern of variation across the study period.

For soybean, significant differences in mean yield are observed for the majority of the radiation estimates, as was suggested by the larger relative contribution of SD to the MSD values. Mean soybean yields obtained using estimated radiation as input are similar to those from observed radiation for only the empirical model, POWER, and NARCCAP ECP2 radiation sources. Deviations in mean yield are largest (over 15 percent) for the weather generator and NARCAAP WRFG radiation sources, although the signs differed with a negative deviation (underestimation) for NARCCAP WRFG and a positive deviation (overestimation) for the weather generator. An interesting finding is that average simulated yield using the NARR radiation estimates is smaller than that obtained using observed radiation, even though, as seen above, NARR overestimates daily solar radiation. Although the difference in the standard

deviation of the simulated soybean yield, when compared to yields obtained using observed radiation, is larger for the traditional radiation sources (> 15 percent) compared to the modern radiation sources (< 10 percent, respectively), the F-tests indicate that the differences in variance are insignificant for all sources of estimated radiation, in agreement with the small SDSD values seen above. The high correlations suggest that the pattern of variation of the soybean yield simulations is similar whether observed or estimated daily solar radiation is used as input.

Table 3-4. Percent difference in the mean and standard deviation of simulated maize and soybean yields using estimated versus observed daily solar radiation as input, and the correlation between the yield time series for the study period. Two-tailed probabilities are shown in parenthesis for paired t-test for equality of means and F-test for equality of variances.

Radiation Sources	Maize			Soybean		
	<i>Difference in Mean (%)</i>	<i>Difference in Standard Deviation (%)</i>	<i>Correlation</i>	<i>Difference in Mean (%)</i>	<i>Difference in Standard Deviation (%)</i>	<i>Correlation</i>
GEN	2.63 (0.31)	-2.29 (0.95)	0.99	15.58 (0.03)	24.37 (0.58)	0.99
EMP	4.37 (0.16)	1.18 (0.98)	0.98	7.23 (0.10)	15.11 (0.72)	0.99
MEC	1.54 (0.56)	-8.67 (0.82)	0.99	9.80 (0.04)	17.56 (0.68)	0.99
POWER	1.12 (0.72)	9.39 (0.82)	0.99	-0.81 (0.54)	1.00 (0.98)	0.99
NARR	3.34 (0.31)	7.57 (0.85)	0.99	-11.78 (0.01)	-6.66 (0.86)	0.98
CRCM	6.09 (0.09)	4.21 (0.92)	0.98	-7.32 (0.01)*	3.21 (0.94)	0.99
ECP2	4.12 (0.09)	5.32 (0.90)	0.99	-4.37 (0.16)	2.09 (0.96)	0.99
HRM3	3.33 (0.42)	1.69 (0.97)	0.97	-12.48 (0.01)*	-6.82 (0.86)	0.98
WRFG	6.73 (0.10)	9.55 (0.82)	0.98	-17.73 (0.00)*	-7.28 (0.85)	0.98

Note: Bolded values and asterisks indicate significant values at 95% and 99% probability levels, respectively.

3.4. Discussion

The findings presented above suggest considerable potential for the use of non-traditional sources of daily solar radiation estimates for agricultural applications. Although radiation estimates obtained from traditional mechanistic and empirical models generally agreed well with observed daily solar radiation based on a several performance measures (bias, RMSE, equality of means), the gridded POWER satellite-based estimates performed as well, and, along with the radiation estimates obtained from the four NARCCAP models, better captured the variance compared to the traditional measures. The ability of the NARCCAP models to replicate observed solar radiation was shown to be model dependent with smaller biases seen for ECP2 and CRCM and considerably larger biases for WRFG and HRM3, although, collectively, biases were larger for the NARCCAP models compared to the other radiation sources. Depending on the application, daily radiation estimates obtained from NARR need to be used cautiously, as NARR consistently overestimates daily solar radiation. One concern of the commonly-used weather generator is the substantially underestimated variance of daily solar radiation. Afshin and Gerrit (2003) also found that the WGEN weather generator, on which Weatherman is based, poorly simulated the variance of daily solar radiation, and Woli and Paz (2012) warn that the statistical properties of observed data on a daily time step may not be well represented by WGENR, another variation of WGEN.

Several of our findings regarding the agreement of estimated and observed radiation are consistent with those of previous studies. The RSME and R^2 values found here for the POWER radiation estimates for the grid point closest to Hancock, Wisconsin, are similar to those reported for multiple sites in China (Bai et al., 2011) and across the continental USA (White et al., 2011b), suggesting that the POWER gridded dataset is a promising source of daily solar

radiation for multiple midlatitude locations. Previous work which validated NARR fields with ground observations for locations across North America (Markovic et al., 2009), within the Mississippi River Basin (Kumar and Merwade, 2011), and over the Pacific Northwest (Schroeder et al., 2009), also found that NARR tended to overestimate daily solar radiation. As discussed by Schroeder et al. (2009) and Markovic et al. (2009), this overestimation is likely due to the underestimation of cloud cover in the NARR atmospheric model component (i.e., the NCEP Eta model). Tarasova et al. (2006), who evaluated the performance of the solar radiation scheme employed in the Eta model, reported a systematic bias in solar radiation estimates due to inaccuracies in cloud parameterization. The radiation estimates obtained from the NARCCAP regional climate models also display positive biases for most months of the year. One possible explanation is error in cloud cover within the NCEP global reanalysis (Kalnay et al., 1996; Kanamitsu et al., 2002) used as the lateral boundary conditions for the NARCCAP models, and that these errors may propagate to the regional climate model simulations. A tendency for regional climate models to overestimate incoming solar radiation was also found by Rivington et al. (2008b), who validated the output of the Hadley Centre's HadRM3 for multiple sites in the United Kingdom, although they attributed the systematic bias to the underestimation of cloud cover within the regional model itself (Rivington et al., 2008b).

Although our findings indicate that mechanistic and empirical models continue to be viable estimation options of daily solar radiation, concern remains regarding the transferability of the model coefficients. The sensitivity analysis presented here indicates that the model coefficients developed for Hancock, Wisconsin, performed well across the Upper Great Lakes region. Unlike Hunt et al. (1998), who reported that the applicability of mechanistic model coefficients depends on the distance from the calibration station, our results suggest that local

climate variations are more important than distance in determining the transferability of the model coefficients. For example, the mechanistic and empirical models performed poorest at Chatham, which experiences lake effect modification from both Lake Superior and Lake Michigan (Andresen and Winkler, 2009). In line with our findings, Liu and Scott (2001) recommended that models calibrated at a specific station can be used at other locations with a similar climate regardless of distance, in contrast to Hunt et al. (1998) who specified an upper-limit (~390 km) from the calibration station when estimating solar radiation. The greater site sensitivity shown here of the coefficients of the empirical model compared to the mechanistic model suggests that the global solar radiation term as a function of latitude in the mechanistic model provides considerable stability and transferability to mechanistic models.

The primary goal of this research was to evaluate the use of different radiation estimates in crop process models, and our findings suggest that crop-specific differences exist. Maize yield obtained from the CERES-Maize simulations with estimated solar radiation as the input did not differ significantly from yield obtained using observed solar radiation as input, regardless of the source of the estimated radiation. In contrast, significant differences were found in soybean yield for the majority of the radiation sources. For the non-traditional sources, only the simulated soybean yields from the POWER and NARCCAP ECP2 daily radiation estimates were in good agreement with the yields obtained using observed radiation. It is interesting to note that although the POWER satellite-derived estimates agreed well with observations throughout most the growing season, the ECP2 estimates replicated the observed radiation well only during June and July, suggesting that the timing of the biases can affect simulated soybean yield. More difficult to explain is that simulated yield obtained from the other gridded datasets (NARR and the remaining NARCCAP models) was significantly smaller than yield obtained using observed

radiation, in spite of the positive bias in the radiation estimates. This may partly be explained by the relatively lower levels of light saturation for C3 crops. Net photosynthetic rate for C3 species increases with increasing light intensity only at low values of radiation, whereas for C4 crops it tends to increase at higher levels of light intensity (Garcia et al., 2008). Another potential explanation is that the larger positive bias in the radiation estimates led to water stress as increasing solar radiation can trigger greater crop evapotranspiration (Brown and Rosenberg, 1997). Higher levels of solar radiation can also increase the temperature of the plant canopy which in turn results in greater water demand for crop transpiration (Payero and Irmak, 2006).

A limitation of this study and all previous works is the small number of crop types and geographical locations included in the analysis. When our findings are placed in the context of previous studies, potential differences by crop type are highlighted. For example, Garcia et al. (2008) found for nine rainfed agricultural locations in Georgia that the substitution of stochastically-generated solar radiation estimates for observed radiation did not have a significant impact on simulated maize yield, similar to what we found for maize yield at Hancock, Wisconsin. On the other hand, Garcia et al. (2008) also found that differences in simulated yield for peanut, the representative C3 crop in their study, were insignificant. In contrast, simulated yield for soybean, the representative C3 crop for this study, differed significantly when stochastically-generated radiation was substituted for observed radiation. When our findings are compared to previous analyses that employed radiation estimates obtained from mechanistic models, we also find some differences in interpretation. Specifically, Mavromatis and Jagtap (2005) concluded, based on Willmott's index of agreement, that the yield variability for a C3 crop (peanuts) at four locations in Florida displayed greater sensitivity than that for a C4 crop (maize) to the substitution of estimated solar radiation from a mechanistic

model for observed radiation. Our study, in contrast, found no significant differences in variability, based on the F test for equality of variances, for either maize (C4) or soybean (C3). A caveat of these is that variants of the radiation estimation techniques can also influence the interpretation. For example, Cooter and Dhakhawa (1996) found that, at least for maize, the impact of generated solar radiation on simulated yield can vary with the type of weather generator employed to obtain the radiation estimates, although both Garcia et al. (2008) and this study used variants of the popular WGEN. Similarly, Trnka et al. (2007) found that different formulations of mechanistic models had a substantial influence on wheat and barley yield. Differences in the findings between studies may also reflect geographic influences. For example, Bai et al. (2010) found that simulated maize yield obtained when substituting POWER radiation estimates for observed radiation did not differ significantly for three regions in China, similar to our results for Hancock, Wisconsin, but that this was not the case for the other two regions included in their analysis.

Additional considerations also influence the choice of radiation estimate for an application, as summarized in Table 3-5. Availability is a key consideration. One reason for the current wide use of weather generators in agricultural applications is that they are already packaged in software systems such as DSSAT, although users must input the temperature and precipitation time series needed to parameterize the weather generator for an individual location. The non-traditional gridded datasets (POWER, NARR, NARCCAP) are also freely available, although some effort and computer expertise is required to download and extract the radiation information, and these series are shorter in potential length than those obtained with weather generators. As noted previously, an advantage of these radiation estimates over weather generators is that they may better reflect the day-to-day relationships between radiation and other

variables such as temperature and precipitation. The lack of synoptic and temporal synchrony is particularly a concern for weather generators when the intention is to incorporate the generated values with observations of other climate parameters, for example blending observed temperature and precipitation with generated solar radiation. Additional advantages of the gridded datasets are that no additional model development or parameterization is usually required and their large geographic coverage, global in the case of POWER and across North America for NARR and NARCCAP. Mechanistic and empirical models are relatively easy to develop/parameterize without extensive requirements of computer resources (Ball et al., 2004; Yang et al., 2006). Considerable care needs to be taken, however, to apply these models only in regions with a similar climate as the location for which the model was parameterized and those with relatively stable climates (i.e. little or no temporal trends). Another concern of mechanistic and empirical models is the possibility of negative radiation estimates, as these models are usually formulated using multiple regression techniques. Alternative methods that consider daily solar radiation as a zero bound variable such as gamma and semi-log regression could be used, although we found larger biases for daily radiation estimates obtained using these methods (results not shown). For the analyses above, the small number of negative values (0.3% for the mechanistic model and 1.4% for the empirical model) was simply converted to zero. Nonetheless, the frequency of negative estimates must be carefully evaluated whenever mechanistic or empirical models are used to estimate daily solar radiation.

The development of future scenarios (also often referred to as projections) of daily solar radiation for climate change assessments places additional constraints on the applicability of the different sources of radiation estimates investigated here. All have their limitations. POWER is an observation-based dataset, and scenario development is for the most part limited to a “delta

approach” whereby daily time series are adjusted by a mean change. This is also the case for reanalysis datasets such as NARR. Weather generators have frequently been used to develop climate change projections, although future changes in the variable(s) used to condition the weather generator (e.g., precipitation) can have unanticipated effects on the other variables (e.g., solar radiation) being simulated (Wilby et al., 2002; Wilks, 1992). Mechanistic and empirical models can be readily applied to estimate solar radiation for future climate conditions when projected precipitation and temperature datasets are available, under the assumption that the model coefficients are applicable for future climate conditions (i.e., stationarity). A specific advantage of the NARRCAP simulations is that projections for a control and future period are already available. However, larger biases occur when output from global climate models (GCMs) is used in place of large-scale reanalyses as the lateral boundary conditions for the region climate models (Olesen et al., 2007; Wilby and Harris, 2006), and a debiasing step may be necessary (e.g., Rivington et al., 2008a; Themeßl et al., 2011).

Table 3-5. Strengths and limitations of traditional and non-traditional sources of daily solar radiation estimates.

Radiation Source	Strengths	Limitations
<i>Traditional Methods</i>		
Weather Generator	• Often included within widely-used crop process software systems. • Requires only temperature and precipitation observations to parameterize. • Can be used for climate change projections, although future changes in the variable(s) used to condition the weather generator can have unanticipated effects on the other variables being simulated (including radiation).	• Relatively long time series of temperature and precipitation needed for parameterization. • Day-by-day interrelationships between estimated radiation and observed temperature and precipitation are not directly retained. • Underestimated variance of daily solar radiation at study location* throughout the year.

Table 3-5. (cont'd)

		When used as input to CROPGRO-Soybean (but not CERES-Maize), resulted in significant overestimation of soybean yield at study location compared to when observed radiation served as input.
Empirical Models	- Modest deviations in monthly mean daily solar radiation when compared to observations at study location. - For study location, simulated maize (CERES-Maize) and soybean (CROPGRO-Soybean) yield obtained using radiation estimates did not differ significantly from simulated yield obtained with observed radiation. - Can be easily applied to the development of future scenarios of solar radiation, under the assumption of stationarity of the model with time.	- Model development required by user. - Daily radiation observations needed for model development. - Negative values for daily solar radiation possible. - Regional climate variations influence transferability of model to other locations. - Underestimated the variance of daily solar radiation at study location during growing season.
Mechanistic Models	- Modest deviations in monthly mean daily solar radiation compared to observations at study location. - Coefficients of mechanistic model appear less sensitive to local site conditions compared to those of empirical models. - Can be easily applied to the development of future scenarios of solar radiation, under the assumption of stationarity of the model with time.	- Model development required by user. - Daily radiation observations needed for model development. - Negative values for daily solar radiation possible. - Regional climate variations influence transferability of model to other locations. - Underestimated variance of daily solar radiation at study location throughout the year. - When used as input to CROPGRO-Soybean (but not CERES-Maize), resulted in significant overestimation of soybean yield at study location compared to when observed radiation served as input.
<i>Non-Traditional Methods</i>		
POWER satellite-based estimates	- Downloadable gridded dataset. - Global coverage (1° latitude x 1° longitude). - Continuously updated.	Coarser resolution (1° latitude x 1° longitude) may be insufficient in areas with steep gradients in cloud cover.

Table 3-5. (cont'd)

	• Modest deviations in monthly mean daily solar radiation compared to observations at study location. • For study location, simulated maize (CERES-Maize) and soybean (CROPGRO-Soybean) yield obtained using radiation estimates did not differ significantly from simulated yield obtained with observed radiation.	• Overestimated the mean and standard deviation of daily solar radiation at the study location during the cool season (October-February). • Observation-based dataset; not applicable for climate change projections.
NARR	• Downloadable gridded dataset. • Coverage includes entire North America (32 km resolution). • Continuously updated.	• Overestimates daily solar radiation. • When used as input to CROPGRO-Soybean (but not CERES-Maize), resulted in significant underestimation of soybean yield at study location compared to when observed radiation served as input. • Not applicable for climate change projections.
NARCCAP regional climate models (CRCM, ECP2, HRM3, WRFG)	• Downloadable gridded dataset. • Coverage includes entire North America (~50 km resolution). • NARCCAP models were able to simulate the variance of daily solar radiation at study location. • Projected values of daily solar radiation available for future period (2041-2070).	• Available only for specific time slices (present-day time slice of 1971-2000 and future period of 2041-2070). • Ability to simulate daily solar radiation varies by regional climate model. • When used as input to CROPGRO-Soybean (but not CERES-Maize), resulted in significant overestimation of soybean yield at study location compared to when observed radiation served as input. • Error introduced when global climate model (GCM) output is used for lateral boundary conditions may require debiasing before application.

*Study location is Hancock, Wisconsin.

3.5. Conclusions

The sensitivity of simulated maize and soybean yield at Hancock, Wisconsin, to different sources of daily solar radiation estimates used as input the CERES-Maize and CROPGRO-Soybean crop process models was investigated. The radiation estimates were obtained from traditional (stochastic generation, empirical and mechanistic models) and modern (satellite estimation, reanalysis datasets, and regional climate model simulations) approaches. Comparisons of the radiation estimates to observed radiation at the study location indicated that the nature (e.g., magnitude, sign, and timing) of the biases differs considerably among the different radiation estimates, but that, in general, the biases associated with the non-traditional radiation sources are of similar magnitude to those of the traditional radiation sources.

Which sources of daily solar radiation estimates are then preferable as input to crop process models? Our results indicate that the answer to this question is likely crop dependent. The choice of radiation source did not significantly impact maize yield simulations from CERES-Maize, whereas significant differences at the 95% probability level were found for simulated soybean yield from CROPGRO-Soybean for all but three of the radiation sources. Two of the three insignificant results were for non-traditional sources of radiation estimates (POWER satellite-based estimations and the NARCCAP EPC2 regional climate simulation) suggesting that non-traditional radiation datasets provide a viable alternative to traditional radiation estimates as input to CROPGRO-Soybean.

Impacts of the different radiation estimates on yield simulations need to be investigated for additional crops and geographic locations before broad recommendations regarding preferred sources of radiation estimates for crop process models can be made. Furthermore, additional considerations, such as data availability and model transferability need to be considered when

selecting a source of daily solar radiation estimates for agricultural applications, including climate change assessments for agriculture.

Acknowledgements

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CHAPTER 4.

Spatial Variability of Regional Climate Change Impacts on Crop Production in High Latitude Regions: A Case Study of the Upper Great Lakes Region of the United States

In collaboration with

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4.1. *Introduction*

Climate parameters, including precipitation, air temperature, and carbon dioxide (CO₂), are key factors that control crop growth and development. Numerous studies have demonstrated that crop production has been highly sensitive to historical climate variability (e.g., Chen et al., 2004; Goldblum, 2009; Porter and Semenov, 2005) and recent climatic trends (e.g., Almaraz et al., 2008; Lobell and Asner, 2003; Lobell et al., 2011). Projected anthropogenic climate change triggered by elevated atmospheric greenhouse gas concentrations is expected to substantially impact crop production worldwide (e.g., Parry et al., 2004; Rosenzweig and Parry, 1994). Additionally, the impacts of climate change on crop production are projected to be unevenly distributed across the globe (Cline, 2007). In general, adverse impacts are anticipated in low latitude regions where increased water stress and more rapid crop development and shorter time to crop maturity due to warmer temperatures are expected to reduce yield, in contrast to high latitude regions where a projected longer growing season and increased precipitation are anticipated to provide more favorable growing conditions (Fischer et al., 2005; Jaggard et al., 2010; Parry et al., 2005).

These generalizations are complicated, however, by longitudinal, in addition to latitudinal, differences in projected climate change, particularly for precipitation; differences between locations in agriculture production systems; and spatial variations in other environmental factors important for agricultural production, such as soil fertility. Furthermore, most previous climate impact assessments have primarily focused on changes in productivity in current production regions (e.g., Brown and Rosenberg, 1999; Izaurralde et al., 2003; Parry et al., 1999), and, with few exceptions (e.g., Thomson et al., 2005; Tubiello et al., 2002), have not explicitly evaluated the potential poleward expansion of crop production.

This research focuses on the impacts of future climate change on county-level corn and soybean production in the Upper Great Lakes Region (UGLR) of the United States, defined as the states of Michigan, Wisconsin and Minnesota (Safir et al., 2008). This region, located between approximately 41.5°N-49.5°N latitude (Figure 4-1) serves as an excellent case study for evaluating potential latitudinal shifts in favorable growing regions. The southern portion of UGLR is located along the northern edge of the agricultural heartland of the United States; and Michigan, Wisconsin and Minnesota rank 11(12), 10(15) and 4(3) for grain corn (soybean) production, respectively (Hatfield, 2012). In contrast, little crop production currently occurs in the extreme northern portion of the UGLR, an area occupied primarily by forests and other natural vegetation (Andresen et al., 2013). Additionally, several environmental factors complicate future northward expansion of crop production, most notably the decrease in soil fertility from the deep, rich prairie soils of southern Minnesota and Wisconsin to the thinner, sandier spodosol soils of northeastern Minnesota and northern Wisconsin and Michigan. The moderating influences of the Great Lakes, particularly cooler spring and summer temperatures, also may impact the future expansion of favorable growing regions.

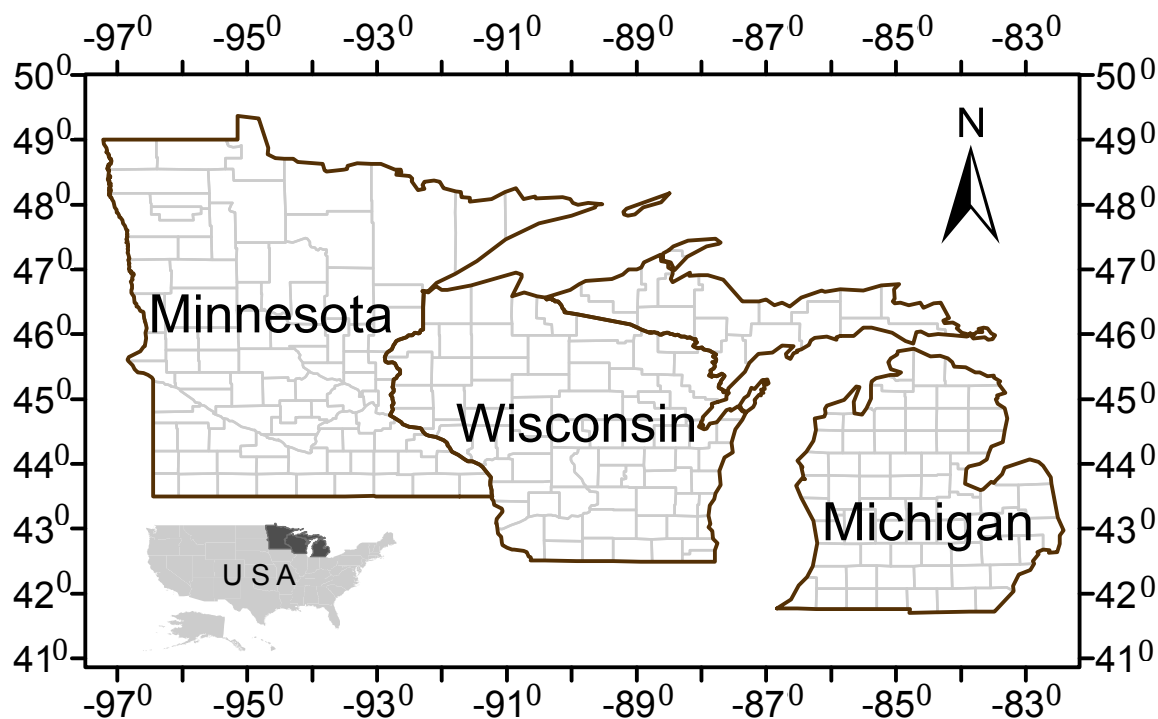


Figure 4-1. Geographical location of the Upper Great Lakes Region

Only few previous studies have investigated the potential impacts of climate change on agriculture in the UGLR, all of which considered a limited number of representative locations in their analyses. In an early study, Andresen et al. (2000) employed empirically-derived climate projections for the 21st century from two global climate models (GCMs) to assess future corn, soybean, and alfalfa yield at 13 study sites across Minnesota, Wisconsin and Michigan, including several locations where crop production is currently limited. Applying crop simulation models to a single cultivar for each crop type, the authors reported higher simulated average yield of corn, soybean, and alfalfa for the 21st century compared to a historical period (1896-1996), with the greatest increases found at the more northern study locations. Additionally, larger yield increases were obtained when CO₂ enrichment was included in the simulations. A recent update of the earlier study that focuses on corn and wheat production (Andresen et al., 2013) suggests a

more nuanced interpretation of future yield changes. Employing a smaller number of study sites (five locations in Michigan, eastern Wisconsin and western New York), but a much larger ensemble of climate projections, Andresen et al. (2013) found that the direction and magnitude of projected yield change for the 21st century varied with crop type and location. Under current CO₂ concentrations, simulated corn yield decreased for the majority of the empirically-derived climate projections at all but the northernmost location, whereas wheat yield increased for most locations and climate projections. Furthermore, CO₂ enrichment substantially increased projected yield for wheat (a C3 crop) but not corn (a C4 crop).

In contrast to Andresen et al. (2013; 2000), Southworth et al. (2002; 2000) limited their impact assessments to established crop production areas in the portion of the Great Lakes region extending from central and southern Michigan and Wisconsin to southern Illinois, Indiana and Ohio. Based on empirically-downscaled climate projections from a single GCM and small number (10) locations across the study area, Southworth et al. (2000) found that the sign of the projected change in simulated corn yield for a future period (2050-2059) relative to a baseline period (1961-1990) varied with location and crop cultivar. Simulated yield for long-season corn varieties increased at the Wisconsin and Michigan study sites but not at sites located farther south, whereas the projected average yield of medium-season varieties decreased at all locations although the decrease was less for the Wisconsin and Michigan locations. A projected decrease in yield for short-season varieties was also found, with the exception of the study site in extreme western Illinois. Based on nine locations within the study region, geographical and varietal differences were also found for projected soybean yield, with large increases in yield simulated for the Wisconsin and Michigan locations and only small increases, or even a decrease, projected

for the southern study locations (Southworth et al., 2002). In general, yield gains were greatest for late maturing rather than the early maturing cultivar (Southworth et al., 2002), and CO₂ fertilization had a positive influence on future yield.

These previous analyses point to considerable complexity in projected future changes in productivity in the UGLR, but, nonetheless, all suggest the potential for increased productivity at more northern locations. Any generalization is limited, however, by the small number of locations employed in these earlier assessments. Thus, there is considerable need for a more spatially-detailed assessment of future crop productivity that explicitly considers the potential for the poleward expansion of crop productivity, specifically for the UGLR but with implications for high latitude regions worldwide. In order to fill this gap, the major goal of this research is to provide a county-level assessment of the spatial variability of the impacts of projected future climate change by the mid century (2041-2070) on corn and soybean production across the UGLR, including spatial variations in future planting dates, time to maturity, seasonal evapotranspiration (i.e., cumulative evapotranspiration at maturity), and crop yield. Additionally, the sensitivity of the projected changes to CO₂ concentration and, for corn only, to crop cultivar are assessed. Corn and soybean are employed in the assessment as they represent the major crop rotation in the current UGLR agricultural production regions and are a C4 and C3 crop, respectively. The assessment presented here also differs from previous assessments for the study region in that dynamically-downscaled, rather than empirically-downscaled, climate projections are utilized. An ensemble of climate projections obtained from the recently-released *North American Regional Climate Change Assessment Program* (NARCCAP) (Mearns et al., 2009) is employed.

4.2. Data and Methods

4.2.1. Regional Crop Model Simulation

Regional simulation of corn and soybean production for all counties in the study region was completed using the CERES-Maize and CROPGRO-Soybean models incorporated in the Decision Support System for Agrotechnology Transfer (DSSAT) ver. 4.5 (Hoogenboom et al., 2010). DSSAT is a cropping system model that integrates different computer programs (i.e. modules) to simulate daily crop growth and development (Jones et al., 2003). Each module specifically handles weather inputs, soil conditions, soil-plant-atmosphere interactions, plant growth and development, and farming management. Inputs required for DSSAT simulation are climate/weather variables (daily solar radiation, precipitation, maximum and minimum temperature), soil information, and farming management. The DSSAT system shares common routines to simulate fluctuations of soil parameters; whereas, crop growth processes are simulated by individual plant growth modules (Jones et al., 2003). In the DSSAT system, corn and soybean are grouped into cereals and legumes, respectively.

DSSAT has been used widely around the world to investigate the consequences of environmental changes and crop management practices (e.g. Hartkamp et al., 2004; O'Neal et al., 2005; Thorp et al., 2008; Vucetic, 2011), including climate change impact and adaptation assessments (e.g. Brassard and Singh, 2008; Meza and Silva, 2009). DSSAT's capabilities and performances have also been reviewed widely (e.g. Mera et al., 2006; Southworth et al., 2002; Southworth et al., 2000). According to White et al. (2011a), who reviewed 221 articles on climate change impacts on crop production, the CERES family of models are regularly implemented (~40% articles) to evaluate crop responses to climate change scenarios. Although, CROPGRO is not as well known as the CERES family (White et al., 2011a), CROPGRO-

Soybean often has been used for climate change impact assessments in high latitude regions (e.g., Alexandrov et al., 2002; Brassard and Singh, 2008). As noted above, both CERES-Maize and CROPGRO-Soybean were employed in previous climate impact assessments for the UGLR (e.g., Andresen et al., 2013; 2000; Southworth et al., 2002; 2000). In this research, DSSAT was run for each growing season for 30-year historical (1971-2000) and future (2041-2070) periods.

DSSAT was originally developed for plot level simulations, although it subsequently has been employed to estimate yield at a range of spatial scales including for large non-uniform areas (e.g., Irmak et al., 2005; Jagtap and Jones, 2002). For this study, DSSAT was used to simulate the spatial distribution of county-level corn and soybean yield. In this we follow the lead of, among others, Haskett et al. (1995) who utilized a crop simulation model (SOYGRO) to simulate county-level yield in Iowa. As pointed out by Irmak et al. (2005, 2344), an implicit assumption is that “the impacts of climate at the aggregate spatial scale are the same as those produced by the crop models, which have limited inputs over space”.

County-level corn and soybean yield were simulated for 30-year historical and future time slices. A 30-year time series has been considered sufficient by a number of authors (e.g., White and Hoogenboom, 2011) for climate change impact assessments. Detailed descriptions of the inputs for the model simulations including the future climate scenarios are presented below.

(a) Historical Climate Observations

Preparing climate data for DSSAT simulation on the county-scale poses some challenges as climate stations are distributed unevenly over the study region. Several previous studies have employed gridded fields of precipitation and temperature as inputs to crop model simulations at a regional scale (e.g., Irmak et al., 2005; Jagtap and Jones, 2002; Quiring and Legates, 2008). Although, the “regular” grid is an obvious advantage, the spatial interpolation is sensitive to the

density of climate stations, their geographic distribution across a region, and topographical terrain (Hoogenboom, 2000). Gridded time series also are sensitive to inhomogeneities in the original station data (Guentchev et al., 2010). When gridded fields of daily temperature and precipitation are used, an issue that is of particular concern for this study is that the gridded fields overestimate the number of days with precipitation and underestimate daily minimum temperature (Pollyea, 2013; Quiring and Legates, 2008; West et al., 2007).

Recognizing these constraints of gridded fields, we elected to directly employ observed time series of daily temperature and precipitation. Simply assigning a county to a nearby climate station is complicated by differences between climate stations in the length of record, the frequency of missing observations, and the inhomogeneities introduced into the record by changes in instrumentation, time of observation, and station relocation. Thus, we sought to identify a modest number of high quality observing stations that capture the spatial variations in climate across the UGLR. To accomplish this, an objectively-defined climate regionalization developed using k-means cluster analysis (see Chapter 2) was utilized to assist in the selection of representative climate stations (Figure 4-2). The climate regionalization grouped monthly means of precipitation and maximum and minimum temperature for the period of 1971-2000 from 180 climate stations within the UGLR and its neighboring states that are included in the United States Historical Climate Network ver 2.0 (Menne et al., 2012a; Menne et al., 2009). The results of the climate regionalization suggest that the climate stations within the study region can be categorized into seven climate types (Figure 4-2, top) that are distinguished by differences in the deviation of the annual cycle of temperature and precipitation from the UGLR average.

Each county was then assigned to a climate region, and based on the county-climate memberships, we selected two or more representative climate stations for each climate group,

including spatially-fragmented county-climate clusters. A primary consideration in station selection was the completeness of the daily time series. Even though the USHCN stations are considered to be the highest quality climate stations in the United States, data completeness and record length vary dramatically among the USHCN stations. Another consideration was to select stations that captured the north-south and east-west extents within a climate region. Thus, more stations were selected for larger regions compared to smaller regions.

A total of 36 stations out of 79 USHCN climate stations within the UGLR were selected to capture the spatial climate variability of the region (Figure 4-2-bottom). Daily data completeness over the growing season (April to October) of the historical period (1971-2000) is more than 85% for the majority of the stations. The distribution of daily data completeness (in brackets) at five percentage intervals by station is: 34 stations (>85%), 31 stations (>90%), 27 stations (>95%), and 12 stations (>99%). To assign a representative climate station to each county, we identified counties and representative climate stations that fell within the same climate group memberships, and then assigned a county to the closest representative climate station within the climate region based on Euclidian distance between the climate station location and the county centroid (Figure 4-2, bottom).

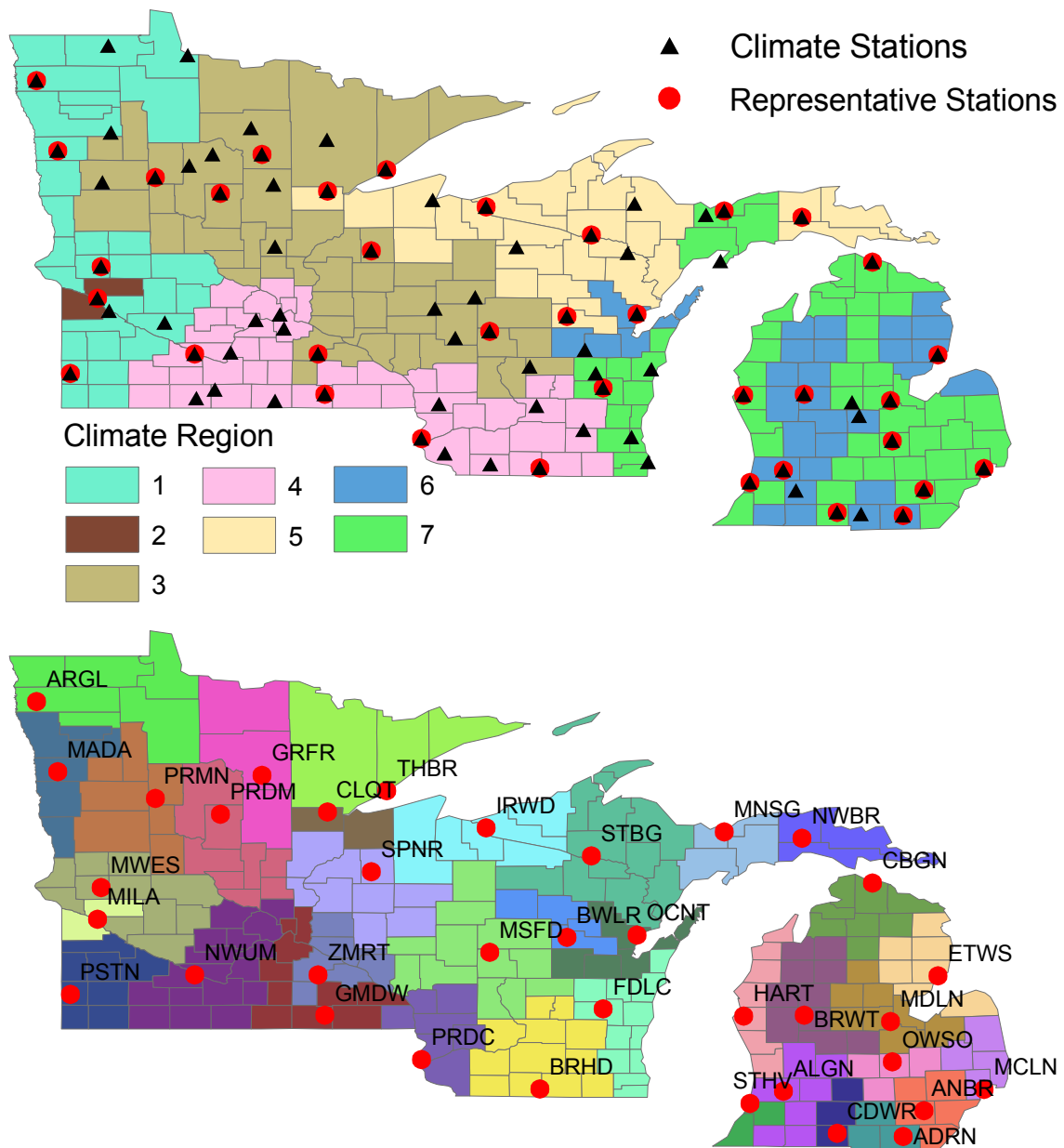


Figure 4-2. Selection of representative climate stations for the regional climate change impact assessment on corn and soybean production in the UGLR based on an objective climate regionalization (top) and their assignment to counties (bottom). Each station is referenced by a four character identifier and the colors in the lower panel show the counties assigned to the same representative climate station.

Missing values of precipitation, maximum and minimum temperature for the USHCN stations were filled in using daily climate values obtained from the Iowa Environmental Mesonet (IEM) Network (IEM, 2013) for either the same station or a nearby station. IEM recently made available complete daily time series for many climate stations in the Midwestern states including Michigan, Wisconsin and Minnesota. IEM filled in missing data using an inverse distance weighted interpolator applied to climate data from NCEP Stage IV precipitation, airport weather data (ASOS/AWOS), and available NWS COOP reports (Drayl, 2012, personal communication).

Daily solar radiation is a required input for the crop simulations, but this variable is infrequently measured. For this analysis, daily solar radiation was estimated using a mechanistic radiation model proposed by Hunt et al. (1998) which requires daily maximum and minimum temperature and precipitation as inputs. The choice of this approach was based on a systematic evaluation of several alternative estimation procedures for daily solar radiation (see Chapter 3). The mechanistic radiation model was calibrated using observed data from 1990-2008 for a climate station, at Hancock, Wisconsin, and applied to the 36 representative climate stations.

(b) Soil data

As soil characteristics vary spatially, for each county we selected the “dominant” soil based on areal coverage. Soil data were obtained from the State Soil Geographic (STATSGO) database published by the Natural Resources Conservation Service of the United States Department of Agriculture (NRCS-USDA) (Soil Survey Staff, 2010). STATSGO has been regularly employed for crop model simulations in the United States (e.g., Carbone et al., 2003; Safir et al., 2008). Soil Data Viewer (NRCS, 2012), which is supplied to read STATSGO database, was used to extract soil information stored in STATSGO layer by layer, with the midpoint of each layer roughly corresponding to the depths in the generic soil requirements in

DSSAT. The eight soil depths employed in the DSSAT based on the extracted layers are: 5 cm (0-10 cm), 15 (10-20), 25 (20-30), 40 (30-50), 60 (50-70), 80 (70-90), 105 (90-120), and 135 (120-150).

Soil parameters specifically extracted from STATSGO for each soil layer are soil classification (e.g., loam, silty loam, sandy loam), slope, drainage, runoff potential, soil texture (percent silt and clay), organic content, pH and cation exchange capacity. Soil color and fertility factor were retrieved based on soil texture and taxonomy from the National Cooperative Soil Survey (NCSS, 2011) and the generic soil database available in DSSAT package, respectively. SBuild, a DSSAT supporting package (Uryasev et al., 2003), was employed to prepare soil inputs and calculate specific soil information, such as drainage upper and lower limit, required for the DSSAT simulations.

(c) Cropping Management

DSSAT requires information on agronomic practices, e.g., planting densities, row spacing, planting date, and crop cultivar. The agronomic practices were generally adopted from Andresen et al. (2001), who applied DSSAT for thirteen locations in the UGLR. The planting densities were determined at 75 cm spacing with the plant population of 6 plants/m² and 20 plants/m² for corn and soybean, respectively. These agronomic practices reflected farming management and technology in the late 1990s (Andresen et al., 2001), which overlaps with the historical time slice used in this study.

Selecting a crop cultivar for the DSSAT simulations of corn yield is challenging as multiple cultivars are grown within each county. Furthermore, the relative proportion of different cultivars varies spatially across the UGLR (Coulter et al., 2010b) and also annually as

farmers consider weather conditions and economic profits for planting a particular corn hybrid (Hao et al., 2010). Given the focus of this analysis we selected, from several options, the cultivar for the DSSAT simulations that best reproduced the spatial distribution of county-level corn yield. As potential options we considered the modified short season cultivar employed by Andresen et al. (2001), and the three corn cultivars (i.e., short, medium and long season) used by Southworth et al. (2000). Based on visual comparisons and statistical indexes (i.e., spatial correlation and the Willmott Index (Willmott, 1981)), we found that for the 1971-2000 historical period the median values of simulated corn yield for the medium season cultivar better captured the spatial variability of observed county-level corn yield defined as crop production divided by planted areas. This was true even when compared to simulating the yield for multiple cultivars and selecting the yield value that best matched the observed county yield (results not shown). The cultivar characteristics for the medium season are presented in Table 4-1.

Table 4-1. Cultivar characteristic of the medium season corn cultivar used in the DSSAT simulations.

P1	Degree days (base 8 °C) from emergence to end juvenile phase	200
P2	photoperiod sensitivity (0-1)	0.3
P5	degree days (base 8 °C) from silking to physiological maturity	800
G2	potential kernel number	700
G3	potential kernel growth rate (mg/d)	6.3
PHINT	degree days required for a leaf tip to emerge (phyllochron interval) (°C d)	38.9

Source: Southworth et al. (2000)

In contrast to the simulations for corn, four maturity groups were preselected for the soybean DSSAT simulations. The maturity groups were roughly assigned to each county based on the distribution of soybean maturity groups in the United States published by the National Soybean Research Laboratory (NSRL, 2013). These different maturity groups reflect the

sensitivity of soybean to photoperiods (Carbone, 1995). The cultivar characteristics for the four maturity groups were available from the soybean cultivar file supplied by DSSAT version 4.5.

Planting dates were determined using the DSSAT automatic planting option. Planting occurs when percentage soil water and soil temperature in the top 10 cm are at least 20% and 10 °C, respectively, during a specified planting window. For the historical simulations, five and six different planting windows were employed for the corn and soybean simulation, respectively. The planting windows were determined by moving the starting date of a planting window later by roughly 15 days during the period April 1st to June 10th for corn and from April 1st to June 30th for soybean (e.g., planting windows of April 1st-June 10th, April 16th-June 10th, and so on). The end dates of the planting windows for both crops were obtained from the typical planting and harvesting dates for corn and soybean in Michigan, Minnesota and Wisconsin as reported by (NASS-USDA, 1997). For the future simulations, the starting date of the planting windows was set earlier to March 1st considering the potential warming condition for the region. For both the historical and future periods, the highest annual simulated yield for each county from the different planting windows was retained for the analysis. Harvesting dates for both the historical and future simulations were determined at maturity stage (i.e., R6 for corn and R8 for soybean) following Andresen et al. (2001).

The different planting windows were used to take into account the short ‘optimum’ time period to grow corn in the UGLR (Thelen, 2007) and to allow for replanting decisions following adverse climate conditions (Benson, 1990; Laurer, 1997). Additionally, the multiple planting windows in part compensate for the use of a single soil type to represent the soil conditions for a county, as suggested by Moen et al. (1994).

No change in cropping practices over time was assumed. The crop simulations assumed rainfed conditions were initiated at the first of January each season with soil water initialized at drained upper limit. The nitrogen option within the DSSAT environment was turned off for corn simulations, but turned on for the soybean simulations to capture nitrogen fixation as soybean is a leguminous crop that is able to fixate nitrogen (Coulter et al., 2010a).

4.2.2. *Climate Change Scenarios*

Future climate change scenarios were developed based on the outputs of the NARCCAP simulations, available at a 50 km² resolution. Eight combinations of RCM/gcm simulations were available for a future (2041-2070) and control (1971-2000) period (Table 4-2). The model combinations are CRCM-ccsm, CRCM-cgcm3, HRM3-hadcm3, HRM3-gfdl, RCM3-cgcm3, RCM3-gfdl, WRFG-ccsm, and WRFG-cgcm3. The model ID presented in Table 4-2 will be used as a reference for the model identifier in the figures included in this Chapter.

Table 4-2. The NARCCAP model combinations employed for the study

ID	Model	ID	Model	ID	Model	ID	Model
A	CRCM-ccsm	B	CRCM-cgcm3	C	HRM3-gfdl	D	HRM3-hadcm3
E	RCM3-cgcm3	F	RCM3-gfdl	G	WRFG-ccsm	H	WRFG-cgcm3

Daily maximum and minimum temperature and precipitation from the land grid points nearest each of the 36 representative climate stations were extracted to calculate monthly means for the future (2041-2070) and control (1971-2000) periods. Differences (ΔT) in monthly means of temperature and percentage changes ($\% \Delta P$) in monthly precipitation were calculated between the two periods for each RCM/gcm simulation and applied to the observed historical daily time series of maximum and minimum temperature and precipitation for the 36 representative climate stations. This simple approach of developing future climate change scenarios has been

previously applied for numerous climate change impact assessments (e.g., Mearns et al., 1997; Tubiello et al., 2002; Wang et al., 2011).

For reference, delta values for the growing season (March-October) are shown in Figure 4-3. The projected change in seasonal mean maximum and minimum temperature and precipitation for the region depends upon the combination of RCM/gcm (Figure 4-3). HRM3-gfdl projects larger increases in temperature and greater decreases in precipitation, particularly for the southern areas of the UGLR, than the other NARCCAP models. WRFG-cgcm3 and WRFG-ccsm project slightly warmer and relatively wetter conditions compared to the other RCM-gcm combinations. In general, the regional climate of the UGLR by mid century, as derived from the majority of the NARCCAP models, is projected to be warmer than currently, particularly in the southern UGLR, and wetter than currently, especially for the northern UGLR (Figure 4-3).

Atmospheric CO₂ concentration for the historical period (1971-2000) was set at 370 ppm (i.e., approximate CO₂ concentration at the end year of the historical period). The SRES A2 emissions scenario, the CO₂ scenario used in the NARCCAP simulations, projects CO₂ increases from about 490 ppm to 635 ppm during the mid-century (2041-2070) future period (IPCC-DDC, 2011). We selected the projected CO₂ values at the start and end of the mid century period (i.e., 490 and 635 ppm) as input to the DSSAT simulations to assess the spatial variability of carbon fertilization on corn and soybean production.

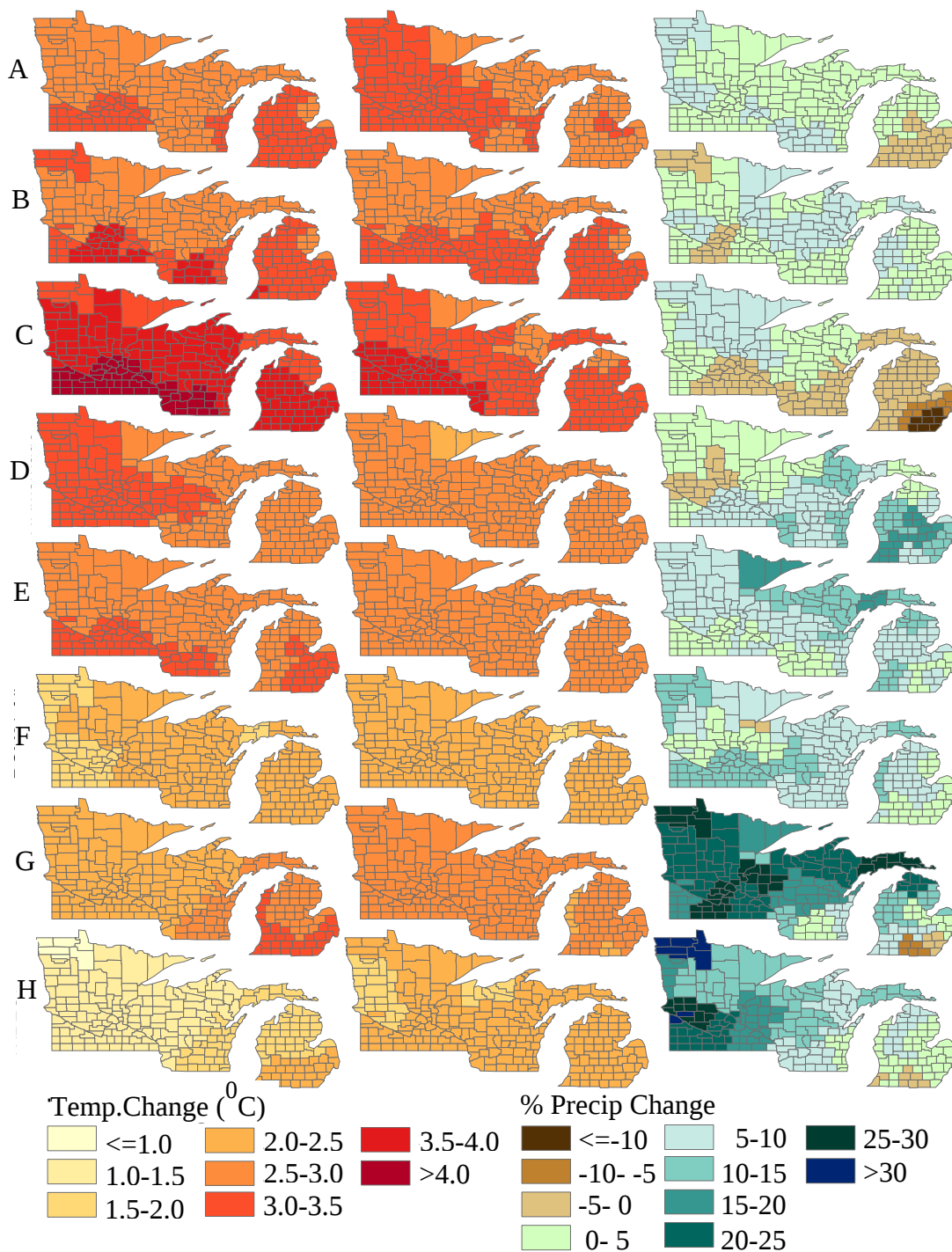


Figure 4-3. Projected changes in $^{\circ}\text{C}$ for simulated average maximum temperature (left) and minimum temperature (middle), and percent change in precipitation (right) for the growing season (March-October) between the future (2041-2070) and the control (1971-2000) periods for the eight NARCCAP models. Letters of A-H are the NARCCAP model identifiers (Table 4-2).

4.2.3. Evaluation of CERES-Maize and CROPGRO-Soybean

Before the NARCCAP simulations were used as input to the crop models, simulations using observed climate time series were first compared to historical county yields to evaluate how well the simulated yields capture the observed spatial variability across the UGLR. This evaluation is essential background for interpreting the spatial variations in projected future yield.

Observed county-level crop yields were calculated by dividing crop production by planted areas as reported by the National Agriculture Statistics Service, United States Department of Agriculture (NASS-USDA, 2011). Because of advancement in farming practices and technology, such as new cultivars and pest management which significantly contributes to increased crop yields (Egli, 2008), temporal trends are expected in observed yields, whereas temporal trends are not expected for simulated yields as farming practices and technology are held constant throughout the simulation period. Thus when comparing observed and simulated yield, any temporal trends in the observed yield should first be removed (e.g., Andresen et al., 2001; Jagtap and Jones, 2002) . We detrended observed yields separately for each county with at least five years of available data to the base year of 2000 using the approach proposed by Tannura et al. (2008) that assumes a linear temporal trend in crop yield.

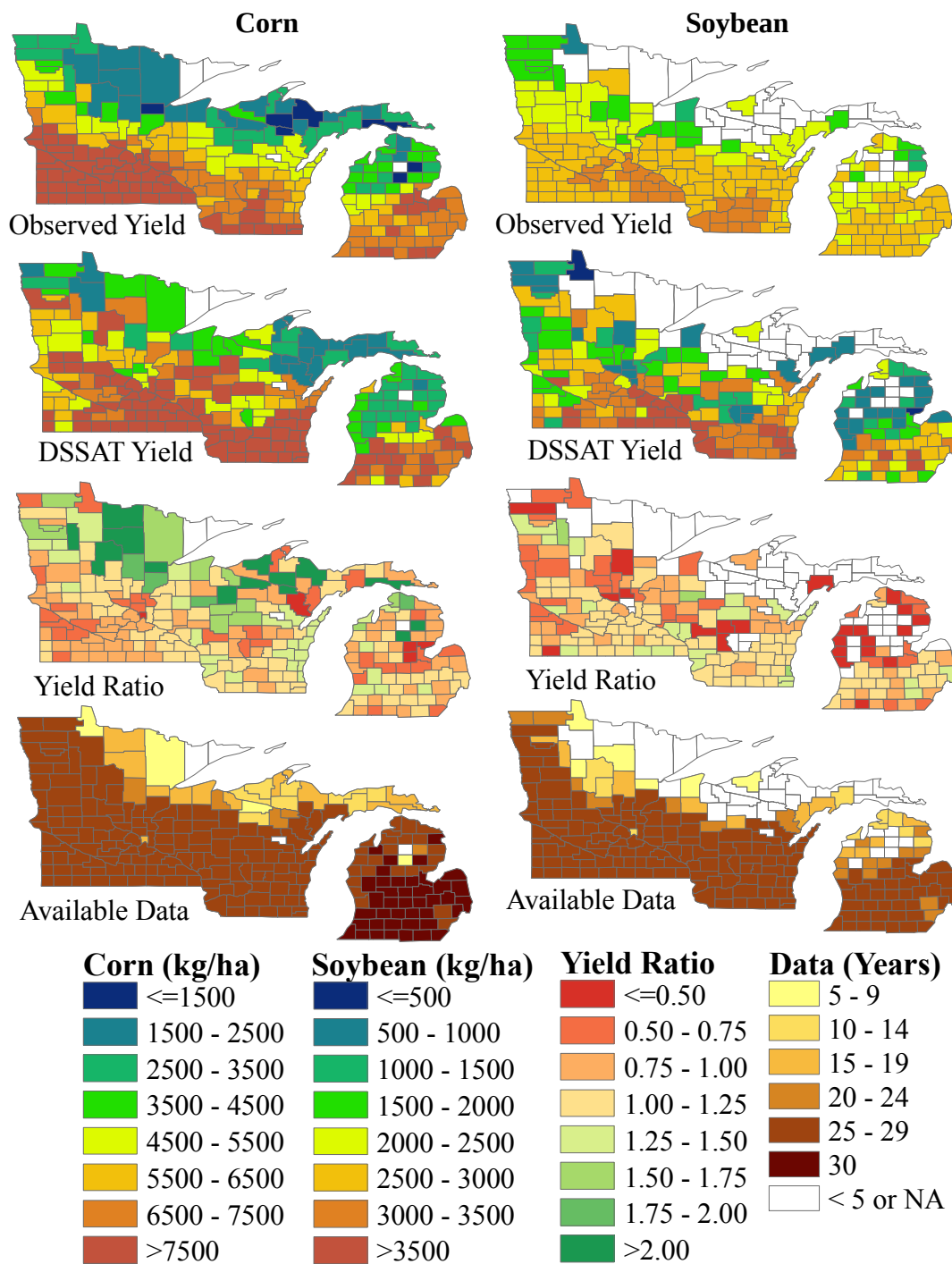


Figure 4-4. The median value of observed and DSSAT simulated yields for corn (left) and soybean (right). The yield ratio was calculated by dividing simulated yield by observed yield for each county. Available data refers to the numbers of years with reported yield for each county.

Note: The scale for median yield is different for corn and soybean.

Figure 4-4 shows that the simulated corn and soybean yields are generally able to capture the spatial distribution across the study area of observed yield for both crop types. Observed corn and soybean yields gradually decrease from south to north across the UGLR. Higher yields are specifically found in southern Minnesota and Wisconsin for both crops. This pattern is generally captured by the DSSAT simulated yields, although some discrepancies appear. For corn, underestimations are seen in southwestern Minnesota and northern Michigan, whereas yield is overestimated in the northern portion of the study area, especially in areas where little crop production currently occurs. Simulated soybean yields exceed observed yields particularly in the southern part of the region, while underestimations appear in most northern counties. Overall, the median value of simulated yield, averaged across all counties, is higher for corn by about 136 kg/ha (~2.3%) and lower for soybean by about 244 kg/ha (~9.5%), than the reported county statistics. The Willmott Index of agreement and the spatial correlation of the median yields are 0.83 and 0.70 for corn, while the two indices are both 0.65 for soybean. The Willmott Index ranges from 0 to 1 with 1 indicating good agreement (Willmott, 1981). The modest high values of the Willmott Index and the small deviations in region-wide median yields indicate the simulated county-level yields of corn and soybean capture the observed yield patterns well.

4.2.4. Regional Impact Assessment of Projected Climate Change

The potential consequences of future climate change were assessed by estimating the median changes in planting dates, time to maturity (defined as the days from planting to full maturity, i.e., to R6 for corn and R8 for soybean), seasonal evapotranspiration, and grain yield for all NARCCAP climate model combinations at 370, 490 and 635 ppm. The first CO₂ concentration was defined as a reference, while the other two are used to evaluate sensitivity of

the simulated outcomes to elevated atmospheric CO₂ concentrations. We also compared the coefficient of variation (COV) of crop yields between the future and the historical period to evaluate potential change in future yield variability (Tubiello et al., 2002). COV was calculated for each county by dividing the standard deviation of the crop yield for a time slice by the mean value. High values of COV indicate high interannual yield variability, whereas small values imply more stable annual production (Tubiello et al., 2002).

Specifically for corn, we also evaluated the sensitivity of future climate change impacts to different corn cultivars, recognizing that a range of cultivars are grown in the UGLR. In addition to the medium season cultivar, we compared yield changes between the future and historical periods for short season and long season cultivars. These comparisons were limited to simulations using only the highest CO₂ concentration (635 ppm) for the future period.

Potential shifts in major growing regions were estimated by modifying, for each county, the median value of the reported historical county-level yield by the suite of projected changes in median corn and soybean yield from DSSAT simulations obtained using the eight NARCCAP climate simulations and the three levels of atmospheric CO₂ concentration.

4.3. Results

4.3.1. *Historical Simulation*

The DSSAT simulated median values of planting date, time to maturity, cumulative seasonal evapotranspiration and grain yield for the historical period provide a reference for evaluating potential future changes. The spatial variations in the simulated values are briefly summarized below.

The simulated median planting dates (PDAT) for the historical (1971-2000) period fall between Julian day (JD) 120-127 (~April 30 to May 7). There is a slight latitudinal variation in planting date (Figure 4-5), with median planting dates between JD 113 (~Apr 23) to JD 127 (~May 7) for the majority of the counties in northern Michigan and in central and northern Wisconsin and Minnesota. Earlier simulated planting dates (before JD 106 (~April 16)) are seen for a small number of counties in northwestern Minnesota, whereas for the majority of the southern counties simulated planting dates for corn fall between JD 120 (~April 30) and JD 141 (~May 21). Simulated median planting dates are considerably later for a small number of counties in the central and southern Lower Peninsula of Michigan (Figure 4-5). For soybean, simulated median planting dates lie between JD 120 and JD 127 for the majority of counties in Minnesota and between JD 120 and JD 141 for the Upper Peninsula of Michigan, and northern Wisconsin. On the other hand, a wider range (JD 120 – JD 156) in simulated median soybean planting dates is seen for counties in the Lower Peninsula of Michigan with simulated planting dates as late as early to mid June (>JD 156) for a small number of counties in the central Lower Peninsula.

The simulated median time to maturity (TMAT) for corn displays a marked south-to-north gradient (Figure 4-5), with a generally shorter TMAT of almost 20 days for counties in the southern compared to northern portion of the UGLR. Simulated median TMAT for soybean is generally between 120 and 140 days for most counties in the UGLR. A few counties in northeastern Minnesota and the eastern Upper Peninsula Michigan display simulated median TMAT values of 140-160 days.

The regional distribution of the simulated median values of cumulative seasonal evapotranspiration (ET) exhibits higher ET for counties in the south than for counties in the north

with only a slight difference in ET between corn and soybeans (Figure 4-5). Simulated ET for corn is about 550 to 700 mm for the southern UGLR counties and about 400 to 600 mm for the majority of the northern counties. Simulated ET for soybean is in the range of 500 to 700 mm for the southern counties and about 400 to 550 mm for the northern counties. For some counties in the northern Lower Peninsula of Michigan, simulated ET is lower than 400 mm.

A south-north gradient is also seen in the distribution of simulated median yield for corn and soybeans. Simulated median yield in southern Michigan, Minnesota and Wisconsin exceeds 7500 kg/ha, whereas the median yields fall between 1500 – 4500 kg/ha for most of the northern counties. For soybean, the simulated median yields are about 2500 to 3500 kg/ha for the southern counties with several counties having median yields over 3500 kg/ha, while the northern counties display yields of 500 – 2500 kg/ha with a few counties in the northern Minnesota and the Upper Peninsula of Michigan having higher (2500-3000 kg/ha) and lower (≤ 500 kg/ha) simulated yields, respectively.

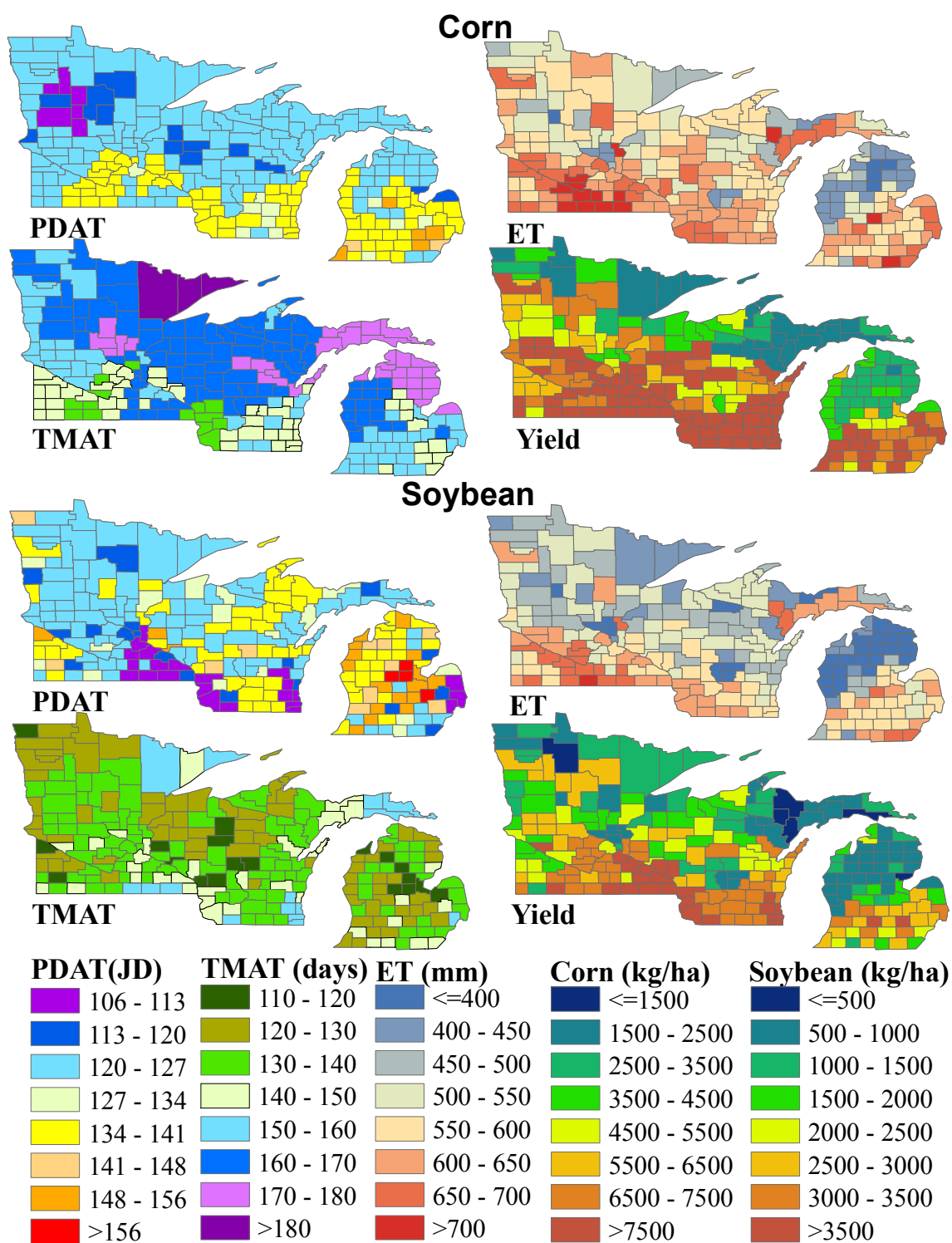


Figure 4-5. Median values of simulated planting date (PDAT), time to maturity (TMAT), cumulative seasonal evapotranspiration (ET), and grain yield (Yield) for corn (top four panels) and soybean (bottom four panels) in the UGLR for the historical period (1971-2000)

4.3.2. Future Climate Impacts

Planting Dates and Time to Maturity

Substantial future changes in the spatial distribution of planting date (PDAT) for corn production are suggested for the future time slice (Figure 4-6). In spite of differences between climate scenarios, earlier planting dates are projected for most counties in the southern portion of the study area. Earlier planting dates are projected for a larger number of southern counties for the HRM3-gfdl, CRCM-cgcm3 and RCM3-cgcm3 simulations compared to the other NARCCAP simulations; whereas, the projected future climate from WRFG-cgcm3 suggests later planting dates for most southern counties except for the southeast Michigan. Later planting dates (<20 days) are projected for most counties in the central and the northern UGLR, particularly when corn production is simulated using climate scenarios from CRCM-ccsm, CRCM-cgcm3, HRM3-gfdl, HRM3-hadcm3, and RCM3-gfdl. For the extreme northern UGLR, slightly earlier planting dates (0-10 days) are projected by most climate models (particularly WRFG-ccsm and WRFG-cgcm3), with the exception of HRM3-hadcm3 for which later planting dates are projected (Figure 4-6). When the projected changes in PDAT are averaged across all climate scenarios (Figure 4-6, average), earlier and later planting dates are seen for the southern and northern counties, respectively, with the exception of three counties in northern Minnesota where earlier planting dates are projected.

Projected changes in time to maturity (TMAT) for simulated corn production suggest, a shorter TMAT for most UGLR counties, with the exception of counties in the Upper Peninsula of Michigan and a few counties in northwest Minnesota. For these counties, a slightly longer TMAT (<10 days) is projected when climate simulations from WRFG-ccsm and WRFG-cgcm3 served as input to CERES-Maize.

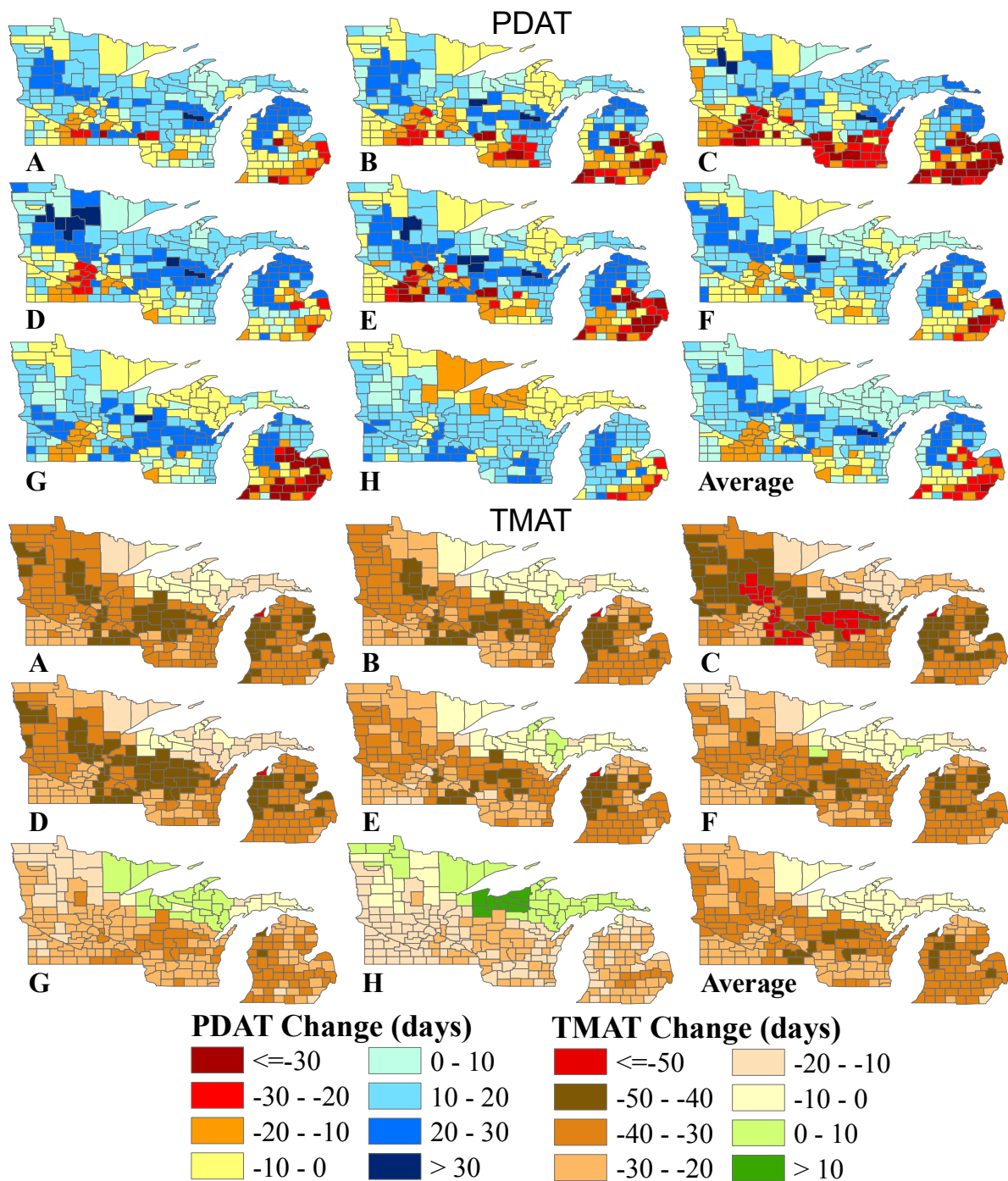


Figure 4-6. Projected change in the median of planting date (PDAT, above) and time to maturity (TMAT, below) between the historical (1971-2000) and the future (2041-2070) period for corn production in the UGLR at the reference level of CO₂ (370 ppm) concentration. Letters of A-H are the NARCCAP model identifiers (Table 4-2).

For soybean production, planting dates are projected to occur earlier for most counties located in Minnesota, Wisconsin and the Upper Peninsula of Michigan based on the climate scenarios obtained from CRCM-cgcm3, RCM3-cgcm3, RCM3-gfdl, WRFG-ccsm, and WRFG-cgcm3. On the other hand, later planting dates (10-30 days) for soybean production are estimated for counties in Wisconsin and the Lower Peninsula Michigan by CRCM-ccsm, HRM3-gfdl, HRM3-hadcm3, RCM3-gfdl, and WRFG-ccsm. When the average change in planting dates across all climate scenarios is considered (Figure 4-7, average), a primarily west-east gradient is observed across the UGLR, with earlier planting dates projected in the western UGLR and later planting dates projected in the central and eastern UGLR.

The changing pattern of time to maturity (TMAT) for soybean production, when averaged over all climate scenarios, suggests a shorter TMAT (~20 days) for most counties in the UGLR, although a slightly longer (<10 days) TMAT is projected for several counties in south-central Minnesota (Figure 4-7, average). Four RCM-gcm combinations (i.e., CRCM-cgcm3, RCM3-cgcm3, WRFG-ccsm, and WRFG-cgcm3) project more counties with longer TMAT compared to the other NARCCAP combinations, particularly in the western and southern UGLR (Figure 4-7).

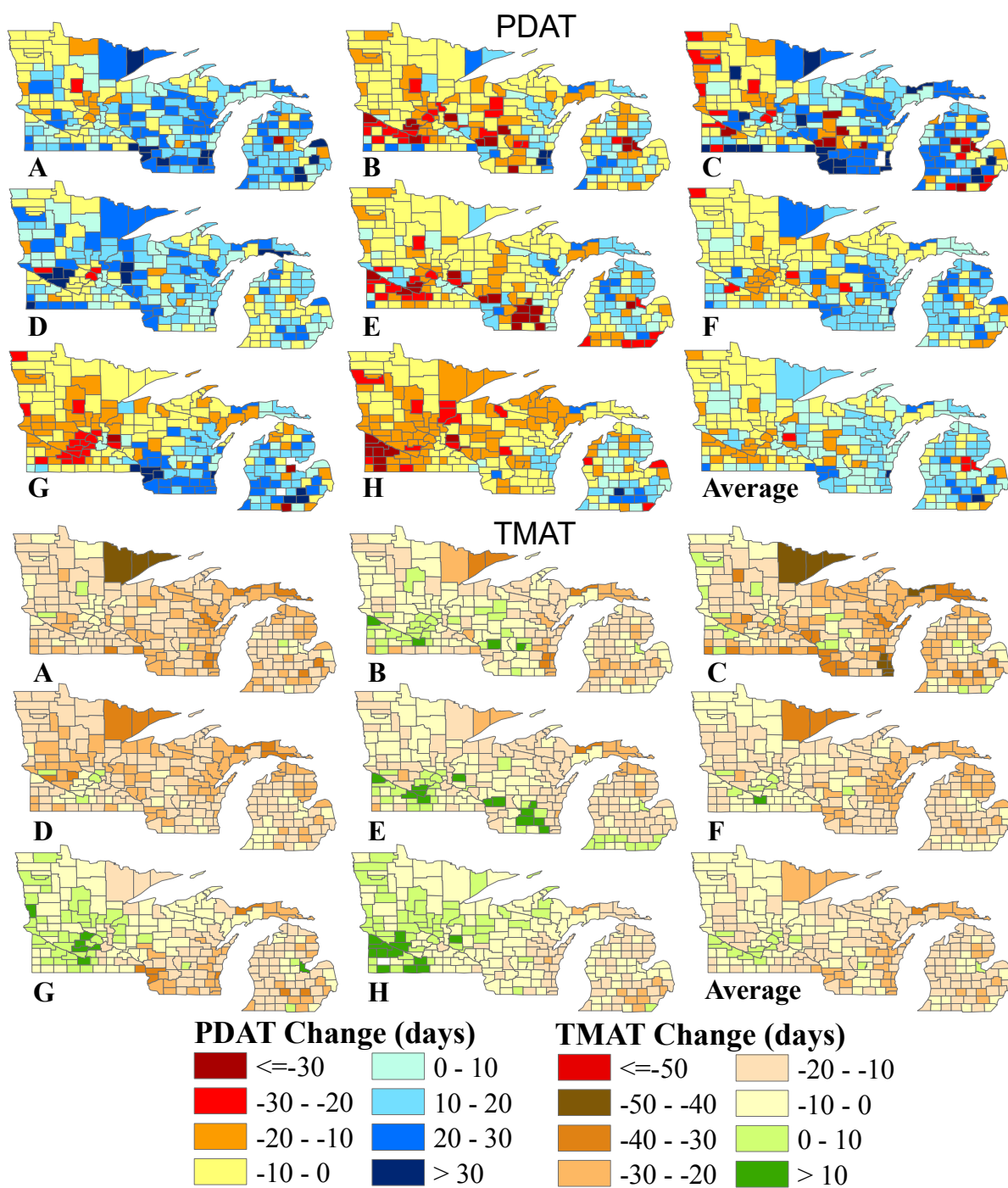


Figure 4-7. As Figure 4-6, but for soybean production

Evapotranspiration and Crop Yield

The spatial pattern of projected change between the future (2041-2070) and the historical (1971-2000) period in the median value of simulated cumulative seasonal evapotranspiration (ET) for corn production, when averaged across all climate scenarios, clearly displays a north-south gradient with decreased ET projected for the southern UGLR and increased ET for the northern UGLR (Figure 4-8, average). Moreover, this general pattern is seen for the majority of NARCCAP models, although some differences exist. Substantially larger decreases in ET (<-15%) are projected for counties in the Lower Peninsula of Michigan by CRCM-ccsm, CRCM-cgcm3, HRM3-gfdl, and WRFG-ccsm. On the other hand, the area projected to experience higher ET in the future is larger for the RCM3-cgcm3, RCM3-gfdl, WRFG-ccsm and WRFG-cgcm3 climate scenarios.

Similar to the spatial pattern of ET change, corn yield is projected to decrease for most southern counties and increase in the northern counties (Figure 4-8, below). A substantial portion of the southern and central UGLR is projected to have decreased yield for the HRM3-gfdl, CRCM-ccsm, CRCM-cgcm3, and HRM3-hadcm3 scenarios, with projected decreases as large as -25% to -50%. Increased yield in the northern UGLR is seen for all climate scenarios, although the area with projected yield increases is larger for WRFG-ccsm and WRFG-cgcm3 compared to the other climate scenarios.

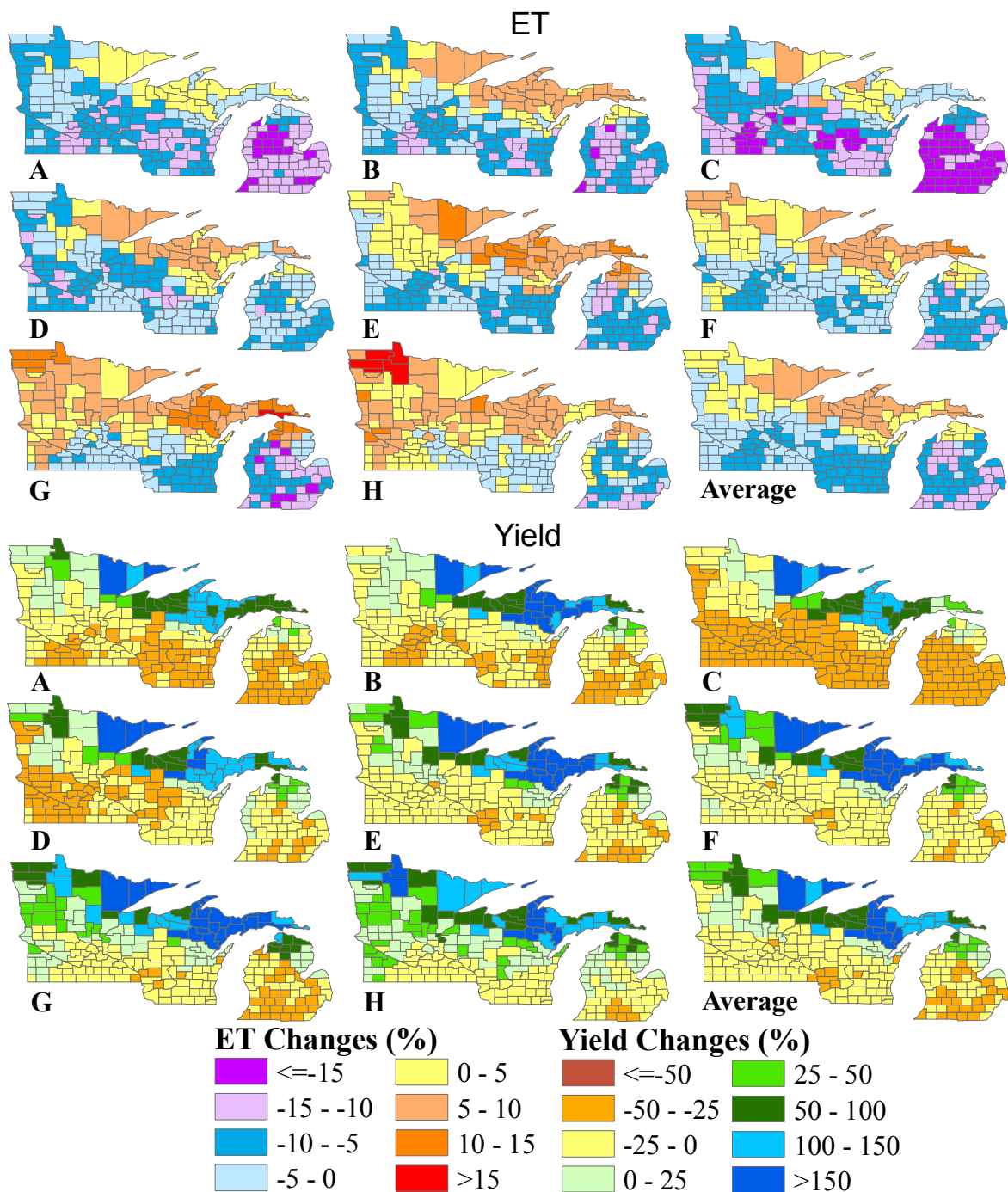


Figure 4-8. Change in the median of cumulative seasonal evapotranspiration (ET, above) and crop yields (Yield, below) between the historical (1971-2000) and the future (2041-2070) period for corn production in the UGLR at the reference level of CO₂ (370 ppm) concentration. Letters of A-H are the NARCCAP model identifiers (Table 4-2).

For soybean production, small (-5% to 5%) changes in ET are projected for almost all counties in the UGLR with no clear spatial pattern evident (Figure 4-9, average). A notably larger area, particularly in Wisconsin and Minnesota, is projected to have increased (although small) ET for RCM3-cgcm3, RCM3-gfdl, WRF3-ccsm, and WRF3-cgcm3 compared to the other climate scenarios (Figure 4-9), whereas future ET simulated using future climates obtained from CRCM-ccsm and HRM3-gfdl exhibits a slight decrease (~-10%) for the majority of counties in the UGLR.

Future climate change is projected to benefit soybean yield for the majority of the northern counties of the UGLR, although a slight decrease in soybean yield is seen for the HRM3-gfdl climate scenario (Figure 4-9). The climate projections from HRM3-gfdl also result in a notable decrease in yield (ranging from -25% to more than -50%) for most counties located in the southern and central part of the UGLR. Moreover, a slight (~-25%) decrease in yield is projected by RCM3-cgcm3, RCM3-gfdl and WRF3-cgcm3 for the central and southern counties, whereas CRCM-ccsm, CRCM-cgcm3, HRM3-hadcm3, RCM3-cgcm3 and WRF3-ccsm project a moderate decrease (~-50%) for the southern counties, particularly those in Minnesota and Michigan (Figure 4-9). Overall, the projected change in soybean yield averaged across all climate projections (Figure 4-9, average) shows a distinct south- north gradient with decreased yield in the southern part of the UGLR and increased yield in the northern part.

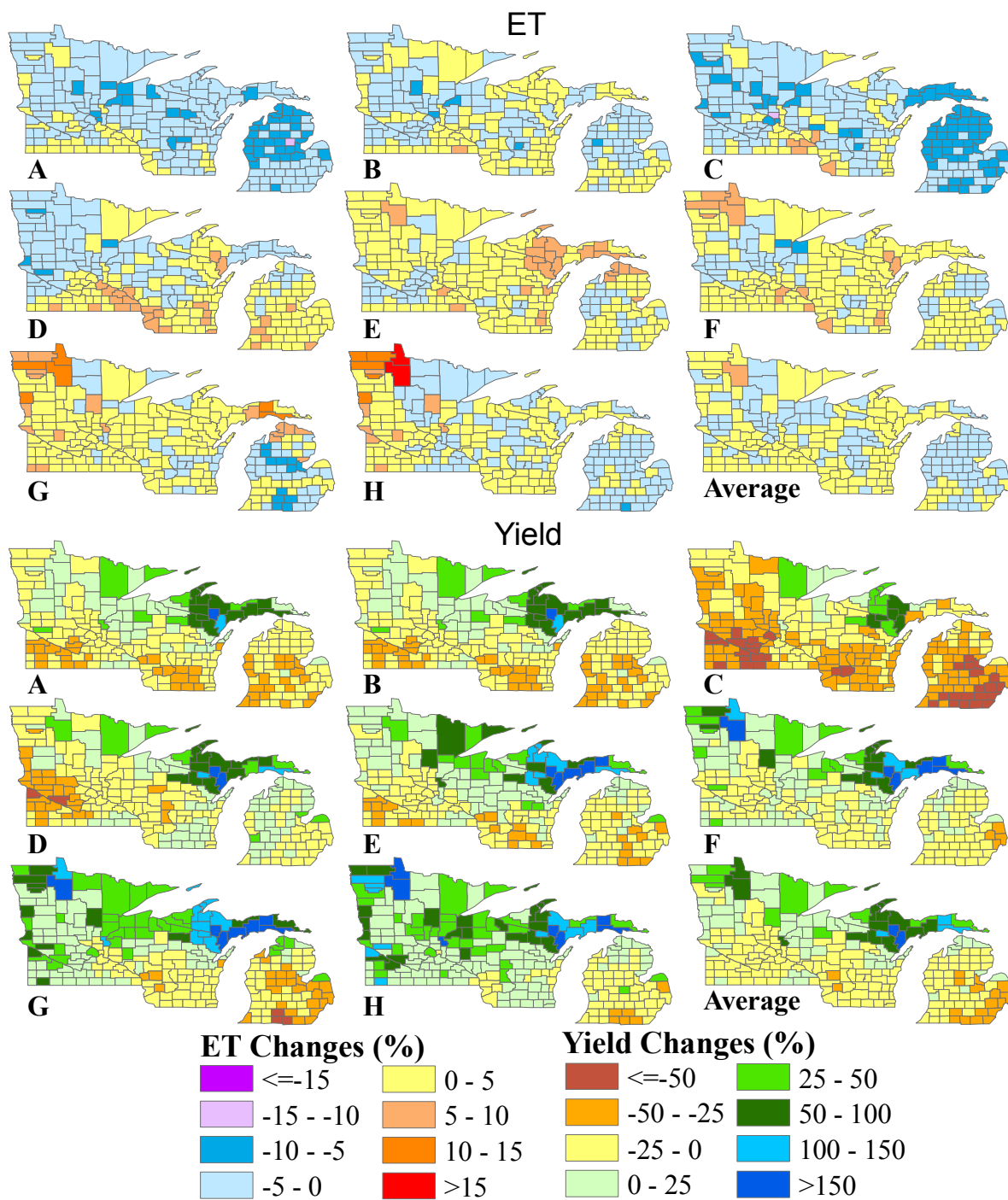


Figure 4-9. As Figure 4-8, but for soybean production

4.3.3. Carbon Fertilization Effects

The consequences of different levels of atmospheric CO₂ concentration on crop production are assessed by evaluating the average changes in simulated PDAT, TMAT, ET and Yield between the future (2041-2070) and the historical (1971-2000) period between elevated CO₂ concentrations of 490 ppm and 635 ppm and in comparison to the reference level (370 ppm) CO₂ level. The analysis reveals that PDAT and TMAT are relatively insensitive to elevated CO₂ concentration compared to ET and Yield. This pattern is consistent for both corn (Figure 4-10) and soybean (Figure 4-11) production. Thus, we explore below only the sensitivity of the spatial distribution of ET and Yield to elevated CO₂ concentrations.

For corn production, the north-south gradient in projected changes in ET and Yield seen for the reference CO₂ concentration also are evident for the higher CO₂ concentrations. However, the projected decrease in ET for the southern and central counties is larger, and the projected increase in ET for the extreme northern counties is smaller, for the higher CO₂ concentrations, particularly for the simulations employing CO₂ levels of 635 ppm. These projections suggest less future moisture stress under higher CO₂ concentrations, potentially benefiting corn production (Figure 4-10).

For soybean production, the higher CO₂ concentrations appear to have little effect on the projected spatial distribution of ET across the study region. In contrast, the projected increase in soybean yield across much of the study area is larger for the elevated CO₂ concentrations and the

number of counties in the southern Wisconsin and Michigan with a projected decrease in yield is smaller for the higher CO₂ concentrations (Figure 4-11).

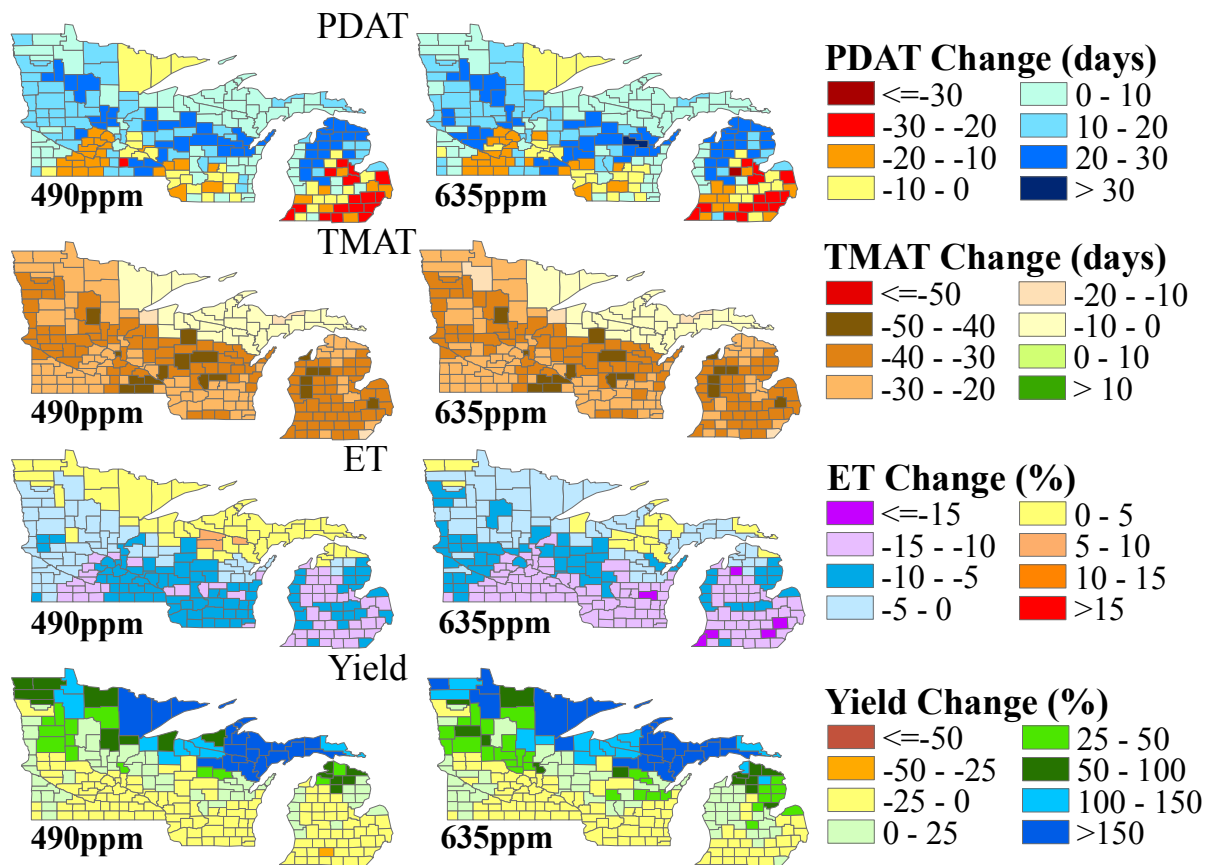


Figure 4-10. Change in median planting date (PDAT), time to maturity (TMAT), seasonal evapotranspiration (ET) and crop yields (Yield) between the historical (1971-2000) and the future (2041-2070) period averaged across all climate model combinations for corn production in the UGLR under elevated CO₂ concentration of 490 ppm (left) and 635 ppm (right)

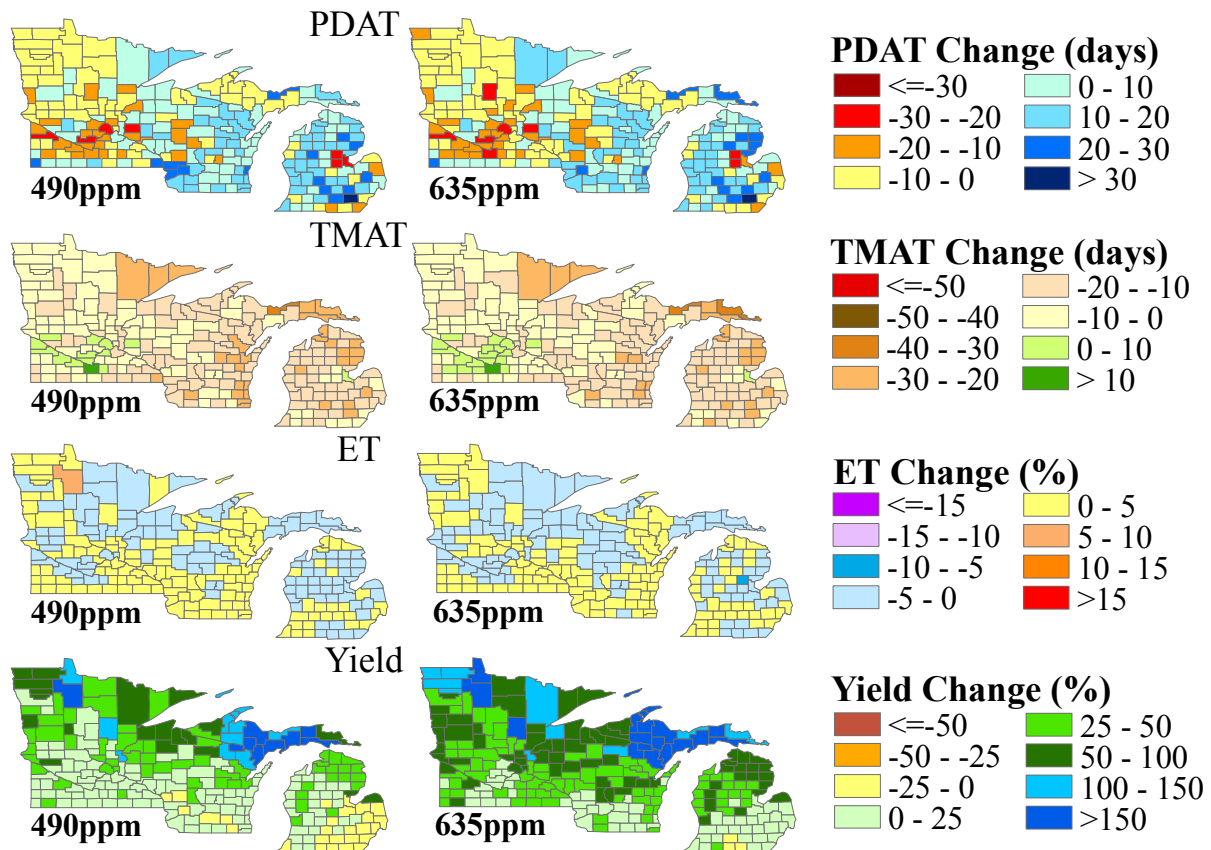


Figure 4-11. As Figure 4-10, but for soybean production

When the projected changes in ET and Yield for the future period (2041-2070) are expressed as a percent difference between the projected values under the elevated CO₂ level (490 or 635 ppm) and the projected values under the reference CO₂ level (370 ppm), e.g. $(ET_{490} - ET_{370} / ET_{370}) * 100$, the smaller projected ET with increasing CO₂ concentrations is more clearly seen for corn production Figure 4-12). The percent changes in projected ET under CO₂ concentration of 490 ppm and 635 ppm with respect to projected ET under the reference CO₂ level (370 ppm) ranges from -2% to -6% and -2% to -8% , respectively. The spatial pattern is not as uniform for soybean production, although, as noted above, the number of counties

projected to have increased future ET is smaller for the higher CO₂ concentration levels compared to the reference CO₂ level.

Corn yield in the UGLR is expected to increase moderately as the CO₂ concentration increases. At 635 ppm corn yield in the northern areas could increase up to 80% with respect to the reference CO₂ level (370 ppm). As for corn, soybean yield likely also will benefit from higher concentrations of atmospheric CO₂. All counties in the study region are projected to have substantially higher yields as atmospheric CO₂ concentration is increased to 635 ppm (Figure 4-12). Overall, soybean grown in the UGLR is expected to benefit more from increasing CO₂ concentration than corn production.

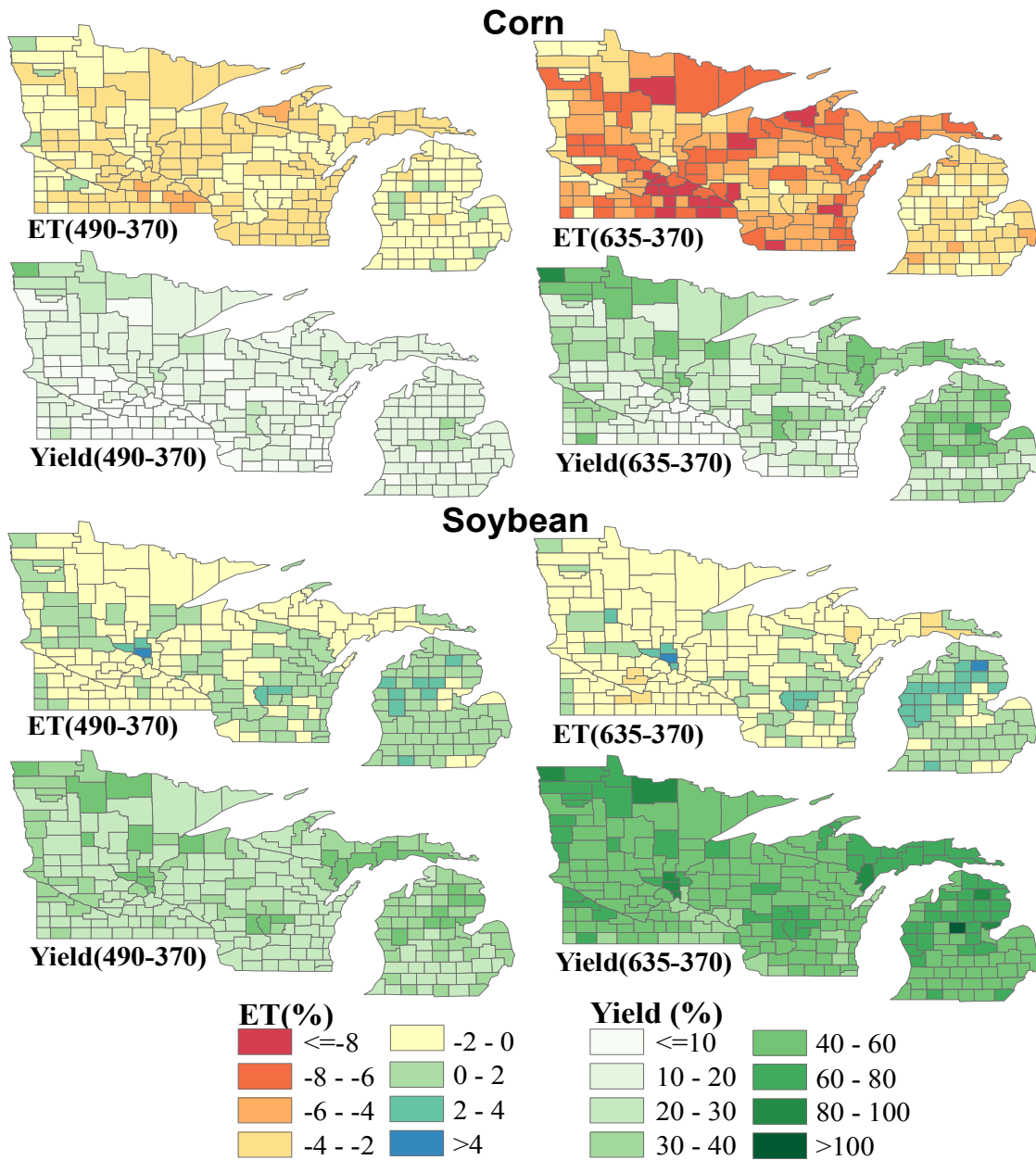


Figure 4-12. Percent change of projected seasonal evapotranspiration (ET) and crop yield (Yield) for the future period (2041-2070) under elevated CO₂ concentration of 490 ppm (490-370, left) and 635 ppm (635-370, right) for corn (above) and soybean (below) with respect to projected ET and Yield for the future period (2041-2070) under the reference level of CO₂ concentration (370 ppm). ET and Yield are obtained by averaging estimated future ET and Yield across all NARCCAP climate models.

4.3.4. *Cultivar Sensitivity*

Specifically for corn, we also evaluated the potential impacts of future climate change on grain yield for short and long season cultivars. This evaluation was performed for only the highest (635 ppm) CO₂ concentration. The projected changes in future yield for the short cultivar displays a south-north gradient similar to that seen earlier for the median season cultivar with small yield reductions in the southern and central portions of the UGLR and modest increases in the northern UGLR (Figure 4-13). This pattern is seen for the majority of the NARCCAP climate scenarios. In contrast, the sign of the projected changes in future yield is positive across almost the entire study area for the long season cultivar (Figure 4-13), with only a small numbers of counties in southern Wisconsin and Michigan projected to experience a small (~-25%) yield decrease. The projected increases in yield are substantial (50-100%) and are seen for all the NARCCAP climate scenarios, although the HRM3-gfdl scenario is slightly less favorable for some counties in south Minnesota, south-west Wisconsin and south-east Michigan (Figure 4-13, Long).

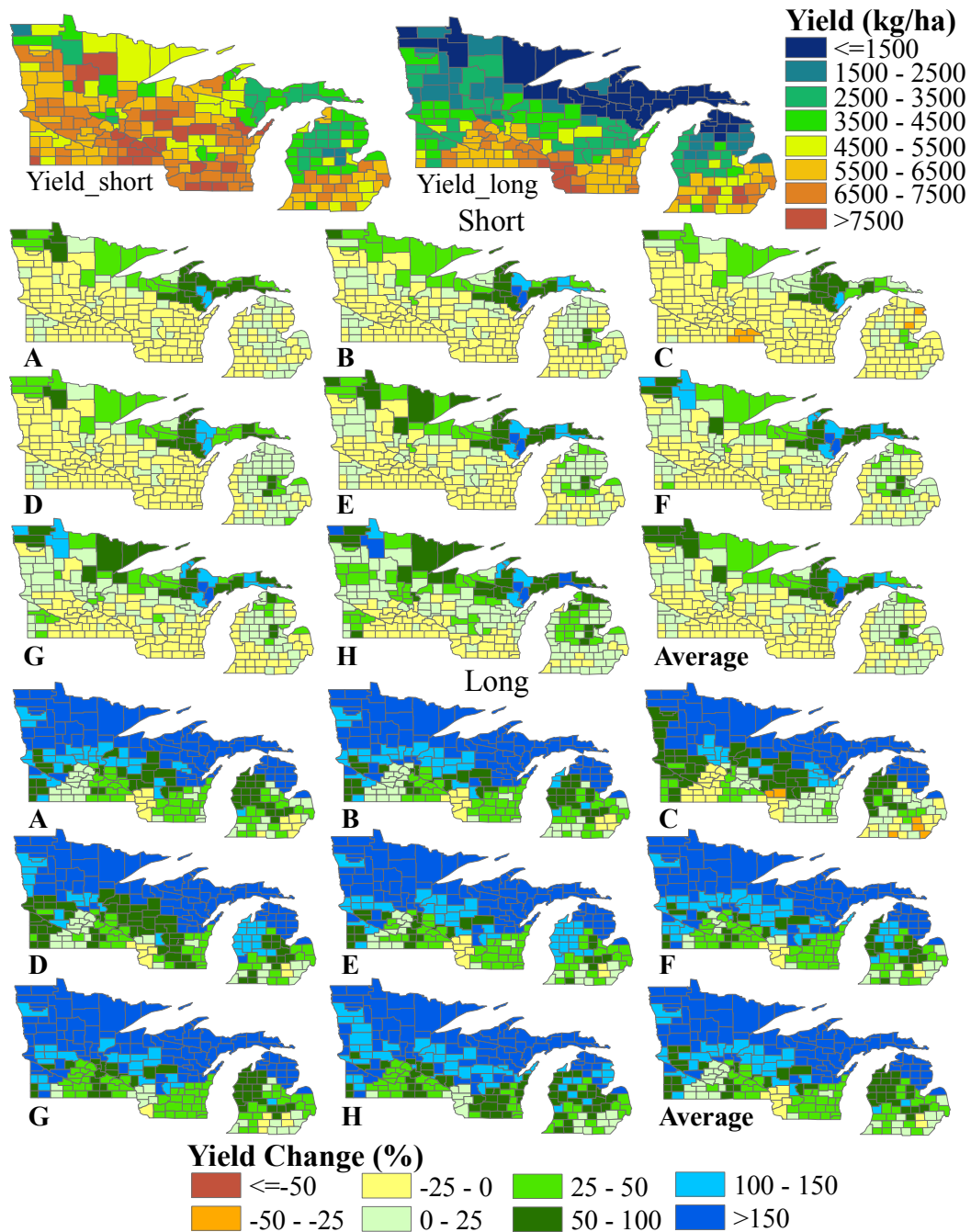


Figure 4-13. Change in the median value of corn yield between the future (2041-2070) and the historical period (1971-2000) for short season (Short) and long season cultivar (Long) under different climate change projections and elevated CO₂ of 635 ppm. The median values of simulated yield for the historical period for each cultivar are presented in the first row as a reference. Letters of A-H are the NARCCAP model identifiers (Table 4-2).

4.3.5. Coefficient of Variation

Calculation of the coefficient of variation (COV) for the historical period (1971-2000) indicates that annual corn yield variability is higher for the northern areas of the region than for the major corn production regions in the south where values of COV are not more than 0.4 and can be less than 0.1 (Figure 4-14). Future projections, holding CO₂ concentrations constant at 370 ppm and employing a medium season cultivar, suggest a slight increase in the annual variability of corn yield in the southern UGLR, particularly for southern Wisconsin and the Lower Peninsula of Michigan, as indicated by the ratio of future COV to historical COV which falls between 1 and 1.25. Comparison among the eight climate scenarios reveals that those derived from CRCM-ccsm, HRM3-hadcm3 and HRM3-gfdl project COV ratios greater than 1 for a larger number of counties in the southern UGLR compared to the other remaining scenarios. On the other hand, yield variability is projected to decrease by approximately half for the mid century time slice for most counties in the northern UGLR (Figure 4-14). When the COV ratio is averaged across the all climate scenarios, the number of counties in southeast Wisconsin and southern with a slight increase in annual yield variation decreases as CO₂ concentrations increase from 490 to 635 ppm. On the other hand, the number of counties in northern Minnesota and Wisconsin and in the Upper Peninsula of Michigan with substantially smaller projected future annual yield variability increases as CO₂ levels increase (Figure 4-14).

For soybean yield, the majority of counties in the UGLR have a COV less than 0.55 for the historical period with several counties in the Upper Peninsula of Michigan and few counties in northwestern Minnesota possessing a relatively high COV (> 0.7 or higher) (Figure 4-15). By the mid century, and assuming a reference CO₂ level for the DSSAT simulations, the climate

scenarios obtained from six of NARCCAP climate models (i.e., CRCM-ccsm, CRCM-cgcm3, HRM3-gfdl, HRM3-hadcm3, RCM3-cgcm3, RCM3-gfdl) project higher COV values for the majority of counties in Minnesota, whereas WRFG-ccsm and WRFG-cgcm3 suggest smaller COV values for the majority counties in the UGLR with the exception of increased annual yield variability for southern Wisconsin and Michigan. The HRM3-gfdl scenario projects substantially larger future yield variability in the southern UGLR. When averaged across all climate scenarios, annual variability of soybean yield is likely to increase slightly (COV 1-1.25) for most counties in south-central Minnesota, central Wisconsin and the eastern Lower Peninsula Michigan, whereas a relatively higher annual yield variation (COV 1-1.50) by the mid century is projected for southern Wisconsin and the southern Lower Peninsula of Michigan. On the other hand, a majority of counties in the currently unproductive northern UGLR likely will have lower COV values in the future (Figure 4-15). Elevated CO₂ concentration is expected to reduce the area experiencing increased future yield variability, although a slight increase in annual yield variability in the southern UGLR is projected, even for the highest CO₂ concentration employed in this study (Figure 4-15).

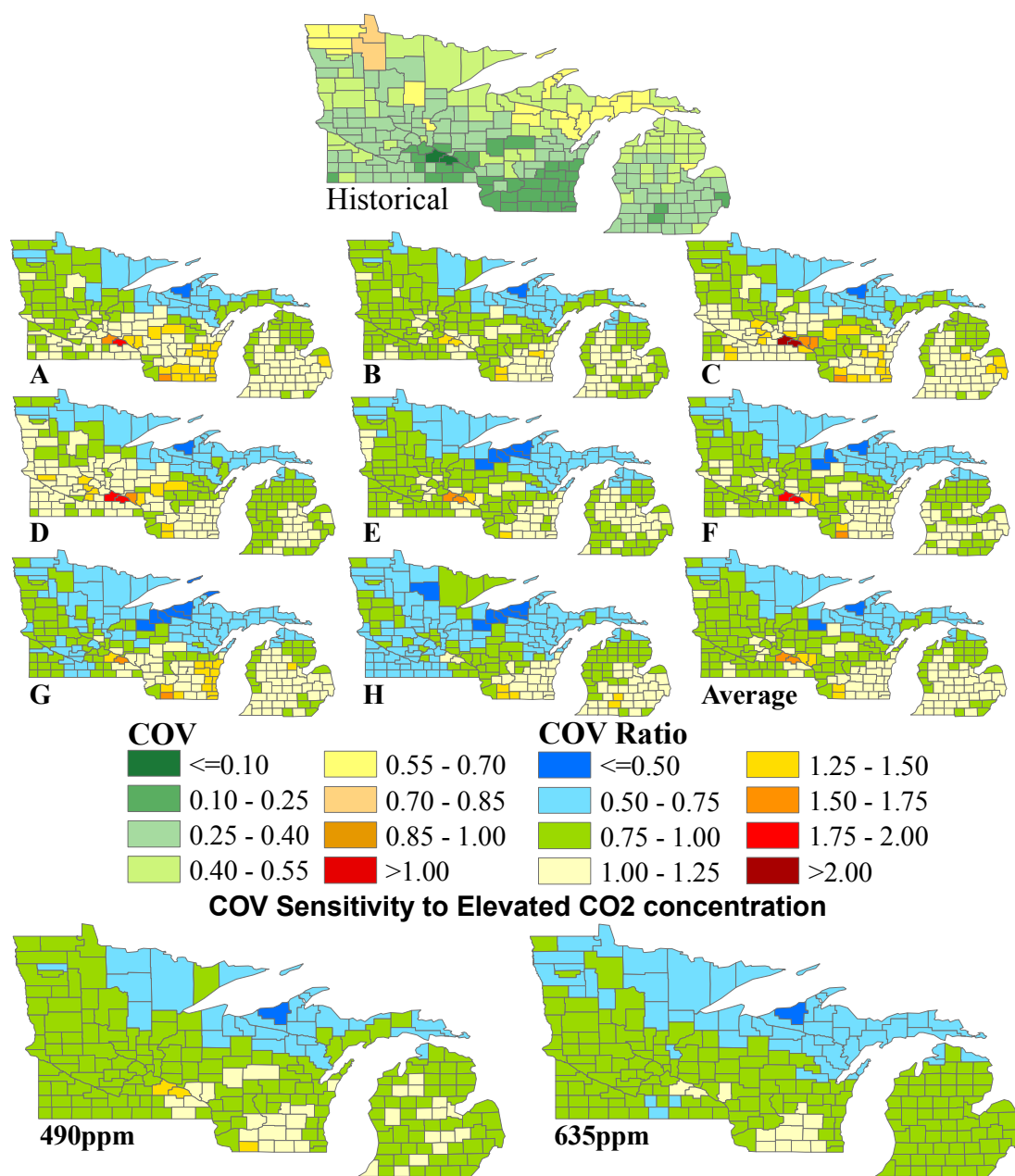


Figure 4-14. Ratio of coefficient of variation (COV Ratio) of corn yield for the future period (2041-2070) with respect to the historical period (1971-2000) under different climate projections derived from NARCCAP models at the reference CO₂ (370 ppm) level. Average is the COV ratio averaged across all climate projections. Below two panels are the average COV Ratio under elevated CO₂ of 490 (left) ppm and 635 ppm (right). Letters of A-H are the NARCCAP model identifiers (Table 4-2).

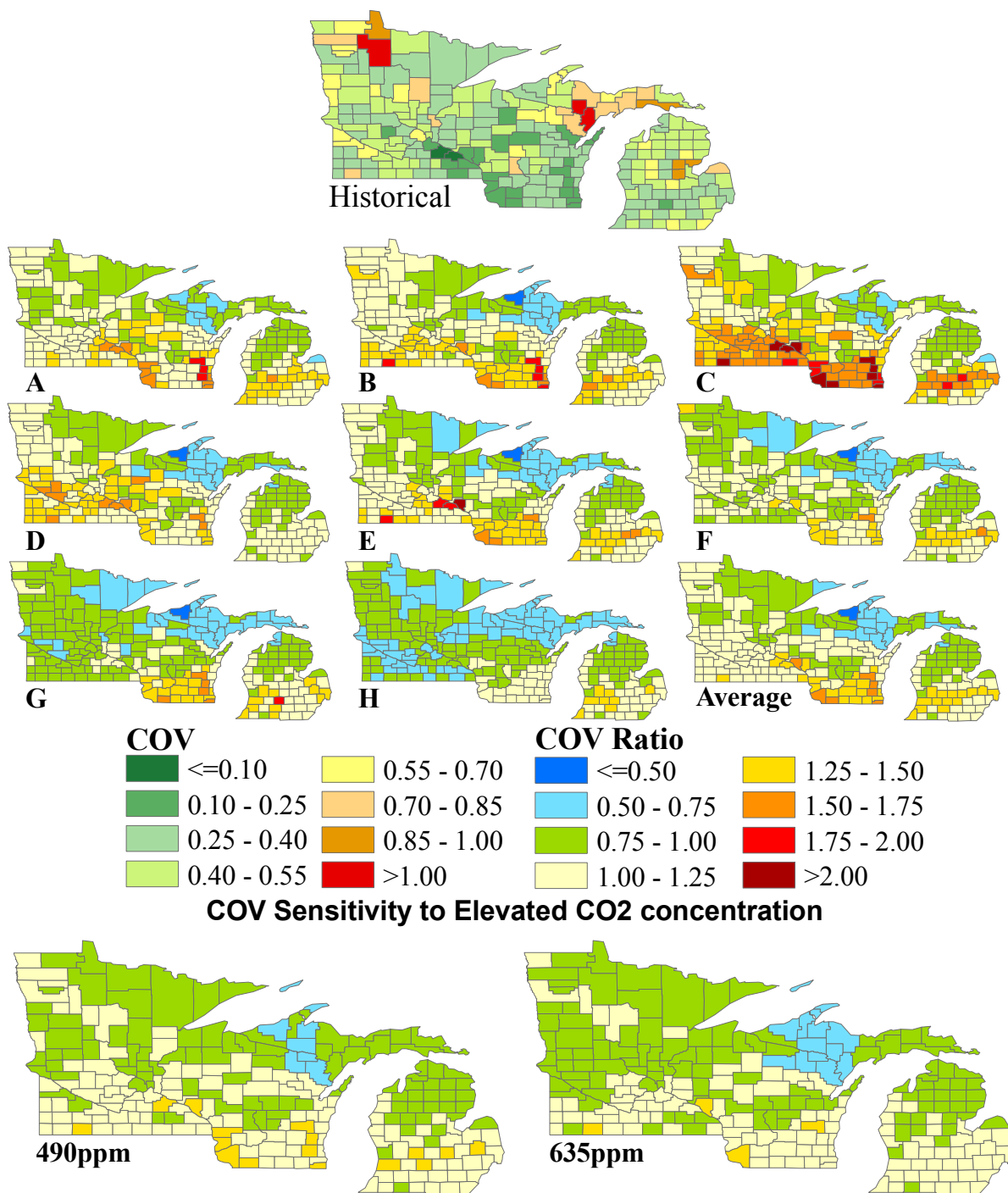


Figure 4-15. As Figure 4-14, but for soybean yield

4.3.6. *Potential Expansion in Major Growing Areas*

In order to better visualize the potential spatial changes in corn and soybean production, several yield thresholds were selected and projected future county yield was categorized as falling above or below the threshold. For corn the yield thresholds are 5000, 6000, 7000, 8000 and 9000 kg/ha, and for soybean the thresholds are 2000, 2500, 3000, 3500, and 4000 kg/ha. The lower threshold categories were chosen based on current yields in the major production regions within the UGLR; the higher thresholds were added given the projections discussed above of future higher yield in some parts of the UGLR.

Starting with the lowest threshold (5000 kg/ha), corn production regions is anticipated to expand northward into northern Minnesota and the Upper Peninsula of Michigan, especially under the highest (635 ppm) CO₂ concentration (Figure 4-16), but to contract in southern Wisconsin and the southern Lower Peninsula of Michigan, at least for the reference (370 ppm) CO₂ concentration. This same pattern is seen for the 6000 kg/ha threshold. For the higher threshold of 7000 kg/ha, and assuming the reference CO₂ concentrations in the DSSAT simulations, counties with projected yields, above the threshold are confined primarily to southern Minnesota, similar to the spatial pattern seen for the historical simulations. A larger number of counties, including some counties in south-central Wisconsin, east-central Michigan and the Upper Peninsula of Michigan, have projected yields above this threshold when the elevated CO₂ levels were employed in the DSSAT simulations. Increasing the yield threshold to 8000 and 9000 kg/ha results in the projected yield for a smaller number of counties exceeding the threshold, as expected, although the spatial pattern is more “scattered” compared to that for

the historical simulations where counties with yields exceeding these high thresholds are confined to primarily southern Minnesota (Figure 4-16).

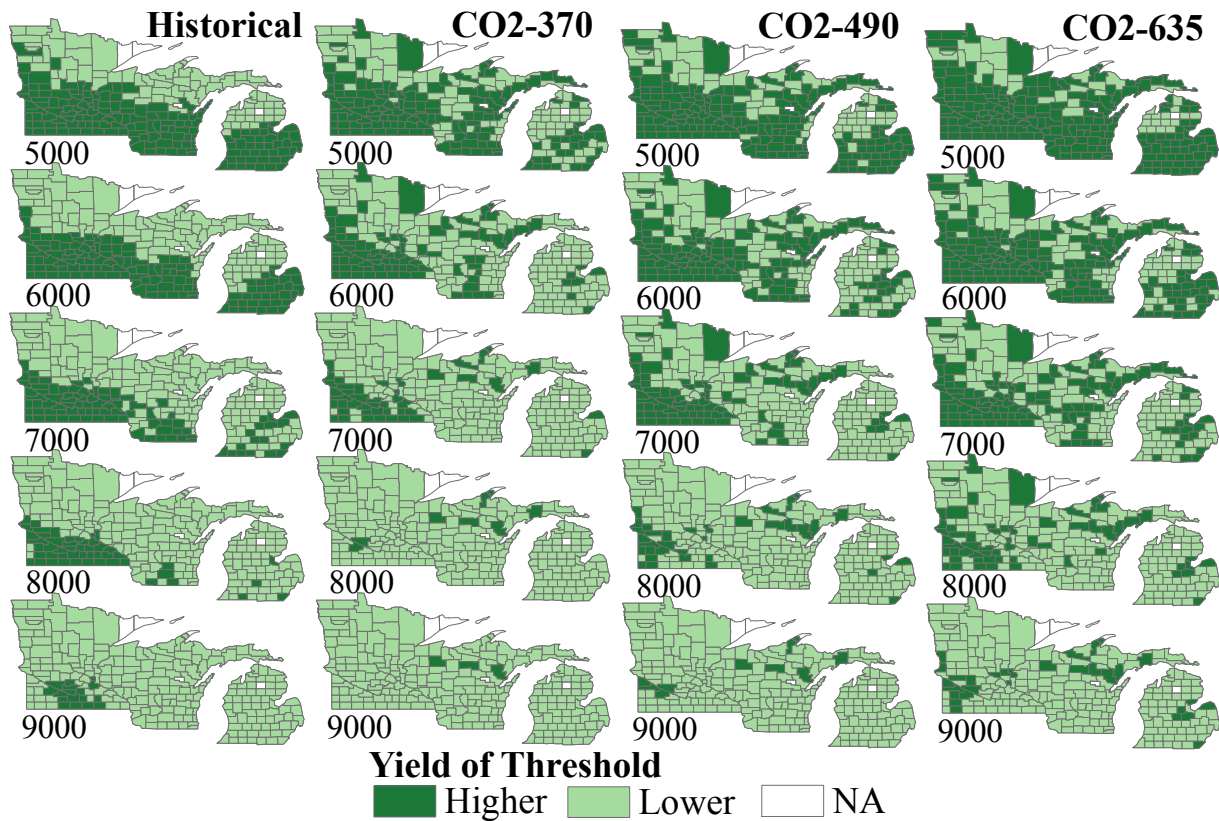


Figure 4-16. Potential expansion in major corn production regions of the UGLR assessed by categorizing the median simulated corn yields for the future period (2041-2070) is equal to or higher than a given yield threshold, namely: 5000 kg/ha (first row), 6000 (second row), 7000 (third row), 8000 (fourth row), and 9000 (fifth row).

At the lowest threshold for soybean production (i.e., 2000 kg/ha), the spatial distribution of counties with yields above the threshold is generally similar for the historical and mid-century periods when the lower (370 ppm) CO₂ concentrations were used in the DSSAT simulations

4.4. Summary and Discussion

4.4.1. Spatial Variation of the Climate Change Impact

This study was primarily purposed to evaluate the potential consequences of future climate change on the spatial variability of corn and soybean production in the UGLR by the mid century (2041-2070) with reference to a historical period (1971-2000) using DSSAT crop models and climate scenarios obtained from NARCCAP simulations. The crop model simulations for the historical period demonstrate that these models are able to capture spatial variations in planting dates for corn and soybean in the UGLR, and the simulated planting dates fell within the range of usual planting dates reported by NASS-USDA (NASS-USDA, 1997). The south-north gradient of observed county-level yield also was well depicted by the DSSAT simulated yields.

The impacts of future climate change on corn and soybean production in the UGLR are complex considering non-linear interactions between a changing climate and crop growth and development. The inclusion of eight climate scenarios derived from the NARCCAP simulations (i.e., RCM-gcm “combinations”) results in a range of possible climate change impacts for corn and soybean planting date, time to maturity, evapotranspiration and grain yield.

Assuming for the DSSAT simulations a constant level of CO₂ at 370 ppm, planting dates for corn were projected to occur earlier for counties located in the southern UGLR and slightly later for counties in the northern UGLR for most of the climate scenarios. In contrast, a west-to-east gradient was found for soybean production with earlier planting dates in the western UGLR and later dates in the eastern UGLR. The changes in planting date may be associated with the relative magnitude of warmer and wetter condition projected across the region and possible future changes in ‘optimum’ planting windows. A number of planting windows were used in the DSSAT simulations, and the highest yield from the different planting windows was selected for

further assessment. This criterion assumed that the highest yield reflected the ‘optimum’ planting window (Thelen, 2007). Future climate change is projected to moderately shorten time to maturity (TMAT) for corn production but slightly decrease TMAT for soybean production. These findings likely reflect changes in the thermal time (i.e., growing degree days) for corn or in photothermal period for soybean needed to complete crop growth and development.

For corn production, the projected decrease ET in the southern UGLR, in contrast to a projected increase in the northern UGLR, may reflect a shorter future TMAT. Theoretically, ET will increase as temperature increases, but a shorter TMAT will reduce the amount of time to accumulate ET during the corn growing season.

For soybean production, only small changes in ET are projected with no clear spatial pattern. These small changes likely reflect opposing changes in ET, precipitation and temperature. For example, the HRM3-gfdl climate scenario suggests that a shorter TMAT, warmer temperatures and drier conditions in Michigan will result in lower ET. However, for other parts of the study area the increasing temperature and wetter conditions associated with this climate scenario result in a slightly higher future ET, even though the crop growth period is projected to be shorter.

A relatively moderate decrease in corn and soybean yield is estimated for the majority of counties located in the central and southern areas; whereas counties in the Upper Peninsula of Michigan, northern Wisconsin and Minnesota will benefit from climate change. This result supports and provides more spatial detail regarding the potential positive impacts of climate change on crop yields as suggested by previous studies for a small number of northern locations in the UGLR (e.g., Andresen et al., 2013; Tubiello et al., 2002). On the other hand, the projected

moderate decrease in yields for the southern UGLR may occur due to a shorter TMAT resulting from warmer conditions, even with wetter future conditions.

Elevated CO₂ concentrations are expected to affect the magnitude of seasonal evapotranspiration (ET) and grain yield. Increasing CO₂ levels ppm are expected to slightly decrease ET for corn production; whereas the impact of elevated CO₂ is less for soybean production. The reduction in ET for corn production is likely because a C₄ crop is assumed to have higher stomatal resistance than a C₃ crop (Rosenzweig and Iglesias, 1998; White and Hoogenboom, 2011) under elevated CO₂. The higher stomatal resistance reduces the daily transpiration rate, potentially leading to decreased seasonal evapotranspiration.

Elevated atmospheric CO₂ concentrations are projected to benefit corn and soybean yield. Of the two crops, soybean (a C₃ crop) appears to benefit more from elevated CO₂ than corn (a C₄ crop) perhaps because C₃ crops have higher photosynthesis rates than C₄ crops under elevated CO₂ concentrations (Rosenzweig and Iglesias, 1998). In addition, increased CO₂ levels may lead to increased radiation use efficiency for C₃ crops; whereas, elevated CO₂ levels have a smaller effect on C₄ crops (Stöckle and Kemanian, 2009). Therefore, soybean production is anticipated to benefit more from carbon fertilization than corn production. This potential benefit from carbon fertilization on crop yield also has been identified by previous studies for the UGLR (e.g., Andresen et al., 2013; Southworth et al., 2002; Southworth et al., 2000). However, the results presented here, especially for corn, suggest that a moderate decrease (~25%) in yield may still occur by mid century in the southern UGLR even under elevated CO₂ concentrations.

For corn, we also examined potential consequences of future climate change under the highest (635 ppm) CO₂ level to different cultivars (i.e., short and long) considering that farmers in the study region plant a mixture of different cultivars (Coulter et al., 2010b). The analysis for the long season cultivar suggests that yield will increase for almost all counties in the study area. Relatively high percentage changes are projected for the northern UGLR where long season varieties are currently not widely produced. As for the short season hybrid, projected changes are similar for those the medium season cultivar with yield increasing in the northern UGLR and a slight yield decrease in the southern UGLR. These results strengthen previous analyses done by Southworth et al. (2000) for a few locations in Michigan and Wisconsin which reported that long season cultivars will benefit more from future climate change compared to short and medium season cultivars likely due to a longer growing season in the future.

As mentioned above, an ensemble of climate scenarios derived from the NARCCAP simulations with “combinations” of RCM and GCM models was used to evaluate the regional impacts of climate change in the UGLR. When the driving GCM was held constant, the RCMs were found to produce substantially different temperature and precipitation projections for the UGLR, illustrating the importance of including multiple RCMs to dynamically downscale GCMs in an ensemble of future climate projections. The variation of regional climate conditions projected by different RCMs nested within the same GCM could happen because each RCM may employ different grid structures, numerical schemes, surface boundary conditions and model parameterizations to solve sub-grid scale processes, even though the RCMs were developed using the same fundamental conservation laws and dynamic equations (Winkler et al., 2011).

4.4.2. Future Yield Variability and the Potential Expansion in Production Region

This study revealed that regional variations in projected maximum and minimum temperature and precipitation by mid century likely will impact corn and soybean production in the UGLR. The northern areas are projected to benefit from climate change; whereas a slight decrease in crop yield may occur for the southern areas, especially for corn yield, regardless of carbon fertilization. This result to some extent clarifies the regional variations associated with the expectation of potential benefits from future climate change in higher latitude regions (Cline, 2007; Fischer et al., 2005; Jaggard et al., 2010).

Furthermore, analysis of future yield variability based on the coefficient of variation (COV) suggests that the temporal variability of corn yield will increase slightly for the southern UGLR, particularly in Wisconsin and the Lower Peninsula of Michigan, regardless of climate scenario. For soybean, annual yield variability for the southern and central counties, including the current major production regions, is also expected to increase in the future, regardless of climate scenario and CO₂ level. As most of these regions have historically low COV values (<0.4), a slight increase may still result in “reasonable” annual yield variability (<0.6). Nonetheless, the southern areas of the UGLR likely will be more vulnerable to yield variability than at present.

Our analysis of the potential spatial shifts in crop production suggests that favorable growing conditions and elevated CO₂ concentrations in the future may create an opportunity for growing corn and soybean in the northern UGLR, i.e. the Upper Peninsula of Michigan, and northern Minnesota and Wisconsin, where historically little production has occurred (Andresen et al., 2013; Miller et al., 2005). However, growing conditions will continue to remain favorable within the current major crop production areas in the southern UGLR.

4.4.3. Limitations

As for other modeling studies, there are a number of some limitations related to the development of the climate scenarios and to model assumptions. The future climate projections were derived from a single emissions scenario (i.e., SRES A2) as this is the only emissions scenario employed in the NARCCAP simulations. Although, we attempted to overcome this limitation by using two elevated CO₂ concentrations for the future time slice to capture the potential benefits of carbon fertilization, the use of a single emissions scenario does not permit a comparison of future yield under different emissions scenarios which may also result in different future climate conditions.

Furthermore, future daily climate series were obtained by modifying daily observed climate data (i.e., maximum and minimum temperature and precipitation) with corresponding monthly changes calculated from the NARCCAP simulations. Although this approach has been regularly applied in climate impact assessments to remove systematic bias involved in future climate simulations (Moriondo et al., 2011), it assumes that the variability of the temperature and precipitation daily series remain constant in time. Only the magnitude of temperature and precipitation is adjusted to reflect future conditions.

The underlying assumptions of the crop models employed for the assessment also impose limitations. The DSSAT models simulate non-linear interaction between abiotic factors (i.e. climate and soil condition) and crop growth processes. The models do not simulate well pest and disease infestations (Soussana et al., 2010) which may increase under climate change (Diffenbaugh et al., 2008; Luck et al., 2011) and do not include exposure to other factors affecting yield variability such as economic conditions (Kaufmann and Snell, 1997). Current crop models also estimate the effects of carbon fertilization based on experiments conducted in

enclosed carbon chambers (Challinor et al., 2009). Thus, the models may overestimate the benefits of elevated CO₂ concentration (Long et al., 2006), as environmental conditions and applied agricultural management practices may influence the crop response to elevated CO₂ concentration (Rosenzweig and Tubiello, 2007). For example, low soil nutrients and irrigation may reduce the benefit of carbon fertilization as discussed by many authors (e.g., Rosenzweig and Tubiello, 2007; Tubiello and Ewert, 2002).

Additionally, except for planting date, farming management and technology (i.e., cultivar, row and spacing, and planting density) employed for the DSSAT simulations are assumed constant for each county in the future (2041-2070) period to isolate the consequences of climate change on crop production. This assumption neglects that farmers may use different farming practices in the future as farming management and agricultural technology evolve with time (Egli, 2008).

4.5. Conclusion

Agricultural production has been identified as a key sector susceptible to global climate change, and changes in global crop production will challenge the future global food supply. This study provides more detailed spatial information regarding potential regional climate change impacts on crop production in a high latitude region, which generally are expected to benefit from future climate change. The analysis suggests that future climate change will alter planting date, time to maturity, seasonal evapotranspiration, and grain yield of corn and soybean production in the UGLR.

For corn production, the southern areas, i.e., the current major production areas, may experience earlier planting dates by mid century, whereas slightly later planting dates may occur

in the northern areas. For soybean production, climate scenarios derived from the majority of the NARCCAP simulations suggest earlier planting dates for most counties in Minnesota and some counties in Wisconsin and Michigan with an west-east gradient of changing planting dates from earlier planting dates in the western UGLR and later planting dates in the eastern UGLR. Warmer temperatures are expected to reduce time to maturity for both crops in the majority counties in the region, including in the major production areas in the southern UGLR.

Seasonal evapotranspiration for corn production in the southern UGLR is expected to decrease in the future under warmer conditions, possibly because of a shorter time to maturity, and increase in the northern UGLR. For soybean production, seasonal ET is projected to change only slightly by the mid century. Furthermore, under the assumption of a constant level of CO₂ concentration, warmer conditions likely result in slightly decreased corn and soybean yield in the southern UGLR, partly due to a shorter time to maturity. On the other hand, favorable growing conditions in the northern UGLR likely will increase corn and soybean yield. Elevated CO₂ concentrations also are anticipated to benefit crop yield and partially alleviate potential negative impacts of climate change in the southern counties, especially for soybean production. Specifically for corn, we also found that a long season cultivar is expected to benefit more from climate change than medium and short season cultivars.

It is important to note that the interpretation of future impacts varied somewhat depending upon the NARCCAP simulations employed to derive future climate projections. For example, warmer and drier growing season conditions for the southern UGLR projected by HRM3-gfdl will more adversely impact corn and soybean yield compared to the relatively mild and wetter conditions projected by the other NARCCAP simulations (e.g. WRFG-ccsm and WRFG-cgcm3). We also found that the utilization of different RCMs to downscale GCM output

can introduce uncertainty into the impact assessment, in addition to the uncertainty introduced by the choice of GCM.

More favorable growing conditions in the northern UGLR likely will create an opportunity to grow corn and soybean with relatively high productivity more widely across the study region. Interestingly, we did not observe a shift of major production regions to the north as the major growing areas in the south are expected to still be productive in the future in spite of the potential slight reduction in grain yield. Instead we observe an expansion of the crop production in the future. However, farmers in the current major production areas should be aware of several potential negative impacts of future climate change, including a potential increase in annual yield variability. The potential opportunity of the ‘new’ production regions in the northern areas of the UGLR hints that further exploration is needed. Further analysis that employs more dynamic farming practices (Howden et al., 2007; Tubiello and Rosenzweig, 2008) would be particularly useful.

CHAPTER 5.

Development of Crop Yield Interdisciplinary Model for Regional Climate Change Impact Assessments: A Case Study for the Upper Great Lakes Region of the United States

In collaboration with

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5.1. *Introduction*

Crop production is susceptible to climate variability and change as can be inferred from the impacts of recent climatic trends on crop yield (e.g., Kucharik and Serbin, 2008; Lobell et al., 2011). The potential consequences of projected future climate change on regional crop production have been extensively studied around the world as reviewed by White et al. (2011a). These efforts have focused on the impacts of climate change on crop productivity which directly influences future world food supply (e.g., Parry et al., 2005; Rosenzweig and Parry, 1994).

Ecophysiological models, commonly known as crop models (White and Hoogenboom, 2011), are regularly employed for climate change impact assessments as summarized by previous reviews (e.g., Kang et al., 2009; White et al., 2011a). Crop models utilize a set of mathematical equations derived at a field-scale level to quantify non-linear interactions between climate, soil, agronomic practices and crop growth and development. Thus, crop models simulate, although imperfectly, the biophysical responses of a particular crop to environmental changes at a particular location (Hoogenboom et al., 2004; Meinke et al., 2001). These models also consider the effects of agronomic practices (e.g., cultivar, planting dates, row and spacing) on crop yield.

A challenging issue in the application of crop models for regional climate change impact assessments is how to explicitly include the impacts of potential changes in regional farming management associated with economic stressors. The inclusion of economic factors has been recommended by the climate impact research and modeling community in recognition of the significant contribution of economic factors to crop yield variability (Challinor et al., 2009). Unfortunately, crop models currently are not designed to capture the effects of changes in economic factors associated with farming management such as the use of machinery, labor, and pesticides that can influence crop production.

Taking into consideration the limitations of crop models, Kaufmann and Snell (1997) proposed an empirical model that integrates the outputs of crop models with economic determinants to capture the consequences of ecophysiological and socio-economic drivers on crop yield. This ‘hybrid’ model was referred to by Kaufmann and Snell as an “*interdisciplinary model*”. The authors developed an interdisciplinary model for corn yield by relating climate variables for corn phenological stages, with the phenological stages being estimated by a crop model, representative economic variables (i.e., purchase inputs and loan rate) and technical/scale variables (i.e. the use of machinery and agricultural acreage). A more recent application of an interdisciplinary model is the soybean yield model developed by Vera-Diaz et al. (2008) that combines simulated yields from a crop model, geographic location (i.e., latitude and longitude) and economic variables (i.e., credit, transports costs) to explain soybean yield spatial variability in the Brazilian Amazon. Geographic location was included to capture the effects of photoperiod and environmental gradients on yield; the effects of climatic and edaphic conditions are captured by simulated yields; and the economic variables adjust the simulated yields to reflect the effects of economic factors on observed soybean yield.

This study proposes an alternative specification for interdisciplinary models that is derived from an asymmetric production function as proposed by Guan et al. (2006). The Guan et al. model is essentially a modification of the traditional translog production function. The uniqueness of the Guan et al. model compared to the traditional translog production function is that the model specification distinguishes between two types of crop yield, namely: attainable and actual yield. This classification differentiates yield on the basis of governing factors (Rabbinge, 1993; vanIttersum and Rabbinge, 1997). Attainable yield is governed by growth-defining factors (i.e., plant characteristics, solar radiation, and temperature) and growth-limiting factors (i.e., nutrients and water). Actual yield fluctuates following growth-reducing factors such as weeds, pests, and diseases, in addition to the growth-defining and the growth-limiting factors. Guan et al. used growth inputs (i.e., land, seed, fertilizer, and water) and dummy variables (farm and year dummy) to represent growth environment (i.e., farm and weather condition) to estimate attainable yield and facilitating inputs (i.e., labor, capital, and pesticides) to adjust the attainable yield to estimate actual yield. Although, a translog production function such as the Guan et al. model offers an advantage to simulate the effects of possible changes in farming management strategies on crop productivity, the use of dummy variables prevent the application of Guan et al. model for climate change impact assessments. The model developed here replaces the attainable yield component of the Guan et al. model with simulated yield, as the crop model can better capture the effect of climate on yield compared to the use of dummy variables by Guan et al. The interdisciplinary model is developed to estimate county-level corn yield in the Upper Great Lakes Region (UGLR) of the United States. This region is selected as agriculture is considered as one of key economic activities in the UGLR, and corn is the major agricultural commodity (Hatfield, 2012; Niyogi and Mishra, 2013; Safir et al., 2008).

Future climate change is expected to impact regional corn production in the UGLR (e.g., Andresen et al., 2013; Southworth et al., 2000). However, the effects of possible changes in economic factors have not been included in the previous assessments. Thus, we also demonstrate the potential application of the interdisciplinary model for climate change impact assessments. The use of the interdisciplinary model is expected to provide a better interpretation of the potential future impacts of climate change on crop production compared to the use of crop simulation models alone.

5.2. *Materials and Methods*

5.2.1. *Study Area*

The Upper Great Lakes Region (UGLR), consisting of the states of Michigan, Minnesota and Wisconsin is located in the United States Midwest (Figure 5-1) The southern and central UGLR is part of the US Corn Belt (Aref and Pike, 1998), and the states of Michigan, Wisconsin and Minnesota rank number 11th, 10th and 4th for corn production in the nation, respectively.

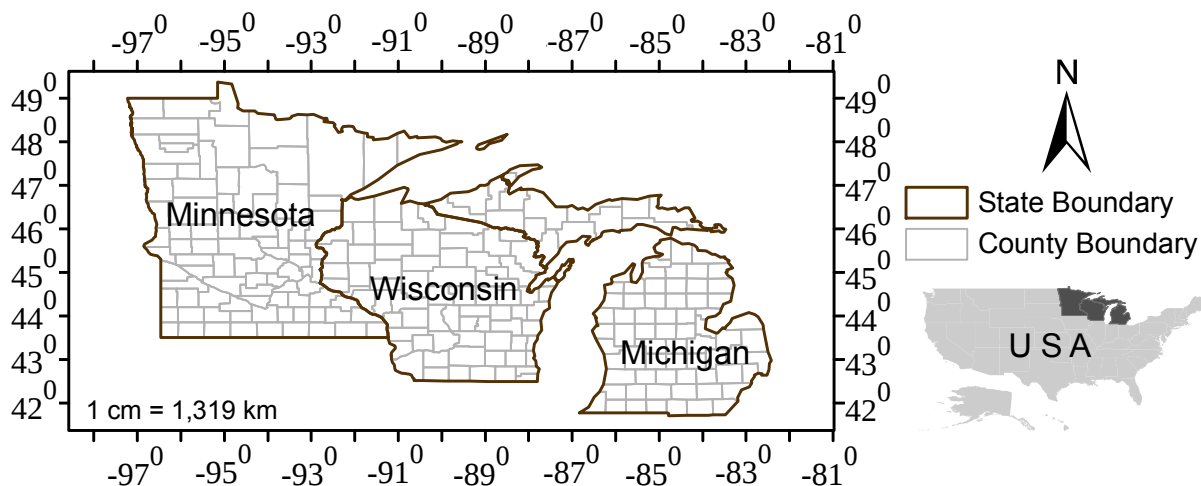


Figure 5-1. Location of the Upper Great Lakes Region

5.2.2. Model Specification

The asymmetric framework proposed by Guan et al. (2006) distinguishes between two broad categories of agronomic inputs. Pesticides, labor and capital, which are required to create favorable conditions for farming activities, are classified as *facilitating inputs*. On the other hand, factors that affect plant biophysical processes, such as land, seed, nutrients, and water, are grouped as *growth inputs* (Guan et al., 2006). Based on these classifications, the model is represented as (Guan et al., 2006, p. 206),

$$y = G(x_1, x_2, x_3, h; E) \bullet F(z_1, z_2, z_3) \quad (\text{Eq.5-1})$$

where, y is crop-yield; x_1, x_2, x_3 and h are growth inputs (i.e., land, seed, fertilizer, and water);

z_1, z_2 , and z_3 are facilitating inputs (i.e., labor, capital, and pesticides); E represents the growth

environment (i.e., dummy variables to capture differences in biophysical condition and

management across farms and interannual variations in yield due to varying weather conditions);

$G(\cdot)$ defines attainable yield; and $F(\cdot)$ is a scaling function that has a value from zero to one.

For the modified model proposed here, $G(\cdot)$ in Eq.5-1 is replaced with estimated yield (y_a)

obtained from simulations of the CERES-Maize model, a crop model including in the Decision

Support System for Agrotechnology Transfer (DSSAT). If agronomic practices are held

constant across space and time for the CERES-Maize simulations, the farm dummy variable of

the E term is no longer needed, and if temporal variability is assumed to be smaller than spatial

variability the year dummy can also be omitted.

The scaling function $F(\cdot)$ can be estimated following Guan et al. (2006, p. 208):

$$F(z_1, z_2, z_3) = \exp[-(\beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3)^2] \quad (\text{Eq.5-2})$$

where, β_0 is intercept; β_1 , β_2 , and β_3 are coefficients for labor, capital, and pesticides.

This function ensures that values of the scaling factor range from zero to one. Eq.5-1 can now be rewritten as

$$y = y_a \bullet \exp[-(\beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3)^2] \quad (\text{Eq.5-3})$$

Further modifications can facilitate the application of this model to county-level yield. If crop production is defined as crop yield multiplied by area, county-level economic costs can be used instead of unit costs (costs per unit area) and Eq.5-3 can be rewritten as:

$$y * \text{area} = y_a * \text{area} \bullet \exp[-(\beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3)^2] \bullet \exp(e) \quad (\text{Eq.5-4})$$

where, Z_1 , Z_2 , and Z_3 are the county-level costs of facilitating inputs such as chemicals, machinery, and labor; e is the error term. The term “area” on the left hand side of the equation can be removed by applying the natural logarithm, and Eq.5-4 can be written as:

$$\ln(y/y_a) = -(\beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3)^2 + e \quad (\text{Eq.5-5})$$

The model predictors (i.e., the Z terms) can be extended to include additional variables beyond the three terms (chemicals, machinery and labor) originally employed by Guan et al. (2006), in order to incorporate additional facilitating factors that are not captured in the crop model simulations. For this study, total cost of fertilizer (Z_4) and total area of agricultural land (Z_5) in each county in the UGLR are added to Eq.5-5.

$$\ln(y/y_a) = -(\beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + \beta_5 Z_5)^2 + e \quad (\text{Eq.5-6})$$

Fertilizer cost was added to capture spatial and temporal variations in the amount of fertilizer applied across the UGLR. Although, DSSAT allows users to include fertilizer in the crop simulations, obtaining fertilizer information, including the type of fertilizer application (e.g.,

nitrogen, potassium), for all counties and years is difficult. Additionally, non-limiting nutrients are often assumed for DSSAT simulations in order to isolate the consequences of climate fluctuations on yield (e.g., Andresen et al., 2001). In this study, we also simulated DSSAT yields under the assumption of non-limiting nutrients. The amount of agricultural land was added to capture variations by county of the amount of land available or suitable for agriculture. The inclusion of this term is based in part on Kaufmann and Snell's (1997) assertion that crop models have a limited ability to simulate the scale effects that the amount of land available for agriculture may have on the choice of farming management practices.

The final form of the model, with “^” indicating estimated terms is:

$$\hat{y} = y_a \bullet \exp[-(\hat{\beta}_0 + \hat{\beta}_1 Z_1 + \hat{\beta}_2 Z_2 + \hat{\beta}_3 Z_3 + \hat{\beta}_4 Z_4 + \hat{\beta}_5 Z_5)^2] \quad (\text{Eq.5-7})$$

5.2.3. Model Implementation

An overview of the data preparation and model implementation steps is shown in Figure 5.2 and discussed in more detail below.

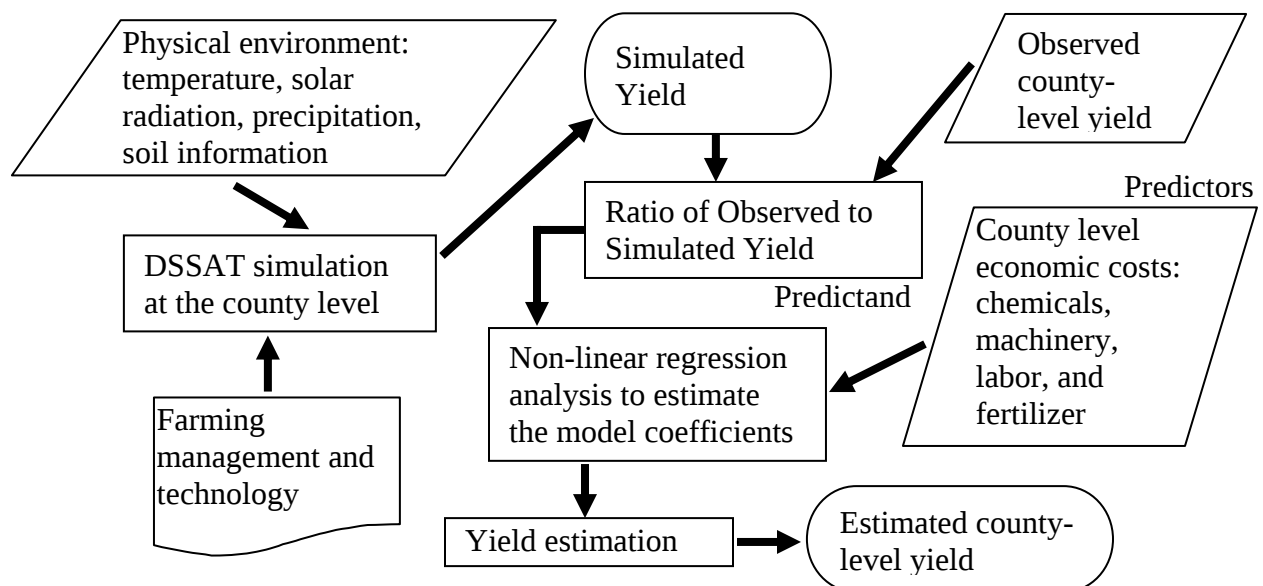


Figure 5-2. Components of the interdisciplinary model

5.2.4. Economic Data

County-level economic data were obtained from Quick Stats 2.0 provided by the National Agriculture Statistics Service, United States Department of Agriculture (NASS-USDA, 2011). This database includes information from the agricultural censuses conducted in 1997, 2002 and 2007. We extracted from Quick Stats 2.0. total corn yield and planted area; total costs of chemicals, machinery, labor (contract/hire), and fertilizers; and economic price indices with based year of 1990-1992 for each economic variable, and agricultural land area per county.

County-level economic data reported by the NASS-USDA are aggregated across all major crops within a county. The proportion of total cost for each economic variable specific to corn was roughly estimated following the procedures used by Guan et al. (2006) to estimate the share of farm-level labor and capital for individual crops. Itemized production costs by major crop for the three analysis years (1997, 2002, and 2007) published by the Economic Research Service – United States Department of Agriculture (ERS-USDA, 2011) for the three ERS-USDA farm resource regions encompassing the UGLR (see Figure 5-3) were employed to calculate the total cost proportion for corn production. Based on planted area, six out of the ten crops included for the farm resource regions were considered to be major crops in the UGLR. These crops are barley, oats, wheat, sugar beets, corn, and soybean. The total cost for each economic variable (i.e., chemicals, machinery, labor and fertilizer) was estimated by multiplying unit costsⁱ by the county-level planted area for each of the six major crops with detail procedure of the calculation is explained below.

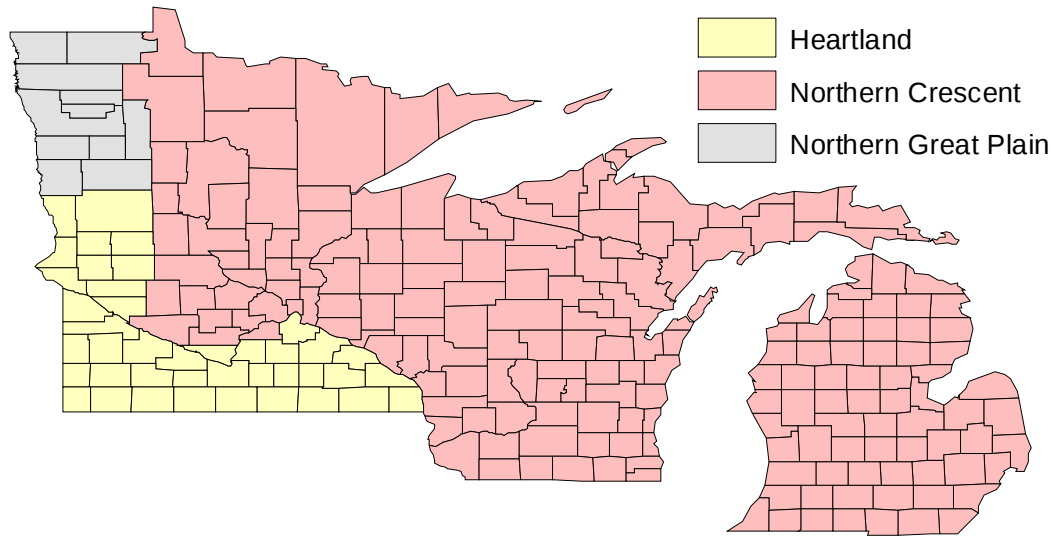


Figure 5-3. The United States farm resource regions used to calculate the share of production costs for corn. Data Source: the Economic Research Service – United States Department of Agriculture (ERS-USDA, 2011).

Each county within a United States farm resource region was assumed to have the same unit cost for a particular crop (PCA_{kj} , where k refers to crop type and j to the U.S. farm resource region). PCA_{kj} was multiplied by the total planted area for a particular crop in each county to estimate the total costs for that crop by county (TPC_{ki} where i refers to county). Next, the total costs (TPC_{ki}) for the six major crops were totaled, giving the total costs by county (TPC_i). The proportion (S_{ki}) by county of an economic cost (i.e., chemicals, machinery, labor and fertilizer) was calculated by dividing TPC_{ki} by TPC_i . The calculations were performed separately for each analysis year (i.e, 1997, 2002, and 2007) and for each economic variable (i.e., chemicals, machinery, labor and fertilizer). Estimated S_{ki} varies spatially and temporally, in response to variations in planted area by crop and year. The estimation procedure is summarized as:

$$TPC_{ki} = A_{ik} * PCA_{kj} \quad (Eq.5-8)$$

where, PCA_{kj} is the unit cost of an economic variable (i.e., chemicals, machinery, labor and fertilizer) for crop k in NASS-region j , A_{ik} is the total planted area of crop k for county i , and TPC_{ki} is the total cost of an economic variable for crop k at county i .

$$S_{ki} = TPC_{ki}/TPC_i \quad (\text{Eq.5-9})$$

where, S_{ki} is the proportion of an economic variable for crop k at county i , TPC_i is the total costs of an economic variable for all major crops by county i .

5.2.5. *Observed Yield*

Observed county-level corn yield was standardized by dividing total corn production by total area planted to corn. We chose to use total planted area instead of harvested area as the denominator because, especially in years with environmental stress (i.e., extreme weather conditions), some of the planted area is often not harvested which inflates the standardized yield and reduces the spatial and temporal variations in yield.

Temporal trends in the standardized observed county-level yields were removed so that the observed yield is comparable with simulated yield, as suggested by previous studies (e.g., Andresen et al., 2001; Jagtap and Jones, 2002). Advancement in farming practices and technology, such as new cultivars and pest management, substantially contribute to yield increases with time (Egli, 2008). The observed yields from 1990 through 2008 were detrended separately by county following the procedure applied by Tannura et al. (2008). The linear trend between observed yield as the predictand and year as the predictor was calculated and used to adjust observed yields to a base year of 1990, chosen as it corresponds to the time of the economic indices (see above). The detrended county-level observed yields for 1997, 2002, and 2007 were extracted for the model development.

5.2.6. Crop Model Simulation

The CERES-Maize model included in DSSAT version 4.5 (Hoogenboom et al., 2010) was used to simulate corn grain yield for all UGLR counties. The CERES family has been implemented worldwide to simulate crop responses to environmental changes as summarized by Jones et al. (2003) and specifically to climate change as reviewed by White et al. (2011a). Data inputs required for the model simulations are climate variables, soil information, and farming practices. The primary required climate variables are daily solar radiation, maximum and minimum air temperature, and precipitation. Soil data includes general physical soil properties (e.g., soil texture, soil classification) and layer-specific soil information (e.g., soil fertility, drainage upper and lower limit). Farming practices include agronomic practices such as crop variety, row spacing, and planting date. The data preparation for the DSSAT simulation generally followed the procedures described in detail in Chapter 4 and summarized below. DSSAT simulations were performed for the period 1990 to 2008, which encompasses the three years (1997, 2002, and 2007) with available economic data. The year of 1990 was selected as the beginning year for the simulations considering the base year of the economic indices used to detrend the economic variables.

(a) Climate data

Climate data (i.e., precipitation and maximum and minimum temperature) was obtained from 36 representative climate stations (Figure 5-4) from the United States Historical Climate Network-USHCN (Menne et al., 2012b; Menne et al., 2009). These representative stations were selected and assigned to individual counties with the assistance of a climate regionalization that grouped USHCN stations based on their deviations from the regionally-averaged annual cycle of precipitation and maximum and minimum temperature (see Chapter 2).

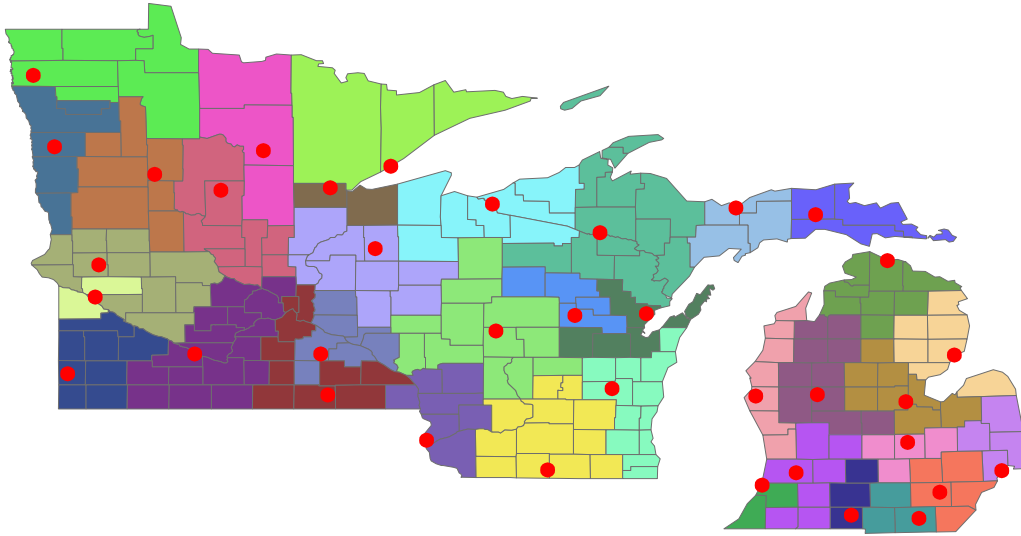


Figure 5-4. The representative climate stations (red dots) assigned to the UGLR counties for the interdisciplinary model development. The colors indicate the counties assigned with the same representative climate station.

One criterion in the selection of the representative stations was a small amount of missing observations. When missing observations did occur in the time series of the representative USHCN stations, “filled in” values were obtained from the Iowa Environmental Mesonet (IEM) network (IEM, 2013), either for the same station or for a nearby station. . IEM recently published temporally complete series many climate stations in the Midwest including stations located in Michigan, Wisconsin and Minnesota. IEM filled in missing observations using an inverse distance interpolation applied to climate data from NCEP Stage IV precipitation, airport weather data (ASOS/AWOS), and available NWS COOP reports (Drayl, 2013, personal communication).

Daily solar radiation, an important variable for the DSSAT simulation but not recorded by the climate stations, was estimated using the Hunt et al. (1998) mechanistic radiation model, parameterized using concurrent observations of daily maximum and minimum temperatures,

precipitation and solar radiation for 1990-2008 at Hancock, Wisconsin, located roughly in the center site of the UGLR. The mechanistic radiation model was selected to estimate solar radiation as a systematic evaluation of various daily solar radiation sources (Chapter 3) suggested that the mechanistic approach is a viable option for the generation of daily solar radiation required for crop process models. The mechanistic model utilizes latitude to estimate daily global solar radiation, and an empirical relationship derived from temperature and precipitation is used to calculate atmospheric transmittance (Hunt et al., 1998; Liu and Scott, 2001).

Atmospheric CO₂ concentrations for the DSSAT simulations were set at 355 ppm, the CO₂ level for early 1990 as reported by the Intergovernmental Panel on Climate Change-Data Distribution Center (IPCC-DDC, 2011).

(b) Soil Data

County-level soil data were extracted from the STATGO database published by the Natural Resources Conservation Service of the United State Department of Agriculture (NRCS-USDA) (Soil Survey Staff, 2010) for the dominant soil type in each county based on areal coverage. Soil parameters included soil classification, slope, drainage, runoff potential, the soil texture, organic content, pH and cation exchange capacity. SBuild, a DSSAT supporting package (Uryasev et al., 2003), was used to calculate specific soil information, such as drainage upper and lower limits which are not available in STATGO, and to prepare soil inputs for the DSSAT simulations. Soil color and fertility, which are also required by SBuild, were obtained based on soil texture and taxonomy published by the National Cooperative Soil Survey, (NCSS, 2011) and the generic soil database available in DSSAT.

(c) Cropping Scenarios

CERES-Maize was run under rainfed conditions using a medium season corn cultivar. The corn cultivar was selected after evaluating the performance of multiple corn cultivars employed by previous studies within the UGLR (i.e., Andresen et al., 2001; Southworth et al., 2000) in capturing the spatial variability of observed corn yield in (see Chapter 4). The cultivar characteristics are presented in Table 5-1.

Table 5-1. Characteristics of medium season corn cultivar used in CERES-Maize simulations

P1	degree days (base 8 °C) from emergence to end juvenile phase	200
P2	photoperiod sensitivity (0-1)	0.3
P5	degree days (base 8 °C) from silking to physiological maturity	800
G2	potential kernel number	700
G3	potential kernel growth rate (mg/d)	6.3
PHINT	degree days required for a leaf tip to emerge (phyllochron interval) (°C d)	38.9

Planting densities were determined at 75 cm spacings with plant populations of 6 plants/m² following Andresen et al. (2001). Planting date was determined automatically using the DSSAT automatic planting option that initiates planting when, during a specified planting window, the percent soil water and soil temperature in the top 10 cm are at least 20% and 10 °C, respectively. The simulations were started on January 1st with soil water initialized at the drained upper limit. Five different planting windows were defined by offsetting the starting date of the planting window by roughly 15 days from April 1st to June 10th (i.e., April 1st-June 10th, April 16th-June 10th, May 1st-June 10th, May 16th-June 10th, and May 31th-June 10th). The end date of the planting window reflects the typical observed range of planting dates for corn in Michigan,

Minnesota and Wisconsin (NASS-USDA, 1997). Harvesting was considered to occur when corn reached physiological maturity. The highest annual simulated yields from the different planting windows were selected for the development of the interdisciplinary model. The DSSAT simulations assumed no change in agronomic practices over time along with non-limiting nutrient conditions.

(d) DSSAT Simulated Attainable Yield

As discussed above, the DSSAT simulations provide the estimates of “attainable yield” for the interdisciplinary model development, and attainable yield is assumed to be larger than observed yield. When the simulated corn yields for 1997, 2002 and 2007 are compared with the observed yields reported by NASS-USDA, a modest number (150 out of a total of 587) of county-year combinations are seen to have observed yield greater than simulated yield (Figure 5-5). No distinct spatial or temporal variation is seen in the distribution of observed county yields greater than observed yield. These differences could reflect a number of factors such as the use of irrigation in some counties, higher yields on soils within a county that are not dominant in terms of areal coverage, the use of different (e.g., long season) cultivars, uncertainty in the county-level yield values, among others. The county-year combinations with DSSAT simulated yield less than observed yield were removed from the development of the interdisciplinary model.

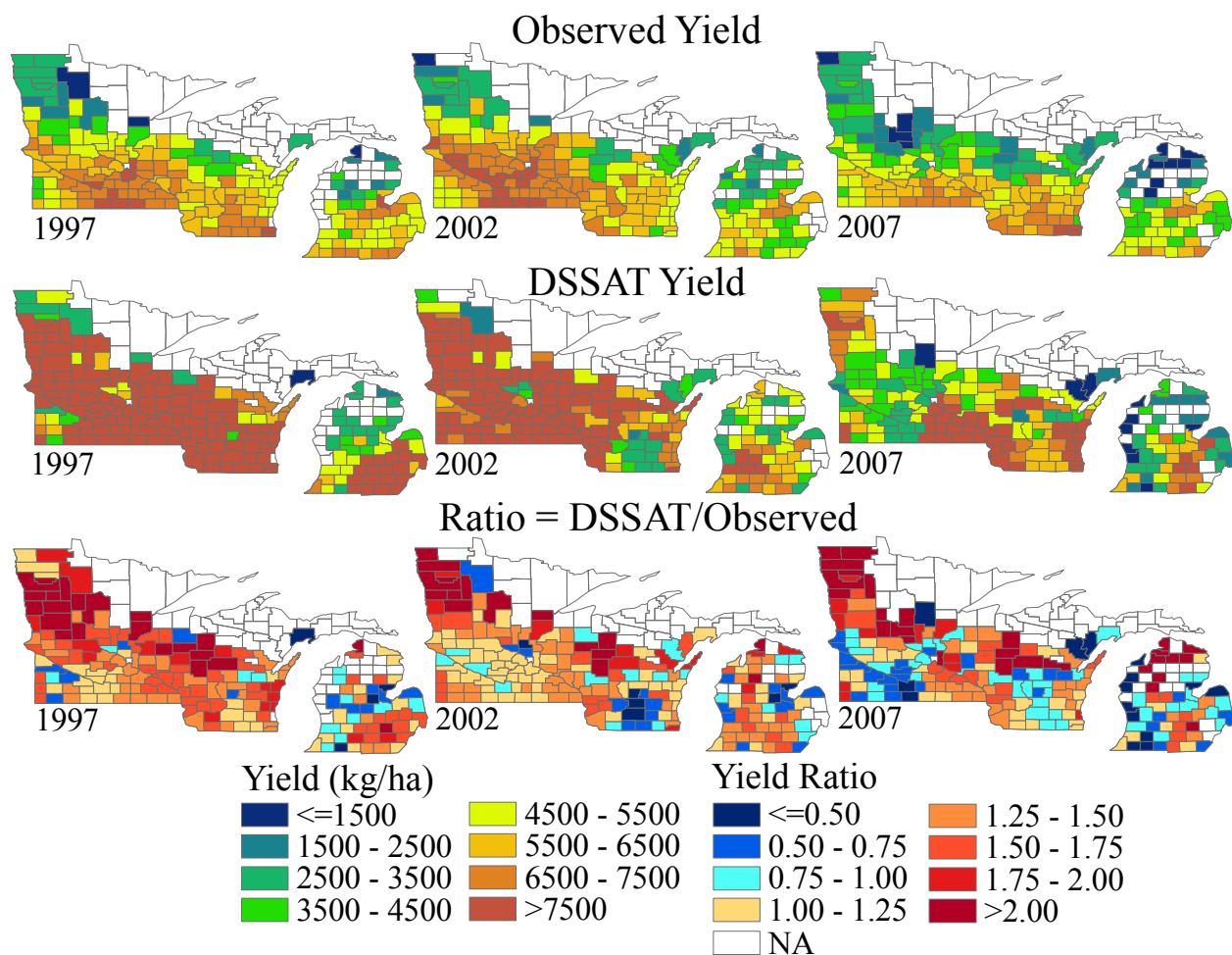


Figure 5-5. Observed yield (top), DSSAT simulated yield (middle), and the ratio of simulated to observed yield (bottom) for the UGLR for 1997, 2002 and 2007

5.2.7. Model Estimation

The nonlinear least square (NLS) estimator was employed to solve Eq.5-6 giving the nonlinear form of the equation. Initial values of the model coefficients are needed as NLS solves nonlinear equations iteratively until convergence is achieved (Greene, 2003). To obtain initial estimates, the error term in Equation 5-6 was assumed to be zero and multiple regression was applied to solve the liner form of the equation (Eq.5-10).

$$\sqrt{\ln(ya/y)} = \hat{\beta}_0 + \hat{\beta}_1 Z_1 + \hat{\beta}_2 Z_2 + \hat{\beta}_3 Z_3 + \hat{\beta}_4 Z_4 + \hat{\beta}_5 Z_5 \quad (\text{Eq.5-10})$$

Across-section data analysis (i.e., varied in time and place) is likely to introduce heteroscedasticity as explained by Gujarati (2003, p.401). Although, heteroscedasticity does not affect the values of the model coefficients, the standard errors and the t-statistics may be no longer valid (Gujarati, 2003). To deal with this issue, heteroskedasticity consistent (HC) estimators included in the sandwich package (Zeileis, 2006) of the R statistical software was employed to obtain robust estimation of the standard errors and the t-statistics.

Given the non-linear form of the interdisciplinary model, elasticity analysis was performed to evaluate the contribution of each economic predictor to the yield deviation assigned as the predictand in Eq.5-6. First, the derivation of the model (Eq.5-6) with respect to each economic predictor was obtained separately. Second, using the derived models, the elasticity values of each economic predictor were calculated at the mean values of each economic variable ($\bar{Z}_x$). Below is the example of the elasticity calculation for pesticides (Z_1). The standard errors for the elasticity values were computed using the delta method (Greene, 2003, p.70) available in R statistical software.

$$\frac{d(\ln(y/ya))}{dZ_1} \cdot \frac{\bar{Z}_1}{\ln(y/ya)} = -2\beta_1 \cdot (\beta_0 + \beta_1 \bar{Z}_1 + \beta_2 \bar{Z}_2 + \beta_3 \bar{Z}_3 + \beta_4 \bar{Z}_4 + \beta_5 \bar{Z}_5) \cdot \frac{\bar{Z}_1}{\ln(y/ya)} \quad (\text{Eq. 5-11})$$

5.2.8. *Application for a Climate Change Impact Assessment*

The interdisciplinary model is used to evaluate the sensitivity of future corn yield to variations in facilitating inputs in addition to projected climate change. As an example, we evaluated the sensitivity of yield changes by the mid century (2041-2070) with respect to the

baseline period (1971-2000) to a reduction from the “current” investment in chemical applications of 30%, 50% and 70%. The reduction scenario was selected to represent possible changes in the regulation of chemical applications in the future. The values for the “current” investment were obtained from the average values of available economic data for the three analysis years (i.e., 1997, 2002 and 2007). Attainable corn yields for the future and the baseline period by county were estimated from the DSSAT simulations of corn yield by county using the projected temperature and precipitation obtained from climate scenarios developed from the North American Regional Climate Change Assessment Program (NARCCAP) simulations (see Chapter 4 for more information on the climate scenario development and DSSAT simulations). Atmospheric CO₂ concentration for the crop model simulations for both the future and the baseline period was set constant at 370 ppm. For attainable yield, we used the median values of the 30-year future and baseline periods of simulated corn yields. Specifically for the future period, the county-level median corn yields were obtained by averaging the simulated county-level median corn yield obtained from the DSSAT runs for all eight of the NARCCAP-derived climate projections.

5.3. Results

The interdisciplinary model explains about 62% of yield variability over the UGLR for the three analysis years (Table 5-2). The model coefficients for chemicals, labor, and fertilizer have a negative sign, whereas the coefficients for the other predictors are positive. A negative coefficient indicates that additional chemicals, labor, or fertilizer will decrease the deviation between simulated DSSAT yields and observed yields. In other words, observed yields will be closer to DSSAT yields as chemical, labor or fertilizer inputs increase. The opposite occurs for machinery and amount of agricultural land. The elasticity analysis suggests that labor contributes

less to the yield deviations compared to the other economic variables, and the significant test for the model coefficients shows that only the labor term is insignificant.

Table 5-2. Model coefficients and elasticity analysis for the interdisciplinary model of county-level corn yield for the UGLR parameterized using available data of 1997, 2002 and 2007

	Model coefficients		Elasticity Analysis	
	Uncorrected	Corrected	Uncorrected	Corrected
Intercept	7.53E-01***	7.53E-01***		
Chemical	-5.28E-08*	-5.28E-08**	-0.278*	-0.278**
Machinery	4.76E-09***	4.76E-09***	0.468***	0.468***
Labor	-7.36E-09	-7.36E-09	-0.067	-0.067
Fertilizer	-7.30E-08***	-7.30E-08***	-0.661***	-0.661***
Agricultural Land	9.21E-07***	9.21E-07***	0.224***	0.224***
R ² -fit	0.62			

Note: *** *significant at 1%*, ** *significant at 5%*, **significant at 10%*

The interdisciplinary model was applied to estimate the spatial distribution of corn yield for the UGLR using the simulated DSSAT yield and economic inputs for 1997, 2002 and 2007 (Figure 5-6). Visual comparison suggests that the estimated yields obtained from the interdisciplinary model better capture the spatial yield variability than the simulated DSSAT yields for each of the three years (Figure 5-6), especially in the southern UGLR. Statistical indices (Pearson's product moment correlation coefficient, the Willmott Index of Agreement (Willmott, 1981)) clarify that the estimated yields obtained from the interdisciplinary model better imitate the spatial pattern across the UGLR than do the simulated DSSAT yields. Also, the deviations in the mean and standard deviation between observed and estimated yield are smaller for the interdisciplinary model than those for the DSSAT simulation (Table 5-3).

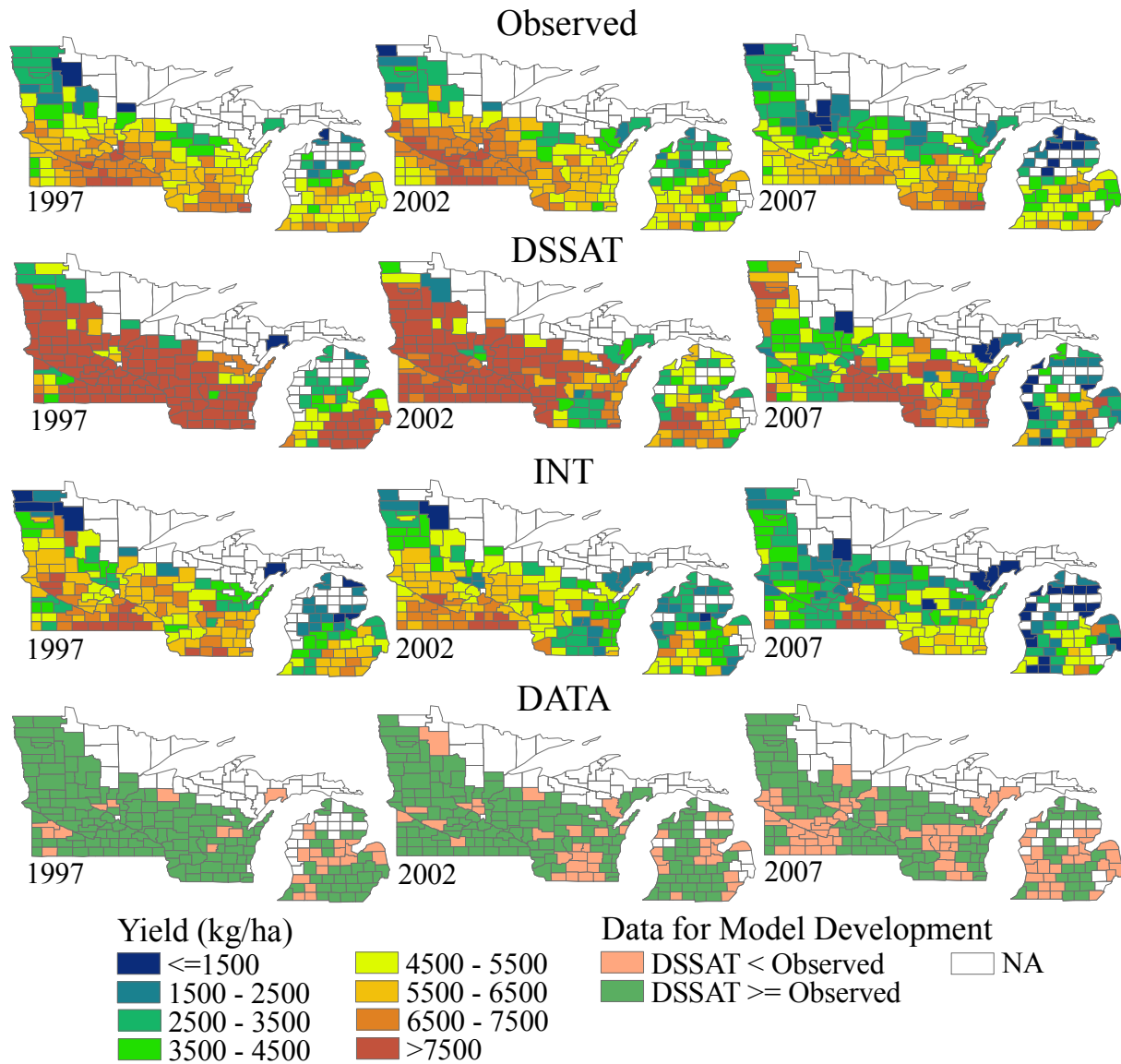


Figure 5-6. Comparison between observed county-level yields (Obs), estimated yields obtained from DSSAT simulation (DSSAT) and estimated yields obtained from the interdisciplinary model (INT) for 1997, 2002 and 2007. The three maps in the last row (Data) display county-level data employed for the model development.

Table 5-3. Statistical comparison between observed yields (Obs) and estimated yield (Est) obtained from DSSAT simulation and the Interdisciplinary model across the UGLR

Variable	DSSAT simulation			The Interdisciplinary Model		
	1997	2002	2007	1997	2002	2007
Willmott Index	0.57	0.59	0.63	0.77	0.74	0.74
Correlation	0.40	0.39	0.44	0.62	0.61	0.61
Mean.Obs	5439.7	5471.9	4573.1	5439.7	5471.9	4573.1
Mean.Est	7832.7	6746.1	5247.9	5062.2	4597.8	3696.5
StDev.Obs.	1533.9	1556.1	1738.1	1533.9	1556.1	1738.1
StDev.Est.	2672.8	2081.4	2350.0	1908.3	1686.7	1817.0

As noted above, the interdisciplinary model was also used to explore the potential impacts of a reduction in the amount of chemical application under projected climate change for the mid century. Figure 5-7 shows that projected climate change under the reference CO₂ level (370 ppm) will slightly decrease corn yield for the majority UGLR counties, particularly those located in the southern UGLR, and moderately (up to 50%) decrease corn yield in southern Michigan. When chemical inputs are reduced, the interdisciplinary model suggests that the number of counties in the southern UGLR with a moderate (25-50%) reduction in yield will increase. A similar reduction is not seen in the northern UGLR (Figure 5-7).

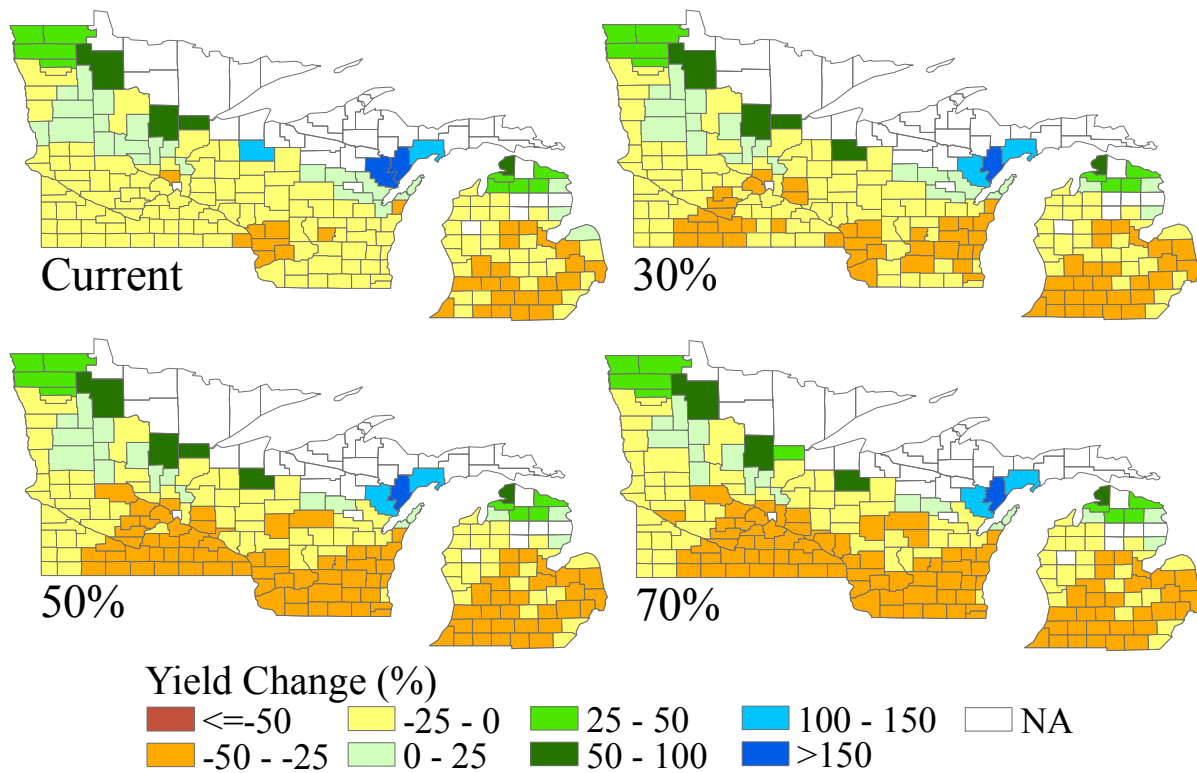


Figure 5-7. Sensitivity of yield changes under projected climate change for the UGLR by the mid century (2041-2070) to the reduction in the amount of chemical application by 30% (second row), 50% (third row) and 70% (fourth row). A CO₂ concentration of 370 ppm was assumed for the DSSAT simulations.

5.4. Summary and Discussion

The impacts of projected climate change on agricultural production have been extensively studied during the past decade. Crop models that are designed to operate at a field scale are commonly applied to evaluate the complexity of crop responses to future climate change. A challenging issue associated with applications of crop models, particularly at a regional scale, is how to incorporate economic factors that reflect farming management but are not included in the crop model simulation. This study attempted to improve the utilization of a

field-based crop model called CERES-Maize incorporated in the DSSAT system to estimate county-level corn yield for the Upper Great Lakes Region (UGLR). The model was developed by integrating simulated DSSAT yields and county-level economic costs, namely: chemicals, machinery, labor, and fertilizer, and the amount of agricultural land per county.

An underlying assumption for the model development is that observed yields (i.e., actual yield) should always be smaller than simulated DSSAT yields (i.e., attainable yield). The reasoning behind this assumption is that growth limiting factors such as pest and disease that can reduce crop yields are not included in the DSSAT simulations. Simulated DSSAT yield primarily is dictated by climatic conditions, i.e., solar radiation, temperature and precipitation, although soil factors and some management practices (e.g., crop cultivar) also are important. Although simulated yields tended to be higher than observed yields for most counties and years, there were a few counties during the three-year model development period with observed yields higher than simulated yields. In particular, DSSAT yields for 2007 underestimated county yield in the Lower Peninsula Michigan. The possible reason is that the DSSAT, which was run under the assumption of rainfed conditions, may exacerbate the effect of the 2007 drought, considered as one of the worst drought in the last two decades in Michigan (Andresen, 2008), on yield. On the other hand, farmers may apply irrigation to combat with the drought condition. Assumptions made for agronomic practices used for the model simulation also may contribute to the deviation between simulated and observed yields as uniform agronomic practices was assumed for the entire region. Smaller simulated yields than observed yields were also found for some years by previous studies that applied crop models to simulate maize (e.g., Safir et al., 2008), soybean and/or wheat (e.g., Alexandrov et al., 2002; Jagtap and Jones, 2002) yield for a region.

The model coefficients for the interdisciplinary model were estimated based on empirical relationships of the deviation between simulated yields and observed yields as the predictand and county-level economic costs as the predictors. The model coefficients for chemicals, labor and fertilizer have a negative sign which means they have a positive impact on the estimated yield, although labor contributes less to the estimated yield than the other two economic variables. The signs for chemicals and fertilizer are reasonable as chemicals and fertilizer are applied to create favorable growing conditions for corn growth and development. Chemicals (i.e., pesticide) are applied to manage pest and disease infestations that can decrease corn yields. Fertilizer is applied to supply adequate nutrients to support crop growth and development. Consequently, application of chemicals and fertilizer is expected to result in estimated yields (i.e., actual yield) closer to simulated yields (i.e., attainable yield). For machinery and amount of agricultural land per county, the signs of the coefficients are positive which means any increase in these two variables results in larger deviations between simulated and observed yields. Machinery, likely functions as a capital stock in the interdisciplinary model, partially captures the scale of corn production, as does the amount of agricultural land.

The estimated corn yields from the interdisciplinary model better capture the spatial variability of observed county-level corn yield in the UGLR compared to the simulated DSSAT yields. For this application, the interdisciplinary model essentially “corrects”, using a scaling factor, simulated yields so that they are closer to observed yields. The interdisciplinary model was also applied, as an example, to investigate the sensitivity of yield changes under projected climate change to a reduction in chemical applications. The results revealed that decreasing the amount of chemicals applied to corn production can exacerbate the potential negative impacts of climate change on corn yields in the southern UGLR which is currently the major production

region. This consequence may happen because warmer conditions in the future will shorten the time to maturity which eventually will reduce the period for grain yield production as discussed in Chapter 4. Furthermore, the decrease in chemical applications will increase the yield deviation between simulated DSSAT yields (i.e., attainable yield) and actual yield, which means actual grain yield will decrease as the chemical application decreases. This example of applying the interdisciplinary model for climate change impact assessments suggests that the interdisciplinary model can provide an option for extending the use of crop model simulations for regional climate change impact assessments. Using the interdisciplinary model, we can experiment with different scenarios of possible changes in the county-level economic costs, rather than assume, as is done for most assessments, that the current farming management also applies to a future period (Tubiello et al., 2002).

5.5. Conclusion

The impacts of climate change on crop yield have been extensively evaluated. In this study, we developed an interdisciplinary model based on an asymmetric production function that distinguishes between attainable and actual yield to model county-level corn yield for the Upper Great Lakes Region (UGLR). The model integrates observed (i.e., actual yield) and simulated (i.e., attainable) yields with county-level economic costs. The model parameters were estimated using a nonlinear least square (NLS) estimator.

This study shows that the interdisciplinary model can improve upon the utilization of simulations from crop models alone and can be used to evaluate the sensitivity of crop yield to possible changes in a crop production system as reflected by changing county-level economic costs. As an example, we applied the model to assess a simple scenario of reduced chemical applications for controlling pest and disease under a future perturbed climate. The analysis

revealed that reduced chemical applications may exacerbate the potential negative impacts of climate change on corn yields, especially in the southern UGLR.

End Notes

ⁱ When a specific agricultural input cost was not available for a resource region, the corresponding input cost from the closest resource region or an older regional classification was used. The older classification of farm resource regions is found in the online documentation provided by ERS-USDA (2011b).

CHAPTER 6.

Summary and Conclusion

This study evaluates the potential impacts of projected climate change for the mid century (2041-2070) on county-level corn and soybean production in the Upper Great Lakes Region (UGLR) of the United States, encompassing the states of Michigan, Wisconsin and Minnesota. Future climate scenarios were derived from simulations obtained from eight “combinations” of RCMs and GCMs released by the North American Regional Climate Change Assessment Program (NARCCAP). The CERES-Maize and CROPGRO-Soybean models included in DSSAT were employed to simulate corn and soybean production for historical (1971-2000) and future (2041-2070) periods. CO₂ concentrations for the crop simulations included a reference level (370 ppm) and two elevated CO₂ concentrations (490 and 635 ppm).

A major challenge in the application of crop models such as DSSAT is the availability of daily climate data (e.g., temperature, precipitation and solar radiation), due to the relatively coarse and non-uniform spatial distribution of climate observing stations. This study proposed the utilization of a climate regionalization procedure to group climate stations into subregions with similar characteristics, based on deviations from the regionally-averaged annual cycle of maximum and minimum temperature and precipitation. The climate regionalization can be applied to help choose representative climate stations for an impact assessment and to assign these stations to individual counties based on their geographic proximity. This approach is an improvement on previous assessments for regional agriculture that selected a small number of climate stations based on data availability or their location with respect to major agricultural production areas. A concern for these earlier studies is that the selected climate stations may not

fully capture the spatial variability of climate conditions across the study region. Selecting representative stations based on a climate regionalization helps to ensure that the spatial gradients of temperature and precipitation across the study area are captured. Additionally, this approach provides an alternative to the utilization of gridded datasets for regional crop model simulations. Gridded data need to be used cautiously as they are extremely sensitive to the density and inhomogeneities of the original observed climate series.

To overcome the limited availability of daily solar radiation, this study systematically evaluated the sensitivity of simulated corn and soybean yield to different solar radiation sources. The sources considered included point-based radiation estimates from empirical and mechanistic models and a stochastic weather generator, and radiation estimates obtained from available satellite, reanalysis and regional climate model gridded datasets. The comparison of different daily solar radiation estimates provides a guideline to help select an appropriate daily solar radiation source for a specific application. A mechanistic radiation model that estimates daily solar radiation based on maximum and minimum temperature and precipitation as inputs was selected for assessing the potential impact of future climate change on crop production in this study. Comparison of simulated yields obtained from observed solar radiation and from estimated daily solar radiation obtained from the mechanistic model showed relatively small yield differences. Additionally, the mechanistic model maintains the daily relationships among climate variables, is easily implemented for different locations in the UGLR, and can be readily applied to estimate daily solar radiation for a future period using projected maximum and minimum temperature and precipitation as inputs.

A detailed spatial analysis of the potential climate change impacts on corn and soybean production in the UGLR provides a more rigorous exploration of the spatial distribution of the

potential impacts compared with previous studies that employed a limited locations to represent the entire region. For the mid century, assuming the reference CO₂ level of 370 ppm for the DSSAT simulations, the assessment revealed that corn and soybean yield for the northern part of the study region likely will increase due to more favorable growing season conditions than at present; whereas a small reduction in yield due to a shorter time to maturity may occur in the southern part which is currently the major crop production area within the UGLR. Elevated CO₂ concentration is expected to benefit crop yield, particularly soybean yield.

In contrast to previous work, the climate change impact assessment conducted in this dissertation employed an ensemble of climate change scenarios developed from simulations from different RCM-GCM “combinations” where the RCMs were used to downscale GCM output, with lateral boundary conditions obtained from the GCMs. This assessment illustrates that the utilization of different RCMs and/or GCMs provides varying future climate projections and implies that the direct use of outputs from a single or few GCMs may not capture well the uncertainty associated with climate change impact assessments. While recognizing that the coarse resolution of GCMs is not sufficient to capture regional climate variation, climate impact researchers also need to be aware of the additional uncertainty introduced by the choice of RCMs to dynamically downscale GCM outputs. The use of an ensemble of GCMs and RCMs as implemented by NARCCAP enhances our understanding of the uncertainty introduced into climate impact assessments by the climate scenarios.

This dissertation also contributes to an increased understanding of the potential spatial shifts in crop production and of future temporal yield variability. A potential northward shift in crop production has been highlighted by previous studies at the national scale for the United States. The findings of this county-level analysis indicate that more favorable growing conditions

by the mid century likely will benefit crop production in the northern UGLR where some counties may produce relatively high corn and soybean yields especially under elevated CO₂ concentrations. Crop yield in the southern UGLR is likely to remain high, partly due to the positive impacts of elevated CO₂ concentrations. However, producers in these areas should be aware that future climate change may result in somewhat increased temporal yield variability, as indicated by a projected small increase in the coefficient of variation by the mid century.

Although this dissertation uses the UGLR as a case study for evaluating the regional impacts of climate change on crop production, the results imply that the consequences of projected climate change by the mid century for high latitude regions can be complex. Climate change cannot be expected to always benefit crop production in high latitude regions because of the complexity of crop responses to spatial variations in temperature and precipitation changes. Regional soil variations also add to the complexity of crop responses to future climate change.

All climate impact assessments have limitations, and the one presented in this dissertation is no exception. One limitation is that the NARCCAP simulations employed a single emissions scenario (i.e., SRES A2), thus the uncertainty introduced by the choice of greenhouse gas emissions scenario is not considered. Another limitation is the use of the delta method to modify daily climate observations (i.e., maximum and minimum temperature and precipitation) by projected monthly changes calculated from the NARCCAP simulations, as future changes in climate variability are not considered.

The underlying assumptions of the DSSAT simulations also need to be considered. The simulations do not include the effects of pest and disease infestations and exposure to other factors affecting yield variability such as economic exposures. Additionally, the effects of carbon fertilization are simulated under rainfed conditions, whereas different environmental

conditions and agricultural management practices such as irrigation may influence the crop response to elevated CO₂ concentration. Except for planting date, farming management and technology (i.e., cultivar, row and spacing, and planting density) employed for DSSAT simulations were held constant for the historical and future periods. This allows the consequences of climate change on crop production to be isolated, but is unrealistic in that management and technology will continue to evolve in the future with large impacts on crop production.

A prototype interdisciplinary model that integrates simulated yields obtained from DSSAT simulations with economic determinants was also developed to overcome some of the limitations of the DSSAT simulations. This model was purposed to explore the contribution of economic determinants (i.e., costs of pesticides (chemicals), machinery, labor and fertilizer) to corn yield variability in the UGLR. The model was developed using an asymmetric production function that distinguishes two yield types, namely: attainable and actual yield. The attainable yield was obtained from DSSAT simulations, whereas actual yield was acquired from reported observed yields. The interdisciplinary model was shown to improve the utilization of the DSSAT (i.e., CERES-Maize) simulations on a regional scale and offers an approach to evaluate not only the potential impacts of climate exposures but also economic stresses on crop production. Although, the interdisciplinary model was developed only for corn yield in the UGLR, the procedures can be applied to other crops and regions.

Overall, this study suggests that more favorable growing conditions will increase corn and soybean yields in the northern UGLR especially under elevated CO₂ concentrations. The positive impacts of higher CO₂ levels will also counteract, or at least minimize, potential small

reductions in crop yields projected for the southern UGLR. Given that the United States is one of the major players in world grain markets, potential changes in corn and soybean production across all parts of the United States, including the UGLR, will significantly influence future world food supply. Indeed, additional grain production from high latitude locations such as the northern UGLR can help offset the potential adverse impacts of climate change on crop production in low latitude regions. Hopefully, this dissertation will stimulate further research that applies or extends the methods used here in order to devise plausible adaptation strategies that can minimize the risks and maximize the benefits of climate change.

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