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Impacts of Past and Future Changes in Climate and Atmospheric CO_2 on Wisconsin Agriculture

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Executive Summary

Background

Both farmers and agricultural policy-makers need information about how climate change will affect agriculture. For growers and agri-business to respond to market and policy incentives on energy crops, they will need to understand the long-term viability of their investments in the face of shifting climate conditions. The programs of state and federal agriculture and energy agencies will be more efficient and effective if we know what kind and how much biomass a given region can produce under average and extreme conditions in the future.

The grand challenge confronting agriculture is to better understand how these cropping systems and farmers have responded to changes in the climate system, and whether future climate change and increasing atmospheric CO_2 may make agro-ecosystems more vulnerable to failure. Climate change and increased variability pose a real threat to the stability of agro-ecosystems in the long term, jeopardizing food and economic security. While many studies have demonstrated the sensitivity of cropping systems to climate, no consensus has yet emerged regarding the specific mechanisms responsible for causing such changes, or how these play out in specific regions. This makes it virtually impossible to implement local policy to protect agricultural lands. Our studied focused on a single important question: ***How has previous climate change and variability impacted corn and soybean production across Wisconsin, and how might future atmospheric changes challenge farmers?***

Research Objectives

To address our key research question, we focus on three main objectives geared towards studying the connection of Wisconsin climate with agriculture: 1) Develop a multi-decadal, high-resolution gridded (8 km) daily record of maximum and minimum temperature and precipitation observations, and annual crop yields (corn and soybeans) across Wisconsin for the 1950 to 2006 period; 2) quantify the actual trends in climate and quantify statistical relationships between seasonal weather indices and corn and soybean yields for 1950-2006 to determine how climate change and weather variability have contributed to trends and variability in U.S. Department of Agriculture (USDA) yield data; 3) use statistical modeling in conjunction with results from (2) and Global Circulation Model (GCM) scenarios of future climate change through the year 2100 to delineate how crop yields may respond to atmospheric changes.

Methods

We used a combination of newly gridded climate data across Wisconsin, USDA county level corn and soybean yield data, and statistical modeling tools to study the relationships between monthly average maximum and minimum temperatures and precipitation during the period of 1950-2006. Statistical relationships for this period were then used in combination with GCM output of future climate across Wisconsin to better understand how global warming through the year 2100 may impact crop productivity at the district level. Here, we summarize the work performed as part of each segment of our project:

1. Development of multi-decadal, high-resolution gridded daily climate dataset for Wisconsin

A multi-decadal climatic data set was developed for 57 years (1950 – 2006) consisting of daily and monthly precipitation (P_{Total}), maximum temperature (T_{max}), and minimum temperature (T_{min}) across Wisconsin using observations from ~176 weather observation stations. The data set was constructed at 8 km (5.0’) latitude-longitude resolution using an automated Inverse Distance Weighting (IDW) interpolation scheme. We performed a rigorous test of the predictive accuracy of the IDW gridded surfaces using 104 stations withheld in the production of the climate grids in a post-gridding validation step. The mean bias errors were reasonable, ranging from -0.75 to 0.96 °C for temperature and -0.04 to 0.08 mm for precipitation, on average, across all climate divisions. Our results suggest a high degree of explained variation for daily temperature ($R^2 \geq 0.97$) and a moderate degree for daily precipitation ($R^2 = 0.66$), whereby the realism improves considerably for monthly precipitation accumulation totals (R^2=0.87). We also observed a small seasonal variation in accuracy of the climate grids, with decreasing predictive capability as precipitation totals increased during the wetter summer months, when more precipitation originates from convective forcing. The grids show clear and coherent spatial patterns in temperature and precipitation that are to be expected for this region. For example, latitudinal gradients in temperature and precipitation are observed across the state, with decreasing temperature towards the north and increasing accumulation of precipitation toward the Northwest in the summer.

2. Examining the connections between climate variables and crop yields across Wisconsin

An important area of agronomic research is the study of connections between crop productivity and climate so that new crops, hybrids, and management strategies can either combat any negative impacts of future climate change, or take full advantage of new, favorable climate regimes. In Wisconsin, because an ecological *tension zone* dissects the main corn and soybean-growing region, agro-ecosystems in northeastern counties may respond differently to climate changes comparatively to southwestern counties. Therefore, a spatially explicit study is warranted to better understand how previous climate variability has impacted crop productivity. To address this need, we studied corn and soybean yields in relation to climate using county level USDA-NASS data and our gridded 8-km daily climate dataset from 1950 to 2006. The daily climate dataset was aggregated to the county level to match USDA county yield information. Maximum (*tmax*), minimum (*tmin*), and average (*tavg*) temperature and total precipitation (*prcp*) were determined for each Wisconsin county (n=72) at daily and monthly temporal scales for the entire period.

In order to study the response of each crop to climate variability in each county, we used regression models based on monthly maximum temperature, minimum temperature, and precipitation as predictor variables. We first studied independent regression relationships between percent yield anomalies and climatic variables for each crop in every county. We chose to assess the relationships for months spanning March through October, which encompasses the general growing period length. We used a second order polynomial regression given that temperature and precipitation can have a non-monotonic effect on yields each year.

3. Quantifying the impact of recent climate change on corn and soybean yield trends

We focused on the last 31 years (1976-2006) of the data record and calculated monthly climate and corn and soybean yield trends for each county. The beginning year of 1976 was chosen to coincide with the initiation of the most recent period of sustained warming in the 20th century, which followed a period of cooler temperatures from the 1950s through the early 1970s. We calculated trends for (1) county corn and soybean yields (Mg ha^{-1} yr^{-1}) and the (2) county average monthly *tmax*, *tmin*, *and tavg* temperatures (ºC yr^{-1}) and *prcp* (mm yr^{-1}) for each month of the year using linear regression analysis and the JMP (v.5.01) statistical software package (SAS, Cary NC). We determined that 61 counties in Wisconsin had continuous corn and soybean yield records for 1976-2006, and computed a total of 2928 climate variable regressions (12 months x 4 variables x 61 counties) and 128 total crop yield regressions as a first step. We also computed multiple month average climate values for *two* and *three* consecutive month periods (e.g., Mar.-Apr., Jun.-Aug., Aug.-Sep., etc.), allowing for additional predictor variables to be tested as part of the regression analysis.

In order to study the relationship between crop yield trends and climate trends across Wisconsin, we developed multiple regression models using the monthly, two-month, and seasonal (i.e. three-month) composite *tmax*, *tmin*, *tavg*, and *prcp* values as predictor variables and corn and soybean yield trends as the response variables. To do so, we first studied the independent regression relationships between all climate variable trends and yield trends using all 61 counties as replicates. We selected the most important predictor variables based on their coefficient of determination (R^2) values. In general, all predictor variables that were ranked high (based on R^2 values) had a significant relationship with corn and soybean yield trends ($P < 0.001$).

4. Assessing potential impacts of future climate change and increased atmospheric CO_2 on Wisconsin corn and soybean yields

We used a meta-analysis and results from recent field experiments in Illinois and other locations in the U.S. Midwest to investigate how increasing atmospheric CO_2 may impact corn and soybean yields in Wisconsin. We then coupled output from two Global Circulation Models (GCMs) with our statistical analyses of how corn and soybean yields have been previously affected by climate variability across Wisconsin to numerically model how future changes in climate may impact agricultural productivity through the year 2100. The approach calculates what the percent yield deviation would be compared to 10-year average yields during the 1997-2006 time period. Results were developed for each of Wisconsin's nine climate districts to better understand whether some regions will be more or less impacted by future changes in climate.

Key Results

Climate dataset accuracy

We performed a rigorous test of the predictive accuracy of the inverse distance weighting gridded climate data surfaces using 104 stations withheld in the production of the climate grids in a post-gridding validation step. The mean bias errors appear reasonable, ranging from -0.75 to 0.96 °C for temperature and -0.04 to 0.08 mm for precipitation, on average, across all climate divisions. Our results suggest a high degree of explained variation for daily temperature ($R^2 \geq 0.97$) and a moderate degree for daily precipitation ($R^2 = 0.66$), whereby the realism improves considerably for monthly precipitation accumulation totals (R^2=0.87). We also observed a small seasonal variation in accuracy of the climate grids, with decreasing predictive capability as precipitation totals increased during the wetter summer months, when more precipitation originates from convective forcing. The grids show clear and coherent spatial patterns in temperature and precipitation that are to be expected for this region. For example, latitudinal gradients in temperature and precipitation are observed across the state, with decreasing temperature towards the north and increasing accumulation of precipitation toward the Northwest in the summer.

Wisconsin Climate trends

As part of our work, we calculated trends in climate variables across the state of Wisconsin from 1950-2006 to quantify recent climate change. In summary, annual average nighttime low temperatures have increased by 0.6 to 2.2ºC, whereas the annual average daytime high temperatures have warmed by 0.3 to 0.6ºC. Annual average precipitation has increased by 50-100 mm in the central and southern portions of the state, while precipitation across the far northern portion of the state appears to have declined by 20-60 mm since 1950, with the most pronounced decrease occurring during summer. On a seasonal basis, warming temperatures are more pronounced during winter and springtime, and nighttime temperatures are warming faster than daytime high temperatures. Some cooling trends in daytime high temperatures were observed during late summer and fall, particularly in the northeast and far southwest portions of the state. We calculated that the length of the growing season has increased by 5 to 20 days, with the greatest change in the central and northern part of Wisconsin. The annual number of days each year with low temperatures less than 0ºF has diminished substantially, while the number of days each year with highs greater than 90ºF has remained relatively constant, which is in contrast to what has been projected by climate models.

Climate effects on Wisconsin corn and soybean yields

Across southwestern regions, corn yield variability was most influenced (ranked by R^2 values) by July maximum temperatures and July precipitation whereas across the northeast, daily high temperatures in September impacted corn yield variability the most. In contrast, soybeans were most affected by precipitation in July and August over the west central and southeast, and by minimum daytime temperatures during May for northeastern counties close to Lake Michigan. Small increases in average high temperatures during July and August (e.g., 2 – 4ºC), which are on the same order of magnitude that is projected under future warming scenarios with climate models, were correlated with annual yields that were 10 to 30% lower than the expected, average values. Surprisingly, positive summertime precipitation anomalies of +50-100% translated into yield increases of only 3% to 11%. Overall, crop yields were favored by cooler than average daytime high temperatures in late summer, and above normal temperatures in September.

The IPCC (2007) reported that a mean local temperature increase of 1-2ºC in the mid- to high-latitudes where agricultural adaptation took place could boost corn yields by 10-15% above the baseline. A 2-3ºC increase in mid- to high-latitudes coupled with adaptation could still allow crop yields to increase above baseline values, but a 3-5ºC increase would mean yields would fall to the approximate baseline value, and would decrease by 5-20% without some type of adaptive strategy. Our composite results support these generalizations, as an increase of 2ºC in the maximum monthly average temperatures in July and August translated into yield losses of 6% for corn and 2-4% for soybean. A warming magnitude of 4ºC in monthly average maximum temperatures in July and August across Wisconsin could lead to corn and soybean yield losses of 22-28% and 13-24%, respectively, if adaptive measures do not occur.

Impacts of recent climate change on Wisconsin corn and soybean yield trends

Corn and soybean yield trends across Wisconsin have been favored by cooling and increased precipitation during the summer growing season. Trends in precipitation and temperature during the growing season from 1976-2006 explained 40% and 35% of county corn and soybean yield trends, respectively. Using county level yield information combined with climate data, we determined that both corn and soybean yield trends were supported by cooler and wetter conditions during the summer, whereby increases in precipitation have counteracted negative impacts of recent warming on crop yield trends. Our results suggest that for each additional degree (ºC) of future warming, corn and soybean yields could potentially decrease by 13% and 16%, respectively, whereas modest increases in precipitation (i.e. 50 mm) during the summer could help boost yields by between 5-10%, counteracting the negative effects of increased temperature. While northern U.S. Corn Belt regions such as Wisconsin may benefit from climate and management changes that lengthen the crop-growing period in spring and autumn, they are not immune to decreased productivity due to warming during meteorological summer.

Potential impacts of future climate changes and increased atmospheric CO_2 on Wisconsin corn and soybean yields

New experimental data suggests that C_4 photosynthesis (corn) is already saturated at the current levels of atmospheric CO_2, and thereby any more increases in CO_2 will not be effective at boosting productivity in the future. In one key study by Leakey et al. (2006) performed in Illinois, they found that elevated CO_2 (550 ppm) did not stimulate an increase in photosynthesis or yield compared to current levels. In the case of soybeans, it appears that increases in yield could still occur as CO_2 increases in the atmosphere, but the projected increase is approximately 50% less than the original studies that were performed using enclosures or chambers. It is suggested that across Wisconsin, soybean yields may be increased by approximately 13-15% as CO_2 levels climb towards 550 ppm by 2050.

The first result that we saw when looking at crop yield responses in the future is that there are very large discrepancies in the future projections between the two sets of climate model runs, signaling that there are significant differences in the climate output between the two scenarios we used. In general, the largest changes in corn yields are expected to occur in the southern part of the state (climate districts 7-9), and towards the latter half of the 21st century. Those deviations, when normalized according to current average yields, suggest that 30-60% corn yield losses (e.g., ~40-80 bu ac^{-1}) are possible in the latter half of the 21st century attributed to climate change. Across the northern districts, a warmer climate during the growing season may actually favor increases in corn yields by up to 10% according to the CCC climate model (e.g., climate district 2), but those results were generally not replicated when using HAD climate model output to drive the simulations.

In general, the largest changes in soybean yields are expected to occur in the southern part of the state in climate districts 7 and 8, after about 2060. Those deviations, when normalized according to current average yields, suggest that 30-60% soybean yield losses (e.g., ~15-30 bu ac^{-1}) are possible in the latter half of the 21st century attributed to climate changes. Across the northern and central districts – along with climate district 9 – the impacts of climate change on soybean yields are mixed. For example, the results using the CCC climate model output suggest that soybean yields will remain around +/- 10% of the current yield values through the end of the century, while the HAD model climate output causes soybean yields to decrease by 30-60% during the middle part of the 21st century, only to rebound in the late stages of this century.

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Section 1. Background

Both farmers and agricultural policy-makers need information about how climate change will affect agriculture. For growers and agri-business to respond to market and policy incentives on energy crops, they will need to understand the long-term viability of their investments in the face of shifting climate conditions. The programs of state and federal agriculture and energy agencies will be more efficient and effective if we know what kind and how much biomass a given region can produce under average and extreme conditions in the future.

The grand challenge confronting agriculture is to better understand how these cropping systems and farmers have responded to changes in the climate system, and whether future climate change and increasing atmospheric CO_2 may make agro-ecosystems more vulnerable to failure. Climate change and increased variability pose a real threat to the stability of agro-ecosystems in the long term, jeopardizing food and economic security. While many studies have demonstrated the sensitivity of cropping systems to climate, no consensus has yet emerged regarding the specific mechanisms responsible for causing such changes, or how these play out in specific regions. This makes it virtually impossible to implement local policy to protect agricultural lands.

Wisconsin is considered one of the nation's leading and most diverse agricultural producers, generating approximately $51 billion dollars in economic activity while relying on 44% of the total land area in the state. The combination of a suitable climate and fertile soils allow farming to be one of the mainstays of the Wisconsin economy, and with a new focus on producing renewable energy crops, additional value will be placed on the agricultural land base. Consider the following (taken directly from the Wisconsin Working Lands Initiative Report):

- Agriculture is responsible for a direct economic impact of $22.3 billion annually, which tops forestry ($22.1 billion) and tourism ($11.9 billion)
- Agriculture provides a diversity of ecosystem goods and services that enhance the economy and improve the quality of life
- Agriculture supports growth of a bioeconomy through growing biomass that can be used for fuel (e.g., ethanol) and other products, thereby decreasing our dependence on fossil fuels
- Protecting agriculture provides security for the future: production of food and fiber for humans and animals of the region if transportation systems cannot deliver a sustained supply from abroad

However, the reliance of producers on the climate system makes them particularly vulnerable to global warming, timely precipitation, and rising atmospheric CO_2. Plant available moisture during the growing season continues to be the most substantial influence on yields of most common crops in Wisconsin. To the extent that climate change increases the likelihood of periods of drought, it will increase risks associated with crop production. Changing climate and atmospheric CO_2 have great potential to alter soil moisture availability, plant physiology, and phenological development, but climate change alone can also impact farmer behavior by influencing planting dates, hybrid selection, or even the planted crop type.

The overall goals of this project are to provide growers, state agencies, policy makers, the energy industry, NGOs, and other researchers a quantification of (1) how previous changes in climate have occurred spatially across Wisconsin, (2) how previous agricultural production may have been influenced by these changes in mean climate and weather variability, and (3) a better understanding of how future changes in climate and atmospheric CO_2 may continue to perturb agricultural systems, either directly through physiological functioning, altered rates of phenological development, or by causing the need for adaptive management by producers (e.g., planting and harvest dates, hybrid and crop type selections). Future climate change may translate into a need for better land-use planning to help maintain high levels of agricultural production and other services derived from the Wisconsin landscape. While producers may be able to combat some of the effects of global warming through adaptive measures, there is great uncertainty as to whether these can combat all of the impacts of global warming, precipitation variability, and increased atmospheric CO_2 that may induce additional stress to these ecosystems.

The work here will help support a larger effort being undertaken by the Wisconsin Department of Agriculture, Trade, and Consumer Protection (DATCP), which recently completed work on the Wisconsin Working Lands Initiative and the Governor's Consortium on the BioBased Industry (see attached letter of support from DATCP). Our efforts here will help support more strategic land-use planning so areas that are particularly suited for particular crop types can be highlighted and preserved in future land-use decision making.

Acknowledgements

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Section 2. Development of a multi-decadal, high-resolution gridded daily climate dataset for Wisconsin

Introduction

An increasingly prognostic understanding of the key terrestrial-atmospheric feedback mechanisms has been gained through the development and proliferation of ecosystem process models, which utilize climatic inputs to drive plant physiological processes (Churkina and Running, 1998; Kucharik et al., 2000; Thornton et al., 2002; Turner et al., 2006). With this increased processed-based understanding of biospheric responses to climate change and variability, there is a rapidly rising demand for quality, high-resolution gridded climatological datasets that provide detailed information on the variability of temperature and precipitation at regional scales. These data enable the spatially explicit assessment of human activities on regional environments and ecosystem services, which is important for local policy decisions and natural resource management (e.g. Cooter et al., 2000).

In addition, such data allow for basic climatological research and numerous other applications, such validation of climate models (Widmann and Bretherton, 2000), monitoring or detecting and assessing potential impacts of regional climate changes (Zhang et al., 2000; Lobell et al., 2006), as well as risk assessment (New, 2002; Kaplan and New, 2006). However, the availability of high-resolution meteorological data has been problematic, mainly due to the difficulties of extrapolation of data from sparse observation networks to a regular grid over very broad regions and often complex terrain. Some existing datasets (e.g. Thornton et al., 1997; New et al., 2002; Kittel et al., 2004; McKenney et al., 2006) may not be adequate for a variety of regional applications, such as crop monitoring, risk and climate change assessment due to the spatial scale, time-step (i.e. monthly, annuals, or normals) or the use of stochastic methods for daily weather generation (e.g. Kittel et al, 2004). Furthermore, the temporal extent of high-resolution meteorological data may not be sufficient for more contemporary analyses (e.g. Thornton et al., 1997).

Here we describe the methodology used to generate the high-resolution daily and monthly multi-variable (i.e. Temperature and Precipitation) historical climate grids for the period 1950-2006, covering the state of Wisconsin. We then present a detailed accuracy assessment of the spatio-temporal patterns of the climate grids using stations withheld from the interpolation process. A summary of the potential uses and limitations of the data are then presented.

Data and methodology

Study region

The study region for this analysis is Wisconsin or an area extending from about -86.8° to -92.9° W and 42.5° to 47.1° N (Figure 1.). While the focus of this research was mapping climate observations for Wisconsin, we used daily station observations from the surrounding states of Illinois, Iowa, Michigan and Minnesota within 70km of the Wisconsin state boundary to mitigate edge effects during interpolation. Thus the entire interpolated domain was from about 86.8° to -93.3° W and 42.1° to 47.1° N.

The physiography of Wisconsin is characterized by generally minor topographic variations, with gently rolling landscapes. Elevation varies from a minimum along the shore of Lake Michigan to a peak of 595 meters above sea-level in Price County. Apart from the driftless area, Wisconsin is mostly covered by glacial drift (about 80%) and northern portions are underlain by pre-Cambrian bedrock (Dopp, 1913; Curtis, 1959). Climate is humid-continental (Moran and Hopkins, 2002) with cold winters (mean January temperature from 1950-2006 was -9.5 °C) and mild to humid summers (mean July temperature from 1950-2006 was 21.1 °C), moderated by the Great Lakes. Total annual precipitation averaged 808 mm (± 165 mm) across Wisconsin. A few medium to large population centers are found within Wisconsin (e.g. cities of Milwaukee, Madison, Greenbay) while the remaining land is comprised of smaller cities, towns and tribal lands with farmlands, national and state forests comprising ~45% and ~45.3% of the land area, respectively.

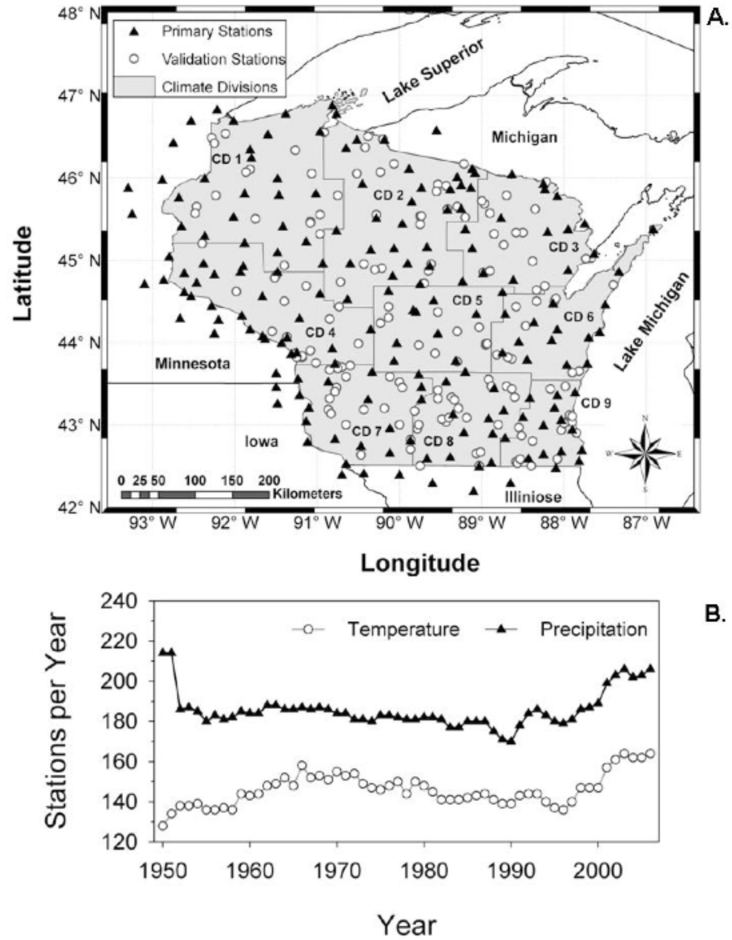


Figure 1. *(a) Location of observation stations used, and (b) changes in number of available stations each year.*

Climate data

Time-series of daily climate station observations of maximum temperature (T_{max}), minimum temperature (T_{min}) and total precipitation (P_{Total}) from the cooperative observer (COOP) network for the years 1950-2006 were obtained directly from the National Climatic Data Center (NCDC) website (http://www.ncdc.noaa.gov/oa/ncdc.html/). The longest running stations go back to 1895 although many do not have continuously observed data. The COOP stations used were distributed relatively evenly across Wisconsin (Figure 1a) with a slightly lower station density towards the north. Stations that did not have at least 53 years of data record (1950-2006) were removed to avoid synthetic bias in long term trend analysis through the addition of stations during interpolation. The retained Wisconsin stations amounted to approximately 46% (144/315) of the potential station data. The remaining independent station observations or validation stations failing to satisfy the long-term temporal restriction were later used to generate a validation data set to examine the predictive accuracy of climate surfaces (See validation section). Some stations in the COOP network only provided precipitation and thus there were more daily precipitation observations then temperature in each climate division. The final data record was comprised of a maximum of 133 T_{max} and T_{min} stations and 176 P_{Total} COOP observation stations within Wisconsin and neighboring states (Figure 1). The number of station-days per climate element also varied slightly between the variables. Station elevation ranged from approximately 179 to 541m. The average first-order (i.e. first nearest neighbor) distance between all primary observation stations was 21.2 km (from 3.2 to 65.4 km) and 25.0 km (from 4.3 to 65.4 km) for precipitation and temperature stations, respectively.

Preprocessing and quality control

Several data quality and consistency checks were performed on the primary station list (i.e. those with ≥ 53 years of generally contiguous data) prior to further data processing steps. The primary station list was filtered separately for temperature and precipitation observations. First, the raw daily T_{max}, T_{min}, and P_{Total} were extracted from the primary station observation data set and checked for quality. Values of precipitation less than zero or flagged as erroneous values were replaced with a missing data flag value. In addition, values of $T_{min} > T_{max}$, values of T_{max} or T_{min} less than -50° C or greater than 55° C (i.e. outside historical bounds) were also replaced with the flag value (i.e. -9999). These steps were intended to screen out implausible values due to observer or data entry error, as well as misinterpretation of written data fields.

Finally, we assed the homogeneity of each primary station prior to further processing steps. We evaluated station history metadata to account for errors and discontinuities due to station moves throughout the record (Easterling et al., 1996; Peterson et al., 1998). If a station was found to change geographical position and this change was not large (< 10 km) we retained the station in the data set and corrected the coordinates to reflect the most current position; the occurrence of known station moves was less than 2% (3 out of 176). Thus all stations in the data set maintained one location for the entire record. In addition, the moves we could account for occurred in the early part of the record (<1960) and thus should not greatly influence trends, such as moves from urban to rural stations (Hansen et al., 2001).

Filling missing data

Estimates for missing data were generated with the multiple imputation (MI) procedure in the statistical program SAS (SAS Institute Inc., 2002). The MI procedure is a Monte Carlo technique in which missing values are replaced or "imputed" with several simulated values generated by stochastic modeling of the observed data variability (Rubin, 1987; Schafer, 1997; Levy, 1999). The imputed data sets are complete with observed non-missing data remaining unchanged while the original missing observations are replaced with new estimated values. This procedure produces data that can then be used with normal parametric statistics (Levy, 1999). MI has been utilized in a range of disciplines such as medical research (Barnard and Meng, 1999), public and occupational health (Zhou et al., 2001; Emenius et al., 2003), and more recently for environmental and global change sciences (Hui et al., 2004; Hanson et al., 2007). More detail on the multiple imputation technique for estimation of missing data can be found in Rubin, (1987) and Schafer, (1997), as well as Hui et al., (2004) for environmental monitoring and modeling purposes. There were approximately < 1% and < 1.5% missing or flagged observations for temperature and precipitation, respectively. The MI procedure was only used for brief periods of missing data (< 1 month) and imputed values were held within historical bounds. We used the median for each missing observation from the distribution of plausible values created using 1000 imputations. A final set of consistency checks were run on the filled data sets to ensure that the estimates did not violate obvious constraints associated with recording maximum and minimum temperatures, such as those described in the previous section.

Gridding Interpolation

Following all the preprocessing and data gap filling steps, the interpolation of daily climate data, from the relatively irregularly spaced station locations to the nodes of a regularly spaced grid, was accomplished using the Inverse Distance Weighting (IDW) spatial interpolation algorithm. The IDW procedure determines unknown cell values using a linear-weighted combination of included sample points within a specific neighborhood (Nalder and Wein, 1998; Bolstad, 2002); in this analysis we used the 12 nearest stations, which is common (Jarvis and Stuart, 2001b). IDW interpolation explicitly implements the assumption of spatial autocorrelation, or objects that are closer together are more similar in character than those that are farther apart. Furthermore, IDW is an exact interpolator, whereby the interpolated surface passes through all points whose values are known (i.e. IDW honors the observed data points) and as such, the maximum and minimum values in each interpolated surface can only occur at the observed

locations. Given this criterion, exact interpolation techniques tend to dampen extreme values at un-sampled locations, as is the case with IDW, but preserve the natural variability (i.e. roughness) in the data, which is important for preserving the spatial patterns in the data at a regional scale.
After an initial analysis of different spatial interpolation techniques (e.g. kriging, and smoothing splines) and due to the large, well dispersed station density throughout the data record, we determined IDW to be adequate to characterize the daily spatial patterns of both temperature and precipitation for this relatively low topographic complexity region. The final IDW grids were produced at 5' (8-km) latitude-longitude resolution using an automated procedure programmed using the object-oriented language ArcObjects in the Environmental Sciences Research Institute (ESRI) geographical information system software ArcGIS (version 9.2).

Once the interpolator (IDW) was chosen, we analyzed a subset of data to determine the optimum power parameter (n) to be use with the automated gridding of both temperature and precipitation; we used data covering all four of Wisconsin's meteorological seasons (i.e. winter, spring, summer, fall). The criteria for choosing the optimal n for the variables was a value that best minimized the mean bias and absolute errors (see validation section), plot as a function of the power value (data not shown), over an entire year; the mean error was given precedence if there was a disparity between this and the absolute errors. We chose a value of n equal to 1.1 for T_{max} and T_{min} and 2 for precipitation (P_{Total}) to preserve the broad patterns in temperature and local variation (i.e. spatial detail) in precipitation events.

Methodology of product validation

To evaluate the spatial coherence and overall accuracy of the interpolated climate surfaces, we used actual T_{max}, T_{min} and P_{Total} observations from the previously withheld stations to perform an independent validation. There were 104 withheld or validation stations available with sufficient observational record to be used in the validation, for the 1950 to 2006 period. Several stations had variable records (e.g. 5-49 years), but nonetheless provide an extremely useful test of our output climate grids; stations varied by climate division with a minimum of 9 to a maximum of 21. Furthermore, the number of stations and distribution (Figure 1) is comparable to or better than other studies using withheld stations for validation (e.g. Price et al., 2000; Vicente-Serrano et al., 2003). The geographic locations for each station was used to extract a predicted value from each grid cell centroid for each surface (T_{max}, T_{min} and P_{Total}) and organized into a consistent time-series for comparison with the observed values at daily and monthly time-steps using the Starspan utility (Rueda et al., 2005). The performance of the IDW interpolated surfaces were then evaluated with two measures of efficiency with the mean error (ME) and mean absolute error (MAE).

The mean error provides an assessment of the trend in residuals or bias, either producing generally higher (i.e. over-prediction) or lower (i.e. under-prediction) values with respect to observations. The MAE is an absolute measure of the deviation of the predicted mean from the observed values at each validation station, ignoring its sign and thereby providing an indicator of the overall performance of the interpolator; high MAE's indicate poor prediction performance, while low MAE's suggest high confidence in the gridded values, such that the interpolated values reproduce the observations well (Daly, 2006; Willmott and Matsuura, 2006). We avoid using the root mean square error (RMSE) as this statistic generally inflates, often non-monotonically, the mean errors and thus provides an overly ambiguous measure of predicted surface accuracy, especially when error variance is large (Willmott and Matsuura, 2005; Willmott and Matsuura, 2006). We instead provide the standard deviation of signed errors (i.e. ME's) to evaluate the spread in the distribution of errors. In addition, we provide a subjective but nonetheless important analysis of the grid spatial representation with respect to known weather patterns using empirical knowledge of the climate in Wisconsin for evaluation (Daly et al., 2002). The evaluation of the climate surfaces allowed the assessment of (1) the realism and reasonableness of the spatial interpolated values and (2) the accuracy of the gridded values for unknown (i.e. validation) locations as the interpolation is essentially a prediction of values at locations for which physical data does not exist. Unless notes otherwise, all statistical tests were considered significant at $\alpha = 0.05$ level.

Results

Observed climate patterns

The observed average annual minimum (T_{min}) and maximum (T_{max}) air temperatures were 1.05 and 12.61 °C for Wisconsin, respectively. The values of T_{min} and T_{max} ranged from, respectively, a minimum of -0.87 °C in CD 2 to a maximum of 2.99 °C in CD 3, and a minimum of 11.11 °C to a maximum of 14.04 °C in CD 9. Both the average T_{min} and T_{max} steadily increased from the Northwest to the Southeast, with CD's 1 and 2 having the coolest and CD's 8 and 9 having the warmest observed temperatures. For CD 6, Lake Michigan decreases the average annual maximum temperature, averaging 1.4 °C cooler than surrounding CD's while T_{min} is 1.3 °C warmer than other CD's within the same latitudinal band (i.e. CD's 4 & 5). Mean annual air temperatures (MATs) ranged from a minimum of 5.12 °C to a maximum of 8.25 °C, for climate divisions (CD's) 2 and 9, respectively, and averaged 6.8 °C for the entire state.

Annual precipitation (P_{Total}) was 808 mm/yr^{-1} for Wisconsin, with the mean accumulation totaling 6.72 to 7.94 mm day^{-1} on days with rain, across all CD's. Precipitation totals were generally higher in the southern-most CD's (7-9) than northern CD's. Extreme high-precipitation events were moderately similar across the state with generally higher values in the South Central to South East climate divisions (CD's 5-9). The distribution of precipitation events was dominated by days with no measurable precipitation (i.e. 0 mm), followed by

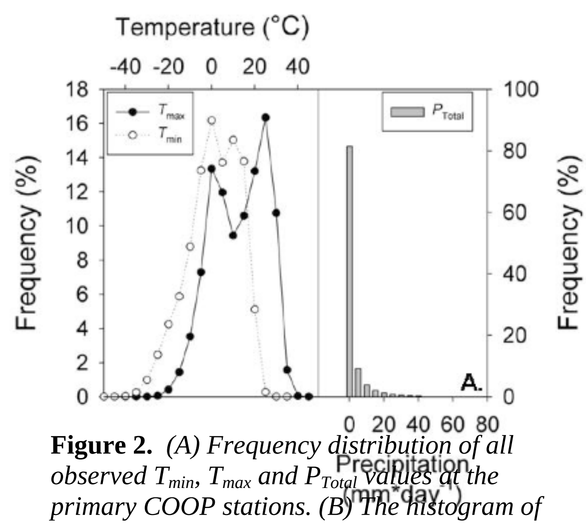
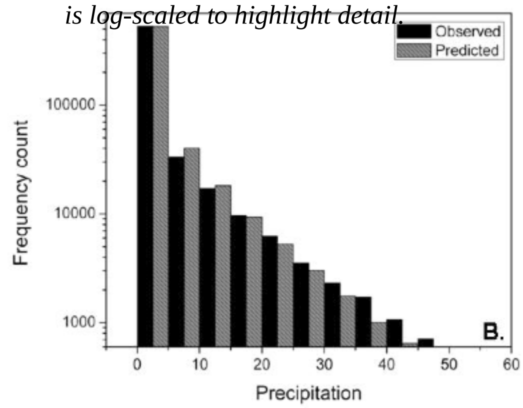


Figure 2. *(A) Frequency distribution of all observed T_{min}, T_{max} and P_{Total} values at the primary COOP stations. (B) The histogram of observed and predicted P_{Total} values; vertical axis is log-scaled to highlight detail.*



precipitation events ≤ 5mm day^{-1} comprising 9% of the observed record (Figure 2). The statewide observed monthly precipitation follows a simple seasonal cycle and is highest in the summer (June – August) and at a minimum in the winter months (December – February). For a given month, the inter-annual variability in total precipitation can be 42% to 64% over the record (1950-2006), with a maximum and minimum annual rainfall of 972.6 mm (±137.9 mm) and 532.8 mm (± 102.3 mm) in 1951 and 1976, respectively.

Interpolation results

Seasonal aggregates of the predicted daily climate grids are shown, with P_{Total}, T_{max} and T_{min} shown as seasonal means for the current World Meteorological Office (WMO) 30 year normal's period of 1971-2000 for two meteorological seasons in the region: winter and summer (Figure 3). P_{Total} is illustrated as the mean total precipitation for the three months comprising the season. The spatial patterns in the average temperatures typically show a decreasing temperature with increasing latitude with slightly warmer and cooler temperatures near Lake Michigan in the winter and summer, respectively (Figure 3). Seasonal averages of gridded precipitation clearly show that the summer months are the wettest season in Wisconsin with higher total accumulation in the Northwest, while the winter months are the driest with the greatest accumulation located nearest the Great Lakes, and in the Southeast, due to lake effect snow accumulation. During the summer months the South Central and Southwest portions of the state are the warmest, with daytime temperatures averaging about 28 °C and nighttime temperatures (i.e. minimum temperatures) hovering between 14 to 15 °C. In addition, during the summer months, the spatial coherence of the T_{max} grids clearly shows the influence of Lake Michigan with cooler temperatures at the lake front, increasingly steadily inward (Figure 3).

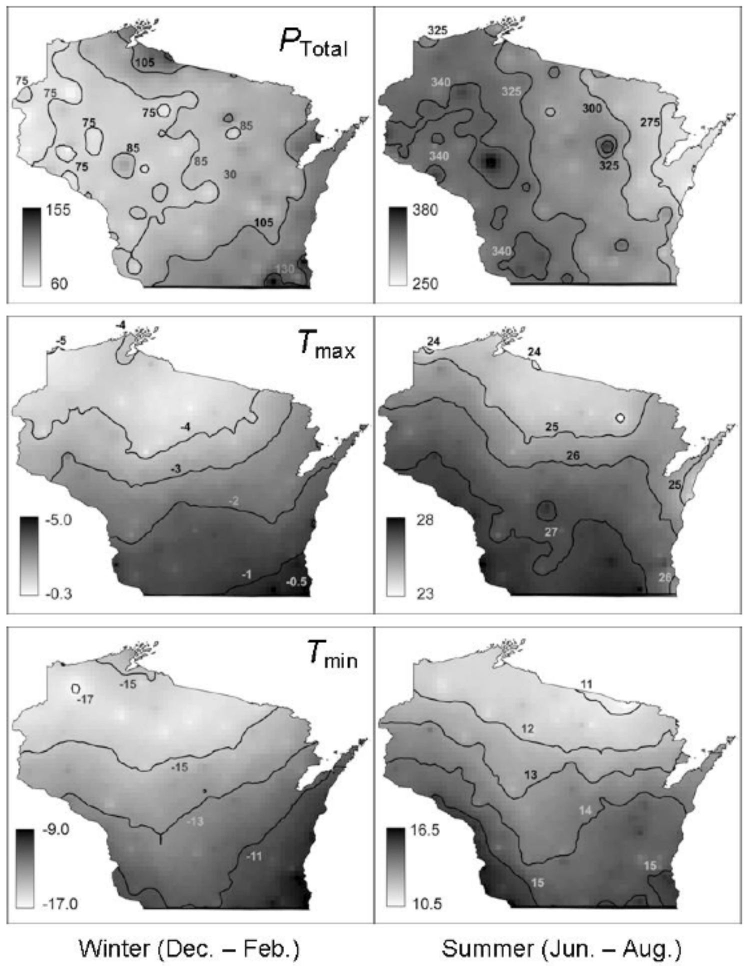


Figure 3. *Meteorological winter and summer means (WMO 1971-2000 normals) for Wisconsin derived from the gridded temperature and precipitation data sets.*

Validation of climate grids

The full available record for all primary stations used in the generation of the daily (and monthly) gridded climate surfaces, between 1950 and 2006, consist of over 2.1 million daily T_{min} and T_{max} and over

2.5 million values of precipitation. Stations in Illinois, Iowa, Michigan and Minnesota were used in the interpolation to reduce edge effects (Figure 1).

Generally, we find the mean predicted values of temperature closely mirror the observed values (Table 2); the mean annual values of T_{max} are within 3% and generally within 16% for T_{min} (averaging 11%). The ME's and MAE's for the entire state are small, ranging from 0.23 °C and 1.51°C, while -0.03 °C and 1.31 °C for T_{min} and T_{max}, respectively. The values for T_{min} and T_{max} in each climate division (CD) vary from, respectively, -0.75 to 0.96 °C and 1.05 to 1.89 °C. Excluding CD's 8 and 9, average minimum temperature bias is positive and significantly different (paired *t*-test, $p < 0.0001$) from zero (i.e. no bias), while T_{max} ME's are generally negative and significant (paired *t*-test, $p \leq 0.025$) with generally smaller standard deviation of errors relative to T_{min}. Correlation analysis for T_{min} and T_{max} illustrate the overall high agreement ($R^2 = 0.97$ for T_{min} and $R^2 = 0.98$ for T_{max}) between observed and predicted values for the majority of observed temperature range. Largely, the daily predicted T_{min} values had higher residuals (i.e. ME) and larger MAE's than T_{max} as the interpolator generally predicted T_{max} more accurately than T_{min}.

While on the whole, the errors are minimal, individual days can have comparatively large errors. Examination of the pattern in the prediction bias (i.e. ME) demonstrates that there is an underestimation of the maximum values and overestimation of minimum values by the interpolated temperature grids. There is also modest differentiation in error between CD's. For example, T_{min} bias for CD 9 is relatively flat (i.e. near zero) with a peak underestimation of ~5° C, while the remaining CD's average 10% bias for T_{min} < -30 °C; CD 7 has the largest bias (14%). Excluding CD's 1 & 7, the CD's have relatively similar error patterns for T_{max}, where the former average a 9% underestimation of high temperatures (> 35 °C). Overall however, the majority (99%) of observed T_{min} values fell between -30 to 20 °C and 98% of the values for T_{max} ranged from -20 to 30 °C (Figure 2) which comprise the range where ME's show minimal deviation from 0 (i.e. Predicted – Observed).

For precipitation, the predicted annual P_{Total} was within 2% of the observed values for each CD. Daily ME's and MAE's are small, ranging between a minimum of 0.68 mm to a maximum error magnitude of 1.71 mm for CD's 4 and 8, respectively, for P_{Total} MAE. The ME's for P_{Total} were generally about 0.1 mm or less and had generally higher standard deviations (i.e. error variances) than temperature, owing to the generally larger distribution of errors. For example, the variation in the ME's (i.e. standard deviations) was 50% larger for CD 8 than CD 4, where former receives only about 22 mm more precipitation than the later, annually.

Figure 2b presents the frequency distribution of observed and predicted P_{Total} amounts at the validation locations and shows a moderate but consistent underprediction of event frequency in the upper portion of the observed range (~25 to 60 mm day-1) while a slight overprediction of event frequency ≤ 15 mm day^{-1}. This highlights the difficulty of mapping precipitation accurately at daily time-steps due to the generally patterned nature of precipitation events (i.e. spotty across large regions), resulting in the occurrence of small amounts (generally < 2 mm) of predicted precipitation in regions where none was observed. For example, the predicted occurrence of days with no precipitation was about 14% less than that observed at the validation stations, while events < 2 mm were over-predicted by ~57%.

The correlation analysis between daily observed and predicted P_{Total} (Predicted = 0.67*Observed + 0.74, $R^2 = 0.66$, RMSE = 3.23, $p < 0.0001$) is lower, with a higher offset, than what we found for temperature, but still significantly correlated. Examining the relationship between predicted and observed monthly accumulation totals we find the correlation increased substantially indicating that the errors associated with an abundance of predicted low P_{Total} events (i.e. < 2 mm day^{-1}) does not strongly effect longer accumulation periods (i.e. monthly totals).

The daily and monthly P_{Total} residuals highlight the tendency to underestimate the accumulation totals > 12 mm day^{-1} and about 100 mm month^{-1} for the daily and monthly P_{Total} grids, respectively. To understand the affect daily biases had on the overall accuracy, we examined the mean (1950-2006) frequency of observed daily precipitation values. There were an average of 113 precipitation events per grid cell, annually, over the period of record (i.e. 1950 – 2006) and 82% of the observed total accumulation, on days with rain, was comprised of precipitation events of 10 mm or less. Within this range of daily P_{Total}, the average ME bias is ≤ -2.5 mm, thus a maximum of a 25% error. For the monthly data, the majority (86%) of monthly accumulation falls between 0 and 115 mm month^{-1}. Within this range, there is close agreement between predicted and observed values with the error averaging -4.88 mm (4%). This illustrates that the overall affect these biases have on annual totals is small and thus results in only a slight overprediction in annual totals by CD.

Seasonal patterns in error

Finally, we examined the data for seasonality in errors. Results for T_{max} show that summer months, with the lowest range in daily temperature variation have the best prediction accuracy, while spring and autumn months with greater daily range in T_{max} have the lowest prediction accuracy; CD 4 has the greatest ME's and the largest variation in monthly T_{max} with the average standard deviation equal to 12.9 °C. Additionally, MAE's for T_{max} are generally less, by C.D., relative the errors in T_{min}, which reflects the results from the regression analysis. For T_{min}, the spread in ME's is larger than that for T_{max} with CD's 3 and 9 having the largest seasonal biases; the seasonal ME was 0.23 °C. The average T_{min} ME's across Wisconsin increased slightly from May through August, while the MAE's were largest in the winter. For both T_{min} and T_{max} the winter months were more prone to extreme errors than the summer, with standard deviations of the ME's about 30% higher from December through February.

Seasonal patterns were significantly more apparent in the diagnostics of the gridded P_{Total} data. Summer months (i.e. June – August) show greater error in the average daily precipitation with a slightly positive bias, relative to the drier autumn and winter months (October – March) across the state. The MAE's for daily P_{Total} ranged from ~0.5 to 3 mm during the year; for monthly accumulation totals we found a range in MAE's from ~15 mm in the winter and spring to 25 mm in the summer (data not shown). While in absolute terms the errors are small, they do constitute a highly variable percentage of the daily precipitation totals given the seasonal winter dry and summer wet climate of Wisconsin (see Figure 2). For example, in the winter months, ME's were about 4.4% of the daily precipitation statewide, while in the wettest months the ME's average up to 35%, peaking at 36% in July across Wisconsin. The regional differences between CD's illustrate the variation in predictive accuracy and highlight the large spatial differences in total precipitation accumulation, with larger errors in CD's receiving greater accumulation (CD's 7-9). Furthermore, despite the difficulty of measuring frozen or snowfall precipitation (e.g. conversion to liquid water equivalent), the higher accumulation of precipitation during the spring and summer appears to surpass the inherent error at individual observation stations in monitoring snowfall. This is likely related to the occurrence of generally higher spatial variation in precipitation during these months due to convective processes producing relatively localized, high intensity rainfall events.

Discussion

Demand for high-resolution climate grids that provide reliable estimates over broad geographic areas at regional, continental, and global scales has increased as scientists, resource managers, and policy making rely on spatially explicit models to assess perturbations to ecosystems by anthropogenic and natural processes. The main purpose of this work was to derive a spatially coherent and temporally complete gridded climate data set for Wisconsin, an important food and fiber producing state. The minimum and maximum temperatures (T_{min}, T_{max}) and total precipitation (P_{Total}) grids were generated for the period 1950-2006 at 5' (8-km latitude-longitude) resolution. The substantial number of grids generated here (64,509 in total) from the COOP station network limited our ability to provide a thorough presentation of the output, thus visual representation of the gridded 30-year mean winter and summertime values are provided (Figure 3). This data set presents a comprehensive, mutli-decadal, spatio-temporally complete database that is useful for regional climate analysis, risk assessment, ecosystem modeling, management and planning purposes with a much higher station density and spatio-temporal resolution or data record than was feasible in previous gridded databases (Thornton et al., 1997; Kittel et al., 2004; McKenney et al., 2006).

Accuracy of climate grids

On average, validation results illustrated that the output accuracy is high and we find that the spatial patterns in temperature and precipitation are realistic (Figure 3). The correlation between observed and predicted temperatures was found to be quite good and comparable to cross-validation results from existing daily climate databases (Thornton et al., 1997). Prediction biases (i.e. ME's) for temperature were generally larger (and positive, indicating overestimation) for T_{min} than the corresponding errors for T_{max}. Similarly, the MAE's and the average variation (i.e. SD's) were higher for T_{min}. This pattern has been observed previously (Thornton et al., 1997; Bolstad et al., 1998; Stahl et al., 2006) and is likely related to the increased spatial complexity in nighttime (minimum) temperatures across the landscape. For example, the influence of thermal inversions can be greater in minimum temperature mapping (Bolstad et al., 1998; Daly et al., 2002; Daly et al., 2007) and the occurrence of cloud cover can increase the spatial variation in nighttime temperatures, resulting in larger disparity between predicted and observed values at validation stations.

We observed seasonal patterns in prediction accuracy for the temperature and precipitation grids, which was generally modest. A similar pattern in seasonality has been observed previously for areas of differing terrain, station densities, and interpolation techniques (e.g. Price et al., 2000; Gyalistras, 2003; Stahl et al., 2006). In Wisconsin, the four meteorological seasons (winter, spring, summer and fall) vary significantly in temperature and precipitation (Moran and Hopkins, 2002). Furthermore, geography plays a key role in the differences in seasonal weather. For example, CD 4 had a consistently larger seasonal bias (underestimation) in T_{max} compared to the other CD's, as well as the statewide average error, while CD 5 had the smallest MAE, which was significantly lower than the average. The region encompassing CD 4 was not glaciated and as such contains some of the most complex terrain found in Wisconsin, resulting in larger daily temperature variation (Moran and Hopkins, 2002) which may not be adequately observed in the COOP station data (e.g. valley versus ridgetop observing stations), while CD 5 is situated in the central portion of the state where topography is more gently rolling and daily temperature variation is similar between stations.

With some exception (e.g. Vicente-Serrano et al., 2003) the accurate mapping of precipitation totals is generally more difficult than corresponding maximum and minimum temperatures (Thornton et al., 1997; Daly et al., 2007), as temperature is generally a much smoother variable than precipitation, where the latter is generally more heterogeneous across broad regions. Here daily precipitation was significantly more challenging to model than temperature due to several issues. In Wisconsin, the heterogeneity of precipitation can result in a large P_{Total} gradient across the state, owing to the often highly localized precipitation events, prevailing weather, and Lake effects (Moran and Hopkins, 2002), which can be difficult to adequately predict spatially. Second, issues with the timing of daily observations (Peterson et al., 1998) can result in differences in daily totals between nearby stations which could influence our comparisons with the validation stations. In addition, the parameters used in the IDW can influence the accuracy of the climate grids (Jarvis and Stuart, 2001a). The difficulties in measuring solid precipitation (i.e. snow and ice) accurately through collection and appropriate conversion to liquid water equivalent (LWE) can influence our results, producing an underreporting of precipitation during the winter months.

Despite the issues with producing the P_{Total} grids, we found that the overall performance of the IDW grids is adequate and comparable to daily (Thornton et al., 1997; Daly et al., 2007) and monthly (Price et al., 2000; McKenney et al., 2006) gridded climate datasets. By examining a longer temporal period (e.g. monthly data) we found the accuracy and realism of the P_{Total} grids increased, suggesting the propagation of error with occurrence of abundant small precipitation events is minimal, which was also found by Thornton et al (1997). A suggested remedy for the daily P_{Total} is to use a desired threshold of minimum precipitation (e.g. <1 mm) when using the data for such things driving water balance calculations in a process model and hydrological applications (e.g. estimating runoff and levels in catchments). We also recommend the use of monthly data for the analysis of some climatological trends.

Lastly, in addition to quantitative error statistics, it is important to evaluate qualitatively, the spatial patterns and results of the temperature and precipitation mapping (Daly et al., 2002; Daly, 2006). We provide an example of the spatial patterns in the 30 year mean (1971-2000) meteorological winter and summertime T_{min}, T_{max} and P_{Total}. We find that the resulting IDW climate grids adhere to the expected latitudinal, longitudinal, and seasonal trends in temperature and precipitation across the region. Although we did not utilize a more complex interpolation scheme that included a covariate (e.g. elevation, slope) or mathematical correction factor for areas nearest (< 100 km) to the Great Lakes (i.e. Superior and Michigan), the patterns seem reasonable and corroborate more detailed analyses of Wisconsin's seasonal weather patterns (Moran and Hopkins, 2002). At this scale, the high station density seems to adequately account for proximity effects and topography, which generally requires additional modeling and assumptions when station density is sparse (Daly et al., 2002). Qualitatively, precipitation grids correctly generate the winter dry and summer wet seasonal pattern of P_{Total}, the west to east gradient of precipitation that is common for the winter and summer months, and the pattern of high snowfall accumulation in the Lake Superior snowbelt in the far north (Moran and Hopkins, 2002).

Input data issues and caveats

The NCDC cooperative observer (COOP) station observations may be affected by various data quality and consistency issues, some of which can be considerable, and these issues have been outlined in depth in previously (Peterson et al., 1998; Hansen et al., 2001). These issues range from, among other things, long-term observation inhomogeneities related to urbanization and land-use biases, changing observing practices (i.e. time of observation biases), issues related to error checking and instrumentation (Peterson et al., 1998). For example, station moves from rural to urban locations can result in a sharp discontinuity in the observational trend (Hansen et al., 2001). Differences in the time-of-observation (TOB) may result in significant differences in the observed daily temperatures and precipitation between nearby stations (Karl et al., 1986; Peterson et al., 1998) while others can cause a more gradual bias, such as a change in the environment around the station through mechanisms such as urbanization.

Therefore, the accuracies of our resulting temperature and precipitation climate grids are bound by both the spatial interpolation (e.g. parameterization, algorithm) and input data quality. We attempted to minimize several key issues such as missing or ambiguous data in the original data through consistency checks and a gap filling procedure, and lessened the influence of station moves by maintaining station locations throughout the entire observational record. It can also be argued that if the objective is to obtain the best estimate of long-term change, in the absence of metadata defining all the changes to a particular station, it is better not to adjust discontinuities (Hansen et al., 2001). We did not explicitly account for differences in TOB between stations as well as increasing urbanization. Changes in instrumentation should be minimal as our database covers the years 1950-2006, which follows the broad upgrades of observational equipment (Peterson et al., 1998). Therefore the end user is cautioned of these data issues and we recommend the user consider these and the following section prior to the use of these data.

Limitations and potential uses of the data

Given the limitations inherent in any gridded climate data set such as this we provide a list of uses that should not be investigated with this dataset. Because these gridded data were generated from a spatial interpolation algorithm (i.e. IDW) a given location (i.e. grid cell) will likely contain a degree of "smoothing" of the data extremes (i.e. high and low temperatures and precipitation), particularly where there was no observed data (i.e. in the sampled locations). In the case of IDW for example, un-sampled locations will be held within the bounds of observed locations and therefore extreme events at these locations will be minimized with respect to the actual observations. Thus, the prediction of record events of T_{max}, T_{min}, or P_{Total} for a given day will not be adequately represented in the gridded data and as such should not be used for these purposes. Similarly, the use of these data for legal purposes (i.e. trials and litigations) is not recommended and those seeking information on the climate of a particular day in a specific location should always consult original station data or a climate expert. In a similar vein, large scale analysis of extreme weather for comparison with other regions should always be done with the original station observations and not with this gridded database.

Despite the aforementioned limitations, regional interpolated climatic grids of daily and monthly temperatures and precipitation are useful for various purposes. As with previous datasets for which predicted values are based on observational records (Thornton et al., 1997; Rawlins and Willmott, 2003; McKenney et al., 2006) our dataset represents historical information and variability that can be used to generate the occurrence and general trends of key events such as the last and first frosts, as well as daily statistics such as accumulated growing-degree days (AGDD). As other large climatic datasets which use stochastically simulated daily observations (e.g. Kittel et al., 2004) are appropriate for ecosystem modeling over expansive regions, this gridded dataset provides a high-resolution alternative for regional-scale analyses such as risk assessment and input to ecological process models. The methodology is sufficiently portable, in that the methods can be used to derive climate databases for other regions where a dense network of COOP stations exist, with or without increased algorithm complexity depending on the region of interest, topographic characteristics, and other key factors controlling gridded accuracy (Daly, 2006).

Concluding remarks

The societal importance of Wisconsin and other key forestry and agricultural states will continue to increase as the global population rises and an emerging market for biofuels develops in the next few decades. As we become increasingly reliant on the goods and services that are provided by our ecosystems in the Midwest, changes in mean climate and the frequency of extreme events may result in increased variability in ecosystem productivity across key forestry and agricultural regions, potentially compromising food and fiber supplies, and bioenergy feedstocks (Kucharik and Ramankutty, 2005; Scheller and Mladenoff, 2005; Lobell et al., 2006). Detailed assessments of the historical influence of climate on such things as forest productivity, water quality and changes to hydrological systems, as well as crop production and yields stands to be highly beneficial for the development of adaptive management and future planning purposes (Kucharik, 2006). In order to facilitate these types of studies, high-resolution climate datasets for management and modeling purposes are increasingly desired, and development of such datasets will help society better understand how previous climate change has impacted ecosystem functioning and could help to develop adaptive strategies to combat the undesired consequences of continued climate shifts. . We hope that our scientific colleagues, fellow resource managers, and policy makers make use of the new dataset here in their own research objectives.

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Section 3. Examining the connections between climate variables and crop yields across Wisconsin

Introduction

Given the important connection between climate, weather, and crop production, an important challenge confronting farmers is to better understand how previous climate change and interannual variability have impacted crop productivity and management decisions in a *spatial context*. With advanced knowledge of how weather fluctuations have influenced agricultural productivity, we might increase our understanding of how future climate change may affect crop yields, thereby leading to improved adaptive strategies to climate change, if deemed necessary (Howden et al., 2007).

There is a long tradition of researchers studying the connections between agricultural production and climate (Tubiello et al., 2007). The most comprehensive spatial studies of crop yield variability in relation to climate variability and change in the U.S. using observations have been performed by Huff and Neill (1982), Carlson et al. (1996), and Andresen et al. (2001) across the Midwest, Lobell and Asner (2003) across the continental U.S., and Lobell et al. (2007) in California. Huff and Neill (1982) analyzed the temporal and spatial relationships between corn yield and weather over five Midwestern states. Carlson et al. (1996) investigated Midwestern corn yield variability in relation to extremes in the Southern Oscillation. Lobell and Asner (2003) concluded that some of the observed increases in U.S. corn and soybean yields might be partially attributed to temperature trends during the 1982-1998 period, and yields were favored by cooler and wetter conditions from June through August. Other investigators such as Hu and Buyanovsky (2003) analyzed a long-term connection between climate and corn yields in Missouri, and Thompson (1988) studied crop-climate relationships in Illinois and Iowa.

Wisconsin is considered one of the nation's leading and most diverse agricultural producers, generating approximately $51.5 billion dollars in economic activity, while relying on 45% of the total land area in the state to do so (Deller, 2004). Of the total economic impact to the state due to agriculture, corn and soybean production contribute approximately 16%. In order to consistently attain high productivity, farmers in Wisconsin – like many others across the Corn Belt – rely on optimal weather conditions during the growing season (Hu and Buyanovsky, 2003). However, the climate regime across this region leads to considerable interannual weather variability, causing frequent hardships to farming related to flooding rains, pest outbreaks, drought, and heat waves. Given a significant gradient in annual average temperature and growing season length from the southwestern to northeastern portions of Wisconsin, the highest corn and soybean yields generally occur in the south and west where long-season hybrids with higher yield potential can be planted, and the lowest average yields are harvested in the north and east where short-season hybrids dominate (Carter, 1992; Lauer et al., 1999). This pattern of productivity is roughly dissected by an ecological *tension zone* across the state (Curtis, 1959), which could potentially shift with future climate change. The average growing season lasts as long as 170 days over southern and far western portions of Wisconsin, but only up to 130 to 140 days in the central and north (Moran and Hopkins, 2002). These general spatial patterns cause total growing degree-days (GDD; base 10ºC from April 1 through September 30, inclusive) to range from 1100ºC in the far northwest to near 1500ºC in the far south (Kucharik, 2008), thereby driving a wide variation in hybrid selection. While GDD fluctuations from year to year can impact yield variability, it is still hypothesized that variability in summertime precipitation is the dominant factor contributing to year-to-year fluctuations in Midwest yields from their expected values (Changnon and Hollinger, 2003).

One reason for this hypothesis is that the large majority of Midwest U.S. farmers do not irrigate corn and soybeans, so they are particularly reliant on sufficient and timely rainfall in July and August. This coincides with the period of corn pollination in mid-to-late July, and for soybeans, optimal soil moisture during the pod and seed filling period in August helps boost yields. During meteorological summer in Wisconsin, the polar front and mid-latitude jet stream have pushed further north into Canada (Moran and Hopkins, 2002), leaving farmers vulnerable to prolonged periods of dry weather and sometimes drought coupled with extreme heat, but also to the periodic influx of moist, tropical air from the Gulf of Mexico that can help fuel intense thunderstorms. These storms deliver beneficial rains, but occasionally produce flash flooding and other extreme weather events (i.e., hail, wind, tornadoes) that can completely wipe out crops. Because much of the total precipitation during the growing season is delivered in convective form, there is significant spatiotemporal variability of precipitation across the state each growing season, potentially contributing to large variations in corn and soybean yields. Given these weather patterns across Wisconsin, coupled with a wide range in hybrids, planting dates, and corresponding differences in phenological development and growing degree requirements, we hypothesized that the overall importance of specific meteorological variables on crop productivity would vary spatially. However, there is currently no significant source of information on previous climate-crop yield connections in Wisconsin.

To address this lack of knowledge, we performed an analysis of how climate effects corn and soybean yields across Wisconsin at the county level over several decades. Using a daily climate dataset for minimum and maximum temperature and precipitation that was gridded at an 8 km spatial resolution from station observations for the period 1950-2006 (Serbin and Kucharik, submitted), we used common statistical techniques (ANOVA, linear regression, multiple regression) to quantify the relationships between monthly weather variables and corn and soybean yields. The overall goal of this paper is to provide a quantitative understanding of how crop productivity has been affected by climate variability in spatially explicit context across Wisconsin. Our hope is that by forming a better understanding of how climate impacts crop yields across Wisconsin, predictions of their response to future climate changes can be improved.

Methods

Climate data

We used a newly constructed 8km x 8km gridded daily climate dataset for the state of Wisconsin (Serbin and Kucharik, submitted). Daily minimum and maximum temperature along with total daily precipitation data were obtained from the NOAA cooperative (COOP) observer network for the period 1950-2006. These observations were subsequently interpolated to a terrestrial 5-min x 5-min grid using an inverse distance-weighting (IDW) algorithm within ArcGIS to generate a continuous 57-year time series. Approximately 133 temperature stations and 176 precipitation stations were used in the development of the dataset, giving an average distance between observing stations of 25.0 km for temperature, and 21.2 km for precipitation. Average values of maximum and minimum temperature and precipitation were determined for each county (n=72) at both the daily and monthly temporal scales for the entire timeseries. To do so, the 8km daily and monthly gridded data were linearly interpolated to 1km, and county level averages were calculated for all pixels within each county based on political boundaries that corresponded with latitude and longitude information available from the U.S. Census website (www.census.gov/geo/www/cob/co2000.html).

Crop yield and harvested area data

We utilized the USDA-NASS data on county-level data for crop yields, harvested area, and total production for 1950-2006 (available at http://www.nass.usa.gov). In their raw form, the USDA NASS crop yield data cannot be used in statistical analyses to quantify the direct impacts of climate on productivity. Embedded in these multidecadal timeseries of yield data are a very low-frequency technological trend that corresponds to improvements in agronomic practices and management (i.e., nitrogen fertilizers, pesticides, planting dates), seed technologies, and other nonclimatic factors that are known to have caused the significant increase in U.S. crop yields since the 1940s (Naylor et al., 1997; Lobell and Asner, 2003; Kucharik, 2006; Lobell et al., 2007; Kucharik, 2008). Therefore, we fit a linear trend to each county's timeseries of yield values to separate the high-frequency year-to-year changes in yields due largely to weather fluctuations from the technology trend (Lobell et al., 2007; Lobell and Field, 2007). These annual yield anomalies were normalized using the expected trendline yield value for each year in every county to produce percent deviations that are used in our analysis.

Regression modeling

In order to study the response of each crop to climate variability in each county, we followed the approach of Lobell et al. (2007), whereby regression models were developed using monthly maximum temperature, minimum temperature, and precipitation as predictor variables. To do so, we first studied independent regression relationships between percent yield anomalies and climatic variables for each crop in every county. We chose to assess the relationships for months spanning March through October, which encompasses the general growing period length. We used a second order polynomial regression given that temperature and precipitation can have a non-monotonic effect on yields each year (Lobell et al., 2007). The equation we used follows the form:

$$YA_{i,j} = aX_{i,j} + bX_{i,j}^2$$

where $YA_{i,j}$ is the annual percentage yield anomaly for county *i* and crop *j*, and the $X_{i,j}$ is the climate variable being tested. Given that approximately 61 counties in Wisconsin had continuous corn and soybean yield records for 1950-2006, we tested a total of 1464 regressions (8 months x 3 variables x 61 counties) and for each county, selected up to three of the most important variables based on their coefficient of determination (R^2) values, and only chose values that had a relationship with yields where $P < 0.05$. In some counties, only one or two climatic variables had a significant ($P < 0.05$) relationship with yields. All statistical analysis was performed using the JMP (v.5.01) statistical software package (SAS, Cary NC). After this process, we performed multiple regression analysis for each county using up to three predictor variables deemed to be the most influential in effecting interannual variability for corn and soybeans, separately. This allowed for a measure of how much year-to-year variability could be explained by a predictive model with key climatic variables.

Results and discussion

Spatiotemporal patterns of corn and soybean yields

Here we present a brief overview of the long-term changes in corn and soybean yields across Wisconsin since 1950. For reference, we provide a map of the Wisconsin counties (Fig. 1). Wisconsin is positioned on the northern fringe of the Corn Belt, with the highest average county corn and soybean yields occurring across the southern and western portions. This is attributed to a longer growing season coupled with the highest average temperatures during the peak crop growth period from late May through early September. This leads to a larger accumulation of GDD, allowing farmers in the southern and western regions to plant longer-season hybrids with higher yield potential (Carter, 1992). Many eastern counties that border Lake Michigan experience a prolonged growing season than counties further inland at similar latitudes, but at the expense of a decreased GDD accumulation due to cooler land surface temperatures during late spring and early summer (Serbin and Kucharik, submitted).

In order to illustrate temporal yield changes in a spatial context, we compared average yields between decades at the beginning and end of the study period. During the 1950-1959 timeframe, corn yields ranged from 3 to 5 Mg ha^{-1} across the south to 1.5 to 3 Mg ha^{-1} across the northern one-third of the state (Fig. 2a). Approximately 50 years later (1997-2006), corn yields averaged 8.5 to 10 Mg ha^{-1} across the southwest, 7 to 8 Mg ha^{-1} in the central and eastern counties that border Lake Michigan, and 6 to 7 Mg ha^{-1} in the far north (Fig. 2b). Currently, Lafayette County in the south central region attains the highest average corn yields (Fig. 2b), and has seen the largest increase in corn yields (0.1189 Mg ha^{-1} yr^{-1}) since 1950. Lincoln County (north central) has seen the lowest annual average increase since 1950 (0.0764 Mg ha^{-1} yr^{-1}). While corn yields were reported in the far northern tiers of counties in the early 1950s, they no longer grow any substantial amounts of corn. All counties have seen a significant increase in average corn yields during the study period, but counties in the south and west have seen the largest gains, on the order of 5 to 6 Mg ha^{-1}, and the far north central the least, about 3 to 4 Mg ha^{-1} (Fig. 2c). The annual average yield trend has been 0.08 to 0.11 Mg ha^{-1} yr^{-1}.

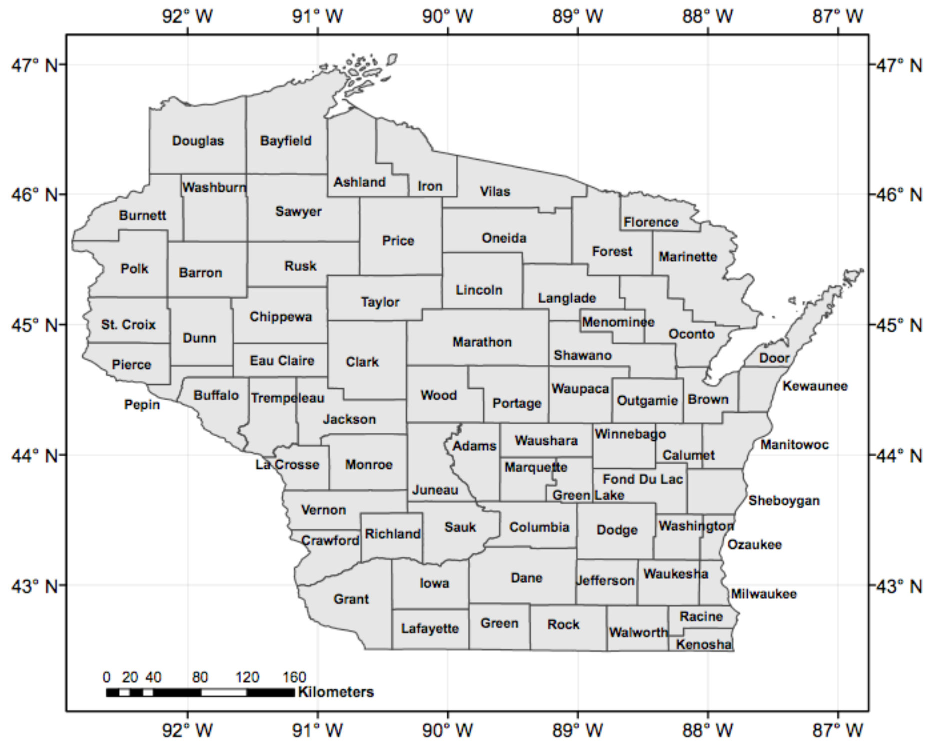

Figure 1. *Map of Wisconsin counties.*

From 1950 to 1959, soybean yields were highest across southern Wisconsin, averaging 1.2 to 1.6 Mg ha^{-1} (Fig. 2d). In central counties, yields averaged 0.8 to 1.2 Mg ha^{-1}, and across the far north, soybean productivity averaged between 0.2 to 0.8 Mg ha^{-1} (Fig. 2d). In contrast, average soybean yields during 1997-2006 were 2.8 to 3.2 Mg ha^{-1} over southern and central regions, with the highest yields in the far southwest and south central counties of Grant and Iowa (Fig. 2e). In these counties, average soybean yields now exceed 3.2 Mg ha^{-1}, while soybean yields north of a Green Bay to Eau Claire line have averaged around 2.0 to 2.4 Mg ha^{-1} over the past ten years. Soybeans are not typically grown in the far northern regions. While all counties have seen average soybean yields increase by 1.2 to 2.0 Mg ha^{-1} (Fig. 2f) since 1950, the far southeast and the far north central and northwest had smaller total productivity increases, averaging 0.8 to 1.2 Mg ha^{-1}. Grant County, has had the highest annual average soybean yield increase over the last 57 years (0.0496 Mg ha^{-1} yr^{-1}), while Washburn County in the northwest has experienced the smallest increase in productivity (0.0211 Mg ha^{-1} yr^{-1}) (Table 1).

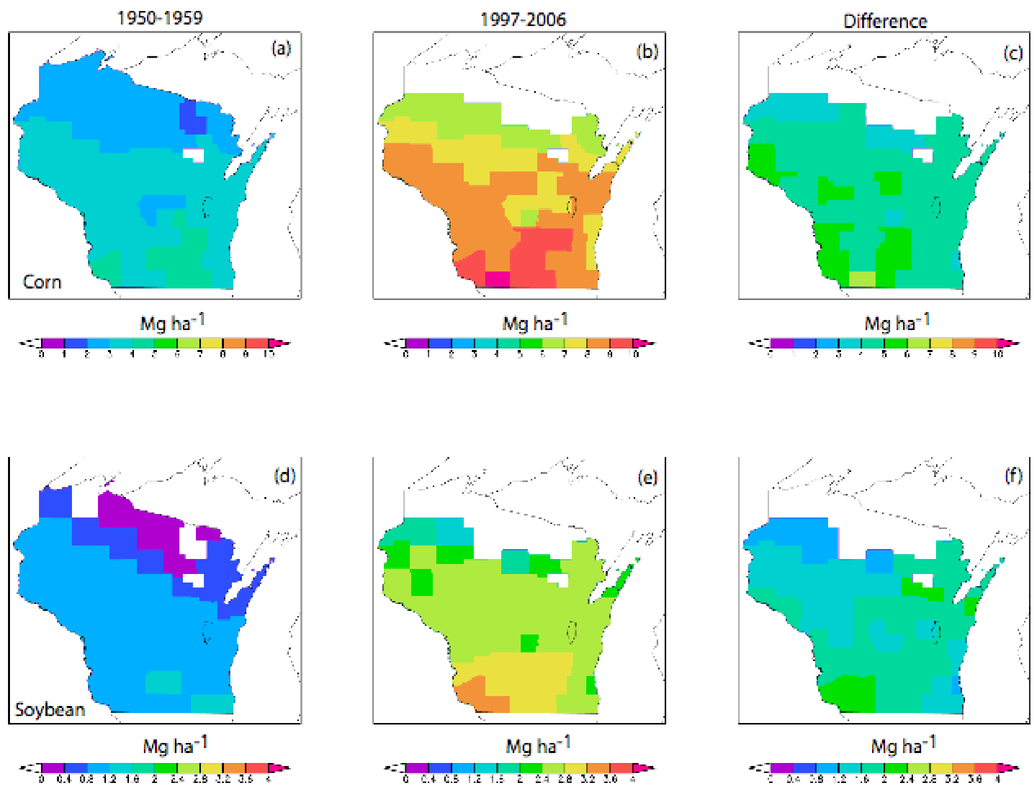

Figure 2. *Average county corn yields (Mg ha^{-1}) for (a) 1950-1959, (b) 1997-2006, and (c) difference in corn yields (Mg ha^{-1}) between (b) and (a). Average county soybean yields (Mg ha^{-1}) for (d) 1950-1959, (e) 1997-2006, and (f) difference (Mg ha^{-1}) in soybean yields between (e) and (d).*

Spatiotemporal patterns of harvested area

We present a short overview of changes in corn and soybean harvested area for three decadal time periods at the beginning, middle, and end of the study period in a spatial context: (1) 1950-1959 (Fig. 3a,b), (2) 1971-1980 (Fig. 3c,d), and (3) 1997-2006 (Fig. 3e,f). The overall spatial patterns of high corn and soybean harvested acreage, particularly since 1970, roughly coincides with the spatial pattern of highest productivity. From 1950 to 1959, corn harvested area was highest across the south and in some western counties that border the Mississippi River. Several counties (i.e. Grant, Dane, and Rock) had harvested area in excess of 40,000 ha. Others in the south and west had harvested totals of 15,000-30,000 ha (Fig. 3a). For soybeans, harvested areas were all generally below 3000 ha in all counties during the 1950s (Fig. 3b). By the 1971 to 1980 time period, expansion of corn harvested area had taken place in the majority of central and southern counties, with the highest concentration of harvested corn acreage still occurring in the far south. However, regions near the Fox River Valley and also in the far west saw significant increases in corn harvested area from the 1950s to the 1970s (Fig. 3c). Many counties in the southern part of the state had harvested areas greater than 50,000 ha. Soybeans were still not planted in significant numbers during the 1970s, with most counties still below 3000 ha, but a few counties in the extreme southeast were harvesting between 6,000 and 12,000 ha (Fig. 3d).

By the 1997-2006 period, increases in corn harvested area since the 1970s were limited to the far north central and northwest portions of the corn growing region in Wisconsin, with those counties now harvesting just as much corn as counties across the south (Fig. 3e). In the south, harvested corn areas stayed relatively constant or decreased slightly from the 1970s to the late 1990s. However, soybean harvested area saw explosive growth since the 1970s, and generally mirror the regions where corn harvested areas are highest today (Fig. 3f). The south central portion of Wisconsin is currently harvesting the highest numbers of soybeans, topping 30,000 hectares in several counties (Fig. 3f). Many other counties also harvest between 6,000-21,000 ha each year in the current era.

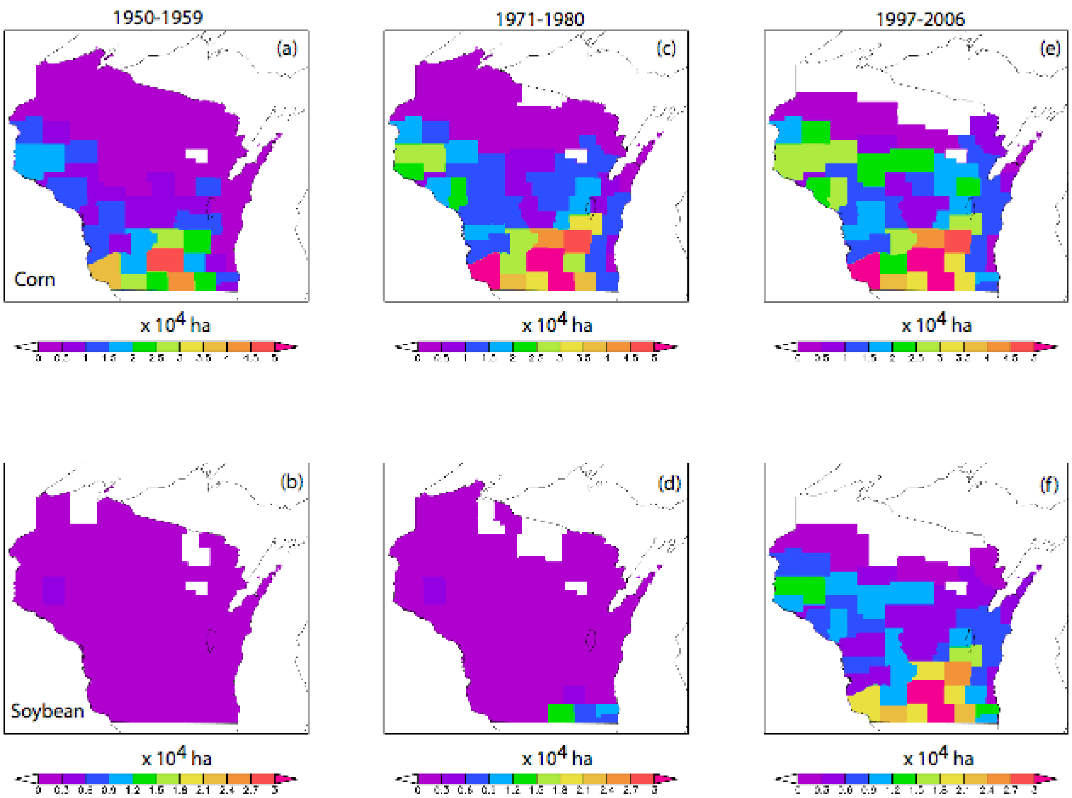

Figure 3. *Average county harvested area (x 10^4 ha) for (a) corn and (b) soybeans during 1950-1959; for (c) corn and (d) soybeans during 1971-1980; and for (e) corn and (f) soybeans during 1997-2006.*

Seasonal climate impacts on year-to-year corn yield variability

We draw upon work by Lobell et al. (2007) that highlighted the uncertainty when using R^2 values from linear regression to determine which monthly climate variables are most important to controlling interannual yield variability. According to Lobell et al. (2007), a relatively high R^2 value suggests one of three things: (1) that a variable does indeed effect yield variability; (2) that a variable is closely connected to another variable that influences yields; or (3) the apparent connection between a meteorological quantity and yield results from chance. A correlation between unique, but not independent, meteorological variables in Wisconsin is most likely to result during the growing season when cooler and wetter conditions are often correlated, as are hotter and drier conditions. Thus, it would be difficult to determine with a high degree of accuracy the true impact of a particular month and quantity on yields. We are not striving for that level of precision, but are rather interested in determining whether spatial patterns exist, and which monthly meteorological variables exert the most influence on the 57-year time series of corn and soybean yield anomalies. Therefore, our results presented here need to be interpreted with some caution.

Given that high R^2 values could occur simply by random, we repeated the procedure used by Lobell et al. (2007) to determine the threshold R^2 value that should be used to indicate a more accurate assessment of a statistically significant ($P < 0.05$) relationship. We generated normal distributions of random variables in a 57-year time series (using JMP statistical software), computed the R^2 values using Equation (1) and determined that the 95th percentile distribution was 0.10. In a few isolated cases some variables, when tested independently, produced an R^2 slightly below the 0.10 threshold, particularly for soybeans. In all of the regression tests that were performed, we found that R^2 values below approximately 0.07 were generally not significant at the 95% confidence level. Therefore, we have fairly high confidence that the chance occurrence of high correlation has been minimized.

Table 1. *Rankings of the most important monthly climate variables driving interannual corn and soybean yield variability across Wisconsin based on the frequency of occurrence (e.g., % of Wisconsin counties that had a significant [P < 0.05] relationship present between annual yield % deviation and monthly climate data).*

Rank	Corn	(%)	Soybean	(%)
1	July precipitation	70.5	July precipitation	55.7
2	July max temperature	67.2	Aug precipitation	55.7
3	Sept min temperature	47.5	June max temperature	49.2
4	June precipitation	45.9	July max temperature	36.1
5	Aug max temperature	44.3	Aug max temperature	32.8

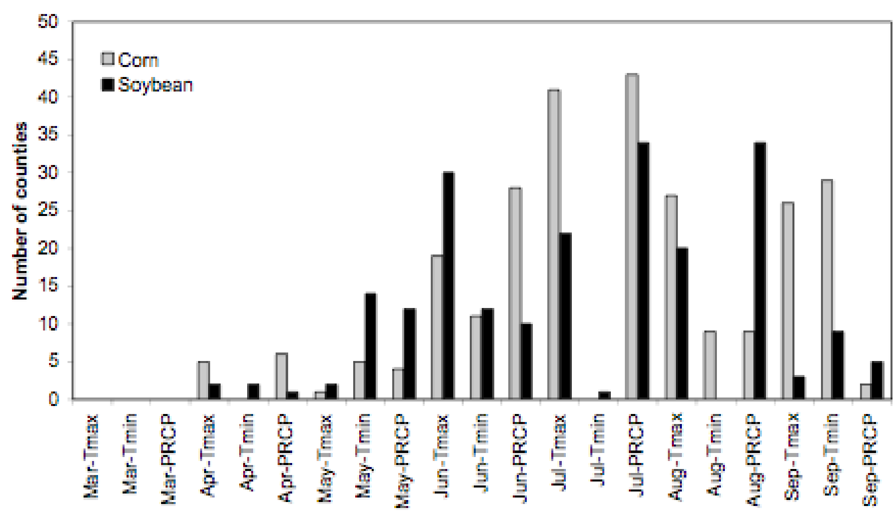

Figure 4. *Histogram depicting the number of counties that had a significant (P < 0.05) relationship between independent meteorological variables and corn and soybean yield anomalies for 1950-2006 (Tmax – maximum temperature, Tmin – minimum temperature, PRCP – precipitation).*

As part of our regression analysis, we ranked the monthly climate variables, in terms of frequency of occurrence across all counties that had a significant ($P < 0.05$) relationship with annual crop yield anomalies. We found that of the 61 counties in our analysis, July precipitation was the most important quantity in explaining interannual variability in both corn and soybean yields (Table 1, Fig. 4). Approximately 71% and 56% of counties growing corn and soybeans, respectively, showed a significant correlation between July precipitation and yield anomalies. For corn, other quantities that were most important in explaining yield variability were July maximum temperature, September minimum temperature, June precipitation, and August maximum temperature (Table 1). For soybeans, the next more important variables were August precipitation, and June, July, and August maximum temperature. Some notable differences existed between the two crops; namely, a rather small number of counties showed a significant correlation between August precipitation and corn yields, but that was not the case for soybeans as many counties had a significant relationship between August precipitation and yield anomalies (Fig. 4). This is indicative of soybeans being more sensitive to soil moisture conditions during the pod- and seed-filling period. Across the state, corn yields were much more sensitive to September maximum temperature than soybeans, presumably related to growing season length. Corn also appeared to be more sensitive to July maximum temperature (Fig. 4).

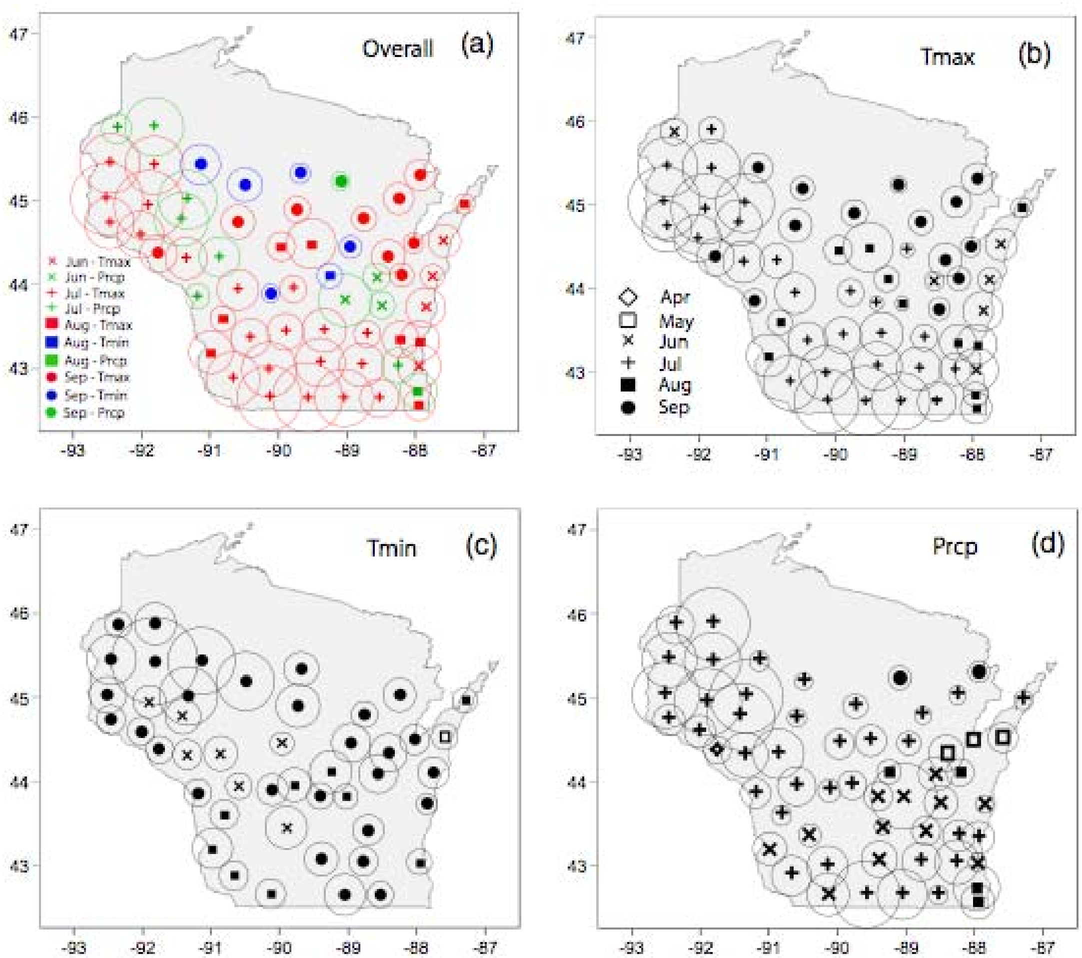

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Figure 5. *Results of linear regression analysis between monthly meteorological variables and county corn yield anomalies depicting which quantities explained the highest degree of yield variability from 1950-2006. (a) Overall, the most important meteorological variable and month based on R^2; (b) month when maximum temperatures were most influential, (c) month when minimum temperatures were most influential, (d) month when total precipitation was most influential. In (a), red corresponds to maximum temperatures, blue corresponds to minimum temperatures, and green represents precipitation. In all figures, the radius of the circle drawn around each point is proportional to R^2 values, ranging from minimum to maximum values. The figure legend in (b) also applies to (c) and (d).*

e 5a illustrates the most important monthly climate variables in terms of explaining the highest amount of corn yield variability from 1950-2006. This is based on R^2 values produced after linear regression of climate variables and yield anomalies in each county. Results in Figure 5a do not imply that other variables were not important, but rather highlight the monthly quantities that explained the highest amount of variability. The radius of each circle drawn in Figures 5a-d is scaled between the minimum and maximum regression (R^2) value for each independent analysis. Maximum monthly temperatures clearly dominate the resulting pattern, but the time periods (months) that are most important to influencing corn yields vary considerably from north to south across the state. For example, across the south central and far northwest, July maximum temperature is the most important factor influencing yield variability (Fig. 5a). Across the far northeast, September maximum temperature is the most important meteorological variable, presumably because of its relationship to growing season length in a region that experiences a shorter growing period. Lastly, several counties along the Lake Michigan shoreline show that June maximum temperature was the most influential meteorological variable, which might be an indication of how cooler temperatures along the lake early in the growing season can inhibit growth and contribute to lower than average corn yields. The R^2 values ranged from 0.36 in St. Croix County for July maximum temperature, to 0.094 in Juneau County for September minimum temperature. Therefore, single monthly meteorological quantities in the south central and far northwest sections of the Wisconsin corn growing area typically explain between 20-35% of the interannual variability in corn yields. Monthly precipitation yielded the highest R^2 value in 12 counties (July – 7; June – 2; September – 1; August – 1), monthly maximum temperature in 42 counties (June – 4; July – 21; August – 8; September – 9), and monthly minimum temperature in 6 counties (August – 1; September – 5).

Figure 5b shows the geographic distribution of the specific months when maximum temperatures influence corn yield variability the most. Given the predominance of July maximum temperature being the most important meteorological variable overall controlling corn yield variability for many counties (Fig. 5a), followed closely by September maximum temperature in the north and east, and June maximum temperature along the Lake Michigan shoreline, this graphic looks similar to Figure 5a. Over most of the south, west, and northwest portions of the corn-growing region in Wisconsin, July and August is the period when maximum temperatures have the most influence on corn interannual yield variability. Over a large portion of the north central and northeast, September is a dominant time period when daily high temperatures are important. The R^2 values depicted in Figure 5b range from 0.07 (Marquette County) to 0.36 (St. Croix County). Maximum temperatures in June were most influential in 6 counties, in July for 28 counties, in August for 11 counties, and September for 14 counties.

The results in Figure 5c depict when monthly nighttime minimum temperatures matter the most to corn yields. The map suggests that in counties that had a significant relationship between the timeseries of individual monthly minimum temperature and yield anomalies, September was the most important time period for many counties in the south central, northeast, northwest, and far west central. To a lesser extent, August was most important in the far southwest and few central counties, and in a small section of the west central part of the state, June was when minimum temperatures had a major influence. The R^2 values depicted in Figure 5c range from a low of 0.07 (Wood County) to a high of 0.26 (Barron County). Minimum temperatures in May were most influential in one county, in June for six counties, in August for nine counties, and September for 29 counties.

Figure 5d shows that for counties that had at least one month where precipitation was significantly correlated with corn yield anomalies, July was the most important time period for the majority of the southern and western counties, and for several counties in the far north. June was also a critical period for receiving timely precipitation in many counties across the southwest to east central part of the state. The distribution showed two counties had precipitation being most important in September, four for August, eight for June, and 36 for July. The R^2 values depicted in Figure 5d range from a low of 0.07 (Taylor County) to a high of 0.29 (Chippewa County).

Seasonal climate impacts on soybean yield variability

Figure 6a shows the spatial distribution of the most important meteorological variable (month and quantity) that independently explained the highest amount of interannual variability of soybean yields (from ranked R^2 values) from 1950-2006. In contrast to the analysis for corn yields (Fig. 5a), a large number of counties showed that *precipitation* in July and August was most important over large sections of the west central portion of the state and the far south and east, including many counties along the Illinois border and Lake Michigan shoreline. Minimum temperatures in May were most influential for several counties in the east central part of the state, and maximum temperatures in July (northwest) and June (northeast) appear to be the most influential. The R^2 values ranged from 0.29 in La Crosse County for July precipitation, to 0.07 in Wood County for August precipitation. Monthly precipitation yielded the highest monthly R^2 value in 31 counties (July – 16; May, June, and September 1 each, and August – 12), monthly maximum temperature was most significant in 20 counties (June – 7; July – 7; August – 4; September – 2), and monthly minimum temperature was most significant in 9 counties (May – 5; June, July – 1; September – 2).

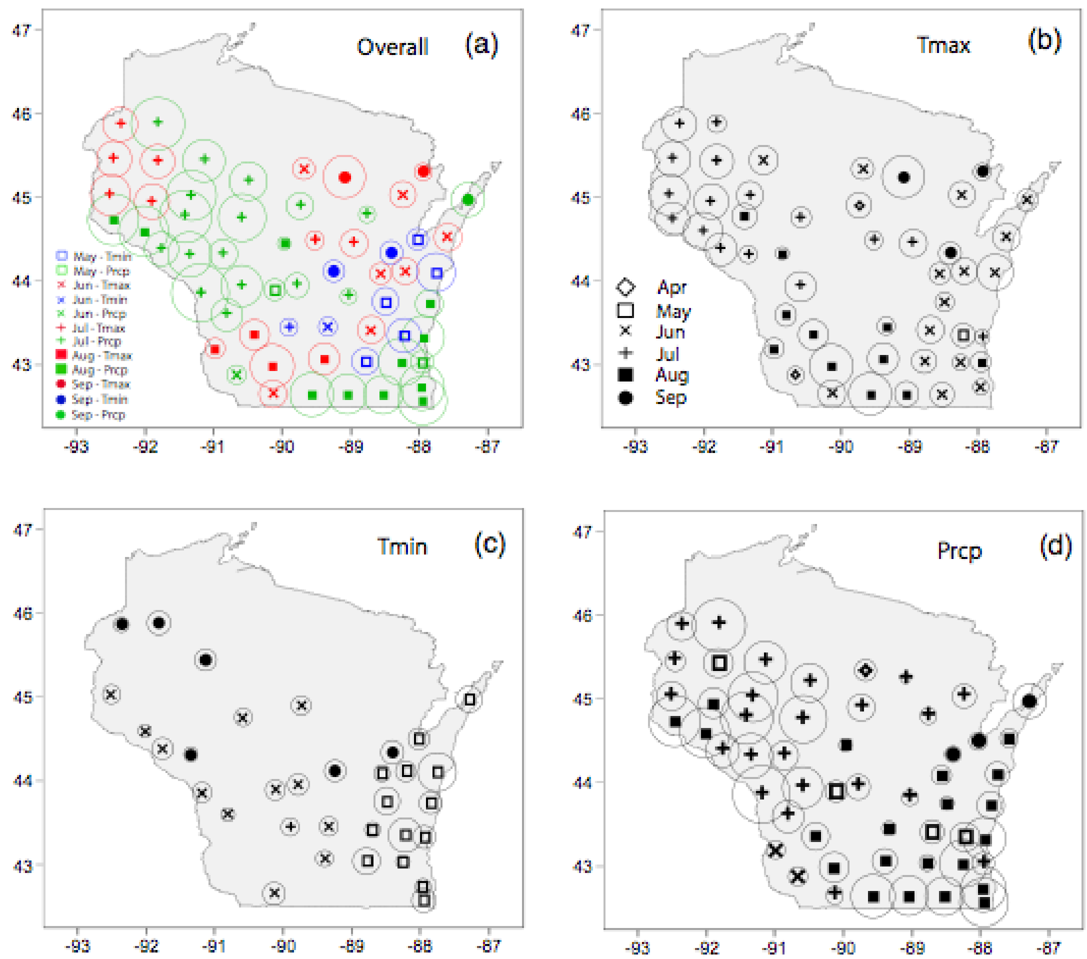


Figure 6. *Results of linear regression analysis between monthly meteorological variables and county soybean yield anomalies depicting which quantities explained the highest degree of yield variability from 1950-2006. (a) Overall, the most important meteorological variable and month based on R^2; (b) month when maximum temperatures were most influential, (c) month when minimum temperatures were most influential, (d) month when total precipitation was most influential. In (a), red corresponds to maximum temperatures, blue corresponds to minimum temperatures, and green represents precipitation. In all figures, the radius of the circle drawn around each point is proportional to R^2 values, ranging from minimum to maximum values. The figure legend in (b) also applies to (c) and (d).*

Figure 6b depicts when monthly maximum temperature has had the greatest impact on soybean yield variability, based on linear regression results in each county. One difference between this depiction and the analysis for corn yield variability is that fewer counties had a significant correlation between yield anomalies and monthly maximum temperatures, particularly in the central part of the state. Over the eastern portions of the state (and a few counties elsewhere), maximum temperatures were most influential to soybeans during June. Over most of the northwest portions of the soybean growing region in Wisconsin, July is the period when maximum temperatures had the most influence on interannual yield variability, and in the southwest the most influential period is August (Fig. 6b). The R^2 values that are depicted in Figure 6b range from 0.07 (Jackson Co.) to 0.22 (Iowa co.). Maximum temperatures in April were most influential in 2 counties, in May for 1 county, in June for 15 counties, in July for 16 counties, in August for 11 counties, and September for 3 counties.

There was a significant decline in the number of counties that were significantly influenced by minimum monthly temperatures compared to maximum temperatures (Fig. 6c); only 33 counties had a significant correlation between monthly minimum temperatures and soybean yield anomalies. The range in R^2 values from the individual linear regressions was 0.07 in Pepin Co. (June) to 0.20 in Manitowoc Co. (May). There appear to be three key geographic regions that have been impacted: (1) in the western portions of the state, further away from Lake Michigan, June is the time period when soybeans are most impacted by nighttime minimum temperatures; (2) on the northern perimeter, five counties were most influenced by nighttime lows during September; and (3) along the far eastern counties, soybean yields were strongly affected by nighttime low temperatures during May (Fig. 6c). Minimum temperatures in May were most influential in 14 of the 33 counties, during June in 12 counties, during July in 1 county, and September in 6 counties. We hypothesize that water temperatures and wind direction during the spring impact soybean management and growth near Lake Michigan in the southeast and east central part of the state. If significantly cooler than normal temperatures occur due to easterly winds blowing over cooler lake waters, planting may be delayed and a slower warming of soils may also result. This may lead contribute to shorter season hybrids being planted, or slower crop development – both of which could contribute to lower yields.

Because monthly precipitation was found to be the most important factor in controlling soybean yield variability in many counties (Fig. 6a), Figure 6d appears quite similar to those results. A total of 54 counties showed a significant correlation between precipitation in at least one month and yield anomalies over the 57-year period. Here, we reiterate that precipitation during August is the most crucial time for rainfall over many locations in the southeastern two-thirds of the state, and in particular across the far south and east. Precipitation during July was dominant spatially across the northwest and west central regions (Fig. 6d). A potential reason for the differences might be related to the developmental stages of the crop being further along in the western portions of the state, and therefore more sensitive to precipitation earlier in summer (July), compared to regions further to the east. The range in R^2 values from the individual linear regressions was 0.07 in Wood Co. (August) to 0.29 in La Crosse Co. (July). Monthly precipitation during April was most important in one county, in May in four counties, in June in two counties, in July in 23 counties, in August in 17 counties, and September in three counties.

Results of multiple regression modeling

We took our individual county level results, whereby we have identified up to the three most important meteorological variables and month impacting corn and soybean variability from 1950-2006, and used them within multiple regression analysis. This allowed us to assess how much of the interannual yield variability for each crop could be explained by variations in seasonal weather conditions during this time period. For corn, the average amount of yield variability that could be explained at the county level was 33%, and for soybeans 27%. The highest amount of variability explained for corn was in Green Co. (53%), and the lowest was 10% in Lincoln Co., which only had one monthly variable as part of the model. There were five counties with R^2 values between 0.1 – 0.19, 21 counties between 0.2 –

0.29, 16 counties between 0.3 – 0.39, eleven counties between 0.4 – 0.49, and eight counties above 0.5 (Table 1). The highest amount of variability explained for soybeans was 46% in Chippewa Co. and Pepin Co., and the lowest was 7% in Wood Co. We also note that Marquette Co. did not have a single predictor variable that was significantly correlated with soybean variability (Table 1). For soybeans, there were six counties with R^2 below 0.1, six counties between 0.1 – 0.19, 21 counties between 0.2 – 0.29, 19 counties between 0.3 – 0.39, and eight counties between 0.4 – 0.49.

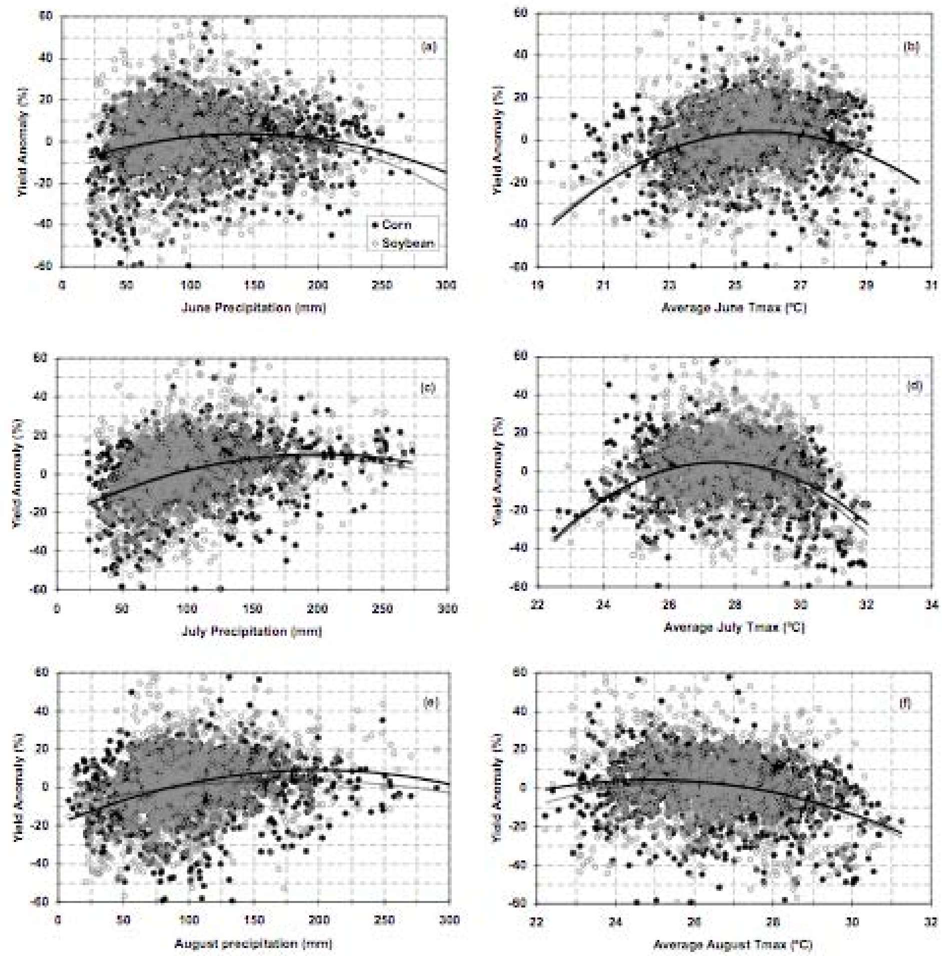
One hypothesis for the slightly lower variability explained by these models for soybeans compared to corn is that in the long term, there has been significantly less harvested soybean during the first 40 years or so of this analysis. Therefore, for a large portion of the time period used in this analysis, there was less harvested area contributing to county level yields each year, which likely contributed to weaker correlations with weather variables given the county level yield averages were based on a rather low fractional soybean cover. Weather conditions across the entire county may not be indicative of the conditions that the smaller soybean harvested regions were experiencing, particularly for precipitation totals. However, we did not detect a significant correlation between the R^2 values we found in our regression modeling and average harvested area for the last 10 years at the county level for either crop.

The predictive capabilities of our models at the county level were considerably less than the results shown in Lobell et al. (2007), however the crops studied there were not the same and the Lobell et al. (2007) analysis was done at the aggregated state level. Given that only about one-third of interannual yield variability could be explained by monthly climate variables, this suggests that many other factors are influencing the year-to-year fluctuations in yields. Because we looked at an extensive 57-year time period, it is conceivable that improvements in hybrids over time have allowed crops to become more resistant to stresses caused by weather. Other management changes, such as earlier planting may also have helped offset adverse weather effects such as drought and extreme heat in mid to late summer (Kucharik, 2006). However, increased planting density and higher production have potentially increased the demand for soil moisture, thereby making these crops potentially more sensitive to drier than normal conditions during the mid to late growing season.

Response of crop yields to critical meteorological variables and time periods

Here, we discuss the general response of corn and soybean yields across Wisconsin to changes in summertime (June through August) monthly average maximum temperatures and precipitation, along with monthly average minimum temperatures in September (Fig. 7). These time periods and meteorological variables coincide with the list of factors presented in Table 1 that were found to be the most influential in creating year-to-year corn and soybean variability from 1950-2006. An average statewide response was calculated by fitting a 2nd order polynomial to all county level data that was available over the 57-year study period. Therefore, 3477 data points (i.e. 61 counties with crop yield data x 57 years) were used in each independent regression (of each variable) for corn and soybeans, respectively. We caution that the regression results presented here are rather generalized because of climate gradient from north to south across Wisconsin. A more detailed analysis can be performed by fitting regression curves for each individual county.

In the month of June, the critical monthly precipitation threshold to achieve the expected or average corn and soybean yields is around 70-100 mm (the statewide average June precipitation from 1950-2006 was calculated as 104 mm from county level data), but considerable variability is noted from county to county (Fig. 7a). Given that average temperatures are likely cooler with increased cloudiness and precipitation in June, monthly precipitation totals greater than 200 mm appear to increase the likelihood for lower than expected yields. Increased precipitation and cooler temperatures during this time period likely delays early season plant growth, which can lead to lower than average yields. Soybean and corn yield response to average monthly June maximum temperatures suggests that there is a finite temperature range for average to better than average yields, and temperatures either too cool or too hot during June can both contribute to yield losses (compared to the long-term expected average) of 20-30% (Fig. 7b). However, crop yields appear to be more at risk in the case of cooler than normal conditions in June. According to our overall results, the optimum average daily highs in June for growing corn and soybeans are between 24ºC and 27.5ºC. Departures of equal to or greater than 2ºC from the overall statewide average June tmax (25.4ºC) generally contributed to lower than expected corn and soybean yields, but we



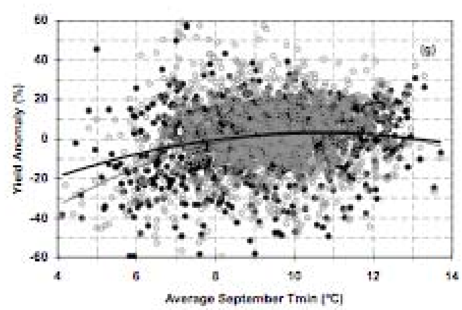


Figure 7. *Representative plots of corn and soybean yield anomalies for every county and every year compared with the following county average monthly meteorological variables for 1950-2006: (a) June precipitation, (b) June maximum temperature, (c) July precipitation, (d) July maximum temperature, (e) August precipitation, (f) August maximum temperature, (g) September minimum temperature. The best-fit regression line (thick line for corn, thin line for soybean) is in the form of a 2nd degree polynomial.*

iterate that the localized responses vary significantly from county to county.

Clearly, given the important phenological changes that typically occur during July for crops in Wisconsin (e.g., rapid expansion of leaf area, silking, tasseling, and pollination), it is no surprise this time period and its weather conditions exert a strong influence on crop yields. Corn and soybean yields are enhanced by higher amounts of July precipitation, and to achieve an "average" expected yield in any year, a total amount of approximately 80-90 mm is generally needed (Fig. 7c). While monthly precipitation totals greater than 100 mm may help to increase the likelihood of better than average yields, our results suggest only modest increases in corn and soybean yields are likely. For example, a 50% increase in July precipitation only contributed to an average yield increase of 6.5% for corn and 8.7% for soybean. The average yield response from a 100% increase in July precipitation corresponded to an increase of 7.6% for corn and 11.4% for soybean (Fig. 7c). This might be attributed to the fact that because precipitation during this month is largely delivered from convective processes, high rainfall events may occur with an intensity that is not beneficial to improving soil moisture because of higher surface runoff and less infiltration. It appears that as monthly precipitation falls below 75mm in July, the likelihood of lower than expected yields increases substantially. A 50% decrease in July precipitation corresponded to a 7.9% decline in corn yields, and an 8.6% decrease in soybean yields. A 75% decrease in July precipitation corresponded to 14% and 15% declines in corn and soybean yields, respectively (Fig. 7c).

Across Wisconsin, corn and soybean yields are sensitive to average July maximum temperatures (Fig. 7d), which were 27.8ºC across the state over the 57-year period. The optimal daily maximum temperature to achieve either average or better than average yields is approximately between 25.5ºC and 29ºC, and average maximum temperatures on either side of this range appear to inhibit yields due to cooler than expected conditions or extreme heat, particularly above 29.5ºC. This type of response has been reported previously by Thompson (1986), who analyzed Midwest U.S. corn yields. The second order polynomials that were fit to these data suggest corn and soybean yields were more sensitive to the upper temperature threshold of July maximum temperature, most likely because it is likely correlated with drier than normal conditions and because higher temperatures accelerate the rate of phenological development, potentially decreasing the leaf area that is attained before the grain fill period is initiated. Extreme heat during pollination and a lack of soil moisture also work against plant growth in July in Wisconsin. Increases in average July daily high temperatures of 2ºC and 4ºC corresponded to corn yield losses of 6% and 28% respectively, and soybean yield losses of 4% and 24%, respectively. This demonstrates the sensitivity of these cropping systems to small changes in monthly average maximum temperatures, on the same order of changes that are proposed to occur with continued climate change and global warming (IPCC, 2007). The yield responses to warmer than average temperatures are in contrast to the crop yield responses to a similar magnitude of cooler than normal July daytime high temperatures. For example, decreases in average July average daytime maximum temperatures of 2ºC did not contribute to lower than expected corn and soybean yields on average, and decreases in July maximum temperatures of 4ºC only led to average yield losses of between 10-12%.

In the case of August precipitation, a total of 80-90 mm (we calculated the statewide average to be 101 mm over the 57-year period) appears to be a crucial threshold to attaining the expected yields for any given year (Fig. 7e). As is the case for July precipitation, only modest increases in corn and soybean yields resulted from significant increases in rainfall. For example, the average response suggested that for a 50% increase in August precipitation, corn and soybean yields increased by 3% and 7%, respectively, and 100% increases in August precipitation corresponded to 4% and 8% increases in corn and soybean yields, respectively. Yield losses attributed to decreased August precipitation appeared to be less in magnitude than for similar decreases in precipitation during July. A 50-75% decrease in August precipitation corresponded to a 3-9% decline in corn yields and a 6-12% decline in soybean yields. Therefore, soybeans appear to be more sensitive to drier August conditions than corn.

Cooler than normal temperatures during August (the average statewide August daily maximum temperature was 26.5ºC) were not as detrimental to corn yields, and in fact, appear to favor higher than average yields (Fig. 7f). Cooler daytime high temperatures during August might help prolong the grain fill period due to a slowing of phenological development attributed to a slower accumulation of GDD.

Average monthly high temperatures above approximately 28ºC appear to contribute to lower than expected yields in the case for both corn and soybean, however the response is not as severe as observed during the month of July. In the case of corn, this is probably because the crop across the state is passed the crucial tasseling-silking period. The optimum August average daily high temperature was approximately 24 to 27.5ºC for corn and 22.5 to 27.5 for soybean, but temperatures much cooler than these ranges did not lead to significant yield losses, and according to the typical response, cooler Aug daytime highs increased the likelihood for slightly above-average yields. Extreme heat in August did not appear to have as adverse an effect as extreme heat during July based on the shape of the regression relationships plotted (Fig. 7f).

In the case of September minimum temperatures (statewide average September daily minimum temperature was 9.3ºC), cooler than expected conditions generally lead to lower than average yields, but from county to county, there is an extreme amount of variability that is likely related to latitude (Fig. 7g). Our results suggest average minimum temperatures above approximately 7ºC can help to significantly boost yields by a few percent, although the increase could be significantly more in individual northern locations, and we hypothesize that in northern and central portions of the state, this is correlated with an extension of the growing season and a lengthening of the grain fill period. Average minimum monthly temperatures below 6ºC in September increase the likelihood of lower than expected yields (Fig. 7g). Extremely cold Septembers in Wisconsin, particularly across the northern and central regions where the growing season length is already shorter, appear to have the potential to contribute to large yield losses, possibly due to an abrupt end to growing season early in the first week of the September.

Concluding remarks

Our investigation showed that previous corn and soybean yield variability across Wisconsin was impacted by a wide variety of monthly meteorological variables, and that the influence of these varied spatially across the state for each crop type. In fact, we identified time periods and weather conditions that were the most influential to creating uncertainty in year-to-year crop yields. Our results also provided some rather intriguing results that are relevant for studies of future climate change impacts. For example, increases in summertime precipitation by 50% would likely contribute to only modest increases in corn and soybean yields, up to approximately 8% for corn and 11% for soybeans. This result is in agreement with previous field observations in Illinois reported by Changnon and Hollinger (2003), and goes against previous projections of Midwest U.S. crop yield response (e.g., increases of 15-30%) in association with increased rainfall by 2030 and 2090 (Changnon and Hollinger, 2003).

The regression analysis between yield anomalies and monthly average daytime high temperatures during June, July, and August also showed that optimal temperature ranges, which are associated with expected or better than average yields, have a very narrow range, on the order of 3-4ºC in most cases. Therefore, given that projected increases in growing season temperatures may approach 4ºC across Wisconsin by the end of the 21st century (IPCC, 2007), it is clear that rather large changes in yields could occur under scenarios of projected mean warming. But, given that the magnitude of warming across the region has been occurring more rapidly at nighttime (Karl et al., 1993; Easterling et al., 1997), and there was a general lack of correlation between nighttime minimum temperatures and crop yield variability for both corn and soybeans in our study (except during the time of planting and harvest), yield decreases attributed to future climate change may not be as severe, and additional warming during the spring and early fall may actually help support higher yields.

The IPCC (2007) reported that a mean local temperature increase of 1-2ºC in the mid- to high-latitudes where agricultural adaptation took place could boost corn yields by 10-15% above the baseline. A 2-3ºC increase in mid- to high-latitudes coupled with adaptation could still allow crop yields to increase above baseline values, but a 3-5ºC increase would mean yields would fall to the approximate baseline value, and would decrease by 5-20% without some type of adaptive strategy. Our composite results support these generalizations, as an increase of 2ºC in the maximum monthly average temperatures in July and August translated into yield losses of 6% for corn and 2-4% for soybean. A warming magnitude of 4ºC in monthly average maximum temperatures in July and August across Wisconsin could lead to corn and soybean yield losses of 22-28% and 13-24%, respectively (Fig. 7), if adaptive measures do not occur. The impacts of future climate changes on corn and soybean yields in Wisconsin can be further investigated using the relationships between climate and yield anomalies here, and future projections of climate changes (Hu and Buyanovsky, 2003; Lobell et al., 2007; Sun et al., 2007). Of course, these relationships cannot account for potential future changes in management practices (i.e. planting dates, hybrid selection, fertilizer, and irrigation), or continued changes in atmospheric chemistry – most notably CO_2 and O_3.

Across Wisconsin, we concluded that increased temperatures during the springtime would likely help to facilitate earlier seed sowing and improve early season vigor and root development, but additional heating during the mid-summer during flowering or grain-fill could effectively cause an increased rate of development, increase respiratory loss, causing total photosynthetic uptake to decrease, leading to lower yields. In contrast, springtime temperatures that are too cool can impede seed germination and the rate of development and also cause decreased yields. In the case of precipitation, extremely low and high values tend to decrease yields because these conditions are often associated with extended dry periods and drought or flooding and decreased radiation, but generally above average precipitation in July and August are associated with higher yields. However, higher precipitation is often generally correlated with lower temperatures, particularly in late spring, which can delay planting and lead to lower yields. In late summer, particularly September, increases in nighttime temperatures will likely extend the growing season in this region, which would have a favorable impact on end-of-season yields. Many of these generalized responses were also reported by Hu and Buyanovsky (2003) for corn in Missouri, so it appears that at least for this crop, some regional scale relationships are valid.

As a result of this investigation, we have formed a better understanding of how soybean and corn agroecosystems may respond to future changes in climate, and what the magnitude of those changes are. We also now understand that responses will differ – quite significantly – in a spatial sense across Wisconsin, and look to be correlated with the orientation of the ecological tension zone (Curtis, 1959). Our research suggests that while some now understood consequences of climate change and variability will likely occur, these systems are complex and are deserving of additional research in the years to come as climate and management continue to evolve. Our future research agenda will continue to utilize the two key datasets in this project, and continue to look at whether previous climate changes have contributed to changes in crop yields, and how future projections of climate change in the Midwest may affect future crop management decision-making and productivity.

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Section 4. Impacts of Recent Climate Change on Wisconsin Corn and Soybean Yield Trends

Introduction

Worldwide agricultural production is governed by the combination of climate, soil tilth, technology, genetic resources, and farm management decisions such as tillage, manure and fertilizer applications, and crop variety selection [1, 2]. In general, advances in technology and changing agronomic practices are responsible for significant increases in corn and soybean yields across the U.S. Corn Belt [1, 3-7]. Kucharik [8] suggested that trends toward earlier planting [9], helping to support the adoption of longer-season hybrids, contributed between 19 to 53% of state level increases in corn yield across the northern Corn Belt from 1979 through 2005. Additionally, recent climate change may be playing a significant role in observed yield trends. Lobell and Asner [10] suggested that trends toward cooler growing season temperatures from 1982 to 1998 were responsible for up to 20% of U.S. corn and soybean yield increases, thereby decreasing the previous contribution of technological advance. On a global scale, warming temperatures have been shown to impact crop productivity and phenological development [11-13], potentially contributing to significant yield and economic losses [14].

An improved understanding of the contributions of technological advances to yield trends compared to climate and management changes could help formulate adaptive strategies to take advantage of, or counteract, new climate regimes in agricultural regions [15, 16]. Across the U.S. Corn Belt, a significant gradient in growing period length (GPL), growing degree-days (GDD), rainfall, and crop varieties exists; therefore, recent climate change may have affected corn and soybean yield trends differently in a spatial context. Furthermore, monthly or seasonal meteorological quantities that are significant drivers to change in one locale may not have the same impact in another location. Consequently, future variability in climate change may dictate the need for one set of adaptive measures in one region, and a different strategy elsewhere. Therefore, it is necessary to continue to synthesize new climate and crop yield data for regions that share similar climate and management regimes, such as crop reporting districts or entire states [17-19].

Here, our investigation focuses on quantifying the previous impact of temperature and precipitation trends on corn and soybean yield trends across Wisconsin from 1976 through 2006 (figure 1). In this region, the latest IPCC [20] projections suggest mean summer (June-August) temperatures will increase 3 to 4ºC by the end of the current century (e.g., approximately 0.35 to 0.5ºC decade^{-1}), while the outlook for summertime precipitation is for slightly drier (i.e. around –5%) conditions. Results of this study can be used to quantify how corn and soybean productivity may be affected by projected climate change over the next few decades based on regression model results.

Methods

We used an 8km x 8km gridded daily climate dataset for the state of Wisconsin [21]. Daily minimum and maximum temperature along with total daily precipitation data were obtained from the NOAA cooperative (COOP) observer network for the period 1950-2006. These observations were interpolated to a terrestrial 5-min x 5-min grid using an inverse distance-weighting algorithm within the ArcGIS software package to generate a continuous 57-year time series of daily weather. Approximately 133 temperature and 176 precipitation stations were used in the development of the dataset, giving an average distance between observing stations of 25.0 km for temperature, and 21.2 km for precipitation. The 8km daily and monthly gridded data were linearly interpolated to 1km to improve edge matching within the boundaries of interest, and county level averages were calculated for all pixels within each county based on political boundaries that corresponded with latitude and longitude information available from the U.S. Census website (www.census.gov/geo/www/cob/co2000.html). Maximum (*tmax*), minimum (*tmin*), and average (*tavg*) temperature and total precipitation (*prcp*) were determined for each Wisconsin county (n=72) at daily and monthly temporal scales for the entire period. For corn and soybean crop data, we utilized the U.S. Department of Agriculture's (USDA) National Agricultural Statistic Service (NASS) data on Wisconsin county-level yields (available at http://www.nass.usa.gov).

We focused on the last 31 years (1976-2006) of the data record and calculated monthly climate and corn and soybean yield trends for each county. The beginning year of 1976 was chosen to coincide with the initiation of the most recent period of sustained warming in the 20th century, which followed a period of cooler temperatures from the 1950s through the early 1970s. We calculated trends for county corn and soybean yields (Mg ha^{-1} yr^{-1}) and the county average monthly *tmax*, *tmin*, *and tavg* temperatures (ºC yr^{-1}) and *prcp* (mm yr^{-1}) for each month of the year using linear regression analysis and the JMP (v.5.01) statistical software package (SAS, Cary NC). We determined that 61 counties in Wisconsin had continuous corn and soybean yield records for 1976-2006 (figure 1), and computed a total of 2928 climate variable regressions (12 months x 4 variables x 61 counties) and 128 total crop yield regressions as a first step. We also computed multiple month average climate values for *two* and *three* consecutive month periods (e.g., Mar.-Apr., Jun.-Aug., Aug.-Sep., etc.), allowing for additional predictor variables to be tested as part of the regression analysis.

In order to study the relationship between crop yield trends and climate trends across Wisconsin, we developed multiple regression models using the monthly, two-month, and seasonal (i.e. three-month) composite *tmax*, *tmin*, *tavg*, and *prcp* values as predictor variables and corn and soybean yield trends as the response variables [10]. To do so, we first studied the independent regression relationships between all climate variable trends and yield trends using all 61 counties as replicates (e.g., figure 2). We selected the most important predictor variables based on their coefficient of determination (R^2) values. In general, all predictor variables that were ranked high (based on R^2 values) had a significant relationship with corn and soybean yield trends ($P < 0.001$). The analyses were performed separately for corn and soybean, so predictor variables could potentially be different for each crop type. We limited the selection of variables to one unique temperature related quantity and one unique precipitation variable for each crop.

The common belief is that empirical regression models relating crop yields to climate capture the composite effect of all climate change impacts on yield trends, and cannot offer a true explanation of the underlying cause of the changes, whether it be phenological, biological, biophysical, or management related [14]. However, by focusing on a small region of the Corn Belt, we are attempting to minimize the varied contribution of slowing changing factors such as crop management and assume that changes in management are consistent for each Wisconsin county through the period. Improvements in hybrids and technology that are used by farmers are assumed to be uniform across the entire region as we have no reason to believe that farmers in one portion of the state would have a decisive edge over others in obtaining new hybrids or equipment that might help support a trend towards higher productivity.

We believe that the largest management change, besides selecting the newest available corn and soybean varieties, has been earlier planting, and this management change has been widespread across the entire Midwest. For example, Wisconsin corn planting dates have shifted to approximately 10 days earlier since the late 1970s [9], and Kucharik [8] suggested that earlier planting across Wisconsin during the 1979 to 2005 timeframe has contributed 22% to corn yield trends. That contribution is largely believed to be due to the ability to plant longer-season hybrids with higher yield potential via a prolonged GPL. However, Kucharik [9] noted that the trend towards earlier planting was not strongly correlated with warmer springtime temperatures during this period, and was more likely due to improvements in technology and management that have been implemented statewide to allow for earlier planting to take place.

Results

Spatial patterns of county level crop yield and climate trends

Corn yield trends across Wisconsin varied between approximately 0.040 Mg ha^{-1} yr^{-1} in far northwest, northcentral, and far southeast counties, to 0.140 Mg ha^{-1} yr^{-1} in southwestern and some westcentral counties (figure 1(a)). Several counties in central Wisconsin also had lower yield increases ranging between 0.05 – 0.08 Mg ha^{-1} yr^{-1}. We determined that the June-Aug. *tavg* trend had the strongest correlation with corn yield trends ($R^2 = 0.28$) (figure 2(a)) compared to all other temperature predictor variables. For precipitation, the two-month June through July composite *prcp* trend yielded the highest correlation ($R^2 = 0.27$) (figure 2(b)) with corn yield trends. The majority of Wisconsin counties experienced warming trends in monthly *tavg* during meteorological summer (i.e. June – August) of between 0.05 and 0.2ºC $decade^{-1}$ (figure 1(b)), with the largest increases in far northcentral, westcentral, and southeast. However, several counties in the southwest corner of the state have experienced a trend towards cooler June-August *tavg*, up to –0.1ºC $decade^{-1}$. The observed June-July total *prcp* trends suggested that the majority of locations have been receiving more precipitation, centered on an axis from the southwest through northeast portion of the state (figure 1(c)). For example, many areas saw increased *prcp* in June-July, ranging between 5 – 20 mm $decade^{-1}$. However, this pattern was not uniform and several northcentral and southeastern counties saw a decreasing trend in *prcp* during this period of –5 to –15 mm $decade^{-1}$.

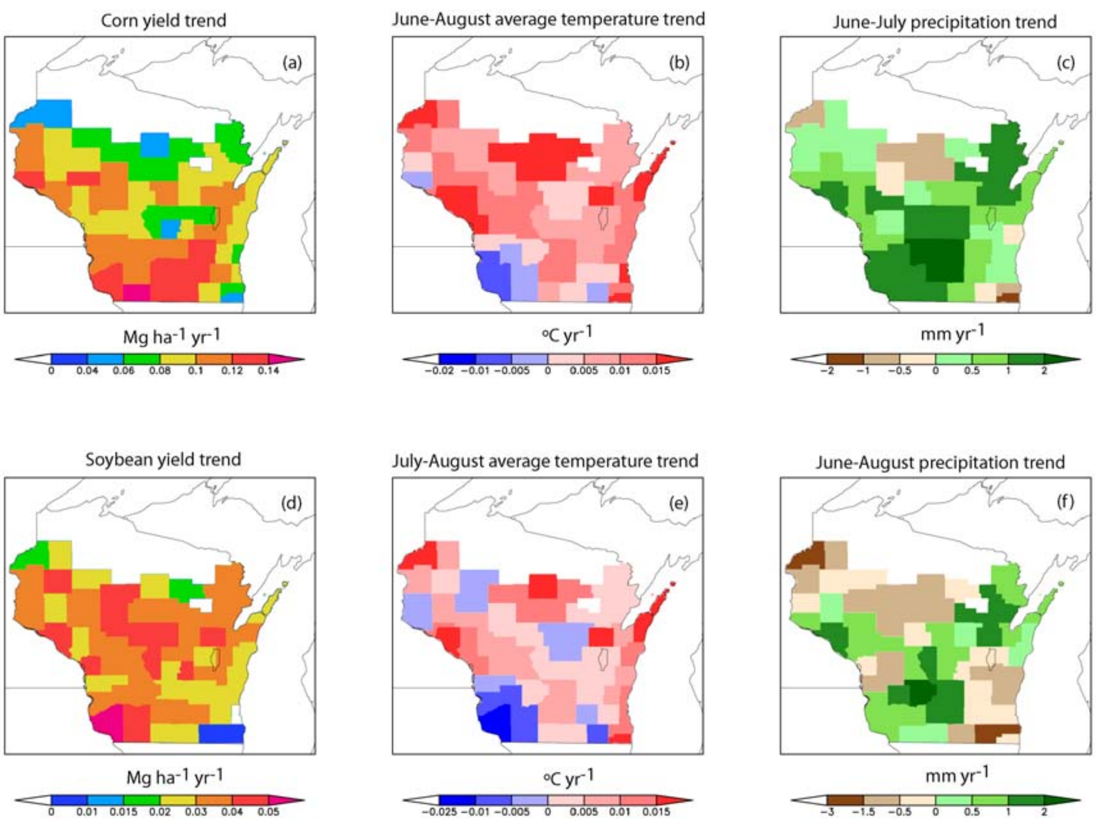

Figure 1. *Wisconsin county level trends from 1976-2006 for (a) corn yields, (b) June-August average temperature, (c) June-July total precipitation, (d) soybean yields, (e) July-August average temperature, and (f) June-August total precipitation.*

Soybean yield trends have varied between a minimum of 0.005 Mg ha^{-1} yr^{-1} in the far southeast counties to as high as 0.050 Mg ha^{-1} yr^{-1} in the southwest (figure 1(d)). The northern extent of the soybean growing region saw a yield trend around 0.015 Mg ha^{-1} yr^{-1}, while the large majority of counties in the central portion of the state have seen increases of 0.030 – 0.040 Mg ha^{-1} yr^{-1}. We found that the July-Aug. *tavg* trend (figure 1(e)) had the strongest correlation with soybean yield trends (R^2 = 0.16) (figure 2(c)) compared to all other temperature predictor variables that were tested. For precipitation, we determined that the three-month composite total for the summer growing season (June-Aug.) had the highest correlation with soybean yield trends (R^2 = 0.26) (figure 1(f), 2(d)).

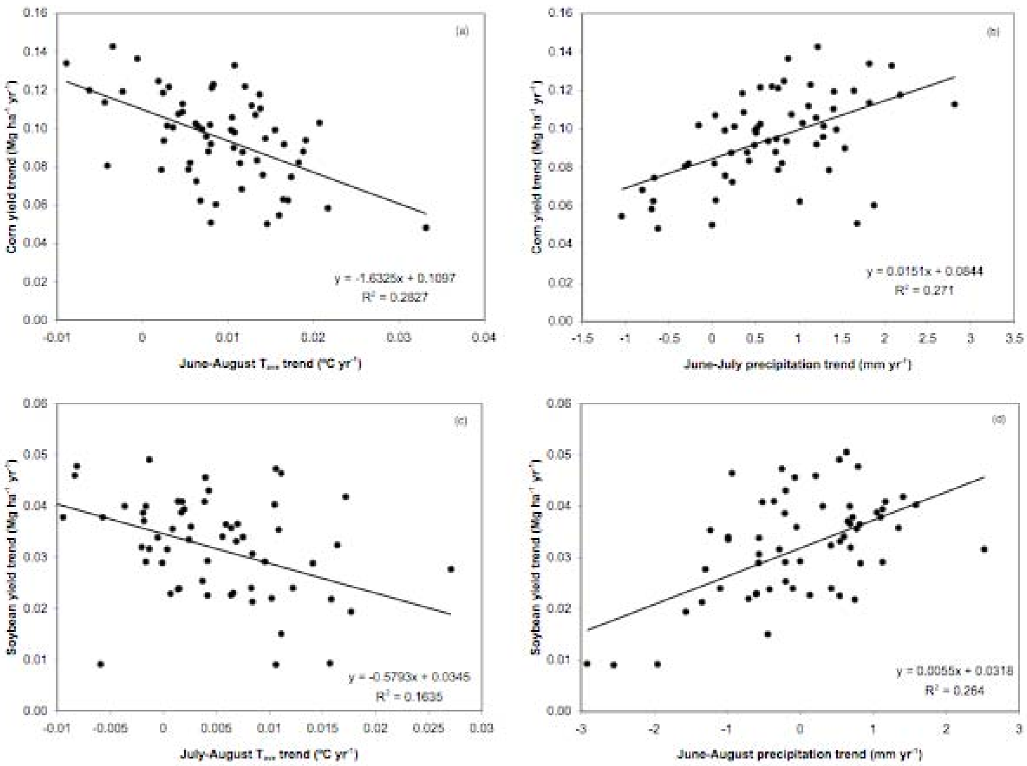

Figure 2. *Scatter plots and regression statistics of county trends (61 counties analyzed from 1976-2006) in (a) corn yields and June-August average temperature, (b) corn yields and June-July total precipitation, (c) soybean yields and July-August average temperature, and (d) soybean yields and June-August total precipitation. A best-fit linear regression line is plotted in each graph.*

A large number of Wisconsin counties experienced warming trends in monthly *tavg* during July-Aug. of between 0.05 and 0.15ºC $decade^{-1}$ (figure 1(e)), with the largest increases within lakeshore counties, the far northcentral, and westcentral. However, the southwest corner of the state experienced a trend towards cooler July-Aug. *tavg*, up to –0.25ºC $decade^{-1}$, and several other counties across the state also experienced cooling trends. The June-Aug. total *prcp* trends suggested that a trend towards more precipitation was centered on a small axis from the southwest through northeast portion of the state (figure 1(f)). In this region, and a small portion of the westcentral part of the state, total *prcp* in June-Aug. increased by 5 – 20 mm $decade^{-1}$. However, many counties clustered in the northwest, northcentral, and southeastern counties saw a significant trend of decreasing *prcp* during this period of –5 to –30 mm $decade^{-1}$ (figure 1(f)).

General relationships of crop yields and temperature and precipitation trends

The impacts of recent climate trends on corn and soybean yield trends in Wisconsin support previous results found by Lobell and Asner [10] for the entire U.S., with the important new discovery that precipitation was a significant contributor to the spatial distribution of yield trends for both crops in Wisconsin. First we take a look at the simple regression results for temperature and precipitation independently, which will be compared with results from multiple linear regressions. Overall, the highest corn and soybean yield increases were supported by a trend towards cooler and wetter conditions during the summer (figures 2(a)-(d), figures 3(a)-(b)).

The linear regression between county level trends in corn yield and trends in interpolated Jun.-Aug *tavg* suggested that a climate-adjusted average yield trend (Lobell and Asner, 2003) was 0.1097 Mg ha^{-1} yr^{-1}, which was 15.5% higher than the observed trend of 0.095 Mg ha^{-1} yr^{-1}. This suggests that the trends in corn yields should have been greater than what was observed, and were suppressed by increasing temperatures across the state. For the linear regression between county level precipitation (Jun.-Jul.) and corn yield, the climate-adjusted average yield trend was 0.0844 Mg ha^{-1} yr^{-1}, suggesting that if trends in precipitation were not present, yield trends would have been 11.2% lower than observed. The linear regression between county level trends in soybean yield and trends in Jul.-Aug *tavg* suggested that a climate-adjusted average yield trend was 0.0345 Mg ha^{-1} yr^{-1}, which was 11.3% higher than the observed

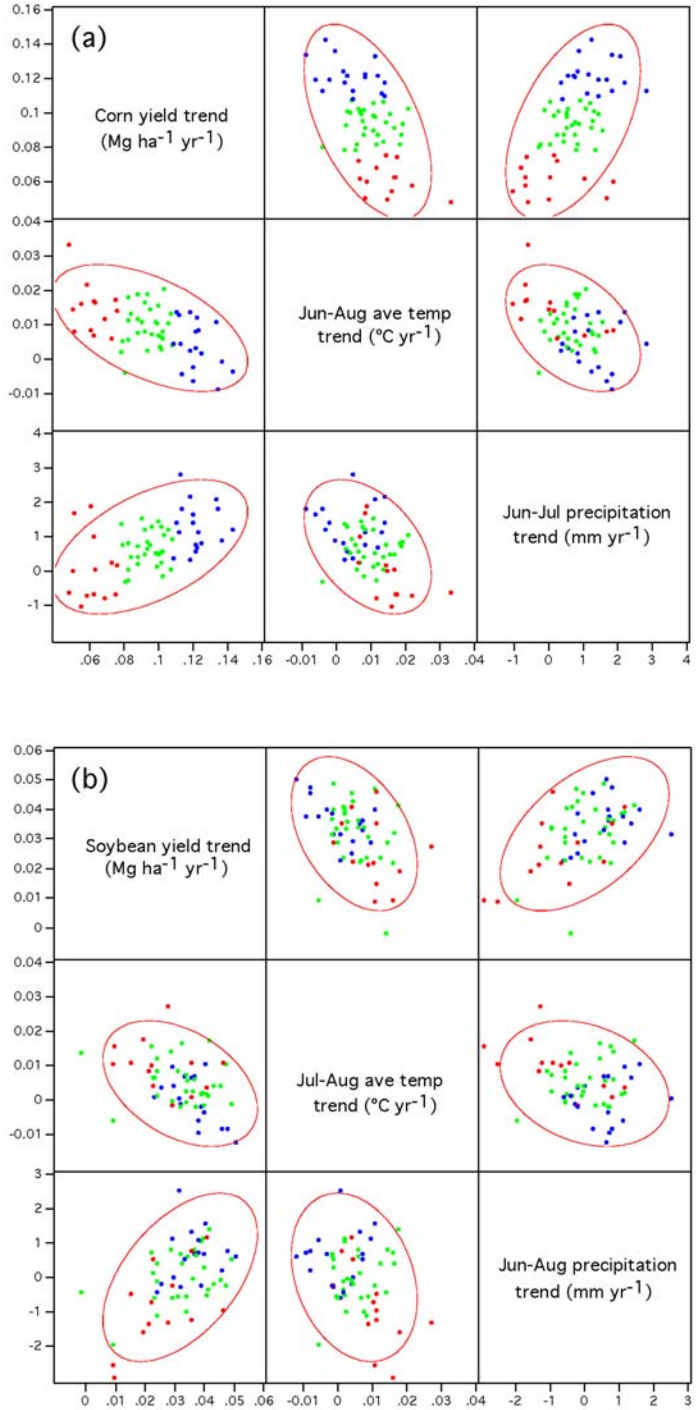

Figure 3. *Scatterplot matrix depicting relationships between (a) corn yield trends, June-August average temperature trends, and June-July total precipitation trends; (b) soybean yield trends, July-August average temperature trends, and June-August total precipitation trends. A 95% bivariate normal density ellipse is plotted in each graph. The county data points have been categorized into three groups in (a) and (b) based on ranked corn yield trends; top 25% (blue dots), middle 50% (green dots), and bottom 25% (red dots).*

trend of 0.031 Mg ha^{-1} yr^{-1}. For the linear regression between county level precipitation (Jun.-Aug.) and soybean yield, the climate-adjusted average yield trend was 0.0318 Mg ha^{-1} yr^{-1}, or comparable to the observed trend.

For corn, each degree of warming during June-Aug. (*tavg*) appears to be capable of suppressing yields by as much as –1.63 Mg ha^{-1} (figure 2(a)), which is equivalent to a 19% decrease compared to current (i.e. 2000-2007 average) state average yields. For Jun.-Jul. total *prcp*, every 50 mm of additional precipitation could potentially boost yields by 0.75 Mg ha^{-1} higher (figure 2(b)), or 9% higher compared to the current average state yields of 8.5 Mg ha^{-1}. For soybeans, based on the independent linear regression models, for each degree of warming during July-Aug. (*tavg*) a decrease in yields of –0.58 Mg ha^{-1} (figure 2(c)) could occur, which is a 22% decrease compared to the current state average yield of 2.6 Mg ha^{-1}. For June-Aug. total *prcp*, soybean yields were 0.28 Mg ha^{-1} higher with each additional 50 mm of precipitation (figure 2(d)), which is a 11% increase compared to the current state average.

While the general effects of temperature and precipitation are apparent on corn and soybean yield trends, there appears to be a weak correlation between temperature and precipitation trends (figure 3(a)-(b)). It is not surprising that trends toward warmer conditions are correlated with trends toward less precipitation, which is an important discovery in helping to better understand how climate change is actually occurring. Figure 3 also illustrates that corn and soybean yield trends have been impacted differently by climate trends. For example, figure 3a depicts a grouping of county corn yield trends based on a ranking of the top 25% (blue color), middle 50% (green), and bottom 25% (red) of county vales. When those rankings are used in figure 3b for soybeans, it is clear that the ordering is no longer applicable. This suggests that climate changes have had varied impacts on these two crops. In some counties, the climate changes have benefited corn more than soybeans, and vice-versa in other locations.

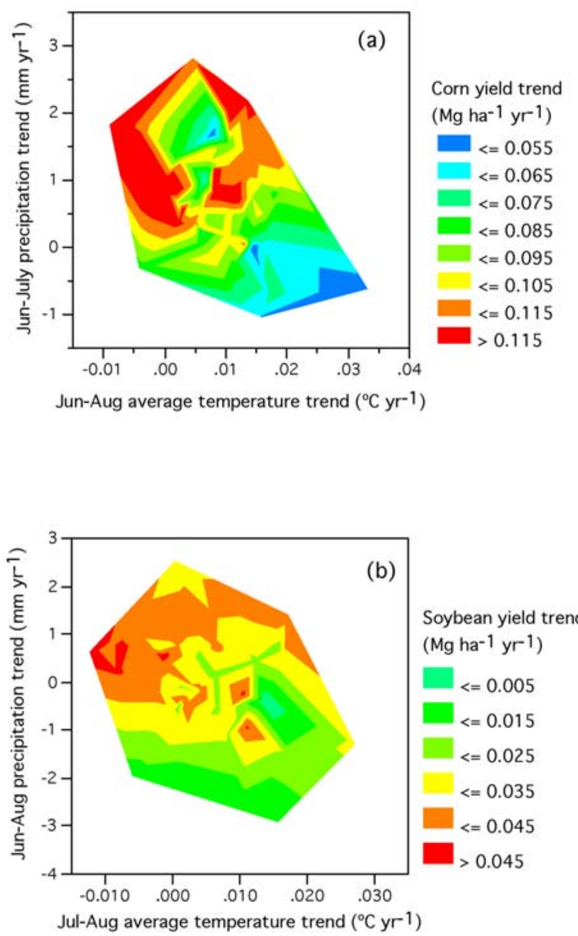

Figure 4. *Distribution of trends in county (a) corn and (b) soybean yields when compared simultaneously to county level trends in temperature and precipitation.*

Figure 4 is presented to depict the very clear relationship between climate space and crop yields trends across Wisconsin at the county level. For example, in figure 4(a), the bottom-end county level yield trends in Wisconsin (i.e. ~0.050 Mg ha^{-1} yr^{-1}) were predominantly found when the Jun.-Aug. *tavg* temperature trends were highest (~ 0.25 - 0.3ºC decade^{-1}), and Jun.-Jul. *prcp* trends were lowest (~ -5 to –10 mm decade^{-1}). The highest trends in recent corn yields (i.e. > 0.115 Mg ha^{-1} yr^{-1}) were mostly found where Jun-Aug. *tavg* trends were negative, and Jun.-Jul. precipitation was increasing through the period. The same general response was observed for soybeans, although precipitation plays a slightly more dominant role given similar soybean yield trends were found across a larger continuum of Jul.-Aug. *tavg* trends (-0.1 to 0.15ºC decade^{-1}) (figure 4(b)). The highest soybean yield trends (> 0.045 Mg ha^{-1} yr^{-1}) occurred in counties that saw increases in Jun.-Aug. precipitation, and a cooling trend in Jul.-Aug.

Contribution of climate trends to yield trends

We used multiple linear regression analysis, with temperature and precipitation trends at the county level as independent, predictor variables, and trends in corn and soybean yields as the dependent variables, to quantify the separate effects of those factors. Overall, approximately 40% of corn and 35% of soybean yield trends could be explained by a combination of the most important climate factors (table 1). The climate-adjusted average corn yield trend was 0.100 Mg ha^{-1} yr^{-1}, or 5.3% higher than the observed value. For soybeans, the climate-adjusted average soybean yield trend was 0.034 Mg ha^{-1} yr^{-1}, or 9.7% higher than the observed average trend (table 1). Therefore, it appears that climate changes have suppressed yield trends by 5-10% during the 1976 to 2006 period. However, trends toward warmer conditions during the growing season, which clearly have a negative impact on yield trends for both crops, have been counterbalanced by increases in precipitation during these months in many areas, thereby helping to offset yield losses.

Table 1. *Summary of multiple regression statistics and models between trends in crop yields and climate at the county level for 1976-2006.*

Crop	2000-'07 yield average (Mg ha^{-1})	Average yield trend (Mg ha^{-1} yr^{-1})	Predictor variables	Intercept (Mg ha^{-1} yr^{-1})	R^2	*P-value*	*tavg* coefficient (Mg ha^{-1} ºC^{-1})	*prcp* coefficient (Mg ha^{-1} mm^{-1})	*Δyield per tavg ±1ºC* (%)	*Δyield per prcp ±50mm* (%)
Corn	8.5	0.095	June-Aug. *tave* June-Jul. *prcp*	0.100	0.40	<0.0001	-1.14	0.0101	13.4	5.9
Soybean	2.6	0.031	July-Aug. *tavg* June-Aug. *prcp*	0.034	0.35	<0.0001	-0.42	0.005	16.1	9.6

The partial correlations of corn yield trends with the *tavg* and *prcp* variables were -0.53 and 0.52, respectively, suggesting that the two contributed almost equally to the end result. Likewise, the partial correlations of soybean yield trends with predictor variables were -0.40 and 0.51 for *tavg* and *prcp*, respectively. In the case of soybeans, trends in precipitation had a slightly larger impact on the overall multiple regression results. Cross-correlations between temperature and precipitation were not significant predictors for either corn or soybeans ($P > 0.3$).

The resulting coefficients for *tavg* and *prcp* for corn (-1.14 Mg ha^{-1} ºC^{-1}, 0.0101 Mg ha^{-1} mm^{-1}) from the multiple regression analysis suggest that for every 1ºC perturbation in temperature for Jun.-Aug. *tavg*, yields could be affected by 13.4% when compared with the current statewide corn yield average. For every 50mm change in *prcp* during Jun.-Jul., yields could either increase or decrease by 5.9% (table 1). In comparison, the multiple regression results for soybean suggest yield sensitivity of 16.1% for 1ºC changes in *tavg* in Jul.-Aug., and 9.6% for 50mm perturbations in Jun.-Aug. total *prcp* (table 1) when compared with the current state average soybean yield.

Conclusions

Corn and soybean yield trends across Wisconsin have been favored by cooling and increased precipitation during the summer growing season. The approximate quantitative contribution of temperature trends to corn and soybean yields here agrees with previous results presented at a much larger scale by Lobell and Asner [10], but we detected a significant contribution of precipitation in our regression modeling. It appears that a significant amount of spatial variability in climate trends has led to variable trends of soybean and corn yields at the county level. Some regions with the highest yield gains over the past 30 years have experienced a trend towards cooler and wetter conditions during the summer, while other areas that have experienced a trend towards drier and warmer conditions have experienced suppressed yield gains. There was no apparent latitudinal gradient of climate changes or yield trends.

Given that the magnitude of recent temperature changes are 0.1 to 0.3ºC decade^{-1}, which are on the lower end of the projected rate of temperature increases (0.3 to 0.4ºC decade^{-1}) through the end of the 21st century of [20], there is strong evidence that Wisconsin cropping systems will continue to be impacted by future climate change. It appears that more widespread suppression of yield gains across the state would have resulted had many counties not experienced an increase in precipitation. Our study suggests that locations along the northern perimeter of the Corn Belt with a cooler climate could be adversely affected by continued temperature rises, and the response could be even greater than anticipated if heat and drought combine together. Our overall corn yield response to warming (13% for 1ºC) in this mid-latitude location is also much greater than discussed in the IPCC 4th assessment, where corn yields are projected to decrease by 5-20% with up to 3-4ºC of warming without adaptation. With adaptive measures, yields were projected to be able to remain at or slightly above current levels [20].

While we did not account for other management changes or trends in atmospheric CO_2 [22], ozone, or pests and disease in this study [23], we presume that these had minimal impact on our overall results given their contributions would have likely been uniform across a small region. However, results should be interpreted with caution here regardless given limitations with empirical studies. Furthermore, the period we have chosen for the analysis could also bear to have an impact on the quantitative results. These shortcomings emphasize the continued need for additional research in these areas.

A trend towards warmer and drier conditions during the spring planting time and fall harvest will undoubtedly help boost yields in northern regions that are currently experiencing a shorter growing season compared to points further south, which forces farmers to choose crop hybrids with lower yield potential due to their planting in a shorter growing season region. Farmers are likely to be aware of, and will adjust to, changes in springtime conditions given they are always looking to get their crops into the ground as early as possible to plant higher yield potential varieties in northern regions. It is already understood that the arrival of spring has been occurring earlier in Wisconsin [24, 25]. However, if warming would continue to occur during the middle of the growing season, it could work against crop productivity by accelerating phenological development, causing the plant to mature more rapidly, losing valuable calendar days in the field to accumulate biomass during grain fill. Furthermore, additional heat and soil moisture stress during pollination and an increased frequency of very warm days (e.g., $tmax >$ 35ºC) could counteract the potential benefits of an extension of the growing season via decreased rates of carbon uptake through photosynthesis. Given that earlier planting of corn and soybeans has been occurring simultaneously with these climate changes, it appears that this is one potential adaptive strategy to warming temperatures that hasn't completely offset decreased productivity due to warming during meteorological summer.

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Section 5. Assessing potential impacts of future climate change and increasing CO_2 on Wisconsin corn and soybean yields

Introduction

Wisconsin is home to a $22-billion per year agricultural economy that serves as part of a Midwest U.S. hub for both national and global food production. Agricultural production is particularly vulnerable and responsive to climate variability and land-use management decisions. The reliance of producers on the climate system makes them particularly vulnerable to global warming, timely precipitation, and rising atmospheric CO_2. Plant available moisture during the growing season continues to be the most substantial influence on yields of most common crops in Wisconsin. To the extent that climate change increases the likelihood of periods of drought, it will increase risks associated with crop production. Changing climate and atmospheric CO_2 have great potential to alter soil moisture availability, plant physiology, and phenological development, but climate change alone can also impact farmer behavior by influencing planting dates, hybrid selection, or even the planted crop type.

Therefore, an important question remains to be answered: **Will human-induced changes in climate and atmospheric CO_2 jeopardize Wisconsin's high levels of corn and soybean productivity in the coming decades?** This question is especially difficult to answer because agricultural production results from complex interactions between human, physical and biological systems. As part of our work, we are keeping the following related questions in mind:

(1) *Can we pinpoint "hot spots" of change across Wisconsin – at the crop reporting district level – where climate change could be particularly important in the future to corn and soybean production?*

(2) *How might crop productivity change in the future due to the combined effects of changing climate and atmospheric CO_2?*

The anticipated response of Wisconsin agriculture to changing climate, atmospheric composition, and land management contains a great deal of uncertainty. For example, southern regions may not be significantly limited by temperature, but future changes in the timing of precipitation and increased warming during the growing season may significantly alter the rate of development of corn and soybeans. Furthermore, future increases in atmospheric CO_2 could increase soybean production, but the effects may vary under different precipitation regimes (Long et al., 2006; Leakey et al., 2006). Environmental changes in the future might make some watersheds more suitable for agriculture and others more affected by drought and other extreme weather events. In a policy context, some of these new results may illustrate how farming might need to adapt to cope with future atmospheric conditions (such as changes in optimum planting dates or hybrids) to prevent yield losses.

Methods

Global circulation model (GCM) data for future climate conditions across Wisconsin

The future climate scenarios utilized in this study were developed by VEMAP, the Vegetation/Ecosystem Modeling and Analysis Project (Kittel et al. 2004). The VEMAP-2 community dataset has been used in a variety of research (e.g. Coops et al. 2005; Hicke et al. 2006; Morrison et al. 2005) and was designed to provide a common climatic input for driving ecosystem models over the continental United States. The VEMAP dataset contains both a topographically adjusted gridded climate history for the continental United States for the years 1895-1993 and general circulation climate (GCM) scenarios, on a relatively coarse-resolution 0.5° grid. The historical VEMAP temperature and precipitation data are based on measurements from the United States Historical Climate Network (USHCN), NOAA cooperative networks, and the snowpack telemetry (SNOTEL) dataset, where the later two are used to fill spatial gaps in the USHCN network.

The VEMAP Phase 2 (transient dynamics) dataset provides two general circulation model climate scenarios, which were downscaled to the VEMAP grid resolution (0.5°) for the period 1994-2100, and topographically adjusted. The climate projections include runs from the Canadian Climate Center (CCC) (CGCM1; 3.75° x 3.75°, with 19 vertical levels) and the United Kingdom Hadley Center (HAD) (HADCM2; 2.5° x 3.75°, 10 vertical levels) models. These models included increasing atmospheric CO_2 and sulfate emissions at an idealized rate of 1% per year; measured atmospheric concentrations for both constituents were used until 1993. This emissions rate comprises a middle of the range scenario that was used in the 2001 Intergovernmental Panel on Climate Change (IPCC) assessment in terms of CO_2 concentrations in 2100 (IPCC, 2001). For this study we report results using both the CCC and HAD models. We note however that the temporal extent of the HAD model included in VEMAP-2 is 1994-2099. Both these models tend to predict a global mean temperature increase slightly larger than the mean of the collection of models used in the third IPCC assessment report (IPCC, 2001). The historical temperature and precipitation data for the years 1895-1993 are identical in the VEMAP-2 CCC and HAD model outputs.

Description of statistical forecasting of yields and uncertainty analysis

To model the response of corn and soybean yields in Wisconsin under future climate conditions we applied our previously developed statistical crop models (Chapter 4 of this report and Kucharik and Serbin 2008), aggregated to the climate district (CD) level, to the VEMAP-2 output. First, the historical data and future climate scenarios from the two models (i.e. CGCM1 and HADCM2) were averaged by climate district and output as a complete time-series of data (i.e. 1993-2100). As both the corn and soybean yields were differentially sensitive to nighttime and daytime temperatures, we output both tmin and tmax and used only models that incorporated both tmin and tmax as predictor variables (e.g., Table 1). The yield models were first applied to the observed monthly climate data (Serbin and Kucharik 2008) to generate the parameter estimates and error statistics for each parameter in the model and then to the VEMAP-2 data for the years 1976-2100 to asses the impacts of climate change on yields.

In this study we considered two aspects of crop model uncertainty in our projections of corn and soybean yields across Wisconsin: (1) the uncertainty due to the empirical crop models not completely describing the historical yield-climate relationship (**sampling uncertainty**) and (2) the added uncertainty related to differences in climate model output. The sampling uncertainty (i.e. crop model uncertainty) was assed by creating 35,000 separate statistical crop models based on stochastic resampling of the equation parameters using the parameter standard errors in the original crop models (Table 1) in the SAS 9.1.3 MODEL procedure (SAS Institute Inc., 2001, Cary North Carolina). Each of the resulting crop models were then fit to the separate GCM outputs to generate a mean and median yield projection by year as well as the corresponding 95%

confidence intervals from the 35,000 crop models. The uncertainty related to the differences in the parameterization of the two climate models was assessed by comparing the modeled results using both the CCC and HAD GCM outputs. Finally, we present the results as % yield anomaly relative to the final 10-year average yield responses to historical climate. For each climate district, the projected yield deviations (in bu/acre) were compared to the 1997-2006 average yields resulting in a percent yield change by crop, climate model, and by climate district. The resulting normalized projections are then compared to investigate the impacts of potential future climate change on crop yields in Wisconsin.

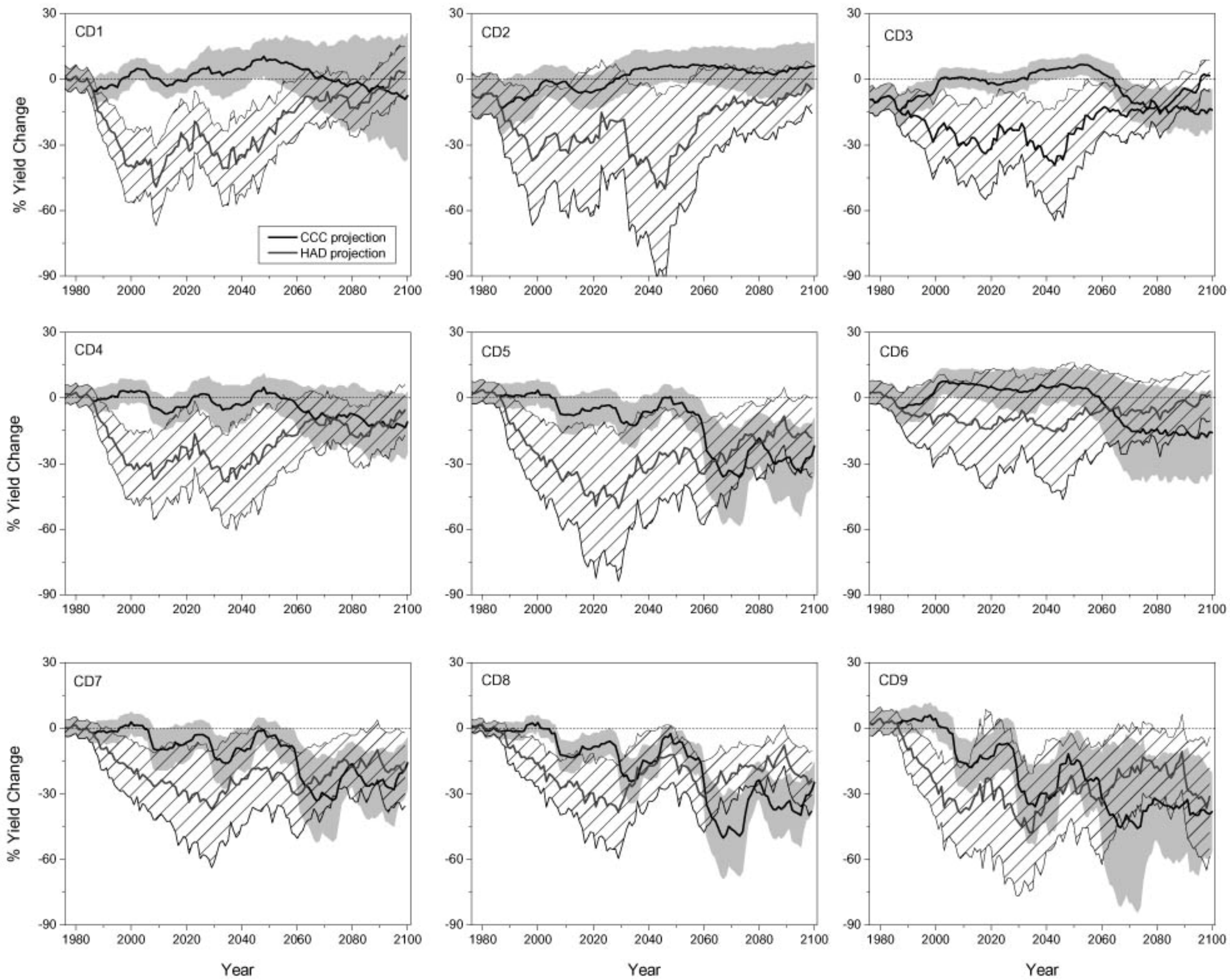

Figure 1. Projected corn yield changes under future climate scenarios, not constrained to historical extremes. Yields are expressed in units of percent anomaly from the 1997-2006 average yields, by climate district (CD), and are plotted as 15-year moving averages to highlight trends rather than year-to-year variations. The black and dark grey lines show the median CCC and HAD based projections, respectively, while the grey shaded area shows the 95% confidence interval for the CCC projections while the hatched area shows the 95% confidence interval for the HAD projections.

Results and discussion

Future climate change impacts on corn yields

The CCC climate model data, combined with our statistical models relating climate and yields (based on data from the 1976-2006 period), was able to reproduce the observed average yields for the 1976-2006 period, but the HAD climate data was clearly not similar to the CCC, causing rather large errors in simulated yield variability within that timeframe (Fig. 1). So, immediately the first result that we see is that there are very large discrepancies in the future projections between the two sets of climate model runs, signaling that there are significant differences in the climate output between the two scenarios we used. In general, the largest changes in corn yields are expected to occur in the southern part of the state (climate districts 7-9), and towards the latter half of the 21st century. Those deviations, when normalized according to current average yields, suggest that 30-60% corn yield losses (e.g., ~40-80 bu ac^{-1}) are possible in the latter half of the 21st century attributed to climate change. Across the northern districts, a warmer climate during the growing season may actually favor increases in corn yields by up to 10% according to the CCC model (e.g., climate district 2), but those results were generally not replicated when using HAD model output to drive the simulations. The largest discrepancies between climate model output and their influence on corn yield trends appears to be across the central and northern regions of Wisconsin, especially during the 2010 to 2050 time period (Fig. 1). From our analysis here, it appears that the HAD model output suggests that climate changes will be more detrimental to corn yield losses in the future than suggested by the CCC model.

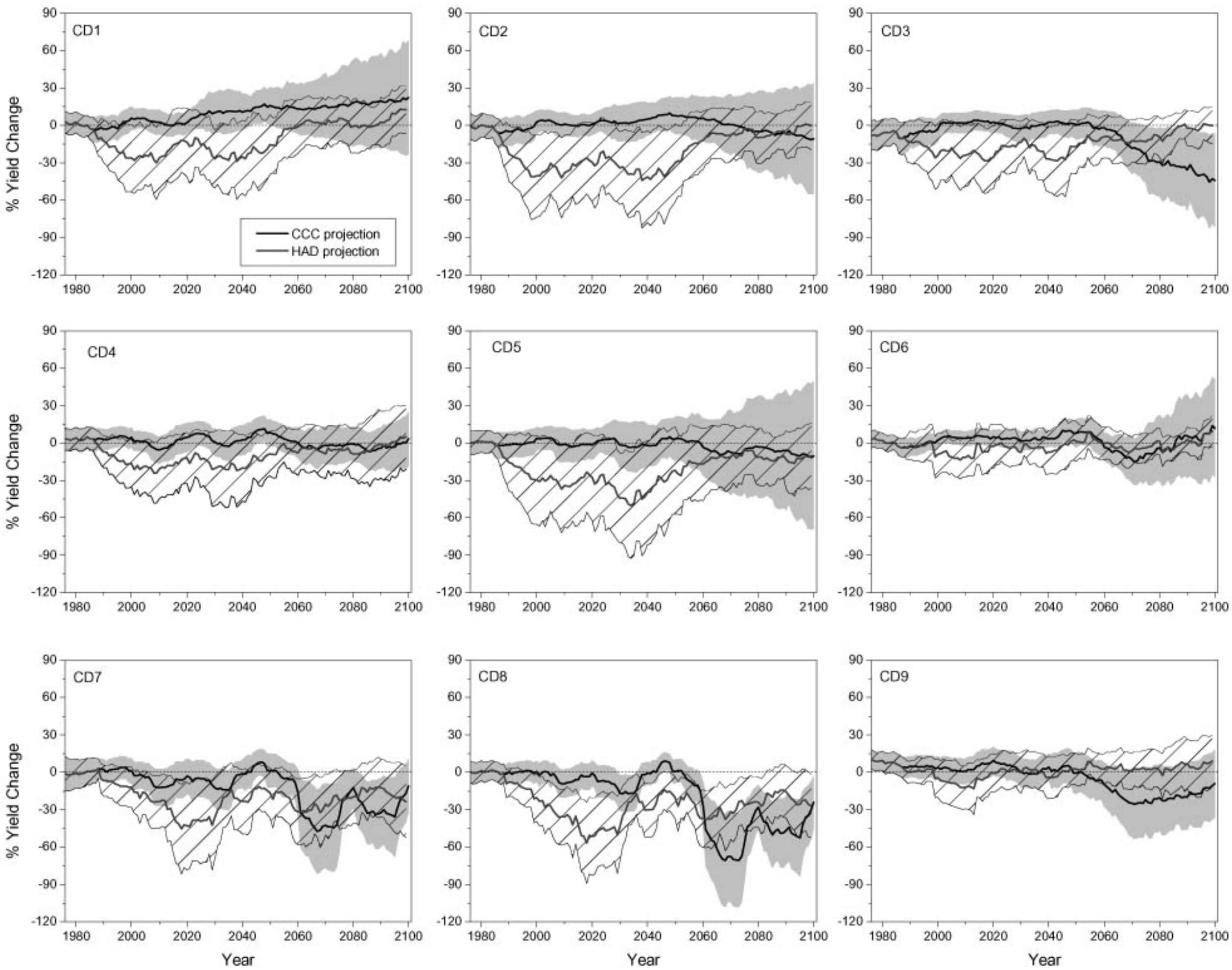

Figure 2. Projected soybean yield changes under future climate scenarios, not constrained to historical extremes. Yields are expressed in units of percent anomaly from the 1997-2006 average yields, by climate district (CD), and are plotted as 15-year moving averages to highlight trends rather than year-to-year variations. The black and dark grey lines show the median CCC and HAD based projections, respectively, while the grey shaded area shows the 95% confidence interval for the CCC projections while the hatched area shows the 95% confidence interval for the HAD projections.

Future climate change impacts on soybean yields

Similar to the simulated corn yield results, the CCC climate model data, combined with our statistical models relating climate and soybean yields, was able to reproduce the observed average yields for the 1976-2006 period (Fig. 2). However, the HAD climate data was clearly not similar to the CCC, causing rather large errors in simulated yield variability within the 1990-2005 timeframe (Fig. 2). But, the differences between the two sets of model projections appear to be less magnified for soybeans compared to corn. In general, the largest changes in soybean yields are expected to occur in the southern part of the state in climate districts 7 and 8, after about 2060. Those deviations, when normalized according to current average yields, suggest that 30-60% soybean yield losses (e.g., ~15-30 bu ac^{-1}) are possible in the latter half of the 21st century attributed to climate changes. Across the northern and central districts – along with CD 9 – the impacts of climate change on soybean yields are mixed. For example, the CCC model suggests that soybean yields will remain around +/- 10% of the current yield values through the end of the century, while the HAD model climate output causes soybean yields to decrease by 30-60% during the middle part of the 21st century, only to rebound in the late stages of this century. The largest discrepancies between climate model output and their influence on soybean yields appears to be across the western regions of Wisconsin, especially during the 2010 to 2050 time period. Interestingly, in the eastern climate districts of the state (CD3, 6, and 9), the HAD and CCC models appear to have similar impacts on future soybean yields, which wasn't the case with corn yield results (Fig. 1). In fact, the bottom line for the eastern regions of the state suggest that future climate changes might not have much of an impact on soybean yields. Overall, it appears that soybeans would be impacted to a lesser extent by climate change compared to the results produced for corn.

Problems with future projections

There are several issues that need to be considered when performing projections of future climate change impacts on crop productivity using a statistical modeling approach. First, we have not considered potential changes in hybrids, planting dates, other farmer management responses, or new technology in the future. All of these factors could in fact help the farming community adapt to future climate changes, and thereby decrease the detrimental impacts of future global climate change on productivity. The largest uncertainty is the impact that new technology in seed engineering will have on adapting to a new climate regime, particular in terms of drought tolerance or resistance to new pests/diseases. Thus, the future projections that we discuss here could be worst case scenarios based on the previous relationship between weather and climate. We need to remain hopeful that if climate change occurs gradually, farmers will be able to adapt to those changes through time by adjusting their planting schedule, or by selecting new hybrids that are better suited for a new climate regime.

Global circulation models are also continually being updated and improved so that they can make more accurate predictions of seasonal weather conditions. In the case of Midwest cropping systems, rainfall and temperatures during specific weeks of the growing season can have large impacts on end-of-season yields. For example, corn reaches a critical stage when it reaches the silking/tasseling stage in the mid to late stages of July, and if soil moisture is not optimal, significant yield losses can occur. Unfortunately, GCMs do not have the capability to predict changes in week-to-week rainfall or temperature in the future, and at best, do a satisfactory job in getting monthly changes correct. In agriculture, however, the time-series of weather events that happen (week to week or even day-to-day) can have significant consequences on yields. Therefore, the results presented here offer just one perspective on how yields could change, based on a limited capacity of GCMs, and ignoring the potential adaptation of agriculture to continued climate changes in the future.

Table 1 Monthly climate variables that explained the greatest amount of interannual yield variability at the crop reporting district (CD) level across Wisconsin for 1976-2006. The variable "P" is precipitation, "Tmx" is maximum temperature, and "Tmn" minimum temperature.

	CD1 (NW)	**CD2 (NC)**	**CD3 (NE)**	**CD4 (WC)**	**CD5 (CN)**	**CD6 (EC)**	**CD7 (SW)**	**CD8 (SC)**	**CD9 (SE)**
Corn	July Tmx	July P	Jun Tmx	Jul Tmx	Jul Tmx	Jun Tmx	Jun P	Jun P	Jul Tmx
	Jul P	Sep Tmx	Jul P	Jul P	Jul P	Jun P	Jul Tmx	Jul Tmx	Jul P
	Sep Tmn		Sep Tmx	Sep Tmx	Aug Tmx	Sep Tmx	Aug Tmx	Aug Tmx	Aug Tmx
Soybean	Jul Tmx	Jul P	Jun Tmx	Jul Tmx	Jul Tmx	May Tmn	Jul P	Jun Tmx	Jun Tmx

	Jul P	Jul Tmx	Jul P	Jul P	Sep Tmn	Jun Tmx	Aug Tmx	Aug Tmx	Jul P
	Sep Tmn	Sep Tmn	Sep Tmn	Aug P		Sep Tmn	Aug P	Aug P	Aug P

Likely impacts of increasing atmospheric CO_2 on future corn and soybean yields

Changes in atmospheric chemistry, most notably the concentration of carbon dioxide [CO_2] and ozone [O_3] have strong potential to directly impact crop biomass growth, carbon partitioning, and end-of-season yields. Changes in atmospheric CO_2 concentrations have been occurring for over 150 years, rising from levels near 260 ppm to near 380 ppm in 2006. The process of photosynthesis in plants is directly impacted by CO_2 concentration, as well as stomatal conductance. Many studies conducted with chambers in greenhouses or other artificial settings over the past several decades have suggested that increases in CO_2 will cause a "fertilization" effect on *all* plants, effectively increasing their rate of photosynthesis, biomass, and yields. However, depending on the plant categorization, those fertilization impacts have been hypothesized to be quite large or small.

For instance, in C_3 crops (e.g., soybeans and wheat), the mesophyll cells that contain Rubisco (ribulose-1,5-bisphosphate carboxylase-oxygenase, an enzyme), are positioned in a way that they have a connection to the outside atmosphere through stomates, or small pores in the leaf surface. Rubisco is best described as an important enzyme [protein] that is key to catalyzing the fixing of carbon through photosynthesis. It is an abundant protein that all biological plant life depends on as it allows inorganic forms of carbon to enter the soil-plant system from the atmosphere's CO_2 storage tank. In C_3 the mesophyll cells are essentially in contact with intercellular air space that is a pipeline to the atmosphere (Long et al., 2006). This arrangement means that Rubisco is not CO_2-saturated with respect to today's atmospheric conditions, and thus an increase in CO_2 in the atmosphere effectively translates into increased productivity. The situation is different for C_4 crops, which includes corn. The Rubisco is not found in mesophyll cells but is rather within bundle sheath cells where the internal concentration of carbon dioxide is often three to six times the concentration in the outside atmosphere (Long et al., 2006). Therefore, because CO_2 is already high enough to saturate Rubisco, additional CO_2 from the atmosphere would not be able to increase the concentration in the bundle sheath cells, and thus would not effectively cause more CO_2 to be taken up (Long et al., 2006). From this fundamental knowledge, the bottom line is that C_3 crops such as soybeans have a distinct advantage over C_4 crops like corn – in terms of increasing production – as atmospheric CO_2 continues to increase. However, early experimental results using chambers and enclosures have suggested otherwise.

In fact, many chamber-based studies suggested that yields in corn would increase by 18-27% when CO_2 in the atmosphere reached 550 ppm, which was somewhat comparable, but lower, to the numbers arrived at for wheat and soybeans (~33%) (Morgan et al., 2005; Long et al., 2006). Unfortunately, the very nature of the experiments used to arrive at these plant responses are not all that representative of natural growing conditions; field chambers, greenhouse experiments, and plants grown in pots are not good examples of open-air growing conditions. New studies that make use of Free-Air Concentration Enrichment (FACE) experiments are beginning to shed new light on the likely response of corn and soybean crops to increasing atmospheric CO_2 (Leakey et al., 2006; Schimel, 2006). These experiments effectively encompass large portions of crop fields in a manner by which the levels of CO_2 inside a concentric ring of piping can be controlled via computer using data observations of wind speed, direction, and CO_2 concentration occurring simultaneously. The bottom line is that FACE allows a portion of a field to be subjected to a particular increased concentration of atmospheric CO_2 (in this case 550 ppm), while the rest of the field outside of the experiment is exposed to ambient CO_2 concentrations (e.g., 380 ppm). This design allows for all of the important weather variables such as precipitation, temperature, humidity, and radiation to impact plant growth in a real life setting.

These exciting new results suggest a much different response than earlier projected for Midwest corn and soybean yields to increasing carbon dioxide in the atmosphere. The experimental data backs up the idea that C_4 photosynthesis (corn) is already saturated at the current levels of atmospheric CO_2, and thereby any more increases in CO_2 will not be effective at boosting productivity in the future. In one key study by Leakey et al. (2006) performed in Illinois, they found that elevated CO_2 (550 ppm) did not stimulate an increase in photosynthesis or yield compared to current levels. Instead, the increased CO_2 caused water use efficiency to increase through a decrease in stomatal conductance of 34%. What really happened in the crop plants was that increased concentrations of CO_2 caused stomata to decrease the average opening size during the growing season (e.g., because a higher concentration of CO_2 was available to perform photosynthesis), and therefore less water was lost through respiration. However, when a corn plant is not experiencing water stress, the impact on productivity is likely to be zero. Only under drought like conditions is increased CO_2 likely to help boost corn productivity in the Midwest, including Wisconsin. Given projections of more frequent droughts across the central U.S. in the next century, it is conceivable that increased CO_2 could help corn crops through increased water use efficiency, effectively reducing water stress during growing season droughts, but more fieldwork appears needed to back up this hypothesis. Nonetheless, earlier projections of large increases in corn production across the Midwest due to increased CO_2 appear to be in question now given new evidence.

In the case of soybeans, it appears that increases in yield could still occur as CO_2 increases in the atmosphere, but the projected increase is approximately 50% less than the original studies that were performed using enclosures or chambers. It is suggested that across Wisconsin, soybean yields may be increased by approximately 13-15% as CO_2 levels climb towards 550 ppm by 2050 (Morgan et al., 2005; Long et al., 2006; Leakey et al., 2006).

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