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Interpreting Temperature- and Precipitation-related Scientific Information for the Agricultural Community In the U.S. Corn Belt

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INTERPRETING TEMPERATURE- AND PRECIPITATION-RELATED SCIENTIFIC INFORMATION FOR THE AGRICULTURAL COMMUNITY IN THE U.S. CORN BELT

by

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INTERPRETING TEMPERATURE- AND PRECIPITATION-RELATED SCIENTIFIC INFORMATION FOR THE AGRICULTURAL COMMUNITY IN THE U.S. CORN BELT

Shuwei Dai, Ph.D.

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Advisor: Martha D. Shulski

Climate change has been widely recognized in the U.S. Corn Belt, but what does it really mean to the agricultural community? In an era of explosive information, isolating useful climate change data and interpreting these data in usable ways is critical to the success of the broad corn production industry. In this study, three key questions are answered: (1) How have temperature and precipitation changed in the Midwest since 1980? (2) What is the best method to estimate thermal time for corn when temperature data are limited to a daily timescale? and (3) What are the historical effects of temperature and precipitation on field-level corn grain yield under irrigated and rainfed conditions? Different high-quality and representative datasets have been used for the study, together with several scientifically-proven statistical methods and spatial analysis tools. The results show that: (1) Growing season for corn has become warmer over the Midwest, mainly caused by the statistically significant increases of minimum temperature in early season in the southeast part and maximum temperature in late season in the northeast part. Meanwhile, growing season for corn has become wetter (not statistically significant), due to increased precipitation in early season outweighing a drier late season. (2) In Nebraska, six methods have been commonly used to estimate thermal time for corn by different agricultural groups. Among them, the single- and double-sine methods generally perform better estimations with one exception where the T_{avg}-based rectangle

method outperforms them. However, the most widely used adjusted T_{max} and T_{min} rectangle method provides the poorest estimation for total degree-days during the active growing season for corn. (3) In the past decade, temperature and VPD plays a more important role on corn grain yield at the irrigated and rainfed sites near Mead, Nebraska, respectively. For the variance in corn grain yield, variation in growing season DD_{35+} explains 46% of it at the irrigated continuous corn site; variation in daytime air temperature during the 31-day period centered around silking explains 88% of it at the irrigated corn-soybean rotation site; variation in reproductive stage VPD_{max} explains 87% of it at the rainfed corn-soybean rotation site.

ACKNOWLEDGEMENTS

I am very grateful that my advisor Dr. Martha D. Shulski accepted me into this PhD program. I had wanted to become a scientist since I was little and had an American dream to get a Doctoral degree in Science from an American institute since I was in high school. This program fits perfectly with my background, expertise, and area of interest. I am one of the luckiest students to have an advisor who has supported me academically, emotionally, and financially. Dr. Shulski has allowed me to freely pursue my various scientific ideas, offering nothing but help and encouragement. She always remembers to recognize my progress no matter how small it is, which is important to me, and I truly appreciate her doing that all through these years. She never bothered me with anything about the budget and instead encouraged me to go to various conferences to learn new things and network with other colleagues. When I was having a difficult time in my life and could not finish the program on time, she foresaw the problem before I even mentioned it and found new funding to extend my program for another semester. This means much more than I could express with words to me and my family. Besides being a role model as a professional, she is also a good role model of wife and mom for me. Whenever I am in need, I know she is right there, as my advisor and as a like-family member. I owe my doctoral degree to Dr. Shulski because without her I could not have accomplished so much in my academic and personal life.

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CHAPTER 1: INTRODUCTION

10 words that summarize the “Big Five” facts about global climate change are:

“It’s real.

It’s us.

It’s bad.

Scientists agree.

There’s hope.” (Leiserowitz, 2015).

Climate disruptions to agricultural production have increased in the past four decades, and these interruptions will lead to consequences for food security in the U.S., for example, through changes in crop yields. Food security could affect national security, therefore, it is important to study the agricultural effects of climate disruptions. U.S. is the largest corn producer in the world, and the national heart of corn production is in the Midwest. In 2015, the Midwest contributed about 28% of world corn production (USDA and NASS, 2016). Among the many agricultural regions that have experienced declines in crop production from climate change induced stresses, the Midwest has been vulnerable to weather and climate extremes. In the Midwest, increasing trends were observed in heat wave intensity and frequency, extreme rainfall events and flooding in the last century. And these trends are expected to continue, with the magnitudes of expected changes exceeding those experienced in the last century. As these increasing extremes in temperature and precipitation continue to challenge both rainfed and irrigated agriculture, existing adaptation and planning efforts would not be adequate to respond to

these projected changes, and innovative conservation methods will be in an urgent need (Hatfield *et al*., 2014; Pryor *et al*., 2014; Shafer *et al*., 2014).

In the U.S. corn belt, weather is a major driving force of the success or failure of cropping systems. As the heart of the national corn production industry, this region's ability to sustainably produce enough crops under a more-variable-than-ever climate background is critical for food security and rural livelihoods in the United States (Prokopy 2012). However, almost a quarter of Midwestern farmers and agricultural advisors believe the main source of climate change is natural causes, and 22%–31% state that there is not sufficient evidence to know with certainty whether it is occurring or not (Prokopy *et al*., 2015). These misconceptions reveal a need for agricultural climatologists to communicate climate science to agricultural stakeholders in ways that are more efficient and convincing to encourage adaptation to climate change and climatic stress mitigation. This study aims to interpret temperature- and precipitation-related scientific information that is up-to-date and relevant to corn production for the agricultural community in the U.S. corn belt. In order to do so, this study focuses on two issues: first, extracting climate variability and change information that is useful to corn producers in the U.S. corn belt from existing data; and second, developing easy-to-use tools the agricultural community can use to learn about the up-to-date climate change information that is relevant to them. Specifically, the useful data include: temperature and precipitation trends during the growing season for corn from 1980 to 2013 in the entire region; the best method to estimate degree-days for corn during the active growing season with daily temperature data; and historical effects of temperature and precipitation on corn grain yield under both irrigated and rainfed conditions for both continuous and

rotated corn systems. One web-based tool has been developed for the agricultural community in the U.S. corn belt to help them easily look up the temperature and precipitation trends at the timescales and locations that interest them. This tool has been advocated in a variety of local, regional, and national events. Hopefully, these efforts will assist the agricultural community in striving to make more sustainable farming operations and lead to greater resilience to the faster changing climate in the long run.

References

Hatfield J, Takle G, Grotjahn R, Holden P, Izaurralde RC, Mader T, Marshall E, Liverman D. 2014. Ch. 6: Agriculture. In *Climate Change Impacts in the United States: The Third National Climate Assessment*, Melillo JM, Richmond TC, Yohe GW (eds). U.S. Global Change Research Program, 150–174.

Leiserowitz AA. 2015. *Climate Change in the American Mind*. University of Nebraska–Lincoln: Heuermann Lectures, March 10 2015. Lincoln, NE.

Prokopy LS. 2012. *Useful to Usable Project Fact Sheet*. https://mygeohub.org/resources/485/download/U2U_FactSheet_Oct2012.pdf

Pryor SC, Scavia D, Downer C, Gaden M, Iverson L, Nordstrom R, Patz J, Robertson GP. 2014. Ch. 18: Midwest. In *Climate Change Impacts in the United States: The Third National Climate Assessment*, Melillo JM, Richmond TC, Yohe GW (eds). U.S. Global Change Research Program, 418–440.

Prokopy LS, Morton LW, Arbuckle JG, Mase AS, Wilke AW. 2015. Agricultural stakeholder views on climate change: Implications for conducting research and outreach. *Bull. Am. Meteorol. Soc*. **96**: 181–190.

Shafer M, Ojima D, Antle JM, Kluck D, McPherson RA, Peterson S, Scanlon B, Sherman K. 2014. Ch. 19: Great Plains. In *Climate Change Impacts in the United States: The Third National Climate Assessment*, Melillo JM, Richmond TC, Yohe GW (eds.). U.S. Global Change Research Program, 441–461.

USDA, NASS. 2016. *Crop production 2015 summary*. http://www.usda.gov/nass/PUBS/TODAYRPT/cropan16.pdf (accessed 27 October 2016).

CHAPTER 2: A SPATIOTEMPORAL ANALYSIS OF MIDWEST US TEMPERATURE AND PRECIPITATION TRENDS DURING THE GROWING SEASON FROM 1980 TO 2013

ABSTRACT: Since late 1970s, climate warming has been widely recognized. In the Midwest, farmers cannot rely on the normal calendar anymore, and it has become critically necessary to evaluate the most recent climate trends relative to growing season in order to conduct adaptation efforts for agriculture. Based on the homogenized historical monthly temperature and precipitation records during the period of 1980–2013 from 302 observing stations in the 12 Midwestern US states, this study investigates the climate trends on four timescales: monthly, early growing season, late growing season, and the entire growing season. The climate metrics include maximum temperature, minimum temperature, average temperature, diurnal temperature range, and precipitation. Nonparametric Sen's Slope together with the nonparametric Mann-Kendall test is used to estimate the decadal trend and to detect the statistical significance. The results show that growing season average temperature has increased at a rate of 0.15 °C decade^{-1} over the Midwest United States. Within the growing season, minimum temperature is increasing faster in the early growing season, especially in June, while maximum temperature is increasing faster in the late growing season, especially in September. Spatially, statistically significant ($p \leq 0.05$) growing season warming is more focused in the southern part of the region in the early growing season but in the northern part of the region in the late growing season. Over the Midwest, dominant trends in diurnal temperature range are decreasing during most months, with the exception of September.

The majority of the locations show increasing trends in growing season precipitation, yet few are statistically significant. Furthermore, precipitation has been increasing in the early growing season but decreasing in the late growing season. This within-season reversing trend in precipitation is found in 8 of 12 Corn Belt states: Illinois, Iowa, Michigan, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin.

2.1 Introduction

Climate change is now one of the greatest challenges facing humanity. Analyses reveal that climate change has indeed started to impact crop production (Hatfield, 2010; Lobell *et al*., 2011), and the challenges being faced by agriculture relative to climate change are imminent (Hatfield, 2013). Because of climate change, today's farmers are increasingly less able to rely on historical climate 'norms' or calendar dates for making agronomic decisions (Wolfe, 2013; Takle *et al*., 2014). The positive effects of climate change (such as longer growing season, better soil moisture recharge, and increased atmospheric CO_2) and technology on agricultural productivity may be partially or totally offset by the negative impacts because of the higher temperatures shortening grain-fill duration and increasing evapotranspiration rates (Adams *et al*., 1990; Lobell *et al*., 2011). Climate warming has been observed in many parts of the world (Field *et al*., 2012), resulting in higher risks of crop failure (Wolfe, 2013). The impacts of climate change on agriculture will not be equal across regions, which can be attributed in part to regional variation in the nature and magnitude of climate change impacts, but also variability in farmer recognition that a climate change signal plays a role (Fischer *et al*., 2005; Adger *et al*., 2007; Easterling *et al*., 2007; Lobell *et al*., 2008). Increased attention has been given

to temperature impacts on crop yields in recent years (Schlenker and Roberts, 2009; Lobell *et al*., 2011), and this has induced a greater sense of urgency to understand the impacts of past climate on crop production and to develop a more robust observational framework for the assessment of agricultural impacts in the United States (Hatfield, 2013). Longer growing seasons increase the number of insect generations per year, warmer winters lead to larger spring populations of marginally overwintering species, and earlier springs lead to the earlier arrival of migratory insects and birds (Wolfe *et al*., 2008; Hatfield *et al*., 2011; Courtier *et al*., 2013).

Observations from 1951 to 2010 confirmed the continuing declines in the number of frost days and increases in thermal time in the western half of the North America (Terando *et al*., 2012). In the Great Plains region, 2012 was warmest on record at locations over the six states (Colorado Springs, CO; Topeka, KS; Valentine, NE; Fargo, ND; Rapid City, SD; Cheyenne, WY) and driest on record in Nebraska (Grand Island, and Scottsbluff) (Umphlett, 2012). Reduction in snow pack and earlier snow melt in the western United States will exacerbate the potential threat of drought for farmers because reduced runoff will result in a reduction in the water stored in reservoirs for irrigation (Lettenmaier *et al*., 2008). In the Platte River Basin in central Nebraska, the recent warming trend (1980–2000) is much stronger than during the Dust Bowl era (1930s), especially for the minimum values of daily maximum and minimum temperatures (Irmak *et al*., 2012).

Trends in temperature variables such as maximum, minimum and average temperatures, and diurnal temperature range will have impacts on crop production. Lobell and Burke (2008) concluded that progress in understanding the magnitude of regional

temperature changes is one of the most important needs for climate change impact assessments and adaptation efforts for agriculture. Monthly, seasonal, and interseasonal information is used for production decisions during the growing season, and multiyear or decadal information is used for long-term decisions (Takle *et al*., 2014). The overall goal of this study is to document the characteristics of trends in maximum, minimum, and average temperatures, diurnal temperature range, as well as precipitation in the Midwest United States for the most recent climatological time period. This would lead to a better understanding of how past climate has been changing in the heartland of corn and soybean production, and to offer scientific support for agricultural adaptation policies or agricultural adaptive management improvement.

2.2 Data and methods

In this study, the research area includes the 12 Midwestern US states where the national corn and soybean production is concentrated: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, North Dakota, and Wisconsin (USDA and NASS, 2009). In this article, this specific region is referred to as the Midwest United States. Monthly temperature (including maximum, minimum, and average temperatures) and precipitation data for the Midwest US stations were compiled from the United States Historical Climatology Network (USHCN) Version 2.5 Serial Monthly Dataset (Menne *et al*., 2014). During the period of 1980–2013, the maximum number of days with missing data allowable for our analyses is set as 9 to incorporate as many stations as possible. A total of 302 observing stations (36.17°–48.97°N and 80.82° –103.63°W, Figure 2.1) were chosen for the spatiotemporal analysis of temperature and

precipitation trends, and the elevation of these stations ranges from 82.3 to 1435.0 m. Specifically, the number of observing stations for the trend analysis in precipitation, maximum temperature, minimum temperature, and average temperature is 181, 264, 215, and 186, respectively. Diurnal temperature range is calculated as (maximum temperature − minimum temperature), and the amount of stations used for trend analysis is the same as average temperature. The mean temperatures (maximum, minimum, and average temperatures, as well as diurnal temperature range) and total precipitation are calculated during the early season, late season, and growing season based on the monthly data. In this study, April through October is referred to as growing season, although these months may not be representative for all locations across the 12-state region. The growing season is further divided into two components, early season – corresponding to the vegetative phase of crops (such as corn) and late season – corresponding to the reproductive phase of crops. The time periods are April to June for the early season and July to October for the late season.

A nonparametric method, Sen's Nonparametric Estimator of Slope, is used in determining the presence of decadal slope (Brauner, 1997). And the nonparametric Mann-Kendall test is used to detect significance levels of the decadal Sen's slopes in temperature and precipitation metrics (Burkey, 2006). This nonparametric test has been widely used in detecting temporal trends in large data sets (Libiseller and Grimvall, 2002). And the combination of Sen's Slope and Mann-Kendall test has been used in evaluating climate variations and trends (e.g. Irannezhad *et al*., 2014; Nguyen *et al*., 2014).

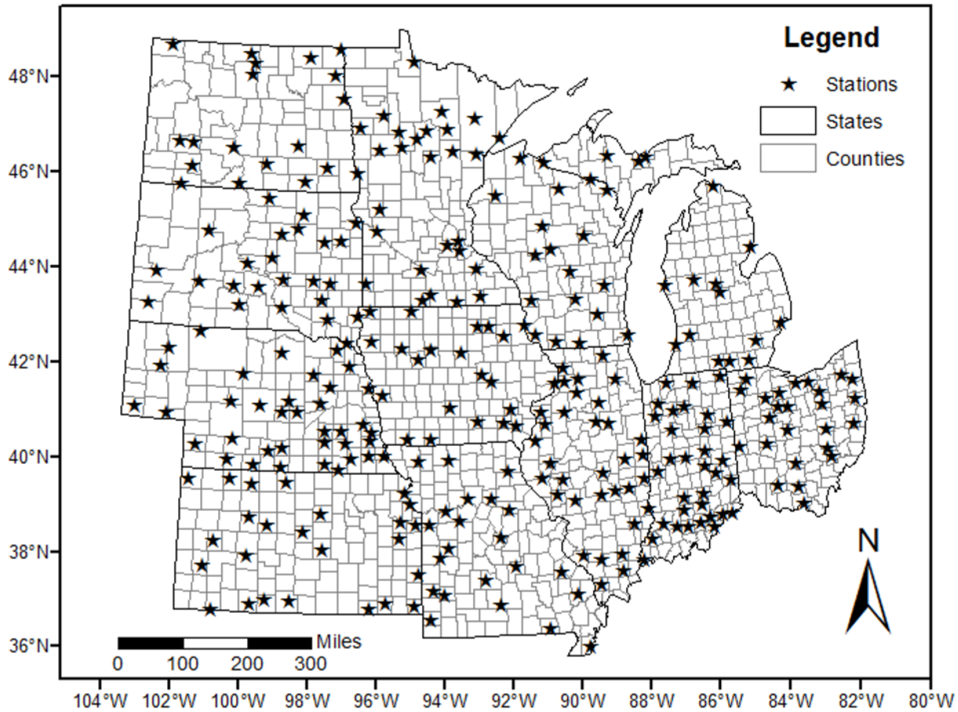

Figure 2.1 Locations of the 302 meteorological stations in the 12 Midwestern US states.

2.3 Results and discussion

2.3.1 Trends in maximum, and minimum temperatures

Over the study area, the composite trends for growing season maximum and minimum temperatures during the period of 1980–2013 are 0.13 and 0.17 °C decade^{-1}, respectively. During the growing season, statistically significant ($p \leq 0.05$, herein unless otherwise specified) increasing trends in maximum temperature have been detected in the southern part of the region in the early season and in the northern part of the region in the late season (Figure 2.2(a) and (b)). It is worth noting that dominant trends for maximum temperature in the early season are decreasing in the northwestern part of the region. In addition, there are a greater number of stations demonstrating statistically significant warming in maximum temperature in the late season than in the early season. Therefore,

the composite warming trend in the maximum temperature is smaller in the early season than in the late season (Table 2.1). Within the growing season, statistically significant increasing trends in minimum temperature are concentrated in the southeastern part of the region in the early season, but in the northwestern part of the region in the late season (Figure 2.2(c) and (d)). On a monthly basis, dominant trends for maximum temperature show an increase, with an exception in July (Table 2.1). During July, more than half of the locations show decreasing trends in maximum temperature, but few are statistically significant. Feng and Hu (2004) identified a substantial decrease in summer maximum temperature in western Missouri, Illinois, Indiana, and Ohio area during the period of 1951–2000. In this study, a subregional cooling trend in July maximum temperature is detected in the southeast part of the research region during the period of 1980–2013. Over the period of 1900s–2009, July and August were found to be the months with the greatest decreases in maximum temperature for the central part of Nebraska (Skaggs and Irmak, 2012). Overall, maximum temperature has the greatest magnitude of warming in September, especially in the northern part of the region (Figure 2.3(b)). Dominant trends for monthly minimum temperature show an increase for all seven growing months (Table 2.1). In particular, the composite warming trend in June minimum temperature has the greatest magnitude, when increasing trends occur throughout the study area (Figure 2.3(a)).

2.3.2 Trends in average temperature and diurnal temperature range

Since 1980, growing season average temperature has increased by 0.15 °C decade^{-1} on an average in the Midwest United States, and a total of 90% of the research locations

shows increasing trends (12% are statistically significant, and they are scattered in the southern and eastern parts of the region). The magnitude in growing season average temperature trend over the Midwest United States covering the period 1980 through 2013, calculated only for the stations with statistically significant trends identified by the Mann-Kendall test, is 0.33 ± 0.06 °C decade^{-1}. This compares with trends of 0.09 ± 0.07 °C decade^{-1} and 0.33 °C decade^{-1} in mean annual temperature over the contiguous United States for the periods 1898 through 2008 (Capparelli *et al*., 2013) and 1979 through 2008 (Vose *et al*., 2012), respectively. The regional warming trend in the Midwest is more driven by the increase in growing season minimum temperature than by that in growing season maximum temperature. Within the growing season, statistically significant warming in average temperature is focused in Indiana, Ohio, Illinois, and Missouri in the early season (a total of 22% of the locations), and in Minnesota, Wisconsin, and Michigan in the late season (a total of 23% of the locations). Over the 12 Midwestern states, average temperature is increasing faster in the late season than in the early season (Figure 2.4). In the early season, dominant trends in average temperature are cooling in North Dakota, South Dakota, and Minnesota (Figure 2.4), owing to a decrease in maximum temperature for this area. Over the entire Midwest, however, average temperature is uniformly increasing in the seven growing months (Table 2.1). The greatest warming rate in average temperature occurs in September, when statistically significant warming trends are detected in North Dakota, Minnesota, and Wisconsin (18% of the locations).

From 1980 to 2013, dominant trends in growing season diurnal temperature range (DTR) are negative with a composite trend of -0.04 °C decade^{-1}. More than half of the

locations show decreasing trends in growing season DTR, and 13% are statistically significant (they are scattered throughout the region). Within the growing season, the majority of the locations show decreasing trends in DTR both in the early season and in the late season. However, DTR is decreasing faster in the early season than in the late season (Table 2.1). On the monthly timescale, the dominant trend in DTR is a decrease in all months except September. In September, DTR has been increasing because maximum temperature has increased nearly twice as fast as minimum temperature during the period of 1980–2013. The percentage of locations that show decreasing trends in monthly DTR is 55% in April, 66% in May, 79% in June, 74% in July, 58% in August, and 62% in October. The greatest decreasing magnitude in DTR occurs in June, when minimum temperature has increased four times as fast as maximum temperature.

Table 2.1. Composite trends in maximum, minimum, and average temperatures as well as diurnal temperature range on monthly, early season (ES), and late season (LS) timescales from 1980 to 2013 for the locations of this study (unit: °C decade^{-1}, trends for the early season and late season timescales are set in italics).

Timescale	Trend in T_{max}	Trend in T_{min}	Trend in T_{avg}	Trend in DTR
Apr	0.15 ± 0.43	0.20 ± 0.24	0.20 ± 0.32	-0.03 ± 0.35
May	0.01 ± 0.43	0.15 ± 0.31	0.09 ± 0.35	-0.08 ± 0.35
June	0.07 ± 0.31	0.28 ± 0.18	0.17 ± 0.20	-0.21 ± 0.29
ES	*0.08 ± 0.33*	*0.21 ± 0.20*	*0.14 ± 0.25*	*-0.08 ± 0.27*
July	-0.02 ± 0.25	0.12 ± 0.22	0.05 ± 0.20	-0.12 ± 0.25
August	0.19 ± 0.20	0.13 ± 0.18	0.15 ± 0.13	-0.01 ± 0.27
September	0.34 ± 0.34	0.18 ± 0.25	0.24 ± 0.26	0.13 ± 0.30
October	0.27 ± 0.26	0.19 ± 0.23	0.21 ± 0.20	-0.06 ± 0.24
LS	*0.21 ± 0.19*	*0.17 ± 0.17*	*0.18 ± 0.13*	*0.00 ± 0.22*

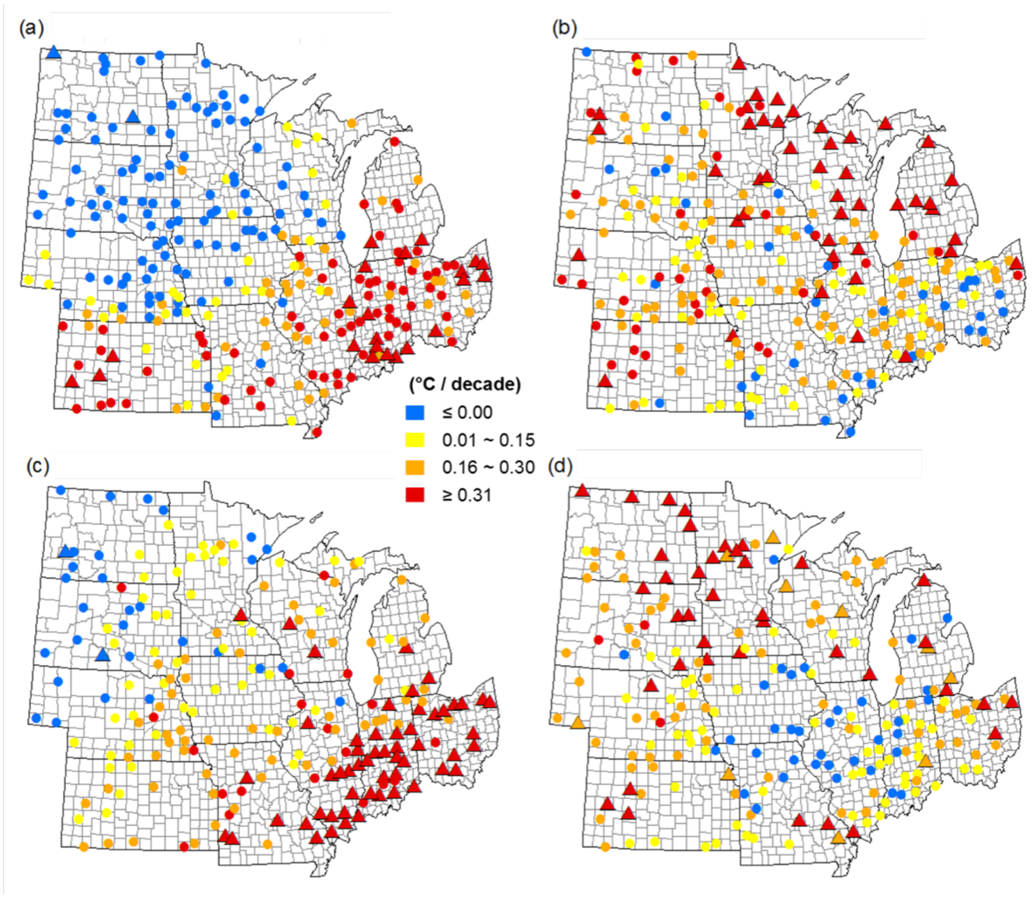

Figure 2.2. Geographical distribution of the decadal trends in maximum and minimum temperatures during the early season and late season for the period of 1980–2013 for the locations of this study. Note: Circle symbol indicates statistically not significant ($p > 0.05$) trend, and triangle symbol indicates statistically significant ($p \leq 0.05$) trend. These definitions are also used in the remaining maps in Figures 2.3, 2.5, and 2.8. (a) Early season maximum temperature. (b) Late season maximum temperature. (c) Early season minimum temperature. (d) Late season minimum temperature.

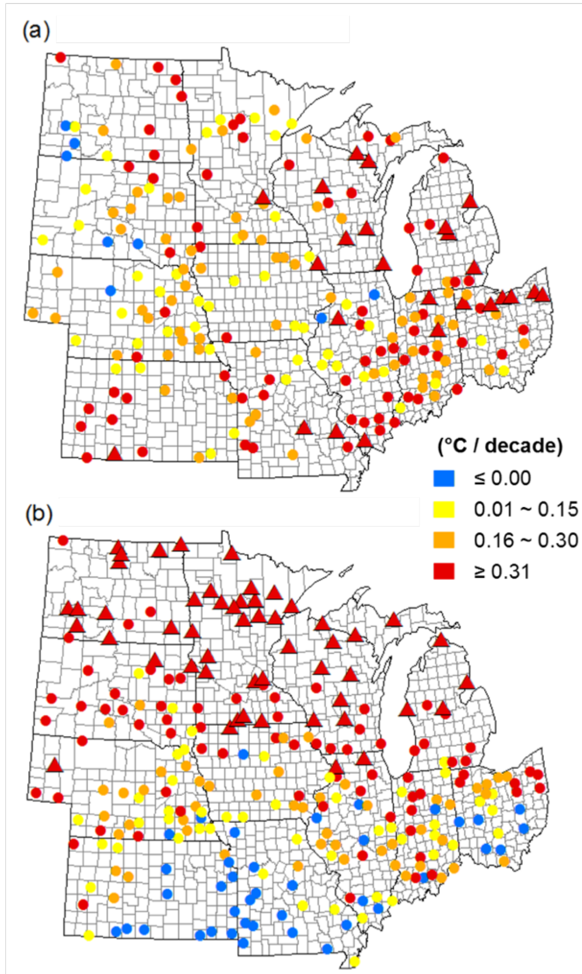

Figure 2.3. Geographical distribution of the decadal trends in (a) June minimum temperature and (b) September maximum temperature from 1980 to 2013 for the locations of this study.

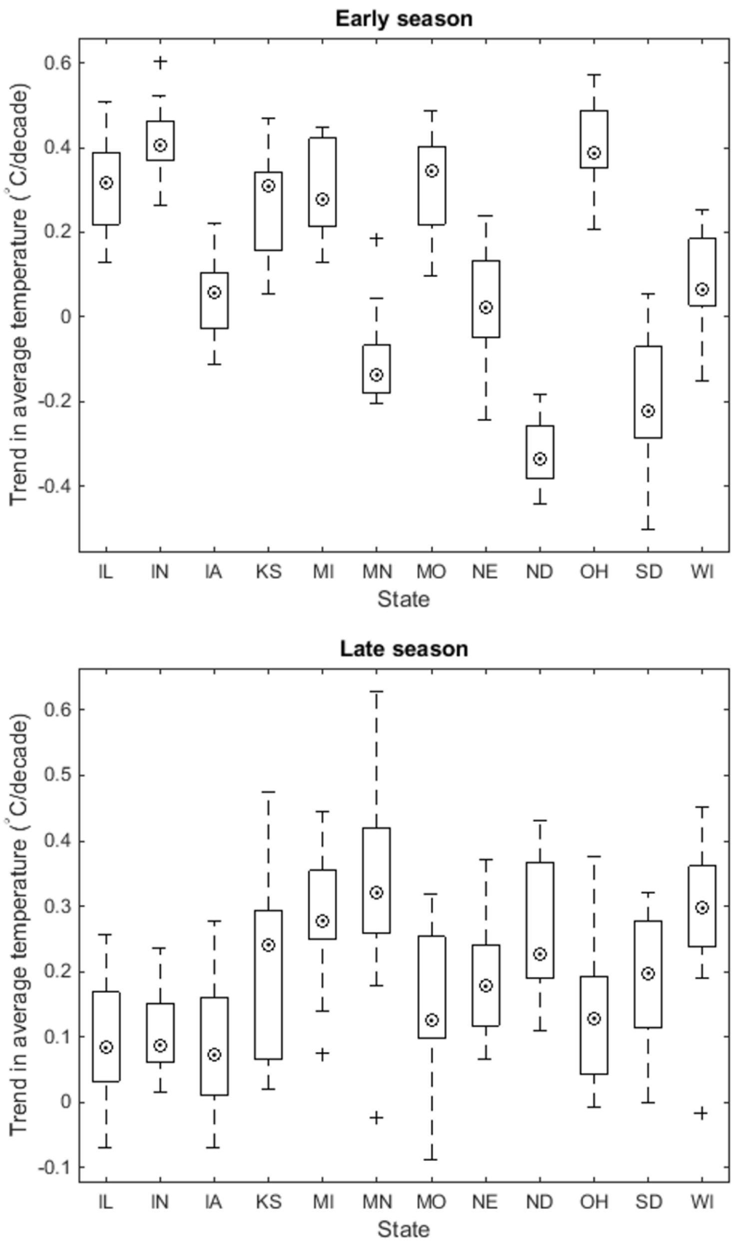

Figure 2.4. Box-and-whisker plots of the decadal trends in average temperature during the early season and late season from 1980 to 2013 for the locations of this study in the 12 Midwestern US states. Note: The 'central box' represents the central 50% of the data, its lower and upper boundary lines are at the first and third quartile of the data, and the central target indicates the second quartile (median) of the data. Two dashed vertical lines extending from the central box indicate the remaining data outside the central box that are not regarded as outliers. The plus signs indicate the remaining outliers. Same definitions apply in the remaining box-and-whisker plots in Figures 2.6 and 2.7.

2.3.3 Trends in precipitation

From 1980 to 2013, growing season precipitation has increased by 12.20 ± 21.27 mm decade^{-1} for the study locations in the Midwest United States. The majority of the research locations show increasing trends in growing season precipitation, but only 4% of these are statistically significant. This result is consistent with that identified by Feng and Hu (2004), in which a wetting climate has occurred during the period 1951–2000 in the Midwest. Within the growing season, the majority of the locations are becoming wetter in the early season but drier in the late season (Figure 2.5). On average, early season precipitation is increasing by 16.79 mm decade^{-1} and late season precipitation is decreasing by 4.73 mm decade^{-1}. Among the 12 Midwestern states, this within-season reversing trend in precipitation is found in: Illinois, Iowa, Michigan, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin (Figure 2.6). In particular, the drying trend in the late season is of greater magnitude than the wetting trend in the early season for these four states: Iowa, Michigan, Minnesota, and Wisconsin. On the monthly timescale, the majority of the locations are becoming wetter in April, May, June, and October, but drier in July, August, and September (Figure 2.7). Overall, the greatest wetting magnitude occurs in April, when 95% of the locations are becoming wetter (11% are statistically significant, see Figure 2.8(a)). The greatest drying magnitude occurs in August, when 72% of the locations are becoming drier (6% are statistically significant, see Figure 2.8(b)).

By combining analyses of temperature and precipitation trends, it is found that in May and June, weak positive trends in maximum temperature are accompanied by positive trends in precipitation. But in July, negative trend in maximum temperature is

not accompanied by positive trend in precipitation. And these results are interpreted as follows: in May and June, higher precipitation leads to increased recharge of deep soil moisture and increased amounts of surface evaporation. Therefore, this leads to increased crop transpiration in July by deep rooting crops like corn. The increased solar energy-partitioning to latent heat during May–July leads to (1) reduced daytime energy-partitioning to sensible heat (reduction of maximum temperature), (2) increase of absolute humidity (Takle, 2011) with accompanying reduction of nighttime surface longwave radiation, and hence (3) increase in minimum temperature. Item (2) may also be accompanied by increased cloudiness during May–July, which is consistent with item (3), although could cover data are lacking to confirm this.

The reduction of daytime maximum temperature by increased precipitation as described in the previous paragraph has substantial implication for agriculture in the region. This mechanism protects crops like corn from extreme high temperatures during the pollination period (July) and also masks a potential threat for dry years. Undesirably, if May–June precipitation is insufficient to suppress high daytime maximum temperatures in June and July, the underlying warming, evidenced by the increase in minimum temperature, will not be offset and could lead to extreme high daytime temperatures and eventually yield reductions. Take the year of 2012 as an example, the dry spring and summer in Iowa led to the hottest July since 1936 (Hillaker, 2013), and reduced corn grain yield to the lowest level since 1995 (Swoboda, 2013).

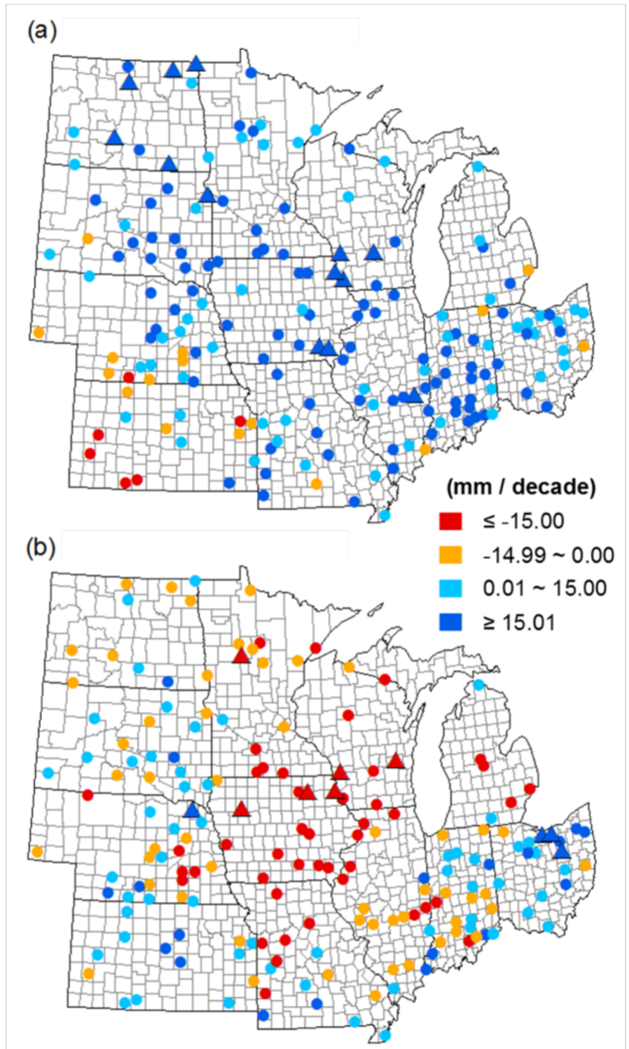

Figure 2.5. Geographical distribution of the decadal trends in precipitation during the (a) early season and (b) late season from 1980 to 2013 for the locations of this study.

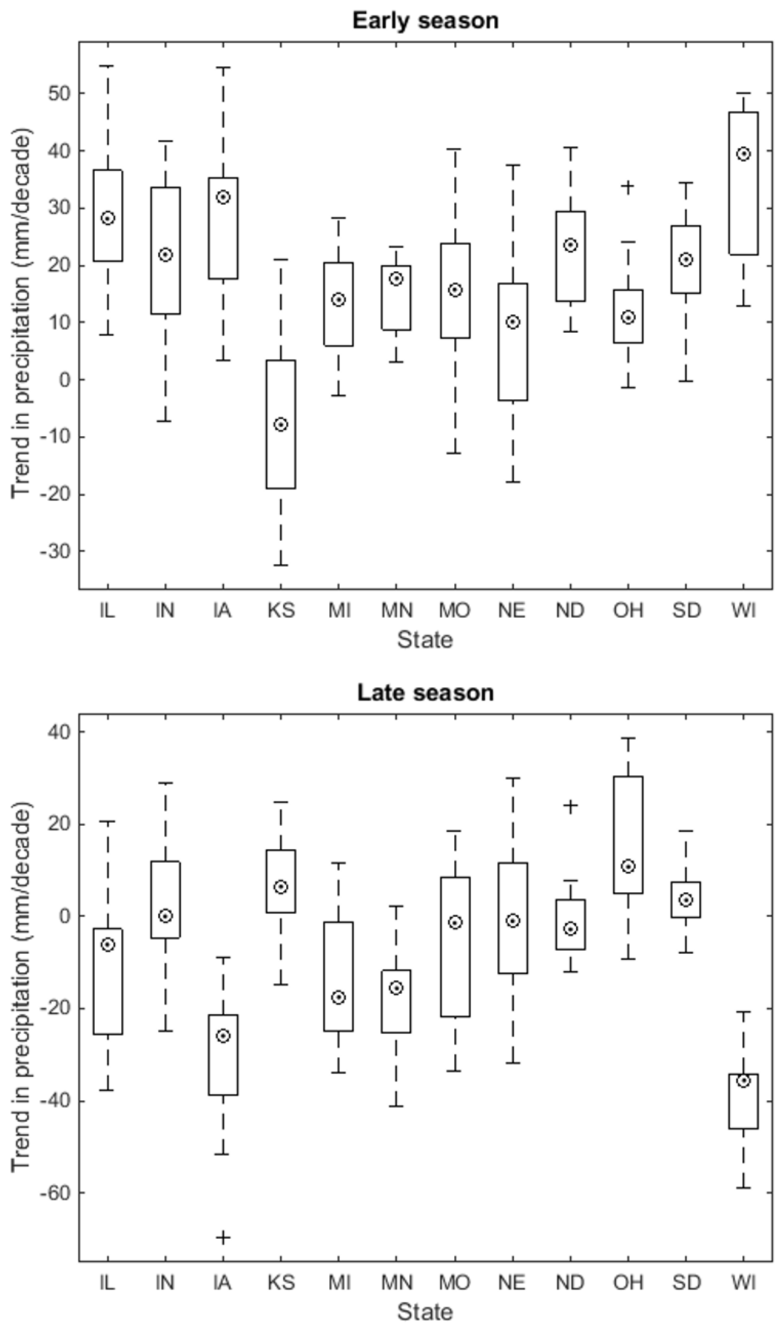

Figure 2.6. Box-and-whisker plots of the decadal trends in precipitation during the early season and late season from 1980 to 2013 for the locations of this study in the 12 Midwestern US states.

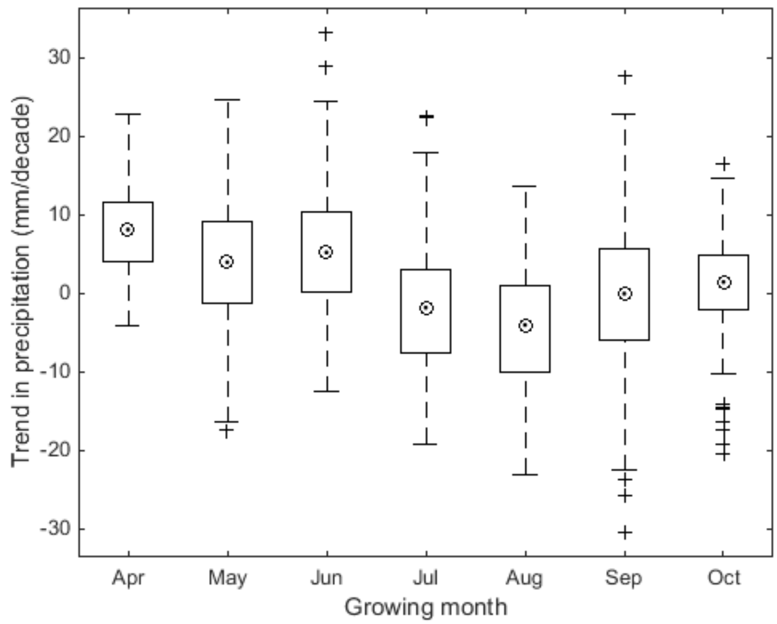

Figure 2.7. Box-and-whisker plot of the decadal trends in precipitation during the growing months from 1980 to 2013 for the locations of this study in the 12 Midwestern US states.

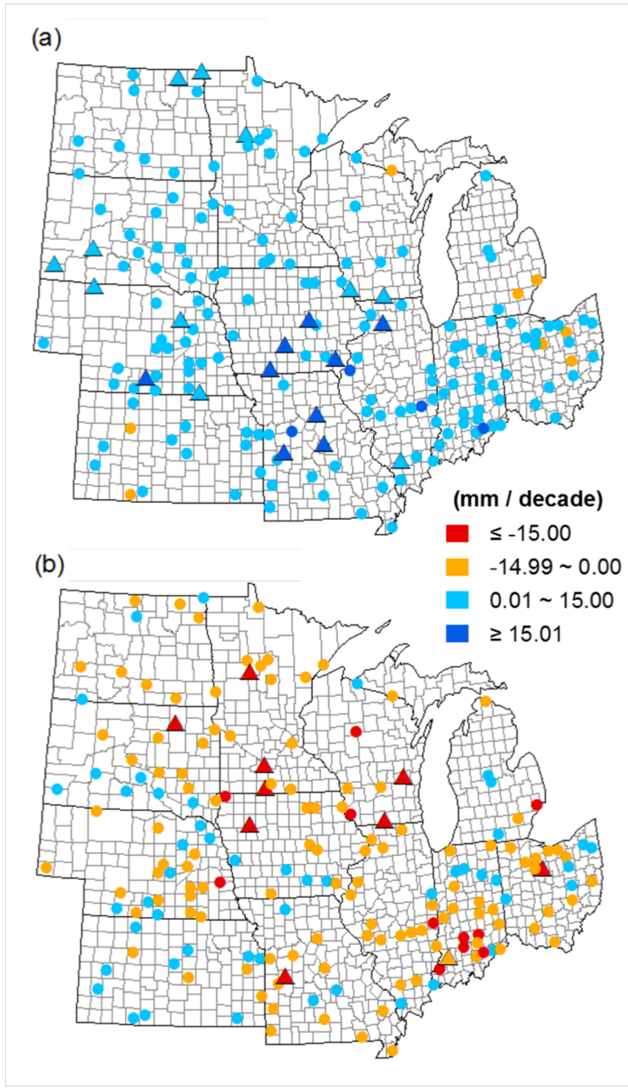

Figure 2.8. Geographical distribution of the decadal trends in precipitation in (a) April and (b) August from 1980 to 2013 for the locations of this study.

2.4 Conclusions

The results of this study exhibit a high degree of spatial consistency where meteorological stations with the largest warming magnitudes in maximum and minimum temperatures during the early season and late season were generally in close proximity,

and such spatial consistency relative to growing season in the Midwest United States has not been found in other climate trend studies. This study concludes that an extensive warming in growing season average temperature has occurred in the Midwest United States during the most recent three decades. This regional warming is contributed more by the greater increase in growing season minimum temperature as compared with the increase in growing season maximum temperature. Within the growing season, average temperature is increasing more in the late season than in the early season. And this is because of the much greater warming magnitude in maximum temperature in the late season, especially in Minnesota, Wisconsin, and Michigan. Faster increases in maximum temperature in the late season could imply higher risks of high temperature extremes, and local agricultural producers need to address the potential risk of grain yield reduction, especially for non-irrigated sites. Both laboratory- and site-based studies have revealed the negative effects of high temperature extremes in critical reproduction stages on corn yields, such as after pollination, between tasseling and silking, and during grain filling (Cheikh and Jones, 1994; Southworth *et al*., 2000). During the early season, dominant trends in maximum temperature are a decrease in North Dakota, South Dakota, Minnesota, the northern parts of Nebraska and Iowa, as well as the western part of Wisconsin. Overall, minimum temperature is increasing more in the early season than in the late season. Interestingly, there is an evident spatial pattern difference for the statistically significant warming in minimum temperature during the early season and late season. In the early season, statistically significant warming in minimum temperature is focused in Missouri, Illinois, Indiana, and Ohio. But in the late season, statistically significant warming in minimum temperature is focused in North Dakota, South Dakota,

and Minnesota. It is noteworthy that, decreasing or even significantly decreasing trends in early season minimum temperature are detected in the northwest part of the study region, covering the western portions of North Dakota, South Dakota, and Nebraska. This is not contrary to the climate warming, and Wolfe (2013) already stated that despite a well-documented trend for warmer winters and earlier springs across the globe, the risk of freeze damage continues. Local producers should think of the potential freeze damage when planning on earlier planting, according to Neild and Newman (1990). Poor germination resulting from below-normal temperatures rather than freezing temperatures is the greatest hazard of planting too early. On the basis of monthly analysis, this study concludes that the dominant trends in average temperature are positive for all seven growing months. The greatest warming magnitude occurs in September, when maximum and minimum temperatures are increasing by 0.34 and 0.18 °C decade^{-1}, respectively. The smallest warming magnitude occurs in July, when the majority of the locations show decreasing trends in maximum temperature. Observed changes in temperature have shifted corn phenology and affected corn grain yields during the period of 1981–2000 in China (Tao *et al*., 2006). Increased monthly minimum temperature in May and September has been found to be significantly correlated with the increase of corn yield in Northeast China (Chen *et al*., 2011). By contrast, Lobell and Field (2007) found a clearly negative response of global yields to increased temperatures for corn. Because of the different subregional patterns in temperature trends in the Midwest United States, this study strongly suggests that further research should include crop modelling as well as statistical analysis to evaluate the impacts of temperature increases on corn grain yields. Also because the growing season minimum temperature has a greater increase than the

increase in maximum temperature, the majority of the locations show decreasing trends in growing season DTR. Within the growing season, dominant trends in DTR are decreasing both in the early season and late season, and the magnitude is greater in the early season than in the late season. Dominant trends in monthly DTR show a decrease, except in September when maximum temperature has increased nearly twice as fast as minimum temperature during the study period. The greatest decreasing magnitude in monthly DTR occurs in June, when minimum temperature has increased four times as fast as maximum temperature on average.

From 1980 to 2013, this study concludes that the growing season precipitation has been increasing for the majority of the locations in the Midwest United States, however, few of these wetting trends are statistically significant. It is worth noting that this wetting trend is driven by the increasing precipitation in the early season, while precipitation is decreasing in the late season. This wetter early season–drier late season phenomenon is found in 8 of the 12 Midwestern states: Illinois, Iowa, Michigan, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin. Taking Wisconsin as an extreme example, growing season precipitation is increasing during the period of 1980–2013, but early season (and late season) precipitation is increasing (and decreasing) by more than 30 mm decade^{-1} on average. Although only seven meteorological stations are used in the precipitation trend analysis in Wisconsin, the small sample size could be part of the reason for the extreme results. These results indicate some potential concern about the tendency in extreme weather events such as flood in the early season and drought in the late season. Grassini *et al*. (2009) pointed out that rainfed crops grown in the Western Corn Belt are frequently subjected to episodes of transient and unavoidable water stress,

especially in the critical development stage (around and after silking). Mishra and Cherkauer (2010) found that corn yield was negatively correlated with meteorological drought during the sensitive period in late season (grain-filling period). In the north-central part of the study area, covering Minnesota, Wisconsin, and Iowa, climate has become warmer (statistically significant) and drier in late season, the combination of potential heat stress together with rainfall deficit would hurt the local corn production. Future research could focus on the precipitation indices based on finer timescales (e.g. weekly) when homogenization techniques become available. The most recent National Climate Assessment has pointed out that, in the next few decades, temperatures are projected to continue rising in the Midwest, more specifically, average temperatures are expected to increase faster in the northern part while days above 35 °C are expected to increase more in the southern part of the region (Pryor *et al*., 2014). In addition, under the A2 scenario (higher emissions), the number of consecutive dry days is projected to increase in Nebraska and Kansas, whereas the number of heavy precipitation days is projected to increase in North Dakota and South Dakota (Shafer *et al*., 2014). As a result, the benefits of longer growing seasons and rising CO_2 levels will be progressively offset by extreme weather events (Pryor *et al*., 2014). Hence, this study suggests further research be focused on quantifying the impacts of historical climate trends on cereal grain crop yields in the Midwest United States, in order to offer a scientific basis for the long-term adaptation strategies.

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2.5 A web-based tool for the corn community

Climate change plays an important role in Midwestern corn production. Before Christmas, when other people are busy shopping for gifts, farmers are busy making decisions about the next growing season. These agricultural decisions (Takle *et al*., 2014) are climate based and tend to be more strategic in nature, such as when to plant, which seed varieties to choose, and so forth. In this information age, farmers have more data than ever to help them make these decisions. However, much of these data are either irrelevant, unreliable, or otherwise unusable. How can the average farmer know what data to use when planning for the next growing season? The main goal of developing this web-based tool, the Corn Belt Climate Trends (1980–2013) is to help Midwestern agricultural community get useful data in a usable format with reliable results (http://www.hprcc.unl.edu/climatetrends.php). This tool could help users more easily understand how local or regional temperature and precipitation have changed in the last three decades. With this tool, users can examine climate trends on a monthly, seasonal (Spring, Summer, Fall, Winter, and early growing season, late growing season, as well as the entire growing season for corn), and annual basis.

This tool is usable because: (a) it provides climate trends information that matters to farmers in a more visually appealing way; taking average temperature during the growing season for corn as an example, the available products include a detailed station report as a pop-up window (Figure 2.9), a map image of the regional-level climate trends (Figure 2.10), and a report file about the state-level climate trends (Table 2.2); and (b) the web interface is user-friendly, so a farmer can choose the time frame and climate variable or variables in which he is interested (e.g., average temperature, diurnal temperature range,

maximum temperature, minimum temperature, precipitation, and climate) to generate the information and obtain the desired products. This tool is also useful because: (a) it uses high quality data to reveal not only how much warmer (cooler) the climate is becoming, but also whether the warming (cooling) trend is statistically significant or not; (b) it provides information that is tailored to local users; for example, if the farmer sees that his local area is experiencing a warming (cooling) trend during the growing season for corn, he would need to plan for earlier (later) planting or using late-maturing (early-maturing) seeds in order to possibly maximize the grain yield. In sum, farmers can use this tool to assist their planning for the next growing season more efficiently and effectively.

Since the initial development of this tool, several presentations have been made in order to advertise it (Table 2.3). Since its inception on August 15 2015, this tool webpage has had a total of 1, 585 pageviews (the number of times a visitor views a page) until October 12 2016. Of which there are a total of 1, 353 unique pageviews, which means if the same visitor visits a product page five times in the same session, it will only be counted as one visit. The average time spent on this tool webpage is 1 minute and 56 seconds. The entrances that are registered as the first pageview of a session are 205. The bounce rate is 54.15%, which measures through a percentage all of the single-page sessions. And the exit rate is 37.92%, which measures through a percentage all of the pageviews to the page that were the last in the session.

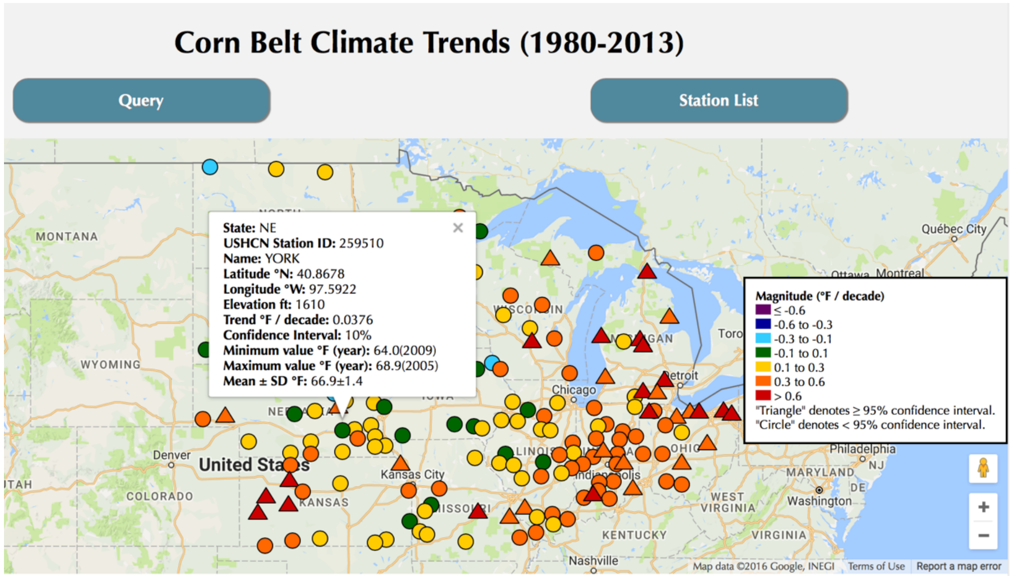

Figure 2.9. A pop-up window about details of average temperature during the growing season for corn (Apr–Oct) from 1980 to 2013 at York, Nebraska.

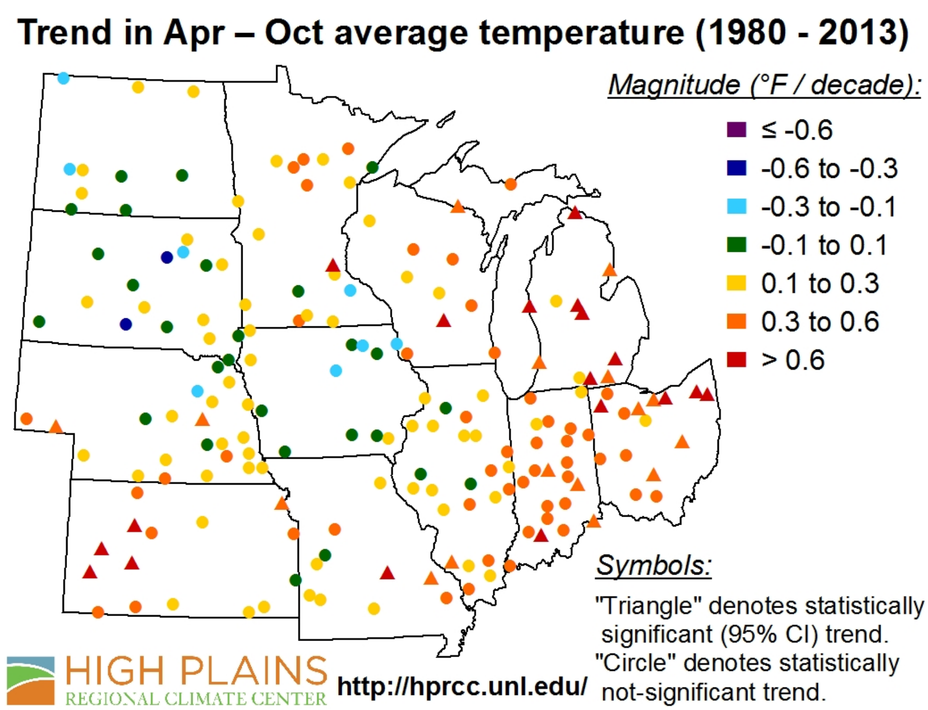

Figure 2.10. A map image of the regional trends in average temperature during the growing season for corn (Apr–Oct) from 1980 to 2013 at the tracked meteorological stations in the Midwest.

Table 2.2. A report file about the state-level trends in average temperature during the growing season for corn from 1980 to 2013 at the meteorological stations in Nebraska.

Nebraska	Apr – Oct average temperature	
	Trend (°F / decade)	Confidence Interval
ASHLAND NO 2	0.29	33%
AUBURN 5 ESE	0.20	33%
BEAVER CITY	0.19	33%
BROKEN BOW 2 W	0.00	1%
CRETE	0.42	66%
FRANKLIN	0.36	66%
GENOA 2 W	0.50	95%
HARTINGTON	-0.06	10%
HEBRON	0.14	10%
IMPERIAL	0.21	66%
KIMBALL 2NE	0.38	66%
LODGEPOLE	0.47	95%
MADISON	0.12	33%
MINDEN	0.24	33%
NORTH LOUP	0.29	66%
OAKDALE	-0.17	33%
SEWARD	0.13	33%
SYRACUSE	0.11	33%
TECUMSEH 1S	0.15	33%
TEKAMAH	0.26	66%
WAKEFIELD	0.16	33%
YORK	0.04	10%

Table 2.3. Presentations for the advertisement of the web-based Corn Belt Climate Trends tool.

Time	Event name	Location	Presentation type and title
October 2013	Changes: Climate, Water and Life on the Great Plains	Lincoln, NE	Poster, “Temperature and Precipitation Trends in the Midwest U.S. from 1981 to 2012”
December 2013	American Geophysical Union Fall Meeting	San Francisco, CA	Poster, “Growing Season Temperature and Precipitation Variability and Extremes in the U.S. Corn Belt from 1981 to 2012”
April 2014	School of Natural Resources Graduate Student Association Poster Symposium	Lincoln, NE	Poster, “Growing season temperature and precipitation trends in the Midwest U.S. (1981–2012)”
April 2014	40th Annual Center for Great Plains Studies Symposium	Lincoln, NE	Poster, “Growing season climate change in the Midwest U.S. from 1981 to 2012”
April 2014	School of Natural Resources Elevator Speech Contest Preliminary	Lincoln, NE	Oral speech, “Growing Season Climate Trends in the Midwest (1981–2012)”

October 2014	NOAA's 39th Climate Diagnostics and Prediction Workshop	St. Louis, MO	Poster, "Midwestern Climate Trend Viewer – A web-based tool for the agricultural community"
January 2015	2015 Crop Production Clinic	Ithaca, NE	Oral speech, "Use of Climate Information for Agricultural Decisions"
January 2015	2015 Crop Production Clinic	Norfolk, NE	Oral speech, "Use of Climate Information for Agricultural Decisions"
February 2015	School of Natural Resources Elevator Speech Contest Finale	Lincoln, NE	Oral speech, "Midwestern Climate Trends – A web-based tool for the agricultural community"

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References

Adams RM, Rosenzweig C, Peart RM, Richie JT, McCarl BA, Glyer JD, Curry RB, Jones JW, Boote KJ, Allen LH Jr. 1990. Global climate change and US agriculture. *Nature* **345**: 219–224.

Adger WN, Agrawala S, Mirza MMQ, Conde C, O'Brien K, Pulhin J, Pulwarty R, Smit B, Takahashi K. 2007. Assessment of adaptation practices, options, constraints and capacity. In *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Parry ML, Canziani OF, Palutikof JP, Linden PJ, Hanson CE (eds). Cambridge University Press: Cambridge, UK, 717–743.

Brauner JS. 1997. *Environmental sampling & monitoring primer: nonparametric estimation of slope: Sen's method in environmental pollution*. http://www.webapps.cee.vt.edu/ewr/environmental/teach/ smprimer/sm-intro.html (accessed 1 November 2012).

Burkey J. 2006. *A Non-Parametric Monotonic Trend Test Computing Mann-Kendall Tau, Tau-b, and Sen's Slope Written in Mathworks-MATLAB Implemented Using Matrix Rotations*. King County, Department of Natural Resources and Parks, Science and Technical Services Section: Seattle, WA.

Capparelli V, Franzke C, Vecchio A, Freeman MP, Watkins NW, Carbone V. 2013. A spatiotemporal analysis of U.S. station temperature trends over the last century. *J. Geophys. Res. Atmos*. **118**: 7427–7434.

Cheikh N, Jones RJ. 1994. Disruption of maize kernel growth and development by heat stress (role of cytokinin/abscisic acid balance). *Plant Physiol*. **106**: 45–51.

Chen C, Lei C, Deng A, Qian C, Hoogmoed W, Zhang W. 2011. Will higher minimum temperatures increase corn production in northeast China? An analysis of historical data over 1965–2008. *Agric. For. Meteorol*. **151**: 1580–1588.

Courtier JR, Johnson RJ, Bridges WC, Hubbard KG. 2013. Assessing migration of ruby-throated hummingbirds (*Archilochus colubris*) at broad spatial and temporal scales. *Auk* **130**: 107–117.

Easterling WE, Aggarwal PK, Batima P, Brander KM, Erda L, Howden SM, Kirilenko A, Morton J, Soussana J-F, Schmidhuber J, Tubiello FN. 2007. Food, fiber and forest products. In *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Parry ML, Canziani OF, Palutikof JP, Linden PJ, Hanson CE (eds). Cambridge University Press: Cambridge, UK, 275–313.

Feng S, Hu Q. 2004. Changes in agro-meteorological indicators in the contiguous United States: 1951–2000. *Theor. Appl. Climatol*. **78**: 247–264.

Field CB, Barros V, Stocker TF, Qin D, Dokken DJ, Ebi KL, Mastrandrea MD, Mach KJ, Plattner G-K, Allen SK, Tignor M, Midgley PM. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*. World Meteorological Organization: Geneva, Switzerland.

Fischer GM, Shah M, Tubiello FN, Velthuizen H. 2005. Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080. *Philos. Trans. R. Soc. B* **360**: 2067–2083.

Grassini P, Yang H, Cassman KG. 2009. Limits to maize productivity in the Western Corn-Belt: a simulation analysis for fully irrigated and rainfed conditions. *Agric. For. Meteorol*. **149**: 1254–1265.

Hatfield JL. 2010. Climate impacts on agriculture in the United States: the value of past observations. In *Handbook of Climate Change and Agroecosystems: Impact, Adaptation and Mitigation*, Hillel D, Rosenzweig C (eds). Imperial College Press: London, 239–253.

Hatfield JL. 2013. North American perspectives on potential climate change and agricultural responses. In *Handbook of Climate Change and Agroecosystems*, Hillel D, Rosenzweig C (eds). Mainland Press: Singapore, 33–55.

Hatfield JL, Boote KJ, Kimball BA, Izaurralde RC, Ort D, Thomson A, Wolfe DW. 2011. Climate impacts on agriculture: implications for crop production. *Agron. J.* **103**: 351–370.

Hillaker HJ. 2013. *Preliminary Iowa weather summary-2012*. http://www.iowaagriculture.gov/climatology/weatherSummaries/ 2012/pas2012.pdf (accessed 16 March 2015).

Irannezhad M, Marttila H, Klove B. 2014. Long-term variations and trends in precipitation in Finland. *Int. J. Climatol*. **34**: 3139–3153.

Irmak S, Kabenge I, Skaggs KE, Mutiibwa D. 2012. Trend and magnitude of changes in climate variables and reference evapotranspiration over 116-yr period in the Platte River Basin, central Nebraska-USA. *J. Hydrol*. **420–421**: 228–244.

Lettenmaier DP, Major D, Poff NL, Running S. 2008. Water resources. In *The Effects of Climate Change on Agriculture, Land Resources, Water Resources and Biodiversity in the United States. A Report by the U. S. Climate Change Science Program and the Subcommittee on Global Change Research*, Walsh M (ed). U.S. Department of Agriculture: Washington, DC, 121–150.

Libiseller C, Grimvall A. 2002. Performance of partial Mann-Kendall tests for trend detection in the presence of covariates. *Environmetrics* **13**: 71–84.

Lobell DB, Burke MB. 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environ. Res. Lett*. **3**: 1–8.

Lobell DB, Field CB. 2007. Global scale climate-crop yield relationships and the impacts of recent warming. *Environ. Res. Lett*. **2**: 1–7.

Lobell DB, Burke MB, Tebaldi C, Mastrandrea MD, Falcon WP, Naylor RL. 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science* **319**: 607–610.

Lobell DB, Schlenker W, Costa-Robberts J. 2011. Climate trends and global crop production since 1980. *Science* **333**: 616–620.

Menne MJ, Williams CN, Jr., Vose RS. 2014. *USHCN Version 2.5 Serial Monthly Dataset*. http://cdiac.ornl.gov/ftp/ushcn_v2.5_monthly/ (accessed 9 October 2014).

Mishra V, Cherkauer KA. 2010. Retrospective droughts in the crop growing season: implications to corn and soybean yield in the Mid-western United States. *Agric. For. Meteorol*. **150**: 1030–1045.

Neild RE, Newman JE. 1990. *Growing Season Characteristics and Requirements in the Corn Belt. National Corn Handbook-40*. Purdue University Cooperative Extension: West Lafayette, IN.

Nguyen D, Renwick J, McGregor J. 2014. Variations of surface temperature and rainfall in Vietnam from 1971 to 2010. *Int. J. Climatol*. **34**: 249–264.

Pryor SC, Scavia D, Downer C, Gaden M, Iverson L, Nordstrom R, Patz J, Robertson GP. 2014. Ch. 18: Midwest. In *Climate Change Impacts in the United States: The Third National Climate Assessment*, Melillo JM, Richmond TC, Yohe GW (eds). U.S. Global Change Research Program: Washington, DC, 418–440.

Schlenker W, Roberts MJ. 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *PNAS* **106**: 15594–15598.

Shafer M, Ojima D, Antle JM, Kluck D, McPherson RA, Petersen S, Scanlon B, Sherman K. 2014. Ch. 19: Great Plains. In *Climate Change Impacts in the United States: The Third National Climate Assessment*, Melillo JM, Richmond TC, Yohe GW (eds). U.S. Global Change Research Program: Washington, DC, 441–461.

Skaggs K, Irmak S. 2012. Long-term trends in air temperature distribution and extremes, growing degree-days, and Spring and Fall frosts for climate impact assessments on agricultural practices in Nebraska. *J. Appl. Meteorol. Climatol*. **51**: 2060–2073.

Southworth J, Randolph JC, Habeck M, Doering OC, Pfeifer RA, Rao DG, Johnston JJ. 2000. Consequences of future climate change and changing climate variability on maize yields in the midwestern United States. *Agric. Ecosyst. Environ*. **82**: 139–158.

Swoboda R. 2013, January 14. Iowa's corn yield is lowest since 1995. *Wisconsin Agriculturist*. http://farmprogress.com/story-iowas-2012- corn-yield-lowest-since-1995-9-93371 (accessed 16 March 2015).

Takle ES. 2011. *Assessment of potential impacts of climate changes on Iowa using current trends and future projections*. http://climate.engineering.iastate.edu/Document/Climate_Changes_for_Iowa_ 18.pdf (accessed 16 March 2015).

Takle ES, Anderson C, Andresen J, Angel JR, Elmore R, Gramig B, Guinan P, Hilberg S, Kluck D, Massey R, Niyogi D, Schneider J, Shulski M, Todey D, Widhalm M. 2014. Climate forecasts for corn producer decision-making. *Earth Interact*. **18**: 1–8.

Tao F, Yokozawa M, Xu Y, Hayashi Y, Zhang Z. 2006. Climate changes and trends in phenology and yields of field crops in China, 1981–2000. *Agric. For. Meteorol*. **138**: 82–92.

Terando A, Keller K, Easterling WE. 2012. Probabilistic projections of agro-climate indices in North America. *J. Geophys. Res*. **117**: 1–16.

Umphlett N. 2012. *December 2012 climate summary*. http://www.hprcc. unl.edu/publications/ les/2012_12_climatesummary.pdf (accessed 9 September 2014).

USDA and NASS. 2009. *U.S. 2007 census of agriculture*. http://www.agcensus.usda.gov/Publications/2007/Full_Report/usv1.pdf (accessed 5 May 2014).

Vose RS, Applequist S, Menne MJ, Williams CN Jr, Thorne P. 2012. An intercomparison of temperature trends in the U.S. historical climatology network and recent atmospheric reanalyses. *Geophys. Res. Lett*. **39**: 1–6.

Wolfe DW. 2013. Chapter 2: contributions to climate change solutions from the agronomy perspective. In *Handbook of Climate Change and Agroecosystems*, Hillel D, Rosenzweig C (eds). Mainland Press: Singapore, 11–29.

Wolfe DW, Ziska L, Petzoldt C, Seaman A, Chase L, Hayhoe K. 2008. Projected change in climate thresholds in the northeastern U.S.: implications for crops, pests, livestock, and farmers. *Mitig. Adapt. Strateg. Glob. Change* **13**: 555–575.

CHAPTER 3: EVALUATION OF DEGREE-DAYS ESTIMATED WITH SEVERAL METHODS FOR CORN IN NEBRASKA

ABSTRACT: In Nebraska, the concept of thermal time is widely used among the agricultural community, for decisions such as, choosing corn (*Zea Mays* L.) varieties, predicting corn phenology, quantifying heat stress and so on. Instead of the real-time temperatures that are experienced by corn plants, most of the widely available temperature data are limited to daily timescale observations from standard meteorological stations. Therefore, a variety of equations are used to estimate degree-days for corn based on the daily temperature data. Not only could these estimation methods be lacking in accuracy, but also there are differences among the same metric of degree-days that are estimated by them. Different agricultural groups, such as researchers, advisors, farmers, and seed companies, often use different methods to estimate thermal time for corn for the same purpose. Furthermore, different lower and upper thresholds are often used among these different agricultural groups for the same purpose, yet without specifying the thresholds being used. Consequently, if the details about estimation methods or lower and upper thresholds are not known, citing the results from one another could lead to biased decisions in corn production. By assuming that the thermal time approximated with hourly temperature data as true, this study evaluates six most commonly used degree-day methods for corn at 14 long-term observing locations in Nebraska. They are: T_{avg}-based rectangle method, adjusted T_{max} and T_{min} rectangle method, single-sine method, double-sine method, single-triangulation method, and double-triangulation method. Six metrics of total growing season (from May through September) degree-days are analyzed,

including $DD_{8,\,29}$, $DD_{10,\,30}$, $DD_{8,\,34}$, DD_{29+}, DD_{30+}, and DD_{34+}. A combination of statistical parameters, RMSE and MAE, is used to quantify the estimation errors. This study analyzed the sensitivity of these methods to different temperature threshold and also to extreme cool and warm years. In particular, four representative cases of location-year are chosen to describe the six methods' estimation performance on a daily timescale in extreme cool and warm years. In sum, the single- and double-sine methods as well as the T_{avg}-based method are superior to other three methods. But the adjusted T_{max} and T_{min} rectangle method, though being the most commonly used for corn in the study area, provides poor estimation for actual growing season degree-days.

3.1 Introduction

The concept of heat units, or thermal time, measured in degree-days is widely used in crop research and field management to track crop phenological development (Cross and Zuber, 1972; Gilmore and Rogers, 1958; Russelle *et al*., 1984). Thermal time is the cumulative measure for temperature-based crop development, and ideally would be measured with temperatures that are actually experienced by the plants. However, most of the widely available temperature data are restricted to observations from meteorological stations that are in the vicinity of crop fields, usually including daily maximum and minimum temperatures. Thermal time is commonly estimated based on these two daily temperatures, with three types of methods as follows: (1) averaging (or so called rectangle) methods, such as T_{avg}-based method (T_{avg} is the arithmetic mean of daily maximum and minimum temperatures) and adjusted T_{max} and T_{min} method (Arnold, 1960; McMaster and Wilhelm, 1997); (2) sine-wave methods, such as single-sine method

(Baskerville and Emin, 1969), double-sine method (Allen, 1976), and corrected-sine method (Roltsch *et al*., 1999); and (3) triangulation methods, such as single-triangulation method (Lindsey and Newman, 1956; Neild, 1967), double-triangulation method (Sevacherian *et al*., 1977), and corrected triangulation method (Roltsch *et al*., 1999). Averaging methods are relatively simple to use, especially the T_{avg}-based method, however, using such methods raises a concern that the arithmetic mean of daily maximum and minimum temperatures may not accurately represent the true daily average temperature, as illustrated by Bigelow (1909). The principal assumption of sine-wave and triangulation methods is that the diurnal temperature curve is similar to the trigonometric sine curve or triangulation curve. Double-sine and double-triangulation methods account for the fact that minimum temperature at the beginning and the end of a specific 24-hour period may not necessarily be the same; hence, they use the next day's minimum temperature. Specifically, double-sine and double-triangulation methods divide each day into two 12-hour periods and then represent the first 12-hour period by daily minimum and maximum temperatures of that day while representing the second 12-hour period by daily maximum temperature of that day and daily minimum temperature of the following day (Allen, 1976; Sevacherian, *et al*., 1977).

According to Kumudini *et al*. (2014), the above-mentioned estimation methods for thermal time are all categorized as empirical linear, based on their temperature response and derivation. Usually, two temperature thresholds are involved in an empirical linear estimation method, including a lower threshold below which crop development ceases and an upper threshold above which crop development rate will not further increase. When daily average temperature, the arithmetic mean of daily maximum and minimum

temperatures, is used to estimate thermal time, there are three possible situations that need to be considered: (1) daily average temperature is at or above the upper threshold; (2) daily average temperature is at or above the lower threshold but remains below the upper threshold; and (3) daily average temperature is below the lower threshold. When daily maximum and minimum temperatures are directly used to estimate thermal time, there are six possible situations that need to be considered: (1) daily minimum temperature is below the lower threshold, and daily maximum temperature is either: (a) below the lower threshold, (b) at or above the lower threshold but below the upper threshold, or (c) at or above the upper threshold; (2) daily minimum temperature is at or above the lower threshold but below the upper threshold, and daily maximum temperature is either: (a) at or above the lower threshold but below the upper threshold, (b) at or above the upper threshold; or (3) both daily minimum temperature and daily maximum temperature are at or above the upper threshold.

When observing hourly temperature data are available, there would be no need to depict the diurnal temperature curve with daily maximum and minimum temperatures. Instead, thermal time could be more realistically approximated as the number of degree days that hourly temperatures fall between the lower and upper thresholds (Zalom *et al*., 1983). Zalom *et al*. (1983) compared thermal time derived from five different estimation methods with thermal time based on hourly temperature, with a lower threshold of 12.8 °C and an upper threshold of 32.2 °C, but used only one dataset of a 14-day period. McMaster and Wilhelm (1997) compared the two types of averaging methods for corn, with a lower threshold of 10 °C and an upper threshold of 30 °C, and emphasized the importance of precisely describing the used estimation method for thermal time so that

the results could be interpreted and applied correctly by others. Roltsch *et al*. (1999) evaluated seven different estimation methods for thermal time with different upper threshold cut-off techniques (e.g., horizontal, vertical, and intermediate), at nine locations in California during a two-year study period.

In Nebraska, the concept of degree-days is widely used among agricultural community for corn; for example, it is used when choosing corn variety, predicting corn phenology, and so on. However, different groups (e.g., researchers, agricultural advisors, farmers, seed companies, etc.) have used divergent methods for estimating degree-days for corn. In addition, each group uses different lower and upper thresholds for the same purpose, often times without specifying the thresholds they are using. In particular, researchers use T_{avg}-based averaging method with a lower threshold of 10 °C and an upper threshold of 30 °C (Feng and Hu, 2004); agricultural advisors use adjusted T_{max} and T_{min} method with a lower threshold of 10 °C and an upper threshold of 30 °C (https://drinet.hubzero.org/groups/u2u/tools/gdd); seed company Monsanto uses T_{avg}-based averaging method with a lower threshold of 10 °C but no upper threshold, although this is not well documented; crop simulation model CERES-Maize (Jones and Kiniry, 1986) uses a combination of averaging method and 3-hour correction method with a lower threshold of 8 °C and an upper threshold of 34 °C, while Hybrid-Maize model (Yang *et al*., 2004) uses single-sine wave method with the same lower and upper thresholds. Without knowing the differences among these estimation methods or lower and upper thresholds, citing each other’s thermal time results could lead to inconsistent decisions. Therefore, a comprehensive evaluation of these different estimation methods for thermal time is critically important. Focusing on the active corn growing season, this

study analyzes estimation errors of thermal time derived from those commonly used empirical linear methods with daily temperatures, and thermal time approximated with hourly temperature is seen as the true value. Two assumptions are made for this study: first, thermal time approximated with hourly temperatures is superior to thermal time estimated with empirical linear methods based on daily temperature; second, these estimation errors are significant enough to be considered when being applied in corn production, such as predicting corn phenology, though observed corn phenology data would be needed in order to test this, as described in Kumudini *et al*. (2014). The goal of this study is to evaluate the performance of these commonly used estimation methods for thermal time of corn in Nebraska.

3.2 Data and methods

The study area is the state of Nebraska, which is one of the main corn production states in the United States (USDA NASS, 2014; USDA NASS, 2015). Hourly air temperature data are obtained from the High Plains Regional Climate Center's Automated Weather Data Network (AWDN) through the online Climate Data Services (http://www.hprcc.unl.edu/services, accessed 10 December 2015). The data are quality controlled with a spatial regression test; the advantages of this test were stated by Hubbard and You (2005), Hubbard *et al*. (2007), and You *et al*. (2008). A combination standard of data completeness and corn production representativeness is used to choose the study locations. From the beginning year of record to 2015, the maximum acceptable amount of missing data for each station for this study is set at 5%. Missing data are replaced by reliable estimates, estimates based on weighted linear regression from

surrounding stations, or unreliable estimates (HPRCC, 2015). Only two of the stations have no unreliable estimates of hourly temperature data, but that would be too few to represent the entire state's climate. Therefore, stations with up to 0.03% unreliable estimates are included in this study; these unreliable estimates have been manually checked to ensure that they are climatologically reasonable. By consulting with local agronomists, a total of 14 observing stations (40.08°–42.47°N and 96.48°–101.72°W, Figure 3.1) that are in active corn production areas are chosen for the analysis. The beginning year of study spans from 1982 to 1991, depending on the station, and the elevation of the stations ranges from 347 to 1029 m. In this study, active corn growing season is defined as from May 1 to September 30 based on the USDA reports (USDA NASS Agricultural Statistics Board, 1997; USDA NASS, 2010). The obtained hourly temperature data are used to compute daily temperatures, including maximum, minimum, and average temperatures. During a 24-hour period (i.e., from 1:00 to 24:00), the highest hourly temperature is considered as daily maximum temperature; the lowest hourly temperature is considered as daily minimum temperature; and the arithmetic mean of hourly temperature is considered as daily average temperature. This daily average temperature often differs from that derived from daily maximum and minimum temperatures alone.

In order to test the sensitivity of estimation methods to different temperature thresholds, three sets of lower and upper thresholds that are commonly used for corn are included in the analysis. They are: 8° and 29°C (Butler and Huybers, 2012), 10° (predominantly used by seed companies) and 30°C (McMaster and Wilhelm, 1997), as well as 8° (used in crop models such as CERES-Maize and Hybrid-Maize) and 34°C

(Kropff and van Laar, 1993). In addition to degree-days that are between lower and upper thresholds ($DD_{8,\,29}$, $DD_{10,\,30}$, $DD_{8,\,34}$), the performance of different estimation methods on degree-days that are above upper thresholds (DD_{29+}, DD_{30+}, DD_{34+}) are also analyzed in this study because accumulated above-upper-threshold temperatures have often been used to measure heat stress (Butler and Huybers, 2012; Lobell *et al*., 2011).

First, total growing season degree-days are calculated based on the observed hourly temperature data for each metric of thermal time at the study locations using Eqs. (3.1), (3.2), and (3.3), as described in Lobell *et al*. (2011):

$$DD_{lower,upper} = \sum_{d=1}^{N} DD_d \tag{3.1}$$

$$DD_d = \sum_{h=1}^{24} DD_h \tag{3.2}$$

$$DD_h = \begin{cases} 0 & if\ T_{\mathrm{h}} < T_{\mathrm{lower}} \\ (T_{\mathrm{h}} - T_{\mathrm{lower}})/24 & if\ T_{\mathrm{lower}} \leq T_{\mathrm{h}} < T_{\mathrm{upper}} \\ (T_{\mathrm{upper}} - T_{\mathrm{lower}})/24 & if\ T_{\mathrm{h}} \geq T_{\mathrm{upper}} \end{cases} \tag{3.3}$$

Where N is the number of days (153) for crop development over the growing season spanning from May 1 to September 30, unitless; DD_d is the daily degree-day, °C·day; DD_h is the hourly degree-day, °C·day; T_h is the hourly temperature, °C; T_{lower} is the lower threshold, °C; and T_{upper} is the upper threshold, °C.

Second, daily degree-days are estimated based on the calculated daily temperature data for each metric of thermal time at the study locations. A total of six estimation methods are analyzed in this study: T_{avg}-based rectangle method, adjusted T_{min} and T_{max} rectangle method, single-sine method with horizontal cut-off technique, double-sine method with horizontal cut-off technique, single triangulation method with horizontal cut-off technique, and double triangulation method with horizontal cut-off technique. For the two rectangle methods, Eqs. (3.4) and (3.5) are used to estimate daily degree-days,

respectively. The detailed formulas to estimate daily degree-days for single-sine, double-sine, single-triangulation, and double-triangulation methods with horizontal cut-off technique are found at the UC IPM (2005). Eq. (3.1) is used to calculate total growing season degree-days for the six estimation methods.

$$DD_{\text{lower,upper}} = T_{\text{avg\_adj}} - T_{\text{lower}} \tag{3.4}$$

$$DD_{\text{lower,upper}} = \frac{(T_{\text{max\_adj}} + T_{\text{min\_adj}})}{2} - T_{\text{lower}} \tag{3.5}$$

Where $T_{\text{avg\_adj}}$ is the adjusted daily average temperature, °C; $T_{\text{max\_adj}}$ is the adjusted daily maximum temperature, °C; and $T_{\text{min\_adj}}$ is the adjusted daily minimum temperature, °C. They are adjusted to lower threshold if they are below the lower threshold, and to upper threshold if they are above the upper threshold.

For the six metrics of thermal time analyzed in this study, degree-days approximated with hourly temperature as taken as true. The differences between degree-days estimated with daily temperature and degree-days approximated with hourly temperature are considered as errors. According to the recommendations from Chai and Draxler (2014), a combination of statistical metrics of root mean square error (RMSE) and mean absolute error (MAE) is used to assess the performance of different estimation methods. At every study location, Eqs. (3.6) and (3.7) are used to calculate RMSE and MAE for each metric of thermal time during the study period at each study location, respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {e_i}^2} \tag{3.6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \tag{3.7}$$

In these equations, n is the number of total study years at the study location, unitless; e_i is the error of total growing season degree-days, °C·day.

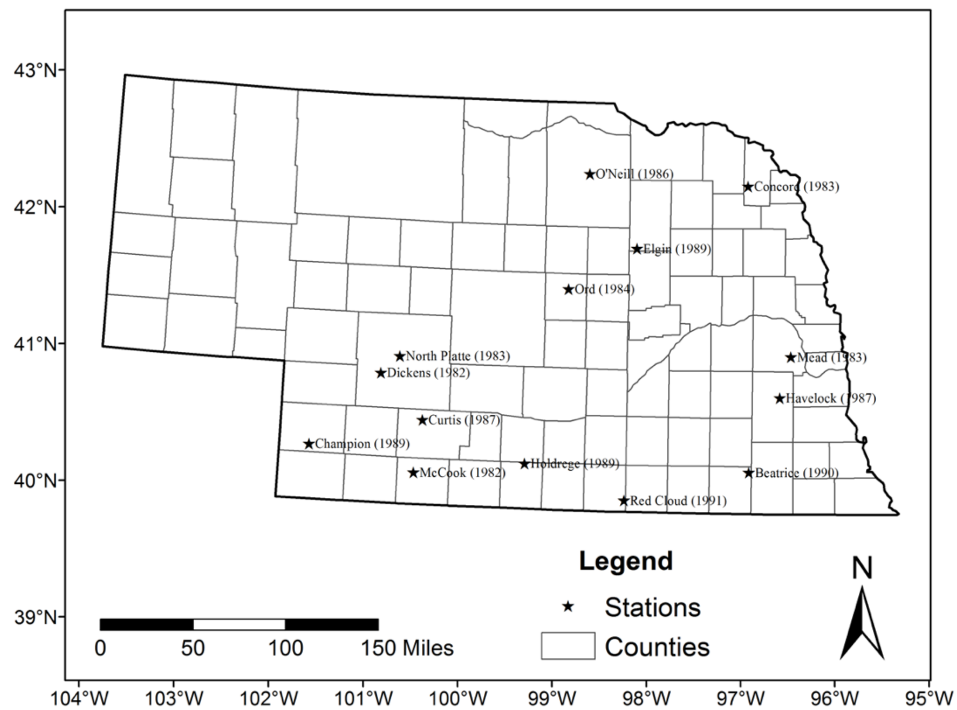

Figure 3.1. Locations of the 14 meteorological stations in Nebraska, U.S., the beginning year of study for each location is included in parentheses after the name of the station.

3.3 Results and discussion

3.3.1 Estimation errors of the six methods

During the study period, the composite RMSE of total growing season degree-days for the six estimation methods at the 14 study locations ranges from 12.2 to 40.8 °C·day for the three metrics of thermal time that are defined as between lower and upper thresholds (i.e., $DD_{8, 29}$, $DD_{10, 30}$, $DD_{8, 34}$), and from 0.6 to 60.2 °C·day for the three metrics of thermal time that are defined as above upper thresholds (i.e., DD_{29+}, DD_{30+}, DD_{34+}) (Table 3.1). Meanwhile, the composite MAE ranges from 10.5 to 34.7 °C·day for the three metrics of $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$; and from 0.4 to 56.5 °C·day for the three metrics of DD_{29+}, DD_{30+}, and DD_{34+}. For all six metrics of thermal time, the adjusted $T_{\min}$ and $T_{\max}$ rectangle method uniformly shows the greatest composite RMSE

and MAE. Therefore, using the adjusted T_{min} and T_{max} rectangle method to estimate total growing season degree-days for corn is not recommended in Nebraska, though it has been the most widely used method in general. In contrast, the single-sine method shows the smallest composite RMSE and MAE for $DD_{8,\,29}$ and $DD_{10,\,30}$; the T_{avg}-based rectangle method shows the smallest composite RMSE and MAE for $DD_{8,\,34}$; the double-sine method shows the smallest composite RMSE for DD_{29+} and DD_{30+}. Both single-sine and double-sine methods show the smallest composite RMSE and MAE for DD_{34+}.

At the majority of the study locations, the single-sine method shows the smallest estimation error for $DD_{8,\,29}$ and $DD_{10,\,30}$. At a total of 13 (12) out of the study locations, the T_{avg}-based method shows the smallest RMSE (MAE) for $DD_{8,\,34}$ (Table 3.2). In other words, the single-sine method is sensitive to the lower and upper thresholds; it performs the best when the upper threshold is relatively low (e.g., 29 and 30 °C). When the upper threshold is relatively high (e.g., 34 °C), the T_{avg}-based method outperforms the single-sine method. For the three metrics of thermal time that are defined as above upper thresholds (i.e., DD_{29+}, DD_{30+}, and DD_{34+}), the double-sine method uniformly shows the smallest estimation error at the majority of the study locations. For the adjusted T_{min} and T_{max} rectangle method, the smallest RMSE and MAE of total growing season degree-days for corn only occurs in two cases: $DD_{8,\,29}$ at Elgin and $DD_{10,\,30}$ at Holdrege. This supports our suggestion that more attention should be paid to the estimation error when the adjusted T_{min} and T_{max} rectangle method is used to estimate total growing season degree-days for corn with daily temperature data in Nebraska.

Table 3.1. Composite RMSEs and MAEs (in parentheses) of total growing season degree-days for corn for the six estimation methods during the study period at the 14 study locations in Nebraska, (unit: °C·day).

Method	$DD_{8,\,29}$	$DD_{10,\,30}$	$DD_{8,\,34}$	DD_{29+}	DD_{30+}	DD_{34+}
T_{avg}-based	40.4 (34.1)	24.5 (19.7)	12.2 (10.5)	51.6 (46.4)	38.9 (33.9)	8.2 (6.0)

Adjusted $T_{\max}$ and $T_{\min}$	40.8 (34.7)	28.1 (22.7)	23.6 (20.7)	60.2 (56.5)	48.2 (44.2)	14.1 (11.1)
Single-sine	17.2 (14.3)	17.7 (14.9)	18.5 (15.6)	3.9 (3.3)	2.9 (2.4)	0.6 (0.4)
Double-sine	17.5 (14.6)	18.0 (15.1)	18.9 (15.9)	3.8 (3.2)	2.8 (2.3)	0.6 (0.4)
Single-triangulation	23.3 (20.2)	21.0 (17.7)	18.8 (15.4)	15.5 (14.2)	12.6 (11.1)	3.7 (2.7)
Double-triangulation	23.9 (20.9)	21.5 (18.1)	19.2 (15.7)	15.7 (14.3)	12.7 (11.3)	3.7 (2.7)

Table 3.2. Numbers of study locations that show the smallest RMSE and MAE (in parentheses) of total growing season degree-days for corn for the six estimation methods during the study period in Nebraska.

Method	$DD_{8, 29}$	$DD_{10, 30}$	$DD_{8, 34}$	DD_{29+}	DD_{30+}	DD_{34+}
T_{avg}-based	0 (0)	3 (3)	13 (12)	0 (0)	0 (0)	0 (0)
Adjusted $T_{\max}$ and $T_{\min}$	1 (1)	1 (1)	0 (0)	0 (0)	0 (0)	0 (0)
Single-sine	8 (9)	5 (6)	0 (0)	4 (4)	4 (4)	4 (5)
Double-sine	2 (0)	4 (3)	1 (2)	10 (10)	10 (10)	10 (9)
Single-triangulation	2 (3)	1 (1)	0 (0)	0 (0)	0 (0)	0 (0)
Double-triangulation	1 (1)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

3.3.2 Comparison of estimated degree-days with true degree-days

During the study period, estimated total growing season degree-days with the adjusted $T_{\max}$ and $T_{\min}$ rectangle method uniformly shows the largest deviation from that approximated with the observed hourly temperature data for the three metrics of thermal time that are defined as between lower and upper thresholds (i.e., $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$), performing the worst for total growing season $DD_{8, 29}$ (Figure 3.2(a)) and the best for $DD_{8, 34}$ (Figure 3.3(a)). In particular, this deviation is caused by overestimation of the relatively small values and underestimation of the relatively great values. Meanwhile, estimated total growing season degree-days with the single-sine method shows the smallest deviation from that approximated with the observed hourly temperature data for both $DD_{8, 29}$ and $DD_{10, 30}$, and the single-sine method performs better for total growing season $DD_{8, 29}$ than for total growing season $DD_{10, 30}$ (Figure 3.2(b)). Estimated total growing season degree-days with the T_{avg}-based rectangle method shows the smallest deviation from that approximated with the hourly observed temperature data for $DD_{8, 34}$ (Figure 3.3(b)). As compared with degree-days approximated with the observed hourly

temperature data, the six estimation methods show a similar performance pattern for the three metrics of thermal time that are defined as above upper thresholds (i.e., DD_{29+}, DD_{30+}, and DD_{34+}): the T_{avg}-based rectangle method drastically underestimates, the adjusted T_{max} and T_{min} rectangle method largely overestimates, the single-sine and double-sine methods perform similarly and provide the best estimation, and the single-triangulation and double-triangulation methods tend to underestimate (Figure 3.4). Moreover, during relatively warm growing seasons, the adjusted T_{max} and T_{min} rectangle method overestimates the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} to a greater extent (Figure 3.4(b)); the single- and double-triangulation methods underestimate the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} to a greater extent as well (Figure 3.4(e), (f)).

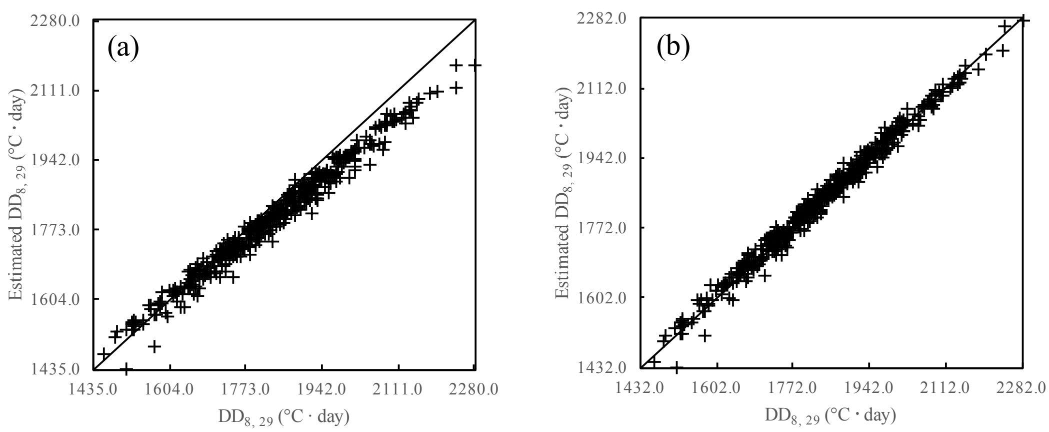

Figure 3.2. Comparison of estimated total growing season $DD_{8,\,29}$ with (a) the adjusted T_{max} and T_{min} rectangle method and (b) the single-sine method with approximated total growing season $DD_{8,\,29}$ based on the observed hourly temperature data during the study period at the 14 study locations in Nebraska.

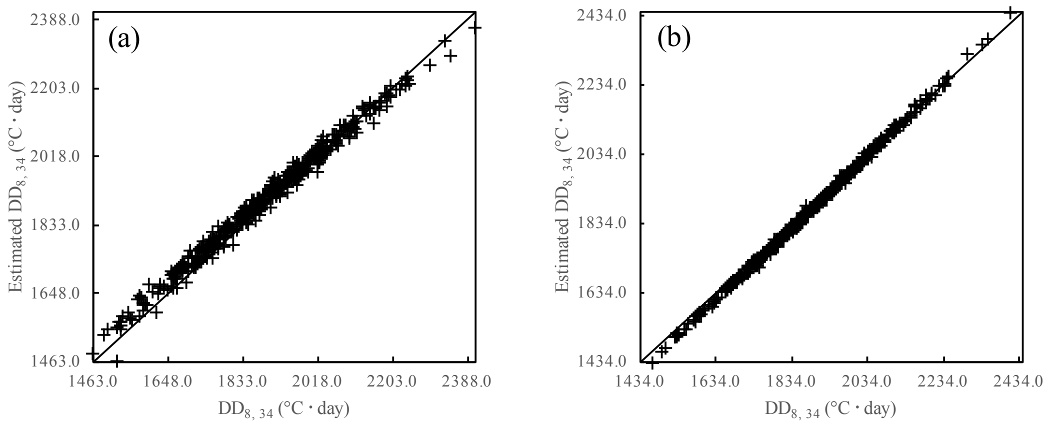

Figure 3.3. Comparison of estimated total growing season $DD_{8,34}$ with (a) the adjusted T_{max} and T_{min} rectangle method and (b) the T_{avg}-based rectangle method with approximated total growing season $DD_{8,34}$ based on the observed hourly temperature data during the study period at the 14 study locations in Nebraska.

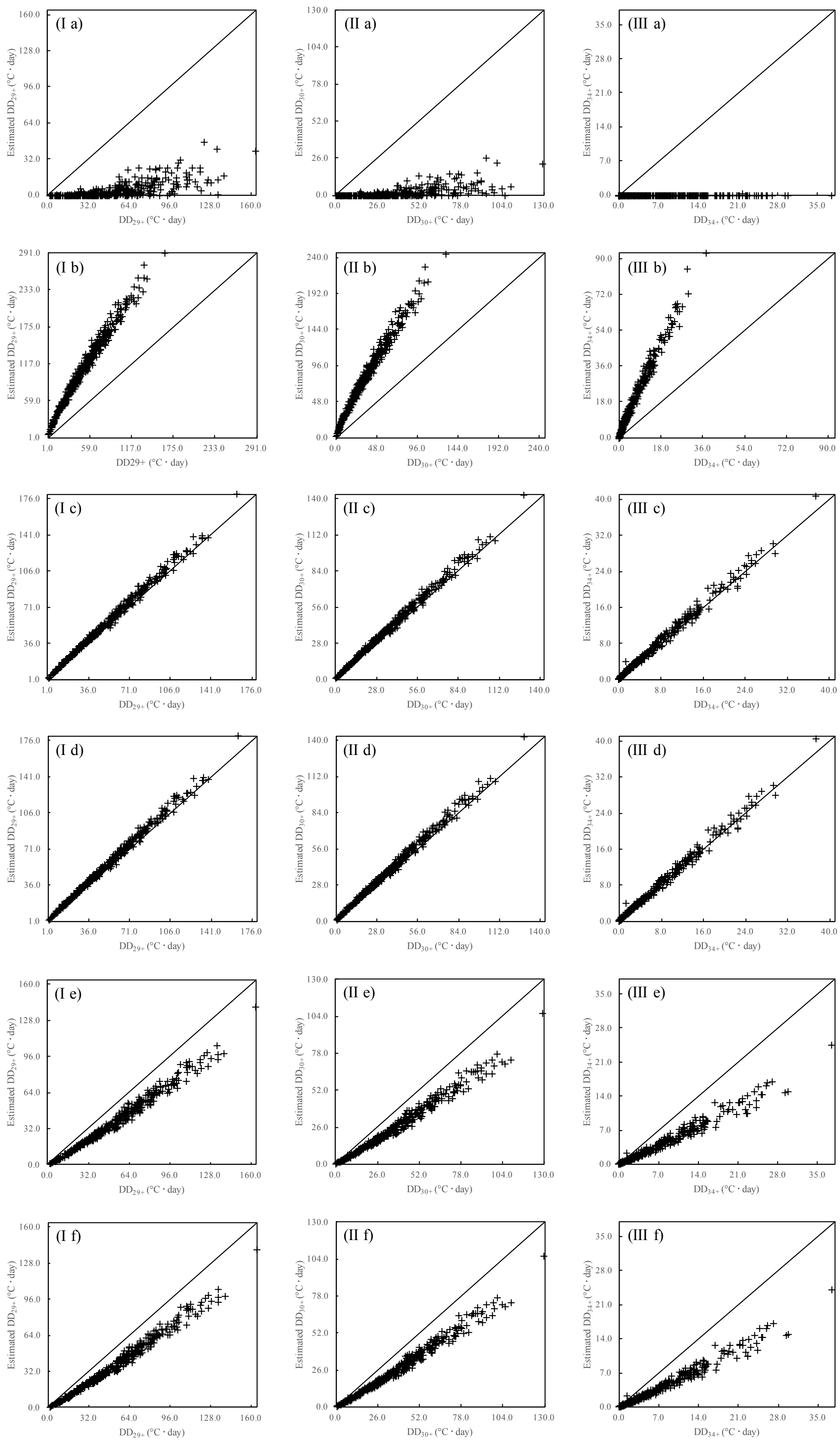
(I a)
(II a)
(III a)
(I b)
(II b)
(III b)
(I c)
(II c)
(III c)
(I d)
(II d)
(III d)
(I e)
(II e)
(III e)
(I f)
(II f)
(III f)
Estimated DD_{29+} (°C・day)
Estimated DD_{30+} (°C・day)
Estimated DD_{34+} (°C・day)
DD_{29+} (°C・day)
DD_{30+} (°C・day)
DD_{34+} (°C・day)
DD29+ (°C・day)

Figure 3.4 Comparison of estimated total growing season degree-days with the six methods with approximated total growing season degree-days based on the observed hourly temperature data during the study period at the 14 study locations in Nebraska. (I) DD_{29+}. (II) DD_{30+}. (III) DD_{34+}. (a) The T_{avg}-based rectangle method. (b) The adjusted T_{max} and T_{min} rectangle method. (c) The single-sine method. (d) The double-sine method. (e) The single-triangulation method. (f) The double-triangulation method.

3.3.3 Selected cases in the extreme cool and warm years

In order to test the performance of the six estimation methods during extreme cool and warm years, which are defined based on the mean growing season average temperature during the study period at the 14 study locations in Nebraska (Table 3.3). The six estimation methods show an inverse pattern in total growing season degree-days for corn that are defined as between lower and upper thresholds (i.e., $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$) in extreme cool years vs. in extreme warm years (Figure 3.5 and 3.6). At the majority of the study locations, the T_{avg}-based method underestimates the three metrics of $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$ in extreme cool years but overestimates them in extreme warm years. The opposite holds true for the adjusted T_{max} and T_{min} rectangle method, single-sine method, and double-sine method, which overestimate the three metrics of $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$ in extreme cool years and underestimate them in extreme warm years. For single- and double-triangulation methods, this inverse pattern between extreme cool and warm years is relatively weak due to the internal inconsistency in estimation performance. In extreme cool years, the single- and double-triangulation methods underestimate $DD_{8, 29}$ at half of the study locations and overestimate $DD_{8, 29}$ at the remaining half of the study locations; the single- and double-triangulation methods underestimate $DD_{10, 30}$ and $DD_{8, 34}$ at a total of 8 out of 14 study locations. In extreme warm years, the single- and double-triangulation methods overestimate $DD_{8, 29}$ and $DD_{10, 30}$ but underestimate $DD_{8, 34}$ at the majority of the study locations.

In extreme cool years, the T_{avg}-based rectangle method shows the smallest composite MAE for $DD_{8, 29}$ and $DD_{8, 34}$, and the single-sine method shows the smallest composite MAE for $DD_{10, 30}$. In extreme warm years, the single-sine method shows the smallest composite MAE for $DD_{8, 29}$ and $DD_{10, 30}$, and the T_{avg}-based rectangle method shows the smallest composite MAE for $DD_{8, 34}$. In contrast, the adjusted T_{max} and T_{min} rectangle method shows the greatest composite MAE for the three metrics of $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$ in both extreme cool and warm years, with the exception of $DD_{8, 29}$ in extreme cool years. In extreme cool years, the double-triangulation method shows the greatest composite MAE for $DD_{8, 29}$. Among all the cases for the three metrics of $DD_{8, 29}$, $DD_{10, 30}$, and $DD_{8, 34}$ in extreme years, the worst performance occurs to $DD_{8, 29}$ with the adjusted T_{max} and T_{min} rectangle method in extreme warm years, with an underestimation error ranging from 36.3 to 118.0 °C·day (Figure 3.6(a)).

In extreme cool and warm years, the six methods show similar predominant patterns in estimation performance for the three metrics of thermal time that are defined as above upper thresholds (i.e., DD_{29+}, DD_{30+}, and DD_{34+}) in Nebraska. At the majority of the study locations, the T_{avg}-based rectangle method underestimates the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} in both extreme cool and warm years; the adjusted T_{max} and T_{min} rectangle method overestimates the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} in both extreme cool and warm years; the single- and double-sine methods overestimate the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} in both extreme cool and warm years; and the single- and double-triangulation methods underestimate the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} in both extreme cool and warm years (Figure 3.7 and 3.8). While the double-sine method shows the smallest composite MAE for the three metrics of DD_{29+}, DD_{30+}, and

DD_{34+} in extreme years, the adjusted T_{max} and T_{min} rectangle method shows the greatest composite MAE for the three metrics of DD_{29+}, DD_{30+}, and DD_{34+} in extreme years. In extreme cool years at the three locations of Havelock, Elgin, and Red Cloud, the estimated DD_{34+} is zero with the six methods, as is the approximated DD_{34+} based on the observed hourly temperature data (Figure 3.7(c)).

In order to further understand how the six estimation methods perform on a daily timescale in extreme cool and warm years, a total of four representative cases are selected for the analysis. They are the metrics of thermal time at locations in extreme years that have the greatest total absolute errors for the six methods. For the three metrics of thermal time that are defined as between lower and upper thresholds, $DD_{8,\ 34}$ at Concord in 1985 and $DD_{8,\ 29}$ at Red Cloud in 2000 are chosen to represent the extreme cool and warm years, respectively. At Concord, all six methods underestimate total growing season $DD_{8,\ 34}$ in the extreme cool year of the study period, among which the T_{avg}-based rectangle method shows the smallest estimation error, with the estimation error remaining steady within the growing season. By contrast, the double-triangulation method shows the greatest estimation error, with the estimation error increasing with time during the growing season (Figure 3.9(a)). In the extreme warm year of the study period at Red Cloud, the T_{avg}-based rectangle method shows the greatest overestimation error and the adjusted T_{max} and T_{min} rectangle method shows the greatest underestimation error for $DD_{8,\ 29}$. Within the growing season, both of these two overestimation and underestimation errors increases with time on a daily timescale (Figure 3.9(b)).

For the three metrics of thermal time that are defined as above upper thresholds, DD_{29+} at McCook in 1992 and DD_{29+} at Champion in 2012 are chosen to represent the

extreme cool and warm years, respectively. The six methods show similar performance for DD_{29+} at McCook in the extreme cool year of the study period as for DD_{29+} at Champion in the extreme warm year of the study period. The T_{avg}-based rectangle method and both the single- and double-triangulation methods underestimate, while the adjusted T_{max} and T_{min} rectangle method and both the single- and double-sine methods overestimate, DD_{29+} at McCook in the extreme cool year and DD_{29+} at Champion in the extreme warm year. Among which the T_{avg}-based method and the adjusted T_{max} and T_{min} rectangle method shows the greatest underestimation and overestimation errors, respectively. As would be expected, the T_{avg}-based method drastically underestimates DD_{29+} for these two cases. In particular, estimated daily DD_{29+} with the T_{avg}-based method is zero throughout the growing season at McCook, NE, in the extreme cool year. In both cases, the adjusted T_{max} and T_{min} rectangle method overestimates daily DD_{29+} more and more within the growing season. And this worsening overestimation tendency is rougher at McCook in the extreme cool year than at Champion in the extreme warm year. The single- and double-sine methods perform well for daily DD_{29+} in early growing season in both cases, but start to overestimate in the middle-to-late growing season. In both cases, the single- and double- triangulation methods underestimate daily DD_{29+} worse within the growing season, especially in the second half of the growing season (Figure 3.10).

Table 3.3. Years and mean growing season average temperatures (in parentheses, unit: °C) for the extreme cool and warm years during the study period at the 14 study locations in Nebraska.

Location name	Extreme cool year	Extreme warm year
Beatrice	1992 (19.7)	2012 (22.6)
Champion	1993 (17.9)	2012 (21.3)
Concord	1985 (17.7)	1988 (21.2)
Curtis	1992 (18.5)	2012 (22.2)
Dickens	1993 (17.5)	2012 (21.4)
Elgin	1992 (17.9)	2012 (21.0)
Havelock	1992 (19.4)	2012 (23.5)

Holdrege	1992 (18.7)	2012 (21.6)
McCook	1992 (18.8)	2012 (22.4)
Mead	1992 (19.2)	1988 (22.4)
North Platte	1992 (17.8)	2012 (21.7)
O'Neill	1992 (17.4)	2012 (21.5)
Ord	1992 (18.3)	1988 (21.8)
Red Cloud	1992 (19.4)	2000 (24.0)

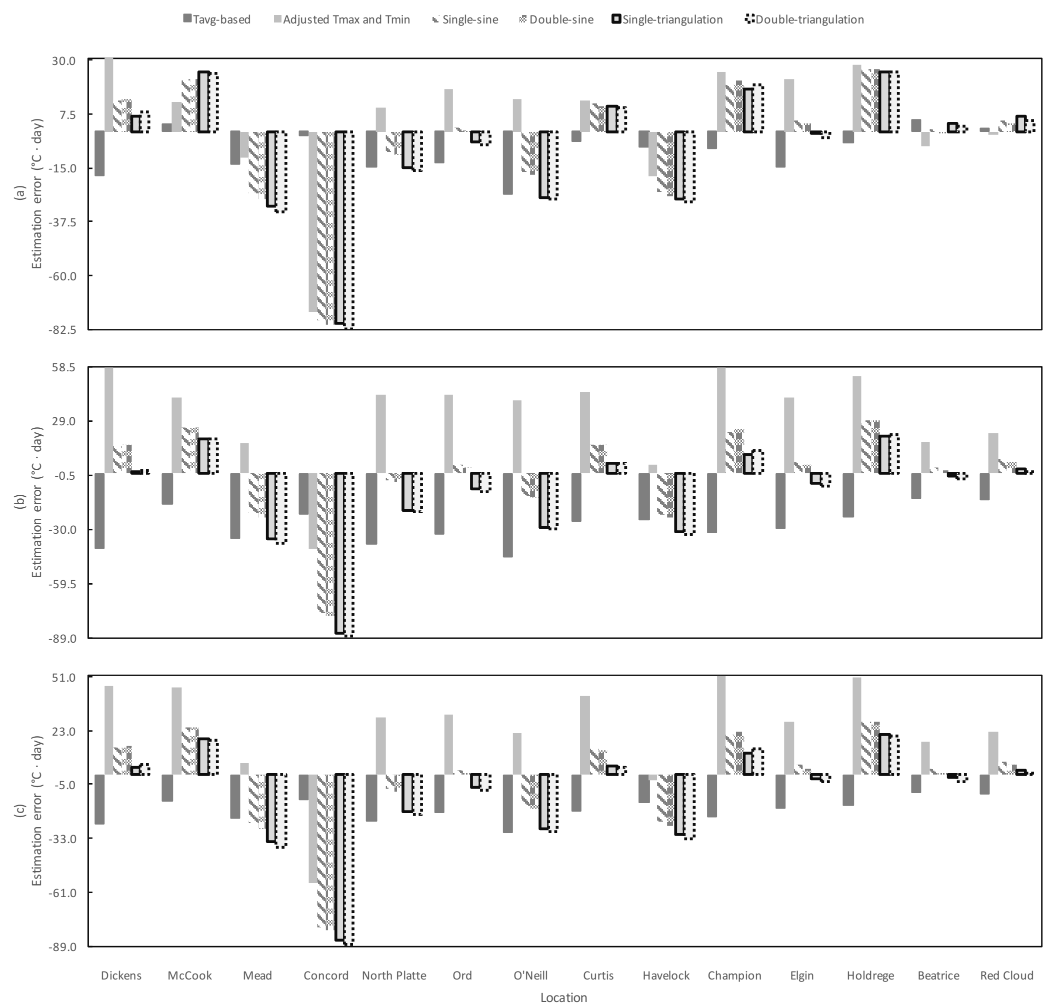

Figure 3.5. Estimation errors of the six methods in total growing season degree-days in extreme cool years for the 14 study locations in Nebraska. (a) $DD_{8, 29}$. (b) $DD_{10, 30}$. (c) $DD_{8, 34}$.

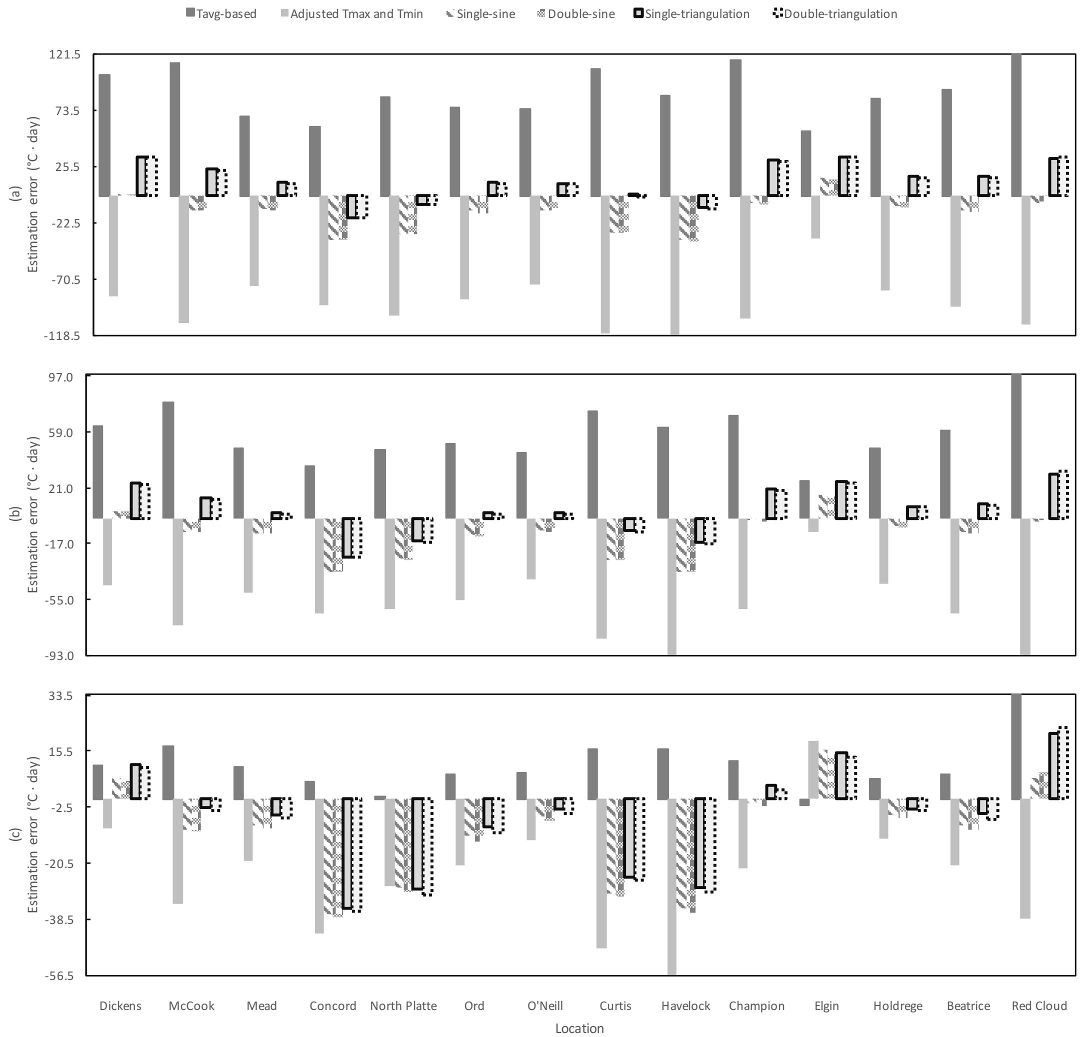

Figure 3.6. Estimation errors of the six methods in total growing season degree-days in extreme warm years for the 14 study locations in Nebraska. (a) $DD_{8,\,29}$. (b) $DD_{10,\,30}$. (c) $DD_{8,\,34}$.

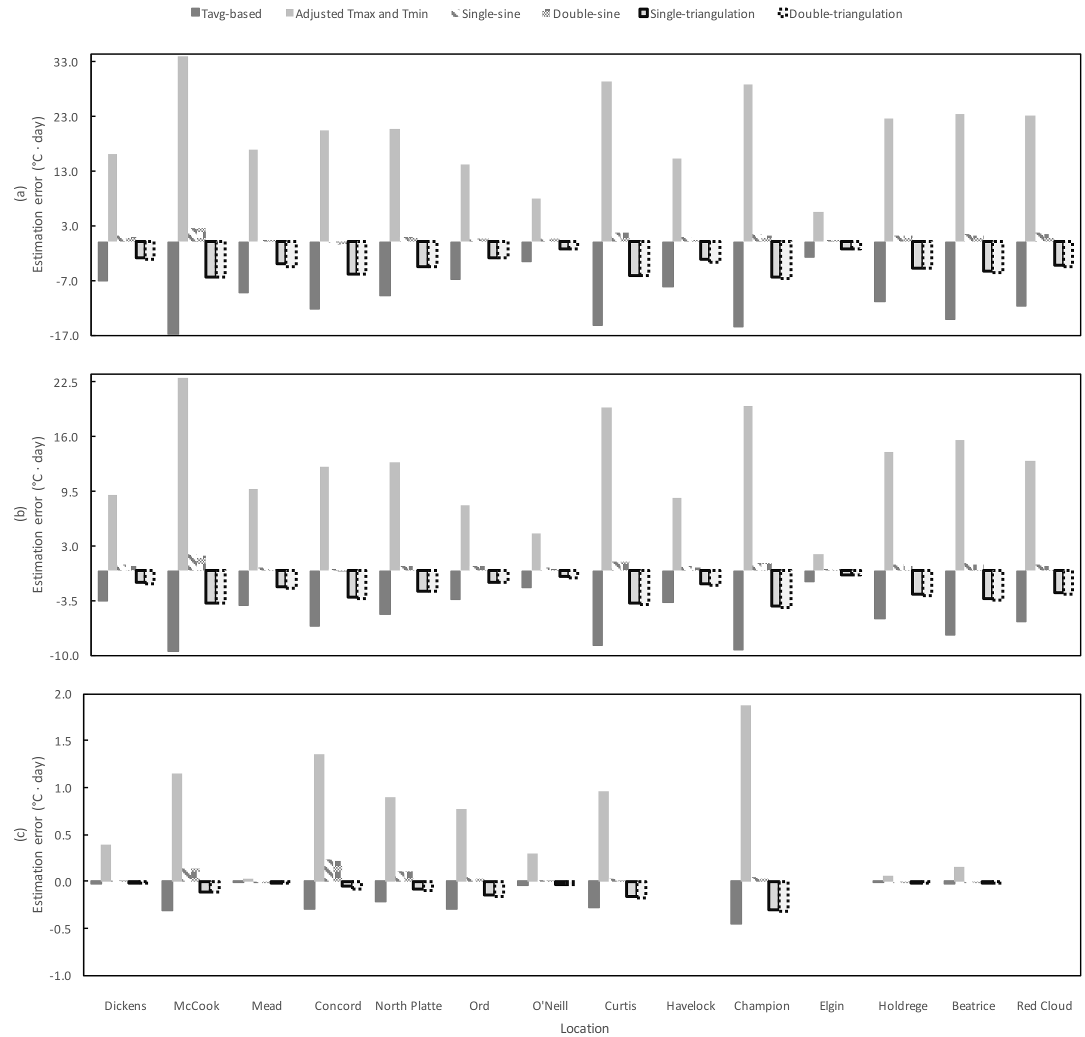

Figure 3.7. Estimation errors of the six methods in total growing season degree-days in extreme cool years for the 14 study locations in Nebraska. (a) DD_{29+}. (b) DD_{30+}. (c) DD_{34+}.

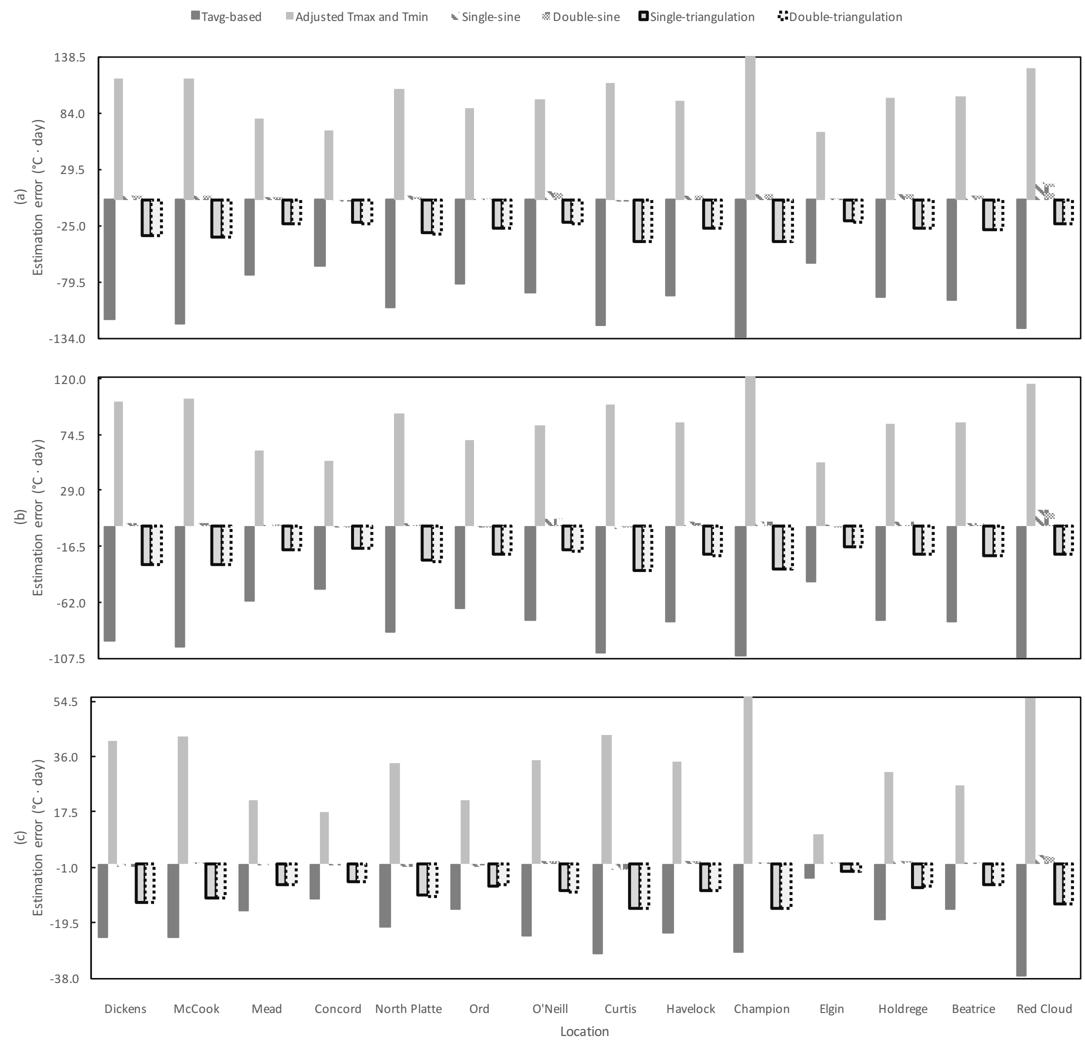

Figure 3.8. Estimation errors of the six methods in total growing season degree-days in extreme warm years for the 14 study locations in Nebraska. (a) DD_{29+}. (b) DD_{30+}. (c) DD_{34+}.

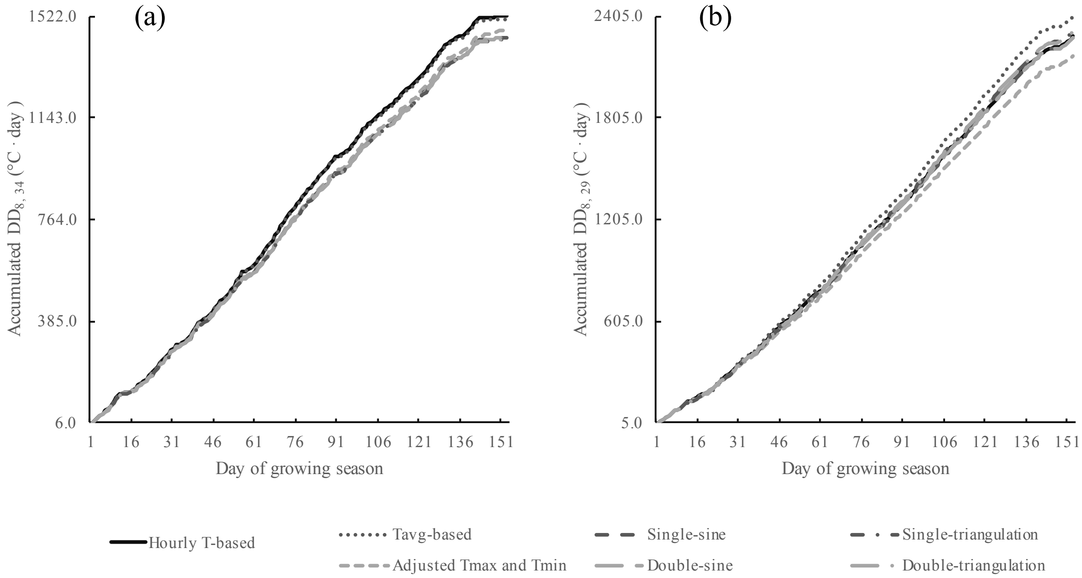

Figure 3.9. Accumulated degree-days within the growing season of extreme years at particular locations. (a) $DD_{8,\,34}$ at Concord, NE in the extreme cool year of 1985. (b) $DD_{8,\,29}$ at Red Cloud, NE in the extreme warm year of 2000.

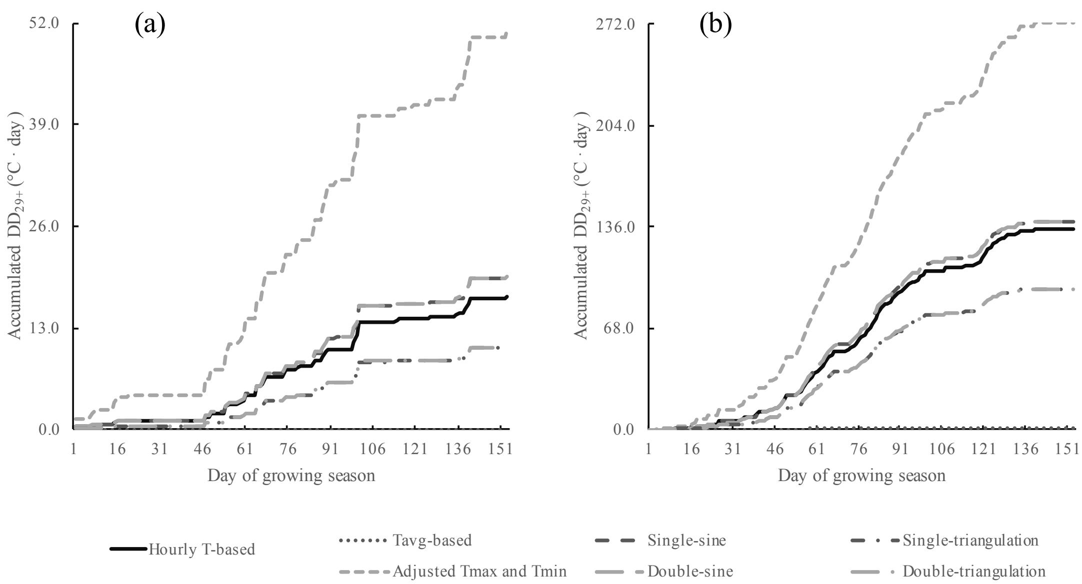

Figure 3.10. Accumulated degree-days within the growing season of extreme years at particular locations. (a) DD_{29+} at McCook, NE in the extreme cool year of 1992. (b) DD_{29+} at Champion, NE in the extreme warm year of 2012.

3.4 Conclusions

This study uses an hourly air temperature dataset for the 14 study locations in Nebraska to evaluate the six most commonly used methods to estimate thermal time for corn when weather data are limited to the daily timescale. The single- and double-sine methods generally perform the best estimation for all the studied metrics of thermal time for corn, with an exception of $DD_{8,\,34}$ that the T_{avg}-based rectangle method performs the best estimation. In other words, the single- and double-sine methods are sensitive to the lower and upper thresholds. Though being the most widely used method in the study area, the adjusted T_{max} and T_{min} rectangle method shows the greatest composite RMSE and MAE for all six metrics of thermal time for corn. Hence, this study suggests that the adjusted T_{max} and T_{min} rectangle method does not accurately estimate growing season thermal time for corn in Nebraska.

All six methods perform differently for the three metrics of thermal time that are defined as between lower and upper thresholds in extreme cool years vs. in extreme warm years at the majority of the study locations. In particular, the adjusted T_{max} and T_{min} rectangle method overestimates the three metrics of $DD_{8,\,29}$, $DD_{10,\,30}$ and $DD_{8,\,34}$ in extreme cool years but underestimates them in extreme warm years; the single- and double-sine methods tend to overestimate the three metrics of $DD_{8,\,29}$, $DD_{10,\,30}$ and $DD_{8,\,34}$ in extreme cool years but underestimate them in extreme warm years. In both extreme cool and warm years, the adjusted T_{max} and T_{min} rectangle method shows the greatest composite MAE among the six methods. In particular, the six studied estimation methods perform the worst for $DD_{8,\,34}$ at Concord and $DD_{8,\,29}$ at Red Cloud in extreme cool and warm years, respectively. At Concord, all six methods uniformly underestimate total

growing season $DD_{8,34}$ in the extreme cool year of the study period. At Red Cloud, for total growing season $DD_{8,29}$ in the extreme warm year of the study period, the T_{avg}-based rectangle method and the adjusted T_{max} and T_{min} rectangle method shows the greatest overestimation and underestimation error, respectively. On a daily timescale, these two overestimation and underestimation errors worsen with time within the growing season.

For the three metrics of thermal time that are defined as above upper thresholds, the six methods perform similar dominant patterns in extreme cool and warm years. At the majority of the study locations, the T_{avg}-based rectangle method, single- and double-triangulation methods underestimate the three metrics of DD_{29+}, DD_{30+}, DD_{34+}; while the adjusted T_{max} and T_{min} rectangle method, single- and double-sine methods overestimate the three metrics of DD_{29+}, DD_{30+}, DD_{34+}. In both extreme cool and warm years, the double-sine method and the adjusted T_{max} and T_{min} rectangle method shows the smallest and the greatest MAE for the three metrics of DD_{29+}, DD_{30+}, DD_{34+}, respectively. In particular, the six studied methods perform the worst for DD_{29+} at McCook and DD_{29+} at Champion in extreme cool and warm years, respectively. Within the growing season, the adjusted T_{max} and T_{min} rectangle method overestimate daily DD_{29+} at McCook in the extreme cool year and daily DD_{29+} at Champion in the extreme warm year. This overestimation error worsens over time within the growing season, especially at McCook in the extreme cool year of the study period.

This study concludes that when the weather data are limited to a daily timescale, the following methods are recommended to estimate different metrics of degree-days during the growing season for corn in Nebraska:

- $DD_{8,29}$: single-sine method

- $DD_{10, 30}$: single-sine method
- $DD_{8, 34}$: T_{avg}-based rectangle method
- DD_{29+}: double-sine method
- DD_{30+}: double-sine method
- DD_{34+}: double-sine method

For the three metrics of thermal time that are defined as between lower and upper thresholds, the recommended methods could be used by corn producers to choose the varieties to replant to compensate for the loss of the emerged corn plants in early growing season when destroying weather events occur but replanting is still an option. For the three metrics of thermal time that are defined as above upper threshold, the recommended methods could provide high-accuracy degree-days to quantify the potential heat stress for corn plants. In contrast, the adjusted T_{max} and T_{min} rectangle method, though being used the most in the study area, is not recommended to estimate total growing season degree-days for corn with daily temperature data. In particular, the adjusted T_{max} and T_{min} rectangle method overestimates the three metrics of $DD_{8, 29}$, $DD_{10, 30}$ and $DD_{8, 34}$ in extreme cool years but underestimates them in extreme warm years at the study locations. The adjusted T_{max} and T_{min} rectangle method is found to overestimate the three metrics of DD_{29+}, DD_{30+}, DD_{34+} in both extreme cool and warm years at the study locations; furthermore, this overestimation tends to worsen with time within the growing season. However, the 14 study locations in Nebraska may not cover all the climate regimes in the entire Corn Belt. Therefore, additional verifications are necessary when applying these recommendations to other corn-belt states.

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References

Allen JC. 1976. A modified sine wave method for calculating degree days. *Environ. Entomol.* **5**: 388–396.

Arnold CY. 1960. Maximum-minimum temperatures as a basis for computing heat units. *J. Am. Soc. Hortic. Sci*. **76**: 682–692.

Baskerville GL, Emin P. 1969. Rapid estimation of heat accumulation from maximum and minimum temperatures. *Ecology* **50**: 514–517.

Bigelow FH. 1909. *Report on the temperatures and vapor tensions of the United States reduced to a homogenous system of 24 hourly observations for the 33-year interval, 1873–1905*. U.S. Department of Agriculture Weather Bureau Bulletin S. Washington: Government Printing Office.

Butler EE, Huybers P. 2012. Adaptation of US maize to temperature variations. *Nat. Clim. Chang.* **3**: 68–72.

Chai T, Draxler RR. 2014. Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geosci. Model Dev*. **7**: 1247–1250.

Cross HZ, Zuber MS. 1972. Prediction of flowering dates in maize based on different methods of estimating thermal units. *Agron. J*. **64**: 351–355.

Feng S, Hu Q. 2004. Changes in agro-meteorological indicators in the contiguous United States: 1951–2000. *Theor. Appl. Climatol.* **78**: 247–264.

Gilmore EC Jr., Rogers JS. 1958. Heat units as a method of measuring maturity in corn. *Agron. J*. **50**: 611–615.

High Plains Regional Climate Center. 2015. *Flags on Data and What they Mean*. http://hprcc6.unl.edu/online/help/FlagHelp.html (accessed 3 March 2015).

Hubbard KG, Guttman NB. You J, Chen Z. 2007. An improved QC process for temperature in the daily cooperative weather observations. *J. Atmos. Oceanic Technol.* **24**: 206–213.

Hubbard KG, You J. 2005. Sensitivity analysis of quality assurance using the spatial regression approach – A case study of the maximum/minimum air temperature. *J. Atmos. Oceanic Technol.* **22**: 1520–1530.

Jones CA, Kiniry JR.1986. *CERES-Maize: A simulation model of maize growth and development*. Texas A&M University Press: College Station, Texas USA.

Kropff MJ, van Laar HH. 1993. *Modelling crop-weed interactions*. CAB International in association with the International Rice Research Institute: Wallingford, UK.

Kumudini S, Andrade FH, Boote KJ, Brown GA, Dzotsi KA, Edmeades GO, Gocken T, Goodwin M, Halter AL, Hammer GL, Hatfield JL, Jones JW, Kemanian AR, Kim S-H, Kiniry J, Lizaso I, Nendel C, Nielsen RL, Parent B, Stöckle CO, Tardieu F, Thomison PR, Timlin DJ, Vyn TJ, Wallach D, Yang H, Tollenaar M. 2014. Predicting maize phenology: Intercomparison of functions for developmental response to temperature. *Agron. J.* **106**: 2087–2097.

Lindsey AA, Newman JE. 1956. Use of official weather data in spring time-temperature analysis of an Indiana phenological record. *Ecology* **37**: 812–823.

Lobell DB, Bänziger M, Magorokosho C, Vivek B. 2011. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nat. Clim. Chang.* **1**: 42–45.

McMaster GS, Wilhelm WW. 1997. Growing degree-days: one equation, two interpretations. *Agric. For. Meteorol.* **87**: 291–300.

Neild RE. 1967. Maximum-minimum temperatures as a basis for evaluating thermoperiodic response. *Mon. Weather Rev*. **95**: 583–584.

Roltsch WJ, Zalom FG, Strawn AJ, Strand JF, Pitcairn MJ. 1999. Evaluation of several degree-day estimation methods in California climates. *Int. J. Biometeorol*. **42**: 169–176.

Russelle MP, Wilhelm W, Olson RA, Power JF. 1984. Growth analysis based on degree days. *Crop Sci*. **24**: 28–32.

Sevacherian V, Stern VM, Mueller AJ. 1977. Heat accumulation for timing *Lygus* control measures in a safflower-cotton complex. *J. Econ. Entomol*. **70**: 399–402.

University of California Statewide Integrated Pest Management Program (UC IPM). 2005. *How to Manage Pests: Degree-days: Methods*. http://www.ipm.ucdavis.edu/WEATHER/ddfigindex.html (accessed 10 June 2015).

U.S. Department of Agriculture National Agricultural Statistics Service, Agricultural Statistics Board. 1997. *Usual planting and harvesting dates for U.S. field crops*. Agricultural Handbook Number 628.

U.S. Department of Agriculture National Agricultural Statistics Service. 2010. *Field crops usual planting and harvesting dates*. Agricultural Handbook Number 628, pp. 9.

U.S. Department of Agriculture National Agricultural Statistics Service. 2014. *2012 Census of Agriculture Nebraska State and County Data*. Volume 1, Geographic Area Series, Part 27, pp. 8.

U.S. Department of Agriculture National Agricultural Statistics Service. 2015. *2014 State Agriculture Overview*. http://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=NEBRASKA (accessed 19 June, 2015).

Yang H, Dobermann A, Lindquist JL, Walters DT, Arkebauer TJ, Cassman KG. 2004. Hybrid-maize – a maize simulation model that combines two crop modeling approaches. *Field Crop. Res.* **87**: 131–154.

You J, Hubbard KG, Goddard S. 2008. Comparison of methods for spatially estimating station temperatures in a quality control system. *Int. J. Climatol.* **28**: 777–787.

Zalom FG, Goodell PB, Wilson LT, Barnett WW, Bentley WJ. 1983. *Degree-days: calculation and use of heat units in pest management*. University of California, Division of Agriculture and Natural Resources, Leaflet 21373, pp.10.

CHAPTER 4: HISTORICAL EFFECTS OF TEMPERATURE AND PRECIPITATION ON CORN GRAIN YIELD AT A MID-LATITUDE LOCALE: MEAD, NEBRASKA

ABSTRACT: In Nebraska, corn production is highly dependent on the weather even with advances in farming practices and irrigation resources. It is critically important to conduct a comprehensive analysis on the most up-to-date historical effects of temperature and precipitation on corn grain yield for both irrigated and rainfed corn. In this study, three high-quality field-level datasets gathered from the corn sites near Mead, Nebraska together with statistical methods are used to quantify the historical climatic effects on corn grain yield from 2003 to 2013. A total of 102 climate variables are used in the analysis, including temperature, precipitation, and VPD indices. At the two irrigated sites, temperature plays a more important role on corn grain yield with or without the extreme year 2012 included: three metrics of extreme degree-days are found to be negatively correlated with corn grain yield at a statistically significant level for the irrigated continuous corn; four metrics of temperature indices show statistically significant negative correlations with corn grain yield for irrigated rotated corn. In contrast, VPD plays a more important role on corn grain yield at the rainfed corn-soybean rotation site. In particular, the variation in maximum VPD during the reproductive stage could explain 87% of the variance in corn grain yield. As for precipitation indices, statistically significant negative correlations are found between: (1) total precipitation during the 11-day period centered around silking and corn grain yield during the entire study period at the irrigated continuous corn site; (2) total precipitation during the period spanning from the day after harvest in the past year to the day before planting in the current year and

corn grain yield when year 2012 is excluded at the irrigated corn-soybean rotation site; and (3) total precipitation during the 30-day period before planting and corn grain yield during the entire study period at the rainfed corn-soybean rotation site.

4.1 Introduction

Corn (*Zea mays L.*) is considered a warm-weather crop, and growing season climate (e.g., temperature and precipitation) is known to persistently affect corn grain yield (Brown and Darrah, 1985; Hollinger and Hoeft, 1986; Garcia *et al*., 1987). For example, high temperature decreases the duration of corn plant growth, shortening the duration of grain filling. Moreover, heat stress reduces pollen germination, disrupts corn kernel development and reduces seed size. Therefore, corn grain yield might be reduced in a warming climate if no adaptation measures were taken (Herrero and Johnson, 1980; Badu-Apraku *et al*., 1983; Muchow *et al*., 1990; Cheikh and Jones, 1994; Singletary *et al*., 1994). High temperatures can be beneficial to corn gain yield if moisture available to corn plants is adequate, which includes soil moisture from preseason precipitation and growing season precipitation (Runge, 1968; Neild *et al*., 1987). However, drought and heat stress mostly occur in combination, especially during the reproductive stage (i.e., prior to and after anthesis) when corn plants are generally more sensitive to environmental stresses, which could significantly hurt corn grain yield regardless of the length of exposure time (Runge, 1968; Muchow *et al*., 1990; Prasad *et al.*, 2008). In addition, the negative effects of temperature extremes on corn grain yield also include poor germination caused by below-normal temperatures (Neild and Newman, 1990).

Understanding the climate-crop yield relationships to date can provide a foundation for coping with expected changes in climate, gauging the importance of near-term climate change, forecasting crop production in the short term, and projecting the agricultural impact of future climate change on crop production (Rowhani *et al*., 2011; Lobell *et al*., 2007; Lobell *et al*., 2011b). Statistical methods have commonly been used in assessing historical effects of temperature and precipitation on crop grain yield in different areas and on various spatial scales, from global to local (sub-provincial) scales (Lobell *et al*., 2011b; Lobell and Field, 2007; Lobell *et al*., 2011a; Klink *et al*., 2014; Lobell and Asner, 2003; Tao *et al*., 2006; Rowhani *et al*., 2011; Lobell *et al*., 2014; Chen *et al*., 2011; Lobell *et al*., 2007; Almaraz *et al*., 2008; Cabas *et al*., 2010). Statistical-methods-based models of predicting crop yield responses to climate change have been systematically evaluated and compared to process-based crop models by Lobell and Burke (2010). The disadvantages of process-based crop models include: omission of the effects of crop pests and diseases (Lobell *et al*., 2007); dependence on a given set of data including weather, soil conditions, and management scenarios that are at plot scale (Bannayan *et al*., 2004); and requiring some serious upscaling work to be applied at spatial scales that are larger than the plot (Hansen and Jones, 2000). Though the empirical/statistical models do not capture details of plant physiology or crop management, they capture the net effect of the entire range of processes by which climate (e.g., temperature and precipitation) affects yields and enable a quantitative evaluation of uncertainties (Lobell *et al*., 2006; Lobell and Field, 2007). In general, there are three components of the climate portion of a climate-crop yield relationship analysis; they are: a) climatic indices, such as minimum temperature, maximum temperature, average

temperature, growing degree-days, extreme degree-days, precipitation, and vapor pressure deficit; b) timescales of the climatic indices, such as daily, weekly, biweekly, monthly, critical periods (e.g., reproductive stage), the pre-planting season, and the entire growing season (i.e., from planting to physical maturity); and c) forms of the climatic indices, such as mean values, shifts in mean values (e.g. inter-seasonal temporal trends), and intra-seasonal variability of the climatic indices.

The importance of temperature-related impacts on corn production has been emphasized in the literature due to significant global temporal trends in recent decades (Lobell *et al*., 2011b; Lobell and Burke, 2008). There has clearly been a negative response of global corn yield to climate warming since the 1980s, and this yield loss is worse under drought conditions than under optimal rainfed conditions (Lobell and Field, 2007; Lobell *et al*., 2011a). For example, from 1980–2008, global corn production would have been roughly 4% higher had agriculture not been exposed to the trends in growing season temperature that exceeded one standard deviation of historical year-to-year variability (Lobell *et al*., 2011b).

The United States has not been immune from these global trends. As the largest corn producer in the world, the U.S. has been experiencing substantial climate-related changes in corn production. From 1982–1998, gradual temperature changes have caused a measurable impact on corn grain yields in the United States (NOAA, 2011; Lobell and Asner, 2003). From 1981–2005, the total corn growth period lengthened; this was driven mainly by the increase in the number of growing degree-days needed for corn to progress through the reproductive stage (Sacks and Kucharik, 2011). In the U.S. corn belt, spring freeze, summer heat, fall freeze, and rainfall timing (especially for the 3-week period

centered around tasseling) are all key variables affecting corn grain yield (NOAA, 2011; Neild and Newman, 1990). Because of the unfavorable within-season distribution of precipitation, rainfed corn in the western part of the U.S. corn belt is frequently subjected to episodes of transient and unavoidable water stress, especially around silking time (Smika, 1992; Grassini *et al*., 2009). The combination of heat stress and rainfall deficit often occurs in late July and August in the southern part of the U.S. corn belt (Brown and Darrah, 1985). Since the 1980s, the rate of temperature increase has accelerated, and the impact of climate variability on agricultural production has become a hotter topic than ever. Several studies have investigated the historical impacts of temperature and precipitation on corn production in both the U.S. corn belt and the Midwest (Rosenzweig, 1993; Kucharik, 2006; Schlenker and Roberts, 2009; Misha and Cherkauer, 2010).

Nebraska is one of the most important states for corn production in the United States. It has both rainfed corn in the eastern half of the state (humid continental climate) and irrigated corn in the western half of the state (semi-arid climate). Even with advances in farming practices and irrigation resources, corn production remains highly dependent on the weather in Nebraska. A comprehensive analysis on the most up-to-date historical effects of temperature and precipitation on corn grain yield could be helpful for planning local corn production, especially when the effects of climatic impacts have been addressed for irrigated and rainfed corn. In this study, a high-quality field-level dataset was gathered at Mead, Nebraska, including micrometeorological observing data, corn phenology, and grain yield data to investigate the relationships between climate variables (e.g., temperature and precipitation) and corn grain yield. Statistical methods were adopted to quantify these historical effects for both irrigated and rainfed corn at the study

locale. The primary attributes of this study are that it a) provides the most up-to-date results on the relationships between climate variables and corn grain yield during the study period of 2003–2013; b) pinpoints additional climatic indices that are important to corn grain yield that other similar studies have not previously reported; c) uses actual corn phenology data rather than a broad conception of growing season months (e.g., May through September), and micrometeorological data collected in situ instead of weather data from the closet observing station.

As part of a regional, multi-institutional project titled "Useful to Usable (U2U): Transforming Climate Variability and Change Information for Cereal Crop Producers," this study is aimed at local agricultural advisors. This study provides scientific evidence of temperature- and precipitation-related effects on corn grain yield in Nebraska. Therefore, local agricultural advisors could use it when making management practice suggestions to Nebraskan corn farmers in order to help them take advantage of or counteract the related climatic benefits or challenges.

4.2 Data and methods

4.2.1 Study sites and data

In this study, the three corn study sites from the Carbon Sequestration Program (http://csp.unl.edu/Public/sites.htm, accessed 4 March, 2016) are chosen for the analysis. They are located at the University of Nebraska Agricultural Research and Development Center near Mead, NE, and are within 1.6 km of each other. Site 1 (41.1651° N, 96.4766° W, with an elevation of 361 m) has continuous corn, irrigated with a center-pivot irrigation system. Site 2 (41.1649° N, 96.4701° W, with an elevation of 362 m) has corn-

soybean rotation, and corn is also irrigated with a center-pivot irrigation system. Site 3 (41.1797° N, 96.4396° W, with an elevation of 362 m) has a corn-soybean rotation but with no irrigation applied; in other words, corn is rainfed at this site. The three study sites have the same soils; they are deep silty clay loams consisting of four soil series of Yutan, Tomek, Filbert, and Filmore. Prior to initiation of the Carbon Sequestration Program in 2001, all three study sites were uniformly tilled by disking to homogenize the top 10 cm of soil and incorporate fertilizers (e.g., phosphorus and potassium) and previously accumulated surface residues. Since then, all three study sites have been under a no-till management practice. At each site, crop management practices (e.g., plant populations, herbicide and pesticide applications, irrigation, etc.) have been employed in accordance with standard best management practices prescribed for production-scale corn systems. For example, corn plant densities were lower at the rainfed Site 3 than at the irrigated Sites 1 and 2 to account for differences in water-limited attainable yield. Nitrogen fertilizer was applied as urea ammonium nitrate solution for the three study sites in corn years. At the irrigated Sites 1 and 2, nitrogen fertilizer was applied in three applications to improve the use efficiency, including two thirds of the total amount before planting and the remaining one third in two fertigations through the sprinkler system during the growth period. By contrast, at the rainfed Site 3, only a single nitrogen fertilizer application was made before planting in corn years. Each spring before planting, soil samples were taken from each study site for residual nitrate measurement, and the total nitrogen fertilizer rate was adjusted based on the measured residual nitrate at each site following recommended guidelines.

This study uses corn phenology (i.e., planting, emergence, silking, maturity, and harvest dates) and grain yield (adjusted to 15.5% moisture content) data gathered during the Carbon Sequestration Program period at the three study sites. All of the years with complete data records are included in the analysis; there are a total of 10 study years (2003–2009 and 2011–2013) at Site 1, a total of 6 study years (2005, 2007, 2009, 2011–2013) at Site 2, and a total of 6 study years (2003, 2005, 2007, 2009, 2011, and 2013) at Site 3. During each study period, the required growing degree-days to physical maturity for the corn cultivar ranged from 2680 to 2930 °C·day at Site 1, from 2680 to 2910 °C·day at Site 2, and from 2680 to 2800 °C·day at Site 3. Meanwhile, corn planting dates ranged from April 20 to May 18 at Site 1, from April 21 to May 18 at Site 2, and from April 22 to May 13 at Site 3. Historical corn grain yields during the study period for the three study sites are shown in Table 4.1.

The in situ micrometeorological data for the three study sites during the study periods are compiled from the FLUXNET 2015 Dataset (http://fluxnet.fluxdata.org/data/fluxnet2015-dataset/, accessed 20 July 2016). In the FLUXNET 2015 Dataset, measurements are taken at a half-hourly interval, and data that are at larger timescales (e.g., hourly, daily) are derived from the half-hourly data. Micrometeorological variables at both hourly and daily timescales are obtained for this study, and more than 95% of them are from measurement records. Missing data are less than 5%, and FLUXNET 2015 provides them as the proposed optimal combinations of two products: gap filled variables with the method in Reichstein *et al*. (2005) and downscaled at site level variables from ETA-interim reanalysis data (Vuichard and Papale, 2015). The obtained hourly micrometeorological variables include air

temperature and vapor pressure deficit. Hourly air temperature data are used to compute daily maximum and minimum air temperatures, diurnal temperature range (calculated as daily maximum air temperature – daily minimum air temperature), as well as daily degree-days for corn based on the methods and cutoff temperature thresholds described in Chapter 3 – 3.2 Data and methods. Hourly vapor pressure deficit data are used to compute daily maximum and minimum vapor pressure deficits. The obtained daily micrometeorological variables include average air temperature, nighttime air temperature, nighttime air temperature standard deviation, daytime air temperature, daytime air temperature standard deviation, vapor pressure deficit, and precipitation. According to the FLUXNET technician, nighttime and daytime are differentiated based on the measured potential incoming shortwave radiation; when the radiation is measured at zero it is considered nighttime and when the radiation is measured at above zero it is considered daytime. In general, this is a highly representative dataset because it a) represents the micrometeorological environment of the study sites; b) contains fine-timescale measurements, for example, daily average air temperature is derived from half-hourly air temperature measurements rather than the arithmetic mean of observing daily maximum and minimum air temperatures; and c) contains some innovative variables that have rarely been tested in other past similar studies, for example, daily nighttime and daytime air temperatures as well as their standard deviations. Rather than using daily nighttime and daytime air temperatures, other similar studies typically use alternative variables such as daily minimum and maximum air temperatures. While the daily nighttime and daytime air temperatures used in this study are the means of half-hourly air temperatures during the nighttime and daytime of the same day, the daily minimum and

maximum air temperatures used in previous studies could be seen as the extremes of air temperatures during the nighttime and daytime of the same day. The daily nighttime and daytime air temperature standard deviations are measures of the variations of half-hourly air temperatures during the nighttime and daytime of the same day. If an identical mean air temperature was derived from differing air temperature combinations, it could result in a different crop performance (Bannayan *et al*., 2004). Therefore, it might be potentially meaningful to include the two variables of daily nighttime and daytime air temperature standard deviations in the climate-yield analysis for corn in this study. In addition, the variable of vapor pressure deficit is included in the analysis, and it was found to be a better crop drought predictor than the Palmer Drought Severity Index for corn in the Midwest (Lobell *et al*., 2014).

This study was conducted based on several assumptions: a) The corn-soybean rotation treatment at Sites 2 and 3 provides sufficient soil fertility for the corn plants, but this does not affect the climate-yield relationships; b) During the relatively short study periods, technological effects on the inter-annual variations in corn grain yield are minimal at the study sites, e.g., corn cultivar could be seen as genetically stable, and it is not necessary to de-trend corn grain yields; c) Crop management practices (e.g., planting date) have not shifted to an extent sufficient to affect the temporal distribution of weather effects on corn grain yield during the study periods (Changnon and Winstanley, 2000); and hence, d) Climate variability is the most important contribution to year-to-year variance in corn grain yield at the study sites (McQuigg, 1981). In this study, three timescales are adopted for the micrometeorological variables: pre-planting season, growing season, and special periods for corn. A total of 102 climate variables at a variety

of time frames are tested in the analysis, and they are computed based on the obtained and hourly-data-derived daily data (Table 4.2).

Table 4.1. Historical corn grain yields during the study period for the three study sites at Mead, NE (unit: Mg·ha^{-1}).

Year	Yield at Site 1	Yield at Site 2	Yield at Site 3
2003	12.12	--	7.72
2004	12.24	--	--
2005	12.02	13.24	9.10
2006	10.46	--	--
2007	12.80	13.21	10.23
2008	11.99	--	--
2009	13.35	14.18	12.00
2011	11.97	12.54	9.73
2012	13.02	13.10	--
2013	13.05	13.89	10.48

Table 4.2. Climate variables at different timescales that are chosen for the climate-corn grain yield relationship analysis at the three study sites (units for temperature, precipitation, VPD, and DD are °C, mm, hPa, and °C·day, respectively).

Timescale	Time frame	Description	Climate variable
Pre-planting season	PS0	the period from the day after harvest in the past year to the day before planting in the current year	total precipitation
	PS1	the 120-day period before planting	total precipitation
	PS2	the 90-day period before planting	total precipitation
	PS3	the 60-day period before planting	total precipitation
	PS4	the 30-day period before planting	total precipitation
	PS5	the 31-day period centered around planting	total precipitation
Growing season	GS	the entire growing season: from planting to maturity	total precipitation, mean temperature indices [a], mean VPD indices [b], DD indices [c]
	VE	vegetative stage: from emergence to the day before silking	total precipitation, mean temperature indices [a], mean VPD indices [b], DD indices [d]
	RE	reproductive stage: from silking to maturity	total precipitation, mean temperature indices [a], mean VPD indices [b], DD indices [e]
Special period	S1	the 31-day period centered around emergence	total precipitation, mean temperature indices [a], mean VPD indices [b]
	S2	the 31-day period centered around silking	total precipitation, mean temperature indices [a], mean VPD indices [b]
	S3	the 21-day period centered around silking	total precipitation, mean temperature indices [a], mean VPD indices [b]
	S4	the 11- day period centered around silking	total precipitation, mean temperature indices [a], mean VPD indices [b]

[a] mean temperature indices include average air temperature (TA), nighttime air temperature (NTA), nighttime air temperature standard deviation (NTASD), daytime air temperature (DTA), daytime air temperature standard deviation (DTASD), minimum air temperature (TA_{min}), maximum air temperature (TA_{max}), and diurnal temperature range (DTR).
[b] mean VPD indices include vapor pressure deficit (VPD), minimum vapor pressure deficit (VPD_{min}), and maximum vapor pressure deficit (VPD_{max}).
[c] DD indices during the entire growing season include $DD_{8,\ 29}$, $DD_{10,\ 30}$, $DD_{8,\ 34}$, DD_{29+}, DD_{30+}, DD_{34+}, DD_{35+}.
[d] DD indices during the vegetative stage include $DD_{8,\ 34}$.
[e] DD indices during the reproductive stage include $DD_{8,\ 34}$, $DD_{18,\ 22}$, DD_{34+}, and DD_{35+}.

4.2.2 Data processing

This study is focused on historical relationship analyses between temperature- and precipitation-related indices and corn grain yield at the three field sites near Mead, Nebraska. As already explained in the introduction, using statistical methods is better than using process-based crop models for this study. Typically, studies utilizing statistical methods to undertake climate-yield relationship analyses do not use field-level datasets and therefore produce coarse resolution results with high levels of uncertainty. However, that is not a problem for this study because field-level datasets are used in addition to statistical methods. Furthermore, although correlation found using statistical methods does not necessarily indicate causation, this study is supported by commonly known crop physiology and other similar previously-published studies.

First, the linear correlation coefficient (r) is computed between the yearly values of each climate variable and corn grain yield for the three study sites. If the correlation coefficient is statistically significant at $\alpha = 0.05$, the climate variable is considered as being important to corn grain yield production at the study site. The same statistical significance level has been used throughout the study, unless otherwise specified. When the linear correlation is weak, it might mean that there is a strong non-linear relationship between the climate variable and corn grain yield, but that is not part of the analysis for

this study. When the linear correlation is strong, it could be that the climate variable is closely related to another climate variable which is important to corn grain yield. In order to address this issue, the linear correlation coefficients are also computed between the yearly values of different climate variables that are considered to be important to corn grain yield computed at each study site. If a statistically significant correlation is detected between two climate variables that are both considered to be important to corn grain yield at the same study site, only the climate variable that has a closer correlation with corn grain yield is kept. This process would be repeated until one of the following situations occurs at each study site: either (1) only one of the climate variables remains or (2) more than one of the climate variables remain, but the remaining variables are not correlated with each other at a statistically significant level. The remaining climate variable(s) would be deemed as the most important climate variable(s) for corn grain yield at each study site.

Second, independent linear regression(s) is(are) run between the most important climate variable(s) and corn grain yield at each study site. The advantages of the regression approach have been addressed by Thompson (1969), and linear regression is used in this study because the results are consistent with corn physiology and are also comparable to the results of other similar studies. The study period is relatively short-term at the three study sites, and the number of degrees of freedom is small. Hence, a first order polynomial regression might be able to nicely represent the relationship between the most important climate variable and corn grain yield. However, climate variables, such as temperature and precipitation, often have a non-monotonic effect on crop yields (Lobell *et al*., 2007). In other words, increased temperature (precipitation) improves crop

yield in a cool (dry) climate but reduces crop yield in a hot (wet) climate. Therefore, both first and second order polynomial regressions are run between the yearly values of the most important climate variable(s) and corn grain yield at each study site. The adjusted coefficient of determination (R^2_{adj}) is used to assess the goodness of fit for the two types of regression, and the one with higher R^2_{adj} is chosen to represent the independent climate-yield relationship. For the independent regression, yearly value of climate variable is the predictor, normalized by mean and standard deviation, and yearly value of corn grain yield is the criterion variable. In order to minimize the influence of outliers (i.e., extreme values of climate variables), robust least-squares regression with the bisquare weights method in MATLAB is used in the analysis. Unlike the usual least-squares approach, the bisquare weights method minimizes a weighted sum of squares, where the weight given to each data point depends on how far the point is from the fitted line: points near the line get full weight, points farther from the line get reduced weight, and points that are farther from the line than would be expected by random chance get zero weight (http://www.mathworks.com/help/curvefit/least-squares-fitting.html#bq_5kr9-4, accessed 6 September 2016).

Third, if more than one of the climate variables are deemed as the most important for corn grain yield at the study site, a multiple polynomial regression is performed. In general, two problems may arise during a multiple regression: overfitting (caused by adding too many independent variables, which accounts for more variance but adds nothing to the model) and multicollinearity (happens when some or all of the independent variables are correlated with each other). In order to avoid overfitting, no more than two predictors are chosen in the multiple regression. According to the first step mentioned

above, multicollinearity has been minimized because the climate variables that are deemed as the most important to corn grain yield at each site are not statistically significantly correlated with each other. In a multiple polynomial regression, the most important climate variables are predictors, normalized by mean and standard deviation, and corn grain yield is the criterion variable. The robust least-squares regression with the bisquare weights method in MATLAB is used. When the sample size is allowed (i.e., the number of degrees of freedom is large enough), polynomial degrees of the predictors are set as 1 or 2 until the regression reaches the highest R^2_{adj}. And R^2_{adj} from the optimal multiple regression is used to quantify the composite effect of the most important climate variables on corn grain yield.

In addition, Sites 1 and 2 have year 2012 as part of the study period, which was a historic hot and dry year at the study area. In order to test the sensitivity of these climatic effects on corn grain yield to this extreme year, the above three steps are repeated at Sites 1 and 2 when year 2012 is excluded. This analysis is not applicable to Site 3 because year 2012 was not a corn year. The statistics for the independent regression between the most important climate variables and corn grain yield are presented in Table 4.3, including both during the entire study period and when year 2012 is excluded from the study period for Sites 1 and 2, and during the entire study period for Site 3.

4.3 Results and discussion

4.3.1 Irrigated continuous corn site

At the irrigated continuous corn site near Mead, NE (Site 1), no statistically significant positive correlations are detected between the 102 study climate variables and

corn grain yield. In contrast, a total of 5 and 8 of the climate variables show statistically significant negative correlations with corn grain yield during the entire study period and when year 2012 is excluded, respectively (Table 4.3). Three metrics of extreme degree-days, including DD_{34+} and DD_{35+} during the entire growing season as well as DD_{35+} during the reproductive stage, are found to be negatively correlated with corn grain yield at a statistically significant level, with or without year 2012 included. During the entire study period, the strongest statistically significant negative correlation occurs between DD_{35+} during the entire growing season and corn grain yield. When year 2012 is excluded from the study period, the strongest statistically significant negative correlation occurs between DD_{35+} during the reproductive stage and corn grain yield. During the entire study period, total precipitation during the 11-day period centered around silking shows a statistically significant negative correlation with corn grain yield at the irrigated continuous corn site. When the extreme hot and dry year 2012 is excluded, this negative correlation is no longer statistically significant. This might be explained by the fact that more irrigation was applied for corn plants in 2012, so although total precipitation during the 11-day period centered around silking was low, the extra irrigation could have made up for the corn grain yield loss that might have resulted from crop drought in the absence of irrigation. In addition, maximum air temperature during the 31-day period centered around silking shows a statistically significant negative correlation with corn grain yield when year 2012 is excluded from the study period. But the statistical significance for this negative correlation does not hold true when year 2012 is included in the study period. This could imply that heavier than usual irrigation applications during the 31-day period centered around silking in 2012 masks the negative effect of maximum air temperature

on corn grain yield. Mahmood *et al*. (2013) has reported the significant cooling effect of agricultural irrigation on growing season temperatures over the High Plains aquifer region of the Great Plains. In this study, the results confirmed this cooling effect on maximum air temperature during the 31-day period centered around silking time. However, this cooling effect has not been strong enough to offset the negative effects of extreme degree-days above 35 °C during the growing season on corn grain yield at the irrigated continuous corn site.

During the entire study period, DD_{35+} during the entire growing season and total precipitation during the 11-day period centered around silking time are found to be the two most important climate variables for corn grain yield at the irrigated continuous corn site. With a first order polynomial regression, 46% and 33% of the variance in corn grain yield could be explained by the variation in DD_{35+} during the entire growing season and total precipitation during the 11-day period centered around silking time, respectively. In a multiple regression model, 61% of the variance in corn grain yield could be explained by the variation of these two climate variables (Figure 4.1(a)). When year 2012 is excluded from the study period, DD_{35+} during the reproductive stage and maximum air temperature during the 31-day period centered around silking are deemed as the two most important climate variables at the irrigated continuous corn site. With a first order polynomial regression, 56% and 37% of the variance in corn grain yield could be explained by the variation in DD_{35+} during the reproductive stage and maximum air temperature during the 31-day period centered around silking, respectively. In a multiple regression model, 62% of the variance in corn grain yield could be explained by the variation of these two climate variables (Figure 4.1(b)).

Table 4.3. Linear correlation coefficients (r) between climate variables and corn grain yield that are statistically significant for the three study sites. At Site 1, the number of degrees of freedom is 8 during the entire study period and 7 when year 2012 is excluded from the study period; at Site 2, the number of degrees of freedom is 4 during the entire study period and 3 when year 2012 is excluded from the study period; at Site 3, the number of degrees of freedom is 4 during the entire study period. Climate variable that are deemed the most important for corn grain yield at the study sites are set in bold.

Timescale	Site 1 Study period Variable	r	Site 1 Exclude 2012 Variable	r	Site 2 Study period Variable	r	Site 2 Exclude 2012 Variable	r	Site 3 Study period Variable	r
Pre-planting season							**PS0P**	-0.90	**PS4P**	-0.85
Growing season	$GSDD_{34+}$	-0.67	$GSDD_{34+}$	-0.80	$VETA_{max}$	-0.84	VETA	-0.89	$GSVPD_{max}$	-0.85
	$\mathbf{GSDD_{35+}}$	-0.76	$GSDD_{35+}$	-0.82			**VEDTA**	-0.93	$\mathbf{REVPD_{max}}$	-0.86
	$VETA_{max}$	-0.65	$VEVPD_{max}$	-0.70			$VETA_{max}$	-0.89		
	$REDD_{35+}$	-0.74	$REDD_{34+}$	-0.79						
			$\mathbf{REDD_{35+}}$	-0.83						
Special period	**S4P**	-0.67	S1VPD	-0.72	S2TA	-0.91	S2TA	-0.91		
			$S1VPD_{max}$	-0.67	S2NTA	-0.87	S2DTA	-0.93		
			$\mathbf{S2TA_{max}}$	-0.68	**S2DTA**	-0.93	$S2TA_{max}$	-0.92		
					$S2TA_{min}$	-0.87				
					$S2TA_{max}$	-0.92				
					S3DTA	-0.83				
					$S3TA_{max}$	-0.83				
					$S4TA_{max}$	-0.83				

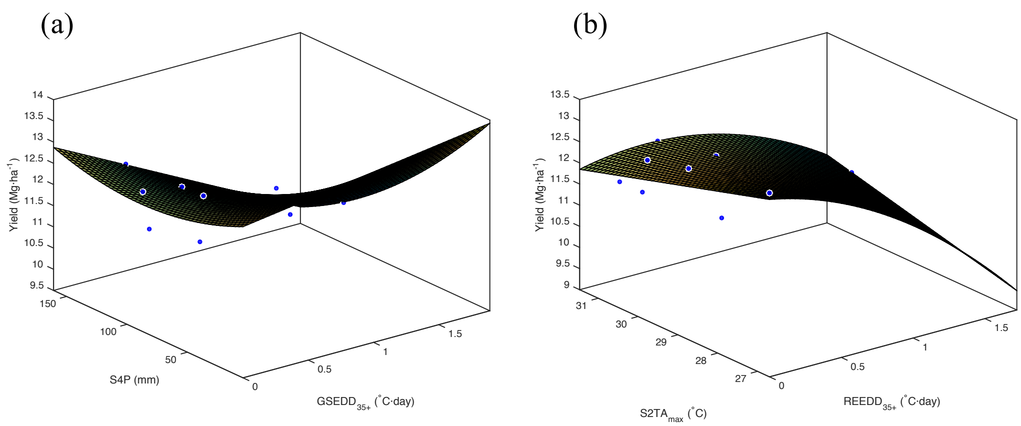

Figure 4.1. Multiple regression between the most important climate variables and corn grain yield at the irrigated continuous corn site. (a) Yield vs. $GSDD_{35+}$ and S4P during the entire study period. (b) Yield vs. $REDD_{35+}$ and $S2TA_{max}$ when year 2012 is excluded from the study period.

4.3.2 Irrigated corn-soybean rotation site

At the irrigated corn-soybean rotation site near Mead, NE (Site 2), a total of 19 and 26 of the climate variables are found to have positive correlations with corn grain yield during the entire study period and when year 2012 is excluded, respectively. The strongest positive correlation occurs between nighttime air temperature standard

deviation during the 21-day period centered around silking and corn grain yield, whether or not year 2012 is included, but it is not statistically significant. Four metrics of temperature indices show statistically significant negative correlations with corn grain yield whether the extreme year 2012 is included or not. They are average, daytime, and maximum air temperatures during the 31-day period centered around silking, and maximum air temperature during the vegetative stage. During the entire study period, a total of 9 of the climate variables show statistically significant negative correlations with corn grain yield; the strongest correlation occurs with daytime air temperature during the 31-day period centered around silking. When the extreme year 2012 is excluded, a total of 7 of the climate variables show statistically significant negative correlations with corn grain yield; the strongest correlation occurs with daytime air temperature during the vegetative stage (Table 4.3). Maximum air temperatures during the 21-day period and 11-day period centered around silking show negative correlations with corn grain yield at the corn-soybean rotation site, but these negative correlations are only statistically significant when year 2012 is included in the study period. This indicates that even with irrigation applications in accordance with standard best management practices during the extreme hot year 2012, corn plants are still susceptible to high maximum air temperatures around silking time (e.g., during the 21-day, and 11-day periods centered around silking) at the corn-soybean rotation site. Total precipitation during the period spanning from the day after harvest in the past year to the day before planting in the current year shows a negative correlation with corn grain yield, but this negative correlation is only statistically significant when year 2012 is excluded from the study period. None of the VPD indices shows statistically significant correlation with corn grain yield, whether or

not year 2012 is included in the study period. This might be because of the irrigation applications, and also the study period has a relatively short length.

After considering the inherent correlations among these temperature indices that are statistically significantly correlated with corn grain yield, the most important climate variables for corn grain yield at the irrigated corn-soybean rotation site are identified as: daytime air temperature during the 31-day period centered around silking during the entire study period; daytime air temperature during the vegetative stage and total precipitation during the period spanning from the day after harvest in the past year to the day before planting in the current year when year 2012 is excluded from the study period. Neild *et al*. (1987) found that corn grain yields are above normal when the preseason season precipitation (1 September–15 May) is above average during a 58-year period of 1925–1983 in eastern Nebraska. In this study, because irrigation is involved at Site 2, a negative correlation is detected between total precipitation from the day after harvest in the past year to the day before planting in the current year with corn grain yield. During the entire study period, in a second polynomial regression, the variation in daytime air temperature during the 31-day period centered around silking explains 88% of the variance in corn grain yield (Figure 4.2(a)). When year 2012 is excluded, in a second polynomial regression, the variation in total precipitation from the day after harvest in the past year to the day before planting in the current year explains 90% of the variance in corn grain yield (Figure 4.2(b)). Due to the short length of the study period at Site 2, the sample size is not large enough to perform a second order multiple regression. Therefore, the composite climatic effect of the two most important climate variables on corn grain yield is not quantified for when year 2012 is excluded from the study period.

(a) (b)

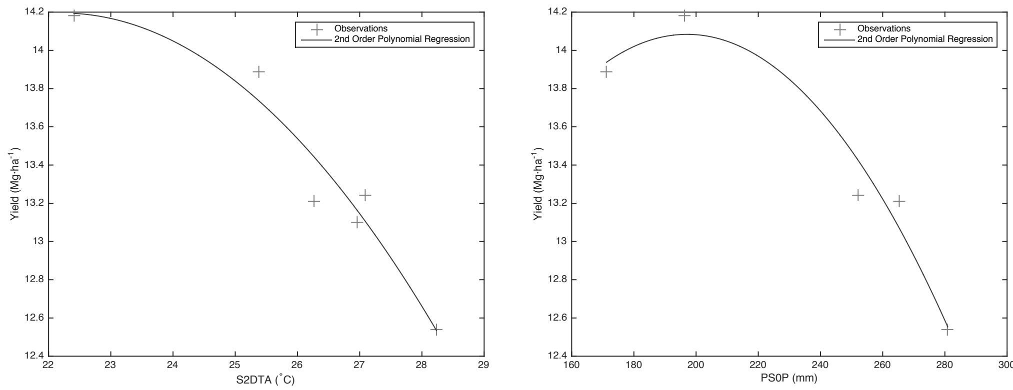

Figure 4.2. Independent regression between climate variable and corn grain yield at the irrigated corn-soybean rotation site. (a) Yield vs. S2DTA during the entire study period. (b) Yield vs. PS0P when year 2012 is excluded from the study period.

4.3.3 Rainfed corn-soybean rotation site

At the rainfed corn-soybean rotation site, a total of 26 climate variables show positive correlations with corn grain yield during the study period; the strongest correlation occurs with total precipitation during the 11-day period centered around silking. However, none of the positive correlations is statistically significant, probably due to the limited size of study sample. A previous study pointed out that rainfall timing greatly influences corn grain yield in the U.S. Corn Belt, especially for the 3-week period centered around tasseling (Neild and Newman, 1990). In this study, the results show that total precipitation during the 11-day period centered around silking has a stronger positive correlation with corn grain yield than total precipitation during the 21-day period centered around silking at the rainfed corn-soybean rotation site. This positive correlation agrees with corn physiology that corn plants are more sensitive to water availability around silking time when irrigation is not applied.

Three metrics of climate variables show statistically significant negative correlations with corn grain yield during the study period, which are as follows: maximum VPD

during the reproductive stage, maximum VPD during the entire growing season, and total precipitation during the 30-day period before planting. The strongest negative correlation occurs with maximum VPD during the reproductive stage. The most likely reason that maximum VPD during the entire growing season shows a statistically significant correlation with corn grain yield is that it is closely related to maximum VPD during the reproductive stage. In a first order polynomial regression, the variation in maximum VPD during the reproductive stage explains 87% of the variance in corn grain yield during the study period (Figure 4.3(a)). When VPD increases, stomatal closure occurs (Bell, 1982; Ball *et a*l., 1987; Bunce, 1996; Campbell and Norman, 1998; Buckley *et al*., 2003; Wang *et al*., 2009), as a result, photosynthesis is reduced. Total precipitation during the 30-day period before planting does not have a statistically significant correlation with maximum VPD during the reproductive stage, therefore, it is considered as another most important climate variable to corn grain yield at the rainfed corn-soybean rotation site. In a first order regression, the variation in total precipitation during the 30-day period before planting explains 57% of the variance in corn grain yield during the study period (Figure 4.3(b)). This negative correlation could be explained by the soil type at the study site, which has the advantages of holding soil moisture when precipitation takes place. When precipitation is ample during the 30-day period before planting, the corn plants have access to water resources in the shallow layer of soil and fail to root deep, which makes it more difficult to absorb water that is deeper in the soil layer during the later water-sensitive stage. In a first order multiple regression, the variation in the two most important climate variables explains 73% of the variance in corn grain yield during the study period.

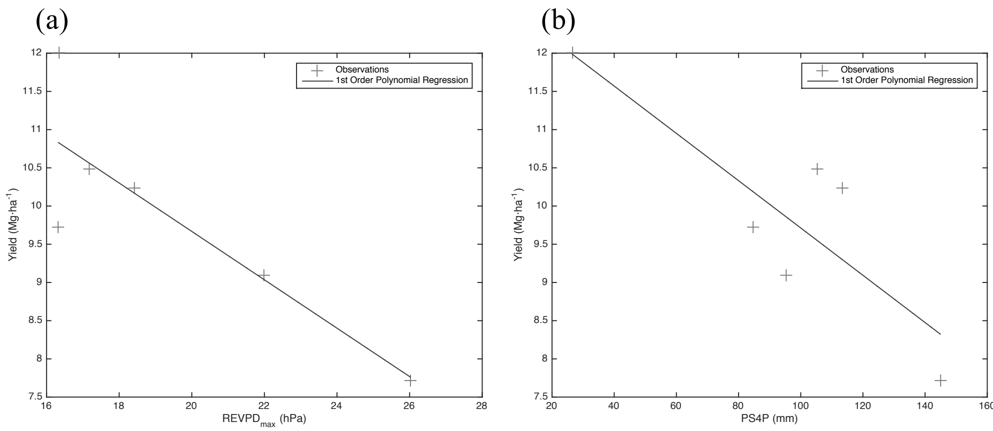

Figure 4.3. Independent regression between climate variable and corn grain yield at the rainfed corn-soybean rotation site. (a) Yield vs. $REVPD_{max}$ during the entire study period. (b) Yield vs. PS4P during the entire study period.

4.4 Conclusions

This study results show both similarities and differences in the historical effects of temperature and precipitation on corn grain yield at the three study sites. The similarity is that none of the climate variables shows a statistically significant positive correlation with corn grain yield at any of the three study sites. At the irrigated continuous corn site, the strongest positive correlation occurs between minimum VPD during the 21-day period centered around silking and corn grain yield during the entire study period. At the irrigated corn-soybean rotation site, the strongest positive correlation occurs between nighttime air temperature standard deviation during the 21-day period centered around silking and corn grain yield when year 2012 is excluded from the study period. At the rainfed corn-soybean rotation site, the strongest positive correlation occurs between total precipitation during the 11-day period centered around silking and corn grain yield during the entire study period. One possible reason for the lack of statistical significance in these positive correlations is that the study period is relatively short-term. At the two irrigated Sites 1 and 2, maximum air temperature during the vegetative stage shows a statistically

significant negative correlation with corn grain yield when year 2012 is included in the study period. This could be explained by the fact that: irrigation application is more focused in the reproductive stage than in the vegetative stage at the two study sites, therefore, the cooling effect of agricultural irrigation on growing season temperatures is weaker in the vegetative stage than in the reproductive stage. Besides the maximum air temperature during the vegetative stage, other temperature variables that show statistically significant negative correlations with corn grain yield are during: growing season time frames (i.e., during the entire growing season, during the reproductive stage) at the irrigated continuous corn site; and specific time frames (i.e., during the 31-day, 21-day, and 11-day periods centered around silking) at the irrigated corn-soybean rotation site.

The biggest difference between the irrigated and rainfed sites is that: temperature indices play a more important role at the irrigated sites while VPD indices play a more important role at the rainfed site. The climate variable which shows the strongest negative correlation with corn grain yield during the study period is: DD_{35+} during the entire growing season at the irrigated continuous corn site (explains 46% of the variance in corn grain yield), daytime air temperature during the 31-day period centered around silking at the irrigated corn-soybean rotation site (explains 88% of the variance in corn grain yield), and maximum VPD during the reproductive stage at the rainfed corn-soybean rotation site (explains 87% of the variance in corn grain yield). When year 2012 is excluded from the study period, the climate variable that shows the strongest negative correlation with corn grain yield is: DD_{35+} during the reproductive stage at the irrigated continuous corn site (explains 56% of the variance in corn grain yield), and daytime air temperature

during the vegetative stage at the irrigated corn-soybean rotation site (explains 83% of the variance in corn grain yield). Interestingly, there is a difference in correlation of DTR and corn grain yield at continuous and rotated corn sites: DTR shows a uniformly negative correlation with corn grain yield at the irrigated continuous corn site, but mixed correlations with corn grain yield at the two irrigated and rainfed corn-soybean rotation sites. Though the magnitude of correlation coefficient between DTR and corn grain yield is greater than that between average air temperature and corn grain yield in some cases, no statistically significant correlations are found between DTR and corn grain yield. This agrees with the findings from Lobell (2007) that historical effects of DTR on US corn yields for 1961–2002 were not statistically significant.

Though the study period is relatively short for the statistical analysis at the three study sites, the results provide some innovative meaningful information for the climate-corn grain yield relationship studies. The new climate variables that show statistically significant correlation with corn grain yield in this study but have not been reported in other previous climate-yield studies include: daytime air temperature, nighttime air temperature, and maximum VPD. The new time frames that are found to be critical for corn grain yield in this study but are rarely reported in other similar studies are: from the day after harvest in the past year to the day before planting in the current year, the 30-day period before planting, the 31-day period centered around silking, and the 11-day period centered around silking.

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References

Almaraz JJ, Mabood F, Zhou X, Gregorich EG, Smith DL. 2008. Climate change, weather variability and corn yield at a higher latitude locale: Southwestern Quebec. *Clim. Chang.* **88**: 187–197.

Badu-Apraku B, Hunter RB, Tollenaar M. 1983. Effect of temperature during grain filling on whole plant and grain yield in maize (*Zea mays* L.). *Can. J. Plant Sci.* **63**: 357–363.

Ball JT, Woodrow IE, Berry JA. 1987. A model predicting stomatal conductance and its contribution to the control of photosynthesis under different environmental conditions.

In *Progress in photosynthesis research*, Biggins J (ed.). Nijhoff Publishing, Dordrecht, 221–224.

Bannayan M, Hoogenboom G, Crout NMJ. 2004. Photothermal impact on maize performance: a simulation approach. *Ecol. Model.* **180**: 277–290.

Bell CJA. 1982. Model of stomatal control. *Photosynthetica* **16**: 486–495.

Buckley TN, Mott KA, Farquhar GD. 2003. A hydromechanical and biochemical model of stomatal conductance. *Plant Cell Environ* **26**: 1767–1785.

Bunce JA. 1996. Does transpiration control stomatal responses to water vapour pressure deficit? *Plant Cell Environ* **19**: 131–135.

Brown WL, Darrah LL. 1985. Origin, adaptation, and types of corn. *National Corn Handbook* **10**: 1–6.

Cabas J, Weersink A, Olale E. 2010. Crop yield response to economic, site and climatic variables. *Clim. Chang.* **101**: 599–616.

Campbell GS, Norman JM. 1998. An introduction to environmental biophysics. 2nd Edition. Springer-Verlag, New York, 305.

Changnon SA, Winstanley D. 2000. Long-term variations in seasonal weather conditions important to corn production in Illinois. *Clim. Chang.* **47**: 353–372.

Cheikh N, Jones RJ. 1994. Disruption of maize kernel growth and development by heat stress. *Plant Physiol*. **106**: 45–51.

Chen C, Lei C, Deng A, Qian C, Hoogmed W, Zhang W. 2011. Will higher minimum temperatures increase corn production in Northeast China? An analysis of historical data over 1965-2008. *Agric. For. Meteorol.* **151**: 1580–1588.

Garcia P, Offutt SE, Pinar M, Changnon SA. 1987. Corn yield behavior: Effects of technological advance and weather conditions. *J. Clim. Appl. Meteorol.* **26**: 1092–1102.

Grassini P, Yang H, Cassman KG. 2009. Limits to maize productivity in the Western Corn-Belt: A simulation analysis for fully irrigated and rainfed conditions. *Agric. For. Meteorol.* **149**: 1254–1265.

Hansen JW, Jones JW. 2000. Scaling-up crop models for climate variability applications. *Agric. Syst.* **65**: 43–72.

Herrero MP, Johnson RR. 1980. High temperature stress and pollen viability of maize. *Crop Sci.* **20**: 796–800.

Hollinger SE, Hoeft RG. 1986. Influence of weather on year-to-year yield response of corn to ammonia fertilization. *Agron. J.* **78**: 818–823.

Klink K, Wiersma JJ, Crawford CJ, Stuthman DD. 2014. Impacts of temperature and precipitation variability in the Northern Plains of the United States and Canada on the productivity of spring barley and oat. *Int. J. Climatol*. **34**: 2805–2818.

Kucharik CJ. 2006. A multidecadal trend of earlier corn planting in the central USA. *Agron. J.* **98**: 1544–1550.

Lobell DB. 2007. Changes in diurnal temperature range and national cereal yields. *Agric. For. Meteorol.* **145**: 229–238.

Lobell DB, Asner GP. 2003. Climate and management contributions to recent trends in U.S. agricultural yields. *Science* **299**: 1032.

Lobell DB, Bänziger M, Magorokosho C, Vivek B. 2011a. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nat. Clim. Chang.* **1**: 42–45.

Lobell DB, Burke MB. 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environ. Res. Lett.* **3**: 1–8.

Lobell DB, Burke MB. 2010. On the use of statistical models to predict crop yield responses to climate change. *Agric. For. Meteorol.* **150**: 1443–1452.

Lobell DB, Cahill KN, Field CB. 2007. Historical effects of temperature and precipitation on California crop yields. *Clim. Chang.* **81**: 187–203.

Lobell DB, Field CB. 2007. Global scale climate-crop yield relationships and the impacts of recent warming. *Environ. Res. Lett.* **2**: 1–7.

Lobell DB, Field CB, Cahill KN, Bonfils C. 2006. Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. *Agric. For. Meteorol.* **141**: 208–218.

Lobell DB, Roberts MJ, Schlenker W, Braun N, Little BB, Rejesus RM, Hammer GL. 2014. Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. *Science* **344**: 516–519.

Lobell DB, Schlenker W, Costa-Robberts J. 2011b. Climate trends and global crop production since 1980. *Science* **333**: 616–620.

Mahmood R, Keeling T, Foster SA, Hubbard KG. 2013. Did irrigation impact 20th century air temperature in the High Plains aquifer region? *Appl. Geogr.* **38**: 11–21.

McQuigg JD. 1981. Climate variability and crop yield in high and low temperate regions. In: *Food-Climate Interactions*, Bach W, Pankrath J, Schneider SH (eds.). 121–137.

Mishra V, Cherkauer KA. 2010. Retrospective droughts in the crop growing season: Implications to corn and soybean yield in the Midwestern United States. *Agric. For. Meteorol.* **150**: 1030–1045.

Muchow RC, Sinclair TR, Bennett JM. 1990. Temperature and solar-radiation effects on potential maize yield across locations. *Agron. J.* **82**: 338–343.

Neild RE, Newman JE. 1990. Growing season characteristics and requirements in the Corn Belt. *National Corn Handbook* **40**: 1–11.

Neild RE, Wilhite DA, Hubbard KG. 1987: Preseason precipitation probabilities as an aid to corn planting decisions. *Agric. For. Meteorol.* **41**: 259–266.

National Oceanic and Atmospheric Administration (NOAA). 2011. *9th Annual Climate Prediction Applications Science Workshop Report*. Des Moines, Iowa, 1–31.

Prasad PVV, Staggenborg SA, Ristic A. 2008. Chapter 11, Impacts of drought and/or heat stress on physiological, developmental, growth, and yield processes of crop plants. In: *Response of crops to limited water: Understanding and modeling water*

stress effects on plant growth processes, Ahuja LR, Reddy VR, Saseendran SA, Yu Q (eds.). ASA, CSSA, SSSA: USA, 301–355.

Reichstein M, Falge E, Baldocchi D, Papale D, Aubinet M, Berbigier P, Bernhofer C, Buchmann N, Gilmanov T, Granier A, Grünwald T, Havránková K, Ilvesniemi H, Janous D, Knohl A, Laurila T, Lohila A, Loustau D, Matteucci G, Meyers T, Miglietta F, Ourcival J, Pumpanen J, Rambal S, Rotenberg E, Sanz M, Tenhunen J, Seufert G, Vaccari F, Vesala T, Yakir D, Valentini R. 2005. On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm. *Glob. Chang. Biol.* **11**: 1–16.

Rosenzweig C. 1993. Modeling crop responses to environmental change. In: *Vegetation Dynamics and Global Change*, Solomon AM, Shugart HH (eds.). Chapman & Hall, 306–321.

Rowhani P, Lobell DB, Linderman M, Ramankutty N. 2011. Climate variability and crop production in Tanzania. *Agric. For. Meteorol.* **151**: 449–460.

Runge ECA. 1968. Effect of rainfall and temperature interactions during the growing season on corn yield. *Agron. J.* **60**: 503–507.

Sacks WJ, Kucharik CJ. 2011. Crop management and penology trends in the U.S. Corn Belt: Impacts on yields, evapotranspiration and energy balance. *Agric. For. Meteorol.* **151**: 882–894.

Schlenker W, Roberts MJ. 2009. Nonlinear temperature effects indicate severe damages to U. S. crop yields under climate change. *Proc. Natl. Acad. Sci. U.S.A.* **106**: 15594–15598.

Singletary GW, Banisadr R, Keeling PL. 1994. Heat stress during grain filling in maize: effects on carbohydrate storage and metabolism. *Aust. J. Plant. Physiol*. **21**: 829–841.

Smika DE. 1992. Cereal systems of the Northern American Central Great Plains. In: *Field Crop Ecosystem*, Pearson CJ (ed.). Elsevier, Amsterdam, 401–406.

Tao F, Yokozawa M, Xu Y, Hayashi Y, Zhang Z. 2006. Climate changes and trends in phenology and yields of field crops in China, 1981-2000. *Agric. For. Meteorol.* **138**: 82–92.

Thompson LM. 1969. Weather and technology in the production of corn in the U.S. Corn Belt. *Agron. J.* **61**: 453–456.

Vuichard N, Papale D. 2015. Filling the gaps in meteorological continuous data measured at FLUXNET sites with ERA-Interim reanalysis. *Earth Syst. Sci. Data* **7**: 157–171.

Wang S, Yang Y, Trishchenko PA, Barr A, Black TA, McCaughey H. 2009. Modeling the response of canopy stomatal conductance to humidity. *J. Hydrometeorol.* **10**: 521–532.

CHAPTER 5: SUMMARY

This study aims to interpret temperature- and precipitation-related scientific information from 1980 onward for the agricultural community in the U.S. Corn Belt. By using high quality and representative datasets together with scientifically proven methods, this study delivers some innovative results as follows:

(1) From 1980 to 2013, there is an extensive warming tendency during the growing season for corn across the Midwest United States. This warming tendency is largely reflected in the increase in minimum temperature in early growing season (especially in June) and the increase in maximum temperature in late growing season (especially in September). In the early growing season, statistically significant warming in minimum temperature is found in Missouri, Illinois, Indiana, and Ohio. In the late growing season, statistically significant warming in maximum temperature is found in Minnesota, Wisconsin, and Michigan. In the past three decades, total precipitation has increased during the growing season for corn at the majority of the study locations in the Midwest United States, but few of these wetting trends are statistically significant. It becomes more complicated as this overall wetting trend is driven by increasing precipitation in early growing season, while precipitation is decreasing in the late growing season. This raises some potential for concern about a climatic tendency towards extreme weather events such as flood in the early growing season and drought in the late growing season, particularly in 8 of the 12 studied Midwestern states: Illinois, Iowa, Michigan, Minnesota, Missouri, Nebraska, North Dakota, and

Wisconsin. In the north-central part of the study region covering Minnesota, Wisconsin, and Iowa, climate has become significantly warmer and drier in the late growing season, which could potentially hurt the local corn production with simultaneous heat stress and rainfall deficit. The take-away messages are as following:

- In the Midwest, the growing season for corn is becoming significantly warmer, especially the nights in early season and the days in late season.
- The growing season for corn is becoming not-significantly wetter, with a wetter early season and a drier late season.

(2) Taking thermal time that is directly derived from hourly temperature as true, six commonly used methods to estimate thermal time for corn with daily temperature data have been evaluated at a total of 14 study locations in Nebraska. The single- and double-sine methods generally provide better estimations of thermal time for corn during the active growing season than the other four methods. However, these two methods are sensitive to the lower and upper thresholds; for example, when estimating $DD_{8,\ 34}$, the single- and double-sine methods are surpassed by the T_{avg}-based rectangle method. For thermal time that is defined as above upper threshold, the double-sine method is usually superior than the single-sine method until the upper threshold reaches a certain point (e.g., 34 °C). By contrast, the adjusted T_{max} and T_{min} rectangle method provides the poorest estimation of thermal time for corn, even though it has been the most widely used method in the study area. In particular, this method overestimates thermal time for corn that

is defined as between lower and upper thresholds in extreme cool years but underestimates them in extreme warm years; it is found to overestimate thermal time for corn that is defined as above upper threshold in both extreme cool and warm years, with a worsening overestimation tendency on a daily basis within the growing season. Therefore, this study does not recommend using the adjusted $T_{\max}$ and $T_{\min}$ rectangle method estimate total degree-days during the active growing season for corn. The take-away messages are as following:

- In Nebraska, when using daily temperature data to estimate thermal time during the growing season for corn, the adjusted $T_{\max}$ and $T_{\min}$ rectangle method is not recommended.
- Depending on the metric of degree-days, the better alternatives could be: T_{avg}-based rectangle method, single-sine, and double-sine methods.

(3) In the most recent decade, historical effects of temperature and precipitation on corn grain yield have been evaluated with statistical methods at three field sites near Mead, NE. During each study period, the strongest positive correlation occurs between (a) minimum VPD during the 21-day period centered around silking and corn grain yield at the irrigated continuous corn site; (b) nighttime air temperature standard deviation during the 21-day period centered around silking and corn grain yield when year 2012 is excluded at the irrigated corn-soybean rotation site; and (c) total precipitation during the 11-day period centered around silking and corn grain yield at the rainfed corn-soybean rotation site. However, none of these strong positive correlations between climatic indices and corn grain

yield is statistically significant, which could possibly be due to the relatively short length of study period. At the two irrigated sites, temperature plays a more important role than precipitation in each study period; in particular, maximum air temperature during the vegetative stage shows a statistically significant negative correlation with corn grain yield. At the irrigated continuous corn site, variation in DD_{35+} during the entire growing season explains 46% of the variance in corn grain yield during the study period; variation in DD_{35+} during the reproductive stage explains 56% of the variance in corn grain yield when year 2012 is excluded. At the irrigated corn-soybean rotation site, variation in daytime air temperature during the 31-day period centered around silking explains 88% of the variance in corn grain yield during the study period; variation in daytime air temperature during the vegetative stage explains 83% of the variance in corn grain yield when year 2012 is excluded. By contrast, VPD index plays a relatively more important role at the rainfed corn-soybean rotation site; in particular, variation in maximum VPD during the reproductive stage explains 87% of the variance in corn grain yield. The take-away messages are as following:

- At Mead, NE, temperature indices are critical for corn grain yield under irrigated conditions, for example, growing season degree-days above 35°C and daytime air temperature during the 31-day period centered around silking.

- Without irrigation, vapor pressure deficit is critical for corn grain yield, especially the maximum vapor pressure deficit during the reproductive stage for corn.

For the future studies, the first author would suggest to: (1) perform a similar study as in Chapter 2 on a finer timescale, e.g. weekly, or daily, when the homogenized dataset is available, quantifying the impacts of historical climate trends in the Midwest United States on cereal crop grain yields in order to offer scientific evidence for long-term adaptation strategies; (2) extend similar studies as in Chapter 3 to other corn-belt states, conducting extension workshops to educate agricultural advisors about the accuracy of different estimation methods for degree-days during the growing season for corn; (3) expand the study in Chapter 4 to more locations for longer study periods when the crop phenology and yield data as well as the in situ micrometeorological data become available, incorporating climatic variables that are critical to corn grain yield into short-term weather forecast for the agricultural community.