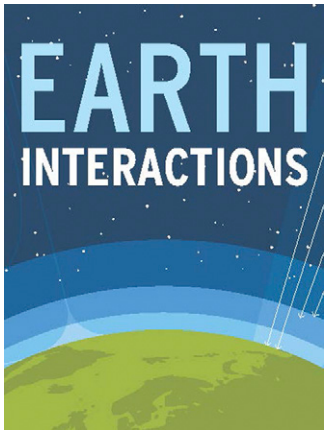


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Climate Variability and the U.S. Corn Belt: ENSO and AO Episode-Dependent Hydroclimatic Feedbacks to Corn Production at Regional and Local Scales*

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ABSTRACT: El Niño–Southern Oscillation (ENSO) and Arctic Oscillation (AO) climatology (1980–2010) is developed and analyzed across the U.S. Corn

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Belt using state climate division weather and historic corn yield data using analysis of variance (ANOVA) and correlation analysis. Findings provide insight to agroclimatic conditions under different ENSO and AO episodes and are analyzed with a perspective for potential impacts to agricultural production and planning, with findings being developed into a web-based tool for the U.S. Corn Belt.

This study is unique in that it utilizes the oceanic Niño index and explores two teleconnection patterns that influence weather across different spatiotemporal scales. It is found that the AO has a more frequent weak to moderate correlation to historic yields than ENSO when correlated by average subgrowing season index values. Yield anomaly and ENSO and AO episode analysis affirms the overall positive impact of El Niño events on yields compared to La Niña events, with neutral ENSO events in between as found in previous studies. Yields when binned by the AO episode present more uncertainty. While significant temperature and precipitation impacts from ENSO and AO are felt outside of the primary growing season, correlation between threshold variables of episode-specific temperature and precipitation and historic yields suggests that relationships between ENSO and AO and yield are present during specific months of the growing season, particularly August. Overall, spatial climatic variability resulting from ENSO and AO episodes contributes to yield potential at regional to subregional scales, making generalization of impacts difficult and highlighting a continued need for finescale resolution analysis of ENSO and AO signal impacts on corn production.

KEYWORDS: Arctic Oscillation; Interannual variability; Intraseasonal variability; Seasonal variability; Southern Oscillation; Agriculture

1. Introduction

Agricultural production in the United States contributes to 40% of the world's supply of corn [U.S. Department of Agriculture (USDA) 2013]. Crop yield potential for a given growing season is largely dependent on temperature and precipitation (Kellner and Niyogi 2014), stressing the importance of understanding climate variability and projected climate change impacts in order to continue successful agricultural production in the future (Rosenzweig 2001; Rosenzweig et al. 2013; Pielke 2013). Research efforts have led to a better understanding of crop production under climate variability and change through analysis using historic weather, climate, and crop data (e.g., Cadson et al. 1996; Hansen et al. 1998; Legler et al. 1999; Phillips et al. 1999; Niyogi et al. 2015). Efforts to disseminate this useful information in a usable manner have been implemented across the world [e.g., the Agricultural Model Intercomparison and Improvement Project (AgMIP); Rosenzweig et al. 2012], while others more specifically focus on production in a designated region, such as the Useful to Usable (U2U)[1] project for the North Central Region (i.e., U.S. Corn Belt) in the United States (Takle et al. 2014). The U2U project is composed of teams of researchers that focus specifically on developing improved weather and climate tools [such as this El Niño–Southern Oscillation (ENSO) and Atlantic Oscillation (AO) climatologies] to address producers' needs for more usable and useful weather and climate information to make more

[1] Useful to Usable: Transforming climate variability and change information for cereal crop producers. USDA–National Institute of Food and Agriculture (NIFA) Agriculture and Food Research Initiative Competitive Grant 2011–68002–30220 (www.AgClimate4U.org).

informed decisions (e.g., Crane et al. 2010; Meza et al. 2008). The efforts of the U2U research group aim to improve current and future growing season profitability and to help farmers mitigate and adapt to future climate variability and change.

Climate variability can be broadly described as the weather conditions a region experiences outside what is considered climatologically normal but that does not result in a systematic change to the climate system mean state. Initial evidence suggests climate variability more readily impacts agricultural production than climate change since agricultural production moves at a pace greater than climate change (Reilly 2002). Agricultural production practices last 6–12 months (depending on the crop) with climate variability following a similar time period of several weeks, years, or decades (depending on the climate index/teleconnection). Climate change is projected to occur over a much longer period of time. Examples of key drivers of climate variability (Goddard et al. 2001) include ENSO, AO, the North Atlantic Oscillation (NAO), and the Madden–Julian oscillation (MJO). Examples of climate change include the drying trends expected in the subtropics and the projected shifts in the intensity (heavier) and duration (over a shorter period of time) of rainfall events in the midlatitudes over the next 50–80 years that are expected to produce longer dry spells of weather in between rainfall events (Stocker et al. 2013).

This paper focuses specifically on the historic behavior of ENSO and AO in the United States Corn Belt for the years 1980–2010 and the impacts these teleconnections and their resulting climate variability have had on corn yield. ENSO and AO are chosen in that ENSO is a longer-range (months to years) teleconnection index with long-term predictability, and the AO is a short-term teleconnection (several weeks) with greater forecast uncertainty. These two time frames encompass exploring the impacts of growing season variability (ENSO) and subgrowing season variability (several weeks; AO). The working hypothesis of this study is that both growing season and subseason variability driven by ENSO and subgrowing season variability driven by AO impact corn yields through positive and negative relationships dependent on teleconnection and episode, and both temporal scales of teleconnections need to be considered in producer decision-making during the growing season. The initial impetus for the development of this climatology is the expressed need from producers (or other applied users) for more usable and useful weather and climate data analyses and decision support tools (DSTs) for a given growing region (i.e., ‘‘my county’’) (e.g., Arbuckle et al. 2013; Takle et al. 2014). This also builds off the investigation by Mase and Prokopy (2014) that discusses current producers’ understanding and viewpoints of weather and climate data in decision-making. This climatology reviews and highlights the applicability of weather and climate data to agricultural decision-making when an ENSO or AO outlook is issued.

While ENSO impacts to United States and global yields have been a topic of research for decades (e.g., Adams et al. 1999; Brunner 2002; Cadson et al. 1996; Hollinger et al. 2001; Legler et al. 1999; Mauget and Upchurch 1999; Rosenzweig 2001), several variations exist among these studies that result in a further need for ENSO analysis and impact on agricultural production. The need for further study is driven by the following reasons: 1) study domains of previous research have varied in scope (global, continental United States, north-central region, Great Plains, and Midwest) and are not local scale; 2) previous research has varied in temporal

methodology (e.g., yearly signal, growing season signal, and 3-month intervals of the growing season) and statistical analysis [e.g., regression, binning, quartile analysis, analysis of variance (ANOVA), and deviation inconsistency with random sampling] that can overwhelm producers unfamiliar with science and statistics; 3) published studies vary in ENSO classification such as using sea surface temperature (SST) anomalies, the Southern Oscillation (SO), the Southern Oscillation index (SOI), or the multivariate ENSO index (MEI) [this results in varying conclusions on teleconnection feedbacks and crops (e.g., Hollinger et al. 2001; Mauget and Upchurch 1999) causing confusion regarding the exact impact information to producers and crop advisors]; 4) past research uses historic weather and crop data of various spatial resolutions with a majority of the studies using state-level yield analysis and not yield at crop-reporting district-level, removing localized feedbacks; and 5) past research tends to focus on more than one crop such as corn and soybeans (e.g., Hollinger et al. 2001) or corn and winter wheat (e.g., Mauget and Upchurch 1999), instead of focusing on one crop specifically.

To alleviate the variations among prior studies as described, this study is developed to be comprehensive and simple for end users in the following ways: the study domain is chosen specifically to be of service to the primary corn production region in the United States (north-central region). The climatology herein will be developed into a map-based, visual online decision support tool for cereal producers in the region through the U2U project team so that the producers and crop advisers may apply the useful weather and climate information of this climatology into their decision-making process. This study is unique in that multiple temporal resolutions of the ENSO episode are investigated. These include the annual ENSO signal [event based on the oceanic Niño index (ONI) definition of consecutive 3-month running mean of SST in the Niño-3.4 region (5°N–5°S, 120°–170°W)], the growing season ENSO signal (April–October), a subgrowing season ENSO signal {first 3 months of production [April–June (AMJ)] and 3 months of summer important to yield potential [June–August (JJA)]}, and a monthly ENSO signal. This study also applies a more finescale spatial resolution of weather data by incorporating specific National Weather Service (NWS) Cooperative Observer Program (COOP) site locations and aggregated weather data at the climate division level to analyze with more finite historic crop data at the crop-reporting district level (instead of state level data like some past studies). The use of historic corn yields at the crop-reporting district level provides more localized feedback analysis. The analysis of corn production alone provides a detailed investigation of the mostly widely produced and utilized crop in the United States. Regarding the AO climatology and impacts to agriculture, it has yet to be adequately researched. Thus, the following climatology of the two separate teleconnections adds further analysis to ENSO/yield research and brings forth new findings of AO relationships to yield, suggesting it may have more influence on yield production than ENSO.

2. Data and methodology

2.1. Data

The data of this climatological analysis are collected from the Applied Climate Information System (ACIS) through the Midwest Regional Climate Center (MRCC)

cli-MATE user interface.[2] Climate division data for the north-central region [domain of the U2U research project: North Dakota (ND), South Dakota (SD), Nebraska (NE), Kansas (KS), Missouri (MO), Iowa (IA), Minnesota (MN), Wisconsin (WI), Illinois (IL), Indiana (IN), Michigan (MI), and Ohio (OH)] are collected and analyzed for the years 1980–2010. Observed weather data are used in an effort to maintain the true integrity of observed weather datasets, as reanalysis data are subjected to data algorithms for automated quality control processes and development of spatial homogeneity that by design may reduce the impact of meso- and microclimates resulting from local features shown to influence production (e.g., Kravchenko and Bullock 2000). Observed weather data are also used rather than gridded reanalysis because of producers mentioning having high confidence in observed weather data and a stronger connection to observed weather data.

While the time frame of 1980–2010 seems short for statistical analysis and raises the issue of uncertainty in results, 30 years of temperature and precipitation data have been deemed by the World Meteorological Organization (WMO) as a sufficient amount of time to capture longer climatic trends while simultaneously filtering out variability and anomalies (e.g., Trewin 2007; Wright 2012). This suggests that climate variability and anomalies can be detected across shorter time frames, as discussed in the results section. It is recognized that the process of categorizing years by ENSO or AO episode for analysis further reduces the number of years (n) in each group (a breakdown of categorization for each analysis is provided for each teleconnection in the supplemental materials); however, since variability is expressed as being detectable in the 31 years of data reviewed, it is felt that the sizes of the subgroups are sufficient to capture statistical significance. It is further noted that statistical significance and sample size are interlinked (Ellis and Steyn 2003). With a small n for subgroups of ENSO and AO, significance is kept high at a 90% CI. Furthermore, the number of climate divisions reviewed (106) and the number of climate divisions showing statistically significant relationships of temperature or precipitation by month because of an ENSO or AO episode agrees with previous findings spanning longer time frames (highlighted in the previous section), suggesting that 30 years is sufficient for variability detection from teleconnections. Loikith and Broccoli (2014) use a similar time frame to investigate modes of climate variability as well, finding significant results in the 30-yr dataset. In the context of agronomic processes, there is also a trade-off between the climatic time period and the agronomic crop yield that has technological influences. It is felt that because of this, the 30-yr time period provides a good compromise of time to include both the climatic time period and use of more recent technology.

Historic yield data are obtained for the same years from the USDA's National Agricultural Statistics Service by crop reporting the district level. The years 1980–2010 are selected for the following purposes: 1) the latest climatic normal period for comparison is 1981–2010, and 2) the time frame is mostly post–Green Revolution (e.g., Fuglie 2012; Pingali 2012), with gains in production attributable to increases in the total factor productivity allowing for easier detection of climate

[2] Data are from the DRD964x climate observations dataset as it was collected prior to the dataset (nClimDiv) currently available and in use in ACIS (NCDC 2014). The ACIS system is inclusive of in situ observations reported to federal, regional, state, and local weather networks and can be found online (at http://rcc-acis.unl.edu/index.php).

variability signals in crop production. Note that the crop yield data (reported in bushels per acre) showed significant autocorrelation [tested using the Durbin–Watson statistic (Montgomery et al. 2006)]. Therefore, the crop yields are detrended with a 1-yr lag linear regression analysis to account for autocorrelation in this time series dataset. The regression model used to detrend the crop yield data uses the 2010 predicted yield as the benchmark yield. This accounts for technological improvements in agriculture that have positively influenced yield and makes any weather or climate impacts on annual yields more apparent.

ENSO and AO data are obtained from the National Oceanic Atmospheric Administration (NOAA)'s Climate Prediction Center (CPC). ENSO data can be found online (at www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml) and AO data can also be found online (at www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/monthly.ao.index.b50.current.ascii.table). ONI is used for ENSO events, which are based on the 3-month running mean of SST in the Niño-3.4 region (5°N–5°S, 120°–170°W) centered on the 30-yr base periods that are now updated every 5 years. Since the time of data collection for this project, some months and years classified as El Niño, La Niña, or neutral have changed because of the efforts made to classify ENSO events on a moving 30-yr base period (Lindsey 2013). The data are the representative of historic ONI episodes when collected in 2011/12. Classification of months as El Niño, La Niña, or neutral episodes in this climatology are based on the 3-month running mean of SSTs as classified in the historic ONI data using values of 0.5 or greater and −0.5 or less as warm (El Niño) and cold (La Niña) thresholds, respectively, with neutral events ranging from −0.4 to 0.4. Events are not further classified by −0.5 and +0.5 deviations into weak, moderate, or strong events for ease of use when product users are exploring the climatological data through the online tool interface. The same classification scheme is applied to the AO. The Arctic Oscillation is monitored through the application of an empirical orthogonal function to monthly mean sea level (1000 hPa) north of 20°N and is characterized by the departure of atmospheric pressure from normal of one sign (positive or negative) in the Arctic to the departure of atmospheric pressure of one sign (positive or negative) centered over the midlatitudes (37°–45°). It is normalized through application of the standard deviation of the monthly index–based period from 1979 to 2000 (Climate Prediction Center 2005b). Seeing as the computational methodologies of ENSO and AO monthly values are departures from a base state and have been normalized through base-period centering (ENSO) and standard deviation of the monthly index from a base period (AO), the possibility of autocorrelation between consecutive months should be minimized and no further adjustments have been made to the dataset.

2.2. Methodology

2.2.1. ENSO and AO climatologies

To develop the ENSO and AO climatologies, the average monthly observed precipitation and monthly averaged observed mean temperature by climate division is collected for the Corn Belt using cli-MATE. Separation of months into ENSO and AO by episode (warm, cold, or neutral for ENSO and positive, negative, or neutral for AO) is completed manually based on historic data as classified through ONI.

The average value of monthly observed mean temperature or monthly observed precipitation by teleconnection and type of episode is determined to develop a general climatology of average observed monthly precipitation and monthly mean temperature by teleconnection episode classification. The data are analyzed using an ANOVA approach at a 90% confidence interval (CI). Because ENSO and AO are each grouped into three different types of episode classifications, a simple Student's *t* test cannot be completed, as the population of each group is no longer equal. ANOVA analyzes the means of the three groups, determining through analysis of each group's variance if the means of each group are equal or not. Simply stated, ANOVA is a generalization of the Student's *t* test to more than two groups (Devore 2003). Where ANOVA supports rejection of the null hypothesis (all means of the group are equal), the difference between the means among ENSO or AO episodes is large enough to suggest statistical significance between the different mean temperatures and observed precipitation experienced during different ENSO and AO episodes. During months where ANOVA findings are found to be significant, the variable with significance (temperature or precipitation) is suggested to be considered with more weight during agroclimatic decision-making. The average monthly mean temperature is investigated in this climatology instead of the average monthly maximum temperature and average monthly minimum temperature because growing degree-day (GDD) computation uses mean temperature in its formulation. While it is understood that mean temperature can fail to capture extreme maximum and minimum temperatures (e.g., Schlenker and Roberts 2009), keeping the climatology simple but still usable to agricultural decision-making is the main goal of this project. Furthermore, since ANOVA compares groups of data creating discontinuous samples, autocorrelation of temperature and precipitation data is typically not a factor.

2.2.2. ENSO and AO extremes climatologies

The monthly climatic summaries used for the analysis of extreme data (number of days per month where $T_{max} \geq 90°F$, $T_{max} \leq 32°F$, $T_{min} \leq 32°F$, Prcp ≥ 0.1 in., and Prcp ≥ 1.0 in.) are gathered from the National Climatic Data Center (NCDC) Image and Publication Center (IPC) Local Climatological Data (LCD) repository. All sites [specific locations, not crop-reporting district levels (CRDs)] within the U2U 12-state domain with available data for the years 1980–2010 are queried. Spatially, the 62 cities span the Corn Belt in a broadly uniform manner, and thus no spatial interpolation is undertaken. The annual summary for each year 1980–2010 is reviewed, and the data for the number of days per month are collected. These months are then further separated by ENSO and AO episodes and undergo ANOVA at the 90% CI. While all sites have temperature data from 1980 onward, precipitation data broken down at number of days per month with observed precipitation greater than or equal to 0.10 and 1.0 in. are only available from 1993 (Kansas and Nebraska) or 1996 (all other states) onward. Thus, ENSO and AO monthly episode analysis had to be limited to a shorter number of years. The variables of $T_{max} \geq 90°F$, $T_{max} \leq 32°F$, and $T_{min} \leq 32°F$ are selected to assess teleconnection episode categorization (ENSO or AO) on heat stress, freeze, and frost damage, respectively, while Prcp ≥ 0.1 in. and Prcp ≥ 1.0 in. are selected to assess precipitation (0.10 in. has been deemed enough to break through the vegetation canopy) and heavy

precipitation events (1.0 in. breaks the vegetation canopy and provides sufficient soil moisture recharge in the top layer of soil), a similar approach to agroclimatic analysis in Negri et al. (2005).

2.2.3. ENSO and AO climatologies and yield analysis by crop-reporting district

Teleconnections result in climate variability influencing weather patterns across the United States. The influence of climate variability teleconnections in the form of weather can influence the potential yield of planted crops for a given growing season because of the dependence of crop yields on temperature and precipitation during phenological development (Elmore 2013; Hanway 1963; Neilson 2012; Neilson 2013a). Instead of only analyzing the impact of the teleconnection episode for an entire growing season, three separate time frames are assessed: 1) average ENSO and AO episode categorization for the growing season (April–October); 2) average ENSO and AO episode categorization during the beginning months of the growing season (April, May, and June); and 3) average ENSO and AO episode categorization during the months of crop silking, grain fill, and beginning of maturity (June, July, and August) (Neilson 2013b). The average episode classification of each teleconnection for each year spanning the specified time period is correlated to the historic, detrended yield time series at crop district level for each state in the Corn Belt to test for potential teleconnection influence on crop yield. Two-tailed significance is tested at the 90% CI for each crop-reporting district.

3. Results

3.1. Climatology

The results of ENSO and AO climatologies developed at the state climate division level are expected to provide information on monthly averaged, observed precipitation and monthly averaged, observed mean temperature for forecasters and agriculture producers. ENSO and AO climatologies and spatial impacts are analyzed separately; however, it is known that the two teleconnections can act synergistically. The intent of this separated analysis is to highlight the impact of each teleconnection on climate and agricultural production. Most climate divisions show distinct differences between teleconnection episodes. A composite analysis of the two teleconnections will be completed after initial testing of the online decision support tool and will be discussed in a future study. The developed climatology values are not represented as above or below climatological normal because the computation of climatological normal values includes all episodes of each teleconnection. The average values of the three possible episode classifications are compared to each other (negative, neutral, or positive). Seasonal climatologies for winter (December–February), spring (March–May), summer (June–August), and fall (September–November) are developed as well and are provided as supplemental material for conciseness.

3.1.1. Teleconnection impacts to temperature and precipitation: ANOVA

The spatial distribution of temperature and precipitation across the Corn Belt is impacted by the different ENSO and AO episodes as classified in this study. Some

climate divisions in a state are impacted significantly (90% CI), while others are not. Impacts from each teleconnection are broadly similar, affecting temperature and precipitation patterns during the seasonal transition months of spring and early summer and the seasonal transition months of late summer into early fall except with ENSO, which has a large impact on mean temperatures during the month of December. Findings show more detailed information on the spatial distribution of ENSO and AO impacts across the Corn Belt rather than a general state or regional application of findings that may be too broad in scope, as found in prior work that has utilized more spatially coarse datasets (such as state-level data). This can potentially enhance smaller-scale spatial variability of weather and climate patterns that may be present with specific teleconnections being missed by larger-scale analysis. These findings provide more of a localized climatology instead of a regional climatology to end users.

The figures referred to in the following sections provide a map detailing ANOVA significance for 1 month of mean temperature or average, observed precipitation data for simplicity. Each parameter analyzed and discussed results in numerous maps. A comprehensive review of maps showing the different teleconnection episodes and impacts to temperature and precipitation will be available through the online decision support tool user interface (http://agclimate4u.org). The detailed development, usability, and applicability of this interface for improved agronomic decision-making will be the focus of a future paper.

3.1.1.1. El Niño–Southern Oscillation. Monthly mean temperatures are impacted by ENSO primarily in August, October, and December (fall and winter months). These impacts are concentrated in climate divisions in the states of Illinois (December), Indiana (August, October, and December), Michigan (August, October, and December), Wisconsin (August, October, and December), Minnesota (August, October, and December), Iowa (August and December), North Dakota (December), South Dakota (December), Nebraska (December), and Missouri (October and December). July mean temperatures are also episode dependent but spatially do not impact a cohesive subregion of the domain (Figure 1). These temperature relationships likely result from the shift of the polar jet stream farther north of the U.S. Corn Belt during El Niño events, allowing warmer air to advect northward into these regions. During a La Niña event, the polar jet stream is more meridional due to blocking high pressure over the north-central Pacific Ocean, resulting in a trough over the eastern half of the United States (Climate Prediction Center 2005a, and references therein).

The most notable precipitation impacts due to ENSO are during the month of September across the Ohio River Valley (parts of Illinois, Indiana, Ohio, and far southeast Michigan), which may share a link to the number of land-falling tropical cyclones that migrate across the region during different ENSO episodes. The probability of two or more hurricanes making landfall in the United States during an El Niño year is 28%, whereas in a neutral or La Niña year, it is 48% and 66%, respectively (Bove et al. 1998). Furthermore, findings from Kellner et al. (2015, manuscript submitted to *Wea. Climate Extremes*) show that land-falling hurricanes that impact the Midwest occur most frequently in the month of September and occur most frequently during neutral ENSO events, followed by La Niña years.

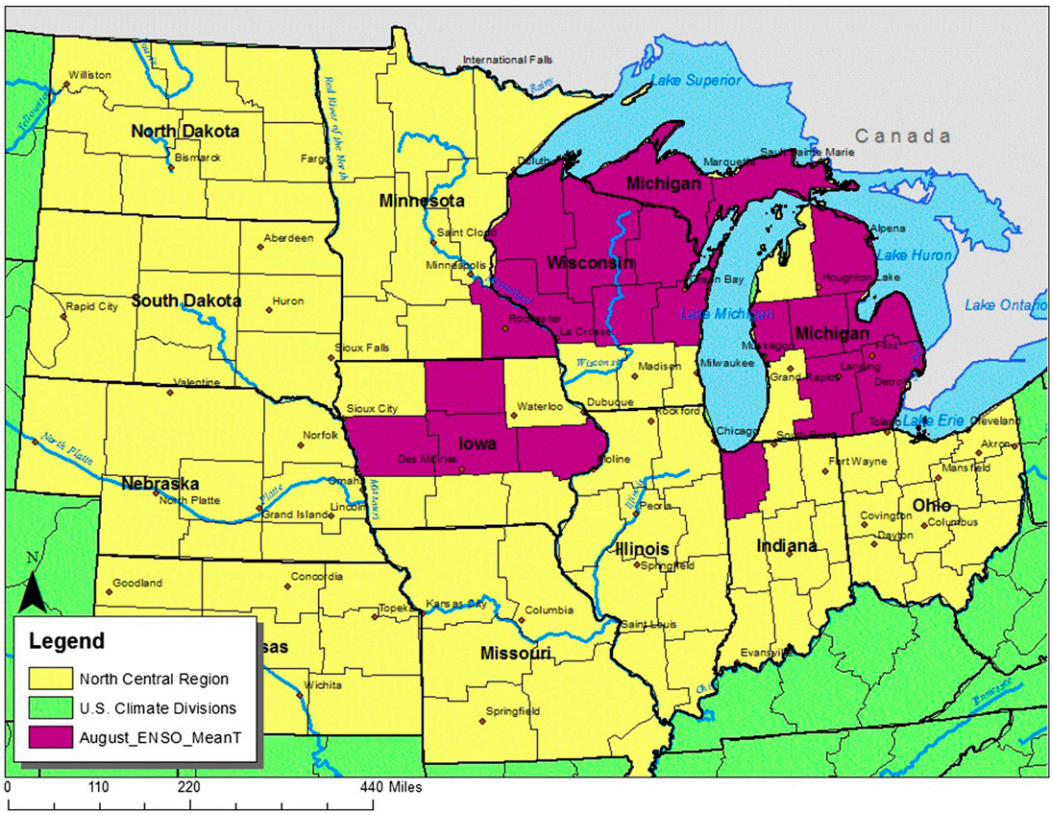


Figure 1. An example of a map highlighting climate divisions where average monthly mean temperatures in August are found to be significantly impacted (ANOVA, 90% CI) by ENSO episode 1980–2010.

Precipitation is impacted as well in February across northern Michigan [climate divisions (CDs) 1–6] along with northeast and central Indiana (CDs 3–6). March precipitation is episode dependent across western Iowa (CDs 1, 4, and 7) and much of Nebraska (minus CD 7), northwest Kansas (CDs 1 and 2), and CD 8 in South Dakota (Figure 2).

3.1.1.2. Arctic Oscillation. ANOVA results show significant ENSO-related impacts on average, monthly, observed mean temperatures in the months of March, April, July, August, October, November, and December in climate divisions and states in the Corn Belt. The AO statistically influences March mean temperatures in Illinois, Indiana, Ohio, Michigan, southeast Wisconsin (CD 3, 5–9), western Kansas (CDs 1, 4, and 7), and southeast Missouri (CDs 2, 5, and 6). April mean temperatures are significantly influenced by the AO in northern Illinois, northeast Indiana, far northwest Ohio, Michigan, Wisconsin, Minnesota, Iowa, North Dakota, and most of South Dakota (CDs 1–3 and 6–9). Summer months appear to be impacted by the AO as well. The difference between the average mean temperatures by AO episode during the month of July is found to be statistically significant in the states of Ohio (CDs 2, 3, 6, 7, and 10) and Michigan (CDs 4–10). August

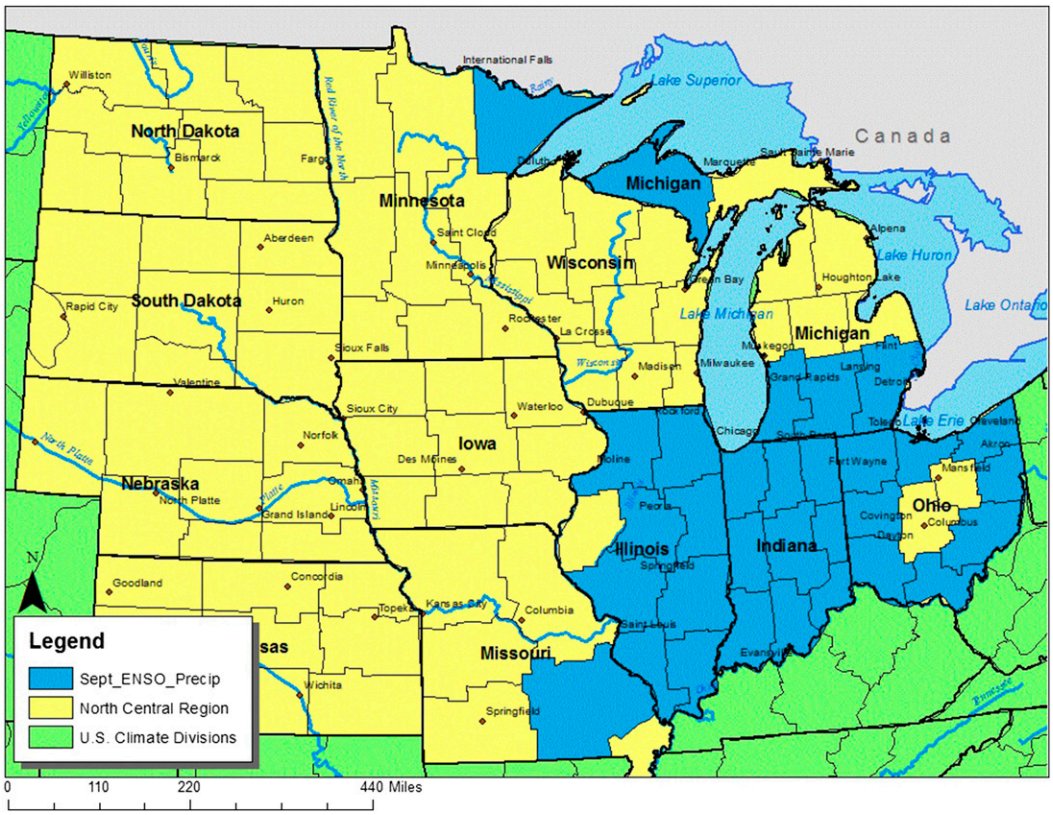


Figure 2. As in Figure 1, but displaying average monthly observed precipitation for the month of September.

mean temperatures are significantly impacted by the AO across the northern climate divisions of the Corn Belt: CDs 1–3 in Illinois; CDs 1–5, 7, and 8 in Wisconsin; all of Minnesota; CDs 1, 2, and 4–7 in Iowa; all of North Dakota; CDs 1–3, 7, and 9 in South Dakota; and finally eastern Nebraska (CDs 3, 6, and 9). During fall months, October, by far, experiences the largest spatially different mean temperatures by AO episode, with a statistical significance in average, observed mean temperature by episode impacting all or portions of states in the Corn Belt. November mean temperatures are impacted in Illinois (CDs 4, 5, and 7), Indiana, Ohio, and southern Michigan. December mean temperatures are impacted in Illinois, Indiana, Ohio, southern Michigan, and the southeast half of Missouri (Figure 3).

Precipitation patterns are also influenced by the AO, however, not to the spatial and temporal scale of mean temperatures. The AO primarily impacts average, observed precipitation during the spring and fall months of March, April, October, and December in states across the Corn Belt. March precipitation is significantly impacted across southwest Ohio (CDs 1, 4–8, and 10), southwest to northeast through central Wisconsin (CDs 3, 5, 7, and 8), and northeast Minnesota (CDs 3 and 6). April impacts skirt the northern climate divisions of Michigan (CD 1),

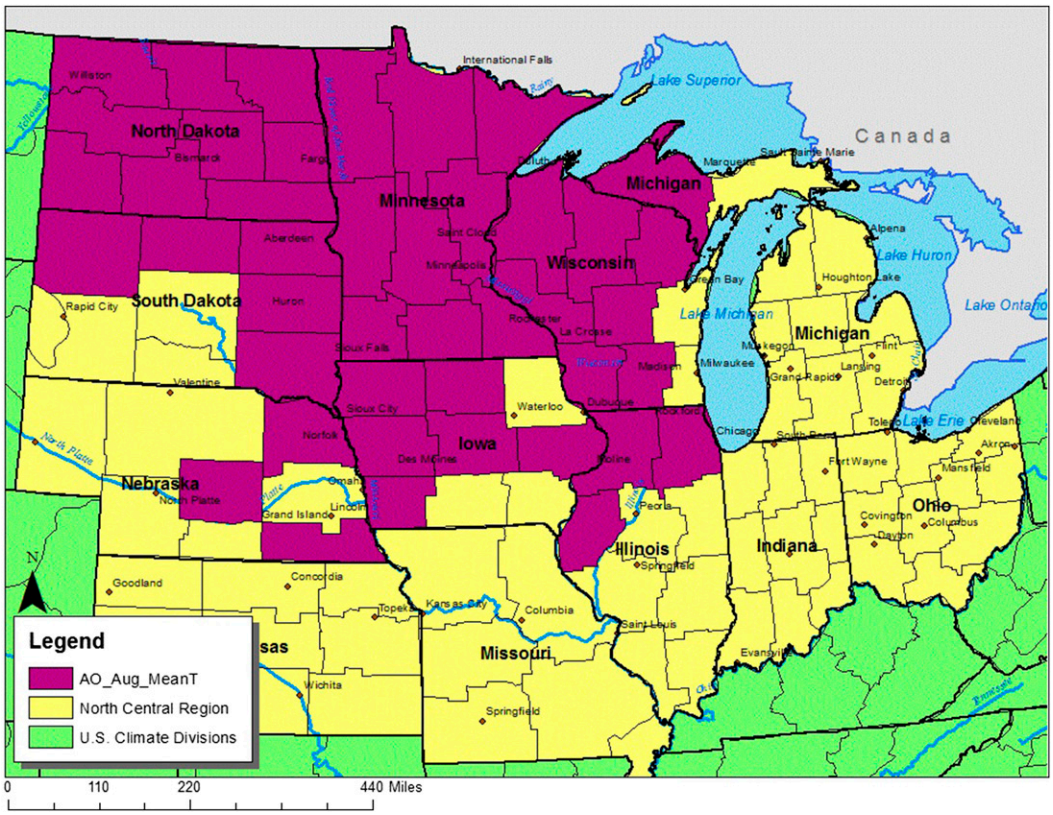


Figure 3. An example of a map highlighting climate divisions where average monthly mean temperatures in August are found to be significantly impacted (ANOVA, 90% CI) by AO episode 1980–2010.

Wisconsin (CD 2), and Minnesota (CDs 1, 2, and 5). October precipitation is found to be significantly impacted across southern Indiana (CDs 5–9) and much of Ohio (minus CDs 3, 6, and 7). This southwest to northeast orientation of observed precipitation significance across Indiana and Ohio is suggestive of a possible shift in the polar jet stream/mean storm track due to changes in AO pressure oscillations. States having precipitation significantly influenced by the AO during the month of December include Kansas (CDs 1–3, 5, 6, 8, and 9), northwest Missouri (CDs 1 and 3), Indiana (CDs 1, 2, 8 and 9), Ohio (CDs 5 and 8), and northeast-central Illinois (Figure 4).

3.1.2. Teleconnection episodes and historic crop yields: Correlation

Agroclimatogy shows that temperature and precipitation are the primary meteorological variables that impact corn growth and phenological development, with the potential for temperatures having slightly more of an impact than precipitation over the length of the growing season (e.g., Kellner and Niyogi 2014). However, precipitation is highly important, especially during the grain fill period, and thus it

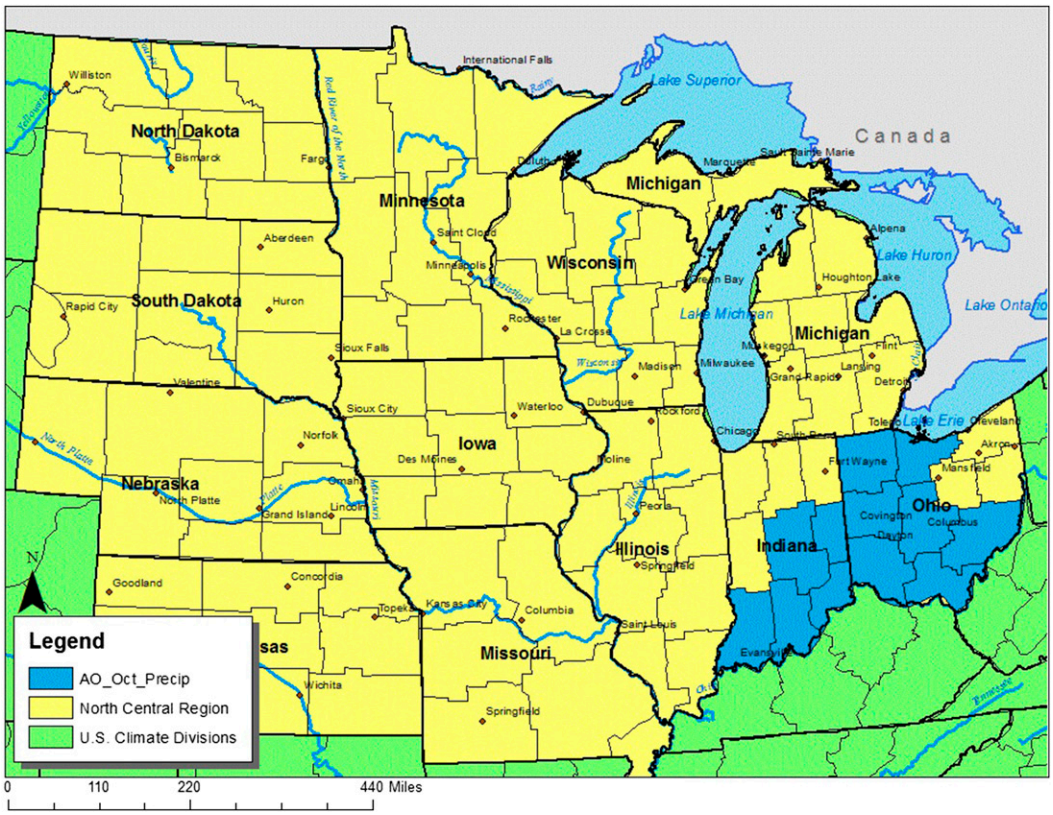


Figure 4. As in Figure 3, but displaying average monthly observed precipitation for October.

cannot be considered less of a contributor to yield production compared to temperature (Niyogi and Mishra 2012). Knowing that teleconnections influence climate variability, it is important to review the impacts of ENSO and AO on historic corn yield. AO is found to have a stronger impact than ENSO on the detrended yield time series for the period 1981–2010. Because the detrending methodology introduces a 1-yr lag, the regression analysis is completed for the years 1981–2010, while ANOVA and the climatology development includes the years 1980–2010.

3.1.2.1. El Niño–Southern Oscillation. ENSO has minor impact on the 1-yr lag detrended yield time series when analyzed through correlation analysis (90% CI) at CRD for the three different time frames considered across the growing season. A more detailed analysis of the ENSO impacts on the observed and agroclimatic model-simulated crop yields for the study domain is reported in Niyogi et al. (2013, 2015).

3.1.2.2. Arctic Oscillation. The AO is found to have a larger impact on the detrended yield time series using correlation analysis. Significance is found at 90% CI across states, across several of the different time frames analyzed in this study, and across more than one CRD in a state. This highlights the role of the AO in

short-term climate variability and its possible impacts on agricultural production across the U.S. Corn Belt. For the months of April–October and June, July, and August, all relationships are negatively correlated. For the months of April, May, and June, the relationship is positively correlated. Table 1 provides all states, time frames, and statistically significant findings between the average AO episode for the specified time frame and detrended yield time series at the 90% CI. Relationships as presented in Table 1 indicate that the more positive the AO signal, the lower the yield, and the more negative the AO signal, the higher the yield for late summer and the growing season. A positive relationship between AO and yield exists in spring, meaning that a positive AO would result in higher yields and a negative AO would result in reduced yields. The negative relationship found during the months of June, July, and August suggest either a positive AO signal results in decreased yield or a negative AO results in increased yields. The work of Hu and Feng (2010) identify that a negative AO episode in summer results in more summer rainfall because of the stronger transverse circulation in the polar jet and that a positive AO episode in summer results in less rainfall in the central United States. The findings of Hu and Feng (2010) and the June–August AO episode relationship with crop yields identified by this climatology support each other in that increased rainfall during silking, and grain fill periods could likely contribute to historically higher yields. Table 2 highlights those states with climate divisions that have the highest average amount of observed precipitation during warm season months, while the AO is in a negative episode.

3.1.2.3. AO and ENSO crop anomaly analysis. Detrended yield time series values are taken as an anomaly above or below the CRD mean for the 1981–2010 period to assess whether historic crop yields, when grouped into ENSO or AO episodes, are above or below the mean historic trend similar to Hansen et al. (1998). For simplicity, anomalies of the detrended yield time series are binned into annual ENSO events (either El Niño, La Niña, or neutral, as previously defined), average ENSO episode by growing season (April–October), and average AO signal for the growing season. While ENSO events have been named by ''years'' (i.e., the 1997/98 El Niño year/event), the AO is not classified as such because the teleconnection varies on a weekly to monthly time scale. Thus, the AO anomalies are only binned by the average AO signal for the growing season.

Results for ENSO years/episodes generally agree with those of previous findings (e.g., Cadson et al. 1996; Hollinger et al. 2001; Mauget and Upchurch 1999; Rosenzweig 2001; and those studies mentioned therein) in that El Niño years experience higher than average yields in much of Missouri, Kansas, Minnesota, the southern two-thirds of Ohio, Iowa, central Michigan, Wisconsin, Nebraska, North Dakota, and South Dakota. However, Indiana and Illinois have seen larger yields during ENSO neutral episodes. During a La Niña episode, all of these states and/or regions of these states experience lower than average yields. A slight difference is present in the northern two-thirds of Michigan and Wisconsin, Minnesota, North Dakota, and South Dakota. These states experience lowest yields during ENSO neutral episodes.

Analysis of detrended yield time series crop anomalies for the average growing season ENSO episode changes yield anomalies so that in Illinois, Indiana, and Ohio yields are lowest during El Niño episodes and highest during ENSO neutral

Table 1. Correlation (90% CI) of average teleconnection episode 1981–2010 to detrended historic yields by growing season and subgrowing season intervals. The plus sign (+) denotes a positive correlation and the minus sign (−) denotes a negative correlation. Correlation of average ENSO episode and historic yields for specified time frames resulted in no relationships of significance. NA refers to those climate divisions in which crop yield data were not complete for the 1981–2010 period.

90% CI: Average AO episode
April–June and yield, 1980–2010

CRD	10	20	30	40	50	60	70	80	90
ND	NA	+		+		+	NA		+
SD			+			+			
NE				NA	+			+	
KS									
MO		+							
IA	+	+	+	+	+	+	+	+	+
MN		NA	NA	+	+		+	+	+
WI			+		+	+	+	+	+
IL	+		+	+	+	+			
IN									
MI									
OH									

90% CI: Average AO episode
June–August and yield, 1980–2010

CRD	10	20	30	40	50	60	70	80	90
ND	NA						NA		+
SD					−		−	−	
NE									
KS								−	−
MO			−						
IA									
MN		NA	NA						
WI									
IL							−	−	
IN									
MI									
OH				−					

90% CI: Average AO episode
April–October and yield, 1980–2010

CRD	10	20	30	40	50	60	70	80	90
ND	NA						NA		
SD									
NE				NA					
KS					−		−	−	−
MO	−		−	−	−	−	−	−	−
IA									
MN		NA	NA						
WI									
IL						−	−	−	−
IN	−	−	−	−	−	−	−	−	−
MI									
OH				−			−		

Table 2. Difference between average warm season rainfall for each AO episode at state climate division level to the average, observed, warm season rainfall for the respective state climate division. Bold numbers denote those states and climate divisions having the highest, average, observed, warm season precipitation shown as a positive departure from the mean during a negative AO episode. Negative values indicate that the average, warm season rainfall for that AO episode is below the warm season normal.

		Above/below normal average observed warm season Rainfall (April–September) by AO episode (1980–2010)									
	CD	1	2	3	4	5	6	7	8	9	10
ND	Positive	−0.15	−0.22	−0.23	−0.08	−0.18	−0.07	−0.15	−0.21	−0.12	
	Negative	−0.20	−0.25	−0.16	−0.05	−0.05	−0.16	**0.13**	**0.06**	−0.08	
	Neutral	0.11	0.16	0.13	0.04	0.08	0.07	0.02	0.05	0.07	
SD	Positive	−0.30	−0.25	−0.06	−0.17	−0.22	−0.28	0.14	−0.10	−0.14	
	Negative	**0.30**	0.04	−0.30	**0.37**	**0.24**	**0.26**	−0.13	**0.15**	**0.05**	
	Neutral	0.02	0.07	0.11	−0.05	0.00	0.02	−0.01	−0.01	0.04	
NE	Positive	−0.23	−0.05	0.09		−0.07	−0.34	−0.09	−0.17	−0.64	
	Negative	**0.20**	**0.10**	−0.22		−0.01	−0.06	**0.19**	−0.16	0.15	
	Neutral	0.02	−0.01	0.04		0.03	0.14	−0.03	0.11	0.18	
KS	Positive	−0.30	−0.36	−0.73	−0.05	−0.34	−0.61	0.01	−0.11	−0.50	
	Negative	**0.24**	0.02	0.29	**0.06**	**0.22**	**0.39**	**0.08**	**0.36**	**0.69**	
	Neutral	0.03	0.12	0.17	0.00	0.05	0.10	−0.03	−0.07	−0.03	
MO	Positive	−0.65	−0.30	−0.52	−0.29	−0.16	0.31				
	Negative	**0.23**	**0.17**	**0.54**	**0.63**	**0.30**	−0.19				
	Neutral	0.16	0.06	0.02	−0.09	−0.03	−0.05				
IA	Positive	0.03	−0.26	−0.31	−0.16	−0.26	−0.61	−0.64	−0.61	−0.61	
	Negative	−0.36	−0.48	−0.19	−0.17	−0.04	**0.47**	**0.25**	0.13	**0.39**	
	Neutral	0.10	0.24	0.17	0.11	0.11	0.07	0.15	0.18	0.10	
MN	Positive	−0.01	0.07	−0.06	0.03	0.11	−0.02	0.15	0.05	0.05	
	Negative	−0.28	−0.53	−0.45	−0.37	−0.59	−0.66	−0.15	−0.32	−0.42	
	Neutral	0.09	0.14	0.16	0.10	0.14	0.21	−0.01	0.08	0.11	
WI	Positive	−0.05	−0.05	−0.17	0.06	−0.02	−0.10	−0.24	−0.05	0.19	
	Negative	−0.62	−0.37	−0.24	−0.47	−0.36	−0.28	−0.24	−0.30	−0.27	
	Neutral	0.20	0.13	0.13	0.12	0.12	0.12	0.16	0.11	0.01	
IL	Positive	−0.31	−0.01	−0.35	−0.11	−0.10	−0.05	−0.05	−0.04	0.07	
	Negative	**0.40**	**0.16**	**0.10**	−0.13	−0.05	−0.12	−0.02	**0.52**	**0.28**	
	Neutral	−0.01	−0.05	0.09	0.08	0.05	0.05	0.02	−0.14	−0.11	
IN	Positive	−0.19	0.03	−0.04	0.03	0.06	−0.10	0.12	0.02	−0.02	
	Negative	0.01	−0.11	−0.04	−0.06	−0.03	−0.01	**0.20**	**0.46**	**0.32**	
	Neutral	0.06	0.02	0.03	0.01	−0.01	0.04	−0.10	−0.15	−0.09	
OH	Positive	0.01	0.00	0.02	0.05	0.02	−0.10	−0.04	0.03	0.10	0.12
	Negative	**0.10**	**0.22**	**0.12**	−0.20	−0.07	**0.09**	**0.18**	**0.23**	**0.18**	**0.14**
	Neutral	−0.04	−0.07	−0.04	0.04	0.02	0.01	−0.04	−0.08	−0.09	−0.08
MI	Positive	−0.25	−0.17	−0.14	−0.01	0.12	0.04	0.02	−0.07	0.14	0.04
	Negative	−0.15	**0.12**	−0.04	−0.11	−0.27	−0.27	−0.01	−0.13	−0.05	**0.19**
	Neutral	0.14	0.02	0.06	0.04	0.04	0.07	−0.01	0.06	−0.03	−0.07

episodes. Michigan and Wisconsin do not shift much except in the northern two-thirds of the state, which experiences the lowest yields during an ENSO neutral or La Niña event. Minnesota shifts so that the lowest yields occur during La Niña episodes instead of during neutral episodes. Growing season analysis for Iowa changes so that higher yields occur during ENSO neutral events. Kansas reveals no favored ENSO phase for higher or lower than normal years. Missouri shows lowest

yields occurring during El Niño episodes in most CRDs and highest yields occurring during La Niña or neutral episodes. Growing season yield anomalies in the Dakotas become more variable with no trend except that an ENSO neutral to El Niño episode predominantly reduces yield. The yield anomaly for Nebraska when reviewed by growing season shows that the lowest yields occur during El Niño episodes and the highest yields occur while in an ENSO neutral episode during the growing season.

AO anomalies of detrended yield time series show much larger variability above or below trend. However, results remain inconclusive because of the AO signal being predominantly neutral through the time period (1-yr AO negative and 2-yr AO positive) and the fact that much larger than normal yields occurred during the two AO positive years and greatly reduced yields occurred during the one AO negative year. This creates a large bias toward neutral episode events and the anomalous yields in AO negative and positive years. Table 3 provides a summary by state and crop-reporting district of ENSO and AO yield anomalies by episode of each teleconnection for the growing season. Differences between crop anomalies when looking at annual AO episode values versus growing season values are that a positive or negative AO episode results in reduced yields, and the largest yields occur during AO neutral episodes.

In this analysis of growing season versus annual episode, the time frame in which the detrended yield time series is analyzed by ENSO and AO episodes determines detrended yield time series crop anomalies. The authors wish to express that these findings are not of magnitude to warrant making a prognostic decision of above or below normal yields based on the average growing season or average annual forecast of ENSO or AO episode. Rather, the general trends of above or below normal yields based on identified weather conditions could continue to be considered more heavily in the decision-making process. The quantitative yield anomalies will also be dictated by agronomic practices such as planting dates, seed characteristics, and technology. Therefore, while ENSO or AO signatures may not translate or often times not be the dominant drivers for the quantitative statistically significant anomaly, we assert that the qualitative trends are still useful. One such example of a qualitative trend is the strong La Niña (warmer and drier conditions) that contributed to the anomalously warm spring of 2012 and earlier than normal planting dates.

3.2. Extremes climatology

Takle et al. (2014) highlight climatic conditions throughout the year and the needed weather and seasonal forecast content that affects corn production. Among these weather conditions are soil moisture, extreme heat, frost damage, growing degree-days, extreme weather, and early freezes before harvest [McKeown et al. (2006) and Elmore (2013) provide a general review of such conditions]. The goal of developing this "extremes" climatology for ENSO and AO episodes is to investigate the occurrence of such events as related to a given episode so that producers can be better acquainted with the potential likelihood of occurrence of warmer daytime maximum temperatures (heat stress), increased likelihood of experiencing a frost or freeze event (damage to newly planted crops), or increased/decreased

Table 3. Crop anomaly (detrended minus the detrended mean) values in bushels per acre by teleconnection and episode for the growing season (April–October). ND denotes where data were insufficient for analysis. For the AO, Neg denotes negative episode (≤−0.5), Pos denotes positive episode (≥0.5), and Neu denotes a neutral episode (−0.4 to 0.4). For ENSO, L denotes a cold episode (≤−0.5), E denotes a warm episode (≥0.5), and N denotes a neutral episode (−0.4 to 0.4). Positive values indicate yields greater than the mean and negative values indicate yields less than the mean.

Growing season														
		ENSO			AO				ENSO			AO		
State	CRD	E	L	N	Pos	Neg	Neu	State	E	L	N	Pos	Neg	Neu
IL	10	−8.5	−9.1	7.7	−10.4	−27.8	1.8	MO	−1.9	−3.0	2.1	−49.1	−50.1	5.5
	20	−11.4	−1.2	6.1	−8.2	−18.9	1.3		−1.6	0.1	0.8	−33.9	−39.9	4.0
	30	−8.4	−7.1	6.9	−51.8	−25.5	4.8		0.4	−2.7	0.8	−49.5	−9.7	4.0
	40	−11.7	−4.1	7.4	−25.5	−12.5	2.3		−5.3	3.7	1.3	−29.0	−33.2	3.4
	50	−10.1	−3.3	6.3	−18.5	−16.6	2.0		−2.6	2.0	0.6	−32.4	−21.5	3.2
	60	−9.0	−2.7	5.5	−31.8	−7.2	2.6		−6.9	0.8	3.2	−30.2	−25.8	3.2
	70	−9.9	−1.0	5.3	−28.9	−1.1	2.2		1.3	−0.7	−0.4	−22.2	−23.2	2.5
	80	−8.7	−1.4	4.9	−32.0	−6.6	2.6		−7.3	−5.3	5.6	−33.3	−18.0	3.1
	90	−10.5	−0.1	5.3	−29.2	0.5	2.1		−9.2	0.3	4.5	−28.3	−26.8	3.1
State	CRD	E	L	N	Pos	Neg	Neu	State	E	L	N	Pos	Neg	Neu
IN	10	−6.8	−5.5	5.5	−16.1	−15.0	1.8	IA	−5.2	−2.7	3.6	−18.6	−78.8	4.3
	20	−8.7	−9.2	7.8	−13.7	−11.0	1.4		−2.9	−1.4	2.0	−21.4	−86.9	4.8
	30	−6.1	−8.3	6.2	−18.3	−13.1	1.8		−0.2	−10.5	4.1	−6.7	−72.4	3.2
	40	−11.7	−3.3	7.1	−19.4	−5.6	1.6		−0.7	−3.4	1.6	−25.5	−73.3	4.6
	50	−6.5	−5.4	5.3	−23.3	0.3	1.7		1.5	−7.9	2.2	−10.9	−74.4	3.6
	60	−7.9	−3.9	5.4	−27.8	−5.9	2.3		−6.6	−14.5	8.7	−12.3	−60.6	3.2
	70	−13.9	−0.3	7.0	−24.3	−7.7	2.1		1.9	−3.3	0.3	−26.3	−70.5	4.6
	80	−14.0	−2.4	7.9	−30.4	5.0	2.1		−1.1	−4.2	2.1	−37.7	−65.7	5.2
	90	−12.4	−0.8	6.5	−32.2	−0.9	2.4		−5.4	−11.1	6.9	−53.3	−57.1	6.1
State	CRD	E	L	N	Pos	Neg	Neu	State	E	L	N	Pos	Neg	Neu
OH	10	−8.6	−3.4	5.6	−13.8	−31.0	2.2	KS	−1.7	3.0	−0.3	−8.3	−13.7	1.1
	20	−9.7	1.4	4.4	−15.9	−37.9	2.6		−1.4	−7.5	3.5	−5.8	0.3	0.4
	30	−10.4	2.2	4.3	−18.9	−35.3	2.7		−3.1	2.4	0.6	−18.6	−22.6	2.2
	40	−10.9	2.3	4.6	−35.0	−13.5	3.1		−4.2	−2.4	3.0	1.4	−18.4	0.6
	50	−4.7	2.2	1.5	−30.2	−22.4	3.1		1.4	−3.1	0.5	−14.7	−12.7	1.6
	60	−8.7	−0.4	4.5	−16.1	−20.2	1.9		0.9	0.9	−0.8	−12.8	−17.7	1.6
	70	−4.2	−0.3	2.2	−29.8	−18.4	2.9		−7.8	0.3	3.8	−58.5	−43.3	5.9
	80	−3.3	−3.0	2.8	−21.6	−22.6	2.4		−3.7	1.2	1.4	−24.9	−30.8	3.0
	90	−6.3	1.6	2.5	−24.0	−13.6	2.3		−0.3	8.7	−3.1	−18.9	−25.1	2.3
State	CRD	E	L	N	Pos	Neg	Neu	State	E	L	N	Pos	Neg	Neu
MI	10	0.5	11.7	−4.6	−10.1	−29.0	1.8	ND	ND	ND	ND	ND	ND	ND
	20	2.4	−3.0	−0.1	−10.9	−3.2	0.9		−8.1	3.2	2.8	−14.5	−49.1	2.9
	30	−1.8	4.1	−0.6	−15.1	−12.7	1.6		−4.5	−2.7	3.3	−29.5	−29.5	3.3
	40	7.1	3.0	−4.7	−3.0	12.3	−0.2		−6.7	4.5	1.6	−19.4	−47.1	3.2
	50	0.9	4.8	−2.2	−7.1	5.3	0.3		−8.8	−2.2	5.2	−13.9	−40.0	2.5
	60	4.0	−2.8	−1.0	4.4	6.9	−0.6		−5.5	−2.5	3.7	−18.3	−40.2	2.8
	70	5.9	−6.7	−0.4	11.5	−1.0	−0.8		ND	ND	ND	ND	ND	ND
	80	0.9	−2.8	0.6	12.3	−1.0	−0.9		−7.1	8.0	0.6	−1.6	−31.3	1.3
	90	−2.7	−3.7	2.7	15.0	−9.2	−0.8		−2.6	−2.9	2.4	4.1	−53.1	1.7

Table 3. (*Continued*)

		Growing season												
		ENSO			AO				ENSO			AO		
State	CRD	E	L	N	Pos	Neg	Neu	State	E	L	N	Pos	Neg	Neu
WI	10	7.5	−4.9	−1.9	8.0	−34.1	0.7	SD	−4.1	3.3	0.8	−13.0	−32.4	2.2
	20	5.6	−4.7	−1.0	−7.7	−61.5	2.8		−3.2	4.5	−0.1	−1.9	−14.6	0.7
	30	1.8	1.6	−1.5	−8.3	−36.7	2.0		−3.9	−4.8	3.7	5.4	−56.6	1.7
	40	6.4	−8.8	0.1	5.7	−28.0	0.6		3.2	−6.2	0.7	3.6	−9.9	0.1
	50	2.9	−1.0	−1.1	−1.7	−26.1	1.1		−0.8	1.4	−0.1	−23.5	−15.8	2.3
	60	4.2	0.2	−2.2	−8.1	−43.5	2.2		−6.8	−1.2	3.9	−29.1	−64.8	4.6
	70	3.2	−11.4	2.7	9.3	−24.4	0.2		2.4	−4.9	0.7	−16.1	−16.3	1.8
	80	−2.7	−9.6	5.0	0.5	−21.0	0.7		−5.0	−7.6	5.3	−15.2	−1.1	1.2
	90	−2.4	−5.4	3.2	4.9	−13.2	0.1		−12.3	−4.2	7.7	−27.2	−39.0	3.5
State	CRD	E	L	N	Pos	Neg	Neu	State	E	L	N	Pos	Neg	Neu
MN	10	−3.5	−2.8	2.8	−21.8	−47.8	3.4	NE	−2.1	−0.5	1.2	−21.0	−44.4	3.2
	20	ND	ND	ND	ND	ND	ND		−4.0	−4.4	3.6	−15.0	−3.9	1.3
	30	ND	ND	ND	ND	ND	ND		−10.7	−5.0	7.2	−30.5	−33.0	3.5
	40	−0.4	−9.9	3.9	3.8	−66.5	2.2		−5.5	−3.8	4.2	−19.7	−26.8	2.5
	50	1.9	−11.7	3.5	−6.4	−64.0	2.8		−2.7	−1.2	1.8	−24.0	−50.4	3.6
	60	7.5	−10.8	0.3	−0.7	−35.2	1.4		−0.3	1.1	−0.3	−16.3	−23.6	2.1
	70	−2.3	−7.2	3.9	−9.6	−90.8	4.1		−3.5	0.0	1.8	−16.9	−47.2	3.0
	80	−0.6	−9.7	3.9	−10.3	−73.7	3.5		−4.3	0.6	1.9	−21.8	−45.7	3.3
	90	2.6	−11.6	3.1	8.5	−60.2	1.6							

frequency of heavy rainfall events (applications of nitrogen and irrigation). The variables $T_{max} \geq 90°F$, $T_{max} \leq 32°F$, $T_{min} \leq 32°F$, Prcp ≥ 0.10 in., and Prcp ≥ 1.0 in. show statistically significant findings at the 90% CI with ANOVA across spatial scales, spanning locations either broadly across the Corn Belt or impacting as few as one location in the Corn Belt. These extremes are impacted by both teleconnections with similar and different statistical relationships. Only those impacted CDs with neighboring impacted CDs (essentially a subregion) are included in the discussion for brevity.

3.2.1. El Niño–Southern Oscillation

3.2.1.1. Extreme event frequency: ANOVA. El Niño–Southern Oscillation episodes do appear to impact the average number of days per month of extreme precipitation amounts and temperatures occurring in the Corn Belt. Precipitation is impacted significantly (90% CI; ANOVA) during the months of April (Prcp ≥ 1.0 in.), July (Prcp ≥ 0.10 in.), September (Prcp ≥ 0.10 in. and Prcp ≥ 1.0 in.), and November (Prcp ≥ 0.10 in.). Temperatures are impacted significantly in March ($T_{min} \leq 32°F$), September ($T_{max} \geq 90°F$), October ($T_{max} \leq 32°F$), and December ($T_{max} \leq 32°F$). Figures 5 and 6 show the regional, subdomain-scale distribution of these variables.

3.2.1.2. Extreme event frequency impacts to historic yield: Correlation. To determine if the average frequency of monthly extreme events during a given ENSO episode impacts detrended yield time series, correlation is completed between yields and the average number of days per month an extreme event occurs by

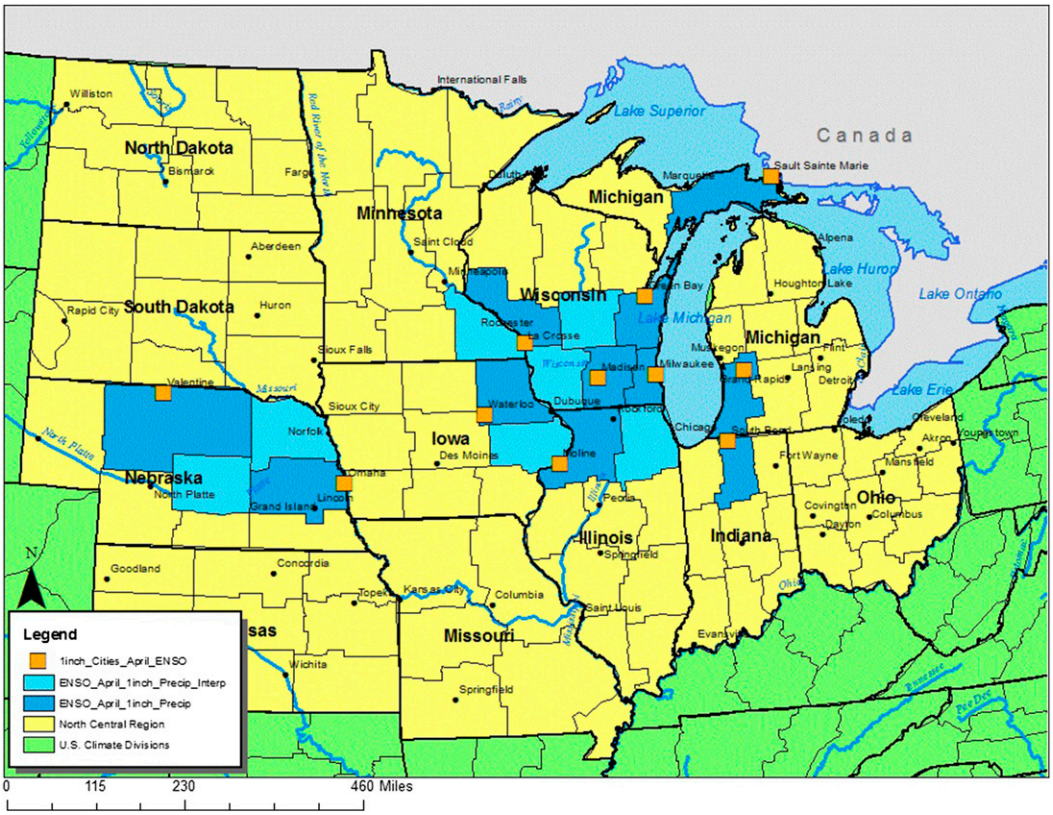


Figure 5. An example of a map highlighting climate locations and state climate divisions in which the cities reside, where the average number of days per month extreme precipitation event of Prcp ≥ 1.0 in. for the month of April is found to be significantly impacted (ANOVA, 90% CI) by ENSO episode 1996–2010. Orange squares denote the cities where findings are significant. Dark blue climate divisions house those cities. The light blue climate divisions are spatially interpolated (neighbored by two state climate divisions with noted significance) for aesthetics.

ENSO episode. The number of days per month $T_{\max} \geq 90^{\circ}$F shows a moderate, positive relationship during the month of May in an El Niño episode and a negative relationship during an El Niño August. March and October during all ENSO episodes are the primary months having moderate to strong negative relationships between detrended yield time series and the average number of days per month $T_{\max} \leq 32^{\circ}$F (indicating reduction in yield the more days per month that experience freezing temperatures). This highlights the vulnerability of freezing temperatures impacting field conditions during early spring (delayed planting dates) and also potentially impacting harvest in fall through frost or freeze damage. During all ENSO episodes $T_{\min} \leq 32^{\circ}$F results in moderate to strong negative relationships.

Positive and moderate to strong correlations exist between the average number of days per month Prcp ≥ 0.10 in. during an El Niño June (less average observed precipitation compared to the other two episodes) and a neutral August when correlated to

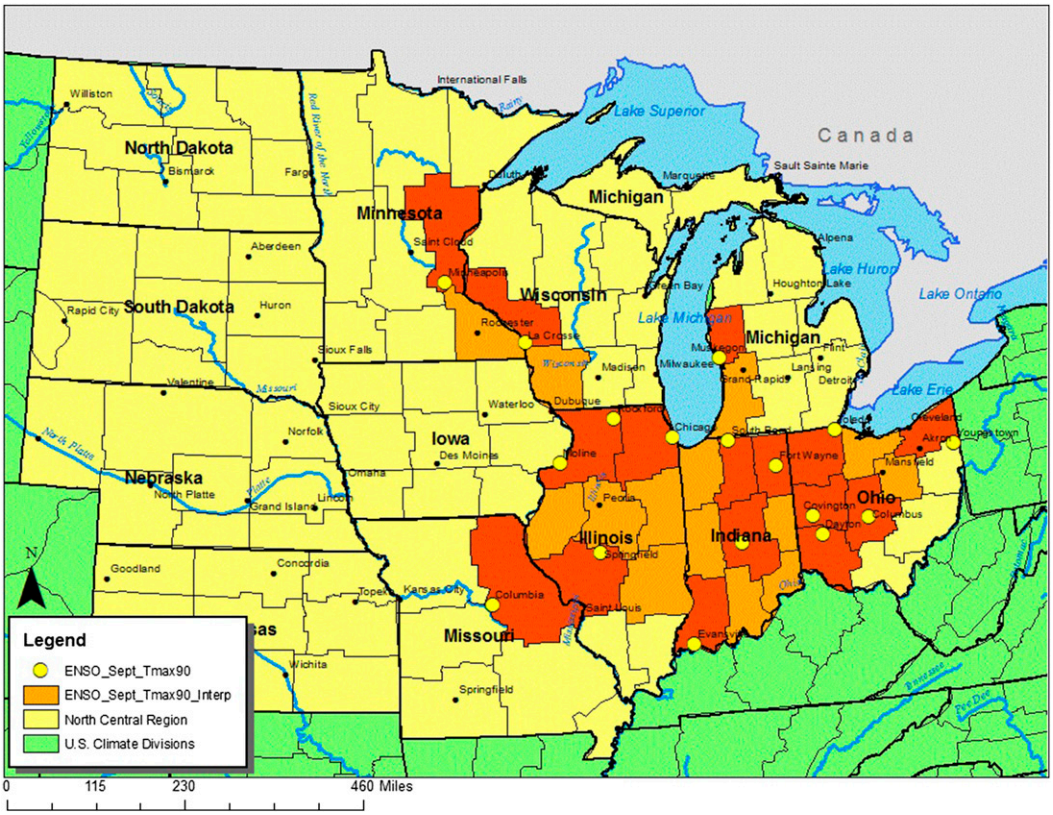


Figure 6. An example of a map highlighting climate locations where the average number of days per month the extreme temperature event of $T_{max} \geq 90°F$ is found to be significantly impacted (ANOVA, 90% CI) by ENSO episode 1980–2010. Yellow circles denote those cities where findings are significant. Dark red climate divisions house those cities. Orange climate divisions are spatially interpolated (neighbored by two state climate divisions with noted significance) for aesthetics.

historic detrended yield time series. A neutral ENSO episode in August has the strongest correlation to yields having on average one more day per month Prcp $\geq$ 0.10 in. across the Corn Belt. The average number of days per month where Prcp $\geq$ 1.0 in. when correlated to detrended yield time series has weak, positive correlations to La Niña Aprils and weak to moderate positive correlations during La Niña Augusts.

3.2.2. Arctic Oscillation

3.2.2.1. Extreme event frequency: ANOVA. Statistically significant impacts of the Arctic Oscillation are seen at subregional scales across the Corn Belt as well. The number of months impacted by each type of extreme event is greater than ENSO. Precipitation is impacted significantly during the months of February, March, April, June, and September when analyzed for the number of days per month Prcp $\geq$ 0.10 in. and the month of March when analyzed for number of days

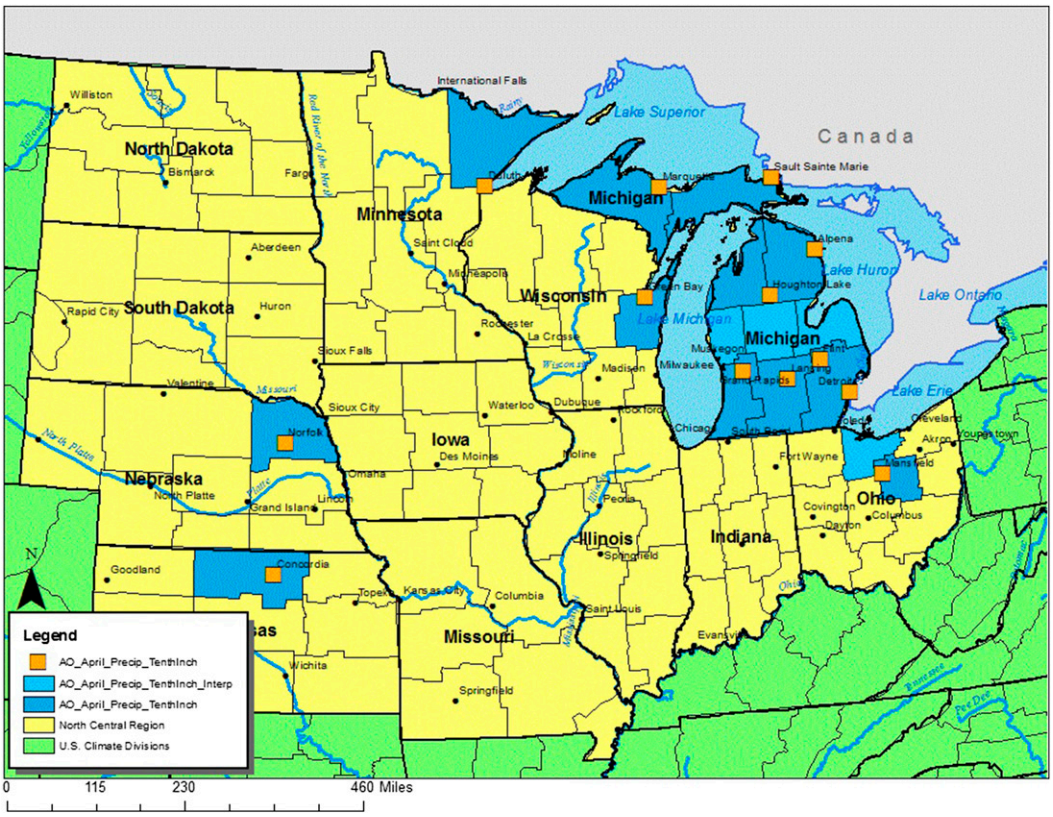


Figure 7. An example of a map highlighting climate locations where the average number of days per month in April that precipitation events of Prcp ≥ 0.10 in. are found to be significantly impacted (ANOVA, 90% CI) by AO episode 1996–2010. Orange squares denote the cities where findings are significant. Dark blue climate divisions house those cities. The light blue climate divisions are spatially interpolated (neighbored by two state climate divisions with noted significance) for aesthetics.

per month Prcp $\geq$ 1.0 in. Extreme temperatures are impacted by the AO in months preceding planting dates or after crops begin maturing: $T_{\max} \geq 90^{\circ}$F (September), $T_{\max} \leq 32^{\circ}$F (January, April, October, November, and December), and $T_{\min} \leq 32^{\circ}$F (March, April, October, November, and December). Figures 7 and 8 show maps of these findings.

3.2.2.2. Extreme event frequency impacts to historic yield: Correlation. Like ENSO, the correlation of extreme events by episode of each teleconnection to detrended yield time series is completed to see if a relationship is present between the average number of days per month a given parameter occurs and yields. Only statistically significant relationships (95% CI) are discussed. Correlation analysis shows that a negative AO in August and a neutral AO in May are important months to consider the number of days $T_{\max} \geq 90^{\circ}$F. A negative AO in August has a negative, weak correlation (the fewer days $T_{\max} \geq 90^{\circ}$F, the

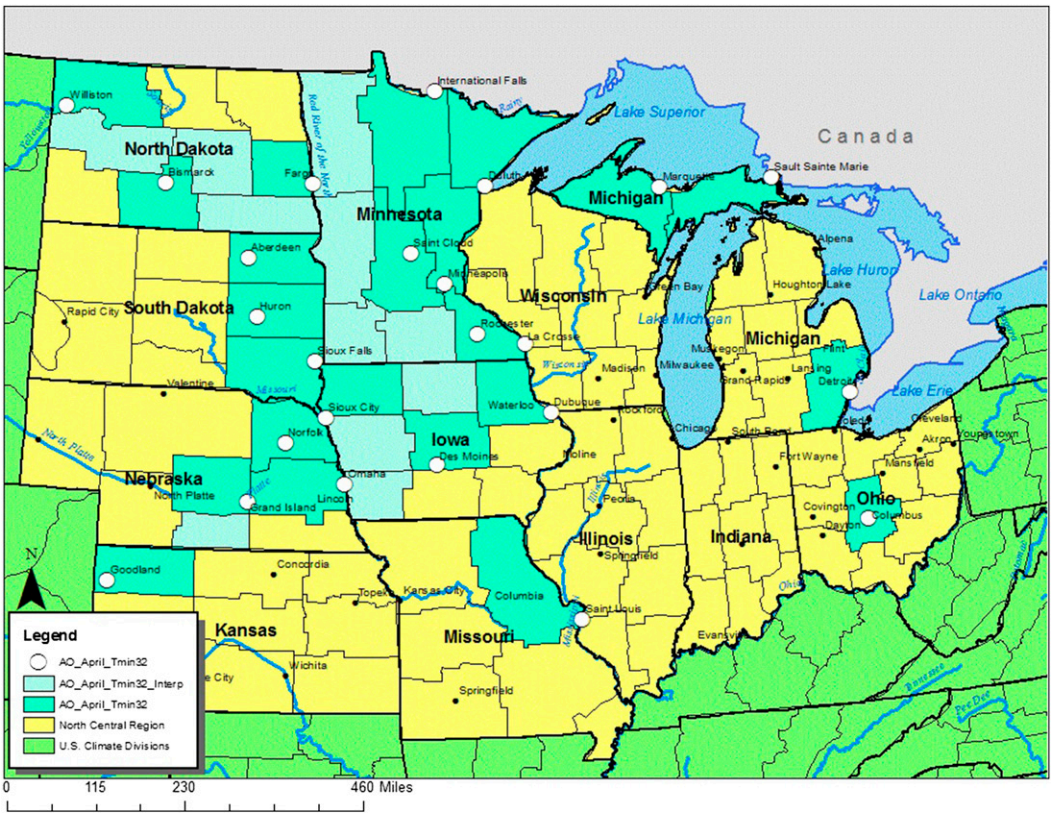


Figure 8. An example of a map highlighting climate locations where the average number of days per month the extreme temperature event of $T_{min} \leq 32°F$ (greater likelihood for frost/freeze events) is found to be significantly impacted (ANOVA, 90% CI) by AO episode 1980–2010. White circles denote the cities where findings are significant. Dark green/teal climate divisions house those cities. The light blue climate divisions are spatially interpolated (neighbored by two state climate divisions with noted significance) for aesthetics.

higher the yield), and a neutral May has a positive relationship in that more days with $T_{max} \geq 90°F$, the higher the yield. The months of April, May, and September all show moderate to strong negative correlations with $T_{min} \leq 32°F$ with no AO phase taking dominance over other episodes. However, May (all phases) has the strongest relationship with the number of days $T_{min} \leq 32°F$. The relationship apparent through analysis is that the larger the number of days in May $T_{min} \leq 32°F$, the lower the yield, or the fewer number of days $T_{min} \leq 32°F$, the higher the yield.

Analysis of historic, detrended yield time series and precipitation highlights no relationship between historic yields and the average number of days per month Prcp ≥ 0.10 in. The average number of days per month Prcp ≥ 1.0 in. has the strongest, positive correlations during the months of April, May, and July. A neutral episode during the month of April has a moderate to strong positive relationship,

and a positive episode in May has a weak to moderate positive relationship between the number of days per month Prcp $\geq$ 1.0 in. and yields.

4. Relating to agronomic decision-making and yield impacts

ANOVA for the meteorological season is completed (spring as March–May, summer as June–August, fall as September–November, and winter as December–February) and briefly discussed in terms of teleconnection episodes (AO is positive, negative, or neutral; ENSO is El Niño, La Niña, or neutral) and which episode leads to the wettest or driest and warmest or coldest conditions during that season. Findings are then briefly discussed in terms of impacts to agronomic decision-making. Specific climate divisions and data can be viewed in the supplemental material. A more detailed spatial and temporal analysis (maps and bar graphs by month and episode) of ENSO and AO influences to weather patterns and how these weather patterns may in turn affect agronomic decision-making will be discussed in more detail in a follow-up paper. This paper is intended to prepare and analyze the meteorological/climatological data that can be used for the development of an online tool to help agricultural stakeholders make more informed decisions.

The statistically significant spatial and temporal influence of the AO on mean temperatures and precipitation across the domain during the seasons of spring, summer, and fall are broad in scope for mean temperatures and more focused into subregions of the domain for precipitation. The difference of average mean temperatures and mean observed precipitation between episodes is also greater when binned into AO episodes rather than ENSO episodes.

4.1. ENSO seasonal impacts and agronomic decision-making

4.1.1. Mean temperatures

Compared to AO, ENSO episodes impart less spatial and temporal influences to weather patterns across the U.S. Corn Belt. Spring shows no statistically significant relationships for mean temperatures through ANOVA. Summer temperatures are warmest during La Niña summers across Minnesota, Wisconsin, Michigan, Iowa, northern Illinois, and the northern two-thirds of Indiana. This suggests that during summer in these locations, crops may be more likely to experience heat stress, which may reduce yield (as discussed in previous studies). Provided rainfall is below normal during this time, evapotranspiration rates may be enhanced, putting crops under moisture stress, which may be alleviated through irrigation scheduling. A few climate divisions in far east Nebraska, central and southeast Kansas, and Missouri (CDs 1 and 6) are on average warmest during neutral ENSO episodes in summer. However, average temperatures are within several tenths of a degree of the La Niña average temperature. During the summer mean, temperatures are coolest during an El Niño episode for the same locations. Cooler temperatures could be indicative of less heat stress on crops, likely boosting the yield if adequate GDDs are met (as also discussed in previous studies). Fall, like spring, shows no statistically significant relationships between ENSO episodes and mean temperature.

4.1.2. Average, observed precipitation

Statistically significant relationships for precipitation are not present during spring and are minimal during summer (3 of 106 climate divisions). Fall has statistically significant precipitation relationships focused around the Great Lakes region in northwest and central Indiana, southern Michigan, and north-central and northeast Ohio. During an ENSO neutral episode, these CDs are on average the wettest during the fall and are driest during La Niña episodes. In this region, farmers may consider delayed harvest during ENSO neutral events due to wet fields and delayed dry down of crops. A La Niña episode may allow a producer to plan for earlier harvest due to drier conditions. Figure 9 provides a flowchart example of how this climatology and embedded information may be used in a decision-making process, and the DST is being developed.

4.2. Arctic Oscillation seasonal impacts and agronomic decision-making

4.2.1. Mean temperatures

As related to agricultural decision-making, spring is warmest across the domain when the AO is in a neutral episode. The coldest mean temperatures in spring occur during a negative AO episode across the southern two-thirds of the domain and across the roughly northern one-third of the domain during a positive AO episode. Thus, a neutral AO episode would provide for possibly earlier planting dates, while a negative AO in the spring could delay planting by several weeks. Summer mean temperatures are coolest across the domain when the AO is in a negative episode and predominantly warmest when the AO is neutral, except in the far northwest and western edge of the domain. An AO neutral episode in summer may provide greater chance of heat stress on crops (and the possible need for compensative irrigation), while cooler temperatures with a negative AO during the summer may inhibit temperatures needed for full crop development potential. Fall temperatures are coldest across the domain except for North and South Dakota when the AO is negative (possibility for earlier frosts) and warmest when the AO is in a neutral episode (better dry-down conditions with little delay in harvest dates).

4.2.2. Average observed precipitation

The AO results in statistically significant precipitation relationships predominantly located over the central portions of the domain during the spring and the periphery of the domain during the fall. During the spring, precipitation is highest during a neutral AO across the central part of the domain (roughly Minnesota, Wisconsin, west-central Michigan, Iowa, southeast Nebraska, and northwest Missouri), which may lead to delayed planting due to increased soil moisture and soil compaction that inhibits field work days. The least amount of precipitation occurs during a negative AO in the aforementioned states. ANOVA of summer precipitation by AO episode results in only two of 106 CDs having noteworthy relationships. Fall precipitation is influenced by the AO predominantly during

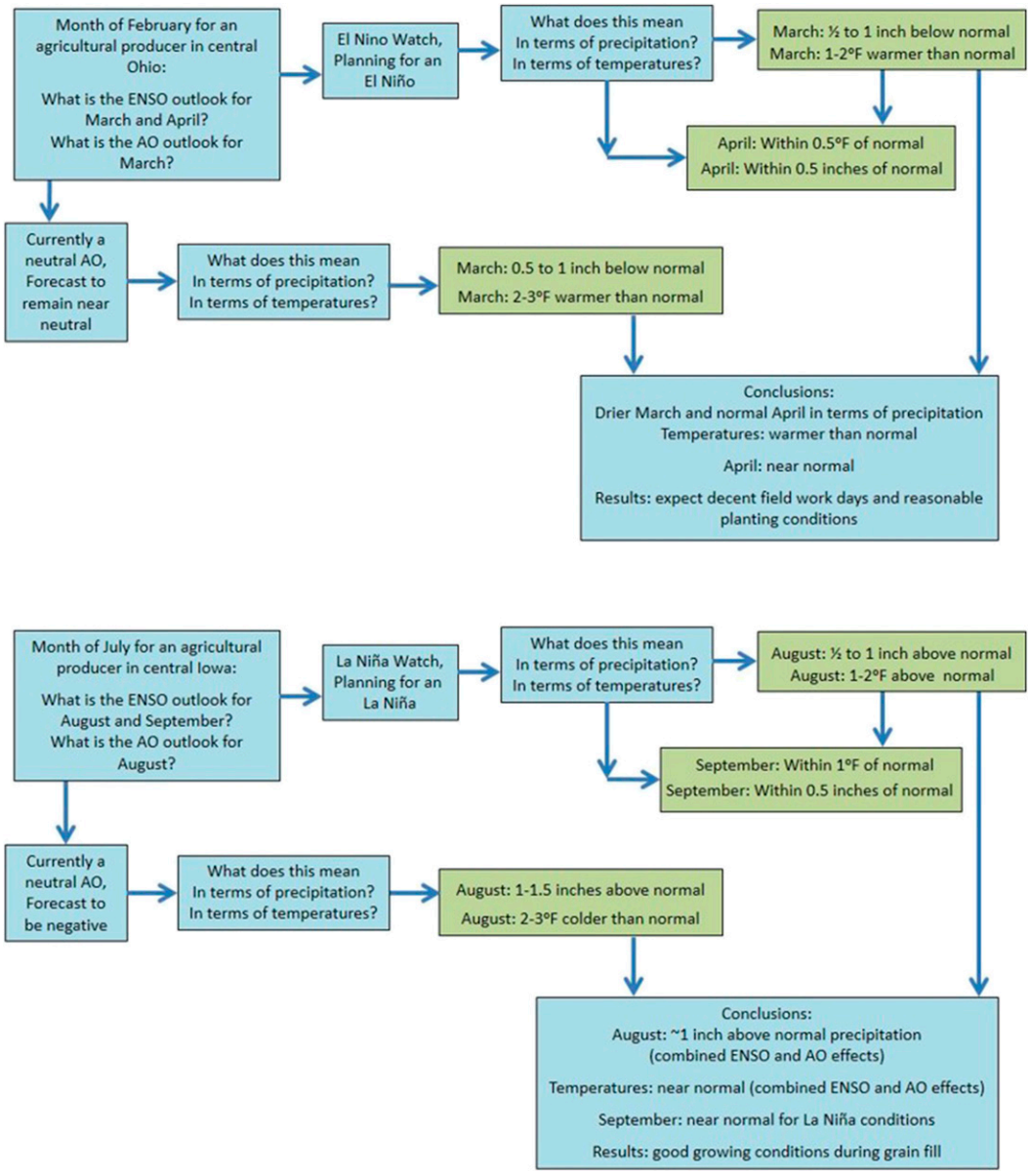


Figure 9. A flowchart presenting an example of the agroclimatic decision-making process that can be adopted using the information available from the ENSO and AO climatology. The top chart highlights a springtime decision-making scenario and the bottom chart highlights a midgrowing season scenario. Historic oceanic Niño index data can be found online (at www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml).

positive AO episodes and negative AO episodes, with the wettest and driest conditions nearly opposite of each other. Western North Dakota and the far north-central region of the domain are driest in fall when the AO is positive (more suitable for timely crop dry down and harvest) and wettest when the AO is neutral

(delayed dry down and harvest). Those climate divisions in Indiana and Ohio near to (Ohio CDs 4 and 5) and bordering the Ohio River are wettest during a positive AO episode (delayed dry down and harvest) and driest in a neutral AO episode (timely crop dry down and harvest).

5. Conclusions

Climate change projections indicate shifts in regional/global climate and increased climate variability. This ENSO and AO climatology explores the weather and climate information applicable to producers in the U.S. Corn Belt/north-central region that will be implemented into a decision support tool for agricultural producers to make more informed agronomic decisions. Climate variability in the form of precipitation and mean temperature is analyzed for each teleconnection across the U.S. Corn Belt with analysis completed for historic detrended corn yield time series down to the climate division/crop-reporting district level. ENSO and AO are studied because of the temporal impacts of each teleconnection. It has been noted that ENSO impacts weather over several months, whereas AO impacts weather patterns for several weeks. No gridded or reanalysis datasets are used in this study to maintain the integrity of historically observed weather data and the agricultural producers preference to utilize station data rather than gridded products. Findings of significance occur from single climate divisions/crop-reporting districts to subregional (i.e., smaller regions within a 12-state domain) and near-regional spatial scales.

This climatology explores the common climatological variables of mean temperature and precipitation while also exploring extreme events. Analyzing two temporally different teleconnections and finding similar, yet unique, feedbacks highlight the importance of understanding climatological feedbacks across the Corn Belt. ANOVA of ENSO and AO episodes by climate division shows the significance (or nonsignificance) of shifts in temperature and precipitation patterns as associated with ENSO and AO with AO impacts emerging more frequently (e.g., by month) throughout the year in this analysis. Previously discussed studies tend to highlight seasonal changes. ANOVA of extreme events ($T_{\max} \geq 90$°F, $T_{\max} \leq 32$°F, $T_{\min} \leq 32$°F, Prcp ≥ 0.1 in., and Prcp ≥ 1.0 in.) by ENSO and AO episodes provides similar results. These findings show a need for more detailed information on the subregional spatial distribution of ENSO and AO impacts across the Corn Belt rather than a general state or regional application of findings that appear too broad in scope or value for agronomic decision-making.

The most significant impacts of ENSO and AO (according to ANOVA) occur during the spring, fall, and winter months, which lie outside the primary months of the production/growing season (April–October), suggesting indirect impact to crop production/yield. Correlation of each teleconnection and episode across different time frames (April–June, June–August, and April–October) to historic detrended yield time series at crop-reporting district level shows that the AO affects historic yield (either positively or negatively). The consistent relationship with AO is that the more positive the AO phase in spring, the higher the yield. For summer and the growing season, the more positive the AO phase, the lower the yield, and the more negative the AO phase, the higher the yield. Evaluation of historic detrended yield time series above or below trend when grouped by ENSO episodes agrees with

prior studies in that yields are historically greater than average during El Niño years and less than average during La Niña years. Historic yields when binned by the average ENSO episodes during the growing season results in similar findings. The average AO episode during the growing season shows inconclusive results due to a majority of seasons being in a neutral episode. While the quantitative yield anomalies found in this climatology are also dictated by agronomic practices such as planting dates, seed characteristics, and technology, it is felt that the general trends of above or below normal yields based on identified weather conditions could be considered in the decision-making process. Therefore, while ENSO or AO signatures may not translate or oftentimes not standout as the dominant drivers for the quantitative statistically significant anomaly, we assert the qualitative trends could still be useful for the agronomic decision-making at local scales. The monthly frequency of extreme temperatures and precipitation when correlated to historic, detrended yield time series demonstrate that the month-specific teleconnection episode and impacts to daily rainfall and temperature are important to production as well and can be of value in decision-making.

As part of the U2U project, the goal of this climatology is to investigate the hydroclimate of the U.S. Corn Belt. The data herein are currently being developed into an online decision support tool for cereal producers and other applied users so that they will be able to make more informed production decisions in the light of climate variability and change. The climatology by design is simple in scope (averaging of observed weather variables, using only 30 years of weather, climate, and crop data and basic statistical analysis) so that applied users can understand and use the data. This climatology is also intended to convey the importance of understanding spatial and temporal relationships of teleconnections such as ENSO and AO and how they impact agroclimatic patterns affecting yield potential in a growing season. It is clear through the different spatial and temporal agroclimatic impacts of AO episodes (broad in scope for mean temperatures and more focused into subregions of the domain for precipitation) and ENSO episodes (impacts are more concentrated across the central portions of Corn Belt) on seasonal mean temperatures and precipitation that further investigation could benefit from analyzing additional teleconnections that influence midlatitude weather regimes so that an optimal understanding of climate variability can be communicated to producers. Findings further show that the AO imparts greater variability (mean observed precipitation and average observed mean temperature) between episodes than ENSO. The findings herein and planned analysis with development into an online tool will allow for better mitigative and adaptive efforts by producers that will help maximize yield as the world shifts toward climate uncertainty. The primary goal of this paper is to develop the data and climatological framework that can be translated into useful information for stakeholders.

The subregional impacts found in the climatology show the need for higher-resolution analysis of ENSO and AO impacts in order to help provide a predictive potential at finer scales (i.e., county level) when the ENSO or AO episode is known in advance. ENSO forecasts and discussions are readily issued by agencies around the world (Zebiak et al. 2015), potentially providing sufficient lead time for users to make informed decisions, provided the forecast is issued in a timely manner and verifies (Takle et al. 2014). Because the AO is a teleconnection influencing weather and climate variability across shorter time

frames, its predictability is less certain and is only forecast about two weeks out. This limits applicability by users to make informed decisions for the longer term but still provides applicability in short-term decision-making such as increased likelihood of a frost or freeze event or episodes of heat stress over the next 14 days. With the goal of this climatology and DST to result in more effective decision-making by the user in light of climate variability and change by using existing data and models (www.agclimate4u.org), the uncertainty associated with timely forecast issuance for climate variability indices is not reduced or removed through this climatology and associated DST. Rather the climatology and DST is developed so that climate variability is better understood by users to make more informed decisions with current weather and climate data when it is made available.

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References

Adams, R., C. Chen, B. McCarl, and R. Weiher, 1999: The economic consequences of ENSO events for agriculture. *Climate Res.,* **13,** 165–172, doi:10.3354/cr013165.

Arbuckle, J. G., and Coauthors, 2013: Corn Belt farmers and climate change: Beliefs, perceived risk, and support for action. *Climatic Change Lett.,* **117,** 943–950, doi:10.1007/s10584-013-0707-6.

Bove, M. C., J. B. Elsner, C. W. Landsea, and X. Niu, 1998: Effect of El Niño on U.S. landfalling hurricanes, revisited. *Bull. Amer. Meteor. Soc.,* **79,** 2477–2482, doi:10.1175/1520-0477(1998)079<2477:EOENOO>2.0.CO;2.

Brunner, A., 2002: El Niño and world primary commodity prices: Warm water or hot air? *Rev. Econ. Stat.,* **84,** 176–183, doi:10.1162/003465302317332008.

Cadson, R., D. Todey, and S. Taylor, 1996: Midwestern corn yield and weather in relation to extremes of the Southern Oscillation. *J. Prod. Agric.,* **9,** 347–352, doi:10.2134/jpa1996.0347.

Climate Prediction Center, 2005a: The ENSO cycle. National Weather Service Climate Prediction Center, accessed 14 November 2014. [Available online at www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensocycle/enso_cycle.shtml.]

——, 2005b: Teleconnection pattern calculation procedures: Arctic/Antarctic Oscillation. National Weather Service Climate Prediction Center, accessed 27 October 2014. [Available online at www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/history/method.shtml.]

Crane, T. A., C. Roncoli, J. Paz, N. Breuer, K. Broad, K. T. Ingram, and G. Hoogenboom, 2010: Forecast skill and farmers' skills: Seasonal climate forecasts and agricultural risk management in the southeastern United States. *Wea. Climate Soc.,* **2,** 44–59, doi:10.1175/2009WCAS1006.1.

Devore, J. L., 2003: *Probability and Statistics for Engineering and the Sciences.* 6th ed. Duxbury Press, 816 pp.

Ellis, S. M., and H. S. Steyn, 2003: Practical significance (effect sizes) versus or in combination with statistical significance (p-values): Research note. *Manage. Dyn.: J. South. Afr. Inst. Manage. Sci.,* **12** (4), 51–53.

Elmore, R. W., 2013: Advances, vulnerabilities, and opportunities for corn: A perspective from Iowa. *Vulnerability of Food Resources to Climate,* D. Niyogi, Ed., Vol. 2, *Climate Vulnerability: Understanding and Addressing Threats to Essential Resources,* Elsevier, 3–15, doi:10.1016/B978-0-12-384703-4.00203-3.

Fuglie, K., 2012: Productivity growth and technology capital in the global agricultural economy. *Productivity Growth in Agriculture: An International Perspective,* K. Fuglie, S. L. Wang, and E. Ball, Eds., CAB International, 335–368.

Goddard, L., S. J. Mason, S. E. Zebiak, C. F. Ropelewski, R. Basher, and M. A. Cane, 2001: Current approaches to seasonal to interannual climate predictions. *Int. J. Climatol.,* **21,** 1111–1152, doi:10.1002/joc.636.

Hansen, J. W., A. W. Hodges, and J. W. Jones, 1998: ENSO influences on agriculture in the southeast United States. *J. Climate,* **11,** 404–411, doi:10.1175/1520-0442(1998)011<0404:EIOAIT>2.0.CO;2.

Hanway, J. J., 1963: Growth stages of corn. *Agron. J.,* **55,** 487–492, doi:10.2134/agronj1963.00021962005500050024x.

Hollinger, S. E., E. J. Ehler, and R. E. Carlson, 2001: Midwestern United States corn and soybean yield response to changing El Niño-Southern Oscillation conditions during the growing season. *Impacts of El Niño and Climate Variability on Agriculture,* C. Rosenzweig, Ed., American Society of Agronomy, 31–54.

Hu, Q., and S. Feng, 2010: Influence of the Arctic Oscillation on central United States summer rainfall. *J. Geophys. Res.,* **115,** D01102, doi:10.1029/2009JD011805.

Kellner, O., and D. Niyogi, 2014: Agroclimatology. *Encyclopedia of Natural Resources: Air,* Y. Wang, Ed., Taylor & Francis. [Available online at www.tandfonline.com/doi/full/10.1081/E-ENRA-120047622#.VFKEn_ldXTo.]

Kravchenko, A. N., and D. G. Bullock, 2000: Correlation of corn and soybean grain yield with topography and soil properties. *Agron. J.,* **92,** 75–83, doi:10.2134/agronj2000.92175x.

Legler, D., K. Bryant, and J. O'Brien, 1999: Impact of ENSO-related climate anomalies on crop yields in the U.S. *Climatic Change,* **42,** 351–375, doi:10.1023/A:1005401101129.

Lindsey, R., 2013: In watching for El Niño and La Niña, NOAA adapts to global warming. National Oceanic and Atmospheric Administration, ClimateWatch Magazine, accessed 21 May 2014. [Available online at www.climate.gov/news-features/understanding-climate/watching-el-ni%C3%B1o-and-la-ni%C3%B1a-noaa-adapts-global-warming.]

Loikith, P. C., and A. J. Broccoli, 2014: The influence of recurrent modes of climate variability on the occurrence of winter and summer extreme temperatures over North America. *J. Climate,* **27,** 1600–1618, doi:10.1175/JCLI-D-13-00068.1.

Mase, A. S., and L. S. Prokopy, 2014: Unrealized potential: A review of perceptions and use of weather and climate information in agricultural decisions making. *Wea. Climate Soc.,* **6,** 47–61, doi:10.1175/WCAS-D-12-00062.1.

Mauget, S. A., and D. R. Upchurch, 1999: El Niño and La Niña related climate and agricultural impacts over the Great Plains and Midwest. *J. Prod. Agric.,* **12** (2), 203–215, doi:10.2134/jpa1999.0203.

McKeown, A. W., J. Warland, and M. R. McDonald, 2006: Long-term climate and weather patterns in relation to crop yield: A mini review. *Can. J. Bot.,* **84,** 1031–1036, doi:10.1139/b06-080.

Meza, F. J., J. W. Hansen, and D. Osgood, 2008: Economic value of seasonal climate forecasts for agriculture: Review of ex-ante assessments and recommendations for future research. *J. Appl. Meteor. Climatol.,* **47,** 1269–1286, doi:10.1175/2007JAMC1540.1.

Montgomery, D. C., E. A. Peck, and G. G. Vining, 2006: *Introduction to Linear Regression Analysis.* 4th ed. John Wiley and Sons, 504 pp.

NCDC, 2014: Transitioning to a gridded climate divisional dataset. National Oceanic and Atmospheric Administration, accessed 4 June 2014. [Available online at www.ncdc.noaa.gov/news/transitioning-gridded-climate-divisional-dataset.]

Negri, D. H., N. R. Gollehon, and M. P. Aillery, 2005: The effects of climatic variability on U.S. irrigation adoption. *Climatic Change,* **69,** 299–323, doi:10.1007/s10584-005-1817-6.

Neilson, R. L., 2012: Corn management for extreme conditions. Corny News Network Articles, Purdue University, accessed 7 July 2014. [Available online at www.agry.purdue.edu/ext/corn/news/timeless/extremecornmgmt.html.]

——, 2013a: When will my corn crop mature? Corny News Network Articles, Purdue University, accessed 7 July 2014. [Available online at www.agry.purdue.edu/ext/corn/news/articles.13/EstCornMaturity-0801.html.]

——, 2013b: Effects of stress during grain filling in corn. Corny News Network Articles, Purdue University, accessed 7 July 2014. [Available online at www.agry.purdue.edu/ext/corn/news/timeless/GrainFillStress.html.]

Niyogi, D., and V. Mishra, 2012: Climate-agriculture vulnerability assessment for the midwestern United States. *Climate Change in the Midwest: Impacts, Risks, Vulnerability and Adaptation,* S. C. Pryor, Ed., Indiana University Press, 69–80.

——, X. Liu, J. Andresen, A. Jain, A. Kumar, O. Kellner, and A. Elias, 2013: Can crop models simulate the ENSO impacts on regional corn yield in U.S. Corn Belt? *2013 Fall Meeting,* San Francisco, CA, Amer. Geophys. Union, Abstract GC33A-1096.

——, ——, ——, Y. Song, A. K. Jain, O. Kellner, E. S. Takle, and O. C. Doering, 2015: Crop models can capture the impacts of climate variability on corn yield. *Geophys. Res. Lett.,* doi:10.1002/2015GL063841, in press.

Phillips, J., B. Rajagoplan, M. Cane, and C. Rosenzweig, 1999: The role of ENSO in determining climate and maize yield variability in the U.S. Cornbelt. *Int. J. Climatol.,* **19,** 877–888, doi:10.1002/(SICI)1097-0088(19990630)19:8<877::AID-JOC406>3.0.CO;2-Q.

Pielke, R. A., Sr., 2013: *Climate Vulnerability: Understanding and Addressing Threats to Essential Resources.* Elsevier, 1570 pp.

Pingali, P. L., 2012: Green Revolution: Impacts, limits, and the path ahead. *Proc. Natl. Acad. Sci. USA,* **109,** 12 302–12 308, doi:10.1073/pnas.0912953109.

Reilly, J. M., Ed., 2002: *Agriculture: The Potential Consequences of Climate Variability and Change for the United States.* Cambridge University Press, 150 pp.

Rosenzweig, C., 2001: Impacts of the El Niño Southern Oscillation on agriculture: Guidelines for regional reanalysis. *Impacts of El Niño and Climate Variability on Agriculture,* C. Rosenzweig et al., Eds., ASA Special Publication, Vol. 63, American Society of Agronomy, 21–30, doi:10.2134/asaspecpub63.c2.

——, and Coauthors, 2012: The Agricultural Model Intercomparison and Improvement Project (AgMIP): Integrated regional assessment projects. *Handbook of Climate Change and Agroecosystems: Global and Regional Aspects and Implications,* ICP Series on Climate Change Impacts, Adaptation, and Mitigation, Vol. 2, Imperial College Press, 263–280.

——, and Coauthors, 2013: The Agricultural Model Intercomparison Improvement Project (AgMIP): Protocols and pilot studies. *Agric. For. Meteor.,* **170,** 166–182, doi:10.1016/j.agrformet.2012.09.011.

Schlenker, W., and M. J. Roberts, 2009: Nonliner temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc. Natl. Acad. Sci. USA,* **106,** 15 594–15 598, doi:10.1073/pnas.0906865106.

Stocker, T. F., and Coauthors, Eds., 2013: C*limate Change 2013: The Physical Science Basis.* Cambridge University Press, 1535 pp.

Takle, E. S., and Coauthors, 2014: Climate forecasts for corn producer decision making. *Earth Interact.,* **18,** doi:10.1175/2013EI000541.1.

Trewin, B., 2007: The role of climatological normals in a changing climate. World Climate Data and Monitoring Program 61, WMO-TD No 1377, 130 pp., accessed 14 October 2014. [Available online at www.wmo.int/pages/prog/wcp/wcdmp/documents/WCDMPNo61.pdf.]

USDA, 2013: Crop production. National Agriculture Statistical Service, accessed 3 June 2013. [Available online at www.epa.gov/agriculture/ag101/cropmajor.html.]

Wright, W., 2012: Discussion paper on the calculation of the standard climate normals: A proposal for a dual system. World Climate Data and Monitoring Program, accessed 14 October 2014. [Available online at www.wmo.int/pages/prog/wcp/wcdmp/documents/Rev_discussion_paper_May2012.pdf.]

Zebiak, S. E., and Coauthors, 2015: Investigating El Niño-Southern Oscillation and society relationships. *Wiley Interdiscip. Rev.: Climatic Change,* **6,** 17–34, doi:10.1002/wcc.294.

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