

Climate impacts and crop responses in US corn and wheat production region

by

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B.S., Heilongjiang Bayi Agricultural University, 2016

M.S., Heilongjiang Bayi Agricultural University, 2019

AN ABSTRACT OF A DISSERTATION

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Abstract

The global impact of climate change on food production poses a critical challenge in sustaining the world's population. Projections of climate demonstrate changes of temperature and precipitation in the future, challenging the security of global food including the US Great Plains and Midwest, which are wheat and maize breadbaskets, respectively. While wheat yields have increased in the US Great Plains over the past several decades, the persisting threat of climate change has led to stagnation and even collapse in some states. Conversely, maize yields in the US Midwest have exhibited a consistent upward trend since the 1930s. However, understanding the driving forces behind the changes in crop yields remains an open empirical question. This dissertation is structured to address three primary objectives: 1) identifying the impact of compound climate extreme on wheat yields; 2) determining the contributors of maize yield trends; and 3) quantifying the adaptation of maize hybrids to climate change.

The study employs an array of datasets encompassing long-term surface climate, regional satellite observations, crop varieties/hybrids, crop phenology, yields, and field management practices (e.g., planting densities). Both statistical- and crop progress- based models (Hybrid-Maize model) were the main approaches used in this study. Firstly, statistical modeling of winter wheat yield variations indicated that compound hot-dry-windy (HDW) events are main drivers resulting in yield losses in the past four decades (1982-2020), accounting for a 4% yield reduction per 10 hours of HDW during the growth period from heading to maturity. Furthermore, climate change has significantly increased HDW events, which are associated with yield reduction rates of up to 0.09 t ha^{-1} per decade. Additionally, HDW variations are atmospheric-bridged with the Pacific Decadal Oscillation. We quantify the “yield shock”, which is spatially distributed, with the losses in severely HDW-affected areas, the same areas affected by the Dust Bowl of the 1930s.

Secondly, analysis of drivers of maize yield trends indicated that surface solar radiation (SSR) shows only a weak contribution to maize yield gains because SSR did not change significantly in the US Midwest in the past four decades. Conversely, non-environmental factors (e.g., genetic and management improvement) are the main drivers of yield increases, supported using the Hybrid-Maize model which is a process-based model. Finally, we analyze an extensive dataset from maize hybrid field performance tests conducted in five maize-producing states in the US Corn Belt between 2000 and 2020. We found a consistent increase in maize yields under varying environmental stress levels, with an average of $0.15 \text{ t ha}^{-1} \text{ yr}^{-1}$. We also found that breeding efforts have enhanced the resilience of maize yields to VPD, with an average increase of $0.06 \text{ t ha}^{-1} \text{ kPa}^{-1} \text{ yr}^{-1}$. However, even when cultivating current hybrids under high-emission shared socio-economic pathways (SSP5-8.5) climate scenarios, additional increases in VPD caused a 4% reduction in maize yield relative to averaged historical yield losses. This dissertation explored the impact of climate change on winter wheat and maize yield variability and trends, highlighting the adaptation of winter wheat crop varieties and corn hybrids in the US breadbasket. These insights offer valuable considerations for farmers and agronomists, emphasizing the need for proactive measures to adapt to the challenges posed by climate change in the future.

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Chapter 1 - U.S. winter wheat yield loss attributed to compound hot-dry-windy events

Haidong Zhao, Lina Zhang, M. B. Kirkham, Stephen M. Welch, John W. Nielsen-Gammon, Guihua Bai, Jiebo Luo, Daniel A. Andresen, Charles W. Rice, Nenghan Wan, Romulo P. Lollato, Dianfeng Zheng, Prasanna H. Gowda, Xiaomao Lin (*Published in Nature Communications*)

Abstract

Climate extremes cause significant winter wheat yield loss and can cause much greater impacts than single extremes in isolation when multiple extremes occur simultaneously. Here we show that compound hot-dry-windy events (HDW) significantly increased in the U.S. Great Plains from 1982 to 2020. These HDW events were the most impactful drivers for wheat yield loss, accounting for a 4% yield reduction per 10 hours of HDW during heading to maturity. Current HDW trends are associated with yield reduction rates of up to 0.09 t ha⁻¹ per decade and HDW variations are atmospheric-bridged with the Pacific Decadal Oscillation. We quantify the “yield shock”, which is spatially distributed, with the losses in severely HDW-affected areas, presumably the same areas affected by the Dust Bowl of the 1930s. Our findings indicate that compound HDW, which traditional risk assessments overlooked, have significant implications for the U.S. winter wheat production and beyond.

Keywords: hot-dry-windy events, winter wheat, U.S. Great Plains, yield shocks

1. Introduction

Despite continued increase worldwide, wheat yields in some parts of the world have stagnated and even collapsed (M. Lin & Huybers, 2012; Ray, Ramankutty, Mueller, West, & Foley, 2012), raising serious concerns associated with sustainable production in the face of climate change (Alexandratos & Bruinsma, 2012; Field, Barros, Stocker, & Dahe, 2012). Recent studies have examined the risks of single, extreme climatic events in causing yield losses (Porter & Semenov, 1999), such as drought (precipitation-based) (Porter & Semenov, 2005; Richter & Semenov, 2005), heat waves (Lobell, Sibley, & Ortiz-Monasterio, 2012), or cold events (Tack, Barkley, & Nalley, 2015). There are also studies that have examined the effects of multiple extreme climate events on agricultural yields in conjunction, but not as compound events (Lesk et al., 2021; Vogel et al., 2019). However, events that combine adverse climate variables, not all of which are necessarily extremes, could lead to more significant impacts on wheat yields than any single type of shock acting alone. The Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate Extremes (SREX) in 2012 (Field et al., 2012) first defined compound events as “(1) two or more extreme events occurring simultaneously (spatial) or successively (temporal), (2) combinations of extreme events with underlying conditions that amplify the impact of the events, or (3) combination of events that are not themselves extremes but lead to an extreme event or impact when combined.” This definition has recently evolved into “a combination of multiple drivers and/or hazards that contribute to societal or environmental risk” (Leonard et al., 2014; Raymond et al., 2020; Zscheischler et al., 2018). With respect to such compound events, few efforts have evaluated their impacts, and most of the existing research has focused on changes or distribution shifts of crop water supply and temperature. The simultaneous combination of high temperature, low relative humidity, and high wind events in the near-surface atmospheric

boundary layer [hereafter referred to as hot-dry-windy events (HDW)] poses a particular climate risk to global crops (Feng, Hao, Zhang, & Hao, 2019; Lesk et al., 2021; Ridder et al., 2020), especially in the United States Great Plains that experience irregular, hot, dry, and windy conditions coupled together (Romm, 2011; Zhu & Burney, 2021; Zscheischler & Seneviratne, 2017). For example, a decade of drought occurred in the 1930s in the U.S. and this decadal drought desiccated much of the agricultural land surface of the U.S. Great Plains causing one of the most severe environmental and social catastrophes in the world, namely the 1930s “Dust Bowl” (Schubert, Suarez, Pegion, Koster, & Bacmeister, 2004). The Dust Bowl area is the world’s largest, contiguous land mass with low rainfall (Tack et al., 2015) and is the U.S. heartland for winter wheat production. In this agricultural area, the spring-summer HDW events have statistically increased since the 1950s (Romm, 2011; Tavakol, Rahmani, & Harrington Jr, 2020). However, to our knowledge, the consequence of HDW with respect to hard winter wheat production in the U.S. has not yet been assessed.

Previously, the standard practice in determining climate-crop relationships for winter wheat has been to partition its growth stages by fall, winter, and spring calendar seasons (Tack et al., 2015; Zhu & Burney, 2021). The use of such fixed calendars with subsets of seasons or months, however, might potentially misrepresent the climate-crop association (Butler & Huybers, 2013) due to varied local phenological timings, stage-specific crop sensitivity to adverse weather, differences in crop management, and spatially-variable regional climates (Porter & Semenov, 2005). Hence, unlike most studies using annual and/or seasonal climate extreme indices, we used climate indices directly derived from the winter wheat life cycle, which we divided into three phenological stages: planting to jointing (PT-JT), jointing to heading (JT-HD), and heading to maturity (HD-MT) based on phenological data (Figures A.1 and 2; and Table A.1). We digitized

most of these phenological data from hard copies of Winter Wheat Performance Tests Reports or scanned imageries across South Dakota (SD), Nebraska (NE), Colorado (CO), Kansas (KS), Oklahoma (OK), and Texas (TX) in the U.S. Great Plains. The subdivision of the growing season based on crop phenology has a biological meaning as PT-JT represents wheat conditions associated with crop establishment, tillering, and winter survival; JT-HD encompasses a large portion of the critical period for grain number determination; and HD-MT corresponds to both the later portion of grain number determination and the majority of the individual grain weight determination (Dupont et al., 2006).

Crop growth and development as well as yield formulation showed a threshold response to climate variation (Porter & Semenov, 2005) including temperature (Asseng et al., 2015; Porter & Semenov, 1999; Stone & Nicolas, 1995), atmospheric humidity (Xue, Weiss, Arkebauer, & Baenziger, 2004), and ambient wind speed (Berry et al., 2000). We defined hourly HDW events as the hours of co-occurrence of temperature ($T \geq 32^{\circ}\text{C}$), relative humidity ($\text{RH} \leq 30\%$), and wind speed ($U \geq 7 \text{ m s}^{-1}$ at 10 m above the ground, as described in previous studies (Lydolph & Williams, 1982; Tavakol et al., 2020). Crop water stress can be due to excessive loss of water or an inadequate soil water supply (Kramer, 1969). For the former, the main cause is a rapid transpiration of the crop, often occurring in less than a few hours due to atmospheric dryness. Specifically, low atmospheric humidity creates a demand that pulls water from plants and causes excessive transpiration which induces a water deficit in the crop that restricts growth. The latter, however, can result from long-term precipitation deficits or inadequate soil moisture over a period of several days (Barrs, 1968). In recent studies (Hamed, Van Loon, Aerts, & Coumou, 2021; Ribeiro, Russo, Gouveia, Páscoa, & Zscheischler, 2020), the main focus was on the relationship between crop yields and inadequate soil water supply determined by precipitation or soil moisture.

However, some studies have indicated that atmospheric dryness, a rapid water demand occurring in less than a few hours, impacts plants severely even if soil water supply is adequate (Kimm et al., 2020) and concluded that low relative humidity in the atmosphere can be more important to gauge the ecosystem impacts of dryness (Novick et al., 2016; Shimoda, Terasawa, & Nishio, 2022). In our study, the hot-dry-windy (HDW) combination is a transient and compound extreme event including atmospheric dryness that commonly occurs within several hours. Hence, we used low relative humidity to define a dry event.

We focused primarily on the effects of often overlooked hourly HDW events during HD-MT ($\text{HDW}_{\text{HD-MT}}$), i.e., grain-filling periods on 1982-2020 winter wheat yields in the U.S. winter wheat belt that includes the states of SD, NE, CO, KS, OK, and TX. These states produce nearly all the high-quality hard red winter wheat in the U.S. (Tack et al., 2015).

2. Material and Methods

2.1 Winter wheat county selection

To ensure robust analysis and modeling, county-level yields were collected only for those counties with more than 5,000 acres of harvested hard winter wheat and at least 20 years of available yield data. Accordingly, yield data from 339 counties across six states, i.e., South Dakota (SD), Nebraska (NE), Colorado (CO), Kansas (KS), Oklahoma (OK), and Texas (TX), were used in the study. The county-level hard winter wheat yield data between 1982 and 2020 were obtained from information provided by the United States Department of Agriculture's National Agricultural Statistics Service (USDA-NASS). All yield data in this study were directly taken from survey yields, and the irrigation fraction was less than five percent on average in our study domain (Zhu & Burney, 2021).

2.2 Climate

Hourly climate data of 2-m air temperatures (T , °C) and relative humidity (RH, %), computed from dew point temperature (X. Lin & Hubbard, 2004), and 10-m wind speed (U , m s^{-1}) were obtained from the ERA5-Land dataset from 1982 to 2020. The ERA5-Land is a global atmospheric reanalysis product produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Muñoz-Sabater et al., 2021). The Centre recently has significantly improved the accuracy of the data for all types of land surface applications. Daily precipitation (mm) data were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) data, which was developed based on observing networks and was commonly used to assess the relationship between precipitation and crop growth and development (Bocinsky & Kohler, 2014; Daly et al., 2008). The county-level climate data were from the nearest grid points to the county centroid. We also used quality-assured station observations from the Met Office Hadley Centre's global sub-daily station dataset (HadISD) (Dunn, Willett, Morice, & Parker, 2014) to verify the spatial distribution of annual HDW during the heading to maturity stage (Figure 1.1). The climate dataset sources are listed in Table A.4.

2.3 Phenology

The phenological data included planting dates from 230 experimental stations and harvesting dates from 186 experimental stations (Figure A.2a,d). There were three stations in Texas documenting the heading dates (Figure A.2c). The maturity dates were inferred from dates 14 days prior to harvesting dates (Robertson, 2004) for all county-years. Wheat jointing and heading dates were estimated using the accumulated GDD required for winter wheat maturity (Peairs, 2010). In

each county-year combination, we partitioned the life cycle of winter wheat into three phenological stages: planting to jointing (PT-JT), jointing to heading (JT-HD), and heading to maturity (HD-MT) (Tables A.1 and A.5; Figures A.1 and A.2).

2.4 Model development

We used a linear mixed-effects model to examine the impacts of climate indices including HDW (hours), freezing days (Frez, days), extreme degree days (EDD, °C days), and precipitation (Prcp, mm) (Figure A.1). The model with site- and year- fixed effects was used to estimate the impacts of climate indices on yields:

$$Y_{i,t} = f(W_{i,t}; \beta_{env}) + c_i + y_t + \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ is the yield at county i in year t . The $f(W_{i,t}; \beta_{env})$ represents the effects of county-specific weather ($W_{i,t}$) in either standard units or original units on yields. Two control predictors are a county-specific vector (c_i) to account for time-invariant spatial heterogeneity and a time-fixed effect vector (y_t) to control yield improvements and/or changes in crop breeding technologies and innovations in crop production practices over time (Figure A.8). $\varepsilon_{i,t}$ is the random error term. The error terms $\varepsilon_{i,t}$ might be heteroskedastic and autocorrelated in year and county domains. Therefore, two-way clustering standard errors (SEs) (Cameron, Gelbach, & Miller, 2011) were implemented to consider the effects of heteroskedastic and autocorrelation in estimating coefficients in Eq. (1). This adjusted standard error leads to more conservative adjusted p-values (p_{adj}) (Tables A.2 and A.3) that we used. Models that logarithmically transformed yields were also tested, and all the results were similar or consistent when using logarithm yields rather than original yields. Our preferred specification used yields because this model had more explanatory power and more normally distributed residuals.

To directly compare the yield sensitivity to climate indices, we standardized the original climate data as “standardized anomaly” (also known as z-score) by subtracting the mean and then dividing by one standard deviation. This transformation achieved the standardized regression coefficients and can be used to explain sensitivities with respect to individual climate indices (referred to as ‘per standard unit’) (Ettinger et al., 2020), and is also widely used to assess the impacts of excessive rainfall on maize yields (Li, Guan, Schnitkey, DeLucia, & Peng, 2019). In addition to the modeling with standardized predictors (Figure 1.2a and Table A.2), climate indices without any data transformation were also used to fit the model for straightforward interpretation on their natural scales (Table A.3).

2.5 Yield sensitivity

The yield sensitivity was reported based on phenological stages ($p = 1, 2$, and 3 for PT-JT, JT-HD, and HD-MT stages, respectively) (Figures A.1 and A.2) for each county-year, representing a life cycle of winter wheat. The weather function is defined as follows:

$$f(W_{i,t}; \beta_{env}) = \sum_{p=1}^2 \beta_{1,p} Frez_{i,p,t} + \sum_{p=2}^3 \beta_{2,p} EDD_{i,p,t} + \sum_{p=1}^3 (\beta_{3,p} Prcp_{i,p,t} + \beta_{4,p} Prcp_{i,p,t}^2) + \beta_5 HDW_{i,t} \quad (2)$$

where *Frez* measured the exposure days where the minimum temperatures were below the thresholds (Warrick, 1999). *EDD* referred to the accumulation of degree days over 32 °C (Schauberger, Gornott, & Wechsung, 2017), and *Prcp_{i,p,t}* and *Prcp_{i,p,t}²* accounts for a quadratic polynomial effect for the cumulative precipitation during the phenological phase *p*. *HDW* is accumulated over the HD-MT period. *Frez_{HD-MT}*, *EDD_{PT-JT}*, *HDW_{PT-JT}*, and *HDW_{JT-HD}* were not included in the model due to their infrequent occurrence under actual conditions (less than 5% of the year-county combination). The thresholds selected for specific phenological stages are detailed in Figure A.1. Additionally, we further expanded the model (Eq. 2) to assess the impact of HDW

occurrence on wheat yields during the specific sub-stage of heading to maturity. We partitioned the heading–maturity stage into three sub-stages (i.e., early, middle, and last sub-stages) and statistically estimated the sub-stage specific HDW influence on yields.

Whether or not the compound HDW events amplified the impacts on wheat yields during the HD-MT stage motivated us to compare impacts of individual and compound extreme events on wheat yields. we re-analyzed extreme climate events into individual, bivariate, and trivariate compound events: 1) only hot [H: $T \geq 32^{\circ}\text{C}$ but ($\text{RH} > 30\%$ & $U < 7 \text{ m s}^{-1}$)]; 2) only dry [D: $\text{RH} \leq 30\%$ but ($T < 32^{\circ}\text{C}$ & $U < 7 \text{ m s}^{-1}$)]; 3) only high winds [W: $U \geq 7 \text{ m s}^{-1}$ but ($T < 32^{\circ}\text{C}$ & $\text{RH} > 30\%$)]; 4) compound hot-dry [H&D: ($T \geq 32^{\circ}\text{C}$ & $\text{RH} \leq 30\%$) but $U < 7 \text{ m s}^{-1}$]; 5) compound hot-windy [H&W; ($T \geq 32^{\circ}\text{C}$ & $U \geq 7 \text{ m s}^{-1}$) but $\text{RH} > 30\%$]; 6) compound dry-windy [D&W; ($\text{RH} \leq 30\%$ & $U \geq 7 \text{ m s}^{-1}$) but $T < 32^{\circ}\text{C}$]; and 7) compound hot-dry-windy [HDW: $T \geq 32^{\circ}\text{C}$ & $\text{RH} \leq 30\%$ & $U \geq 7 \text{ m s}^{-1}$]. These classified events are treated separately so that we could evaluate their individual impacts within our statistical model (Eqs. 1 and 2). The impact of climate indices on yields (Figure 1.3) were quantified (Butler, Mueller, & Huybers, 2018; Mourtzinis et al., 2015) by multiplying the yield sensitivity with respect to climate indices in original units (Table A.3) and the trend values of corresponding climate indices (Figure A.9e-h).

2.6 Statistical analysis

All trend values in this study were estimated by ordinary least-square regression, but the statistical significance was tested by Mann-Kendal analysis throughout our study at a 95% confidence level (Wilks, 2011) or otherwise indicated. The Mann-Kendal method can accommodate data that are not normally distributed, and is insensitive to outliers. Because the HDW could be viewed as count data, as an alternative, Poisson regression (Wilks, 2011) was also

used in the HDW trend analysis. The results showed that the p-values from Poisson regression were consistent with the Mann-Kendal method and their trend values were also consistent with the least-square regression (Figure A.6). Finally, linear correlation measures (both the Pearson and Spearman methods) were used to evaluate correlations at the 95% confidence level. We analyzed temporal-spatial correlation between PDO and HDW with 70-year data (1951-2020). To minimize the climate change effects on correlations between PDO and HDW, we used partial Spearman's rank correlation to estimate correlation between the PDO and HDW anomaly by controlling mean temperature (April-June) effects.

2.7 Yield shock drivers

Relative yield change percentage (Y') for county i in year t was calculated as,

$$Y'_{i,t}(\%) = \frac{Y_{i,t} - \frac{1}{5} \sum_{i=t-2}^{i=t+2} Y_i}{\frac{1}{5} \sum_{i=t-2}^{i=t+2} Y_i} \times 100 \quad (3)$$

Here, Y' is relative to the 5-year running mean yield (Y_i), thus removing the interannual variation (Zhu & Burney, 2021). We then defined a yield shock year in each county as a year in which Y' fell below the 25th percentile over total yield years. The concurrent changes in climatic indices, calculated by the difference between the mean during yield shock years and the mean over the whole period (1982-2020) for each county (Figure 1.5b-f), were considered potential climate drivers for yield shocks.

2.8 Robustness checks

To consolidate our analysis, we conducted a series of robustness checks. We first re-calculated HDW events using a total of 36-threshold combinations: 4 temperatures [30, 31, 32, and 33°C] $\times$ 3 relative humidity [25, 30 and 35%] $\times$ 3 wind speeds [6, 7, and 8 m s⁻¹] (Figure A.10). Then, we

assessed the model (Eqs. 1 and 2) for each threshold combination. Results showed that the sensitivity of wheat yield to HDW events was $-0.09 \text{ t ha}^{-1} (10 \text{ hours})^{-1}$ on the average of these 36 combinations, ranging from -0.06 to $-0.13 \text{ t ha}^{-1} (10 \text{ hours})^{-1}$ (Figure A.11). The averaged HDW effect is equal to the result we showed (Figure 1.2a). This result indicates that the threshold we used can represent an averaged-level HDW effect.

To increase the confidence of HDW influence on wheat yields, we used both the quadratic temperature and the temperature bins' model (Supplementary Text 4). We found that including temperature bins' variables during three phenological stages provides an explicit nonlinear turning point of temperature (i.e., 27°C during PT-JT, 29°C during JT-HD, and 32°C during HD-MT periods) but it did not offset the parameter estimate for HDW impacts in the model (Figure A.12). Specifically, yield sensitivity derived from model of Eqs. 1 and 2 is slightly lower than the sensitivities in the quadratic temperature model and slightly larger than that in the temperature bins' model (Figure A.12b).

3. Results and Discussion

3.1 HDW trends

We found that the main, annual HDW-affected areas occurred in southwest Kansas and the panhandle areas of Oklahoma and Texas in the U.S. (Figure 1.1a red and gray boundaries). These frequent HDW-affected areas were also verified by independent climate observing stations (Figure 1.1b) (Supplementary Text A.2 and A.3). More importantly, the majority of the upward $\text{HDW}_{\text{HD-MT}}$ trends at county levels were statistically significant and were located inside the area above the 75th percentile of annual $\text{HDW}_{\text{HD-MT}}$ (Figure 1.1a). Both the frequent, annual HDW-affected area and the locations with the greatest upward $\text{HDW}_{\text{HD-MT}}$ trend from 1982 to 2020 were the same as

the Dust Bowl-affected locales of the 1930s (Egan, 2006; Schubert et al., 2004) (Figure 1.1b). Such averaged spatial patterns and increasing trend patterns of HDW were consistent with limited, individual station observations from 1982 to 2020 (Figures A.3 and A.4).

Upward trends in all relevant individual extreme climate events (Figure A.5) increased as did the frequency of occurrence of HDW_{HD-MT} for most of the counties across all six states (Figure 1.1a and Figure A.6). Increased trends of HDW_{HD-MT} were statistically significant in the most HDW-affected areas at a rate up to 8 hours per decade (Figure 1.1a). A partial correlation analysis conducted to examine the most critical factor modulating the occurrence of HDW, suggests that high temperature events are a major control variable (Figure A.7).

3.2 HDW impacts on wheat yields

To assess impacts of HDW and single-variable climate extremes on wheat yield variability at different phenological stages, a linear mixed-effects model (Peng & Lu, 2012) was constructed for climate-crop interaction mechanics including freezing days (Frez, days), extreme degree days (EDD, °C days), precipitation (Prcp, mm), and HDW (hours) (Figure A.1) in the U.S. winter wheat belt (Porter & Semenov, 2005; Warrick, 1999). In the following, standardized climate indices (Pendergrass et al., 2020) are referred to as ‘standard units’ to explain their effects on yields (Figure 1.2a and Table A.2). The linear mixed-effects model was also tested with untransformed climate indices in their original units (Table A.3) to directly interpret impacts using their natural scales (see Methods for model equations and details). The results showed that 59% of the variation in yields can be explained by climate indices ($r^2 = 0.59$). HDW_{HD-MT} significantly dominated yield variability with a 3.5% yield loss per standard unit or a 4% yield loss per 10 hours ($p_{adj} < 0.001$), followed by EDD_{JT-HD} (2.2% yield loss per standard unit) ($p_{adj} < 0.001$) (Figure 1.2a and Tables

A.2 and A.3). Next, we compared impacts of individual, bivariate, and trivariate compound events on yields. We found that hot (H) and compound hot-windy (H&W) did not significantly impact wheat yields, nor did the windy (W) and compound (D&W) events but yields were significantly reduced when the compound hot-dry (H&D) event occurs (Figure 1.2c). Interaction of high temperature and dry events reduces the storage capacity of the wheat grain by decreasing the number of cells, starch granules, the duration of cell division, and dry matter accumulation (Nicolas, Gleadow, & Dalling, 1984). Importantly, we found that HDW events show the largest negative influence on wheat yields (Figure 1.2c). Dry winds accompanying high temperature damage plant parts that actively and photosynthetically supply the head (e.g., the flag leaf in wheat), resulting in sterile florets and yield loss (Paulsen, 1994; Smika & Shawcroft, 1980). The impacts of the HDW on wheat yields were further assessed during early, middle, and last sub-stages of the HD-MT stage. We found that the HDW occurrence during the middle sub-stage (around the floral stage) of the HD-MT stage shows the largest influence on yields (Figure 1.2d).

The climate-driven yield trends (Figure 1.3) indicated that single climate extreme events provided negative impacts during phenological stages. HDW_{HD-MT} are associated with a yield loss at a rate of up to 0.09 t ha^{-1} per decade in counties severely affected by HDW_{HD-MT} (Figure 1.3a), suggesting HDW_{HD-MT} were the most influential drivers among those studied associated with yield variability (or loss) in the U.S. winter wheat belt. We further disentangled the total effects of HDW trends into three sub-stages during HD-MT stage and found the severe impacts mainly occur during the middle and last sub-stages (Figure 1.3b). This was generally consistent with the results from heat shock experiments in a controlled environment (Corbellini et al., 1997) where it is concluded that the middle and last sub-stages cause more damage and reduction compared to the early sub-stage of heading to maturity in wheat yield. These severe HDW_{HD-MT} impacts were

spatially located in the same area as the Dust Bowl that occurred in the 1930s (Figure 1.3b).

3.3 HDW teleconnections relations

We think the Pacific Decadal Oscillation (PDO) (Newman et al., 2016), as displayed in Figure 1.4a (color shading), is the atmospheric bridge and provides natural decadal changes in the climate system for these severe HDW_{HD-MT} counties, where they also have high rate of increase during the past forty years (Figure 1.1a, gray colors). A decadal variation of HDW_{HD-MT} signals showed a clear opposite pattern correlated with the PDO ($\rho = -0.65$) from 1951 to 2020 (Figure 1.4b). The 9-year moving average trends (Figure 1.4b) coupled with PDO variations (McCabe, Palecki, & Betancourt, 2004; Newman et al., 2016) suggested that the approximate HDW_{HD-MT} periodicity was longer than 40 years and the HDW_{HD-MT} anomalies mostly fluctuated from -30 to 30 hours during April to June. Such decadal variations of HDW_{HD-MT} provide important implications for U.S. wheat production (Figures 1.2, 1.3, and 1.4).

3.4 Climate-driven yield shocks

To further examine climate impacts (Figure 1.2) using spatial patterns of yield loss, we studied the anomalous behavior of climate indices during yield shock years. We defined a “yield shock” year as a year in which the yield change percentage from a five-year moving average fell below each county’s 25th percentile from 1982 to 2020 inclusive (Figure 1.5a) (see Methods for details). The yield shocks could accordingly be attributed to multiple causative climate indices. Specifically, when a yield shock occurred, we found the main climate indices corresponding with anomalous wheat yields were EDD_{JT-HD} in the central winter wheat belt, diagonally distributed from the panhandles of OK and TX to northeastern KS, and EDD_{HD-MT} in the western areas. Both

of these factors impaired wheat physiological processes critical to reproduction (Zambreski). Excessive $\text{Pr}_{\text{HD-MT}}$ that occurred in the eastern U.S. Southern Great Plains (Lollato, Edwards, & Ochsner, 2017) are associated with yield reductions via soil moisture saturation, waterlogging, disease exposure, and lodging (Mäkinen et al., 2018). Additionally, drought conditions (lower precipitation) are associated with reduced yields in the western and northern parts of the study domain. The most HDW affected areas corresponding to the yield shocks were located in the western U.S. hard winter wheat belt within the same footprint as the 1930s Dust Bowl (Romm, 2011; Schubert et al., 2004) (Figure 1.1 and Figure 1.5f). These anomalous climate indices are most likely the main yield shock drivers across the states and sub-regions, and they support our findings drawn from statistical modeling (Figure 1.2a,b) and provide the spatial sensitivities of winter wheat yields with respect to climate indices including compound HDW events (Figure 1.5).

In this study, we focused on the impacts of HDW along with other main climate indices (Frez, EDD, and $\text{Pr}_{\text{HD-MT}}$) on winter wheat yields. The mechanism of compound HDW exposure, like other climate compound events (Lesk et al., 2021; Raymond et al., 2020; Zscheischler & Seneviratne, 2017), is shaped by extreme climate drivers, agronomic management, and cropping forces, which cause their impacts to be amplified compared to the impacts from those same events (Figure 1.2c) occurring in a univariate way (Lesk et al., 2021; Raymond et al., 2020). Crop vulnerability under HDW exposure can be complicated depending on the wheat varieties not only due to varying phenology, but also inherent genetic heat stress tolerance, water management, and the interaction of other hazards such as pests and diseases at various climate and agronomic scales. This is particularly true for winter wheat systems, given the long growing season that spans three distinct calendar seasons (fall, winter, and spring). To possibly mitigate HDW impacts on wheat yields, the observed HDW trends and impacts in the context of climate change underscore the need to

adapt crop management and genetics to concurrent hot, dry, and windy conditions. The likelihood of the continuation of HDW in the U.S. Great Plains might be ‘atmospheric-bridged’ by the PDO variations. Unlike El Niño and La Niña events (an inter-annual scale), the PDO temporal evolution is marked by a variability of ~50 to 70 years periodicity (MacDonald & Case, 2005). Cropping adaptations might avoid antagonisms among individual stress processes considering compound HDW events could ramp up in the future, especially when their occurrence is modulated with locations (climate), wheat varieties (genetics), and crop management conventions (water and chemical management by local or regional farmers). Thus, further studies are needed to better understand the relationship between compound extreme events and crop yield, including evaluating impacts directly associated with changes of frequency and intensity (i.e., amplitudes) of HDW occurrence during the grain filling period in the U.S. wheat belt. The exploration of the HDW-yield relationship in this study is a first step towards understanding the impacts of potential compound climate extreme events on crop yields, because HDW involves the co-occurrence of three, dependent hazards: unusual heat, drought, and high winds. Our results showed that compound HDW are associated with negative impacts at a scale well beyond which any one of them, being in an extreme state, might have caused on its own.

4. Conclusion

In summary, the severe HDW-affected areas over the past 39 years were similar to the areas affected by the Dust Bowl of the 1930s, and HDW trends during the HD-MT period significantly increased in the U.S. hard winter wheat belt. HDW during the HD-MT stage was the most influential climate index affecting winter wheat yields, and winter wheat productivity has apparently been reduced by increased HDW events during the last 39 years. The statistical

significance of climate extreme indices coincided with the spatial patterns of hard winter wheat yield shocks in the U.S. winter wheat belt. Our results highlight the fact that climate change can significantly impact winter wheat production not only through changes or distribution shifts from single-variable climate extremes such as heat stress, drought events, and cold damage but also more importantly through climate change-related compound climate events, which amplified the impacts on wheat yields. In the context of climate change adaptation, our study shows that the combination of hot, dry, and windy conditions is an under-appreciated risk to food production in the U.S. as well as in the world's winter wheat production areas.

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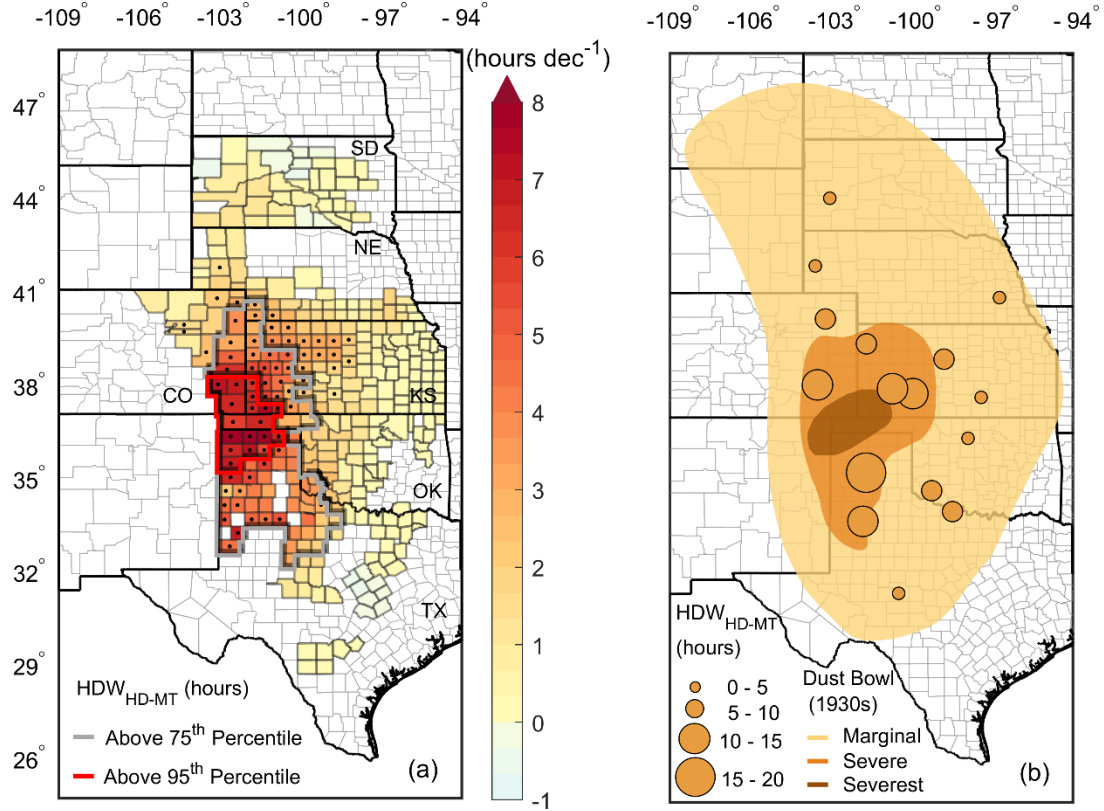


Figure 1.1. Hot-dry-windy events (HDW) trends (hours per decade) during the heading-maturity stage (HDW_{HD-MT}) from 1982-2020 and annual average of HDW_{HD-MT} from climate observing stations. a Annual HDW_{HD-MT} trends for all winter wheat counties; the black dots indicate that HDW trends were statistically significant; and the gray and red boundaries indicate HDW areas above the 75th (>5 hours) and 95th (>15 hours) percentiles of annual averaged HDW_{HD-MT} hours in our study domain including South Dakota (SD), Nebraska (NE), Colorado (CO), Kansas (KS), Oklahoma (OK), and Texas (TX). b Annual averaged HDW_{HD-MT} estimated from climate observing stations; the shading indicates marginal, severe, and severest 1930s Dust Bowl areas.

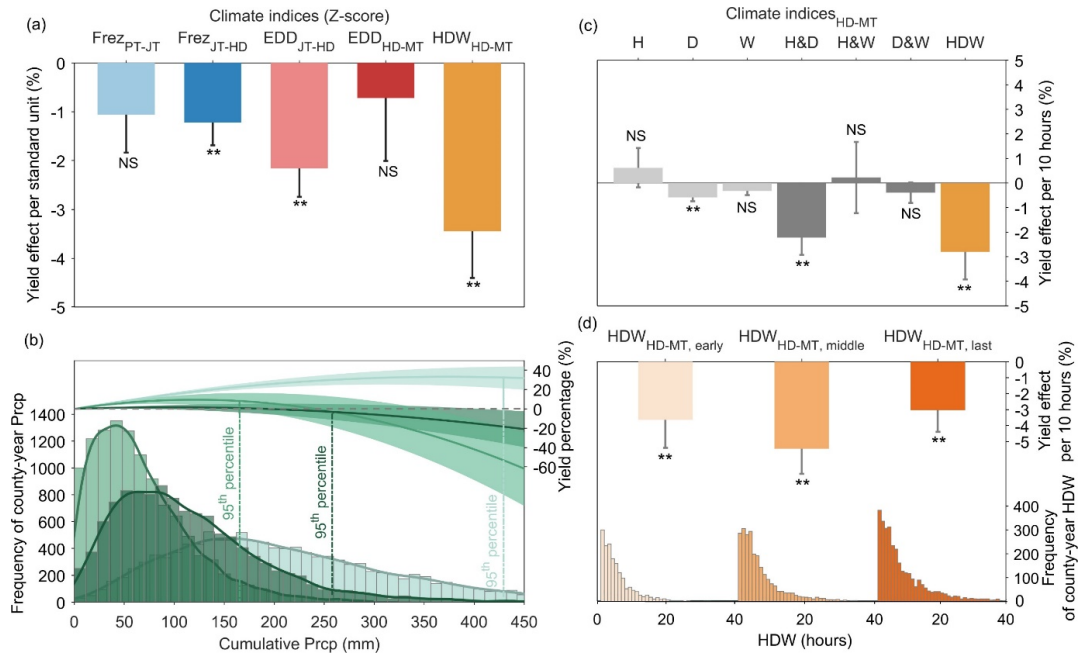


Figure 1.2. Estimated effects of climate indices on winter wheat yields relative to the average yield. a The yield effects are expressed as a percent of area-weighted average yield (grand average = 2.4 t ha⁻¹) across our study domain per standard unit of climate indices (Table A.2). One standard unit of climate indices in their distributions across the study domain is 14.77 days for $Frez_{PT-JT}$, 0.89 days for $Frez_{JT-HD}$, 0.35°C days for EDD_{JT-HD} , 2.81°C days for EDD_{HD-MT} , and 9.03 hours for HDW. Frez stands for freezing; EDD stands for extreme degree days; HDW stands for hot-dry-windy events. PT-JT is the planting to jointing stage; JT-HD is the jointing to heading stage; HD-MT is the heading to maturity stage. b The percent change in yield as a function of the cumulative precipitation (Prpc) by growth stages. The shaded bands represent the one adjusted standard error of regression in the original units (mm). Histograms show the frequency of county-year accumulated precipitation for specific phenological stages. The three vertical lines represent the 95th percentile of Prpc for corresponding phenological stages. c Yield effects of climate indices including individual extreme events (hot, H; dry, D; wind, W), bivariate events (hot-dry, H&D; hot-windy, H&W; dry-windy, D&W), and trivariate compound events (hot-dry-windy, HDW). d Yield sensitivity to HDW (bars) and frequency of county-year HDW (histograms) during early, middle, and last sub-stages from HD to MT stage. The error bars indicate one clustering standard error (SE) and asterisks denote the significance (** $p \leq 0.05$); NS, not significant ($p > 0.05$).

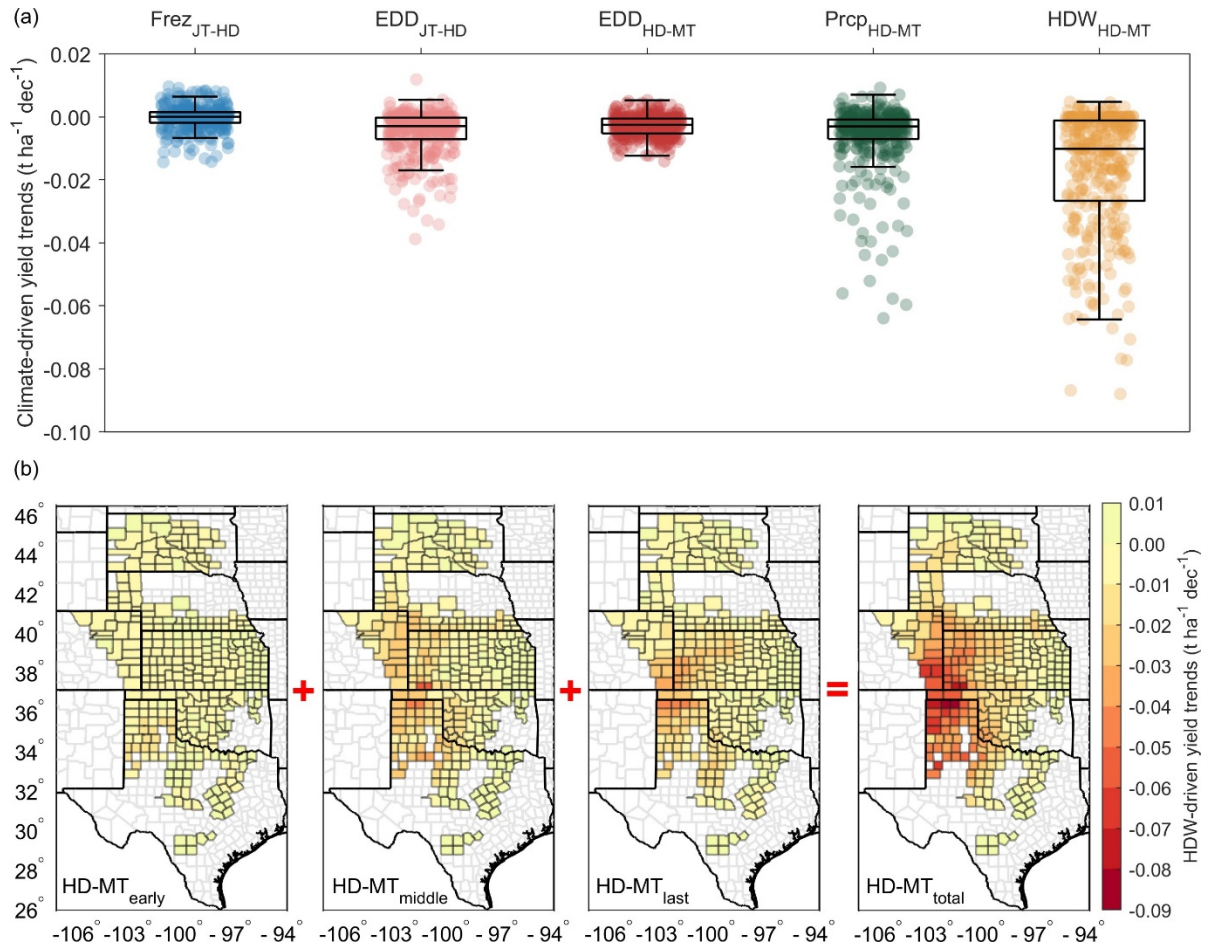


Figure 1.3. Climate contributions to yield trends from 1982 to 2020. a Yield trends associated with freezing days (Frez) and extreme degree days (EDD) during the jointing (JT) to heading (HD) stages, and with the EDD, precipitation (Prcp), and hot-dry-windy (HDW) during the heading (HD) to maturity (MT) stages. Box plots indicate median (middle line), 25th, 75th percentile (box) and 5th and 95th percentile (whiskers). Each dot represents individual county-level climate-driven yield trends. b The spatial distribution of HDW-driven yield trends during early, middle, and last sub-stages of HD-MT stage and total HD-MT stage.

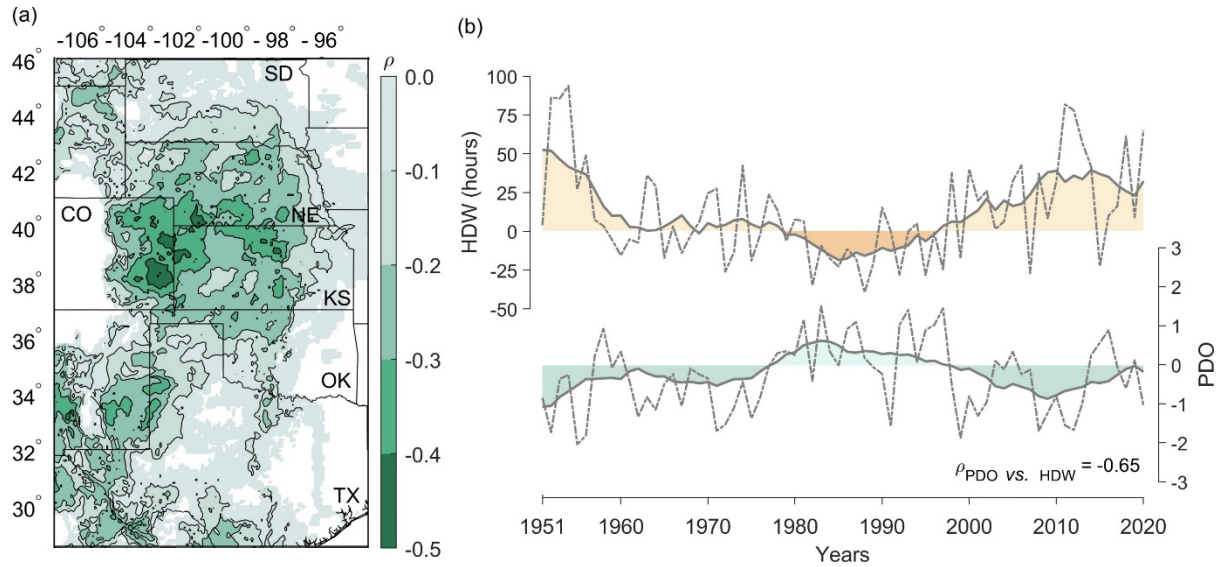


Figure 1.4. The partial Spearman's rank correlation coefficient between Pacific Decadal Oscillation (PDO) and hot-dry-windy (HDW) anomalies (after detrended) during April-June from 1951 to 2020 in our study domains including South Dakota (SD), Nebraska (NE), Colorado (CO), Kansas (KS), Oklahoma (OK), and Texas (TX). a The spatial correlation coefficient between PDO and HDW anomalies where the temperature effect was controlled. b Time series of both PDO and HDW detrended anomalies. The HDW anomaly time series was averaged from the region with above the 95th percentile of annual averaged HDW (Figure 1.1a). Dashed lines represent the raw anomaly (base period for anomaly: 1981-2010) and solid lines with shadowed areas represent the smoothed time series. The smoothing was conducted by a 9-year moving average. ρ refers to correlation coefficient.

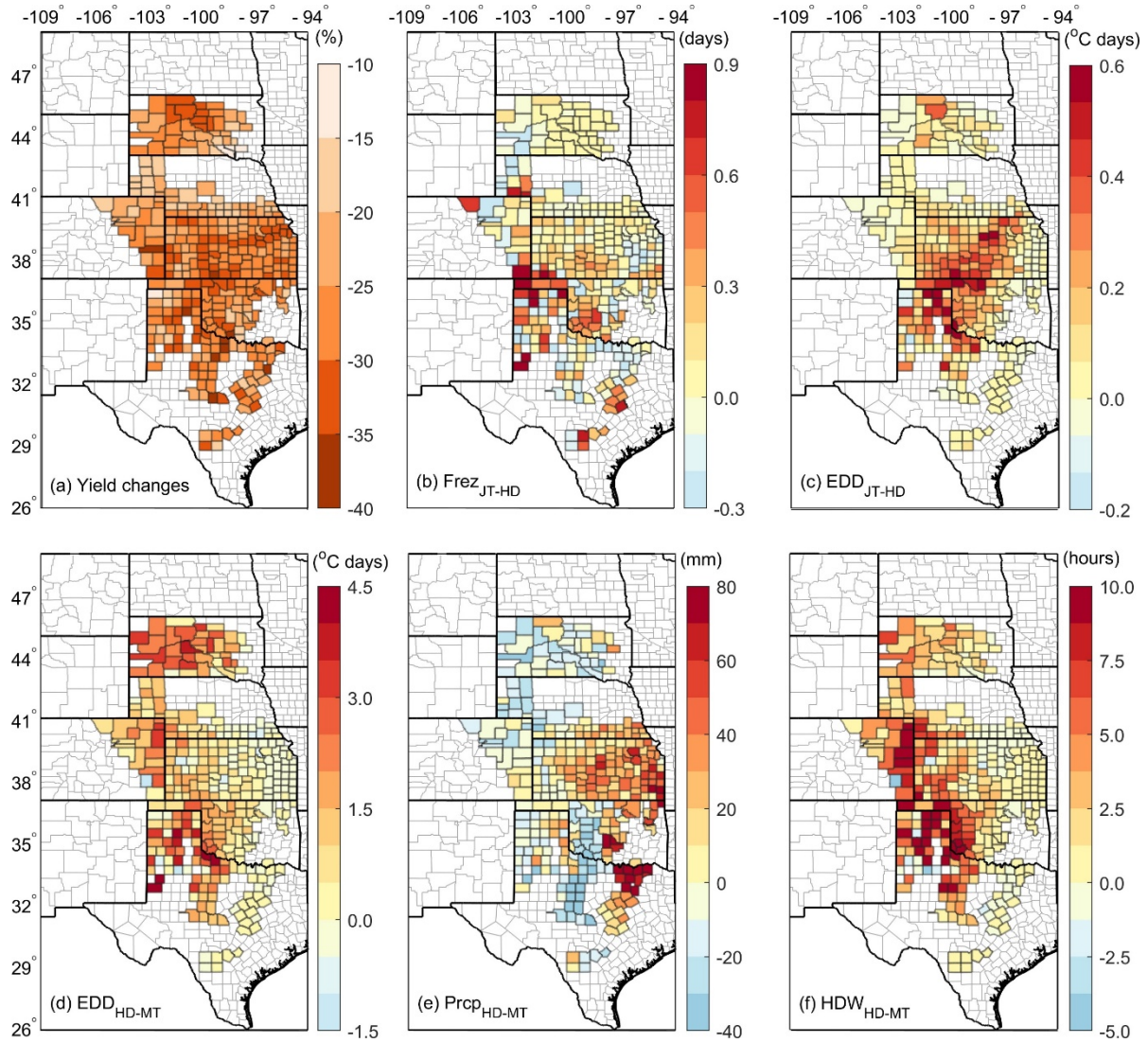


Figure 1.5. Yield shock distributions and a decomposition of yield shock drivers. a Spatial distribution of the county-level yield shock. b-f The concurrent changes in climate indices including freezing days ($Frez$, b), extreme degree days (EDD , c) from the jointing (JT) to heading (HD) stage, as well as including EDD (d), precipitation ($Prcp$, e), and hot-dry-windy (HDW , f) from the heading (HD) to maturity (MT).

Chapter 2 - Nonlinear contribution of surface solar brightening to maize yield gains in the US Corn Belt

(Under revision in Agricultural and Forest Meteorology)

Abstract

Surface solar radiation (SSR) determines the energy and climate of the Earth's biosphere, critically powering photosynthesis, thus contributing to productivity of crops like maize. SSR-use efficiency decreases nonlinearly with incident SSR, particularly at increasing SSR intensities, which are inefficiently converted into crop biomass. Here we analyze trends in SSR using both satellite- and ground-based data, enabling implementation of a process-based Hybrid-Maize model for determination of the contribution of SSR trends to maize yield gains throughout the 1980s to 2020 in the US Corn Belt. We conclude that decadal maize yield gains across the US Corn Belt exhibit nonlinear responses to SSR trends, even when considering an overestimated solar brightening rate of 6.9 W m^{-2} per decade. We show that contributions of SSR changes to maize yield gains are statistically insignificant, whereas non-environmental factors, such as genetics and management practices, account for steady and significant contributions to decadal yield gains.

Keywords: surface solar radiation, maize, yield gains, nonlinear, agronomical management technology

1. Introduction

The United States typically accounts for 40% of the global annual maize production, which represents a significant portion of the global food supply chain. Two primary pathways are recognized to improve maize crop productivity: first, by increasing the total incident solar radiation absorbed by plants during the growing season, and second, by enhancing the efficiency with which plants convert intercepted or absorbed solar radiation into biomass (Kromdijk et al., 2016; Long et al., 2006). Solar energy reaching the Earth's surface through direct and diffuse radiation is known as global surface solar radiation (SSR), and about 50% of the total SSR represents photosynthetically active radiation (PAR), which is responsible for photosynthesis. However, a maximum of 6% of the total SSR is captured, in theory (Zhu et al., 2008, 2010), by photosynthetic organisms responsible for gross primary productivity. Therefore, it is critical to understand the trends and variability in SSR and its contribution to gains in maize yields, especially given that trends in SSR have been found to vary across regions over the past decades (Pinker et al., 2005; Wild, 2009; Yuan et al., 2021).

Maize yields are governed by genetics, environment, management, and their interactions (Hatfield et al., 2018; Hatfield & Walthall, 2015). Environmental factors, e.g., SSR, temperature, precipitation, and soil, are multifaceted and vary both seasonally and regionally. Non-environmental factors, including genetics, breeding technologies (Cooper et al., 2021; Duvick, 2005), and agronomic management (Kucharik, 2008; Sacks & Kucharik, 2011; Sinclair et al., 2019), have been primarily responsible for gains in maize yields during past 80 years. US maize yields have increased steadily from 2-3% per year during 1950s, with a peak of 3-5% during 1960s, a slight reversal of 2-3% between 1970s and 1990s, and more recently less than a 1% per year since 2000 (Kucharik & Ramankutty, 2005). Such yield gains have been attributed to Green

Revolution technologies, including the use of new high yield hybrids, application of fertilizers, novel irrigation practices, and pesticides (Cooper et al., 2021; Duvick, 2005; Kucharik & Ramankutty, 2005). From the 1960s to the 2000s, about 50% of the US maize yield gains has been due to improved management and 50% to advanced breeding technologies (Duvick, 2005; Duvick & Cassman, 1999). Note that without considering interactions between advances in genetics and optimization of management practices under a stationary climate, neither of them could have reached such progress alone.

Climate change interjects a new dimension into this intricate interaction among genetics, management, and the environment (Lobell et al., 2011; Porter et al., 2014). The impact of climate change on crop yields is evident at various scales, with negative impacts being more commonly observed than positive ones (Field et al., 2012), particularly due to increases of extreme temperature and precipitation events (Porter & Semenov, 2005; Porter et al., 2014; Zhao et al., 2022), either alone or in combination. The impact of variations in SSR on maize yields, from a climate change perspective, remain underexplored, even though extensive studies have demonstrated increases of radiation-use efficiency (RUE) through breeding improvements and agronomic management, along with invariant or sufficient SSR above canopies (Messina et al., 2022; Monteith, 1977; Sinclair & Muchow, 1999; Tollenaar & Aguilera, 1992).

A recent study (Tollenaar et al., 2017) used a linearized approach to analyze putative contributions of solar brightening ($0.06 \text{ MJ m}^{-2} \text{ d}^{-1} \text{ yr}^{-1}$) to gains in US maize yield from 1984 to 2013, wherein solar brightening was derived from a satellite- and simulation-based product (Zhang et al., 2009) (NASA POWER, hereafter PWR). Results of the study indicated, under non-water stressed conditions, that solar brightening during the grain-filling period (GFP) contributed 27% to gains in US maize yield, of which 24% was due to a direct effect (i.e., solar brightening) and

the remainder to an interaction between solar brightening and technology. However, the SSR data from the PWR product are not measured directly, but inferred from top-of-atmosphere reflectance using models to correct for atmospheric attenuation (Wild, 2012). Major weaknesses to this approach include limitations of satellite spatial and temporal resolution, challenges of cloud cover interference, limited data validation and calibration, and surface heterogeneity. For example, Pinker et al. (Pinker et al., 2005) found that solar radiation changed -0.5 W m^{-2} per decade for land areas and 2.4 W m^{-2} per decade for oceanic regions from 1982 to 2001. Currently, estimates of solar brightening derived from PWR and their attributions on a continental scale (e.g., North America, China, and Europe) (Wild, 2009, 2012; Wild et al., 2005) remain debatable, especially for small scales (e.g., state and national levels) (Hinkelman et al., 2009; Yuan et al., 2021). Moreover, the potential for either solar brightening or solar dimming to elicit a linear response in maize biomass production, especially at low or high levels of surface solar radiation (Medlyn, 1998), raises further questions. This complexity is accentuated by the distinctly nonlinear relationship at the leaf level between photosynthesis and absorbed PAR (aPAR) (Figure B.1). Earlier studies also showed nonlinear relationships between biomass production and aPAR, resulting in RUE decreasing as a function of aPAR (Beadle & Long, 1985; Edreira et al., 2020; Medlyn, 1998; Thornley, 2002).

Here we conducted extensive simulations with the Hybrid-Maize Model (HMM) (Yang et al., 2004), enabling evaluation of the contributions of observed changes in SSR to maize yield trends under actual climate conditions (Figures B.2 and B.3). All SSR data used in the simulations were from 29 automated weather stations (AWS) located in US Corn Belt from the 1980s to 2020s. The main question of interest here is: to what extent have trends and variations in SSR, either solar brightening or solar dimming, contributed to maize yield gains over the past few decades in the

US Corn Belt, relative to non-environmental factors that can influence maize productivity? These non-environmental contributions to maize yield gains include changes and advances in genetic engineering, plant density (Smith et al., 2015), changes of planting dates (Kucharik, 2008), and their interactions over the past few decades (Figure B.4).

2. Material and Methods

2.1 Data sources

Surface solar radiation (SSR) data as commonly measured by pyranometers were obtained from 29 state automated weather stations (AWS) (Mahmood et al., 2017) across four larger maize-producing US states from the 1980s to 2020: Iowa (1989-2020), Illinois (1990-2020), Nebraska (1984-2018), and Ohio (1986-2020), accounting for 50% of all grain maize grown in the US. The following criteria were used for evaluating and selecting AWS stations: 1) stations should have at least 30 years of consecutive observations; 2) no stations should have two consecutive missing years; and 3) a crop year would be considered as missing in a station record if this station had more than 10% of missing daily data during the maize growing season (May-September). Data quality control and quality assurance (QC/QA) were implemented through QC/QA protocols coded in the *in-situ* dataloggers of AWS and the offline QC/QA algorithms at climate data centers (Table B.1) (Mahmood et al., 2017). Missing daily data were statistically refilled using a regularized expectation maximization (rEM) algorithm based on an iterative imputation technique (Schneider, 2001). We also extracted daily SSR data from the Prediction of Worldwide Energy Resources, National Aeronautics and Space Administration (NASA/POWER) (Zhang et al., 2009) (PWR) for the same period as AWS data. We used the nearest-neighbor interpolations to obtain the daily PWR SSR data to pair with each AWS station. The station-level SSR data from AWS and PWR

were averaged to state-level by weighting harvested maize acres in each county. No more than one AWS station was used from each county in our study. Daily maximum (Tx) and minimum (Tn) air temperature, precipitation (Prcp), relative humidity (RH), and wind speeds were obtained from the gridMET dataset, which was developed based on observation networks and was commonly used to assess the relationship between climate change and crop production (Abatzoglou, 2013). Daily soil moisture (SM) data, 0-30 cm for top-soil and 30-100 cm for sub-soil layers, are from ERA5-Land, a global reanalysis product produced by the European Centre for Medium-Range Weather Forecasts (Muñoz-Sabater et al., 2021). Data on static soil properties at a county level including soil texture and bulk density are extracted from the SSURGO (Chaney et al., 2016).

Maize yields under rainfed (Iowa, Illinois, and Ohio) and irrigated (Nebraska) conditions and harvested acreage at the county-level, and plant density (PD) as well as phenology dates at the state-level were retrieved from reports of the United States Department of Agriculture's National Agricultural Statistical Service (USDA-NASS). Because the NASS Crop Progress Report is released on a weekly basis as a progress percentage, we interpolated the weekly crop progress into daily data using the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) approach (Fritsch & Carlson, 1980). We then estimated the dates of planting, silking, and maturity, and defined them as dates when the crop's progress toward each stage reached 50% across the state. We combined phenological data with daily temperature to calculate maize Growing Degree Days (GDD) (Sacks & Kucharik, 2011) from planting to silking and to maturity. We also aggregated county-level yields to state-level following the SSR aggregation procedure above. Dataset sources used in this study are shown in Table B.2.

2.2 Trend analysis for SSR and yields

We examined station- and state-level trends of SSR for both PWR and AWS datasets over a fixed grain-filling period that was bracketed by the earliest silking and the latest maturity dates for each state from 1980s to 2020. Trends were estimated using the standard least-square linear regression of SSR anomalies. The statistical significance of the computed trends for SSR was determined using a two-sided Student's t test at a 95% confidence level. The SSR anomalies were defined as departing from a base period (1991-2020) except in Nebraska where base period is defined as 1991-2018.

2.3 Simulation of SSR-driven yield gains

To estimate the contribution of observed changes in SSR to maize yield trends under actual climate and management conditions in the US Corn Belt, we conducted two simulated scenarios with observed SSR *versus* constant SSR using the Hybrid-Maize Model (HMM). These two scenarios are 1) Scenario A: we simulated maize yields by Eq. (1) for each year from the 1980s to 2020 at individual stations using observed climate data, initial soil moisture at planting, CO₂ concentrations, planting dates, plant densities, and linearly growing degree days (GDD) from planting to silking and from planting to maturity, which represent gradual changes in hybrids (Figure B.4); 2) Scenario B: we conducted all yield simulations by Eq. (2) with the identical settings as those in Scenario A, but we maintained a constant daily SSR for each year at individual stations, achieved by taking the daily average SSR from the first five years of each station. We used the identical planting dates and plant densities for all stations within a state in a given year, allowing for variations in GDD to accommodate the cultivation of shorter-season hybrids in the cooler regions. Specifically, we assumed that phenological periods remain constant across all stations within a state for a particular year. Subsequently, we calculated GDD using state-level

phenology and station-level air temperature data. We ensured the same trend values of GDD for all stations in a state (Sacks & Kucharik, 2011). For Nebraska, we estimated contributions of changes in SSR to yield trends under irrigated condition as this is the largest irrigated maize-production domain in the US (Cassman & Grassini, 2013). The effects of observed SSR changes on maize yields under actual climate and management conditions were calculated using Eq. (3):

$$Y_{a,c,y} = F_{HMM}(C_{lm_{c,y}}, SSR_{c,y}, SM_{c,y}, CO_{2,y}, M_{c,y}, G_{c,y}, S_c) \quad (1)$$

$$Y_{f,c,y} = F_{HMM}(C_{lm_{c,y}}, \widehat{SSR}_c, SM_{c,y}, CO_{2,y}, M_{c,y}, G_{c,y}, S_c) \quad (2)$$

$$\Delta Y_{c,y} = Y_{a,c,y} - Y_{f,c,y} \quad (3)$$

Where $Y_{a,c,y}$ represents simulated yields ($t\ ha^{-1}$) using the observed SSR in county “c” and year “y”; F_{HMM} indicates the function of HMM; C_{lm} refers to input climate variables; M defines management protocols including planting dates and planting densities; G is GDD (hybrid factors); S refers to static soil properties including soil texture and bulk densities. Y_f indicates simulated yields ($t\ ha^{-1}$) using the constant SSR scenario ($\widehat{SSR}$) in Eq. (2). Thus, ΔY represents yield difference driven by observed SSR changes under actual climate and management conditions. We aggregated ΔY to the state-level by weighting averaged harvested maize acres by Eq. (4), then estimated yield trends (β_{ssr}) by fitting a linear regression between state-level ΔY and years, and calculated the contribution ($\%SSR_s$) of observed changes in SSR to observed maize yield trends (β_{obs}) using Eq. (5):

$$\Delta Y_{s,y} = \sum_{c=1}^n (w_c \times \Delta Y_{c,y}) \quad (4)$$

$$\%SSR_s = \frac{\beta_{ssr,s}}{\beta_{obs,s}} \times 100 \quad (5)$$

Where $\Delta Y_{s,y}$ indicates yield difference at state “s” and year “y”; w_c refers to weighted coefficient by harvested areas, ranged from 0 to 1. We also implemented solar brightening and dimming

conditions by imposing daily increases and decreases of $0.06 \text{ MJ m}^{-2} \text{ d}^{-1} \text{ yr}^{-1}$ to the constant SSR. We then repeated the simulations shown in Eq. (1) for each of these two scenarios to obtain $Y_{a,c,y}$. Next, we calculated impacts of solar brightening and dimming on yield trends using Eqs. (2) to (5).

2.4 Nonlinear response of maize yields to SSR changes

We altered SSR from -20% to 20% in a 1% stepwise manner for each station-year. This approach resulted in both 10,045 simulations (245 station-year climates $\times$ 41 steps) for irrigated conditions (Nebraska) and 28,905 simulations (705 station-year climates $\times$ 41 steps) for rainfed conditions (Iowa, Illinois, and Ohio), respectively. We held management and hybrids to the averages of historical data for each station, and CO_2 concentration was fixed at 412 ppm. We selected a dry subset (41 dry station-year cases) from rainfed conditions when the mean water-stress index ($1 - \text{crop evapotranspiration} / \text{potential evapotranspiration}$) (Yang et al., 2017) in HMM simulations was above the 90th percentile of the local historical distribution from the 1980s to 2020. Similarly, we defined the cold and hot conditions for each station under non-water stress conditions when mean temperatures are below the 10th percentile and above 90th percentile, respectively. In this way, both water stress effects and the station's regionality were removed.

2.5 Non-environmental factor-driven maize yield gains

We used the HMM model to quantify effects of changes in non-environmental factors on maize yields trends. These factors encompassed planting dates, plant densities, and hybrids characterized by GDD. We conducted eight simulations, covering possible combinations of fixed *versus* changing managements for three sets of variables above (details see Table B.3). Among

these simulations, the “Constant in non-environmental factors” run represents a scenario in which three non-environmental factors remained at the levels of their first five-year average, reflecting the effects of climate change on maize yield trends. The “Planting date + Plant density + Hybrid” run was used to estimate the contributions of changes in non-environmental factors to yield trends. The remaining six runs involved combinations of these three variables to isolate their individual effects.

2.6 Data collection for relations between solar radiation and grain yields during GFP

We reviewed recent literature for investigating changes in conversion efficiency of the intercepted photosynthetically radiation (iPAR) into plant matter as well as the partition of this plant matter into grain yields (measured at 0% moisture) during the maize GFP period. Collectively, 65 papers were found, published between 1978 and 2022. From these papers, we were able to extract 107 paired biomasses *vs.* iPAR as well as 897 paired grain yields *vs.* biomass during the GFP period among 72 locations worldwide (Table B.4).

3. Results

3.1 SSR trends

Figure 2.1 compares trends in surface solar radiation during the grain-filling period (SSR_{GFP}) from 29 AWS stations with those based on PWR over the period from the 1980s to 2020. Based on AWS, our examination revealed there exist significant changes in SSR_{GFP} over the short-term segments (10-20 years) with variations among states (Figure 2.1a-d). Specifically, the SSR_{GFP} trend significantly increased in Iowa at an average rate of $1.0 \text{ MJ m}^{-2} \text{ decade}^{-1}$ when the time windows start before 1993 (Figure 2.1a). Conversely, Nebraska and Ohio exhibited decreasing

trends in SSR_{GFP} , averaging rates of $1.2 \text{ MJ m}^{-2} \text{ decade}^{-1}$ (Figure 2.1c,d), which are consistent with a previous study (Irmak et al., 2012). When extending to long-term variations (>25 years), however, we observed no significant changes in SSR across the Corn Belt, except for Illinois, where the SSR_{GFP} trend increased with a rate of $0.4 \text{ MJ m}^{-2} \text{ decade}^{-1}$ on average (Figure 2.1b). In contrast, upon consideration of the PWR datasets, we observed a statistically significant increase in SSR_{GFP} (ranging from 0.6 to $2.0 \text{ MJ m}^{-2} \text{ decade}^{-1}$) in all states, indicating an overestimation of solar brightening relative to the observed data (Figure 2.1a-h). We also showed the station-level trends in SSR_{GFP} using the longest time window (from 1980s to 2020) based on the observed data. Results showed that trends in SSR_{GFP} at 21 of 29 AWS stations were statistically insignificant (Figure 2.1i).

3.2 Contributions of SSR trends to yield gains

The performance of the HMM has been tested in both irrigated and rainfed maize fields throughout the US Corn Belt; a root mean square error of 1 t ha^{-1} was obtained (Figure B.5a) (Yang et al., 2017). We also identified a strong Pearson's correlation between simulated and observed yields, averaging 0.64 and ranging from 0.4 to 0.9 (Figure B.5b). Using the ground-based AWS data and HMM simulations, we found that changes in observed SSR did not significantly contribute to yield gains across the US Corn Belt from the 1980s to 2020 (Figure 2.2a). There was even a negative influence on yield trends in Nebraska due to solar dimming (Figure 2.1c,i). When imposing a rate of solar brightening of $0.06 \text{ MJ m}^{-2} \text{ d}^{-1} \text{ yr}^{-1}$, which was derived from PWR data (Figure 2.1e-h), upon ground-based SSR observations (see Methods), we found an 8% contribution to yield gains (Figure 2.2a). The magnitude of this contribution is three times lower than was reported in the previous study using a linearized approach (Tollenaar et al., 2017). As a theoretical

exercise, we also considered solar dimming during the growing season. When the same rates, but inverted to impose a dimming effect, were imposed upon ground-based SSR data, there was a 12% decline in yield gains, which was 4% larger in absolute magnitude than the impact of solar brightening (Figure 2.2a). At the station level, yield changes from solar dimming were systematically higher than the corresponding yield changes from solar brightening (Figure 2.2b,c). This discrepancy in absolute magnitudes between effects of solar brightening and solar dimming on yield showed a consistent declining efficiency of solar radiation on biomass production and grain yields.

3.3 Nonlinear response of yields to SSR changes

To further investigate the nonlinear relationship, we used the HMM model to conduct an analysis by estimating yield responses under various environmental conditions. We altered observed SSR from -20% to +20% in a 1% stepwise manner during the period of planting to maturity for each station-year (see Methods). Our results showed a nonlinear response of maize yields to changes in SSR. Overall, yields increased with increases in SSR but the rate of response in yield declined with successive increases in SSR, a clear demonstration of declining efficiency of SSR on plant biomass production (Figure 2.3). The exception was under dry conditions (Figure 2.3b) where yield was already limited by water stress and any increase in SSR did not increase yields. Rather, it aggravated the stress and added to yield losses. Additionally, yield responses to increases in SSR under rainfed conditions (with water stress a possibility) was less than that under irrigated conditions (no water stress). Moreover, a greater response of yield to changes in SSR was observed under cold conditions than under hot conditions (Figure 2.3c), demonstrating the impact of temperature on the response of crop yield to changes in SSR when the regionality or geographic

influence was removed. For instance, in cold conditions, a 20% reduction in SSR resulted in a maize yield decrease of 1.5 t ha⁻¹, while a yield loss of 0.9 t ha⁻¹ occurred under hot conditions.

3.4 Contributions of non-environmental factors

We employed the HMM model to estimate the impact of changes in management practices and hybrids on maize yield trends. We first estimated the influence of individual factors on yield trends while maintaining all other variables at their average values during the first five-year observations of time series. Averaging across the US Corn Belt, we found that changes in planting dates did not impact yield trends in a statistically significant manner (Figures 2.4 and B.4a), which aligns with the previous study (Sacks & Kucharik, 2011). However, changes in plant densities across the four states went from 53,619 plants ha⁻¹ in the 1980s to 73,326 plants ha⁻¹ in 2020 (Figure B.4b), which increased yields by 0.4 t ha⁻¹ per decade for an average of studied states, accounting for 32% of observed yield trends (Figure 2.4). Genetic advances allowed for the use of higher planting densities. Changes in hybrids, characterized by growing degree days (GDD) (Figure B.4c,d), resulted in a significant upward yield trend, with 0.56 t ha⁻¹ decade⁻¹ on average, accounting for 40% of observed yield trends (Figure 2.4). Increases in yields were attributed to use of longer-season hybrids, particularly during the grain filling period (Figure B.4d) that reflects environmental adaptations. Second, we estimated the impact of interactions between management and hybrids on yield trends. Overall, changes in non-environmental factors together contributed 76% to observed yield trends on average, ranging from 73% in Illinois to 88% in Nebraska (Figures 2.4 and B.5c). Our results are comparable with findings summarized in recent studies (Duvick, 2005; Kucharik, 2008; Smith & Kurtz, 2018). Other crop management practices, such as increased efficiency of harvest equipment and weed and pest control (Duvick, 2005; Smith et al., 2015), may

have also contributed to yield gains, but were not included in this study. Non-environmental contributions vary from state to state, but overall, they dominated the total contributions of upward trends in the US maize yields.

4. Discussion

SSR is the energy source for the global ecosystem. In theory, maximally 6% of SSR can be converted into plant biomass (Beadle & Long, 1985; Long et al., 2006). Therefore, having accurate and reliable long-term SSR observations is crucial not only for climate change assessment, as SSR is a primary climate driver (Wild et al., 2005), but also for efforts to exploit increased photosynthetic potential of the entire plant canopy during the crop cycle (Araus et al., 2021; Sinclair et al., 2019). Although a few studies have recently reported that global SSR experienced an increase from the 1980s to the 2010s (Wild, 2009, 2012; Wild et al., 2005), within the US Corn Belt, only two stations (Driemel et al., 2018; Wild, 2012) (Bondville, Illinois and Sioux Falls, South Dakota) have been included in these global or regional assessments (Figure B.6). The scientific community has not yet reached consensus concerning solar brightening and its attributions on either large scales (global or regional levels) (Arias et al., 2021; Wild, 2012) or small scales (state or national levels) (Hinkelman et al., 2009; Yuan et al., 2021). We examined two climate variables that are most often correlated with SSR (Yuan et al., 2021): daily diurnal temperature range (DTR) and available monthly average cloud cover percent (CLD). Neither DTR nor CLD statistically supported the results that SSR trends have significantly changed (Figures B.7 and B.8) during that time period. Aerosols in the atmosphere can significantly affect the solar radiation received at the Earth's surface (Proctor, 2021). Aerosols vary spatially and temporally due to both natural sources (e.g., dust, volcanic emission) and human activities (e.g., industrial

pollution, prescribed wildfires), the effect of which should be further examined as it is associated with direct and diffuse radiation distributions (Proctor, 2021) in both spatial and temporal patterns. The AWS ground-based SSR observations are the most reliable and densest long-term solar radiation networks available for the US Corn Belt. SSR data from satellite-based products should be used cautiously, especially when exploring the quantities of varying SSR in predicting long-term gains in maize yield.

From the 1980s to 2020, quantitative assessment indicated that changes in SSR do not significantly contribute to yield gains. To date, RUE integrated throughout the crop cycle has increased over the past four decades. These increases are attributed to optimizing canopy photosynthetic rates (Lee & Tollenaar, 2007; Thornley, 2002), photosynthetic duration (stay-green, particularly for increasing radiation intercepted in lower portions of canopy profile) (Araus et al., 2021; Lee & Tollenaar, 2007), plant water uptake and nitrogen accumulation (Medlyn, 1998; Sinclair et al., 2019), and their interactions in the RUE (Tollenaar et al., 2017). Therefore, of relevance are the observations that daily or monthly RUE is a nonlinear, but more importantly, decreasing function of average incident SSR (Medlyn, 1998) due to a non-rectangular hyperbolic and sigmoidal light-response of photosynthesis (Araus et al., 2021; Beadle & Long, 1985; Thornley, 2002) and photoprotection (Kromdijk et al., 2016), respectively.

Considering that crop yields (Y) depend on the product of solar input (S), the efficiencies of sunlight interception by the leaves (ε_i), the conversion efficiency of the intercepted energy into plant matter (ε_c), and the partitioning efficiency of the plant matter into the harvested grain product (ε_p), the relationship is expressed as $Y = S \times \varepsilon_i \times \varepsilon_c \times \varepsilon_p$ (Long et al., 2015). We conducted a world-wide meta-analysis (Figure 2.5a) and found with maize that ε_c decreases with intercepted photosynthetically active radiation, defined as product of S and ε_i (Figure 2.5b). Furthermore, we

observed that ε_p decreases with biomass during the GFP (Figure 2.5c), which were also identified in recent studies (Edreira et al., 2020; Liu et al., 2023; Proctor, 2021). These responses in ε_c and ε_p stress consistent declining efficiency of solar radiation on biomass production and grain yields (Figures 2.2, 2.3, and B.1).

In contrast to the linearized approach, HMM-simulated maize growth and development uses intrinsic photosynthetic and respiratory mechanisms (Yang et al., 2004). The small contribution to yield gains attributable to SSR changes quantified here was supported not only by the origin of the definition of RUE (classically called Monteith's yield formation model in 1977 (Monteith, 1977), who highlighted that impact by either temperature or precipitation was three to four times larger than the impact of solar radiation on crop yields) but also by the amount of contributions attributed to non-environmental factors (Sinclair et al., 2019; Smith et al., 2015; Smith & Kurtz, 2018) (Figure 2.4).

5. Conclusion

Our analyses using AWS datasets and the HMM model indicate a nonlinear and marginal contribution of SSR trends and variations to maize yield gains in the US Corn Belt during the period between the 1980s and 2020. The SSR trends derived rather from the PWR datasets appear to be systematically skewed towards an apparent brightening artifact. Over the past four decades, non-environmental factors such as genetics and management, along with their interactions, have been the primary drivers of maize yield gains. Our analyses confirm that trends and variations in SSR that result from climate variability and climate change have not significantly influenced decadal yield gains in maize. Changes in climate, particularly characterized by increased warming and extreme events that are now being observed in temperature and precipitation, are more likely

to have substantial negative impacts. Deconvolving contributions of individual climate drivers to grain yields at a large scale becomes intricate without dependable observational data, particularly from a climate change perspective.

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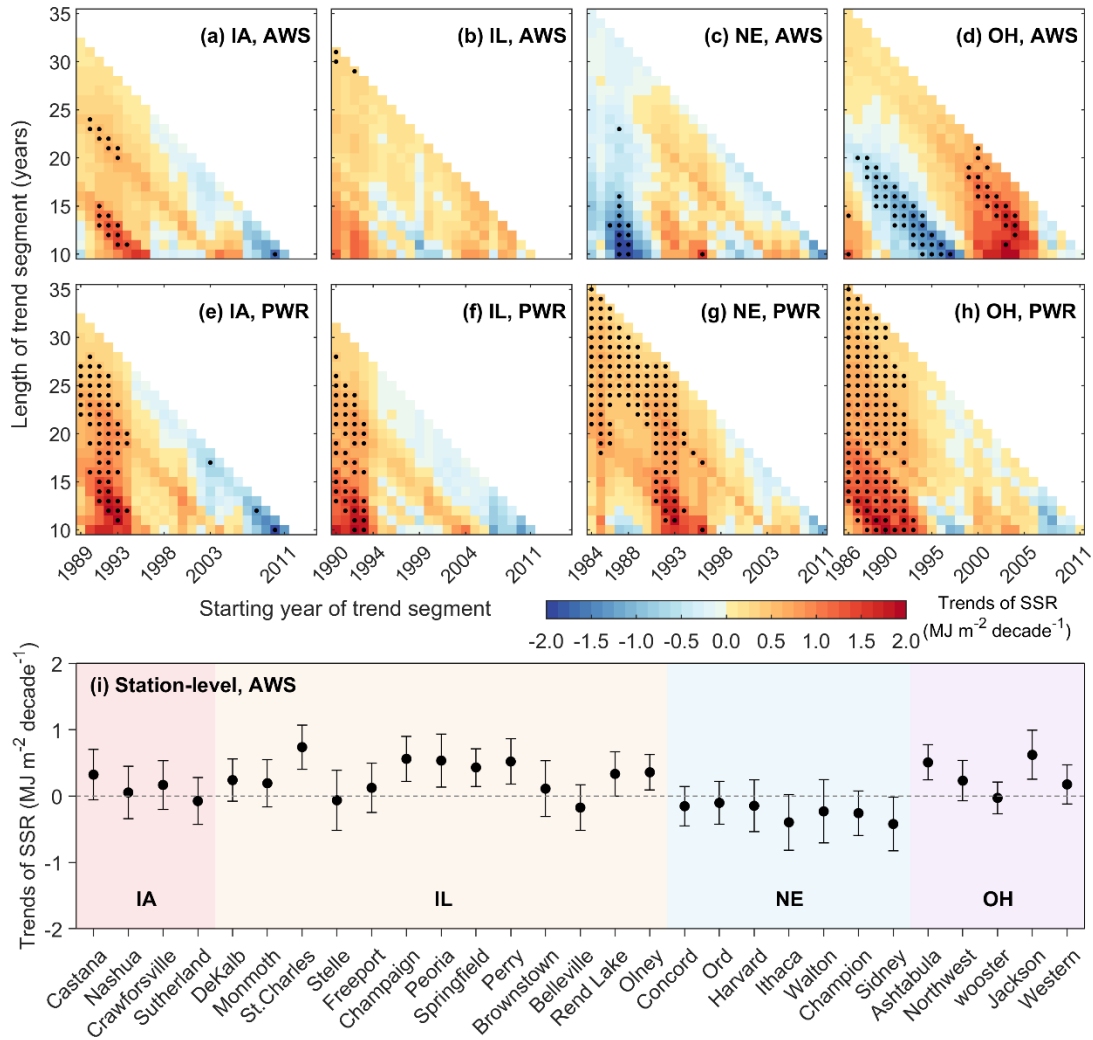


Figure 2.1. Comparison of the surface solar radiation anomaly during maize grain filling period (SSR) between automated weather station (AWS) observations and NASA POWER (PWR) data products in Iowa (IA), Illinois (IL), Nebraska (NE), Ohio (OH). State-level trends of SSR in (a) IA, (b) IL, (c) NE, and (d) OH over 1980s-2020 (with length ranging from 10-35 years) using AWS data. Panels (e-h) are same with panels a-d but using PWR data products. Black dots indicate statistical significance at the 95% confidence level. Station-level SSR trends (i) using the longest time window based on AWS data. Solid black circles represent averaged magnitude and error bars show 95% confidence interval.

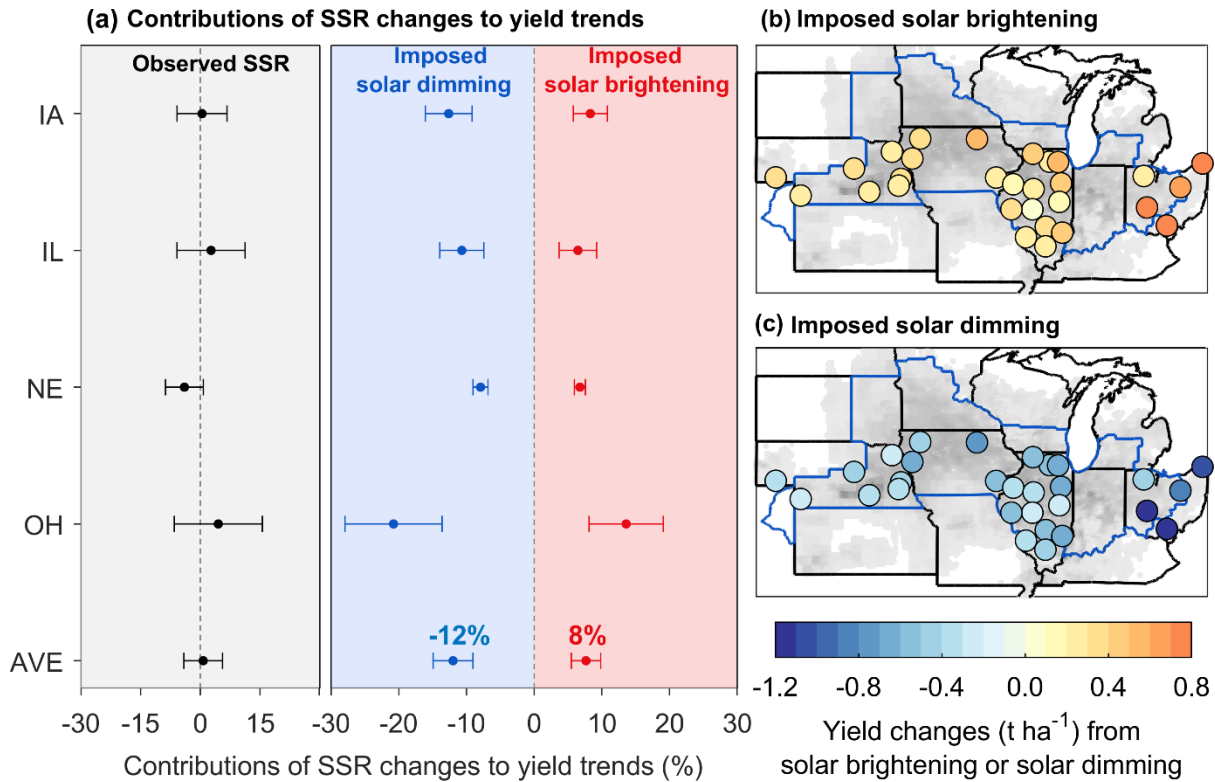


Figure 2.2. State- and station-level contributions of surface solar radiation (SSR) to changes in maize yield trends from the 1980s to 2020 in Iowa (IA), Illinois (IL), Nebraska (NE), Ohio (OH), and a harvested-area weighted-average of all four states, representing the US Corn Belt (AVE) based on Hybrid-Maize Model (HMM) simulations. Contributions of changes in observed SSR (a, left panel), imposed solar dimming ($-0.06 \text{ MJ m}^{-2} \text{ d}^{-1} \text{ year}^{-1}$; a, middle panel), and imposed solar brightening ($+0.06 \text{ MJ m}^{-2} \text{ d}^{-1} \text{ year}^{-1}$; a, right panel) at state level and the US Corn Belt. The horizontal bars indicate the 95% confidence interval of the average value (solid dots). Station-level yield changes (t ha^{-1}) driven by imposed solar brightening (b) and solar dimming (c). Mapping backgrounds illustrate color-coded intensities of maize harvested area in the decade of 2000s. The blue boundary indicates the US Corn Belt suggested by the National Centers for Environmental Information, NOAA (<https://www.ncei.noaa.gov/access/monitoring/reference-maps/corn-belt>).

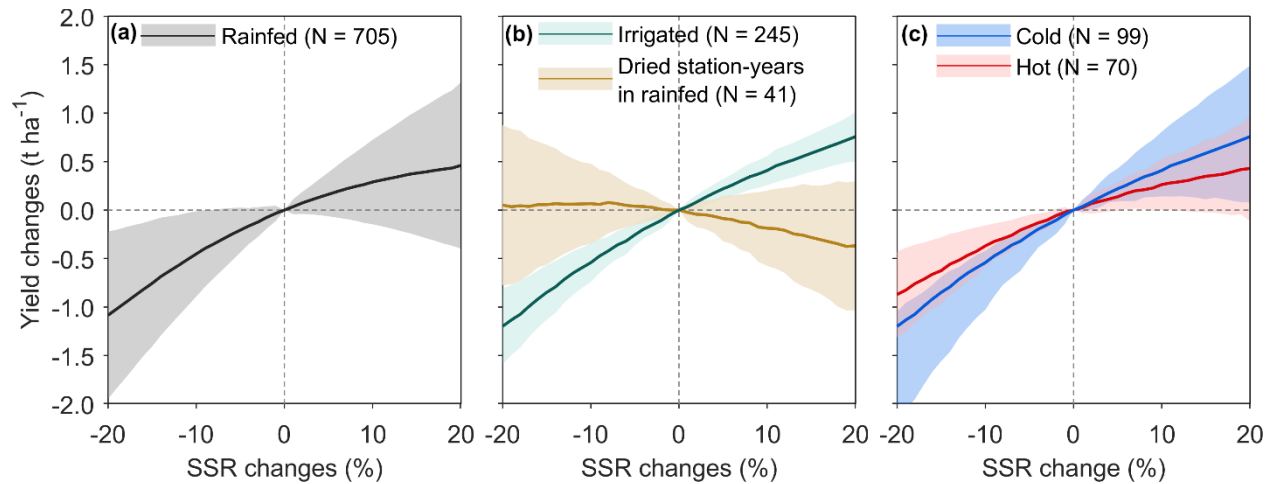


Figure 2.3. Response of maize yields to surface solar radiation (SSR) changes under (a) rainfed (black) conditions, (b) irrigated (green) and dried (yellow) conditions, where dried conditions were a subset of rainfed conditions, (c) cold (blue) and hot (red) conditions after removing the impact of regionality. Solid curve represents average response. Shadow area indicates one standard deviation. N indicates the number of climate conditions (station-year).

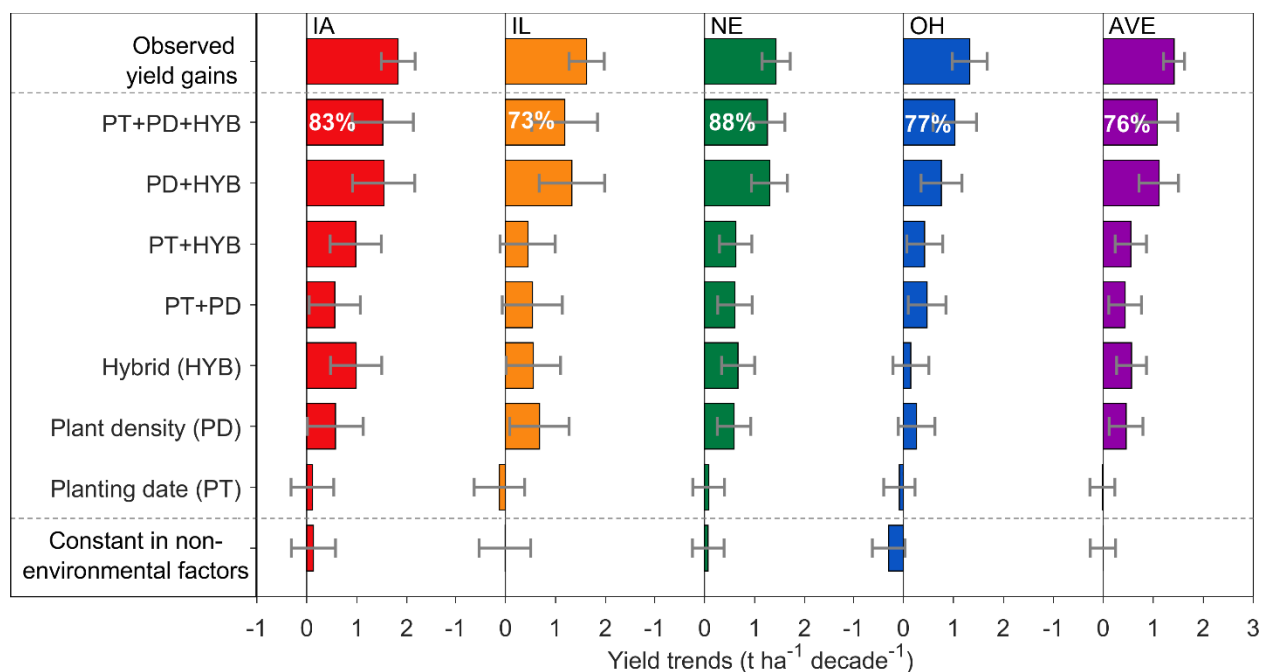


Figure 2.4. Contributions of changes in non-environmental factors to maize yield trends from the 1980s to 2020 in Iowa (IA), Illinois (IL), Nebraska (NE), Ohio (OH), and a harvested-area weighted-average of all four states, representing the US Corn Belt (AVE). Bars refer to mean yield trends driven by specific non-environmental factors. Error bars indicate the 95% confidence interval of the average value. Numbers in bars define the mean contribution of changes in non-environmental factors to observed yield trends. “Constant in non-environmental factors” in Y-axis refers to no changes in non-environmental factors over the 1980s to 2020. “Observed yield gains” are observed yield trends.

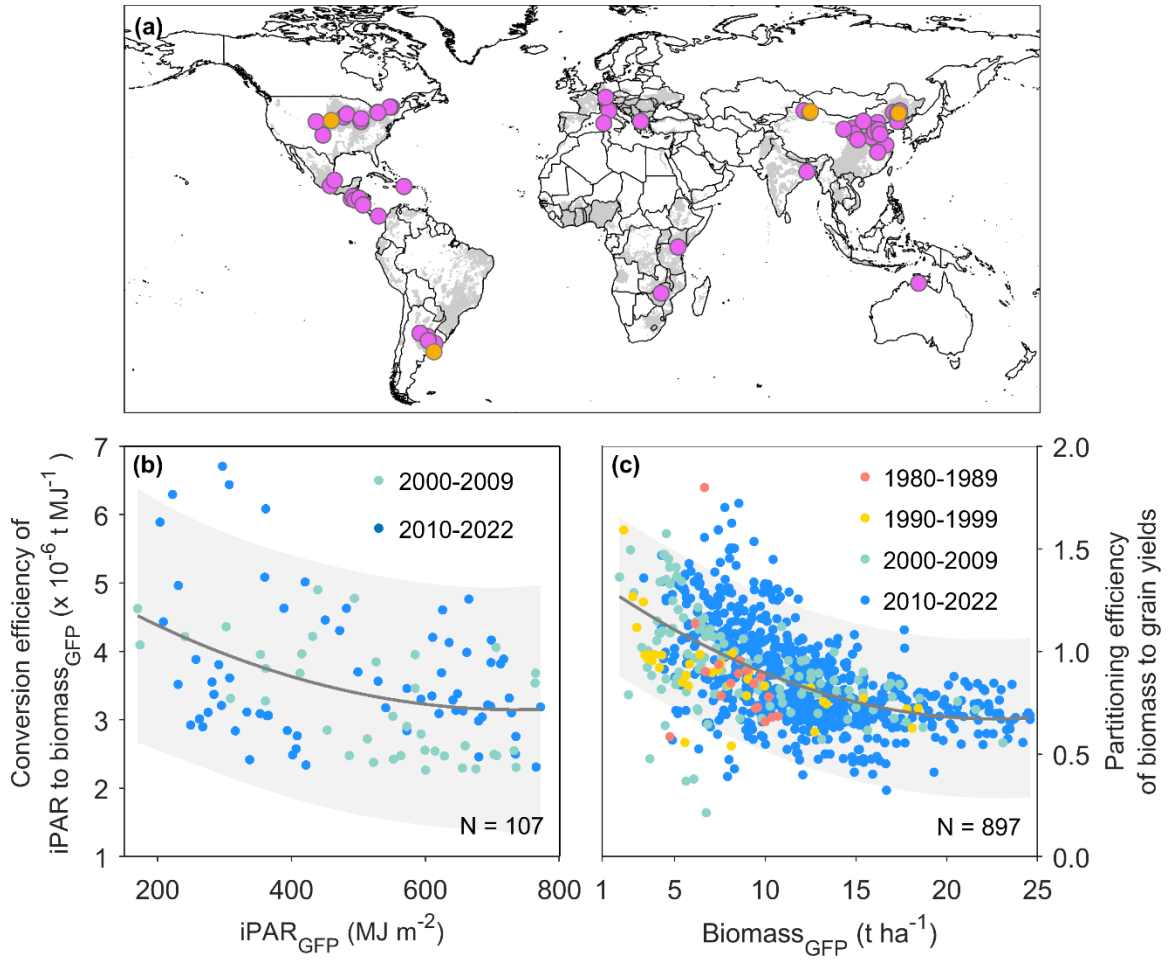


Figure 2.5. Efficiency of solar radiation to maize grain yields (measured at 0% moisture) during grain filling period (GFP). (a) The 72 locations of studies collected including 4 locations (yellow circles) that enabled to show relationships between intercepted photosynthetically active radiation (iPAR) and biomass (b), and 68 locations (pink circles) to show the relationship between grain yields and biomass (c). Mapping backgrounds are color-coded by maize harvested area in the 2000s. Total experimental data points are 107 and 897 (N), respectively. The gray solid lines are the quadratic fitted line. Color indicates the decade that study results were published.

Chapter 3 - Increasing resilience of maize in U.S. breeding program to vapor pressure deficit

Abstract

Rising vapor pressure deficit (VPD) associated with climate warming threatens agricultural yields globally. Previous studies have highlighted the detrimental impact on crop yields of rising VPD, especially around the silking period of maize (*Zea mays* L.). A key question for adapting to climate warming is whether current breeding increases resilience to VPD, thereby potentially accelerating future genetic gains. Here, we investigated the changes in yield gains from breeding under different environmental stress levels and estimated sensitivity of maize hybrids to VPD. We analyzed an extensive dataset from maize hybrids field performance tests conducted in primary maize-producing states in the US Corn Belt including Iowa, Illinois, Minnesota, Ohio, and Wisconsin between 2000 and 2020. We found a consistent increase in maize yields under varying environmental stress levels, with an average of $0.15 \text{ t ha}^{-1} \text{ yr}^{-1}$. We also found that breeding efforts have enhanced the resilience of maize yields to VPD, with an average increase of $0.06 \text{ t ha}^{-1} \text{ kPa}^{-1} \text{ yr}^{-1}$. However, under the SSP5-8.5 scenario, which limits surface warming to $4.6\text{-}5.2 \text{ }^{\circ}\text{C}$ at 2100, maize yields of current hybrids still show an additional decline of about 4% relative to average historical losses. While our findings offer optimism regarding the potential of plant breeders to enhance VPD resilience in maize hybrids, projected VPD in future climate change also exacerbated yield loss across all hybrids.

Keywords: vapor pressure deficit, maize yields, breeding, resilience, US Corn Belt

1. Introduction

Vapor pressure deficit (VPD), the difference between the water vapor pressure at saturation and the actual water vapor pressure for a given temperature, plays a dominant role in plant water demand (Grossiord et al., 2020). The rise in air temperature increases the saturation vapor pressure of the atmosphere resulting from the Clausius-Clapeyron relationship, leading to a corresponding increase in VPD when the actual vapor pressure does not rise at the same rate. This phenomenon, known as “atmospheric drying,” is currently underway on Earth, with VPD increasing at a rate of $0.03 \text{ kPa dec}^{-1}$ (Fang et al., 2022), a trend expected to become exacerbated with ongoing climate warming.

Elevated VPD levels have been linked to detrimental effects on terrestrial ecosystems (Zhong et al., 2023), vegetation growth (Yuan et al., 2019), and crop productivity (Lopez et al., 2021). Historical increases in VPD have particularly impacted major food crops such as maize (Lobell et al., 2014; Roberts et al., 2012), wheat (*Triticum aestivum* L.) (Rashid et al., 2018), rice (*Oryza sativa* L.) (Tack et al., 2015), soybean (*Glycine max* (L.) Merr.) (Sun et al., 2023), and sorghum (*Sorghum bicolor* (L.) Moench) (Hoffman et al., 2020), resulting in yield reductions across major agricultural production areas worldwide, including the United States Corn Belt (Hsiao et al., 2019; Lobell et al., 2014; Rigden et al., 2020). This poses significant challenges to food production and global food security (Grossiord et al., 2020; Mickelbart et al., 2015).

In the United States, which accounts for 50% of corn exports globally (Wu & Guclu, 2013), increased VPD during a critical stage in maize growth, typically around two weeks before and after silking (Campos et al., 2006; Shaw, 1977; Tollenaar et al., 2017), has emerged as a primary driver of maize yield penalties, with an estimated 30% decline on average (Lobell et al., 2014). Projections for the climate in the US Corn Belt in 2050 indicate a further 15% increase in the

probability of maize yield reduction due to a projected roughly 20% rise in average VPD (Lobell et al., 2014). These limitations in maize yields raise concerns within scientific communities about the sustainability of current production levels (Kimm et al., 2020; Ort & Long, 2014). To address these challenges, a potential adaptation strategy involves the development by breeders of maize hybrids more resilient to VPD. Therefore, understanding the adaptive trajectory of past breeding towards VPD tolerance is crucial for research efforts to accelerate future genetic gains.

Previous studies have assessed changes in crop breeding for abiotic stress resilience, such as heat or drought, by comparing absolute yields of crop hybrids with different release years at a limited number of site-years (Campos et al., 2006; Duvick, 2005). However, whether maize hybrids effectively adapt to VPD stress across broad regions remains an open empirical question. This study aims to address two key questions: a) has maize breeding increased resilience to VPD around the maize silking period, the most vulnerable growth stage of maize to VPD; and b) how could VPD affect maize yields in the future climate projections considering the possible change in resilience of maize hybrids? To answer these questions, we collected public yield trial data, including hybrid-specific maize yields and phenological dates, comprising 92,096 data points across 63 field sites in five maize-producing states from 2000 to 2020 (Figure 3.1a). We then utilized a linear mixed-effects model to assess the change in resilience of maize hybrids to VPD. Finally, we projected the effects of VPD using future climate scenarios.

2. Material and Methods

2.1 Yield and weather data

Maize- hybrid data (Table C.1) including observed hybrid-specific yields and phenological dates (planting and harvest) were collected and digitized from rainfed field performance tests of

maize hybrids from 2000 to 2020 for five states, including Iowa, Illinois, Minnesota, Ohio, and Wisconsin, accounting for 50% of the US maize harvested area (Figure 3.1a). Note that we did not cover Indiana due to data limitation. In total, the database we used included 92,096 data points across 63 field sites (Figure 3.1 and Figure C.1). The original purpose of these trials was to test performance of new hybrids under diverse environmental conditions, aiming to identify resilient hybrids suitable for release to farmers. Trials were carried out under ‘optimal’ rainfed management conditions, employing site-specific agronomic treatments to optimize nutrients and minimize disease and other stresses. We segmented maize phenological periods into vegetative growth period (VEG, sowing-silking) and grain filling period (GFP, silking-maturity). Based on observed planting and harvest dates, we used state-level phenological data from the United States Department of Agriculture’s National Agricultural Statistical Service’s (USDA-NASS) Crop Progress Report to estimate silking and maturity dates for each trial site. Details are shown in “Text C.1” and Figures C.2 and C.3.

Daily surface observational weather data, including maximum (T_x ; °C), minimum (T_n ; °C), and dew point (T_d ; °C) temperatures, along with precipitation (P_{rcp} ; mm), were derived from Integrated Surface Dataset (ISD) (Smith et al., 2011) and interpolated with a Delaunay Triangulation (Barber et al., 1996) to the field trial sites (Figure 3.1a) to approximate the daily weather experienced by the crop. We used the ISD data due to its high-quality measurement of T_d , which is a critical weather variable to calculate VPD. Using hourly temperature (T_h), estimated by using daily T_x and T_n (Cesaraccio et al., 2001), we calculated 1) growing degree days (GDD; °Cd, Eq. 1) between the base and optimum growth temperature thresholds; and 2) extreme growing-degree days (EDD; °Cd, Eq. 2) above the optimum growing temperature threshold for specific growing periods.

$$GDD = \sum_{h=1}^H DD_h; \quad DD_h = \begin{cases} 0 & T_h < T_{base} \\ \frac{T_h - T_{base}}{24} & T_{base} \leq T_h \leq T_{opt} \\ \frac{T_{opt} - T_{base}}{24} & T_h > T_{opt} \end{cases} \quad (1)$$

$$EDD = \sum_{h=1}^H DD_h; \quad DD_h = \begin{cases} 0 & T_h \leq T_{opt} \\ \frac{(T_h - T_{opt})}{24} & T_h > T_{opt} \end{cases} \quad (2)$$

where T_{base} and T_{opt} are the base (10 °C) and optimum (30 °C) growing temperature thresholds, which are common thresholds for growth and development in maize (Schauberger et al., 2017; Schlenker & Roberts, 2009).

We also calculated VPD (kPa, Eqs. 3-5) (Allen et al., 1998) using daily mean air temperature and dew point temperature during a 4-week period centered around silking, the most vulnerable period of maize yields to VPD (Andrade et al., 1999; Shaw, 1977; Tollenaar et al., 2017).

$$e_s = 0.611 \times \exp\left(\frac{17.3 \times T_m}{T_m + 237.3}\right) \quad (3)$$

$$e_a = 0.611 \times \exp\left(\frac{17.3 \times T_d}{T_d + 237.3}\right) \quad (4)$$

$$VPD = e_s - e_a \quad (5)$$

where e_s is saturation vapor pressure (kPa) at a given daily average air temperature (T_m ; °C); e_a refers to actual vapor pressure (kPa) for a given daily dew point temperature (T_d).

2.2 Yield gains of maize breeding

To assess the yield gains of maize breeding under various environmental stress levels, we calculated the environment index (EI) for each site-year. The environment index is defined as the average yield across all hybrids grown at a given site-year (Finlay & Wilkinson, 1963), providing a reliable measure of stress level in field trials. We then categorized the EI of all trial sites for each year into five percentile intervals: $\leq 5^{\text{th}}$, $5^{\text{th}} - 25^{\text{th}}$, $25^{\text{th}} - 75^{\text{th}}$, $75^{\text{th}} - 90^{\text{th}}$, and $\geq 90^{\text{th}}$ and calculated

average yields. These intervals signify different degrees of environmental stress, with the smallest interval representing the strongest stress level and the highest interval showing the lowest stress level. It is important to note that we established the threshold of each percentile separately based on all sites in a specific year, which eliminates variations in technology and management between bins within each year. Next, we estimated yield trends for each environmental stress level using the standard least-square linear regression. The statistical significance of the computed trends for EI was determined using a two-sided Student's *t* test at a 95% confidence level. We also tested other threshold intervals (20th, 40th, 60th, and 80th) to estimate yield gains of maize hybrids (Figure C.4).

2.3 Statistical yields model

To better estimate the response of maize yields to VPD, we developed a linear-mixed effects model as (Eq. 6),

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_{t,s} + \sum_{p=1}^2 (\beta_p GDD_{i,l,t,s,p} + \gamma_p EDD_{i,l,t,s,p} + \delta_p Prcp_{i,l,t,s,p} + \vartheta_p Prcp_{i,l,t,s,p}^2) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad (6)$$

where $Y_{i,l,t,s}$ is maize yield for hybrid i at location l in trial year t for specific state s . The first three terms ($\alpha_i, \alpha_l, \alpha_{t,s}$) are effects across hybrids, locations, and specific state-year group. β, γ, δ , and ϑ refer to sensitivity of GDD, EDD, precipitation and precipitation square at a specific phenological period. The p refers to phenological periods including vegetative period and grain filling period; θ is the sensitivity of maize yields to VPD around the silking period; and ε is the error term. Note that it is possible that error term is heteroskedastic and autocorrelated. Therefore, we clustered standard errors (SEs) (Cameron et al., 2011) by hybrid-year, allowing consideration of the effects of heteroskedastic and autocorrelation in estimating the *p*-values of coefficients. The adjusted SEs

could produce more conservative adjusted p-values. Our model used actual yields, because this model had more explanatory power and more normally distributed residuals (Figure C.5). We also considered five alternative model specifications including linear and quadratic effects of years instead of state-year fixed effects and found that they substantially reduced model performance (Text C. 2 and Table C.2 for details). The preferred model was selected based on the relatively small Akaike information criterion (AIC) values and better coefficient of determination (R^2). The AIC is a measure used in statistics to evaluate and compare the goodness-of-fit of different mathematical models; when comparing multiple models, the one with the lowest AIC value is generally preferred (Akaike, 2011).

To investigate heterogeneous effects of VPD across breeding process, we modified the preferred model (Equation 6) to allow the effect of VPD to vary across the years in which the hybrids first appeared in the trials (first trial-year; f) by including the interaction term between VPD and dummy variables for first trial-year. This approach was also well-used to estimate crop breeding (e.g., wheat and sorghum) adaptation to climate extremes (Shew et al., 2020; Tack et al., 2017). The specification of the model is,

$$Y_{i,f,l,t,s} = \alpha_i + \alpha_l + \alpha_{t,s} + \sum_{p=1}^2 (\beta_p GDD_{i,f,l,t,s,p} + \gamma_p EDD_{i,f,l,t,s,p} + \delta_p Prcp_{i,f,l,t,s,p} + \vartheta_p Prcp_{i,f,l,t,s,p}^2) + \theta_f VPD_{i,f,l,t,s} + \varepsilon_{i,f,l,t,s} \quad (7)$$

where the terms in the model are same with those in the preferred model above.

2.4 Future projections

In order to investigate how VPD around the maize silking period would change in the future and its influence on maize yields, we downloaded the climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6), using six climate models (ACCESS-CM2, CESM2,

CNRM-CM6-1, CNRM-ESM2-1, INM-CM4-8, and INM-CM5-0) (Eyring et al., 2016) and four climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) (Meinshausen et al., 2019). The SSP1-2.6 scenario, also known as the "2 °C scenario" within the "sustainability" socio-economic family, is characterized by a radiative forcing level of 2.6 W m⁻² projected for the year 2100. The SSP2-4.5 scenario belongs to the "middle of the road" socio-economic family and is associated with a nominal radiative forcing level of 4.5 W m⁻² anticipated by the year 2100. The SSP3-7.0 scenario is a medium-high reference scenario within the “regional rivalry” socio-economic family, while the SSP5-8.5 marks the upper edge of the SSP scenario spectrum with a high reference scenario in a high fossil-fuel development world throughout the 21st century. We then interpolated these projections to each field site with a Delaunay Triangulation (Barber et al., 1996) to calculate VPD. Climate-model-projected variables were bias corrected using the differences in the mean and variability between SSP outputs and historical observations of ISD data from 2000 to 2020 (Hawkins et al., 2013; Ho et al., 2012). Because projections for dew point temperature were not available, we used specific humidity, which describes the mass of water vapor present in a unit mass of moist air, to calculate VPD (Peixoto & Oort, 1996). Because we cannot know future maize silking dates for certain, an average of observed historical silking dates (DOY 200; Figure C.3) was used to calculate VPD around projected silking dates. Finally, VPD derived from the six climate models, along with sensitivity of maize yields to VPD, was used to estimate the average yield effects. Data sources including crop data and weather data are shown in Table C.1.

2.5 Impact of VPD on maize yields

We estimated maize yield losses resulting from VPD change as follows,

$$imp_{VPD} = \frac{VPD \times \theta}{\bar{Y}} \times 100 \quad (8)$$

where imp_{VPD} refers to impact of VPD change on maize yields (%). The θ is the sensitivity of VPD around the silking period, derived from Equation 7. $\hat{Y}$ refers to average maize yields (12.5 t ha⁻¹).

Statistical analysis was conducted by using the MATLAB R2023a. The statistical model was conducted using linear mixed-effects model using “fitlme” function in the MATLAB.

3. Results

3.1 Yield gains of maize hybrids

The environment index, defined as average yields of all hybrids grown in a specific site-year, was 12.5 t ha⁻¹ on average with average yields ranging from 9.1 t ha⁻¹ under the highest environmental stress level to 15.4 t ha⁻¹ under the lowest stress level (Figures 3.1b and 3.2). Our analysis revealed significantly positive trends ($p < 0.05$) in maize yields over time across different environmental stress levels (Figure 3.2). These findings suggest that genetic improvements have been achieved not only under low-stress conditions but also in high-stress conditions, as emphasized in previous studies of improved stress tolerance in maize (Campos et al., 2006). Although the yield trend under the lowest environmental stress level (0.17 t ha⁻¹ yr⁻¹) were slightly higher than that under the highest environmental stress levels (0.13 t ha⁻¹ yr⁻¹), these differences were not statistically significant, tested by using Student’s t-test approach. Importantly, our results demonstrate consistent yield gains in maize hybrids across varying environmental stress levels, a robust finding that held true even when considering additional thresholds of the environment index (Figure C.4).

3.2 Climate impacts on maize yields

We used a linear mixed-effects model (Equation (6)) to estimate the impacts of climate variables on maize yields (Table C.2). The negative effects of VPD on maize yields were robust in six model specifications (Table C.2). Model 4 (Table C.2, column 4) emerged as the preferred model, demonstrated by relatively small Akaike information criterion (AIC) values and better coefficient of determination (R^2). Our analysis revealed several results. (1) Growing degree days (GDD) during both the vegetative (VEG) and grain-filling (GFP) periods had a significant, positive effect ($p < 0.05$) on maize yields. (2) We did not see a significant impact of EDD during the VEG period on yields ($p > 0.10$), but a significant, negative effect ($p < 0.05$) was observed during the GFP period. This aligns with previous studies suggesting that EDD during the maize VEG stage may not negatively impact yield due to its lack of adverse effects on leaf area or biomass (Butler & Huybers, 2015; Hatfield & Prueger, 2015). (3) A nonlinear relationship between precipitation and maize yields was characterized by a significant positive impact of first-order precipitation and a notable negative effect from second-order precipitation. (4) Our analysis identified VPD around the maize silking period as a significant driver of maize yield loss.

3.3 Changes in sensitivity of maize hybrids to VPD

We explored the genotype $\times$ environment interactions to evaluate how various maize hybrids respond to VPD. Utilizing a varying-slope multilevel model (Equation 7), we aimed to examine the variation in VPD impacts across different maize hybrids. However, due to the limited observations of yields for each hybrid (Figure C.1), we adopted a grouping approach based on the initial appearances of maize hybrids in the trials (first trial-years), which spanned from 2000 to 2020. For example, the hybrids with same first trial-year are defined as one group. This approach was also used to estimate adaptation of sorghum yield in breeding programs to climate change

(Tack et al., 2017). We found a consistent, statistically significant negative response to VPD around the silking period across all maize hybrid groups (Figure 3.3). Notably, we observed an improved resilience of hybrids to VPD over time, with a trend of $0.06 \text{ t ha}^{-1} \text{ kPa}^{-1} \text{ yr}^{-1}$ (Figure 3.3). The improvement of maize yield tolerance to VPD remained robust even when accounting for varying EDD effects across maize hybrids (Figure C.6). We further analyzed the impact of VPD on maize yields at the site level, comparing different maize hybrids (Equation 8). For the “old hybrids,” defined as those from the initial five years of testing hybrids (indigo shaded area, Figure 3.3a), historical average VPD (2011-2020) was associated with a 11.5% yield decline, ranging from 8.4% to 16.5% (Figure 3.3b). In contrast, the “current hybrids” (chartreuse shaded area, Figure 3.3a) experienced a relatively lower yield decline of 4.3% associated with historical average VPD, ranging from 3.2% to 6.2% (Figure 3.3c) which is 7.2% less than the influence on yields observed in the “old hybrids”.

3.4 Projected vapor pressure deficit-driven influences on maize yields

Having quantified the sensitivities of maize yields to VPD, we proceeded to project the future impacts of VPD on average maize yields across four climate scenarios driven by six climate models in the Coupled Model Intercomparison Project Phase 6 (CMIP6). Analysis of ensemble means from the CMIP6 models revealed a consistent upward trend in VPD across the US Corn Belt, albeit with variations among different climate scenarios (Figure C.7). Before 2060, VPD is projected to steadily increase with a relatively narrow range, independent of mitigation model scenarios (Figure C.7). However, discernible differences emerge among scenarios thereafter, with the most substantial increases projected under the no-mitigation scenario SSP5-8.5, followed by

SSP3-7.0 and SSP2-4.5, while a slight decrease was expected under the early mitigation efforts in SSP1-2.6 (Figure C.7).

These escalating projections of VPD result in increased maize yield losses. By the 2050s, utilizing averaged sensitivity of “old hybrids” to VPD, maize yield is projected to decline by 3.1% in SSP1-2.6 and 4.2% in SSP5-8.5 (Figure 3.4) relative to historically average impacts (Figure 3.3b) due to increasing VPD. By the 2090s, yield losses among these hybrids are projected to escalate across all scenarios except the SSP1-2.6. For example, VPD-induced yield reduction is estimated at 9.3% in SSP5-8.5, tripling the magnitude observed in the 2050s (Figure 3.4). When considering the cultivation of “current hybrids,” yield further declines by 3.5% in the SSP5-8.5 scenario (Figure 3.4) relative to the historical average impact (Figure 3.3c). This implies that sustainable maize yields in the US Corn Belt remain a challenge due to future climate change.

4. Discussion

This study investigated yield gains achieved through maize breeding across different environmental stress levels and estimated the sensitivity of maize hybrids to VPD during the critical phenological period of silking. We utilized both field-trial data obtained from maize performance tests conducted in primary maize-producing states including Iowa, Illinois, Minnesota, Ohio, and Wisconsin in the US Corn Belt, along with in situ measured weather data. Understanding the historical changes driving breeding is essential for guiding future research efforts and adapting to climate change. Our findings reveal that maize yields significantly increased over the course of breeding. This increase was consistent across all environmental stress levels. Notably, the increased resilience of maize yields to VPD emerged as a key factor driving the sustainability of yield gains, particularly under stressful environmental conditions.

Recent advancements in VPD resistance within maize hybrids may be attributed to several factors. Firstly, genetically engineered crops are developed with traits such as herbicide tolerance and insect resistance. These traits improved the plant health and growth including the improvement in root system architecture (McFadden et al., 2019). These improvements increased the capacity of maize to extract the available soil water (Cooper et al., 2014). Additionally, phenotypic changes in maize hybrids, such as increased leaf rolling in response to high VPD during the flowering period, have been observed, facilitating water conservation and increasing ear size and kernel numbers in later growth stages (Barker et al., 2010; Duvick, 2005). Furthermore, improvement in the limitation of maize transpiration rate under high VPD can increase drought tolerance by limiting gas exchange and conserve soil water early in the growing season for use to sustain plant activity during late growing season (Gholipour et al., 2013; Messina et al., 2015; Sinclair et al., 2017). Our findings give optimism for the capacity of plant breeders to improve VPD resilience in maize hybrids, but projected VPD in future climate also shows exacerbated yield loss not only for “old hybrids” but also for “current hybrids.” Our results also have implications for crop-yield modelers, because they show the importance of incorporating the evolving effects of genetic changes on VPD resilience for accurate yield predictions.

Increasing adaptation of maize yields to future climate change is important for sustainable food production. In addition to increasing adaptation of maize hybrids to VPD, a concurrent strategy to mitigate the pace of climate warming (Ort & Long, 2014) is needed. For example, focusing on mitigation efforts aligned with the SSP1-2.6 could attenuate the increase in VPD over the next 80 years. Conversely, under the high SSP scenario (SSP5-8.5), continued warming will lead to a rapid escalation in VPD, resulting in serious yield losses. Another plausible approach is

to adjust agricultural practices by sowing maize crops earlier to escape the peak period of high VPD that currently coincides with the sensitive growth period.

The main limitation in this study is the estimation of VPD sensitivity of specific hybrids due to the limited amount of data on any given hybrid sown in multiple environments. Specifically, in evaluating VPD sensitivity across hybrids, we used a hybrid's first trial-year, a proxy for the specific hybrids available at that point in time. Indeed, identifying the VPD sensitivity of a specific hybrid provides an opportunity for breeders to develop new hybrids to adapt to climate change, which should be further studied.

5. Conclusion

In summary, our findings suggest that recent genetic efforts increase VPD resilience of maize yields. However, even when cultivating current hybrids, under high-emission shared socioeconomic pathways (SSP5-8.5) climate scenarios, increased VPD caused a further maize yield declines of 4% relative to averaged historical yield losses. While our findings offer optimism regarding the potential of plant breeders to enhance VPD resilience in maize hybrids, they also underscore the threat of future climate change to yield losses across all maize hybrids.

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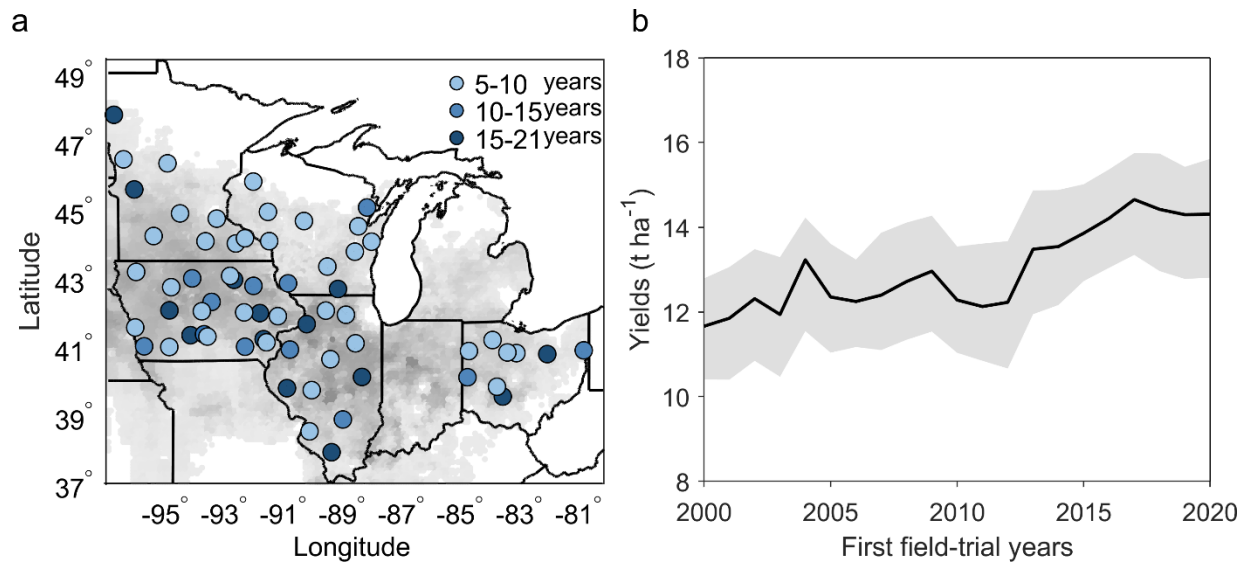


Figure 3.1. Maize field-trial sites and time series of yield. (a) Map of the main study region with individual colored-circles showing trial years. The mapping background refers to main maize harvested area in the 2000s. (b) Time series of field-level maize yields across years in which the hybrids first appeared in the field-trial data. Black curve shows time series of mean maize yields. Shaded area refers to 95% confidence interval.

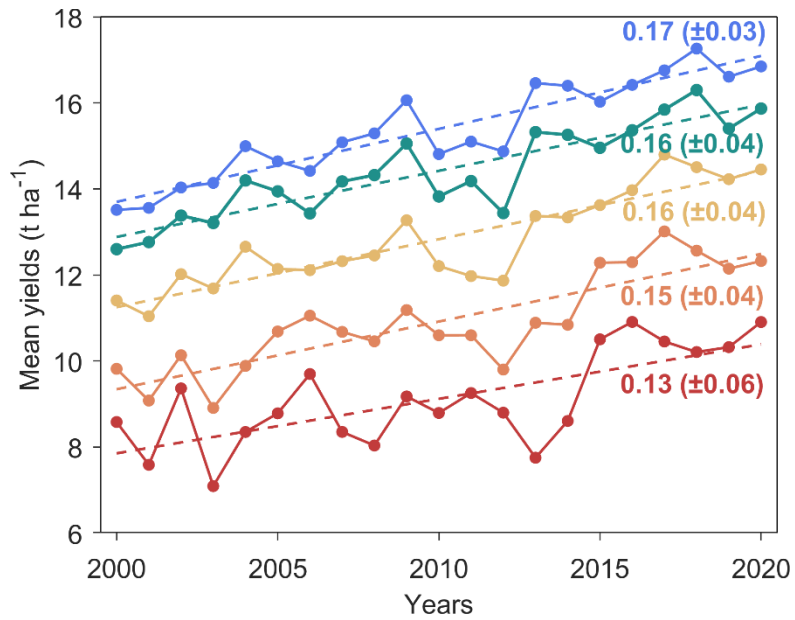


Figure 3.2. Time series of mean maize yields across different environmental stress levels from 2000 to 2020. The red line represents the highest environmental stress index (mean yields are less equal than 5 percentiles) and the blue line represents the lowest environmental stress index (mean yields are larger equal than 90 percentiles). For example, mean yields are 8.6 t ha⁻¹ and 13.5 t ha⁻¹ under the “worst” and “best” environment in 2000, respectively. Dashed lines refer to best-fit linear regression for each quantile. The numbers outside the parentheses define the trend value, with those inside indicating twice the standard errors.

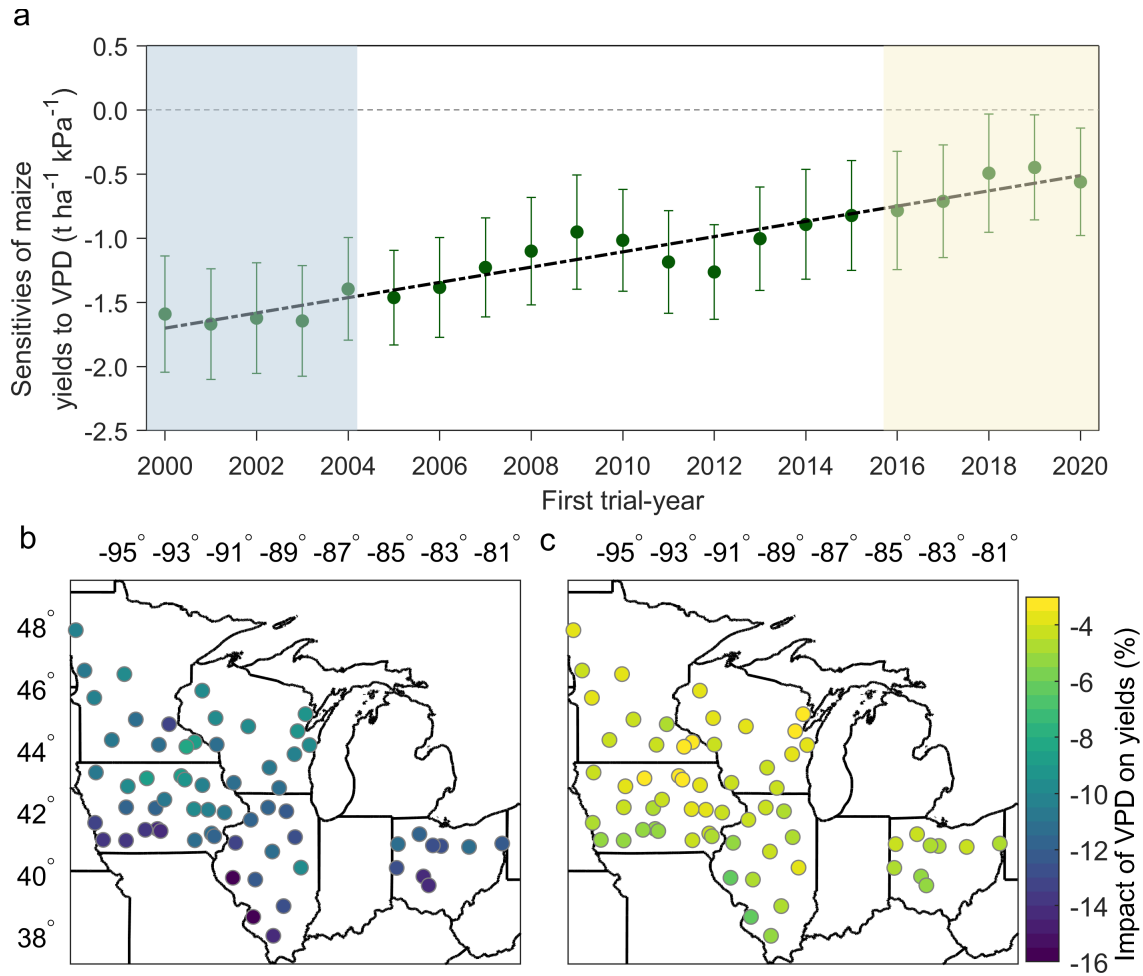


Figure 3.3. (a) Changes in sensitivity of maize yields to vapor pressure deficit (VPD) around silking with the innovation of breeding efforts over time. The year on the x-axis refers to the field trial year in which the hybrids first appeared. The solid circles show estimated mean coefficients from the regression model. The error bars refer to clustered 95% confidence interval. The smaller the number in absolute value, the more drought-resilient the hybrid is. Black dashed line shows fitted values from a linear regression. Station-level impact of historical VPD (2011-2020) around silking period on maize yields (12.5 t ha^{-1}) when using the mean sensitivity of the “old hybrids” (b, 2000-2004; indigo shaded area) and when using the mean sensitivity of the “current hybrids” (c, 2016-2020; chartreuse shaded area). The color bar refers to impact of VPD on maize yield losses (%).

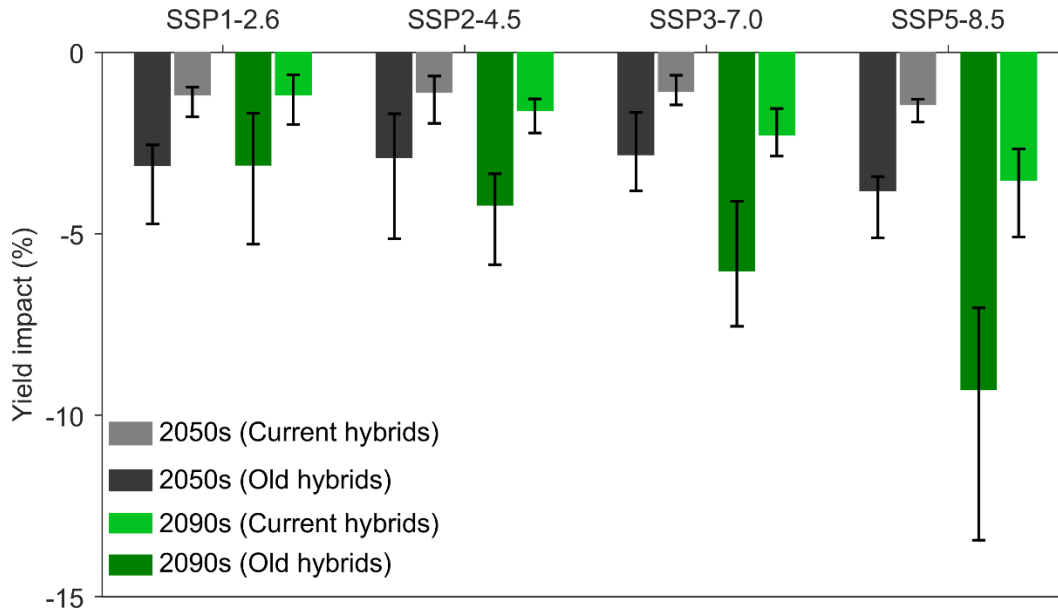


Figure 3.4. Estimated impact of mean vapor pressure deficit (VPD) projections on average maize yield. Averaged impact of VPD projections on maize yields using either sensitivity values of “old hybrids” or “current hybrids” in both 2050s (2050-2059) and 2090s (2090-2099) periods under four climate scenarios. Error bars refers to 25 and 75% percentiles of model projections. The SSP1-2.6 “2 °C scenario” of the “sustainability” SSP1 socio-economic family, whose nameplate 2100 radiative forcing level is 2.6 W m^{-2} . The SSP2-4.5 of the “middle of the road” socio-economic family SSP2 with a nominal 4.5 W m^{-2} radiative forcing level by 2100. The SSP3-7.0 scenario is a medium-high reference scenario within the “regional rivalry” socio-economic family, while the SSP5-8.5 marks the upper edge of the SSP scenario spectrum with a high reference scenario in a high fossil-fuel development world throughout the 21st century.

Chapter 4 - Conclusions and agricultural implications

Chapter 1

In this chapter, we focused on the impacts of compound hot-dry-windy (HDW) along with other main climate indices (extreme low temperature, high temperature, and precipitation) on winter wheat yields. This study was published in *Nature Communications*, 2022. The mechanism of compound HDW exposure consists of extreme climate, agronomic management, and cropping forces, which amplified their impacts compared to the impacts from the single extreme climate events. Crop vulnerability under HDW exposure can be complicated depending on the winter wheat varieties not only due to varying phenology, but also inherent genetic heat stress tolerance, water management, and the interaction of other hazards such as pests and diseases at various climate and agronomic scales. This is particularly true for winter wheat systems, given the long growing season that spans three distinct calendar seasons (fall, winter, and spring). The observed HDW trends increasing and HDW impacts in the context of climate change underscore the urgent need to adapt crop management and genetics to concurrent hot, dry, and windy conditions. Further studies are needed to better understand the relationship between compound extreme events and crop yield, including evaluating impacts directly associated with changes of frequency and intensity (i.e., amplitudes) of HDW occurrence during the grain filling period in the U.S. wheat belt. The exploration of the HDW-yield relationship in this study is a first step towards understanding the impacts of potential compound climate extreme events on crop yields, because HDW involves the co-occurrence of three, dependent hazards: unusual heat, drought, and high winds. Our results showed that compound HDW events are associated with negative impacts at a scale well beyond which any one of them, being in an extreme state, might have caused on its own.

In addition to its direct impact on crop yields, the significance of HDW events lies in their

potential interactions with other critical factors, notably diseases and insect pests. For instance, diseases such as wheat stem rust (Prank et al., 2019), and Fusarium head blight (De Wolf et al., 2003), can be exacerbated by HDW conditions, affecting wheat plant resistance and susceptibility, and further decreasing yields. Furthermore, the wind dispersal of these diseases during HDW events can lead to the rapid spread of infections across wheat fields, amplifying yield losses. In addition to diseases, insect pests such as the Hessian fly in western Kansas (Yuan et al., 2022), pose a significant threat to wheat production. These interactions underscore the complex nature of HDW events and emphasize the importance of considering multiple factors, including complex environmental factors, in crop management strategies to mitigate their adverse effects and ensure food security.

Chapter 2

In the second chapter, we focused on contributions to the U.S. maize yield gains in the past four decades. This study is under reviewed (moderate revision) in *Agricultural and Forest Meteorology*, 2024. Our analyses using automated weather station datasets and the Hybrid-Maize model, which is a process-based model, indicate a nonlinear and marginal contribution of surface solar radiation (SSR) trends and variations to maize yield gains in the US Corn Belt during the period between the 1980s and 2020. The SSR trends derived from the NASA POWER datasets appear to be systematically skewed towards an apparent brightening artifact. Over the past four decades, non-environmental factors such as genetics and management, along with their interactions, have been the primary drivers of maize yield gains. Our analyses confirm that trends and variations in SSR that result from climate variability and climate change have not significantly influenced decadal yield gains in maize. Changes in climate, particularly characterized by

increased warming and extreme events that are now being observed in temperature and precipitation, are more likely to have substantial negative impacts. Deconvolving contributions of individual climate drivers to grain yields at a large scale becomes intricate without dependable observational data, particularly from a climate change perspective.

In our investigation of U.S. maize yield gains spanning the last four decades, we encountered some challenges concerning data acquisition, accessibility, quality, accuracy, and control. The precision and reliability of our results may be influenced by the types of sensors employed and the frequency of data collection. Variations in sensor types and collection frequencies had the potential to introduce biases or inconsistencies, thus impacting the precision of our findings. Additionally, constraints in data sharing practices and spatial coverage posed obstacles in achieving comprehensive analyses. To mitigate these challenges, we implemented rigorous quality control measures to address data inaccuracies and uphold the integrity of our findings. Furthermore, considering the spatial range covered by the data was crucial, as spatial heterogeneity could limit the generalizability of our results to broader geographical regions. By navigating these challenges meticulously, we aimed to enhance the accuracy and reliability of our analysis, facilitating more robust interpretations and insights into the drivers of maize yield gains in the U.S. Corn Belt.

Chapter 3

Our final chapter determined vapor pressure deficit (VPD) impact on the U.S. maize yields and adaptation of maize hybrids to VPD by using statistical modeling. We demonstrated a negative impact of VPD on maize yield in the U.S. Corn Belt. This adverse impact would be exacerbated further with anticipated VPD increases in future climate scenario. Breeding programs that have focused on improvement in drought-tolerance as a form of climate adaptation could alleviate

sensitivity of maize yield to VPD with changing maize hybrids. Based on field trial datasets and a panel regression analysis, we found that newer hybrids have a greater yield response in the face of high VPD around silking period. However, under the SSP5-8.5 scenario, which limits surface warming to 4.6-5.2 °C at 2100, maize yields of current hybrids still show an additional decline of about 4%, over and above average historical losses. While our findings offer optimism regarding the potential of plant breeders to enhance VPD resilience in maize hybrids, they also underscore the urgent need for a directed breeding pace to counteract potential yield reductions resulting from escalating VPD due to climate change. Efforts in adapting crop yields to future warming must be strengthened to meet the demand of the growing population for food. One possible strategy is to limit the pace of climate warming. For example, mitigation toward SSP1-2.6 would alleviate yield losses over the next 80 years; The other plausible route is to establish crops earlier to escape the high VPD that is currently coinciding with sensitive growth period.

Summary

In total, examining the intricate interplay between weather patterns and plant growth is paramount for enhancing agricultural productivity and ensuring food security in the face of climate change. Throughout this thesis, we have explored the multifaceted impacts of extreme weather events, such as compound hot-dry-windy conditions on winter wheat yields, contributions of changes in surface solar radiation to U.S. maize yield gains, and the implications of vapor pressure deficit on maize yields. By delving into these topics, we have elucidated critical insights into the vulnerabilities of crop production systems and the potential pathways for adaptation. Understanding the complex interactions between weather phenomena and crop responses is essential for informing the development of directed genetic programs and management protocols

aimed at enhancing crop resilience and productivity. Through our collective efforts, we can leverage these insights to forge a path towards sustainable agricultural practices and ensure food security for future generations.

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Appendix A - Supplemental Information for Chapter 1

Text A.1. Phenology of winter wheat

Because weather varies in both space and time, uniform and homogenous responses of crops to weather during the growing season should not be expected. Thus, phenological dates for each county-year were estimated separately, which allows us to analyze yield responses physiologically in terms of climate change and variability that sub-regions (states or counties) were experiencing in a wheat life cycle (Figure A.1). The phenological observations, including planting and harvest dates, were collected from 230 and 186 experimental stations, respectively (Figure A.2a,d). Each state had more than 12 years of phenological observations with 15 stations per year on average. To fulfill a complete dataset, we first interpolated available data to the centroid of each county using a Delaunay Triangulation method (Barber, Dobkin, & Huhdanpaa, 1996). Due to missing dates, especially in Oklahoma and Texas, we constructed linear regression models between phenological dates across Kansas (KS) and Nebraska (NE), where the data were nearly complete, and available phenological dates mostly located in Oklahoma (OK) and Texas (TX). We evaluated the completeness of our phenological date estimates by a leave-one-out approach (Vehtari, Gelman, & Gabry, 2017). The selection of the optimum coefficients for each model was based on the minimum root mean square error (RMSE) between fitted and observed phenological datasets (Table A.5). The selected model was then used to gap-fill missing planting and harvest dates for each county from 1982-2020. An empirical relationship, where physiological maturity occurred approximately 2 weeks prior to harvest (Robertson, 2004), was used to estimate maturity dates in our study.

Growing degree days (GDD, °C days) is a common matrix used to partition phenological periods of winter wheat in the Great Plains (Peairs, 2010). For example, the jointing and heading

dates were defined as reaching 35% and 57% of accumulated GDD (Lobell, Sibley, & Ortiz-Monasterio, 2012) required for winter wheat maturity from January 1 to the maturity date, respectively (Peairs, 2010). Based on this averaged accumulated GDD, the jointing and heading dates for all counties were estimated. Note that, even though there were no available documented harvest dates in Texas, the observed heading dates were collected over 20 years covering three counties including Bushland, Chillicothe, and Dallas in Texas, which represent three diverse climate sub-regions: Great Plains, North Central Plains, and Coastal Plains, respectively (Figure A.2c). The accumulated GDD from January 1 to the heading dates were used to reversely estimate average accumulated GDD from January 1 to maturity dates across these three counties for each year. We then estimated the maturity dates in TX. Similar to SD, CO, and OK, the estimated jointing dates and heading dates were also obtained in TX. Finally, we partitioned the wheat phenology into three stages, including planting to jointing (PT-JT), jointing to heading (JT-HD), and heading to maturity (HD-MT) (Figures A.1 and A.2). All phenological data can be directly obtained from the links listed in Table A.1, but KS data from 1982-2007 were from printed documents that we digitized at the Department of Agronomy and Kansas Climate Center, Kansas State University.

Text A.2. HadISD data to identify HDW

The HadISD is a global sub-daily dataset based on the U.S. Integrated Surface Database (ISD) from NOAA's National Centers of Environmental Information (NCEI). The dataset covers 1931 to the present and is designed to study the long-term changes of extreme temperature, pressure, and humidity (Dunn, Willett, Parker, & Mitchell, 2016). The station selection criteria were based on a suite of quality control tests, and data homogeneity assessments were conducted for air temperature, dew point temperature, sea-level pressure, and wind speed (Dunn et al., 2016). We

retrieved observed hourly 2-m air temperature and air relative humidity and 10-m wind speed from 1982 to 2020. We screened 16 stations with less than 5% missing data for all three variables during the grain-filling periods, except for 4 stations in CO and OK that had less than 10% missing data. We then used the regularized expectation maximization (rEM) procedures to refill data gaps (Schneider, 2001). Finally, we presented the spatial pattern of HDW based on the HadISD dataset.

Text A.3. Intercomparison between ERA5-Land and HadISD datasets

To evaluate HDW variations derived from ERA5-Land datasets in both spatial and temporal domains, we calculated correlation coefficients between HadISD and ERA5-Land datasets. We screened 34 stations from HadISD datasets based on our data quality control procedure. Stations were selected with at least 30 years of data for analysis. A year was treated as missing in any station if this station contained more than 8% missing hourly data from April 1 to July 31st from 1982 to 2020, which generally covered the grain filling period (HD-MT) across our study domain. Outside of this window there were rare HDW events. Then we trimmed all ERA5-Land datasets to hourly, in order to match with the HadISD dataset that we selected (Figure A.3). We then counted annual mean HDW events for each station-year by using HadISD and ERA5-Land datasets. The temporal HDW anomalies, calculated by taking all of 1982 to 2020 as the base period, were used to get a correlation coefficient between HadISD and ERA5-Land datasets for each station (Figure A.4a). The spatial HDW anomalies were calculated based on all available stations for a year (Supplementary Fig. 4b). We found both temporal and spatial correlation coefficients of 0.8 in most stations and years (Figure A.4a,b). Changes of HDW events between the latest 20 years and the early 19 years indicated there were increasing HDW events (Figure A.4c), suggesting not only an increasing trend of HDW events in both datasets but also changes in magnitudes that were consistent in both datasets.

Text A.4. Additional statistical models tested

To increase the confidence of HDW influence on wheat yields, we used both the quadratic temperature model (M1, Eq. S1) and the temperature bins' model (M2, Eq. S2), which are temperature orientated. Note that we did not include EDD and FDD when considering temperature as a predictor because the quadratic temperature and temperature bins have captured the extreme heat (EDD) and the extreme cold (FDD) effects (Lobell, Schlenker, & Costa-Roberts, 2011). Both the M1 and M2 structures are shown following:

$$Y_{i,t} = \sum_{p=1}^3 (\beta_{1,p} T_{i,p,t} + \beta_{2,p} T_{i,p,t}^2) + \sum_{p=1}^3 (\beta_{3,p} Prcp_{i,p,t} + \beta_{4,p} Prcp_{i,p,t}^2) + \beta_5 HDW_{i,t} + c_i + y_t + \varepsilon_{i,t} \quad [\text{M1, Eq. S1}]$$

$$Y_{i,t} = \sum_{p=1}^3 \int_h^{\bar{h}} g_p(h) \phi_{i,p,t}(h) dh + \sum_{p=1}^3 (\beta_{1,p} Prcp_{i,p,t} + \beta_{2,p} Prcp_{i,p,t}^2) + \beta_3 HDW_{i,t} + c_i + y_t + \varepsilon_{i,t} \quad [\text{M2, Eq. S2}]$$

where T refers to mean temperature during specific phenological stage. The observed temperatures (h) during each time period range between the lower bound h and the upper bound $\bar{h}$. The $g(h)$ is the fixed coefficient function for the temperature exposure, h , on yield. The $\phi_{i,p,t}(h)$ is the time distribution given the hours of exposure to temperature h . Other factors are the same using model Eqs. 1 and 2 as in the Method section of Main text. We here used temperature bins of 2°C interval during three phenological stages.

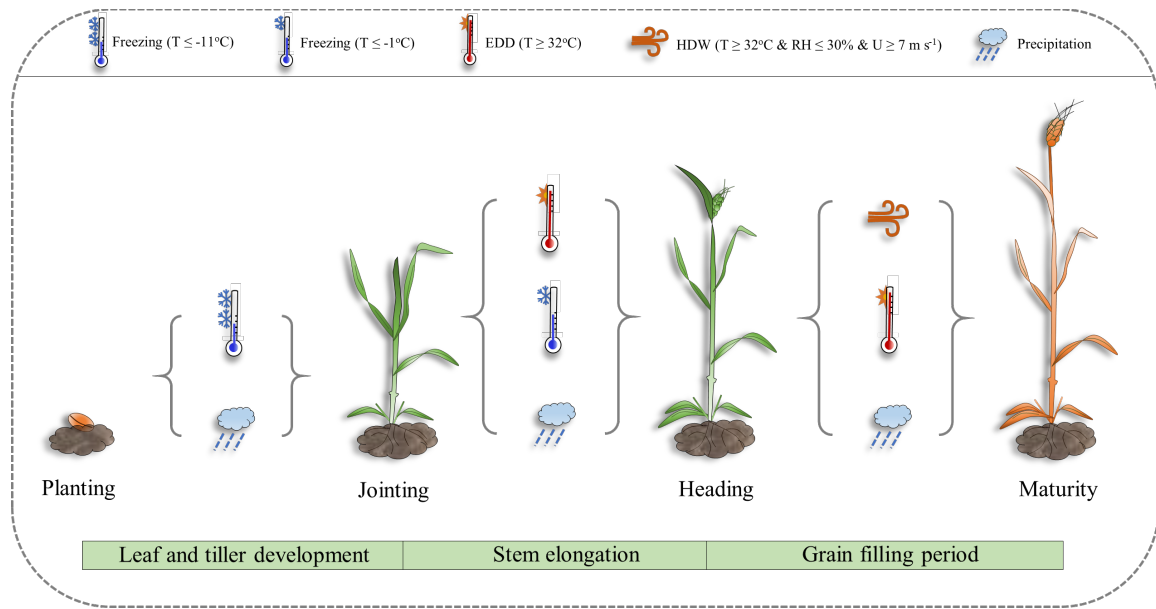


Figure A.1. Flowchart of main climate indices throughout three phenological stages in winter wheat. The thresholds selected (at the top) and three phenological stages (at the bottom) were used in our modeling process (at the middle, for example, we used EDD (extreme degree days), Freezing at $T \leq -1^{\circ}\text{C}$, and precipitation during the jointing to heading stage. The planting-jointing (PT-JT), jointing-heading (JT-HD), and heading-maturity (HD-MT) stages were included during modeling.

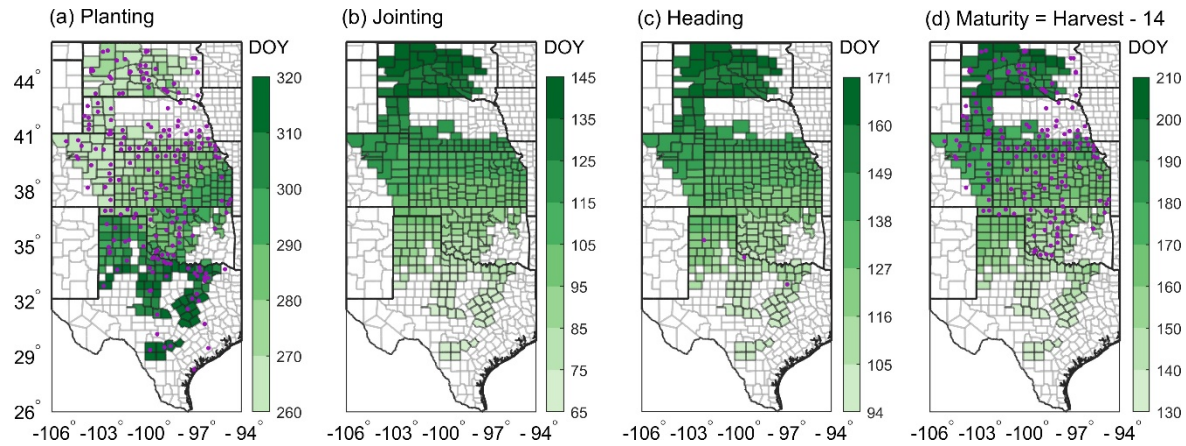
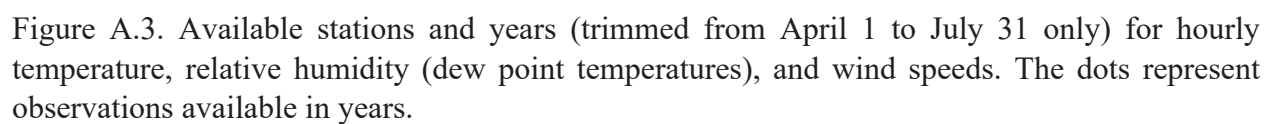


Figure A.2. Average phenology (days of year, DOY) estimated from 1982-2020. The estimated county-level phenology included (a) planting, (b) jointing, (c) heading, and (d) maturity dates. The purple dots in (a), (c), and (d) indicate the 230, 3, and 186 field experiment stations respectively, where planting, heading, and harvest dates were documented by observations (details in Supplementary Text 1).



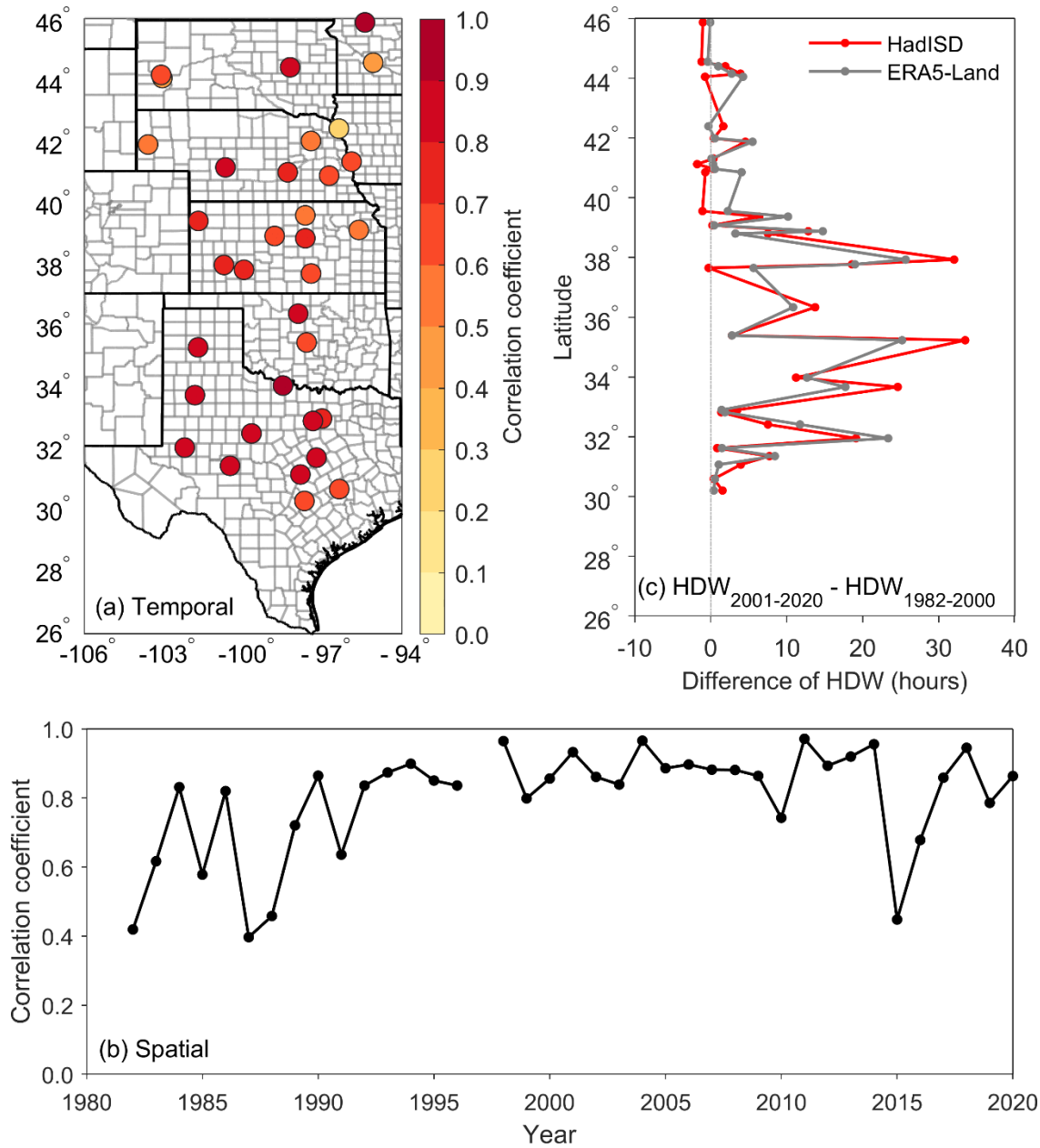


Figure A.4. The 34-station (a) temporal and (b) 39-year spatial correlation coefficients as well as (c) difference of averaged hot-dry-windy (HDW) events for the latest 20 years (2001-2020) and the earliest 19 years (1982-2000). All correlations calculated were based on either a temporal anomaly (average of available years as a base for a station) or a spatial anomaly (average of all available stations as a base for a year) from HadISD stations and ERA5-Land datasets.

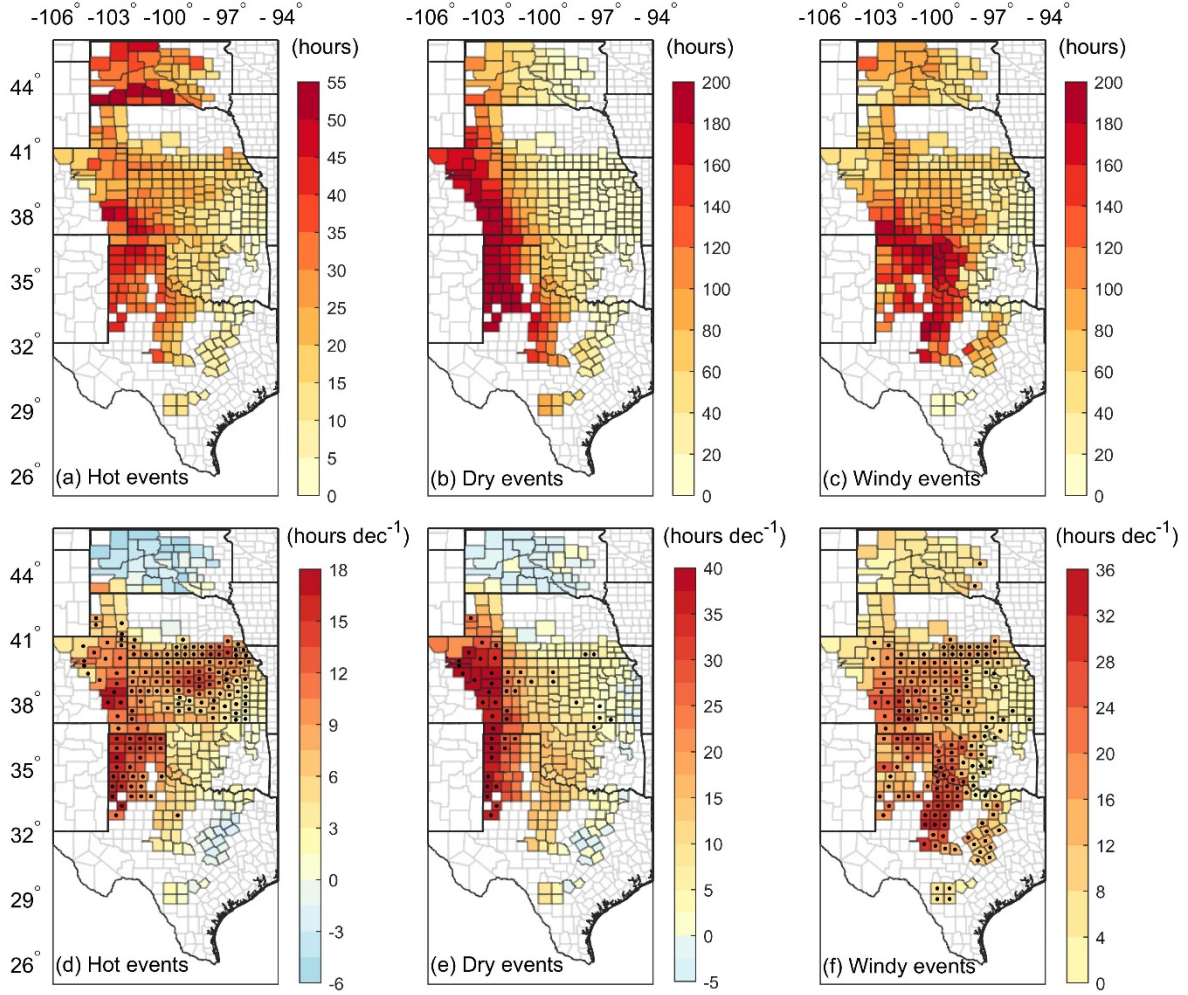


Figure A.5. Annual mean (a-c) and trends (d-f) of three individual climate extreme events during the heading-maturity (HD-MT) stage from 1982 to 2020. The annual mean of (a) hourly hot ($T \geq 32^\circ\text{C}$), (b) dry ($\text{RH} \leq 30\%$), and (c) windy ($U \geq 7 \text{ m s}^{-1}$) events during HD-MT. The black dots indicate statistically significant trends at a 95% confidence interval based on the Mann-Kendall test ($p \leq 0.05$).

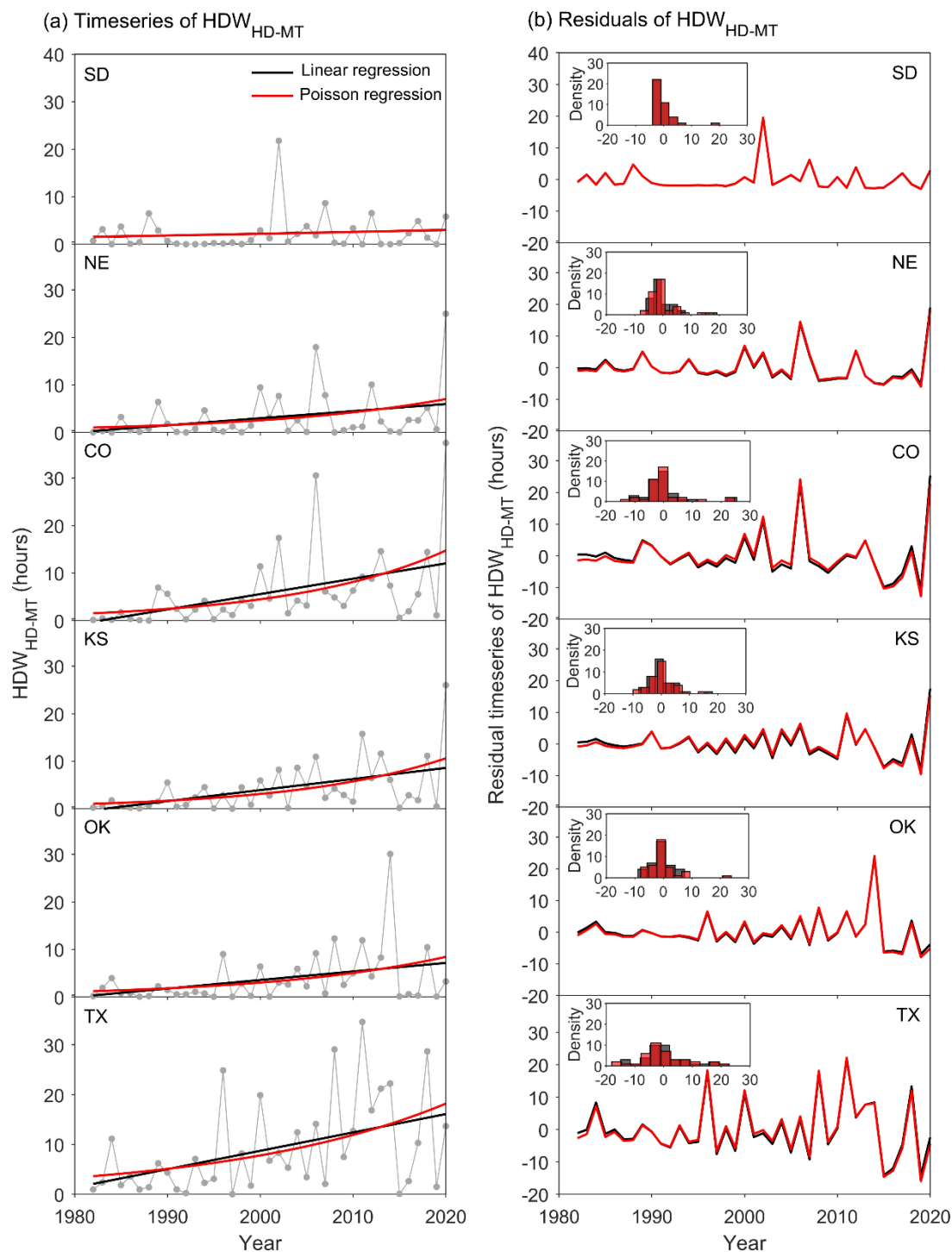


Figure A.6. Statewide hot-dry-windy (HDW) trends during the heading-maturity (HDW_{HD-MT}) stage when area-weighted averages were conducted from 1982 to 2020. a, Trends of HDW_{HD-MT} detected by ordinary linear regression and Poisson regression, which should not be extrapolated because trend analyses (including other methods not used here), on average, best represent an approximation. b, residuals and their histograms.

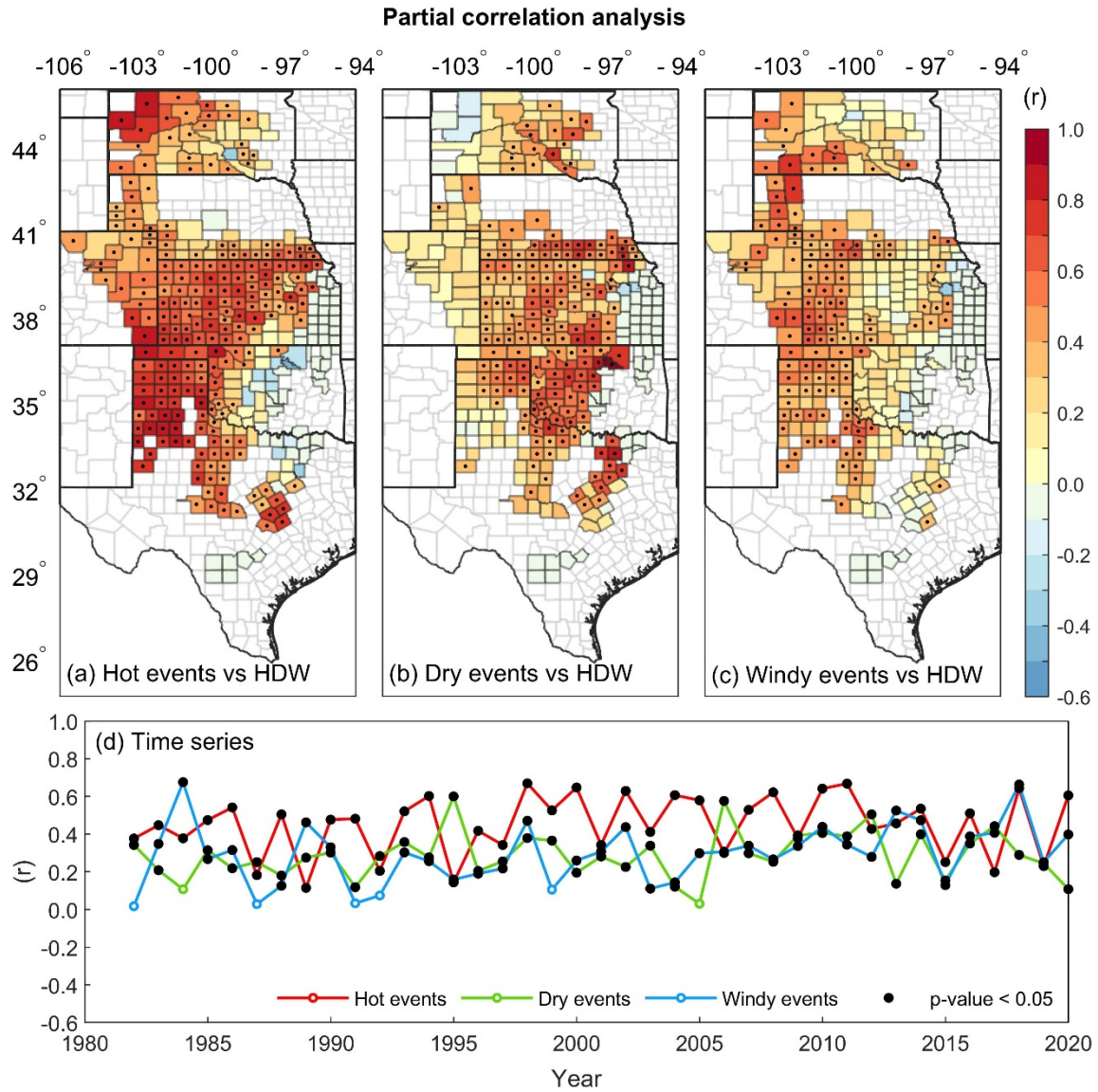


Figure A.7. Spatial (a-c) and temporal (d) patterns of partial correlation coefficients between three individual events and HDW during the heading-maturity (HD-MT) stage from 1982 to 2020. The black dots represent the statistically significant correlation years ($p \leq 0.05$).

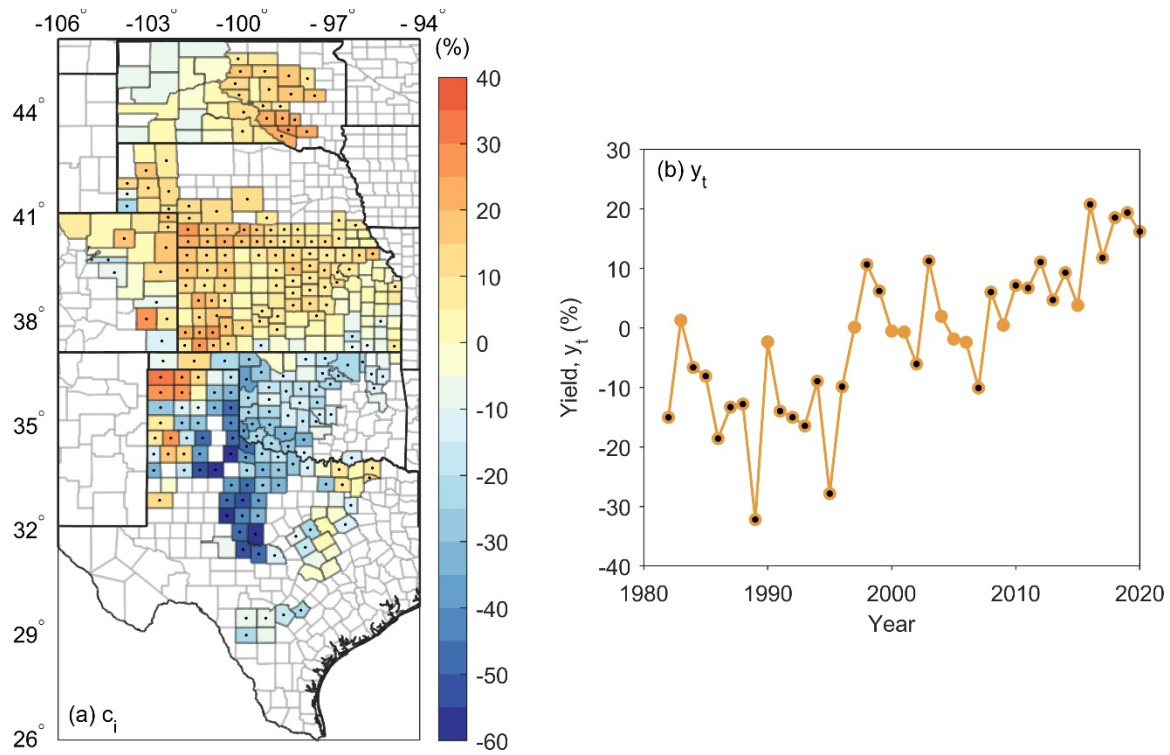


Figure A.8. The random effect of counties and years derived from the linear mixed-effects model relative to averaged yields (%). a, c_i term in Eq. (1). The color bar shows the effect sizes. b, y_t term in Eq. (1) showing a general upward trend whose overall magnitude is consistent with the rates of wheat breeding progress and improvements in agronomic production practices. The black dots indicate statistical significance in the model ($p \leq 0.05$).

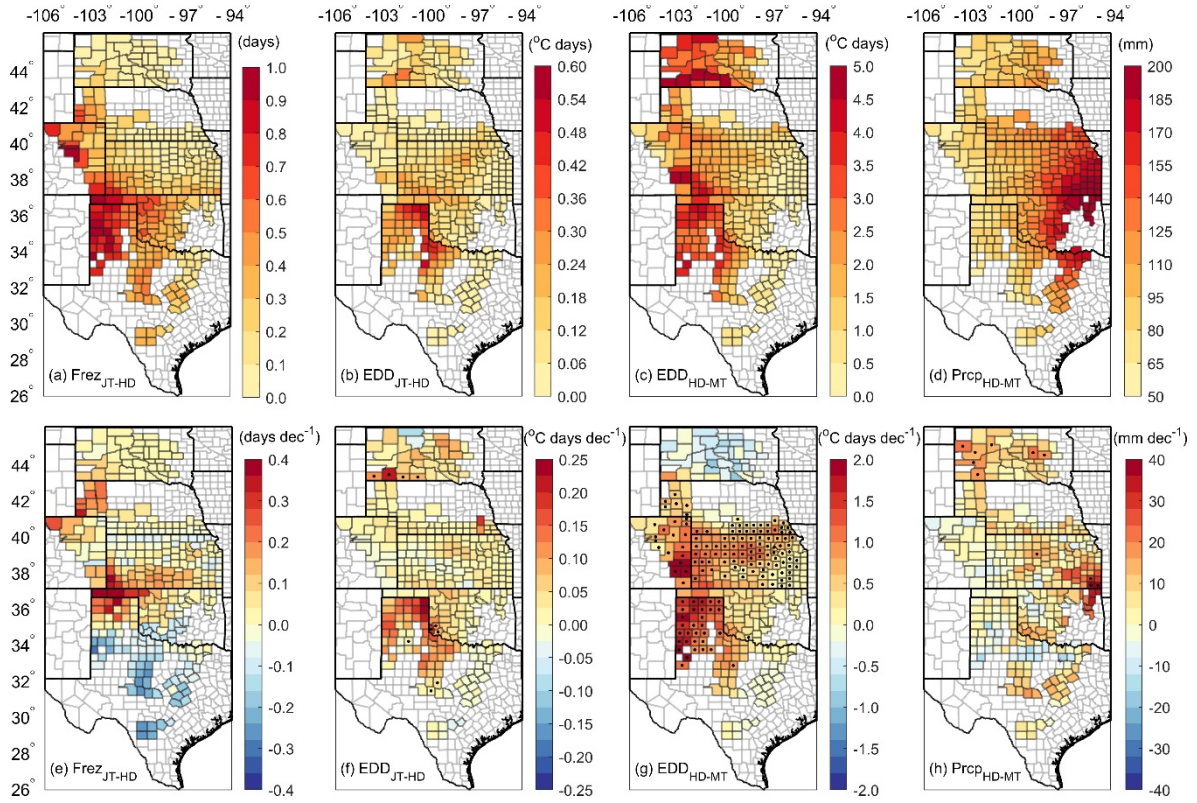


Figure A.9. Annual mean (a-d) and trends (e-h) of climate indices from 1982 to 2020. The black dots in (e-h) represent trends that were statistically significant in these counties ($p \leq 0.05$).

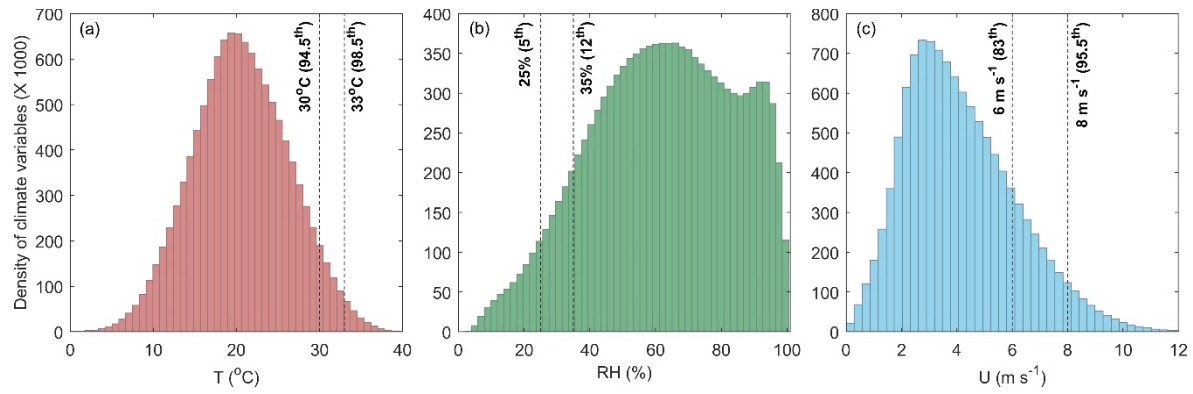


Figure A.10. Distributions of (a) hourly temperature (T , $^{\circ}\text{C}$), (b) relative humidity (RH , %), and (c) ambient wind speeds (U , m s^{-1}) during the heading to maturity period across our study domain from 1982-2020. The black vertical dotted lines indicate the percentiles in brackets and their corresponding values.

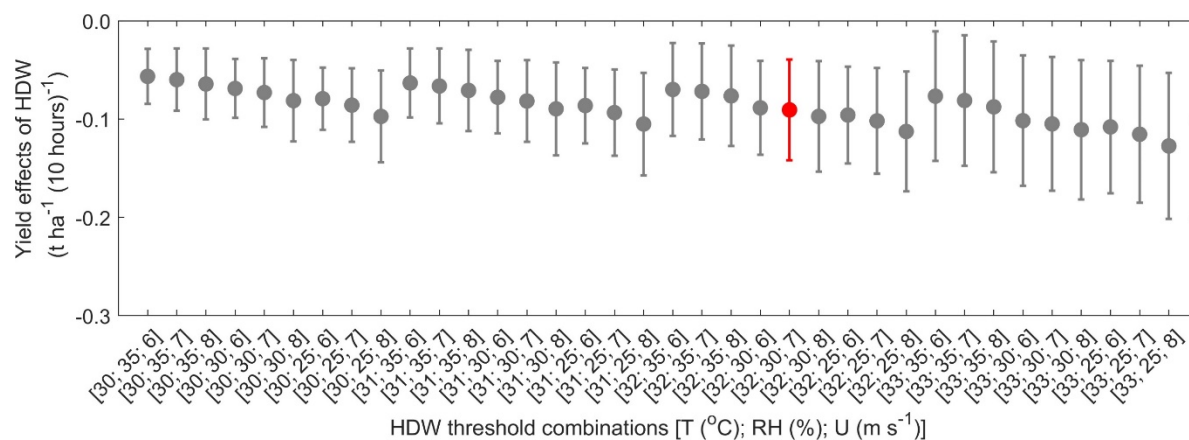


Figure A.11. Yield sensitivity of hot-dry-windy (HDW) events from 1982 to 2020 estimated using the 36 combinations of the thresholds tested. Red color indicates the combination we used in the Main text. Numbers in the square brackets represent thresholds of temperature (T), relative humidity (RH), and wind speeds (U), respectively. The error bars indicate a 95% confidence interval.

(a) Temperature effects from M2 Model

(b) HDW effects from M0, M1, and M2

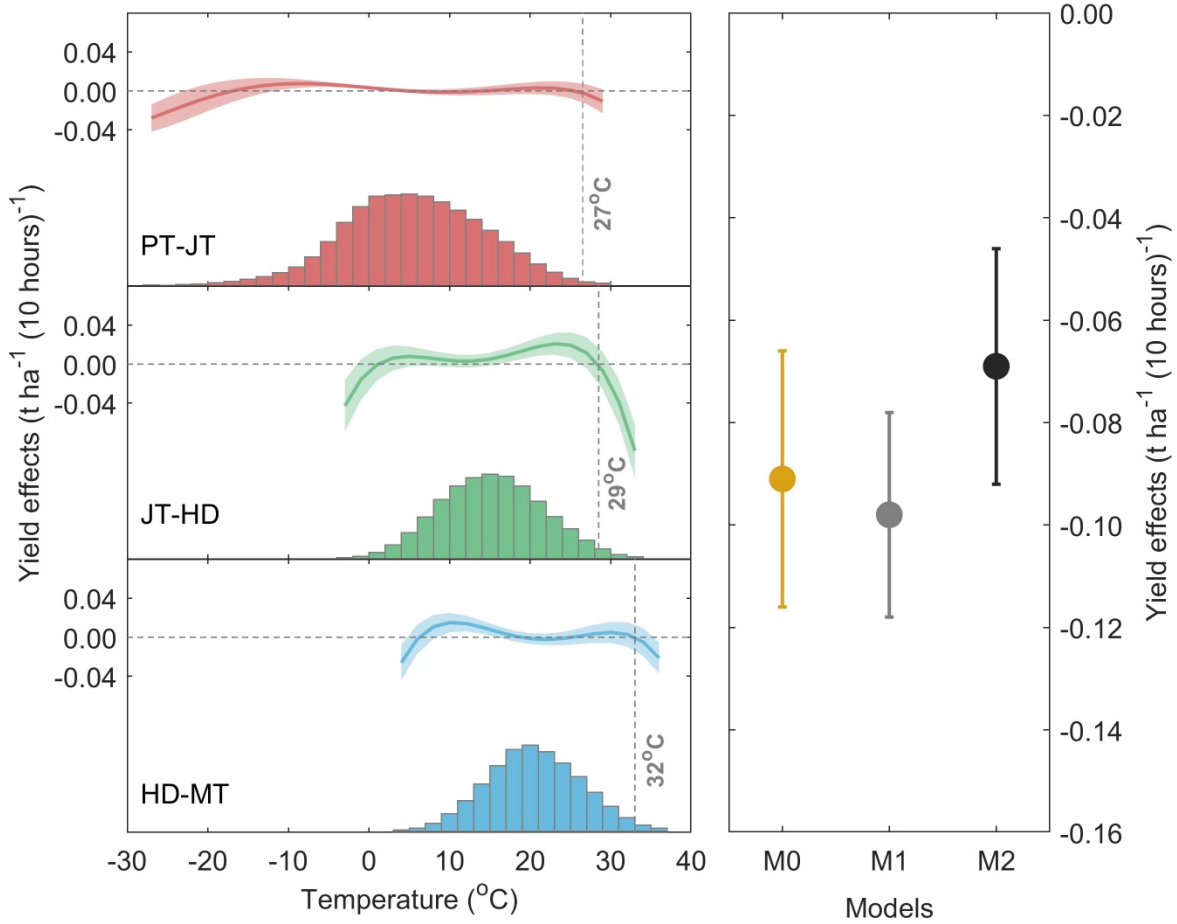


Figure A.12. Yield sensitivity to temperature bins and hot-dry-windy (HDW) effects tested in three models. a, Yield sensitivity to temperature bins at three phenological stages: planting to jointing (PT-JT; red); jointing to heading (JT-HD; green); and heading to maturity (HD-MT; blue). Histograms show exposure times (hours) for each phenological stage across county-years in 2°C temperature bins. The solid lines indicate the mean yield effects per 10 hours of temperature bin, and the shaded regions around the solid lines indicate the 95% confidence interval. Temperature “32°C” in the panel (blue) indicates that yield would be lost when temperature is higher than this threshold. b, Yield effects (t ha⁻¹ per 10 hours of HDW events) during the HD-MT stage using the original model (here called M0, Eqs. 1 and 2 in Methods), the quadratic temperature model (M1, Eq. S1), and the temperature bins’ model (M2, Eq. S2). Error bars show one clustering standard error (SE).

Table A.1. Links of publicly available data for phenology.

States	Links
South Dakota	https://extension.sdstate.edu/winter-wheat-variety-trial-results
Nebraska	https://cropwatch.unl.edu/winter-wheat-variety-test-results https://digitalcommons.unl.edu/extensionhist/
Colorado	https://agsci.colostate.edu/csucrops/winter-wheat-trial-results/#Wheat2011
Kansas	https://www.agronomy.k-state.edu/services/crop-performance-tests/winter-wheat/index.html
Oklahoma	http://croptrials.okstate.edu/wheat/grain-yield/ https://digitalprairie.ok.gov/digital/collection/stgovpub/id/23993 https://www.okwheat.org/research-documents/variety-trials/
Texas	http://varietytesting.tamu.edu/wheat/ https://www.ars.usda.gov/plains-area/lincoln-ne/wheat-sorghum-and-forage-research/docs/hard-winter-wheat-regional-nursery-program/pre-2010-nursery-data/

Table A.2. Parameter estimates from standardized modelling regression. Standard errors (SEs) were clustered by county and year.

Climate indices	β	SEs	p_{adj}
Frez _{PT-JT}	-0.026	0.019	0.170
Frez _{JT-HD}	-0.029	0.011	0.009
EDD _{JT-HD}	-0.052	0.014	<0.001
EDD _{HD-MT}	-0.017	0.031	0.575
Prcp _{PT-JT}	0.500	0.051	<0.001
Prcp _{JT-HD}	0.190	0.044	<0.001
Prcp _{HD-MT}	0.062	0.043	0.144
Prcp _{PT-JT} Squared	-0.383	0.051	<0.001
Prcp _{JT-HD} Squared	-0.173	0.035	<0.001
Prcp _{HD-MT} Squared	-0.118	0.040	0.003
HDW _{HD-MT}	-0.083	0.023	<0.001
R-squared	0.590		
p-value (F-test)	<0.001		

Table A.3. Parameter estimates from original modelling regression.

Climate indices	β	SEs	p_{adj}
Free _{PT-JT} (10 days)	-0.017	0.012	0.161
Free _{JT-HD} (1 day)	-0.033	0.013	0.013
EDD _{JT-HD} (1 °C day)	-0.147	0.038	<0.001
EDD _{HD-MT} (10 °C days)	-0.062	0.107	0.564
Prcp _{PT-JT} (50 mm)	0.214	0.017	<0.001
Prcp _{JT-HD} (50 mm)	0.189	0.036	<0.001
Prcp _{HD-MT} (50 mm)	0.041	0.022	0.059
Prcp _{PT-JT} Squared (50 ² mm)	-0.014	0.002	<0.001
Prcp _{JT-HD} Squared (50 ² mm)	-0.039	0.007	<0.001
Prcp _{HD-MT} Squared (50 ² mm)	-0.011	0.003	<0.001
HDW _{HD-MT} (10 hours)	-0.091	0.026	<0.001
R-squared	0.590		
p-value (F-test)	<0.001		

Table A.4. Climate dataset links.

Data sources	Links
ERA5-Land	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview
HadISD	http://www.metoffice.gov.uk/hadobs/hadisd/
Pacific Decadal Oscillation (PDO)	https://psl.noaa.gov/pdo/

Note: PDO data are calculated using the National Oceanic and Atmospheric Administration's Extended Reconstructed SST data set, version 5 (ERSST.v5), on a $2^\circ \times 2^\circ$ latitude-longitude grid.

Table A.5. Root mean square error (RMSE) for estimated planting (PT) and maturity (MT) dates across South Dakota, Colorado, Oklahoma, and Texas.

South Dakota				Colorado			
Locations		RMSE (days)		Locations		RMSE (days)	
Latitude	Longitude	PT	MT	Latitude	Longitude	PT	MT
43.19°	-99.19°	1	3	37.32°	-102.56°	5	2
43.19°	-100.72°	2	4	37.96°	-103.07°	4	2
43.19°	-101.66°	4	4	37.96°	-102.39°	3	2
43.21°	-98.59°	2	2	38.43°	-102.74°	3	2
43.24°	-103.53°	6	5	38.83°	-102.60°	3	2
43.33°	-97.75°	3	2	38.99°	-103.51°	4	4
43.34°	-102.55°	4	4	39.29°	-104.14°	4	4
43.35°	-99.88°	1	1	39.31°	-102.60°	2	3
43.39°	-98.37°	1	0	39.65°	-104.34°	5	4
43.58°	-100.76°	5	0	39.87°	-104.34°	4	4
43.67°	-98.15°	2	2	39.97°	-103.20°	3	3
43.69°	-101.63°	3	1	40.00°	-102.42°	2	2
43.72°	-98.56°	5	1	40.26°	-103.81°	3	4
43.72°	-99.08°	1	0	40.55°	-104.39°	5	4
43.90°	-99.85°	0	2	40.59°	-102.36°	3	2
43.96°	-100.69°	1	1	40.67°	-105.46°	5	6
44.00°	-102.82°	3	4	40.72°	-103.11°	2	3
44.07°	-98.63°	4	1	40.88°	-102.35°	4	3
44.08°	-99.20°	3	0				
44.29°	-101.54°	0	1				
44.37°	-97.49°	0	2				
44.39°	-100.00°	0	0				
44.41°	-100.74°	0	1				
44.41°	-98.28°	1	1				
44.55°	-99.49°	1	2				
44.55°	-99.00°	1	4				
44.57°	-102.72°	0	2				
44.72°	-100.13°	0	1				
44.86°	-97.73°	2	1				
44.91°	-103.51°	2	4				
44.94°	-98.35°	1	1				
44.98°	-101.67°	2	1				
45.06°	-99.96°	0	0				
45.07°	-99.15°	0	3				
45.16°	-100.87°	3	1				
45.42°	-99.22°	1	2				
45.43°	-100.03°	3	1				
45.49°	-102.48°	2	3				
45.71°	-101.20°	1	4				

Table A.5. Continued.

Oklahoma				Texas			
Locations		RMSE (days)		Locations		RMSE (days)	
Latitude	Longitude	PT	MT	Latitude	Longitude	PT	MT
33.96°	-96.26°	9	6	28.87°	-99.76°	3	5
34.11°	-97.84°	9	6	28.87°	-99.11°	4	4
34.29°	-98.37°	9	5	29.36°	-99.11°	2	4
34.37°	-98.92°	10	4	29.36°	-99.76°	6	5
34.49°	-97.85°	7	6	29.45°	-98.52°	3	4
34.59°	-99.41°	8	5	29.58°	-97.95°	3	4
34.66°	-98.47°	8	3	30.65°	-97.60°	5	4
34.70°	-97.31°	5	4	30.79°	-96.98°	4	4
34.74°	-99.85°	7	5	31.04°	-97.48°	5	4
34.92°	-98.98°	7	3	31.16°	-98.82°	4	5
34.94°	-99.56°	6	4	31.20°	-99.35°	6	6
35.01°	-97.44°	4	4	31.25°	-96.94°	2	4
35.02°	-97.88°	5	4	31.33°	-99.86°	5	6
35.17°	-98.38°	5	3	31.39°	-97.80°	5	5
35.20°	-97.33°	5	5	31.40°	-100.46°	7	4
35.21°	-96.95°	5	4	31.55°	-97.20°	2	4
35.27°	-99.68°	5	4	31.70°	-98.11°	5	5
35.29°	-98.99°	6	4	31.77°	-99.45°	6	5
35.54°	-97.98°	6	5	31.83°	-99.98°	5	6
35.55°	-97.41°	8	5	31.90°	-97.63°	5	5
35.62°	-95.38°	11	7	31.99°	-97.13°	5	3
35.64°	-99.00°	4	3	32.05°	-96.47°	5	3
35.69°	-99.70°	6	3	32.30°	-99.37°	8	5
35.88°	-98.43°	4	4	32.30°	-99.89°	9	5
35.92°	-97.44°	7	3	32.30°	-100.41°	6	7
35.95°	-97.94°	5	4	32.35°	-96.79°	6	3
35.96°	-95.52°	9	5	32.38°	-97.37°	6	3
35.99°	-99.01°	4	3	32.60°	-96.29°	6	4
36.08°	-96.98°	7	5	32.74°	-99.35°	8	5
36.22°	-99.75°	5	3	32.74°	-99.88°	9	5
36.30°	-95.23°	9	5	32.74°	-102.64°	10	7
36.31°	-98.54°	4	4	32.74°	-100.40°	9	7
36.32°	-96.70°	7	4	32.77°	-96.78°	7	3
36.37°	-95.60°	8	5	33.12°	-96.09°	10	4
36.38°	-97.78°	4	4	33.17°	-102.34°	10	7
36.39°	-97.23°	6	5	33.18°	-98.69°	10	4
36.42°	-99.26°	4	3	33.18°	-99.21°	7	5
36.63°	-96.40°	6	5	33.18°	-99.73°	7	5
36.72°	-95.90°	8	5	33.18°	-100.25°	8	7
36.73°	-98.32°	7	5	33.19°	-96.57°	8	4
36.75°	-101.49°	3	4	33.21°	-97.12°	8	4
36.75°	-102.52°	4	7	33.39°	-95.67°	10	4
36.75°	-100.48°	3	3	33.59°	-96.11°	7	4
36.76°	-95.21°	6	5	33.60°	-102.83°	9	7
36.77°	-98.87°	4	4	33.61°	-99.74°	7	5
36.79°	-99.67°	5	3	33.61°	-101.82°	11	7
36.80°	-97.79°	3	5	33.61°	-101.30°	9	7
36.82°	-97.14°	6	4	33.62°	-98.69°	8	4
36.84°	-94.81°	7	5	33.62°	-99.21°	7	5

Table A.5. Continued.

Texas				Texas			
Locations		RMSE (days)		Locations		RMSE (days)	
Latitude	Longitude	PT	MT	Latitude	Longitude	PT	MT
33.62°	-100.78°	9	7	34.96°	-100.27°	10	7
33.63°	-96.68°	9	4	34.96°	-101.36°	3	7
33.64°	-97.21°	10	4	34.97°	-101.90°	4	7
33.67°	-95.57°	11	4	34.97°	-102.60°	7	7
33.68°	-97.72°	11	5	35.40°	-100.81°	5	7
33.79°	-98.21°	10	5	35.40°	-100.27°	11	8
33.97°	-99.78°	7	4	35.40°	-101.89°	4	7
33.99°	-98.70°	10	4	35.40°	-101.35°	2	7
34.07°	-102.83°	7	7	35.41°	-102.60°	6	7
34.07°	-102.35°	11	7	35.84°	-100.27°	6	8
34.07°	-101.83°	11	7	35.84°	-101.89°	6	7
34.07°	-101.30°	8	7	35.84°	-100.81°	5	7
34.08°	-100.28°	5	7	35.84°	-101.35°	4	7
34.08°	-99.24°	7	4	35.84°	-102.60°	8	7
34.29°	-99.75°	6	5	36.28°	-101.35°	6	7
34.53°	-100.21°	7	7	36.28°	-101.89°	9	7
34.53°	-102.26°	7	7	36.28°	-100.27°	8	8
34.53°	-102.78°	5	7	36.28°	-102.60°	11	7
34.53°	-101.21°	11	7	36.28°	-100.82°	6	8
34.53°	-101.74°	8	7				

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Appendix B - Supplemental Information for Chapter 2

This Supplementary Information provides details with respect to 1) leaf-level measurements of absorbed light, incident light, maize assimilation rate (A_{net}), excess heat dissipated by non-photochemical quenching (NPQ), and quantum yield of CO_2 fixation (Φ_{CO_2} , an analogy of radiation-use efficiency at a leaf level) (Figure B.1) conducted in Mead, Nebraska from June 19 to June 30, 2017; 2) time series of temperature anomalies (a base period of 1991 to 2020) during growing seasons from 1984 to 2020 (Figure B.2) across all ten states in the US Corn Belt; 3) time series of precipitation anomalies (a base period of 1991 to 2020) during growing seasons from 1984 to 2020 (Figure B.3) across all ten states in the US Corn Belt; 4) time series in planting dates, plant density, growing degree days from planting to silking and from silking to maturity in maize fields over 1984 to 2020 across four main maize-producing states (Figure B.4); 5) Hybrid maize model performance to predict maize yields in the US Corn Belt (Figure B.5); 6) long-term surface solar radiation (SSR) sites used in the global or regional solar radiation assessment, and which sites are located in the US Corn Belt (Figure B.6); 7) time series of daily diurnal temperature range (DTR) and monthly cloud cover percent (CLD) (Figures B.7 and B.8); 8) Table B.1 is the quality control and quality assurance of ground-based AWS solar radiation measurements; 9) Table B.2 provides the data sources we used in our study; 10) Table B.3 shows the model runs to estimate contributions of changes in non-environmental factors to maize yield trends; 11) Table B.4 lists published papers by authors and countries that we collected, with available data on maize yields and biomass during grain filling period.

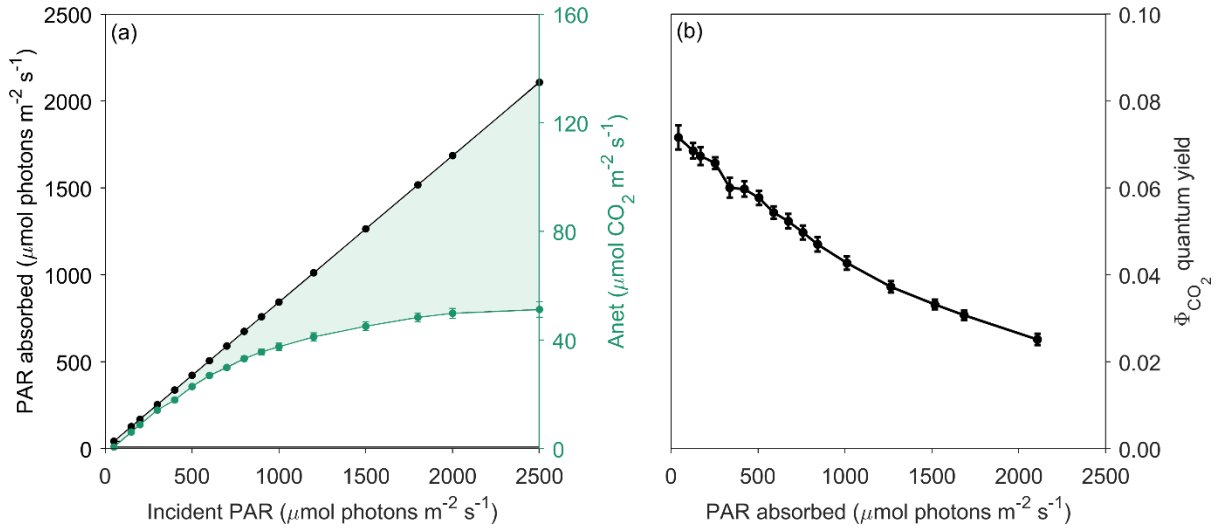


Figure B.1. Leaf-level measurements for maize photosynthetic process. (a) Leaf-level measurements of photosynthesis rate (A_{net} , $\mu\text{mol CO}_2 \text{ m}^{-2} \text{s}^{-1}$) and relation between photosynthetically active radiation (PAR) absorbed and incident PAR. The shaded area indicates that the excess heat is dissipated by non-photochemical quenching (NPQ) at a leaf level. (b) Quantum yield of CO_2 fixation ($\Phi_{\text{CO}_2} = \frac{A_{\text{net}} - R_d}{\alpha \text{PAR}_{\text{inc}}}$, an analogy of radiation-use efficiency at the leaf level; R_d , PAR_{inc} , and α correspond to dark respiration, incident PAR, and leaf absorbance, respectively). Data in both (a) and (b) were taken in Mead, Nebraska over an irrigated maize field from June 19 to June 30, 2017 by LI-6800 Photosynthesis System (LI-COR Bioscience Inc., Lincoln, Nebraska, USA) and error bars indicate one standard deviation of measurements.

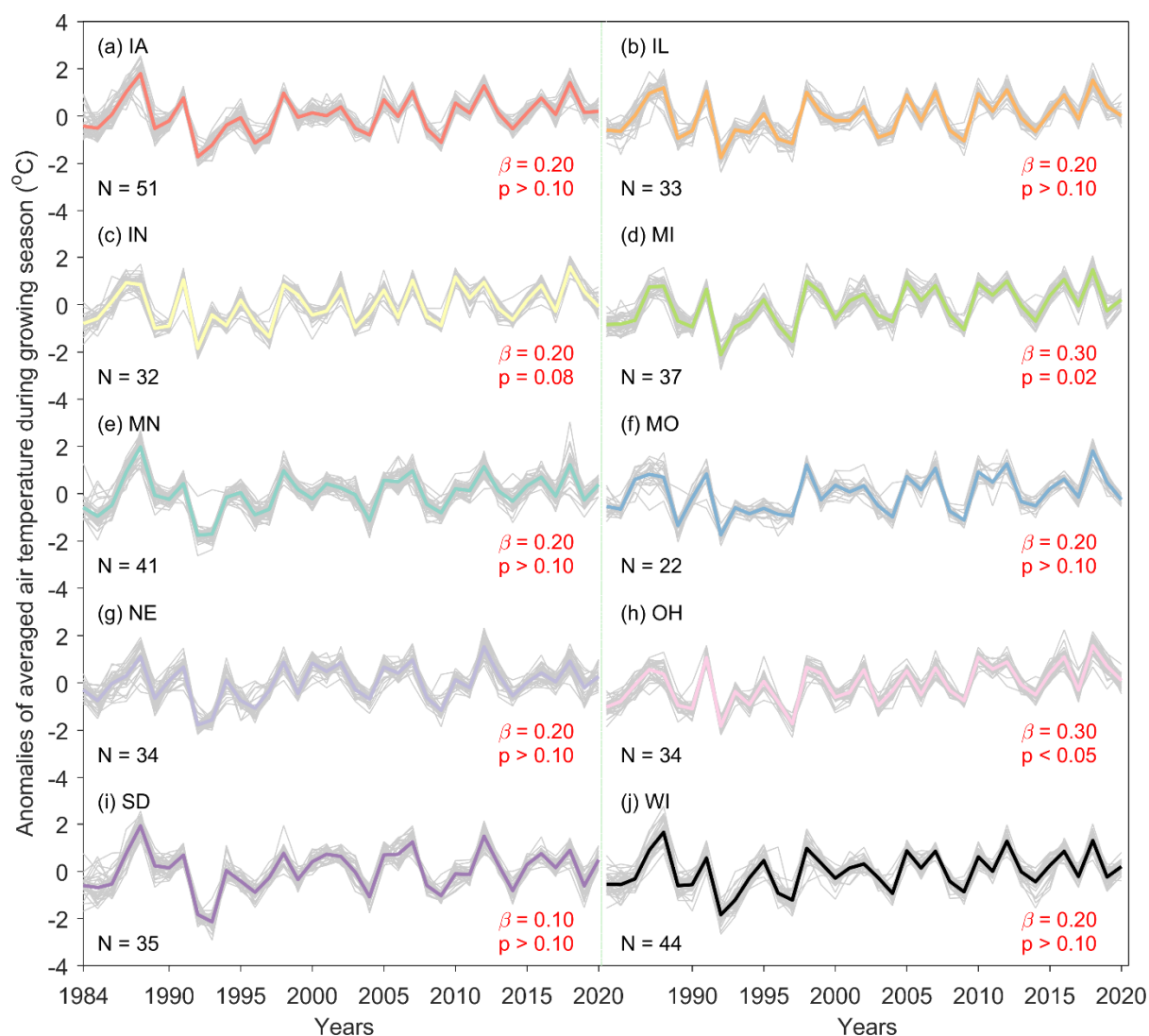


Figure B.2. Time series of air temperature anomalies departing from a base period (1991-2020) from 1984 to 2020 for: Iowa (IA, a), Illinois (IL, b), Indiana (IN, c), Michigan (MI, d), Minnesota (MN, e), Missouri (MO, f), Nebraska (NE, g), Ohio (OH, h), South Dakota (SD, i), and Wisconsin (WI, j). Gray lines represent the time series of station-specific temperature anomalies, and colored lines show the ensemble mean. “N” indicates that number of stations used for each state. “ β ” indicates the trend per decade ($^{\circ}\text{C dec}^{-1}$) from 1998 to 2020 and the p values shown for any statistical significance. Data were obtained from the monthly Global Historical Climatological Network (GHCN) (Menne et al., 2012).

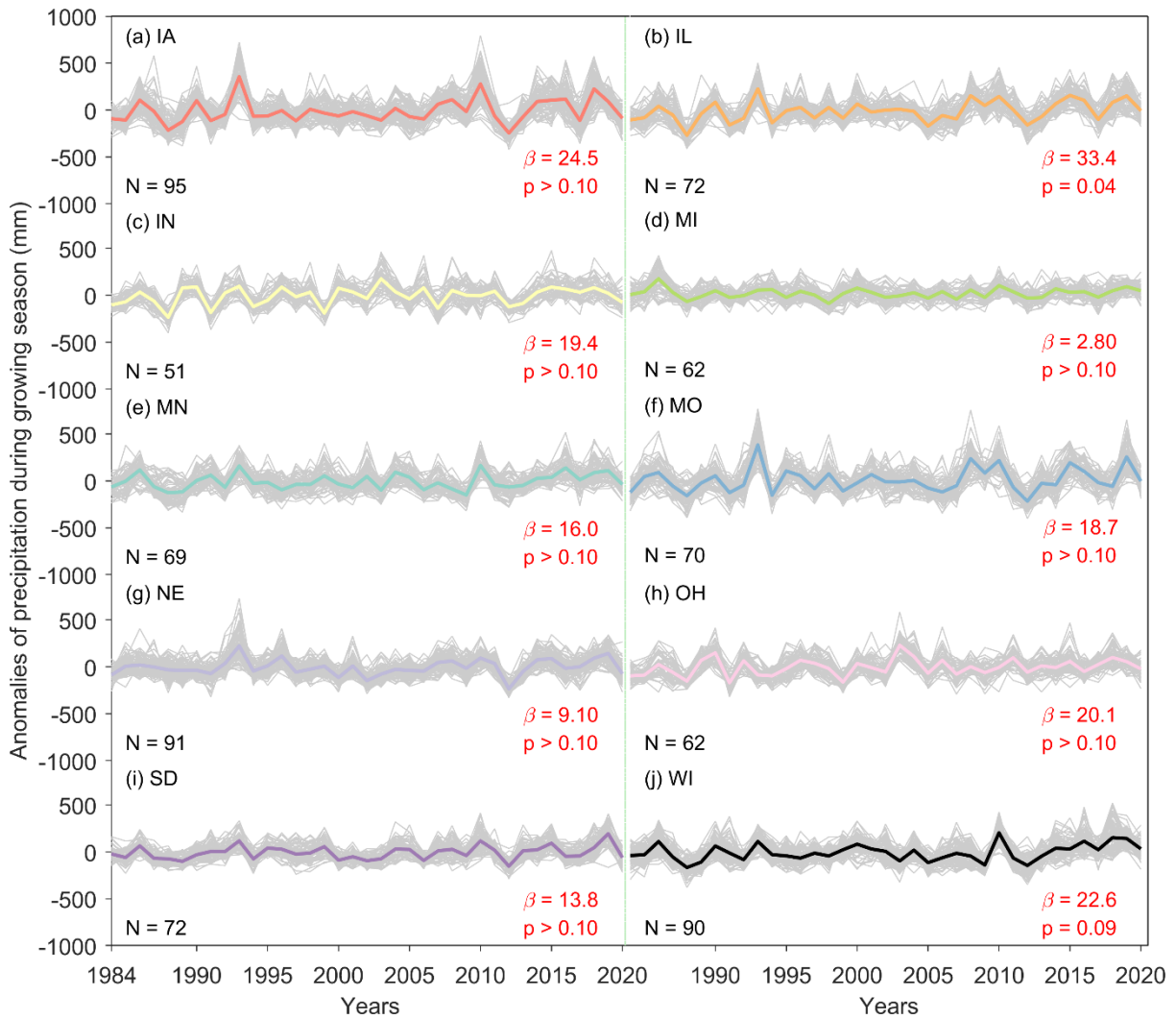


Figure B.3. Time series of precipitation anomalies departing from a base period (1991-2020) from 1984 to 2020 for: Iowa (IA, a), Illinois (IL, b), Indiana (IN, c), Michigan (MI, d), Minnesota (MN, e), Missouri (MO, f), Nebraska (NE, g), Ohio (OH, h), South Dakota (SD, i), and Wisconsin (WI, j). Gray lines represent the time series of station-specific precipitation anomalies, and colored lines show the ensemble mean. “N” indicates that number of stations used for each state. “ β ” indicates the trend per decade (mm dec⁻¹) from 1998 to 2020 and the p values shown for statistically significant or not. Data were obtained from the monthly Global Historical Climatological Network (GHCN) (Menne et al., 2012).

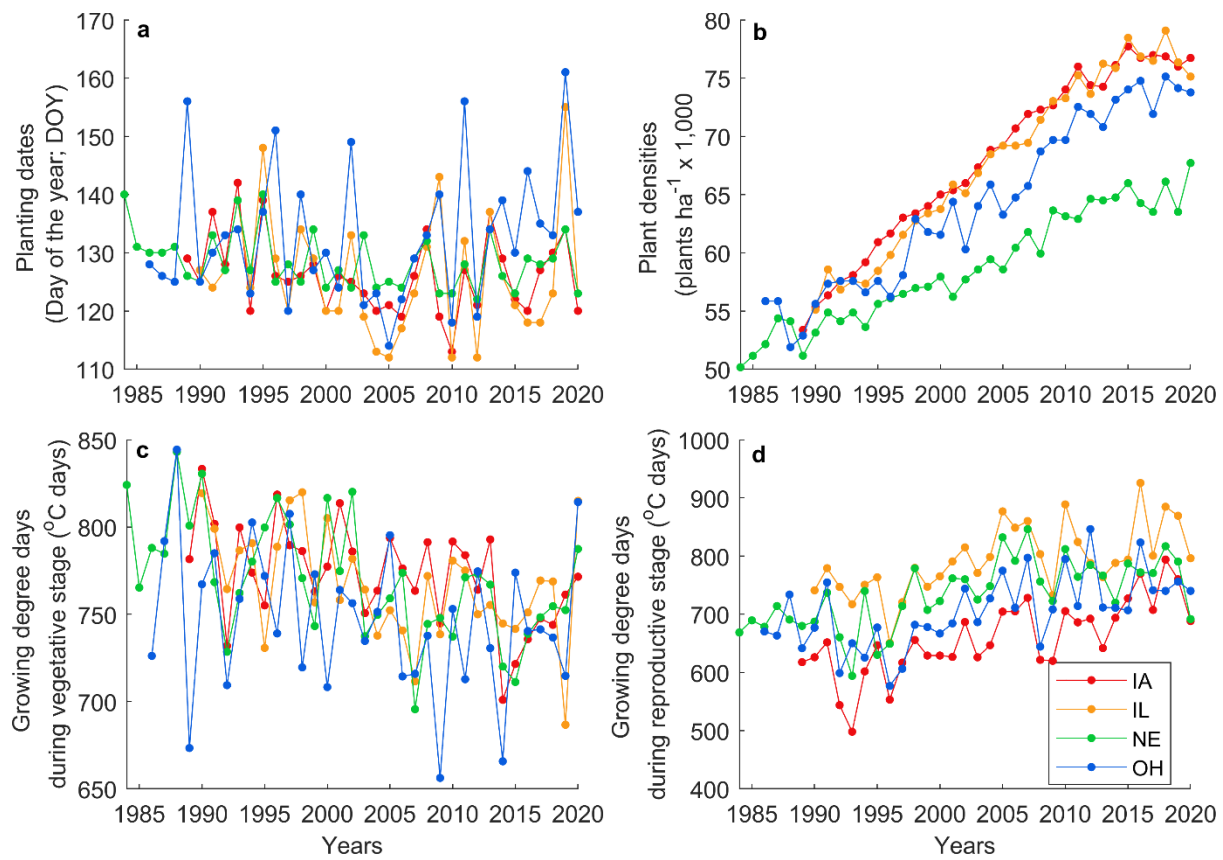


Figure B.4. Time series of planting dates (a), plant density (b), growing degree days from planting to silking (c) and from silking to physiological maturity (d) in maize fields from 1984 to 2020 in Iowa (IA), Illinois (IL), Nebraska (NE), Ohio (OH).

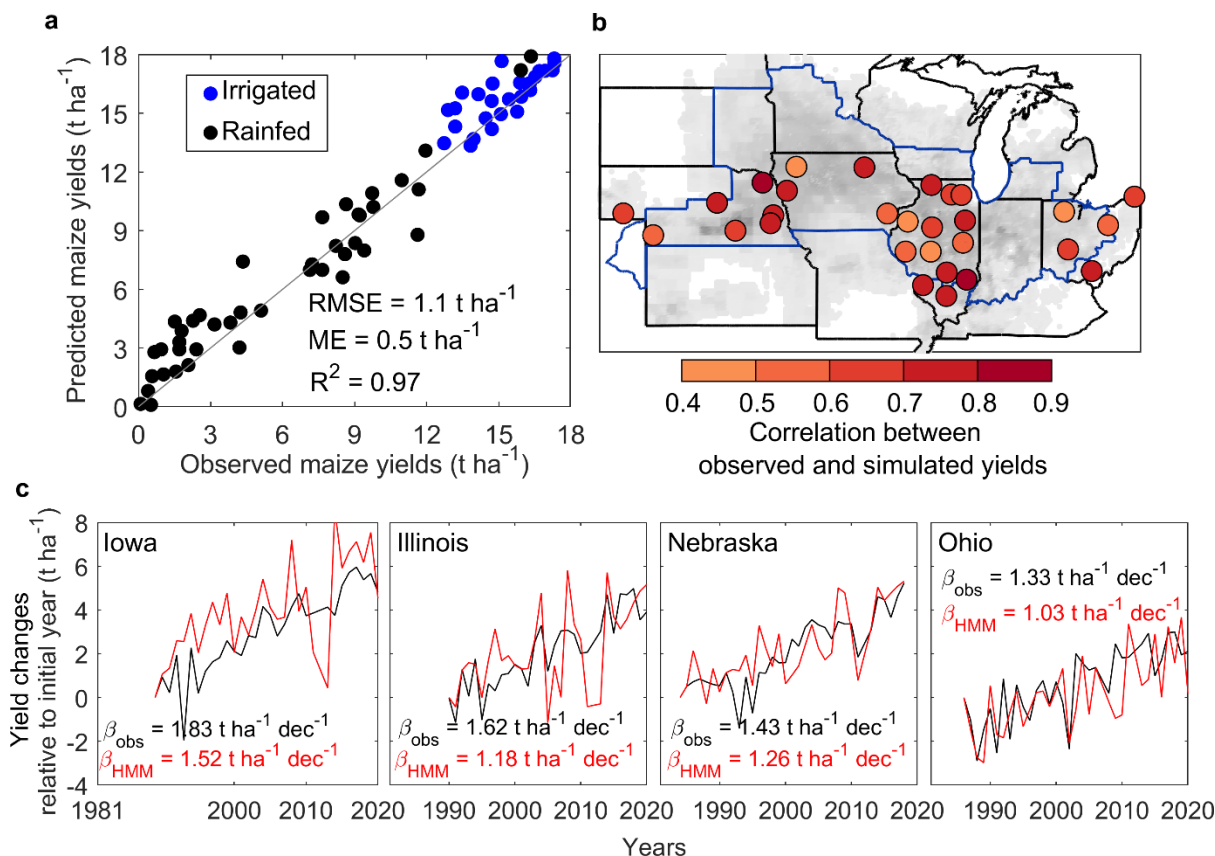


Figure B.5. Simulated versus observed maize yields in Iowa, Illinois, Nebraska, and Ohio using the Hybrid-Maize (HMM) model. (a) Simulated vs. observed yields under both rainfed (black circles) and irrigated (blue circles) maize field conditions. Data sources are extracted from the previous study (Yang et al., 2017). Root mean square error (RMSE), mean error (ME), and R square (R^2) are indicated for model performance. (b) Pearson's correlation between simulated and observed maize yields at station levels. Mapping backgrounds illustrate color-coded intensities of maize harvested area in the decade of 2000s. The blue boundary indicates the US Corn Belt. (c) Time series of changes in both simulated (red) and observed (black) maize yields relative to initial year at state level. " β " refers to trends of maize yields per decade.

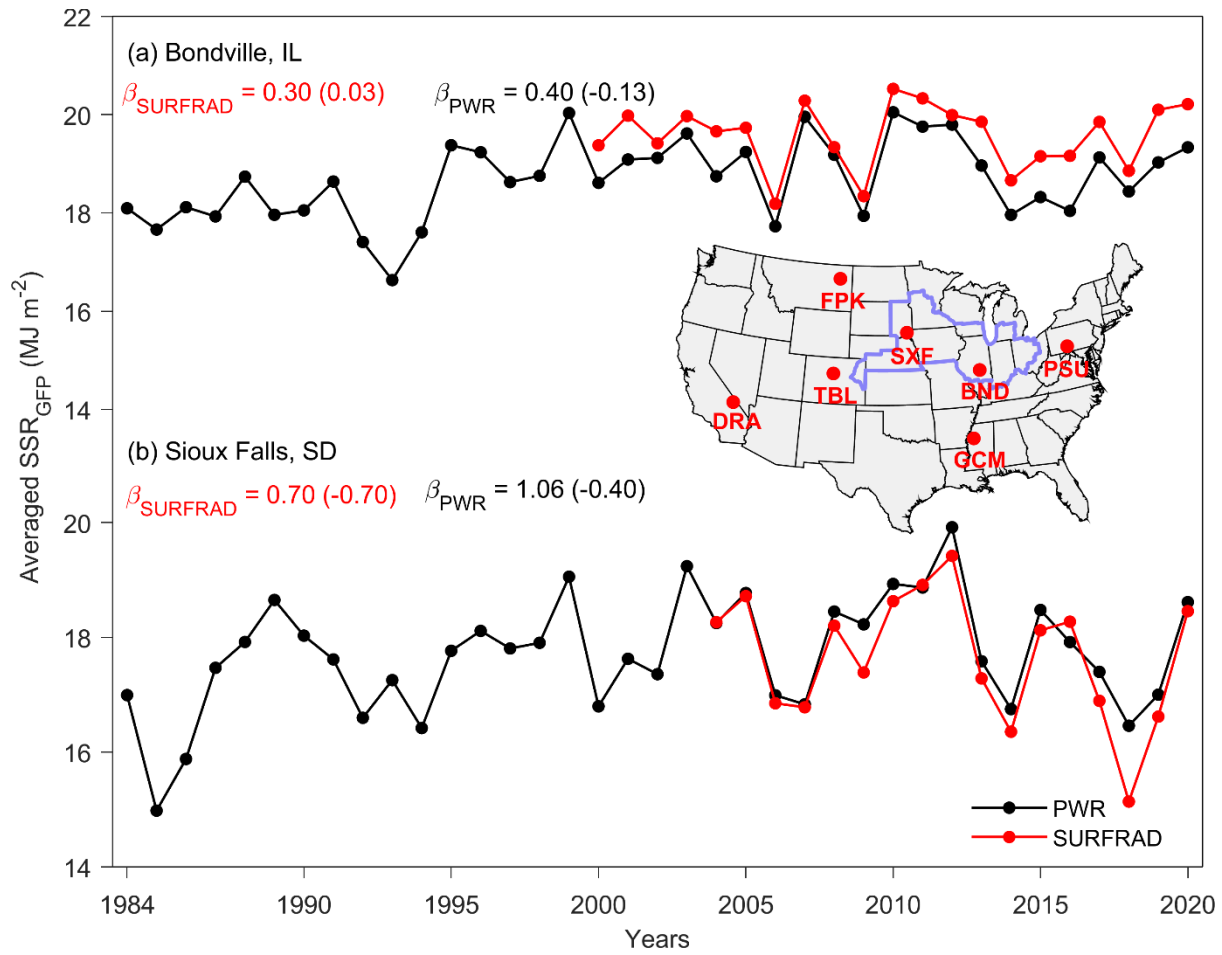


Figure B.6. Time series of average surface solar radiation (SSR) during the maize grain filling period for observation stations in: (a) Bondville, Illinois (IL) and (b) Sioux Falls, South Dakota (SD) using SURFRAD (red lines) and NASA POWER (PWR) datasets (black line). “ β ” values indicate trends of SSR per decade ($\text{MJ m}^{-2} \text{d}^{-1} \text{dec}^{-1}$) from the start year to 2013 (numbers shown inside brackets are trends calculated from the start year to 2020). There are no statistically significant trends of SSR_{GFP} ($p > 0.10$). The map shows the SURFRAD stations (Augustine et al., 2000; Hacker et al., 2016). The light purple line indicates the US Corn Belt boundary.

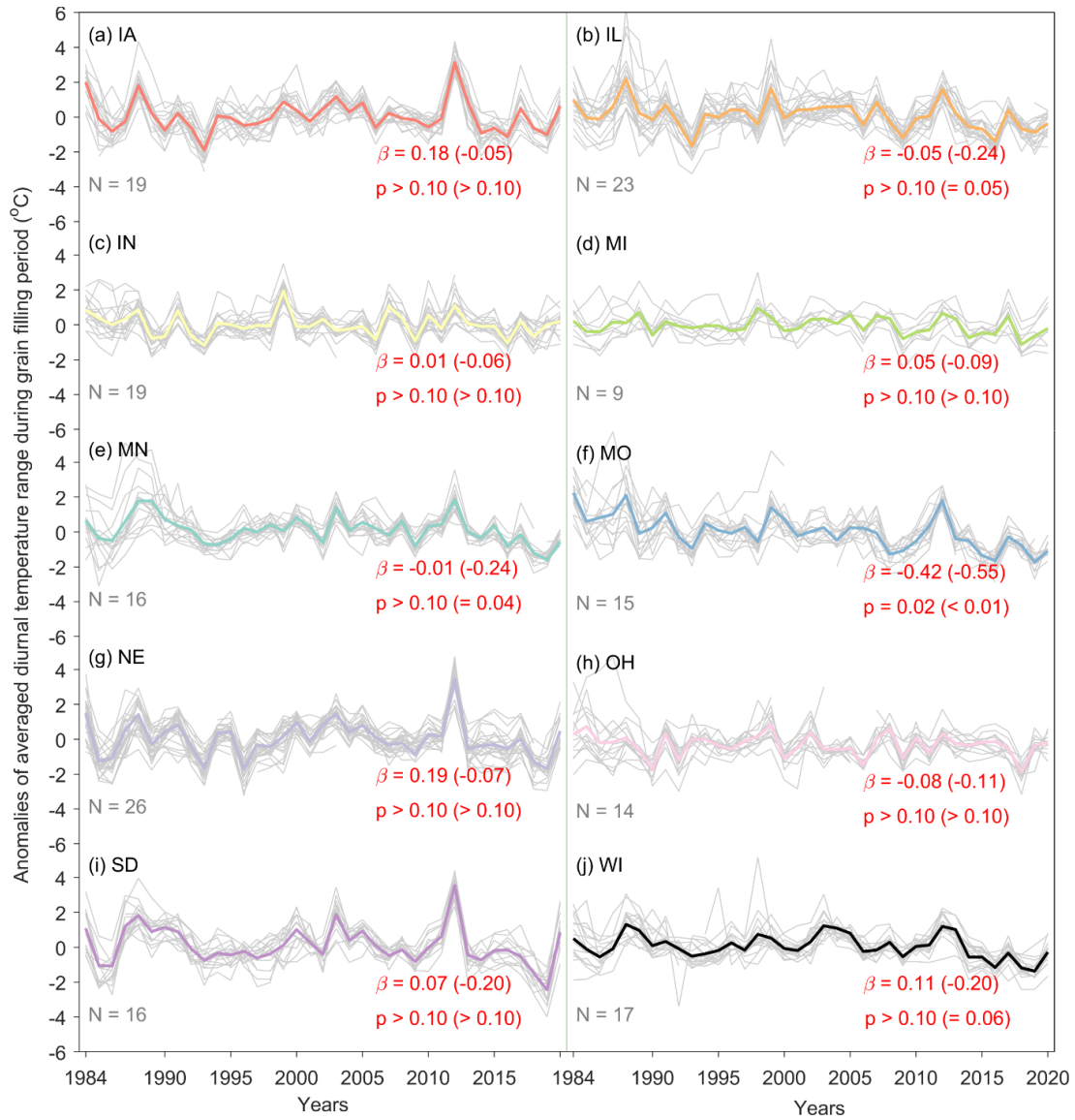


Figure B.7. Time series of diurnal temperature range (DTR) anomalies departing from a base period (1991-2020) during the maize grain filling period from 1984 to 2020 for: Iowa (IA, a), Illinois (IL, b), Indiana (IN, c), Michigan (MI, d), Minnesota (MN, e), Missouri (MO, f), Nebraska (NE, g), Ohio (OH, h), South Dakota (SD, i), and Wisconsin (WI, j). Gray lines represent the time series of station-specific DTR, and colored lines show the ensemble mean. “N” refers to the number of available stations for each state; “ β ” indicates the trend of DTR per decade ($^{\circ}\text{C dec}^{-1}$) from 1984 to 2013 (numbers shown inside brackets are trends calculated from 1984 to 2020). The p values show any statistical significance. Note that daily DTR is defined as the difference between daily maximum and minimum temperature taken from the Global Historical Climatological Network (GHCN) (Menne et al., 2012).

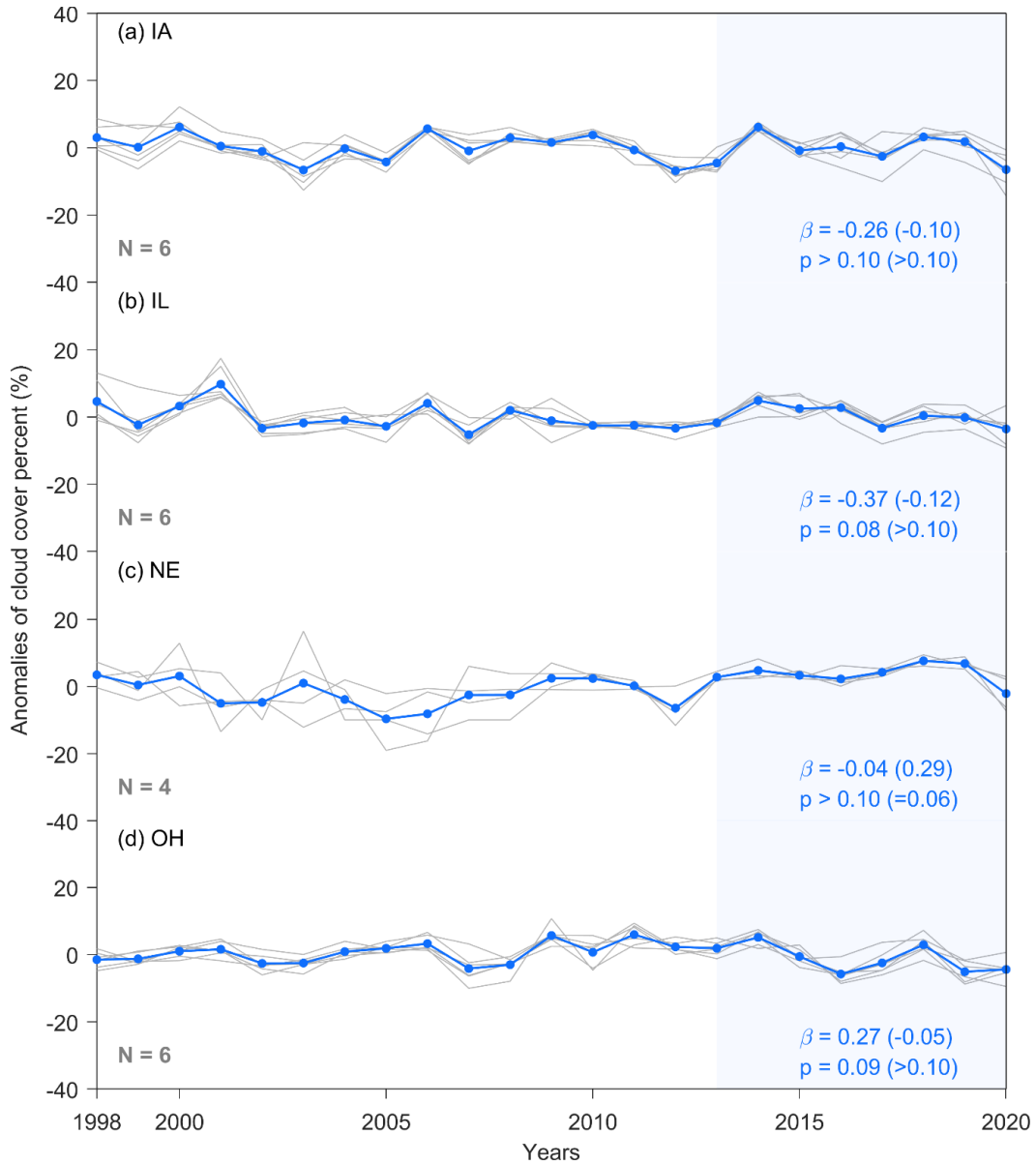


Figure B.8. Time series of cloud cover anomalies departing from overall average during the maize grain filling period from 1998 to 2020 in Iowa (IA, a), Illinois (IL, b), Nebraska (NE, c), and Ohio (OH, d). Gray lines represent the station-level time series of cloud cover anomalies, and blue lines show the averaged station-level time series of cloud cover anomalies; “N” refers to the number of available stations for each state; “ β ” indicates the trend per decade ($\% \text{ dec}^{-1}$) from 1998 to 2013 (numbers shown inside brackets are trends calculated from 1998 to 2020). The p values show any statistical significance. Cloud data was reported in the form of descriptive sky conditions that must be converted to numeric values to compute total cloud in a percent as in Free and Sun (2014) (Free & Sun, 2014). Note that prior to 1998, the observation instruments were different from the instruments used from 1998 to the present (Dai et al., 2006) so that we restricted our cloud data to the period from 1998 to 2020.

Table B.1. Numbers of days for the solar radiation observations at AWS stations. The pyranometer measurements may be flagged as “E” and QA/QC check as “e” indicating “we are not confident of the measurement” in the data center of automated weather station networks during maize grain filling period (GFP; minimum silking to maximum physiological maturity dates during the 1980s to 2020) for each station in Iowa, Illinois, Nebraska, and Ohio in U.S. Corn Belt.

Days of GFP (84)	Stations in Iowa			
Year	CAS	CRA	NAS	SUT
1989	0	84	0	0
1990	17	0	17	0
1991	0	3	0	0
1992	10	0	0	0
1993	0	0	53	0
1994	84	0	0	84
1995	84	84	0	84
1996	84	84	84	84
1997	18	0	0	0
1998	0	0	0	0
1999	0	0	0	0
2000	0	0	0	0
2001	0	0	0	0
2002	45	0	0	0
2003	0	0	0	0
2004	0	26	0	0
2005	43	0	0	0
2006	45	0	0	0
2007	0	0	0	0
2008	0	1	21	3
2009	0	8	0	0
2010	1	1	1	1
2011	28	1	1	2
2012	84	0	0	0
2013	84	13	0	0
2014	0	0	0	0
2015	0	0	0	0
2016	0	0	0	0
2017	0	0	0	0
2018	0	0	0	0
2019	0	0	0	0
2020	0	0	0	0

Abbreviations of stations: Castana (CAS), Crawfordsville (CRA), Nashua (NAS), and Sutherland (SUT).

Table B.1. Continued.

Days of GFP (98)	Stations in Illinois												
Years	BRO	CHA	DEK	FRE	BEL	PEO	SPR	MON	OLN	PER	REN	STC	STE
1990	0	0	0	0	0	0	0	0	0	0	0	0	0
1991	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0	0	0	0	0
1996	0	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	1	0	0	0	1	0	0	0	1	0	1	0	0
2000	0	0	0	0	0	0	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0	0	0	0	0	0	1
2004	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	1	0	0	1	0
2008	0	0	0	0	0	0	0	0	0	0	0	0	0
2009	0	0	0	0	0	0	1	0	0	0	0	0	0
2010	0	0	0	0	0	0	0	0	0	0	0	0	0
2011	0	0	0	0	0	0	0	0	0	0	0	1	2
2012	0	0	0	0	0	0	0	0	0	0	0	0	0
2013	0	0	0	0	2	0	0	0	0	0	0	0	0
2014	0	0	0	0	0	6	0	0	0	0	0	0	0
2015	0	0	0	0	0	0	0	0	0	0	0	0	0
2016	0	0	0	0	0	0	0	0	0	0	0	0	0
2017	0	0	0	0	0	0	0	0	0	0	0	0	0
2018	0	0	0	0	0	0	0	0	0	0	0	0	0
2019	0	0	0	0	0	0	0	0	0	0	0	0	0
2020	0	0	0	0	0	0	0	0	0	0	0	0	0

Abbreviations of stations: Brownstown (BRO), Champaign (CHA), Dekalb (DEK), Freeport (FRE), Belleville (BEL), Peoria (PEO), Springfield (SPR), Monmouth (MON), Olney (OLN), Perry (PER), Rend lake (REN), St. Charles (STC), and Stelle (STE).

Table B.1. Continued.

Days of GFP (86)	Stations in Nebraska						
Years	CHA	CON	HAR	ITH	ORD	SID	WAL
1984	0	0	0	0	0	0	0
1985	0	0	0	0	0	0	0
1986	0	0	0	0	0	0	0
1987	0	0	0	0	0	0	0
1988	0	0	0	0	0	0	0
1989	0	0	0	0	0	0	0
1990	0	0	0	0	0	0	0
1991	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0
1996	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0
2000	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0
2004	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0
2006	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0
2008	0	0	0	0	0	0	0
2009	0	0	0	0	0	0	0
2010	0	0	1	0	0	0	0
2011	0	0	0	0	0	0	0
2012	0	0	0	0	0	0	0
2013	0	0	0	0	0	0	0
2014	0	0	0	0	0	0	0
2015	0	0	0	0	0	0	0
2016	0	0	0	0	0	0	0
2017	0	0	0	0	0	0	0
2018	0	0	0	0	0	0	0

Abbreviations of stations: Champion (CHA), Concord (CON), Harvard (HAR), Ithaca (ITH), Ord (ORD), Sidney (SID), and Walton (WAT).

Table B.1. Continued.

Days of GFP (96)	Stations in Ohio				
Years	ASH	JAC	NOR	WES	WOO
1986	1	3	2	1	1
1987	0	0	0	1	0
1988	0	0	0	0	0
1989	0	0	0	1	0
1990	0	0	1	0	0
1991	4	5	1	0	0
1992	1	0	6	0	0
1993	1	0	0	0	0
1994	7	2	4	2	2
1995	0	0	0	0	0
1996	0	0	0	0	0
1997	0	0	0	0	0
1998	0	0	1	1	0
1999	0	0	0	0	0
2000	0	0	0	0	0
2001	1	0	1	1	0
2002	1	0	1	0	0
2003	0	0	1	1	0
2004	0	0	0	0	0
2005	0	0	0	0	0
2006	0	0	0	0	0
2007	36	0	0	0	0
2008	0	0	0	0	1
2009	0	0	0	0	0
2010	0	1	0	0	0
2011	0	0	0	0	0
2012	0	0	0	0	0
2013	2	1	1	1	1
2014	2	0	0	0	0
2015	1	0	1	0	0
2016	0	0	0	0	0
2017	0	0	0	0	0
2018	2	3	3	3	0
2019	0	0	0	0	0
2020	0	0	0	0	0

Abbreviations of stations: Ashtabula (ASH), Jackson (JAC), Northwest (NOR), Western (WES), Wooster (WOO).

Table B.2. Datasets used for climate and crops.

Climate datasets	States	Links
Automated weather Networks	Iowa	https://mesonet.agron.iastate.edu/agclimate/hist/daily.php
	Illinois	https://www.isws.illinois.edu/warm/about.asp
	Nebraska	https://hprcc.unl.edu/awdn/
	Ohio	http://www.oardc.ohio-state.edu/newweather/
GridMET	Four states	https://www.climatologylab.org/gridmet.html
SURFRAD	Four states	https://gml.noaa.gov/grad/surfrad/
NASA POWER	Four states	https://power.larc.nasa.gov/data-access-viewer/
GHCN-Daily	Four states	https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily
GHCN-Month	Four states	https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-monthly
Cloud cover	Four states	https://mesonet.agron.iastate.edu/sites/locate.php
Carbon dioxide concentration	Four states	https://gml.noaa.gov/ccgg/trends/data.html
Layer soil moisture	Four states	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview
Soil properties	Four states	https://gee-community-catalog.org/projects/polaris/#earth-engine-snippet-hydro-additional-layers
Crop datasets	States	Links
County-level yields		
State-level phenology		
State-level densities	Four states	https://quickstats.nass.usda.gov/

Table B.3. The model runs to estimate contributions of changes in non-environmental factors to maize yield trends in the US Corn Belt.

Name	Description	PT	PD	GDD to silking	GDD to maturity
Constant	No trends in planting dates, plant densities, and hybrids	Fixed	Fixed	Fixed	Fixed
Planting date (PT)	Trends in PT only	Observed time series	Fixed	Fixed	Fixed
Plant density (PD)	Trends in PD only	Fixed	Observed time series	Fixed	Fixed
Hybrid (HYB)	Trends in HYB only	Fixed	Fixed	Linearized observations	Linearized observations
PT + PD	Trends in both PT and PD	Observed time series	Observed time series	Fixed	Fixed
PT + HYB	Trends in both PT and HYB	Observed time series	Fixed	Linearized observations	Linearized observations
PD + HYB	Trends in both PD and HYB	Fixed	Observed time series	Linearized observations	Linearized observations
PT + PD + HYB	Trends in both PT, PD, and HYB	Observed time series	Observed time series	Linearized observations	Linearized observations

Note: In the runs with changing management for planting date and/or plant density, we used the actual, observed time series specific to each station. In the runs with “fixed” planting date and/or plant density, we used the average of the first five years in each station’s time series. In the runs with transient hybrid, we used the linearized values of GDD from sowing to silking and GDD from sowing to maturity. This choice was made to reflect gradual changes in hybrid and capture the true management change, as we anticipated that hybrid variations would not exhibit significant year-to-year fluctuations (Sacks & Kucharik, 2011). In the runs with fixed hybrid, we used a fixed value of the average during first five years in each station’s time series.

Table B.4. List of data sources used in the metadata analysis including references (source), and experiment locations (country). Black fonts for data sources of grain yields *vs.* biomass and gray colors for data sources of biomass *vs.* intercepted photosynthetically active radiation.

Source	Country	Source	Country
(Wilson & Allison, 1978)	Africa	(Piao et al., 2016)	China
(Tollenaar & Bruulsema, 1988)	Canada	(Shi et al., 2016)	China
(Muchow, 1990)	Australia	(Zhou et al., 2016)	China
(Tollenaar & Aguilera, 1992)	Canada	(Gao et al., 2017)	China
(Cirilo & Andrade, 1994)	Argentina	(Huang et al., 2017)	China
(Tollenaar et al., 1994)	Canada	(Mueller et al., 2017)	US
(Bolaños, 1995)	Mexico	(Ning et al., 2017)	China
(Tollenaar et al., 2004)	Canada	(Xu et al., 2017)	China
(Licht & Al-Kaisi, 2005)	US	(Zhai et al., 2017)	China
(Paponov et al., 2005)	Germany	(Zhou et al., 2017)	China
(Subedi & Ma, 2005)	Canada	(Jia, Sun, Ali, et al., 2018)	China
(Subedi & Ma, 2007)	Canada	(Jia, Sun, Mou, et al., 2018)	China
(Dordas et al., 2008)	Greece	(Tian et al., 2019)	China
(Cirilo et al., 2009)	Argentina	(Comas et al., 2019)	US
(Liu & Tollenaar, 2009)	Canada	(Hu et al., 2019)	China
(Pampana et al., 2009)	Italy	(Yu et al., 2019)	China
(Ciampitti & Vyn, 2011)	US	(Zhang et al., 2019)	China
(Klocke et al., 2011)	US	(Li et al., 2020)	China
(Worku et al., 2012)	Africa	(Qi et al., 2020)	China
(Acciaresi et al., 2014)	Argentina	(Ray et al., 2020)	India
(Antonietta et al., 2014)	Argentina	(Zhang et al., 2020)	China
(Chen et al., 2014)	China	(Bassu et al., 2021)	Italy
(Liu et al., 2014)	China	(Cao et al., 2021)	China
(Wang et al., 2014)	China	(Li et al., 2022)	China
(Y. Chen et al., 2015)	China	(G. Li et al., 2021)	China
(K. Chen et al., 2015)	US	(Wang et al., 2021)	China

(Cheng et al., 2015)	China	(Amas et al., 2022)	Argentina
(Liu et al., 2015)	China	(Gonzalez et al., 2021)	Canada
(Bonelli et al., 2016)	Argentina	(Guo et al., 2022)	China
(Ge et al., 2016)	China	(Zhang et al., 2022)	China
(Hao et al., 2016)	US	--	--
(Lindquist et al., 2005)	US	(Capristo et al., 2007)	Argentina
(R. Li et al., 2021)	China	(Shi et al., 2022)	China

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Appendix C - Supplemental Information for Chapter 3

Text C.1 Phenological dates of maize

Phenological dates for both sowing and harvest of maize were recorded for specific location-year from the states' maize hybrids field performance tests from 2000 to 2020. Silking and maturity dates were not available. Therefore, we used the ratio of growing degree days (GDD) between sowing-silking ($GDD_{SD-SK, USDA}$) and sowing-harvest ($GDD_{SD-HV, USDA}$), calculated based on phenological data of United States Department of Agriculture's National Agricultural Statistics Service (USDA-NASS), and daily temperature data from the Global Historical Climatological Network (GHCN) (Menne et al., 2009), to estimate silking dates by: 1) calculating state-level maize phenological dates from USDA-NASS data. Because the NASS Crop Progress Report is issued only on a weekly basis in a progress percentage, we interpolated the weekly crop progress into daily data using the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) approach (Fritsch & Carlson, 1980) and estimated the dates of sowing, silking, and harvest defined as dates when the crop progress reached 50% completion at each phenological progress across the state (Figure C.2); 2) estimating separately $GDD_{SD-SK, USDA}$ and $GDD_{SD-HV, USDA}$ using equation 1 in the main text; 3) calculating GDD between sowing and harvest dates based on recorded data in field sites ($GDD_{SD-HV, OBS}$) similar to step 2; 4) calculating GDD between sowing and silking dates required for specific site-year maize fields ($GDD_{SD-SK, OBS}$) using equation 1 follows; and 5) estimating silking date based on $GDD_{SD-SK, OBS}$ and daily temperature data (Figure C.3). The same steps also were used to estimate maturity date. Note that we assumed the ratio of $GDD_{SD-HV, USDA}$ to $GDD_{SD-SK, USDA}$ is the same among sites within a state for a specific year.

$$GDD_{SD-SK, OBS} = \frac{GDD_{SD-HV, OBS} \times GDD_{SD-SK, USDA}}{GDD_{SD-HV, USDA}} \quad [1]$$

Text C.2 Selection of year effects in preferred model

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_t + f(W_{i,l,t,s}; \gamma) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad [M1]$$

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_0 \times YR + f(W_{i,l,t,s}; \gamma) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad [M2]$$

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_0 \times YR + \alpha_1 \times YR^2 + f(W_{i,l,t,s}; \gamma) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad [M3]$$

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_{t,s} + f(W_{i,l,t,s}) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad [M4]$$

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_{0,s} \times YR + f(W_{i,l,t,s}; \gamma) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad [M5]$$

$$Y_{i,l,t,s} = \alpha_i + \alpha_l + \alpha_{0,s} \times YR + \alpha_{1,s} \times YR^2 + f(W_{i,l,t,s}; \gamma) + \theta VPD_{i,l,t,s} + \varepsilon_{i,l,t,s} \quad [M6]$$

where YR refers to years; α_0 , $\alpha_{0,s}$, α_1 , and $\alpha_{1,s}$ are coefficients of linear and quadratic year trends for states “s,” respectively. $f(W_{i,l,t,s})$ refers to impacts of climate on crop yields

$[\sum_{p=1}^2 (\beta_p GDD_{i,l,t,s,p} + \gamma_p EDD_{i,l,t,s,p} + \delta_p Prcp_{i,l,t,s,p} + \vartheta_p Prcp_{i,l,t,s,p}^2)]$, which is the same as in the main text.

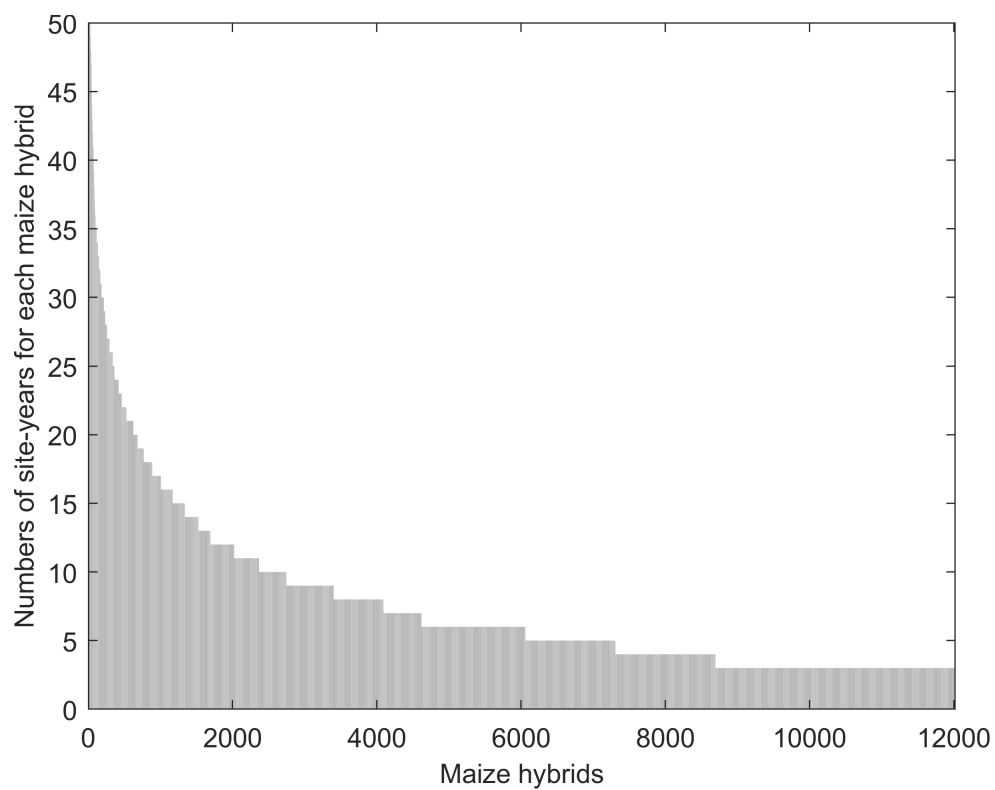


Figure C.1. Hybrids ranked by the total number of site-years in which they appear. The height of the bars is the total number of site-years that each hybrid appeared in.

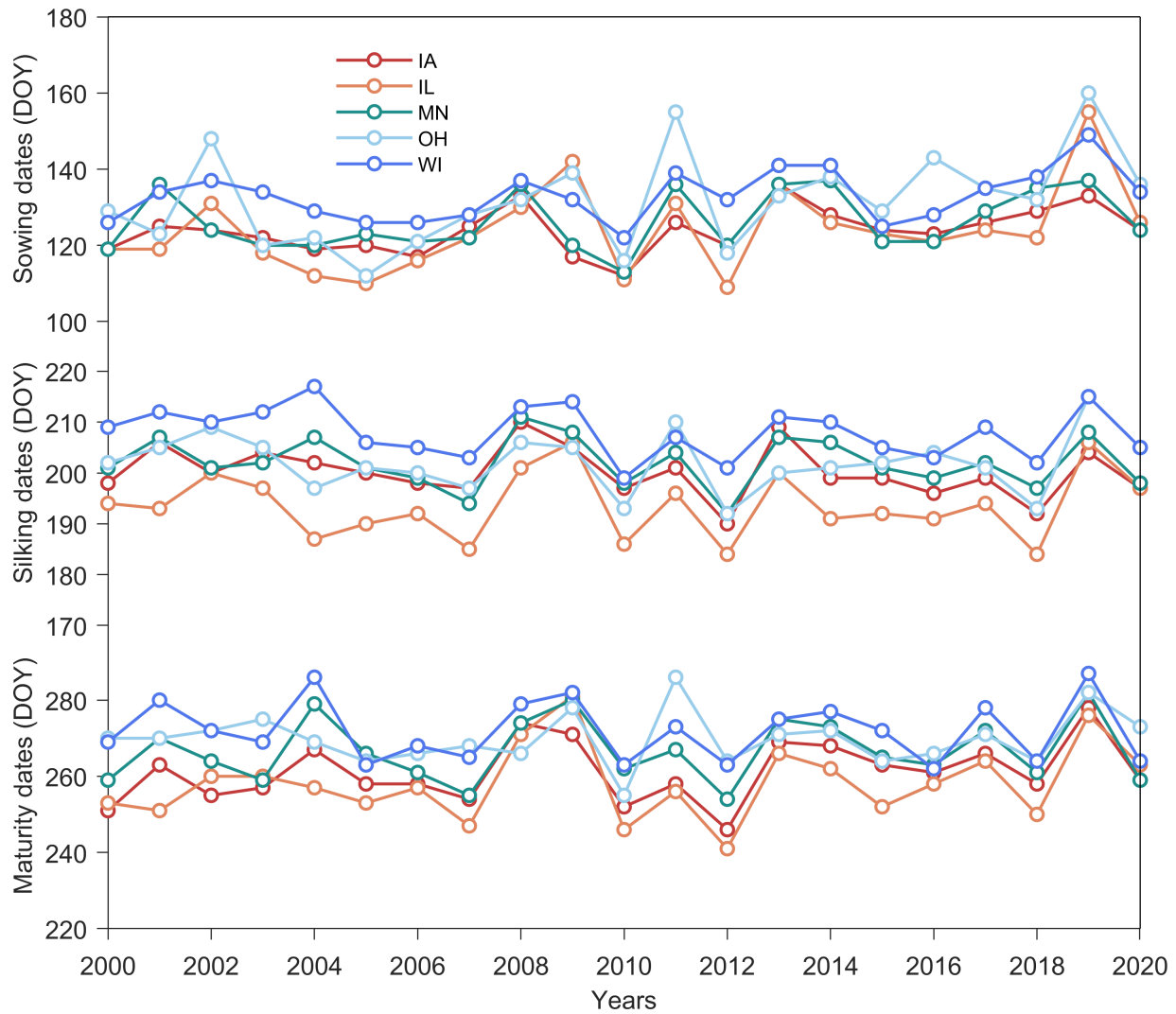


Figure C.2. State-level time series of maize phenological dates derived from United States Department of Agriculture's National Agricultural Statistics Service (USDA-NASS) including sowing, silking, and maturity in Iowa (IA), Illinois (IL), Minnesota (MN), Ohio (OH), and Wisconsin (WI).

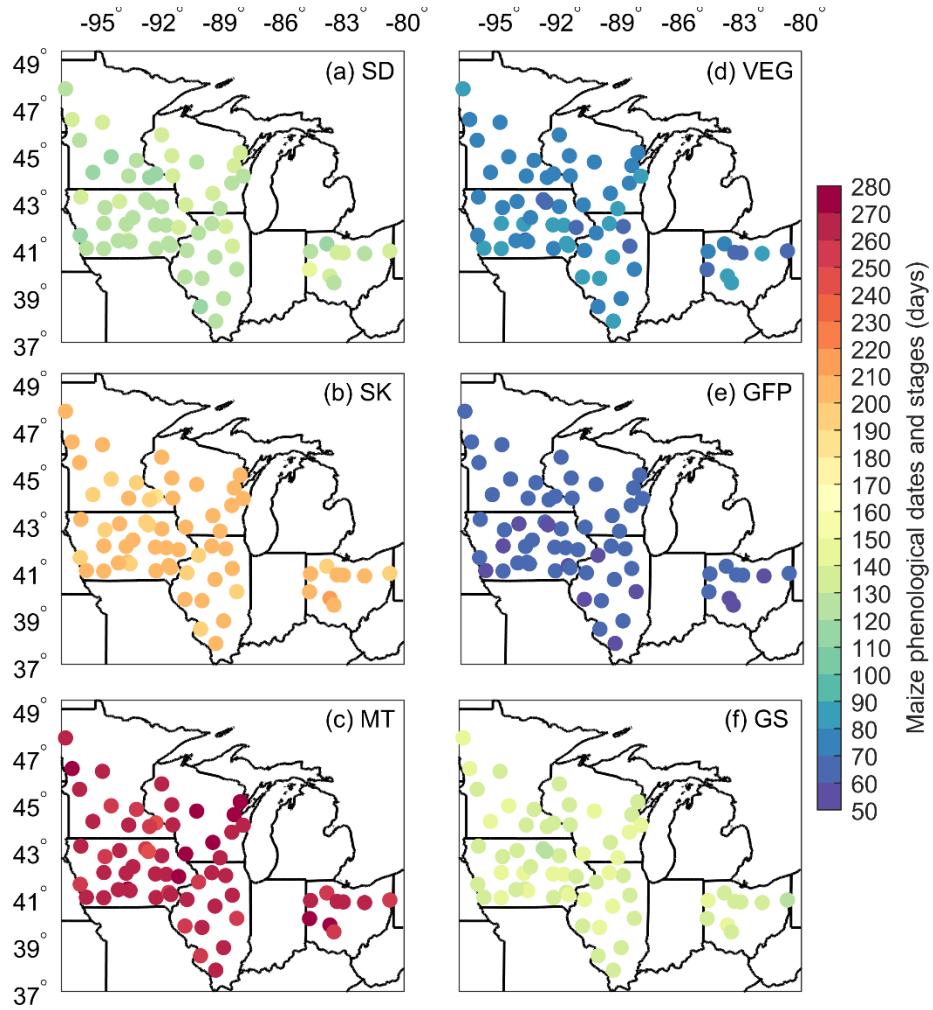


Figure C.3. Phenological dates and duration of maize in the field-sites. (a-c), phenological dates: sowing date (SD), silking date (SK), and maturity (MT). (d-f), phenological duration: sowing-silking (VEG), silking-maturity (GFP), and sowing-maturity (GS).

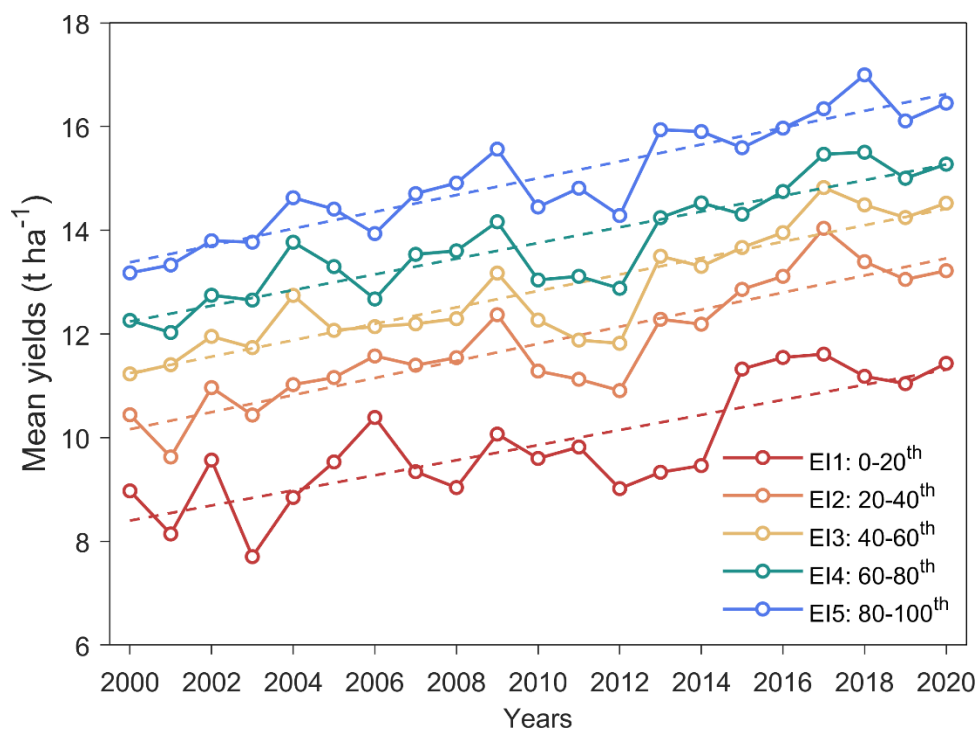


Figure C.4. Time series of mean maize yields across different magnitude environmental quantiles from 2000 to 2020. The red line represents the worst environmental stress index and the blue line represents the best one. Dashed lines refer to best-fit linear regression for each quantile. “EI” in legend refers to environment index with the smallest for the lowest environment index and with the largest numbers for the strongest environment index.

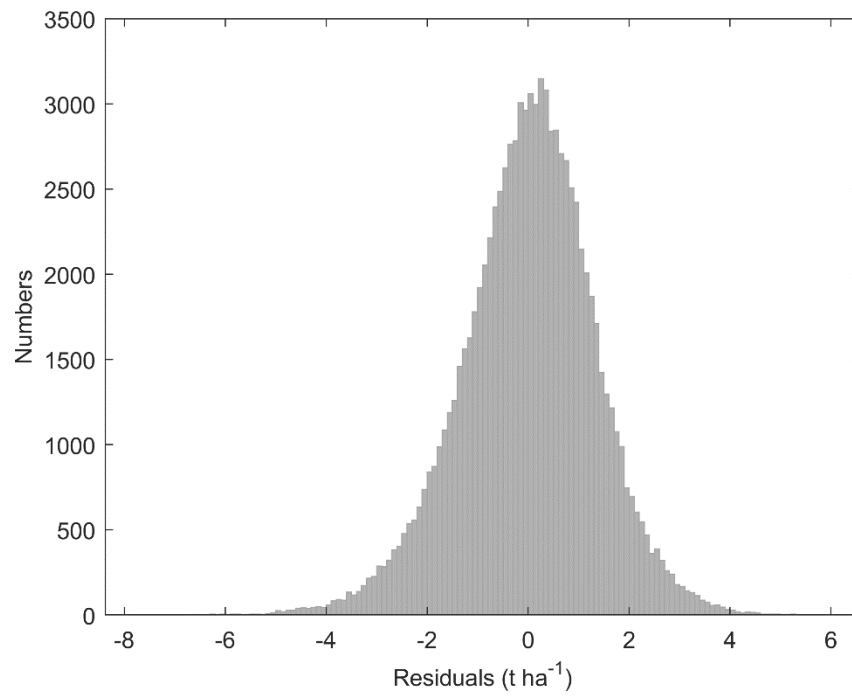


Figure C.5. Distribution of residuals from our preferred model (Table C.1, column 4).

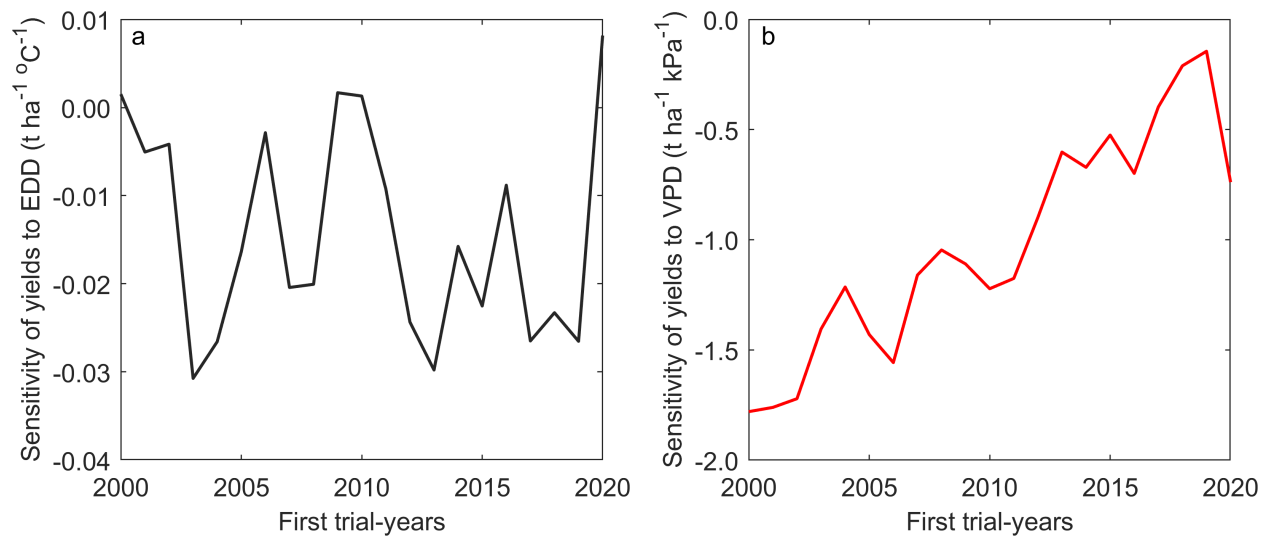


Figure C.6. Changes in sensitivity of maize yields to extreme degree days (EDD, a) and vapor pressure deficit (VPD, b) with the innovation of breeding efforts over time.

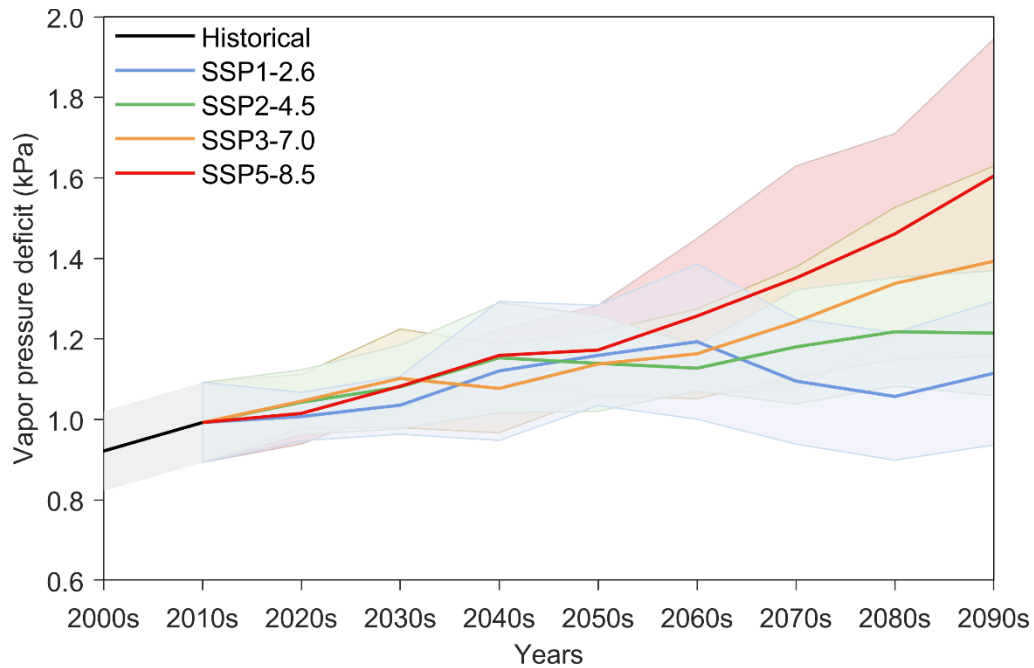


Figure C.7. Average decadal vapor pressure deficit around maize silking period at field-trial sites for observed (black line; 2000-2020) and projected (colored lines; 2010s-2090s) periods by six climate models (ACCESS-CM2, CESM2, CNRM-CM6-1, CNRM-ESM2-1, INM-CM4-8, and INM-CM5-0) under four climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Shaded areas show 95% confidence interval of model projections based on six climate models.

Table C.1. Links of public datasets for crop data, and climate data.

Crop datasets	Links
Iowa (2000-2004)	http://www.croptesting.iastate.edu/corn/reports.aspx
Iowa (2006-2020)	https://dr.lib.iastate.edu/entities/series/2857a5c3-257e-4aba-9a9f-7a0b1af472c0
Illinois (2000-2020)	https://varietytesting.web.illinois.edu/corn/
Minnesota (2000-2020)	https://varietytrials.umn.edu/corn-grain
Ohio (2000-2020)	https://u.osu.edu/perf/archive/
Wisconsin (2000-2020)	http://corn.agronomy.wisc.edu/HT/Default.aspx
USDA-NASS (2000-2020)	https://quickstats.nass.usda.gov/
Climate datasets	Links
ISD	https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00532
GHCNd	https://www.ncei.noaa.gov/data/global-historical-climatology-network-daily/
CMIP6	https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6?tab=form

Table C.2. Regression results for alternative specifications for maize yields (t ha⁻¹).

Impact of weather variables on maize yields						
Dependent variable:	(M1)	(M2)	(M3)	(M4)	(M5)	(M6)
maize yield						
GDD_veg [0, 30]	0.002**	0.001**	0.002**	0.003**	0.001*	0.003**
EDD_veg [30 +]	-0.019**	0.002	-0.014**	-0.003	0.002	-0.017**
prcp_veg	0.002*	0.002*	6.5e-04	0.003**	0.002*	4.5e-04
prcp_veg Sq.	-3.2e-06	-3.8e-06*	-2.1e-06	-4.8e-06**	-3.8e-06*	-1.9e-06
GDD_gfp [0, 30]	0.0025**	0.005**	0.002**	0.002**	0.004**	0.002**
EDD_gfp [30 +]	-0.012**	-0.021**	-0.021**	-0.014**	-0.021**	-0.022**
prcp_gfp	0.011**	0.010**	0.009**	0.011**	0.010**	0.009**
prcp_gfp Sq.	-1.9e-05**	-1.9e-05**	-1.7e-05**	-1.8e-05**	-1.9e-05**	-1.7e-05**
VPD_sk	-0.621**	-0.890**	-0.741**	-1.159**	-0.891**	-0.686**
Year		0.004**	-0.151**			
Year Sq.			7.8e-05**			
Year_IA					0.0035**	-0.145**
Year_IA Sq.						7.4e-05**
Year_IL					0.0043**	-0.157**
Year_IL Sq.						8.0e-05**
Year_MN					0.0039**	-0.140**
Year_MN Sq.						7.2e-05**
Year_OH					0.004**	-0.231**
Year_OH Sq.						1.2e-04**
Year_WI					0.0041**	-0.143**
Year_WI Sq.						7.3e-05**
Observations	92096	92096	92096	92096	92096	92096
Rsqr.	0.61	0.61	0.60	0.62	0.61	0.60
AIC	33383	34362	33647	32443	34361	33621

Note: The numbers at the top of the columns refers to model identifier (equations M1-M6 in Text C.2)

Supplementary References

- Fritsch, F. N., & Carlson, R. E. (1980). Monotone piecewise cubic interpolation. *SIAM Journal on Numerical Analysis*, 17(2), 238-246.
- Menne, M. J., Williams, C. N., & Vose, R. S. (2009). The U.S. Historical Climatology Network Monthly Temperature Data, Version 2. *Bulletin of the American Meteorological Society*, 90(7), 993-1008. doi:10.1175/2008bams2613.1