Publisher: AGRONOMY; Journal: AGROJNL:Agronomy Journal; Copyright: Will notify...

Volume: Will notify...; Issue: Will notify...; Manuscript: aj-2017-08-0123-a; DOI: ; PII: <txtPII>

TOC Head: ; Section Head: ; Article Type: ARTICLE

Core Ideas

- USDA crop condition ratings are a statistically significant covariate for yield and can be used in practice.
- Crop conditions tend to deteriorate as the season progresses while historically variability increases.
- Crop conditions were poorest on average and had the highest interannual variability in the southern Great Plains.
- Since 1986, crop conditions in the Great Plains have deteriorated significantly while variability has increased.
- The southwestern and southeastern U.S. significantly improved in crop conditions, while variability decreased.

United States Crop Conditions: 1986–2022

Abbreviations: CCIndex, Crop Condition Index

ABSTRACT

USDA National Agricultural Statistics Service general crop condition data are used to quantify the relationship between crop conditions and yield, condition tendencies during the growing season, how conditions vary across the U.S., and how conditions have trended for the 1986–2022 period for a variety of crops: barley (*Hordeum vulgare L.*), corn (*Zea mays L.*), cotton (*Gossypium hirsutum L.*), oats (*Avena sativa L.*), peanuts (*Arachis hypogaea L.*), rice (*Oryza sativa L.*), sorghum (*Sorghum bicolor L.*), soybeans (*Glycine max L.*), and spring and winter wheat (*Triticum aestivum L.*). Crop conditions are a statistically significant

covariate (90% significance level) for yield and can be used in practice on a weekly basis. This becomes increasingly important as, historically, crop conditions not only deteriorated on average, but became more variable throughout the growing season. Spatial differences in conditions, variability, and trends in condition ratings and variability are caused by crop selection, regional climate, and management practices such as irrigation. Crop conditions were poorest and had the highest interannual variability across the southern Great Plains region. Since 1986, crop conditions in the Great Plains region have deteriorated significantly, while variability has increased. Meanwhile, crop conditions across the southwestern and southeastern U.S. have significantly improved, while interannual variability in conditions experienced robust declines. Given climatic and hydrologic trends, to maintain a positive trend in yield, continued advancements in production management and technology are required. Critical decisions regarding real-time or future management can be supplemented by using crop condition risk assessment information along with actively monitoring weekly conditions.

1 INTRODUCTION

Agriculture across the U.S. is vast and diverse, promoting global food security, economic growth, nationwide development, and environmental sustainability. Significant increases in agricultural productivity over the past century unequivocally make the U.S. enterprise a global leader in product export, supplying commodities to markets across the globe to keep pace with population growth and resource use (International Trade Administration, 2012; Jung et al., 2021). Therefore, ensuring a resilient agricultural system requires advancements in technology, management, and hybrids, especially within the context of an evolving climate leading to more frequent weather extremes that will consequently amplify the risk of crop production losses (Nicholls, 1996; Milly et al., 2002; Schmidhuber & Tubiello, 2007; Delgado et al., 2013; Ray et al., 2013; Walthall et al., 2013; Wheeler & Von Braun, 2013; Pryor et al., 2014; Lesk et al., 2016; Mase et al., 2017; Bundy et al., 2022). These frequent weather extremes include observed and future projected increases in drought severity and occurrences (Strzepek et al., 2010; Wehner et al., 2017; Jin et al., 2017; Martin et al. 2020), extreme precipitation episodes (Min et al., 2011; Westra et al., 2013; Zhang et al., 2013; Bindoff et al., 2013; Feng et al., 2016; Easterling et al., 2017; Changnon & Gensini, 2019), warmer than normal temperatures (Dittus et al., 2015; Vose et al., 2017; Angel et al., 2018), and an increased number of severe thunderstorms leading to increased regional wind and hail damage in the U.S. (Gensini et al., 2014; Gensini & Mote, 2015; Brimelow et al., 2017; Gensini & Brooks, 2018; Tang et al., 2019; Gensini, 2021; Ashley et al., 2023; Kaminski, 2023). Moreover, changes in climate amplify the risk of other nontrivial agricultural facets that ultimately affect crop production, which include changes in phenological stage timing (Hartfield et al., 2011, 2015), soil integrity (Rosenzweig et al., 2002; Pruski & Nearing, 2002; Delgado et al., 2013), nutrient requirements (Takle et al., 2006; Cai et al., 2015), weed competition (Wolfe et al., 2008; Clements & Ditommaso, 2011; Jinger et al., 2017; Ramesh et al., 2017), and other pest and disease pressures (Munkvold & Yang, 1995; Anderson et al., 2004; Wu et al., 2011; Bebber et al., 2013; Hurburgh, 2016; Wienhold et al., 2017; Angel et al., 2018).

Given the importance that climate has on agricultural production, it is critical to continuously monitor crop conditions from early stages of growth through harvest. By frequently examining crop health, quality, and productivity through the growing season, agricultural stakeholders gain insight on crop production and make decisions in situ to maximize yield potential (Lehecka, 2014; Khaki et al., 2021). Satellites and other remote-sensing mechanisms that derive the normalized difference vegetation index, temperature condition index, enhanced vegetation index, leaf area index, and others monitor crops globally throughout their growth cycle (Anastasiou et al., 2018; da Silva et al., 2017). Agrometeorological models and machine learning approaches are also widely used to monitor conditions and estimate yield (Geipel et al., 2014; Khaki et al., 2021). The weekly release of the USDA National Agricultural Statistics Service (NASS) Crop Progress and Condition (CPC) report is one of the most widely used resources and the most requested publication distributed by NASS (Lehecka, 2014). These reports provide subjective estimates of crop progress and condition ratings, which are crucial in the agricultural market (Bain & Fortenbery, 2013; Lehecka, 2014). Previous literature has noted that, given the size of farming operations, these manual field surveys are not as efficient as other mechanisms such as remote sensing (Van Wart et al., 2013). Despite this claim, it is argued the NASS CPC report can capture the complexities of assessing the conditions of a crop better than any agrometeorological model or remote sensing product since the elaborate network of "people as sensors" contains expert knowledge from thousands of surveyors (Begueria & Maneta, 2020). Not only are these data crucial for speculators in agriculture future markets, but they are also commonly used as a first-look for in-season yield predictions (Fackler & Norwood, 1999; Kruse & Smith, 1994; Irwin & Good, 2017a, 2017b; Irwin & Hubbs, 2018; Begueria & Maneta, 2020) and for overall risk assessment of intergrowing season trends and variability in crop conditions over the historical record (Bundy & Gensini, 2022). More recently, there have been efforts to analyze the response of crop conditions to extreme weather perils such as tropical cyclones (Bundy et al., 2023). Yet, no study has examined all crops in the CPC report to verify the relationship between conditions and yield, quantify condition tendencies during the growing season, or quantify crop condition trends over the historical record for all qualifying crops.

This research expands on Bundy & Gensini (2022), which examined corn conditions throughout the Midwest U.S., to encompass all crops with a sufficient historical dataset and expand analyses for the entire conterminous U.S. USDA NASS general crop condition data are used to 1) quantify the relationship between crop conditions and yield to justify using these data in research and for risk assessment, 2) quantify the spatiotemporal climatology of conditions, and 3) quantify spatiotemporal trends in conditions across ten different major field crops: barley (*Hordeum vulgare L.*), corn (*Zea mays L.*), cotton (*Gossypium hirsutum L.*), oats (*Avena sativa L.*), peanuts (*Arachis hypogaea L.*), rice (*Oryza sativa L.*), sorghum (*Sorghum bicolor L.*), soybeans (*Glycine max L.*), and spring and winter wheat (*Triticum aestivum L.*). Collectively, these crops contribute nearly 90% of total U.S. cropland production, with over 240 million acres harvested annually (USDA, 2023a). Thus, recognizing seasonal patterns of crop conditions and how they have trended during the general crop condition historical record (1986–2022) is useful for market speculators, policymakers, insurers, farmers, and other stakeholders involved in agricultural or applied sciences. This research is novel in that, for the first time, it quantifies vital spatiotemporal condition tendencies and trends for a multitude of U.S. crops to support key decision-making processes for farming strategies. The results are to serve as the baseline condition climatology for each state-crop combination and be utilized in future investigations pertaining to agricultural sustainability. Stakeholders may use these results to implement effective management strategies to maximize resilience against an evolving climate, maximize productivity and economic well-being, and ensure a sustainable agricultural future.

2 MATERIALS AND METHODS

2.1 USDA NASS data procedures

Approximately 3,600 survey respondents, primarily consisting of extension agents and Farm Service Agency staff, are asked to report subjective estimates of crop progress and conditions based on standard definitions for the entire week ending on Sunday (USDA, 2023b). These reported data are reviewed for reasonableness and consistency by comparing them with data from previous weeks, historical averages, and data from surrounding counties. USDA Field Offices summarize these raw data to state levels while weighting each county's reported data by NASS county acreage estimates. Although data are collected at county level, the weekly USDA NASS CPC survey is designed to provide national and state estimates in part to protect the confidentiality of growers whose operations may cover much of the production in a county (Rosales, 2021). State estimates are submitted to the Agricultural Statistics Board, where they are compared with those of surrounding states and assembled into a national aggregated summary by weighting each state by its respective acreage estimates.

For the general crop conditions portion of the report, reporters are asked to estimate the percent of their crop in excellent, good, fair, poor, or very poor condition. General crop condition categories defined by the USDA are as follows (USDA, 2016):

- *Excellent*: Yield prospects are above normal. Crops are experiencing little or no stress. Disease, insect damage, and weed pressures are insignificant.
- *Good*: Yield prospects are normal. Moisture levels are adequate, and disease, insect damage, and weed pressures are minor.

- *Fair*: Less-than-normal crop condition. Yield loss is a possibility, but the extent is unknown.
- *Poor*: Heavy degree of loss to yield potential, which can be caused by excess soil moisture, drought, disease, etc.
- *Very Poor*: Extreme degree of loss to yield potential; complete or near crop failure.

The USDA-defined Crop Condition Index (CCIndex) was calculated for each report through the following (Rosales, 2021):

$$CCIndex = (5 * \%Excellent + 4 * \%Good + 3 * \%Fair + 2 * \%Poor + \%Very\ Poor) / 100 \quad (1)$$

This weighted index provides a rating summarizing the current state of weekly conditions for the five crop conditions. The CCIndex ranges from [1, 5], with an index rating of 5 corresponding to 100% of the surveyed crop being reported in excellent condition and an index rating of 1 corresponding to 100% of the crop being reported in very poor condition. Since excellent and good conditions are more conducive to normal to above-normal yields, an increase in these two ratings results in an increase in the CCIndex (Supplemental Figure S1). Fair conditions, while a less than normal crop condition, lower the CCIndex, and poor and very poor conditions lower the CCIndex as well with higher explanatory power. There are other approaches to using the USDA general crop condition information, including adding the percent of crops rated excellent or good (Irwin & Good, 2017a, 2017b; Irwin & Hubbs, 2018). Though, it has been argued that only using good and excellent rating information is a disadvantage since the bottom three categories (fair, poor, and very poor) are not considered in weekly analyses (Bain & Fortenbery, 2016). Other approaches used an index that combines all condition categories and ranges from [0, 100] to assess market responses to crop condition changes (Bain & Fortenbery, 2016), yield responses to crop condition changes (Fackler and Norwood, 1999; Jorgensen, 2014; Jorgensen & Diersen, 2014; Bundy & Gensini, 2022), and weather peril impacts on crop condition changes (Bundy et al., 2023). The decision to use the USDA version of a crop condition index (Rosales, 2021) attempts to attain consistency across future research endeavors using these state-level data and to stay consistent with the newer gridded crop condition dataset that dates to 2015 (Rosales, 2021). The breakdown of results for each condition category (excellent, good, fair, poor, very poor) for each crop and state may also be appealing to a wide range of stakeholders and may be found in the Supplemental Material for this research (Supplemental Figure S1–S5, Supplemental Table (S1–S4).

While these data have been proven reliable in a peer-reviewed research setting, there are still limitations worth noting. Limitations include: 1) the USDA NASS crop condition data are subjective estimates, meaning human error and biased interpretation are a possibility (Begueria & Maneta, 2020); though, the quality control process performed by the USDA helps to limit error; 2) state-level aggregation, which is a limitation for particularly larger states (e.g., Texas) that may have considerable condition variability within the state; 3) these data do not account for double-cropping, which may impact timing of planting dates, growth cycle, and, in turn, variability in crop conditions; 4) these data do not account for irrigation, thus rainfed and irrigated crops are not separated; 5) it has been speculated there may have been changes to the methodology of estimating crop conditions or changes in the make-up of crop observers over time (Irwin & Good, 2017b), which could impact these data and the subsequent results. Nonetheless, results of this research will still appeal to those in the industry, as any insight on seasonal condition tendencies and trends adds value to what could perhaps be critical decisions needing to be made in future agricultural management.

2.2 Data collection

General crop condition data were collected from the USDA NASS for barley, corn, cotton, oats, peanuts, rice, sorghum, soybeans, winter wheat, and spring wheat (USDA, 2023a). These ten crops were selected due to their complete historical record. All other crops in the USDA NASS database have historical condition data dating to 2014, and not all have national aggregated data. Weekly condition data were available at national level aggregation for the 1986–2022 period (37 years) for all crops except oats, peanuts, and rice, which were available for the 1996–2022 period (27 years). Crop condition data at the state level were also gathered over the same epochs for each crop but varied temporally as not all states had the same number of years of data for each crop (**Table 1**). Each state needed to have at least 90% of the 37-year data (barely, corn, cotton, sorghum, soybeans, spring wheat, and winter wheat) or 27-year data (oats, peanuts, and rice) for each week in their respective growing seasons to be used for this analysis. While not every crop-producing state was used in this analysis, states that were used combined for a high percentage of the total U.S. production. Specifically, these states accounted for the following average U.S. yields of the following crops during this period: barley, 77%; corn, 92%; cotton, 98%; oats, 68%; peanuts, 97%; rice, 95%; sorghum, 98%; soybeans, 93%; spring wheat, 98%; winter wheat, 89%.

Table 1. Number of years of crop condition data by state and crop, and percent of U.S. production of the crop in each state (1986–2022). Top three producing states are bolded for each respective crop.

State	**Barley**		**Corn**		**Cotton**		**Oats**		**Peanuts**		**Rice**		**Sorghum**		**Soybean**		**S Wheat**		**W Wheat**	
Alabama			9	0.2%	37	3.7%	0	0.7%	27	**11.7%**			0	0.2%	23	0.3%			9	0.4%
Arizona	9	1.3%	0	0.0%	35	4.0%							1	0.2%					3	0.1%
Arkansas			9	0.5%	37	8.0%	0	0.8%	8	3.4%	37	**45.4%**	34	2.9%	37	3.9%			37	2.0%
California	0	2.5%	0	0.2%	36	**10.3%**	0	1.3%			36	**20.4%**	1	0.2%					37	1.7%

Colorado	9	3.2%	37	1.3%	1	0.0%	0	0.9%					33	1.8%			5	0.5%	37	5.0%
Connecticut			9	0.0%																
Delaware	9	0.7%	9	0.2%											9	0.2%			9	0.3%
Florida			0	0.1%	6	0.7%			27	8.4%									0	0.1%
Georgia			23	0.4%	37	**10.3%**	9	1.2%	27	**45.9%**			4	0.3%	23	0.3%			23	0.8%
Idaho	27	**19.3%**	9	0.1%			8	1.1%									37	7.1%	37	3.9%
Illinois			37	**16.0%**			4	3.0%					33	1.7%	37	**15.4%**			37	3.4%
Indiana			37	7.5%			0	1.3%							37	8.2%			37	1.9%
Iowa			37	**18.2%**			27	8.9%							37	**15.2%**			0	0.1%
Kansas	0	0.3%	37	3.9%	18	0.4%	0	2.1%					37	**42.8%**	37	3.5%			37	**23.1%**
Kentucky	0	0.3%	37	1.5%			0	0.3%						0.3%	37	1.9%			9	1.6%
Louisiana			9	0.5%	37	4.5%					37	**14.2%**	34	2.1%	37	1.3%			9	0.5%
Maine	7	0.4%	9	0.0%			9	1.3%												
Maryland	9	1.2%	9	0.5%			0	0.4%					0	0.1%	9	0.6%			9	0.8%
Massachusetts			9	0.0%																
Michigan	7	0.3%	37	2.5%			13	3.6%							37	2.4%			37	2.4%
Minnesota	27	6.2%	37	9.6%			27	**12.0%**							37	**9.1%**	37	**15.7%**	0	0.1%
Mississippi			9	0.6%	37	9.0%			10	2.1%	37	7.0%	20	1.0%	37	2.3%			9	0.6%
Missouri			37	3.3%	37	3.5%	0	0.9%			21	5.3%	33	5.0%	37	6.4%			37	2.9%
Montana	27	**16.8%**	9	0.0%			9	1.7%							1	0.0%	37	**15.6%**	37	4.7%
Nebraska	0	0.3%	37	**11.8%**			27	3.6%					37	**9.4%**	37	6.8%			37	4.3%
Nevada	0	0.2%	1	0.0%													1	0.1%	1	0.0%
New Hampshire			9	0.0%																
New Jersey		0.1%	9	0.1%			0	0.2%							9	0.1%			9	0.1%
New Mexico		0.2%	9	0.1%	23	0.6%			9	0.8%			29	1.0%					13	0.4%
New York	9	0.2%	9	0.6%			9	3.2%							9	0.4%			9	0.4%
North Carolina	9	0.5%	37	0.8%	37	4.7%	9	1.1%	27	8.2%			9	0.2%	37	1.5%			37	1.7%
North Dakota	27	**28.4%**	23	1.7%			27	11.3%							23	3.3%	37	**45.7%**	9	0.5%
Ohio	0	0.1%	37	4.3%			27	3.8%					1		37	6.5%			37	3.5%
Oklahoma	0	0.2%	9	0.3%	37	1.9%	9	0.7%	27	2.9%			37	3.0%	9	0.3%			37	**8.4%**
Oregon	9	2.1%	8	0.1%			8	1.8%									9	1.0%	37	3.1%
Pennsylvania	8	1.4%	37	1.1%			27	4.8%					0	0.1%	9	0.6%			9	0.6%
Rhode Island			9	0.0%																
South Carolina	0	0.1%	9	0.3%	37	1.9%	5	0.9%	21	3.4%				0.1%	23	0.4%			9	0.6%
South Dakota	8	2.5%	37	4.4%			27	**11.7%**					37	2.1%	37	4.6%	37	9.7%	37	3.3%
Tennessee			23	0.8%	37	4.1%							4	0.5%	37	1.6%			9	1.2%
Texas	0	0.2%	37	2.0%	37	**31.6%**	18	3.3%	27	**13.6%**	37	7.7%	37	**27.4%**	9	0.2%			37	5.9%
Utah	9	1.7%	9	0.0%			5	0.4%									5	0.2%	9	0.4%
Vermont			9	0.0%																
Virginia	9	1.3%	9	0.4%	23	0.7%	4	0.2%	27	3.4%					9	0.6%			9	0.8%
Washington	27	6.3%	9	0.2%			7	0.7%									23	4.6%	37	**7.6%**
West Virginia			9	0.0%			0	0.2%							9	0.0%			9	0.0%
Wisconsin	0	0.8%	37	3.8%			27	**12.0%**							23	2.0%	0	0.1%	9	0.8%
Wyoming	9	2.6%	9	0.1%			5	0.8%									5	0.1%	9	0.3%

Annual national yield data were gathered from the USDA QuickStats portal for each crop used in this analysis and summarized for each growing season in the study period (USDA, 2023a). A linear trend adjustment was applied to national annual yield data to eliminate long-term increasing or decreasing crop yield trend biases. The linear trend adjustment equation used is as follows (Irwin & Good, 2017a; Bundy & Gensini, 2022):

$$Y_{adj} = Y + [\beta_1(x_i - x_n)] \tag{2}$$

where Y is the respective year's crop yield, β_1 is the rate of change in the 37-year or 27-year yield data, x_i is the total number of years used, and x_n is the year number. Crop production data were also gathered by state and aggregated nationally from the USDA QuickStats portal (USDA, 2023a). Data were converted to *kg* and used to compute growing season crop production means over the study period and compared with the national mean to compute the percent of each state's crop that contributes to national production (**Table 1**).

2.3 Methods

An exploratory correlation analysis was first conducted to understand the relationship between weekly and annual average crop condition ratings and yield. Pearson's correlation coefficient was computed between weekly national CCIndex ratings and national yield for each crop during the study period. Standardized anomalies were computed for national detrended crop yield numbers and correlated against each crop's annual CCIndex average. Standardized anomalies were computed as:

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

where z represents the number of standard deviations the yield is above or below the mean, χ is the detrended yield for the specific year, μ is the yield mean, and σ is the yield standard deviation. Next, a crop condition spatiotemporal analysis was generated using weekly CCIndex ratings and annual CCIndex averages from national and state perspectives. To characterize conditions during the entire growing season as opposed to just one week or month, annual CCIndex averages were analyzed for each state and crop. Evaluating crop condition variability was a key component of performing a risk assessment of crop conditions across the nation. Interannual standard deviations were examined using year-to-year average

CCIndex ratings for each state. Standard deviations were calculated using the 1986–1987 CCIndex, then 1987–1988, and so on through the 2021–2022 CCIndex ratings for each crop and state. Trends were calculated at state and national levels using Theil-Sen's slope analysis due to its efficient computation and insensitivity to outliers (Wilcox, 2010). Statistical significance of Theil-Sen's slope was assessed using Kendall's τ statistic at a 90% significance level (*p*-value <0.10). For simplification, a final analysis aggregated all crops by state to compute the annual CCIndex. State-crop-weighted averages, variability, and trends were computed as follows:

$$weighted\ CCIndex = \sum_{n=1}^{n}(CCIndex * production\ percentage) \quad (4)$$

where *n* is the total number of crops by state. States with no crops were disregarded. The CCIndex rating for a crop was multiplied by the percent of production that crop has in the state (**Table 1**). The result of the multiplied values for each crop was then summed together to attain the weighted CCIndex rating for each respective state. This same procedure was replicated for trends, standard deviations, and *p*-values for each state.

3 RESULTS AND DISCUSSION

3.1 Exploratory correlation

Historically, as the growing season progressed, the correlation coefficient between U.S. crop conditions (CCIndex) and crop yield generally increased, meaning the predictability of yield prospects using USDA NASS general crop condition data was apparent (**Fig. 1**). For corn, which is the most widely produced crop in the U.S. (Economic Research Service, 2020), the increasingly positive relationship occurred from late May into mid-July, as the correlation coefficient peaked at 0.87 during week 29. After which, the correlation remained significant and steady between 0.84 and 0.87 for the remainder of the growing season. Other crops such as barley, sorghum, soybeans, and spring wheat started their shorter growing seasons with a medium-to-large correlation (Cohen, 1988) between CCIndex and yield ranging from 0.46–0.57 and finished their seasons with a large correlation above 0.80. Oats and peanuts are two crops that also finished their seasons with large correlation coefficients of 0.50 and 0.57, respectively. Meanwhile, cotton and rice held a steadily small correlation through July, then, in general, increased linearly from August through September before ending with a medium correlation at 0.40 and 0.35, respectively. Notably, these were the only two crops to end the growing season with only a medium correlation (>0.30, <0.50).

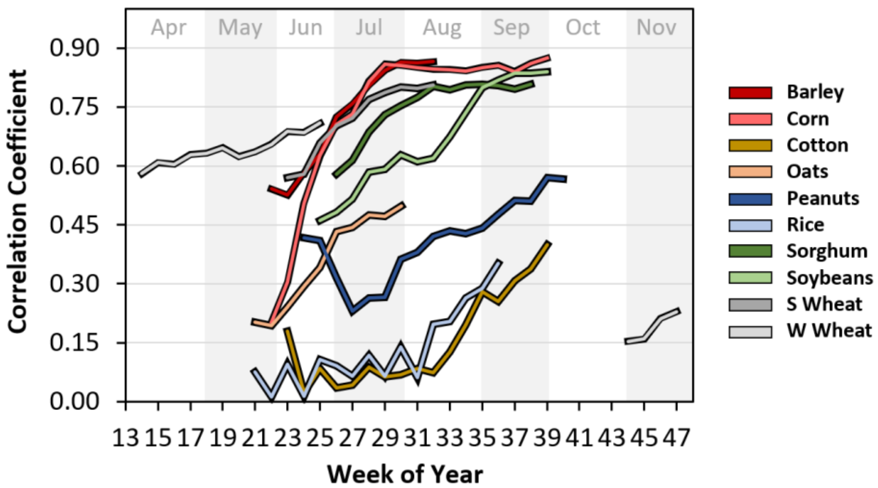

Figure 1. Pearson correlation coefficient between weekly CCIndex ratings and annual detrended yield for each crop examined over the study period (1986–2022).

However, this does not disregard using cotton and rice condition data for yield prospect analysis, as the relationship through September was still statistically significant at the 90%

significance level. For winter wheat, which was the only crop in this analysis with a boreal winter growing season, correlations between CCIndex ratings and yield in the beginning portion of the growing season (November) were small (ranging from 0.15–0.23). When general crop condition reporting resumed in April, this positive relationship improved from 0.58 to 0.71 by the end of June. Overall, an increasing correlation between crop conditions and yield was present for each crop examined, which may arise from potential difficulties in early-season assessments during vegetative crop stages. Lower early-season correlations are also attributed to the effects of weather and other variables having relatively small influences on yield when compared to more weather-sensitive stages such as pollination (Wescott & Jewison, 2013). It was typically during critical early reproduction periods in the growing cycle when crop condition ratings adjusted to information on growing conditions, and, as a result, correlations between crop condition ratings and yield were larger (Irwin & Good, 2017a; Bundy & Gensini, 2022). Additionally, management practices may also impact the correlation between crop conditions and yield. For example, rice and cotton receive the most irrigation of any other crop in this research—all of rice is produced in irrigated fields, and over one-third of cotton production is also irrigated (USDA, 2019; USDA, 2023a; USDA, 2023c), and this may impact the subjective assessment of crop conditions, resulting in lower predictability between crop conditions and yield. For crops such as corn, soybeans, sorghum, and spring and winter wheat, less than 15% of the national production for each of these crops receives irrigation (USDA, 2019; USDA, 2023a). Therefore, using the general crop condition data for dryland or rainfed crops is perhaps more useful for the entire growing season (i.e., for each week) than heavily irrigated crops.

Despite the subjectivity of the general crop condition survey, the average annual national CCIndex was a statistically significant covariate for yield for each crop except rice and cotton (**Fig. 2**). The statistically significant (90% significance level) explanatory power suggests annual average CCIndex ratings can be used to predict yield prospects not only for Midwest corn (Bundy & Gensini 2022), but also for national barley, corn, oats, peanuts, sorghum, soybeans, spring wheat, and winter wheat (**Figs. 2a, 2b, 2d, 2e, 2g, 2h, 2i, 2j**). As the CCIndex increases (as crop conditions improve), in general, yield prospects will also increase, and vice versa. It should be noted that the best predictor for yield when using general crop condition data was the final week CCIndex (**Fig. 1**), especially for cotton and rice. Though, using the annual average CCIndex incorporates the entire growing season's crop conditions and can be efficiently evaluated from year to year. In addition, even when averaging CCIndex ratings to annual levels for each crop, over 50% of the variation in barley, corn, sorghum, soybean, and spring wheat yield could be explained by the respective annual average CCIndex. To a lesser explanatory power (15–40%), variation in oats, peanuts, and winter wheat yield could also be explained by the annual average CCIndex.

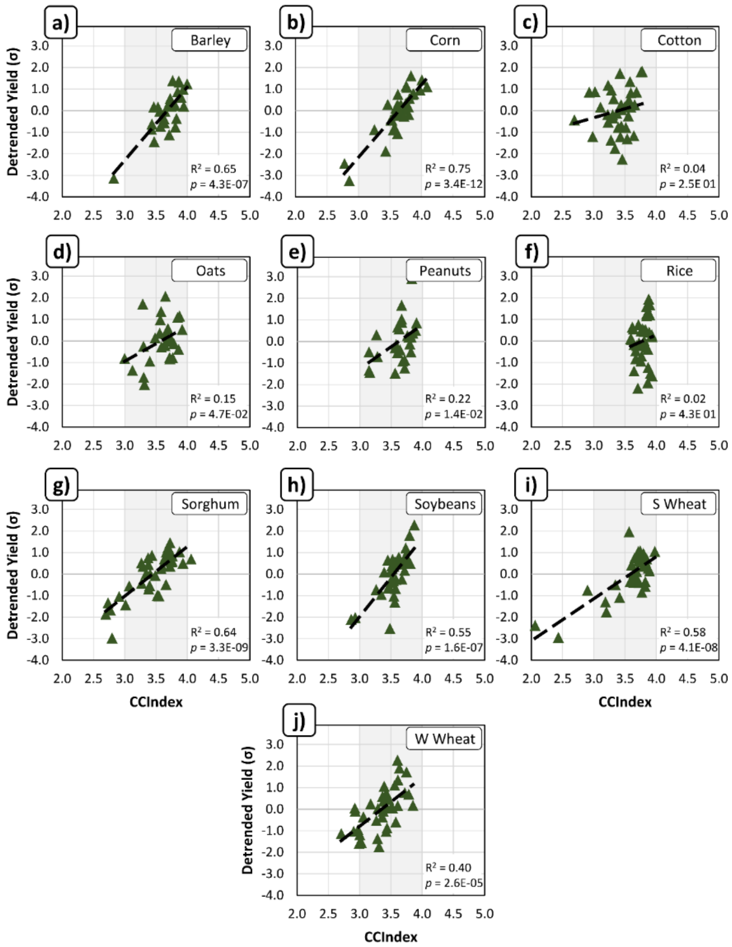

Figure 2. U.S. annual average CCIndex ratings plotted against detrended yield standardized anomalies for each crop and growing season (1986–2022). Regression r^2 and p values are listed for each crop.

Therefore, the existing relationship between weekly and annual CCIndex ratings with yield provides additional merit to exploring spatiotemporal patterns and trends in crop conditions across the U.S. The consideration of multiple influences on crop conditions, such as advancements in technology and hybrids, weather variability, soil variability, pest and disease pressure, genetic variability, and aforementioned management practices (e.g., irrigation), are also contributing factors to the variation between crop conditions and yield. Nonetheless, the relationship between crop conditions and yield was still significant and may be used in practice with accuracy.

3.2 Climatology

3.2.1 Temporal climatology

Given the positive linear relationship between CCIndex and crop yield, the trend of crop conditions on a weekly basis through the growing season has important implications for yield prospects. On average, crop conditions throughout the growing season tended to either 1) remain steady, then decline at a certain point before stabilizing or slightly improving, 2) remain steady before declining for the rest of the season, or 3) improve for much of the season before stabilizing in the final weeks (**Fig. 3**). Crops that remained steady, transitioned to a decline, and then stabilized toward the end of the season include corn, which transitioned to a decline by weeks 26 and 27 (early July) and then stabilized by week 36 (early September), and cotton and peanuts, which both decreased later in the growing season by weeks 31 and 32 (early to mid-August) before stabilizing by the end of September (**Figs. 3b, 3c, 3e**). The major difference between these crops was their seasonal CCIndex averages, as corn was the highest among these three crops at 3.64, peanuts at 3.62, and cotton at 3.39. To an extent, soybeans and sorghum followed a similar seasonal pattern to corn, though the later start to their respective growing seasons resulted in a steady decrease generally in mid-June before stabilizing in mid-September (**Figs. 3g, 3h**). Both soybeans and sorghum were in the bottom half of seasonal CCIndex averages across all crops at 3.55 and 3.49, respectively. Barley, oats, and spring wheat conditions tended to start steady within the first few weeks after emergence before deteriorating for the remainder of their growing seasons through August (**Figs. 3a, 3d, 3i**). These three crops also had considerable differences in their seasonal CCIndex averages, as barley was the highest at 3.68, spring wheat at 3.60, and oats at 3.58. Winter wheat conditions generally started steady in weeks 44–47 (November) before subtly declining to the lowest CCIndex on average of any crop at 3.25 in June (**Fig. 3j**). Winter wheat possessed the lowest seasonal condition of any crop in the U.S. on average, with a seasonal CCIndex average of 3.36.

For most crops, total CCIndex rating declines from the start of the growing season to the end were from -0.10 to -0.25 on average; i.e., the total area of crops more favorable for normal or above-normal yield decreased as the growing season progressed.

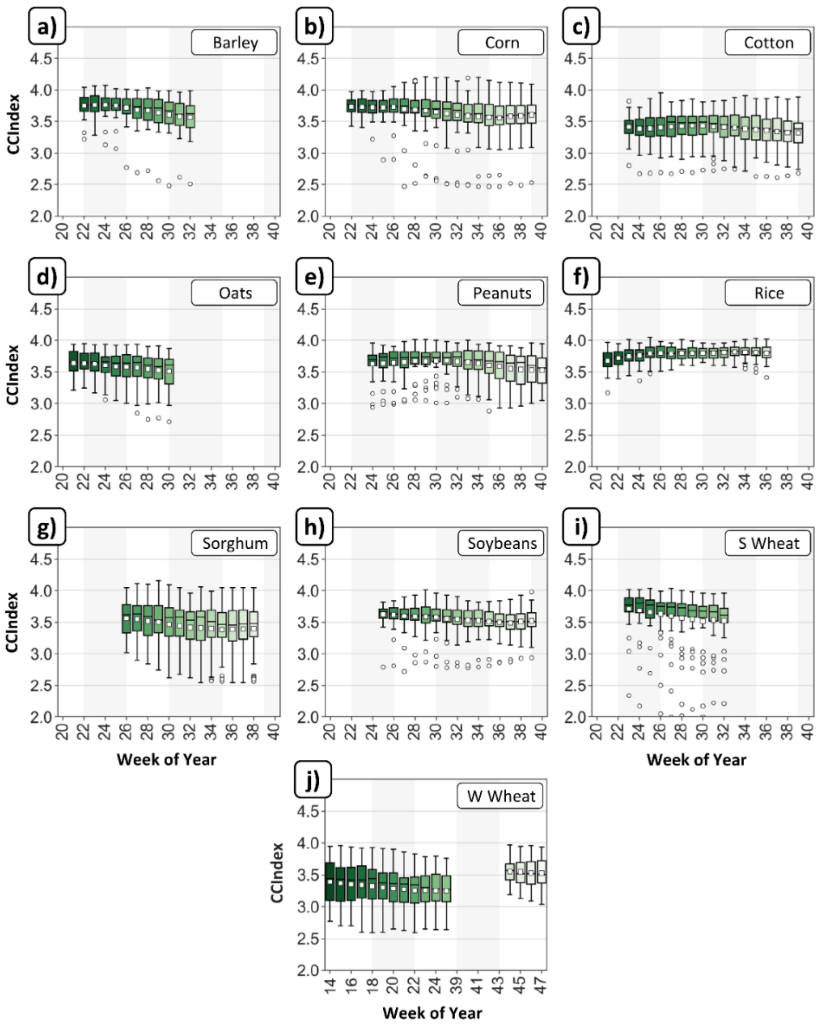

Figure 3. Box and whisker plots of weekly CCIndex ratings by crop over the 1986–2022 study period. Each box and whisker present a seven-number summary: white circles represent outliers; whiskers represent the 1.5 multiple of the inner-quartile range; boxes represent first quartile (25th percentile) and third quartile (75th percentile) values; black horizontal line within boxes represent the median value; white squares represent the mean value. Gray-shaded and white areas represent monthly intervals.

Of the 37 growing seasons examined (27 total for barley, oats, and peanuts), at least 70% of these seasons exhibited a negative slope between the first week's CCIndex and the final week's rating for each crop (except rice). Deteriorating conditions were especially noteworthy around critical reproduction periods, which are particularly weather-sensitive periods for U.S. crops. Overall, crop condition depletion during the growing season can be caused by water stress, nutrient depletion, disease, pests, weed pressure, soil structure, crop management practices (or lack thereof), and severe weather events (e.g., August 2020 Corn Belt derecho; Hosseini et al., 2020). Previous research has quantified the correlation between weather and climatic variables with crop conditions and observed increasingly higher correlation coefficients ($r > 0.50$) between Palmer Drought indices and precipitation accumulation with crop conditions throughout the growing season (Bundy & Gensini, 2022). Therefore, the high degree of explanatory power between weather and climate variables with weekly crop conditions inherently requires close monitoring of weather throughout the growing season.

Rice was an exception to these overall deteriorating conditions, as, on average, CCIndex ratings increased subtly by 0.12 from the end of May through the beginning of September (**Fig. 3f**). This increasing slope from the end of emergence to the start of harvest occurred in 29 of the 37 rice-growing seasons (78%). Rice also had the highest-rated crop conditions, with a seasonal CCIndex average of 3.78. In large part, this was due to rice having maintained the lowest weekly CCIndex variability and being the only crop to decrease in condition variability as the growing season progressed (a decrease in CCIndex standard deviation between the first and last growing season weeks of -0.05), which can be explained by all U.S. rice being produced in irrigated fields (USDA, 2023c). All other crops examined increased in CCIndex variability as the growing season progressed. While there were fluctuations throughout the season, the CCIndex standard deviation difference between the first couple weeks of the growing season and final weeks was between 0.07 and 0.17 for all crops. In total, there were eleven seasons that had at least one week for at least one crop with a CCIndex rating outlier, and all these years were driven by some degree of drought conditions (e.g., 2012; Rippey, 2012). This lends additional credence to previous findings that indicate drought is the leading peril for crop loss across the U.S. (Perry et al., 2020; Bundy & Gensini, 2022). Condition coverage by category (excellent, good, fair, poor, very poor) provides additional perspective on condition exposure and vulnerability to change, which can be examined from Supplemental Figures S2 and S3.

3.2.2 Spatial climatology

When examining crop conditions across the U.S., a discernible spatial pattern in annual CCIndex averages and annual variability can be recognized across all crops (**Figs. 4, 5**).

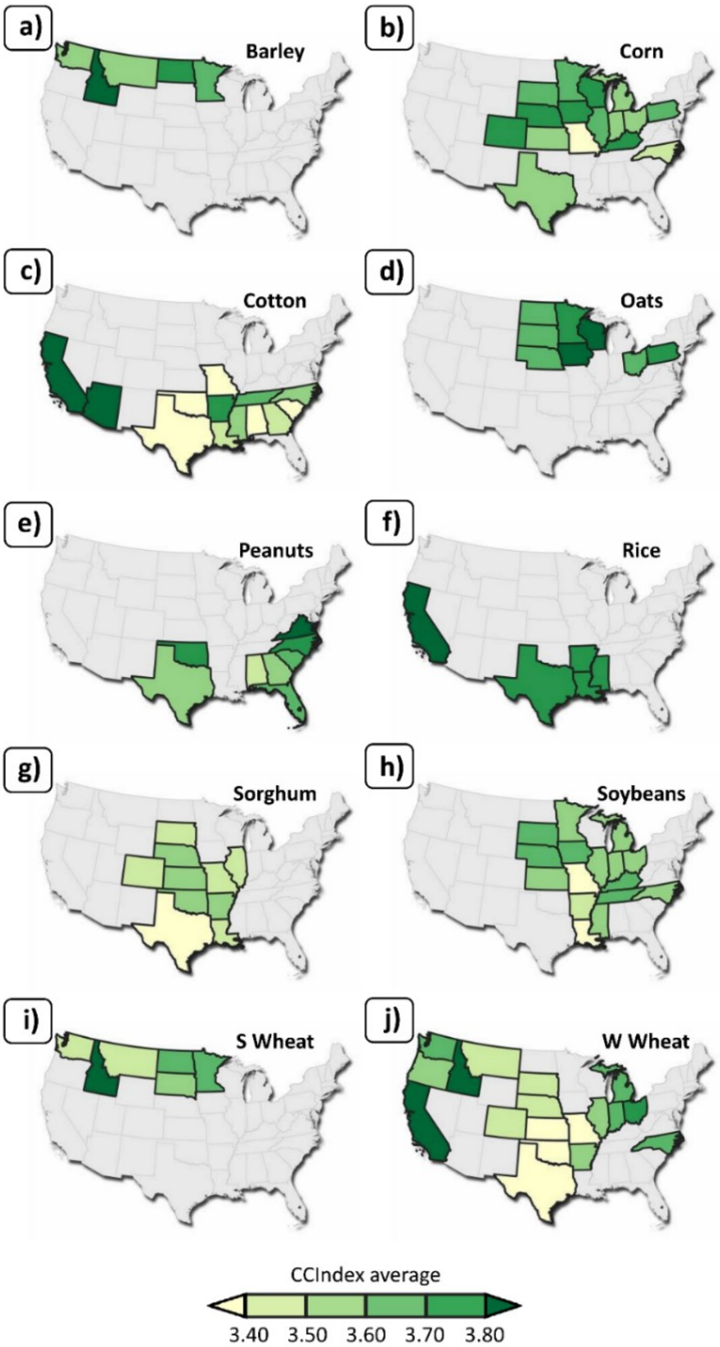

Figure 4. Annual average CCIndex ratings by state over the 1986–2022 study period for each crop.

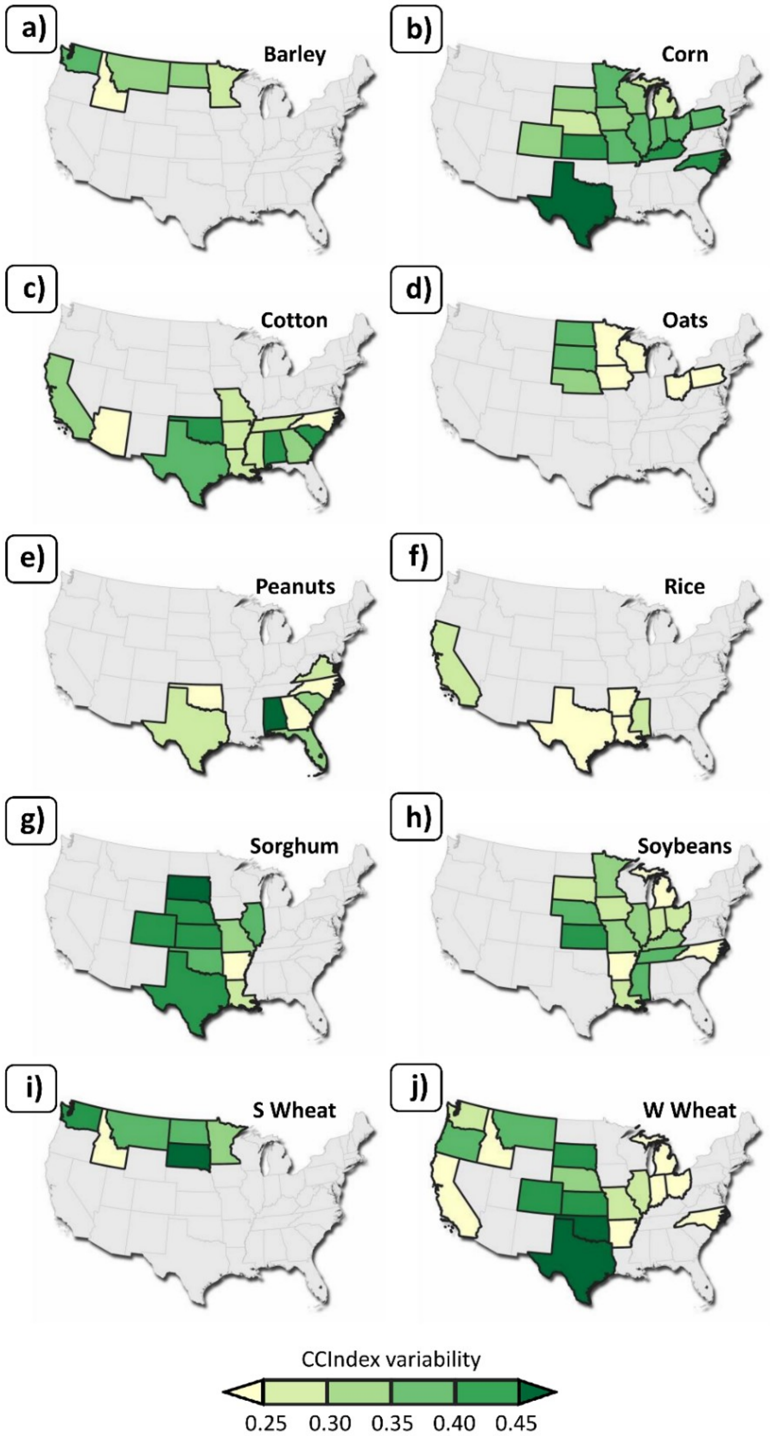

Figure 5. Annual average CCIndex standard deviations by state over the 1986–2022 study period for each crop.

Annual averages and variability for each condition and each state-crop combination are provided in Supplemental Tables S1 and S2. States with crops in better condition (higher CCIndex average) generally retained lower interannual variability (correlation coefficient of -0.55) and were, therefore, at less risk for interannual crop condition fluctuations. Spatial variability in crop conditions among states can be explained by large-scale factors such as regional climate (Li et al., 2019), soil suitability and water requirements (Trnka et al., 2014), and agricultural practices including crop selection, harvest area, technology, hybrids, and irrigation (Li et al., 2019). Starting with northern-tier crops, barley and spring wheat conditions exhibited analogous spatial patterns, as Idaho held the highest annual CCIndex average of 3.92 and 3.85, respectively, both of which were in the top ten highest ratings for any state-crop combination (**Figs. 4a, 4i**). Idaho also exhibited the lowest condition variability, with an annual CCIndex average standard deviation for both barley and spring wheat of < 0.10 (**Figs. 5a, 5i**). Spatially, eastern barley and spring wheat growing areas (North Dakota and Minnesota) maintained slightly better crop conditions compared to western growing areas (Washington and Montana). For oats, which is another crop generally grown across the northern U.S., conditions were marginally better in central portions of oat acreage than elsewhere—including Minnesota, Wisconsin, and Iowa (**Fig. 4d**). Oat crop variability displayed a distinct spatial pattern, with the northern Great Plains acreage possessing a higher CCIndex standard deviation (σ difference over 0.25) when compared to states east of the Missouri and Red Rivers (**Fig. 5d**). Additionally, five oat states with exceedingly low CCIndex variability ($\sigma < 0.18$) were in the bottom ten lowest for all state-crop combinations.

For crops with core acreage in the Midwest (corn and soybeans), conditions were lowest on average generally in southern U.S. states—including Texas, Kansas, Missouri, North Carolina for corn, and Missouri, Arkansas, and Louisiana for soybeans (**Figs. 4b, 4h**). Missouri displayed the worst corn and soybean conditions, with annual CCIndex averages below the national average of just 3.39 and 3.32, respectively. Corn Belt states—Illinois, Indiana, Iowa, Minnesota, and Nebraska—that collectively consist of over 60% of U.S. corn and soybean production, occupied above-normal corn and soybean conditions with CCIndex ratings above national averages (except Indiana). Meanwhile, the central and southern Great Plains had the highest condition variability, with annual CCIndex standard deviations exceeding 0.40 (**Figs. 5b, 5h**). Sorghum also had particularly variable conditional averages across the Great Plains. Texas and Kansas, which consist of 70% of U.S. sorghum production, retained an annual CCIndex average of 3.38 (lowest of sorghum states) and 3.55 (second highest of sorghum states), respectively (**Fig. 4g**). Also, variability for sorghum conditions was high, as standard deviation values in seven of the ten sorghum-growing states were exceedingly higher than the national annual CCIndex standard deviation average of 0.32 (**Fig. 5g**).

Southern U.S. dominant crops such as cotton, peanuts, and rice vary amongst each other for their respective crop conditions. For cotton, Texas maintained the second lowest annual CCIndex average of any state-crop combination at 3.17, which was 0.37 below the national cotton CCIndex average (**Fig. 4c**). Furthermore, Texas was the only state to have a higher percent coverage of fair-conditioned cotton crops than good-conditioned ones (Supplemental Table S1), and notably, Texas produces over one-third of U.S. cotton. These below-normal cotton conditions extended throughout the southern Great Plains and into Missouri. Meanwhile, southwestern U.S. states—Arizona and California—displayed the best conditions among cotton states with CCIndex ratings of 3.90 and 4.08, respectively. Both cotton condition ratings were in the top ten for any state-crop combination. California rice was also in the top ten for highest CCIndex averages at 3.90, and further, each rice state was at least 0.10 higher than the national CCIndex average of 3.59 (**Fig. 4f**). Condition variability for all rice and peanut states (except Alabama) was generally low, with standard deviations below the national average (**Figs. 5e, 5f**). Alabama and Texas held the poorest conditions of all peanut states, with improving conditions northward through the mid-Atlantic region (**Fig. 4e**). Winter wheat also displayed a distinct spatial pattern, as below-normal conditions were prevalent across the southern Great Plains while conditions improved through eastern and western winter wheat acreage (**Fig. 4j**). Texas, Oklahoma, and Kansas winter wheat CCIndex averages were in the bottom 10 lowest ratings across all state-crop combinations, with the Texas rating of 2.99 being the lowest of any state-crop combination. Texas is the only state to have a higher percentage of winter wheat crops in fair condition than in good condition for any state-crop combination (Supplemental Table S1). Conversely, winter wheat in California held the highest annual CCIndex average of any state-crop combination at 4.14. Seasonal predictability of winter wheat conditions was difficult in the Great Plains with observed higher variability (standard deviation exceeding 0.40 with three states being in the top ten of any state-crop combination), but was generally lower in year-to-year fluctuations across eastern and western wheat acreage (**Fig. 5j**).

When aggregating all qualifying crops together (and weighting each state by their respective production averages), a comprehensive overview of U.S. crop conditions reveals distinguished spatial variances (**Fig. 6**).

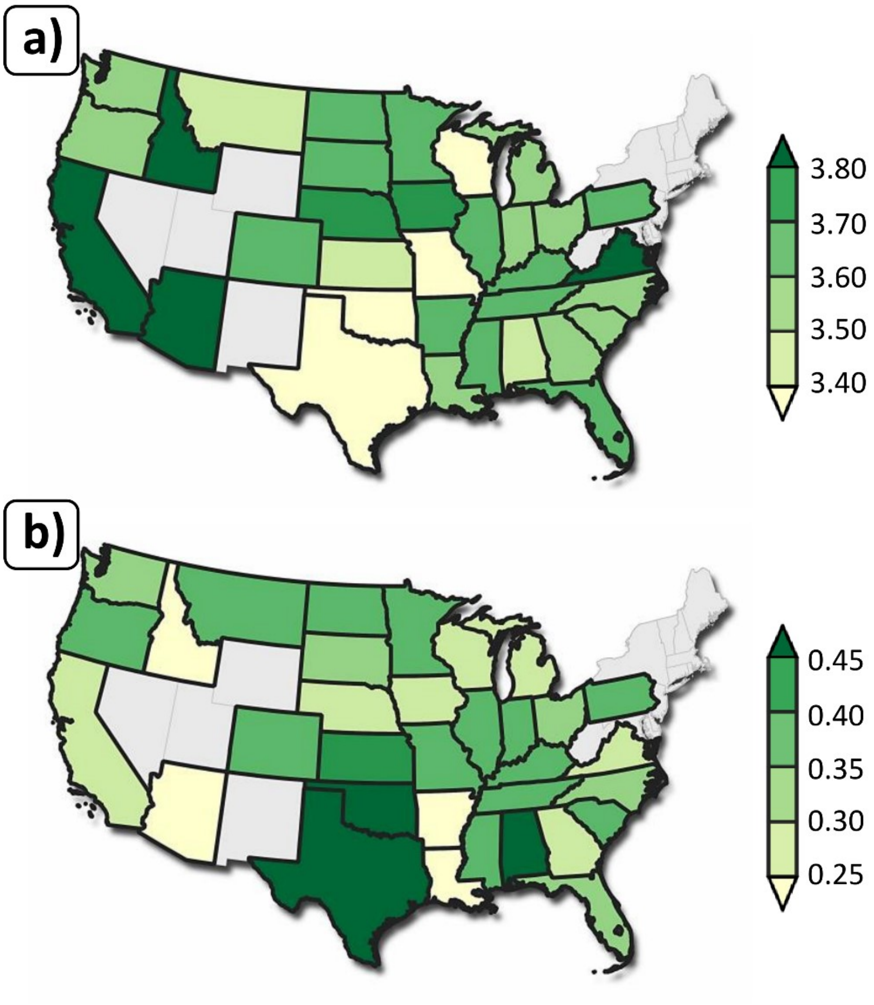

Figure 6. Annual average production weighted CCIndex a) ratings and b) standard deviations for each state.

Overall, three general assessments were made: 1) crop conditions across portions of the western U.S. (Arizona, California, and Idaho) were better on average, with annual CCIndex ratings above 3.80; 2) much of the southern Great Plains experienced the worst crop conditions, with annual CCIndex ratings below 3.40; and 3) crop conditions across the northern Great Plains, Midwest, and Southeast U.S. regions were generally near-normal on average, deviating only slightly from the national CCIndex average of 3.60 (**Fig. 6a**). From worst to fifth-worst—Oklahoma, Wisconsin, Missouri, Texas, and Alabama were the bottom five states in terms of crop conditions; crop conditions in California, Arizona, Idaho, Virginia, and Nebraska were the top five (from best to fifth-best). Notably, each of these top-conditioned states is heavily irrigated, except Virginia (Ruess et al., 2023). The western U.S. also generally held the lowest interannual condition variability, with average CCIndex standard deviations below 0.30 (**Fig. 6b**). Low crop condition variability was also prevalent across the Mississippi Delta region. Meanwhile, neighboring states in the southern Great Plains (Oklahoma and Texas, in particular) maintained high crop condition variability, with annual CCIndex standard deviations above 0.45. The southern Great Plains is a region where notable crop expansion occurred, particularly during the 2008–2016 period (Lark et al., 2020). This expansion has not necessarily led to a positive yield differential for corn, soybeans, and wheat in the region, and the examination of crop conditions confirm that these croplands occupy areas with marginal biophysical characteristics such as nutrient or moisture deficiencies and/or climatic stress (Scanlon et al., 2012; Xie et al., 2019).

3.3 Trends

3.3.1 Temporal trends

At the national level, barley and peanuts were the only two crops to have distinguished improvements in conditions in most weeks (**Fig. 7**). Increases were especially noteworthy and statistically significant from August onward, with CCIndex increases exceeding $0.010 \cdot yr^{-1}$. Moreover, ten of the sixteen weeks with an increasing trend in peanut conditions were statistically significant at the 90% significance level. Increasing peanut condition trends from weeks 35–40 were the most robust of any weekly trends for all crops, with a max CCIndex increase of 0.018 · yr^{-1} (week 37).

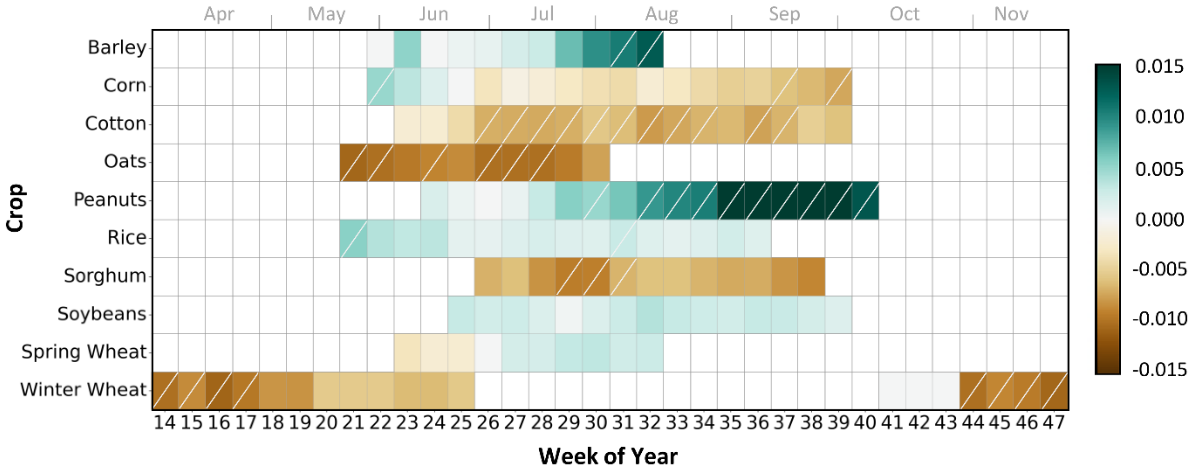

Figure 7. Theil-Sen slope results of interweekly trends in U.S. CCIndex ratings by crop (1986–2022). Slope units are rating increases or decreases in CCIndex per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.

Crops with practically no trend in conditions at the national level include rice, soybeans, and spring wheat, with most weeks exhibiting a statistically insignificant subtle CCIndex increase of less than 0.005 · yr^{-1}. Crops with predominantly a decreasing trend in conditions over most weeks include corn, cotton, oats, sorghum, and winter wheat. For corn, the first few weeks of the growing cycle from the end of May into early June (weeks 22–24) have subtly improved in conditions before changing to a subtle decline from late June (week 26) onward. The most robust decreasing corn condition trends occurred in September, with CCIndex trends lower than -0.005 · yr^{-1}, though only two of the fourteen weeks with a decreasing trend were statistically significant. For cotton, each growing season week experienced a deterioration in conditions, with eleven of the seventeen weeks with statistically significant declining trends in CCIndex ratings. Cotton has the longest weekly streak of any crop with a statistically significant deteriorating trend, which was nine weeks in a row from July through August. The most distinct decreasing trends in conditions were with oat crops, as six of the eleven growing seasons underwent statistically significant declines in the CCIndex lower than -0.008 $\cdot$ yr^{-1}. Each week during the winter wheat growing season has experienced a decline in conditions since 1986. Winter wheat also experienced a long streak (eight weeks in a row) of decreasing statistically significant condition trends starting at the end of October, continuing into November, and then into April of the following calendar year within its respective growing season. CCIndex trends ranged from -0.009 to -0.010 $\cdot$ yr^{-1} for winter wheat throughout the season. Despite deteriorating condition trends at the national level for some crops, yield for each crop has experienced a general linear increase since the start of the study period (USDA, 2023a). The contradicting trends between conditions and yield reflect advancements in yield-enhancing technology, new hybrids, crop genetics, nitrogen management and timing, other pest and nutrient management, and precision planting that result in higher per-hectare plant populations (Gehl et al., 2005; Schmidt et al., 2002; Kant et al., 2012; Wescott & Jewison, 2013; Hartfield & Walthall, 2015; Watson et al., 2018).

3.3.2 Spatial trends

Consistent with state-level averages and variability, distinct spatial trends were also observed for both CCIndex rating and variability trends (**Figs. 8, 9**). General condition rating and variability trends, along with specific state-crop categorical results, can be examined in Supplemental Figures S4, S5, and Supplemental Tables S3, S4. Barley and spring wheat, which are comparable in growing area and displayed related patterns in conditions, also displayed similar spatiotemporal trends in conditions to an extent (**Figs. 8a, 8i**). Noteworthy trends include barley in Montana with a statistically significant CCIndex increase of 0.015 · yr^{-1}; spring wheat and barley in Minnesota with CCIndex increases exceeding 0.012 · yr^{-1}; and CCIndex trends for both crops in Idaho of less than -0.006 · yr^{-1}. Annual trends in condition variability for barley and spring wheat were mostly insignificant across growing areas (**Figs. 9a, 9i**). Further east for oat crops, conditions across most states were mostly increasing, except for the Great Plains, where the most robust CCIndex decrease (-0.012 · yr^{-1}) occurred in South Dakota (**Fig. 8d**). While decreasing condition trends for oats in Nebraska were insignificant, the decreasing trend in annual variability was significant with a CCIndex trend of -0.015· yr^{-1} (**Fig. 9d**). Improvements in oat conditions in the northern Midwest were also generally insignificant (Ohio is the exception, with the highest increase in conditions at 0.0054 · yr^{-1}).

Midwest and Great Plains dominant crops such as corn, soybeans, and sorghum displayed similar spatiotemporal patterns in condition trends over time. These three crops underwent some of the most robust trends in both improving and deteriorating directions at the state level. Across primary Corn Belt acreage, condition trends were mostly insignificant for corn and soybeans. Though, trends throughout much of the Great Plains have degraded significantly for corn, soybeans, and sorghum, with CCIndex decreases worse than -0.0083 · yr^{-1} (**Figs. 8b, 8g, 8h**).

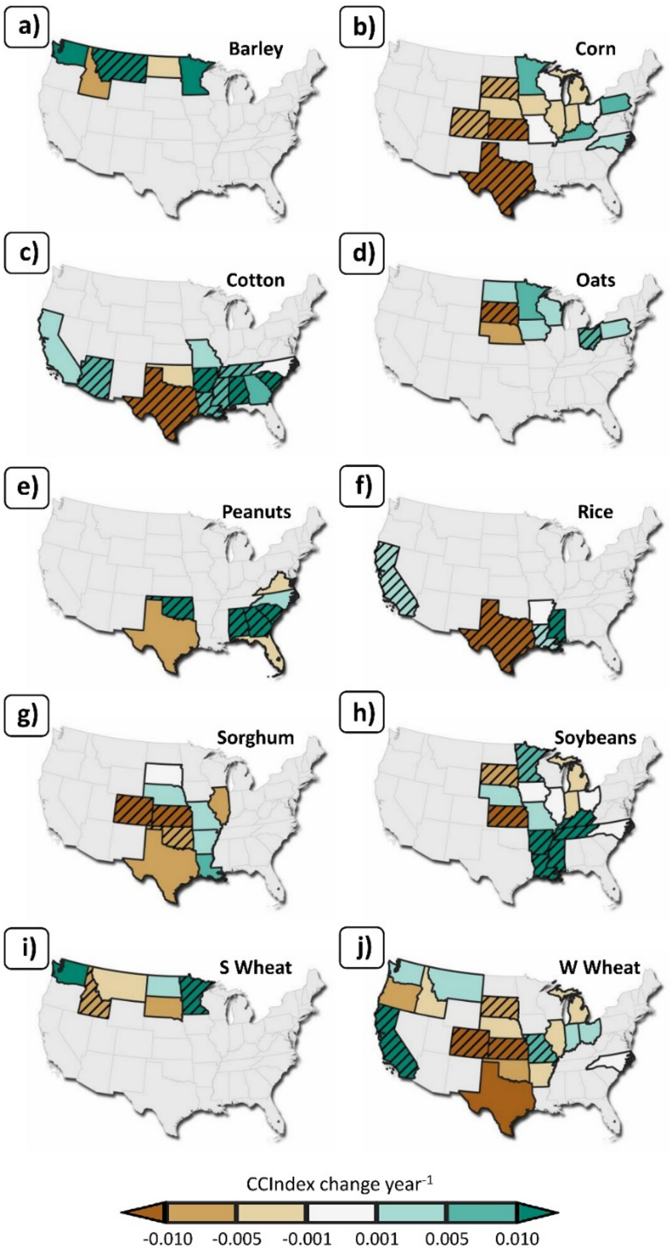

Figure 8. Theil-Sen slope results for annual trends in CCIndex ratings by U.S. state for each crop (1986–2022). Slope units are rating increases or decreases in CCIndex per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.

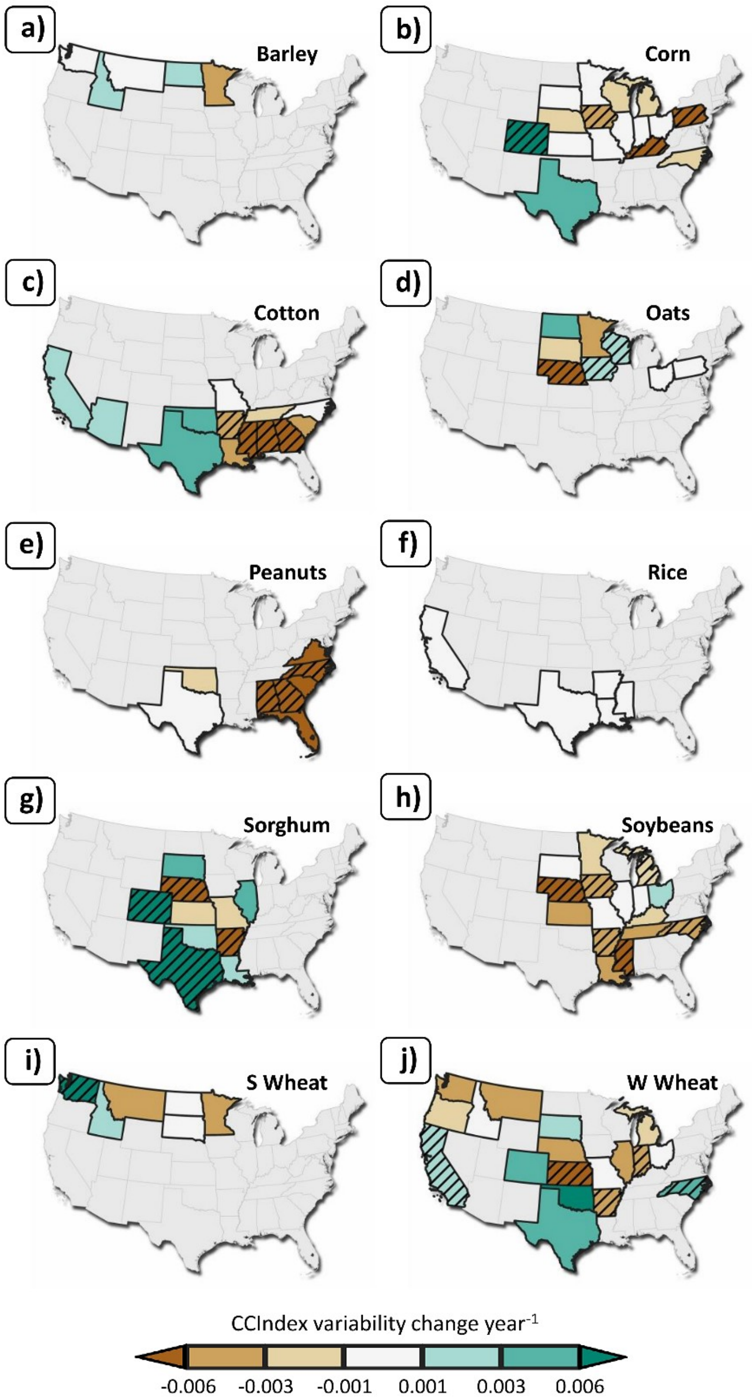

Figure 9. Theil-Sen slope results for trends in CCIndex annual-averaged standard deviations by U.S. state for each crop (1986–2022). Slope units are standard deviation increases or decreases per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.

In fact, both corn and soybeans in Kansas have experienced the two most robust declines in conditions (CCIndex decreases below -0.017 · yr^{-1}) of any state-crop combination. Sorghum in Kansas also experienced a significant deterioration of conditions (tenth worst trend of any state-crop), with CCIndex trends of -0.014 · yr^{-1}. In the Mississippi Delta and southeastern U.S. regions, conditions have increased significantly, especially for soybeans, with CCIndex increases greater than 0.010· yr^{-1}. Mississippi soybeans experienced a top-ten increasing trend with CCIndex increases of 0.018· yr^{-1}. When examining variability trends for these three crops, trends were generally opposite to condition rating trends (**Figs. 9b, 9g, 9h**). Condition variability has decreased in various states throughout the Midwest, while variability increases were observed in the southern Great Plains, where conditions have deteriorated throughout the historical record. Though for corn and soybeans in Kansas, which displayed robust decreases in conditions, variability has also decreased over time. Decreasing trends in soybean condition fluctuations were especially notable, with the most states with a statistically significant decreasing trend in interannual CCIndex variability (six states total).

Southern U.S. dominant crops such as cotton, peanuts, and rice displayed similar spatial trends in conditions as, in general, the southern Great Plains (Texas in particular) experienced significant declines while the southwestern and southeastern U.S. experienced significant improvements in conditions (**Figs. 8c, 8e, 8f**). Texas cotton experienced a top-ten deterioration of conditions with a CCIndex trend of -0.014 · yr^{-1}. Peanut crops in South Carolina and Alabama, along with cotton crops in Arkansas, South Carolina, and Alabama, were in the top ten for improving condition trends (CCIndex increases exceeding 0.015 · yr^{-1}). For condition variability, trends were most distinct in the southeastern U.S., with cotton and peanut conditions decreasing (**Figs. 9c, 9e**), while rice variability trends were nonexistent (**Fig. 9f**). For winter wheat, conditions have decreased significantly in the Great Plains while only increasing statistically significantly in California (**Fig. 8j**). Winter wheat in Colorado, Kansas, and Texas was in the top ten for most robust declines in conditions of any state-crop combination. Meanwhile, variability in winter wheat conditions has subtly increased in the southern Great Plains and for much of the southern half of the U.S. (**Fig. 9j)**. Notably, variability has decreased significantly in Kansas, and this, coupled with a decline in conditions over time, increases confidence in year-to-year deteriorating conditions.

When aggregating all crops together and weighting each state by production, distinct trends in crop conditions have been observed (**Fig. 10a**). Overall, rating trends in general were not statistically significant across the northern half of the U.S., except for South Dakota. Across the Great Plains, a substantial degradation in crop conditions was noted, with CCIndex decreases exceeding $-0.010 \cdot yr^{-1}$, particularly in Kansas, Texas, and Colorado, which were driven by declining conditions in corn, cotton, rice, sorghum, soybeans, and winter wheat. The southwestern U.S. experienced a statistically significant increase in conditions, which were driven by improvements in cotton, rice, and winter wheat conditions. Also, the southeastern U.S. also experienced substantial increases in the CCIndex, with trends exceeding $0.010 \cdot yr^{-1}$—largely driven by improvements in cotton, peanuts, rice, and soybeans. Increasing condition trends in the southeastern and southwestern U.S. are highly influenced by higher irrigated acreage when compared to other agricultural regions (Ruess et al., 2023). This is especially true for the Mississippi Delta and southeastern U.S., where irrigation for agriculture has significantly increased since 1997 (Hrozencik, 2021), and these changes are reflected in the increase in crop condition ratings and decrease in rating variability.

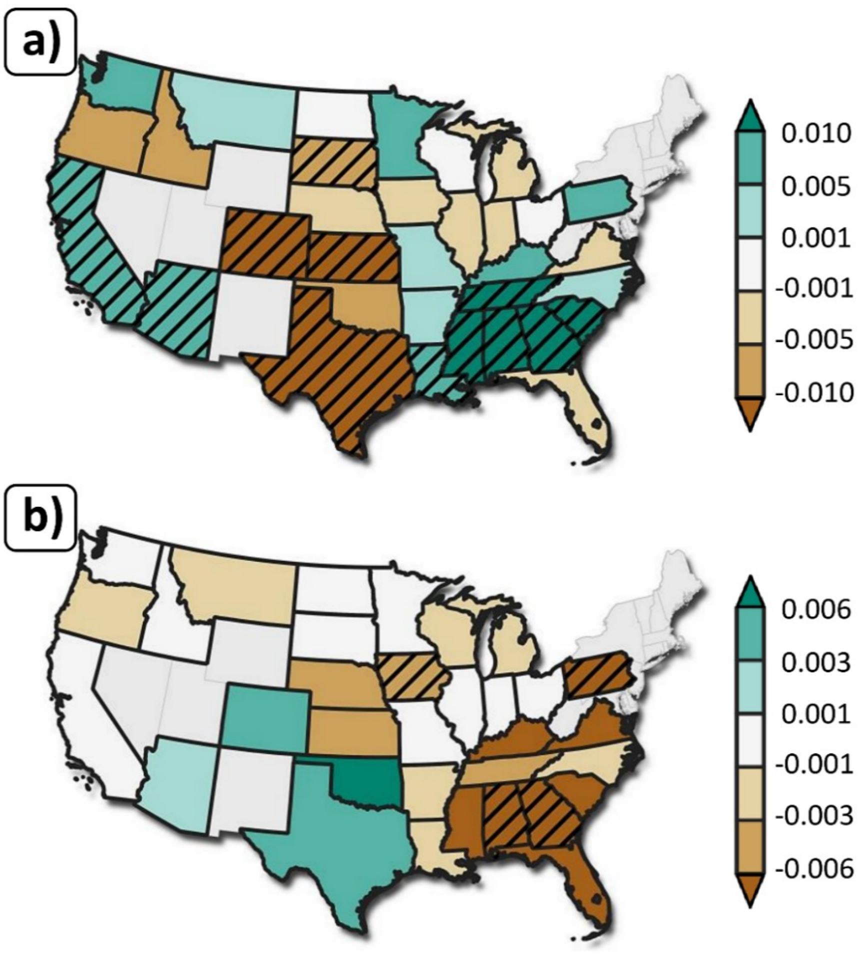

Figure 10. Theil-Sen slope results for a) production-weighted annual CCIndex rating trends in crop conditions by state and b) production-weighted trends in annual-averaged CCIndex standard deviation (1986–2022). Slope units are increases or decreases in a) CCIndex rating and b) standard deviation per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.

South Carolina, Alabama, Mississippi, Tennessee, and Georgia are the top five states with the most robust improvements in crop conditions since 1986. For variability trends, the only significant trends were on the decreasing side and were for Iowa, Pennsylvania, Alabama, and Georgia (**Fig. 10b**). Overall, the area with the poorest crop conditions on average and the highest annual variability was also where the most robust declines in conditions and increases in variability were located, which was the southern Great Plains. This is a region where the overall deteriorating trends and lower-than-normal crop conditions can be traced to increases in average and extreme temperatures (Vose et al., 2017), vulnerability to drought (Kloesel et al., 2018), and significant declines in irrigated acreage due to increasing scarcity in groundwater resources in the Ogallala Aquifer (McGuire, 2017; Hrozencik, 2021). Since crop expansion in the region has resulted in only marginal yield differentials, and as crop conditions continue to decline, it needs to be considered whether the return on crop production is worth the costs to wildlife and other natural habitats (Lark et al., 2020).

4 CONCLUSIONS

USDA NASS general crop condition ratings within weekly CPC reports are critical for monitoring near-real-time conditions and gaining insight on yield prospects. As the correlation coefficient between condition ratings and yield for barley, corn, cotton, oats, peanuts, rice, sorghum, soybeans, spring wheat, and winter wheat increases during the growing season, weekly monitoring of these ratings becomes increasingly important and is a respectable approach for forecasting yield. The correlation between crop condition ratings and yield was notably higher during critical reproduction phenological stages in the growing cycle, which was when weekly crop condition declines became more apparent for most crops on average. Spatial differences in conditions, variability, and trends in condition ratings and variability are highly impacted by crop selection, regional climate, and management practices such as irrigation. The highest risk for lower-than-normal annual crop conditions, along with where crop condition declines were observed over the historical record (1986–2022), was in the Great Plains. Therefore, the total coverage for corn, cotton, rice, sorghum, soybean, and winter wheat crop conditions that are more favorable for some degree of yield loss has increased significantly in the region. This is especially concerning given observed climatic and hydrological trends as well as future projections across the Great Plains, including increasing temperatures, increasing occurrences of drought, and depleting groundwater levels. Meanwhile, crop conditions across the southwestern and southeastern U.S., which are driven by cotton, peanuts, rice, and soybeans, have improved significantly, while interannual variability in conditions has decreased. Overall, advancements in management, technology, and hybrids need to continue under a changing climate to reverse declining crop condition trends and maintain stabilized or improving trends in the U.S. Despite these data being subjective estimates of crop conditions, they have proven to provide value in research and practical settings. These findings, along with using weekly USDA NASS crop condition ratings across all crops, can provide essential risk assessment information for producers and other stakeholders. Future crop condition analyses should also continue to further our understanding of state-crop risk on a weekly and annual basis, potential future changes in yield, and responses to both optimal and adverse weather conditions. Additionally, each state-crop condition result should be investigated further to understand why conditions have trended and how to sustain or improve them. Such efforts will increase the overall understanding of the U.S. agricultural landscape and ensure a sustainable future for generations to come.

SUPPLEMENTAL MATERIAL

Supplemental material provides specific crop condition percentages for each general condition category (excellent, good, fair, poor, very poor).

REFERENCES

Anastasiou, E., Balafoutis, A., Darra, N., Psiroukis, V., Biniari, A., Xanthopoulos, G., & Fountas, S. (2018). Satellite and proximal sensing to estimate the yield and quality of table grapes. *Agriculture*, 8(7), 94. https://doi.org/10.3390/agriculture8070094

Anderson, P. K., A. A. Cunningham, N. G. Patel, F. J. Morales, P. R. Epstein, & P. Daszak. (2004). Emerging infectious diseases of plants: Pathogen pollution, climate change and agrotechnology drivers. *Trends in Ecology & Evolution*, 19 (10), 535–544. https://doi.org/10.1016/j.tree.2004.07.021

Angel, J., C. Swanston, B.M. Boustead, K.C. Conlon, K.R. Hall, J.L. Jorns, K.E. Kunkel, M.C. 647 Lemos, B. Lofgren, T.A. Ontl, J. Posey, K. Stone, G. Takle, and D. Todey. (2018). Midwest. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 872–940. https://doi.org/10.7930/NCA4.2018.CH21

Ashley, W. S., Haberlie, A. M., & Gensini, V. A. (2023). The Future of Supercells in the United States. *Bulletin of the American Meteorological Society*, *104*(1), E1-E21. https://doi.org/10.1175/BAMS-D-22-0027.1

Bain, R., & Fortenbery, T.R. (2013). Impacts of crop conditions reports on national and local wheat markets. In Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. http://www.farmdoc.illinois.edu/nccc134

Bain, R. &. T.R. Fortenbery. (2016). Impact of crop condition reports on national and local wheat markets. *J. Agric. Appl. Econ.*, 49, pp. 1-23. https://doi.org/10.1017/aae.2016.31

Bebber, D. P., M. A. T. Ramotowski, & S. J. Gurr. (2013). Crop pests and pathogens move polewards in a warming world. *Nature Climate Change*, 3 (11), 985–988. https://doi.org/10.1038/nclimate1990

Beguería, S., & Maneta, M. P. (2020). Qualitative crop condition survey reveals spatiotemporal production patterns and allows early yield prediction. *Proc. Natl. Acad. Sci.*, 117(31), 18317-18323. https://doi.org/10.1073/pnas.1917774117

Bindoff, N. L., P. A. Stott, K. M. AchutaRao, M. R. Allen, N. Gillett, D. Gutzler, K. Hansingo, G. Hegerl, Y. Hu, S. Jain, I. I. Mokhov, J. Overland, J. Perlwitz, R. Sebbari, & X. Zhang. (2013). Detection and attribution of climate change: From global to regional. T.F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P.M. Midgley, Eds., Cambridge University Press, 867–952. https://www.climatechange2013.org/full-report/

Brimelow, J. C., W. R. Burrows, & J. M. Hanesiak. (2017). The changing hail threat over North America in response to anthropogenic climate change. *Nature Climate Change*, 7, 516–522. https://doi.org/10.1038/nclimate3321

Bundy, L. R., & Gensini, V. A. (2022). An assessment of USDA corn condition ratings across the US Corn Belt. *Agronomy Journal*, *114*(1), 601-617. https://doi.org/10.1002/agj2.20973

Bundy, L. R., Gensini, V. A., & Russo, M. S. (2022). Insured Corn Losses in the United States from Weather and Climate Perils. *Journal of Applied Meteorology and Climatology*, *61*(8), 969-988. https://doi.org/10.1175/JAMC-D-21-0245.1

Bundy, L. R., Gensini, V. A., & M.S. Van Den Broeke. (2023). Tropical cyclone impacts on crop condition ratings and yield in the Coastal Southern United States, *Agricultural and Forest Meteorology*, Volume 340, 109599, ISSN 0168-1923. https://doi.org/10.1016/j.agrformet.2023.109599

Cai, X., X. Zhang, P. H. Noël, & M. Shafiee-Jood. (2015). Impacts of climate change on agricultural water management: A review. *Wiley Interdisciplinary Reviews: Water*, 2 (5), 439–455. https://doi.org/10.1002/wat2.1089

Changnon, D., & V. A. Gensini. (2019). Changing spatiotemporal patterns of 5- and 10-day Illinois heavy precipitation amounts, 1900-2018. *J. Appl. Meteor. Climatol.*, 58, 1523– 1533. https://doi.org/10.1175/JAMC-D-18-0335.1

Clements, D. R., & Ditommaso, A. (2011). Climate change and weed adaptation: can evolution of invasive plants lead to greater range expansion than forecasted?. *Weed research*, 51(3), 227-240. https://doi.org/10.1111/j.1365-3180.2011.00850.x

Cohen, J. (1988). Statistical Power Analysis For the Behavioral Sciences, 2nd ed. Erlbaum, Hillsdale, NJ. https://doi.org/10.1111/1467-8721.ep10768783

da Silva, C. A., Nanni, M. R., Teodoro, P. E., & Silva, G. F. C. (2017). Vegetation indices for discrimination of soybean areas: A new approach. *Agronomy journal*, 109(4), 1331-1343. https://doi.org/10.2134/agronj2017.01.0003

Delgado, J. A., M. A. Nearing, & C. W. Rice. (2013). Conservation practices for climate change adaptation. Advances in Agronomy. Sparks, D. L., Ed., Vol. 121 of, Academic Press, 47–115. https://doi.org/10.1016/B978-0-12-407685-3.00002-5

Dittus, A. J., D. J. Karoly, S. C. Lewis, & L. V. Alexander. (2015). A multiregion assessment of observed changes in the areal extent of temperature and precipitation extremes. *Journal of Climate*, 28, 9206–9220. https://doi.org/10.1175/JCLI-D-14-00753.1

Easterling, D.R., K.E. Kunkel, J.R. Arnold, T. Knutson, A.N. LeGrande, L.R. Leung, R.S. Vose, D.E. Waliser, and M.F. Wehner. (2017). Precipitation change in the United States. In: Climate Science Special Report: *Fourth National Climate Assessment*, Volume I [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 207-230. https://doi.org/10.7930/J0H993CC

Economic Research Service. (2020). Feedgrains sector at a glance. USDA, accessed February 2021. https://www.ers.usda.gov/topics/crops/corn-and-other-feed-grains/feed-grains-sector-at-a-glance/

Fackler, P.L. & Norwood, B. (1999). Forecasting crop yields and condition indices. Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, (pp. 1–18), Chicago. https://legacy.farmdoc.illinois.edu/nccc134/conf_1999/pdf/confp13-99.pdf

Feng, Z., L. R. Leung, S. Hagos, R. A. Houze, C. D. Burleyson, & K. Balaguru. (2016). More frequent intense and long-lived storms dominate the springtime trend in central US rainfall. *Nature Communications*, 7, 13429. https://doi.org/10.1038/ncomms13429

Gehl, R. J., Schmidt, J. P., Maddux, L. D., & Gordon, W. B. (2005). Corn yield response to nitrogen rate and timing in sandy irrigated soils. *Agronomy Journal*, 97(4), 1230-1238. https://doi.org/10.2134/agronj2004.0303

Geipel, J., Link, J. & Claupein, W. (2014). Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system. *Remote. Sens.* 6, 10335–10355. https://doi.org/10.3390/rs61110335

Gensini, V. A. (2021). Severe Convective Storms in a Changing Climate. Book chapter in Climate Change and Extreme Events. Fares, A. Ed., Springer. ISBN: 978-0-12-822700-8, https://doi.org/10.1016/C2019-0-04922-9

Gensini, V. A., & H. E. Brooks. (2018). Spatial trends in United States tornado frequency. *npj Climate Atmos. Sci.*, 1, 38, https://doi.org/10.1038/s41612-018-0048-2

Gensini, V. A., & T. L. Mote. (2015). Downscaled estimates of late 21st century severe weather from CCSM3. *Climatic Change*, 129, 307–321. https://doi.org/10.1007/s10584-014-1320-z

Gensini, V. A., C. A. Ramseyer, & T. L. Mote. (2014). Future convective environments using NARCCAP. *Int. J. Climatol.*, 34, 1699–1705. https://doi.org/10.1002/joc.3769

Hatfield, J. L., & C. L. Walthall. (2015). Meeting global food needs: Realizing the potential via genetics × environment × management interactions. *Agronomy Journal*, 107 (4), 1215–1226. https://doi.org/10.2134/agronj15.0076

Hatfield, J. L., K. J. Boote, B. A. Kimball, L. H. Ziska, R. C. Izaurralde, D. Ort, A. M. Thomson, & D. Wolfe. (2011). Climate impacts on agriculture: Implications for crop production. *Agronomy Journal*, 103 (2), 351–370. https://doi.org/10.2134/agronj2010.0303

Hatfield, J., C. Swanston, Maria Janowiak, R. F. Steele, J. Hempel, J. Bochicchio, W. Hall, M. Cole, S. Hestvik, & J. Whitaker. (2015). USDA Midwest and Northern Forests Regional Climate Hub: Assessment of Climate Change Vulnerability and Adaptation and Mitigation Strategies. U.S. Department of Agriculture, 55 pp. https://www.climatehubs.usda.gov/sites/default/files/Midwest%20Region%20Vulnerability%20Assessment%203_20_2015.pdf

Hosseini, M., Kerner, H. R., Sahajpal, R., Puricelli, E., Lu, Y. H., Lawal, A. F., & Becker-Reshef, I. (2020). Evaluating the impact of the 2020 Iowa derecho on corn and soybean fields using synthetic aperture radar. *Remote Sensing*, 12(23), 3878. https://doi.org/10.3390/rs12233878

Hrozencik, R. A. (2021). Trends in U.S. Irrigated Agriculture: Increasing Resilience Under Water Supply Scarcity. http://dx.doi.org/10.2139/ssrn.3996325

Hurburgh, C. (2016). Wet Weather Creates Challenges for Harvest. Iowa State University, Extension and Outreach, Ames, IA. https://crops.extension.iastate.edu/cropnews/2016/09/wet-weather-creates-challenges-harvest

International Trade Administration (2012). *Chapter 13: Government-Backed Agricultural Export Financing*, November 2012. http://export.gov/static/TradeFinanceGuide_Ch13_Latest_eg_main_055043.pdf

Irwin, S. and D. Good. (2017a). When Should We Start Paying Attention to Crop Condition Ratings for Corn and Soybeans?. *Farmdoc daily*, 7, 96. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. https://farmdocdaily.illinois.edu/2017/05/when-start-paying-attention-crop-condition-ratings.html

Irwin, S., & D. Good. (2017b). How should we use within-season crop condition ratings for corn and soybeans? *Farmdoc daily*, 7, 96. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. https://farmdocdaily.illinois.edu/2017/06/how-to-use-within-season-crop-condition-ratings.html

Irwin, S., & Hubbs, T. (2018). Measuring the Accuracy of Forecasting Corn and Soybean Yield with Good and Excellent Crop Condition Ratings. *Farmdoc daily*, 8. 118. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. https://farmdocdaily.illinois.edu/2018/06/measuring-the-accuracy-of-forecasting-corn-and-soybean-yield.html

Jin, Z., Q. Zhuang, J. Wang, S. V. Archontoulis, Z. Zobel, & V. R. Kotamarthi. (2017). The combined and separate impacts of climate extremes on the current and future U.S. rainfed maize and soybean production under elevated CO2. *Global Change Biology*, 23 (7), 2687–2704. http://doi.org/10.1111/gcb.13617

Jinger, D., Kaur, R., Kaur, N., Rajanna, G. A., Kumari, K., & Dass, A. (2017). Weed dynamics under changing climate scenario: A Review. *Int. J. Curr. Microbiol. App. Sci*, 6(3), 2376-2388. http://doi.org/10.20546/ijcmas.2017.603.272

Jorgensen, N. (2014). *A comparison of corn yield forecasting models*. Masters Thesis, South Dakota State University, Department of Economics. https://openprairie.sdstate.edu/etd/339

Jorgensen, N. & Diersen, M. (2014). *Forecasting corn and soybean yields with crop conditions. Economics Commentator*. Paper 538. https://openprairie.sdstate.edu/cgi/viewcontent.cgi?article=1537&context=econ_comm

Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. *Current Opinion in Biotechnology*, 70, 15-22. https://doi.org/10.1016/j.copbio.2020.09.003

Kaminski, K. (2023). *The Future of Extreme Windstorms in the United States: Insights from Convection-Permitting Simulations*. Masters Thesis, Northern Illinois University, Department of Earth, Atmosphere and Environment.

Khaki, S., Pham, H., & Wang, L. (2021). Simultaneous corn and soybean yield prediction from remote sensing data using deep transfer learning. *Scientific Reports*, 11(1), 1–14. https://doi.org/10.1038/s41598-021-89779-z

Kloesel, K., Bartush, B., Banner, J., Brown, D.P., Lemery, J., Lin, X., Loeffler, C., McManus, G., Mullens, E., Nielsen-Gammon, J., Shafer, M., Sorensen, C., Sperry, S., Wildcat, D., Ziolkowska, J. (2018). Southern Great Plains. In: Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart. Impacts, Risks, and Adaptation in the United States: *Fourth National Climate Assessment*, Volume II. Washington, DC, USA: U.S. Global Change Research Program. p. 978-1026. https://doi.org/10.7930/NCA4.2018.CH23

Kruse, J. R., & Smith, D. (1994). Yield estimation throughout the growing season. Center for Agricultural and Rural Development. https://core.ac.uk/download/pdf/38940539.pdf

Lark, T. J., Spawn, S. A., Bougie, M., & Gibbs, H. K. (2020). Cropland expansion in the United States produces marginal yields at high costs to wildlife. *Nature communications*, 11(1), 4295. https://doi.org/10.1038/s41467-020-18045-z

Lehecka, G. V. (2014). The value of USDA crop progress and condition information: Reactions of corn and soybean futures markets. *Journal of Agriculture and Research Economics*, 39(1), 88–105. https://www.jstor.org/stable/44131316

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84– 87. https://doi.org/10.1038/nature16467

Li, Y., Guan, K., Schnitkey, G. D., Delucia, E., & Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. Global Change Biology, 25(7), 2325–2337. https://doi.org/10.1111/gcb.14628

Martin, J. T., Pederson, G. T., Woodhouse, C. A., Cook, E. R., McCabe, G. J., Anchukaitis, K. J. & King, J. (2020). Increased drought severity tracks warming in the United States' largest river basin. *Proceedings of the National Academy of Sciences*, 117(21), 11328-11336. https://doi.org/10.1073/pnas.1916208117

Mase, A. S., B. M. Gramig, & L. S. Prokopy. (2017). Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern U.S. crop farmers. *Climate Risk Manage*., 15, 8–17. https://doi.org/10.1016/j.crm.2016.11.004

McGuire, V. L. (2017). Water-level and recoverable water in storage changes, High Plains aquifer, predevelopment to 2015 and 2013–15. 2017-5040. Scientific Investigations Report 2017-5040. U. S. Geological Survey, Reston, VA, 24 pp. https://doi.org/10.3133/sir20175040

Milly, P. C. D., R. T. Wetherald, K. Dunne, & T. L. Delworth. (2002). Increasing risk of great floods in a changing climate. *Nature*, 415, 514–517. https://doi.org/10.1038/415514a

Min, S. K., X. Zhang, F. W. Zwiers, & G. C. Hegerl. (2011). Human contribution to more-intense precipitation extremes. *Nature*, 470, 378–381. https://doi.org/10.1038/nature09763

Munkvold, G. P., & X. B. Yang. (1995). Crop damage and epidemics associated with 1993 floods in Iowa. *Plant Disease*, 79 (1), 95–101. https://doi.org/10.1094/PD-79-0095

Nicholls, N. (1996). Long-term climate monitoring and extreme events. *Long-Term Climate Monitoring by the Global Climate Observing System*, Springer, 101–115. https://doi.org/10.1007/978-94-011-0323-7_8

Perry, E. D., Yu, J., & Tack, J. (2020). Using insurance data to quantify the multidimensional impacts of warming temperatures on yield risk. *Nature communications*, *11*(1), 4542. https://doi.org/10.1038/s41467-020-17707-2

Pruski, F. F., & M. A. Nearing. (2002). Climate-induced changes in erosion during the 21st century for eight U.S. locations. *Water Resources Research*, 38 (12), 34-1-34–11. https://doi.org/10.1029/2001WR000493

Pryor, S. C., Scavia, D., Downer, C., Gaden, M., Iverson, L., Nordstrom, R., Patz, J., & Robertson, G. P. (2014). Midwest. Climate change impacts in the United States: The third national climate assessment. In J. M. Melillo, T. C. Richmond, & G. W. Yohe (Eds.), *National climate assessment report* (pp. 418–440). U.S. Global Change Research Program. https://doi.org/10.7930/NCA4.2018.CH21

Ramesh, K., Matloob, A., Aslam, F., Florentine, S. K., & Chauhan, B. S. (2017). Weeds in a changing climate: vulnerabilities, consequences, and implications for future weed management. *Frontiers in plant science*, 8, 95. https://doi.org/10.3389/fpls.2017.00095

Ray, D. K., Mueller, N. D., West, P. C., & Foley, J. A. (2013). Yield trends are insufficient to double global crop production by 2050. PLOS ONE, 8(6), e66428. https://doi.org/10.1371/journal.pone.0066428

Rippey, B. R. (2015). The US drought of 2012. *Weather and climate extremes*, 10, 57-64. https://doi.org/10.1016/j.wace.2015.10.004

Rosales, A. (2021). *Crop progress and condition layers*. USDA. https://www.nass.usda.gov/Research_and_Science/Crop_Progress_Gridded_Layers/CropProgressDescription.pdf#:~:text=Crop%20Progress%20and%20Condition%20Layers%20are%20gridded%20geospatial,at%20a%20weekly%20cadence%20during%20the%20growing%20season.

Rosenzweig, C., Tubiello, F. N., Goldberg, R., Mills, E., & Bloomfield, J. (2002). Increased crop damage in the US from excess precipitation under climate change. *Global Environmental Change*, 12, 197–202. https://doi.org/10.1016/S0959-3780(02)00008-0

Ruess, P. J., Konar, M., Wanders, N., & Bierkens, M. (2023). Irrigation by crop in the Continental United States from 2008 to 2020. *Water Resources Research*, 59, e2022WR032804. https://doi.org/10.1029/2022WR032804

Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon, P. B. (2012). Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *Proceedings of the national academy of sciences*, 109(24), 9320-9325. https://doi.org/10.1073/pnas.1200311109

Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceeding National Academic Science (USA)*, 104(50), 19703–19708. https://doi.org/10.1073/pnas.0701976104

Schmidt, J. P., DeJoia, A. J., Ferguson, R. B., Taylor, R. K., Young, R. K., & Havlin, J. L. (2002). Corn yield response to nitrogen at multiple in-field locations. *Agronomy Journal*, 94(4), 798–806. https://doi.org/10.2134/agronj2002.7980

Strzepek, K., Yohe, G., Neumann, J., & Boehlert, B. (2010). Characterizing changes in drought risk for the United States from climate change. *Environmental Research Letters*, 5(4), 044012. https://doi.org/10.1088/1748-9326/5/4/044012

Takle, E. S., C. Anderson, M. Jha, & P. W. Gassman. (2006). Upper Mississippi River Basin Modeling Systems Part 4: Climate change impacts on flow and water quality. Coastal Hydrology and Processes. Singh, V. P., and Y. Jun Xu, Eds., Water Resources Publications LLC, Highlands Ranch, CO, 135–142. https://dr.lib.iastate.edu/entities/publication/6d7bf131-d7f6-44e5-8e57-db0779c2f938

Tang, B. H., V. A. Gensini, & C. R. Homeyer. (2019). Trends in United States large hail environments and observations. *npj Climate Atmos. Sci.*, 2, 45. https://doi.org/10.1038/s41612-019-0103-7

Trnka, M., Rötter, R. P., Ruiz-Ramos, M., Kersebaum, K. C., Olesen, J. E., Žalud, Z., & Semenov, M. A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change*, 4, 637–643. https://doi.org/10.1038/NCLIMATE2242

USDA. (2016). *National Agricultural Statistics Service: Crop progress/Crop weather terms and definitions*. https://www.nass.usda.gov/Publications/National_Crop_Progress/terms_definitions
USDA. (2019). *2018 Irrigation and Water Management Survey.* https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/fris.pdf
[dataset] USDA. (2023a). *National Agricultural Statistics Service: Quick stats*. USDA. https://www.nass.usda.gov/Quick_Stats/
USDA. (2023b). *Crop Progress*. https://usda.library.cornell.edu/concern/publications/8336h188j?locale=en
USDA. (2023c). *Rice Sector at a Glance.* Economic Research Service. https://www.ers.usda.gov/topics/crops/rice/rice-sector-at-a-glance/
Van Wart, J., Kersebaum, K. C., Peng, S., Milner, M., & Cassman, K. G. (2013). Estimating crop yield potential at regional to national scales. *Field Crops Research*, 143, 34–43. https://doi.org/10.1016/j.fcr.2012.11.018
Vose, R. S., Easterling, D. R., Kunkel, K. E., LeGrande, A. N., & Wehner, M. F. (2017). Temperature changes in the United States. In D. J. Wuebbles, D. W. Fahey, K. A. Hibbard, D. J. Dokken, B. C. Stewart, & T. K. Maycock (Eds.), *Climate Science Special Report: Fourth National Climate Assessment* (Volume I, pp. 185–206). U.S. Global Change Research Program. https://doi.org/10.7930/J0N29V45
Watson, A., S. Ghosh, M. J. Williams, W. S. Cuddy, J. Simmonds, M.-D. Rey, M. Asyraf Md Hatta, A. Hinchliffe, A. Steed, D. Reynolds, N. M. Adamski, A. Breakspear, A. Korolev, T. Rayner, L. E. Dixon, A. Riaz, W. Martin, M. Ryan, D. Edwards, J. Batley, H. Raman, J. Carter, C. Rogers, C. Domoney, G. Moore, W. Harwood, P. Nicholson, M. J. Dieters, I. H. DeLacy, J. Zhou, C. Uauy, S. A. Boden, R. F. Park, B. B. H. Wulff, & L. T. Hickey. (2018). Speed breeding is a powerful tool to accelerate crop research and breeding. *Nature Plants*, 4 (1), 23–29. https://doi.org/10.1038/s41477-017-0083-8
Walthall, C. L., Anderson, C. J., Baumgard, L. H., Takle, E., & Wright-Morton, L. (2013). Climate change and agriculture in the United States: Effects and adaptation. *Geological and Atmospheric Sciences Reports*. https://www.usda.gov/sites/default/files/documents/CC%20and%20Agriculture%20Report%20(02-04-2013)b.pdf
Wehner, M. F., J. R. Arnold, T. Knutson, K. E. Kunkel, & A. N. LeGrande. (2017). Droughts, Floods, and Wildfires. Climate Science Special Report*: Fourth National Climate Assessment, Volume I*. Wuebbles, D. J., D. W. Fahey, K. A. Hibbard, D. J. Dokken, B. C. Stewart, and T. K. Maycock, Eds., U.S. Global Change Research Program, Washington, DC, USA, 231–256. https://doi.org/10.7930/J0CJ8BNN
Westcott, P. C., & M. Jewison. (2013). *Weather effects on expected corn and soybean yields*. USDA Economic Research Service Doc. FDS-13g-01, 31 pp., https://www.ers.usda.gov/webdocs/outlooks/36651/39297_fds-13g-01.pdf?v=737
Wehner, M. F., K. A. Reed, F. Li, Prabhat, J. Bacmeister, C.-T. Chen, C. Paciorek, P. J. Gleckler, K. R. Sperber, W. D. Collins, A. Gettelman, & C. Jablonowski. (2014). The effect of horizontal resolution on simulation quality in the Community Atmospheric Model, CAM5.1. *Journal of Advances in Modeling Earth Systems*, 6, 980–997. https://doi.org/10.1002/2013MS000276
Wheeler, T., & Von Braun, J. (2013). Climate change impacts on global food security. *Science*, 341(6145), 508–513. https://doi.org/10.1126/science.1239402
Wienhold, B. J., Vigil, M. F., Hendrickson, J. R., & Derner, J. D. (2018). Vulnerability of crops and croplands in the US Northern Plains to predicted climate change. *Climatic Change*, 146, 219-230. https://doi.org/10.1007/s10584-017-1989-x
Wilcox, R. R. (2010). *Fundamentals of Modern Statistical Methods: Substantially Improving Power and Accuracy*. Springer, 249 pp.

Wolfe, D. W., Ziska, L., Petzoldt, C., Seaman, A., Chase, L., & Hayhoe, K. (2008). Projected change in climate thresholds in the Northeastern US: implications for crops, pests, livestock, and farmers. *Mitig Adapt Strateg Glob Change*, 13, 555-575. https://doi.org/10.1007/s11027-007-9125-2

Wu, F., D. Bhatnagar, T. Bui-Klimke, I. Carbone, R. Hellmich, G. Munkvold, P. Paul, G. Payne, & E. Takle. (2011). Climate change impacts on mycotoxin risks in US maize. *World Mycotoxin Journal*, 4 (1), 79–93. https://doi.org/10.3920/WMJ2010.1246

Xie, Y., Lark, T. J., Brown, J. F., & Gibbs, H. K. (2019). Mapping irrigated cropland extent across the conterminous United States at 30 m resolution using a semi-automatic training approach on Google Earth Engine. ISPRS *Journal of Photogrammetry and Remote Sensing*, 155, 136-149. https://doi.org/10.1016/j.isprsjprs.2019.07.005

Zhang, X., H. Wan, F. W. Zwiers, G. C. Hegerl, & S.-K. Min. (2013). Attributing intensification of precipitation extremes to human influence. *Geophysical Research Letters*, 40, 5252–5257. https://doi.org/10.1002/grl.51010