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Crop Ecology and Physiology

United States crop conditions: 1986–2022

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Abstract
USDA National Agricultural Statistics Service general crop condition data are used
to quantify the relationship between crop conditions and yield, condition tenden-
cies during the growing season, how conditions vary across the United States, and
how conditions have trended for the 1986–2022 period for a variety of crops: bar-
ley (*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 also became more variable throughout the growing season. Spatial
differences in conditions, variability, and trends in condition ratings and variabil-
ity are caused by crop selection, regional climate, and management practices such
as irrigation. Crop conditions were poorest and had the highest interannual vari-
ability 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 United States
have significantly improved, while interannual variability in conditions has experi-
enced 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 sup-
plemented by using crop condition risk assessment information along with actively
monitoring weekly conditions.

1 | INTRODUCTION

Agriculture across the United States is vast and diverse, pro-
moting global food security, economic growth, nationwide
development, and environmental sustainability. Significant
increases in agricultural productivity over the past century
unequivocally make the US 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, espe-
cially within the context of an evolving climate leading
to more frequent weather extremes that will consequently
amplify the risk of crop production losses (Bundy et al.,
2022; Delgado et al., 2013; Lesk et al., 2016; Mase et al.,
2017; Milly et al., 2002; Nicholls, 1996; Pryor et al., 2014;

Abbreviation: CCIndex, crop condition index.

Ray et al., 2013; Schmidhuber & Tubiello, 2007; Walthall et al., 2013; Wheeler & Von Braun, 2013). These frequent weather extremes include observed and future projected increases in drought severity and occurrences (Jin et al., 2017; Martin et al., 2020; Strzepek et al., 2010; Wehner et al., 2017), extreme precipitation episodes (Bindoff et al., 2013; Changnon & Gensini, 2019; Easterling et al., 2017; Feng et al., 2016; Min et al., 2011; Westra et al., 2014; Zhang et al., 2013), warmer than normal temperatures (Angel et al., 2018; Dittus et al., 2015; Vose et al., 2017), and an increased number of severe thunderstorms leading to increased regional wind and hail damage in the United States (Ashley et al., 2023; Brimelow et al., 2017; Gensini, 2021; Gensini & Brooks, 2018; Gensini & Mote, 2015; Gensini et al., 2014; Kaminski, 2023; Tang et al., 2019). 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 (Delgado et al., 2013; Pruski & Nearing, 2002; Rosenzweig et al., 2002), nutrient requirements (Cai et al., 2015; Takle et al., 2006), weed competition (Clements & Ditommaso, 2011; Jinger et al., 2017; Ramesh et al., 2017; Wolfe et al., 2008), and other pest and disease pressures (Anderson et al., 2004; Angel et al., 2018; Bebber et al., 2013; Hurburgh, 2016; Munkvold & Yang, 1995; Wienhold et al., 2018; Wu et al., 2011).

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 (Khaki et al., 2021; Lehecka, 2014). 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 that 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

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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 United States significantly improved in crop conditions, while variability decreased.

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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 (Begueria & Maneta, 2020; Fackler & Norwood, 1999; Irwin & Good, 2017a, 2017b; Irwin & Hubbs, 2018; Kruse & Smith, 1994) 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 and Gensini (2022), which examined corn conditions throughout the US Midwest, 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 10 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 US 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 US 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 3600 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*: It is a less than normal crop condition. Yield loss is a possibility, but the extent is unknown.

- *Poor*: It includes heavy degree of loss to yield potential, which can be caused by excess soil moisture, drought, disease, and so forth.
- *Very poor*: It includes extreme degree of loss to yield potential, complete or near crop failure.

The USDA-defined crop condition index (CCIndex) was calculated for each report using the following equation (Rosales, 2021):

$$CCIndex = (5 \times \%Excellent + 4 \times \%good + 3 \times \%fair$$
$$+ 2 \times \%poor + \%very\ poor)/100 \qquad (1)$$

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 (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 (Bundy & Gensini, 2022; Fackler and Norwood, 1999; Jorgensen, 2014; Jorgensen & Diersen, 2014), 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, and very poor) for each crop and state may also be appealing to a wide range of stakeholders and may be found in the Supporting Information of this study (Figures S1–S5; Tables 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 10 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 US production. Specifically, these states accounted for the following average US 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%; and winter wheat, 89%.

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 adjust-

ment equation used is as follows (Bundy & Gensini, 2022; Irwin & Good, 2017a):

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

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 kilograms 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 follows:

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

where z represents the number of standard deviations the yield is above or below the mean, x 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 1 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,

TABLE 1 Number of years of crop condition data by state and crop, and percent of US production of the crop in each state (1986–2022).

State	Barley		Corn		Cotton		Oats		Peanuts		Rice		Sorghum		Soybean		Spring wheat		Winter wheat	
	yr	%	yr	%	yr	%	yr	%	yr	%	yr	%	yr	%	yr	%	yr	%	yr	%
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%			5	0.5%	37	1.7%
Colorado	9	3.2%	37	1.3%	1	0.0%	0	0.9%					33	1.8%					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	9	0.1%	9	0.1%			0	0.2%							9	0.1%			9	0.1%
New Mexico	9	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%

(Continues)

TABLE 1 (Continued)

State	Barley		Corn		Cotton		Oats		Peanuts		Rice		Sorghum		Soybean		Spring wheat		Winter wheat	
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%					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%

Note: Top three producing states are mentioned in bold for each respective crop.
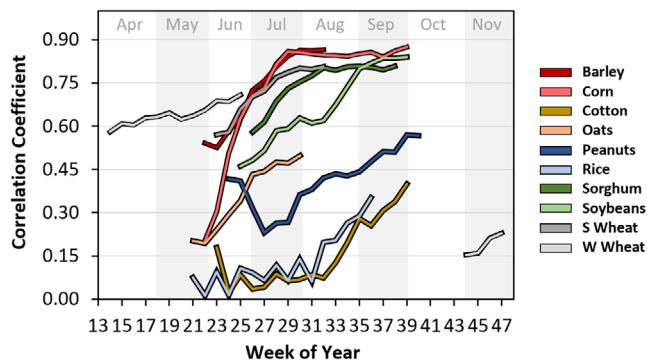
FIGURE 1 Pearson correlation coefficient between weekly CCIndex ratings and annual detrended yield for each crop examined over the study period (1986–2022).

and trends were computed as follows:

$$\text{Weighted CCIndex} = \sum_{n=1}^{n} (\text{CCIndex} \times \text{production percentage}),$$
(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 US crop conditions (CCIndex) and crop yield generally increased, meaning the predictability of yield prospects using USDA NASS general crop condition data was apparent (Figure 1). For corn, which is the most widely produced crop in the United States (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 to 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 to 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 and <0.50).

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 to 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 (Bundy & Gensini, 2022; Irwin & Good, 2017a). 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, 2023a, 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, 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 (Figure 2). The statistically significant (90% significance level) explanatory power suggests annual average CCIndex ratings can be used to predict yield prospects not only for US Midwest corn (Bundy & Gensini, 2022), but also for national barley, corn, oats, peanuts, sorghum, soybeans, spring wheat, and winter wheat (Figure 2a,b,d,e,g–j). 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
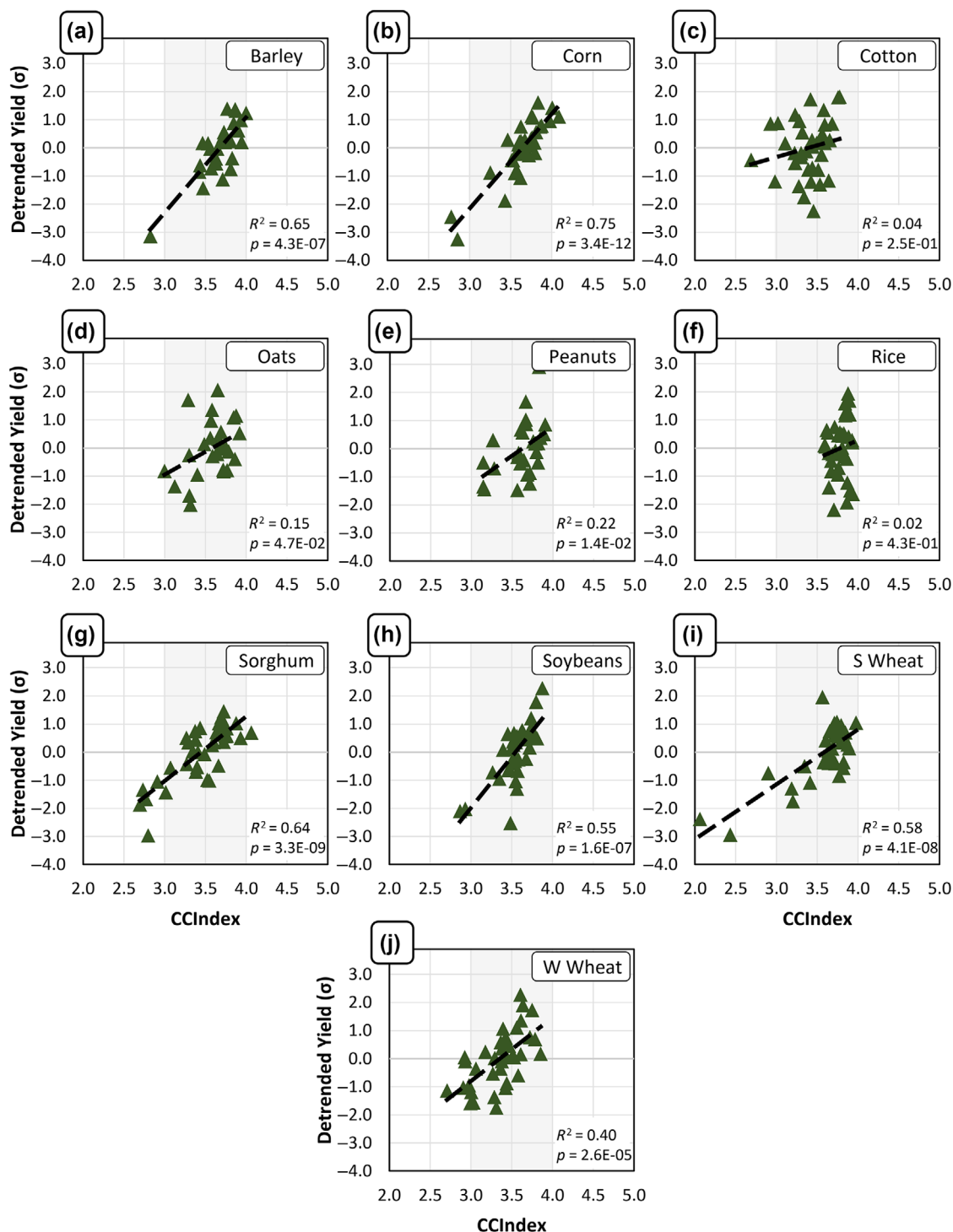
FIGURE 2 US annual average crop condition index (CCIndex) ratings plotted against detrended yield standardized anomalies for each crop and growing season (1986–2022). Regression r^2 and p-values are listed for each crop.

using general crop condition data was the final week CCIndex (Figure 1), especially for cotton and rice. However, 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.

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 United States. 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 (Figure 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 (Figure 3b,c,e). 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 (Figure 3g,h). 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 (Figure 3a,d,i). 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 (Figure 3j). Winter wheat possessed the lowest seasonal condition of any crop in the United States 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; that is, the total area of crops more favorable for normal or above-normal yield decreased as the growing season progressed.

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 US 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 (Figure 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 US 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 11 seasons that had at least 1 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, 2015). This lends additional credence to previous findings that indicate drought is the leading peril for crop loss across the United States (Bundy & Gensini, 2022; Perry et al., 2020). Condition coverage by category (excellent, good, fair, poor, and very poor) provides additional perspective on condition exposure and vulnerability to change, which can be examined from Figures S2 and S3.
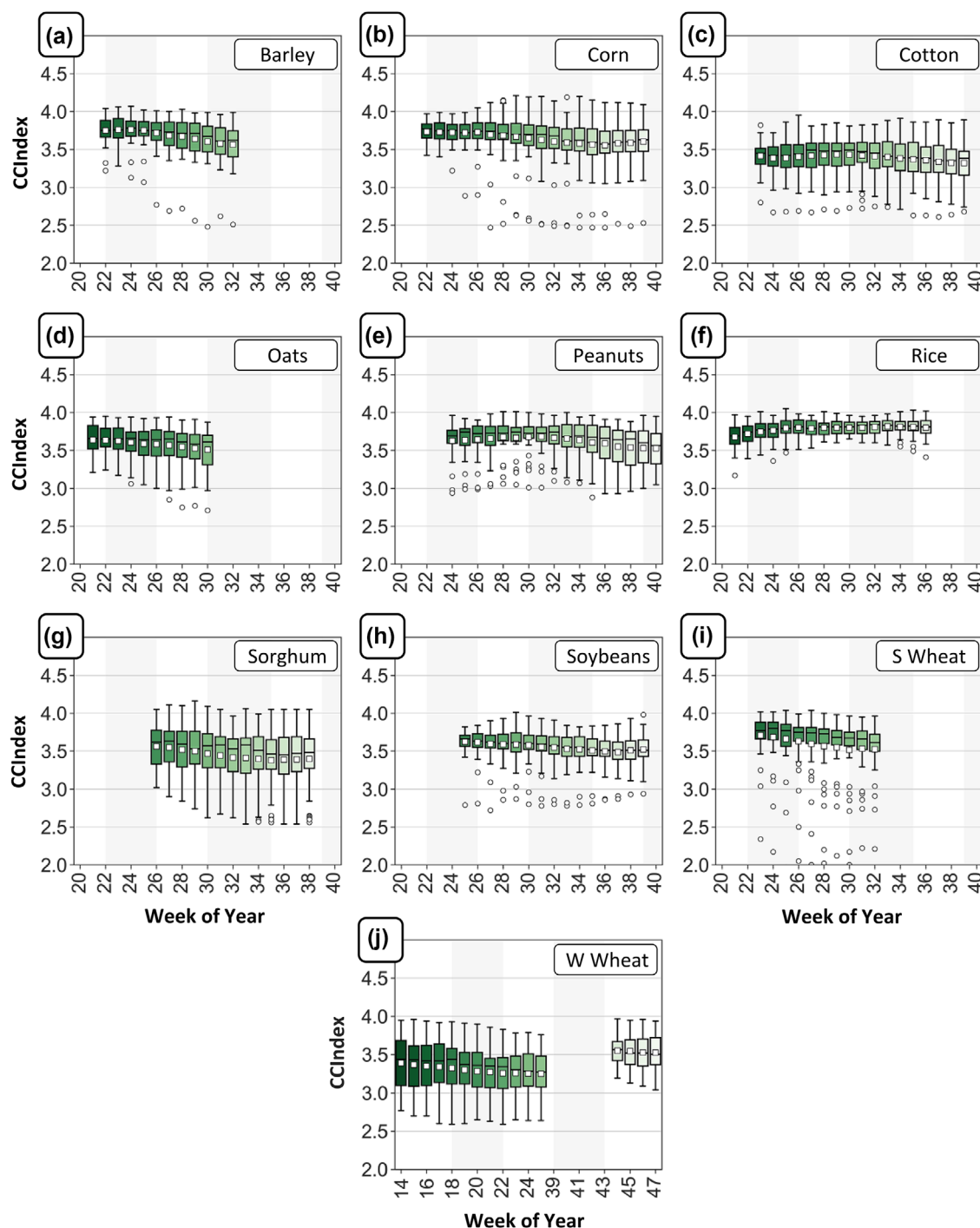
FIGURE 3 Box and whisker plots of weekly crop condition index (CCIndex) ratings by crop over the 1986–2022 study period. Each box and whisker present a seven-number summary: white circles represent outliers; whiskers represent the 1.5 multiple of the inner-quartile range; boxes represent first quartile (25th percentile) and third quartile (75th percentile) values; black horizontal line within boxes represent the median value; and white squares represent the mean value. Gray-shaded and white areas represent monthly intervals.

3.2.2 | Spatial climatology

When examining crop conditions across the United States, a discernible spatial pattern in annual CCIndex averages and annual variability can be recognized across all crops (Figures 4 and 5).

Annual averages and variability for each condition and each state–crop combination are provided in Tables S1
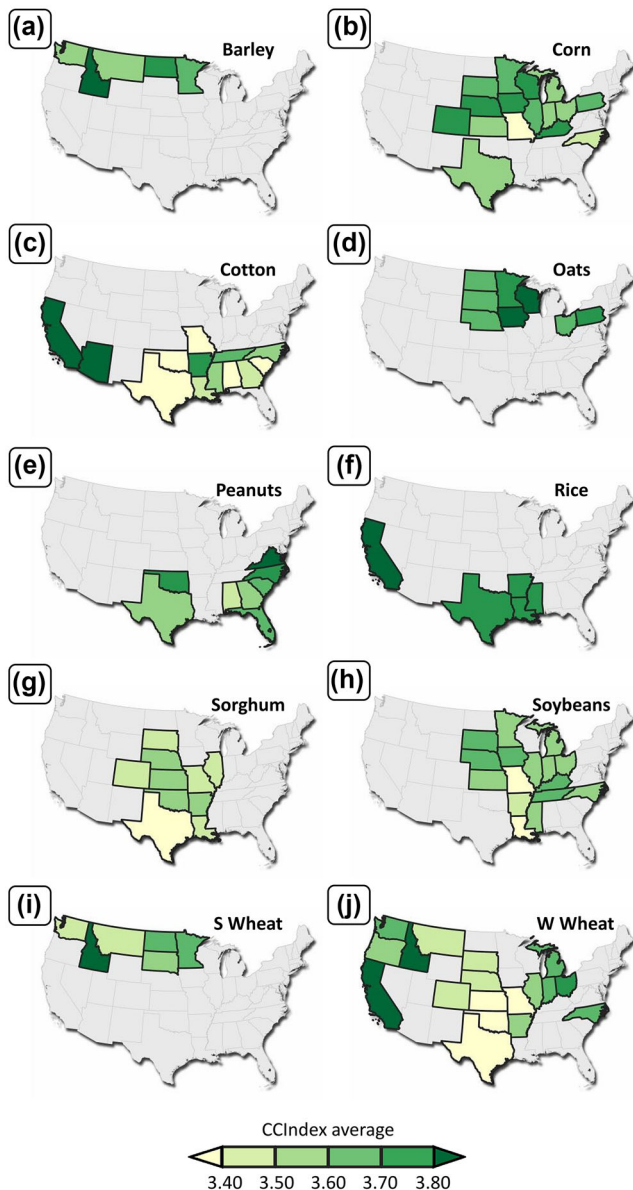
FIGURE 4 Annual average crop condition index (CCIndex) ratings by state over the 1986–2022 study period for each crop.

FIGURE 5 Annual average crop condition index (CCIndex) standard deviations by state over the 1986–2022 study period for each crop.

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 10 highest ratings for any state–crop combination (Figure 4a,i). Idaho also exhibited the

lowest condition variability, with an annual CCIndex average standard deviation for both barley and spring wheat of <0.10 (Figure 5a,i). 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 United States, conditions were marginally better in central portions of oat acreage than elsewhere—including Minnesota, Wisconsin, and Iowa (Figure 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

(Figure 5d). Additionally, five oat states with exceedingly low CCIndex variability ($\sigma < 0.18$) were in the bottom 10 lowest for all state–crop combinations.

For crops with core acreage in the US Midwest (corn and soybeans), conditions were lowest on average generally in southern US states—including Texas, Kansas, Missouri, and North Carolina for corn, and Missouri, Arkansas, and Louisiana for soybeans (Figure 4b,h). 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 US 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 (Figure 5b,h). Sorghum also had particularly variable conditional averages across the Great Plains. Texas and Kansas, which consist of 70% of US sorghum production, retained an annual CCIndex average of 3.38 (lowest of sorghum states) and 3.55 (second highest of sorghum states), respectively (Figure 4g). Also, variability for sorghum conditions was high, as standard deviation values in seven of the 10 sorghum-growing states were exceedingly higher than the national annual CCIndex standard deviation average of 0.32 (Figure 5g).

Southern US dominant crops such as cotton, peanuts, and rice vary among 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 (Figure 4c). Furthermore, Texas was the only state to have a higher percent coverage of fair-conditioned cotton crops than good-conditioned ones (Table S1), and notably, Texas produces over one-third of US cotton. These below-normal cotton conditions extended throughout the southern Great Plains and into Missouri. Meanwhile, southwestern US 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 10 for any state–crop combination. California rice was also in the top 10 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 (Figure 4f). Condition variability for all rice and peanut states (except Alabama) was generally low, with standard deviations below the national average (Figure 5e,f). Alabama and Texas held the poorest conditions of all peanut states, with improving conditions northward through the mid-Atlantic region (Figure 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 (Figure 4j). Texas,
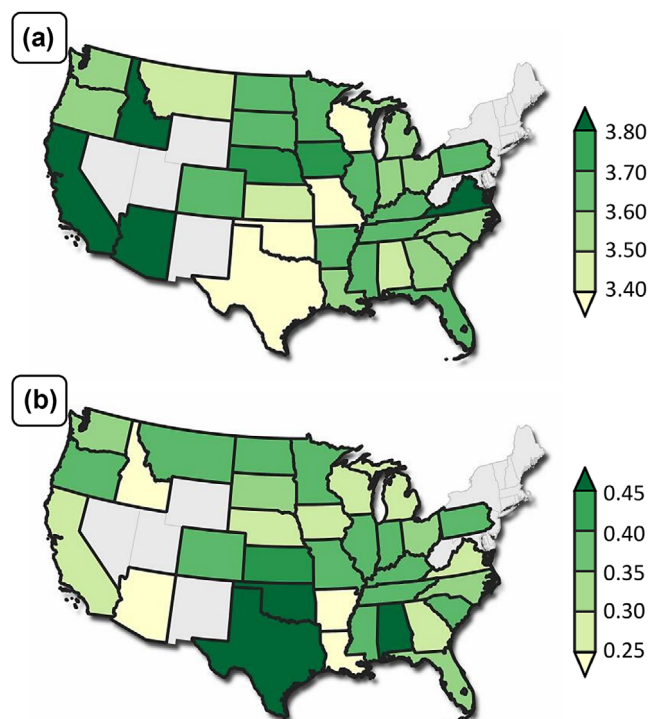

FIGURE 6 Annual average production weighted crop condition index (CCIndex) (a) ratings and (b) standard deviations for each state.

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 (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 10 of any state–crop combination), but was generally lower in year-to-year fluctuations across eastern and western wheat acreage (Figure 5j).

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

Overall, three general assessments were made as follows: (1) crop conditions across portions of the western United States (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, US Midwest, and Southeast US regions were generally near-normal on average, deviating only slightly from the national CCIndex average
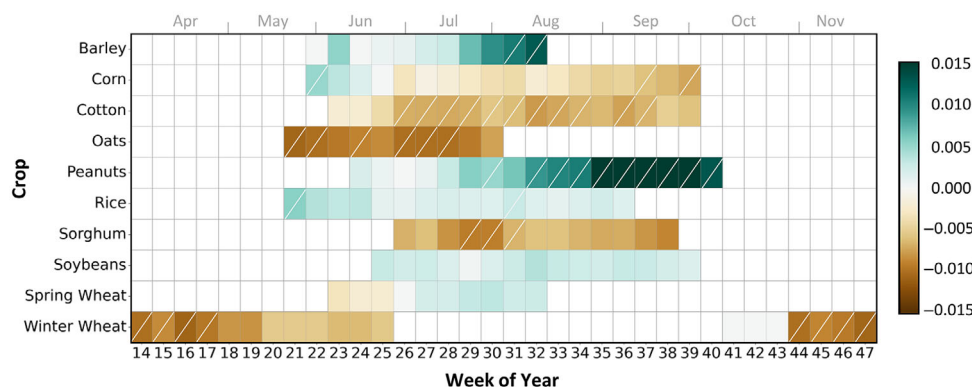
FIGURE 7   Theil–Sen slope results of interweekly trends in US crop condition index (CCIndex) ratings by crop (1986–2022). Slope units are rating increases or decreases in CCIndex per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.

of 3.60 (Figure 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 United States also generally held the lowest interannual condition variability, with average CCIndex standard deviations below 0.30 (Figure 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 confirms 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 (Figure 7). Increases were especially noteworthy and statistically significant from August onward, with CCIndex increases exceeding 0.010 year^{-1}. Moreover, 10 of the 16 weeks with an increasing trend in peanut conditions were statistically significant at the 90% significance level. Increasing peanut condition trends from weeks 35 to 40 were the most

robust of any weekly trends for all crops, with a max CCIndex increase of 0.018 year^{-1} (week 37).

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 year^{-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 year^{-1}, though only 2 of the 14 weeks with a decreasing trend were statistically significant. For cotton, each growing season week experienced a deterioration in conditions, with 11 of the 11 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 9 weeks in a row from July to August. The most distinct decreasing trends in conditions were with oat crops, as six of the 11 growing seasons underwent statistically significant declines in the CCIndex lower than −0.008 year^{-1}. Each week during the winter wheat growing season has experienced a decline in conditions since 1986. Winter wheat also experienced a long streak (8 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 year^{-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; Hartfield & Walthall, 2015; Schmidt et al., 2002; Watson et al., 2018; Wescott & Jewison, 2013).

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 (Figures 8 and 9). General condition rating and variability trends, along with specific state-crop categorical results, can be examined in Figures S4 and S5 and Tables S3 and 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 (Figure 8a,i). Noteworthy trends include barley in Montana with a statistically significant CCIndex increase of 0.015 year^{-1}; spring wheat and barley in Minnesota with CCIndex increases exceeding 0.012 year^{-1}; and CCIndex trends for both crops in Idaho of less than −0.006 year^{-1}. Annual trends in condition variability for barley and spring wheat were mostly insignificant across growing areas (Figure 9a,i). 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 year^{-1}) occurred in South Dakota (Figure 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 year^{-1} (Figure 9d). Improvements in oat conditions in the northern US Midwest were also generally insignificant (Ohio is the exception, with the highest increase in conditions at 0.0054 year^{-1}).

US 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. However, trends throughout much of the Great Plains have degraded significantly for corn, soybeans, and sorghum, with CCIndex decreases worse than −0.0083 year^{-1} (Figure 8b,g,h).

In fact, both corn and soybeans in Kansas have experienced the two most robust declines in conditions (CCIndex decreases below −0.017 year^{-1}) of any state–crop combination. Sorghum in Kansas also experienced a significant deterioration of conditions (10th worst trend of any state crop), with CCIndex trends of −0.014 year^{-1}. In the Mississippi Delta and southeastern US regions, conditions have increased significantly, especially for soybeans, with CCIndex increases greater than 0.010 year^{-1}. Mississippi soybeans
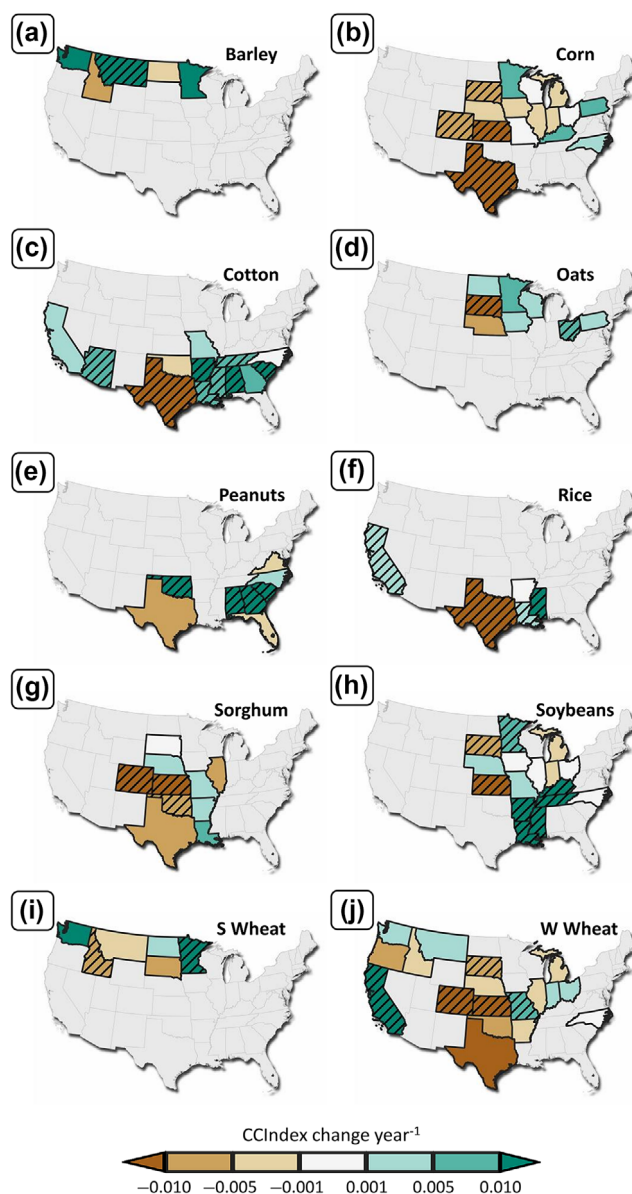

FIGURE 8 Theil–Sen slope results for annual trends in CCIndex ratings by US state for each crop (1986–2022). Slope units are rating increases or decreases in crop condition index (CCIndex) per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.

experienced a top 10 increasing trend with CCIndex increases of 0.018 year^{-1}. When examining variability trends for these three crops, trends were generally opposite to condition rating trends (Figure 9b,g,h). Condition variability has decreased in various states throughout the US 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
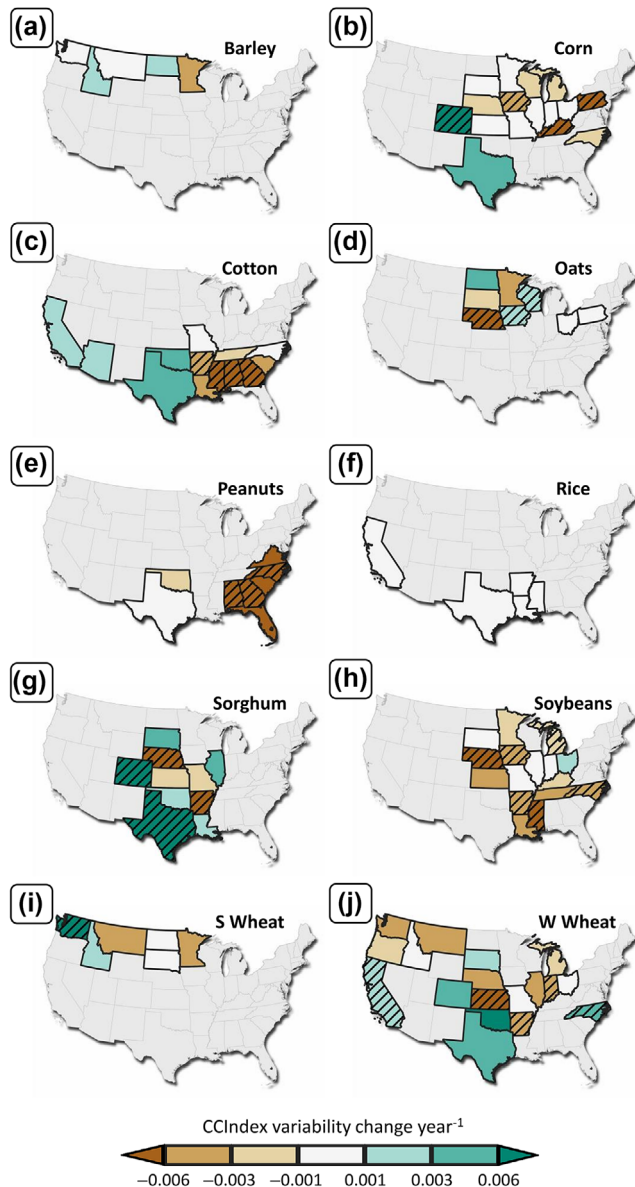
FIGURE 9 Theil–Sen slope results for trends in crop condition index CCIndex annual-averaged standard deviations by US state for each crop (1986–2022). Slope units are standard deviation increases or decreases per year. Hatching signifies statistical significance at the 90% confidence level using Kendall's Tau statistic.
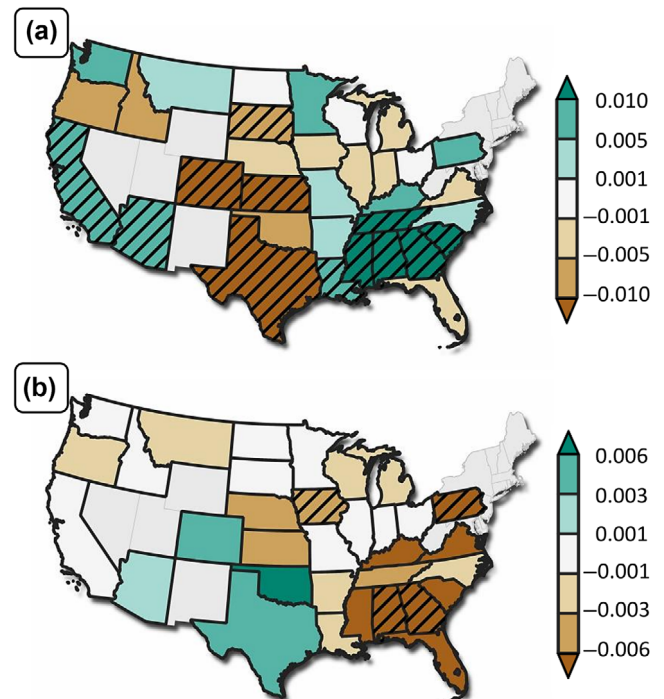

FIGURE 10 Theil–Sen slope results for (a) production-weighted annual crop condition index (CCIndex) rating trends in crop conditions by state and (b) production-weighted trends in annual-averaged CCIndex standard deviation (1986–2022). Slope units are increases or decreases in (a) CCIndex rating and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

with a statistically significant decreasing trend in interannual CCIndex variability (six states total).

Southern US 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 United States experienced significant improvements in conditions (Figure 8c,e,f). Texas cotton experienced a top 10 deterioration of conditions with a CCIndex trend of -0.014 year^{-1}. Peanut crops in South Carolina and Alabama, along with cotton crops in Arkansas, South Carolina, and

Alabama, were in the top 10 for improving condition trends (CCIndex increases exceeding 0.01 year^{-1}). For condition variability, trends were most distinct in the southeastern United States, with cotton and peanut conditions decreasing (Figure 9c,e), while rice variability trends were nonexistent (Figure 9f). For winter wheat, conditions have decreased significantly in the Great Plains while only increasing statistically significantly in California (Figure 8j). Winter wheat in Colorado, Kansas, and Texas was in the top 10 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 United States (Figure 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 (Figure 10a). Overall, rating trends in general were not statistically significant across the northern half of the United States, except for South Dakota. Across the Great Plains, a substantial degradation in crop conditions was noted, with CCIndex decreases exceeding -0.010 year^{-1},

particularly in Kansas, Texas, and Colorado, which were driven by declining conditions in corn, cotton, rice, sorghum, soybeans, and winter wheat. The southwestern United States experienced a statistically significant increase in conditions, which were driven by improvements in cotton, rice, and winter wheat conditions. Also, the southeastern United States also experienced substantial increases in the CCIndex, with trends exceeding 0.010 year^{-1}—largely driven by improvements in cotton, peanuts, rice, and soybeans. Increasing condition trends in the southeastern and southwestern United States 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 United States, 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.

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 (Figure 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 (Hrozencik, 2021; McGuire, 2017). 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 United States, 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 United States. 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 US agricultural landscape and ensure a sustainable future for generations to come.

AUTHOR CONTRIBUTIONS
Logan R. Bundy: Data curation; formal analysis; investigation; methodology; visualization; writing—original draft. **Vittorio A. Gensini**: Project administration; supervision; writing—review and editing. **Walker S. Ashley**: Funding acquisition; supervision; writing—review and editing. **Alex M. Haberlie**: Writing—review and editing. **David Changnon**: Writing—review and editing.

CONFLICT OF INTEREST STATEMENT
The authors declare no conflicts of interest.

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