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Statistics

On the quality of USDA gridded crop condition layers

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Abstract

Precise, accurate, and reliable crop condition data continues to be in demand for farmers, agribusiness, government agencies, agroclimatologists, and research institutions. This study evaluated the data quality of four major United States field crops: corn (*Zea mays* L.), cotton (*Gossypium hirsutum* L.), soybeans (*Glycine max* L.), and winter wheat (*Triticum aestivum* L.) from the USDA National Agricultural Statistics Service's (NASS) Gridded Crop Progress and Condition dataset. Upon aggregating the weekly 9 km gridded data to the county level (and further to the state and national level) over the 2015–2023 period, no statistically significant differences emerged between the gridded condition data and the tabular condition data from the USDA NASS Crop Progress and Condition Report (CPCR). In line with state and national-level analyses, a strong linear relationship between crop conditions and yield existed at the county scale. County-level crop condition ratings were a statistically significant covariate of yield during the critical reproduction period through harvest for 90% of corn, 78% of cotton, 90% of soybean, and 96% of winter wheat-producing counties. In addition, intramonthly county-level crop conditions changed accordingly based on the magnitude of temperature and precipitation anomalies during certain phenological stages. In at least 80% of counties for each respective crop, temperatures and precipitation were statistically significant covariates for crop condition changes. The relationships between USDA NASS gridded crop condition data, CPCR data, yield, and climate substantiate the utility and fidelity of this dataset as a representation of confidential crop condition reports, supporting its practical application in research and operational decision-making.

1 | INTRODUCTION

United States croplands are vulnerable to a multitude of abiotic and biotic effects, including drought, excessive rainfall, severe thunderstorms, weeds, pests, and disease pressures throughout the boreal summer growing season (Bundy & Gensini, 2022; Bundy et al., 2022, 2023, 2024; Delgado et al., 2013; Lesk et al., 2016; Mase et al., 2017; Pryor et al., 2014; Ray et al., 2013; Schmidhuber & Tubiello, 2007; Walthall et al., 2013; Wheeler & Von Braun, 2013). Ultimately, these pressures can result in deteriorating crop conditions, especially during critical phenological stages (e.g., pollination), consequently leading to a reduction of yield (Bundy & Gensini, 2022; Bundy et al., 2024; Eck et al., 2020; Westcott & Jewison, 2013). Hence, there is

Abbreviations: CCIndex, crop condition index; CPCR, Crop Progress and Condition Report; GCPC, Gridded Crop Progress and Condition.

an inherent need to continuously monitor crop conditions, or quality, through the growing season to gain insight on production potential and make informative, data-driven management decisions to maximize yield potential. Crop condition monitoring is arguably more important now than ever given the nontrivial risks associated with anthropogenic climate change, which fosters regional increases in drought severity and excessive rainfall episodes (Bindoff et al., 2013; D. Changnon & Gensini, 2019; Easterling et al., 2017; Feng et al., 2016; Jin et al., 2017; Martin et al., 2020; Min et al., 2011; Strzepek et al., 2010; Wehner et al., 2017; Westra et al., 2014; Zhang et al., 2013), an increase in severe thunderstorm activity (Ashley et al., 2023; Brimelow et al., 2017; Gensini, 2021; Gensini & Brooks, 2018; Gensini & Mote, 2015; Gensini et al., 2014, 2024; Kaminski et al., 2024; Tang et al., 2019), changes in phenological stage timing (Hatfield & Walthall, 2015; Hatfield et al., 2011), an increasing risk for 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).

There are a variety of methods to frequently monitor crop conditions, including the use of satellite products and other remote sensing mechanisms that derive crop quality data, consisting of the normalized difference vegetation index, vegetation condition index, temperature condition index, and the vegetation health index (F. N. Kogan, 1997; F. N. Kogan & Zhu, 2001; NOAA, 2024a). While these quantitative, objective condition estimates do predict yield with a respectable degree of accuracy through the growing season (e.g., F. Kogan et al., 2005, 2018; Rahman et al., 2009; Salazar et al., 2008), these indices are primarily used to monitor agricultural drought conditions (Bento et al., 2018; F. N. Kogan, 1997; F. N. Kogan & Zhu, 2001; Vicente-Serrano et al., 2015). Another product that has especially gained attention is the USDA National Agricultural Statistics Service's (NASS) Crop Progress and Condition Report (CPCR), as previous literature verified that the use of the general crop condition data from the CPCR is of high quality for monitoring crop conditions on a weekly basis to (1) forecast yield (Beguería & Maneta, 2020; Bundy & Gensini, 2022; Bundy et al., 2024; Irwin & Good, 2017a, 2017b; Irwin & Hubbs, 2018a, 2018b), (2) quantify the impacts of weather perils like tropical cyclones (Bundy et al., 2023), and (3) quantify impacts on agricultural future markets (Bain & Fortenbery, 2013; Fernandez-Perez et al., 2018; Isengildina-Massa et al., 2016; Karali, 2012; Karali et al., 2016; Lehecka, 2013, 2014; Lehecka et al., 2014; McKenzie & Ke, 2022). These works have demonstrated that, despite the general crop condition dataset being subjective estimates, these data can capture the complexities of assessing crop conditions that may not be fully represented by individual agrometeorological models or remote sensing products (Beguería & Maneta, 2020). The USDA invests millions of dollars annually, using "people as sensors" who contain expert crop knowledge to collect data, which are then processed and disseminated in the weekly release of the CPCR. Although raw data are collected at the county level, the CPCR provides weekly information on phenological stage progress and the qualitative crop condition ratings at state and national levels to protect the confidentiality of farmers whose operations may comprise much of, if not all, the production in a county (Rosales, 2021). Demand for higher resolution crop condition data has increased. In response, NASS generated geospatially referenced, gridded datasets that represent the raw county data while still protecting farmer confidentiality (Rosales, 2021). These gridded data have already been used in machine learning applications to forecast conditions using meteorological data and forecast agricultural commodity market expectations (Cao et al., 2023). However, the validity of this recently (i.e., 2021) generated gridded crop condition dataset has not yet been examined, leaving a degree of uncertainty if the dataset should be used for agricultural applications (e.g., weekly condition monitoring, commodity market trading, spatiotemporal statistical analyses).

Core Ideas

- USDA county-level crop condition data were statistically significant covariates of state-level data.
- County-level crop condition data were statistically significant covariates to yield.
- Temperatures and precipitation explain a significant portion of the variance in crop condition changes.
- USDA gridded crop condition data are of high quality and can be used practically with confidence.

This research investigated the condition data from the USDA NASS Gridded Crop Progress and Condition (GCPC) dataset and assessed whether these data are of quality use for agricultural-related applications. Quality assessment was based on the ability to aggregate the gridded dataset to county, state, and national levels and compare it with the weekly published state and national condition data from the CPCR. Quality assessment was also performed via correlation between the aggregated county-level crop condition ratings with crop yields and climatological variables. GCPC data encompasses a 9-year historical record (2015–2023), covering four major field crops—corn (*Zea mays* L.), cotton (*Gossypium hirsutum* L.), soybeans (*Glycine max* L.), and winter wheat (*Triticum aestivum* L.). These results serve as confirmation of whether these data can be of value for practical applications and provide merit into whether the gridded dataset should be expanded back further historically, if possible. Moreover, confirmation of the quality in these data compliments the work of the survey respondents, underscoring the need and value to the agricultural community. Examining the quality of the gridded crop condition layers on a weekly basis can provide farmers and other agricultural stakeholders with another high-quality dataset to monitor crop conditions, understand climate impacts on agriculture, and estimate yield potential on a weekly, monthly, and seasonal basis.

2 | MATERIALS AND METHODS

2.1 | USDA NASS Crop Progress and Condition Reports

On average, about 3600 survey respondents contribute to the CPCR on a weekly basis, compromised by one or two respondents per crop-producing county (Rosales, 2021; USDA, 2024a). These survey respondents primarily consist of extension agents and Farm Service Agency staff who are asked to report subjective estimates of crop progress and conditions based on standard USDA definitions (USDA, 2016) for the entire week ending on Sunday (USDA, 2024a). For quality control measures, each datapoint is reviewed by NASS for reasonableness and consistency by comparing it with prior weeks' data, historical averages, and reports from adjacent counties. USDA Field Offices aggregate these quality-controlled data to the state level by weighting each county's reported data by NASS county acreage estimates (USDA, 2024a). However, this aggregation results in the loss of detailed information about conditions and spatiotemporal patterns at the county level (Rosales, 2021).

2.2 | Gridded crop condition data procedures

Gridded crop condition layers are curated using the raw reports within each county participating in the survey for a particular crop. These reports contain the percentage of a particular crop that is in excellent, good, fair, poor, and very poor condition. The standard definitions for these condition categories 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, and so on.
- Very poor: Extreme degree of loss to yield potential; complete or near crop failure.

For the gridded condition dataset, the weekly datasets do not contain the condition categories; rather, the USDA uses a numeric index, the crop condition index (CCIndex), calculated based on the condition categories (Rosales, 2021; Equation 1):

$$\begin{aligned}\text{CCIndex} = (&5 \times \%\text{Excellent} + 4 \times \%\text{Good} + 3 \times \%\text{Fair}\\ &+ 2 \times \%\text{Poor} + \%\text{Very Poor}) / 100. \end{aligned} \tag{1}$$

The CCIndex ranges from 1 to 5—An index rating of 5 corresponds to 100% of the surveyed crop being reported in excellent condition, while an index rating of 1 corresponds to 100% of the crop being reported in very poor condition. By converting the percentage-in-category data into a single numerical index, the USDA ensures both the confidentiality of individual survey responses and the consistency of the data for broader analytical use.

To obtain weekly 9 km gridded crop conditions, NASS takes each of the raw condition reports and expresses them geographically as a set of points that correspond with the land cover extent of the crop of interest, using polygons to represent the extent of cropland within each county based on NASS Cropland Data Layers (Rosales, 2021). Within each polygon, random points corresponding to the county acreage of the crop are created, even for counties with negligible cropland. Kriging spatial interpolation is then used to predict crop condition values in unobserved locations based on values in observed locations, followed by using a focal statistics filter to average the gridded values across a local neighborhood, resulting in a smoothing effect that obscures original datapoints. Finally, the smoothed, gridded layers are masked only to states that had reported data, even if the state only had a single county with reported data (Figure 1a).

The result is a 9-km horizontal grid spacing gridded crop condition dataset, henceforth referred to as the GCPC dataset, at the weekly temporal interval level for corn, cotton, soybeans, and winter wheat currently dating back to the 2015 growing season. The USDA selected 9 km resolution for the gridded data to better align with county-level estimates, enhancing the accuracy and applicability of analyses, especially in major crop-producing counties.

2.3 | Quality assessment methods

Since the gridded crop condition dataset uses kriging interpolation methods to derive crop conditions, specific raw

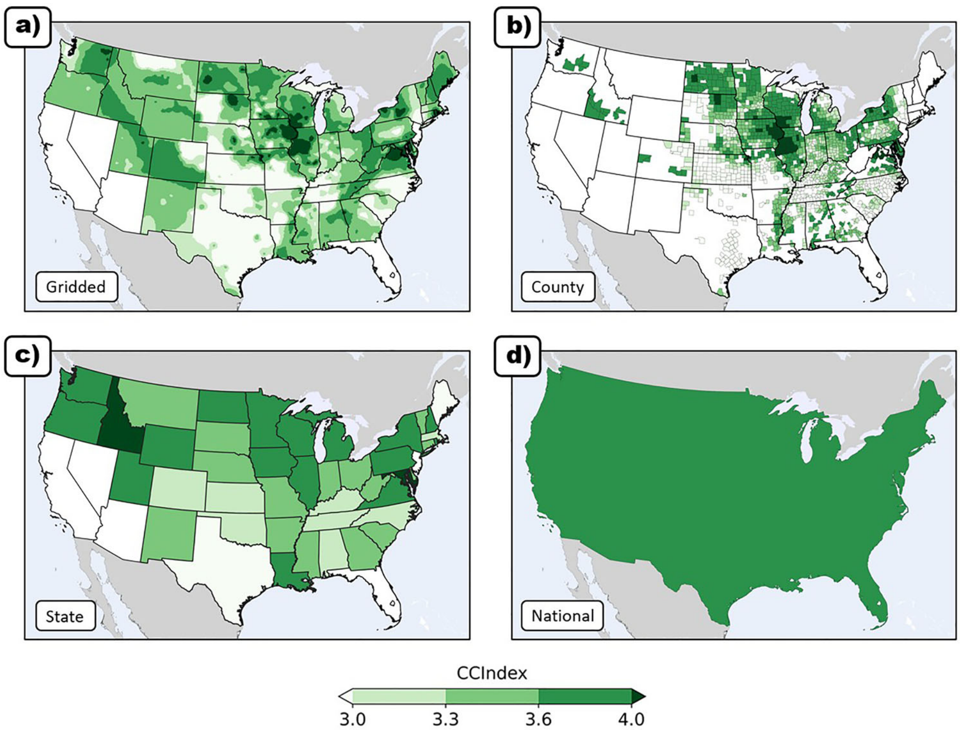

FIGURE 1 Example of corn crop condition index (CCIndex) ratings from week 31 in 2022 showing the (a) kriging-based condition layer from the Gridded Crop Progress and Condition (GCPC), (b) the gridded data aggregated to county level and masked for only the counties with yield data in 2022, (c) the raw county reports from the Crop Progress and Condition Report (CPCR) at the state level, and (d) the national-level summary of the CCIndex for the specified week.

condition information may be lost in the process, and the data from the gridded layers may not be exactly representative of what was occurring at both surveyed and unobserved locations. Therefore, quality assessment measures are needed to validate the practical use of the dataset. The same methods NASS implements when summarizing the raw condition estimates at the state and national level were used herein on the GCPC data. GCPC data were collected for corn, cotton, soybeans, and winter wheat for each growing season week dating to 2015 (USDA, 2024b). County-level crop conditions were compiled by computing the weighted mean of the GCPC condition estimates within each county for each week and crop. The weighted mean was based on the coverage of a 9-km grid cell in a particular county, as grid cells that were divided between counties received a lower weight than grid cells that were completely within a county. These grid-derived county-level condition estimates were masked by only the counties with planted acreage over the past 3 years for the crop of interest (Figure 1b). To go from county to state level, county-level condition estimates were weighted using the county's mean CCIndex by NASS county acreage estimates for the given crop year and summed for each state (Figure 1c), following the NASS methodology (USDA, 2024a, 2024c). To go from state to national level, CCIndex estimates were weighted using each state's planted acres over the previous 3 crop years and then summed to the national level (Figure 1d).

To statistically compare GCPC and CPCR datasets, the Mann–Whitney U test was used at the 95% significance level (p-value < 0.05) to assess the potential differences in central tendency of the two datasets. The Mann-Whitney U test was performed for the entire dataset distributions, for the state-level data at the weekly level, and for each individual state. Additionally, the correlation coefficient (R) and the coefficient of determination (R^2) were calculated as additional metrics to quantify the explanatory power and variance between the GCPC and CPCR datasets. This analysis was completed from June through September for corn, cotton, and soybeans, while the analysis for winter wheat was from April through July, as these months contained the most complete data over the 2015–2023 historical record of GCPC data.

One of the key considerations in assessing the practicality of GCPC data is quantifying whether county-level condition estimates serve as a statistically significant covariate of crop yield, analogous to how state and national-level conditions are for crop yields at those respective spatial scales (Beguería & Maneta, 2020; Bundy & Gensini, 2022; Bundy et al., 2023, 2024; Irwin & Good, 2017a). County-level yield data were collected within the 1990–2023 period for each of the respective crop-producing counties. Further, crop yield data were detrended to compute the annual yield standardized anomalies respective to each crop and county. Each county needed to have at least 20 years of available yield data in the 1990–2023 period and have at least 8 of the 9 years with yield data in the 2015–2023 period to be included in this analysis. To detrend the yield data, a linear regression adjustment equation (Equation 2) was used for each crop-county combination (Bundy & Gensini, 2022; Bundy et al., 2024; Irwin & Good, 2017a):

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

where Y is the respective year's crop yield, β_1 is the rate of change in the 34-year yield data, x_i is the total number of years used, and x_n is the year number. While limited to only 9 years of county-level crop condition data (2015–2023), R^2 values along with the regression p-values were still computed between the CCIndex and detrended crop yields at the weekly level for each county.

The final part of the analysis was to quantify the general relationship between the CCIndex and intramonthly climate variability to determine if changes in crop conditions align with known temperature and precipitation impacts on crop phenology. Monthly county-level climatological data were collected from the nClimDiv dataset (NOAA, 2024a) to establish the correlation with CCIndex changes from month to month. The nClimDiv data are derived from area-weighted means of 5 km grid-point estimates that are interpolated from daily Global Historical Climatology Network station data (NOAA, 2024b). Although the goal of this research was not to develop precise models of county-level crop conditions using climatological data, quantifying the correlation between these variables is still important due to its relevance for agroclimatology applications and future research, such as generating weekly forecasts of crop conditions based on weather forecasts. Climatological variables examined include the monthly standardized anomalies—relative to the 1980–2010 period—of mean temperatures and precipitation totals within the respective month.

Modeling the relationship between crop conditions and temperature and precipitation is complex due to regional variability, phenological stage, and crop selection (e.g., Bundy et al., 2022; Dill et al., 2020; Li et al., 2019; Schlenker & Roberts, 2009; Westcott & Jewison, 2013). To address these complex relationships, a unique second-order polynomial regression model—based on empirical and Agricultural Model Intercomparison and Improvement Project (AgMIP) global crop model simulation evidence (Li et al., 2019)—was computed for each county, month, and climate variable. After the quadratic adjustment in the observed climate data, linear regression was once again used to calculate if climatological variables were a statistically significant (95% significance level) covariate of CCIndex ratings. It should be noted that temperatures and precipitation do not solely account for the change in crop conditions and, subsequently, crop yield prospects, as additional factors such as heat accumulation (Kukal & Irmak, 2018), solar radiation (Hoogenboom, 2000), disease (Carroll et al., 2017), weed pressure (Zimdahl, 2007), nutrient application (Gehl et al., 2005), and management practices (Li et al., 2019) are nontrivial influences on crop health and production. Though, if CCIndex ratings change significantly with temperature, precipitation, and phenological timing, parallel to how crop yield prospects change with intraseasonal climate variability (Li et al., 2019; Lobell et al., 2013, 2014; Pielke & Downton, 2000; Schlenker & Roberts, 2009; Troy et al., 2015; Westcott & Jewison, 2013; Zipper et al., 2016), then this analysis can provide a foundation for further exploration on crop condition modeling using GCPC data.

3 | RESULTS AND DISCUSSION

3.1 | Crop condition data validation

The primary advantage of GCPC data lies in its ability to pinpoint critical crop areas experiencing favorable or unfavorable conditions, which enables more precise and effective risk management interventions (Figure 2). For example, large area crop-producing states (e.g., Illinois) can vary widely in conditions across the state, which is not discernable in the CPCR data. When aggregated to the county level, notable differences in the mean annual conditions and interannual standard deviation of conditions emerged across Illinois and other major crop-producing states. In northern and central Illinois, CCIndex values for corn and soybeans were higher on average and exhibited lower interannual variability compared to southern Illinois (Figure 2a,b,e,f). Over the 9-year climatology, the most optimal corn and soybean conditions (high annual mean CCIndex and low interannual variability) were across portions of eastern Nebraska, eastern Iowa, southern Minnesota, and Wisconsin (Figure 2a,b,e,f). Meanwhile, the least optimal conditions (low annual mean CCIndex and high interannual variability) for corn, cotton, soybeans, and winter wheat were observed mostly throughout the Great Plains during the 2015–2023 period. When considering all crops in this study, annual CCIndex means were below 3.40 (−0.20 below the national mean) for at least 80% of counties in Texas, Oklahoma, Kansas, Colorado, South Dakota, and North Dakota (Figure 2a,c,e,g). With an existing strong negative correlation ($R \leq -0.50$) between the annual CCIndex means and interannual standard deviations, counties with CCIndex means below 3.40 (25th percentile of conditions) generally contained a standard deviation in the 75th percentile of 0.45 or greater (Figure 2b,d,f,h). Notably, the 9-year climatology of county-level crop conditions aligns with the 38-year climatology of CPCR state-level crop

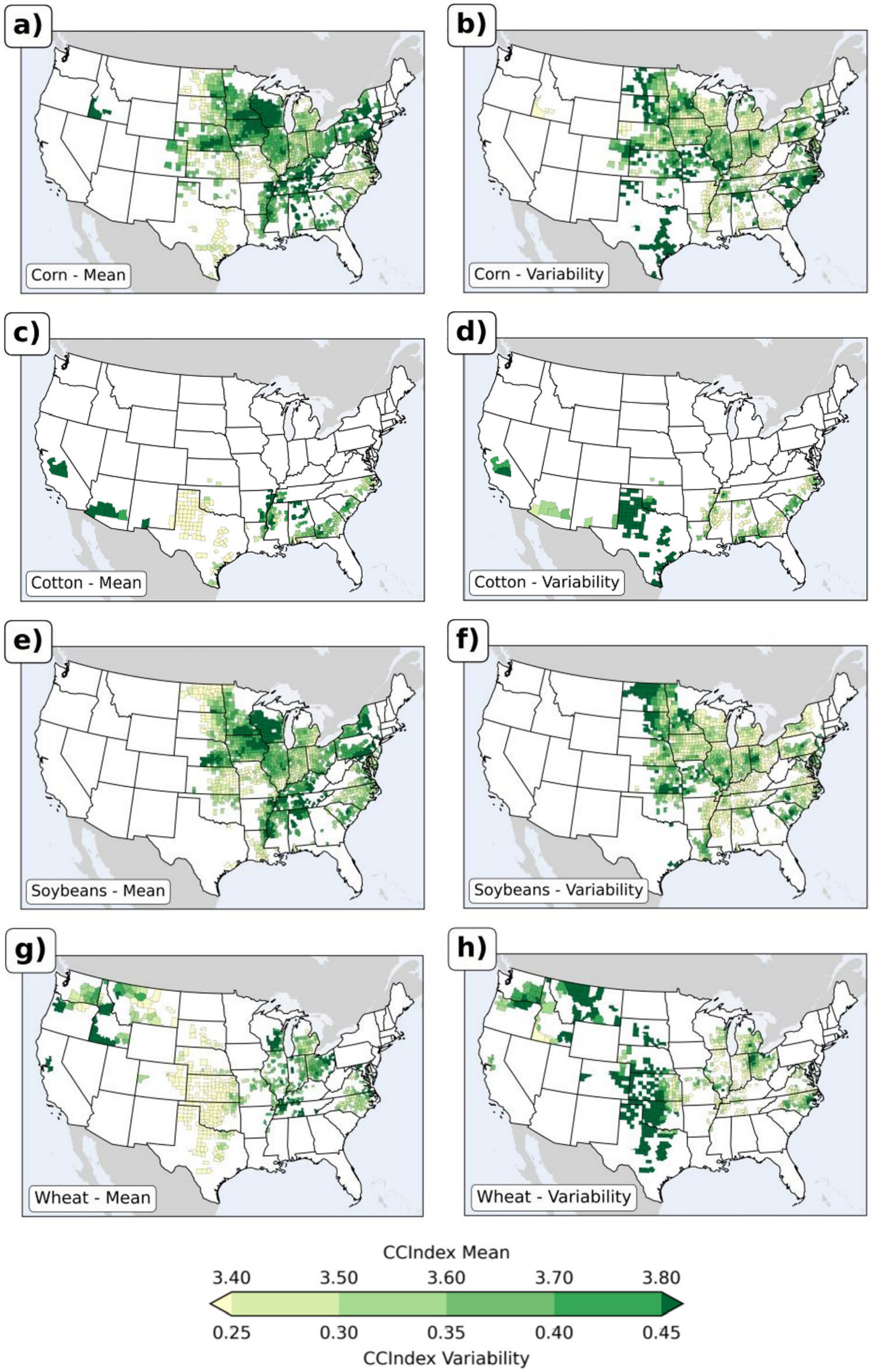

FIGURE 2 County-level annual crop condition index (CCIndex) means (a, c, e, and g; top row of color bar) and annual variability measured as the standard deviation (b, d, f, and h; bottom row of color bar) for the 2015–2023 study period.

conditions, where states in the Great Plains possessed an annual mean CCIndex of less than 3.40 and a standard deviation greater than 0.45 (Bundy et al., 2024). Furthermore, the GCPC county-level condition climatology in the Great Plains aligns with the observed marginal biophysical characteristics (erosive soils, poor drainage, nutrient deficiencies, and climatic stress) and subsequent limited yield returns for select crops in the region (Lark et al., 2015, 2020).

Between GCPC and CPCR datasets at the weekly and state levels, coefficient of determination values were 0.95

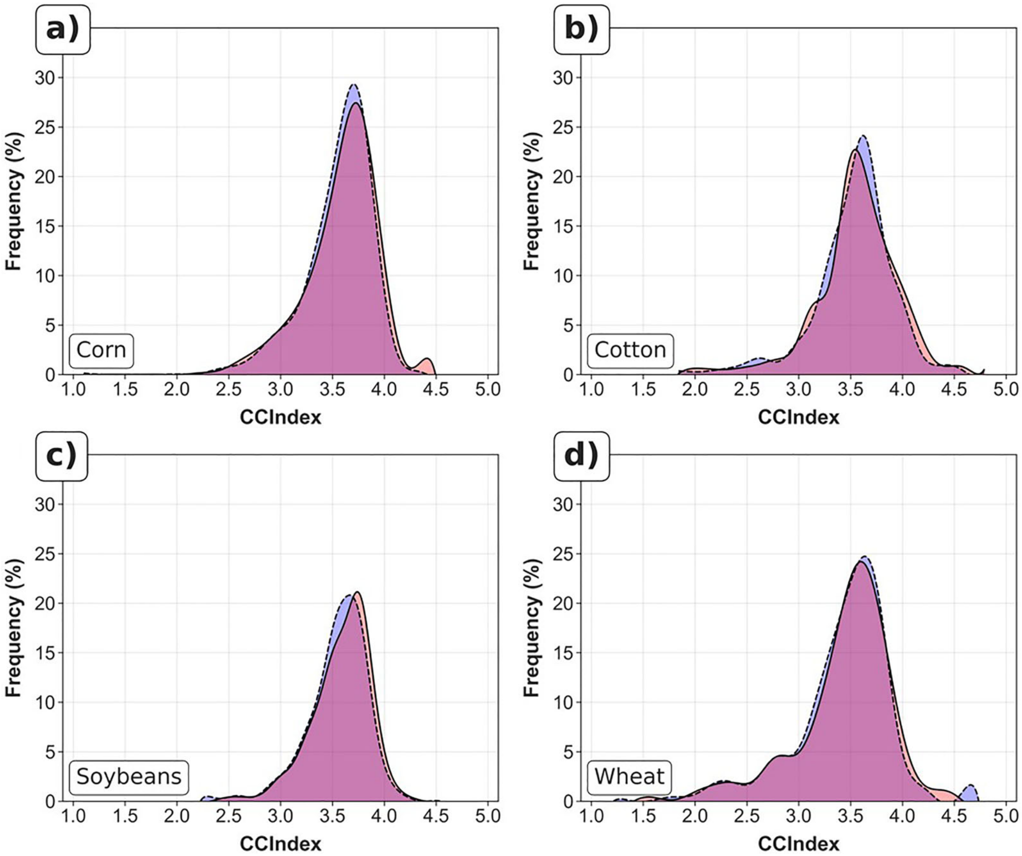

FIGURE 3 Crop condition index (CCIndex) rating distributions displayed as the percent frequency of state-level (a) corn, (b) cotton, (c) soybean, and (d) winter wheat conditions for the 2015–2023 period. Blue shaded areas with the dashed black outline represent the Gridded Crop Progress and Condition (GCPC) dataset, while the orange shade with the solid black outline is the Crop Progress and Condition Report (CPCR) dataset. Magenta areas represent an overlap between the two datasets.

for corn, cotton, soybeans, and winter wheat, meaning the CCIndex in the CPCR dataset was well-replicated with GCPC data during the 2015–2023 period (Figure 3). While both datasets display normal, parabolic distributions of CCIndex, most of the error between the two datasets was around the distribution medians—differences ranging 0.01–0.03. Despite these subtle differences, there were no statistically significant differences between the two dataset distributions and no statistically significant differences between the central tendencies (40th–60th percentiles) at the 95% significance level. At the weekly scale, intraseasonal tendencies of the GCPC dataset follow closely with CPCR data for each crop (Figure 4). The tendency was for a general decline in CCIndex from the first week in June (week 22) through the last week in September (week 39), with a mean decline of −0.25 for corn (Figure 4a), −0.20 for cotton (Figure 4b), and −0.15 for soybeans (Figure 4c) for both GCPC and CPCR datasets during the 2015–2023 period. From weeks 14 (first week in April) through 30 (last week in July), winter wheat displayed some intraweekly variability but subtly improved in CCIndex by 0.10 on a mean basis (Figure 4d). While weekly tendencies between the two datasets display similar characteristics through the growing season, the GCPC dataset slightly underestimated the actual state-level weekly crop condition ratings, as evident by the central tendency (mean, median, and interquartile range) for each crop and week. However, there were still no statistically significant differences between weekly dataset distributions between GCPC and CPCR datasets at the 95% significance level.

When examining GCPC and CPCR dataset differences at the state level, the top five corn, cotton, soybeans, and winter wheat-producing states that contributed to over 60% of the national production (USDA, 2024c) displayed a weekly mean CCIndex difference between GCPC and CPCR datasets ranging from −0.03 to 0.03 (Figure 5). These top five producing states for each respective crop contained a coefficient of determination between the GCPC and CPCR datasets of at least 0.95. States with statistically significant differences at the 95% significance level between GCPC and CPCR datasets were mostly minor crop-producing states—for corn, these states represent less than 1% of the national production (Figure 5a); for cotton, 13% (Figure 5b); for soybeans, 6% (Figure 5c); and for winter wheat, 6% (Figure 5d; USDA, 2024c). Despite these

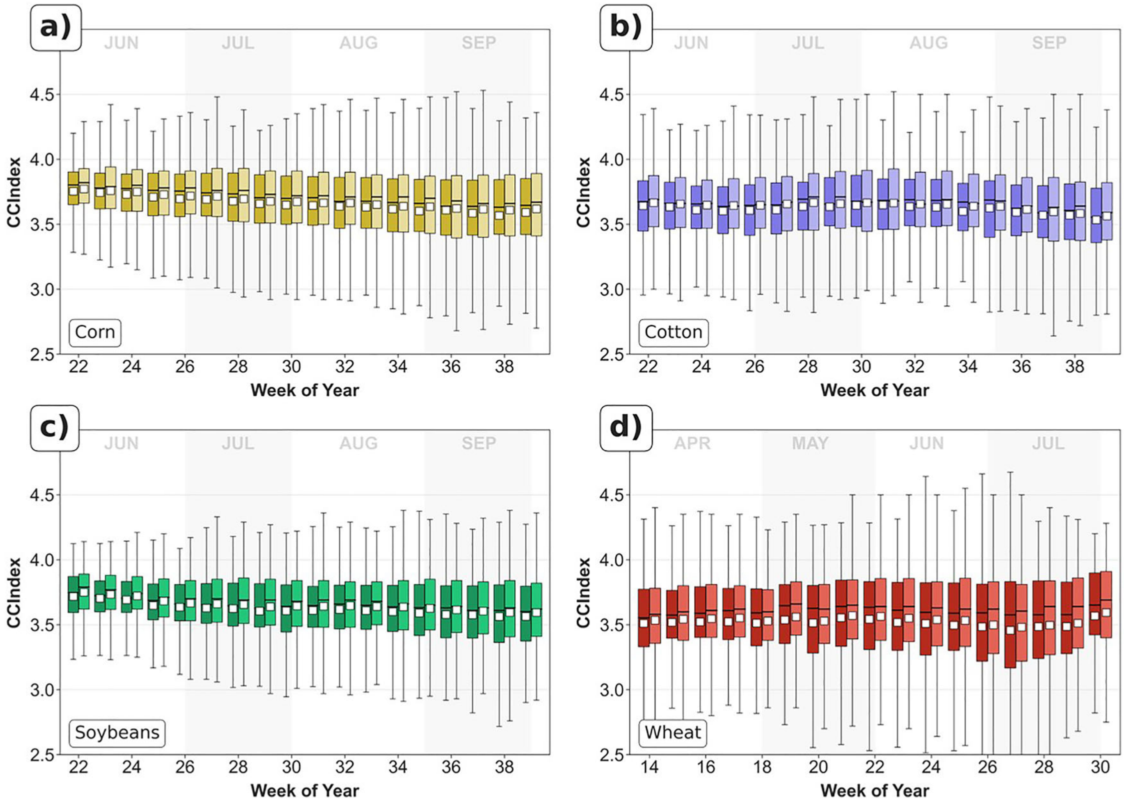

FIGURE 4 Crop condition index (CCIndex) comparisons at the weekly level between the Gridded Crop Progress and Condition (GCPC) (darker hue) and Crop Progress and Condition Report (CPCR) (lighter hue) datasets. Each box and whisker present a six-number summary: Whiskers represent the 1.5 multiple of the inner-quartile range; boxes represent first quartile (25th percentile) and third quartile (75th percentile) values; black horizontal lines within boxes represent the median value; and white squares represent the mean value.

variations, the coefficient of determination for the states with statistically significant differences between GCPC and CPCR datasets remained 0.40 or higher. As such, these states may require bias correction at the county level to achieve a more accurate representation of CPCR state-level crop conditions.

A plausible explanation for statistically significant differences observed in minor crop-producing states is the limited number of crop reports, which may not encompass all crop-producing counties. Gridded crop condition ratings, which are interpolated using kriging-based methods (Rosales, 2021), assign values to counties with and without crop production, despite the potential absence of a dedicated crop reporter for that week. While this does not render the GCPC data unsuitable for these minor-producing states, it is essential that the data exclusively be applied to only counties with confirmed production and used with caution. Furthermore, county-level condition data derived from the GCPC dataset were not masked by cropland boundaries, which may have enhanced the accuracy between GCPC and CPCR datasets. However, the computational efforts required to perform an additional masking may only yield marginal improvements, and, thus, may not justify its weekly implementation before aggregating to the county level, given the demonstrated accuracy of county-to-state-level condition estimates with CPCR data (Figures 3–5). Additionally, when GCPC and CPCR datasets were aggregated to the national level, there were no statistically significant differences between the dataset distributions at the 95% significance level.

3.2 | Crop conditions and yield

As observed at state and national spatial scales, there was also a strong, positive correlation between county-level condition ratings and yield (Figure 6), with higher CCIndex values typically reflecting favorable growing conditions, optimal plant health, and normal to above-normal yield (Bundy & Gensini, 2022; Bundy et al., 2024; Fackler & Norwood, 1999; Irwin & Good, 2016, 2017a, 2017b; Irwin & Hubbs, 2018a, 2018b; Jorgensen, 2014; Jorgensen & Diersen, 2014). In general, CCIndex ratings above 3.50 tended to correlate to yield anomalies at or above normal on average for corn, cotton, and winter wheat; soybeans required a CCIndex above 3.30 for optimal yield anomalies. Despite variations in the magnitude of yield anomalies across the studied crops, the relationship between county-level crop conditions and yield

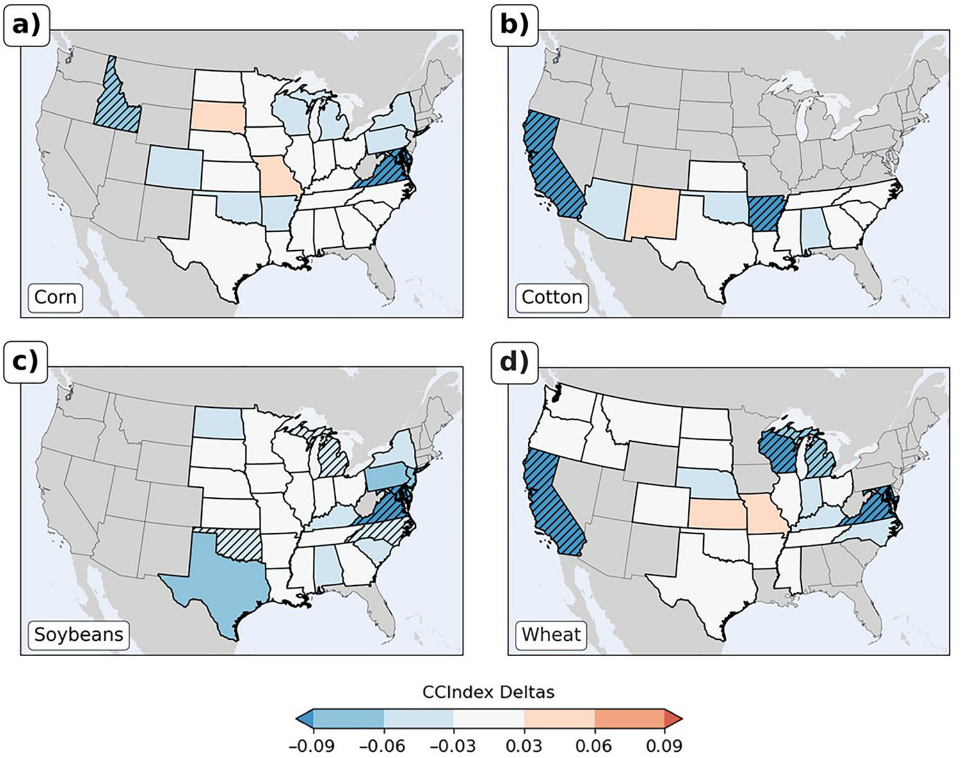

FIGURE 5 Mean crop condition index (CCIndex) delta between weekly Gridded Crop Progress and Condition (GCPC) and Crop Progress and Condition Report (CPCR) conditions for (a) corn, (b) cotton, (c) soybeans, and (d) winter wheat. Blues represent an under-representation of CPCR CCIndex ratings from the GCPC dataset, while the reds represent a higher bias in GCPC ratings. Hatching represents statistically significant differences between the CCIndex ratings from GCPC and CPCR datasets at the 95% confidence level.

exhibits a linear trend, even when constrained by the relatively limited sample size of 9 years (Figure 6). Though, the strength of the linear association fluctuates throughout the growing season—a testament to the dynamic interactions between crop conditions, the environment, weather, and yield.

State and national-level CPCR data revealed increasing explanation of variance between weekly CCIndex ratings and yield as the growing season continues (Bundy et al., 2024). This relationship underscores the importance of monitoring crop conditions throughout the growing season, as the predictability between the CCIndex and yield strengthens during the mid-stages to late stages of the growing cycle due to pollination playing a pivotal role in crop reproduction and yield (Eck et al., 2020; Westcott & Jewison, 2013). Comparable to state and national-level conditions, the explanatory power between the CCIndex and crop yields increased through the growing season at the county level for corn, soybeans, and winter wheat (Figure 7a,c,d). For corn, conditions became a statistically significant covariate to yield during July, coinciding with pollination for most major corn-producing counties in the United States. By the end of the growing season, the mean explanatory power (R^2) reached 45% when considering all corn-producing counties used in this study, with the 90th percentile counties reaching near 75% of the variance in corn yield explained by the CCIndex over the 2015–2023 period (Figure 7a). The high irrigation factor of cotton crops (USDA, 2019) potentially makes subjective crop assessments more difficult, which may result in a lower predictability between crop conditions and yield (Bundy et al., 2024). At the mean county level, about 15% of the variability in cotton yields could be explained by the CCIndex across most growing season weeks in the June–September, 2015–2023 period (Figure 7b). Soybeans displayed similar characteristics to corn, with a maximum of 43% of the variance in yield explained by the CCIndex by the end of the growing season (Figure 7c). Meanwhile, the mean county-level explanatory power between condition ratings and yield was the largest for winter wheat crops, with a county mean of 72% of the variance in winter wheat yield explained by the CCIndex during the final week of July, and 90th percentile counties reaching 90% (Figure 7d). The CCIndex during most weeks of July, August, and September was a statistically significant covariate to yield for corn and soybeans, whereas winter wheat's most critical months for conditions were June and July. Highlighting the key periods when crop condition reports are most critical for forecasting yields is key for stakeholders involved with crop production, though this does not discredit the value of crop reports earlier in the season when explanatory power is not significant. Rather, it implies using early-season condition estimates with caution, as abiotic and biotic factors can rapidly influence conditions and potentially change the entire season's yield outlook.

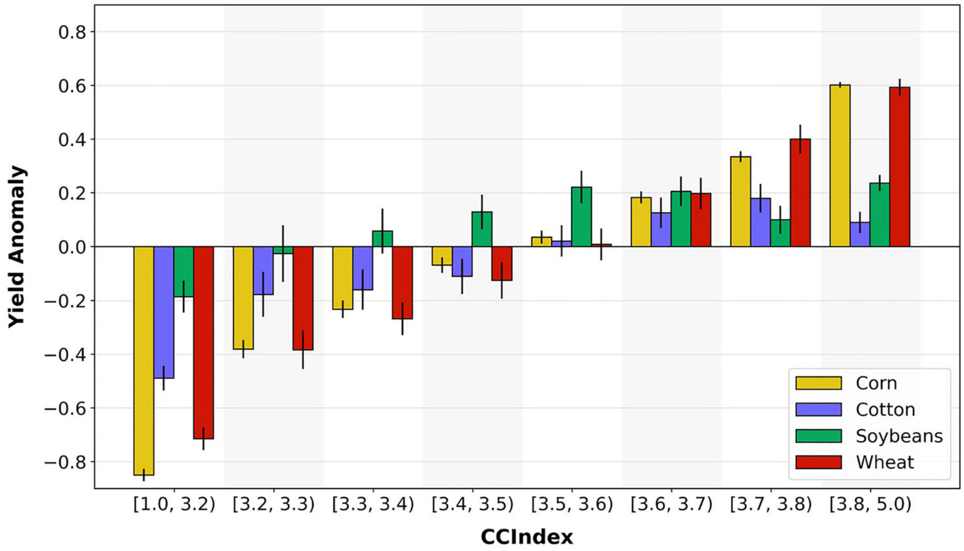

FIGURE 6 Mean crop yield responses to mean county-level crop condition index (CCIndex) ratings over the 2015–2023 period for the conterminous United States. Error bars represent the standard error of the mean across all counties within each CCIndex bin.

When examining the maximum explanatory power of any given week for yield using crop conditions at the county level, more than 50% of the variance in yield was explained by the CCIndex for 72% of corn (Figure 8a), 41% of cotton (Figure 8b), 72% of soybean (Figure 8c), and 86% of winter wheat-producing counties (Figure 8d) in the United States for at least one week. Additionally, CCIndex ratings for 90% of corn, 78% of cotton, 90% of soybean, and 96% of winter wheat-producing counties were at least statistically significant covariates to yield, contributing to 91% of national corn, 80% of national cotton, 89% of national soybean, and 97% of national winter wheat production during the 2015–2023 period. For only the top 50 producing counties for each respective crop, the maximum county-mean explanatory power between the CCIndex and yield was 62% for corn, 46% for cotton, 55% for soybeans, and 78% for winter wheat. Achieving the aforementioned high degree of explanatory power between USDA NASS crop condition ratings and yield at the county level is particularly impressive considering the rather limited historical GCPC dataset of 9 years. Furthermore, this suggests that the county-level CCIndex has not only captured meaningful patterns of crop conditions analogous to CPCR state-level crop conditions, but also that both GCPC and CPCR datasets serve as valuable indicators for forecasting yields at national, state, and county-level spatial scales.

3.3 | Crop conditions and climate

Monthly county-level changes in crop conditions driven by precipitation and temperature anomalies during the 9-year epoch were consistent with theoretical, empirical, and model evidence (e.g., Eck et al., 2020; Li et al., 2019; Lobell et al., 2013; Mourtzinis et al., 2015; Nguyen et al., 2023; Urban et al., 2015; Westcott & Jewison, 2013), highlighting the influence of abiotic factors during the various crop phenological stages (Figure 9). For example, undergoing at least a moderate precipitation deficit ($<-1\sigma$) was generally detrimental to crop conditions during the months of June, July, and August, with mean CCIndex changes up to −0.40 for corn, −0.29 for cotton, −0.30 for soybeans, and −0.10 for winter wheat (Figure 9c–e). Precipitation deficits resulting in drought-like conditions during planting and vegetative stages of the growing season for corn, cotton, and soybeans can have detrimental, regionally varying impacts on yield (Eck et al., 2020; Li et al., 2019). In September, the influence of below-normal precipitation was less apparent (Figure 9f), with some cases of improving crop conditions due to the importance of the dry-down period for corn and soybean maturity along with fieldwork/harvesting conditions (Martinez-Feria et al., 2017; Nielson, 2018). However, the effects of below-normal precipitation on crop conditions and subsequent yield do vary regionally in the United States, as these differences can be explained by large-scale factors such as mean climate conditions, soil and drainage characteristics (Trnka et al., 2014), and agricultural practices such as irrigation and harvest area (Bundy et al., 2022; Li et al., 2019; Lobell et al., 2014).

Above-normal precipitation anomalies manifested varying monthly impacts on crop conditions. Except for cotton in September, all crops tended to benefit from precipitation anomalies in the 0–1σ category (near-normal or minor wetness) throughout the growing season (Figure 9a–e). Precipitation anomalies in at least the moderately wet category ($>1\sigma$) resulted in general crop condition declines during June by

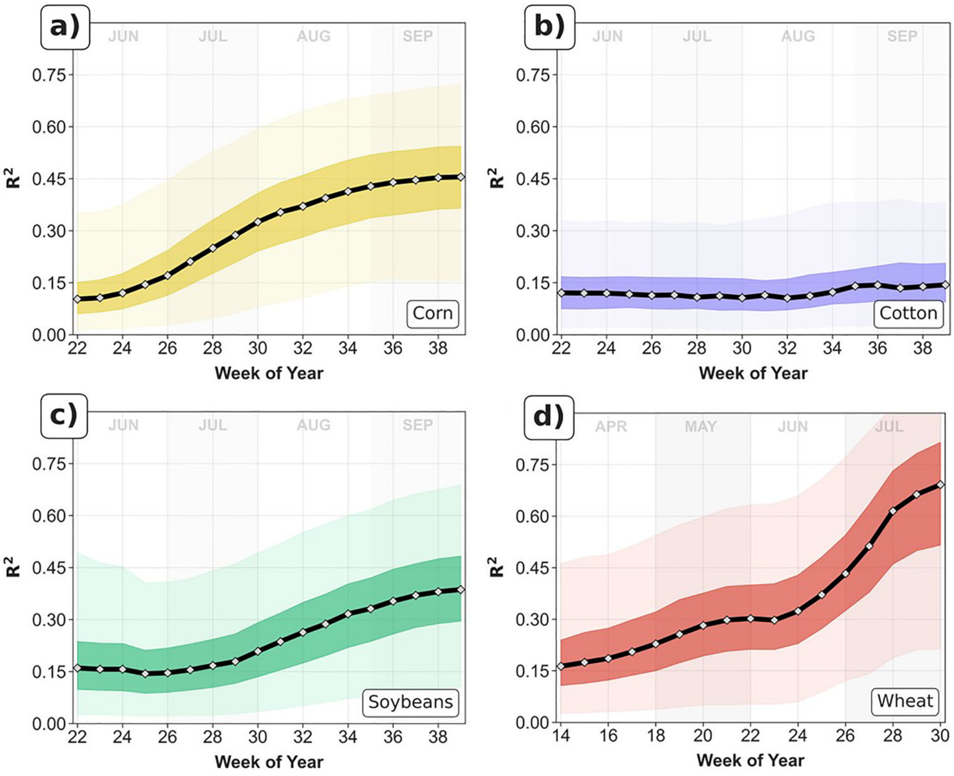

FIGURE 7 Coefficient of determination (R^2) between weekly county-level crop condition index (CCIndex) ratings and detrended yield anomalies for (a) corn, (b) cotton, (c) soybeans, and (d) winter wheat over the 2015–2023 study period. The darker hued colors in each chart represent the 40th–60th percentile range, while the lighter hues represent the 10th–90th percentile range.

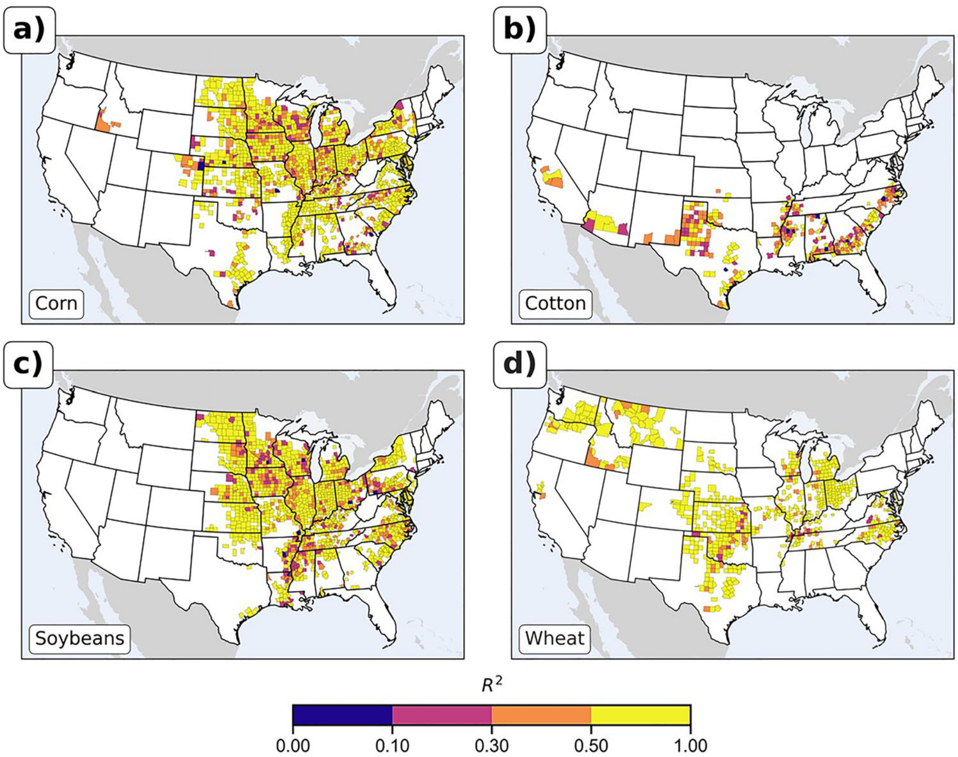

FIGURE 8 Maximum weekly coefficient of determination (R^2) values by county between crop condition index (CCIndex) ratings and detrended crop yield for (a) corn, (b) cotton, (c) soybeans, and (d) winter wheat.

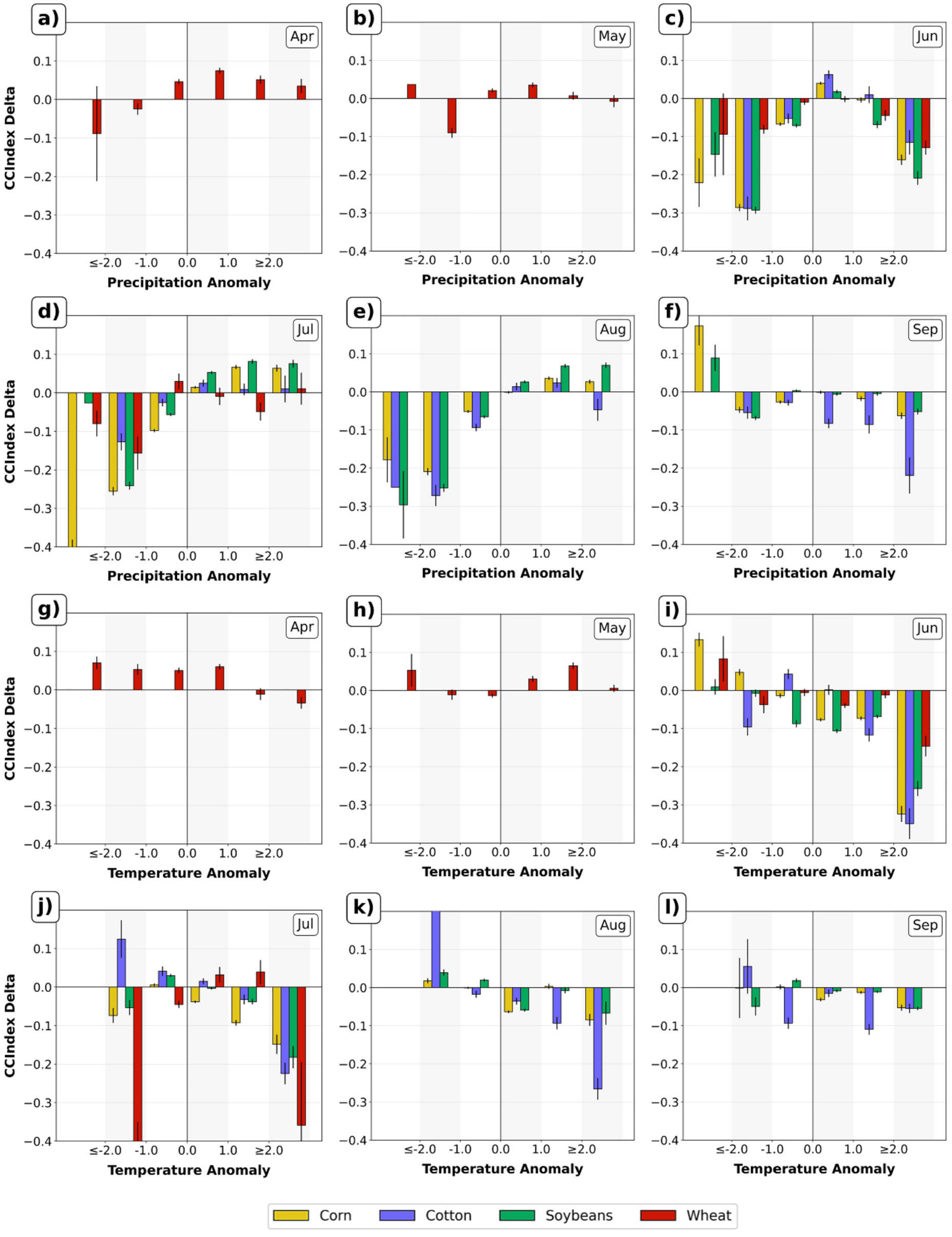

FIGURE 9 Mean crop condition index (CCIndex) rating responses to monthly precipitation (a–f) and temperature (g–l) standardized anomalies at county level for each crop over the 2015–2023 period for the conterminous United States. Error bars represent the standard error of the mean across all counties within each CCIndex bin.

as much as −0.12 to −0.22 when considering all crops, marking a distinguished nonlinear relationship between precipitation and crop conditions—a result parallel with other empirical evidence of yield loss under extreme precipitation scenarios (Li et al., 2019). Condition declines, and subsequent yield loss, can develop from the physical damage that waterlogging and flooding impose, along with restricted root development (Parent et al., 2008; Wenkert et al., 1981), nitrogen deficiency (Jabloun et al., 2015), toxic substances and disease development (Evans & Fausey, 1999; van der Velde et al., 2012), and delayed fieldwork operations (Urban et al., 2015). Otherwise, on an average basis, above-normal precipitation was beneficial for both corn and soybeans in July and for soybeans in August. July for corn (Westcott, 1989; Westcott & Jewison, 2013) and August for soybeans (Egli, 1999) are the two most critical reproduction periods for the success of the crops. During September, the impacts of normal to above-normal precipitation on cotton were especially apparent, with drier conditions favored to maintain optimal quality before harvest. The impacts of wet conditions vary regionally for United States crops, as excessive precipitation is more likely to cause negative impacts on yield in colder states (e.g., northern Great Plains) due to slower evaporation rates, which can foster waterlogging over an extended period (Li et al., 2019). Very few crop models accurately represent excessive precipitation and soil water processes (Shaw et al., 2013); therefore, there is an inherent need to implement empirical relationships between precipitation and crop response on a weekly, monthly, and seasonal basis (Kanwar, 1988; Rosenzweig et al., 2002; Shaw & Meyer, 2015), such as the relationship established in this study. Additionally, crop conditions can deteriorate from adverse weather hazards accompanied with heavy precipitation, such as hail (S. A. Changnon et al., 2009; Lindsey et al., 2024; Schlie et al., 2019) and wind (Botzen et al., 2010; Cleugh et al., 1998; Lindsey et al., 2021), that result in root lodging, defoliation, and green-snapping. Thus, GCPC data may offer as a tool to monitor crop condition responses from severe weather perils at a higher resolution as opposed to detecting the impacts at state and national levels from CPCR data (e.g., Bundy et al., 2023).

While the mean county-level impact of temperatures on GCPC data was not as definitive as precipitation across the examined crops, results still provide valuable insights into the impacts of climate on different phenological stages (Figure 9 g–l). Temperature anomalies during June displayed the most robust detrimental effects on crop condition changes when temperature anomalies increased, especially when anomalies were at or above 2σ (CCIndex rating changes ranged from −0.18 to −0.35). Though, across all growing season months for corn, cotton, and soybeans, above-normal temperature anomalies resulted in a mean decrease in CCIndex ratings, likely resulting in decreased yield prospects as evident from AgMIP crop model simulations (Li et al., 2019) and other observational studies (Eck et al., 2020; Mourtzinis et al., 2015; Westcott, 1989; Westcott & Jewison, 2013). The mean effects of below-normal temperatures on conditions varied with each anomaly category, likely due to the effects of precipitation anomalies on crop conditions during these scenarios. These uncertainties warrant further investigation and promote the continuous efforts on agrometeorological modeling, whether through statistical (Lobell & Asseng, 2017; Urban et al., 2015) or machine learning efforts (Cao et al., 2023), to further the understanding of crop–climate relationships along with the contribution of each climate variable on crop conditions and yield.

When examining the general relationship between climate and crop conditions at the county level, and after applying a unique second-order polynomial transformation to the climate variables for each county, precipitation anomalies were a statistically significant covariate to CCIndex rating changes for 96% of corn, 95% of cotton, 97% of soybean, and 93% of winter wheat-producing counties during at least 1 month (Figure 10a,c,e,g). Moreover, over 50% of the variation of CCIndex rating changes were explained by precipitation anomalies for 74% of corn, 67% of cotton, 79% of soybean, and 74% of winter wheat-producing counties for at least 1 month during the growing season. Over the 9-year study period, temperature anomalies were at least a statistically significant covariate to CCIndex rating changes for 85% of corn, 92% of cotton, 89% of soybean, and 80% of winter wheat-producing counties in the conterminous United States (Figure 10b,d,f,h). Overall, empirical evidence regarding climate effects on agricultural productivity is critical for advancing stakeholder knowledge on crop physiology, yield potential, and the predictability of impacts. The GCPC dataset can be a tool for elucidating the complex interactions between temperature, precipitation, and crop conditions, thereby enhancing the ability to anticipate and mitigate the detrimental impacts of climate variability on crop conditions and yield. Future research could use the results from this study as an initial step into creating more sophisticated models to not only forecast crop conditions using weather, but also to use crop condition ratings to forecast yield at the county level.

4 | CONCLUSIONS

The weekly GCPC dataset offers a high-resolution, spatially explicit representation of the raw, confidential condition reports for agricultural stakeholders. This study provides robust evidence of the validity of the crop condition data by comparing the 9-year dataset with the CPCR state and national-level condition data, quantifying the predictability of yield with weekly county-aggregated conditions, and correlating the condition data with climate variables for four major crops—corn, cotton, soybeans, and winter wheat.

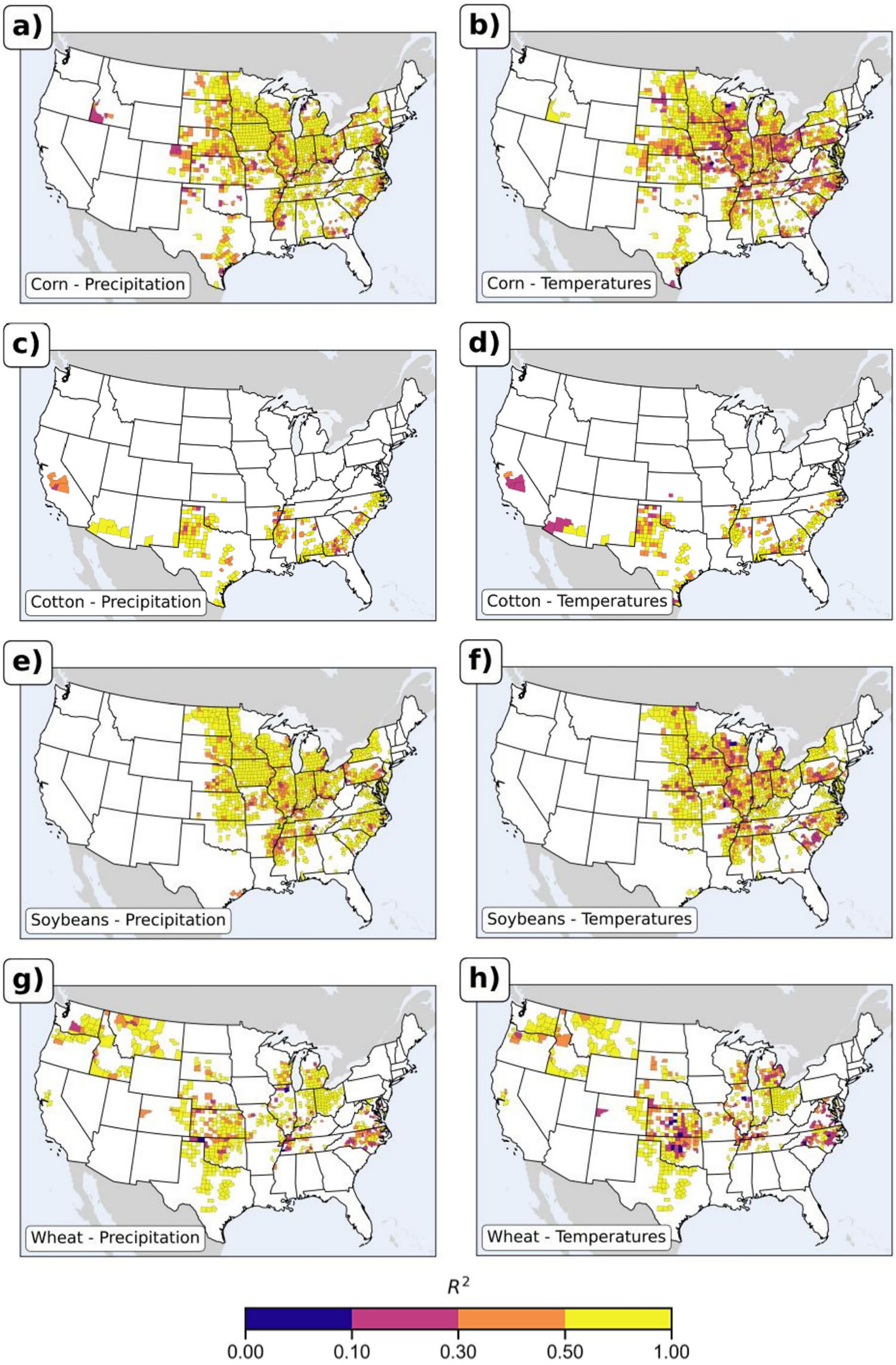

FIGURE 10 Maximum monthly coefficient of determination (R^2) values by county between crop condition index (CCIndex) rating changes with (a, c, e, and g) precipitation anomalies, and CCIndex rating changes with (b, d, f, and h) temperature anomalies for each crop.

When aggregated to county, state, and national levels in accordance with NASS methods, no major crop-producing states displayed any statistically significant differences between GCPC and CPCR data, confirming the cross-dataset consistency. Additionally, county-level crop conditions were statistically significant covariates to yield during reproduction through harvest for most of the key crop-producing counties. County-level crop condition data also displayed sensitivity to monthly climate variability, with temperature and precipitation patterns robustly correlating with changes in crop conditions and aligning with known impacts on crop phenology. These findings substantiate the utility and fidelity of the proxy GCPC dataset as an accurate representation of crop conditions at a finer scale, and the predictive capacity with climatic variables and yield underscores the importance of using GCPC in future research. Furthermore, this validation supports its practical application in operational decision-making for agricultural stakeholders, serving as a critical resource for informed insights into crop productivity amid the challenges posed by observed and projected climate trends and environmental variability.

AUTHOR CONTRIBUTIONS

Logan R. Bundy: Conceptualization; formal analysis; investigation; methodology; visualization; writing—original draft; writing—review and editing. **Vittorio A. Gensini**: Project administration; supervision; validation; writing—review and editing. **Walker S. Ashley**: Funding acquisition; project administration; supervision; writing—review and editing. **Alex M. Haberlie**: Supervision; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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