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Surveys and satellites: Evaluating crop condition monitoring strategies using field observations and vegetation health indices

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Abstract

The ability to make reliable, data-driven crop yield assessments for risk management depends on the quality of the underlying data. This study compares US state- and national-level data from 1986 through 2023 for 10 major field crops using two widely applied approaches: the USDA survey-based crop condition index (CCIndex) and satellite-derived vegetation health (VH) indices. The goals are to characterize seasonal tendencies, quantify yield variance, and examine responses to climatic anomalies using both crop monitoring systems. Results indicate that the onset of natural senescence during the reproductive stage marks a critical turning point, as weekly VH indices correlate significantly with yield in the early to mid-season but lose predictive skill as canopy greenness diminishes; conversely, the CCIndex maintains or even strengthens its yield association through the late season across most crops. Climate-response analyses reveal that CCIndex ratings adequately capture the nonlinear effects of precipitation and temperatures, whereas VH response is weaker. Collectively, findings support a phenology-aware blended monitoring strategy—leveraging VH indices for early detection and the CCIndex for late-season yield relevance and agronomic nuance. This multi-decadal, multi-crop evaluation establishes a robust baseline for operational crop-condition predictability and highlights opportunities to fuse survey and remote-sensing data to enhance yield forecasting and climate resilience.

Plain Language Summary

Reliable information on crop conditions is essential for predicting yields, understanding how weather impacts crops, and for managing agricultural risks. This study compares two major ways of tracking US crops: field-based reports from the USDA and satellite-based vegetation measurements. Over the 1986 through 2023 study period, we found that satellite data work well through the first half of the

Abbreviations: CCIndex, crop condition index; CPCR, Crop Progress and Condition Report; TCI, temperature condition index; VCI, vegetation condition index; VH, vegetation health; VHI, vegetation health index.

growing season, while USDA crop ratings remain reliable indicators of yield through the entire growing season for most crops. Additionally, field-based crop ratings better capture how crops respond to temperature and precipitation extremes. Together, these findings highlight that blending both monitoring systems can improve how we monitor and forecast crop yields, helping farmers and decision-makers better prepare for climate challenges.

1 | INTRODUCTION

A fundamental element of agricultural resilience is the ability to continuously and accurately monitor crop health status from emergence through harvest. In-season assessments of crop quality, vitality, and productivity are essential for enabling stakeholders—from farmers to policy makers—to make timely, data-informed decisions that can mitigate risk and optimize yield (Khaki et al., 2021; Lehecka, 2014). The need for accurate, real-time agricultural insights is increasingly urgent as the global demand for food continues to increase alongside the mounting pressures farmers face from extreme weather events and broader impacts of anthropogenic climate change (Steele & Hatfield, 2018). These impacts occur from both abiotic (e.g., drought, flooding, and severe convective storms) and biotic pressures (e.g., pests, disease, and weed competition), which can significantly disrupt crop productivity during the growing season (Angel et al., 2018; Pryor et al., 2014). Since the United States ranks third globally in agricultural production value with over $176 billion in exported goods in 2024 (ERS, 2025a), the resilience of the agricultural enterprise has far-reaching implications. Domestically, agriculture and related industries contributed $1.54 trillion to the US gross domestic product, a 5.5% share (ERS, 2024). Therefore, safeguarding this vital sector not only requires continued innovation in technologies, management practices, and crop genetics (Bundy et al., 2022; Delgado et al., 2013; Lesk et al., 2016; Mase et al., 2017; Milly et al., 2002; Nicholls, 1996; Ray et al., 2013; Schmidhuber & Tubiello, 2007; Walthall et al., 2013; Wheeler & Von Braun, 2013), but also evaluating crop monitoring tools to ensure they capture the complexities of crop dynamics and correlate with yield outcomes to support timely decision-making.

Remote sensing observations that derive both atmospheric and land surface variables offer a unique advantage of consistent coverage across large spatial and temporal scales (Lakshmi, 2017; Wardlow et al., 2012). Therefore, a common method in crop condition monitoring through the growing season is using operational polar-orbiting satellite data from the National Oceanic and Atmospheric Administration (NOAA) global vegetation health (VH) system (Kidwell, 1997; NOAA, 2025a). This satellite-derived product—including variables such as the normalized difference vegetation index (NDVI), vegetation condition index (VCI), temperature condition index (TCI), and the vegetation health index (VHI)—is a vital tool for assessing vegetation conditions and weather impacts for numerous agricultural regions across the globe (Báez-González et al., 2002; Bento et al., 2018; Dabrowska-Zielinska et al., 2002; Domenikiotis et al., 2004; Kogan, 1997; Kogan et al., 2003, 2005, 2012, 2013, 2016; Liu & Kogan, 2002; Salazar et al., 2007; Unganai & Kogan, 1998; Vicente-Serrano et al., 2015).

In contrast to remote sensing, human-based observations are when individuals effectively serve as sensors and offer essential ground-truth information that is critical for agricultural monitoring. The US Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Crop Progress and Condition Report (CPCR) contains weekly subjective estimates on both crop progress and conditions in the United States. Several studies demonstrated that the CPCR's weekly crop condition data are high-quality indicators for monitoring crop development and are proven useful across multiple applications, including (1) forecasting yields at the state and national level (Beguería & Maneta, 2020; Bundy & Gensini, 2022; Bundy et al., 2024, 2025a; Irwin & Good, 2017a, 2017b; Irwin & Hubbs, 2018a, 2018b), (2) quantifying the impacts of weather-related hazards such as tropical cyclones and derechos (Bundy et al., 2023, 2026), and (3) assessing implications for agricultural futures 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). Although CPCR crop condition assessments are based on subjective observations, the dataset has proven to be a reliable tool for capturing real-time crop health information, and it is argued that expert crop assessments capture the complexities of assessing the "status" of a crop better than any remote sensing retrieval (Beguería & Maneta, 2020).

Despite the demonstrated utility of both survey-based USDA assessments and remotely sensed VH, there remains a literature gap in conducting comprehensive, systematic comparisons of these two monitoring systems in the United States. Over the past decade, yield forecasting using the satellite-derived VH system has rapidly expanded, largely driven by advances in data availability, machine learning techniques, and increasing spatial and temporal resolutions of Earth observation systems (e.g., Becker-Reshef, Vermote, et al., 2010; Becker-Reshef, Justice, et al., 2010; Bolton & Friedl, 2013; Doraiswamy et al., 2005; Johnson et al., 2021; Pham et al., 2022; Rembold et al., 2013; Serban & Maftei, 2025). Joint missions such as the National Aeronautics and Space Administration–Indian Space Research Organization (NASA-ISRO) Synthetic Aperture Radar (NISAR) are expected to further accelerate this progress by providing high-resolution observations capable of capturing crop structural and moisture dynamics with unprecedented detail (NASA, 2025). However, while these developments have and will continue to improve remote sensing-based yield estimation, they rely solely on satellite-derived indicators or incorporate them with meteorological variables, with no evaluation against independent, survey-based measures of crop condition. In particular, the extent to which the VH system capture the same agronomic signals as survey-based crop assessments—and how their relationships with climate and yield evolve throughout the growing season—remains insufficiently understood.

This study addresses the aforementioned research gap by providing a comprehensive, multi-crop evaluation using 38 years (1986–2023) of USDA crop condition and NOAA VH data. Specifically, the objectives are threefold: (1) compare the temporal dynamics of both datasets, (2) assess the explanatory power of each variable in predicting crop yields by week throughout the growing season at the state and national level, and (3) compare changes in crop condition and VH ratings under various climatic anomalies. The analysis includes 10 key 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 both spring and winter wheat (*Triticum aestivum* L.). Importantly, this study does not aim to determine which dataset is "better," thereby proving or disproving the hypothesis by Beguería and Maneta (2020); rather, the goal is to provide statistically driven insights on survey and satellite-based crop condition monitoring strengths, limitations, and complementary value across space and time. By identifying when and where each product performs best, this study provides a foundation for integrating survey-based observations and remote sensing products into more robust and operationally relevant crop monitoring and yield forecasting frameworks.

2 | BACKGROUND

This section provides an overview of each of the 10 crops analyzed in this study and establishes the agronomic and geographic context necessary to interpret differences between survey-based crop assessments and satellite-derived VH ratings. Collectively, this research spans a broad cross-section of US agriculture, including cereal grains (corn, rice, sorghum, barley, oats, spring wheat, and winter wheat), oilseeds and legumes (soybeans and peanuts), and fiber crops (cotton; Table 1). Together, these 10 crops were selected due to the completeness and temporal consistency in the historical USDA crop condition dataset and collectively represent much of the major US field crop production, accounting for approximately 85%–90% of total planted acreage (USDA, 2025a). Crop diversity matters, as these crops differ in photosynthetic pathway, canopy structure, rooting depth, water demand, phenological timing, and management intensity—factors that influence how crop condition evolves on a weekly basis and how it is represented in both field observations and satellite signals. Given that crop phenology, growing season timing, and primary production regions are referenced throughout to interpret the results, establishing this simplified overview of the 10 crops is essential.

Spatially, the selected crops represent the dominant agricultural regions of the United States (Figure 1), with geographic concentration tied to biophysical characteristics, including climate and soil. Of the 10 crops, corn and soybeans are the most widely produced in the United States, extensively covering the US Midwest Corn Belt, where Iowa and Illinois alone account for more than one-third of national production for both crops (ERS, 2025b; USDA, 2025b). Corn accounts for more than 95% of total feed grain production and use, while soybeans account for 90% of US oilseed production (ERS, 2025b, 2025c). The Corn Belt region is characterized by deep, fertile soils, sufficient precipitation, and a growing season well-suited for high-yielding summer crops. Due to advancements in technology and management, corn and soybean production and yields have continued to increase since the beginning of the crop condition historical record (1986).

In the Great Plains, winter wheat, the only winter crop included in this study, is the dominant regional crop, with Kansas, Texas, Oklahoma, Nebraska, Colorado, and Montana accounting for nearly half of national production (ERS, 2025d; USDA, 2025b). Wheat ranks third among US field crops in planted acreage and total production (ERS, 2025d). Since 2000, there has been a general decreasing trend in wheat planting area, which is attributed to lower relative returns for wheat and increased competition in global markets (ERS, 2025d). Sorghum occupies a similar geographic footprint, but is more concentrated in semiarid regions of Texas and Kansas, which together contribute to 75%–80% of national sorghum output (USDA, 2025b). Further south, cotton, rice, and peanuts are concentrated across the broader southern United States, where longer growing seasons and warmer temperatures support their development. Cotton production is dominated by Texas, which alone accounts for a quarter of US output, with additional growing areas in Georgia, Mississippi, and Arkansas (ERS, 2025e; USDA, 2025b). Furthermore, the United States is the world's third-largest cotton producer

TABLE 1 Summary of the 10 crops, including crop type, photosynthetic pathway, major US production region, harvested area, growing season, and USDA crop condition reporting weeks used in this study.

Crop	Type	C3/C4	Major production	Harvest (ha)	Growing season	Condition reporting weeks
Barley	Cereal grain	C3	Northern Plains (ND, MT, ID)	0.9–1.0 M	April–July	Week 21–Week 32
Corn	Cereal grain	C4	US Midwest (IA, IL, NE, MN)	33–34 M	April–October	Week 21–Week 39
Cotton	Fiber crop	C3	Southern United States (TX, GA, MS)	3.4–3.5 M	April–November	Week 23–Week 39
Oats	Cereal grain	C3	Upper US Midwest (ND, MN, IA)	0.3–0.4 M	April–August	Week 21–Week 30
Peanuts	Legume/oilseed	C3	Southeast (GA, AL, FL)	0.6–0.7 M	April–October	Week 23–Week 40
Rice	Cereal grain	C3	MS Delta, CA Central Valley	1.0–1.1 M	April–September	Week 21–Week 36
Sorghum	Cereal grain	C4	Great Plains (KS, TX)	2.1–2.2 M	May–October	Week 26–Week 38
Soybeans	Legume/oilseed	C3	US Midwest (IA, IL, IN, MN)	33–34 M	May–October	Week 24–Week 39
Spring wheat	Cereal grain	C3	Northern Plains (ND, MT, MN)	4.4–4.5 M	April–September	Week 22–Week 32
Winter wheat	Cereal grain	C3	Great Plains (NE, KS, OK, TX)	9–10 M	September–July	Week 14–Week 26

Note: Major production regions and national harvested area are based on the USDA 5-year mean (2019–2023; USDA, 2025b). Condition reporting weeks reflect the most complete and consistent historical record of the USDA crop condition ratings for each crop.

and the leading cotton exporter (ERS, 2025e). Also in the southern United States, rice production is more localized, with Arkansas, California, Louisiana, Mississippi, and Texas together accounting for nearly all of the national production (ERS, 2025f; USDA, 2025b). Peanut production is even more concentrated, with Georgia, Alabama, and Florida typically accounting for 70%–75% of total US output (USDA, 2025b). Meanwhile, cool-season small grains—including barley, oats, and spring wheat—are confined to the northern Plains and upper US Midwest, where generally cooler and shorter growing seasons prevail. Idaho, North Dakota, Montana, and Minnesota dominate spring wheat and barley production (80%–90% of national output), while oats are primarily produced in North Dakota, Iowa, and Minnesota (40% of national output; USDA, 2025b).

Just as important as spatial coverage are the temporal growing windows and phenological development stages of the 10 crops (Figure S1), as phenological factors impact how crop condition is expressed and monitored throughout the growing season. Warm-season C4 crops, including corn and sorghum, are typically planted during boreal spring and progress through rapid vegetative growth before entering critical reproductive stages, such as silking for corn or flowering for sorghum, during mid- to late summer (Westcott & Jewison, 2013). This transition from vegetative to reproductive development represents one of the most yield-sensitive periods, as kernel set and grain number are highly dependent on favorable temperature and moisture conditions during this period (Hatfield & Prueger, 2015). In contrast, cool-season C3 small grains such as barley, oats, and spring wheat are generally planted earlier and complete much of their vegetative growth under cooler climate conditions, often reaching heading and grain fill prior to peak summer heat. As a result, their most critical yield-forming stages typically occur earlier in the season, thus, making them more sensitive to early and mid-summer climate and environmental variability (Klink et al., 2014; Morgounov et al., 2018). Winter wheat exhibits a distinct phenological cycle, with autumn planting, winter dormancy, and spring regrowth, making its condition particularly sensitive to overwinter survival and environmental conditions during spring green-up and grain fill (Stewart et al., 2018).

Oilseed and legume crops—soybeans and peanuts—follow warm-season growth cycles but differ in how yield is determined during reproductive development. For soybeans, flowering (R1–R2) and pod set and filling (R3–R6) stages are especially sensitive to heat and moisture stress, which can reduce crop quality and, ultimately, yield (Anderson, 2020). Peanuts, by contrast, undergo pegging and belowground pod development, such that reproductive sinks develop within the soil profile (Prasad et al., 2010). As a result, yield formation depends not only on canopy conditions, but also on soil

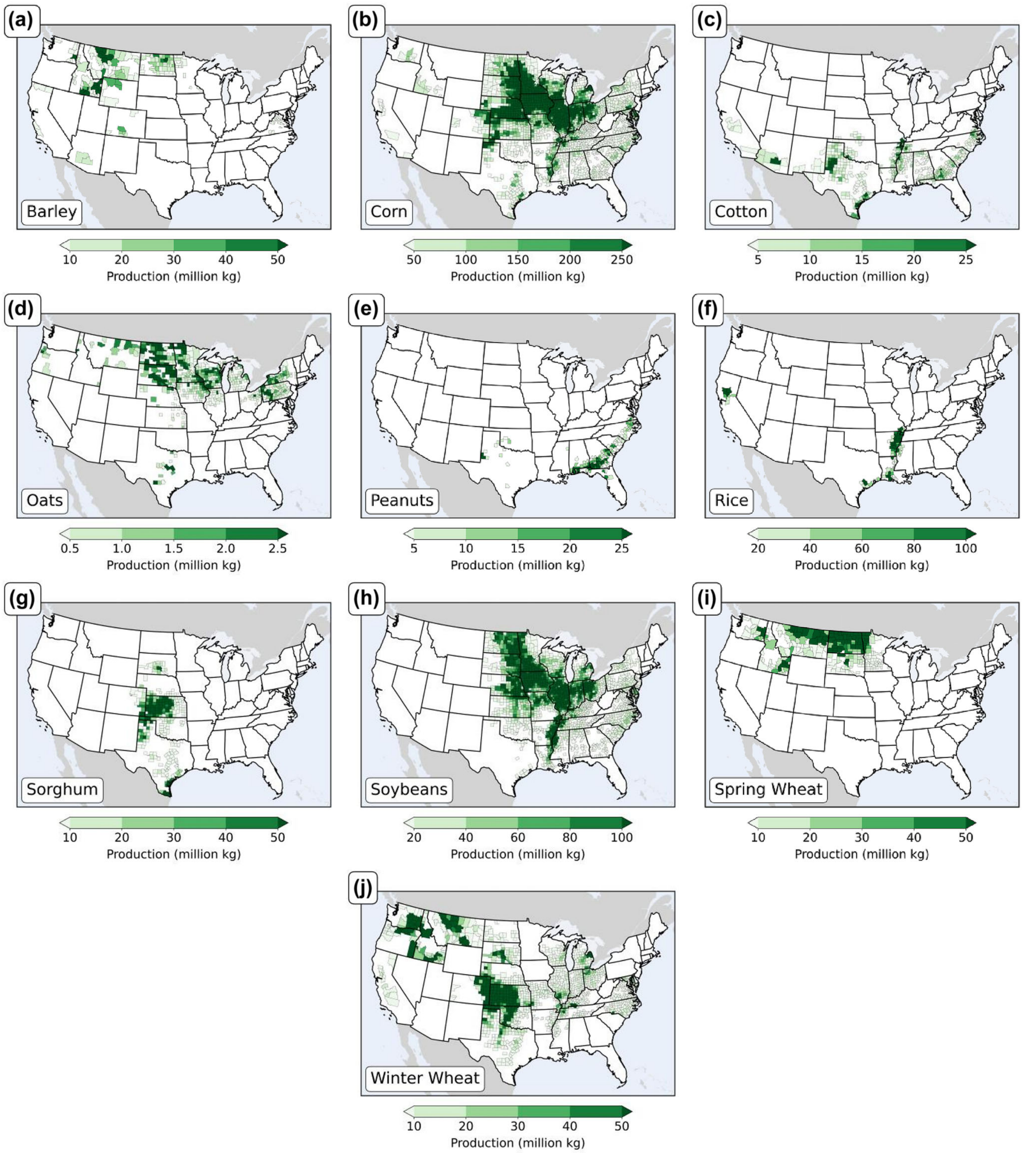

FIGURE 1 Mean county-level production (million kg; 2019–2023) for each crop: (a) barley, (b) corn, (c) cotton, (d) oats, (e) peanuts, (f) rice, (g) sorghum, (h) soybeans, (i) spring wheat, and (j) winter wheat.

moisture and temperature in the pegging zone (Vennam et al., 2022)—factors that are not fully captured by aboveground observations or satellite-derived signals. Cotton and rice further diverge due to strong management influences; cotton yield is tied to boll development and retention during prolonged reproductive periods (Bista et al., 2025), while rice is often grown under flooded or irrigated conditions (ERS, 2025f). Overall, crop-specific growing windows and phenological stages vary substantially across the calendar year, reflecting the diversity in physiological development, management practices, and environmental sensitivities across US cropping systems. This diversity underscores the importance of robust crop monitoring frameworks that can capture critical periods of yield formation and stress exposure throughout the growing season. Integrating survey-based assessments with satellite-derived crop indices provides a more comprehensive understanding of crop condition, particularly during key transitional stages when timely identification of risk is essential for agricultural decision-making.

3 | MATERIALS AND METHODS

3.1 | USDA crop condition and yield data

The USDA invests annually to help support its weekly CPCR, relying on extension agents and Farm Service Agency staff with expert crop knowledge to collect, process, and disseminate data. Widely used by farmers, agribusinesses, commodity traders, government agencies, and researchers (Beguería & Maneta, 2020; Bundy et al., 2024; Lehecka, 2014), the CPCR is the most requested publication issued by NASS (Lehecka, 2014). The reporting network includes approximately 3600 respondents, typically one or two per county, covering over 75% of US crop production (USDA, 2025c). Surveyors submit weekly, subjective assessments based on standard USDA definitions, estimating the percentage of each crop in excellent, good, fair, poor, or very poor condition. Standard definitions for these percent-in-condition categories are as follows (USDA, 2016):

1. *Excellent*: Yield prospects are above normal. Crops are experiencing little or no stress. Disease, insect damage, and weed pressures are insignificant.
2. *Good*: Yield prospects are normal. Moisture levels are adequate, and disease, insect damage, and weed pressures are minor.
3. *Fair*: Less-than-normal crop condition. Yield loss is a possibility, but the extent is unknown.
4. *Poor*: Heavy degree of loss to yield potential, which can be caused by excess soil moisture, drought, disease and so forth.
5. *Very poor*: Extreme degree of loss to yield potential; complete or near crop failure.

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

$$\text{CCIndex} = (5 \times \%\text{Excellent} + 4 \times \%\text{Good} + 3 \times \%\text{Fair} + 2 \times \%\text{Poor} + \%\text{Very Poor})\,/100 \quad (1)$$

The CCIndex summarizes weekly crop condition reports across the five condition categories. This weighted index ranges from 1 to 5, where a value of 5 indicates that 100% of the crop is rated in excellent condition, and a value of 1 reflects 100% rated as very poor. Because excellent and good ratings are typically associated with normal to above-normal yield prospects, increases in these categories raise the CCIndex (Bundy et al., 2024). In contrast, fair ratings, indicative of below-normal conditions, reduce the index moderately, while poor and very poor ratings exert a stronger downward influence on the CCIndex due to their greater relevance in explaining the variance in yield anomalies.

As part of its quality control process, NASS reviews each data point for consistency and plausibility by comparing it with previous weeks' reports, long-term means, and data from neighboring counties. USDA Field Offices then aggregate these vetted data to the state level, weighting county-level reports by NASS acreage estimates (USDA, 2025c). State-level estimates are submitted to the Agricultural Statistics Board, where they are evaluated in the context of adjacent states and subsequently aggregated to the national level using a weighting scheme based on each state's 3-year mean planted acreage for the respective crop (USDA, 2025c).

State- and national-level crop condition data were obtained from the USDA NASS QuickStats database for the 10 crops assessed (USDA, 2025a). National-level weekly condition data were available from 1986 through 2023 (38 years) for all crops except oats, peanuts, and rice, which contained complete records from 1996 through 2023 (28 years). State-level condition data were also collected for the same timeframes, though the temporal coverage varied by state and crop. To be included, states were required to contain at least 90% of their data across the relevant period—38 years for barley, corn, cotton, sorghum, soybeans, spring wheat, and winter wheat, and 28 years for oats, peanuts, and rice. Crop selection and the requirements for each crop and state were consistent with Bundy et al. (2024), which examined the climatology and spatiotemporal trends of USDA crop condition ratings.

Annual state- and national-level yield data were collected from the USDA NASS QuickStats database for each crop (USDA, 2025a). To account for long-term trends in yield—whether increasing or decreasing—a linear trend adjustment was applied to the state and national annual yield data. This adjustment removed underlying yield trend biases that could confound interannual comparisons. The linear detrending process followed Irwin and Good (2017a) and Bundy et al. (2024), using the following equation:

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

where Y represents the observed yield for a given year, β_1 is the linear rate of change in yield over the 38-year or 28-year period, x_i is the total number of years used, and x_n is the year number. To enable standardized comparisons across different crops, the standardized anomaly of annual crop yields was calculated at both state and national levels. Standardized anomalies were calculated using the following equation:

$$z = (\chi - \mu) / (\sigma) \quad (3)$$

where z represents the number of standard deviations by which crop yields were above or below the mean, χ is the yield value, μ is the yield mean, and σ is the yield standard deviation across the study period.

3.2 | NOAA vegetation health data

Weekly composites of the VCI, TCI, and VHI were collected at 4 km spatial resolution over the 1986–2023 period (NOAA, 2025a), aligning with the collection of USDA crop condition data. For further alignment, the weeks and months used for the respective crop, representing the defined growing season, were kept consistent across each state and year (Table 1). Crop-specific masking was applied to the VH data using CROPGRIDS, a ~5 km gridded global dataset that provides geo-referenced crop area information for 173 crop types for the year 2020 (Tang et al., 2024). Because the VH data (4 km) and CROPSGRIDS (~5 km) differ slightly in spatial resolution and grid alignment, masking was performed using a spatial intersection approach in which VH pixels were retained if the full pixel overlapped areas classified as the target crop, without resampling or interpolation. The CROPGRIDS dataset was selected due to its close spatial resolution with VH data. While higher resolution alternatives exist, such as the USDA Cropland Data Layer, they do not extend across the full historical condition period and introduce processing complexity when applied to a 4 km VH dataset. Moreover, the added spatial detail from finer-resolution cropland data does not necessarily improve the explanatory power with yield or climate anomalies when the underlying VH data inputs are coarser, as the effective resolution of the analysis is constrained by the satellite data. This constraint introduces another limitation with the satellite data, in that individual pixels may contain a mixture of irrigated and rainfed fields, particularly in regions with extensive irrigation systems (e.g., the Ogallala Aquifer and California's Central Valley). As a result, VH signals may represent an average of contrasting moisture conditions within a single pixel, potentially masking localized water stress or artificially dampening relationships with yield and climate anomalies.

A limitation of using the CROPGRIDS dataset is the temporal mismatch inherent in a static 2020 mask, as some pixels classified as a given crop in 2020 may not have been cropped (or were cropped differently) in earlier years, and conversely, historical crop areas that later contracted may be underrepresented. This mismatch could admit pixels or non-crop background into the county-level mean of weekly VH data, potentially diluting the crop signal and attenuating comparisons with yield and climatic anomalies. However, this limitation is partially mitigated when aggregating to the state level, as county-level VH data were weighted by the respective county's USDA-reported crop acreage for the given year in accordance with NASS methodology (USDA, 2025c). Thus, counties contributing less production in a given year received proportionally smaller weights than higher-producing counties, with weights updated each growing season to account for shifting crop distributions. For national aggregation, state-level VHIs were weighted by the mean planted acreage over the three preceding crop years and then summed. The resulting state- and national-level datasets for the CCIndex and VH data were then aligned for subsequent analysis.

VH data are derived from satellite observations beginning with data from the Advanced Very High-Resolution Radiometer (AVHRR), operational on NOAA polar-orbiting satellites since 1980, and, more recently, from the Visible Infrared Imaging Radiometer (VIIRS) onboard the Suomi National Polar-Orbiting Partnership (S-NPP) satellite since 2012 (Kogan et al., 2018). These data are processed into 7-day composites, like that of the USDA CPCR data, and at a spatial resolution of 4 km. Spectral differences between AVHRR and VIIRS required adjustments to collate them for analysis (Kogan et al., 2018). Pre- and post-launch calibrated visible (VIS) and near-infrared (NIR) measurements were converted to surface reflectance values for each pixel and week, which were then used to compute NDVI:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{VIS}) \times (\mathrm{VIS} + \mathrm{NIR})^{-1} \quad (4)$$

NDVI was subsequently derived from the surface reflectance values within the source dataset and obtained directly as a precomputed variable. Constructing VHIs is based on how healthy vegetation interacts with solar radiation. For example, healthy vegetation reflects little radiation in the VIS part of the solar spectrum due to its high chlorophyll content, reflects a large portion of NIR light due to higher water content and the specificity of scattering light by internal leaf tissues, and emits less infrared radiation (IR) since transpiration cools the canopy (Kogan et al., 2018). This results in a high NDVI and low IR-derived brightness temperature (BT), which is generally optimal for crop conditions. Though this interpretation assumes that vegetation sufficiently covers the surface, such that spectral and thermal signals are dominated by the crop canopy. However, under suboptimal planting densities, early growth stages, or in sparsely vegetated fields, exposed soil can contribute to both VIS/NIR reflectance and thermal emissions. In these cases, NDVI may be reduced and BT elevated due to soil background effects rather than true crop stress, potentially confounding VH-based assessments of crop condition.

Additionally, BT represents top-of-atmosphere radiance and does not fully account for surface emissivity and atmospheric effects, which can introduce further uncertainty in relating thermal signals directly to crop physiological status.

The VH algorithm includes three key processing steps (Kogan, 1987): (1) radiometric calibration and sensor harmonization; (2) noise reduction from weekly NDVI and BT, which includes the development of weekly NDVI and BT composites from daily data, removing low-frequency noise (clouds, aerosols, etc.), and removing high-frequency noise (heavy aerosols from volcanoes, late equator crossing time, etc.); and (3) calculation of VH based on noise-filtered NDVI and BT values to characterize the satellite-based weather component (Kogan, 1987; Kogan & Zhu, 2001; Kogan et al., 2003, 2017). Notably, the final step in the calculation of VH is theoretically grounded since NDVI and BT quantify the spatial difference in productivity between ecosystems (climate, soils, and topography—the ecosystem component) and weather-related variations in each ecosystem (the weather component). Since the ecosystem component is controlled by long-term factors, short-term weather-related NDVI and BT variations control interannual crop productivity (Kogan et al., 2018). Therefore, the ecosystem component is removed from NDVI and BT (Kogan, 1987; Kogan et al., 2003). Based on these factors, the multiyear climatology of NDVI and BT is generated using Liebig's law of minimum, Shelford's law of tolerance, and the principle of carrying capacity (Kogan et al., 2018). As a result, annual fluctuations of NDVI and BT from their climatological means are approximated using the indicator of moisture content—the VCI, the indicator of thermal conditions—the TCI, and a combination of both—the VHI. NDVI-based VCI, BT-based TCI, and the VCI–TCI combined VHI are approximated:

$$\mathrm{VCI} = 100 \times \left(\mathrm{NDVI} - \mathrm{NDVI}_{\min}\right) / \left(\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min}\right) \quad (5)$$

$$\mathrm{TCI} = 100 \times (\mathrm{BT}_{\max} - \mathrm{BT})/(\mathrm{BT}_{\max} - \mathrm{BT}_{\min}) \quad (6)$$

$$\mathrm{VHI} = \alpha \times \mathrm{VCI} + (1 - \alpha) \times \mathrm{TCI} \quad (7)$$

NDVI, NDVI_{max}, and NDVI_{min} (BT, BT_{max}, and BT_{min}) are no-noise weekly NDVI and BT and their climatological (1981–2023) absolute maximum and minimum, respectively. For the VHI, the α variable is a weight parameter between VCI and TCI that is set as $\alpha = 0.50$ since this share between variables is not known for specific crops and locations (Kogan, 1997; Kogan & Zhu, 2001). The VCI, TCI, and VHI are each scaled from 0 to 100, with values near 0 indicating extreme vegetation stress and values near 100 reflecting highly favorable conditions. Like NDVI, these VH data were already derived within the source dataset and obtained as a precomputed variable.

3.3 | Climatological data

Monthly county-level precipitation data were obtained from the NOAA nClimDiv dataset (NOAA, 2025b) to assess the relationship between mean temperature and precipitation anomalies with changes in the CCIndex, VCI, TCI, and VHI. The nClimDiv dataset provides area-weighted monthly mean temperatures and precipitation totals derived from 5 km grid-point estimates, which are interpolated from daily observations recorded by the Global Historical Climatology Network (NOAA, 2025b). County-level climatological data were aggregated to the state level using the same NASS methods that were applied on the CCIndex ratings and VH data for each crop. State-level, monthly mean temperatures and precipitation totals were calculated as standardized anomalies relative to the 1990–2020 baseline period for each state and crop using Equation 3.

4 | METHODS

Quantifying temporal characteristics of both subjective USDA crop condition ratings (CCIndex) and objective satellite-derived VHIs (VCI, TCI, and VHI) is essential for interpreting their seasonal signals, thereby optimizing their use in agricultural monitoring. Therefore, an exploratory correlation analysis was first completed to characterize the weekly tendencies, annual means, and interrelationships of the CCIndex and VH. Pearson's correlation coefficient (R) was employed to assess relationships among all crop condition variables at weekly and annual levels. Identifying seasonal patterns in CCIndex, VCI, TCI, and VHI, their correlations with crop yields were quantified at multiple temporal and spatial scales, including weekly, annual, state, and national levels. The preceding analyses used the standardized anomalies of the CCIndex, VCI, TCI, and VHI to allow for a fair comparison, as opposed to using the raw values of CCIndex (ranges 1–5) and VH (ranges 0–100). For the yield analysis, the coefficient of determination (R^2) was used to quantify the proportion of yield variance explained by the standardized anomalies of CCIndex, VCI, TCI, and VHI at the weekly–national, annual–national, and weekly–state levels, with $p < 0.05$ indicating a statistically significant difference. While the association between USDA crop condition ratings and yield has been explored in previous studies (e.g., Bundy & Gensini, 2022; Bundy et al., 2024; Irwin & Good, 2017a), and while VHI–yield relationships have also been examined across some US states, this study provides the first comprehensive assessment of both CCIndex and VH in relation to crop yield, with 105 possible state–crop combinations examined.

The final component of the analysis quantified crop condition responses with intramonthly climate anomalies, with the goal of assessing whether fluctuations in CCIndex, VCI, TCI, and VHI reflect known impacts of temperatures and precipitation on crop quality. To reflect monthly changes in crop condition indices (CCIndex, VCI, TCI, and VHI), the delta between the data during the first reported week of the following month and the last reported week of the preceding month was calculated. For example, when calculating the crop condition delta for the month of July, the delta between Week 30 (first week of August) and Week 26 (last week in June) was computed and collated with the standardized anomalies of temperature and precipitation in July of the given season. To address the complexities of modeling the nonlinear relationships between crop conditions and temperatures (Bundy et al., 2025b; Schlenker & Roberts, 2009) and crop conditions and precipitation (Bundy et al., 2022; Dill et al., 2020; Y. Li et al., 2019; Westcott & Jewison, 2013), a second-order polynomial regression model was applied to capture crop condition responses by climate anomalies. In so doing, these methods provide a framework for evaluating crop condition metrics, ensuring statistically robust and agronomically meaningful inferences regarding the utility of USDA crop condition ratings and NOAA VHI.

5 | RESULTS AND DISCUSSION

5.1 | Exploratory correlation

Weekly, national-level mean values of CCIndex ratings and VH displayed distinct, differing trends throughout the growing season for each crop (Figure 2). Except for rice, CCIndex ratings declined through much of the growing season, with mean subtle changes between the first and last condition reporting weeks ranging from −0.20 to −0.05 at the national level over the 38-year study period. Cotton and peanuts were the only two crops where mean CCIndex ratings improved during the first half of the growing season before declining during the second half (August onward). Rice was the only crop to continuously improve in CCIndex rating through the season, with increasing mean CCIndex ratings on the order of 0.09 from the first to last reporting week. In contrast, VH data did not display seasonal trends analogous to CCIndex ratings, as VH generally increased during the early portion of the growing season, peaked in July and August, and subsequently declined or plateaued through the remainder of the season. For example, the mean VHI when considering all summer crops together for the first respective reporting week was 53, which increased to 58 near the respective halfway point and declined to 54 by the final week. Across most crops, the correlation coefficient between the CCIndex and VH increased during the vegetation stages (June and early July; Figure S1) of the growing season, peaked during the transitional reproduction phase (end of July and August; VHI–CCIndex peak mean $R = 0.74$), and declined through the remainder of the season (Figure S2). VH also followed a stacked pattern, with VCI containing the highest values throughout the respective growing seasons, while TCI was the lowest, placing the VHI directly between the two. However, this pattern was not the case on a mean basis for spring wheat oats due to these crops being cultivated in a cooler climate across the northern domain of the United States, where TCI values are higher than those of other crops in this study, resulting in similar temporal behavior to the VCI and nearly identical VHI values on a mean basis.

Equally important is recognizing why CCIndex and VH data behave as they do week after week—a function of not only crop phenology and climate but also of the characteristics of the crop monitoring systems themselves, including differences in spatial resolution (human field observations vs. 4-km satellite observations), sensitivity to canopy structure, and soil characteristics. The early portion of the season for VH effectively captures the onset of greening, rate of canopy development, and overall vegetation biomass and leaf area, all of which are dependent on adequate moisture (higher VCI) and optimal temperatures (higher TCI) (Kogan et al., 2010; H. Li et al., 2022; A. Rahman et al., 2012; Yin & McClure, 2013). The observed upward trend in mean VCI, TCI, and VHI differs from the CCIndex (Figure 2), as USDA crop condition ratings are influenced by holistic field-level assessments that encapsulate all relevant information, including biophysical factors, local technological and management practices, and circumstances that affect the timing and regular progress of a crop (e.g., late planting dates), which is difficult to measure with remote sensing (Beguería & Maneta, 2020). However, previous research has noted that USDA crop condition estimates tend to be upwardly biased early in the season, as crops typically emerge under mostly normal conditions and final yields are also mostly near or above average (Irwin & Good, 2017b). Thus, crop conditions do start high and will remain relatively high or stable throughout much of the growing season. This observed pattern does not reflect a flaw in the dataset but rather an inherent feature of the ratings system arising from the skewed distribution of yield outcomes (Irwin & Good, 2017b).

Despite displaying similar declining trends in long-term means during the second half of the season (Figure 2), beginning in mid-July through mid-August across most crops, the correlation coefficient between the CCIndex and VHIs continuously declined through harvest. This correlation between the CCIndex and VHI peaked during the transitional phase from vegetative growth to reproductive development (R = 0.50–

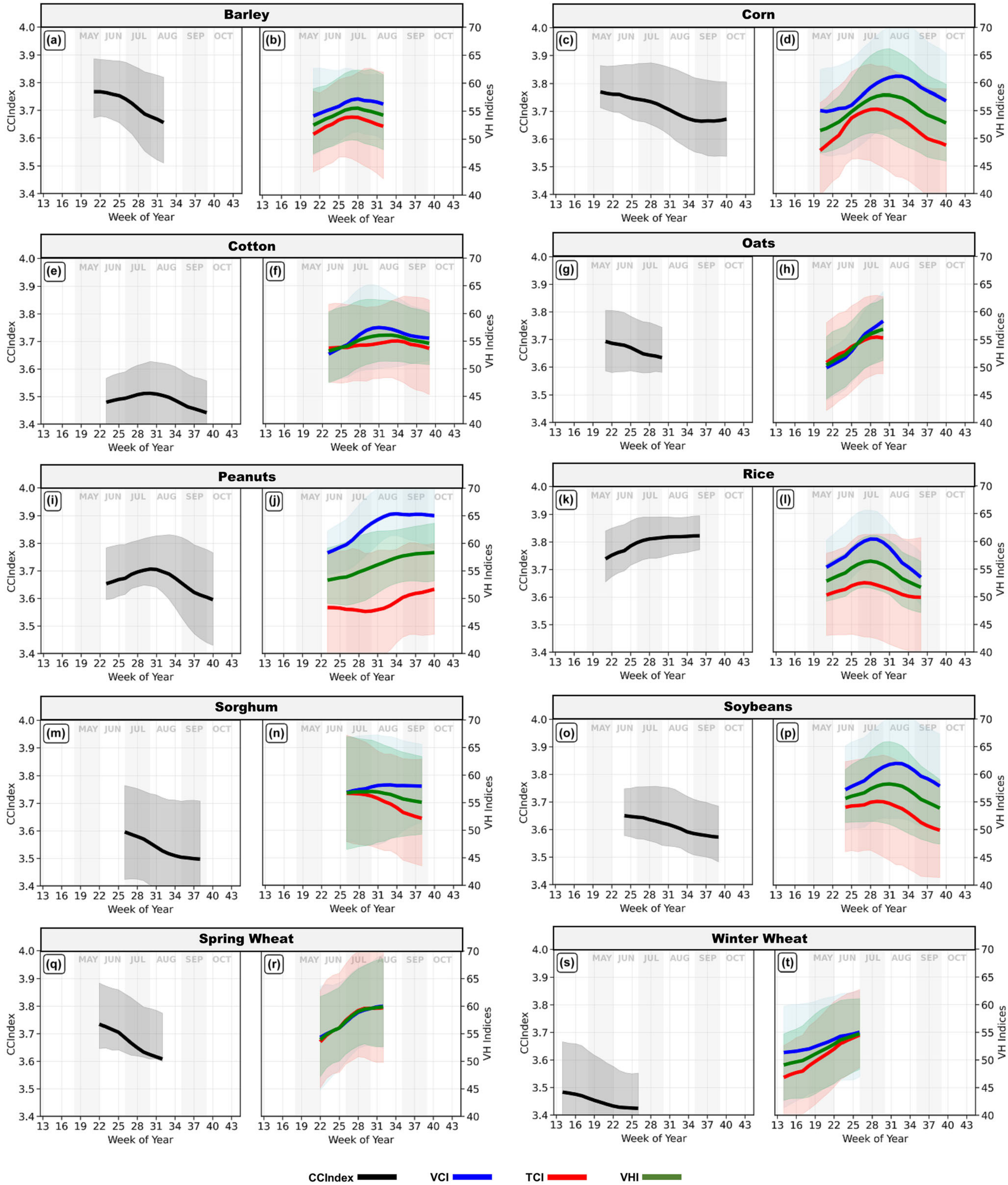

FIGURE 2 Weekly, national-level mean of crop condition index (CCIndex) (black), vegetation condition index (VCI) (blue), temperature condition index (TCI) (red), and vegetation health index (VHI) (green) ratings over the 1986–2023 for each crop. Interquartile ranges (75th–25th percentile) are represented with the shaded areas for each respective metric using the same color scheme.

0.85), a period when both crop monitoring systems captured the pronounced physiological shift (Figure S1). For summer crops, the critical phenological juncture in July and August marks when natural senescence begins, and canopy vigor, leaf area expansion, and chlorophyll content are typically at or near seasonal maxima (Gitelson et al., 2006; H. Yang et al., 2017). Hence, VH ratings naturally plateaued or declined—not necessarily because of environmental stress, but due to the gradual breakdown of green tissues as plants undergo reproductive development, such as grain or pod filling (Honěk & Martinkova, 2002; Sun et al., 2021; Figure S1). Natural senescence observed with the mean VH does not equate to increased crop stress and subsequent yield loss, whereas with CCIndex ratings, surveyor knowledge can account for the distinction between normal physiological decline and stress-induced deterioration, thereby mitigating misclassification of canopy changes as indicators of worsening crop conditions. This late-season divergence reflects the differing sensitivities of the metrics themselves: the CCIndex integrates agronomic factors closely tied to yield potential, whereas VH derived from NDVI and BT are more strongly linked to canopy greenness, leaf area, and vegetation coverage, which typically peak near flowering and decline toward maturity. Therefore, differing sensitivities of CCIndex ratings and VHIs during the growing season underscore the importance of explicitly accounting for crop phenology when interpreting remote sensing-based vegetation metrics and field-assessed crop condition metrics.

Differing seasonal trends and correlations may impose user difficulty when interpreting USDA crop condition ratings and VHIs comparatively. To improve crop condition/VH monitoring, it is essential to quantify how each metric deviates from its long-term weekly average at the state and national levels, since such departures provide additional context for whether observed weekly changes reflect true stress signals, improvement, or expected seasonal dynamics. This is particularly important given that USDA crop condition ratings are defined relative to an agronomic reference (e.g., very poor to excellent conditions), whereas VH represents departures from long-term vegetation and thermal baselines rather than categorical benchmarks. By expressing both datasets as standardized anomalies, these differing reference frames can be reconciled, allowing for a more consistent interpretation of relative crop condition. For example, when examining weekly, national-level corn CCIndex ratings and VHIs during the 2023 growing season, the CCIndex started at 3.70 in Week 22, declined during June, and reached 3.48 following a month when precipitation anomalies in the Corn Belt region ranked the ninth lowest of any June dating to 1895 (Figure 3a; NOAA, 2025b). Subsequent precipitation in July caused CCIndex ratings for corn to modestly improve through the month before stabilizing and declining again toward the season's end, finishing at 3.50. Meanwhile, VH increased during June and July, with the VHI peaking at 64 during Week 29 before declining through the remainder of the season. Without reference to historical averages, however, it is difficult to infer how these ratings and weekly trends may translate to yield prospects.

Standardizing each metric against its respective long-term weekly mean and standard deviation revealed that CCIndex anomalies remained below normal throughout the season, reaching -1.50σ during peak June dryness (Figure 3b). Even after timely July precipitation—often regarded as the most critical month for determining corn yield potential (Westcott & Jewison, 2013)—CCIndex anomalies did not recover to neutral levels, ending the season at -0.85σ. By contrast, VHI standardized anomalies were negative in June but steadily increased through July, remaining above normal from Week 26 to Week 33 (coinciding with corn pollination), before declining below normal in subsequent weeks. Notably, converting the CCIndex and VHIs to standardized anomalies did not materially change their weekly correlation with each other. The 2023 national corn yield ultimately reached 11,130 kg ha^{-1}, which was 1.9% below the trend yield of 11,340 kg ha^{-1} (Paulson et al., 2024)—VHI, TCI, and the CCIndex also contained a negative standardized anomaly prior to harvest; though, the CCIndex contained a negative standardized anomaly for the entire growing season. These outcomes underscore the need to evaluate which weeks of the growing season exhibit the strongest explanatory power between crop condition metrics and yield and to assess how each metric responds to distinct climate anomalies, thereby providing guidance for their interpretation in an operational setting.

Analyzing standardized CCIndex and VH anomalies at the annual level offers a more integrative perspective, permitting broader patterns of agreement between the two crop monitoring systems to emerge. When assessing the standardized anomalies of the interannual means for the four crop condition metrics, the correlation coefficient between the CCIndex and VHIs was statistically significant ($p < 0.05$) for all crops except rice (Figure 4). Among these, the CCIndex–VHI correlation consistently proved strongest across most crops, except for barley and winter wheat, where the CCIndex–VCI correlation was marginally stronger. This is intuitive, as the VHI integrates both moisture and thermal components, thereby offering a more holistic measure of stress (Kogan, 2002; Kogan, Adamenko, et al., 2013) and aligning closer with the subjective USDA crop condition ratings from an interannual perspective. For all summer crops, CCIndex–VHI correlations were particularly moderate, with R exceeding 0.50 for all crops except rice. For rice, flooded field conditions resulting from common irrigation practices during the growing season can alter spectral and thermal signals, dampening VHI signals and weakening its relationship with survey-based condition ratings, highlighting how crop management practices can modulate the relationship between the VHIs and CCIndex. When examining the interannual standardized CCIndex

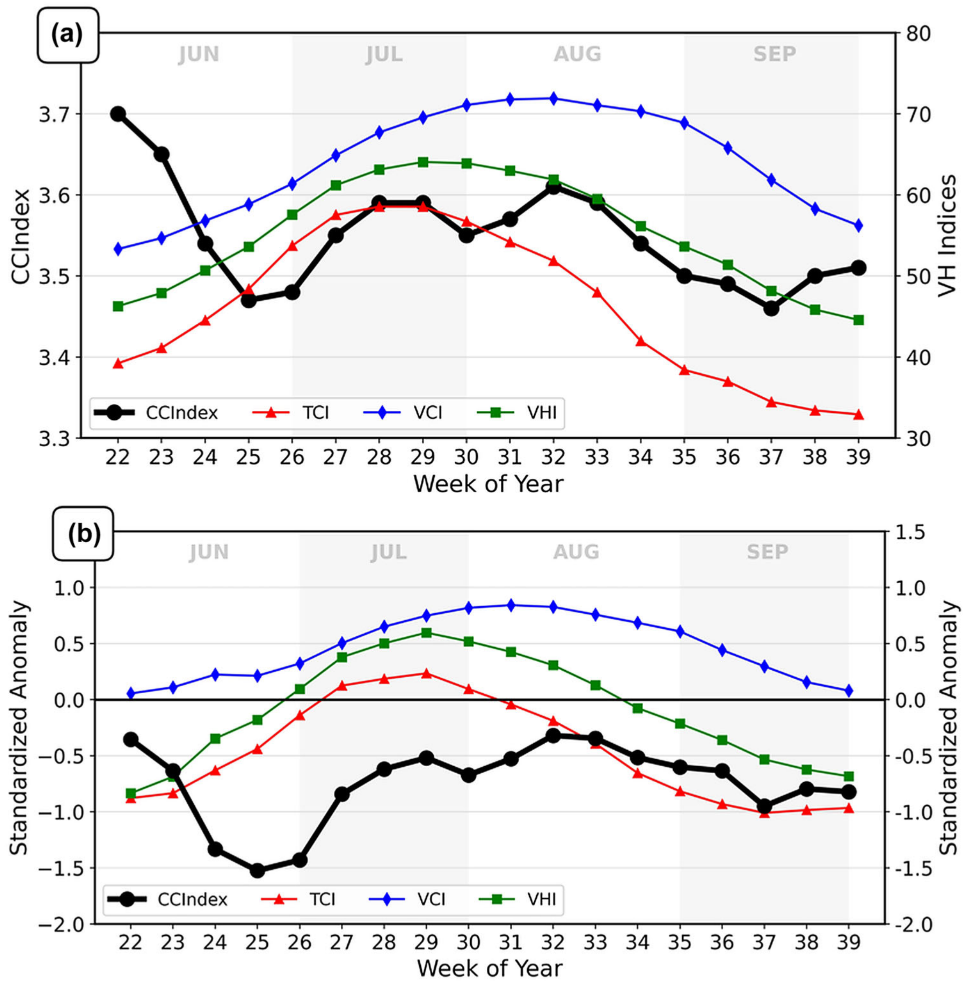

FIGURE 3 Weekly, national-level (a) crop condition index (CCIndex), vegetation condition index (VCI), temperature condition index (TCI), and vegetation health index (VHI) ratings, and (b) standardized CCIndex, VCI, TCI, and VHI anomalies for corn during the 2023 growing season.

and VHI anomalies, sorghum contained the strongest correlation between the two metrics ($R = 0.75$) and the highest number of years when the anomalies of the two metrics agreed (32 of the 38 years exhibiting concordant positive or negative deviations), followed by corn with 29, and soybeans and winter wheat with 28. In years with misalignment in deviations between the CCIndex and VHI, the TCI aligned with the VHI in 82% of cases, while the VCI aligned with the VHI in 65% of cases. Thus, when discrepancies emerged between CCIndex and VH anomalies, they were frequently accompanied by similar inconsistencies in the CCIndex–TCI and CCIndex–VCI relationships. These similar inconsistencies between the CCIndex and VHIs are expected, as VHI is a composite metric derived from the TCI and VCI, and, therefore, is not independent of its components. Consequently, discrepancies between the CCIndex and VHI will inherently reflect corresponding inconsistencies in the CCIndex–TCI and CCIndex–VCI relationships. Misalignments in crop condition anomalies warrant further investigation, as they not only influence the relationship between crop condition metrics and yield outcomes but also shape the understanding of crop condition responses to various climatic conditions.

5.2 | Yield analysis

Of all crops and years examined in this study, anomaly signs between annual mean crop condition metrics and yields were aligned in 70% of cases for the CCIndex, 61% for the VCI, 64% for the TCI, and 65% for the VHI at the national level. Barley, cotton, oats, and sorghum were the only crops in which one or more VH metric annual anomalies aligned with yield anomalies in more years than the CCIndex annual anomalies. This variation in alignment highlights that the relative performance of crop condition metrics is crop-specific, and this necessitates closer examination of their temporal relationships with yield. Across all crops, the explanatory power between standardized CCIndex and VH anomalies with detrended yield anomalies contained distinct seasonal trajectories (Figure 5). At the weekly, national level, the explanatory

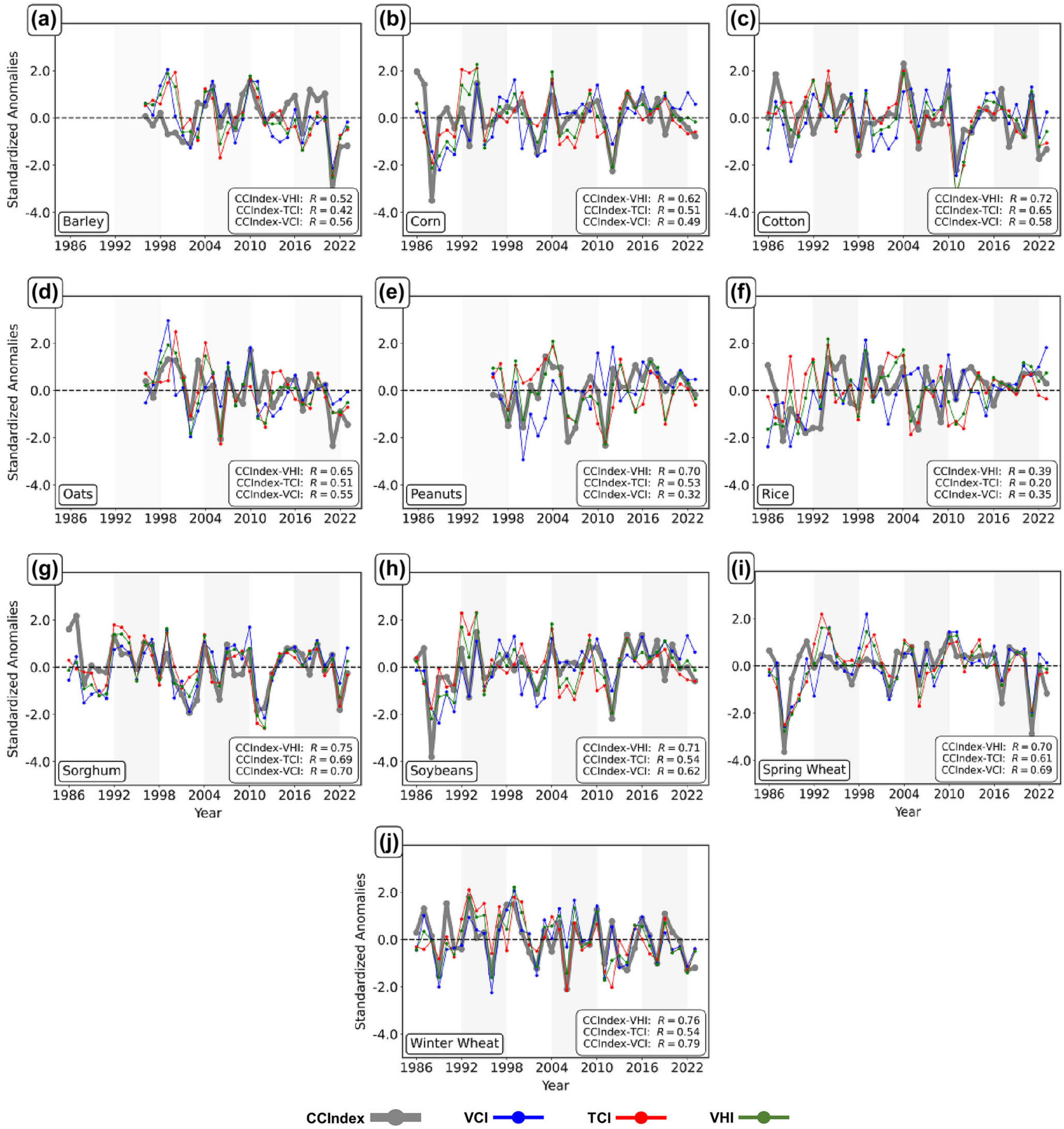

FIGURE 4 Interannual, national-level standardized crop condition index (CCIndex), vegetation condition index (VCI), temperature condition index (TCI), and vegetation health index (VHI) anomalies for each crop over the 1986–2023 study period.

power between the CCIndex and yield consistently increased from early season emergence to harvest, with peak R^2 values occurring within the final respective reporting weeks for each crop. This statistically significant (0.05 significance level) covariate relationship was particularly robust for major row crops, as national CCIndex ratings for barley and corn explained around 75% of the variance in yield, while peanuts, sorghum, soybeans, and wheat CCIndex ratings explained 50%–65% of the variance in yield during the final weeks of the reporting period (Figures 5 and 6). Corn contained the most weeks with an R^2 between the CCIndex and yield above 60%, with twelve, followed by barley with six, and soybeans and spring wheat with five. However, barley, sorghum, spring wheat, and winter wheat were the only crops where the CCIndex was a statistically significant ($p < 0.05$) covariate to yield for every respective week in the season. Also, while

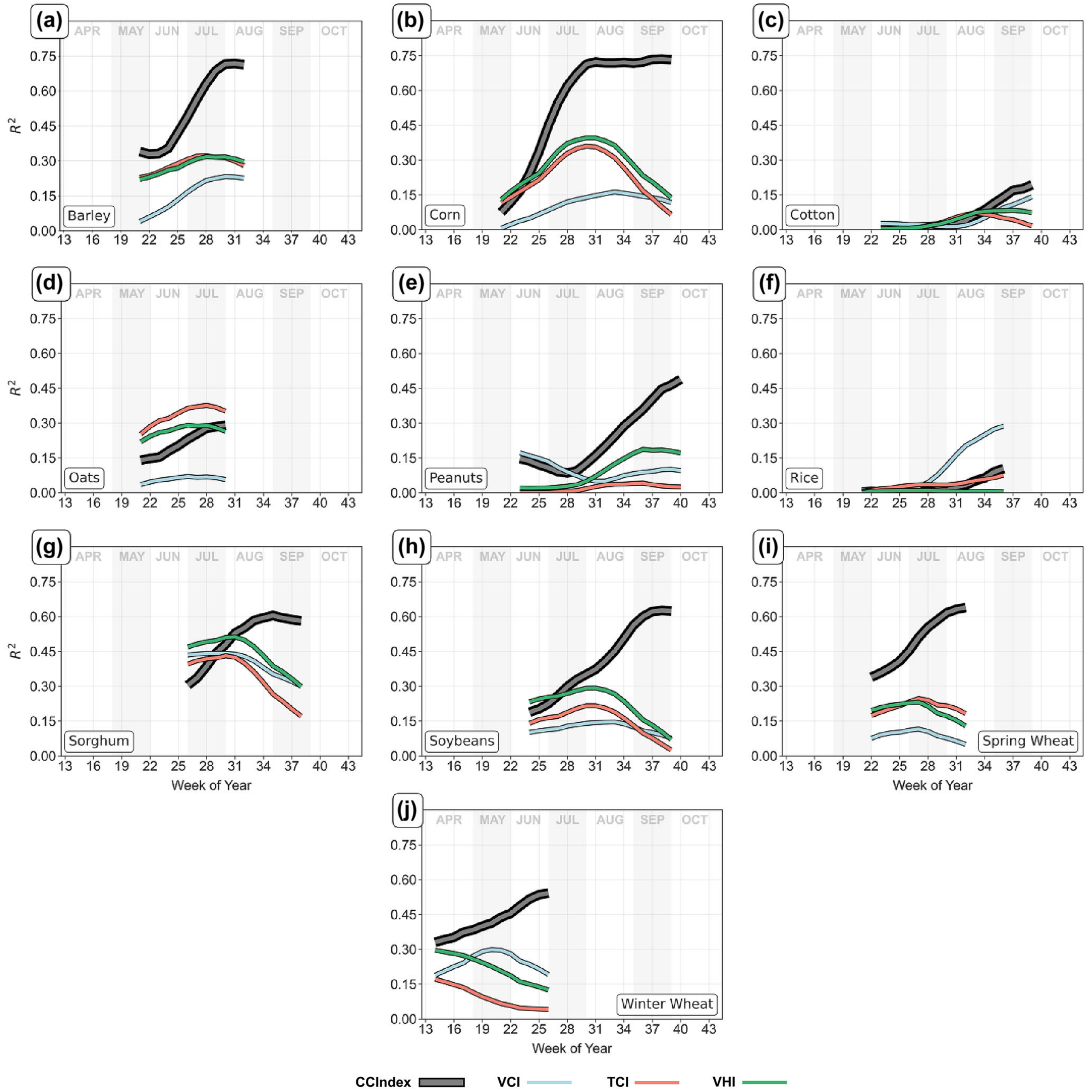

FIGURE 5 Weekly, national-level coefficient of determination (R^2) values between standardized crop condition index (CCIndex) (gray), vegetation condition index (VCI) (blue), temperature condition index (TCI) (red), and vegetation health index (VHI) (green) anomalies with standardized detrended yield anomalies for each crop over the 1986–2023 study period.

the CCIndex for oats was among the lowest in skill (maximum $R^2 = 29\%$ during week 30; Figure 6), the only two crops without a statistically significant week between the CCIndex and yield were cotton and rice.

In contrast to the general CCIndex–yield pattern, VH ratings reached their maximum explanatory power with yield earlier in the season than the maximum CCIndex–yield R^2, typically during the mid-July through early August period, followed by declines in explained variance during maturation and senescence across corn, sorghum, soybeans, and spring wheat (Figure 5). This parabola-like pattern was most evident for corn, sorghum, soybeans, and spring wheat, with corn and sorghum obtaining the highest explanatory power among any of the VH ratings with yield (VHI–yield $R^2 \geq 0.40$; Figure 6). This seasonal divergence in explanatory power reflects fundamental differences in what each monitoring system captures. The CCIndex integrates multiple agronomic attributes directly related to yield formation,

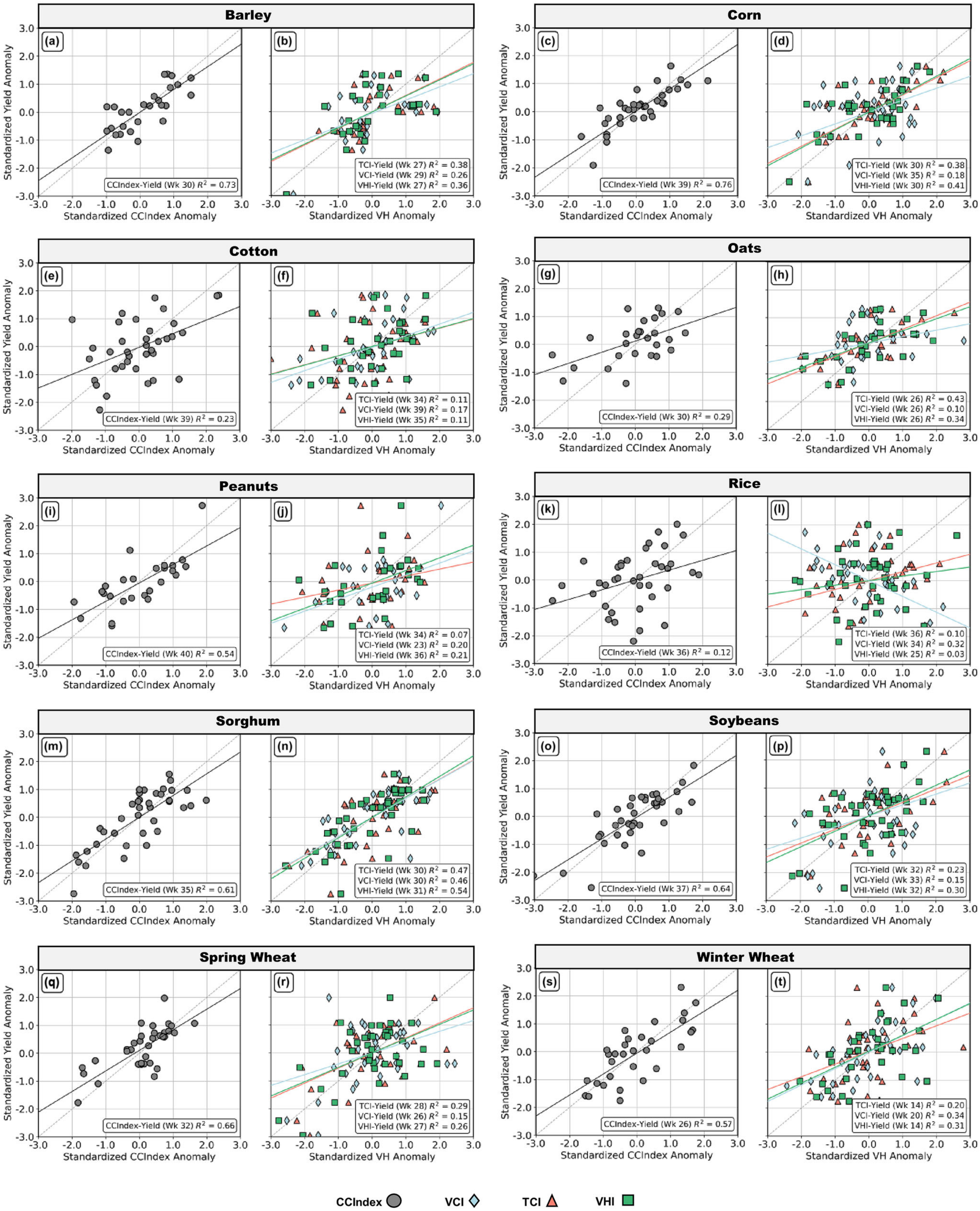

FIGURE 6 Standardized crop condition index (CCIndex), vegetation condition index (VCI), temperature condition index (TCI), and vegetation health index (VHI) anomalies plotted against standardized detrended yield anomalies for only the week with the maximum R^2 during the season for each crop (1986–2023). Gray dashed line indicates a perfect one-to-one linear relationship. Black solid line indicates the linear regression between the CCIndex and yield, while the solid red (TCI), solid blue (VCI), and solid green (VHI) represent the linear regression with yield. Regression coefficients are shown in the lower right corner of each panel.

including aboveground biomass, plant height, foliar structure, and the presence of pests, disease, and other stressors. As crops approach flowering—a critical period for yield determination in many crops—these factors become increasingly indicative of final yield outcomes, resulting in strengthened CCIndex–yield relationships later in the season. In contrast, VH ratings are more closely tied to canopy greenness and leaf area, which typically peak near flowering and subsequently decline during senescence. As a result, VH–yield relationships often reach maximum explanatory power earlier in the season and weaken as crops mature, when distinguishing between natural aging and stress-induced canopy decline becomes more challenging. This pattern highlights the importance of phenological context when interpreting crop condition metrics and suggests that integrative approaches, such as cumulative vegetation metrics, may help better capture the progressive accumulation of biomass and improve yield estimation beyond single-week relationships. Exceptions to this VH–yield seasonal relationship included cotton, peanuts, and rice, with differing, statistically insignificant VH–yield relationship trends throughout the season. Similarly, the VCI explained an increasing proportion of variance in rice and cotton yields during the latter half of the season, highlighting the increased sensitivity precipitation and moisture availability have on crop productivity (Eck et al., 2020; Peng et al., 2004; M. A. Rahman et al., 2017).

The CCIndex consistently outperformed VH ratings in explanatory power with national yield across most crops and most growing season weeks (Figure 5). Except for oats and rice, the peak explanatory power of any of the VHIs never surpassed that of the CCIndex. Moreover, weekly, seasonal maximum CCIndex–yield R^2 values exceeded peak VH–yield R^2 values by more than 30% for barley, corn, peanuts, soybeans, and spring wheat (Figure 6). These differences underscore a divergence in physiological signal: CCIndex ratings, being subjective evaluations, integrate field-level knowledge of crop vigor, stress, and development, therefore retaining a stronger yield-relevant signal all the way through harvest. Conversely, with the VH based on canopy reflectance and thermal properties, these ratings become increasingly decoupled from yield potential once natural senescence begins. The result is a mid-to-late season decline in explanatory power of yield using VHIs, which has been observed in previous research for other global crop areas: Australia wheat (Kogan et al., 2018), China corn (Kogan et al., 2005), Russia grain crops (Kogan et al., 2016), Southern Africa corn (Unganai & Kogan, 1998), Brazil soybeans (Liu & Kogan, 2002), Poland cereal crops (Dabrowska-Zielinska et al., 2002), and Greece cotton (Domenikiotis et al., 2004). Across most crops in this study, while VH ratings are valuable for early- to mid-season yield assessments, the CCIndex provides a more reliable indicator of final yield outcomes across the full growing season at the national level when using linear regression. Despite the observed diverging trends between CCIndex–yield and VH–yield, at their maximum explanatory power, both displayed a positive linear covariance between the condition metric and yield, suggesting that, in general, the higher the CCIndex, VCI, TCI, or VHI, the higher the crop yield potential (Figure 6). Notably, the rice VCI–yield relationship is an exception to the general positive covariance, with a moderate ($R^2 = 0.32$) negative relationship at the national level between the VCI and yield anomalies, which is the strongest explanatory power with yield among all the crop condition indices for rice.

Of the 105 possible state–crop combinations evaluated, only three (Colorado corn, Iowa oats, and Wisconsin oats) did not contain a statistically significant relationship in any week between yield and any of the four crop condition metrics at the 95% significance level (Figure 7). Furthermore, 84% of all state–crop combinations had at least one crop condition metric that displayed a statistically significant relationship with yield in at least half of the respective reporting weeks, and 71% retained significance in 75% or more of the weeks. Sorghum and spring wheat emerged as the only crops with all reporting weeks in all states, except for one state for each crop, having statistical significance (CCIndex–yield). Overall, 63% of all state–crop combinations achieved maximum explanatory power with yield exceeding 50%, with 93% of those combinations driven by the CCIndex. Over the 1986–2023 period, the CCIndex was the highest predictor of yield for 81% (85 of 105) of state–crop combinations, particularly in core production regions for corn, sorghum, soybeans, and winter wheat (Figure 7; Table S1). However, exceptions occurred for certain crops and regions where VHIs provided a stronger explanatory power of yield. In Texas, the VCI and TCI explained more variance in corn, cotton, peanut, and rice yields, while California and Idaho were the only states where VH ratings consistently outperformed the CCIndex across all crops. These regional, crop-specific discrepancies underscore the need for future research to evaluate crop condition metrics at the state level across diverse agroecosystems while also disentangling climatic drivers, crop physiological processes, management practices, and other sensitivities that may explain why some crop condition metrics outperform others.

While this study focuses on direct, week-by-week linear relationships between the CCIndex, VH system, and yield, the authors acknowledge that more advanced modeling approaches can enhance predictive explanatory power and skill beyond the simple linear framework applied here. Methods that incorporate cumulative index approaches, additional agroclimatic predictors, or machine learning techniques have demonstrated improved performance in capturing yield variability (e.g., Becker-Reshef et al., 2010; Doraiswamy et al., 2005; Johnson et al., 2021; Pham et al., 2022; Rembold et al., 2013). Future research could incorporate alternative

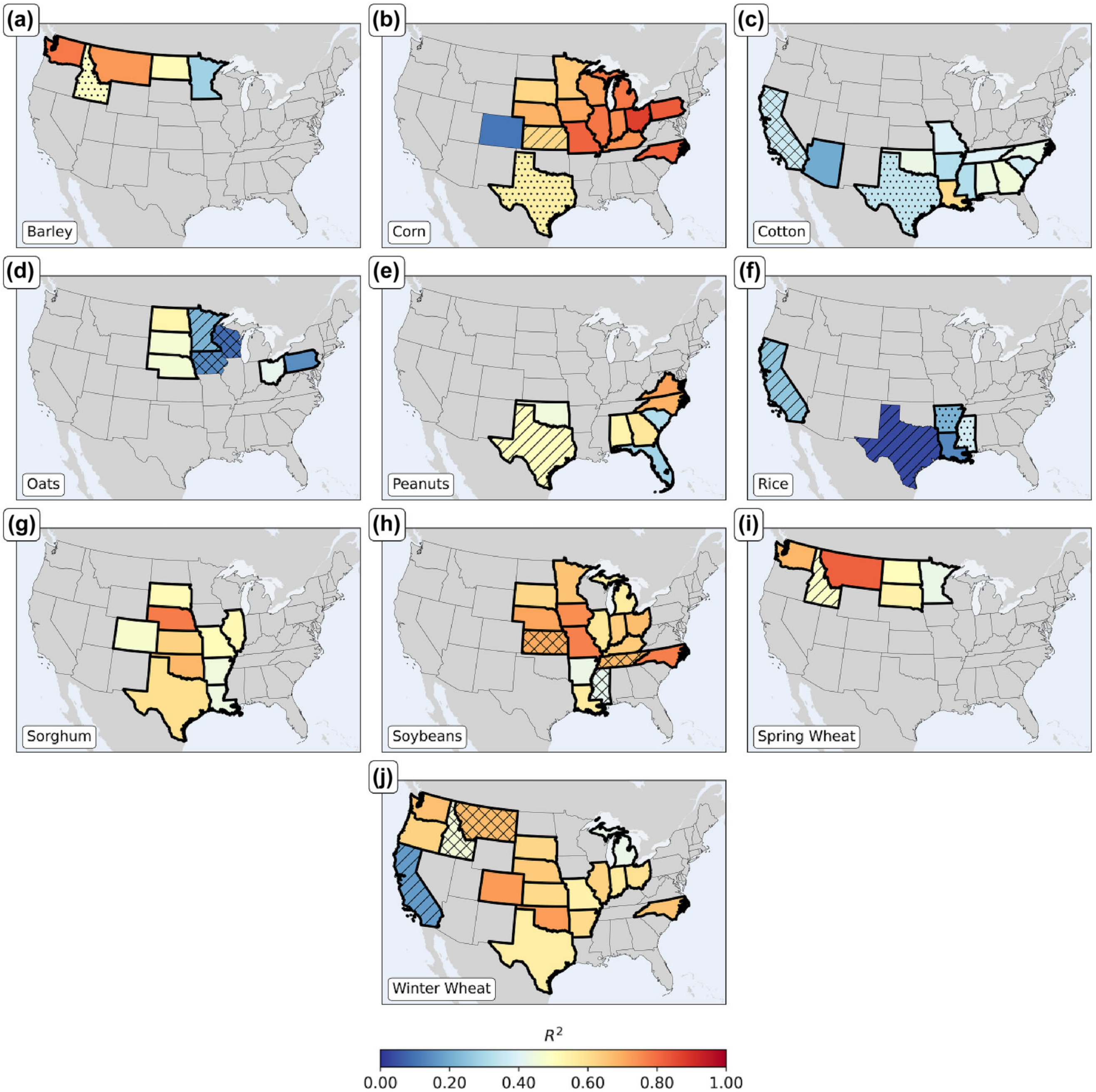

FIGURE 7 Weekly, state-level maximum coefficient of determination (R^2) values between either crop condition index (CCIndex) ratings and yield, vegetation condition index (VCI) and yield, temperature condition index (TCI) and yield, or vegetation health index (VHI) and yield for each crop. Unmarked states indicate the CCIndex contains the highest explanatory power with yield; hatched states indicate TCI; dotted states indicate VCI; and double-hatched states indicate VHI. States with a thicker black border indicate statistical significance at the 0.05 significance level.

vegetation indices, such as the green chlorophyll vegetation index and enhanced vegetation index, which may provide increased sensitivity under high biomass conditions where NDVI and VHI saturation (high values of leaf area or biomass) can occur. Additionally, integrated products such as the vegetation drought response index or evaporative stress index offer complementary perspectives by incorporating soil moisture and evapotranspiration information, potentially improving the detection of crop stress that is not fully captured by greenness-based metrics alone. Incorporating these other indices within a unified framework represents a logical next step for improving yield estimation and extending the applicability of satellite-based monitoring, particularly when combined with survey-based metrics such as the CCIndex.

5.3 | Climatological analysis

The extent to which crop condition metrics capture and respond to climatic conditions (e.g., extreme temperatures and precipitation) is a key determinant of their ability to explain yield anomalies. Moreover, the ability of these metrics to adequately respond to a range of climatic anomalies, based on modeling and empirical evidence from prior research (e.g., Y. Li et al., 2019), enhances their predictive power on a weekly basis. When examining monthly precipitation anomalies alongside corresponding changes in monthly crop condition metric anomalies, the CCIndex (excluding rice) displayed a declining, negative response to below-normal precipitation anomalies (Figure 8). Across most crops, a monthly precipitation anomaly of -2.0σ resulted in a CCIndex anomaly of approximately -1.0σ when using the second-order polynomial regression model. When restricting the analysis to only consider below-normal precipitation ($<0.0\sigma$), the mean correlation coefficient between changes in the CCIndex and negative precipitation was 0.27 across all crops. Positive changes in CCIndex anomalies generally occurred when precipitation anomalies ranged from 0.0σ to 2.5σ. All crops displayed a wider variation in values from excessive precipitation ($>2.0\sigma$; Y. Li et al., 2019), which is reflected in the broader 95% confidence intervals. For corn, cotton, oats, soybeans, and winter wheat, the modeled CCIndex polynomial response declined, and the respective 95% confidence intervals widened at some level of above-normal precipitation totals (typically 2.0σ to 3.0σ). While many crops displayed a degree of negative CCIndex response to excessive precipitation anomalies to a similar magnitude as severe dryness ($<-2.0\sigma$), the correlation coefficient in these responses declined with severity. The mean correlation coefficient between precipitation anomalies greater than 1.0σ and corresponding CCIndex responses was -0.13, though the number of excessive precipitation instances ($n = 1749$) was substantially smaller than dryness cases ($n = 6856$) when considering all crops together, which reduces statistical confidence in the response to excessive precipitation. Still, the low correlation coefficient of -0.13 was statistically significant at the 0.05 significance level across most crops.

Despite these limitations, the observed responses of the CCIndex to both dry and wet conditions broadly reflect historical yield outcomes, particularly for corn, where excess moisture has been shown to produce yield losses comparable to those associated with drought (Y. Li et al., 2019). Notably, most crop models have failed to capture this nonlinear yield response to precipitation, often simulating marginal yield increases or monotonically higher yields with above-normal precipitation totals (Y. Li et al., 2019). Excessive precipitation imposes multiple stressors to all crops examined: waterlogging and flooding, restricted root development (Parent et al., 2008), nitrogen deficiencies (Jabloun et al., 2015), heightened disease risk (van der Velde et al., 2012), and delayed fieldwork operations (Urban et al., 2015). Thus, the CCIndex not only reflects crop responses to moisture deficits but also captures nonlinear declines under excessive precipitation, aligning with other observational studies of precipitation impacts on crop productivity (e.g., Bucior et al., 2025; Eck et al., 2020; Mourtzinis et al., 2015; Westcott & Jewison, 2013).

VH anomaly responses to below-normal precipitation paralleled those of the CCIndex, though with a less pronounced decline in magnitude as dryness severity increased for corn, cotton, oats, peanuts, and soybeans (Figure 8). When isolating negative precipitation anomalies, the VCI exhibited the strongest association across most crops, with a mean correlation coefficient of 0.23. Modeled VH response across all crops ranged from -0.10σ to -0.05σ when precipitation anomalies were -2.0σ, with barley, corn, and cotton displaying the strongest sensitivity among all crops to below-normal precipitation. In contrast, responses to excessive precipitation anomalies were variable across crops, with broader 95% confidence intervals (ranging from -2.0σ to 1.5σ) indicating lower certainty and weaker correlations (mean $R = -0.05$ for precipitation anomalies $\geq 1.0\sigma$). Corn, cotton, and soybeans were notable exceptions, as their VCI responses under wet extremes approached the magnitudes observed during the driest conditions. In some years when yield anomalies were hindered by excessive precipitation (e.g., corn in 1993 and 2019), CCIndex anomalies captured these impacts more clearly than VHIs, underscoring a key peril where crop condition metrics can misalign. This discrepancy is consistent with documented time lags of 1–4 weeks between physiological stress and satellite-detectable canopy impacts, which vary with antecedent moisture and crop phenology (Wang et al., 2001, 2003; W. Yang et al., 1997). Monthly aggregation further compounds these issues, since a single extreme precipitation day can skew monthly anomalies and mask shorter-lived but agronomically important responses. Moreover, collapsing all states and months into a single response surface (Figures 8 and 9) disregards spatiotemporal heterogeneity, such as heightened drought sensitivity in water-limited regions or heightened precipitation impacts during vegetative growth stages (Bundy et al., 2025b; Y. Li et al., 2019). When examining further across all state–crop–month combinations ($n = 387$), robust precipitation-condition linkages were revealed, as 37% of CCIndex relationships with precipitation were statistically significant, with corn, sorghum, and soybeans containing the highest R^2 and the highest number of statistically significant state-month combinations (Table S2). In comparison, precipitation anomalies were statistically significant covariates for 9% of TCI, 34% of VCI, and 31% of VHI datapoints. These findings emphasize the CCIndex's stronger and more consistent precipitation sensitivity, while suggesting that future work should examine

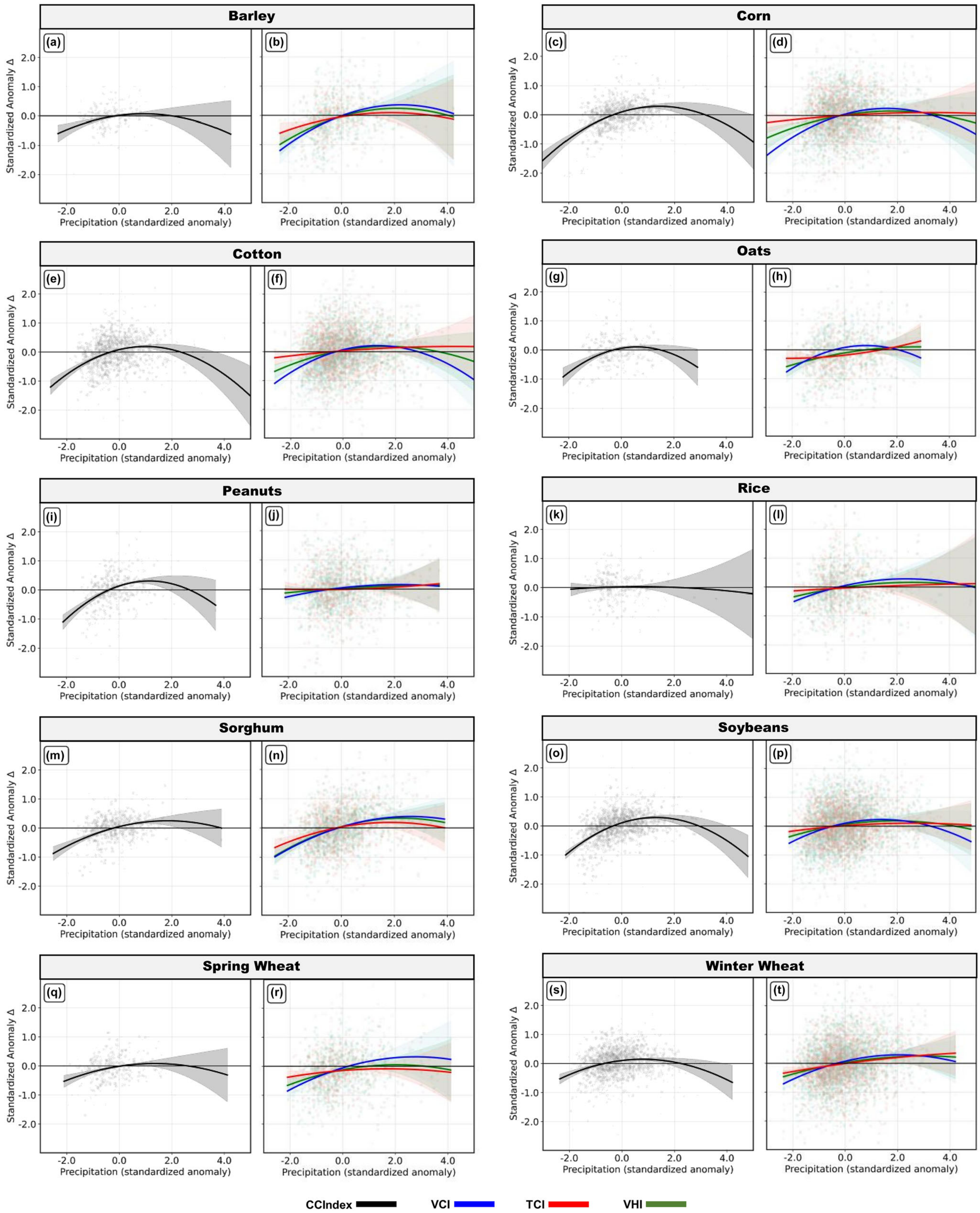

FIGURE 8 Monthly, state-level changes in the standardized crop condition index (CCIndex) (black), vegetation condition index (VCI) (blue), temperature condition index (TCI) (red), and vegetation health index (VHI) (green) anomalies relative to standardized precipitation anomalies for all growing-season months for each crop. Second-order polynomial regression fits with 95% confidence intervals shown for each metric in corresponding colors.

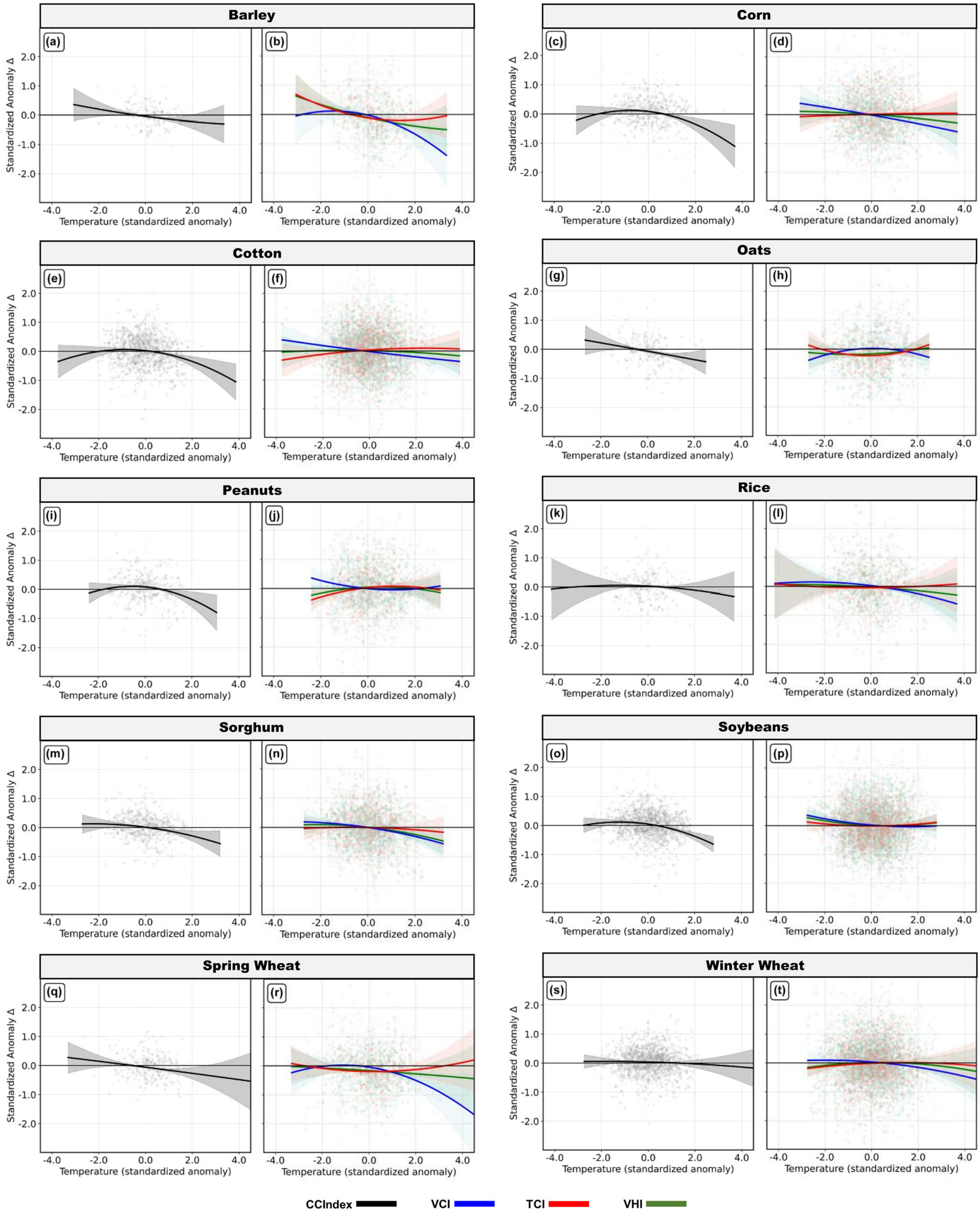

FIGURE 9 Monthly, state-level changes in the standardized crop condition index (CCIndex) (black), vegetation condition index (VCI) (blue), temperature condition index (TCI) (red), and vegetation health index (VHI) (green) anomalies relative to standardized temperature anomalies for all growing-season months for each crop. Second-order polynomial regression fits with 95% confidence intervals shown for each metric in corresponding colors.

VH responses to excessive precipitation at finer spatial and temporal scales.

Like precipitation, temperature effects on crops are also nonlinear, as below-normal temperature anomalies are benign or even beneficial, whereas above-normal temperature anomalies beyond crop-specific thresholds impose accelerating declines in yields for major crops (Y. Li et al., 2019; Schlenker & Roberts, 2009). In this analysis, isolating the pure temperature effects was constrained by the strong covariation with precipitation—mean monthly temperature anomalies contained a statistically significant negative correlation coefficient with precipitation—a pattern that mirrors previous research on temperature–precipitation relationships (Seneviratne et al., 2010; Trenberth & Shea, 2005). Polynomial regression fits across all crops and months captured the general nonlinear effects of temperatures on condition metrics, as under above-normal temperatures, CCIndex anomalies declined at an increasing rate, just with wider confidence bands where observations were sparse (Figure 9). When temperature anomalies were at 2.0σ, the mean CCIndex response across all crops was -0.04, while the mean response was 0.01 when temperature anomalies were -2.0σ. After stratifying by state and crop, 18% of state–month combinations attained statistically significant CCIndex–temperature relationships (Table S3).

VH anomaly responses to temperature anomalies exhibited similar nonlinearity but with smaller magnitudes than CCIndex anomaly changes. Among the VH components, CCIndex anomaly changes aligned the closest with VCI anomaly responses to temperatures (mean $R = 0.31$). At the state–crop level, 8% of VHI state–month combinations were statistically significant, compared with 2% for TCI and 15% for VCI. Several physiological and agronomic pathways plausibly explain this asymmetric heat sensitivity: (1) warming accelerates development and shortens critical periods, such as grain filling, reducing final yield (Hatfield & Prueger, 2015); (2) warmer air increases the vapor-pressure deficit and promotes plant stomatal closure, which depresses photosynthesis and amplifies water stress (Novick et al., 2016); and (3) reproductive stages are especially heat-sensitive, as brief heat waves around flowering can impair pollen viability, fertilization, and kernel/pod set (e.g., in corn), while elevated nighttime temperatures increase respiration and further reduce yields (Sadok & Jagadish, 2020). Collectively, these mechanisms generate threshold-like aggregate crop condition responses, which crop condition metrics must be sensitive to if they are to provide reliable early warnings of yield risk.

Building on this, future work should examine crop condition–climate relationships at finer spatiotemporal resolutions, explicitly incorporate phenology, and explore other modeling methods (e.g., machine learning) to refine the predictive skill of the CCIndex and VHIs. Even at the state and monthly level using second-order polynomial regression, the results underscore the CCIndex's, and the VH ratings to an extent, practical value as an integrative indicator for monitoring crop-climate interactions and for improving model representations of nonlinear weather-yield relationships. Though precipitation and temperature do not solely determine changes in crop conditions or yield, additional factors—solar radiation (Hoogenboom, 2000), nutrient management (Gehl et al., 2005), weed competition (Zimdahl, 2007), and broader management practices (Y. Li et al., 2019)—exert nontrivial influences. As an initial step, the state–month polynomial framework detects hydroclimatic signals in crop condition metrics and establishes an interpretable baseline that can be scaled to finer resolution in future work, laying the foundation for more robust predictability with early yield risk.

6 | CONCLUSIONS

This 38-year (1986–2023) multi-crop analysis offers a comprehensive evaluation of US crop condition indicators derived from ground survey-based assessments and satellite remote sensing. For 10 major field crops, the USDA CCIndex and the NOAA VH system (TCI, VCI, and VHI) contained distinct yet complementary seasonal trajectories. The VH ratings exhibited their highest explanatory power of yield variance from late vegetative through early reproductive stages across most crops, when canopy greenness, temperature, and moisture stress directly modulate reflectance and thermal signals. However, VH and yield association diminished thereafter as senescence reduced the physiological greenness content. In contrast, the CCIndex remained strongly coupled to yield outcomes through critical periods of grain filling and maturation for most crops. Results demonstrate that while the one-to-one analysis quantifies how the CCIndex and VHIs covary with yield, richer transformations and hybrid frameworks can plausibly achieve more accurate yield models than simple weekly linear regression with raw data. Climate-response analyses further quantified the contrasts between the two crop monitoring systems: both CCIndex and VH metrics captured the negative effects of heat and dryness, but CCIndex responses to wet anomalies aligned more closely with agronomic theory and prior empirical evidence, reflecting the adverse effects of excess moisture. The strength to remain statistically robust through maturation and its sensitivity to both tails of moisture distribution likely arise from expert crop assessments that implicitly integrate field-scale management practices, phenological cues, and microclimatic context that may be difficult to resolve through satellite information.

Study results support a blended, phenology-aware monitoring strategy that uses survey and satellite data in conjunction rather than as substitutes. VH products offer globally consistent, weekly coverage at 4 km spatial resolution that enables prompt detection of emerging canopy stress, supporting early- to mid-season surveillance and situational awareness. USDA crop condition ratings contribute agronomic nuance, mid- to end-of-season persistence, and closer alignment to yield outcomes in the United States. When used together, these indicators can reduce blind spots across the growing season, increase decision-making confidence when stress signals emerge, and flag disagreements between ground and spaceborne observations for targeted investigation. Future work should integrate CCIndex ratings and VH data within phenology-explicit models, extend evaluation to a finer spatiotemporal resolution, and test alternative modeling frameworks (e.g., machine learning) that preserve interpretability while improving yield assessment skill. From an operational perspective, such integration is both feasible and increasingly practical, as many existing US agricultural monitoring systems and dashboards already incorporate elements of survey-based and/or satellite-derived information. Enhancing these platforms to explicitly combine CCIndex and VH signals, particularly through anomaly-based frameworks and phenology-aware models, could be achieved with relatively modest adjustments to current workflows. While challenges remain, including differences in spatial resolution, data latency, and user familiarity, the complementary nature of these datasets aligns well with the needs of analysts, producers, and risk managers. Ultimately, the greatest gains will come from integration—combining the spatial reach of satellite VH products with the agronomic insights from the survey-based crop condition reports—and embedding these combined indicators within operational tools to deliver a more resilient, early-warning-capable crop monitoring system for assessing yield risk in an era of increasing climatic volatility.

AUTHOR CONTRIBUTIONS

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

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

All data used in this research are publicly available through the USDA and NOAA.

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