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Spatiotemporal trends in crop yields, yield variability, and yield gaps across the USA

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Abstract

Future crop yield increases are unlikely to keep pace with the dietary needs of a global human population expected to reach nine billion by 2050. This study used United States Department of Agriculture county-level yield data and autoregressive moving-average models to examine how changes in maize (*Zea mays* L.), soybean (*Glycine max* L.), and winter wheat (*Triticum aestivum* L.) yields, temporal variability in yields, and yield gaps have varied across space and time from 1970–2017. The majority of county-level yields have increased linearly, although the increases in wheat lag behind corn and soybean. Where trends were nonlinear, accelerating yields were found in more mesic regions east of the Great Plains, and decelerating yields were found in the drier central and western United States. Mean crop yields were positively correlated with rate of yield increase and negatively correlated with interannual variability. Hotspots were identified in Minnesota, Iowa, Illinois, Nebraska, and some West Coast states where crop yields are currently the largest, have the lowest yield gaps, and since 1970, have had the highest rates of change and/or are experiencing an acceleration of annual yield gains. Across all crop types, the counties with the lowest average yields, highest yield gaps, lowest rates of yield increase over time, and/or deceleration in yield increases were predominantly found in the central United States, including the Dakotas, Kansas, Oklahoma, and Texas. Regions of greatest performance generally have fertile soils, plentiful growing season rainfall, and optimal growing season length and temperatures, or are benefitting from irrigation.

1 | INTRODUCTION

Global demand for food is expected to double by the middle of the 21st century when global population could reach 9.8 billion people (Foley et al., 2011). The increased demand for food puts additional stress on the terrestrial landscape and natural resources, as well as producers and scientists who must meet the challenge of producing more food with less water, fertilizer, and pesticides to reduce agriculture's effect on the environment. Because increasing global cultivated area will not be easy, increasing future food production per unit area in a sustainable manner is essential (Foley et al., 2011). However, increasing crop yields may not always translate into increased food security for all regions alike, particularly if accompanied by rising variance which may signal an ecological regime shift (Carpenter & Brock, 2006). Food shortages can be caused by the increased frequency of weather shocks like short-term drought or flooding, multiyear droughts or longer-term climate change, or abrupt changes in social systems, which can all contribute

Abbreviations: AR, autoregressive model; ARMA, autoregressive moving average models; EWS, early warning signals; GDD, growing degree days; IR, interquartile range; LLR, log-likelihood ratio; PET, potential evapotranspiration.

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to catastrophic crop failure (Cook, Miller, & Seager, 2009; D'Arcy, 2010; Downey, Haas, & Shennan, 2016; Kelley, Mohtadi, Cane, Seager, & Kushnir, 2015; Tigchelaar, Battisti, Naylor, & Ray, 2018). As local to global markets experience greater fluctuations in the availability of agricultural commodities due to an increasing frequency of regional weather shocks, the likelihood of significant food shortages and price spikes increase (Tadesse, Algieri, Kalkuhl, & von Braun, 2014).

Despite their importance to food security, both the pace of future crop yield increases and future resilience to weather shocks are difficult to predict given a variety of interacting drivers, including advances in plant breeding and genetics (Assefa et al., 2017; Ortiz-Bobea & Tack, 2018), social systems and economics (Hertel & Rosch, 2010), climate (Butler, Mueller, & Huybers, 2018; Kang, Khan, & Ma, 2009; Sánchez, Rasmussen, & Porter, 2014; Schmidhuber & Tubiello, 2007; Tigchelaar et al., 2018; Tollenaar, Fridgen, Tyagi, Stackhouse, & Kumudini, 2017; Wheeler & von Braun, 2013), soil fertility, and crop management (Assefa et al., 2017; Butler et al., 2018; Kucharik, 2006, 2008). However, examinations of historical trends and variability in crop yields across a variety of spatial and temporal scales can help us to understand where and why crop production has been most challenged, determine drivers of changes, identify locations of high risk of large year-to-year fluctuations in crop production due to weather extremes (Ben-Ari & Makowski, 2016; Kukal & Irmak, 2018; Leng, 2017), and determine within-field effects of soil and plant management advances like variable-rate technologies (Lobell & Azzari, 2017) or effects of tillage practices (Azzari et al., 2019).

Historical-yield data analysis can also uncover trends of concern for food security, such as a deceleration of yield gains, or shifts in interannual variability, which may be early warning signals (EWS) of regime shifts or future abrupt change in agroecosystems (Carpenter & Brock, 2006; Litzow & Hunsicker, 2016; Ratajczak et al., 2018). However, in agriculture, the idea of "early warning" is more commonly associated with the development of programs that can detect short-term (e.g., weekly to seasonal) changes in weather and crop health to predict the locations of catastrophic yield losses (Otkin et al., 2015b; Otkin, Anderson, Hain, & Svoboda, 2015a; Rembold et al., 2019).

Previous studies have analyzed yield trends at various spatial and temporal scales, and have shown troubling patterns that could influence long-term food security. For instance, some studies report that yield trends have decelerated or stagnated for important crops in the following production regions: maize (*Zea mays* L.) in Morocco, Moldova, and Kansas; rice (*Oryza sativa* L.) in North Korea, Japan, and Nigeria; wheat (*Triticum aestivum* L.) in France and Australia; and soybean (*Glycine max* L.) in Texas and Minnesota (Brisson et al., 2010; Hochman, Gobbett, & Horan, 2017; Kucharik & Ramankutty, 2005; Ray, Ramankutty, Mueller, West, & Foley, 2012). Ray et al. (2012) analyzed trends of four major food crops at a global scale using national and subnational crop datasets, and found that yields have stagnated or decreased across 24–39% of maize, rice, wheat, and soybean growing areas. Grassini, Eskridge, and Cassman (2013) demonstrated that rice and wheat yields are plateauing or decreasing in eastern Asia and northwest Europe. Using small-scale spatial wheat data, Lin and Huybers (2012) reported that some wheat-producing regions in the United States have reached a yield plateau. Other studies have suggested that the yield gap, or the difference between average and potential yields (Lobell, Cassman, & Field, 2009), is widening between the best and worst maize-producing regions in the United States (Assefa et al., 2017; Lobell & Azzari, 2017). Lobell et al. (2009) defines the yield potential as productivity of a crop when grown without experiencing stresses due to water, nutrients, insect pests, or diseases. The actual yield potential for a location is influenced by growing season precipitation or irrigation, interception of solar radiation, and temperature (Licker et al., 2010). While previous studies have advanced our understanding of yield trends, comparisons and syntheses of previous results are difficult because of (i) different spatial extents, such as worldwide (Ray et al., 2012) versus local (Patrignani, Lollato, Ochsner, Godsey, & Edwards, 2014); (ii) different time periods of study that may combine data since the 1960s (Ray et al., 2012) or focus on years that coincide with availability of specific satellite data (Lobell & Azzari, 2017); (iii) focus on single crops (Leng, 2017; Lin & Huybers, 2012); (iv) use of different statistical approaches (Grassini et al., 2013; Kukal & Irmak, 2018; Lin & Huybers, 2012; Ray et al., 2012); (v) and treating trends (Grassini et al., 2013), variability (Leng, 2017), or yield gaps (Patrignani et al., 2014) independently of each other. In addition, all but one (Lin & Huybers, 2012) of these previous studies have not accounted for temporal autocorrelation among residuals in their statistical fitting exercises, thereby leading to overestimation of *P*-values.

We conducted a spatiotemporal analysis that combined information on yield trends, yield gaps, and interannual variability for US maize, soybean, and winter wheat to better understand how productivity has changed and to identify regions of particular concern. We analyzed USDA National Agricultural Statistics Service (NASS) crop databases of US county yield data for maize, soybean, and winter wheat from 1970–2017 (http://www.nass.usda.gov/index.asp). Our main statistical framework uses autoregressive moving-average (ARMA) models which account for temporal autocorrelation among residuals (Box, Jenkins, & Reinsel, 1994). We assessed whether the yield trend is better represented by a linear or quadratic model where quadratic parameters indicate whether yield has accelerated or decelerated. We then used

the residuals from the fitted model to assess the variability of the crop yields. We also analyzed irrigated county trends separately from rainfed and combined management (rainfed or irrigated) categories.

We focused on several questions that depend on crop type and water management: (1) what are the trends in US crop yields at county and national scales? (2) How are the rates of yield increase/decrease and acceleration/deceleration distributed across the United States? (3) Has variability increased through time, and how is it distributed across the United States? (4) Have yield gaps increased or decreased through time, and how are they distributed? (5) Is there any correlation between average yield, rate of yield increase, and temporal variability in yield? (6) How do the answers to these questions differ between different water management practices? (7) Do these analyses suggest that any particular regions are at heightened risk for future abrupt changes in yield?

Historically, the potential for the highest maize and soybean yields are typically found throughout the US Midwest, Great Plains, and southern Mississippi Valley regions (Licker et al., 2010; Lobell et al., 2009). These regions have fertile soils, relatively long growing seasons without extreme heat, and adequate rainfall or the ability to supplement rainfall with irrigation such as in Nebraska and Kansas (Kucharik & Ramankutty, 2005; Licker et al., 2010). In the heart of the Corn Belt regions of Iowa, Illinois, Indiana, and Ohio, many fields are also tile drained to improve drainage and soil conditions supportive of high corn and soybean yield potential. The Great Plains have been a focus for winter wheat production given the number of hectares planted, but do not always experience the highest yield potential given less fertilizer application, lower precipitation, and high heat in early summer that can accelerate development before harvest (Vocke & Ali, 2013). Regions with wheat yield potential are found in cooler regions of the northwestern states, in California where irrigation is used, and locations in the Great Lakes region. Increasing corn and soybean yields through time are attributed to technological advancement such as improved machinery and plant genetics; increasing use of irrigation, fertilizers, and pesticides (Bruns & Abbas, 2006; Duvick & Cassman, 1999); a prolonged photosynthetic period (Tollenaar & Wu, 1999); regional climate change (Lobell & Asner, 2003), solar brightening (Tollenaar et al., 2017); and a trend towards early planting of corn and soybean supported by seeds coated with temperature activated polymers (Gesch & Archer, 2005; Kucharik, 2006; Kucharik, 2008; Sacks & Kucharik, 2011). Trends in winter wheat yields over time have not been as great as for corn and soybean because the pace of genetic modification has been slower: there are currently no genetically modified (GMO) varieties of wheat grown commercially in the United States (Vocke & Ali, 2013).

2 | MATERIALS AND METHODS

2.1 | Crop yield data

For maize, soybean, and winter wheat, we retrieved annual yield data (bushels per acre) from 1970–2017 for all available counties within the contiguous United States from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS; http://www.nass.usda.gov, accessed 30 March 2018). We converted annual yield in bushels per acre to kilogram per hectare for each crop using standard conversion factors for grain at 15% volumetric moisture content. We used 1970 as the starting point to restrict the analyses to the time period when (i) the most abundant data were available across all three crops and (ii) private sectors in the United States had invested heavily in an application of modern genetic hybrids and supporting management and scientific technologies to improve crop production (Evenson & Gollin, 2003; Tilman, 1998).

Where possible, we separately analyzed data for irrigated and nonirrigated (dryland) water management practices. County-level yield data for irrigated and nonirrigated practices were available for maize in Colorado, Delaware, Kansas, Nebraska, and Texas; for soybeans in Arkansas, Delaware, and Nebraska; and for winter wheat in Idaho, Kansas, Nebraska, and Texas. For states that have irrigated yield estimates, the USDA can publish up to three yield estimates for a given county: irrigated, nonirrigated, and all practices (irrigated and dryland combined; J. Johanson, USDA, personal communication, 19 June 2018). Sometimes, there can be zero reports of irrigated yields, but nonirrigated and all practices yield data are published. In other cases, a county may have an irrigated yield value, but none reported for nonirrigated because there were zero reports of that management practice. Therefore, the 'all practices' value sometimes may represent only a single management practice, either irrigated or nonirrigated.

To control for outliers, we first filtered the data and removed counties that reported zero yield or contained less than 404.7 ha of the specified crop. Subsequently, we excluded counties that (i) contained less than 15 data points since 1970, (ii) contained a 10-yr gap between two consecutive time-series data points, and (iii) reported no data after 2000. Any yield data from a group reported as 'combined counties' were also excluded. This process led to yield data available from 42 states and 2290 counties. For maize, 238 counties reported irrigated yield data separately, 199 counties reported nonirrigated yield data separately, and 1912 counties reported yield data combined for all practices. For soybean, 138, 148, and 1547 counties reported yield data as irrigated, nonirrigated, and all practices, respectively. For winter wheat, 235, 603, and 1705 counties reported yield data as irrigated, nonirrigated, and all practices, respectively.

2.2 | Statistical framework: Autoregressive model

Most previous analyses of crop yield trends have not accounted for potential effects of temporal autocorrelation that is a general feature of the time-series. Temporal autocorrelation occurs whenever unexplained variation at one time step has lingering effects over subsequent time steps; thus, if events that affect yield in 1 yr have lasting effects in subsequent years, they will generate autocorrelation. Here, we use models with autoregressive (AR) residuals (Box et al., 1994) that are often used to study ecological time-series data (Ives, Abbott, & Ziebarth, 2010; Jassby & Powell, 1990; Michener, 1997) because they can properly account for temporal autocorrelation. In our time-series models, "unexplained variation" (residuals) refers to any variation that is not captured in the yield trends that are explicitly included in the model. Therefore, even though they are "unexplained" in the model, they will have explanations in reality, such as weather, market forces that change management practices, and deployment of new technologies.

For each crop type, we fit each county-yield time series with two types of regression model with AR residuals. The first model assumes a quadratic relationship:

$$y_t = c_0 + c_1 t + c_2 t^2 + z_t$$
$$z_t = \beta z_{t-1} + \varepsilon_t \quad (1)$$

where y_t denotes yield (kg ha^{-1}) and z_t the residual at year t. The sign of c_2 (kg ha^{-1} year^{-2}) controls the shape of the yield trend through time. A negative or positive c_2 means that yield is decelerating (concave down) or accelerating (concave up) through time, respectively. The parameter β represents autocorrelation in the residuals (AR-process with lag 1). The second model is linear, which is a reduced version of the quadratic form and is obtained by setting $c_2 = 0$. In this case, the increase or decrease in yield is determined by c_1.

We chose the best model by computing the log-likelihood ratio (LLR) between the quadratic and linear model. Since these models are nested, the LLR approximately follows a chi-square distribution. We do not try to formally test for significance using P-values for differences between models using the county-level data, because there are a large number of counties; therefore, the P-value would have to correct for multiple comparisons. However, the data are also likely to be spatially correlated (with neighboring counties having similar yields), and this spatial correlation leaves no direct way to correct for multiple comparisons since standard corrections assume comparisons are independent. Nonetheless, as an informal assessment, we say that the quadratic model has better support than the linear model if the LLR is greater than 3.84, which corresponds to a P-value of .05 for the chi-square distribution with one degree of freedom.

We used R programming software (R Development Core Team, 2019) to conduct the autoregressive moving-average model (ARMA) analyses. Data manipulation, boxplot, and time-series visualizations were constructed using Mathematica 11 (Mathematica version 11), and visual county-level maps were created using QGIS (QGIS version 3.0). All code and data used in the analyses are available at the github repository (https://github.com/ramiadantsoa/Yield_trends).

2.3 | Spatiotemporal analyses of trends, variability, yield gaps, and relationships among them

For each crop (maize, soybean, and winter wheat) and water management category (irrigated, nonirrigated, and all practices), we summarized the trends, variability, and yield gap over space and time, as well as the correlation between these variables. The approaches we used are described in detail in this section.

2.4 | Temporal patterns

To assess trends at the national level, we calculated the annual average yields of all available counties, fitted the models, and selected the best model. For each crop type and management strategy at the national level, we calculated relative variability (v) each year (t) as:

$$v_t = \frac{y_t - \hat{y}_t}{\hat{y}_t} \quad (2)$$

where y_t is the observed annual value, $\hat{y}_t$ is the predicted annual value from the best model, and $y_t - \hat{y}_t$ is the residual or deviation from the model predicted value. For the temporal (decadal) data at the national level, we computed the standard deviation of the yield relative variability within each decade for each county. For each crop and management category at the national level, we computed a yield gap (G) for each decade (d) as:

$$G_d = M - A[y_t] \quad (3)$$

where M is the maximum yield defined as the 99.99% quantile of all county crop yields within each management category across all years, and $A[y_t]$ is the average decadal crop yield across all counties. We defined the maximum county-level yield as the 99.99% quantile instead of the absolute maximum to exclude exceptionally high county yields that could be caused by mis-reporting. We did not compute the yield gap

when there was only a single data point (e.g., one yield record for a particular county during the specified decade).

2.5 | County-level patterns

We use metrics that summarize the entire time-series for each county. The trend is represented by the slope c_1 from the linear model. We also identified counties with nonlinear trends (when the best model is quadratic) and reported the quadratic coefficient c_2 (Equation 1). For the variability, we used a metric similar to the coefficient of variation. Specifically, for each county, we scaled the residuals from the best-fitting linear or quadratic model according to their annual predicted value and then calculated the standard deviation for the entire time series (Equation 2). We also analyzed variability using absolute yield values using the residuals from the best-fitting models without scaling by their means, and those results are shown in the Supplemental Materials. Additionally, we computed the difference in yield gap between the first and last decade. A county-level decadal yield gap is the difference between the maximum yield nationally among all management categories (irrigated, dryland, and all practices) across all years and the decadal average per county. Because the length of our dataset is 48 yr, we partitioned time (1970–1979, 1980–1989, 1990–1998, 1999–2007, 2008–2017) so that the last decade also consists of 10 yr of data.

2.6 | Relationships among variables and determining hotspots

We investigated relationships (pairwise Spearman correlations) between mean yields, yield trends, and yield variability for each crop type and water management category. The mean yield is summarized by the predicted yield at the middle of the time series (1994) from the linear model. The trend is the slope (c_1) and the variability is the county-level variability defined above.

Finally, we identified greatest- and lowest-performing counties during the last decade by computing a cumulative score of four metrics: rate of yield increase (c_1), rate of acceleration or deceleration (c_2) when quadratic model is the best model, the mean yield for 2008–2017, and the yield gap during 2008–2017. For each metric, we assigned a score of +1 if a county is in the top 90% quantile, a score of −1 if it is in the bottom 10%, and zero otherwise. We then added the scores for all four metrics for each county. For instance, a county with a score of −3 indicates that there is a higher risk of lower yields compared to other locations. We excluded yield variability in our score because it was calculated as an average across the entire time series and therefore does not indicate trends toward increasing or decreasing risk of lower crop yields.

3 | RESULTS

3.1 | Trends over time

3.1.1 | Maize

Maize yield increased regardless of management practices (Figure 1a) and was highest for irrigated fields and lowest for non-irrigated categories. Irrigated yields have increased faster (143.6 kg ha^{-1} yr^{-1}) than nonirrigated fields (106.9 kg ha^{-1} yr^{-1}) since 1970, with the average across all practices (111.8 kg ha^{-1} yr^{-1}) being very close to the nonirrigated rate of increase (Table 1).

The decadal distribution of crop yield variability for all the counties showed that irrigated categories have the lowest variability (Figure 1b). For irrigated yields, the median variability peaked in the 1990s (Table 2) although the range of variability was widest in the 1980s (Figure 1b, upper fence). For nonirrigated yields, the median variability first peaked in the 1980s, declined for the next two decades (Table 2), and has increased since 2000s. The interquartile range (25–75%) and extreme variability (upper fence) have also increased since the 1990s reaching up to 80% after 2010. For all practices, the median peaked in the 1980s (Table 2), but the interquartile has widened since the 1990s.

Patterns of decadal yield gap also differed among management practices (Figure 1c). Irrigated yields had the lowest yield gap; the median yield gap was highest in the 1990s (Table 3), declined in the 2000s and increased again after 2010. Irrigated yield gaps for maize were typically around 4–5 T ha^{-1}. For nonirrigated yields, the median yield gap increased and then stabilized in the 1980s (Table 3), with median values around 9–10 T ha^{-1} (Figure 1c). For all practices, the median yield gap and variance among counties (interquartile range) initially increased but have generally plateaued since the 1980s (Table 3), with median values around 6.5 T ha^{-1} (Figure 1c).

3.1.2 | Soybean

Soybean yield has increased, but unlike maize, a nonlinear model best fits all data regardless of the reported category, which suggests that at a national scale, yield increases have accelerated through time (Figure 1d). Nonirrigated soybean yields have increased since 1990, with the rate of increase accelerating (Figure 1d).

Irrigated soybean yields exhibited the lowest variability and peaked in the 1990s (Figure 1e; Table 2). Extreme variability, up to 70% for the nonirrigated and 65% for the all-practices category, occurred during the last decade.

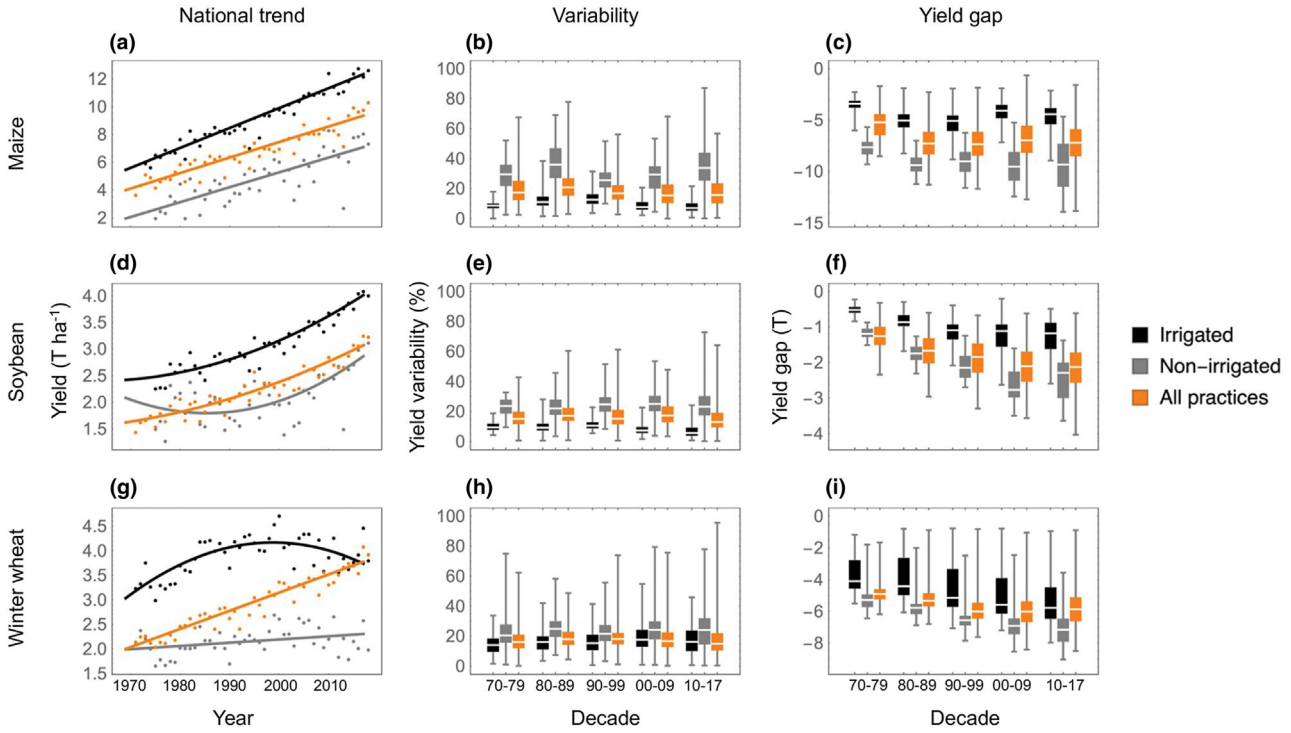

FIGURE 1 National yield trends, relative variability (percent), and yield gap (T ha^{-1}) from 1970–2017 for maize, soybean, and winter wheat. Left to right columns contain national yield trends, distribution of decadal variability, and yield gap, respectively. Rows denote crop type. In the first column, dots represent the annual national average yield and lines show the best-fit model to the data. In the second and third columns, the horizontal white line depicts the median, the shaded area limits the 25% and 75% quantile, and the bars represents the lower and upper fences. Irrigated, non-irrigated, and all-practices categories are shown in black, gray, and orange, respectively

TABLE 1 Parameters of the best model for the temporal trends of crop yield in the United States. When linear is the better-model, c_2 is left blank. The unit of mass used here is kg ha^{-1}

Categories	Intercept (c_0)	Slope (c_1)	Curvature (c_2)
Maize: irrigated	5454	143.6	
Maize: nonirrigated	1955	106.9	
Maize: all practices	3992	111.8	
Soybean: irrigated	2.422	6.602	0.554
Soybean: nonirrigated	2084	−35.06	1.070
Soybean: all practices	1622	14.14	0.335
Winter wheat: irrigated	3037	76.12	−1.280
Winter wheat: nonirrigated	1991	6.575	
Winter wheat: all practices	2003	37.02	

Irrigated soybean yields also exhibited the lowest yield gap (Figure 1f); the median yield gap increased until the 1990s (Table 3) and has since leveled off around 1.1 T ha^{-1}. The interquartile range among counties, however, continued to widen. For nonirrigated and all practices, median yield gap has increased with some leveling off since 2000, with median values around 2.1–2.2 T ha^{-1}. The largest yield gaps (up to 4 T ha^{-1}) occurred during the last decade in the all practices category (Figure 1f). For the nonirrigated category, we also observed the distribution shifted from a positive to negative skew since 2000. This suggests the median yield gap has decreased while many counties were still falling further behind their counterparts where yields were increasing at a faster rate.

3.1.3 | Winter wheat

In contrast to maize and soybean, winter wheat showed different trends among the three reported management categories.

TABLE 2 Percentage change in the median of yield variability relative to 1970–1979 as a function of crop type and management category. The percentages in the brackets denote values for consecutive time periods of analysis {1980–1989, 1990–1999, 2000–2009, 2010–2017}

Crop	Irrigated	Non-irrigated	All practices
Maize	{29, 47, −11, −18}	{22, −13, −1, 14}	{21, −2, −11, −9}
Soybean	{−2, 12, −22, −40}	{−7, 5, 6, −2}	{14, 1, 15, −14}
Winter wheat	{14, 9, 26, 15}	{21, 6, 19, 18}	{13, 13, 5, −7}

TABLE 3 Percentage of change in the median of yield gaps relative to 1970–1979 as a function of crop type and management category. The percentages in the brackets denote values for consecutive time periods of analysis {1980–1989, 1990–1999, 2000–2009, 2010–2017}

Crop	Irrigated	Non-irrigated	All practices
Maize	{48, 49, 20, 30}	{23, 18, 25, 22}	{39, 41, 34, 38}
Soybean	{66, 110, 113, 126}	{46, 80, 132, 92}	{33, 47, 67, 69}
Winter wheat	{8, 26, 36, 41}	{9, 24, 31, 35}	{9, 22, 23, 20}

The all-practices category increased linearly, while nonirrigated yields have remained roughly constant since 1970, with an average increase of 6.58 kg ha^{-1} yr^{-1}. Most notably, average-irrigated US winter wheat yield has been declining since the late 1990s (Figure 1g). The nonintuitive relationship between the all-practices category and the other two categories likely comes from the different sets of counties reporting for each category.

Unlike maize and soybean, the interannual variability in wheat yields among management categories was similar across time (Table 2), especially between the irrigated and the all-practices categories (Figure 1h). There was a slight increase in the median and the interquartile range (or variation among counties). Extreme variability was highest during the last decade and reached up to 90% for the all practices category.

Median yield gaps have generally increased for all categories (Table 3), with some leveling off since 2000 for all practices (Figure 1i). Median yield gaps during the 2010–2017 time period were approximately 5.5 T ha^{-1} for irrigated and all practices, and 7.1 T ha^{-1} for nonirrigated categories (Figure 1i). Differences among counties in winter wheat yield gaps have generally increased over time for all management categories (Figure 1c; Table 3). The distribution of yield gaps was highly positively skewed for irrigated winter wheat.

3.2 | County-level

3.2.1 | Maize

The largest yield increases (over 200 kg ha^{-1} yr^{-1}) have occurred in Arkansas, Louisiana, Mississippi, Georgia, and isolated counties in California, Arizona, and New Mexico (Figure 2a). Other regions of high maize yield trends (150–200 kg ha^{-1} yr^{-1}) include western Minnesota, eastern North and South Dakota, and northeastern Nebraska (Figure 2a). Twenty percent (381) of county yield time series were best fit with a nonlinear yield trend, of which 69% (264) have experienced an accelerating rate of yield gains and 31% (117) have experienced a decelerating rate of yield gains (Figure 2b). There was a clear spatial dichotomy for counties with yield time series that were fit best with a nonlinear trend. Yields in counties east of the central United States generally had accelerating yield trends whereas counties to the west of the central United States had decelerating yield trends (Figure 2b). The largest region with yield deceleration occurred in western Kansas.

There were five hotspots of interannual (relative) variability: western Dakotas, northeastern Kansas, northern Missouri, South Carolina, and southern Texas. Variability was highest in the Dakotas and southern Texas, reaching up to 50%. Regions of low variability include Nebraska, upstate New York, southern Idaho, and eastern Oregon.

Average maize yield gaps in the 1970s were lowest for counties in Nebraska, Kansas, and Texas that had extensive irrigation, as well as across a region of the Corn Belt from central Iowa through central Illinois (Figure 3a). In the 2008–2017 period, the smallest yield gaps for maize were still found across irrigated counties of Nebraska, Kansas, and Texas and portions of southern Minnesota, Iowa, and Illinois. The largest average maize yield gaps from 2008–2017 (greater than 12 T ha^{-1}) were found in western North and South Dakota, Kansas, Oklahoma, and Texas. Across the United States, maize yield gaps have generally decreased since the 1970s across the northwestern States, in Arkansas, Mississippi, Louisiana and southern Georgia, and across a large area of north-central United States in South Dakota, Minnesota, Nebraska, and Iowa (Figure 3c). The remainder of counties that have experienced expanding yield gaps, with hotspots in Kansas, Colorado, the western Dakotas, Texas, Virginia, and the Carolinas, identify regions that have not kept pace with the highest producing counties.

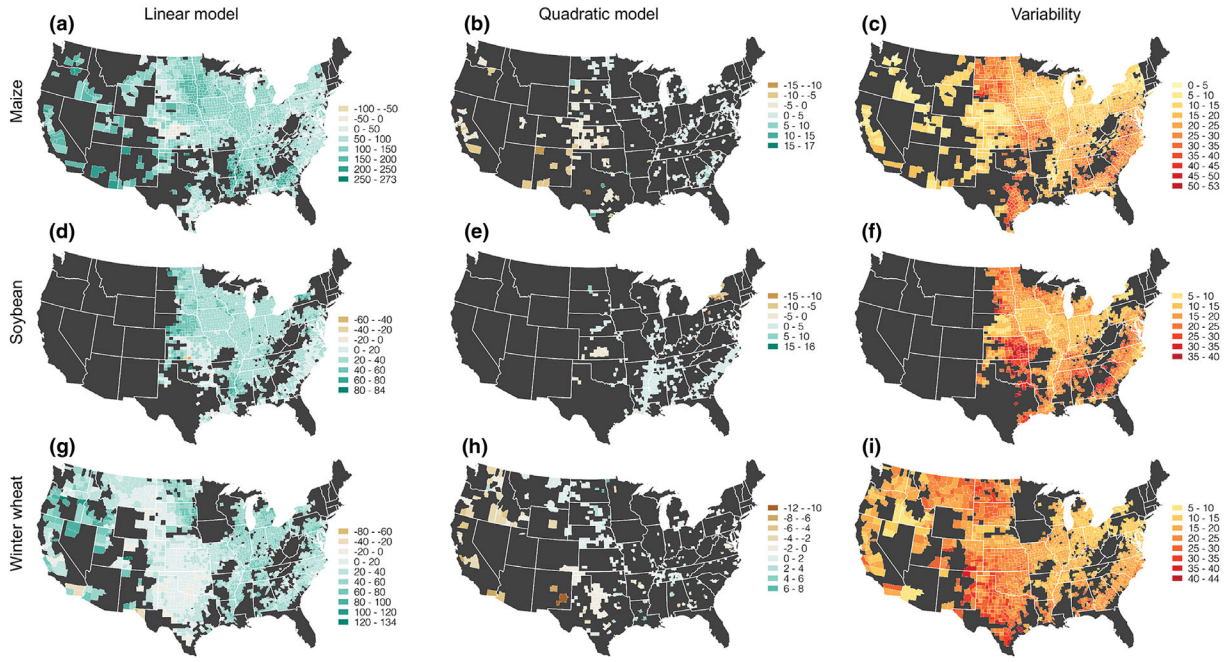

FIGURE 2 County-level trends (kg ha^{-1} yr^{-1}) and relative variability (percent) for each crop (rows) for the all practices management category from 1970–2017. First column represents linear rate of increase (c_1) for all counties. Second column represents the quadratic coefficient (c_2) for counties where quadratic model fits better. Last column represents variability

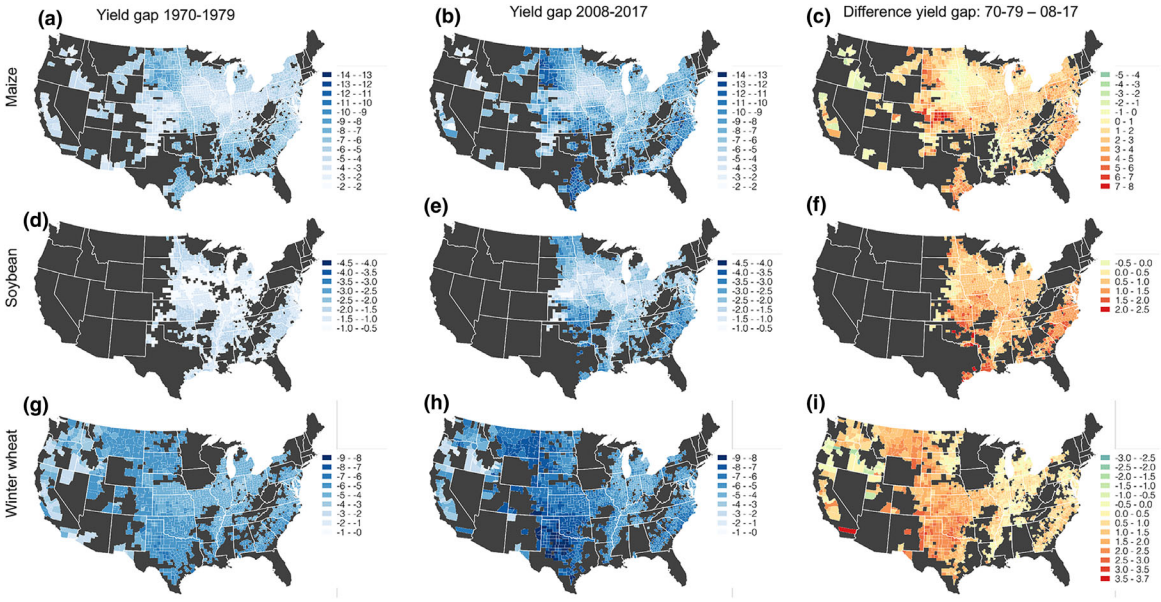

FIGURE 3 County-level yield gap (T ha^{-1}) during the first and last decade of the time-series analysis for the all-practices management data (first and second column) and the difference in yield gap between the first (1970–1979) and last decade (2008–2017; displayed in last column)

3.2.2 | Soybean

Soybean yield has only decreased in a few counties (19); these are located in south-central Kansas, Oklahoma, and Texas. The largest yield increases (>80 kg ha^{-1} yr^{-1}) occurred in the Dakotas, Nebraska, Kansas, and Oklahoma (Figure 2d). Central Nebraska and the southern Mississippi Valley experienced the largest increases.

Twenty-three percent (362) of county-soybean yield time series were better fit with a nonlinear yield trend, of which 88% (317) experienced an accelerating rate of yield gains and 12% (45) experienced a decelerating rate of yield gains (Figure 2d).

Variability was highest in several counties in eastern Kansas (Figure 2f). These counties also showed a low rate of increase and deceleration (Figure 2d, 2e). Other hotspots of variability included the central Dakotas, southern Oklahoma, northern Texas, west-central Georgia, and west-central South Carolina. Overall, there was a spatial correspondence between regions with high rates of yield increase and low variability (Nebraska and the southern Mississippi Valley), and regions with low rates of yield increase and high variability (e.g., central Kansas; Figure 2d, 2f).

Average soybean yield gaps in the 1970s were smallest for the central Corn Belt, specifically counties in Nebraska, Iowa, Illinois, and Indiana (Figure 3d). The largest soybean yield gaps in the 1970s (greater than 1.5 T ha^{-1}) were found on the perimeter of the Corn Belt, in north-central Minnesota and Wisconsin, the Dakotas, Kansas, Oklahoma, and the southeastern states (Figure 3d). In 2008–2017, the smallest average soybean yield gaps were found across irrigated counties of Nebraska, Kansas, and Arkansas and the central Corn Belt states of Iowa, Illinois, and Indiana (Figure 3e). The largest average soybean yield gaps from 2008–2017 (greater than 4 T ha^{-1}) were found in western North and South Dakota, Kansas, Oklahoma, Texas, and the southeast-coastal states (Figure 3e). For soybean, expanding yield gaps were found almost everywhere, except in a few counties in Nebraska, Kansas, Arkansas, Louisiana, and Mississippi, most of which benefitted from irrigation (Figure 3f).

3.2.3 | Winter wheat

A total of 426 of counties fit with a linear trend exhibited yield stagnation, with very small positive or negative trends (−20–20 kg ha^{-1} yr^{-1}) since 1970, and a majority of these were located west of the Mississippi River throughout the southern and central Plains and other western states (Figure 2g). The largest wheat yield increases (100–125 kg ha^{-1} yr^{-1}) occurred in the western states of Oregon, Idaho, and Nevada, as well as the Dakotas, and the lowest increases were found in Montana, eastern Colorado, and Kansas (Figure 2g).

Twenty percent (348) of county-winter-wheat yield time series were best fit with a nonlinear yield trend, of which 55% (192) experienced an accelerating rate of yield gains and 45% (156) experienced a decelerating rate of wheat yield (Figure 2h). Yields in counties east of the Rocky Mountains and Texas generally accelerated, whereas counties throughout Washington, Oregon, Idaho, California, and Texas decelerated (Figure 2h).

The most variable yield occurred in the central United States and Nebraska (Figure 2i). The least variable winter wheat yields were found in Ohio, southern Idaho, and southeastern Arizona. Overall, the spatial distributions of high- and low-yield increases corresponded with low and high variability, respectively.

Average winter wheat yield gaps in the 1970s were smallest for counties in the western States of Idaho, Oregon, Nevada, and California (Figure 3g). The largest winter wheat yield gaps in the 1970s (greater than 5–6 T ha^{-1}) were found broadly across the Great Plains and Rocky Mountain States, as well as the far southeastern states (Figure 3g). In the 2008–2017 period, the smallest average winter wheat yield gaps were found across irrigated counties in Idaho and Oregon (Figure 3h). The largest average winter wheat yield gaps from 2008–2017 (greater than 7–8 T ha^{-1}) were found in Montana, western North and South Dakota, Colorado, Oklahoma, and Texas (Figure 3h). For winter wheat, a few counties in Oregon, Idaho, California, Utah, South Dakota, and other places in the eastern United States saw narrowing yield gaps over time (Figure 3i). Most other places experienced a widening of yield gaps, with notable large increases over time in the Great Plains and in particular counties in Montana, North and South Dakota, Oklahoma, and Texas (Figure 3i).

3.3 | Correlation between mean yield, rate of yield increase, and yield variability

We computed the pairwise correlations between mean yield, rate of yield increase, and yield variability at the county level for each of the three crops (Figure 4). Mean yield, determined as the value for 1994 from the fitted models for each county, and rate of yield increase were positively correlated (Figure 4a–4c). For maize, we found a bimodal pattern for mean yield between 5–7 T ha^{-1} (Figure 4a). In that range, some counties exhibited a high rate of increase (around 150–200 kg ha^{-1} yr^{-1}) which was higher than some counties with higher mean yields (~9–10 T ha^{-1}). The remaining (majority) counties exhibited a moderate rate of increase (Figure 4a). For soybean, the relationship is unimodal; however, the rate of increase plateaued for mean yields higher than 2 T ha^{-1} (Figure 4b). For winter wheat, the correlation between county-yield trend and mean yield was highest, and the relationship was sigmoidal (Figure 4c). Counties with mean yield between 1–2 T ha^{-1} experienced the lowest rate of yield increase, and counties with mean yields higher than 3 T ha^{-1} had a slightly higher rate of yield increase.

Mean yields and yield variability were negatively correlated for all three crops (Figure 4d–4f) and of similar magnitude ($\rho \approx -.76$). The variability measure we used, the residuals from the best-fitting model scaled by the annual means, is similar to a coefficient of variation, in that it assumes that the standard deviation is proportional to the mean. In other words, the variability is relative to the mean. For soybean, counties with the lowest mean yields (<1.75 T ha^{-1}) were

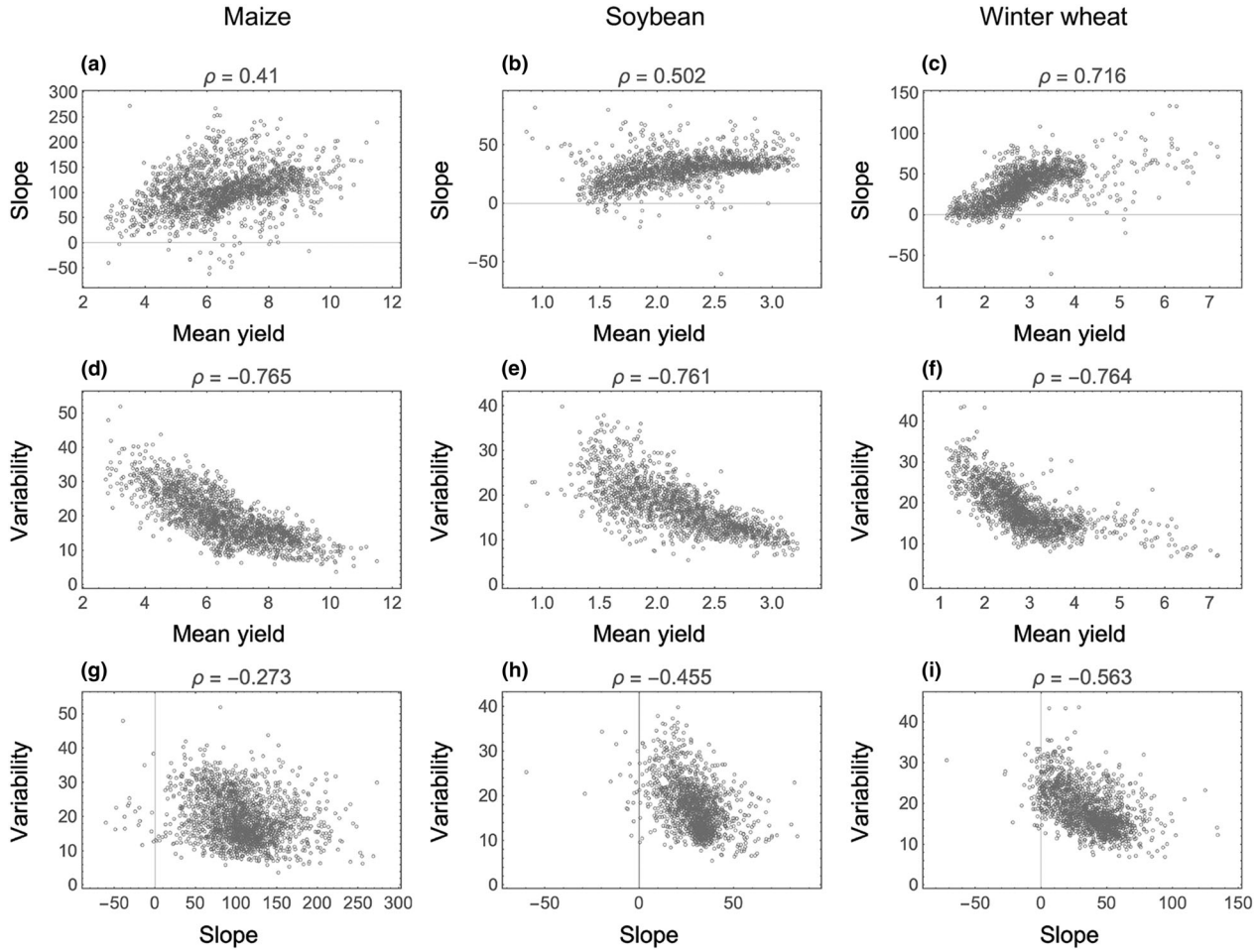

FIGURE 4 Pair-wise Spearman correlations between mean yield (defined as fitted value from the linear model for Year 1994 in T ha^{-1}), slope (in kg dry matter ha^{-1} yr^{-1}), and relative variability (percent) for all practices

the most variable, ranging from 10–35%. In contrast, counties with the highest mean yield (>2.5 T ha^{-1}) had the lowest variability (around 10%; Figure 4e). For winter wheat, although counties with the highest mean yields exhibited the greatest range in the rate of increases (above and Figure 4c), these counties were more homogeneous in their variability (∼10%; Figure 4f).

The annual rate of average yield increase and variability were negatively correlated (Figure 4g–4i), although the correlations were weaker, ρ = −.27, −.45, and −.56 for maize, soybean, and winter wheat, respectively.

3.4 | Top and bottom performing counties

When considering several yield metrics simultaneously for each crop type, including yield trends, acceleration or deceleration, yield gaps, and mean yields (Figure 5), we identified counties that were consistently either top or bottom performers. Based on our scoring methods, top-performing counties across all three crops were generally found across portions of Nebraska, Iowa, and Illinois (Figure 5). Eastern South Dakota and portions of Minnesota also contained top-performing counties for maize yields (Figure 5a). Maize and winter wheat top-performing counties were also found in Oregon, Idaho, and California. Several of the Great Lakes states and eastern South Dakota had counties that were top performers for winter wheat yield trends and current yields (Figure 5c). Across all three crops, most of the bottom-performing counties were found in regions of Kansas, Oklahoma, Texas, and other Great Plains states. For maize, poor-performing counties were located in the western Dakotas (Figure 5a). Another region of concern for maize and soybean production included some southeast locations in North and South Carolina (Figure 5a, 5b).

4 | DISCUSSION

Our analysis has revealed several new findings on the patterns of yield increases, variability, and gaps from 1970–2017. A consistent pattern emerged for maize, soybean, and winter

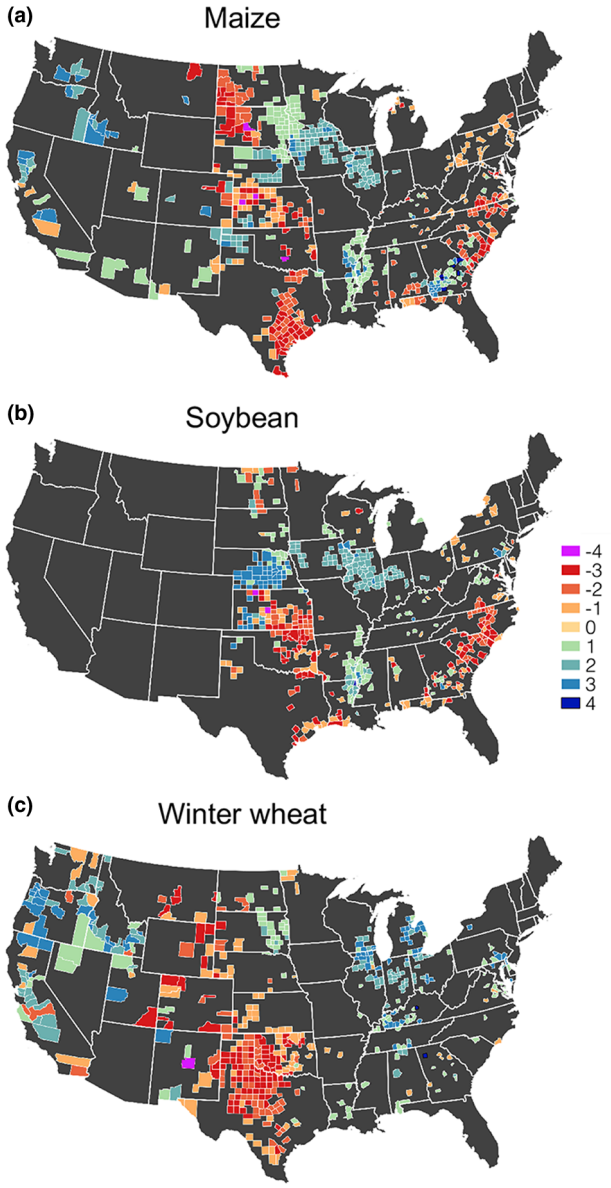

FIGURE 5 Best and worst performing counties based on scoring and ranking system that included the rate of increase or decrease in yield since 1970, acceleration or deceleration of annual yield gains, the yield gap between 2008–2017, and average yields between 2008–2017. The best and worst performing counties have positive and negative values, respectively. Counties with scores equal to zero were omitted

wheat in the central and southern Great Plains, and in particular Kansas, Oklahoma, and Texas, as all three crops are struggling to produce large yields and match large-yield gains found elsewhere (Figure 5). Clear spatial patterns in trends in crop yield over time suggest that select regions have historically struggled both in terms of the mean and variability of yields. Decelerating yields since 1970 generally occurred west of the Great Plains, whereas accelerating yields generally occurred in the east. In particular, winter wheat trends differed from maize and soybean, experiencing yield-trend deceleration, stagnation, and decline over the past 20 yr in portions of the Great Plains. This result alone should be a cause for concern. Our results also clearly show that irrigation management increases the mean yields of all three crops and reduces interannual variability, thus highlighting the dependence on water withdrawals for sustained agricultural production in the Great Plains. Winter wheat also had the most varied responses to different water-management categories reported, including declines for irrigated. In general, yield variability, over both time and geographic space has increased since 1970, particularly for maize and soybean, and yield gaps have also increased.

Our work advances our understanding of crop yield trends in the United States by taking the following approaches: (i) accounting for temporal autocorrelation and analysis of variability that removes the effects caused by increasing mean yields, (ii) analyzing across multiple crop types, and (iii) analyzing across four distinct indicators of risk: yield gap, linear downward trends, deceleration, and increasing variability. Previous studies have fit various models to crop yields, including linear, quadratic (Ray et al., 2012), exponential (Grassini et al., 2013), and smooth and piecewise linear (Grassini et al., 2013; Lin & Huybers, 2012; Patrignani et al., 2014) models, and different methods have been used to fit and select the models, including Akaike information criterion (AIC), root mean square error (RMSE), and/or likelihoods (Grassini et al., 2013; Ray et al., 2012). Performing confidence tests (such as calculating *P*-values), however, is complicated. Lin and Huybers (2012) used a permutation method to randomize the data points to get the distribution associated with the null hypothesis. Here we analyzed the time series using an AR approach that accounts for autocorrelation among the residuals. Given that AR models have been extensively developed, are flexible, and are used in other disciplines (Box et al., 1994; Fuller, 1996), they are a natural choice for analyzing yield time series. Although it is possible to compute *P*-values from single time series (Box et al., 1994), large spatial datasets, such as the ones we have analyzed, present two challenges. First, there are many separate time series, and even if their dynamics all abided a null hypothesis, 5% of them would be counted as significant at the .05 significance level unless steps were taken to correct for multiple comparisons (Benjamini, 2010). Second, a method for correcting for multiple comparisons is difficult, because the time series are not independent, which is a requirement for standard approaches for correcting for multiple comparisons (Miller, 1981). Therefore, we do not report *P*-values. Nonetheless, we do use the likelihood ratio threshold of 3.84 (corresponding to a *P*-value of .05 if the time series were treated as individual tests) between linear and quadratic models as an informal indicator of relative goodness-of-fit.

4.1 | Rates and patterns of US crop yield trends

A consistent pattern emerged for the three crops: in the central and southern Great Plains, in particular, Kansas and Oklahoma, all three crops are struggling to match the large yield gains occurring elsewhere (Figure 2, 5). Winter wheat trends differed from maize and soybean, with yield stagnation and declines in regions of the Great Plains (Figure 2h). For maize and soybean, while yield stagnation and deceleration are also occurring (Figure 2, 5), it is not as widespread as for winter wheat. Winter wheat has the most varied responses to different management categories reported, including yield stagnation for nonirrigated, linear increases across all practices, and declines for irrigated (Figure 1). Irrigated winter wheat yield (Idaho, Nebraska, Kansas, and Texas) is declining, which contrasts with irrigated maize and soybean trends. Nonirrigated winter wheat data were collected in counties in the Great Plains (Nebraska, Kansas), Idaho, and Texas where annual precipitation is low, leading to low-mean yields that are currently 50% of irrigated values (Figure 1). The positive trend for winter wheat in the all-practices category represents a broad range of agroclimatic zones, where many eastern states have positive trends (Figure 2g).

Stagnation of winter wheat yields have been reported in numerous previous studies. One explanation is that yields in irrigated- or higher-precipitation areas are approaching their maximal-potential levels, with an additional contribution of less genetic advancement compared to maize and soybean (Cassman, 1999; Patrignani et al., 2014). In Oklahoma, Patrignani et al. (2014) concluded that yield stagnation since 1980 was due to poor soil quality caused by low organic matter and unfavorable pH, which could limit water and nutrient availability. Ray et al. (2012) suggested that 27% of wheat-growing regions in the United States (mostly in the Great Plains) have stagnated, but did not separate differences between irrigated and nonirrigated averages, or analyze data at the county level. Lin and Huybers (2012) showed that for winter wheat from 1960–2008, trends could be divided into three distinct regions of yield growth, with a change point (transitioning from an increase to a plateau) in the western United States in 1993 and the central United States in 2003. This spatial result agrees with our analyses as the central portion of the United States experienced stagnant yield growth (Figure 2g), the western states experienced a deceleration (Figure 2h), and the eastern states experienced modest winter wheat yield increases since 1970 (Figure 2h). We note that some counties in the western states have, however, boosted wheat yields while their nearest county neighbors, often in the same state, have decelerating yields (Figure 2h). This is indicative of differences in soils and/or management, given the average climate is similar across such short distances (e.g., like adjacent counties).

We hypothesize that the differences in mean yield and rate of increases among the three crops might be explained by agroclimatic differences (soils, weather, and responses to changing climate), photosynthetic response to increasing CO_2 in the atmosphere, management and inputs (e.g., fertilizers and pesticides), and advances in breeding and genetics. Winter wheat is grown across a wider range of agroclimatic zones in the United States (Licker et al., 2010), which would support the hypothesis that it is being grown on soils that are less fertile, with lower organic matter, lower water-holding capacity, and in climates that experience more extreme heat or more variable precipitation. Furthermore, the rate of genetic advances and modification for wheat has been slower than the efforts devoted to corn and soybeans (Vocke & Ali, 2013). This has allowed for corn and soybeans to be planted further north into colder climates and further west into drier regions (Vocke & Ali, 2013), resulting in planted-wheat hectares to decline. In general, because wheat is an important food source in the United States and partially due to public perception, there is currently no commercially grown genetically modified (GMO) wheat grown in the United States that is approved by the USDA.

4.2 | Yield variability over space and time

Yield variability over both time (quantified by the decadal-median instability at the county level) and geographic space (25–75% quantile and the upper fence) has increased since 1970, particularly for maize and soybean (Figure 1). Furthermore, the gap between the median of the standard deviations among irrigated, nonirrigated, and all-practices categories has increased for maize and soybean, but has remained relatively consistent for winter wheat (Figure 1). Lin and Huybers (2012) pointed out that increasing variance in yield time series can be expected, given other processes that change in proportion to increased yields. Changes in agriculture via the green revolution and more recent advances in plant breeding and genetics could decrease variability, but at the same time, reduced genetic diversity across space (Osborne & Wheeler, 2013) and large-scale management acting in greater unison (Kucharik, 2006; Kucharik, 2008) could increase the likelihood of simultaneous effects on crops across large regions.

Weather variability, a primary cause of interannual variability in yield (Kukal & Irmak, 2018; Osborne & Wheeler, 2013), could be increasing in those regions where both irrigated and nonirrigated maize and soybean are reported (e.g., Kansas, Nebraska, Texas, and Colorado), with irrigated crops continuing to have small interannual variability compared to nonirrigated yields. Even though yields of both irrigated and nonirrigated maize continue to increase, irrigation continues to reduce variability, even in the face of a changing climate, while nonirrigated crops are suffering more from increased

instability (Kucharik & Ramankutty, 2005; Kukal & Irmak, 2018; Leng, 2017).

Increased yield variability over time has not been previously reported for maize, soybean, and winter wheat across the entire United States at the county level for 1970–2017. Previous studies have often not addressed changes in variability over time (Ben-Ari & Makowski, 2016; Calderini & Slafer, 1998; Kukal & Irmak, 2018; Osborne & Wheeler, 2013). However, Leng (2017) assessed USDA county trends in maize yield variability from 1981–2010 in the United States and normalized residuals by the mean yield (fitted linear trend) to report a change in relative variability over time. This led to the conclusion that county-level maize-yield variability has decreased over time by as much as 15–20% in some counties of the central Corn Belt across Minnesota, Iowa, Wisconsin, and Illinois (Leng, 2017), which generally agrees with our analyses.

4.3 | Patterns and changes in yield gaps

For all three crops, yield gaps have increased since 1970, and the range in yield gap values across counties has also increased (Figure 1, 3). In general, the magnitude of the largest yield gaps has also increased since the 1980s. While the median changes in yield gaps have been consistently increasing for soybean and winter wheat, maize experienced a leveling-off across the three different management categories since the 1980s. Yield gaps are often used to identify regions where crop yields might be limited by biophysical factors (climate and soils), management (inputs such as fertilizers and irrigation), or genetics (Licker et al., 2010; Lobell et al., 2009). They are often used to help understand how changing land management could help close yield gaps in the future to increase agricultural production, whether soil quality is a main limiting factor and might be difficult to overcome, and if a changing climate might either widen or narrow a perceivable yield gap in a particular region. Our approach to calculating large-scale yield gaps is different than previous work in that we do not calculate yield gaps for separate US states (Patrignani et al., 2014) or categorized agroclimatic regions (Licker et al., 2010) based on available soil moisture, potential evapotranspiration (PET), and/or growing degree days (GDD). Instead, we calculated an average-county yield gap for each decade based on the average yield compared to the 99.99 percentile maximum yields over the 10-yr period, using all available data across all US counties and management categories (irrigated, nonirrigated, and all practices). Some may argue this is not an accurate assessment of a county's true yield gap (Licker et al., 2010). For example, while low precipitation and high PET can be overcome with irrigation, there is little that can be done from a management standpoint to overcome a short growing season, low GDDs, or a frequency of extreme heat that is detrimental to crop growth (Kucharik, 2008; Lobell et al., 2014). However, we wanted to identify regions that were improving against the rest of the United States, regardless of any biophysical limitations and water management. This allowed us to compare among crops whether yield gaps were widening or closing over the past 40+ years. Follow-up studies can focus on where the winners and losers are, and potentially identify the causes of varying trends in the yield gaps.

A recent study by Lobell and Azzari (2017) supports our results of expanding maize yield gaps, although their study was for a shorter time period, 2000–2015. They reported that the largest yield increases for maize across Iowa, Illinois, Indiana, and Ohio were occurring on the most productive lands, where more technology and inputs are applied. Lobell and Azzari (2017) suggested that increasing adoption of variable rate technologies (i.e., technologies that apply fertilizers and water to boost yields in certain parts of fields) may be responsible for the increasing gap. Increased sowing density may be another cause; increased plant density can increase yields in regions and conditions where soils and climate combine to supply ample nutrients and water under more favorable growing temperatures (Assefa et al., 2017; Kucharik & Ramankutty, 2005; Lobell & Azzari, 2017).

4.4 | Regional hotspots of high performance: A forecast for future yields?

The scoring system we implemented identified regional hotspots where crop yields are currently the largest and have the lowest yield gaps, and since 1970, have had the highest rates of change (e.g., largest trend lines) and/or are experiencing an acceleration of annual-yield gains over time. Those regions appear to be hotspots where the highest yield increases in the future will occur if history is a good predictor of long-term projections. These regions are generally found on the most fertile Midwest soils (e.g., Minnesota, Nebraska, Iowa, Illinois), have plentiful growing season rainfall, or are benefitting from irrigation management (e.g., Nebraska and western coast states). Furthermore, previous studies have shown that some of these regions (e.g., Minnesota, Nebraska, and Iowa) have seen a trend towards earlier planting of corn (Kucharik, 2006) and soybean (Sacks & Kucharik, 2011) since the 1970s, which has contributed significantly to yield increases (Kucharik, 2008).The counties and regions that are irrigated and top producers, however, should be a cause for concern given the reliance on irrigation to boost yields (Cotterman, Kendall, Basso, & Hyndman, 2018) and the myriad studies that suggest this is not a long-term sustainable practice in such regions as the Great Plains (Scanlon et al., 2012). Our work also shows that across all three crop types, the

lowest-performing counties (i.e., the lowest average yields, highest yield gaps, lowest rates of yield increase over time, and/or deceleration in yield increases) were predominantly found in the central United States, including the Dakotas, Kansas, Oklahoma, and Texas. The common climate conditions in the central United States compared to other key growing regions has a higher likelihood of extreme heat (i.e., days above 30 °C or extreme degree days) and drought combined, both of which have been suggested as causes of yield reductions, particularly for maize (Basso & Ritchie, 2014; Lobell et al., 2013; Lobell et al., 2014). This suggests that as climate change continues, these regions may be most at risk for falling even further behind other regions. The historical trends and current yields might be a precursor of continued struggles in the next few decades to keep pace with the highest performing counties.

Our findings also agree with the work of Assefa et al. (2017) who used a long-term dataset of Dupont Pioneer maize hybrid-by-seeding-rate trials from 1987–2015 across 23 states and three Canadian provinces to assess how yield increases varied among growing environments and latitudes. They found that high-yielding (10–13 Mg ha^{-1}) and very high yielding (>13 Mg ha^{-1}) environments had significant yield increases over time. However, the yield for medium- (7–10 Mg ha^{-1}) and low-yielding (<7 Mg ha^{-1}) environments did not significantly change over time. They also used USDA state-level yield for 21 states to look at simple yield trends for low-, medium-, and high-yielding categories, and arrived at a similar conclusion (Assefa et al., 2017). They concluded that the majority of maize-yield increases across the Corn Belt area were due to increased yields in favorable environments and an increased proportion of high- and very high yielding environments for maize (Assefa et al., 2017). Our study also suggests that regions with less-favorable growing environments for all three crop types are struggling to keep pace with yield increases elsewhere (Figure 5).

5 | CONCLUSIONS

This study investigated county-level yields of maize, soybean, and winter wheat, building on previous studies (Ben-Ari & Makowski, 2016; Grassini et al., 2013; Kucharik & Ramankutty, 2005; Leng, 2017; Lobell & Azzari, 2017; Ray et al., 2012). This study differs from previous analyses by statistical treatment and by combining national-scale analyses of long-term data through 2017 for three crop types and comparing responses across varied water-management categories (irrigated, nonirrigated, and all practices). Only a small number of states currently report yield split between irrigated and nonirrigated practices, making it more difficult to understand broad-scale responses of irrigated crops in comparison to their rainfed counterparts. However, our results clearly show that irrigation management increases the mean yields of all three crops and reduces interannual variability.

Clear spatial patterns in trends in crop yield over time suggest some regions have historically struggled both in terms of the mean and variability of yields. Deceleration of yield trends in some regions, as well as an overall decline in yields across portions of the southern Great Plains over the past 20 yr, are a cause for concern. In particular, irrigated wheat crops are showing a downward trend in southern Great Plains regions. Changing climate and soil quality (e.g., nutrients, pH, and cation-exchange capacity) might be an explanation (Patrignani et al., 2014), but more work is needed to determine whether this might be an isolated case in locations like Kansas, or represent an early warning to more widespread and abrupt changes with continued environmental change.

Crashes in agricultural productivity can lead to catastrophe, such as the Irish potato famine of the 1840–1850s (D'Arcy, 2010), the US Dust Bowl of the 1930s (Cook et al., 2009), and the recent civil wars in the Fertile Crescent region that came on the heels of prolonged drought (Kelley et al., 2015). The increases in yields of all three crops from 1970–2017 represent a remarkable achievement. Nonetheless, not all regions have benefitted equally, and at least for winter wheat, the maximum yields might have been reached in high-yielding areas. Furthermore, irrigation has been a major factor in increased mean yields and decreases variability, yet in some regions, such as counties dependent on the Ogallala Aquifer, water availability is becoming limited. With changing weather and climate, future yield is less certain, and the Great Plains region appears to be at heightened risk for future abrupt changes in yield.

AUTHOR CONTRIBUTIONS

C. Kucharik designed the experiment. T. Ramiadantsoa and J. Zhang performed the statistical analysis of results. C. Kucharik, T. Ramiadantsoa, and J. Zhang wrote the manuscript. A. Ives assisted with statistical analysis and writing of the manuscript.

DATA AVAILABILITY STATEMENT

All of the county level data and code used to process data are available at: https://github.com/ramiadantsoa/Yield_trends

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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