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Compound impact of drought and COVID-19 on agriculture yield in the USA

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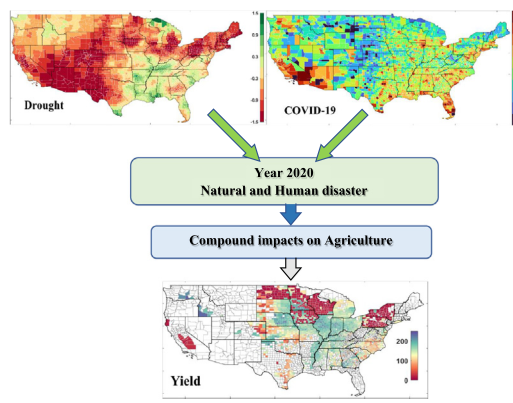
HIGHLIGHTS

- The lower crop yield in 2020 impacted by drought and COVID-19 for the USA.
- Impact of COVID-19 on yield was more prominent than drought severity.
- Compound impact for wheat was more scattered compared to other crops.
- The GWR model can capture the local scale crop yield variability.

GRAPHICAL ABSTRACT



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ABSTRACT

The resilience of agricultural systems in the face of drought has improved over the decades, but the ongoing COVID-19 pandemic presents a new and unexpected challenge to the agriculture sector. The combination of drought and COVID-19 can lead to a compounding impact on farming sectors, including crop yield. This study investigated the potential impact of drought, COVID-19, and their compound effect on three major crop yields in 2020. The analysis was carried out using the Geographically Weighted Regression (GWR) concept to model the spatially varying relationship between Standardized precipitation evaporation index (SPEI), COVID-19 incidence rate, and three crop yields (corn, soybeans, and wheat) across the counties located in the USA. The GWR model was suitable for capturing local scale crop variability, and the potential hotspots are identified where the compound effect is dominant. Although the drought in 2020 was not extreme compared to the past events, the median crop yield during 2020 for the three crop yields was lower than their historical (1980–2020) median values, which highlights the potential role of COVID-19 on reduced crop yields. The compound effect of drought and COVID-19 seem to vary in terms of crop and region wise. For example, the compound effect on corn was prominent in Central California and several counties in Midwest USA. In contrast, the effect was more in eastern South Dakota, Colorado, and more scattered for wheat.

1. Introduction

The Sustainable Development Goals (SDGs) of the United Nations (United Nations, 2015) emphasize global food security by promoting sustainable agriculture, empowering small farmers, and ending rural

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poverty. However, both droughts and pandemics (e.g., COVID-19) can cause significant disruption to global food supply chains (Mishra et al., 2021). The long-lasting droughts can significantly impact farmers and farmworkers; for example, the 2001–2009 droughts in Australia (Edwards et al., 2009) greatly affected agriculture and allied sectors. Drought is a primary concern for society, and its impacts can vary in space and time at local (e.g., counties), regional (e.g., states), and global scales. The drought impacted crop yield in almost three-quarters of the global harvested land (454 million hectares) between 1983 and 2009, translating to a significant economic loss of approximately $166 billion (Kim et al., 2019; Mishra et al., 2021). The droughts are also the most expensive natural disasters affecting agriculture sectors in the USA (Mishra and Singh, 2010). In the USA, the 2012 drought event caused an economic loss of $30 billion (Smith and Matthews, 2015), mainly affecting the agriculture sector. Similarly, another historic drought in 1988 caused extensive losses to the agriculture sector with 40% of the total economic loss (Smith and Katz, 2013).

The farmers adopt different technologies to improve the adverse impact of droughts on crop yields (Sumner et al., 2015; Mishra et al., 2021). These technologies include access to alternative water sources, adapting drought-resistant crops, adopting water-conservation technologies (Schoengold and Zilberman, 2007), advancing agronomical practices (Olen et al., 2016; Burke and Emerick, 2016; Hagerty et al., 2020), or adopting water-conservation technologies (Schoengold and Zilberman, 2007). Therefore, the impact of the drought will vary between the regions (e.g., counties) depending on the technologies adopted in the agriculture sector. Droughts affect both rain-fed and irrigated agriculture. In rain-fed agriculture, severe droughts may directly reduce or eliminate yields, resulting in crop failure, nutritional and revenue deficits. In irrigated agriculture, the impact of drought depends on the availability of water from storage facilities. Different statistical methods are used to study the effect of drought on agriculture yield, such as locally weighted regression models (LOWESS), spline functions (Lobell et al., 2014; Lu et al., 2017), correlation analysis (Liu et al., 2018; Lu et al., 2017; Tian et al., 2018).

In addition to the drought, the COVID-19 pandemic substantially impacted the agriculture sector (Manzanedo and Manning, 2020). The key challenges that triggered the crisis are the travel restrictions on agriculture workers, change in consumer demand, lowered production of food facilities, import or export ban on foods, and financial stress on the supply chain (Mishra et al., 2021). The agriculture supply chain is impacted (Gregorioa and Ancog, 2020) by movement restrictions of transport and labor of farm inputs, produce, and increased food prices. For example, the COVID-19 infections count stood at around 1.9 million during the beginning of June and reached 6.3 million by the end of the crop growing season in August 2020, a more than three-fold increase in infections. This upsurge in infections can lead to a labor shortage and financial stress on farmers, leading to reduced crop production and yield in impacted areas. A recent study investigated the influence of climate variables on COVID-19 risk (Jha et al., 2021). In another study, spatial regression models were used to understand the relationship between the COVID-19 outbreak with 35 environmental, socio-economic, and demographic variables (Mollalo et al., 2020). Their study used the models such as Geographically weighted regression (GWR) and Multiscale GWR to identify local variations in the spatial dependence.

The previous discussion highlighted the impact of individual drought and COVID-19 on crop yields; however, their compound impact can trigger more adverse effects on the agriculture sector (Mishra et al., 2021). For example, in 2020, a combination of a natural disaster (drought) and a human disaster (COVID-19) caused more significant damage (Mishra et al., 2021) to the agriculture yield. A recent study highlighted the compound impact of drought and COVID-19 on the agriculture and food sectors (Mishra et al., 2021). Another study discusses the policy aspects to minimize loss of life, preparedness to mitigate pandemics and droughts, and other climate hazards (Phillips et al., 2020). However, most of these studies focus on understanding the underlying causes and their potential implications on agriculture. Limited studies focus on identifying the potential impact on a local scale (e.g., counties) and attributing their causes to disasters such as COVID-19 and drought on agriculture yield.

Our study focuses on understanding the spatial variability of 2020 crop yield in the USA due to the compounding (drought and Covid-19) event and identifying the hotspots. To the best of our knowledge, this is one of the early studies investigating the spatial distribution of crop yields across the counties in the United States during the pandemic. This study can aid agriculture policymakers and administrators in identifying potential hotspots and their causes for yield reduction. The overall objective of this study are: (a) to quantify the potential impact of drought, COVID-19, and their compound effect on three major crops (Corn, Wheat, and Soybeans) yields in the year 2020, and (b) to identify the potential hotspots where the compound effect is dominant and to highlight the possible reasons for yield variations across the counties located in the USA. We applied the statistical regression-based concept to address these two research questions.

This study intends to test the hypothesis that a compound drought and COVID-19 events are likely to have a higher impact on agriculture crop yields than individual events. However, this compound impact may vary among the regions, which can be attributed to technology adaptation strategy, socio-economic background of the farmers, drought-resistant crops, water availability, and source of irrigation water. We implemented a Geographically Weighted Regression approach to test this hypothesis by capturing the influence of drought and COVID-19 incidence rate and their compound impact on crop yields.

2. Study area and data

The USDA (United States Department of Agriculture) provides crop yield data at the county level and on an annual basis for field crops, and we selected three crops (corn, soybeans, and wheat). The study area comprises counties located in the USA with crop yield data available for 2020. In this study, we used the Standardized Precipitation Evapotranspiration Index (SPEI) as the drought index. We collected monthly precipitation and temperature data from European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA5, 2021). Potential evapotranspiration computation carried out using the Thornthwaite approach (Thornthwaite, 1948) with temperature as a critical input. The ERA5 product used in this study is an improvement over the previous version ERA-Interim in terms of variation in data quality over spatial and temporal resolution. One of the key improvements of ERA5 dataset over the previous iteration is its ability to represent the balance between global precipitation and evaporation. It represents precipitation over the land more accurately around the boundaries of tropical zones (Hennerman and Guillory, 2021).

For COVID-19 data, we used time-series data at the county level provided by the New York Times (https://github.com/nytimes/covid-19-data). We selected this dataset due to its good quality (Ives and Bozzuto, 2021); the data is curated by the New York times by collecting information from various states and local health officials across the USA. In the USA, COVID-19 infections surged by the end of March 2020 and extended until almost the first week of June, and the second wave lasted until September 2020 (Vahabi et al., 2021). Overall, the first two waves of the pandemic in the USA coincide with crop growing periods of significant crops. We calculated the incidence rate at each county by standardizing infection count during crop growing season (by crop) with the population following the recent studies (Mollalo et al., 2020; Paramasivam et al., 2020). Then, we use the incidence rate as a proxy to quantify the geographical distribution of the pandemic among counties in the USA.

3. Methodology

The climate variables precipitation and temperature are generated at the county level using an area-weighted method to transfer gridded information to county polygons. We used the transformed variables for subsequent SPEI calculations. In addition, the COVID-19 incidence rate is available at daily resolution for each county in the USA. Therefore, we use the monthly drought index and COVID-19 incidence rate calculated during crop growing season for respective crops to examine their association with crop yield. Following previous study (Lu et al., 2020), we selected June to August for corn, June to September for soybeans, and May to July for wheat crops in the USA as critical periods.

3.1. Drought index

Various studies used different drought indices to quantify drought severity, such as standardized precipitation index (SPI), SPEI, and self-calibrating Palmer drought severity index (sc-PDSI). This study used SPEI (Vicente-Serrano et al., 2010) as it incorporates precipitation and potential evapotranspiration information and is more relevant to the agriculture sector. The SPEI can be appropriate for predicting agriculture drought due to its highest association with crop yield (Tian et al., 2018). The steps used for calculating SPEI is provided below (Vicente-Serrano et al., 2010):

1) Calculate the water surplus or deficit: $D_i = P_i - PET_i$, where P_i is the monthly precipitation and PET_i is the potential evapotranspiration.
2) A Log-logistic distribution with probability density function: $f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-2}$ is applied to D_i time-series. Where α, β, and γ are scale, shape, and origin parameters, respectively.
3) The probability distribution function of the D series is given by:

$$F(x) = \left(1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right)^{-1}$$

4) Using F(x), the SPEI can easily be obtained as the standardized values of F(x). Following the classical approximation of Abramowitz and Stegun (1965), the SPEI is calculated as:

$$SPEI = W - \frac{C_1 + C_2\,W + C_3\,W}{1 + d_1 W + d_2 W^2 + d_3 W^3}$$

where, $W = -2\,ln\,(P)$ for $P \leq 0.5$, P is the probability of exceeding a determined D value, $P = 1 - F(x)$.
If $P > 0.5$, then the P is replaced with $(1 - P)$ and sign of SPEI is reversed. The constant values are defined as: $C_0 = 2.515$, $C_1 = 0.802$, $C_2 = 0.010$, $d_1 = 1.432$, $d_2 = 0.189$, $d_3 = 0.001$.

3.2. Geographically weighted regression (GWR) method

We constructed a geographically weighted regression (GWR) model at the county level using the crop yield as the dependent variable, while the drought index and COVID-19 incidence rates are independent variables. The coefficients of the GWR method represent the local weights of each independent variable. The GWR applied on geo-tagged county-level datasets estimates local coefficients (Wheeler and Páez, 2010; Wolf et al., 2018) to visually interpret and identify the spatial changes to the regression model.

In the GWR approach, weights are allocated based on a distance criterion at each county for which a local regression model is developed by selecting neighboring counties. The selection of appropriate kernel function helps estimate the weights based on the distance criteria to reduce the influence of counties far away from the local county.

$$y_i = \beta_{i0} + \sum_{j=1}^{m} \beta_{ij}\,X_{ij} + \varepsilon_i, i = 1, 2, \ldots, n \tag{1}$$

where y_i stands for yield during 2020 at county i, intercept term is defined using β_{i0}, the summation term is used to define the j^{th} explanatory variable X_{ij} and ε_i is a random error term (Brunsdon et al., 1998). Parameter estimation can be done by solving the following equation.

$$\widehat{\beta}(i) = \left(X'\,W(i)X\right)^{-1}\left(X'\,W(i)\,y\right) \tag{2}$$

Here, $\widehat{\beta}$ is a vector containing parameter estimates (m x 1); X represents the explanatory variables (n x m); *W(i)* is the spatial weight matrix (n × n); y is the vector of observations of the dependent variable (m × 1). To calculate *W(i)*, a kernel function and bandwidth should be specified. The bandwidth is usually determined based on Euclidean distance or the number of nearest neighbors. The selection of neighborhoods will be affected depending on the different bandwidths at which local weighting is considered. We used Akaike Information Criteria with a correction (AICc) for selecting the bandwidth (Fotheringham et al., 2000) to be used in the GWR method. We also compared the GWR results with ordinary least square (OLS) regression using various statistics including AIC (with no correction).

4. Results

4.1. Revisiting drought, COVID-19 infections, and agriculture yield

The spatial distribution of average drought severity during the summer months (June to August) for the selected counties for the year 2020 is provided in Fig. 2(a). We calculated the number of counties affected by the droughts over the past three decades (1980–2020) to further understand the severity of drought during 2020 compared to the past years (Fig. 2b). The United States experienced severe drought in most counties during 2012 (highlighted in the blue bar, Fig. 2b). In comparison, the year 2020 is considered one of the driest in the last seven years, except for the southeastern part of the USA, which received ample rainfall caused by the North Atlantic hurricane system. The year 2020 can be considered as the above-average drought year concerning spatial extents of drought severity. According to the National drought mitigation center (NDMC), nearly 40% of the counties experienced moderate to exceptional drought, with 8% of the country facing exceptional drought in August 2020. The year 2020 witnessed a higher drought in most areas other than the southeastern USA. The southern tip of Texas and most of southern Florida showed wet spells due to the tropical weather systems experienced by these regions. This process extended to most of the southeast USA.

We noted extreme droughts during the summer months of 2020 across many counties in the USA (Fig. 2a). The severity of the drought also changed drastically between the states located in the northeastern and midwestern USA. Similarly, the southwest region except Texas, Oklahoma, and California indicated these extreme dry patterns.

We also evaluated the spatial changes in three crop yields during 2020 (Fig. 3). The corn yield during the year 2020 showed the highest spatial variability, with counties in the lower Mississippi, Nebraska, Missouri, Indiana, Ohio, Michigan experiencing higher yields of more than 150 bushels (BU)/acre. We compared the median long-term average county-level yield with the 2020 yield using violin plots (Fig. 3d to f). The crop yield in 2020 was lower than the historical yields, and we observed a lower median yield for three crops across the counties. For example, the spatial variability of corn yield has a range of 10 to 225 BU/acre, with a median value around 150 BU/acre. However, during the year 2020, the median value is much lower (60 BU/acre) compared to historical median amounts. Few states like South Carolina, Kansas, and Colorado observed mixed crop yields. Lower corn yield (<50 BU/acre) states in 2020 include California, New York, Pennsylvania, North Dakota, Iowa, Minnesota, and Wisconsin (Fig. 3a). We observed that the soybeans yield during 2020 reduced significantly (median value: 37 BU/acre) than the historical analysis, where the median yield value was 50 BU/acre (Fig. 3a). However, the overall variability in crop yield across the USA during 2020 remained subtle (around 25 to 50 BU/acre). Texas, Oklahoma, North Dakota, South Carolina, and North Carolina, the northern part of Minnesota, the Western part of South Dakota, Southeastern Kansas experienced relatively lower yields during 2020.

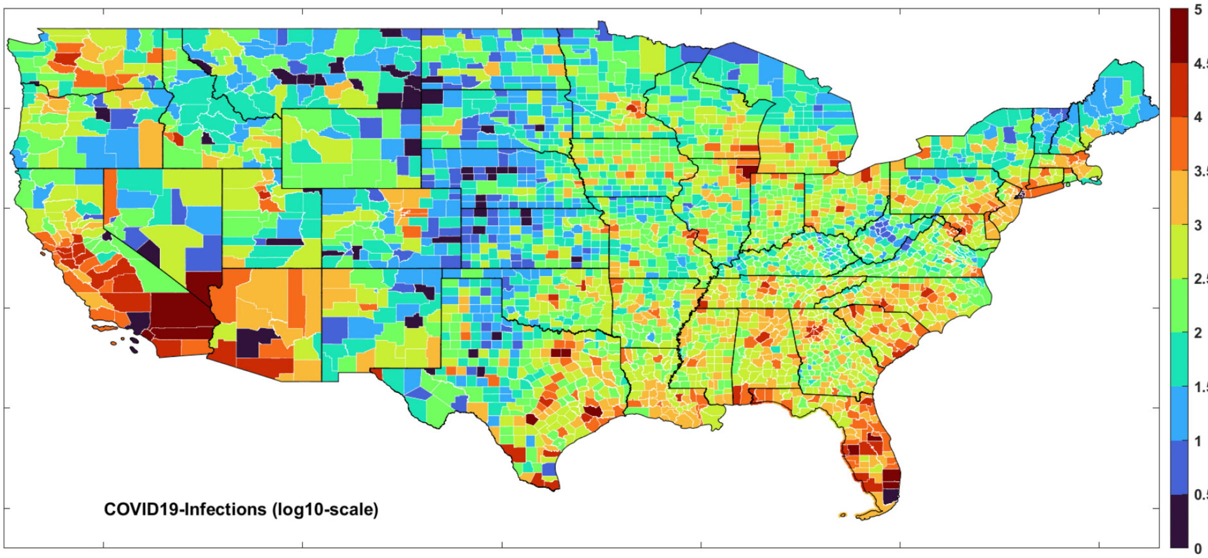

Fig. 1. COVID-19 infections are represented at county level across the continental United States on a log10 scale during crop growing season (June to August 2020).

From historical analysis, we noticed a lower yield (40 BU/acre) for wheat during 2020 compared to the historical average of around 55 BU/acre. Except for few states in the western part of the USA, most of the states with wheat cultivation showed lower yields. The states close to the west coast, such as California, Arizona, Idaho, Oregon, and Washington, indicate higher yield during 2020. States such as Wisconsin, Michigan, Illinois, Indiana, and Ohio experienced medium yield for wheat during 2020.

During the growing season months, we used COVID-19 pandemic incidence to identify the hotspots that might impact agriculture yield (Fig. 1). As pandemics highly related to the human population, the urban areas experienced the most severe COVID-19 infections due to population density and their interactions. The states such as California, Washington, Texas, followed by most of the states in the southeast region, saw a higher infection. The midwestern states of North Dakota, South Dakota, Nebraska, Kansas saw the lowest COVID-19 infections. Even though states such as New York witnessed the highest COVID incidence, the peak infections reached around the 2nd week of April in 2020, which is much before the crop growing season. Therefore, the association with COVID-19 could be negligible in this state.

The impact of the pandemic on crop yield might be a result of labor shortage due to fear of infection or fatality caused by the pandemic. Also, the pandemic can indirectly have a cascading effect on agriculture due to the severe financial stress it causes on farmers (Mishra et al., 2021). Pandemics can hinder the capacity of farmers with essential agricultural and livestock contributions such as quality seeds, fertilizer, and feeds (Ehui, 2020).

The irrigation practices vary among the counties. Previous results show that irrigation significantly reduces the detrimental impact of droughts in maize and soybean but not in wheat (Zhang et al., 2015). The pandemic can have an impact due to labor shortage affecting labor-intensive field management practices such as operating farm machinery, applying fertilizers (pesticides), irrigating the crops, and harvesting crops. Furthermore, the labor shortage along with difference in irrigation practices can potentially influence the compound impact of drought and COVID-19 on agriculture sectors.

4.2. Correlation between drought and crop yields

We performed spatial correlation analysis to understand the potential relationship between the drought index and crop yields for 2020. In correlation analysis, the hypothesis testing identifies if the correlation between any two variables is significantly different from zero. Table 1 (Case 1: no threshold) represents the correlation statistics (and statistical significance) between independent variables and crop yields. The positive correlation of SPEI with the corn yield suggested a positive effect on the yield, indicating that the drought index's lower magnitude (i.e., drought events) reduces crop yields. In contrast, positive magnitude (i.e., wet periods) may increase crop yields. For soybeans, the correlation analysis with drought indicated a statistically significant negative correlation (−0.08). This negative correlation broadly indicates that crop water requirements and irrigation practices might differ for soybeans from other crops. However, the wheat yield suggests a significant correlation (0.17) with the drought index (Table 1) based on our analysis of 975 counties in the USA. The SPEI revealed a statistically significant (<0.05) relationship with three crop yields as a drought index. However, soybeans showed the most drought-resistant characteristic among the three crops.

The drought index consists of wet and dry spells; therefore, we further classified drought into various categories using thresholds (Table 1). We followed SPEI drought classification based on (Vicente-Serrano et al., 2010). The thresholds are selected based on the probability of occurrences; for example, extreme drought (SPEI ≤ -2) has an event probability of 2.3%. As the drought threshold increased, the number of counties impacted by drought reduces (Table 1).

For Case 2 (SPEI threshold <0), this case indicated dry spell periods with all the counties falling in this category impacted by at least minor drought. The drought criteria indicated most northern states and most eastern USA states except few counties in Northwestern states to be drought-impacted regions. For corn yield, California, Minnesota, and Iowa indicated a high correlation with drought. The northeastern states of Pennsylvania and New York yields were low and prone to drought, showing a good correlation. In Texas, the correlation of drought with corn yield seemed lower than in other low yield regions. States of Montana, South Dakota, further south till Oklahoma indicated a lower correlation with drought index and low yield for wheat crop. For soybeans, as discussed earlier, the drought association is overall weak. However, the state of North Dakota indicated a strong impact due to drought. Other states such as South Dakota, Kansas, Oklahoma showed lower yield drought in about 5–10 counties. Even though subject to drought, most of the other soybeans-growing states presented higher yields, indicating strong drought resistance capability of soybeans.

The relationship is similar for different ranges of drought severity (case 3 and 4); hence we used the entire drought index range for further analysis. The multi-year SPEI drought might be more correlated with crop yields (Lund et al., 2018); this might explain the negative

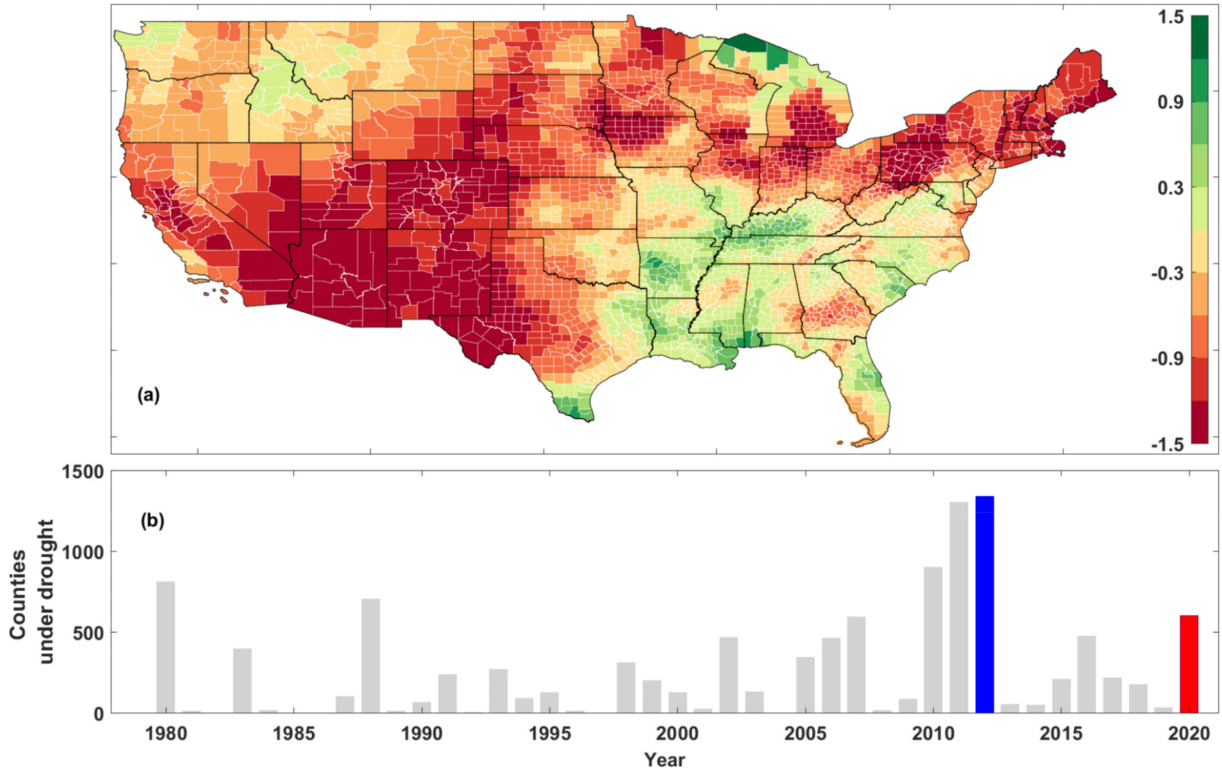

Fig. 2. (a) Spatial distribution of SPEI drought index during June to August of 2020 at county level in within continental United States (b) Historical drought perspective of 2012 (blue) and 2020 (red) drought severity based on the number of counties affected by moderate to extreme drought during summer months (June to August) of each year (1980–2020).

correlation of yield with the drought index for soybeans. Also, the results from our study are consistent with previous studies in quantifying correlation (Lu et al., 2017; Tian et al., 2018) between yield and drought index. The spatial variability of agriculture yield depends on numerous localized factors ranging from best management practices (BMP) used by farmers in each state or county across the United States. The yield also changes with several other factors, such as socio-economic factors surrounding farming which play a crucial role in crop productivity during the growing season.

4.3. COVID-19 impact on crop yield

During a pandemic, socio-economic conditions might impact labor shortage for farming needs. In addition, the financial stress encountered due to contagion could indirectly affect the ability to produce higher yields due to many factors that hinder usual farming practices. We identified this impact by using the COVID-19 incidence rate during the pandemic year 2020. The incidence rate from pandemics such as COVID-19 will most likely have a very localized effect on agriculture activities. The effect can propagate to a regional scale following the harvesting period due to the weakening of supply chain systems.

Correlation analysis indicated a statistically significant relationship between infections and agriculture yield for corn and wheat, as displayed in Table 1. For corn, the counties in California and most counties in Texas showed higher infections in regions of lower corn yield. Also, states such as Minnesota and Iowa showed similar linkage. Few counties in Montana, North Dakota, where wheat crop indicated lower yield, are also affected by high COVID-19 incidence. In Kansas and Oklahoma, the lower yield coincides with a higher COVID-19 incidence rate combination. The relationship between COVID-19 incidence and soybeans yield demonstrates an insignificant relationship. As a result, it was not included in the further analysis as this study primarily focuses on the pandemic impact on agriculture.

4.4. Compound impact of COVID-19 and drought on crop yield

Here we performed the ordinary least square (OLS) and GWR regression models to quantify the compounding impact of drought and COVID-19 on crop yields. We further compared the statistics between these two selected regression methods. In this analysis, the crop yield is selected as a predictand and the predictors include drought index (i.e., SPEI) and COVID-19 incidence cases. Overall, the OLS model did not perform well based on the low correlation coefficients ($R = 0.22$) for Wheat yield and $R = 0.28$ for Corn yield (Table 2). The lower performance is also reflected based on the higher AIC magnitude compared to the GWR model.

GWR uses a cross-validation approach to select the bandwidth used to identify neighboring counties (i.e., surrounding areas) to fit the localized linear regression model. This bandwidth is the maximum distance GWR model will search to filter surrounding counties in local linear regression. In GWR, the bandwidth size is chosen by either distance (fixed kernel) or the number of neighboring observations (adaptive kernel). The adaptive kernel selection process considers the density of observations and returns an optimal proportion of neighborhood observations value at each regression location (Bidanset and Lombard, 2014). We considered the adaptive kernel suitable for this study as the counties are heterogeneous in size and distribution across the USA. Finally, we calculated the geographical weights using the bi-square distance weighting method to assign weights to the neighboring units.

We selected an optimal bandwidth of 205 km to fit the GWR model based on the cross-validation approach for corn yield prediction. The GWR model performed significantly well with a higher correlation coefficient ($R = 0.86$) (Table 2). The GWR model captured the local variability of corn yield during 2020. The lower magnitude of AIC (1657) for corn also highlights the better performance of the GWR model, compared to the OLS model (AIC: 18610). Using the GWR model for the wheat yield, the model parameters were as follows: the bandwidth of

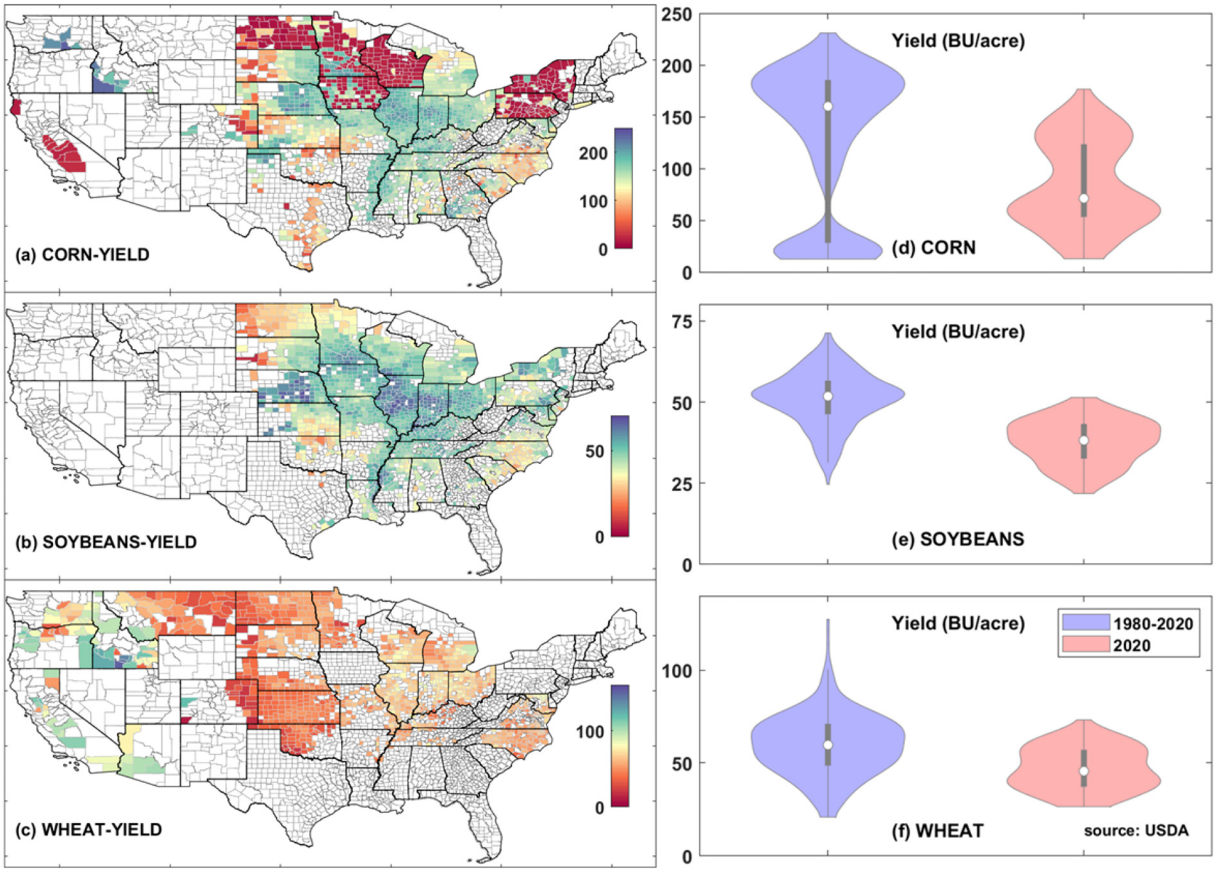

Fig. 3. (a to c) County-level crop yield distribution during 2020 for three crops: Corn, Soybeans, and Wheat; (d to e) for same crops, corresponding crop yield (Bushels/acre) during 2020 compared with historical averages at the county level across the continental United States.

around 1029 km, overall R is about 0.91, and an AIC 2715. The higher correlation coefficient signaled a significant improvement as compared against the OLS model (R of 0.22; AIC of 8415). The lower correlation coefficient (R) indicated local variations are not captured well in an OLS model. Additional goodness-of-fit statistics, such as root means square error (RMSE) and mean absolute error (MAE), also indicated superior performance for the GWR model. Thus, our analysis used GWR model to understand the spatial variability of the crop yields using drought and COVID-19 as predictors. The GWR coefficients help understand the effects of individual dependent variables' contribution to crop yield at each county and identify significant drivers that influence crop yield. Later, we also focus on the spatial distribution of performance of the GWR model using the correlation metric between the predicted and observed yield.

We use the GWR model coefficient to understand the association between crop yield and drought, as indicated in Fig. 4. We noticed a strong spatial relationship with the drought coefficient during 2020, where yield is lowest for the corn yield (e.g., in Pennsylvania). Similarly, in the counties located on the east coast, such as Virginia and North Carolina, the drought presented a substantial factor in predicting corn yield. In the northern part of Texas with low yields, the drought explains the spatial variability in the yield appropriately. The GWR model could not capture the spatial variability for the counties located in transition regions between Minnesota and Iowa, where the yield changes were abrupt for the corn crop. The GWR model's poor performance for these regions is attributed to the additional exogenous factors, such as unemployment, irrigation practices, and other local factors not accounted for by the two independent variables used in this study. The states of Washington, Idaho showed decent predictability with SPEI. The relationship of drought for lower yield is well characterized by SPEI drought index along the western states (Washington, Idaho, and California) of the USA for the corn crop (Fig. 4). The drought coefficients are more prominent in California, where it is considered a predominant factor as we move toward northern counties. We also identified counties highly impacted by drought resulting in reduced yield. These counties include Pennington county within Minnesota, Bowman, Bottineau, Stark County in North Dakota, and Huntingdon in Pennsylvania.

The states with lower wheat yields, such as Oklahoma, Kansas, Nebraska, parts of North Dakota, South Dakota, Montana, and Minnesota, showed a good relationship with the drought, indicating the higher variability with drought than COVID-19. Washington and Oregon states show the strongest association with drought index. On the other hand, the positive drought coefficient presented by the GWR model represents a strong relationship with yield in the counties with higher yields. The counties of Marrow, Gilliam, Wasco in Oregon state, Klickitat, and Douglas in Washington state showed the highest impact on wheat yield in 2020 due to drought.

Further, we analyze the COVID-19 coefficients from the GWR model to identify regions where the pandemic impacts the corn yield. It was observed that COVID-19 significantly affects many counties in the USA. Also, there are regions where we noticed an overall inverse relationship with yield. For example, the counties in North Dakota, California, Iowa-Illinois boundary counties, Northeastern counties in Wisconsin showed a significant adverse effect due to COVID-19 incidence rate. These regions also offer significantly lower yields, as shown in Fig. 5.

For corn yield, the COVID-19 has a milder impact on the counties located in Alabama, Virginia, Southern Texas, Southwestern Missouri, and eastern Kentucky (Fig. 5). One more prominent feature is the relatively lower prediction capability in regions where counties with higher yields and lower yields are next to each other. This rapid transition of the crop

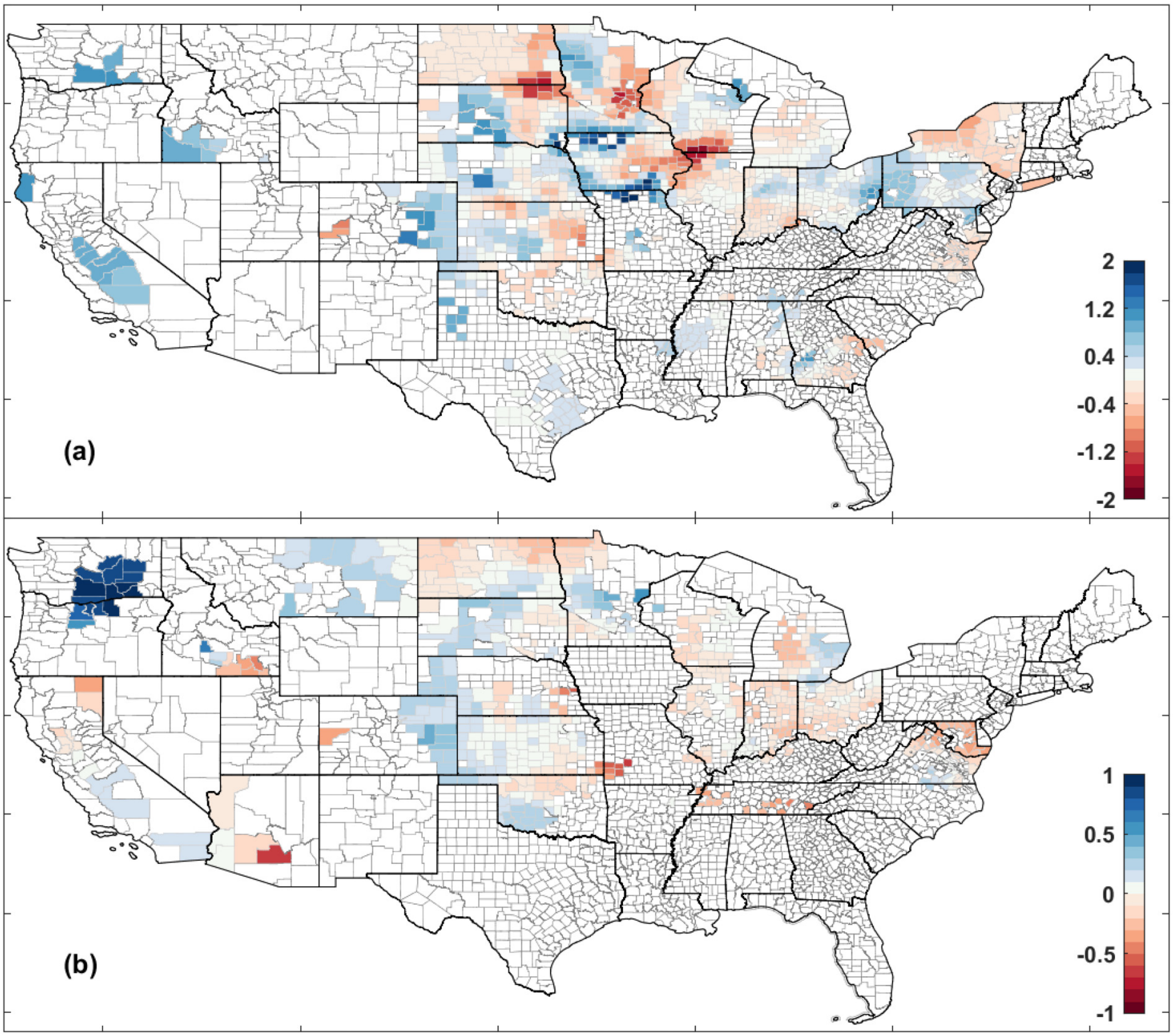

Fig. 4. The spatial map of SPEI drought index coefficients generated based on the GWR model for (a) Corn, and (b) Wheat yield.
[Note: The GWR model is developed based on the SPEI and COVID-19 incidence, this plot only presents coefficients associated with SPEI. Each point represents a county in the continental United States.]

yields between the nearby counties indicates higher spatial variability, which the GWR model may not adequately capture. For example, such a pattern is evident in Minnesota and Iowa, as shown in crop yield spatial distribution. We also identified counties with the highest impact due to COVID-19 incidence rate for corn crops based on GWR coefficients. We noted impact in Swift county in Minnesota, Madison in New York, Cambria in Pennsylvania, and Chickasaw county in Iowa. The compound impact of drought and COVID-19 is evident on corn yield in Hubbard, Roseau in Minnesota, Cambria county in Pennsylvania, Marion, Appanoose counties in Iowa.

The impact of drought and COVID-19 on wheat is different from corn crops. For wheat crops, most of the locations show a decent correlation with the drought. However, there are hotspots with a negative relationship with COVID-19, as indicated in Fig. 5. Kansas showed the highest impact of COVID-19 on wheat yield in counties Rawlins, Thomas, Sherman, Cheyenne, and Decatur. Despite mild drought conditions, few counties in the northern California region showed lower yield, most likely due to a higher COVID-19 case. In the northeast of Kansas, despite a less than moderate drought, the impact on the wheat yield is higher for the counties. Thus, it potentially indicates the possible effects of COVID-19. Similarly, northern Missouri experienced lower yield, where the drought index is close to zero value (no drought condition). The lower yield for this region could be due to higher COVID-19 infections (a 2% incidence rate in this region). The compound impact due to COVID-19 and drought seems to have the highest impact on wheat yield in Washington, Lincoln, Cheyenne, Arapahoe county within Colorado, and Harmon county in Oklahoma.

We further investigated the predictive power of the compound drought and COVID-19 as predictors for the crop yields for GWR model. For corn yield, the combination of drought and COVID-19 has a stronger association as indicated by the correlation coefficient ($R > 0.70$), which also implies that the GWR model explains more than 49% (R^2, coefficient of determination) of the variance in the corn yield in most of the western states: California, Washington, Idaho, and smaller areas around the central US. The regions around South Dakota, Kansas, Indiana, Maryland, and Illinois showed the highest prediction skill for GWR with R (>0.8). In addition, there are clusters of counties with a high correlation coefficient (R > 0.70) around northern Texas, Missouri, and Mississippi. We observed a relatively lower prediction skill for the counties located in North Dakota, Minnesota, South Carolina, and New York (R close to 0.50). In eastern parts of Nebraska and South Dakota, we observed a low R. As illustrated in Fig. 6; we demonstrate the spatial distribution of the R for the two crops analyzed.

For wheat, the GWR model offered a very high R of >0.80 among the counties in the states: Oregon, Washington, Arizona, and western parts of Montana, this indicated descent prediction in these areas. We found

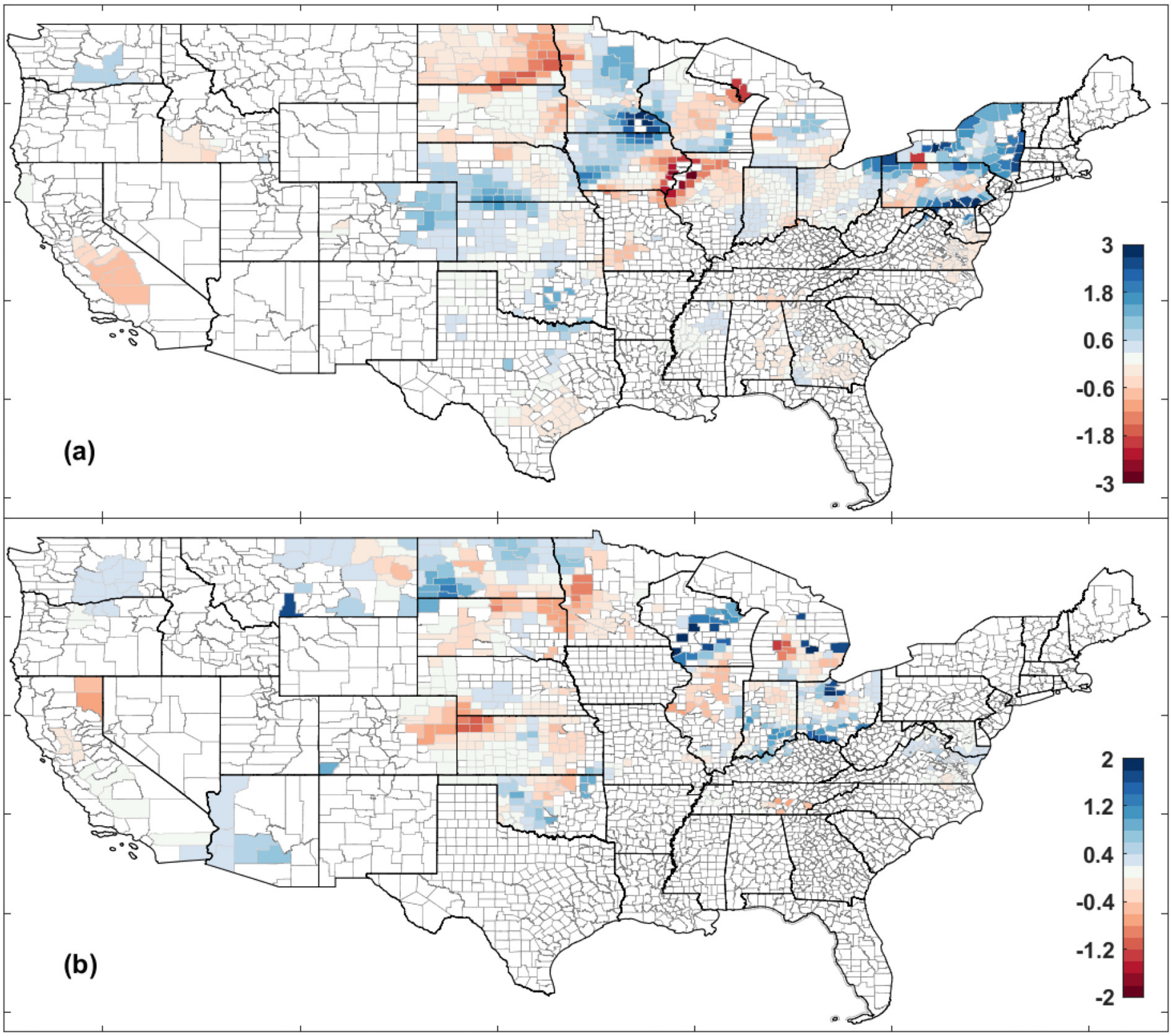

Fig. 5. The spatial map of COVID-19 incidence rate coefficients generated based on the GWR model for (a) Corn, and (b) Wheat yield.
[Note: The GWR model is developed based on the SPEI and COVID-19 incidence, this plot only presents coefficients associated with COVID-19 incidence rate. Each point represents a county in the continental United States.]

an R of less than 0.7 in several counties around the Arkansas, Mississippi, and Tennessee border. Illinois and Wisconsin border counties also presented lower R. Most of the border counties in Illinois showed poor model performance using the GWR approach. Few counties in Kansas also showed very low R.

The 2020 drought-impacted agriculture yield in many regions of the United States. However, the COVID-19 infections played an essential role in further decreasing yield. It is worth highlighting that the agriculture practices (e.g., application of technologies) significantly vary between counties. As a result, we expect that the performance of the OLS model will deteriorate due to the difference in exogenous factors that contributes to the local crop yield. On the other hand, the GWR model can better represent the local effects of dependent variables, thereby accounting for the spatial variability.

5. Discussion

This study investigated the potential influence of drought and COVID-19 on the spatial distribution of the three crop yields. The drought index (e.g., SPEI) can capture the variability of crop yields, and similar findings are highlighted in previous studies (Leng and Hall, 2019; Lu et al., 2017). However, the drought index includes the wet spells (positive values) and may not capture the potential impact of drought events. Besides using a drought index that captures wet and dry spells, we further categorized the drought events during the crop growing periods to analyze the influence of drought severity on the crop yields.

Further, we also demonstrated that the predictability of crop yield using drought index and COVID-19 using regression methods. It is essential to select the regression models that can capture the local scale crop variability. We analyzed the prediction skill using two regression models (OLS and GWR), and the results highlighted the superior performance of GWR models. The prediction accuracy of the models can vary between the states or counties depending on the agricultural management practices and can lead to a sudden transition in crop yields between neighboring counties.

The SPEI index indicated a stronger relationship with yield in the western states, including California, Washington, and Idaho. Many states experienced lower agriculture yield for wheat during 2020. For example, Montana, South Dakota, toward the south till Oklahoma indicated a lower association between drought and yield. However, the states of Washington and Oregon indicated the strongest relationship between crop yield and drought.

The impact of COVID-19 and crop yield seems to be localized compared to the drought. The corn yield indicated a significant negative impact due to COVID-19 infections for the counties witnessing lower yield,

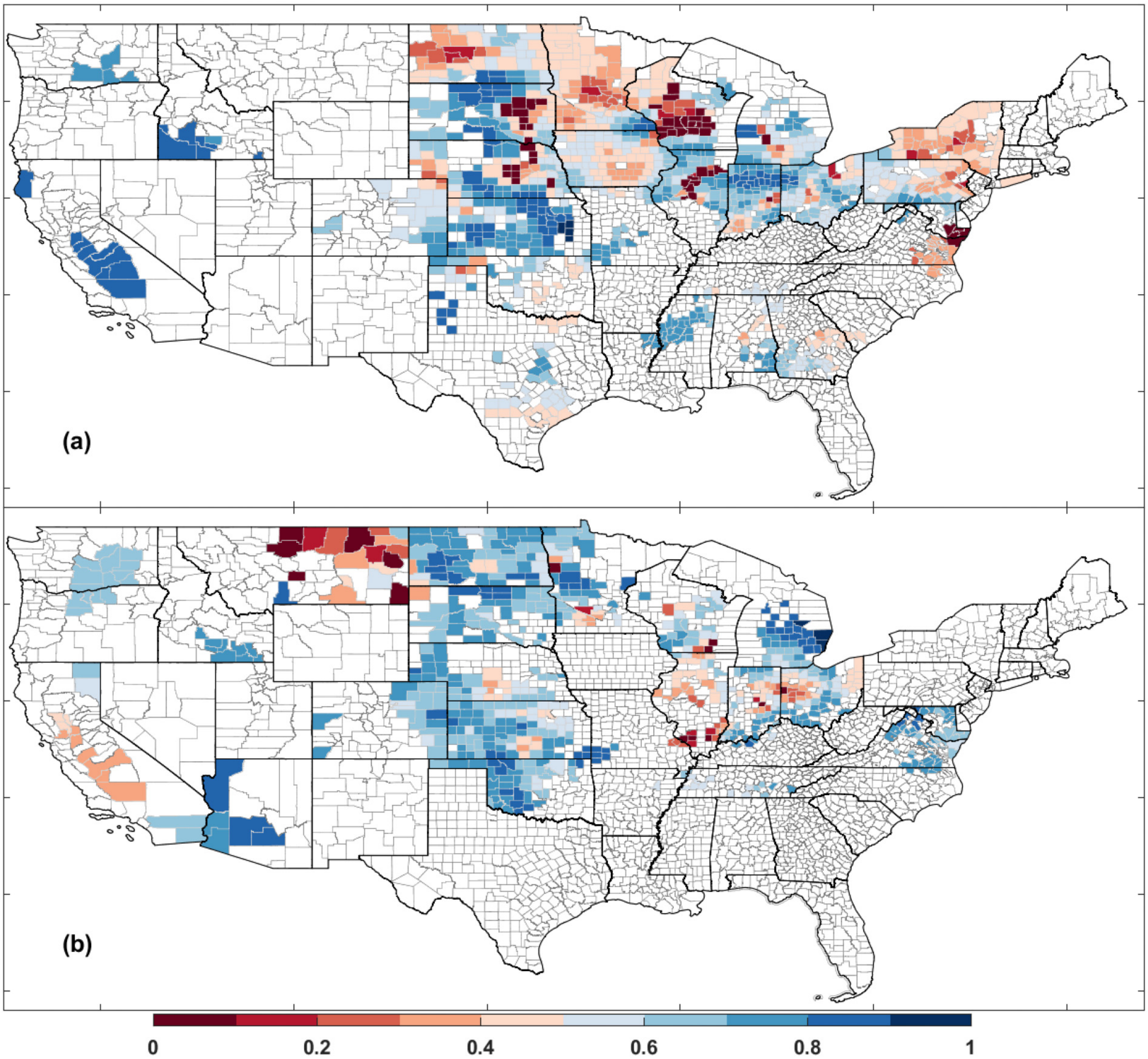

Fig. 6. Performance evaluation of GWR model based on the correlation coefficient (R) between the observed and predicted yield for (a) Corn and (b) Wheat crop. [Note: The GWR model is developed based on the SPEI and COVID-19 incidence. Each point represents a county in the continental United States.]

Table 1
Correlation analysis for different crop yields and drought severity (SPEI: Standardized precipitation evapotranspiration index) during crop growing season and COVID-19 (Coronavirus disease 2019) incidence rate for the year 2020.

Drought threshold	CROP	Number of counties	Correlation between yield and drought		Correlation between yield and COVID-19	
			Statistic	*p*-Value	Statistic	p-Value
SPEI (Case 1)	Corn	1684	0.26	0.00	0.17	0.00
	Soybeans	1466	−0.08	0.00	−0.04	0.09[a]
	Wheat	975	0.17	0.00	0.15	0.00
SPEI <0 (Case 2)	Corn	1154	0.18	0.00	0.19	0.00
	Soybeans	1112	−0.13	0.00	0.00	0.99[a]
	Wheat	687	0.05	0.08[a]	0.18	0.00
SPEI < −0.5 (Case 3)	Corn	579	0.19	0.00	0.19	0.00
	Soybeans	685	−0.02	0.64[a]	0.03	0.38[a]
	Wheat	318	0.10	0.09	0.23	0.00
SPEI < −1 (Case 4)	Corn	86	0.24	0.02	0.21	0.06[a]
	Soybeans	244	0.23	0.00	0.20	0.00
	Wheat	26	−0.04	0.86[a]	0.57	0.00

[a] [Represents statistical insignificance].

and these states include North Dakota, California, parts of Texas, few counties in Iowa-Illinois, northeast of Wisconsin. Despite normal climate conditions, few northern California counties showed lower yield, which could be due to COVID-19.

This study highlights that the COVID-19 indirectly aggravated the impact of drought on agricultural crop yields, although the consequences can differ between the crops. We estimate the compound impact of drought and COVID-19 on crop yield to vary between counties due to the spatial heterogeneity in agriculture management practices,

Table 2
Performance measures of Ordinary least squares (OLS) and Geographic Weighted Regression (GWR) models for crop yield prediction: Akaike information criterion (AIC), Correlation of model prediction (R), Root mean square error (RMSE), Mean absolute error (MAE) and Bandwidth (in kilometers).

Crop	Model	AIC	R	RMSE	MAE	Bandwidth (km)
Corn	OLS	18,610	0.28	59.0	49.4	–
Wheat		8415	0.22	17.8	13.5	–
Corn	GWR	1657	0.86	31.3	20.5	205
Wheat		2715	0.91	7.7	5.3	1029

climate, biophysical conditions, economic activities, population density, COVID-19 cases, a host of other socio-economic indicators (Mishra et al., 2021). Even though the advanced technologies (e.g., drought resistance seeds) can help minimize droughts' impact, the compound impact of drought and COVID-19 is something new that needs more research for developing resilience food security. The compound impact can be significant in rural counties affected by the recession, social restrictions leading to reduced labor and constraints on food products' movement, and lower food demands.

6. Conclusions

This study is one of the early research investigating the potential influence of drought and COVID-19 on three crop yields in the USA. In addition to individual impact, we identify the hotspots impacted by the compound drought and COVID-19. The results highlight that drought and COVID-19 can cause damage to the crop yield; together, their effects can be more conspicuous. The potential impact of drought on crop yields varies based on the type of crops. The results suggest that corn and wheat yields are more impacted by drought and COVID-19 than Soybeans. The drought severity during crop growing periods calculated based on the dry spells can provide more meaningful information to quantify the potential effects of drought on crop yields, and it will exclude the influence of wet spells.

Based on the GWR model, the lower corn yield in 2020 in many counties (e.g., California) can be attributed to the compound drought and COVID-19 cases. For example, lower crop yield states, such as Minnesota, Montana, South Dakota, Nebraska, and Kansas, are positively associated with drought. Comparatively, the wheat crop showed a higher association with the COVID-19 in explaining spatial variation in crop yield. The soybean indicated an insignificant association with COVID-19 incidence rates.

We identified the hotspots of COVID-19 and drought to assess their influence on crop yield. We evaluated the predictive power of two regression models (GWR and OLS); the results suggest the GWR model better captures the local scale variability in crop yield than the OLS model. The results can help identify the regions with lower crop yields due to COVID incidence rate and aids agriculture planners in preparing mitigation measures in case of any future pandemics.

This study used drought and COVID-19 as key influencing variables of 2020 crop yield; however, future studies can include additional variables such as crop management practices, irrigation practices, and various technologies used in different counties across the USA to identify best strategies to minimize the impact of droughts. Besides, the addition of socio-economic indicators impacted by COVID-10, such as unemployment rate and health-related information (e.g., percentage of old age farmers affected) during the 2020 pandemic, can further help to improve our understanding of compounding impacts as well as to develop a comprehensive and robust strategy to deal with natural and human disasters.

CRediT authorship contribution statement

Ramprasad Yaddanapudi: Conceptualization, Formal analysis, Investigation, Writing – original draft. **Ashok K. Mishra:** Conceptualization, Formal analysis, Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

We acknowledge that our manuscript is original and it is not submitted for review in another journal. We have provided references for the data set used in our study.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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