Agricultural and Forest Meteorology 292–293 (2020) 108124

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Mapping the sensitivity of agriculture to drought and estimating the effect of irrigation in the United States, 1950–2016

Junyu Lu[a,b,*], Gregory J. Carbone[c], Xiao Huang[d], Kirsten Lackstrom[c], Peng Gao[c]

[a] School of Community Resources and Development, Arizona State University, Phoenix, AZ 85004, United States
[b] The Hainan University-Arizona State University Joint International Tourism College, Hainan University, Haikou, Hainan Province 570004, China
[c] Department of Geography, University of South Carolina, Columbia, South Carolina 29208, United States
[d] Department of Geosciences, University of Arkansas, Fayetteville, AR 72701, United States

ARTICLE INFO

Keywords:
Drought risks mitigation
Gridded standardized precipitation evapotranspiration index (SPEI)
Gridded standardized precipitation index (SPI)
Analysis of covariance (ANCOVA)
Panel data regression model

ABSTRACT

Drought is a devastating natural hazard posing great threats to agriculture. Identifying the spatial pattern of agricultural sensitivity to drought can provide scientific information for decision-makers to prepare droughts, allocate resources, and mitigate impacts. Here, we use long-term state- and county-level crop data for the 10 major crops: corn grain, soybeans, hay, spring wheat, winter wheat, cotton, corn silage, sorghum, barley, and rice in the United States from 1950 to 2016. First, we perform a correlation analysis between crop yield anomalies and two drought indices (Standardized Precipitation Evapotranspiration Index (SPEI) and Standardized Precipitation Index (SPI)) to identify the sub-seasonal pattern of agricultural sensitivity to drought stress. SPEI performs better than SPI. For most crops, the sensitivity to drought increases in the early period, peaks at the critical months, and then declines. July is the most critical month for crop growth for most crops. Among all crops, soybean and corn grain are most sensitive to drought. Second, we develop an Agriculture Drought Sensitivity Index (ADSI) to quantitatively measure the sensitivity of agriculture to drought stress based on the statistical relationship between the ten major crops and SPEI. We demonstrate that there exists a very strong spatial correspondence between higher sensitivity to drought and the lower percentage of acres irrigated, and vice versa. Also, for those regions with limited irrigation, the sensitivity is higher in arid/semi-arid regions and lower in humid regions in summer. Third, given the importance of irrigation, an analysis of covariance (ANCOVA) shows that the irrigated crop yields have much higher long-run mean yields than non-irrigated crop yields. Fourth, to investigate how irrigation affects drought sensitivity, a panel data regression model shows that the responses of crop growth to drought are non-linear for all crops. Non-irrigated crops are more sensitive to droughts than the irrigated crops, particularly in severe drought conditions. This provides quantitative incentive to use irrigation as an important adaptation and coping strategy to mitigate the drought impacts on agriculture in the US.

1. Introduction

Drought is a very devastating and costly natural disaster. From 1980 to 2017, droughts caused extensive losses in the United States ($239.1B CPI-adjusted economic losses) accounting for roughly 15.3% of total losses from weather and climate disasters (NOAA, 2016). Future drought risks and impacts can be exacerbated by climate change (AMS, 2013; IPCC, 2013). The agricultural sector is the first sector affected by drought since drought can reduce soil-water availability, contribute to crop failure and pasture losses, reduce crop yield, and threaten food security. Agricultural drought is defined as linking meteorological drought characteristics to agricultural impacts, associating precipitation shortages most immediately with higher evapotranspiration levels and soil moisture deficits (AMS, 2013). Agricultural drought usually occurs at the critical time during the growing season, resulting in declining soil moisture and crop failure (Heim, 2002). Drought also can affect livestock industries by compromising forage (e.g. hay or corn silage) supply and quality.

Drought impacts on agriculture depend on its intensity, severity, duration and timing relative to crop growth stages (Kramer and Boyer, 1995). In addition, drought events with similar intensity and duration could have different impacts on agriculture depending on the eco-physiology of the crops and the local adaptive capacity of the system (e.g. management strategies or irrigation facilities). The IPCC Third Assessment Reports (Working Group II: Impacts, Adaptation, and Vulnerability) defined sensitivity as “the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli”

* Corresponding author: School of Community Resources and Development, Arizona State University, Phoenix, Arizona 85004, United States.
E-mail address: Junyu.Lu@asu.edu (J. Lu).

https://doi.org/10.1016/j.agrformet.2020.108124
Received 12 March 2020; Received in revised form 31 May 2020; Accepted 24 July 2020
Available online 08 August 2020
0168-1923/

(IPCC, 2001). Here, we similarly define the sensitivity of agriculture to drought as the degree to which the agricultural system is affected, either adversely or beneficially by drought. Mapping the spatial pattern of the sensitivity of agriculture to drought at the local level can provide objective information with respect to which agricultural areas are most vulnerable and sensitive to droughts, which is key to decision-makers and policymakers for preparing drought, allocating resources, and mitigating risks. However, there are few studies measuring and assessing the sensitivity of agriculture to drought quantitatively and spatially at the local county level over the whole US, across multiple crop types, and over the long term. In addition, irrigation is an important adaptation strategy to mitigate the drought risks to agriculture. Agricultural drought affects both irrigated and rain-fed crop, but with differing effects (AMS, 2013). However, studies empirically estimating and comparing the differing effects of drought on the sensitivities of irrigated and non-irrigated agriculture are rare.

There have been great scientific efforts in developing and using drought indices to assess the drought condition and impacts for better decision making. The Palmer Drought Severity Index (PDSI) (Palmer, 1965) and its variations: the Palmer Z index (Palmer, 1965), Palmer Hydrologic Drought Index (PHDI) (Palmer, 1965), and Palmer Modified Drought Index (PMDI) (Heddinghaus and Sabol, 1991) have been extensively used for drought monitoring and related operational water management decision making. The Standardized Precipitation Index (SPI) developed by McKee et al. (1993) is based on a standardized transformation of the historical probability of precipitation, showing some advantages over PDSI, such as simple calculation, spatially invariant in interpretation, and flexible time scale (Guttman, 1998, 1999). The main issue associated with SPI is that its calculation is only based on precipitation, ignoring the effects of temperature in drought assessments. Adopting the standardizing methods used in SPI, Vicente-Serrano et al. (2010) developed Standardized Precipitation Evapotranspiration Index (SPEI) by incorporating evaporative demand into its calculation and the multiscalar nature of SPI. Both SPI and SPEI allow users to determine the rarity and severity of drought events at any time scale of interest (1-month, 3-month, 6-month, 12-month etc.).

Given the significant impacts of drought on agriculture, there have been great endeavors in connecting drought to agriculture. Different types of drought indices have been widely used to evaluate the drought impacts on agriculture. Quiring and Papakryiakou (2003) evaluated the performance of the four drought indices to predict the spring wheat yield for the 43 crop districts on the Canadian prairies. Mavromatis (2006) evaluated the performance of the drought indices to assess the impact of droughts and climate change on wheat and durum wheat yield for two crop district in Greece. Sun et al. (2012) used various drought indices to assess the drought impacts on spring wheat yields in Canada. Zipper et al. (2016) used SPEI to estimate the spatiotemporal patterns of drought effects on maize and soybean yield at the county level in the US. Matiu et al. (2017) evaluated the interaction between temperature and drought on affecting global and regional crop yield using SPEI. Tian et al. (2018) evaluated the performance of six drought indices to monitor agricultural drought in the south-central US. Peña-Gallardo et al. (2019) analyzed the response of barley, winter wheat, soybean, corn and cotton yield to drought using SPEI. SPEI has been widely used since its development and was found to have a superior capability than uniscalar drought indices (e.g., PDSI and its variations) to capture the drought impacts on the agriculture (Peña-Gallardo et al., 2019; Tian et al., 2018; Vicente-Serrano et al., 2012). SPEI has also been found to be the most representative of soil moisture conditions, which is critical for crop growth (Tian et al., 2018). Most importantly, the multiscalar nature of SPI and SPEI shows advantage to allow identification of a single month or consecutive months critical for crop growth, while by contrast, PDSI has an inherent fixed-time-scale of about 9–12 months (Guttman, 1998).

This study is a purely data-driven empirical study, relying on the actual historical yield losses resulted from the actual field inputs, irrigation, management strategies, and environmental and climate variations, instead of experimental design controlling the environmental conditions, or expert subjective ranking, or qualitative data. We use high-resolution gridded SPI and SPEI to characterize the drought intensity and severity and cover 10 major crops accounting for more than 95% of the total crop harvested areas to represent US agriculture. A sophisticated data self-adaptive detrending approach is applied to automatically separate out the high frequency fluctuations caused by weather and climate factors from the non-linear and non-stationary increasing trend caused mainly by science and technological advances (Lobell and Field, 2007; Najafi et al., 2018) in crop yield time series for thousands of counties, dozens of states, and ten major crop types (Lu et al., 2017). The non-linear and non-stationary feature of crop yield time series and the detrending process are demonstrated in Fig. 1. The non-linear and non-stationary nature of the yield time series is neglected by many studies, which could bias estimates of the relationship between climate variability and yields. We construct a statistical relationship between crop yield anomalies and drought index to estimate the sensitivity of agriculture to droughts and consider subseasonal drought variability, rather than mean conditions for the entire growing season as typical of most previous studies, since the sensitivity of agriculture varies across the growing seasons. The time series data from 1950 to 2016 used in this study for each county or state intrinsically consider the adaptive capacity of the agricultural system (e.g., whether having irrigation infrastructure) and the farmers' year-to-year adaptation to unfavorable conditions (e.g., whether applying extra irrigation to mitigate the risks during extreme dry and hot periods) (Lobell et al., 2011).

Here, we provide a quantitative sensitivity assessment to measure the spatial pattern of sensitivity to drought in the agricultural sector at the local county level in the US. To the best of our knowledge, there has been no empirical assessment on the sensitivity of agriculture to drought based on more than 60 years of crop statistics, 3108 counties, 48 states, and 10 major crop types accounting for more than 95% of the harvested areas in the US. We develop an Agriculture Drought Sensitivity Index (ADSI) to quantitatively measure the sensitivity of agriculture in response to drought stress. Since irrigation plays an important role in drought mitigation, we use an analysis of covariance (ANCOVA) model and a panel data regression model to quantitatively estimate the effects of irrigation in boosting crop yield and reducing the susceptibility of agriculture to drought. This study can provide a general guidance for irrigation management for the ten major crops, scientific and spatial information for allocating resources and preparing drought, as well as quantitative incentives for irrigation infrastructure investment to boost crop yield and mitigate drought risks.

2. Data and methodology

2.1. Agricultural data

The state-level and county-level crop statistics (production, harvested areas, and yield) from 1950 to 2016 were downloaded from the web-based Quick Stats tool provided by USDA's National Agricultural Statistics Service (NASS) (USDA, 2017). We used 48 states and 3108 counties in the conterminous US. We chose the top ten major field crops, including corn grain, soybeans, hay, spring wheat, winter wheat, cotton (Pima and upland), corn silage, sorghum, barley, and rice, which account for more than 95% of the total crop harvested areas in the US, according to 2012 Census of Agriculture (USDA, 2014). USDA's NASS separated statistics of hay into Alfalfa hay and other hay (clover-timothy mixtures, bermuda grass, prairie hay, etc.), separated statistics of cotton into Pima cotton and upland cotton, and separated spring wheat into spring durum wheat and other spring wheat (exclude spring durum wheat). NASS calculated the crop yield as crop production divided by harvested areas. Here, we calculated the cotton yield as the total production of Pima cotton and upland cotton divided by the total harvested area of Pima cotton and upland cotton and did the same to calculate the yield of hay and spring wheat. Our analysis separated wheat into spring wheat and winter wheat because of their different growing seasons. Barley mainly indicates spring barley. For each crop type, we only included counties with at least 30-year data. Majority of the crop statistics from USDA's NASS do not separately account for irrigated vs. non-irrigated fields. The irrigated vs. non-irrigated crop statistics are only available in a part of US covering a short period, which will be used in panel data regression model to investigate the effect of irrigation on the sensitivity of agriculture to drought.

2.2. Gridded standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI)

We calculated gridded SPI and SPEI in the US using the high-resolution 4-km PRISM (Parameter-elevation Relationships on Independent Slopes Model) precipitation and temperature dataset (Daly et al., 2008) from 1895 to 2016. We followed the method of McKee et al. (1993) to calculate SPI and we follow the method of Vicente-Serrano et al. (2010) to calculate SPEI. SPI and SPEI are calculated on a grid-by-grid basis. The SPI is based on only precipitation data and the SPEI is based on the monthly difference between precipitation (PPT) and potential evapotranspiration (PET) representing a simple climatic water balance. The SPEI calculation is similar to SPI. For each grid, we calculated potential evapotranspiration (PET) following the methods of Thornthwaite (1948) and a simple Thornthwaite PET calculation method was chosen due to the same reasons as stated in Vicente-Serrano et al. (2010). We then calculated the monthly difference between PPT and PET and accumulated the monthly difference into different time scales: 1-month, 2-month, 3-month, 6-month, 9-month, 12-month, and 24-month. We fitted a three-parameter log-logistic distribution (two-parameter Gamma Distribution for SPI) using the maximum likelihood estimation (MLE) method (McKee et al., 1993; Vicente-Serrano et al., 2010). The probabilities of PPT minus PET values were then transformed into the quantile of standard Gaussian distribution (normal distribution) with mean of 0 and standard deviation of 1 using an inverse Gaussian distribution function. The transformed variate is the SPEI. The value of SPEI represents the number of standard deviation of PPT minus PET from the mean, usually called Z-score. Following McKee et al. (1993), for both SPI and SPEI, we define the drought categories as: 0 to -0.99 (mild drought), -1.00 to -1.49 (moderate drought), -1.50 to -1.99 (severe drought), and ≤ -2.00 (extreme drought).

Since we used a 4-km high-resolution gridded PRISM dataset to compute gridded SPEI and SPI for multiple time scales across the entire conterminous US from 1895 to 2016, instead of multiple weather stations, we used a High Performance Computing (HPC) system. This parallel and cloud computing system allows us to distribute different time scales and different parts of US into multiple computing nodes and shorten total computing time. We then calculated the county-level and state-level mean for the SPEI and SPI values using an area-weighted mean by the cosine of the latitudes.

2.3. Crop yield anomaly

We used county-level and state-level long-term crop yield data for the ten major crop types from 1950 to 2016 in the US. The long-term crop yield data are influenced by many factors that the long-term nonlinear and nonstationary increasing trend are caused by science and technological advances and the high-frequency fluctuation superimposed on the trend are mainly caused by the weather and climate variations (Lu et al., 2017). We followed the method of Lu et al. (2017) to detrend the long-term crop yield data, using a data self-adaptive detrending method: locally weighted regression model (LOWESS, with 1 degree of freedom) coupled with a multiplicative decomposition model to separate out the weather and climate signals from the long-term nonlinear increasing trend caused by the technological advances (Lu et al., 2017). We calculated the county-level and state-level crop yield anomalies for those ten major crop types, which can represent the percentage of crop yield higher or lower than the normal yield conditions.

2.4. Statistical analysis between crop yield anomalies and drought indices

We performed a correlation analysis between the crop yield anomalies and SPI/SPEI of different time scales (1-month, 2-month, 3-month, 6-month, 9-month, 12-month, and 24-month) in different months during the growing seasons. The growing seasons for each crop type are based on USDA's NASS (USDA, 2010). According to the Pearson correlation coefficients, we identified the best time scales of SPI/SPEI and the most critical months that droughts can severely affect the crop growth. We also compared the performance of SPI and SPEI to correlate with the crop yield anomalies. We then performed a simple linear regression analysis between crop yield anomalies (dependent variable) and the corresponding best drought indices (independent variable) to calculate the slope. Here, we constrained our analysis only to the dry end of SPI and SPEI range (i.e., SPI < 1 and SPEI <1) in the correlation analysis and slope calculation because lower than normal crop yield can be caused by flooding and excessive wetness, rather than droughts, which could lead to non-linearity. Correlation analysis and slope calculation are only applicable to linear relationship. We also excluded the counties that have less than or equal to two drought events (moderate drought or worse; SPI ≤ -1 and SPEI ≤ -1) measured by the corresponding best drought indices for each crop from 1950 to 2016 because it would be not reasonable to calculate drought sensitivity for counties without drought events.

2.5. Agriculture drought sensitivity index (ADSI)

We developed an Agriculture Drought Sensitivity Index (ADSI) to quantitatively measure the sensitivity of agriculture in response to drought. The sensitivity of crops to drought is defined as the slope of the linear regression between the crop yield anomalies and the corresponding best drought index (Samuel et al., 2016; Vicente-Serrano et al., 2013). The slope indicates the change in the mean value of crop yield anomalies associated with a one-unit change in the drought index. A steeper and positive slope means that the crop yield anomalies are lower during severer drought years. We calculated the ADSI as the harvested-area weighted slope for each county or state. The ADSI is based on all crop types that are planted for each unit. Higher ADSI value indicates higher sensitivity and lower resilience, which means that the crop losses are highly associated with droughts, and vice versa. The county-level and state-level ADSI is defined as follows:

$$ADSI_i = \frac{\sum_{c=1}^{10} SLP_{c,i} A_{c,i}}{\sum_{c=1}^{10} A_{c,i}}$$

Where i represents each county or state; c represents the crop type; $SLP_{c,i}$ represents the slope of the linear regression between crop yield anomalies of crop type c and the corresponding drought indices of the best time scale during the most critical month in county or state i; $A_{c,i}$ represents the harvested areas of crop type c in county or state i.

This sensitivity index uses a variety of crop types in the US and takes the importance of the specific crop for each state and each county into consideration. The weighting procedure decreases the weights of the least planted crops and increases the weights of the dominant planted crops. Here, the ADSI is a relative measurement for sensitivity in the US. We fitted empirical cumulative distribution functions (ECDF) for the state-level and county-level ADSI, respectively, since the county-level and state-level crop data are measured in two different spatial scales. We divided ADSI into five categories and categorized the first quintile to the fifth quintile respectively as highest sensitivity, medium-high sensitivity, medium sensitivity, medium-low sensitivity, and lowest sensitivity, i.e., the counties in each category account for 20% of the total counties.

2.6. Panel data regression model

To investigate the effect of irrigation on the sensitivity of agriculture to drought, we built a panel data regression model for each crop. A panel data model combines time series models and cross-section models, considering both interannual and spatial variations (Lobell et al., 2011). We used fixed effects model to include county-specific fixed effect to account for county by county differences in omitted variables (e.g. soil quality) and county-specific linear trend (year as the predictors) to account for county by county differences in science and technological changes.

The data on irrigated and non-irrigated crop yield for those crop types were also obtained from USDA's NASS (USDA, 2017). The irrigated vs. non-irrigated crop yields data from USDA's NASS only cover a part of US. There are no irrigated vs. non-irrigated data for rice since all rice is irrigated. Hence, rice was excluded from this analysis. We included all counties with at least 10-year irrigated data and 10-year non-irrigated data. The numbers of counties are shown in Table 1. Since we do not have more detailed information, we cannot exclude the effects of other factors influencing crop yield, such as fertilization, crop management, or cultivar. The effect of irrigation is often coincident with crop management and fertilization. We will compare the absolute yields for irrigated crops vs. non-irrigated crops, and so we didn't detrend the irrigated yield and non-irrigated yields in the panel data regression model. Also, since the mean length of the irrigated and non-irrigated crop time series are only about 30 years and not in long-term, we parameterize the trend using only linear term, instead of higher-degree polynomials. We used the raw yields data instead of yield anomalies and built a panel data regression model for each crop.

We transformed raw crop yields into natural log yields because yields follow a log-normal distribution (Lobell et al., 2011) and yield fluctuations generally increase over time as the yields increase (Lu et al., 2017). Log-transformed yields are more normally distributed than the raw yields (Lobell et al., 2011). SPEI performs better than SPI to correlate with crop yield anomalies (Fig. 2(a)) and here we used SPEI as the drought index in the panel data regression model. We included the full range of SPEI values here since we have already considered non-linearity in the panel data regression model. We estimated a panel data regression model (fixed effects model) for each crop as the following form:

$$Log(Y_{i,t,g}) = \alpha_{i,g} + \beta_{i,g} * T + \theta_g * SPEI_{i,t} + \delta_g * SPEI^2_{i,t} + \varepsilon_{i,t,g}$$

Where i indicates county, t indicates the time, and g indicates irrigated or non-irrigated. $Y_{i,t,g}$ is the raw irrigated or non-irrigated crop yield for county i and year t. T is year. $SPEI_{i,t}$ is the corresponding best SPEI for the specific crop for county i and year t. $SPEI^2_{i,t}$ is the quadratic term of $SPEI_{i,t}$. We included the quadratic term of SPEI since we hypothesize that drought stress might pose a non-linear effect on the crop growth. $\varepsilon_{i,t,g}$ is the error term. $\alpha_{i,g}$ is the county fixed effect for irrigated or non-irrigated crop which can capture the county by county time-invariant differences (e.g., soil conditions) and irrigated vs. non-irrigated differences. $\beta_{i,g}$ is the coefficient of county-specific and irrigated vs. non-irrigated specific linear time trend. The time trend can capture the differing rates in technological changes for irrigated and non-irrigated crop among different counties. θ_g and δ_g are the parameters of interest, which can identify the differing effects (linear and quadratic) of drought on irrigated and non-irrigated crops.

3. Results

3.1. Crop yield anomalies

The shapes of the crop time series vary state by state and county by county. The long-term soybean yield time series in Illinois is linear and the winter wheat time series in California is non-linear and non-stationary in which the long-term increasing trend is mainly caused by science and technological advances and high-frequency fluctuations are mainly caused by weather and climate variations (Fig. 1). Thus, we detrended the long-term crop yield data following the method of Lu et al. (2017). The soybean yield anomalies in Illinois show a very strong linear correlation with the SPEI (p-value < 0.001), while the winter wheat in California does not show a significant correlation with the drought index (p-value $= 0.875$). The Illinois also has a steeper slope between crop yield anomalies and the SPEI than the California. A one-unit decrease in August 2-month SPEI leads to a 11.2% decrease in soybean yield in Illinois, while a one-unit decrease in May 3-month SPEI does not lead to a decrease in winter wheat yield in California.

From the historical statistical relationship between crop yield anomalies and SPEI, here we consider that the soybean in Illinois is more sensitive to drought than the winter wheat in California.

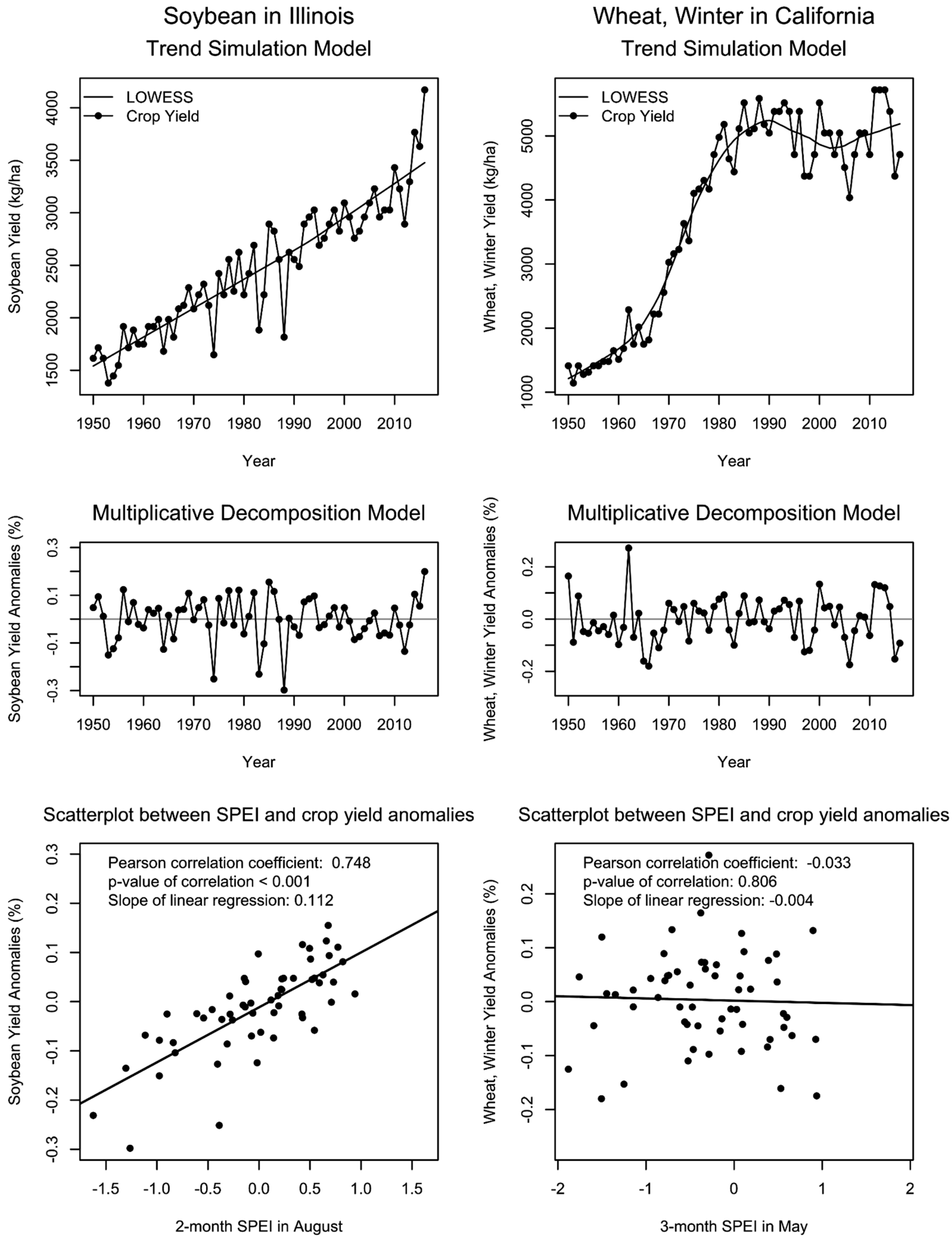

Fig. 1. The first two rows are detrending the soybean yield in Illinois and winter wheat yield in California using locally weighted regression model (LOWESS) coupled with multiplicative decomposition model; The third row is the scatterplots between crop yield anomalies and the corresponding best Standardized Precipitation Evapotranspiration Index (SPEI) for soybean in Illinois and winter wheat in California.

3.2. Statistical analysis between crop yield anomalies and SPEI/SPI

We performed correlation analyses between crop yield anomalies and SPEI/SPI of different time scales at different months during the growing seasons across the ten crops, over 48 states, and 3108 counties. We have identified the best time scale of SPEI/SPI and the most critical month for each crop that shows the highest average correlation with the crop yield anomalies based on both county-level and state-level correlation analysis.

The critical months and best time scale identified here are from an overall national-wide, not a local, perspective. The growing season and the timing of growing stages for each crop differ region by region, for example, for the same crop, the crop planting time for Texas is earlier than the crop planting time in North Dakota because of thermal time differences. Fig. 2(a) shows the averaged Pearson correlation coefficients between the crop yield anomalies and the corresponding best SPEI/SPI at the critical month. We found that SPEI shows higher correlation with crop yield anomalies than SPI for most of the crops (except hay and winter wheat) (Fig. 2(a)) since evapotranspiration play an important role in affecting crop growth. Thus, SPEI is used as the drought indicator for the following analysis.

Fig. 2(b) shows the Pearson correlation coefficients between the crop yield anomalies and 1-month SPEI at different months, which can show the sub-seasonal change of sensitivity to drought stress and help to identify the single month that the crops are most sensitive to drought. The results show that the sensitivity of crop growth to drought

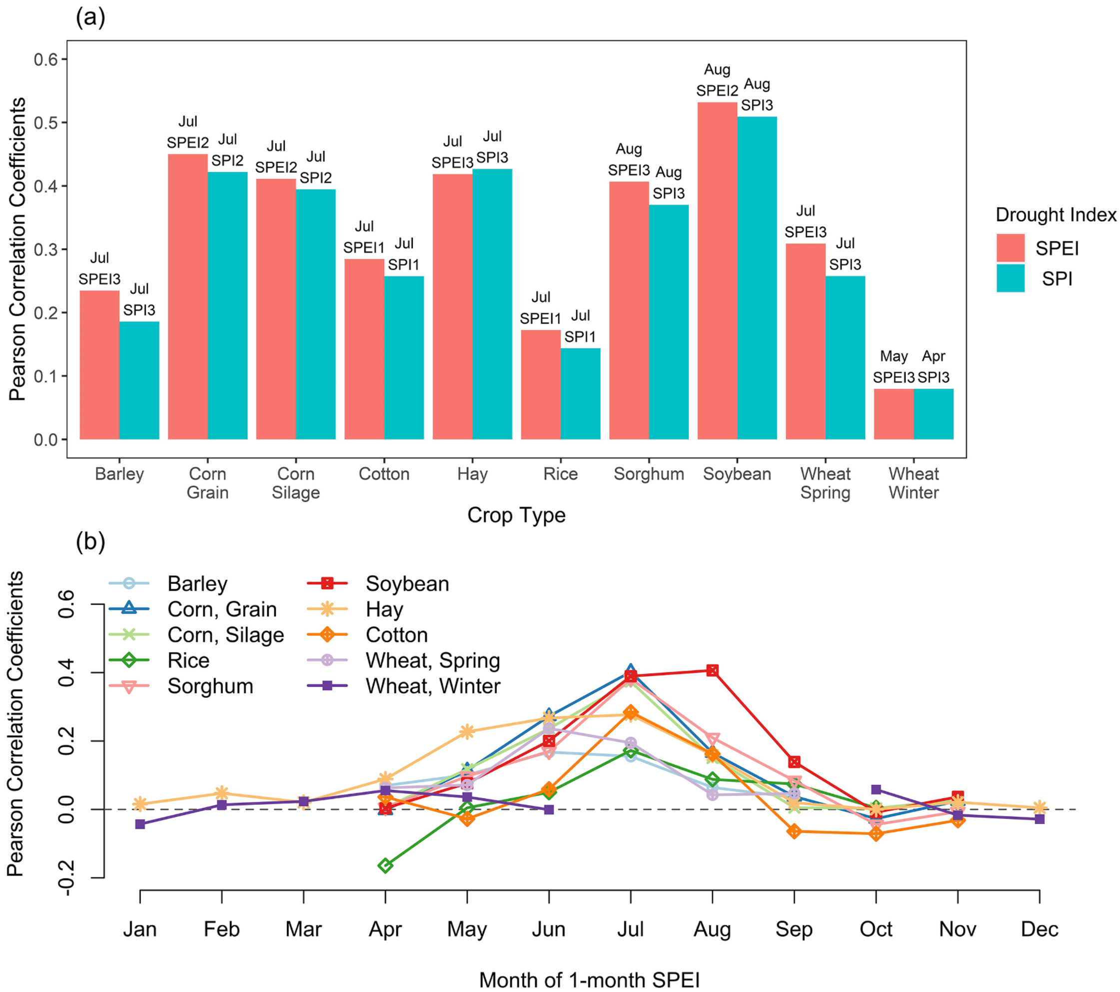

Fig. 2. a) Averaged Pearson correlation coefficients between crop yield anomalies and the corresponding best SPEI/SPI at the critical month; b) Averaged Pearson correlation coefficients between crop yield anomalies and 1-month SPEI at different months during the growing seasons.

is not homogenous across the growing season (Fig. 2(b)). Most of the crops are especially sensitive to drought stress in July. Fig. 3 shows the spatial pattern of county-level slope of linear regression between crop yield anomalies and the corresponding best SPEI, and the state-level map is included in the supplementary material (Fig. S1).

The historical empirical relationship between crop yield anomalies and drought indices show that soybean, corn grain, hay, sorghum, and corn silage are more sensitive to drought stress than spring wheat, cotton, barley, rice, and winter wheat (Fig. 2(a)).

Among all crops, soybean is most sensitive to drought stress (Fig. 2(a)). Soybean shows the highest correlation with 2-month SPEI in August among all SPEIs, which is calculated from July and August precipitation and temperature. Fig. 2(b) shows that both July and August are the critical months for soybean growth. These two months correspond to the reproductive stages of soybean: flowering, pod development, and seed filling stages. Soybean yield is least sensitive to drought stress during the vegetative stage, more sensitive during flowering and pod development, and most sensitive during seed filling stage (Eck et al., 1987; Shaw and Laing, 1966; Sionit and Kramer, 1977). Drought stress occurring during pod development and seed filling stages can lead to reduced number of pods, reduced number of seeds per pod, reduced seed size, and hence reduced yield potential (Kranz and Specht, 2012; Sionit and Kramer, 1977).

Corn grain shows the highest correlation with 2-month SPEI in July calculated from June and July precipitation and temperature; corn silage shows the highest correlation with 1-month SPEI in July calculated from only July precipitation and temperature. The seasonal curve of corn grain and corn silage are very similar since they are the same crop type (Fig. 2(b)). July is the most critical month during the growing season for both corn grain and corn silage since 1-month SPEI in July shows the highest correlation among all 1-month SPEI. July approximately corresponds to the early reproductive stage (tasseling, silking, and pollination) in most states, in which droughts can desiccate the silks and pollen grains and influence the pollination process, resulting in the greatest yield reduction (Burglund et al., 2010; Kranz et al., 2008).

Here, hay is a combination of Alfalfa hay and other hay (clover-timothy mixtures, bermuda grass, prairie hay, etc.). Also, hay is a perennial crop which is harvested several times throughout the year depending on farmers' choice, and thus the critical time identified here does not correspond to any specific growing stage of hay. Hay shows the highest correlation with 3-month SPEI in July, which is calculated from May, June, and July precipitation and temperature (Fig. 2(a)). Fig. 2(b) shows that all those three months are critical for hay yields. Among various physical factors (droughts, diseases, salinity, freezing, and insects) limiting hay yield, drought is the most important (Bin Abd. Halim, 1986) and drought stress can reduce leaf size, stem extension, and root proliferation (Defez et al., 2017). Bin Abd. Halim (1986) shows that drought stress occurring during vegetative stage do not significantly affect the quality of alfalfa, while drought stress occurring during the bud and flowering stages can result in lower total-herbage in-vitro digestible dry-matter and crude-protein (CP)

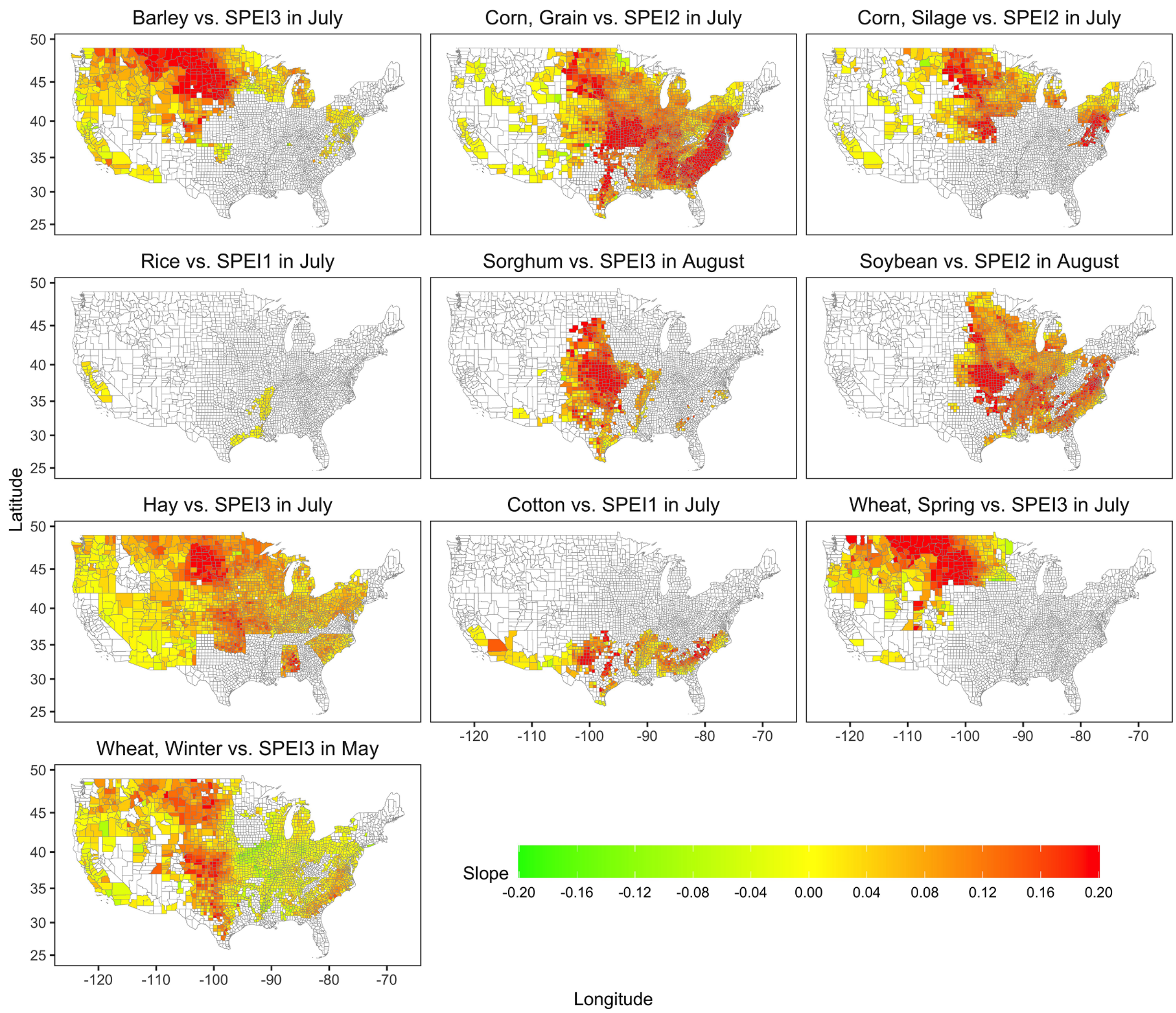

Fig. 3. County-level slope of linear regression between crop yield anomalies and the corresponding best Standardized Precipitation Evapotranspiration Index (SPEI).

concentration because of leaf wilting and leaf losses.

Sorghum shows the highest correlation with 1-month SPEI in July among all SPEIs. Sorghum is most sensitive to drought stress during the reproductive stages (boot stage to flowering), in which drought can stop the development of pollen and ovules, prevent fertilization, and cause abortion of fertilized ovules (Assefa et al., 2010; Eck and Musick, 1979). This stage is approximately in July in most states.

Cotton shows the highest correlation with 2-month SPEI in August (Fig 2(a)), which is calculated from July and August precipitation and temperature, and July is the most critical month for cotton growth (Fig. 2(b)). Previous literature show that cotton is most sensitive to drought stress during the reproductive stages, from first square to peak bloom, in which drought can reduce the number of bolls and number of seeds set in the boll, resulting in substantial yield losses (Loka et al., 2011, 2012). The reproductive stages approximately occur in July. Compared with other crops, cotton is a perennial woody shrub with an indeterminate growth habit. Cotton becomes dormant during the period of drought and resumes growth with favorable rainfall, which makes cotton somewhat tolerant to drought stress (Loka et al., 2011, 2012).

Barley shows the highest correlation with 2-month SPEI in July (Fig. 2(a)). Both June and July are the most critical month for barley growth (Fig. 2(b)). Barley is most sensitive to drought stress during or near the flowering stage (Wells and Dubetz, 1966), in which drought stress can influence the pollination process and significantly reduce the number of kernels produced per head (Robertson and Stark, 2003).

Rice is not highly correlated with SPEI in any month during the growing seasons as other crops (Fig. 2) since rice is a water-intensive crop and the growth of rice requires extensive irrigation. Rice planting is always associated with extensive irrigation.

Overall, winter wheat is not significantly correlated with drought indices as spring wheat (Fig. 2). Part of the reason is because winter wheat is planted across the whole US, while spring wheat is planted in limited areas in the US, mostly in arid regions (Fig. 3). Winter wheat is highly correlated with drought indices in the arid areas where there is little irrigation (Fig. 3 and Fig. 4(b-c)). The correlation between winter wheat and SPEI is weak in the humid areas east of US as well as in the dry areas with irrigations in the west of US (Fig. 3 and Fig. 4(b-c)). For wheat, drought and heat stress during stem elongation and booting stage can increase the rate of tiller mortality and the stress prior to flag leaf appearance can cause spikelet loses and florets abortions, and hence reduce yield potential (Fowler, 2002). For winter wheat, these stages approximately occur in April (Knott, 2016). For spring wheat, these stages come later, and June is the most critical month for spring wheat growth (Fig. 2(b)).

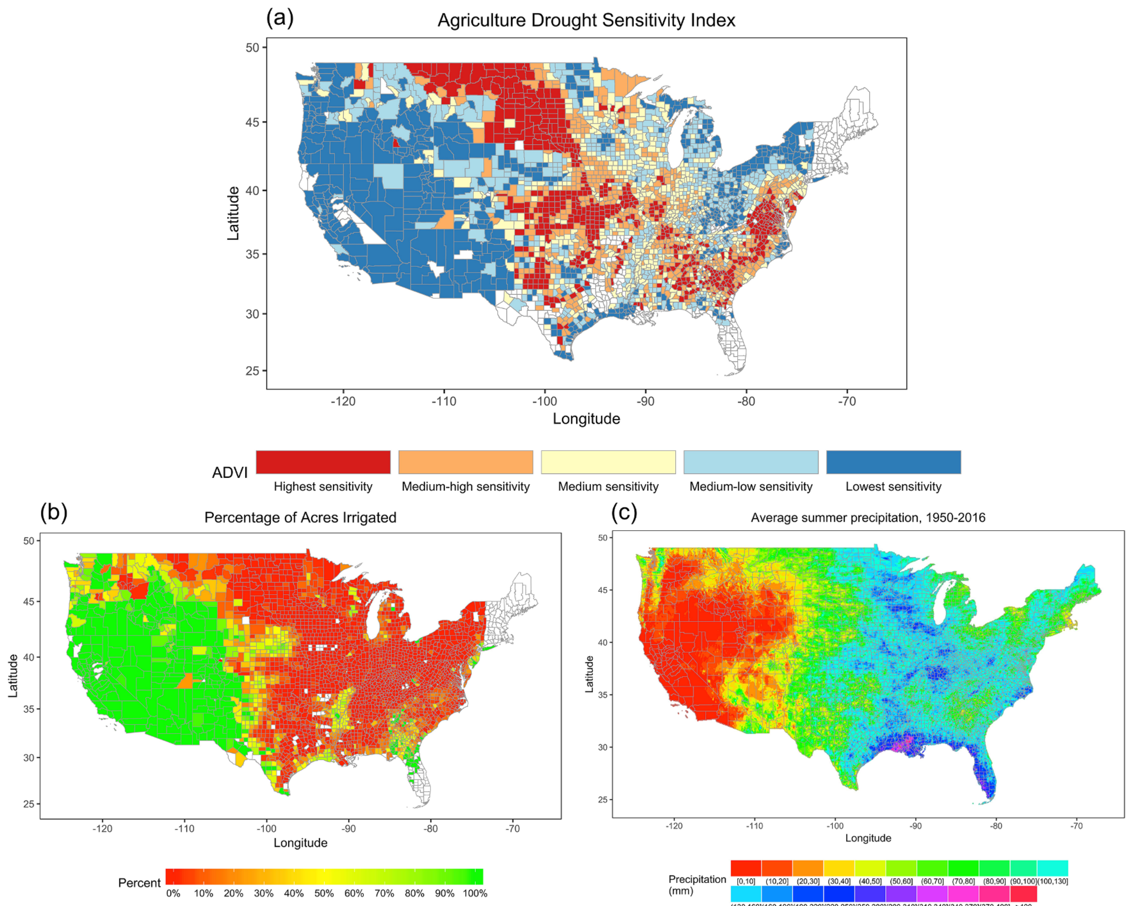

Fig. 4. a) County-level Agriculture Drought Sensitivity Index (ADSI); b) County-level percentage of acres irrigated; c) Average summer (June, July, and August) precipitation from 1950 to 2016.

3.3. Agricultural drought sensitivity index (ADSI)

The state-level ADSI is included in supplementary material (Fig. S2) and the county-level ADSI is shown in Fig. 4(a). The SPEIs used in ADSI for each crop are the SPEI that shows the highest correlation with the crop yield anomalies (Fig. 2(a)). The counties in blank indicate counties that none of the 10 major crop data are longer than 30 years or none of the 10 major crops are planted and harvested in those counties. The ADSI calculated here is based on the yields for both irrigated and non-irrigated crops, that can reflect both eco-physiological response of crops to drought and the local farmers' adaptations to the drought stress.

We also calculated the county-level percentage of acres irrigated as the mean total acres irrigated in 1985, 1990, 1995, 2000, 2005, and 2010 divided by the mean harvested acres from 1985 to 2010 for those ten major crops (Fig. 4(b)). The county-level data of total acres irrigated in 1985, 1990, 1995, 2000, 2005, and 2010 are downloaded from the U.S. Geological Survey's National Water-Use Science Project (Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014). The cases where the total acres irrigated exceeding total harvested acres were truncated to 1. We used June, July, and August precipitation (Fig. 4(c)) as a reference for humid and arid climate for crop growth since those are the most critical months for most crop growth, except for winter wheat.

We find a very strong correspondence between the lower percentage of acres irrigated and the higher sensitivity, and vice versa (Fig. 4). This indicates that effective irrigation can reduce the sensitivity of agriculture to drought. This can also partially indicate the effectiveness and usefulness of our methodology to evaluate the sensitivity. Overall, the spatial pattern of county-level ADSI shows that the eastern parts of US are more sensitive to drought and the western parts of US are less sensitive to drought because extensive irrigations are used in the west (Fig. 4).

The spatial pattern of county-level ADSI also partially reflect the spatial pattern of humid and arid climate in summer. For those regions with limited irrigation, the sensitivity of agriculture to drought is high in arid/semi-arid regions and low in humid regions. For example, Minnesota and Iowa are less sensitive to drought than Montana, North Dakota, and South Dakota because Minnesota and Iowa are much wetter in summer (June, July, and August) (Fig. 4). This result conforms to previous findings that the correlation between NDVI and drought indices is high in arid and semi-arid regions and the correlation is low in humid regions (Lotsch et al., 2003; Lu et al., 2019). Our finding is also consistent to a research that the linkage between crop yield and drought severity is weaker in humid environment than arid environment (Peña-Gallardo et al., 2019).

3.4. Effects of irrigation on crops' sensitivity to drought

Given the close relationship between sensitivity and irrigation, we quantitatively estimate the effect of irrigation on the sensitivity of agriculture to drought. We performed an analysis of covariance (ANCOVA) to compare the long-run mean for irrigated and non-irrigated crop yield by statistically controlling the effects of other covariates: time trend and drought effects for those counties with both irrigated and non-irrigated crop yield data (Table 1). ANCOVA is a general linear model integrating analysis of variance (ANOVA) and regression (Cochran, 1957; Ott and Longnecker, 2008). For all crops, the linear

Table 1
Analysis of covariance (ANCOVA) on the effects of irrigation.

	Barley	Corn Grain	Corn Silage	Sorghum	Soybean	Hay	Cotton	Wheat, Spring	Wheat, Winter
Number of counties	254	306	131	301	180	133	146	218	474
Log(Yield_Irrigated)	8.27	9.16	10.66	8.55	8.04	8.74	6.76	8.27	8.22
	(8.20, 8.33)	(9.13, 9.19)	(10.62, 10.69)	(8.48, 8.62)	(8.02, 8.06)	(8.72, 8.75)	(6.69, 6.83)	(8.10, 8.43)	(8.18, 8.27)
Log(Yield_Non-irrigated)	7.61	8.35	9.82	8.02	7.50	7.87	6.26	7.37	7.64
	(7.50, 7.71)	(8.04, 8.66)	(9.74, 9.90)	(8.00, 8.04)	(7.48, 7.51)	(7.85, 7.88)	(6.23, 6.30)	(7.23, 7.50)	(7.60, 7.68)
Log(Yield_Irrigated) - Log(Yield_Non-irrigated)	0.66	0.81	0.84	0.53	0.54	0.87	0.50	0.90	0.58
	(0.54, 0.78)	(0.49, 1.12)	(0.75, 0.93)	(0.46, 0.60)	(0.52, 0.57)	(0.85, 0.89)	(0.41, 0.58)	(0.69, 1.11)	(0.52, 0.64)
Yield_Irrigated	3893	9472	42,531	5180	3104	6225	862	3903	3719
	(3643, 4160)	(9183, 9769)	(41,142, 43,967)	(4830, 5554)	(3037, 3172)	(6154, 6296)	(801, 928)	(3310, 4601)	(3552, 3894)
Yield_Non-irrigated	2013	4222	18,351	3046	1804	2606	525	1583	2078
	(1815, 2234)	(3091, 5766)	(16,943, 19,875)	(2979, 3115)	(1780, 1828)	(2576, 2638)	(507, 544)	(1385, 1810)	(2000, 2160)
$\frac{\text{Yield\_Irrigated}}{\text{Yield\_Non-irrigated}} - 1$	93%	124%	132%	70%	72%	139%	64%	147%	79%
	(71%, 119%)	(64%, 207%)	(113%, 153%	(58%, 83%)	(68%, 76%)	(135%, 143%	(51%, 78%)	(99%, 205%)	(69%, 90%)

Note: the unit of crops is kg/ha. The values in parenthesis is 95% confidence interval for the least squares means estimation, representing the uncertainty associated with those estimates. The above ANCOVA results are based on adjusting covariates of year to 2000 and the SPEI value to 0 (normal weather conditions).

trend across irrigation and non-irrigation effects and across counties are not equal (Type III F test, p-value <0.0001). Thus, we estimate the long-run mean crop yield by adjusting the covariates of year to 2000 and the SPEI value to 0, for example, the long-run mean irrigated barley yield is 3893 kg/ha and long-run mean non-irrigated barley yield is 2013 kg/ha in 2000 under normal weather condition (adjusting the corresponding SPEI value to 0) (Table 1).

For all crops, there is a very strong evidence (Type III F test, P-value <0.0001) that the long-run mean of the irrigated crop yield is not equal to non-irrigated crop yield. With 95% confidence, for example, the long-run mean irrigated soybean yield is at least 68% and at most 76% higher than the non-irrigated soybean yield adjusting to the year 2000 and normal weather condition. Thus, irrigation plays an important role in boosting the crop yield, with the highest increases for spring wheat (147%), hay (139%), corn silage (132%), and corn grain (124%), and the lowest increases for cotton (64%), sorghum (70%), and soybean (72%) (Table 1).

From the fitting results of the panel data regression model, we have detected that the responses of the crop to drought are non-linear for all crops that the coefficients of the quadratic term of SPEI are all significant at 0.0001 level except hay (p-value <0.01) (Table 2). We also calculated the optimum SPEI for irrigated and non-irrigated crop growth for each crop. We find that the optimum SPEIs for irrigated crops are obviously lower than the non-irrigated crops for most crops, i.e., the irrigated crops require less natural rainfall to achieve optimum crop yields because of irrigation supplements.

We show that the responses of crops to drought are non-linear by calculating the percentage change of crop yield with the change in SPEI under different SPEI bases (Table 3). For different SPEI bases, change in one-unit SPEI value (i.e., one standard deviation of PPT minus PET amounts) will result in different percentage change in crop yield. One-unit decrease in SPEI in drought conditions (e.g., SPEI $= -2$) will result in a larger reduction in crop yield than in wetness conditions (e.g. SPEI $= 2$) (Table 3). Considering only the physiological responses of agriculture to drought, for the non-irrigated crops, corn grain, cotton, soybean, corn silage, sorghum, and barley are more sensitive to drought than spring wheat, hay, and winter wheat (Table 3).

The results also show that the non-irrigated crop is more sensitive to drought than the irrigated crop (Table 3) and effective irrigation can mitigate crop losses to drought. In drought conditions, the same decrease in SPEI on the same SPEI basis will result in larger crop yield reduction for non-irrigated crop than the irrigated crop, for example, one-unit decrease in SPEI when SPEI base value is -2 will result in 30.55% reduction in yields for non-irrigated soybean and only 10.19% reduction for irrigated soybean (Table 3). One-unit decrease in SPEI when SPEI base value is -2 will result in approximately 18% more damage to non-irrigated barley than irrigated barley, 30% to corn grain, 13% to corn silage, 15% to sorghum, 20% to soybean, 8% to hay, 18% to cotton, 12% to spring wheat, and 5% to winter wheat. The irrigation benefits corn grain and soybean the most among all crops when in severe drought conditions.

4. Conclusion and implication

This study identifies single or consecutive months that the ten major crops are most sensitive to drought stress based on the historical empirical relationship between crop yield anomalies and drought indices. The SPEI performs better than the SPI to correlate with crop yield anomalies for most crops (Fig. 2a). Our results show that soybean, corn grain, hay, sorghum, and corn silage are more highly correlated with drought intensity than spring wheat, cotton, barley, rice, and winter wheat. We have also identified the sub-seasonal pattern of sensitivity to drought during the growing season for the ten major crops in the US (Fig. 2b). Our findings on the critical months for crop growth conform to the phenological and

Table 2
Fitting results of panel data model (fixed effects model).

	Barley	Corn Grain	Corn Silage	Sorghum	Soybean	Hay	Cotton	Wheat, Spring	Wheat, Winter
SPEI coefficients (Irrigated)	0.0359***	0.0136***	0.0217***	0.0442***	0.0010	0.0373***	0.0440***	0.0262***	0.0104***
$SPEI^2$ coefficients (Irrigated)	−0.0171***	−0.0340***	−0.0329***	−0.0237***	−0.0213***	−0.0061*	−0.0291***	−0.0093***	−0.0166***
SPEI coefficients (Non-Irrigated)	0.1495***	0.1818***	0.1436***	0.1495***	0.1214***	0.0824***	0.1287***	0.1153***	0.0391***
$SPEI^2$ coefficients (Non-Irrigated)	−0.0407***	−0.0884***	−0.0437***	−0.0422***	−0.0486***	−0.0140***	−0.0603***	−0.0196***	−0.0222***
R square	0.83	0.88	0.85	0.80	0.75	0.84	0.77	0.84	0.79
Optimum SPEI (Irrigated)	1.0472	0.2005	0.3291	0.9315	0.0246	3.0385	0.7560	1.4152	0.3143
Optimum SPEI (Non-Irrigated)	1.8348	1.0280	1.6435	1.7701	1.2482	2.9499	1.0664	2.9427	0.8809

Note: *** indicates significance level at 0.0001, ** indicates 0.001, and * indicates 0.01.

Table 3
Predicted percentage change in crop yield with the change in SPEI using panel data regression models (fixed effects model).

	SPEI value bases	Change in SPEI	Percentage change in crop yield								
			Barley	Corn Grain	Corn Silage	Sorghum	Soybean	Hay	Cotton	Wheat, Spring	Wheat, Winter
Irrigated	**2**	+1	−4.85%	−14.47%	−13.31%	−7.17%	−10.00%	0.66%	−9.66%	−1.99%	−6.99%
		−1	1.56%	9.23%	8.01%	2.73%	6.48%	−1.87%	4.43%	0.16%	4.01%
	1	+1	−1.54%	−8.45%	−7.42%	−2.66%	−6.09%	1.91%	−4.24%	−0.16%	−3.86%
		−1	−1.86%	2.06%	1.13%	−2.03%	2.04%	−3.07%	−1.48%	−1.68%	0.62%
	0	+1	1.89%	−2.01%	−1.12%	2.07%	−2.00%	3.16%	1.50%	1.71%	−0.61%
		−1	−5.16%	−4.65%	−5.31%	−6.57%	−2.21%	−4.25%	−7.05%	−3.49%	−2.66%
	−1	+1	5.44%	4.88%	5.61%	7.03%	2.26%	4.44%	7.59%	3.61%	2.74%
		−1	−8.35%	−10.91%	−11.34%	−10.90%	−6.28%	−5.42%	−12.31%	−5.26%	−5.84%
	−2	+1	9.12%	12.25%	12.79%	12.23%	6.70%	5.73%	14.04%	5.55%	6.20%
		−1	−11.44%	−16.77%	−16.99%	−15.03%	−10.19%	−6.57%	−17.27%	−7.00%	−8.91%
Non-irrigated	**2**	+1	−5.28%	−22.93%	−7.21%	−5.98%	−11.46%	1.26%	−15.89%	1.75%	−6.94%
		−1	−2.69%	8.71%	−1.25%	−2.26%	2.48%	−3.97%	5.37%	−5.50%	2.79%
	1	+1	2.77%	−8.01%	1.26%	2.31%	−2.42%	4.13%	−5.10%	5.82%	−2.71%
		−1	−10.31%	−8.92%	−9.51%	−10.17%	−7.02%	−6.61%	−6.61%	−9.13%	−1.68%
	0	+1	11.49%	9.79%	10.51%	11.33%	7.55%	7.08%	7.07%	10.04%	1.71%
		−1	−17.33%	−23.68%	−17.08%	−17.45%	−15.64%	−9.19%	−17.22%	−12.62%	−5.95%
	−1	+1	20.96%	31.04%	20.60%	21.14%	18.53%	10.11%	20.80%	14.44%	6.33%
		−1	−23.80%	−36.06%	−24.02%	−24.14%	−23.45%	−11.69%	−26.63%	−15.98%	−10.04%
	−2	+1	31.23%	56.39%	31.61%	31.82%	30.64%	13.23%	36.30%	19.02%	11.16%
		−1	−29.76%	−46.43%	−30.37%	−30.29%	−30.55%	−14.12%	−34.97%	−19.21%	−13.95%

physiological pattern of crop growth from previous field experiments and literature. July is the most critical month for crop growth for most crops since July corresponds closely to the reproductive stage of the crops (flowering and pollination). Drought stress occurring during the reproductive stage can severely reduce the crop yields. The sensitivity of agriculture to drought increases in the early period, peaks at the critical months, and then declines (Fig. 2(b)). Our findings can provide a general guidance for farmers to schedule which months are the best timing to irrigate, especially for the dry areas with limited access to fresh water. The specific accurate irrigation amounts and timing depends on local planting time, crop types, crop growing stages, actual rainfall, and local accessibility to fresh water.

This study develops an Agriculture Drought Sensitivity Index (ADSI) to map the sensitivity of agriculture in response to drought at the local county-level in the US. We find a very strong spatial correspondence between the degree of sensitivity and the percentage of acres irrigated, i.e., the higher percentage of acres irrigated corresponds to the lower sensitivity and the lower percentage of acres irrigated corresponds to the higher sensitivity (Fig. 4). Our findings highlight the significance of irrigation on drought risks mitigation and adaptation. In addition to the irrigation, we also demonstrate that the spatial pattern of county-level ADSI partially reflects the spatial pattern of humid and arid climate in summer: for the regions with limited irrigation, the sensitivity of agriculture to drought is high in arid/semi-arid regions and the sensitivity is low in humid regions (Fig. 4). The spatial pattern of sensitivity can provide scientific information for policymakers and decision makers on which areas are the priority to allocate recourses and make investments in irrigation to mitigate the unfavorable drought conditions, particularly for the regions with few irrigations and in the arid/semi-arid climate.

This study also quantitatively estimates the benefits of irrigation, both from the absolute increase in crop yield and stability of crop yields in response to drought stress, which can provide quantitative incentives for future investments in irrigation and related infrastructure as an adaptation strategy to cope with drought. Irrigation plays a very important role in boosting the crop yield by ensuring adequate water in root zone to meet crop water needs consistently, with the highest increases for spring wheat (147%), hay (139%), and corn silage (132%), and the lowest increases for cotton (64%), sorghum (70%), and soybean (72%) (Table 1). The panel data model shows that the responses of crops to drought are non-linear for all crops, no matter for irrigated or non-irrigated crop (Table 2). For different SPEI bases, change in one-unit SPEI value will result in different percentage change in crop yield, for example, one-unit decrease in SPEI in drought conditions will result in larger reductions in crop yield than in wetness conditions (Table 3). The irrigated crops require less natural rainfall to achieve maximum growth than the non-irrigated crops because of irrigation supplements (Table 2). The irrigation can provide sustained and consistent water use for crops and stabilize the crop yield since the droughts could occur at any growing stage with varying duration and severity. The irrigated crops are not highly dependent on the weather and climate variations. The fitting model results also show that the non-irrigated crops are more sensitive to drought than the irrigated crop, especially in severe drought conditions, for example, one-unit decrease in SPEI (base value: −2) can result in approximately 18% more damage to non-irrigated barley than irrigated barley, 30% to corn grain, 13% to corn silage, 15% to sorghum, 20% to soybean, 8% to hay, 18% to cotton, 12% to spring wheat, and 5% to winter wheat. This can provide quantitative evidence and incentive to use irrigation as an effective adaptation strategy to mitigate the effects of drought stress on agriculture.

Declaration of Competing Interest

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.

Acknowledgments

This research has been conducted through the Carolinas Integrated Sciences & Assessments (CISA) program and supported by the National Oceanic and Atmospheric Administration (NOAA) Climate Program Office (grant no. NA16OAR4310163). We also wish to thank the two anonymous reviewers and the editor for providing insights and comments to improve this study.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2020.108124.

Reference

AMS, 2013. In: Drought — An information statement of the American Meteorological Society. American Meteorological Society, Boston, MA, USA.
Assefa, Y., Staggenborg, S.A., Prasad, V.P.V., 2010. Grain sorghum water requirement and responses to drought stress: a review. Crop Management 9 (1), 1–11.
Burglund, D.R., Endres, G.J., McWilliams, D.A., 2010. Corn growth and management quick guide. North Dakota State University, Extension service, Fargo, ND, USA.
Abd, Bin, Bin Abd. Halim, M.R., 1986. Water-stress effects on forage quality of Alfalfa. Iowa State University, Ames, IA, USA.
Cochran, W.G., 1957. Analysis of covariance: its nature and uses. Biometrics 13 (3), 261–281.
Daly, C., et al., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int. J. Climatol. 28 (15), 2031–2064.
Defez, R., et al., 2017. Improved drought stress response in Alfalfa plants nodulated by an IAA over-producing rhizobium strain. Front Microbiol 8 (2466).
Eck, H.V., Mathers, A.C., Musick, J.T., 1987. Plant water stress at various growth stages and growth and yield of soybeans. Field Crops Res. 17 (1), 1–16.
Eck, H.V., Musick, J.T., 1979. Plant water stress effects on irrigated grain sorghum. I. effects on yield. Crop Science 19, 589–592.
Fowler, D.B., 2002. Winter wheat production manual. Crop Development Centre, University of Saskatchewan, Saskatoon, Canada.
Guttman, N.B., 1998. Comparing the Palmer Drought Index and the Standardized Precipitation Index. J Am Water Resour As 34 (1), 113–121.
Guttman, N.B., 1999. Accepting the standardized precipitation index: a calculation algorithm. J Am Water Resour As 35 (2), 311–322.
Heddinghaus, T.R., Sabol, P., 1991. A review of the Palmer Drought Severity Index and where do we go from here. In: Proceedings of the seventh conference on applied climatology. American Meteorological Society, Boston, MA, USA.
Heim, R.R., 2002. A review of twentieth-century drought indices used in the United States. B Am Meteorol Soc 83 (8), 1149–1165.
IPCC, 2001. Climate Change 2001: impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.
IPCC, 2013. Climate Change 2013: the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.
Hutson, S.S., et al., 2004. Estimated use of water in the United States in 2000. U.S. Geological Survey, Denver, CO, USA 1268, Reston, VA.
Kenny, J.F., et al., 2009. Estimated Use of Water in the United States in 2005. U.S. Geological Survey, Denver, CO, USA 1344, Reston, VA.
Knott, C.A., 2016. Identifying Wheat Growth Stages. Cooperative Extension Service, College of Agriculture, Food and Environment, University of Kentucky, Lexington, KY, USA Kentucky, US.
Kramer, P.J., Boyer, J.S., 1995. Water relations of plants and soils. Academic Press, San Diego, CA, USA.
Kranz, W.L., Irmak, S., Van Donk, S.J., Yonts, C.D., Martin, D.L., 2008. Irrigation management for corn (NebGuide G1850). University of Nebraska - Lincoln, Lincoln, NE, USA.
Kranz, W.L., Specht, J.E., 2012. Irrigating soybean (NebGuide G1367). University of Nebraska - Lincoln, Lincoln, NE, USA.
Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ Res Lett 2 (1), 014002.
Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011. Climate Trends and Global Crop Production Since 1980. Science 333 (6042), 616–620.
Loka, D.A., Oosterhuis, D.M., 2012. Water stress and reproductive development in cotton. In: Oosterhuis, D.M., Cothren, J.T. (Eds.), Flowering and Fruiting in Cotton. Cotton Foundation, Memphis, TN, USA, pp. 51–58.
Loka, D.A., Oosterhuis, D.M., Ritchie, G.L, 2011. Water-deficit stress in cotton (Editor) In: Oosterhuis, D.M. (Ed.), Stress physiology in cotton. Cotton Foundation, Memphis, TN, USA, pp. 37–72.
Lotsch, A., Friedl, M.A., Anderson, B.T., Tucker, C.J., 2003. Coupled vegetation-precipitation variability observed from satellite and climate records. Geophys. Res. Lett. 30 (14), 1–4.
Lu, J., Carbone, G.J., Gao, P., 2017. Detrending crop yield data for spatial visualization of drought impacts in the United States, 1895–2014. Agr Forest Meteorol 237–238, 196–208.
Lu, J., Carbone, G.J., Gao, P., 2019. Mapping the agricultural drought based on the long-term AVHRR NDVI and North American Regional Reanalysis (NARR) in the United States, 1981–2013. Applied Geography 104, 10–20.
Matiu, M., Ankerst, D.P., Menzel, A., 2017. Interactions between temperature and drought in global and regional crop yield variability during 1961-2014. PLoS ONE 12 (5), e0178339.
Maupin, M.A., et al., 2014. Estimated Use of Water in the United States in 2010. U.S. Geological Survey, Denver, CO, USA 1405, Reston, VA.
Mavromatis, T., 2006. Drought index evaluation for assessing future wheat production in Greece. Int. J. Climatol. 27 (7), 911–924.
McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th Conference on Applied Climatology. American Meteorological Society, Boston, MA, USA, pp. 179–183 1993.
Najafi, E., Devineni, N., Khanbilvardi, R.M., Kogan, F., 2018. Understanding the changes in global crop yields through changes in climate and technology. Earth's Future 6 (3), 410–427.
NOAA, 2016. U.S. billion-dollar weather and climate disasters. NOAA National Centers For Environmental Information (NCEI). NOAA National Centers for Environmental Information (NCEI), Asheville, NC, USA.
Ott, R.L., Longnecker, M., 2008. An Introduction to Statistical Methods and Data Analysis. An introduction to statistical methods and data analysis, 6th Edition. Cengage Learning, Belmont, CA, USA.
Palmer, W.C., 1965. Meteorological drought, Research Paper No. 45. U.S. Weather Bureau, U.S. Department of Commerce, Washington, DC, USA.
Peña-Gallardo, M., et al., 2019. Response of crop yield to different time-scales of drought in the United States: spatio-temporal patterns and climatic and environmental drivers. Agr Forest Meteorol 264, 40–55.
Quiring, S.M., Papakryiakou, T.N., 2003. An evaluation of agricultural drought indices for the Canadian prairies. Agr Forest Meteorol 118 (1), 49–62.
Robertson, L.D., Stark, J.C., 2003. Idaho spring barley production guide. College of Agricultural and Life Sciences, University of Idaho.
Samuel, C.Z., Jiangxiao, Q., Christopher, J.K., 2016. Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. Environ Res Lett 11 (9), 094021.
Shaw, R.H., Laing, D.R., 1966. Moisture stress and plant response. In: Pierre, W.H., Kirkham, D., Pesek, J., Shaw, R. (Eds.), Plant Environment and Efficient Water Use. American Society of Agronomy, Soil Science Society of America, Madison, WI, USA, pp. 73–94.
Sionit, N., Kramer, P.J., 1977. Effect of water stress during different stages of growth of soybean. Agron J 69 (2), 274–278.
Sun, L., Mitchell, S.W., Davidson, A., 2012. Multiple drought indices for agricultural drought risk assessment on the Canadian prairies. Int. J. Climatol. 32 (11), 1628–1639.
Thornthwaite, C.W., 1948. An approach toward a rational classification of climate. Geogr Rev 38 (1), 55–94.
Tian, L., Yuan, S., Quiring, S.M., 2018. Evaluation of six indices for monitoring agricultural drought in the south-central United States. Agr Forest Meteorol 249, 107–119.
USDA, 2010. Field Crops Usual Planting and Harvesting dates, Agricultural Handbook Number 628, National Agricultural Statistics Service. Field crops usual planting and harvesting dates, Agricultural Handbook Number 628. National Agricultural Statistics Service (NASS), U.S. Department of Agriculture, Washington, D.C., USA.
USDA, 2014. 2012 Census of Agriculture, United States, Summary and State Data. National Agricultural Statistics Service (NASS), U.S. Department of Agriculture, Washington, D.C., USA Washington, D.C.
Vicente-Serrano, S.M., et al., 2013. Response of vegetation to drought time-scales across global land biomes. Proceedings of the National Academy of Sciences 110 (1), 52–57.
USDA, 2017. National Agricultural Statistics Service Database Quick Stats. National Agricultural Statistics Service, U.S. Department of Agriculture, Washington, D.C., USA Washington D.C.
Vicente-Serrano, S.M., et al., 2012. Performance of Drought Indices for Ecological, Agricultural, and Hydrological Applications. Earth Interactions 16 (10), 1–27.
Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: the Standardized Precipitation Evapotranspiration Index. J Climate 23 (7), 1696–1718.
Wells, S.A., Dubetz, S., 1966. Reaction of Barley varieties to soil water stress. Canadian Journal of Plant Science 46 (5), 507–512.
Zipper, S.C., Qiu, J., Kucharik, C.J., 2016. Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. Environ Res Lett 11 (9), 094021.