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Effectiveness of drought indices in identifying impacts on major crops across the USA

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Abstract

In North America, the occurrence of extreme drought events has increased significantly in number and severity. Past droughts have contributed to lower agricultural productivity in major farming and ranching areas across the United States. This study evaluates the relationship between drought indices and crop yields across the U.S. for the period 1961- 2014. Several drought indices commonly used to monitor drought conditions have been calculated in order to assess the correlations with yields from the major cash crops in the country, including four Palmer-based ones and three multi-scalar ones (SPI, SPEI, SPDI). The three multi-scalar drought indices were aggregated at 1- to 12-month timescales. We quantify the similarities or differences between these drought indices using Pearson correlation coefficients. The results demonstrate that the multi-scalar indices can identify drought impacts on different type of crops for a wide range of time periods. The differences of spatial and temporal distribution of the correlations depend on the crop and timescale analysed, but also can be found within the same type of crop.

Key words

Drought; Crop yields; Palmer drought indices; Standardized Precipitation Index; Standardized Precipitation Evapotranspiration Index; Standardized Palmer Drought Severity Index.

1. Introduction

Many different natural hazards exist, but drought is recognized as one of the most costly and catastrophic (Andreadis & Lettenmaier, 2006; Blauhut et al., 2016). Drought can cause a decrease or complete failure of crop yields in agricultural systems (Lobell & Field, 2007; Quiring & Papakryiakou, 2003; Udmale et al., 2014; Wilhite, 2000). Given that crops are not able to meet the needs due to the non-available water supplies, resulting from the weather conditions that determine water availability (decreased rainfall, increased atmospheric evaporative demand, or deficient topsoil moisture) during periods in which there is a demand for water by plants (Lobell et al., 2011; Meze-Hausken, 2004; Mishra & Singh, 2010).

The impact of droughts on crop yields depends on the crop type, the stage of crop development and the biological characteristics of the specific crop and soil (Karim & Rahman, 2015). It is demonstrated that droughts usually reduce the capacity of the active radiation absorption by the canopy (Earl & Davis, 2003).

The adverse impact of drought on crop yields are unequally distributed geographically (Howitt et al., 2015). Natural hazards among which are droughts, induced food crop disasters between 2003 and 2013 affecting more than 1.9 billion people in developing countries, causing over $494 billion USD in estimated crop damages. In addition, these disasters slowed the economic growth in countries where agriculture is the main sector (30% of the GDP in most countries of Africa and 30% of the labor force in India for example). On average, about 22% of the total economic impact produced by natural hazards, especially by droughts, occur in the agricultural sector (FAO, 2015).

There are signals of increasing interannual variability in crop yields due to changes in drought frequency and severity (Asseng et al., 2014; Chen et al., 2016; Liu et al., 2016; Lobell et al., 2011; Lobell & Field, 2007; Olesen et al., 2011; Rossi S & Niemeyer S, 2010; Tack et al., 2015). However, a quantification of the direct crop yield impacts due to drought is difficult given the complexity of drought events (Geng et al., 2016; Wilhite, 1993; Wilhite et al., 2007). In addition, each crop has a differing degree of resilience to drought stress (Asseng et al., 2014; Liu et al., 2016; Lobell et al., 2011; Tack et al., 2015; Wilhelmi et al., 2002). Due to these reasons, the quantification of the drought impacts on crop yields is very important.

Drought indices are the best tool for determining the impacts of droughts on crops. Several studies have used drought indices to identify these impacts at different spatial scales in Europe (Ceglar et al., 2012; Di Lena et al., 2014; Mavromatis, 2007; Páscoa et al., 2016), Australia (Lobell et al., 2015), Asia (Arshad et al., 2013; Kattelus et al., 2016; Sahoo et al., 2015; H. Wang et al., 2016), Africa (Blanc, 2012; Elagib, 2013), America (Kim et al., 2002; Quiring & Papakryiakou, 2003), or at the global scale (Vicente-Serrano et al., 2012; Wang et al., 2014). In general, past research shows that drought indices can be used to quantify reductions in yield that are associated with drought. Many drought indices have been developed since early last century (Wilhite et al., 2014; Zargar et al., 2011). However, not all drought indices perform equally well in accurately quantifying drought severity because of the different variables involved in their calculations (Morid et al., 2006; Vicente-Serrano et al., 2011). Therefore, it is necessary to compare the performance of different drought indices to determine which are most appropriate for assessing the impacts of drought for different crop types and in different regions. Although some studies have addressed this question at the regional scale (Keyantash et al., 2002a; Quiring & Papakryiakou, 2003; Wang et al., 2017), we are unaware of any studies comparing a variety of drought indices across different crop types and large regions (national to continental scale).

Some studies suggest drought vulnerability in the U.S. is increasing (Carrão et al., 2016; Geng et al., 2016; Mishra & Singh, 2010). For example, extreme droughts in the U.S. (i.e., those covering more than the 25% of the country) accounted for $6.7 billion in crop losses for 2000 to 2004 (Wilhite et al., 2007). Thus, extreme drought events have been recorded in the past two decades in the southern Great Plains and Southwest (Hayes et al., 1999), the north-central US (McNeeley et al., 2016), South Carolina (Mizzell et al., 2010), California (Rippey, 2016), Midwest and Great Plains (NOAA, 2017; USDM, 2017), causing widespread impacts across multiple sectors. Ross et al (2003) reported between 1980 and 2003 the U.S. experienced at least one billion-dollar disaster in 20 of 23 years, including 10 major drought/heatwave episodes. NOAA's National Centers for Environmental Information (NCEI) (https://www.ncdc.noaa.gov/billions/events) estimated that U.S. losses from drought were $4.6 billion in 2015, $4.1 billion in 2014, $10.7 billion in 2013 and $31.5 billion in 2012.

The objective of this paper is to determine which drought indices are most suitable for monitoring agricultural drought impacts for different crop types at the regional level. Presently, there is no clear consensus about which index is the most appropriate for this purpose (Esfahanian et al., 2017; Quiring, 2009). We will compare the Standardized Precipitation Evapotranspiration Index (SPEI), the Standardized Precipitation Index (SPI), the Standardized Palmer Drought Severity Index (SPDSI) and four Palmer-related drought indices (Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought Index (PHDI), Palmer Z Index (Z), and Palmer Modified Drought Index [PMDI]).

2. Datasets and methodology

2.1. Crop data

Our analysis of drought indices focuses on the five crops with the broadest geographic distribution and highest production in the U.S.: barley, corn, cotton, soybean and winter wheat (Figure 1). Data on crop production for each county are collected by the United

States Department of Agriculture (USDA) and made available by the National Agricultural Statistics Service (https://quickstats.nass.usda.gov). Only crop statistics under non-irrigated conditions were considered in this study. We created five masks according to the number of crops considered in this analysis in order to delimitate the counties where there are representative lands of cultivations for the different crops. For this purpose, the available crop county maps were taken from USDA (https://www.nass.usda.gov/Charts_and_Maps/Crops_County). Yield (T/Ha) is based on the harvest in each county. The final data set used in this analysis is comprised of 373 counties for barley, 1542 counties for corn, 388 counties for cotton, 1314 counties for soybeans and 1321 for winter wheat (Figure 1). These counties have at least 25 years of data between 1961 and 2014.

Considering the importance of technology in enhancing efficiency in agriculture, crop yields series where de-trended to remove these non-climatic trends from yield data (Lobell & Field, 2007; Xu et al., 2013). The de-trending process was achieved by fitting a linear regression to obtain the yield data and calculating the residuals. These residuals were used in the subsequent analyses.

2.2. Climate data

To calculate the different drought indices at the county level we used gridded data of monthly precipitation and maximum and minimum temperature, which were obtained from the PRISM (Parameter-elevation Relationships on Independent Slopes Model) gridded dataset (http://prism.oregonstate.edu). This dataset was developed and validated by the Oregon State University (Daly et al., 2008) and it has been used in many different climatological and environmental studies (Loarie et al., 2009; Mayer, 2012; Sanford & Selnick, 2013; Tilman et al., 2002; Wei et al., 2016).

Available water holding capacity of the soil is a necessary variable to calculate the Palmer drought indices. The National Resources Conservation Service (NRCS) State Soil Geographic (STATSGO) Database was used to determine the mean available water holding capacity of the soil for each county (https://water.usgs.gov/GIS/metadata/usgswrd/XML/ussoils.xml#stdorder).

2.3. Methods

2.3.1. Drought index calculation

Eleven drought indices were calculated: eight versions of the Palmer Drought Indices suite and three drought indices that are generated at different timescales: SPI, SPEI and SPDI. These indices were selected because they are widely used in quantifying and monitoring of droughts at both regional (Bonaccorso et al., 2003; Keyantash et al., 2002b; Lorenzo- Lacruz et al., 2010; McEvoy et al., 2012; Rohli et al., 2016; Yan et al., 2016) and global scales (Dai et al., 2004; Geng et al., 2016; Trenberth et al., 2013; Vicente-Serrano et al., 2015, 2012).

a) Palmer's Drought Indices. The Palmer Drought Severity Index (PDSI) is a popular meteorological drought index that is commonly used in the U.S. as well as the Palmer Hydrological Drought Index (PHDI) and the Palmer Moisture Anomaly Index (Z-index). Using precipitation and air temperature as inputs, the Palmer indices compute an estimation of moisture supply and demand within a simple two-layered soil moisture simulation. The PDSI has some issues related to the lack of comparability between regions (Alley, 1984; Doesken & Garen, 1991; Hayes et al., 1999; Heim, 2002). To address this problem, Wells et al (2004) developed the self-calibrated (sc) Palmer Indices to automatically determine appropriate regional coefficients. This scPDSI makes the Palmer indices more spatially comparable. Another limitation of the Palmer indices is that they are calculated at a fixed timescale, which limits their ability to accurately monitor and quantify different types of drought (Vicente-Serrano et al., 2011).

b) Standardized Precipitation Index (SPI). Developed by Mckee et al (1993), the SPI quantifies and assesses precipitation shortages on multiple timescales. It is based on the conversion of the precipitation series using an incomplete Gamma distribution to a standard normal variable with a mean equal to zero and variance equal to one. The SPI has been recommended by The World Meteorological Organization as the universal meteorological drought index (WMO, 2012).

c) Standardized Precipitation Evapotranspiration Index (SPEI). Proposed by (Vicente- Serrano et al., 2010), the SPEI calculation rest on a monthly climate water balance (precipitation minus reference evapotranspiration), which is accumulated at different timescales and transformed to a normal standardized variable using a 3-parameter log-logistic distribution. Here the ETo was computed using the Hargreaves and Samani equation (Hargreaves & Samani, 1985), which is recommended by FAO for data scarce regions.

d) Standardized Palmer Drought Index (SPDI). Developed by Ma et al (2014), the SPDI is based on combining the methods of PDSI and SPI. This index shares the multi-scalar concept and the statistical nature of the SPI and SPEI (Vicente-Serrano et al., 2015) and the water balance defined by Palmer (1965). The SPDI is transformed to a standard normal variable using a generalized extreme value distribution.

The different drought indices were calculated from the mean climate series generated for each county. The multi-scalar indices (SPEI, SPI and SPDI) were calculated at timescales from 1 to 12-months. The monthly drought indices for each county were de-trended using the same method that was applied for de-trending the crop yield data.

2.3.2 Relation between crop yields and drought indices

To analyze the relationship between the drought indices and crop yields in each county, we calculated Pearson correlation coefficients (Pearson's r). Since the month of the year when the highest correlation between the drought index and the crop yield were not known a priori, we correlated all 12 monthly series for each index with the annual yields.

Therefore, we obtained 12 correlations per index and crop. In addition, for the three multi- scalar drought indices calculated from 1- to 12-month timescales (SPI, SPEI and SPDI) we obtained 12 correlations (one for each of the monthly series) for each timescale, resulting in a total of 144 correlations for each of the three drought indices for each crop type and each county. In addition, we also identified the timescale (in the case of multi-scalar indices) and month in which the highest correlation was found within each county.

3. Results

Figure 2 shows a boxplot with the maximum Pearson's r correlations recorded in each county between the annual crop yields and the monthly drought indices used in this study. Generally, and independently of the crop type, Pearson's r coefficients showed higher values for the SPI, SPEI and SPDI. Among the five crop types, correlations tended to be higher for soybeans than for the other crop types. The lowest correlations tended to be obtained for cotton. The correlations between the Z-Index, SPI, SPEI and SPDI and crop yields tended to be statistically significant in the majority of counties. The highest mean correlation for soybeans was about 0.56 for the SPEI, SPI and SPDI, for wheat was around $r = 0.46$ using the same indices. It was around $r = 0.44$ for corn, $r = 0.43$ for barley and $r = 0.38$ for cotton. The Palmer Drought Indices, with the exception of the Z-Index and the scZ-Index, generally did not have statistically significant correlations with yield, regardless of the month of the year. Table 1 shows the percentage of counties in which statistically correlations between crop yields and drought indices were found. In general, the different crop types have similar values; however, there are large differences between the drought indices. The Palmer indices are significantly correlated with crop yields in about 50% of the counties. The self-calibrated Palmer indices have a higher percentage of counties with significant correlations than the original (non-calibrated) Palmer indices for all the crops. For this reason, we show only the self-calibrated version of the Palmer indices results. In general, the three multiscalar indices used in this study performed much better than the Palmer indices. The SPI has the highest percentage of counties with significant correlations for barley and soybeans, while the SPEI does best for cotton, corn and wheat. Likewise, the SPDI performs quite similar to the SPI and SPEI. The scZ-index also does relatively well.

The results are described separately for each crop. Figure 3 shows the geographical distribution of the highest correlations between the drought indices and yield for the five crops. Figure 4 displays the correlations between the different monthly series of drought indices and crop yields. Tables 2 through 6 show the seasonal differences in the performance of the drought indices to assess crop impacts. Figure 5 illustrates the drought timescales that were found more useful for the SPI, SPDI and SPEI.

3.1. Barley

Barley yields show the highest correlations ($r > 0.7$) in the state of Montana and in eastern North Dakota. High correlations are recorded in these areas with the SPEI, SPI and SPDI. On the contrary, the lowest correlations are found in the north central and eastern U.S. barley-cultivated lands. Generally, the self-calibrated Palmer drought indices show lower correlations ($r < 0.5$) in the counties where the multi-scalar indices show better results. The Z-index show similar results to the multi-scalar indices, but is characterized by lower r values (Figure 4). Correlations tend to be higher in the summer months and this pattern is identified with the SPEI, SPI, SPDI and z-Index (Table 2). In addition, barley is most sensitive to drought conditions on short timescales (1 to 3 months) (Figure 5a).

3.2. Corn

The highest correlations are found in the eastern Corn Belt (Illinois, Indiana and Ohio), southern Texas, southern Pennsylvania and southeastern Georgia and South Carolina. Lowest correlations are found in central-north states and Michigan. The drought indices with the higher correlations are the SPEI, SPI, SPDI and scZ-index. The scPDSI, scPHDI and scPMDI show large areas with no statistically significant correlations with corn-yield (Figure 3). July and August are the months with the highest correlations for corn yields using the different multi-scalar indices and the scZ-index. The scPDSI does not show as clear of a pattern as the other indices (Figure 4 and Table 3). In general, the strongest response for multi-scalar drought indices is found when considering the shorter (1 to 3 months) timescales (Figure 5b).

3.3. Cotton

The areas where cotton is planted are more geographically concentrated than the other crops- Correlations are low, in general, for all of the indices analyzed. Only the counties from northern Texas and Kansas present high correlations (Figure 3). July and August have the highest correlations for all of the indices analyzed, although there is a less seasonality than the other crops (Figure 4). The multiscalar indices, as well as the Palmer drought indices, also show maximum correlations in summer (Table 4). The highest correlations are found at shorter timescales (Figure 5c).

3.4. Soybeans

North and South Carolina, Central and Northern Plains of the US are the areas where the highest correlations are found between the multiscalar indices (along with the scZ-index) and soybeans yields. These correlations present the same spatial distributions for the SPEI, SPI and SPDI results, while the area with correlations above $r > 0.7$ for the scZ-index is smaller. In general, these indices record lower correlations across northeastern Iowa, Minnesota, Michigan and eastern North Dakota. The results for the scPDSI, scPHDI and scPMDI show low significant correlations in most of the counties except for some counties in Nebraska, Kansas and Pennsylvania (Figure 3). According to the months in which soybeans crops are more vulnerable to drought, August and September clearly have the highest correlations (Figure 4 and Table 5). Again, the Palmer drought indices show lower correlations and no well-defined seasonal patterns. The 2-month timescale has the greatest concentration of high correlations (Figure 5d). The SPEI and SPDI agree with this pattern while the SPI indicates that 1-month timescale is optimal. In 91% of counties in which soybeans are planted, we found that the shorter timescales (1 to 2 months) are optimal.

3.5. Winter wheat

Winter wheat presents a well-defined area in the Southern Plains with highest correlations between annual yields and the drought indices found, while in the Atlantic Coastal Plains, West and the Midwest areas, the lowest correlations are found in the cases of the SPEI, SPI, and SPDI. The correlation values of the SPEI are slightly higher than those of the SPI and SPDI. The scZ-index shows lower correlations in comparison with the multiscalar indices, but it performs better than the other Palmer drought indices. The scPDSI and scPMDI have higher correlations than the scPHDI (Figure 3). March, April and May are that have the strongest response to moisture conditions, although the seasonal pattern for winter wheat is less defined than for the other crops (Figure 4 and Table 6). The best timescale is also more variable than in other crops (Figure 5e). The 12-month timescale for the SPEI and SPI was found to be the most suitable in ~ 15% of counties, while for the SPDI the 1-month timescale had the highest correlations in 12.5% of the counties. In general, only 40% of the counties show that shorter timescales (1 to 3 months) are most suitable.

Figure 6 identifies the drought index with the highest correlation in each county and for each crop. Table 7 shows the percentage of counties where each drought index has the highest correlation with crop yield for each crop. The SPDI is the best drought index for barley in ~30% of counties and these are mainly located along the Canada-U.S. border. The SPI is the best index for Barley in ~ 28% of counties. The SPEI is best in ~ 20% of counties and they are primarily located in North Dakota and North Carolina. The Palmer drought indices are much less important.

Corn has a well-defined area in the Midwestern U.S. where SPDI has the highest correlation. In total, the SPDI is the best drought index for corn in nearly 51% of counties. The SPEI and SPI have similar numbers of counties where they are most strongly correlated with corn yield (12.97% and 12.65% respectively), and these regions are mainly located in south and north Texas, South Atlantic region, and the states of North and South Dakota, Minnesota and New York. The scPHDI is the best drought index for corn in ~ 9% of counties and these are primarily located in northwestern and central Iowa and Michigan. The scZ-index is the best index in only ~ 6% of counties and it lacks a spatially coherent pattern.

For cotton, the SPEI is the drought index that was best in the largest proportion of counties (29.95%), followed by the SPDI (26.82%) and the SPI (19.79%). The scPHDI is the best drought index ~ 8% of counties, and these are located principally in western Tennessee.

Soybeans and winter wheat show similar patterns, with 95% and 90% of the counties being highly correlated with one of the three multiscalar indices, respectively. In general, the SPDI is the best drought index for soybeans and the SPEI is the best drought index for winter wheat. Kernel density curves for each crop and the drought indices of these correlations describe are shown in Figure 7. The scPDSI clearly stands out as the least correlated index (e.g. soybeans), while the multiscalar show greater variability. The correlation differences between the three multiscalar drought indices are small (Figure 8). The correlations for the multiscalar drought indices are significantly higher than the Palmer drought indices. Figure 8 shows maximum correlation scatterplots between pairs of drought indices (SPEI, SPI, SPDI and scZ-index) for the different crops, recording the value of the determination coefficient (r2). There are minimal differences in the maximum correlation values between the three multiscalar indices. The scZ-index is also relatively similar.

The SPEI and SPI have the highest r2 values (above 0.95) for the five crops while the scZ- Index and SPEI and scZ-Index and SPDI have the lowest r2 values (0.7). Based on the r2 the multiscalar indices (SPEI, SPI and SPDI) are similar and either of these indices are suitable for monitoring drought and its impacts on crop yield.

4. Discussion

In this paper, we assessed an appropriateness review of eleven drought indices for monitoring agricultural drought in the five main crops of the U.S. We have identified spatial patterns illustrating the relationship between crop yields and drought indices within the contiguous U.S. For this, we used some of the most widespread drought indices employed for monitoring and scientific purposes, including different versions of the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Index

(SPI), the Standardized Precipitation Evapotranspiration Index (SPEI) and a recent multiscalar index based on the PDSI, the Standardized Palmer Drought Index (SPDI). The last three indices were obtained at several different timescales.

The Palmer drought indices have lower correlations with crop yields than the multiscalar drought indices. Although, the self-calibrated version of the Palmer indices does marginally improve their performance. In northern and central Greece, Mavromatis (2007) carried out an evaluation of the SPI and the variations of the PDSI (the PDSI, the scPDSI and the scZ-index) for assessing common and durum wheat rain-fed yields. The results obtained suggested an outperformance of drought indices based on Palmer's procedure for predicting yield loses, however these results pointed out that the self-calibrated PDSI versions performed best for wheat yields.

Among the Palmer drought indices, the Z-Index was shown to be more responsive to crop yields, recording more significant and higher correlations. These results are supported by previous studies, for example Karl (1986) recommended the use of the Z-Index over the PDSI or PHDI in the U.S. Quiring & Papakryiakou (2003) made a study comparing four drought indices (SPI, PDSI, Z-Index and NDI (NOAA Drought Index)) for estimating spring wheat yields on the Canadian prairies. They found that the Z-Index was the most appropriate index for predicting yield when moisture stress occurs during the growing season, outperforming the PDSI. Sun et al (2012) also found in the Canadian prairies that the PDSI was less relevant during the early stages of spring wheat growth than the Z-Index. Finally, in the Czech Republic, Hlavinka et al (2009) showed that the Z-Index explains the 81% of the barley, 57% of winter wheat and the 48% of corn variability. In our results, the highest percentage of counties where the scZ-Index was found as the most suitable index was attained for cotton crops (6.51%).

We have shown that in general, independent of the type of crop, the three different multiscalar drought indices used in this study have higher correlations with crop yields than the Palmer drought indices. Although Palmer drought indices are used in current drought monitoring systems in the U.S. (e.g. U.S. Drought Monitor, National Integrated

Drought Information System and the National Weather Service's Climate Prediction Center), they still lack of the flexibility of to the multiscalar indices (Vicente-Serrano et al., 2011). Our study demonstrates that multiscalar indices, such as the SPI, SPEI and SPDI are better suited for quantifying drought impacts on a variety of crop types in the U.S. The highest correlations between crop yields and drought indices ranged between 74% and 92% for multiscalar indices, whereas the Palmer indices had percentages ranging from 8% to 26% depending of the crop. Several previous studies have noted the underperformance of the drought indices that are calculated on a single time-scale. For example, McEvoy et al (2012), Vicente-Serrano et al (2012) & Wang et al (2016b) highlighted the advantages of utilizing multiscalar indices to identify crop failure and/or yield reductions associated with drought. This pattern can be explained by diverse environmental conditions (e.g., soil, climate, agricultural practices, disease and pests) that affect the direct response of crop yields to drought severity. For this reason, it is preferable to work with flexible indices, which may adapt to the different times lags of response between climate conditions and crop responses, mostly during the key stages of crop development.

In this study we have proven that there is significant spatial variability in drought index performance, but also solid differences in the response to the drought indices amongst the different crop types. This entails that determining the best-suited drought index for a specific crop region is particularly difficult since the response to drought varies depending on the crop's sensitivity to moisture shortage and the environmental characteristics of the study region (Mavromatis, 2007). In addition, the response of the crop to drought indices also shows strong seasonality. In general, the moisture conditions during the summer are important determinant for barley, corn, cotton and soybeans yield. Summer months correspond to heading and reproductive stages of these crop types, and in these stages, the plants would be more sensitive to water stress (Çakir, 2004; Denmead & Shaw, 1960; Zipper et al., 2016). On the contrary, winter wheat showed a higher sensitivity to drought conditions during the spring, which corresponds to the period when winter wheat is more sensitive to water availability.

Generally, moisture conditions during shorter timescales (1 to 3 months) were more important, except for winter wheat. These conclusions are consistent with the results of previous studies. For example, Moorhead et al (2015) found that crop production of corn, soybeans and cotton was negatively impacted by drought conditions during July, suggesting a fast response to short-term precipitation deficits. Winter wheat responds in a different way since its growing season is different from the crops mentioned above. Páscoa et al (2016) indicated in a study carried out in the Iberian Peninsula that the months that showed the strongest control of drought on wheat yield were May and June, the period that corresponds to the grain filling and ripening phases, and they showed a response to longer SPEI time-scales, since soil water availability in spring and early summer is strongly determined by winter soil moisture recharge given low evapotranspiration rates during the cold season (Austin et al., 1998). Also, Wang et al (2016a, 2016b) showed a similar pattern in Northern China and the Huang Hui Hai Plain respectively and noticed that the highest correlations between soil moisture and winter wheat yields were found in the months prior to the harvest season (i.e. October-December).

Zipper et al (2016) examined the impact of drought on corn and soybeans in the U.S. and confirmed our findings. Thus, corn results show the most sensitivity to drought occurring during July at a 1-month timescale, while soybeans are most sensitive to droughts occurring in August at a 2-month timescale. Similar results for soybeans using the SPEI were also found in Liaoning Province in China (Chen et al., 2016) and within the Elbe River Lowlands in Eastern Europe (Potopová et al., 2016).

Here we would like to stress that agricultural drought impacts are directly dependent on the specific characteristics of each crop, its timings and sensitivity periods (Hlavinka et al., 2009). Thus, overall our results show that droughts are more prone to affect winter crops during the spring growing season (May through June in the US). Short timescales

(1 to 3 months) in agricultural systems respond to the state of the soil moisture levels as the first trigger of crop stress.

The analysis of the performance of a drought index to properly identify the derived drought impacts is key for accurate management and monitoring of drought risk. The indices selected for this study have been applied in many different studies concerning drought (Feng et al., 2017; McEvoy et al., 2012; Meyer et al., 1991).

The advantageous flexibility of the multiscalar drought indices calculated for different timescales (SPEI, SPI and SPDI) to identify drought impacts has been clearly identified in this study. Nevertheless, among the three multiscalar indices analyzed, the SPEI and SPDI showed higher correlations than the SPI for most of the crops. Although the difference of the magnitude of the correlation was small, the role of the atmospheric evaporative demand on drought severity and crop stress cannot be ignored. Different assessment methods have been used to estimate temperature impacts on different types of yields (Asseng et al., 2014; Rosenzweig et al., 2014). In a recent study, Liu et al., (2016) estimated a diminish of an order between 4.1% and 6.4% of wheat yields with a 1ºC global temperature increase and it is suggested that in the US, a decrease of 7.6% in the wheat production for the period 1985 to 2013 may be associated to the increase of temperatures, especially during the growing season (spring months) (Tack et al., 2015). Moreover, Lobell et al (2014) indicated that that the sensitivity of corn yields to drought stress in the US increased in crops associated with high vapor pressure deficits and stressed the need for considering the atmospheric evaporative demand in drought quantification. Therefore, the use of multiscalar drought indices based on both precipitation and the atmospheric evaporative demand (SPEI and SPDI) seem recommendable to better quantify drought severity in comparison to the SPI, even more so when considering the state-of-the-art climate change projections, which predict a significant drying in some of the major agricultural areas of the US toward the end of this century, which will only be enhanced by warmer conditions (Feng et al., 2017).

5. Conclusions

The main results of this study are:

(i) Differences exist between the performance of various drought indices used to identify drought impacts on crop yields, resulting in different temporal and spatial variations among crop types.

(ii) Multiscalar drought indices outperform uniscalar drought indices for monitoring the impact of drought on crop yields.

(iii) SPEI, SPI and SPDI all had very similar correlations and in most cases, any of these indices are suitable for monitoring the impact of drought on various crops.

(iv) Multiscalar drought indices have a high capacity to identify the seasonality of drought impacts. They can properly reflect drought conditions during the critical phenological stages of various crops.

(v) In general, shorter drought time-scales (1 to 3 months) are better at identifying drought impacts on crop yields, with the exception of winter wheat, which is related to longer drought time-scales.

(vi) Before applying a specific drought index for agricultural drought monitoring, it is important to review any previous assessments to determine which indices and time scales are most suitable.

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Commission. Marina Peña-Gallardo was granted by the Spanish Ministry of Economy and Competitiveness.

FIGURES

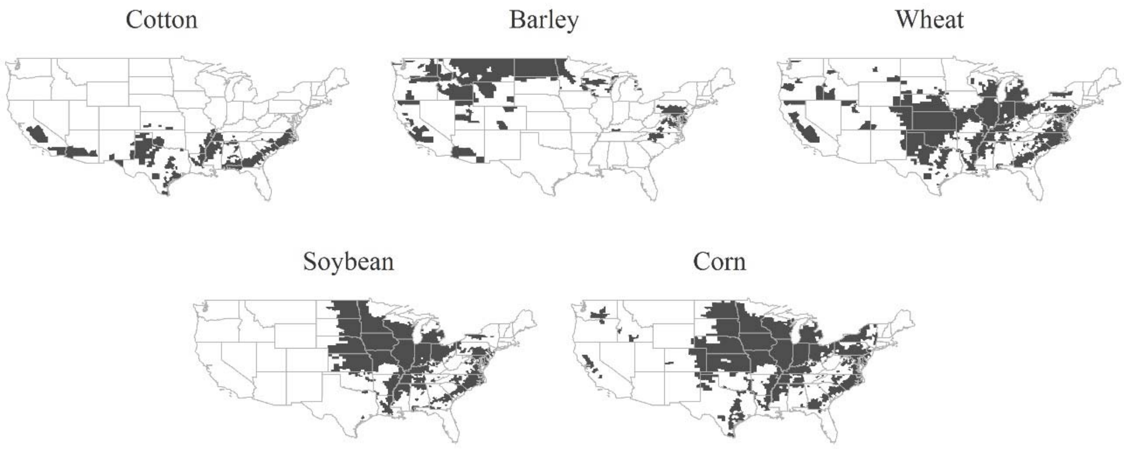

Figure 1. Spatial distribution of selected counties where the different crops are cultivated across United States (USDA-NASS).

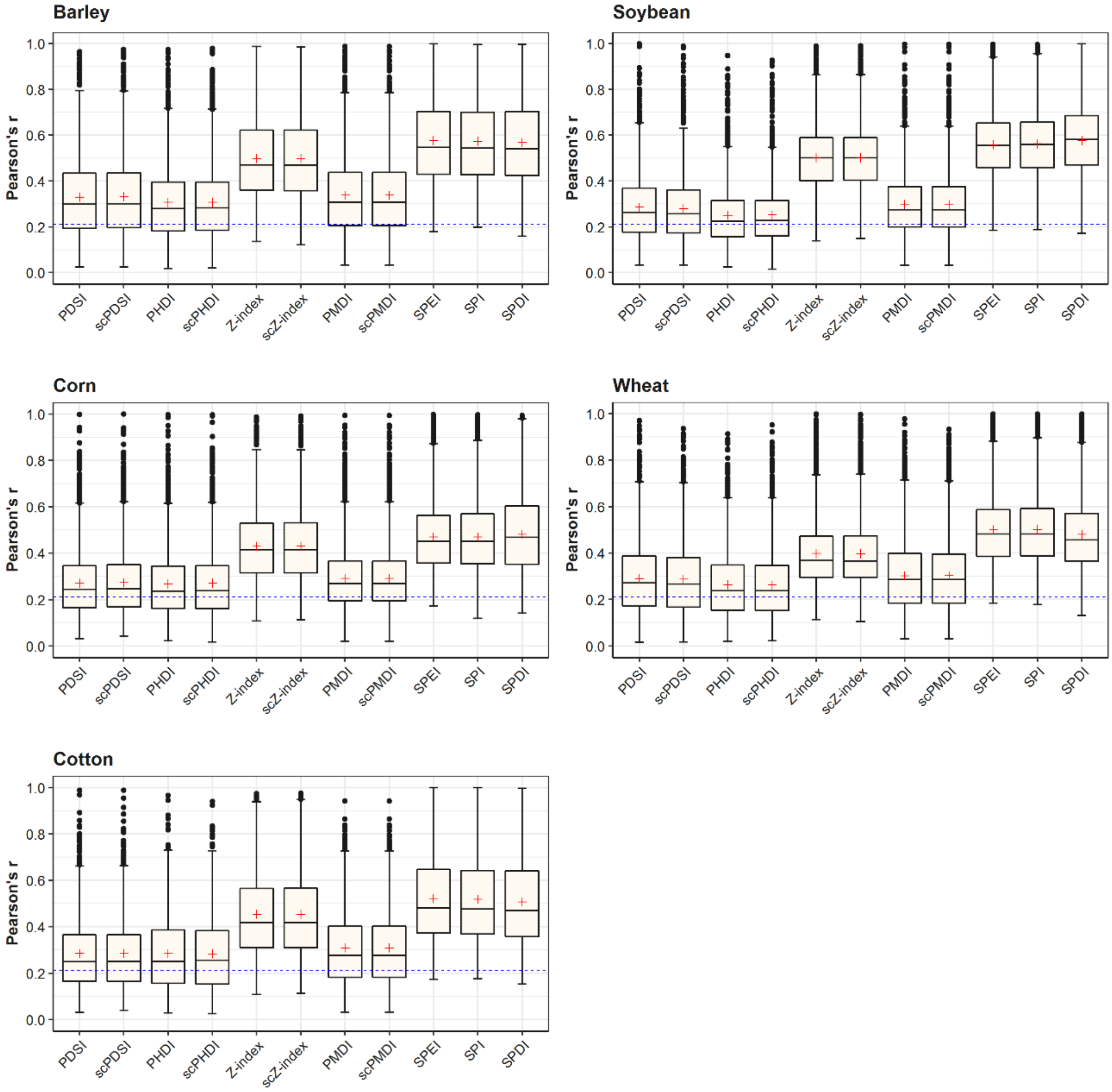

Figure 2. Box plots representing the highest Pearson Correlation Coefficients found between crop yields and the eleven drought indices. The solid black line corresponds to the median, red plus signs mark the mean and dotted dash blue line spots the significant level at $p < 0.05$.

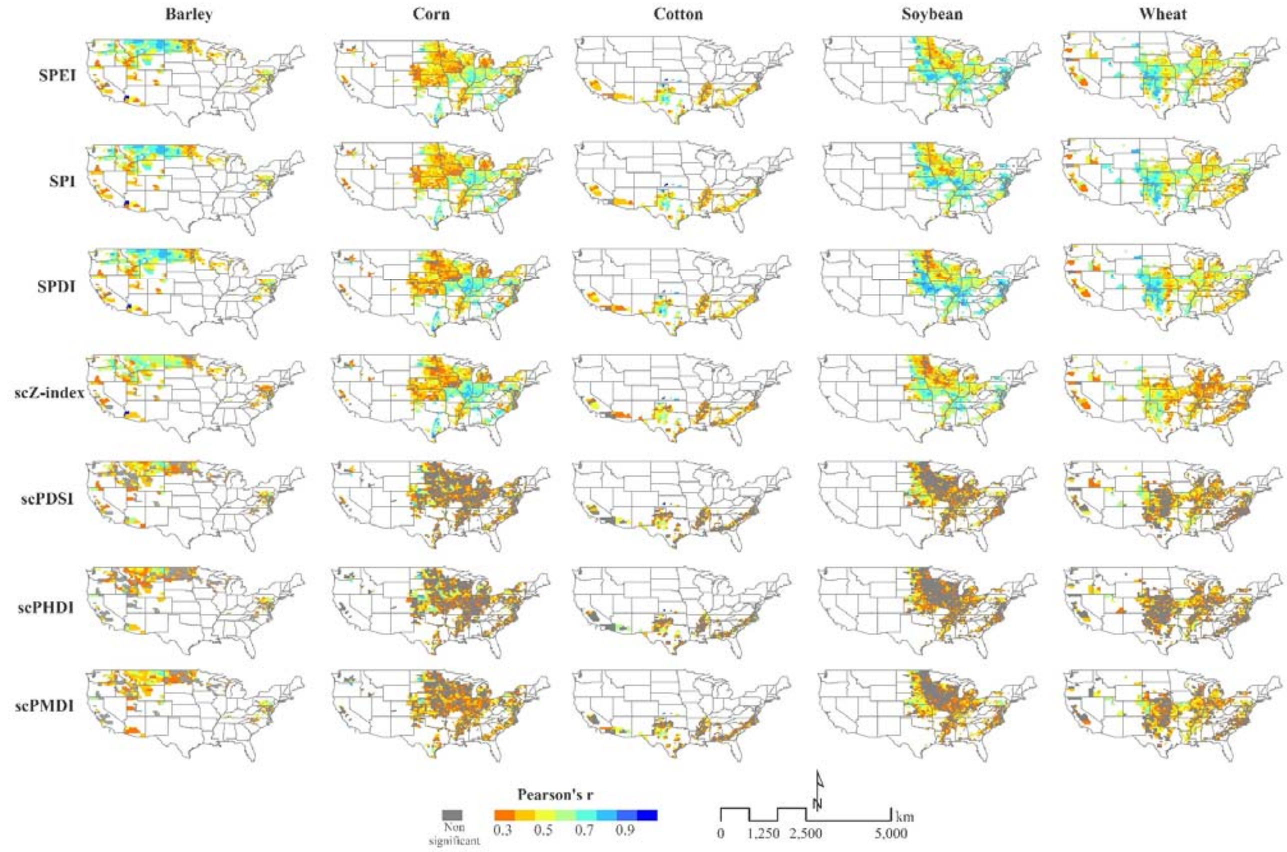

Figure 3. Spatial distribution of the highest Pearson correlation coefficients obtained for the SPEI, SPI, SPDI, scZ-index, scPDSI and crop yields. In grey are colored the counties with non-significant correlations (p-value < 0.05).

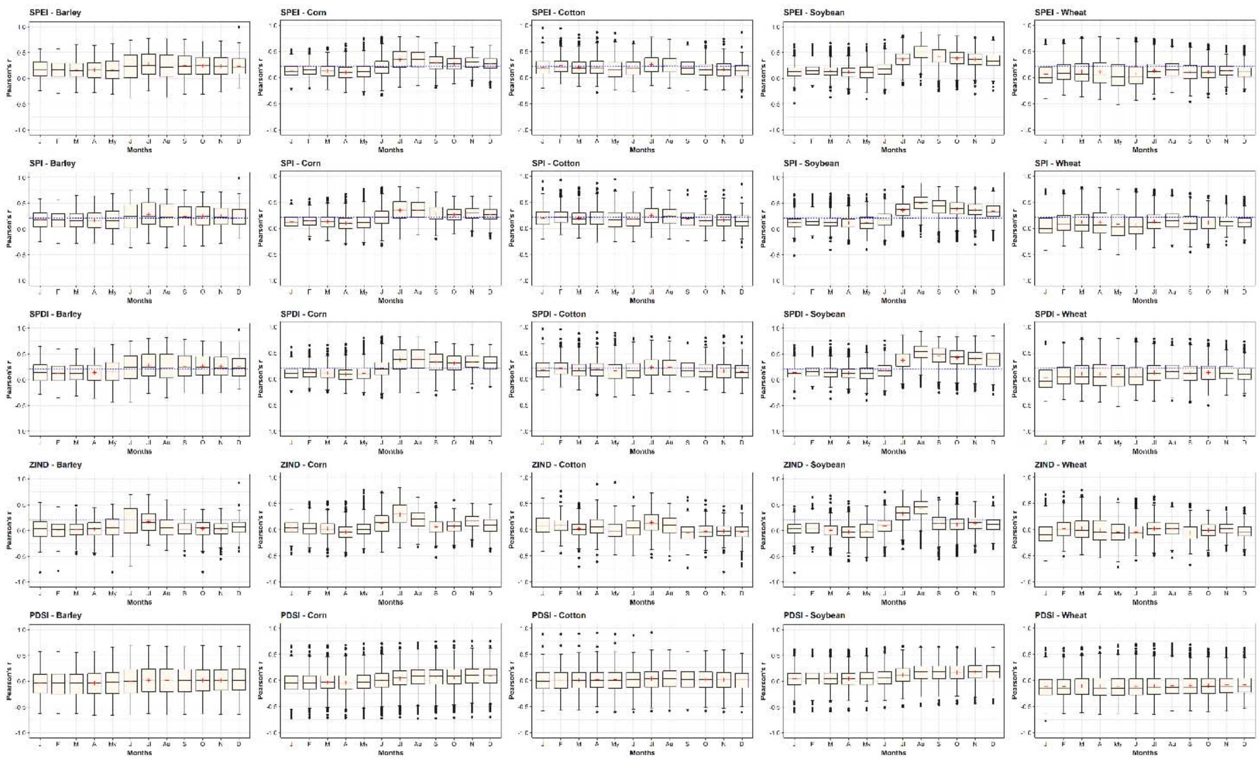

Figure 4. Boxplots showing the Pearson correlation coefficients obtained between the monthly series of the crop yields and the SPEI, SPI, SPDI, scZ-index and scPDSI. The solid black line corresponds to the median, red plus signs mark the mean and dotted dash blue line spots the significant level at $p < 0.05$.

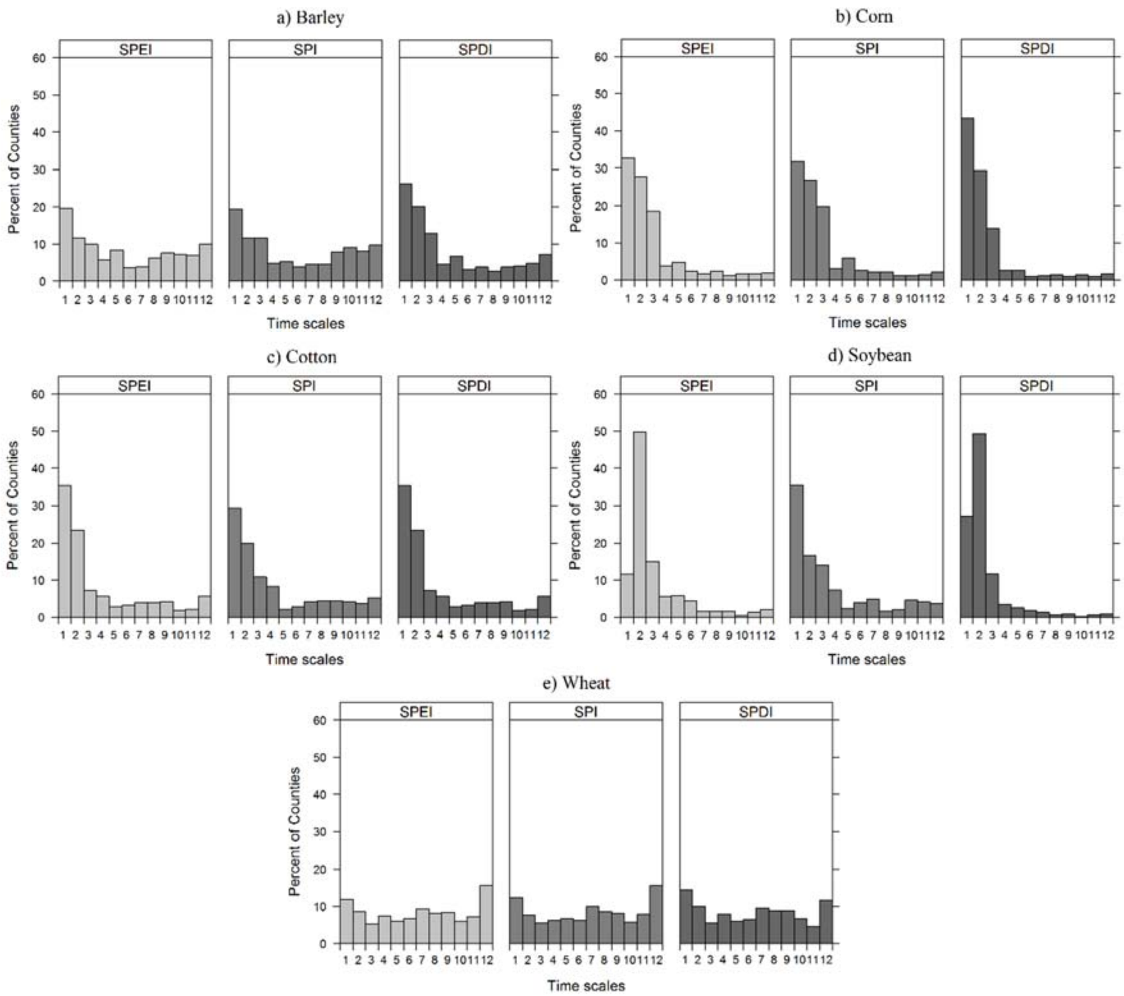

Figure 5. Histograms showing the percentage of counties analyzed for each crop type and timescale at which the maximum correlation is found.

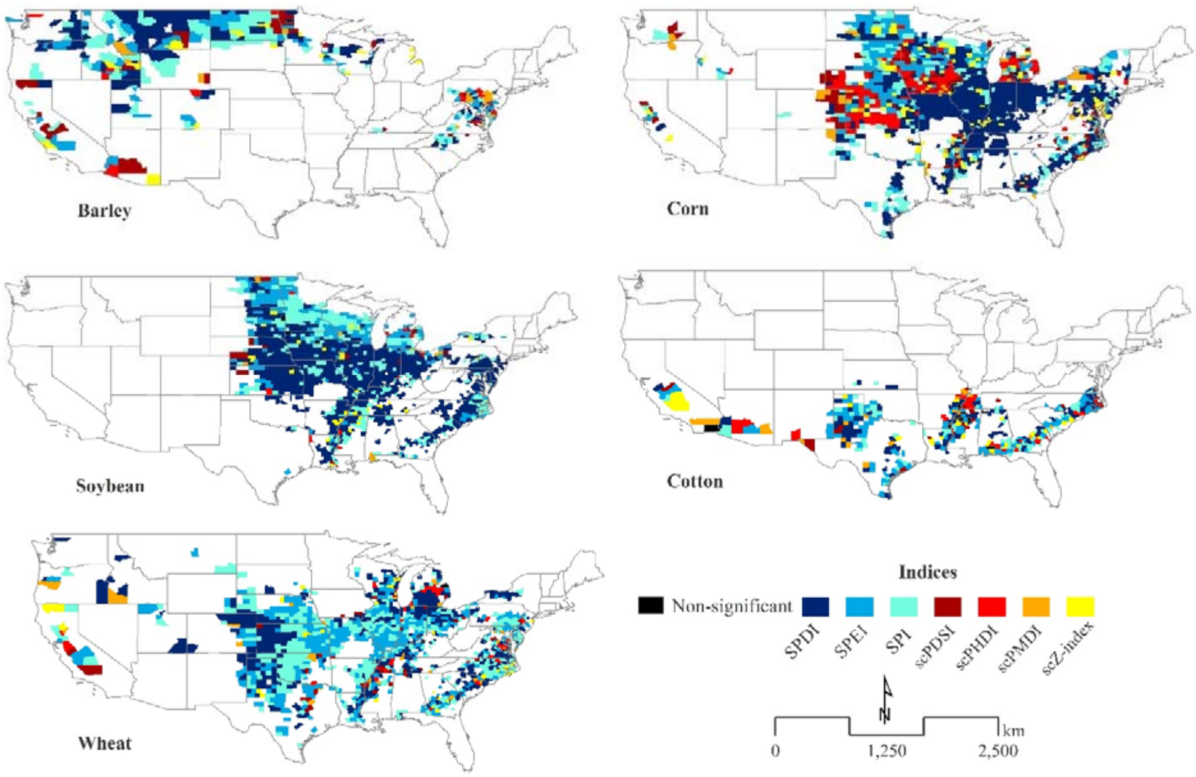

Figure 6. Spatial classification of the counties and crop types according to the drought indices that recorded the highest Pearson *r* correlation coefficient independently by timescale and month.

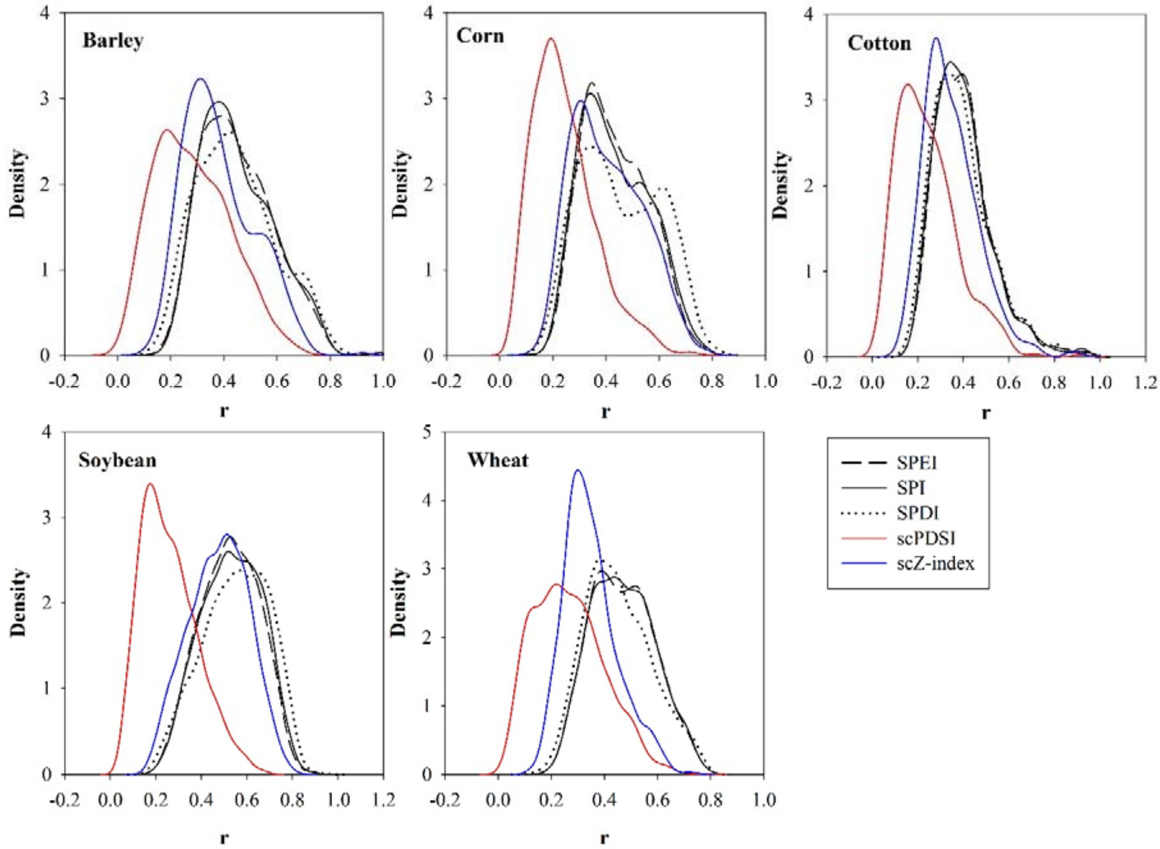

Figure 7. Kernel density plots of the highest correlations found per index and for each crop.

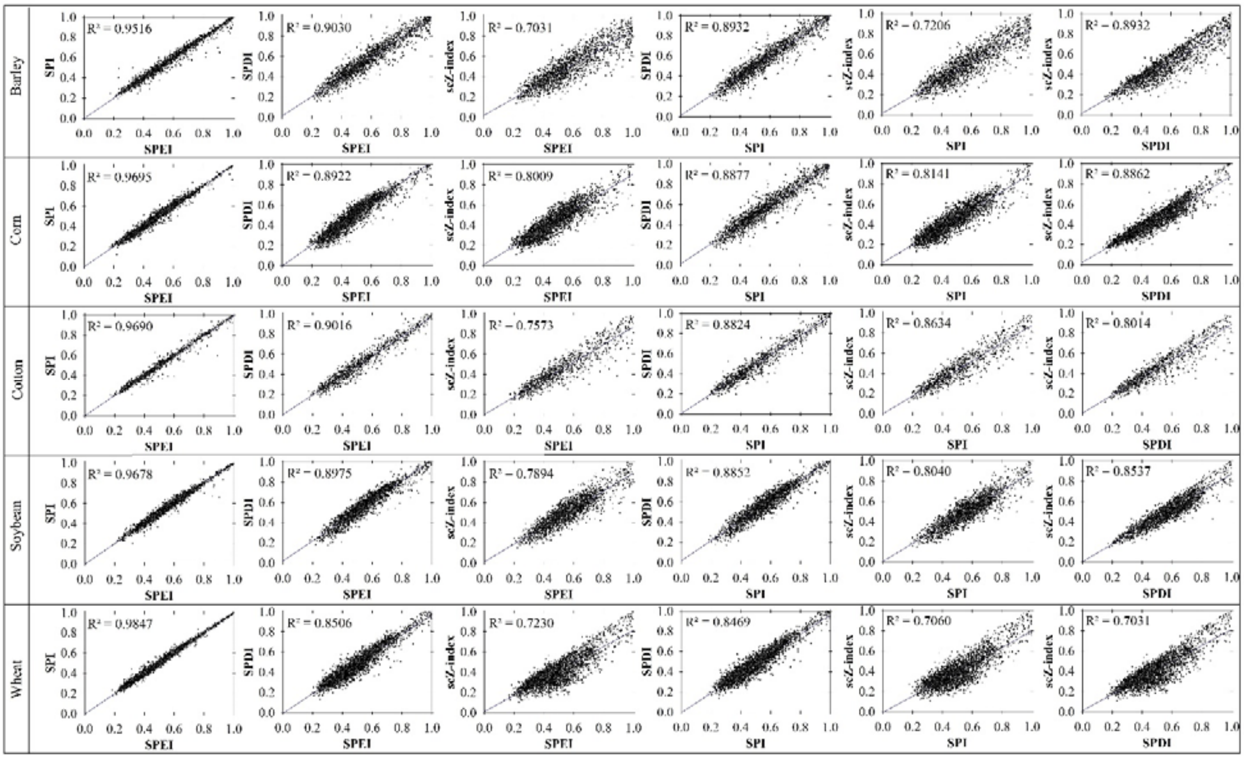

Figure 8. Maximum correlation scatterplots of index pairs (SPEI, SPI, SPDI and scZ-index) for each one of the crops analyzed. Each point corresponds to the maximum correlation recorded within each county. The determinant coefficient and is noted in each plot.

Tble 1. Percentage of counties with significant correlations per index.

Indices	Barley	Cotton	Corn	Soybeans	Wheat
PDSI	58.45	46.89	44.79	52.89	56.55
scPDSI	58.71	47.02	47.40	54.11	58.06
PHDI	53.89	46.95	45.83	42.77	47.69
scPHDI	51.47	47.02	45.83	44.29	48.60
Z-index	90.62	92.93	85.42	97.34	90.01
scZ-index	90.88	93.00	85.16	97.34	90.16
PMDI	62.73	58.50	50.30	59.20	61.10
scPMDI	63.27	60.05	51.30	61.19	62.91
SPEI	98.12	98.18	97.14	99.47	99.32
SPI	99.20	97.54	95.83	99.54	99.17
SPDI	95.44	94.36	93.23	98.17	97.05

Table 2. Percentage of the 373 analyzed counties where barley is cultivated at which the maximum correlation with the seven drought indices is found.

	January	February	March	April	May	June	July	August	September	October	November	December	Total
SPEI	5.90	4.56	3.49	2.68	1.61	14.75	21.72	8.04	10.72	6.70	6.43	13.40	100
SPI	5.90	4.29	3.22	5.36	1.07	15.01	23.59	9.12	7.51	5.63	5.36	13.94	100
SPDI	4.83	4.02	4.29	3.75	2.68	15.55	23.06	9.38	9.12	7.51	6.97	8.85	100
scPDSI	5.36	3.49	2.41	2.95	2.14	3.22	14.48	15.55	7.51	4.83	5.36	32.71	100
scPHDI	18.77	3.22	4.29	2.68	1.88	2.95	4.83	7.77	5.63	7.77	5.36	34.85	100
scZ-index	3.49	2.95	3.75	3.22	4.29	32.17	15.28	5.63	6.97	6.97	6.17	9.12	100
scPMDI	16.09	3.49	2.68	3.49	1.88	2.14	8.04	11.53	5.36	9.12	5.36	30.83	100

Table 3. Same as Table 2, but for corn yields.

	January	February	March	April	May	June	July	August	September	October	November	December	Total
SPEI	3.11	1.56	2.27	1.30	2.66	7.07	33.20	25.16	3.44	2.72	13.42	4.09	100
SPI	3.05	1.43	2.92	0.91	2.98	7.20	31.58	26.39	3.57	3.24	12.84	3.89	100
SPDI	2.14	1.30	2.27	0.52	2.01	6.49	30.61	29.51	3.76	2.59	15.05	3.76	100
scPDSI	4.35	1.62	2.79	0.58	1.43	1.49	4.67	12.39	7.72	4.73	17.38	40.86	100
scPHDI	4.35	1.88	2.27	0.45	0.84	0.71	2.53	6.36	4.41	4.35	15.95	55.90	100
scZ-index	2.08	1.49	2.59	0.65	2.98	11.41	41.12	13.68	2.08	2.59	16.67	2.66	100
scPMDI	3.31	1.56	3.05	0.58	1.17	0.52	3.05	8.43	6.55	3.76	17.90	50.13	100

Table 4. Same as Table 2, but for cotton yields.

	January	February	March	April	May	June	July	August	September	October	November	December	Total
SPEI	13.92	10.31	3.61	8.51	2.06	3.35	19.59	22.68	4.90	1.55	3.35	5.15	100
SPI	14.18	11.08	3.87	8.51	3.35	4.38	17.27	20.88	5.93	2.06	3.35	4.12	100
SPDI	15.72	11.60	3.87	8.76	2.32	2.58	17.78	20.88	6.19	2.06	2.06	4.38	100
scPDSI	9.54	8.51	3.87	8.76	2.58	3.61	9.02	23.45	5.93	6.96	6.44	11.34	100
scPHDI	10.31	10.57	5.67	4.90	2.84	2.06	5.41	15.98	8.76	6.44	10.57	15.46	100
scZ-index	12.37	8.76	6.44	7.47	2.84	4.38	25.77	14.95	5.41	2.58	1.55	6.44	100
scPMDI	11.60	10.57	3.87	7.47	2.58	2.32	5.67	23.20	7.99	5.15	5.93	12.63	100

Table 5. Same as Table 2, but for soybeans yields.

	January	February	March	April	May	June	July	August	September	October	November	December	Total
SPEI	1.07	1.45	0.99	0.99	0.68	0.15	3.58	68.42	10.20	6.09	2.97	3.20	100
SPI	1.37	1.29	0.76	0.46	0.99	0.68	3.65	68.57	9.21	5.86	3.50	3.65	100
SPDI	1.67	2.51	0.53	0.15	0.53	0.15	2.28	69.94	12.86	4.49	2.05	2.21	100
scPDSI	5.18	2.59	1.90	1.60	0.99	0.15	1.52	17.50	12.18	9.67	15.53	31.20	100
scPHDI	4.11	1.37	1.60	0.46	0.23	0.08	0.61	5.33	6.32	6.24	12.56	61.11	100
scZ-index	0.53	2.74	0.61	0.38	0.76	0.91	19.25	67.12	1.37	3.20	1.45	1.67	100
scPMDI	4.49	1.67	1.83	0.38	0.23	0.08	0.76	9.21	10.05	6.39	16.44	48.48	100

Table 6. Same as Table 2, but for winter wheat yields.

	January	February	March	April	May	June	July	August	September	October	November	December	Total
SPEI	3.56	4.69	10.07	14	6.81	2.04	9.92	16.5	5.83	6.43	13.32	6.74	100
SPI	3.48	5.00	8.33	16.28	7.04	2.35	9.84	16.43	5.53	6.06	13.02	6.66	100
SPDI	4.01	4.62	9.99	13.7	9.69	2.73	9.08	16.58	6.43	7.8	9.77	5.60	100
scPDSI	14.00	5.6	5.37	6.81	7.19	3.48	5.00	5.83	5.00	5.00	12.94	23.77	100
scPHDI	28.84	9.84	6.81	5.68	4.16	2.95	6.66	5.22	2.95	3.56	9.16	14.16	100
scZ-index	3.10	7.12	13.78	13.55	6.28	2.65	10.37	14.99	4.54	7.87	10.98	4.77	100
scPMDI	20.36	10.52	6.89	5.9	7.57	3.26	6.51	5.15	4.31	3.48	9.08	16.96	100

Table 7. Percentage of counties where each index has recorded the highest correlation values. Values are expressed in percentages of the total of all counties.

	SPEI	SPI	SPDI	scPDSI	scPHDI	scPMDI	scZ-index
Barley	20.38	27.61	30.29	7.77	4.83	4.29	4.83
Corn	12.97	12.65	50.97	5.25	9.53	2.85	5.77
Cotton	29.95	19.79	26.82	4.69	7.81	4.43	6.51
Soybeans	11.26	22.68	61.19	1.07	0.91	0.61	2.28
Wheat	30.66	31.04	28.61	2.65	2.73	2.2	2.12

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