Vol. 75: 221–240, 2018
https://doi.org/10.3354/cr01519

CLIMATE RESEARCH
Clim Res

Published online August 28

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

Marina Peña-Gallardo[1,*], Sergio M. Vicente-Serrano[1], Fernando Domínguez-Castro[1], Steven Quiring[2], Mark Svoboda[3], Santiago Beguería[4], Jamie Hannaford[5]

[1]Instituto Pirenaico de Ecología, Consejo Superior de Investigaciones Científicas (IPE–CSIC), Zaragoza, Spain
[2]Atmospheric Sciences Program, Department of Geography, The Ohio State University, Columbus, OH 43210, USA
[3]National Drought Mitigation Center, University of Nebraska-Lincoln, Lincoln, NE 68583, USA
[4]Estación Experimental de Aula Dei, Consejo Superior de Investigaciones Científicas (EEAD-CSIC), Zaragoza, Spain
[5]Centre for Ecology and Hydrology, Maclean Building, Crowmarsh Gifford, Wallingford OX10 8BB, UK

ABSTRACT: In North America, the occurrence of extreme drought events has increased significantly in number and severity over the last decades. Past droughts have contributed to lower agricultural productivity in major farming and ranching areas across the US. We evaluated the relationship between drought indices and crop yields across the US for the period 1961–2014. In order to assess the correlations with yields from the major cash crops in the country, we calculated several drought indices commonly used to monitor drought conditions, including 4 Palmer-based and 3 multiscalar indices (Standardized Precipitation Index, Standardized Precipitation Evapotranspiration Index, Standardized Precipitation Drought Index). The 3 multiscalar drought indices were aggregated at 1 to 12 mo timescales. Besides the quantification of the similarities or differences between these drought indices using Pearson correlation coefficients, we identified spatial patterns illustrating this relationship. The results demonstrate that the flexible multiscalar indices can identify drought impacts on different types of crops for a wide range of time periods. The differences in spatial and temporal distribution of the correlations depend on the crop and timescale analyzed, but can also be found within the same type of crop. The moisture conditions during summer and shorter timescales (1 to 3 mo) turn out to be a determining factor for barley, corn, cotton and soybean yields. Therefore, the use of multiscalar drought indices based on both precipitation and the atmospheric evaporative demand (SPEI and SPDI) seems to be a prudent recommendation.

KEY WORDS: Drought · Crop yields · Palmer drought indices · Standardized Precipitation Index · Standardized Precipitation Evapotranspiration Index · Standardized Precipitation Drought 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 (Wilhite 2000, Quiring & Papakryiakou 2003, Lobell & Field 2007, Udmale et al. 2014). Crops are unable to meet their water requirements if insufficient water supplies are available as a result of 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 (Meze-Hausken 2004, Mishra & Singh 2010, Lobell et al. 2011). 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). Droughts usually reduce the capacity for active

*Corresponding author: marinapgallardo@ipe.csic.es

radiation absorption by the canopy (Earl & Davis 2003); thus 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).

The adverse impacts of drought on crop yields are unequally distributed geographically (Howitt et al. 2015). Natural hazards, including droughts, induced food crop disasters between 2003 and 2013 affecting more than 1.9 billion people in developing countries, causing over US$494 billion 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 caused 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 (Rossi & Niemeyer 2010, Lobell et al. 2011, Olesen et al. 2011). However, quantification of the direct crop yield impacts due to drought is difficult given the complexity of drought events (Wilhite 1993, Wilhite et al. 2007, Geng et al. 2016). In addition, each crop has a differing degree of resilience to drought stress (Wilhelmi et al. 2002, Lobell et al. 2011, Tack et al. 2015, Liu et al. 2016). For these reasons, the quantification of the drought impacts on crop yields is very important.

Drought indices represent a reliable tool for monitoring and studying the impacts of droughts on different sectors, such as crop yields (Wilhite & Glantz 1985). Several studies have used drought indices to identify these impacts at different spatial scales in Europe (Mavromatis 2007, Ceglar et al. 2012, Di Lena et al. 2014, Páscoa et al. 2017), Australia (Lobell et al. 2015), Asia (Arshad et al. 2013, Sahoo et al. 2015, Kattelus et al. 2016, Wang et al. 2016), Africa (Blanc 2012, Elagib 2013), America (Kim et al. 2002, Quiring & Papakryiakou 2003) and at the global scale (Vicente-Serrano et al. 2012, Wang et al. 2014). In general, past research has shown 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 (Zargar et al. 2011, Wilhite et al. 2014). 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 & Dracup 2002, 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).

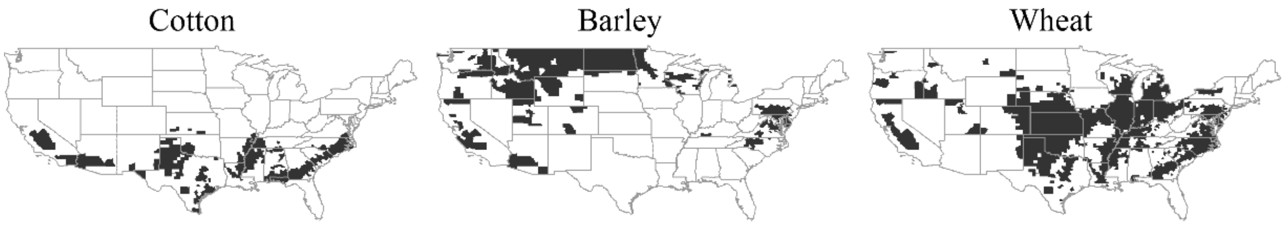
Some studies have suggested that drought vulnerability in the US is increasing (Mishra & Singh 2010, Carrão et al. 2016, Geng et al. 2016). For example, extreme droughts in the US (i.e. those covering >25% of the country) accounted for $6.7 billion in crop losses for 2000–2004 (Wilhite et al. 2007). Extreme drought events have been recorded in the past 2 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 the Great Plains (NOAA 2017, USDM 2017), causing widespread impacts across multiple sectors. Ross et al. (2003) reported that between 1980 and 2003, the US 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/) estimated that US losses from drought were $4.1 billion in 2014, US$4.6 billion in 2015, $10.7 billion in 2013 and $31.5 billion in 2012.

The objective of this study was 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 (Quiring 2009, Esfahanian et al. 2017). Here we compare the Standardized Precipitation Evapotranspiration Index (SPEI), the Standardized Precipitation Index (SPI), the Standardized Precipitation Drought Index (SPDI) and 4 Palmer-related drought indices (Palmer Drought Severity Index [PDSI], Palmer Hydrological Drought Index [PHDI], Palmer Moisture Anomaly Index [Z-index] and Palmer Modified Drought Index [PMDI]).

2. DATASETS AND METHODOLOGY

2.1. Crop data

Our analysis of drought indices focuses on the 5 crops with the broadest geographic distribution and highest production in the US: barley, corn, cotton, soybean and winter wheat (Fig. 1). Data on crop production for each county are collected by the United



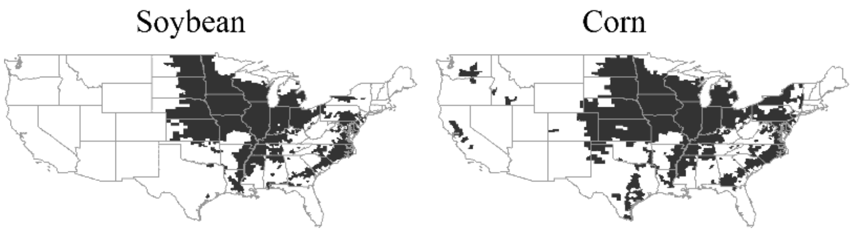


Fig. 1. Spatial distribution of selected counties where the 5 different crops investigated in this study are cultivated across the United States (source: US Department of Agriculture National Agricultural Statistics Service)

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 5 masks based on the 5 crops considered in this analysis in order to identify the counties where there are representative areas of cultivation of these different crops. For this purpose, the available crop county maps were taken from the USDA (https://www.nass.usda.gov/Charts_and_Maps/Crops_County). Yield (t ha^{-1}) is based on the harvest in each county. The final data set used in this analysis comprised 373 counties for barley, 1542 counties for corn (maize), 388 counties for cotton, 1314 counties for soybeans and 1321 for winter wheat (Fig. 1). These counties have at least 25 years of data between 1961 and 2014.

Considering the importance of technology in enhancing efficiency in agriculture, but without knowing the weight of each technological advance that has occurred during the period of time analyzed in this work, crop yield series were de-trended to remove these non-climatic trends from yield data (Lobell & Field 2007, Xu et al. 2013). Based on the assumption that these improvements have changed linearly over time, the de-trending process was achieved by fitting a linear regression to obtain the yield data and calculating the residuals (e.g. Tigkas & Tsakiris 2015, Poudel & Shaw 2016, Zipper et al. 2016, Páscoa et al. 2017). 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 Parameter-elevation Relationships on Independent Slopes Model (PRISM) gridded dataset (http://prism.oregonstate.edu). This dataset was developed and validated by Oregon State University (Daly et al. 2008) and has been used in many different climatological and environmental studies (Tilman et al. 2002, Loarie et al. 2009, Mayer 2012, Sanford & Selnick 2013, 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 calculations

Eleven drought indices were calculated: 8 versions of the Palmer Drought Indices suite and 3 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 droughts at both regional (Keyantash & Dracup 2002, Bonaccorso et al. 2003, Lorenzo-Lacruz et al. 2010, McEvoy et al. 2012, Rohli et al. 2016, Yan et al. 2016) and global scales (Dai et al. 2004, Vicente-Serrano et al. 2012, 2015, Trenberth et al. 2014, Geng et al. 2016).

(1) Palmer drought indices. The PDSI is a popular meteorological drought index that is commonly used in the US, as are the PHDI and the Z-index. Using precipitation and air temperature as inputs, the Palmer indices compute an estimation of moisture

supply and demand within a simple 2-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 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).

(2) 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 mean = 0 and variance = 1. The SPI has been recommended by The World Meteorological Organization as the universal meteorological drought index (WMO 2012).

(3) SPEI. Proposed by Vicente- Serrano et al. (2010), the SPEI calculation rests on a monthly climate water balance (precipitation minus reference evapotranspiration, ETo), 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.

(4) 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 multiscalar 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 multiscalar indices (SPEI, SPI and SPDI) were calculated at timescales from 1 to 12 mo. 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 relationships 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 3 multiscalar drought indices calculated from 1 to 12 mo timescales (SPI, SPEI and SPDI) we obtained 12 correlations (1 for each of the monthly series) for each timescale, resulting in a total of 144 correlations for each of the 3 drought indices for each crop type and each county. In addition, we also identified the timescale (in the case of multiscalar indices) and month in which the highest correlation was found within each county.

3. RESULTS

Fig. 2 shows 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 5 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, and for wheat it was around 0.46 using the same indices. Moreover, we found that r = 0.44 for corn, 0.43 for barley and 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 significant 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 crops. For this reason, we show only results of the self-calibrated version of the Palmer indices. In general, the 3 multiscalar indices used in this study performed much better than the Palmer indices. The SPI had the highest percentage of counties with significant correlations for barley and soy-

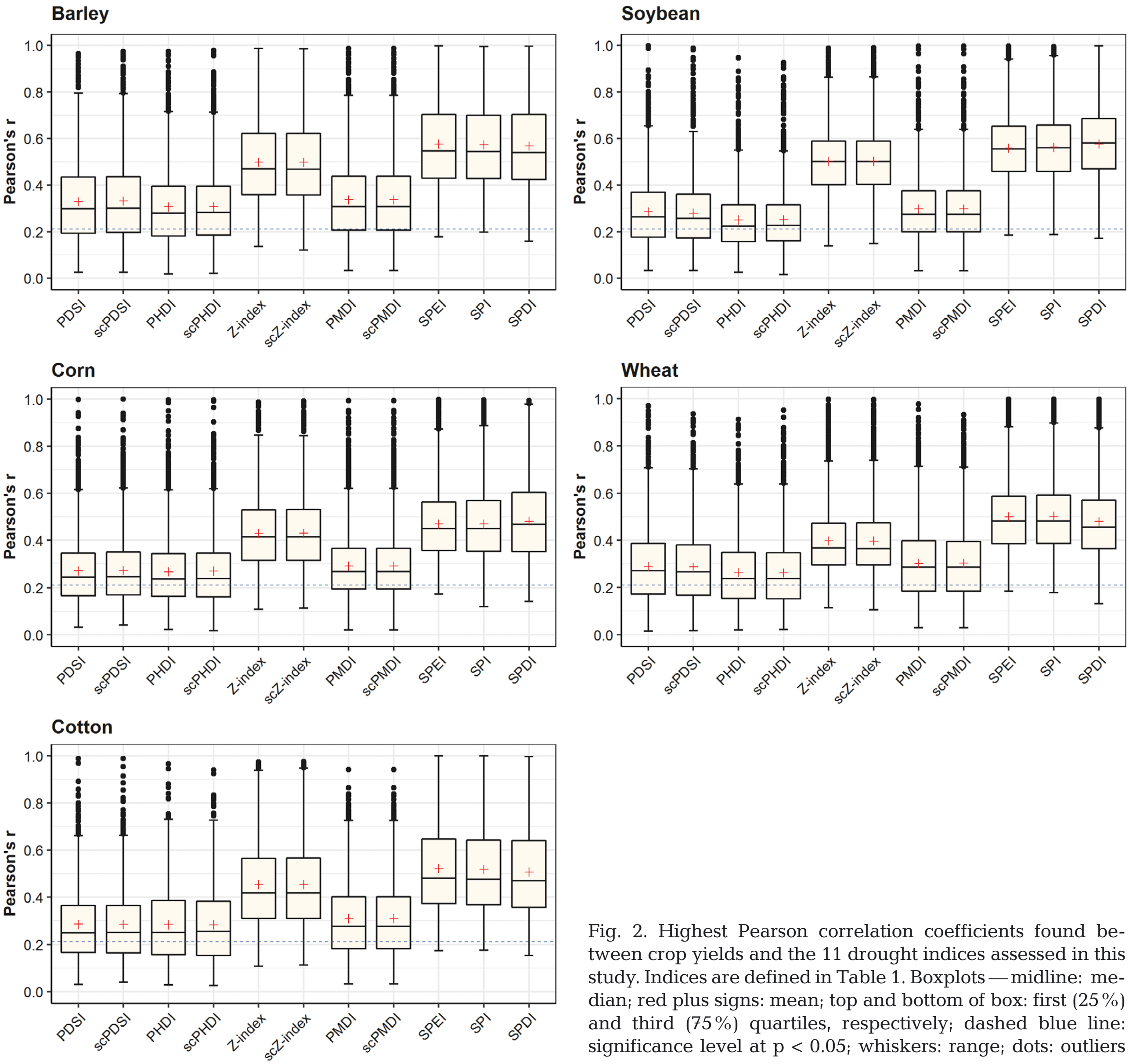


Fig. 2. Highest Pearson correlation coefficients found between crop yields and the 11 drought indices assessed in this study. Indices are defined in Table 1. Boxplots — midline: median; red plus signs: mean; top and bottom of box: first (25%) and third (75%) quartiles, respectively; dashed blue line: significance level at $p < 0.05$; whiskers: range; dots: outliers

Table 1. Percentage of US counties with significant correlations between crop yields and drought indices

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

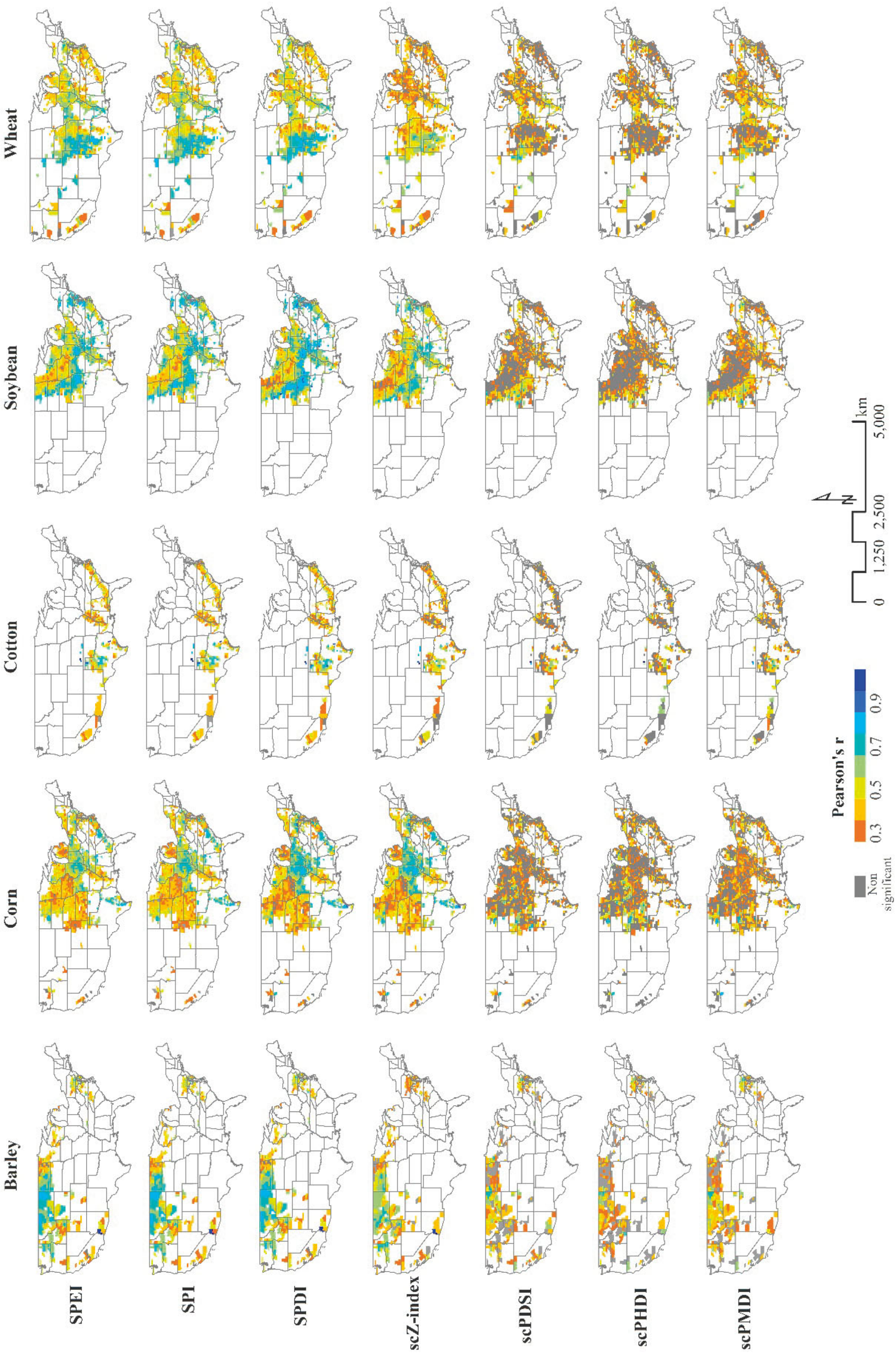


Fig. 3. Spatial distribution of the highest Pearson correlation coefficients obtained for the different indices and crop yields (indices are defined in Table 1). Counties with non-significant correlations ($p < 0.05$) are shown in grey

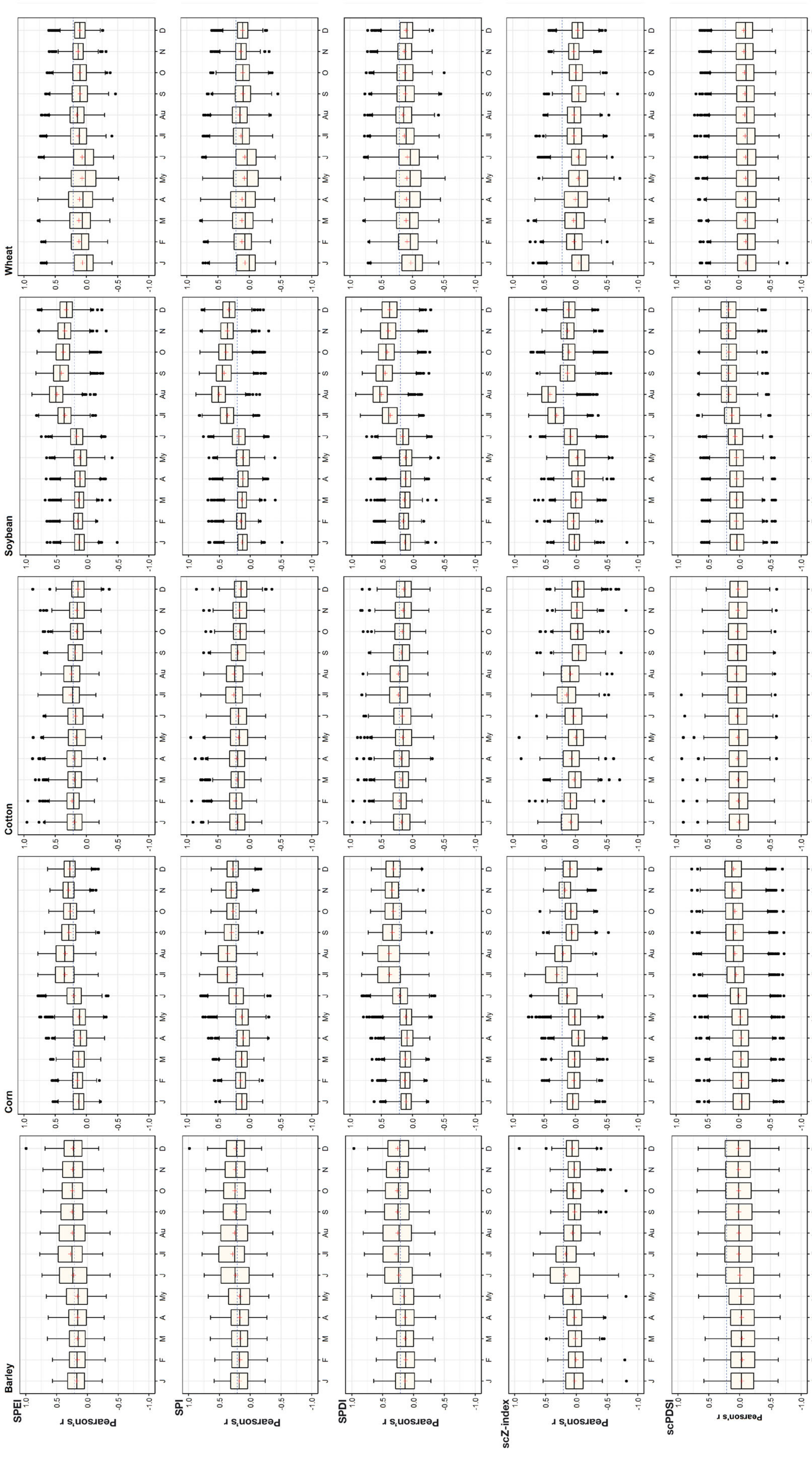


Fig. 4. Pearson correlation coefficients obtained between the monthly series of crop yields and the SPEI, SPI, SPDI, scZ-index and scPDSI. Boxplot parameters as in Fig. 2

Table 2. Percentage of the 373 analyzed US counties where barley, corn, cotton, soybeans and winter wheat are cultivated, and in which the maximum correlations with the 7 drought indices were found. Indices are defined in Table 1. Yearly totals are 100% in all cases

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barley												
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
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
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
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
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
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
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
Corn												
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
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
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
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
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
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
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
Cotton												
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
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
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
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
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
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
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
Soybeans												
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
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
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
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
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
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
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
Winter wheat												
SPEI	3.56	4.69	10.07	14	6.81	2.04	9.92	16.5	5.83	6.43	13.32	6.74
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
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
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
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
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
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

beans, while the SPEI did best for cotton, corn and wheat. The SPDI performed quite similar to the SPI and SPEI. The scZ-index also did relatively well.

The results are described separately for each crop. Fig. 3 shows the geographical distribution of the highest correlations between the drought indices and yield for the 5 crops. Fig. 4 displays the correlations between the different monthly series of drought indices and crop yields. Table 2 and Fig. A1 in the Appendix shows the seasonal differences in the performance of the drought indices to assess crop impacts. Fig. 5 and Fig. A2 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.

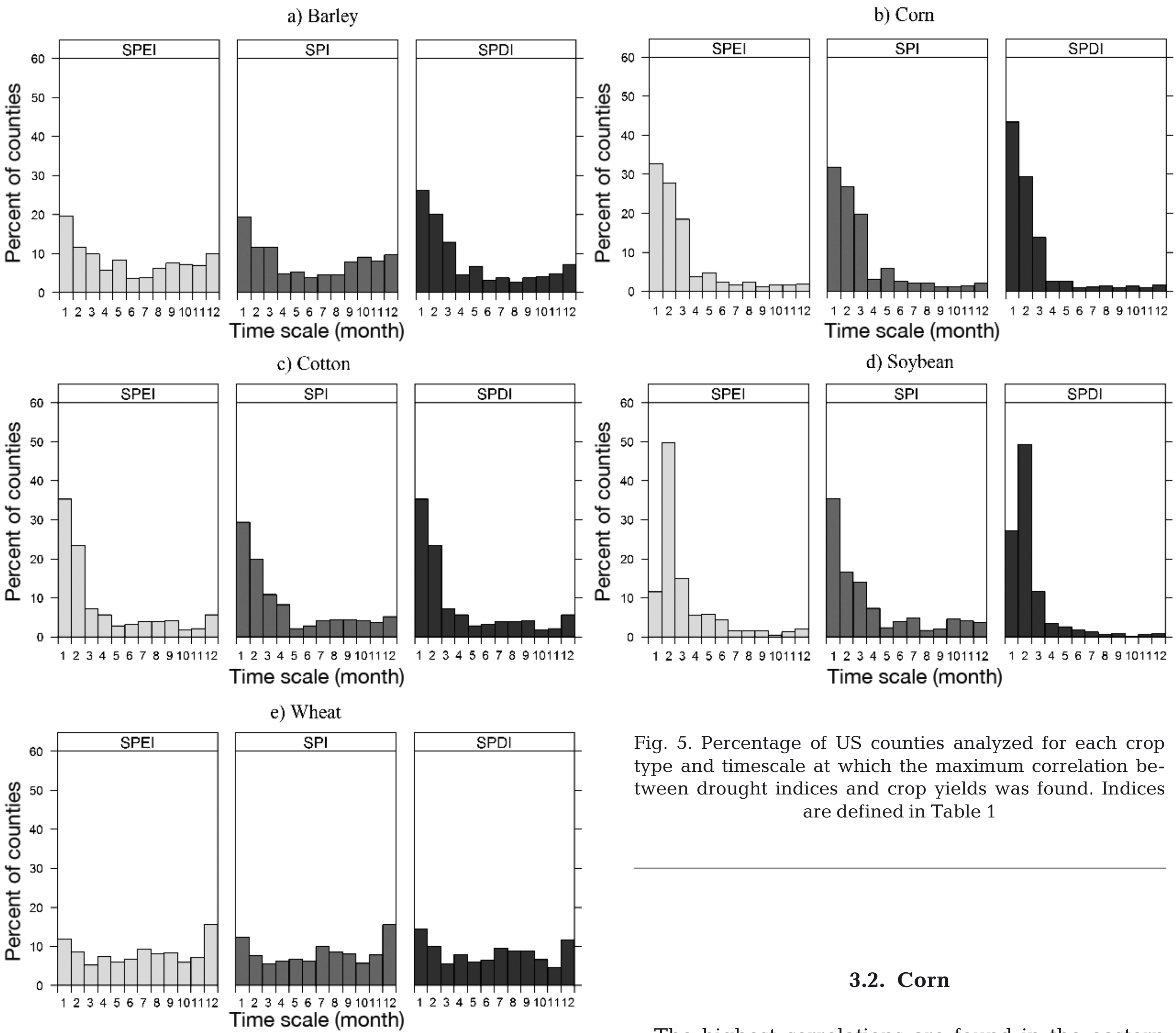


Fig. 5. Percentage of US counties analyzed for each crop type and timescale at which the maximum correlation between drought indices and crop yields was found. Indices are defined in Table 1

High correlations are recorded in these areas with the SPEI, SPI and SPDI. In contrast, the lowest correlations are found in the north central and eastern US barley-cultivated lands. Generally, the self-calibrated Palmer drought indices show lower correlations ($r < 0.5$) in the counties where the multiscalar indices show better results. The Z-index shows similar results to the multiscalar indices, but is characterized by lower r values (Fig. 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 mo) (Fig. 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, whereas the lowest correlations are found in central-northern states and Michigan. The drought indices with 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 (Fig. 3). July and August are the months with the highest correlations for corn yields using the different multiscalar indices and the scZ-index. The scPDSI does not show as clear a pattern as the other indices (Fig. 4, Table 2). In general, the strongest response for multiscalar drought indices is found when considering the shorter (1 to 3 mo) timescales (Fig. 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 (Fig. 3). July and August have the highest correlations for all of the indices analyzed, although there is less seasonality than for the other crops (Fig. 4). The multiscalar indices, as well as the Palmer drought indices, also show maximum correlations in summer (Table 2). The highest correlations are found at shorter timescales (Fig. 5c).

3.4. Soybeans

North and South Carolina and the 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 soybean yields. These correlations present the same spatial distributions for the SPEI, SPI and SPDI results, while the area with correlations of $r > 0.7$ 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 (Fig. 3). According to the months in which soybean crops are more vulnerable to drought, August and September clearly have the highest correlations (Fig. 4, Table 2). Again, the Palmer drought indices show lower correlations and no well-defined seasonal patterns. The 2 mo timescale has the greatest concentration of high correlations (Fig. 5d). The SPEI and SPDI agree with this pattern, while the SPI indicates that a 1 mo timescale is optimal. In 91% of counties in which soybeans are planted, the shorter timescales (1 to 2 mo) 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, 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 (Fig. 3). March, April and May have the strongest response to moisture conditions, although the seasonal pattern for winter wheat is less defined than for the other crops (Fig. 4, Table 2). The best timescale is also more variable than in other crops (Fig. 5e). The 12 mo timescale for the SPEI and SPI was found to be the most suitable in ~15% of counties, while for the SPDI, the 1 mo 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 mo) are most suitable.

3.6. County response to drought indices

Fig. 6 identifies the drought index with the highest correlation in each county and for each crop. Table 3 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–US border. The SPI is the best index for barley in ~28% of counties. The SPEI is best in ~20% of counties, which 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 US 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 southern and northern Texas, the 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 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, which are located principally in western Tennessee.

Soybeans and winter wheat show similar patterns, with 95% and 90% of the counties being highly correlated with 1 of the 3 multiscalar indices, respectively. In general, the SPDI is the best drought index

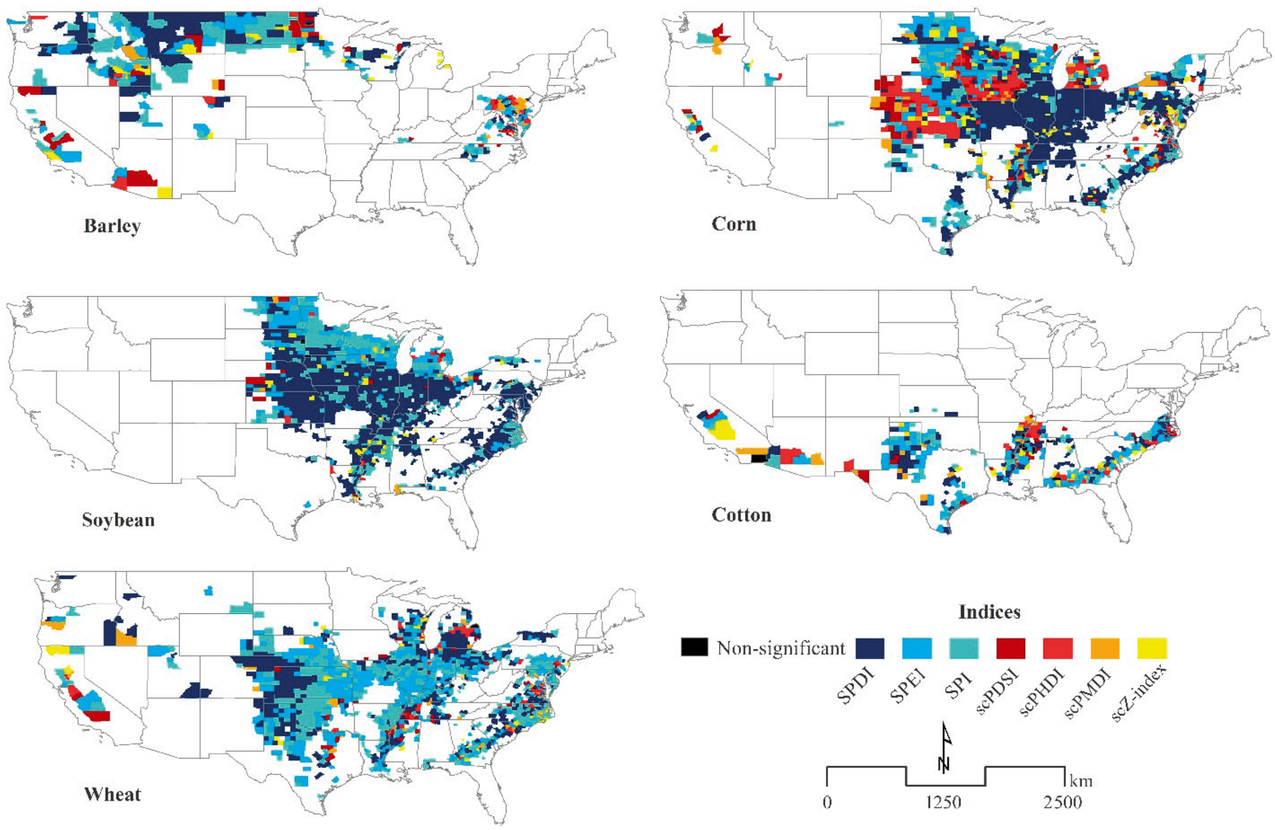


Fig. 6. Spatial classification of the US counties and crop types according to the drought indices that recorded the highest Pearson *r* correlation coefficient independently by timescale and month. Indices are defined in Table 1

Table 3. Percentage of US counties where each index recorded the highest correlation values between the drought index and crop yield. Values are expressed in percentages of the total of all counties. Indices are defined in Table 1

	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

for soybeans, and the SPEI is the best drought index for winter wheat. Kernel density curves for each crop and the correlations with drought indices are shown in Fig. 7. The scPDSI clearly stands out as the least correlated index (e.g. soybeans), while the multi-scalar indices show greater variability. Fig. 8 shows maximum correlation scatterplots between pairs of drought indices (SPEI, SPI, SPDI and scZ-index) for the different crops, including the coefficient of determination (r^2) for each. The correlation differences between the 3 multiscalar drought indices are small (Fig. 8). The correlations for the multiscalar drought indices are significantly higher than the Palmer drought indices. There are minimal differences in the maximum correlation values between the 3 multiscalar indices. The scZ-index is also relatively similar.

The SPEI and SPI have the highest r^2 values (above 0.95) for the 5 crops, while the scZ-index and SPEI and scZ-index and SPDI have the lowest r^2 values (0.7). Based on the r^2, the multiscalar indices (SPEI, SPI and SPDI) are similar, and any one of these indices is suitable for monitoring drought and its impacts on crop yield.

4. DISCUSSION

In this study, we assessed the appropriateness of 11 drought indices for monitoring agricultural drought affecting the 5 main crops grown in the US. We identified spatial patterns illustrating the relationship

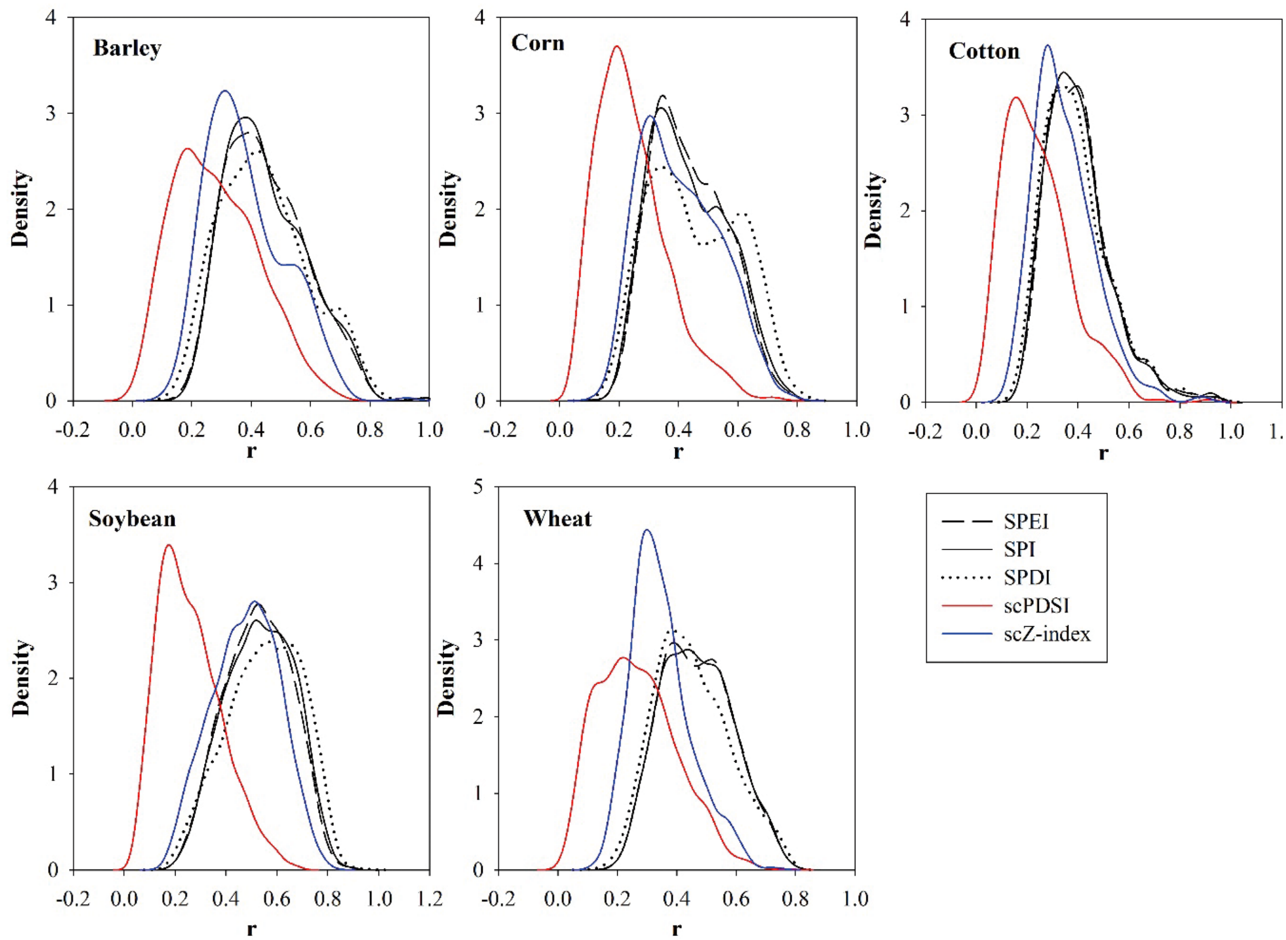


Fig. 7. Kernel density plots of the highest correlations found per index and for each crop. Indices are defined in Table 1

between crop yields and drought indices within the contiguous USA. For this, we used some of the most widespread drought indices employed for monitoring and scientific purposes, including different versions of the PDSI, the SPI, the SPEI and a recent multi-scalar index based on the PDSI, the SPDI. The last 3 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 versions of the Palmer indices marginally improve their performance. In northern and central Greece, Mavromatis (2007) carried out an evaluation of the SPI and 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 that drought indices based on Palmer's procedure have a weaker capacity for predicting yield losses than the multi-scalar ones. Nonetheless, the results also show that the self-calibrated PDSI versions performed best for wheat yields, and in general showed higher correlations than the non-calibrated ones.

Among the Palmer drought indices, the Z-index was 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 USA. Quiring & Papakryiakou (2003) compared 4 drought indices (SPI, PDSI, Z-index and 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 explained 81, 57 and 48% of the variability in barley, winter wheat and

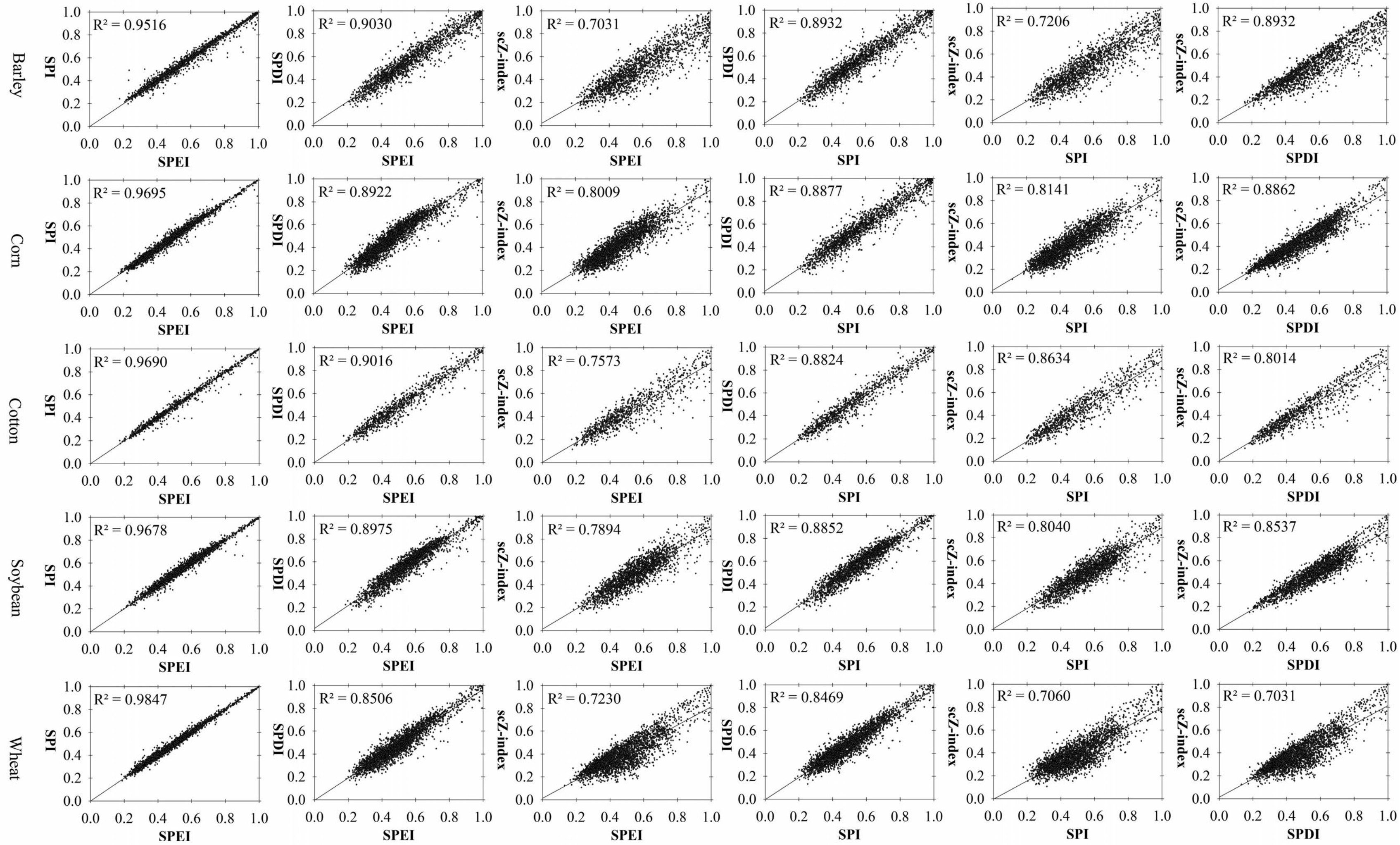


Fig. 8. Maximum correlation scatterplots of index pairs (SPEI, SPI, SPDI and scZ-index; indices are defined in Table 1) for each of the crops analyzed. Each point corresponds to the maximum correlation between drought index and crop yield recorded within each county. The coefficient of determination (R^2) is noted in each plot

corn, respectively. 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 3 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 USA (e.g. US Drought Monitor, National Integrated Drought Information System and the National Weather Service's Climate Prediction Center), they still lack of the flexibility of 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 USA. 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 on the crop. Several previous studies have noted the underperformance of the drought indices that are calculated on a single timescale. For example, McEvoy et al. (2012), Vicente-Serrano et al. (2012) and Q. Wang et al. (2017) highlighted the advantages of using 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 time lags of response between climate conditions and crop responses, mostly during the key stages of crop development.

In this study, we have revealed significant spatial variability in drought index performance, but also solid differences in the response to the drought indices amongst the different crop types. Thus, 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.

Non-irrigated crop moisture requirements, and for instance, the most sensitive stage to soil dryness, usually covers the vegetative growth stages (approximately the first 3 mo after planting), which would explain why meteorological drought is the main explanation for the strongest correlation values found at short timescales which, contrary to longer timescales, do not tend to have a smooth drought time series. As shown in the results, different types of crops are more sensitive, in general, to 1 to 3 mo timescale droughts in July (e.g. corn and barley) and August (e.g. soybean). This agrees with the planting times of the crops analyzed; for corn, these dates go from late March in some counties to May, while barley and soybean are planted between April and May. The results for cotton also indicated that a 1 mo timescale had the highest correlation, although longer timescales were found in ~30% of counties. The response of the month with the highest correlation was less clear, but it mainly corresponded to July and August. In contrast, winter wheat, planted in October and mostly active during spring months, presented a more heterogeneous response to timescales but a well-defined pattern of response to months as seen in the Great Plain where spring months are the most correlated at 3 to 4 mo timescales corresponding with the critical soil moisture recharge state during winter months.

In short, the moisture conditions during summer are important determinants for barley, corn, cotton and soybean yields. Summer months correspond to heading and reproductive stages of these crop types, and in these stages, the plants are more sensitive to water stress (Denmead & Shaw 1960, Çakir 2004, Zipper et al. 2016). In contrast, 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 mo) 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. In a study carried out on the Iberian Peninsula, Páscoa et al. (2017) found 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. They also showed a response to longer SPEI timescales, 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). Wang et al. (2016) and H. Wang et al. (2017) 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 US and confirmed our findings. Thus, corn results show the most sensitivity to drought occurring during July at a 1 mo timescale, while soybeans are most sensitive to droughts occurring in August at a 2 mo 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 stress that agricultural drought impacts are directly dependent on the specific characteristics of each crop, its timing 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 mo) 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 (Meyer et al. 1991, McEvoy et al. 2012, Feng et al. 2017).

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 3 multiscalar indices analyzed, the SPEI and SPDI showed higher correlations than the SPI for most of the crops. Although the difference in 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 (Rosenzweig et al. 2014, Asseng et al. 2015). In a recent study, Liu et al. (2016) estimated a decrease between 4.1 and 6.4 % of wheat yields with a 1°C global temperature increase, and it is suggested that in the US, a decrease of 7.6 % in the wheat production for the period 1985–2013 may be associated with the increase in temperature, especially during the growing season (spring months) (Tack et al. 2015). Moreover, Lobell et al. (2014) indicated that the sensitivity of corn yields to drought stress in the USA 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) seems to be a prudent recommendation, to better quantify drought severity in comparison to the SPI, even more so when considering state-of-the-art climate change projections, which predict a significant drying in some of the major agricultural areas of the USA 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 as follows:

(1) 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.

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

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

(4) 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.

(5) In general, shorter drought timescales (1 to 3 mo) are better at identifying drought impacts on crop yields, with the exception of winter wheat, the growth response of which is related to longer drought timescales.

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

Acknowledgements. This work was supported by the research project I-Link1001 (Validation of climate drought indices for multi-sectorial applications in North America and Europe under a global warming scenario) financed by CSIC, PCIN-2015-220, CGL2014-52135-C03-01, Red de variabilidad y cambio climático RECLIM (CGL2014-517221-REDT) financed by the Spanish Commission of Science and Technology and FEDER, and IMDROFLOOD financed by the Water Works 2014 co-funded call of the European Commission. M.P.-G. received a grant from the Spanish Ministry of Economy and Competitiveness.

LITERATURE CITED

Alley WM (1984) The Palmer Drought Severity Index: limitations and assumptions. J Clim Appl Meteorol 23: 1100–1109

Andreadis KM, Lettenmaier DP (2006) Trends in 20th century drought over the continental United States. Geophys Res Lett 33:L10403

Arshad S, Morid S, Mobasheri MR, Alikhani MA, Arshad S (2013) Monitoring and forecasting drought impact on dryland farming areas. Int J Climatol 33:2068–2081

Asseng S, Ewert F, Martre P, Rötter RP and others (2015) Rising temperatures reduce global wheat production. Nat Clim Chang 5:143–147

Austin RB, Cantero-Martínez C, Arrúe JL, Playán E, Cano-Marcellánc P (1998) Yield–rainfall relationships in cereal cropping systems in the Ebro river valley of Spain. Eur J Agron 8:239–248

Blanc E (2012) The impact of climate change on crop yields in sub-Saharan Africa. Am J Clim Change 1:18072

Blauhut V, Stahl K, Stagge JH, Tallaksen LM, De Stefano L, Vogt J (2016) Estimating drought risk across Europe from reported drought impacts, drought indices, and vulnerability factors. Hydrol Earth Syst Sci 20:2779–2800

Bonaccorso B, Bordi I, Cancelliere A, Rossi G, Sutera A (2003) Spatial variability of drought: an analysis of the SPI in Sicily. Water Resour Manag 17:273–296

Çakir R (2004) Effect of water stress at different development stages on vegetative and reproductive growth of corn. Field Crops Res 89:1–16

Carrão H, Naumann G, Barbosa P (2016) Mapping global patterns of drought risk: an empirical framework based on sub-national estimates of hazard, exposure and vulnerability. Glob Environ Change 39:108–124

Ceglar A, Medved-Cvikl B, Moran-Tejeda E, Vicente-Serrano S, Kajfež-Bogataj L (2012) Assessment of multiscale drought datasets to quantify drought severity and impacts in agriculture: a case study for Slovenia. Int J Spat Data Infrastruct Res 7:464–487

Chen T, Xia G, Liu T, Chen W, Chi D (2016) Assessment of drought impact on main cereal crops using a Standardized Precipitation Evapotranspiration Index in Liaoning Province, China. Sustainability 8:1069

Dai A, Trenberth KE, Qian T (2004) A global dataset of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming. J Hydrometeorol 5:1117–1130

Daly C, Halbleib M, Smith JI, Gibson WP and others (2008) Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int J Climatol 28:2031–2064

Denmead OT, Shaw RH (1960) The effects of soil moisture stress at different stages of growth on the development and yield of corn. Agron J 52:272–274

Di Lena B, Vergni L, Antenucci F, Todisco F, Mannocchi F (2014) Analysis of drought in the region of Abruzzo (Central Italy) by the Standardized Precipitation Index. Theor Appl Climatol 115:41–52

Doesken NJ, Garen D (1991) Drought monitoring in the Western United States using a surface water supply index. Seventh Conference on Applied Climatology, Salt Lake City, UT. American Meteorological Society, Boston, MA, p 266–269

Earl HJ, Davis RF (2003) Effect of drought stress on leaf and whole canopy radiation use efficiency and yield of maize. Agron J 95:688–696

Elagib NA (2013) Meteorological drought and crop yield in Sub-Saharan Sudan. Int J Water Resour Arid Environ 2: 164–171

Esfahanian E, Nejadhashemi AP, Abouali M, Adhikari U, Zhang Z, Daneshvar F, Herman MR (2017) Development and evaluation of a comprehensive drought index. J Environ Manag 185:31–43

FAO (Food and Agriculture Organization of the United Nations) (2015) The impact of natural hazards and disasters on agriculture and food security and nutrition. In: World Conference on Disaster Risk Reduction. Sendai, Japan.

Feng S, Trnka M, Hayes M, Zhang Y (2017) Why do different drought indices show distinct future drought risk outcomes in the U.S. Great Plains? J Clim 30:265–278

Geng G, Wu J, Wang Q, Lei T and others (2016) Agricultural drought hazard analysis during 1980–2008: a global perspective. Int J Climatol 36:389–399

Hargreaves GH, Samani ZA (1985) Reference crop evapotranspiration from temperature. Appl Eng Agric 1:96–99

Hayes MJ, Svoboda MD, Wilhite DA, Vanyarkho OV (1999) Monitoring the 1996 drought using the Standardized Precipitation Index. Bull Am Meteorol Soc 80:429–438

Heim RR (2002) A review of twentieth-century drought indices used in the United States. Bull Am Meteorol Soc 83:1149–1165

Hlavinka P, Trnka M, Semerádová D, Dubrovský M, Žalud Z, Možný M (2009) Effect of drought on yield variability of key crops in Czech Republic. Agric For Meteorol 149: 431–442

Howitt R, MacEwan D, Medellín-Azuara J, Lund J, Sumner D (2015) Economic analysis of the 2015 drought for California Agriculture. UC Davis Center for Watershed Sciences. Davis, CA

Karim MR, Rahman MA (2015) Drought risk management for increased cereal production in Asian Least Developed Countries. Weather Clim Extrem 7:24–35

Karl TR (1986) The sensitivity of the Palmer Drought Severity Index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. J Clim Appl Meteorol 25:77–86

Kattelus M, Salmivaara A, Mellin I, Varis O, Kummu M (2016) An evaluation of the Standardized Precipitation Index for assessing inter-annual rice yield variability in the Ganges-Brahmaputra-Meghna region. Int J Climatol 36:2210–2222

Keyantash J, Dracup JA (2002) The quantification of drought: an evaluation of drought indices. Bull Am Meteorol Soc 83:1167–1180

Kim TW, Valdés JB, Aparicio J (2002) Frequency and spatial characteristics of droughts in the Conchos River Basin, Mexico. Water Int 27:420–430

Liu B, Asseng S, Müller C, Ewert F and others (2016) Similar estimates of temperature impacts on global wheat yield by three independent methods. Nat Clim Chang 6: 1130–1136

Loarie SR, Duffy PB, Hamilton H, Asner GP, Field CB, Ackerly DD (2009) The velocity of climate change. Nature 462:1052–1055

Lobell DB, Field CB (2007) Global scale climate–crop yield relationships and the impacts of recent warming. Environ Res Lett 2:014002

Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. Science 333:616–620

Lobell DB, Roberts MJ, Schlenker W, Braun N, Little BB, Rejesus RM, Hammer GL (2014) Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. Science 344:516–519
Lobell DB, Hammer GL, Chenu K, Zheng B, McLean G, Chapman SC (2015) The shifting influence of drought and heat stress for crops in northeast Australia. Glob Change Biol 21:4115–4127
Lorenzo-Lacruz J, Vicente-Serrano SM, López-Moreno JI, Beguería S, García-Ruiz JM, Cuadrat JM (2010) The impact of droughts and water management on various hydrological systems in the headwaters of the Tagus River (central Spain). J Hydrol (Amst) 386:13–26
Ma M, Ren L, Yuan F, Jiang S, Liu Y, Kong H, Gong L (2014) A new standardized Palmer drought index for hydrometeorological use. Hydrol Processes 28:5645–5661
Mavromatis T (2007) Drought index evaluation for assessing future wheat production in Greece. Int J Climatol 27: 911–924
Mayer TD (2012) Controls of summer stream temperature in the Pacific Northwest. J Hydrol (Amst) 475:323–335
McEvoy DJ, Huntington JL, Abatzoglou JT, Edwards LM (2012) An evaluation of multiscalar drought indices in Nevada and Eastern California. Earth Interact 16:18
McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. Eighth Conf Appl Climatol, 17–22 January 1993 Anaheim, CA. http://www.droughtmanagement.info/literature/AMS_Relationship_Drought_Frequency_Duration_Time_Scales_1993.pdf
McNeeley SM, Beeton TA, Ojima DS (2016) Drought risk and adaptation in the interior United States: understanding the importance of local context for resource management in times of drought. Weather Clim Soc 8:147–161
Meyer SJ, Hubbard KG, Wilhite DA (1991) The relationship of climatic indices and variables to corn (maize) yields: a principal components analysis. Agric For Meteorol 55: 59–84
Meze-Hausken E (2004) Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. Clim Res 27:19–31
Mishra AK, Singh VP (2010) A review of drought concepts. J Hydrol (Amst) 391:202–216
Mizzell H, Carbone G, Dow K, Rhee J (2010) Addressing monitoring needs for drought management. Proc 2010 South Carolina Water Resources Conf, October 13–14, 2010, Columbia Metropolitan Convention Center. www.cisa.sc.edu/Pubs_Presentations_Posters/Conference%20Proceedings%20Papers/2010_Mizzell%20et%20al_Addressing%20monitoring%20needs%20for%20drought%20management.pdf
Moorhead JE, Gowda PH, Singh VP, Porter DO, Marek TH, Howell TA, Stewart BA (2015) Identifying and evaluating a suitable index for agricultural drought monitoring in the Texas High Plains. J Am Water Resour Assoc 51: 807–820
Morid S, Smakhtin V, Moghaddasi M (2006) Comparison of seven meteorological indices for drought monitoring in Iran. Int J Climatol 26:971–985
NOAA (National Oceanic and Atmospheric Administration (2017) State of the climate: drought for August 2017. www.ncdc.noaa.gov/sotc/drought/201708
Olesen JE, Trnka M, Kersebaum KC, Skjelvåg AO and others (2011) Impacts and adaptation of European crop production systems to climate change. Eur J Agron 34:96–112
Palmer WC (1965) Meteorological drought. Res Pap 45. U.S. Department of Commerce Weather Bureau, Washington, DC
Páscoa P, Gouveia CM, Russo A, Trigo RM (2017) The role of drought on wheat yield interannual variability in the Iberian Peninsula from 1929 to 2012. Int J Biometeorol 61:439–451
Potopová V, Štěpánek P, Farda A, Türkott L, Zahradníček P, Soukup J (2016) Drought stress impact on vegetable crop yields in the Elbe River lowland between 1961 and 2014. Cuad Invest Geogr 42:127–143
Poudel S, Shaw R (2016) The relationships between climate variability and crop yield in a mountainous environment: a case study in Lamjung District, Nepal. Climate 4:13
Quiring SM (2009) Developing objective operational definitions for monitoring drought. J Appl Meteorol Climatol 48:1217–1229
Quiring SM, Papakryiakou TN (2003) An evaluation of agricultural drought indices for the Canadian prairies. Agric For Meteorol 118:49–62
Rippey B (2016) U.S. drought coverage increases sharply in November. National Drought Mitigation Center News. http://drought.unl.edu/Publications/News.aspx?id=273
Rohli RV, Bushra N, Lam NSN, Zou L, Mihunov V, Reams MA, Argote JE (2016) Drought indices as drought predictors in the south-central USA. Nat Hazards 83:1567–1582
Rosenzweig C, Elliott J, Deryng D, Ruane AC and others (2014) Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc Natl Acad Sci USA 111:3268–3273
Ross T, Lott N (2003) A climatology of 1980-2003 extreme weather and climate events. Tech Rep 2003-01. US Department of Commerce, NOAA/ NESDIS, National Climatic Data Center, Asheville, NC
Rossi S, Niemeyer S (2010) Monitoring droughts and impacts on the agricultural production: examples from Spain. In: López-Francos A (comp) Economics of drought and drought preparedness in a climate change context. Options Méditerranéennes Série A. Séminaires Méditerranéens 95. CHIHEAM, Zaragoza, p 35–40
Sahoo RN, Dutta D, Khanna M, Kumar N, Bandyopadhyay SK (2015) Drought assessment in the Dhar and Mewat Districts of India using meteorological, hydrological and remote-sensing derived indices. Nat Hazards 77: 733–751
Sanford WE, Selnick DL (2013) Estimation of evapotranspiration across the conterminous United States using a regression with climate and land-cover data. J Am Water Resour Assoc 49:217–230
Sun L, Mitchell SW, Davidson A (2012) Multiple drought indices for agricultural drought risk assessment on the Canadian prairies. Int J Climatol 32:1628–1639
Tack J, Barkley A, Nalley LL (2015) Effect of warming temperatures on US wheat yields. Proc Natl Acad Sci USA 112:6931–6936
Tigkas D, Tsakiris G (2015) Early estimation of drought impacts on rainfed wheat yield in Mediterranean climate. Environ Process 2:97–114
Tilman D, Cassman KG, Matson PA, Naylor R, Polasky S (2002) Agricultural sustainability and intensive production practices. Nature 418:671–677
Trenberth KE, Dai A, van der Schrier G, Jones PD, Barichivich J, Briffa KR, Sheffield J (2014) Global warming and changes in drought. Nat Clim Chang 4:17–22
Udmale P, Ichikawa Y, Manandhar S, Ishidaira H, Kiem AS

(2014) Farmers' perception of drought impacts, local adaptation and administrative mitigation measures in Maharashtra State, India. Int J Disaster Risk Reduct 10: 250–269

USDM (2017) National drought summary. http://drought-monitor.unl.edu/DroughtSummary.aspx

Vicente-Serrano SM, Beguería S, López-Moreno JI (2010) A multiscalar drought index sensitive to global warming: the Standardized Precipitation Evapotranspiration Index. J Clim 23:1696–1718

Vicente-Serrano SM, Beguería S, López-Moreno JI (2011) Comment on 'Characteristics and trends in various forms of the Palmer Drought Severity Index (PDSI) during 1900–2008' by Aiguo Dai. J Geophys Res 116:D19112

Vicente-Serrano SM, Beguería S, Lorenzo-Lacruz J, Camarero JJ and others (2012) Performance of drought indices for ecological, agricultural, and hydrological applications. Earth Interact 16:10

Vicente-Serrano SM, van der Schrier G, Beguería S, Azorin-Molina C, Lopez-Moreno JI (2015) Contribution of precipitation and reference evapotranspiration to drought indices under different climates. J Hydrol (Amst) 526:42–54

Wang H, Vicente-Serrano SM, Tao F, Zhang X and others (2016) Monitoring winter wheat drought threat in Northern China using multiple climate-based drought indices and soil moisture during 2000–2013. Agric For Meteorol 228-229:1–12

Wang H, Pan Y, Chen Y (2017) Comparison of three drought indices and their evolutionary characteristics in the arid region of northwestern China. Atmos Sci Lett 18:132–139

Wang Q, Wu J, Lei T, He B and others (2014) Temporal-spatial characteristics of severe drought events and their impact on agriculture on a global scale. Quat Int 349: 10–21

Wang Q, Wu J, Li X, Zhou H and others (2017) A comprehensively quantitative method of evaluating the impact of drought on crop yield using daily multi-scale SPEI and crop growth process model. Int J Biometeorol 61:685–699

Wei J, Jin Q, Yang ZL, Dirmeyer PA (2016) Role of ocean evaporation in California droughts and floods. Geophys Res Lett 43:6554–6562

Wells N, Goddard S, Hayes MJ (2004) A self-calibrating Palmer Drought Severity Index. J Clim 17:2335–2351

Wilhelmi OV, Hubbard KG, Wilhite DA (2002) Spatial representation of agroclimatology in a study of agricultural drought. Int J Climatol 22:1399–1414

Wilhite DA (1993) The enigma of drought. In: Wilhite DA (ed) Drought assessment, management, and planning: theory and case studies. Kluwer, Boston, MA, p 3–15

Wilhite DA (2000) Drought as a natural hazard: concepts and definitions. In: Wilhite DA (ed) Drought: a global assessment, Vol I. Routledge, London, p 3–18

Wilhite DA, Glantz MH (1985) Understanding the drought phenomenon: the role of definitions. Water Int 10:111–120

Wilhite DA, Svoboda MD, Hayes MJ (2007) Understanding the complex impacts of drought: a key to enhancing drought mitigation and preparedness. Water Resour Manag 21:763–774

Wilhite DA, Sivakumar MVK, Pulwarty R (2014) Managing drought risk in a changing climate: the role of national drought policy. Weather Clim Extrem 3:4–13

WMO (World Meteorological Organization) (2012) Standardized Precipitation Index user guide. WMO-No. 1090. http://www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf

Xu Z, Hennessy DA, Sardana K, Moschini G (2013) The realized yield effect of genetically engineered crops: U.S. maize and soybean. Crop Sci 53:735–745

Yan H, Wang S, Wang J, Lu H and others (2016) Assessing spatiotemporal variation of drought in China and its impact on agriculture during 1982–2011 by using PDSI indices and agriculture drought survey data. J Geophys Res Atmos 121:2283–2298

Zargar A, Sadiq R, Naser B, Khan FI (2011) A review of drought indices. Environ Rev 19:333–349

Zipper SC, Qiu J, Kucharik CJ (2016) Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. Environ Res Lett 11:094021

Appendix. Additional data

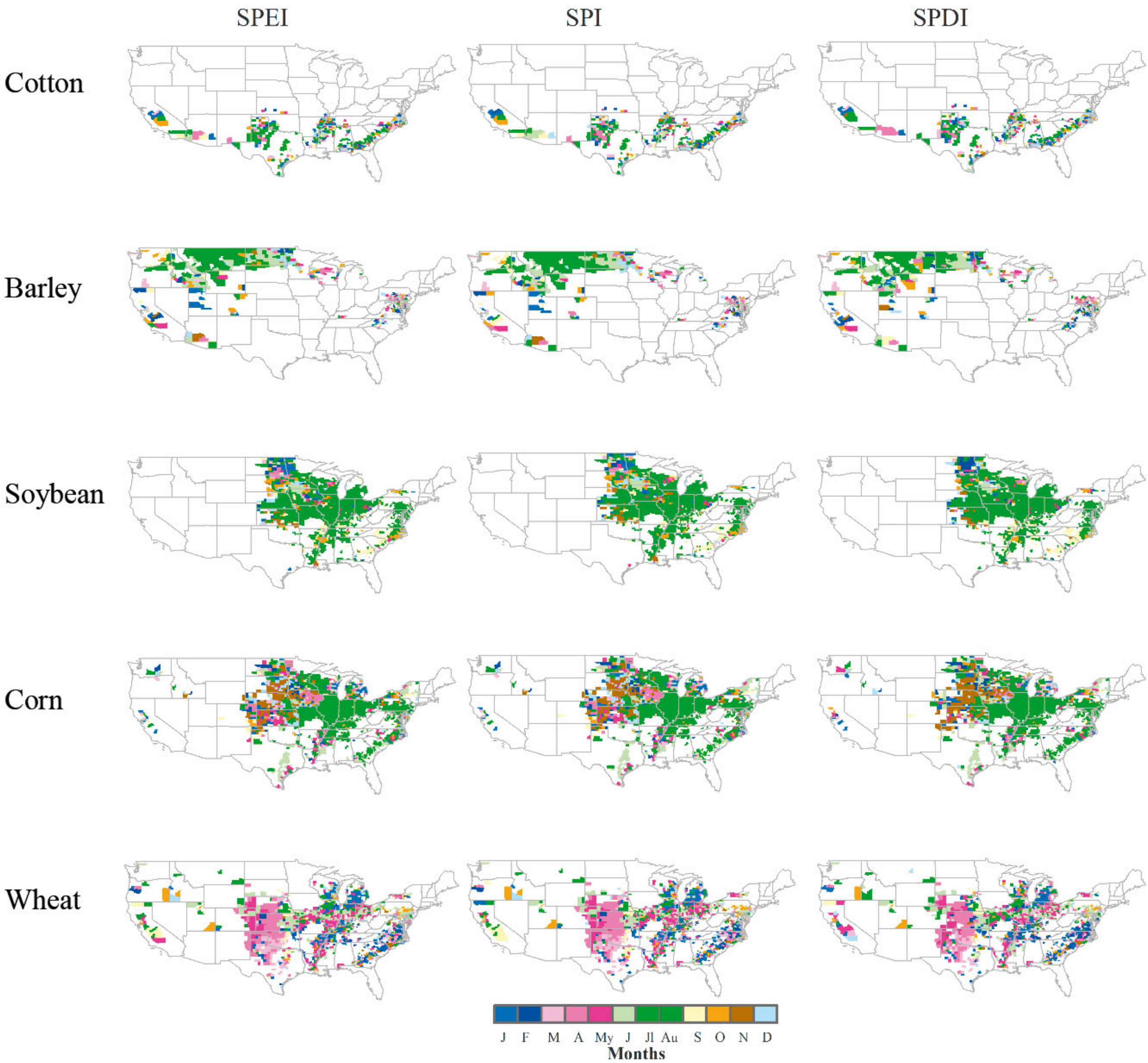


Fig. A1. Spatial distribution of the months in which the highest Pearson correlation coefficients were obtained for the SPEI, SPI and SPDI and crop yields. Indices are defined in Table 1

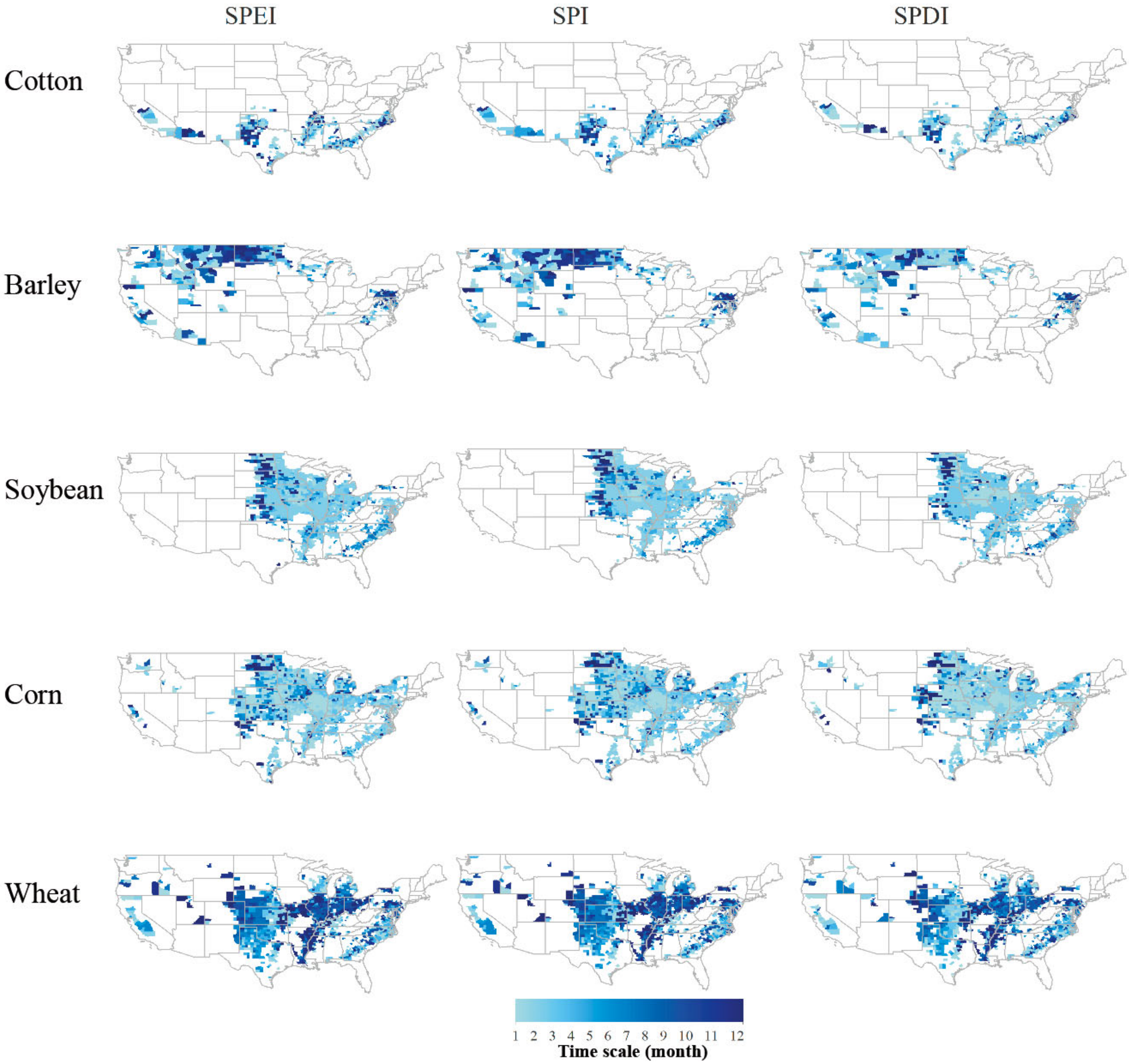


Fig. A2. Spatial distribution of the timescales at which the highest Pearson correlation coefficients were obtained for the SPEI, SPI and SPDI and crop yields. Indices are defined in Table 1

Editorial responsibility: Toshichika Iizumi, Tsukuba, Japan

Submitted: January 25, 2018; Accepted: May 7, 2018
Proofs received from author(s): July 26, 2018