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Response of crop yield to different time-scales of drought in the United States: Spatio-temporal patterns and climatic and environmental drivers

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ABSTRACT

This article presents an analysis of the response of the annual crop yield in five main dryland cultivations in the United States to different time-scales of drought, and explores the environmental and climatic characteristics that determine the response. For this purpose we analysed barley, winter wheat, soybean, corn and cotton. Drought was quantified by means of the Standardized Precipitation Evapotranspiration Index (SPEI). The results demonstrate a strong response in the interannual variability of crop yields to the drought time-scales in the different cultivations. Moreover, the response is highly spatially variable. Crop types showed considerable differences in the month in which their yields are most strongly linked to drought conditions. Some crops (e.g. winter wheat) responded to drought at medium to long SPEI time-scales, while other crops (e.g. soybean and corn) responded to short or long drought time-scales. The study confirms that the differences in the patterns of crop yield response to drought time-scales are mostly controlled by average climate conditions, in general, and water availability (precipitation), in particular. Generally, we found that there is a weaker link between crop yield and drought severity in humid environments and also that the response tends to occur over longer time-scales.

1. Introduction

Long-term changes in large-scale crop production are driven by processes related to management and technical improvement (Fischer and Edmeades, 2010; Grassini et al., 2013). Thus, crop production has substantially increased at the global scale, supporting the needs of the increasing population. Nevertheless, the increase in crop productivity is a non-linear process over time, given that crop yields vary from year to year, with episodes characterized by yield reductions or crop failures (Ciais et al., 2005; Lobell et al., 2011a, b). There are numerous factors that can explain the temporal variability in crop yield. In addition to factors like diseases, social crisis and wars (Stanhill, 1976; Oerke, 2006; Wrather et al., 2001), climate variability is also a key controller of variations in crop yield (Lobell et al., 2007; Schlenker and Roberts, 2009). In particular, some meteorological hazards (e.g. frost, heat waves, hail, floods) may affect plant development and accordingly decrease crop production (Ciais et al., 2005; Lobell et al., 2011b; Asseng et al., 2011). Nevertheless, drought is considered the main climatic hazard impacting crop yield in many areas worldwide (Porter and Semenov, 2005; Barnabás et al., 2008; Farooq et al., 2009).

Although temperature and light are essential for plant growth, as they are important factors for photosynthetic activity (Nemani et al., 2003), water availability, in the form of soil moisture, is essential for plant growth and crop development, specifically during the critical phenological phases for a given crop (e.g. Barnabás et al., 2008; Ramadas and Govindaraju, 2015). However, assessing the impacts of drought on crop yield is not straight forward for a variety of reasons: i) vegetation types may have different resistance, times of response and resilience to water deficits as a consequence of different phenological, physiological and morphological strategies to cope with water deficits

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(Chaves et al., 2003), ii) drought is the most complex natural hazard, which makes it very difficult to study, particularly given the difficulty of establishing an unitary multidisciplinary definition of drought (Wilhite and Glantz, 1985; Lloyd-Hughes, 2014); iii) drought is difficult to quantify since there is no single climatic variable that can be employed to quantify drought severity, with the choice of variable (and appropriate timescale; McKee et al., 1993) being dependent on the type of impact that is of interest (Vicente-Serrano, 2016); iv) there are difficulties in defining the beginning, end, spatial extent and total severity of drought, which makes its quantification much more difficult; and v) the convergence of multiple climate factors trigger drought; although precipitation is the most important variable for determining drought severity, other variables that condition the atmospheric evaporative demand (AED) are also relevant and can be more important than precipitation (Narasimhan and Srinivasan, 2005; Hobbins et al., 2016; McEvoy et al., 2016).

The concept of drought time-scale, developed in the 1990s, altered the way in which drought is quantified and drought impacts are analysed. This concept was introduced to characterize the various response times, or lags, of different components of the terrestrial water cycle (streamflow, groundwater, etc.) to precipitation deficits (McKee et al., 1993), as hydrological drought conditions may be impacted by different climatic drought time-scales, as a function of different hydrological systems and regions (e.g. Lorenzo-Lacruz et al., 2010; 2012; Barker et al., 2015). The term time-scale has recently been applied in the quantification of the drought effects on natural vegetation communities, given the different resistance of vegetation types that makes their response highly dependent on drought time-scale (Ji and Peters, 2003; Pasho et al., 2011; Arzac et al., 2016; Vicente-Serrano et al., 2013, 2015). Robust and flexible drought indices can be calculated on different time scales, among them the Standardized Precipitation Index (SPI) (McKee et al., 1993), the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) and the Standardized Palmer Drought Index (SPDI) (Ma et al., 2014).

Drought indices have been widely used to explain crop yield anomalies (Easterling et al., 1988; Quiring and Papakryiakou, 2003; Kola et al., 2014; Tunalioclu and Durdu, 2012; Benitez and Domecq, 2014; Arshad et al., 2013) and to develop statistical models to predict crop yields (Vicente-Serrano and Cuadrat, 2006; Subash and Ram Mohan, 2011; Sadat Noori et al., 2012; Dutta et al., 2013; Ming et al., 2015; Scian, 2004; Potopova et al., 2016b). Nevertheless, multi-scalar drought indices are more skillful in identifying the influence of drought severity on crop yields, compared to other drought indices (Vicente-Serrano et al., 2012; Wang et al., 2016a,b). Among them, the SPEI has been widely used to analyse the impacts of crops on different cultivations in varied regions worldwide, including China (Ming et al., 2015; Wang et al., 2016a, b; Chen et al., 2016), the Iberian Peninsula (Pescoa et al., 2016), Slovakia (Labudova et al., 2016), Czech Republic (Potopova et al., 2016), Moldova (Potopova et al., 2015), South Africa (Araujo et al., 2016), U.S. (Moorhead et al., 2015) and the whole European continent (Gunst et al., 2015). These studies demonstrate that the SPEI performs better than other indices in identifying drought impacts on crop yields at regional and global scales (Vicente-Serrano et al., 2012; Gunst et al., 2015; Wang et al., 2016a, b; Chen et al., 2016; Labudova et al., 2016). The AED is included in the calculation of the SPEI. This is relevant since different studies have stressed the negative influence of temperature-driven evaporative demand and crop yields, given its influence on soil moisture and vegetation stress conditions (Asseng et al., 2004; Schlenker and Roberts, 2009; Lobell et al., 2003; 2007). A representative example is Lobell et al. (2014) who analysed the sensitivity of corn yields to drought in the U.S., indicating that the sensitivity to drought stress increased in crops associated with high vapor pressure deficits, thus underlining the need for considering AED in drought quantification tools.

The United States is one of the main crop producers in the world, with a high percentage of the total global production of some crops (e.g. corn, soybean and wheat) (FAO, 2013). Numerous studies have analysed the response of crop yields to interannual variability of drought indices in the United States (e.g. Easterling et al., 1988; Moorhead et al., 2015; Rohli et al., 2016). Nevertheless, there are very few studies that consider the connection between different drought time-scales and different crops (e.g. Zipper et al., 2016). Correspondingly, to the authors' knowledge there are no studies that determine the climatic and environmental drivers controlling crop yield responses to drought time-scales. Hence, in this study, we analyse the response of the annual crop yield in five main dryland cultivations in the United States to different time-scales of drought using the SPEI. The objective of this study is to identify possible spatial patterns in the response of crop types to drought at different time scales and to define the environmental and climatic characteristics that determine these patterns.

2. Data and methods

2.1. Data

2.1.1. Crop yield data

We used the entire dataset of the United States Department of Agriculture (National Agriculture Statistics Service), which was obtained through https://quickstats.nass.usda.gov/#AF9A0104-19EF-3BFE-90D2-C67700892F3E. This portal provides production statistics for different cultivations per unit of surface at the county level. We obtained the county production data for five different dryland cultivations: barley, winter wheat, soybean, corn and cotton. We did not include the yield of these cultivations in irrigated lands. Annual productions were obtained for each county and the information was scaled to the same units (Metric Tons/Ha). Data were obtained independently of the surface covered by the different crop types in each county. However, as crop types were not represented over large surfaces in some counties, we decided to exclude those counties with each crop type covering only a low percentage of the total surface of the county ($< 1\%$) (https://www.nass.usda.gov/Charts_and_Maps/Crops_County/#ctp) (Fig. 1).

Annual crop yield series in each county shows a strong positive trend since the 1960s, as a consequence of the ongoing technological and management improvements (Egli, 2008). To eliminate this effect, the series were de-trended by using a linear regression model fitted to crop yield series (dependent variable) and time (independent variable). The average crop yield of each series was added to the residual series of the model to produce the de-trended yield data in Metric Tons/Ha.

2.1.2. Climate data

We employed the PRISM (Parameter-elevation Relationships on Independent Slopes Model) gridded data set developed by the Oregon State University (http://www.prism.oregonstate.edu/). We used monthly data series for precipitation, maximum and minimum air temperatures from 1961 to 2014 at a grid interval of 30 s. PRISM data have already been validated (Daly et al., 2008) and widely used for climatic, hydrological, agricultural and environmental applications (e.g. Lutz et al., 2010; Bandaru et al., 2017; Bodner and Robles, 2017).

2.1.3. Normalized Difference Vegetation Index data and water field capacity

We used the NOAA-AVHRR NDVI dataset (https://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_browse.php) (Vargas et al., 2009) at a spatial resolution of 16 km^2 to characterise the different responses of crop yield to drought time-scales. NDVI is calculated as:

$$\mathrm{NDVI} = \frac{(NIR - VIS)}{(NIR + VIS)}$$

Where NIR and VIS refer to the near-infrared' and visible wavelengths of spectrum.

The NDVI is closely related to the total biomass and leaf area index