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Probabilistic assessment of agricultural droughts using graphical models

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SUMMARY

Agricultural droughts are often characterized by soil moisture in the root zone of the soil, but crop needs are rarely factored into the analysis. Since water needs vary with crops, agricultural drought incidences in a region can be characterized better if crop responses to soil water deficits are also accounted for in the drought index. This study investigates agricultural droughts driven by plant stress due to soil moisture deficits using crop stress functions available in the literature. Crop water stress is assumed to begin at the soil moisture level corresponding to incipient stomatal closure, and reaches its maximum at the crop's wilting point. Using available location-specific crop acreage data, a weighted crop water stress function is computed. A new probabilistic agricultural drought index is then developed within a hidden Markov model (HMM) framework that provides model uncertainty in drought classification and accounts for time dependence between drought states. The proposed index allows probabilistic classification of the drought states and takes due cognizance of the stress experienced by the crop due to soil moisture deficit. The capabilities of HMM model formulations for assessing agricultural droughts are compared to those of current drought indices such as standardized precipitation evapotranspiration index (SPEI) and self-calibrating Palmer drought severity index (SC-PDSI). The HMM model identified critical drought events and several drought occurrences that are not detected by either SPEI or SC-PDSI, and shows promise as a tool for agricultural drought studies.

1. Introduction

The onset of an agricultural drought event is typically marked by a decline in the soil moisture level below a threshold value that affects crops. Precipitation, soil moisture, and temperature are the common variables adopted for agricultural drought studies (Mishra and Singh, 2010). Various indices for characterizing agricultural droughts are listed in Maity et al. (2013). Among these, Palmer Drought Severity Index (PDSI) (Palmer, 1965), Crop Moisture Index (CMI) (Palmer, 1968), Soil Moisture Anomaly Index (Bergman et al., 1988), and Vegetation Condition Index (VCI) (Liu and Kogan, 1996) are popular.

Meteorologic and hydrologic drought indices (e.g., Standardized Precipitation Index SPI, and PDSI) have been often used in agricultural drought studies (Narasimhan and Srinivasan, 2005). The PDSI uses both precipitation and surface air temperature as inputs, in contrast to SPI that uses precipitation alone. However, PDSI is limited as an indicator of soil moisture status or as being capable of identifying agricultural droughts; it demonstrates good correlation with soil moisture content during warm seasons but weak correlation in spring as the underlying model does not account for the effect of snowmelt (Dai et al., 2004). Palmer (1968) developed the Crop Moisture Index (CMI) as an index for short-term agricultural droughts from procedures similar to the PDSI. The CMI is computed from evapotranspiration deficits for monitoring short-term agricultural drought conditions that modulate crop growth. Meyer et al. (1993) developed a Crop Specific Drought Index (CSDI) for corn using evapotranspiration estimates. An alternative drought index—Standardized Precipitation Evapotranspiration Index (SPEI) that possesses the merits of PDSI and SPI in terms of sensitivity to temperature-driven evaporation that is important in crop growth and multi-scalar properties, respectively, was proposed by Vicente-Serrano et al. (2010). The performance of SPEI in drought impact analyses and climate change studies is well documented (Yu et al., 2013; Potop et al., 2012; Vicente-Serrano et al., 2010).

Researchers typically regard soil moisture as the most appropriate indicator of agricultural droughts (Keyantash and Dracup, 2002; Karamouz et al., 2004; Sheffield and Wood, 2008). Estimation of soil moisture from ground measurements is difficult due to heterogeneity caused by the spatially varying precipitation, land cover, soil and topography (Margulis et al., 2002; Vereecken et al., 2008). Temporal and spatial resolution of soil moisture is also crucial for predicting adequate soil profile wetting and drying

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between precipitation events. The role of soil moisture in recurring droughts in North America was studied by Oglesby and Erickson (1989). Sheffield et al. (2004) used soil moisture estimates from the Variable Infiltration Capacity (VIC) model to develop a drought index that identified major drought events of the past and had good correlations with PDSI. Lakshmi et al. (2004) found that the deep layer soil moisture was capable of characterizing droughts in the Mississippi River Basin. The Soil Moisture Deficit Index (SMDI) developed by Narasimhan and Srinivasan (2005), based on weekly soil moisture deficits, had good correlation with indices such as SPI and PDSI, and offered better performance because of its fine spatial and temporal resolution. The authors used SWAT model to simulate daily soil moisture values at 4 km $\times$ 4 km spatial resolution that were then aggregated to a weekly time scale. Tang and Piechota (2009) explored the possibility of deep layer soil moisture as an indicator of climate extremes, and linked it to PDSI, precipitation, and streamflows. Their study utilized soil moisture as a drought indicator for characterizing the hydrologic status for the Colorado River Basin, and further identified the spatial and temporal variability of soil moisture in response to drought events in the region.

Root-zone soil moisture availability is used by agencies such as the United States Department of Agriculture (USDA)-International Production Assessment Division (IPAD)—as a major factor influencing crop yield forecasts (Bolten et al., 2010). When Wu et al. (2011) performed drought vulnerability assessment for China, seasonal crop water deficiency, available soil water-holding capacity and irrigation were adopted as the important drought indicators. The soil water holding capacity is a function of soil type, and varies spatially across a region creating patterns of crop water stress and water resource availability. Maity et al. (2013) characterized drought proneness of Malaprabha Basin, India, via a copula model for resilience and vulnerability values calculated from modeled soil moisture data for the region.

Since water needs vary with crops, agricultural drought incidences in a region can be assessed better if crop responses to soil water deficits are also accounted for in the index. Water stress influences rate of photosynthesis and stomatal closure, and affects crop production (Scholes and Walker, 1993). Denmead and Shaw (1960) studied the effect of soil moisture deficit on the development and yield of corn, by imposing soil moisture deficit at different growth stages. The changes in plant characteristics such as stalk height, cob length, area of the ear leaf, total production of stover and grain, and yield of grain under moisture stress were explored. Holt et al. (1964) investigated the effect of stored soil moisture at planting on corn yields, and developed regression equations for relating soil moisture to corn yield. A quantitative understanding of the plant response to water stress requires detailed study of soil moisture dynamics that include soil–water–air interaction, nutrient uptake by plants, and transpiration. Soil moisture deficits directly control the plant water potential that determines transpiration losses and the turgor pressure in plant cells (Porporato et al., 2001). The role of water stress in the structure and functioning of vegetation in African savannas (grassland ecosystems) was studied by Rodriguez-Iturbe et al. (1999a,b). The authors proposed a measure of "static" vegetation stress that can be calculated from soil moisture levels corresponding to plant wilting and full turgor. The "static" stress is zero when soil moisture is above the level of incipient stomatal closure (full turgor) and reaches a maximum value of one when soil moisture is at the wilting point of a plant. These two stages are based on the effects of water stress on plant physiology (Hsiao, 1973). Porporato et al. (2001) later introduced "dynamic" water stress to address the mean intensity, duration and frequency of soil moisture deficits. Laio et al. (2001) developed a stochastic model for soil moisture and water balance studies.

Drought conditions for crops in the Midwest are, by and large, determined by the soil water availability rather than by precipitation or evaporation. The plant response to water stress in the root zone of a soil could be used to develop a new agricultural drought index. Such an index would take due cognizance of crop needs. However, the changing soil moisture status and different crop rotation patterns followed in agricultural fields require that the drought analysis be performed in a statistical sense. A probabilistic assessment would convey the uncertainty in agricultural drought classification that popular indices (SPEI, PDSI, SPI) do not provide. Madadgar and Moradkhani (2013, 2014) developed a probabilistic forecast model for future hydrologic droughts in a Bayesian framework that allows probabilistic predictions and accounts for uncertainty in drought characterization. In this study, agricultural drought events in the state of Indiana are investigated in a probabilistic framework using graphical models—specifically hidden Markov models (HMMs)—given the temporal dependence that exists between drought states. The crop stress function values derived from soil moisture data are used to define agricultural drought states (1-near normal, 2-moderate drought, 3-severe drought, and 4-extreme drought).

Hidden Markov models have been used for solving numerous practical problems in speech processing (Leggetter and Woodland, 1995), signal processing (Crouse et al., 1998), genomics (Yau et al., 2011), tunneling design (Leu and Adi, 2011), meteorological studies (Hocaoğlu et al., 2010) and air quality modeling (Zhang et al., 2012). Mallya et al. (2013a) utilized HMMs to model meteorologic and hydrologic droughts. Many of these applications used Gaussian emission distributions (Leggetter and Woodland, 1995; Burget et al., 2010; Mallya et al., 2013a). Alternatively, atmospheric ozone levels were modeled using Gamma hidden Markov models by Zhang et al. (2012), and Sun et al. (2013) used HMMs with log-normal, Gamma and generalized extreme value (GEV) distributions to predict particulate matter concentrations.

Unlike previous studies (Mallya et al., 2013a; Zhang et al., 2012), the crop water stress function used in this study is bounded between [0,1], and as a result, previously utilized emission distributions are not suitable. This paper describes a new class of HMMs with beta emission probability distributions. These new models were used for developing probabilistic classification models for agricultural droughts in Indiana. The merits of HMM-based probabilistic agricultural drought index over SPI, self-calibrating PDSI and SPEI were investigated. The organization of rest of the paper is as follows: Section 2 describes the study area and data used, Section 3 explains the methodology adopted in the development of the probabilistic index, followed by results and discussion in Section 4, and finally the conclusions derived from the study are presented in Section 5. In addition, Appendix A provides derivations of equations used in the methodology.

2. Study area and data used

To examine the applicability of the graphical model, the state of Indiana, USA is chosen as the study area. Indiana is nationally ranked for agricultural production, major cultivated crops being corn and soybean. For instance, Fig. 1 illustrates the cultivation pattern followed in a small patch of land in Lake County in northern Indiana during the period 2000–2012, where corn and soybean are predominant. Crop rotation, fallow land, and double cropping practices have been adopted in this area. Winter wheat, alfalfa and pasture grass were grown as minor crops in alternate years. Livestock and dairy farming thrive on agriculture over such farmlands in Indiana and other Midwest states.

Unfortunately, droughts are common in the Midwest, and hamper the prospects of large yields from these farms. Consequences of the recent 2012 drought in US can be found in Mallya et al. (2013b)