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JAG-1120; No. of Pages 11

ARTICLE IN PRESS

International Journal of Applied Earth Observation and Geoinformation xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

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

An empirical standardized soil moisture index for agricultural drought assessment from remotely sensed data☆

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ARTICLE INFO

Article history:
Received 18 December 2014
Received in revised form 15 June 2015
Accepted 23 June 2015
Available online xxx

Keywords:
Remote sensing-based index
Soil moisture
Agricultural drought
Crop yield
South–Central America

ABSTRACT

We propose a simple, spatially invariant and probabilistic year-round Empirical Standardized Soil Moisture Index (ESSMI) that is designed to classify soil moisture anomalies from harmonized multi-satellite surface data into categories of agricultural drought intensity. The ESSMI is computed by fitting a nonparametric empirical probability density function (ePDF) to historical time-series of soil moisture observations and then transforming it into a normal distribution with a mean of zero and standard deviation of one. Negative standard normal values indicate dry soil conditions, whereas positive values indicate wet soil conditions. Drought intensity is defined as the number of negative standard deviations between the observed soil moisture value and the respective normal climatological conditions. To evaluate the performance of the ESSMI, we fitted the ePDF to the Essential Climate Variable Soil Moisture (ECV SM) v02.0 data values collected in the period between January 1981 and December 2010 at South–Central America, and compared the root-mean-square-errors (RMSE) of residuals with those of beta and normal probability density functions (bPDF and nPDF, respectively). Goodness-of-fit results attained with time-series of ECV SM values averaged at monthly, seasonal, half-yearly and yearly timescales suggest that the ePDF provides triggers of agricultural drought onset and intensity that are more accurate and precise than the bPDF and nPDF. Furthermore, by accurately mapping the occurrence of major drought events over the last three decades, the ESSMI proved to be spatio-temporal consistent and the ECV SM data to provide a well calibrated and homogenized soil moisture climatology for the region. Maize, soybean and wheat crop yields in the region are highly correlated ($r > 0.82$) with cumulative ESSMI values computed during the months of critical crop growing, indicating that the nonparametric index of soil moisture anomalies can be used for agricultural drought assessment.

1. Introduction

Drought is a damaging environmental disaster and affects more people than any other natural hazard (Wilhite and Glantz, 1985). There are numerous conceptual and operational drought definitions proposed according to different disciplinary perspectives (Heim, 2002). Fundamentally, drought is a temporary water supply deficit relative to some long-term average condition. Dracup and Lee (1980) and Wilhite and Glantz (1985) proposed a drought typology based on four distinct types, namely meteorological, agricultural, hydrological and socio-economic. The various drought types represent different stages of a continuous meteorological process and reflect the perspectives of different sectors on water supply deficits (Smakhtin and Schipper, 2008). Although drought types occur at different timescales, they are intimately interrelated with each other: the longer the meteorological drought (lack of precipitation) is, the more likely other types of droughts (commonly agricultural and hydrological) will occur as a result (Carrão et al., 2014). Agricultural drought occurs when there is not enough soil moisture to support average crop production on farms or average grass production on range lands (Wilhite and Glantz, 1985). Since most crops are planted, agricultural drought is specifically concerned with cultivated plants, as opposed to natural vegetation (Keyantash and Dracup, 2002). Agricultural drought can occur at the early, middle and latter parts of crop growing season and manifests itself through reduction in average crop yield (Narasimhan and Srinivasan, 2005; Penalba et al., 2007; Nagarajan, 2003; Rhee et al.,

☆ This research received support from the EUROCLIMA regional cooperation program between the European Union (European Commission; DG DEVCO) and Latin America. The authors thank the three anonymous reviewers for their comments and suggestions that served to clarify a number of points and to greatly improve the original version of the manuscript.

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http://dx.doi.org/10.1016/j.jag.2015.06.011

2010; Llano et al., 2012; Martnez-Fernndez et al., 2015; Vyas et al., 2015). Additionally, it diminishes forest productivity and increases fire hazard (Caccamo et al., 2011; Hofer et al., 2012).

Several drought indices, typically based on a combination of precipitation, temperature and soil moisture, have been derived in recent decades to assess the effects of agricultural droughts and define different drought parameters, which include intensity, duration, severity and spatial extent. The deficit of soil moisture volume during crop growing season is a good index of agricultural drought intensity, reflecting recent precipitation shortages and indicating limited conditions for crop production (Keyantash and Dracup, 2002; Sheffield et al., 2004; Carrão et al., 2013; Vyas et al., 2015). Using precipitation and temperature for estimating soil moisture supply and demand within a two-layer soil model, Palmer (1965) formulated what is now referred to as the Palmer drought index (PDI). This was the first comprehensive effort to assess total soil moisture status of a region (Mishra and Singh, 2010). Based on a subset of weekly parameters from the computation of PDI moisture budget, Palmer (1968) developed the Crop Moisture Index (CMI) to estimate short-term changes in soil moisture conditions affecting crops. PDI and CMI have similar limitations in that both assume that parameters like land use/land cover and soil properties are uniform for all climatic regions (Narasimhan and Srinivasan, 2005).

More recently, Narasimhan and Srinivasan (2005) developed the soil moisture deficit index (SMDI) and the evapotranspiration deficit index (ETDI) for agricultural drought monitoring from weekly soil moisture and evapotranspiration values simulated by the Soil and Water Assessment Tool (SWAT) hydrologic model. These drought indices are based on modeled soil moisture and evapotranspiration deficits alone, irrespective of soil properties across different climatic conditions, and are scaled for spatial comparison. Previously, Sheffield et al. (2004) have used retrospective land surface hydrology simulations from the Variable Infiltration Capacity (VIC) model to derive a soil moisture based drought index. Monthly statistical distributions for soil moisture are developed for each model grid cell, and drought intensity is represented as percentiles of a beta probability distribution function fitted to the simulated soil moisture values. Following a similar approach, Dutra et al. (2008) introduced the Normalized Soil Moisture (NSM) index, which is based on percentiles of a normal probability distribution function fitted to simulated soil moisture values calculated by the TESSEL land surface model.

All of these indices can be useful and all indices have inherent strengths and weaknesses. However, none of the aforementioned indices directly uses measured soil moisture observations, but instead are based on estimated values from climatic variables or hydrological modeling (Hunt et al., 2009). Hydrological models perform a water balance assessment of the soil column, using variables such as precipitation, air temperature, soil temperature, soil porosity, and infiltration Keyantash and Dracup (2002). Since land-atmosphere feedback mechanisms are not well understood for many regions of the world, soil moisture estimates there may be prone to large uncertainties (Sheffield et al., 2004; Dorigo et al., 2010, 2015). Therefore, more recently, the soil moisture index (SMI) (Sridhar et al., 2008; Hunt et al., 2009) and the soil water deficit index (SWDI) (Martnez-Fernndez et al., 2015) were proposed as alternative agricultural drought indices and are based on the actual soil moisture content and known field capacity and wilting point at each location.

Although ground-based soil moisture measurements are extremely accurate, they are also extremely hard to compare to large scale data sets because of their point-based nature, their limited coverage, and the well known high variability of soils (Sheffield et al., 2004; Peled et al., 2010). Since the 1980s, many studies have promoted the use of synoptic, timely and spatially continuous remote sensing soil moisture data from active and passive microwave sensors to assess agricultural drought conditions over large areas where ground monitoring instruments are sparse or non-existent (Brown et al., 2008). However, the lack of global consistent and long-term time-series of soil moisture observations from remote sensing data, which are required to derive complete historical data sets to form a basis for the calculation of drought indices, has prevented their operational use in the past (Sheffield et al., 2004).

Recently, the Essential Climate Variable Soil Moisture (ECV SM) product, derived from merged daily soil moisture observations collected by different satellite sensors into a single homogenized global data set covering the period 1978–2013, was presented by Liu et al. (2011, 2012) and Wagner et al. (2012). In this paper, we explore the potential use of the ECV SM data set for assessing the impacts of agricultural drought. To follow our objective, we proposed, formulate and validate a new index of standardized soil moisture and relate its values to agricultural drought intensity. The Empirical Standardized Soil Moisture Index (ESSMI) is based on the works developed previously by Sheffield et al. (2004) and Dutra et al. (2008), but instead of fitting a beta (Sheffield et al., 2004) or a normal (Dutra et al., 2008) (or any other parametric) probability density function (PDF) to soil moisture amounts from ECV SM, we propose to fit an empirical PDF (ePDF) to soil moisture with a nonparametric Kernel Density Estimator (KDE) (Silverman, 1986), as similar as for the Empirical Standardized Precipitation Index (ESPI) (Russo et al., 2013). We choose a nonparametric estimator because: (1) it avoids having to assume the existence of representative parametric distributions (Farahmand and AghaKouchak, 2015); (2) it avoids the bias problems associated with relatively small sample data sets (Sienz et al., 2012); (3) it allows for boundary bias correction of statistical data distributions supported on a finite interval (Bouezmarni et al., 2011). The ESSMI standardizes the observed soil moisture at a particular location during a period of time (e.g. month, season, year) with respect to the soil moisture climatology for the same period of time at that location. ESSMI results correspond to percentiles $p(x)$ of the fitted probability distribution and are given in units of standard deviation: negative values correspond to drier periods than normal and positive values correspond to wetter period than normal.

As a benchmark, we compare the proposed approach with the aforementioned drought indices proposed by Sheffield et al. (2004) and Dutra et al. (2008), and evaluate its ability for monthly, seasonal, half-yearly and yearly soil moisture frequency estimation. To evaluate the spatio-temporal consistency of the ESSMI and ECV SM data set, we analyze a time-series of index values for a region in Bahia (northeast Brazil), as similar as Lloyd-Hughes and Saunders (2002) and Lloyd-Hughes (2012). Finally, to evaluate the suitability and potential of the ESSMI for assessing agricultural drought impacts, we tested it against agricultural productivity, as similar as Narasimhan and Srinivasan (2005), Penalba et al. (2007), Kumar et al. (2009), Nagarajan (2003), Rhee et al. (2010), Llano et al. (2012), Martnez-Fernndez et al. (2015) and Vyas et al. (2015), to cite but a few.

2. Data and methods

In this section, we present the ECV SM data set, the study area, the computation process of the ESSMI, as well as the metrics used for accuracy assessment and statistical comparison with other drought indices.

2.1. The Essential Climate Variable Soil Moisture data set

The ESSMI is calculated by using the ECV SM v02.0 data set (Liu et al., 2011, 2012). The theoretical and algorithmic base of the product is completely described in Chung et al. (2012). The ECV