Remote Sensing of Environment 188 (2017) 141–163

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Multi-sensor integrated framework and index for agricultural drought monitoring

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ARTICLE INFO

Article history:
Received 17 May 2016
Received in revised form 11 October 2016
Accepted 28 October 2016
Available online xxxx

Keywords:
Agricultural drought
Drought evolution
Drought impact
Multi-sensor collaboration
Multivariate drought index
Crop phenology
Crop yield loss

ABSTRACT

Agricultural drought is a complex and insidious natural hazard further complicated by crop impacts. Univariate, bivariate, and multivariate drought analyses have achieved some success, but the analysis of agricultural drought evolution and integration with crop growth is still lacking. In this study, an Evolution Process-based Multi-sensor Collaboration (EPMC) framework was proposed with the realization that effective agricultural drought assessment requires an integrated approach that considers both drought development and crop phenology. Then the Process-based Accumulated Drought Index (PADI) was designed to quantify the accumulative drought impacts on crops. Based on the monitoring of precipitation, soil moisture, and vegetation conditions, EPMC extracted four main agricultural drought evolution phases termed: (i) latency, (ii) onset, (iii) development, and (iv) recovery. Subsequently, the crop growth stages and water-deficit sensitivity coefficients were integrated with the drought evolution process. Experiments conducted in three different climate regions of China demonstrated that the EPMC framework could clearly depict evolution of the different phases of agricultural drought. Three decades of multi-sensor datasets include monthly precipitation from the Global Precipitation Climatology Centre (GPCC), root zone soil moisture from the satellite-model integrated Global Land Data Assimilation System version 2 (GLDAS-2.0), and vegetation condition data from the Advanced Very High Resolution Radiometer (AVHRR). Results indicated that PADI reliably provided a weekly evaluation of accumulative drought severity instead of a "snapshot". PADI was also compared with the Palmer Drought Severity Index (PDSI) and multi-time scale of Standardized Precipitation Index (SPI). Results showed good correlation with short-term SPI at the onset of drought as well as long-term SPI at later stages. Additionally, compared to the correlation with precipitation, soil moisture, and vegetation data alone, it was found that as an integrated model, PADI correlated well with wheat yield loss (Spearman rank correlation coefficient ρ was between 0.66 and 0.77, $p < 0.05$). Therefore, the proposed multi-sensor integrated monitoring framework and index provide a useful and new approach to address the complexity of agricultural drought, with particular relevance to drought impact assessment.

1. Introduction

Drought is a major natural hazard in China and all over the world (Wilhite, 2000; Sheffield et al., 2012; AghaKouchak et al., 2015a). For instance, the 2011 summer drought in China affected over 30 million people causing an economic loss of about 2.4 billion dollars (Yuan et al., 2015). Responding to need for drought monitoring and evaluation by remote sensing, this study seeks a multi-sensor collaboration approach to form a multivariate drought model.

Over the last few decades, studies have focused on drought concepts (Dracup et al., 1980; Wilhite and Glantz, 1985), monitoring (Svoboda et al., 2002; AghaKouchak et al., 2015b), predictions (Hunt, 1991), impacts (Changnon and Easterling, 1989; Mallya et al., 2013), Vulnerability (Charusombat and Niyogi, 2011), and mitigation (Wilhite et al., 2007). A number of drought information systems have been configured to display and integrate drought indices more intuitively. From global to regional scales, examples include Global Integrated Drought Monitoring and Prediction System (GIDMaPS; Hao et al., 2014), Global Drought Information System (GDIS; Heim and Brewer, 2012), Standardized Precipitation-Evapotranspiration Index (SPEI) Global Drought Monitor (Beguería et al., 2010), African Flood and Drought Monitor (AFDM; Yuan et al., 2013; Sheffield et al., 2014), Famine Early Warning System Network in Africa (FEWS NET; Verdin et al., 2005), US-Mexico Drought

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http://dx.doi.org/10.1016/j.rse.2016.10.045
0034-4257/

Prediction Tool (Lyon et al., 2012), US Drought Monitor (USDM; Svoboda et al., 2002), European Drought Observatory (EDO; Estrela and Vargas, 2012), and German Drought Monitor (GDM; Matthias et al., 2016). Some of the global systems, such as GIDMaPS can be applied for country scale assessment as well, and indices in these systems have also been applied for a long time, for example in China (Kogan et al., 2005; Zou et al., 2005; Yu et al., 2014; Zhang et al., 2016). Further, new drought indices also have been proposed for drought monitoring in China, including Drought Severity Index (DSI; Su et al., 2003), Modified Perpendicular Drought Index (MPDI; Ghulam et al., 2007), Optimized Meteorological Drought Index (OMDI; Hao et al., 2015), and Integrated Surface Drought Index (ISDI; Wu et al., 2013, 2015). Building on the need for more perspectives on drought, our broader goal is to develop a novel drought monitoring system based on a new drought monitoring framework and index.

Currently, most drought indices in drought systems have been modeled by univariate analysis, or multivariate (and bivariate) analysis (Mishra and Singh, 2010; AghaKouchak et al., 2015b).

Univariate analysis focuses on one drought-related environmental variable (McVicar and Jupp, 1998), such as the Standardized Precipitation Index (SPI; McKee et al., 1993), Vegetation Condition Index (VCI; Kogan, 1990), Standardized Soil Moisture Index (SSI; AghaKouchak, 2014), and Standard Relative Humidity Index (SRHI; Farahmand et al., 2015). By design, a univariate index can capture anomalous changes that occur in one key environmental variable. However, to define a drought, especially agricultural drought, which is affected by uncertainties (i.e., disease and field management), univariate indices are insufficient to investigate drought associated evolutions and impacts (Charusombat and Niyogi, 2011; Hao and AghaKouchak, 2014).

Table 1 lists a summary of several typical multivariate analyses. In particular, bivariate analysis is a subset of multivariate analysis and typically combines data from land surface temperature (LST) and vegetation condition, such as the Vegetation Health Index (VHI; Kogan, 2002). Similar bivariate indices include the ratio of land surface temperature and Normalized Difference Vegetation Index (NDVI) (McVicar and Bierwirth, 2001) and Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010). Studies such as (Mishra and Singh, 2011) have documented some drawbacks of bivariate analysis and their applicability.

A broader subset of multivariate analysis integrates more than two variables, for example the Microwave Integrated Drought Index (MIDI; Zhang and Jia, 2013), which is combined by precipitation, soil moisture, and land surface temperature. Other proposed multivariate

Table 1
Summary of typical studies using multivariate analysis for agricultural drought monitoring/evaluation, including experiment region and year, data, methodology, and key findings. Some of the readily accessible data/products were listed while its derived data was not included here. Spatial and temporal resolutions were given along with some datasets. Unit of "Data length" is year. "MODIS = Moderate Resolution Imaging Spectroradiometer; LAI = Leaf Area Index; MERRA = Modern-Era Retrospective analysis for Research and Applications; TRMM = Tropical Rainfall Measuring Mission; ESI = Evaporative Stress Index; PDSI = Palmer Drought Severity Index; AVHRR = Advanced Very High Resolution Radiometer; VegDRI = Vegetation Drought Response Index; TCI = Temperature Condition Index; PCI = Precipitation Condition Index; SDI = Synthesized Drought Index; PCA = Principal Component Analysis; AMSR-E = Advanced Microwave Scanning Radiometer-EOS; SM = Soil Moisture; CLSMAS = China Land Surface Soil Moisture Assimilation System; OVDI = Optimized Vegetation Drought Index; RWC = Relative Water Content; CPC = Climate Prediction Center; NOAA = National Oceanic and Atmospheric Administration; KECA = Kernel Entropy Component Analysis; SDCI = Scaled Drought Condition Index; NLCD = National Land Cover Database; DEM = Digital Elevation Model; ISDI = Integrated Surface Drought Index; CART = Classification And Regression Tree". The studies are listed alphabetically.

No.	Reference	Region and year	Data	Data length	Model/algorithm/main steps	Key findings
1	Anderson et al. (2016)	Brazil (2003 – 2013)	MODIS LAI (1 km, 4 day); MODIS LST (1 km, daily); MERRA; TRMM precipitation (0.25°, daily)	10	ESI calculation; index anomalies standardization; yield correlation; does not consider crop modeling	At the state scale, the ESI provided higher yield correlations for most crops and regions in comparison with TRMM and LAI anomalies.
2	Brown et al. (2013)	North-central, U.S. (2002)	SPI (bi-weekly); PDSI (bi-weekly); AVHRR NDVI (1 km); start of season; land cover (30 m); AWC; irrigated agriculture (1 km); ecoregions	16	Eight inputs processing; empirically derived model generation; VegDRI mapping; consider crop modeling	VegDRI represents an objective, repeatable, and high resolution approach to drought monitoring that can be implemented in a near real-time fashion.
3	Du et al. (2013)	Shandong, China (2010 – 2011)	MODIS NDVI (1 km, monthly); LST (1 km, 8 day); TRMM precipitation (0.25°, monthly)	11	VCI, TCI and PCI derivation; SDI calculating by PCA; does not consider crop modeling	SDI is strongly correlated with SPI-3, variation of crop yield and drought-affected crop areas.
4	Hao et al. (2015)	Southwest of China (2005 – 2009)	TRMM precipitation (0.25°, monthly); MODIS LST (1 km, 16 day); AMSR-E SM (25 km); CLSMAS (0.1°); MODIS NDVI (1 km, 16 day)	5	Indices scaling; OVDI combination by empirical weights, PCA, and constrained optimization; does not consider crop modeling	OVDI was best correlated to SPEI-3, and had a similar trend with soil RWC in temporal scale.
5	Hao and AghaKouchak (2013)	California and North Carolina, U.S. (1974 – 1990)	CPC precipitation (monthly); CPC soil moisture (monthly)	78	SPI and SSI preparation; copulas based conjunction; does not consider crop modeling	MSDI describes the drought onset as early as SPI, while it shows drought persistence similar to SSI. MSDI shows a more severe drought condition when both the precipitation and soil moisture exhibit a deficit.
6	Rajsekhar et al. (2015a)	Texas, U.S. (1950 – 1957, 2010 – 2011)	NOAA precipitation (1/8°, monthly); runoff (1/8°, monthly); actual evapotranspiration	63	Inputs transformation into standard normal variates; MDI extraction based on KECA; does not consider crop modeling	MDI is unique in the sense that it accounts for all the physical forms of drought. MDI was found to be competent in capturing the onset, persistence and termination of droughts.
7	Rhee et al. (2010)	Arizona and New Mexico, North Carolina and South Carolina, U.S. (2000 – 2009)	MODIS LST (1 km, 8 days); MODIS NDVI (1 km, monthly), MODIS reflectance (500 m, 8 day); NLCD (30 m), TRMM precipitation (0.25°, monthly)	10	Inputs scaling; SDCI calculation by selected weights combination; regression analysis with crop yield; does not consider crop modeling	SDCI performed better than existing indices such as NDVI and Vegetation Health Index; the year-to-year changes and spatial distributions of SDCI over both arid and humid regions generally agreed to the USDM.
8	Wu et al. (2013, 2015)	Mid-eastern China (2000 – 2009)	MOIDS NDVI (1 km, 16 days); MODIS LST (1 km, 8 day); ecological zoning (1 km); AWC (10 km); irrigation water management distribution (10 km); DEM (1 km)	10	14 inputs processing (PDSI, SPI, NDVI, LST, etc.); integrated multisource data mining technology (CART); evaluation of different integration models; consider crop modeling	ISDI can be used not only to monitor the main drought features, including precipitation anomalies and vegetation growth conditions but also to indicate the Earth surface thermal and water content properties by incorporating temperature information.