



## Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought



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### ARTICLE INFO

#### Article history:

Received 1 October 2015

Received in revised form

22 December 2015

Accepted 28 December 2015

#### Keywords:

Flash drought

Drought monitoring

Soil moisture

Evapotranspiration

Crop impacts

Agriculture

Satellite data

### ABSTRACT

This study examines the evolution of several model-based and satellite-derived drought metrics sensitive to soil moisture and vegetation conditions during the extreme flash drought event that impacted major agricultural areas across the central U.S. during 2012. Standardized anomalies from the remote sensing based Evaporative Stress Index (ESI) and Vegetation Drought Response Index (VegDRI) and soil moisture anomalies from the North American Land Data Assimilation System (NLDAS) are compared to the United States Drought Monitor (USDM), surface meteorological conditions, and crop and soil moisture data compiled by the National Agricultural Statistics Service (NASS).

Overall, the results show that rapid decreases in the ESI and NLDAS anomalies often preceded drought intensification in the USDM by up to 6 wk depending on the region. Decreases in the ESI tended to occur up to several weeks before deteriorations were observed in the crop condition datasets. The NLDAS soil moisture anomalies were similar to those depicted in the NASS soil moisture datasets; however, some differences were noted in how each model responded to the changing drought conditions. The VegDRI anomalies tracked the evolution of the USDM drought depiction in regions with slow drought development, but lagged the USDM and other drought indicators when conditions were changing rapidly. Comparison to the crop condition datasets revealed that soybean conditions were most similar to ESI anomalies computed over short time periods (2–4 wk), whereas corn conditions were more closely related to longer-range (8–12 wk) ESI anomalies. Crop yield departures were consistent with the drought severity depicted by the ESI and to a lesser extent by the NLDAS and VegDRI datasets.

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### 1. Introduction

The 2012 drought that impacted major agricultural areas across the central U.S. was the worst drought to affect this region since 1988 and had similar magnitude and spatial extent to the severe droughts that occurred during the 1930s and 1950s (Hoerling et al., 2014). The almost complete absence of heavy rainfall events during the growing season, combined with record high temperatures,

strong winds, and abundant sunshine, led to rapid decreases in soil moisture content and the rapid emergence of flash drought conditions (Lydolph, 1964; Mozny et al., 2012; Otkin et al., 2013; Mo and Lettenmeier, 2015). According to the U.S. Drought Monitor (USDM; Svoboda et al., 2002), drought coverage and intensity rapidly increased during June and July in response to the anomalous weather conditions, with nearly 80% of the contiguous U.S. characterized by at least abnormally dry conditions by the end of summer. Most of the central U.S., including the Corn Belt, experienced severe drought (or worse) conditions at some point during the growing season (Mallya et al., 2013). Recent modeling studies have shown that this exceptional drought event was not forced by tropical sea

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surface temperature anomalies. Instead, it was associated with natural variations in the weather that led to the development of a persistent upper-tropospheric ridge that inhibited convection and caused exceptionally warm temperatures to occur across the region for several months (Kumar et al., 2013; Wang et al., 2014; Hoerling et al., 2014; Diffenbaugh and Sherer, 2013).

The 2012 drought was one of the most expensive natural disasters in U.S. history with Federal crop indemnity payments alone exceeding \$17 billion (USDA, 2013). Crop losses were especially large because the most severe drought conditions occurred during critical stages of crop development, such as pollination in corn and the grain filling stage in soybeans. Prior work has shown that even short periods (e.g. several days) of intense water stress can result in large crop yield reductions (e.g. Meyer et al., 1993; Saini and Westgate, 1999; Calvino et al., 2003; Earl and Davis, 2003; Barnabás et al., 2008; Mishra and Cherkauer, 2010; Prasad et al., 2011; Kebede et al., 2012; Hunt et al., 2014). In 2012, however, severe moisture and heat stress lasted for more than a month across most major agricultural areas of the country, thereby leading to the lowest corn yields since 1995. If long-term yield trends are accounted for, the percentage yield loss was one of the largest on record going back to 1866 (Hoerling et al., 2014; Boyer et al., 2013). The large yield loss is consistent with a recent study by Lobell et al. (2014) that assessed yield trends during recent decades for different levels of moisture stress. Their analysis showed that yield gains have been smallest on a percentage basis for growing seasons in which large vapor pressure deficits indicative of severe drought conditions occur during critical crop yield development stages. As drought conditions spread westward during the summer, ranchers also experienced substantial impacts through a combination of higher feed prices, a lack of high quality forage, and heat-related animal stress, with many ranchers forced to either sell or relocate their livestock to other parts of the country (USDA, 2012). The rapid onset of severe drought conditions meant that farmers and ranchers had little time to prepare for its adverse effects. It is possible, however, that greater use of drought indicators that respond quickly to changing conditions, such as the satellite-derived Evaporative Stress Index (ESI; Anderson et al., 2007a,b), may promote drought mitigation efforts during future flash drought events by providing earlier warning of drought development (Otkin et al., 2014, 2015a,b).

High-resolution estimates of soil moisture and vegetation health conditions are necessary to accurately assess the severity and geographic extent of drought conditions at spatial and temporal scales sufficient for stakeholders to make informed management decisions. Moreover, an accurate assessment of current conditions is a prerequisite for producing useful drought intensification forecasts over monthly to seasonal time scales. In this paper, the evolution of several drought indicators sensitive to vegetation health and soil moisture conditions will be examined during the onset and development of the 2012 flash drought. These indicators include the ESI, which uses satellite thermal infrared observations and a land surface energy balance model to estimate anomalies in evapotranspiration (ET) and the Vegetation Drought Response Index (VegDRI; Brown et al., 2008) that uses satellite, land, and climate observations to assess vegetation health conditions. The evolution of the satellite-derived datasets will be compared to modeled soil moisture anomalies from the North American Land Data Assimilation System (NLDAS; Xia et al., 2012a,b, 2014) and to time series of precipitation and meteorological conditions. The accuracy of these datasets will be assessed for different locations and time periods through comparison with USDM drought analyses and county-level crop and range condition datasets compiled by the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS). Though the NASS datasets are qualitative, they provide very valuable ground truth of the actual impact of the drought on agriculture. Each of these datasets is

described in Section 2. The overall evolution of the drought and relationships between the drought indicators and crop conditions and yield are assessed in Section 3, with conclusions presented in Section 4.

## 2. Data and methodology

### 2.1. Evaporative Stress Index

The ESI depicts standardized anomalies in ET fraction ( $ET/ET_{ref}$ ), where ET is the actual ET flux retrieved under clear-sky conditions and  $ET_{ref}$  is a reference ET flux based on a Penman-Monteith formulation (Allen et al., 1998). Reference ET is used in this equation to minimize the impact of non-moisture related drivers of ET, such as the seasonal cycle in solar radiation, when assessing anomalies in ET. Similarly, the use of clear-sky ET minimizes impacts of cloud cover on ET variability, again focusing on soil moisture drivers. The Atmosphere–Land Exchange Inverse (ALEXI) model (Anderson et al., 1997, 2007a, 2011) is used to estimate the actual ET flux. ALEXI uses a two-source energy balance model (Norman et al., 1995) and land surface temperature (LST) retrievals obtained from satellite thermal infrared imagery to compute sensible, latent, and ground heat fluxes for vegetated and bare soil components of the land surface. The partitioning of the surface energy fluxes is accomplished using vegetation cover fraction estimates derived from the MODIS leaf area index product (Myneni et al., 2002). The total surface energy budget is computed using the observed increase in LST from  $\sim 1.5$  h after local sunrise until 1.5 h before local noon, with closure of the energy balance equations achieved using the McNaughton and Spriggs (1986) atmospheric boundary layer growth model. Lower-tropospheric temperature profiles used by the boundary layer model are obtained from the Climate Forecast System Reanalysis dataset (Saha et al., 2010). The ALEXI model is run each day over the contiguous U.S. (CONUS) with 4-km horizontal grid spacing using LST retrievals and insolation estimates derived from the Geostationary Operational Environmental Satellite (GOES) imager.

While the ESI ideally includes only clear-sky retrievals of ET, incomplete cloud screening of the thermal infrared-derived LST inputs can add noise to the ET time series used in the index computation. These errors are reduced using a temporal smoothing algorithm that identifies days with ET estimates that differ by more than one standard deviation from surrounding days within a 14 day moving window. Anderson et al. (2013) have shown that this method effectively removes cloud-contaminated ET estimates because abrupt changes in daily ET are more likely to occur because of cloud effects on surface heating than to rapid changes in soil moisture content. The remaining clear-sky ET estimates are then composited over longer time periods to achieve more complete domain coverage.

Standardized ET fraction anomalies, expressed as pseudo z-scores normalized to a mean of 0 and a standard deviation of 1, are computed each week using 2, 4, 8, and 12 wk composite periods. The mean ET fraction and standard deviations for each composite period are computed at each grid point in the CONUS domain using data from 2001 to 2014. Standardized anomalies are computed as:

$$ESI(w, y) = \frac{(v(w, y)) - (1/ny) \sum (v(w, y))}{\sigma(\omega)} \quad (1)$$

where the first term in the numerator is the composite ET fraction for week  $w$  and year  $y$  at a given grid point, the second term is the mean ET fraction for week  $w$  averaged over all years, and the denominator is the standard deviation. By standardizing the anomalies, this means that negative (positive) values depict below (above) average ET fluxes, which are typically associated with lower (higher) than average soil moisture content and poorer (better)

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