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Development of a Demand Sensitive Drought Index and its application for agriculture over the conterminous United States

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SUMMARY

A new drought index is introduced that explicitly considers both water supply and demand. It can be applied to aggregate demand over a geographical region, or for disaggregated demand related to a specific crop or use. Consequently, it is more directly related than existing indices, to potential drought impacts on different segments of society, and is also suitable to use as an index for drought insurance programs targeted at farmers growing specific crops. An application of the index is presented for the drought characterization at the county level for the aggregate demand of eight major field crops in the conterminous United States. Two resiliency metrics are developed and applied with the drought index time series. In addition, a clustering algorithm is applied to the onset times and severity of the worst historical droughts in each county, to identify the spatial structure of drought, relative to the cropping patterns in each county. The geographic relationship of drought severity, drought recovery relative to duration, and resilience to drought is identified, and related to attributes of precipitation and also cropping intensity, thus distinguishing the relative importance of water supply and demand in determining potential drought outcomes.

1. Introduction

Drought leads to high economic and social impacts (Lott and Ross, 2006; National Drought Policy Commission Report, 2000). The diverse sectors affected by drought, its wide spatial and temporal distribution, and most importantly, the demand placed on water supply by human use systems makes it a complex phenomenon that needs systematic understanding (Wilhite, 2000). While many global and national drought indicators exist (Drought.eng.uci.edu, 2015; Drought.gov, 2015; Droughtmonitor.unl.edu, 2015), none directly connect existing or projected water demand to the potential water deficit during the drought. They are essentially supply based. The standardized drought indices (Palmer, 1965; McKee et al., 1993) consider only water supply but not water use by sector or in aggregate. Drought's impacts manifest as a supply–demand imbalance issue, and vary by location and by sector of use. If a location has low demands, drought as manifest in the usual indices does not really have the same impact, as in a region where most water is appropriated or allocated. In this paper, we present a new Demand Sensitive Drought Index (DSDI) that is based on daily water demand for selected crops, and the daily precipitation over the continental United States. Two measures for drought resiliency that are based on the probability of transitioning to a satisfactory state from an unsatisfactory state are presented at the county level. Proposed changes in a crop mix, i.e., the distribution of area allocated to each crop, can be mapped to changes in the DSDI, and hence both the changes in the potential resilience and the drought severity and duration conditional on a crop mix can be evaluated. An application to the conterminous USA is developed and presented. In addition to the computation of the measures, we present a manifestation of the spatial structure associated with the worst droughts in the USA using a *K*-means clustering analysis applied to the onset time and severity of the worst drought in each county over the period 1949–2010.

The background and underlying methodology is presented with a simulated example in Section 2. In Section 3, we present the application of the DSDI for aggregate agriculture (based on eight major field crops) across the continental United States. The spatial distribution of the drought properties such as onset, duration, severity and recovery times for multi-year droughts and the

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resiliency rate and relative recovery rates are also presented in this section. Finally, in Section 4, we present the summary and conclusions from the study.

2. Background and methodology

2.1. A review of existing indices

A detailed review of the current drought metrics and methodologies can be found in Mishra and Singh (2010, 2011). The development of hydro-meteorological drought indicators has a long history (Heim and Richard, 2002). These indicators are derived from direct meteorological and hydrological observations, from land surface models forced with observed atmospheric conditions, and from an increasing number of satellite-derived products, ranging from estimates of hydrological variables (precipitation, evaporation, soil moisture, and terrestrial water storage) to estimates of vegetation condition (Jiang et al., 2010). An approach to aggregate many of these measures into a single analysis portraying the current, overall U.S. drought condition is embodied in the weekly, real-time production of the U.S. Drought Monitor (Ryu et al., 2010, 2014; Svoboda et al., 2002; Wilhite et al., 2007). Other drought indices include Rainfall Anomaly Index (Rooy, 1965), Bhalme and Mooly Drought Index (Bhalme and Mooley, 1980). More recently, the drought indices developed by Narasimhan and Srinivasan (2005) estimate the weekly soil moisture and evapotranspiration in hydrological model to obtain Soil Moisture Deficit Index and Evapotranspiration Deficit Index. Shukla and Wood (2008) suggested Standardized Runoff Index based on the SPI concept. Kwak et al. (2014) suggested a method of hydrological drought analysis using the run theory of Yevjevich (1967). Recently, Rajsekhar et al. (2015) developed a multivariate drought index that combines regional precipitation and streamflow into a drought metric using information theory. Among various drought indices, the Palmer Drought Severity Index (Palmer, 1965), Crop Moisture Index (Palmer, 1968), Surface Water Supply Index (Shafer and Dezman, 1982) and Standardized Precipitation Index (McKee et al., 1993) are commonly used to inform water resources management, agricultural drought monitoring, and forecasting. Much of these drought indices are based on measures of deficiency of rainfall or streamflow compared to long-term average. The incorporation of evapotranspiration as a measure of water demand led to the development of a water-budget-based drought index by Palmer (1965). The Palmer Index has nonetheless been criticized for how it treats factors such as potential evapotranspiration, runoff, snowmelt, and distribution of precipitation and evapotranspiration within a month or week (Alley, 1984; Karl and Knight, 1985; McKee et al., 1995; Guttman, 1997; Willeke et al., 1994). Hayes et al. (1999) have argued that PDSI can be slow to respond to the development and diminishing droughts.

2.2. The case for Demand Sensitive Drought Index

We present a Demand Sensitive Drought Index (DSDI), which considers day-to-day rainfall variability as well as water demands to develop aggregate or disaggregated indices for water uses. The methodology is based on the sequent peak algorithm that is commonly used for the sizing of reservoirs (Thomas and Burden, 1963). Variants of this methodology have been presented earlier to measure current water risk in India (Devineni et al., 2013), China (Chen et al., 2013) and United States (Devineni et al., 2015). Applied to a time series of water supply and demand, the algorithm identifies the drought stress as the cumulative deficit over the period under consideration. DSDI can thus be represented considering daily resolution of time series of supply and demand for a geographic unit j (e.g. U.S. county) as follows:

$$\text{deficit}_{j,t} = \max(\text{deficit}_{j,t-1} + D_{j,t} - S_{j,t}, 0), \quad \text{where deficit}_{j,t=0} = 0 \tag{1}$$

$$\text{DIC}_j = \max_t(\text{deficit}_{j,t}; \quad t = 1 : n * 365) \tag{2}$$

$\text{deficit}_{j,t}$ refers to the accumulated daily deficit, $D_{j,t}$ to total or sector wise daily water demand, $S_{j,t}$ to the total daily water supply volume, for geographical location j, and day t; and n is the total number of years in the analysis. The maximum accumulated deficit estimated over the n-year period without breaking it into sub-periods is defined as DIC_j (Drought Index Cumulated). This measures the potential impact of multiyear droughts per demand sector, or in aggregate. One can develop the corresponding normalized drought index as:

$$\text{DSDI}_j = \frac{\text{DIC}_j}{\text{AP}_j} \tag{3}$$

where AP_j is the average annual rainfall volume (cropped area * average depth of precipitation) for county j. The DSDI thus offers demand sensitive drought indexing tool for disaggregate regional conditions that consider demands per use sector or in aggregate. Given the ease of developing such an index, it is reasonable for water users to input their temporal demand and get a customized index specific to their demand patterns.

The measure provides insights on the time-evolving vulnerability to drought arising from changes in the climate, from that due to changes in non-climatic conditions (e.g., demand). For example, consider the simulated droughts sketched in Fig. 1, where the varying contributions to the water supply are indicated by the blue bars, and the demand is given by the red line (primary y-axis). In this example, the demand (15 units) in Fig. 1a is greater than the demand (7.5 units) in Fig. 1b while the supply is kept constant for both the cases. The case depicted in Fig. 1a (greater demand) shows that the accumulated water supply is never sufficient to meet water demand. In other words, if a water deficit is defined as the difference between the accumulated supply and accumulated demand (for a specific purpose or in aggregate), the cumulative deficit (shown by the green line on the secondary y-axis) never reaches zero, indicating that the supply, while providing partial relief during the drought event, is nonetheless insufficient to meet the overall demand. Consequently, the drought continues through the full period shown. For the location with lower water demand as is shown in Fig. 1b, we can characterize the same overall time period as being divided into five distinct episodes of drought, each with smaller cumulative deficit (since demand is lower) than in Fig. 1a, with the water deficit reset to zero by intervening wet periods. The severity of a drought is defined as the maximum value of the cumulative water deficit over a given period of consideration. The simulation conceptually resembles the impact of drought on a region with greater current demand compared to historical demand or it resembles the comparison of two regions with similar rainfall distribution but varying demands. One could compare this result with the typical hydro-meteorological drought index for the same location (e.g. PDSI or SPI). In terms of assessing drought impacts, the indicator portrayed here has the advantage of breaking supply and demand down into their respective components, allowing us to better understand the causes of drought frequency, duration and severity from an impact perspective. The drought index is also a measure of the storage required to meet the time varying demand patterns in the region (see the classification of DSDI in Table 2 for an interpretation of the values). Hence, one can design the system (based on the estimate) for the worst dry periods in the sequence, thereby providing a robust measure of