**Development of a Demand Sensitive Drought Index and its Application for
Agriculture over the Conterminous United States**

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24 **Abstract**

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

41

42 **Keywords:** Drought Index; Drought Attributes; Demand Induced Stress;
43 Resiliency; Climate Variability; Agriculture.

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47 **1.0 Introduction**

48 Drought leads to high economic and social impacts (Lott, 2006; National
49 Drought Policy Commission Report, 2000). The diverse sectors affected by
50 drought, its wide spatial and temporal distribution, and most importantly, the
51 demand placed on water supply by human use systems makes it a complex
52 phenomenon that needs systematic understanding (Wilhite, 2000). While many
53 global and national drought indicators exist (Drought.eng.uci.edu, 2015;
54 Drought.gov, 2015; Droughtmonitor.unl.edu, 2015) none directly connect existing
55 or projected water demand to the potential water deficit during the drought. They
56 are essentially supply based. The standardized drought indices (Palmer, 1965;
57 McKee et al, 1993) consider only water supply but not water use by sector or in
58 aggregate. Drought's impacts manifest as a supply - demand imbalance issue, and
59 vary by location and by sector of use. If a location has low demands, drought as
60 manifest in the usual indices does not really have the same impact, as in a region
61 where most water is appropriated or allocated. In this paper, we present a new
62 Demand Sensitive Drought Index (DSDI) that is based on daily water demand for
63 selected crops, and the daily precipitation over the continental United States. Two
64 measures for drought resiliency that are based on the probability of transitioning
65 to a satisfactory state from an unsatisfactory state are presented at the county
66 level. Proposed changes in a crop mix, i.e., the distribution of area allocated to
67 each crop, can be mapped to changes in the DSDI, and hence both the changes in
68 the potential resilience and the drought severity and duration conditional on a crop
69 mix can be evaluated. An application to the conterminous USA is developed and

70 presented. In addition to the computation of the measures, we present a
71 manifestation of the spatial structure associated with the worst droughts in the
72 USA using a K-means clustering analysis applied to the onset time and severity of
73 the worst drought in each county over the period 1949-2010.

74 The background and underlying methodology is presented with a simulated
75 example in section 2. In section 3, we present the application of the DSDI for
76 aggregate agriculture (based on eight major field crops) across the continental
77 United States. The spatial distribution of the drought properties such as onset,
78 duration, severity and recovery times for multi-year droughts and the resiliency
79 rate and relative recovery rates are also presented in this section. Finally, in
80 section 4, we present the summary and conclusions from the study.

81

82 **2.0 Background and Methodology**

83 **2.1 A review of existing indices**

84 A detailed review of the current drought metrics and methodologies can be
85 found in Mishra and Singh (2010, 2011). The development of hydro-
86 meteorological drought indicators has a long history (Heim and Richard, 2002).
87 These indicators are derived from direct meteorological and hydrological
88 observations, from land surface models forced with observed atmospheric
89 conditions, and from an increasing number of satellite-derived products, ranging
90 from estimates of hydrological variables (precipitation, evaporation, soil moisture,
91 and terrestrial water storage) to estimates of vegetation condition (Jiang et al,
92 2010). An approach to aggregate many of these measures into a single analysis

93 portraying the current, overall U.S. drought condition is embodied in the weekly,
94 real-time production of the U.S. Drought Monitor (Ryu et al, 2010, 2014;
95 Svoboda et al, 2002; Wilhite et al, 2007). Other drought indices include Rainfall
96 Anomaly Index (Rooy, 1965), Bhalme and Mooly Drought Index (Bhalme and
97 Mooly, 1980). More recently, the drought indices developed by Narasimhan and
98 Srinivasan (2005) estimate the weekly soil moisture and evapotranspiration in
99 hydrological model to obtain Soil Moisture Deficit Index and Evapotranspiration
100 Deficit Index. Shukla and Wood (2008) suggested Standardized Runoff Index
101 based on the SPI concept. Kwak et al. (2014) suggested a method of hydrological
102 drought analysis using the run theory of Yevjevich (1967). Recently, Rajsekhar et
103 al, (2015) developed a multivariate drought index that combines regional
104 precipitation and streamflow into a drought metric using information theory.
105 Among various drought indices, the Palmer Drought Severity Index (Palmer,
106 1965), Crop Moisture Index (Palmer, 1968), Surface Water Supply Index (Shafer
107 and Dezman, 1982) and Standardized Precipitation Index (McKee et al, 1993) are
108 commonly used to inform water resources management, agricultural drought
109 monitoring, and forecasting. Much of these drought indices are based on measures
110 of deficiency of rainfall or streamflow compared to long-term average. The
111 incorporation of evapotranspiration as a measure of water demand led to the
112 development of a water-budget-based drought index by Palmer (1965). The
113 Palmer Index has nonetheless been criticized for how it treats factors such as
114 potential evapotranspiration, runoff, snowmelt, and distribution of precipitation
115 and evapotranspiration within a month or week (Alley, 1984; Karl and Knight,

116 1985; Mc Kee et al, 1995; Guttman, 1997; Willeke et al, 1994). Hayes et al,
117 (1999) have argued that PDSI can be slow to respond to the development and
118 diminishing droughts.

119 **2.2 The case for Demand Sensitive Drought Index**

120 We present a demand sensitive drought index, DSDI, which considers day-to-
121 day rainfall variability as well as water demands to develop aggregate or
122 disaggregated indices for water uses. The methodology is based on the sequent
123 peak algorithm that is commonly used for the sizing of reservoirs (Thomas and
124 Burden, 1963). Variants of this methodology have been presented earlier to
125 measure current water risk in India (Devineni et al, 2013), China (Chen et al,
126 2014) and United States (Devineni et al, 2015). Applied to a time series of water
127 supply and demand, the algorithm identifies the drought stress as the cumulative
128 deficit over the period under consideration. DSDI can thus be represented
129 considering daily resolution of time series of supply and demand for a geographic
130 unit j (e.g. U.S. county) as follows:

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

$$DIC_j = \max_t(deficit_{j,t}; \quad t = 1:n * 365) \quad \dots (2)$$

131 $deficit_{j,t}$ refers to the accumulated daily deficit, $D_{j,t}$ to total or sector wise daily
132 water demand, $S_{j,t}$ to the total water daily supply volume, for geographical
133 location j , and day t ; and n is the total number of years in the analysis. The
134 maximum accumulated deficit estimated over the n -year period without breaking
135 it into sub-periods is defined as DIC_j (Drought Index Cumulated). This measures

136 the potential impact of multiyear droughts per demand sector, or in aggregate.
137 One can develop the corresponding normalized drought index as:

$$DSDI_j = \frac{DIC_j}{AP_j} ; \quad \dots (3)$$

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

144 The measure provides insights on the time-evolving vulnerability to drought
145 arising from changes in the climate, from that due to changes in non-climatic
146 conditions (e.g., demand). For example, consider the simulated droughts sketched
147 in Figure 1, where the varying contributions to the water supply are indicated by
148 the blue bars, and the demand is given by the red line (primary y-axis). In this
149 example, the demand (15 units) in figure 1a is greater than the demand (7.5 units)
150 in figure 1b while the supply is kept constant for both the cases. The case depicted
151 in Figure 1a (greater demand) shows that the accumulated water supply is never
152 sufficient to meet water demand. In other words, if a water deficit is defined as
153 the difference between the accumulated supply and accumulated demand (for a
154 specific purpose or in aggregate), the cumulative deficit (shown by the green line
155 on the secondary y-axis) never reaches zero, indicating that the supply, while
156 providing partial relief during the drought event, is nonetheless insufficient to

157 meet the overall demand. Consequently, the drought continues through the full
158 period shown. For the location with lower water demand as is shown in Figure 1b,
159 we can characterize the same overall time period as being divided into five
160 distinct episodes of drought, each with smaller cumulative deficit (since demand
161 is lower) than in Figure 1a, with the water deficit reset to zero by intervening wet
162 periods. The severity of a drought is defined as the maximum value of the
163 cumulative water deficit over a given period of consideration. The simulation
164 conceptually resembles the impact of drought on a region with greater current
165 demand compared to historical demand or it resembles the comparison of two
166 regions with similar rainfall distribution but varying demands. One could compare
167 this result with the typical hydro-meteorological drought index for the same
168 location (e.g. PDSI or SPI). In terms of assessing drought impacts, the indicator
169 portrayed here has the advantage of breaking supply and demand down into their
170 respective components, allowing us to better understand the causes of drought
171 frequency, duration and severity from an impact perspective. The drought index is
172 also a measure of the storage required to meet the time varying demand patterns
173 in the region (see the classification of DSDI in table 2 for an interpretation of the
174 values). Hence, one can design the system (based on the estimate) for the worst
175 dry periods in the sequence, thereby providing a robust measure of the ability to
176 meet the demands without failure. As such, the index can contribute to developing
177 more effective planning strategies for the managers to minimize drought impacts
178 in the current or future climate and demands.

179 It further provides other important characteristics like the duration, severity,
180 recovery time and the transition states of satisfactory conditions and
181 unsatisfactory conditions. Figure 2 shows a schematic of how these attributes can
182 be estimated from the cumulative deficit. We define drought as the period when
183 the cumulative deficit is greater than zero; i.e., the drought is initiated when the
184 period of deficit is initiated. Within this period, the time until the maximum
185 cumulative deficit (peak) is defined as the drought critical duration when the
186 cumulative deficit creeps from zero to the maximum cumulative deficit. The
187 system is most vulnerable during this time as it is depleting the water reserves in
188 the region. The maximum cumulative deficit is defined as the severity of the
189 drought. The time from the maximum cumulative deficit to the time the deficit
190 recedes back to zero is defined as the recovery time. During the recovery time, the
191 supply at time t is greater than the demand. The excess supply is used to replenish
192 the water reserves used during the critical period. This is analogous to using
193 groundwater during critical days and recharging during normal days to restore the
194 water levels. However, the system is still recuperating and vulnerable.
195 Appropriate management/recovery will depend on how resilient the environment
196 is. Figure 2 also shows how one can differentiate the system into satisfactory (S)
197 and unsatisfactory (F) states. A satisfactory state (S) is identified when the
198 cumulative deficit is either 0 or in the recedence phase (i.e. recovery time). The
199 recovery phase is considered satisfactory since the additional water supply
200 (beyond demand) is used to replenish the system reserves. An unsatisfactory state
201 (F) is identified as the drought duration when the drought has initiated and

202 creeping to the maximum cumulative deficit in that drought event. The transitions
203 from an unsatisfactory state (F) to a satisfactory state (S) can be identified for the
204 entire period of consideration and used to compute the resiliency rate as the
205 probability of recovery from a failure state. Together, the probability distribution
206 of the events (severity or duration or recovery) would also allow consideration of
207 formal risk management strategies or risk exposure analysis relative to existing
208 utilizable storage in an area.

209

210 **3.0 Applications (Detecting Historical Droughts for the Agricultural** 211 **Sector)**

212 The drought index described above is developed and presented for the
213 agricultural sector over the continental United States given that agricultural water
214 demand is dominant over much of the country. For conciseness, we present the
215 results for the total agricultural water demand.

216 **3.1 Data description**

217 We present the results at the county scale, the common spatial unit for datasets
218 representing the demand side of drought. Furthermore, we consider the water
219 supply based on rainfall over the county. We deviated from conventional
220 watershed scale analysis here to address the question of “how sustainable are the
221 water resources in a county during drought conditions”. This allows for direct
222 assessment of counties endogenous water sources and implicitly reveals
223 dependence on exogenous supplies during drought periods. The potential spatial

224 competition between counties and their hinterland for limited resources during
225 drought periods will be revealed as a result. A thorough discussion on the choice
226 of accounting unit is presented in Devineni et al. (2013). The indices can easily be
227 aggregated to various other regional scales depending on the sector and users. We
228 are using the following datasets to estimate the water supply and crop water
229 demand for each county:

230 a) Gridded rainfall data from 1949 to 2010 (62 years) available at 12.5 km by
231 12.5 km spatial resolution developed by Maurer et al (2002) were aggregated
232 to 3111 counties and used to estimate the water supply in each county.

233 b) Daily air temperature and wind speed from Maurer et al (2002) available at
234 the same spatial and temporal resolution were used to estimate the potential
235 evapotranspiration for each grid (and then aggregated to county level) based
236 on the Penman method (Lincoln et al, 2010). Yoder et al (2005) argued that
237 this method gives a better estimate of the daily reference crop
238 evapotranspiration in comparison to other methods such as the Hargreaves
239 method (Hargreaves et al (1982)). The FAO Penman method is also
240 recommended as the sole standard method for estimating the
241 evapotranspiration (Fao.org, 2014) subject to data availability. Terrain
242 elevation data required for the estimation is obtained from Google Elevation
243 API web service (Google Developers, 2014).

244 c) Time series of the crop area planted is obtained from the USDA National
245 Agriculture Statistics Service, NASS (Quickstats.nass.usda.gov, 2014).

246 **3.2 Derivation of the drought index**

247 We derive the index for agriculture that includes 8 major crops (corn,
 248 soybeans, hay, wheat, barley, sorghum, rice, and cotton). Among the \$143 billion
 249 national crop revenue each year (Epa.gov, 2014), those crops contribute to nearly
 250 95% of the revenue (see Table 1). The daily aggregate agricultural water demand
 251 and water supply are computed as follow:

$$D_t^j = \sum_{m=1}^{m=8} \frac{k_{cm}}{\beta_m} ET_{0t}^j CA_t^{j,m} \quad \dots (4)$$

$$S_t^j = \alpha_j P_t^j NCA_j \quad \dots (5)$$

252 Where, D_t^j is the aggregate agricultural water demand time series ($t = \text{day}$) for the
 253 county j , S_t^j is the water supply for the county j , k_{cm} is the FAO recommended
 254 crop coefficient for crop m ; ET_{0t}^j is the potential crop evapotranspiration
 255 determined from the Penman method, $CA_t^{j,m}$ is the area planted for crop m in the
 256 county j . Note that crop area changes every year. The crop water demand within
 257 the year depends on the length of the growing period for the crop and the
 258 temporal variability of the potential evapotranspiration. Furthermore, since the
 259 actual water utilized on the field is greater than the consumptive water use
 260 estimated from the empirical equations, we could choose β_m as the parameter to
 261 adjust for the additional losses affected from the application efficiency. For this
 262 application we used $\beta_m = 1$ to reflect complete efficiency. In reality, a farmer or
 263 planner can input their efficiency (based on their practices and techniques) to
 264 generate a tailored index.

Figure 3 presents the spatial distribution of cropped area for the eight major field crops during 1950, 1970, 1990 and 2010. Notice the spatio-temporal movement of crops indicating the changing demand. P_t^j is the rainfall for day t , over the county j , α_j is the factor that determines the usable fraction of rainfall by the crops over the net cropped area. For this analysis, α_j is estimated based on the long-term runoff ratio of the county. The long-term runoff ratio $\left(\frac{\bar{R}^j}{\bar{P}^j} = \text{average runoff} / \text{average rainfall}\right)$ (an index computed to understand the partitioning of rainfall into runoff and evaporation) is often related to physiographic basin features and regional climate information (Berger and Entekhabi, 2001). We estimate α_j as $1 - \frac{\bar{R}^j}{\bar{P}^j}$ to reflect the average fraction of rainfall that remains for the consumption of the crops after runoff. For this study, we obtain the long-term runoff ratio at the hydrologic unit code level based on Sankarasubramanian and Vogel (2002) and aggregated it to the county level. These runoff ratios are also used in Devineni et al (2015) to develop water risk maps for USA. It is important to note that the net cropped area NCA_j for each county is the current net cropped area distribution. Due to the lack of the data availability, we did not consider the net cropped area that changes over time.

The DSDI, described in section 2 is developed from this data to capture the influence of drought across years. It is computed as one number over the historical climate record. It represents the largest cumulative deficit between renewable supply and water use over the entire period. Consequently, it reflects the stress associated with multi-year drought impacts at a location. The magnitude

287 of water deficits can be interpreted as the storage required to meet the demand
288 given a variable climate and renewable water supply. The main components of
289 drought that are of interest are the implications of the temporal imbalance of
290 supply and demand at a spatial resolution consistent with decision-making. The
291 index presented here focuses on drought as defined through a temporal integration
292 of a cumulative deficit at a daily resolution and, hence, can be examined at
293 different levels of aggregation, e.g., seasonal, annual, or over the period of record.
294 Although the index is represented here based on the aggregate agricultural
295 demand, it can easily be computed as a disaggregated index specific for each crop
296 or sector. Hence, any user can input his demand profile and obtain a customized
297 drought index that represents the specific durations, severities and recovery times.
298 Consequently this serves as a better management and planning tool compared to
299 the existing regional droughts indices.

300 **3.3 Drought Resiliency and Recovery**

301 In this section, we present the spatial distribution of the drought resiliency for
302 the 3111 counties. We estimate the resiliency of a given region using two
303 measures, the resiliency rate (i.e. the probability of recovery from a drought state)
304 and the relative recovery (i.e. the average time it takes to completely recover from
305 a drought compared to the duration of the drought). These two measures are
306 described below:

307 **3.3.1 Resiliency Rate (γ)**

Following Hashimoto et al (1982), we first differentiate the system output space into satisfactory (S) and unsatisfactory (F) states (Figure 2). A satisfactory state (S) is identified when the cumulative deficit is either 0 or in the recedence phase (i.e. recovery time). An unsatisfactory state (F) is identified as the drought duration when the drought has initiated and creeping to the maximum cumulative deficit in that drought event. The transitions from an unsatisfactory state (F) to a satisfactory state (S) are identified for the entire period of consideration and the county's resiliency rate is defined as the probability of recovery from a failure state

$$\gamma^j = \frac{P(\text{deficit}_{j,t} \in F \cap \text{deficit}_{j,t+1} \in S)}{P(\text{deficit}_{j,t} \in F)} \quad \dots (6)$$

Figure 4(a) shows the spatial distribution of the resiliency rates (γ) (presented as percentage) for all the 3111 counties in the United States. We can see from the figure that the southwestern United States, mid-western agricultural belt and the Carolinas have low resilience indicating prolonged drought with low probability of transition to a satisfactory state. This can happen either due to the lack of sufficient drought bursting rainfall events or higher demand or a combination of both with positive feedback mechanism to the atmosphere that leads to persistent dryness. Bravar and Kavvas, (1991a, b) provide a theoretic framework for such prolonged drought events. While a perusal of Figure 3 indicates that the low resilient regions coincide with high cropping intensity, it is also beneficial to know that these regions have low average annual rainfall with high inter-annual

328 variability (Figure not shown here). The regions with high resiliency are also the
329 regions that are well endowed by rainfall with low inter-annual variability.

330

331

332 **3.3.2 Relative Recovery (δ)**

333 We define the relative recovery (δ) as the expected value of the ratio of the
334 drought recovery time to the drought duration time for each county.

$$\delta^j = E \left[\frac{R_i}{D_i} \right] \quad \dots (7)$$

335 In eq. 7, D_i is the drought duration and R_i is the drought recovery time for
336 each drought event i . For each county, a drought event is defined when it has
337 positive cumulative deficit. Within this period, the time until the maximum
338 cumulative deficit is the drought duration and the time to complete recedence is
339 the recovery time. The relative recovery (δ) measures the rate at which a region
340 (county in this case) will bounce back quickly from a prolonged drought. $\delta > 1$
341 indicates that the drought recovery time is greater than the drought duration on
342 average. Such regions have slow recovery relative to the drought duration.
343 Conversely, $\delta < 1$ indicates that the regions have rapid recovery in relation to the
344 duration. Figure 4(b) shows the spatial distribution of the relative recovery for all
345 the 3111 counties. We can observe that much of the southern United States has a
346 relative recovery rate that is less than 0.66 indicating that these regions typically
347 have faster recovery time (less than 2/3) in relation to the corresponding duration

time on average. We can also see that the counties in the Southwestern United States, southern Plains and Carolinas that exhibit low resilience (i.e. those that are subject to prolonged droughts) typically have a low relative recovery time indicating that these regions typically recover quickly once the recedence starts. Regions in the northern and mid-west United States exhibit higher relative recovery rates and low resiliency. These regions have persistent droughts coupled with long bounce back times making them highly vulnerable. An interesting observation worth pointing out is that the northern counties of New York State exhibit high resiliency with low duration droughts, however, they have a high relative recovery rate also. This indicates that although there is a high probability of transitioning to a satisfactory state (S) from an unsatisfactory state (F), the time to complete recovery is long relative to the drought duration.

360

3.4 Spatial Clustering of Drought Attributes

In this section, we present the spatial distribution of the drought properties (onset, duration, severity, recovery and resiliency) for the worst drought in the entire period of observation. The maximum cumulative deficit is first identified for each county as the severity of the worst drought. The corresponding drought onset year, duration, recovery and resiliency are then identified. We analyze the spatial congruence of the drought properties based on the K -means clustering algorithm (MacQueen, 1967). Clustering analysis provides an objective way to classify droughts into sub-categories depending on the multivariate dependence between the variables. Such classification can then be linked to the geographic

371 locations to understand the spatial contiguity of droughts. In this study, we
372 employed the *K*-means method on the onset time and severity of the drought to
373 find *k*-separations of the data based on maximum inter-cluster variations relative
374 to centroid of each cluster.

375 Figure 5 presents the results from the *K*-means clustering on drought onset
376 and severity for aggregate agricultural demand. The optimal number of clusters
377 (four in this case) is determined based on the maximum silhouette value (0.6), a
378 measure of how cohesive each cluster is and how well the clusters are separated.
379 The boxplot of the drought attributes corresponding to each cluster is also
380 presented in figure 5. We can see a clear separation of clusters based on the onset
381 of the worst drought. The counties under cluster 1 (Western States of Oregon,
382 California and Arizona; Great Plains of Dakotas, Kansas and Oklahoma, and
383 Southern States of Alabama and Georgia) had droughts that were initiated in the
384 early 1950s, lasted for an average of less than 5 years and took as much time to
385 recover. These were the regions also reported to have deficit rainfall during the
386 1950s and were reported to have an agricultural yield reduction of up to 50%
387 (http://www.ncdc.noaa.gov/paleo/drought/drght_history.html). Since the index
388 presented here is sensitive to agricultural water demand, we see that the counties
389 that experienced drought in the early 1950s are also the counties that had
390 agriculture prevalent during this time. Cluster 2 corresponding to the regions of
391 southern Plains and the Ohio Valley had worst drought (in the 62 year record)
392 initiated in the 2000s, lasted for an average of two years and recovered quickly.
393 Much of these regions were reported to have experienced droughts based on the

394 SPI or PDSI. The DSDI presented here complements the existing drought indices
395 by providing the impact of drought as seen from demand in the region. Clusters 3
396 and 4 corresponds to the agricultural belt of the mid-west USA and some counties
397 in California. These two clusters are distinctly separate from the other clusters
398 with an onset around 1970s. Furthermore, cluster 4 has a clear separation from
399 other clusters in terms of its severity (DSDI). A DSDI greater than 1 represents
400 the case where the cumulative deficit is greater than the average endogenous
401 rainfall. The annual rate of consumption in these counties is much higher than the
402 average utilizable rainfall rates and they are under chronic water stress. Majority
403 of the counties in this cluster are heavily reliant on groundwater to meet irrigation
404 water needs. Notice that the recovery time for the counties in this cluster is shown
405 as the maximum number of years, since the worst drought never ends. In fact, a
406 county with a high DSDI (>5) usually presents a cumulative deficit that never
407 decreases since its onset in the 1970s (see for example, boxplot of recovery time
408 for cluster 4). This is also seen in the boxplot of the resiliency and relative
409 recovery for the cluster. The counties in cluster 4 have very low overall resiliency
410 and high relative recovery rates. Such counties suffers from chronic water stress.
411 The water deficit is met by means of water imports (inter-basin transfer) or
412 groundwater extraction. Substantial pumping of groundwater in these regions for
413 irrigation since the early 1970s led to a large water table decline. The areas
414 identified in cluster 4 also correspond to the maps of the groundwater depletion or
415 over exploitation recently presented by Konikow (2013). These regions were also
416 reported in Gardner and Kramer, (1986) and Glauber, (2013) as the regions of in-

417 migration in response to the federal crop insurance and disaster relief program
418 since 1970s. An examination of the temporal distribution of annual rainfall and
419 annual agricultural demand along with the temporal distribution of the cropped
420 area for counties in cluster 4 also reveals this trend. Figure 6 presents the time
421 series of the median (across the 207 counties in cluster 4) of annual rainfall and
422 annual agricultural demand and the cropped area. We can observe the dramatic
423 increase in the cropped area since 1970s and the resulting increase in the water
424 demand. Since the average water demand is greater than the average renewable
425 water supply, the region is experiencing a persistent water stress since 1970s. The
426 importance of demand in developing a drought index can also be seen from
427 Figure 7 that shows the drought resiliency for the counties in cluster 4 under three
428 different demand scenarios. In the first case, we hold the demand of 1950s
429 constant for the entire history, simulate drought events and compute the resulting
430 resiliency metric (i.e. the probability of transitioning from drought to a
431 satisfactory state). The second case is the baseline case where the demand
432 changes every year. In the third case, we simulate drought with the current
433 demand (2010s) and then compute the resulting drought resiliency. The
434 agricultural demand in these counties has progressively increased since 1950s.
435 We can clearly see that the drought resiliency decreases as demand increases. The
436 drought index presented here clearly distinguishes the impact on a region
437 resulting from deficit rainfall and increasing demands and hence provides
438 valuable information for water managers who can evaluate the changes in the
439 drought attributes with proposed changes in the crop mix. While the results

presented here are based on the aggregate agricultural water demand, the algorithm can be modified to generate a customized drought index specific to a crop or demand sector.

3.5 Time-series comparison of DSDI with PDSI

We compare the annual maximum cumulative deficit with the annual PDSI from 1949 to 2007 for two contrasting regions; one having low demand induced stress and one having high demand induced drought stress. The data for PDSI is available from the National Center for Atmospheric Research (NCAR) at spatial resolution of 2.5 degrees (Heddinghaus et al, 1991; Guttman, 1991). Hence, for comparative purposes, we average the annual maximum DSDI over the counties that make up the PDSI grids. We select two grids, one having low demand induced stress ($DSDI < 0.3$), and one having high demand induced stress ($DSDI > 5$). While the low stress region represents locations where demand is essentially temperature driven (much like in PDSI), the high stress region represents the locations where demand is driven by intensive agricultural activities. Figure 8 presents this comparison. In general, high DSDI values correspond to negative PDSI values (indicating droughts) in the low stress regions (figure 8 – top-left). However, we do not see a relation between PDSI and DSDI for the region that is driven by demand-induced stress (figure 8 – top-right). The demand accounting in PDSI is only based on potential consumption by grasses (Palmer, 1965). It does not account for total water use in the area. Consequently, our comprehensive drought indicator that covers total water use relative to utilizable precipitation will

not match the PDSI for high stress regions. The time series (1949 - 2007) of PDSI is compared to annual maximum DSDI for the low stress region in Figure 8 (bottom panel). Both PDSI and DSDI reveal the droughts of the 1950s and the 2000s for the low stress region . Moreover, DSDI clearly shows additional drought periods from 1970 to 1990 to reflect the agricultural boom in the 1970s that is not clearly seen from PDSI.

4.0 Summary

While the need for managing water for reliable supply has been acknowledged regularly, there is often a lack of reliable information on water usage/demand at the local level. Consequently, the nature of risk in different socio-economic and geographic settings has not been articulated beyond a simplistic analysis of the potential imbalance between estimates of average annual supply and demand. The considerable debate on the classification of drought and the lack of a uniform methodology has made it difficult to devise a universal drought index. Compared to other natural hazards like floods and hurricanes that develop quickly and last for a short time, drought is a creeping phenomenon that accumulates over a period of time across a vast area and the effect lingers for years even after the end of the drought. This characteristic has impeded the development of accurate, reliable and timely estimates of drought severity relevant to specific uses and ultimately the formulation of long term operations and drought preparedness plans. Regional drought planning often suffers from a general lack of data and clear metrics that inform drought emergence, peaks and recovery at appropriate spatial resolution

486 that are important for decision makers, and as a result, the process of drought
487 identification can become a subjective exercise in interagency communication and
488 coordination rather than an analytical exercise grounded in actual data (Pratt,
489 2012).

490 The drought index presented here focuses on water stress as defined
491 through a temporal integration of deficit at a daily resolution. The average supply
492 demand imbalance is automatically accounted for. The index is presented here for
493 aggregate agriculture based on eight major field crops in the United States, but
494 can be disaggregated into individual crop/demand indices. Furthermore the index
495 can be derived for or integrated with other water use sectors such as industrial and
496 domestic uses. In terms of assessing drought impacts, the indicator portrayed here
497 has the advantage of breaking supply and demand down into their respective
498 components, allowing us to better understand the causes of drought frequency,
499 duration and severity from an impact perspective. As such, the index can
500 contribute to developing more effective planning strategies for the regional
501 managers to minimize drought impacts in the current or future/projected climate
502 and demands. The daily integration feature of the index makes it possible to be
503 examined at different levels of aggregation, e.g., seasonal, annual or over the
504 period of record. The index directly informs storage requirements needed to meet
505 the projected supply-demand imbalance at desired levels of reliability (explicit or
506 implicit), and hence can be connected more directly to infrastructure, planning or
507 water conservation needs, or the size of trans-basin diversions. The index also
508 reveals the dependence of a county on external water source such as groundwater

509 stores or inter-basin transfers. We found that most counties in the mid-west
510 presented chronic stress and can be assumed to fall in this category. The
511 derivation of resiliency measures makes it easy to understand the potential
512 exposure by location, and is hence useful for siting decisions. Future climate
513 scenarios or season ahead climate forecasts can be readily accommodated to
514 provide projected risk per demand sector, and integrated with a drought
515 monitoring plan that indicates the current level of accumulated deficit or stress.
516 Potential impacts of climate change on supply and demand and hence drought
517 impacts can also be explored along with whether conservation/efficiency
518 improvement efforts or different ways of caching surface and groundwater storage
519 access through infrastructure and water transfers are likely to be more effective to
520 mitigate climate/drought impacts in a county/regional situation.

521

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531

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699

700

701 **Table 1:** Major agricultural crops produced in the United States in 2011
702 (excluding root crops, citrus, vegetable, etc).

Crops	Harvested Area (Million Acres)	Cash Receipts from Sales (\$ Billion)	Percent of the total crops revenue (\$ 143 Billion)
Corn	84	63.9	44.7%
Soybeans	73.8	37.6	26.3%
Hay	55.7	6.7	4.7%
Wheat	45.7	14.6	10.2%
Cotton	9.5	8.3	5.8%
Sorghum	3.9	1.3	0.9%
Rice	2.6	2.9	2.0%
Total	275.2	135.3	94.6%

703 Source: EPA, 2015

704

705 **Table 2:** Classification of DSDI

Class names	Ranges	Notes
Very Low	$0 < DSDI \leq 0.3$	The water required to cover the deficit is equivalent to a fraction of the average annual rainfall (the endogenous water) received at the location, i.e. the annual rainfall is sufficient to cover the deficit.
Low	$0.3 < DSDI \leq 0.6$	
Moderate	$0.6 < DSDI \leq 1$	
High	$1 < DSDI \leq 2$	The endogenous water at the location is not enough to cover the deficit. External sources of water (typically groundwater or water transfer from distant locations) is needed to meet the demand.
Very High	$2 < DSDI \leq 5$	
Extreme or Chronic	$DSDI > 5$	

706

707

Figure

Figure 1: Synthetic drought simulations with fluctuating water supply and keeping demand at 15 units (1a) and 7.5 units (1b).

Figure 2: Drought properties derived from the cumulative deficit. A drought event is defined as the period when the cumulated deficit is greater than zero. Transition from unsatisfactory state (F, drought) to a satisfactory state (S, no drought) is also illustrated.

Figure 3: Spatio-temporal evolution of the area planted for eight major field crops. Each column/year (1950, 1970, 1990, and 2010) represent the area planted for that year (a time span of 20 years is used). The colored labels (in percentage) represent the percent of the county planted with that crop.

Figure 4: Spatial distribution of the resiliency rate and relative recovery.

Figure 5: Results from the *K*-means clustering analysis on the onset and severity of the worst drought. The boxplot of the drought attributes is also presented.

Figure 6: Temporal distribution of annual supply and annual agricultural demand for counties in cluster 4. Only the median across the 207 counties in cluster 4 is presented here. The median of the total cropped area is also presented for each year in the secondary y-axis.

Figure 7: Resiliency of counties for cluster 4 under three demand scenarios.

Figure 8: DSDI – PDSI comparison over a region (Oklahoma) with low DSDI (top-left) and a region (Nebraska - Kansas) with high DSDI (top-right) for the period 1949 – 2007. The region with low DSDI shows a negative correlation between the two indices (i.e. higher values of DSDI corresponds to low values of PDSI or lower DSDI corresponds to higher PDSI). The correlation is weak in the case of high values of DSDI. The time series of the two indices for the low water stress region are also presented.