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ORIGINAL PAPER

Drought indices as drought predictors in the south-central USA

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Abstract Drought is among the most insidious types of natural disasters and can have devastating economic and human health impacts. This research analyzes the relationship between two readily accessible drought indices—the Palmer Drought Severity Index (PDSI) and Palmer Hydrologic Drought Index (PHDI)—and the damage incurred by such droughts in terms of monetary loss, over the 1975–2010 time period on monthly basis, for five states in the south-central USA. Because drought damage in the Spatial Hazards Events and Losses Database for the United States (SHELDUS™) is reported at the county level, statistical downscaling techniques were used to estimate the county-level PDSI and PHDI. Correlation analysis using the downscaled indices suggests that although relatively few county–months contain drought damage reports, drought indices can be useful predictors of drought damage at the monthly temporal scale extended to 12 months and at the county-level spatial scale. The varying time lags between occurrence of drought and reporting of damage, perhaps due to varying resilience to drought intensity and duration by crop types across space, along with differing irrigation schedules and adaptation measures of the community to drought over space and time, may contribute to weakened correlations. These results present a reminder of the complexities of anticipating the effects of drought, but they contribute to the effort to improve our ability to mitigate the effects of incipient drought.

Keywords Drought damage · Palmer Drought Severity Index · Palmer Hydrologic Drought Index · Statistical downscaling · SHELDUS™ · South-central USA

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1 Introduction and background

Drought is among the most insidious types of natural disasters and can have devastating economic and human health impacts. The 21 most damaging drought events that occurred between 1980 and 2013 represent 12.4 % of the billion-dollar [consumer price index (CPI) adjusted] natural disasters in the USA and $199 billion, or 19.1 %, of the total losses among those events (Smith and Matthews 2015). Furthermore, the continual increase in drought impacts in the recent historical record (Ma et al. 2013) and projection for continued escalating impacts in the future (Wang 2005; Dai 2013) amid wide uncertainties (Burke and Brown 2008) calls for increased scientific understanding of the physical features related to drought occurrence and associated environmental, economic, and behavioral impacts.

Depending on the context, a drought may be defined based on meteorological, agricultural, hydrological, or socioeconomic impacts (Wilhite and Glantz 1985; National Drought Mitigation Center 2013), or some combination thereof. For management purposes, resource planners have found that relying on an index-based operational definition of drought would be most convenient in decision making.

Several drought indices are available; each captures somewhat different aspects of drought conditions (Heim 2000). The Palmer Drought Severity Index (PDSI; Palmer 1965) and Palmer Hydrological Drought Index (PHDI; Karl 1986) are commonly used, highly regarded, and readily available metrics. The PDSI, a weekly index of long-term moisture conditions, is produced by National Oceanic and Atmospheric Administration's (NOAA's) Climate Prediction Center and is calibrated to "normal" conditions for its own subset of a state known as a climate division, with 0.0 representing average soil moisture conditions at that climate division for that time of year. Positive values represent above-normal moisture conditions for that location and negative values suggest below-normal soil moisture. Because the water balance calculations for PDSI include lags to take into account deep soil moisture conditions, PDSI is often considered in many applications a reasonable and versatile index of medium-term moisture.

For evaluating longer-term hydrological conditions, the PHDI may prove more useful, because its even longer-lagged response to changes in moisture conditions may better reflect the changes in groundwater availability and reservoir supplies that would be characteristic of drought impacts on communities' long-term water supply and demand (Guttman 1991). These two indices remain the most widely used and cited measures of drought. While other drought indices are available and useful, such as the Keetch–Byram Drought Index (KBDI) used by the US Forest Service to indicate the potential hazard of forest fire, and Thornthwaite's (1948) water balance model (Mather 1979), which can be derived from a Web-based program available from the US Geological Survey (2015; originally described by McCabe and Markstrom 2007), the versatility and availability of the PDSI and PHDI on a near-real-time basis make these two indices most desirable for use by environmental planners.

Unfortunately, little work has considered the linkages between drought monitoring indices and the actual damage to crops and properties, despite the substantial savings that can be generated by effective implementation of drought restrictions (Haque et al. 2014). Among the studies that have examined the viability of drought indices as indicators of drought severity and/or impacts, Szinell et al. (1998) commented on the nature of the PDSI time series in Hungary for characterizing historical drought occurrence. Quiring and Papakryiakou (2003) found that Palmer's Z-index outperformed other drought indices, including the PDSI, in assessing impacts to agricultural yield from drought in the Canadian Prairies. Woli et al. (2013) found that artificial neural networks and climate indices could improve drought forecasting in the coastal southeastern USA. Shahabfar and Eitzinger (2013) found that the China-Z index (CZI) and modified CZI outperformed percent of normal precipitation, standardized precipitation index (SPI; Guttman 1998), z-scores, and de Martonne's aridity index (Botzan et al. 1998) as drought predictors in Iran. Wang et al. (2014) noted that the SPI correlates well with the remotely sensed Normalized Difference Vegetation Index (NDVI) as an indicator of drought damage. But to date, little research has considered comprehensively the linkages between drought indices, declared drought events, and the actual economic damage to crops and properties from those events. The ubiquity of the PDSI and PHDI makes these the most logical indices for public use, but the literature appears to be mixed on whether these indices are valuable indicators of drought impacts.

2 Objective

The objective of this research is to test the relationships between the PDSI and PHDI and drought damage across a five-state region in the south-central USA (Arkansas, Louisiana, New Mexico, Oklahoma, and Texas; Fig. 1), an area that is vulnerable to wide ranges of hydroclimatic conditions from humid to arid. Moreover, the most densely and increasingly populated part of this region—central Texas—lies at the ecotone between the humid subtropical and semiarid climate types (Reynolds et al. 2015); numerous citizens may be unfamiliar with the hazard and adaptation measures that go along with living under the

Fig. 1 The study area

wide range of hydroclimatic conditions that can be experienced. Therefore, an improved assessment of the relationship between drought indices and subsequent drought declaration and damage could provide environmental planners with improved information for communicating drought onset and danger to the citizenry.

We hypothesize that existing modeled parameters such as the PDSI and PHDI accurately represent the damage due to droughts in the study region and that spatial differences exist in the relationship between drought exposure and drought damage among different sections of the south-central USA. States that have high drought exposure, such as Oklahoma, may sustain smaller damage (i.e., lower vulnerability), due to relatively higher amenability to mitigation and adaptation strategies in the residential, agricultural, and industrial sectors. In addition, we hypothesize that drought duration is more strongly correlated than drought intensity to drought damage in the south-central USA. For incidents of drought exposure (identified by months with PDSI ≤ -1.0, or in a separate analysis, PHDI ≤ -1.0), is drought damage (in 2011 CPI-adjusted dollars) correlated with the number of consecutive months in the drought (i.e., duration)?

3 Data and methods

The PDSI and PHDI are published weekly and aggregated into a monthly dataset by NOAA, at the climate divisional level. These monthly data are extracted for the 45 climate divisions in the five-state region over the 1975–2010 period, the time corresponding to the rapid population growth over the central part of the study area. Modifications to the PDSI have been introduced based on improved algorithms for estimating potential evapotranspiration (Thornthwaite 1948) and based on probabilistic modeling of moisture departures (Ma et al. 2014), allowing the PDSI to remain the most widely used index for drought monitoring in the USA (Dai 2011). Limitations of the PDSI (Alley 1984; Heim 2002) and the ambiguities involved in using the indices to determine when a drought is declared (Hayes 2015) have been noted.

The University of South Carolina's SHELDUS™ database version 13.1 (Hazards & Vulnerability Research Institute 2014) is used for quantifying drought damage by county. SHELDUS™ data are derived from reports from *Storm Data and Unusual Weather Phenomena* published by National Centers for Environmental Information (NCEI; formerly National Climatic Data Center) and information from the National Geophysical Data Center and the Storm Prediction Center. In SHELDUS™, each drought event causing more than $50,000 in losses (1960–1970), more than $50,000 in losses or any fatalities (1971–1995), and any monetary losses or fatalities (1996–2010) were entered manually into the database. For each drought event, SHELDUS™ records the beginning and ending date, location (county and state), property and crop losses (adjusted to 2011 dollars), injuries, and fatalities in each county. Consultation with NOAA's NCEI confirmed a suspected error for the July 2010 damage in Tensas Parish, Louisiana—the $700 million in damage should have been reported as $700,000 (personal communication, Stuart Hinson, NOAA, 7/17/15); we implemented this change in our dataset.

Use of the damage data is not without its cautions. Despite the fact that SHELDUS™ includes damage due to the drought hazard along with that from landslides, winter weather, heat, severe weather, wind, floods, tornadoes, hurricanes, fires, earthquake, volcano, tsunami, and technological and biological hazards, biases exist in the extent of coverage across the different hazard types and across space, due to differences in the extent to which different hazards are monitored and investigated (Gall et al. 2009). Droughts remain notoriously underreported in all databases, including SHELDUS^{TM} (Svoboda et al. 2002; Gall et al. 2009. Gall et al. (2009) caution that a lag of coverage from ~180 to 600 days is possible in SHELDUS^{TM}. Moreover, Mechler and Bouwer (2015) note the importance of vulnerability as a modulator of the relationship between the extreme event and/or climatic change and losses, and vulnerability can be difficult to measure. These complications may perhaps explain why little scholarly work to date has assessed economic damage from drought. But yet the high and rapidly escalating losses due to drought call for immediate analysis, even with results that invite caution in interpretation.

It was necessary to transform the event-based SHELDUS^{TM} database into monthly county-level economic losses during 1975–2010. Both crop losses and total losses (crop and property) were chosen to represent the damage caused by drought events. Crop losses not only reflect direct responses to hydrological conditions but also contribute to the most of total losses according to historic records. Each event-based crop/total loss was evenly divided into monthly crop/total loss based on the sustaining duration in each month, which was calculated from the beginning and ending date. For example, if a drought event had occurred in Orleans Parish from May 27, 2010, to July 15, 2010, and caused \$1000 in total loss, the duration of this event would have been reported as 5, 30, and 15 days for May, June, and July 2010, respectively, and the total losses from this event would have been 100, 600, and 300 dollars, for May, June, and July 2010, respectively. Finally, the county-level drought index layers and damage layers were connected and output as records of county, year, month, PDSI, PHDI, duration, CPI-adjusted crop damage, and CPI-adjusted total damage. The preprocessing utilized a python script embedded in ArcGIS to handle the 217,296 (503 × 36 × 12) records.

The areal interpolation method (ESRI 2012) in the “Geostatistical Analyst” extension in ArcGIS 10.1 (Environmental System Research Institute (ESRI) 2012) was used for statistical downscaling of the climate division-based PDSI and PHDI to the county level for each of the 432 months of analysis. Areal interpolation reaggregates data from one set of polygons (the source polygons) to another (the target polygons), and different approaches can be used to perform this task (Goodchild and Lam 1980; Lam 1983). The ArcGIS extension uses Kriging theory to conduct areal interpolation (Oliver and Webster 1990; Krivoruchko et al. 2011; Stein 2012). Downscaling drought indices from climate divisions to counties is a two-step process. In the first step, a smooth prediction surface was created from the attribute data (drought index values) input for each climate division. In the second step, this prediction surface of drought indices was re-aggregated to the county-level feature class. To create an accurate prediction surface with “Geostatistical Wizard,” the covariance curve needs to be fitted. Therefore, lag size value, type parameters (K-Bessel and stable), and lattice spacing values were selected carefully to fit the model optimally. The mathematical description of the interpolation procedure is described by Krivoruchko et al. (2011). Predictions and standard errors were calculated for all the target polygons. To generate results with at least 90 % of the empirical covariances falling within the 90 % confidence intervals, a covariance model was specified by fitting a proper covariance curve within the Kriging framework.

For a given county, drought duration was defined as the number of consecutive months in which the downscaled county-level PDSI (and, in a separate analysis, PHDI) was below –1.0. Then, because of the predominance of months with no drought-related damage reported in SHELDUS^{TM}, all months with zero damage were removed from analysis prior to running the correlations. Because of concern about the uncertain and varying lag relationship for reporting drought damage after onset of drought, the county-level damage data were aggregated over a 12-month moving window (including months with no damage) beginning on each month of the time series. This lag was chosen in order to keep one complete growing season within each window to validate comparisons and correlations of intensity/duration to losses, while still taking into account the fact that lags associated with SHELDUS™ could be from 6 to 20 months (Gall et al. 2009). The purpose is to ascertain the extent to which an incipient drought can be used to predict aggregated drought damage over the next 12 months.

4 Results and discussion

4.1 Drought occurrence, persistence, and damage

A total of 70,072 (67,974) of the 217,296 county–months (32.2 (31.3) %) had a PDSI (PHDI) below −1.0. The longest run of consecutive PDSI values below −1.0 in that particular county was for a whopping 70 months—from March 1998 to December 2003, in Jefferson Davis County, Texas (Trans Pecos climate division). The longest run of a PHDI below −1.0 in its county was for 49 months—from October 2000 to January 2005, in San Juan County, New Mexico (Northwestern Plateau climate division).

A total of $15.3 billion in 2011 CPI-adjusted drought damage occurred across the study area during the 1975–2010 period. The impact was widespread, with damage reported at some point in the period in 249 of the 254 counties in Texas, all 77 counties in Oklahoma, 71 of the 75 counties in Arkansas, all 64 parishes in Louisiana, and 2 of the 33 counties in New Mexico. In all, Texas sustained $9.92 billion in damage over the period, with Oklahoma experiencing $2.03 billion, Louisiana having $1.55 billion, Arkansas experiencing $1.81 billion, and New Mexico sustaining $0.02 billion. The most-damaged county was in Louisiana, with Caddo Parish sustaining $134 million in drought damage, mostly from the exceptional drought of 2010 (which continued beyond the study period into 2011). All other counties on the “top ten” list for drought damage are in Texas, with Childress County, in the rural southeastern Texas panhandle, sustaining almost $118 million, followed by Briscoe and Hall ($115 million each), Swisher ($114 million), Castro and Palmer ($112 million each), Kent and Stonewall ($110 million each), and King ($108 million) rounding out the list. Figure 2 provides an example of the relationship between

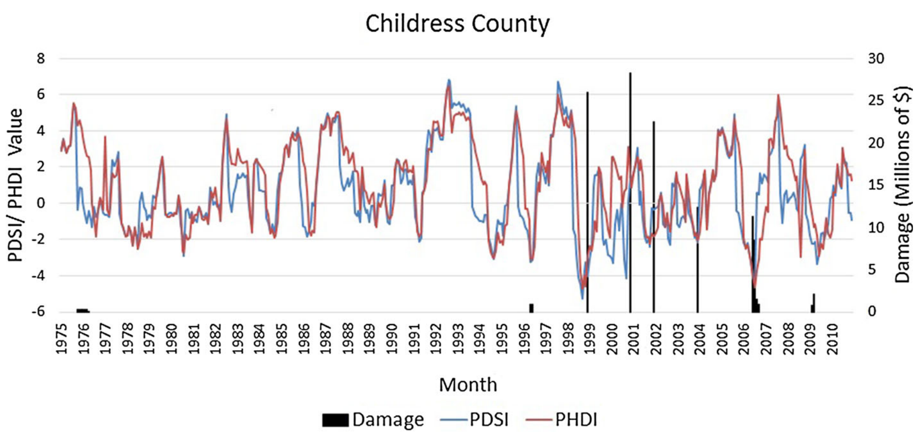

Fig. 2 Damage due to drought in Childress County

drought damage, PDSI, and PHDI for Childress County. Like many counties, drought occurs episodically in Childress County, and not necessarily in the months that have extremely low drought indices or during long runs of months with low drought indices.

General features of the total crop and overall damage due to drought by state are shown across the annual time series (Fig. 3a, b) and by month of the year (Fig. 4a, b). Results generally suggest that crop damage occupies the vast majority of drought damage. Moreover, drought damage is episodic in each state, not surprisingly with far more damage in Texas than any other state. Drought damage is reported throughout the year in Texas, but more damage tends to be reported in summer months than in other months in all states, with a spurious spike in reporting in Texas in December (Fig. 4).

4.2 Relationship between drought damage and drought indices

Relatively strong negative correlations exist between monthly drought index (for both the PDSI and PHDI) and non-lagged monthly drought damage, when analyzed across all 503 counties in the study area (Table 1). Statistically significant negative correlations occur in all seasons except autumn for both the PDSI and PHDI analysis. All months from January through April and June through July also showed statistically significant negative correlations to damage for both indices, with May and September displaying significantly negative correlations for the PDSI only. The correlations were comparable for both the PDSI and PHDI at the monthly scale of analysis. However, the presence of small

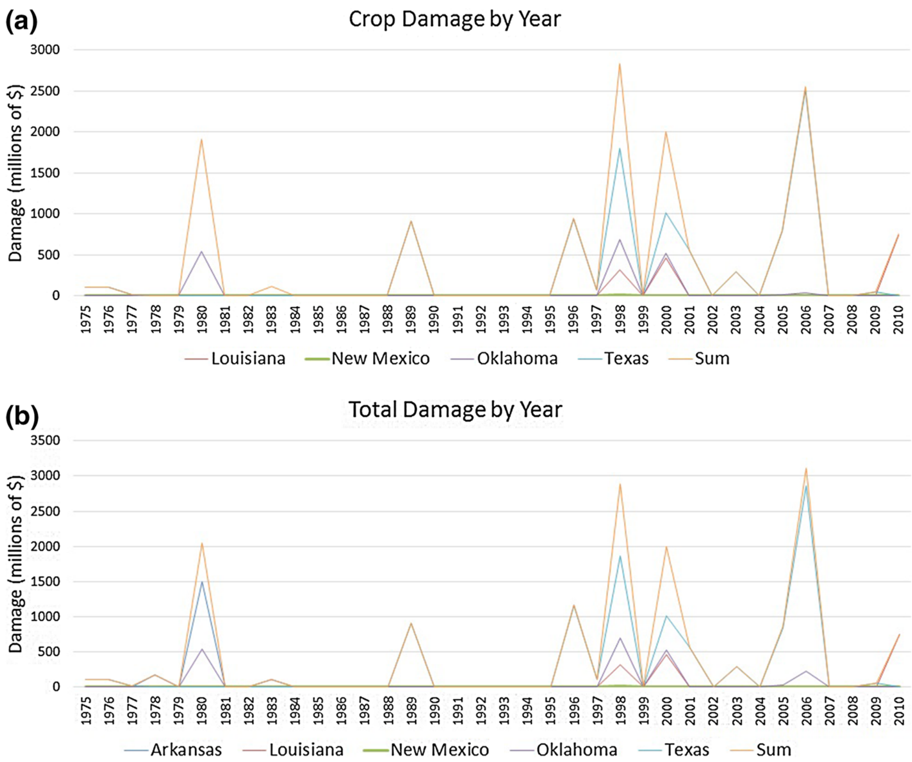

Fig. 3 **a** Crop damage by year. **b** Total damage by year

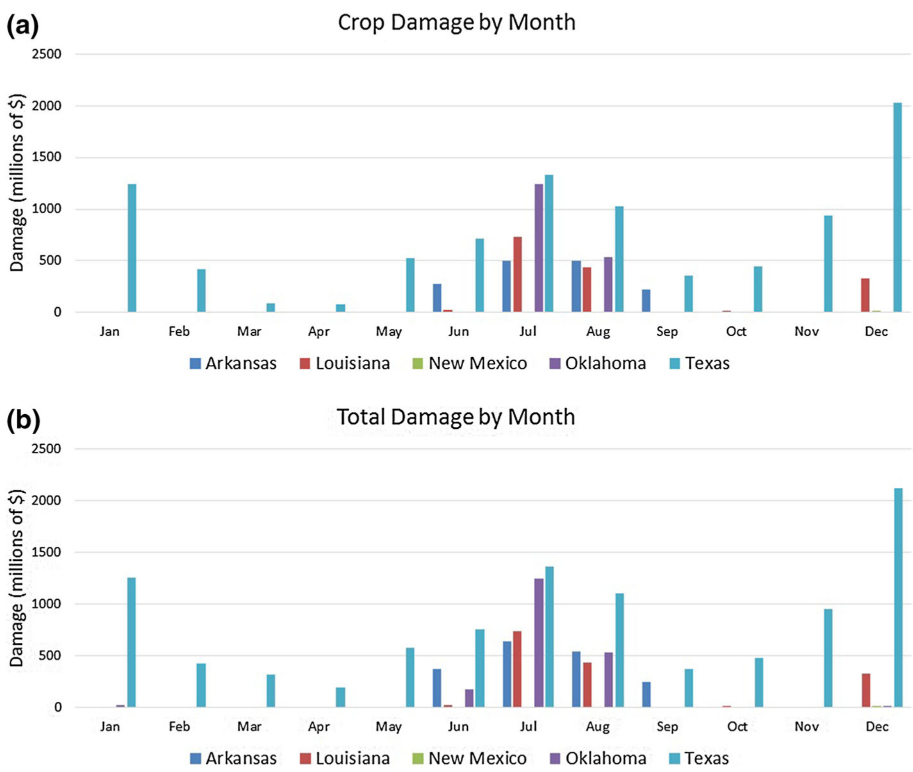

Fig. 4 **a** Crop damage by month. **b** Total damage by month

frequencies of months with drought damage in general (ranging from 328, or 0.018/county–year, in February to 734, or 0.040/county–year, in July; Table 1) seems to support the notion that drought damage is likely to be underreported and invites caution in the interpretation of results.

New Mexico had only 3 county–months of drought damage, and therefore, no further conclusions are drawn for that state. Significantly negative correlations between drought indices and damage were observed for Arkansas and Texas counties, slightly weaker but still significantly negative correlations were found for Louisiana parishes, and Oklahoma counties actually displayed signs of a spurious positive association between drought indices and drought damage, especially for the PHDI (Table 2). The positive correlation in Oklahoma could reflect a dependence on irrigation for averting losses in hydrologic drought conditions. In Oklahoma, Texas, and Louisiana, the PHDI offered stronger year-round correlations than the PDSI.

For all states except Texas, there were too few county–months to analyze correlations by state for each of the 12 months of the year. Texas is of special interest not only because its size permits robust analysis, but also because its central location in the study area minimizes potential downscaling issues introduced along the boundary of the study area. Analysis of the 9144 county–months in Texas (254 $\times$ 36) for each January, each February, etc. of the dataset supports the notion of significant correlations between drought index and drought damage. In fact, the pattern closely mirrors that of the region as a whole, with significantly negative correlations observed throughout the year except in fall, when signs

Table 1 Pearson correlations between drought index (PDSI and PHDI) and drought damage (2011 CPI-adjusted dollars), for county–months with nonzero drought damage totals, 1975–2010

Month or season	Number of nonzero damage county–months (1975–2010)	*r* (PDSI vs. damage)	*p* value	*r* (PHDI vs. damage)	*p* value
Winter (D–J–F)	1212	–.200	<.001	–.267	<.001
Spring (M–A–M)	1292	–.362	<.001	–.163	<.001
Summer (J–J–A)	2097	–.091	<.001	–.108	<.001
Autumn (S–O–N)	1213	.234	<.001	.056	.051
January	379	–.600	<.001	–.438	<.001
February	328	–.260	<.001	–.197	<.001
March	356	–.288	<.001	–.278	<.001
April	425	–.359	<.001	–.343	<.001
May	511	–.364	<.001	–.073	.097
June	648	–.404	<.001	–.374	<.001
July	734	–.129	<.001	–.146	<.001
August	715	.047	.209	.037	.321
September	444	–.217	<.001	–.050	.291
October	382	.421	<.001	.049	.339
November	387	.398	<.001	.082	.109
December	505	.028	.526	–.245	<.001

Table 2 As in Table 1, but by state

	Arkansas	Louisiana	Oklahoma	Texas
Number of nonzero damage county–months (1975–2010)	1137	162	836	3676
Pearson *r* (PDSI vs. damage)	–.366	–.170	.054	–.087
p value	<.001	.030	.119	<.001
Pearson *r* (PHDI vs. damage)	–.273	–.206	.250	–.210
p value	<.001	.008	<.001	<.001

of a positive correlation are present. Generally, stronger significant correlations are found between drought damage and the PDSI rather than the PHDI in the cooler months, with PHDI correlating more strongly in the hottest months (Table 3).

The relationship between drought duration and drought damage is quantified in Tables 4, 5, and 6. Results generally suggest that drought duration, defined as the number of consecutive months in which the drought index (PDSI and PHDI, respectively) falls below -1.0 for that county–month, is also linked (positively) to monthly drought damage (Table 4), especially for the PDSI. The presence of the weakest correlations in summer may be attributable to the fact that by the summer of a persistently dry early growing season, crop damage had already been caused and recorded, leaving little further damage to occur.

The relationship between drought duration and drought damage by state is shown in Table 5. The significant positive correlations in Texas and Arkansas (the latter for PDSI duration only) are not surprising, but again, the notion that long drought durations are associated with less damage in Oklahoma is counterintuitive. These results again may

Table 3 As in Table 1, but for Texas only

Month or season	Number of nonzero damage county–months (1975–2010)	r (PDSI vs. damage)	p value	r (PHDI vs. damage)	p value
Winter (D–J–F)	942	–.259	<.001	–.353	<.001
Spring (M–A–M)	953	–.413	<.001	–.184	<.001
Summer (J–J–A)	893	–.113	.001	–.276	<.001
Autumn (S–O–N)	888	.246	<.001	–.008	.818
January	286	–.699	<.001	–.511	<.001
February	261	–.323	<.001	–.238	<.001
March	289	–.345	<.001	–.323	<.001
April	299	–.431	<.001	–.372	<.001
May	365	–.404	<.001	–.145	.005
June	269	–.373	<.001	–.415	<.001
July	285	–.201	.001	–.262	<.001
August	339	.154	.005	–.278	<.001
September	232	–.395	<.001	–.219	.001
October	314	.470	<.001	–.040	.483
November	342	.413	<.001	.033	.545
December	395	.030	.557	–.346	<.001

suggest that alternative sources of water may prevent damage during long runs of dry hydroclimatic conditions.

The monthly correlations between drought duration and drought indices within Texas are displayed in Table 6. Significant positive correlations to the PDSI are observed for all seasons and for nine of the 12 months, with all nonsignificant months falling between May and August. A slightly weaker set of correlations to the PHDI were found, with only 5 months from January through August displaying significant positive correlations ($p < 0.05$). The reason for significant negative correlations between damage and the number of months of drought duration in June for both drought indices, and for November in the PHDI analysis, is unclear, excepting that a type I error can be expected to occur an average of 5 % of the time in a random distribution.

In recognition of the notion that drought damage may only be reported months after its occurrence, 12-month aggregated damage beginning on the month associated with a given drought index was computed and correlated with drought indices, again by county–month (Table 7). In general, these correlations were strong, but not quite as strongly negative as those for real-time monthly reported damage (compare Tables 1 and 7). Interestingly, at the state level for all states except Texas, many of the correlations become positive when damage is accumulated over the 12-month window (compare Tables 2 and 8). Perhaps losses can be mitigated over longer periods; as once the damage is done, there is little else to damage, even if the drought indices remain low for the duration of the 12-month period. Again, the small number of months with nonzero drought damage prevents an analysis by month and state. Nevertheless, results from Texas suggest that the 12-month aggregated drought damage shows similarly strongly significant correlations between aggregated losses and drought indices (Table 9), as compared with drought index correlated with damage reported in the concurrent month (Table 3). The dominance of Texas drives the trends in the entire dataset.

Table 4 Pearson correlations between drought duration (i.e., number of consecutive months with a drought index of −1.0 or below, beginning on the month when the damage is reported) and drought damage (2011 CPI-adjusted dollars), for county–months with nonzero drought damage totals, 1975–2010

Month or season	PDSI			PHDI		
	Number of nonzero damage county–months (1975–2010)	Pearson *r* (<−1.0 PDSI duration vs. damage)	*p* value	Number of nonzero damage county–months (1975–2010)	Pearson *r* (<−1.0 PHDI duration vs. damage)	*p* value
Winter (D–J–F)	841	.283	<.001	825	.052	.137
Spring (M–A–M)	992	.292	<.001	951	.341	<.001
Summer (J–J–A)	1332	.013	.630	1361	.015	.571
Autumn (S–O–N)	742	.274	<.001	647	–.160	<.001
January	253	.459	<.001	268	.080	.192
February	270	.243	<.001	238	.099	.129
March	302	.522	<.001	286	.432	<.001
April	254	.391	<.001	285	.483	<.001
May	436	.172	<.001	380	.250	<.001
June	412	.028	.568	389	–.023	.651
July	487	.024	.603	479	.012	.788
August	433	–.103	.032	493	.112	.013
September	322	.368	<.001	327	–.086	.120
October	205	.271	<.001	150	.047	.565
November	215	.088	.196	170	–.309	<.001
December	318	.188	.001	319	–.070	.216

Table 5 As in Table 4, but by state

	Arkansas	Louisiana	Oklahoma	Texas
Number of nonzero damage county–months (1975–2010) for PDSI	624	133	620	2530
Pearson *r* (PDSI vs. 12-month damage)	.113	–.022	–.181	.213
p value	.005	.802	<.001	<.001
Number of nonzero damage county–months (1975 − 2010) for PHDI	640	127	723	2291
Pearson *r* (PHDI vs. 12-month damage)	–.001	.005	–.228	.132
p value	.982	.959	<.001	<.001

5 Summary and conclusions

This research examined the relationships between drought intensity and duration (represented by empirically downscaled climate-divisional-level PDSI and PHDI data to the county level) and reported drought damage (standardized to 2011 CPI), across the 503

Table 6 As in Table 4, but for Texas only

Month or season	PDSI			PHDI		
	Number of nonzero damage county–months (1975–2010)	Pearson *r* (<−1.0 PDSI duration vs. damage)	*p* value	Number of nonzero damage county–months (1975–2010)	Pearson *r* (<−1.0 PDSI duration vs. damage)	*p* value
Winter (D–J–F)	695	.330	<.001	598	.177	<.001
Spring (M–A–M)	748	.241	<.001	714	.351	<.001
Summer (J–J–A)	574	.251	<.001	616	.220	<.001
Autumn (S–O–N)	513	.445	<.001	363	–.107	.042
January	202	.434	<.001	184	.226	.002
February	219	.246	<.001	174	.143	.060
March	251	.535	<.001	229	.554	<.001
April	195	.379	<.001	233	.534	<.001
May	302	.005	.938	252	.107	.091
June	207	–.288	<.001	184	–.386	<.001
July	213	.504	<.001	208	.525	<.001
August	154	.066	.413	224	.201	.003
September	166	.586	<.001	140	–.019	.827
October	163	.392	<.001	95	.174	.091
November	184	.192	.009	128	–.259	.003
December	274	.262	<.001	240	.102	.114

counties in a five-state region of the south-central USA. Despite some limitations of the datasets, this study is important because of its use of SHELDUS™, the only "widely used, nonproprietary, Web-based database" (Gall et al. 2009) of its kind, to address drought damage in terms of monetary losses. This research is also valuable because of its investigation of the role of lagging of drought reporting, which supports Gall et al.'s (2009) finding that a lag of coverage from ~180 to 600 days is possible in SHELDUS™. In addition, this study represents one of the first attempts to match the spatial and temporal scale of SHELDUS™ data with PDSI/PHDI index.

Results suggest that relatively few months (only 5749 of the 217,728 county–months) contained any drought damage, supporting the established notion that drought is underreported. Drought damage correlation with index does vary widely by state, with the more drought-exposed state of Oklahoma seeing weaker, and even positive correlations. Drought duration is also correlated with drought indices, with comparable strength between PDSI and PHDI. Furthermore, results suggest that even though drought intensity is an important predictor of simultaneous economic damage, drought damage for the next 12 months is also relatively predictable based on the current month's drought index. Nevertheless, it is likely that relatively little damage may occur near the end of a prolonged drought as compared to a shorter drought of the same intensity, because damage will have already been done in the longer drought, thereby weakening correlations between drought

Table 7 As in Table 1, but for aggregated 12-month drought damage beginning in the month of the index

Month or season	Number of nonzero damage county–months (1975–2010)	*r* (PDSI vs. damage)	*p* value	*r* (PHDI vs. damage)	*p* value
Winter (D–J–F)	5130	–.084	.000	–.081	.000
Spring (M–A–M)	5180	–.079	.000	.056	.000
Summer (J–J–A)	5668	–.137	.000	–.111	.000
Autumn (S–O–N)	5149	–.038	.007	–.071	.000
January	1758	–.144	.000	–.095	.000
February	1745	.007	.770	.023	.334
March	1748	.001	.966	.107	.000
April	1727	–.131	.000	.051	.036
May	1705	–.108	.000	.017	.484
June	1766	–.211	.000	–.099	.000
July	1959	–.228	.000	–.240	.000
August	1943	–.055	.016	–.049	.031
September	1839	–.049	.035	–.058	.013
October	1656	–.005	.839	–.055	.025
November	1654	–.062	.012	–.104	.000
December	1627	–.117	.000	–.138	.000

Table 8 As in Table 2, but for aggregated 12-month drought damage beginning in the month of the index

	Arkansas	Louisiana	Oklahoma	Texas
Number of nonzero damage county–months (1975–2010)	4464	1458	2898	12,271
Pearson *r* (PDSI vs. 12-month damage)	.170	.034	.191	–.219
p value	<.001	.197	<.001	<.001
Pearson *r* (PHDI vs. 12-month damage)	.306	.030	.259	–.215
p value	<.001	.253	<.001	<.001

intensity, duration, and damage. Moreover, drought damage appears to be reported at widely varying time lags and considerable variation may occur in the lag relationship across space and time of year, likely because different crops are grown in different parts of the study area and each crop has a different tolerance and resilience to drought intensity and duration. On the whole, drought indices appear to be useful indicators of drought damage, at least at the monthly temporal scale and/or county-wide spatial scale. This is an important finding, as long-lead climate outlooks continue to provide rapid improvement in our ability to anticipate, plan for, and mitigate the effects of incipient drought. Nevertheless, caution must be exercised in the extent to which drought index is used as a predictor of drought damage. Undoubtedly, the human factor also confounds the correlations. For example, irrigation practices differ spatially and temporally, thereby weakening the relationship, whether lagged or not.

Future research is needed in at least two areas related to this topic. First, a comprehensive analysis of the utility of SHELDUS™ for assessing drought damage should be

Table 9 As in Table 3, but for aggregated 12-month drought damage beginning in the month of the index

Month or season	Number of nonzero damage county–months (1975–2010)	PDSI		PHDI	
		r (PDSI vs. damage)	*p* value	*r* (PHDI vs. damage)	*p* value
Winter (D–J–F)	3100	–.182	<.001	–.209	<.001
Spring (M–A–M)	3083	–.166	<.001	–.007	.706
Summer (J–J–A)	3002	–.313	<.001	–.303	<.001
Autumn (S–O–N)	2985	–.231	<.001	–.360	<.001
January	1074	–.242	<.001	–.208	<.001
February	1068	–.022	.476	–.011	.720
March	1072	–.082	.007	.077	.011
April	1067	–.220	<.001	.004	.894
May	944	–.187	<.001	–.088	.007
June	1006	–.346	<.001	–.240	<.001
July	970	–.324	<.001	–.375	<.001
August	1026	–.277	<.001	–.292	<.001
September	1011	–.282	<.001	–.358	<.001
October	987	–.203	<.001	–.359	<.001
November	987	–.205	<.001	–.365	<.001
December	958	–.296	<.001	–.403	<.001

undertaken, perhaps by linking vulnerability model output to the damage estimates. Second, research is needed to understand more fully the role of policy and land use in exacerbating or mitigating drought damage. Moreover, future research should emphasize the application of a social–ecological resilience framework to examine the linkages between the exposure of residents and farmers to drought conditions, their vulnerability to that exposure (i.e., crop or property damages), and their ability to adapt, so that damages associated with future droughts can be mitigated.

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