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Gauging the Severity of the 2012 Midwestern U.S. Drought for Agriculture

Xiang Zhang [1,2], Chehan Wei [3], Renee Obringer [4], Deren Li [1,5], Nengcheng Chen [1,5,*] and Dev Niyogi [2,4,*]

1 State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS), Wuhan University, Wuhan 430079, China; zhangxiangsw@whu.edu.cn (X.Z.); drli@whu.edu.cn (D.L.)
2 Department of Agronomy-Crops, Soil, Environmental Science, Purdue University, West Lafayette, IN 47907, USA
3 Lyles School of Civil Engineering, Purdue University, West Lafayette, IN 47907, USA; wei188@purdue.edu
4 Department of Earth, Atmospheric, and Planetary Sciences, Purdue University, West Lafayette, IN 47907, USA; robringe@purdue.edu
5 Collaborative Innovation Center of Geospatial Technology, Wuhan 430079, China
* Correspondence: cnc@whu.edu.cn (N.C.); dniyogi@purdue.edu (D.N.); Tel.: +86-27-6877-9996 (N.C.); +1-765-494-6574 (D.N.)

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Abstract: Different drought indices often provide different diagnoses of drought severity, making it difficult to determine the best way to evaluate these different drought monitoring results. Additionally, the ability of a newly proposed drought index, the Process-based Accumulated Drought Index (PADI) has not yet been tested in United States. In this study, we quantified the severity of 2012 drought which affected the agricultural output for much of the Midwestern US. We used several popular drought indices, including the Standardized Precipitation Index and Standardized Precipitation Evapotranspiration Index with multiple time scales, Palmer Drought Severity Index, Palmer Z-index, VegDRI, and PADI by comparing the spatial distribution, temporal evolution, and crop impacts produced by each of these indices with the United States Drought Monitor. Results suggested this drought incubated around June 2011 and ended in May 2013. While different drought indices depicted drought severity variously. SPI outperformed SPEI and has decent correlation with yield loss especially at a 6 months scale and in the middle growth season, while VegDRI and PADI demonstrated the highest correlation especially in late growth season, indicating they are complementary and should be used together. These results are valuable for comparing and understanding the different performances of drought indices in the Midwestern US.

Keywords: agricultural drought; corn yield; drought index; drought severity; Midwestern US; PADI

1. Introduction

Drought is a major hazard that affects many different sectors around the world, especially agricultural production [1]. The 2012 US drought is one example of an extreme, widespread drought disaster which led to serious crop losses throughout one of the largest agricultural regions in the country [2]. In recent decades, studies have focused on a range of drought related topics, including basic concepts [3], monitoring [4], impacts [5], vulnerability [6], and mitigation [7]. In terms of monitoring, both univariate and multivariate drought indices have been proposed to assess the severity of meteorological, hydrological, and agricultural droughts separately and as a whole [8]. Severity is a major component during a drought event, which indicates a cumulative deficiency of a specified drought parameter below a critical level [9]. Drought severity should not be confused with other major components (i.e., intensity), therefore, it is worth highlighting the difference between these features [9,10]: (1) drought onset is the start of the water shortage period; (2) drought end represents the time when the water shortage becomes sufficiently small such that the drought conditions no longer persist; (3) drought duration is the period between the onset and end of a drought; (4) drought intensity is the average value of a specific drought parameter during which it is below some critical levels (this is measured by dividing the drought severity by the duration). The severity and intensity are easy to confuse and should be used with caution [9,11].

As stated earlier, both univariate and multivariate indices have been used to define and monitor drought. Examples of univariate drought indices include the Standardized Precipitation Index (SPI) [12], Standardized Soil Moisture Index (SSI) [13], Vegetation Condition Index (VCI) [14], and Standard Relative Humidity Index (SRHI) [15]. Examples of multivariate indices include the Standardized Precipitation-Evapotranspiration Index (SPEI) [16], Palmer Drought Severity Index (PDSI) [17], Palmer Z-index [18], VegDRI [19], and Process-based Accumulated Drought Index (PADI) [20]. A brief review of these indices can be found in AghaKouchak et al. [8]. Recently, a crop-specific SPEI was developed by Moorhead et al. by replacing reference evapotranspiration (ET) with potential crop ET to better represent actual water demand [21]. Additionally, the Soil Water Deficit Index (SWDI) was also developed by Martínez-Fernández et al. to represent soil water deficit during agricultural droughts and estimate field capacity and wilting point [22]. Finally, a nonparametric framework for standardized drought indices was also developed [23]. While these indices are routinely applied for drought assessment, a question remains regarding their abilities to capture the impacts caused by drought [24,25].

SPI is by far the most common index used for both drought monitoring and drought assessment in climatological studies [26]. Furthermore, Vicente-Serrano et al. found the SPI and SPEI were better at representing drought impacts on hydrological, agricultural, and ecological variables than other common drought indices [24]. However, as precipitation is only one variable in agricultural drought, it is postulated in this study that SPI alone is insufficient in its ability to capture agricultural drought impacts. This hypothesis was tested in our study. There are also anecdotal discussions within the drought community that highlighted the fact that drought, as revealed by some indices, is not accurately portrayed in terms of the corresponding yield loss [27,28]. This lack of correlation between drought indices and crop yield is thought to be a factor of the drought timing, local mitigation strategies adapted by farmers, and seed varieties [6].

Assessing the relationship between indices and impacts is critical. Without any way to assess crop loss, there is little value in monitoring agricultural drought conditions. Moreover, this study is urgent for drought assessment and for guiding ongoing and future drought mitigation strategies. Potopová et al. found SPEI had a relatively strong association with yield loss during critical growth stages of the crops (i.e., April to June in the study region) [29]. More recently, Bachmair et al. found that the drought indices best linked to impacts were SPI and SPEI with long accumulation periods (12–24 months) in the UK, and with short to intermediate accumulation periods (2–4 months) in Germany [25]. Additionally, the index-impact response varied spatially. For example, the Palmer Z-index was found to be the most appropriate index for Canadian prairies [30], SPEI has been shown to be advantageous for drought monitoring in Northern China [31], and the Scaled Drought Condition Index (SDCI) performed better than existing indices in the arid region of Arizona and New Mexico [32]. Therefore, the determination of the most suitable drought index requires site-specific research [33].

Since diverse drought indices are used in US [34], it is important to conduct local comparative performance analyses before selecting the optimal drought index. This study focuses on the 2012 agricultural drought in the Midwestern US as a case study, using six drought indices: SPI, SPEI, PDSI, Palmer Z-index, VegDRI, and PADI, and the United States Drought Monitor (USDM). We were particularly interested in the ability of PADI to compete with more traditional indices (i.e., SPI and PDSI), as PADI is a recent development in the drought index community [20]. The initial results in China demonstrated its advantages over SPI and PDSI [20]; however, PADI has not been tested in the US, and it has not been fully compared with other multivariate drought indices. Therefore, in this study, we first answer the question: How does a crop phenology dependent drought index, such as PADI, compare to precipitation-based SPI in capturing the 2012 Midwestern US drought? We then use the assessment to answer the broader question: What is the ability of different drought indices to capture agricultural drought severity and impact?

2. Study Area and Data

To investigate the impacts on agriculture during the 2012 drought and avoid influences from other land cover types (i.e., urban, grassland and wetlands), we extracted the cropland area in the Midwestern US, shown in Figure 1. The Midwestern US represents one of the most intense agricultural areas in the world. The 2012 Census of Agriculture identified the Midwestern US has a market value of 182 billion dollars, producing over 93% of corn and soybeans in the total US. Corn is the dominant crop in this area and therefore was selected for the impact assessment in this study. According to the 2013 Farm and Ranch Irrigation Survey (FRIS) conducted by the National Agricultural Statistics Service (NASS), US Department of Agriculture (USDA), irrigated farm land in Midwestern US is about 29.3%, while 70.7% is rain-fed [35], making it more susceptible to droughts caused by a precipitation deficit.

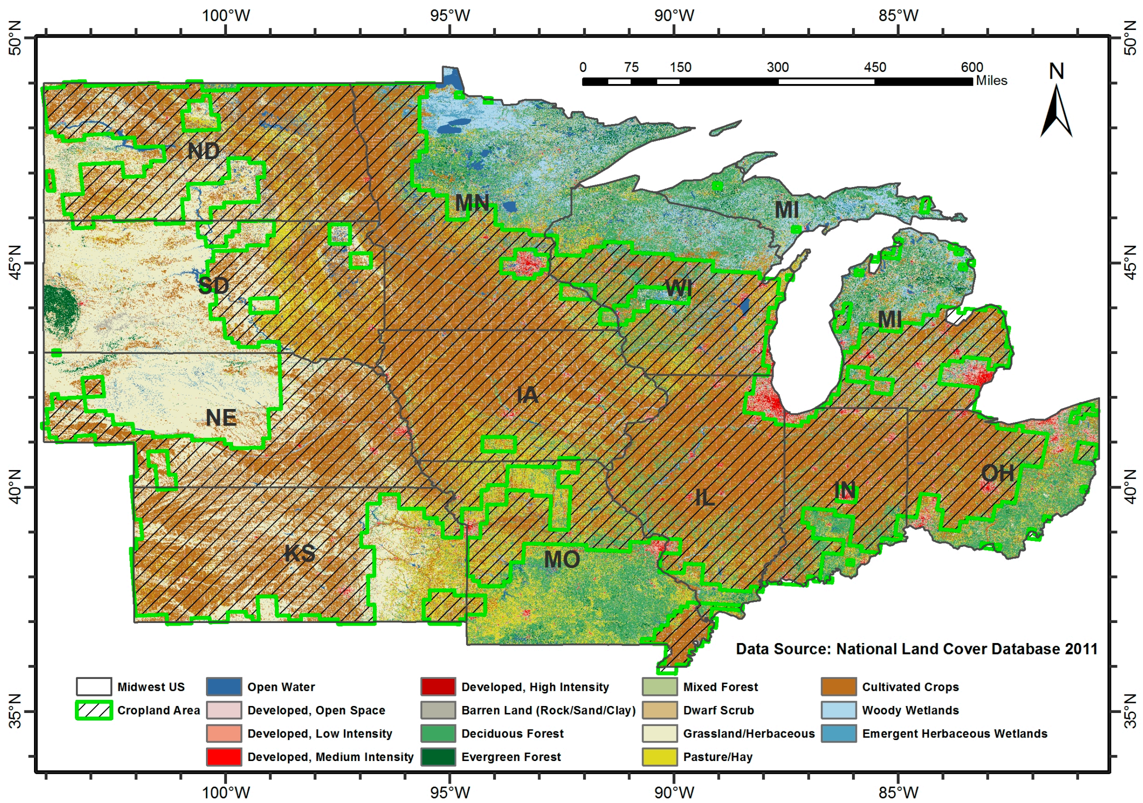

Figure 1. The study area of the cropland (lime green boundary) in Midwest US, which is consisted by 12 states, including North Dakota (ND), South Dakota (SD), Nebraska (NE), Kansas (KS), Minnesota (MN), Iowa (IA), Missouri (MO), Wisconsin (WI), Illinois (IL), Michigan (MI), Indiana (IN), and Ohio (OH).

Both precipitation and root zone soil moisture data from 1979 to 2013 are available from the North American Land Data Assimilation System-Phase 2 (NLDAS-2) maintained by the National Centers for Environmental Prediction (NCEP). Particularly, monthly total precipitation and root zone soil moisture were extracted from NLDAS Noah Land Surface Model L4 Monthly 0.125 $\times$ 0.125 degree V002 [36]. These datasets have been validated [37] and applied in the USDM and National Integrated Drought Information System (NIDIS) [38]. Root zone soil moisture was chosen due to its resistance to temporal environmental changes compared with surface soil moisture and its significances for agricultural production. Using the data described above, the SPI, Precipitation Condition Index (PCI), and Soil Moisture Condition Index (SMCI) were computed as described in the methodology section. In addition, the Advanced Very High Resolution Radiometer (AVHRR)-Vegetation Health Product (VHP) was obtained from the National Oceanic and Atmospheric Administration (NOAA) Center for Satellite Applications and Research. AVHRR-VHP is a reprocessed vegetation health dataset that includes multiple-indices (i.e., NDVI, VCI, and TCI) [39]. In this study, weekly VCI 4 km product from 2011 to 2013 was selected. Finally, data from the US Drought Monitor, VegDRI, Self-calibrated PDSI, SPEI, and Palmer Z-index were obtained for comparison. SPI and SPEI with 1–12 month scale were used in this study due to the relatively short growth period of corn. Details of these datasets are listed below in Table 1. It should be noted that the datasets have different spatio-temporal resolutions and this inconformity may affect the comparison results.

Table 1. Datasets used in this study.

No.	Name	Length of Time	Spatial Resolution	Temporal Resolution	Purpose	URL
1	NLDAS-2 Noah L4 (NLDAS_NOAH0125_ M.002))	1979–2013	0.125°	Monthly	Precipitation for PCI and SPI; Root zone soil moisture for SMCI	[40]
2	AVHRR VHP	2011–2013	4 km	Weekly	VCI	[41]
3	Corn growth	2012	/	/	Corn growth process	[42]
4	Multi-Resolution Land Characteristics Consortium (MRLC)	2011	30 m	/	Land cover	[43]
5	US Drought Monitor	2011–2013	/	Weekly	Comparison	[44]
6	VegDRI	2011–2013	1 km	Weekly	Comparison	[45]
7	Self-calibrated PDSI (sc_PDSI_pm)	2011–2013	2.5°	Monthly	Comparison	[46]
8	SPEI	2011–2013	0.5°	Monthly	Comparison	[47]
9	Palmer Z-index	2011–2013	0.125°	Monthly	Comparison	[48]

Corn phenology information in the Midwestern US was retrieved from the USDA NASS for 2012. Three different corn growth stages are defined with their different water-stress sensitivity coefficients [49] in Table 2 and Appendix A. Based on that, it was found reproduction stage (i.e., July) is particularly vulnerable.

Table 2. Corn phenology stages with corresponding water-stress sensitivity coefficients.

Period	Name	Definition	Sensitivity Coefficients
1	Vegetative	Planting through Silk (before silk)	0.25
2	Reproduction	Silk through Milk	0.50
3	Ripening	Milk through Maturity (after silk)	0.25

In addition, a decadal average (2002–2012) of the planting acreage and production weight of corn were also obtained from NASS at a county-scale. Using the decadal average, the yield anomaly index (YAI) [50] of every county was calculated for 2012. YAI is designed to identify deviation of yield for a particular year from its long term trend. Based on yearly corn yield data from NASS at county-scale, the YAI for a particular year is calculated using the following formula:

$$\mathrm{YAI} = (Y - \mu)/\sigma \tag{1}$$

where Y is the crop yield in the particular year, μ is the long term average yield, and σ is the standard deviation.

Additionally, the SPEI, self-calibrated PDSI, Palmer Z-index, VegDRI, and USDM datasets were obtained from the Global SPEI database [51], National Center for Atmospheric Research (NCAR) [52], West Wide Drought Tracker, United States Geological Survey (USGS), and National Drought Mitigation Center, respectively.

3. Methodology

3.1. Drought Evolution Process Analysis

Agricultural drought depends on the spatial and temporal variability of precipitation, soil moisture, and the availability of soil moisture to cover losses from evapotranspiration. As discussed in Zhang et al. [20], the determination of agricultural drought can be obtained by Evolution Process-based Multisensory Collaboration (EPMC) analysis.

In EPMC, there are four defined evolution phases in an agricultural drought, including: (a) Latency, (b) Onset, (c) Development, and (d) Recovery. Each phase corresponds to one critical change in the life cycle of an agricultural drought discussed below.

The latency phase describes the initial period of a precipitation deficit compared with the long-term mean. This is the start of a meteorological drought, but not the start for an agricultural drought. Due to irrigation and water storage in the soil, the root zone soil moisture will not decline dramatically during this phase. That is to say, the vegetation has not yet been influenced by the drought, though precipitation is below average.

The onset phase represents the period when the root zone soil moisture drops below the long-term mean. This phase indicates the start of water-stress in soil. It is known that not only different types of vegetation, but also vegetation at different growth stages, have different water-stress responses. For example, water-stress in early growth time will usually benefit deeper root development; on the contrary, water-stress in flowering time will result in serious production loss. We will take advantage of this information in calculating drought severity.

The development phase is the period during which the drought has fully developed. In this phase, the impacts on the vegetation caused by the drought can be detected. Here, the vegetation response to drought refers to long-term stable response by leaves, instead of daily response by stoma closure.

The recovery phase describes the period of water-recharge in soil. In this phase, enough rainfall helps to bring the root zone soil moisture back to normal, so the agricultural drought condition is eliminated. Though the precipitation and soil moisture return back to normal, the vegetation condition usually does not return.

Given this evolution process, it is more reasonable to take the preceding drought conditions into consideration when assessing drought impacts than to use the conventional method in which the conditions are refreshed periodically. To quantify these phases using a remote sensing-based approach, three indices were selected: the Precipitation Condition Index (PCI), Soil Moisture Condition Index (SMCI), and Vegetation Condition Index (VCI). PCI, SMCI, and VCI measure the deficit (or stress) of precipitation, root zone soil moisture, and vegetation in the background of more than 30 years. They use the following formula.

$$\mathrm{Index}_i = (Variable_i - Variable_{\mathrm{min}})/(Variable_{\mathrm{max}} - Variable_{\mathrm{min}}) \tag{2}$$

where Index_i is the PCI (or SMCI or VCI) value in month i, while $Variable_i$ is the precipitation/soil moisture/vegetation in month i. $Variable_{\mathrm{max}}$ and $Variable_{\mathrm{min}}$ are the pixel values of precipitation/soil moisture/vegetation in month i, and its maximum and minimum value during more than thirty years, respectively.

Before calculating the indices, outliers determined by a Grubbs test were excluded. PCI/SMCI values range from zero to one, corresponding to changes in precipitation/soil moisture conditions from extremely dry to water logging. For example, during periods of low precipitation, the PCI is close or equal to zero, while during flood conditions, the PCI is close to one [53]. The selection of the threshold for determining the anomaly is a key aspect of the EPMC analysis. We tested several different threshold values for PCI, SMCI, and VCI, and concluded that a value of 0.5 was adequate to represent an anomalous precipitation/soil moisture/vegetation event. This threshold also matched well with our previous study [20]. It is worth noting that the threshold used in the EPMC analysis may differ from place to place [9]. Overall, based on the EPMC method, the evolution process of an agricultural drought can be determined, and therefore, the time length of each phase can be obtained.

3.2. Drought Indices for Comparison

A total of six drought indices were compared and evaluated based on how they portrayed the spatio-temporal characteristics and severity of the 2012 Midwestern US drought. These indices included the SPI, SPEI, PDSI, Palmer Z-index, VegDRI, and PADI. These indices are benchmarked against the crop yield loss.

SPI was designed to be a relatively simple, robust index, which is based on precipitation alone [12]. Positive SPI values indicate greater than median precipitation, while negative values indicate less than median precipitation or drought conditions. Mathematically, the SPEI is similar to the SPI, but it includes the role of temperature, air humidity, wind speed, and solar radiation [16]. The SPEI takes into account both precipitation and potential evapotranspiration with the simplicity of calculation and the multitemporal nature of the SPI. SPEI bears the advantage of being a multi-scalar drought index and is attractive for drought monitoring and applications related to future climate change [26].

PDSI is a classical measure of drought due to moisture condition across regions and time [17], and has been widely used around the world [54]. In this study, a self-calibrated PDSI with Penman-Monteith potential evaporation was adopted [52]. The Palmer Z-index is similar to the PDSI, and reflects the departure of the meteorological conditions of a particular month from the average moisture climatology for that month, regardless of what has occurred in prior or subsequent months [18]. The VegDRI integrates satellite-based observations of vegetation conditions, climate data, and other biophysical information [19], and has shown considerable capability in US [28].

PADI represents the latest multivariate drought index and its application is guided by the EPMC framework, described above. PADI is used to assess the drought severity by integrating drought evolution processes from the EPMC analysis with crop phenology information (see Appendix B). A distinct feature of PADI is the accumulative severity, which quantifies since drought onset, instead of the monthly refreshed severity calculated in SPI or VegDRI.

4. Results and Discussion

4.1. Drought Evolution Process

The evolution of 2012 Midwestern US drought as determined by the EPMC is shown in Figure 2. In particular, the temporal evolutions of PCI (blue line), SMCI (brown line), and VCI (green line) in the study area from 2011 to 2013 were obtained. Corn growth period with three stages in 2012, thresholds, and four drought evolution phases with the inflection time points are marked. These three crop growth stages are marked as light green, green, and bottle green strips, respectively. These four phases are marked as faint yellow, orange, pomegranate, and light blue strips, respectively. An inflection time point presents the change of drought phases defined in EPMC. A period of time between two inflection points is the duration of one phase. It is shown in the figure that from 2011 to 2013, the drought emerged, evolved, and recovered several times. For the 2012 drought, the latency phase actually occurred around June 2011, as the PCI dropped from 0.53 to 0.44, crossing the threshold of 0.5 (discussed in the methodology section). This is the pre-phase of an agricultural drought with below-normal precipitation. Then the drought officially started around September 2011 when the SMCI decreased to 0.42 in response to the precipitation deficit. This is the start of the agricultural drought when root zone soil moisture shows deficit compared with normal value. It should be noted that VCI values were higher than normal when PCI and SMCI were lower than 0.5 during the end of 2011 and the start of 2012. There are several potential explanations for this unusual phenomenon; however, more experiments are needed. The drought persisted until July 2012, after which the development phase began with vegetation in the Midwest showing significant drought impacts. In other words, the length of onset phase in this drought was about 10 months. This time period is affected by multiple environmental variables, such as the timing of soil moisture deficit, follow-up rainfall amount, air temperature, wind speed, storage of underground water, and type of ground vegetation. Further investigation into the inherent reason that caused this long onset period is planned for future studies. It should also be noted that the SMCI reached over 0.5 in November and December 2011, while the PCI was still below 0.5. This indicates that the water deficit condition in this study area was still obvious and ongoing at that time. This means that the recovery phase did not occur, and the onset phase was still ongoing in the late months of 2011. The recovery phase of the 2012 Midwestern US drought occurred around May 2013 when PCI and SMCI returned to 0.67 and 0.62, respectively. Overall, the total life time of 2012 drought was 20 months.

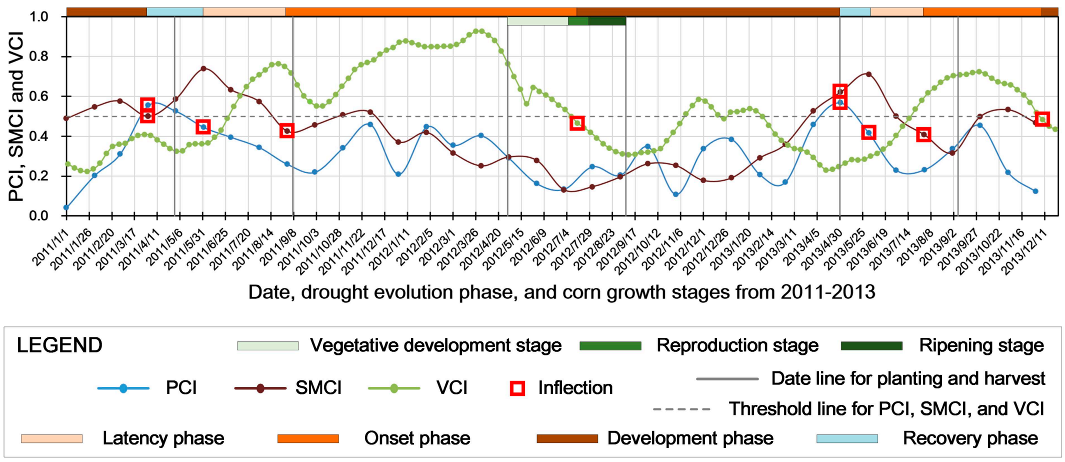

Figure 2. The temporal evolutions of PCI (blue line), SMCI (brown line), and VCI (green line) in the study area from 2011 to 2013 using the EPMC method. Corn growth period with three stages in 2012, thresholds, and four drought evolution phases with the inflection time points are marked. Vegetative development stage is marked as light green strip. Reproduction stage is marked as green strip. Ripening stage is marked as bottle green strip. Latency phase is marked as faint yellow strip. Onset phase is marked as orange strip. Development phase is marked as pomegranate strip. Recovery phase is marked as light blue strip. An inflection time point presents the change of drought phases defined in EPMC. A period of time between two inflection points is the duration of one phase.

Previous studies from Hoerling et al. [55] and Otkin et al. [28] suggested the 2012 Great Plain drought belonged to a "flash drought", as it developed rapidly in May 2012 and had reached peak intensity by that August. The total duration of this drought event is only 4 months. This result can be seen in Figure 2, where there was a dramatic decrease of vegetation condition and precipitation in May 2012. However, using the EPMC method, we found that this change was simply an intensification of long-term drought that had been developing since September 2011. In other words, the Midwestern US actually had been under water deficit long before May 2012, which was not found in previous studies. The key to this result was the use of multiple drought indices in the EPMC framework, through which the drought evolution process becomes traceable. Similar results were also obtained by replacing PCI and SMCI with SPI-1 and SSI-1, as shown in Supplementary Materials Figure S1. Therefore, our study demonstrated that this multi-index integrated analysis method was a useful way to uncover the creeping manifestation of agriculture drought.

Based on the above divisions of this drought event, the length of each drought phase can be calculated in days [20]. The corn growth phase in 2012 (30 April to 7 September, as shown in Figure 2) was impacted by 77 days of drought onset and 54 days of drought development. On the contrary, corn only had 6 days and 37 days of drought onset in 2011 and 2013, respectively. Therefore, only considering the drought duration, the 2012 drought can be considered highly notable. The sensitivity of corn to drought stress is higher in silking stage, but lower in grain filling (blister to dent) and vegetative development (pre-silking), as discussed by Niyogi and Mishra [56]. As shown in the Figure 2, the drought development phase started in the reproduction stages, indicating the potential for significant impacts on the corn yield, as shown in the statistical data [2]. This highlights how short periods of intense water stress can result in large crop yield reductions [28]. The above analysis illustrated the multi-index based analysis method for the evolution and interactions of hydrometeorological variables in forming an agricultural drought [57], as compared to a single indicator.

4.2. Drought Severity Assessment by USDM and Drought Indices

The abilities of different indices and the USDM to describe the spatio-temporal characteristics of agricultural drought are delineated and compared, as shown in Figures 3 and 4, Table 3, and Supplementary Materials Figure S2. Besides that, percentage of drought categories of 2012 Midwest drought from the perspective of different drought indices and USDM was provided in Figure 5. Based on this figure, we analyzed spatio-temporal evolutions of drought severity with its area proportion.

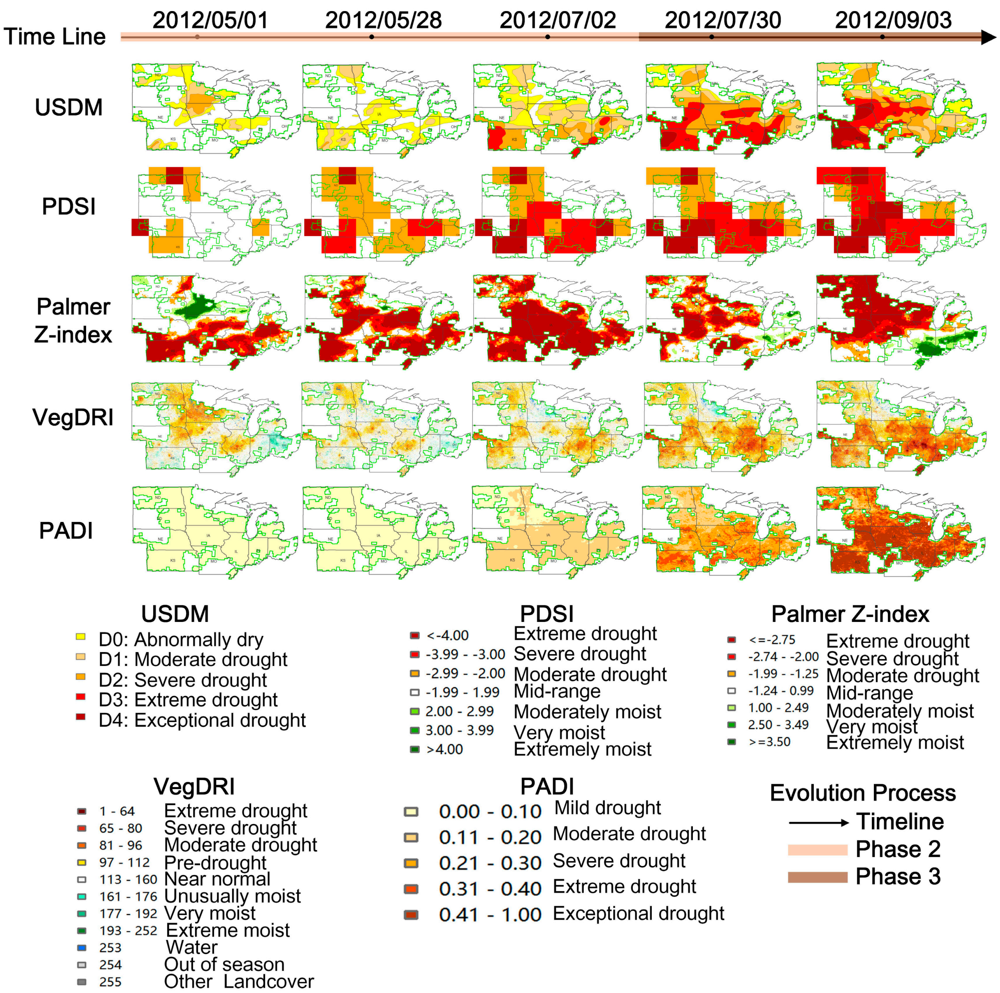

Figure 3. Spatio-temporal distribution of 2012 Midwest drought from the perspective of USDM, PDSI, Palmer Z-index, VegDRI, and PADI.

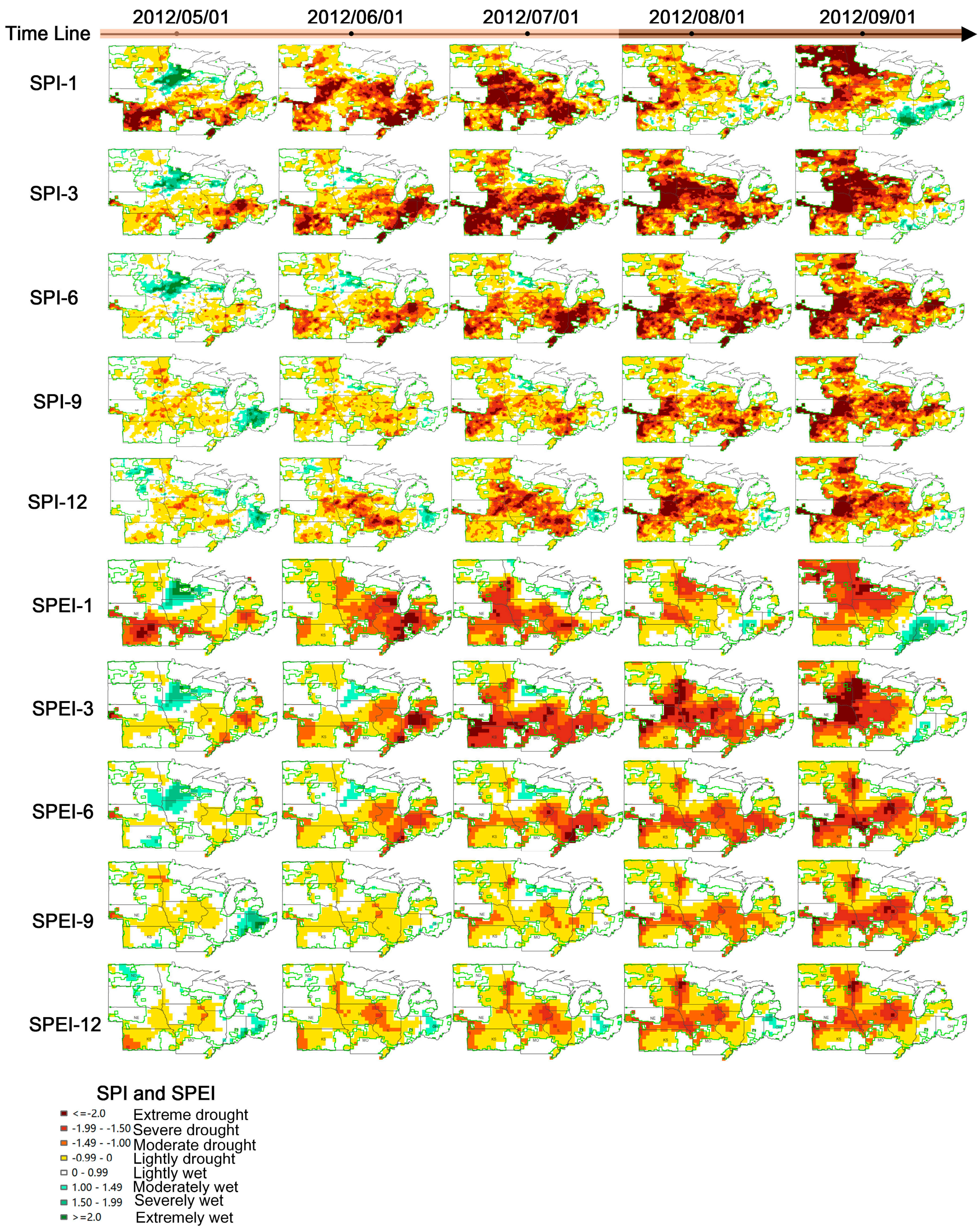

Figure 4. Spatio-temporal distribution of 2012 Midwest drought using SPI and SPEI from the time scale of 1 month to 12 month.

Due to the formulation and computational model used, several similarities and differences emerged: (i) southern and central regions, especially NE, KS, IA, and IL, were impacted the most during the 2012 Midwestern US drought. The minimum PDSI value in NE was down to −7.00, while the VegDRI value in IL was down to 5 in August 2012; (ii) USDM, VegDRI, and SPI-9 showed drought to emerge in MN and IA, while Palmer Z-index suggested that MN was quite moist. Specifically, the SPI-9 and Palmer Z-index values during May 2012 in MN were −0.21 and 2.86 respectively; (iii) most indices suggested drought relief in IL and IN from August to September (the PDSI increased from −3.60 to −2.67 and the Palmer Z-index increased from −0.38 to 1.54), however, only VegDRI and PADI still indicated extreme drought condition (PADI increased from 0.27 to 0.38). This demonstrates the unique feature of PADI, which is designed for accumulative drought impact assessment, instead of periodic refresh; (iv) PDSI and PADI agreed well with USDM in terms of the percentage of evolution. Spearman's rank correlation between PADI and USDM in percentage of different drought categories was 0.87 **, 0.27, 0.71 **, 0.80 **, and 0.83 **, respectively (two stars superscript indicated $p < 0.01$). There is lack of consensus among the indices regarding the spatio-temporal distribution of the 2012 drought. Results indicate that every index could represent its own aspect of drought severity per its definition. The crop phenology integrated drought severity assessment from PADI appeared to improve the impact assessment. As shown in Figure 5, as the drought evolved, so did the drought severity, due to the cumulative consideration in PADI model. For example, mild drought was 100% area in May, while 11.66% of them became moderate drought in 11 June. Then 29.57% area of moderate drought became severe drought in middle July. Note that PADI is not a drought "snapshot" but an accumulative index, similar to the idea of growing degree days which considers temperature (heat) accumulation.

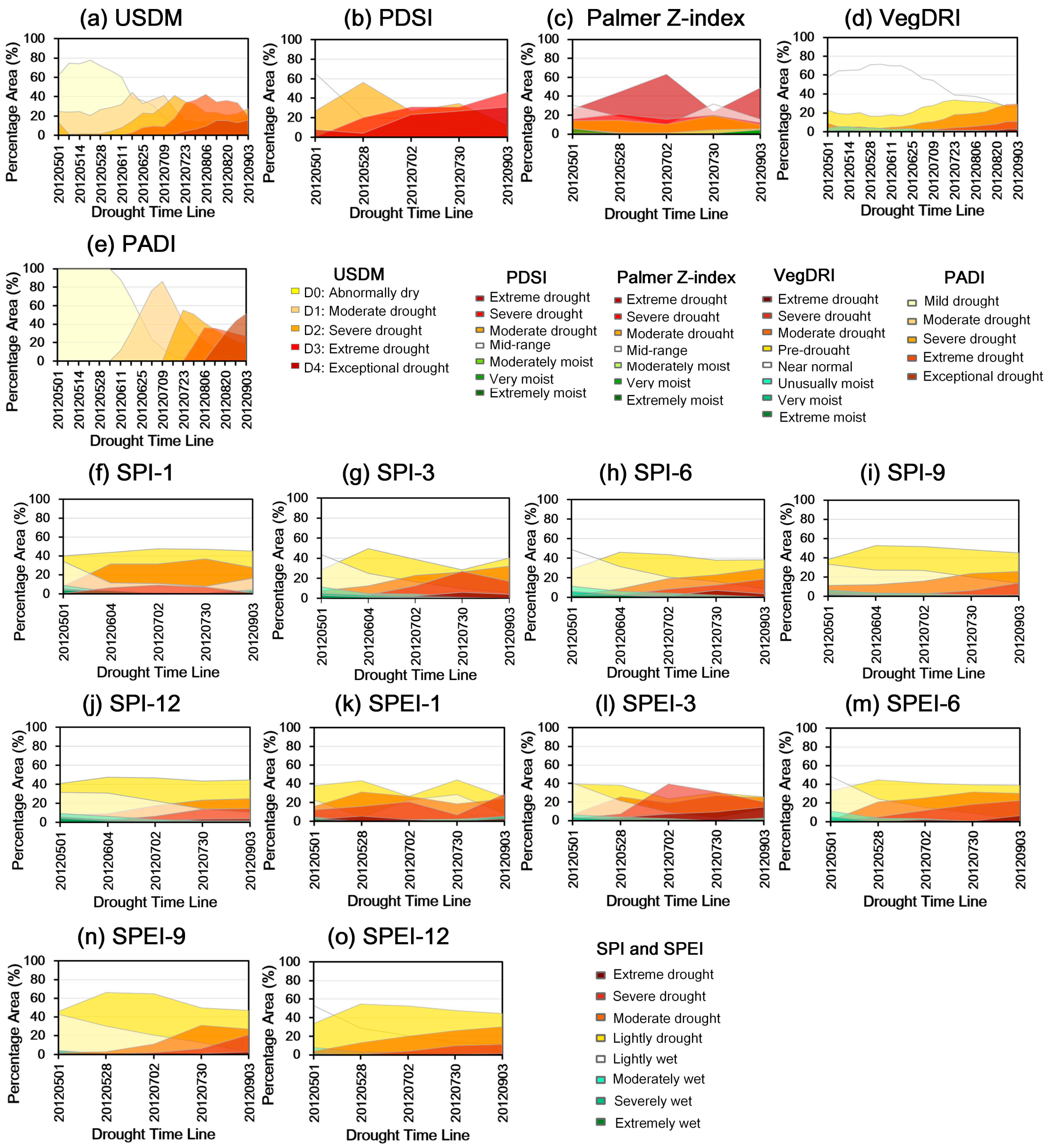

Figure 5. Percentage of drought categories of 2012 Midwest drought using different drought indices, including (**a**) USDM, (**b**) PDSI, (**c**) Palmer Z-index, (**d**) VegDRI, (**e**) PADI, (**f**) SPI-1, (**g**) SPI-3, (**h**) SPI-6, (**i**) SPI-9, (**j**) SPI-12, (**k**) SPEI-1, (**l**) SPEI-3, (**m**) SPEI-6, (**n**) SPEI-9, and (**o**) SPEI-12.

Table 3. Comparison between Different Drought Assessment Methods in Describing Drought Spatial-Temporal Distribution and Evolution.

Approach	Start	Middle	End	Overall
USDM	Central severe drought (MN and IA)	South extreme drought (KS, IL, and IN)	Southwest Exceptional drought (KS and NE)	Southern regions were more than the North; Widespread drought from July
PDSI	ND and MN, NE and KS, IN in moderate drought	ND, NE and KS	Extreme drought in ND, NE, KS, MN, IA	Widespread drought from June
Palmer Z-index	KS, IA, IL and IN in extreme drought; MN in moist	Almost all in extreme drought	IL, IN, and OH in moist; KS and MO in mid-range; others in extreme drought	Most severe drought result, especially in July
VegDRI	ND, MN, IA, and IL in moderate drought	Drought lessened but then enhanced, especially in NE, IL and IN	South in severe drought, especially in IL and MO	Move from north to south; Revived after June
PADI	All in abnormally dry	Moderate and severe drought, except ND, MN and OH	Extreme and exceptional drought, except ND	Southern regions were more than the North
SPI	Emerged in KS, IL and IN by SPI-1, -3 and -6; emerged in NE, MN, and IA by SPI-9 and -12	Worse drought and extreme drought in the south by SPI-1 to -6; small area of extreme drought in SPI-9 and -12	Drought relief in by SPI-1 and -3, especially in IL, IN and IA; Widespread severe and exceptional drought in other regions	More severe drought in SPI-3; More inter-month change in SPI-1; Similar spatial pattern by SPI-3 and -6, SPI-9 and -12 in most time
SPEI	Extreme drought in KS then in WI, IL, and IN by SPEI-1; Drought emerged in IL and IN by SPEI-3 and -6; Moderate drought in the central (MN, IL, and IA)	Worse drought by all SPEIs; More extreme drought in the central south (MN, NE, IA, and IL)	Drought relief in IL, IN and OH by SPEI-1; Extreme drought in the central regions (SD, NE, MN, and IA)	More severe drought in SPEI-3; Similar spatial pattern in SPEIs in most time

A comparison of the time series of PADI with the time series of VCI and SMCI can be found in Figure 6. The results from PADI are also useful in the harvest season, as a summary for the drought impacts on crop in question. Though the accumulated water deficit is also measured by PDSI, it does not correspond to the impact on agricultural production, which will be discussed in the next section. PADI overcomes this deficiency by directly integrating crop phenology and durations, which is further discussed below. However, in the early growth stages of the crop, the PADI may not fully capture drought severity and demonstrated its full capacity as shown in the above results. This limitation will also be discussed in Section 4.4. Therefore, it was suggested we should not use PADI alone. It should also be noted that the different sources of data used for computing the drought indices had different spatio-temporal resolutions, which could have affected the comparison between them.

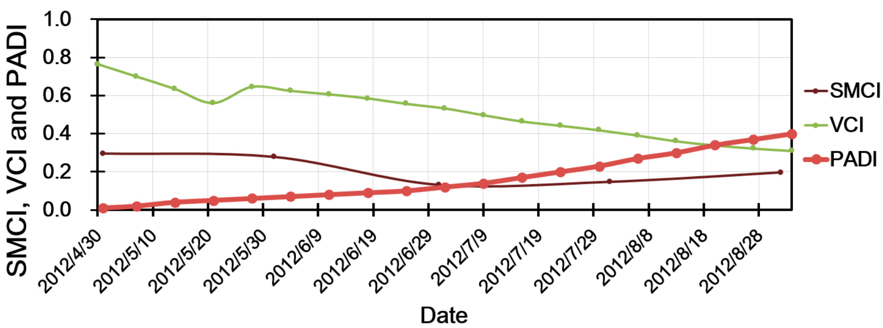

Figure 6. SMCI, VCI, and PADI values throughout the entire drought period.

4.3. Drought Severity Assessment from Yield Loss

With regard to agricultural drought, it is important to assess drought severity based on yield loss. A statistical estimate of crop yield loss caused by the 2012 US drought was demonstrated in Mallya et al. [2], but it has a limited value when gauging ongoing drought severity. In order to aid this process of linking crop loss to severity, we analyzed the performance of the different drought indices in indicating the final yield loss at county-scale. First, correlations between the yield anomaly index (YAI) and nine drought indices (PADI, PCI, SMCI, VCI, PDSI, VegDRI, Palmer Z-index, SPIs, and SPEIs) for September 2012 are given in Figure 7. Each point in Figure 7 represents one county in the study region. Another correlation analysis, shown in Supplementary Materials Figure S3, was also conducted taking only drought conditions into account. This analysis specifically tested the capability of these drought indices to indicate drought impacts. Using the Kolmogorov–Smirnov test at 5% significance level, it was found that the YAI was not normally distributed; therefore, the Spearman rank correlation coefficient (ρ) was used with corresponding p and n values. It should be noted that these datasets do have different periods; however the basic relationship will not be altered.

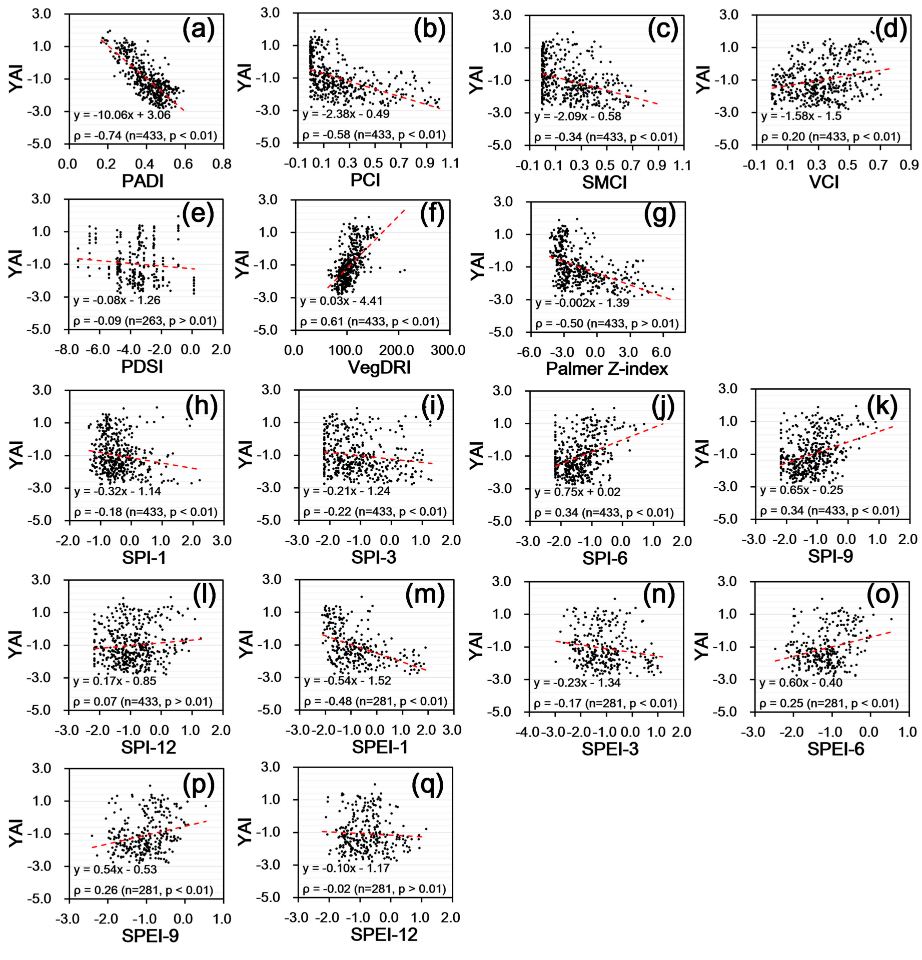

Figure 7. Scatter plot between yield (YAI) and drought indices for all counties in the study area, including (**a**) PADI, (**b**) PCI, (**c**) SMCI, (**d**) VCI, (**e**) PDSI, (**f**) VegDRI, (**g**) Palmer Z-index, (**h**) SPI-1, (**i**) SPI-3, (**j**) SPI-6, (**k**) SPI-9, (**l**) SPI-12, (**m**) SPEI-1, (**n**) SPEI-3, (**o**) SPEI-6, (**p**) SPEI-9, and (**q**) SPEI-12. The regression line and Spearman's rank correlation coefficient value (ρ) are also included.

It is shown that PADI had the highest correlation with YAI, with correlation value (ρ) of −0.74. In addition to PADI, VegDRI also performed well in identifying drought severity in terms of yield (ρ was 0.61, and 0.32 when only drought condition was considered). Out of the three univariate indices integrated in EPMC, PCI had good correlation with YAI (ρ was −0.58, and −0.54 when only drought condition was considered), which was consistent with the finding of Zhang et al. [20]. SMCI and VCI on the other hand had weak correlations, consistent with the findings of Otkin et al. [28]. Given that PADI is calculated by integrating SMCI and VCI, this correlation result demonstrated the added value of PADI in modeling drought severity by fusing multiple sources of information. The Palmer Z-index and PDSI had poor feasibility as an indicator for yield loss caused by drought. As meteorological drought indicators, SPI and SPEI also had weak correlations with YAI. Interestingly, the SPI showed better performance than SPEI. The highest correlation of 0.34 occurred in SPI-6 and -9 indices. The best SPEI index was the SPEI-1, with the highest correlation value of 0.48. This result indicated meteorological drought with 1–9 month scales had more significant impacts on corn yield loss in Midwestern US 2012. When only drought conditions were taken into consideration, similar patterns were observed: SPI-6 and -9 had the highest correlation values of 0.29 and 0.28, and SPEI-6 and -9 highest correlation values were 0.23 and 0.24.

As discussed in the Introduction, the crop-specific SPEI can improve the accuracy when calculating water balance for a specific crop land. Therefore, more studies will be needed in the future to test this crop-specific SPEI in quantifying drought severity compared with traditional SPEI. To assess the robustness of PADI in different sub-regions, its correlation with YAI was investigated for different states in the US Midwest as shown in Figure 8. It was found that PADI showed quite stable performance across the Midwest. Mean correlation value was −0.70, ranging from −0.38 (Missouri) to −0.87 (Michigan). Therefore, within the different drought indices considered, PADI was a good indicator for quantifying drought severity from yield loss. In terms of impact assessment, studies suggested that soil moisture can be one but not the only aspect in assessing agricultural drought severity. This is reflected in the correlation between YAI and SMCI which was only −0.34. Again, PADI as an integrative index, demonstrated the value added by combining soil moisture with drought duration and crop phenology.

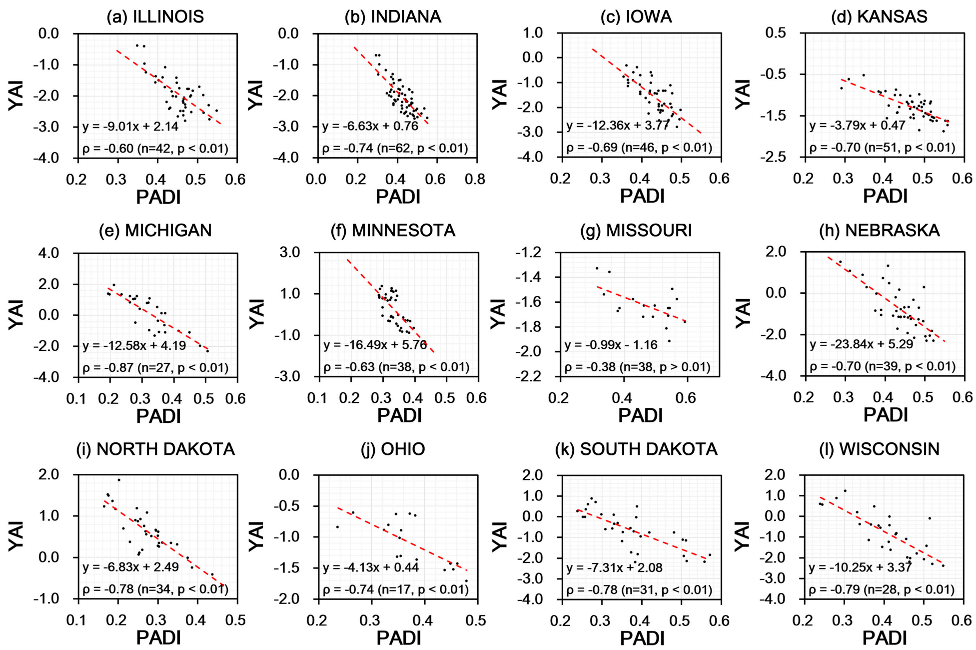

Figure 8. Scattering plot between YAI and the final PADI value in September, 2012 in twelve states of Midwest, including (**a**) Illinois, (**b**) Indiana, (**c**) Iowa, (**d**) Kansas, (**e**) Michigan, (**f**) Minnesota, (**g**) Missouri, (**h**) Nebraska, (**i**) North Dakota, (**j**) Ohio, (**k**) South Dakota, and (**l**) Wisconsin. Linear regression line and Spearman's rank correlation value were given as well.

As shown in Table 4, in different states with different irrigation rates, there was a small advantage of soil moisture integrated drought index (i.e., PADI and VegDRI) in irrigated area compared with drought indices without soil moisture information (i.e., SPI-1 and SPEI-1). In less irrigated area, this advantage was greater. However, it is difficult to quantify the value added by soil moisture in PADI and VegDRI; therefore, we conclude that adding soil moisture alone could lead to a theoretical improvement in agricultural drought assessment, however, this single improvement not be obvious in yield loss analysis due to the complex mechanism of agricultural drought and crop yield. There are many variables that play roles in causing an agricultural drought, and as many as possible should be taken into consideration when assessing the impacts of such droughts.

Table 4. Spearman's rank correlation value between PADI, VegDRI, SPI-1, SPEI-1 and YAI in four Midwestern states. The percentage of irrigated area in each state was also provided. Two star superscript (**) indicates $p < 0.01$.

Drought Index	More Irrigated Land		Less Irrigated Land	
	MO (55.8%)	NE (38.4%)	SD (14.0%)	ND (15.2%)
PADI	−0.38	−0.70 **	−0.78 **	−0.78 **
VegDRI	−0.26	−0.30	0.74 **	0.00
SPI-1	0.41	0.04	0.16	−0.23
SPEI-1	0.36	0.32	0.17	0.16

4.4. Temporal Variation of Drought Severity Assessment

To further investigate the temporal variation of the PADI assessment, we analyzed the relationship between PADI and yield loss over time. Figure 9 shows the correlation coefficient variations from the beginning of the drought to the end. First, continuous improvements were found from about 0.2 to 0.7, indicating PADI could provide a more reliable drought severity assessment as an accumulative drought index. Second, correlation improvements were significant from mid-July onward when the intensification phase of 2012 Midwestern US drought began. In August, one month before the end the drought, the correlation between YAI and PADI began to reach a significantly high level (coefficient around 0.7). This suggests corn yield scenarios can be precisely constructed from the PADI at approximately one month prior to harvest time. Therefore, an integrative phenology based index such as PADI is a good indicator of the amount of yield loss due to drought stress especially in late growing season.

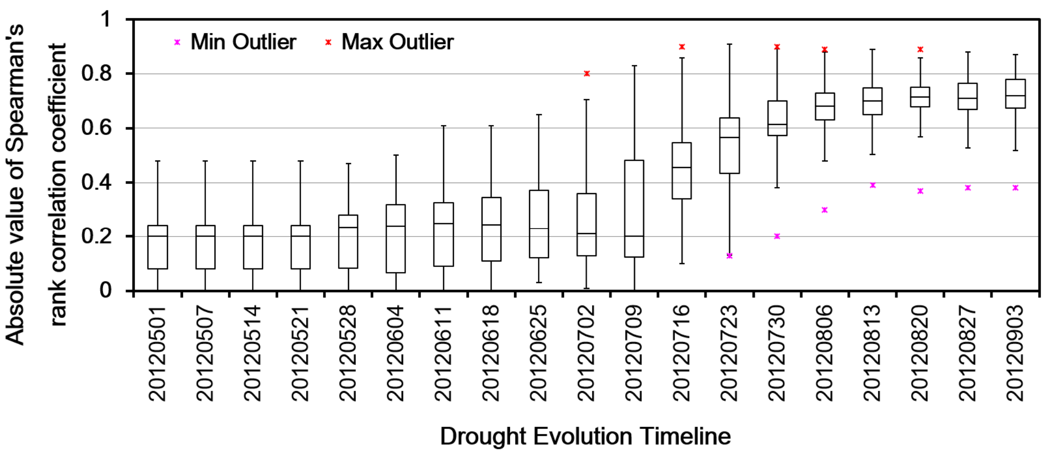

Figure 9. Box plots of correlations between YAI and PADI from the beginning of drought to the end in twelve states in the Midwest. Spearman's correlation coefficients were considered only at significant level of 1%.

Results from Otkin et al. [28] demonstrated that correlation first increased but then decreased along time between conventional drought indices (SPI, Evaporative Stress Index, and soil moisture mean value) and corn yield loss. The strongest correlations existed only in critical crop growth stages, such as July for corn. In this experiment, we calculated the correlation between SPI-12 and corn yield anomaly index from May to September, as shown in Figure 10. It was found that the coefficients exhibited a convex shape. In other words, the coefficients were higher in July (mean value was 0.54), while lower in May and September (mean value was 0.39 and 0.44, respectively). By comparing with PADI performance, it was found that: (1) Overall, SPI-12 performed better than PADI in May and June (0.39 vs. 0.19; 0.49 vs. 0.25), fairly in July (0.54 vs. 0.46), worse than PADI in August and September (0.53 vs. 0.68; 0.44 vs. 0.70). Mean coefficient value was used here for comparison; (2) The highest mean coefficient from PADI is higher than that in SPI-12 (0.70 vs. 0.54); (3) The number of coefficient with $p < 0.01$ is 98.7% in PADI results, while 46.7% in SPI-12. This difference represents the spatial robustness of PADI compared to SPI-12 in Midwestern US. Therefore, based on the above analyses, SPI-12 was a good indicator in the early growing season, while its performance in late growing season and spatial robustness were two limitations when compared to PADI. This highlights the distinctive differences between PADI and a common non-accumulative drought index. However, given the limitations of PADI, we also suggest a more appropriate and complete evaluation results can only be obtained by using PADI and other indices together.

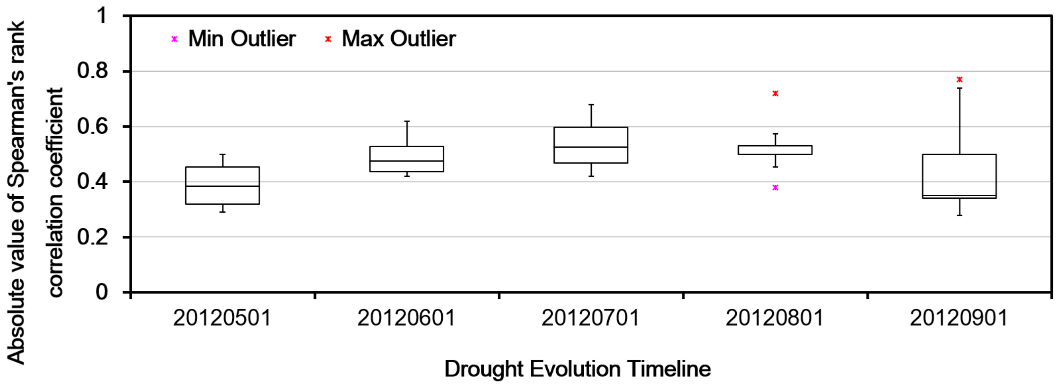

Figure 10. Box plots of correlations between YAI and SPI-12 from the beginning of drought to the end in twelve states in the Midwest. Spearman's correlation coefficients were considered only at significant level of 5%.

When further analyzing the coefficient of SPI and SPEI for different temporal scales and months, more results and details were found, as shown in Table 5: (1) Both SPI and SPEI in middle growth season had the highest coefficients with YAI. (2) SPI basically performed better than SPEI, which is consistent with the results in Section 4.3. (3) SPI-6 and SPEI-6 were the two best indicators to represent yield loss among all SPIs and SPEIs. (4) Compared with PADI, SPI was basically better from May to July, worse in August and September.

Table 5. Spearman's rank correlation value of multi-time scale SPI and SPEI with YAI from May to September. Two star superscript (**) indicates $p < 0.01$. SPI-6 and SPEI-6 were marked in bold to show their superior abilities in representing yield loss anomaly. Sampling size of SPI and SPEI was 433 and 281, respectively.

Index	May	June	July	August	September		May	June	July	August	September
SPI-1	0.42 **	0.54 **	0.43 **	−0.21 **	−0.18 **	SPEI-1	0.19 **	0.58 **	0.27 **	−0.23 **	−0.48 **
SPI-3	0.48 **	0.51 **	0.63 **	0.40 **	−0.22 **	SPEI-3	0.25 **	0.41 **	0.40 **	0.34 **	−0.17 **
SPI-6	**0.37 ****	**0.53 ****	**0.63 ****	**0.59 ****	**0.34 ****	**SPEI-6**	**0.12**	**0.41 ****	**0.47 ****	**0.40 ****	**0.25 ****
SPI-9	0.04	0.38 **	0.44 **	0.52 **	0.34 **	SPEI-9	−0.10	0.13	0.17 **	0.31 **	0.26 **
SPI-12	0.30 **	0.46 **	0.39 **	0.22 **	0.07	SPEI-12	0.31 **	0.46 **	0.35 **	0.08	−0.02

The correlation analysis between VCI and yield anomaly index from May to September was also conducted, as shown in Figure 11. Overall, the correlation coefficient showed double peaks. On peak reached up to 0.60 on 25 June and the other reached up to 0.66 on 30 July. While the lowest correlation coefficients around 0.30 occurred at the beginning and end of this drought. The second feature of this correlation result was that only 26.3% of coefficient values with $p < 0.05$ were obtained. This fact indicates a spatially instable relationship between VCI and YAI across the Midwestern US, which is a contrast to that of PADI. When comparing the correlation results of VCI with PADI, the performance of PADI is still remarkable. The correlation improvements were significant since mid-July. And in August, one month before the end the drought, the correlation between YAI and PADI began to reach a significantly high level (coefficient value was around 0.7). So the coefficient improvement of PADI is more smooth and stable across the Midwestern US.

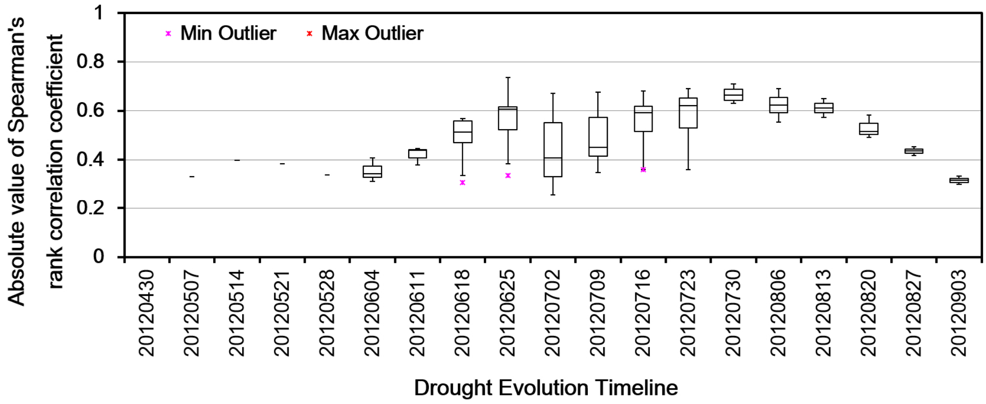

Figure 11. Box plots of correlations between YAI and VCI from the beginning of drought to the end in twelve states in the Midwest. Spearman's correlation coefficients were considered only at significant level of 5%.

4.5. Drought Severity Assessment by Combing Multple Drought Indices

To test the ability of multiple drought indices in simulating crop losses, a multi-linear regression analysis was conducted as shown in Table 6. Several representative drought indices were selected, including SPI-6 and SPEI-6 in July, VCI on 30 July, VegDRI and PADI in September. Total 281 counties were selected as they have all these drought indices values. Precipitation-based and vegetation-based drought indices were combined together, such as SPI and VCI. It was found all these combinations achieved good regression results with $p < 0.01$ at 5% significant level. While the coefficient of determination ranges from 0.23 (when using SPEI and VCI) to 0.63 (when using SPI and PADI or SPI, VegDRI, and PADI). Overall, the combination of multiple drought indices did not significantly improve the ability in simulating crop yield losses. Similar results were also found by [33]. So it was suggested multiple drought indices should be used separately in this case study.

Table 6. Multi-linear regression analysis between representative drought indices and yield loss. One star symbol (*) represents the multiplication function. Regression size of 281 was used here.

No.	Indices	Regression Formula	R^2	Significant Level	p	RMSE
1	SPI, VCI	YAI = 0.71 * SPI + 1.34 * VCI−0.97	0.38	0.01	0.00	0.76
2	SPEI, VCI	YAI = 0.52 * SPEI + 1.62 * VCI − 1.46	0.23	0.01	0.00	0.95
3	SPI, VegDRI	YAI = 0.48 * SPI + 0.02 * VegDRI − 2.58	0.38	0.01	0.00	0.76
4	SPEI, VegDRI	YAI = 0.18 * SPEI + 0.03 * VegDRI − 4.20	0.33	0.01	0.00	0.82
5	**SPI, PADI**	**YAI = 0.37 * SPI − 8.86 * PADI + 2.84**	**0.63**	**0.01**	**0.00**	**0.46**
6	SPEI, PADI	YAI = 0.28 * SPEI − 10.00 * PADI + 3.11	0.60	0.01	0.00	0.50
7	SPI, VCI, VegDRI	YAI = 0.45 * SPI + 1.22 * VCI + 0.01 * VegDRI − 2.92	0.42	0.01	0.00	0.72
8	SPEI, VCI, VegDRI	YAI = 0.15 * SPEI + 1.29 * VCI + 0.03 * VegDRI − 4.52	0.37	0.01	0.00	0.78
9	**SPI, VegDRI, PADI**	**YAI = 0.32 * SPI + 0.004 * VegDRI − 8.63 * PADI + 2.26**	**0.63**	**0.01**	**0.00**	**0.46**
10	SPEI, VegDRI, PADI	YAI = 0.18 * SPEI + 0.01 * VegDRI − 9.09 * PADI + 1.66	0.61	0.01	0.00	0.48

4.6. Comprehensive Comparison

As shown in Table 7, a comprehensive comparison was conducted to demonstrate the differences of these drought indices in gauging the severity of 2012 Midwestern US drought. Their variables, modeling approaches, performances in drought severity, correlation with YAI, and features were analyzed.

Table 7. Comprehensive comparison between PADI and other drought indices.

No.	Index	Variables	Modeling Approaches	Drought Severity	Correlation with YAI	Features
1	SPI	Precipitation	Standardized precipitation deficit	Rapid changes in short term time scales; slow changes in long term scales	High in middle growth season; SPI-6 with the highest correlation (0.63) in July	Different performances among different time scale SPIs
2	VCI	Vegetation	NDVI anomaly	The most visible severity of agricultural drought	Weak correlation during middle June to middle July (0.4~0.5)	Impacted by multiple variables besides drought
4	SPEI	Precipitation Reference evapotranspiration	Standardized deficit of precipitation and reference evapotranspiration	Rapid changes in short term time scales; slow changes in long term scales	High in middle growth season; SPEI-1 with the highest correlation (0.58) in June	Significant different performances among different time scale PEIs
5	PDSI	Temperature Precipitation Available water content	Relative dryness based on water balance model	Middle resolution of severity	No significant correlation with yield loss in late growth season	Sensitive to the method used to calculate potential evapotranspiration
6	Palmer Z-index	Temperature Precipitation Available water content	Relative dryness based on water balance model	Overestimate severity in July	No significant correlation with yield loss in late growth season	Sensitive to short term precipitation
7	VegDRI	Temperature Precipitation Seasonal greenness Available water content Biophysical condition	Data mining algorithm based on climate, vegetation, and biophysical data	High resolution of severity	Significant correlation with yield loss in late growth season (0.61)	Hard to interpret its physical meaning
8	PADI	Precipitation Soil moisture Vegetation Phenology	Accumulated severity based on drought process and crop phenology	Progressive severity accumulation; consistent with USDM	Significant correlation with yield loss in late growth season (−0.74)	Not suitable for flash drought

5. Conclusions

Gauging the severity of drought is critical for precisely assessing drought impacts. It becomes more challenging due to numerous drought indices we have [34]. This study investigated the severity of the 2012 Midwestern US drought based on several popular drought indices, including precipitation based, vegetation based, and hybrid indices. In particular, PDSI, Palmer Z-index, VegDRI, PADI, SPIs, SPEIs, were compared along with the USDM. The drought severity was assessed from three aspects: spatial distribution, temporal evolution, and crop impacts. This study had several new findings in assessing 2012 US drought compared with existing studies [2,28,33,55]. It was concluded as follows.

According to EPMC analysis, the duration of the 2012 Midwestern US agricultural drought was 20 months. It began as a meteorological drought around June 2011, developed into a minor agricultural drought around September 2011, intensified around July 2012, and was eliminated by May 2013. This finding is different from previous studies [28,55], which suggested this drought belonged to a "flash drought", as it developed rapidly in May and reached peak intensity by August. And the total duration of this drought event was only 4 months. Based on our analysis, not only this dramatic change was detected, but also found this change was just the intensification of long lingered 2012 drought since September 2011. In other words, the Midwestern US actually had been under water deficit long before May 2012, which was ignored by previous studies. Only few studies like [2,33] has revealed part of this fact. Therefore, our study demonstrated this multi-index integrated analysis was able to fully uncover the creeping manifestation of agriculture drought.

Although drought spatial distribution of severity varied among different indices as pointed out by [2], southern and central regions, especially NE, KS, IA, and IL were impacted most during the 2012 Midwestern US drought. Different drought emerging places and relief places were determined by different indices. For example, most indices suggested drought relief in IL and IN from August to September (PDSI increased from −3.60 to −2.67, Palmer Z-index increased from −0.38 to 1.54); however, only VegDRI and PADI still indicated extreme drought condition (PADI increased from 0.27 to 0.38). The unique feature of PADI is also distinct, which is designed for accumulative drought impact assessment, instead of periodic refreshment.

According to PADI, 51% of the Midwest was impacted by exceptional drought, 27% by extreme drought, and nearly 20% by severe drought, and KS, IA, MO, WI, and IL had the most impact, which is basically consistent with [55]. Moreover, PDSI and PADI agreed well with USDM in terms of the percentage of evolution. Spearman's rank correlation between PADI and USDM in percentage of different drought categories was 0.87 **, 0.27, 0.71 **, 0.80 **, and 0.83 **, respectively. This finding highlights the advantage of considering an accumulated drought impact index.

With regard to the ability in representing yield loss by drought stress, PADI and VegDRI had the highest significant correlation with corn yield loss (ρ was 0.74 and 0.61, $p < 0.01$), better than precipitation, soil moisture, or vegetation based index alone in September. It was also found that PADI showed quite stable performance across the Midwest. Mean correlation value was −0.70, ranging from −0.38 (Missouri) to −0.87 (Michigan). In addition, strong correlation between PADI and corn yield was noted a month before harvest (ρ was around 0.7, $p < 0.01$) and increased substantially until the end of the drought event. This result highlighted the value of PADI in quantifying the drought impacts [2] using a remote sensing-based approach.

For comparison, the coefficient of SPI/SPEI with YAI was higher in July (mean value was 0.63 when using SPI-6), while lower in May and September (mean value was 0.37 and 0.34, respectively using SPI-6). This result emphasized the importance of choosing a critical period when using SPI/SPEI [29], and an appropriate time scale is also vital [25]. Although both SPI and SPEI in middle growth season had the highest coefficients with YAI, SPI basically performed better than SPEI. This finding highlights the effectivity of SPI [26], but it is different from [24,31] which suggested SPEI was better. The correlation coefficient of VCI with YAI showed double peaks. On peak reached up to 0.60 on 25 June and the other reached up to 0.66 on 30 July. While the lowest correlation coefficients around 0.30 occurred at the beginning and end of this drought. Besides that, the number of coefficient values with $p < 0.05$ was only 46.7% and 26.3% in SPI and VCI, while this number was 98.7% in PADI. PDSI and Palmer Z-index had weak correlation with yield loss, which is consistent with [24] but different from [30]. The above comparison between this study and previous studies did not represent which one is right or wrong because of different drought assessment approaches. Instead, this discrepancy highlights the importance of site-specific drought research [33] and a standardized drought database for thorough comparison in the future. Based on this study, PADI is especially more suitable in late period of drought event, while it should also be used together with other indices like SPI in early and middle drought periods.

This study demonstrated the advantages and limitations of different drought indices in drought monitoring. In particular, distinct features of hybrid drought index like PADI have been found, compare to only precipitation-based SPI, vegetation-based VCI, and other hybrid indices. This is the first comprehensive analysis of PADI in US, as there was only a brief discussion in China before [20]. Although this study selected the 2012 Midwestern US drought as a case study, it also can be easily applied over other regions. And we also emphasis that we should not use single drought index alone.

Supplementary Materials: The following are available online at www.mdpi.com/2072-4292/9/8/767/s1, Figure S1: The temporal evolution from 2011 to 2013 of SPI-1, SSI-1, and VCI in the study area under the

EPMC, Figure S2: Details of 2012 Midwest US drought evolution spanning from May to September 2012 from perspectives of multi-drought indices, including USDM, PDSI, Palmer Z-index, VegDRI, PADI, 1–12 month SPI, and SPEI, Figure S3: Scattering plot between YAI and nine drought indices (PADI, PCI, SMCI, VCI, PDSI, VegDRI, Palmer Z-index, SPIs (SPI-1, -3, -6, -9, and -12) and SPEIs (SPEI-1, -3, -6, -9, and -12)) based on all counties in the study area, Figure S4: Selected nine climate divisions in the study area for testing the relationship between drought category and yield loss, Figure S5: Drought category and corresponding yield anomaly index of USDM, PDSI, Palmer Z-index, VegDRI, PADI, SPIs, and SPEIs with YAI in the early growth season (May), Figure S6: Same as Figure S5, except in the middle growth season (July), Figure S7: Same as Figure S6, except in the late growth season (September).

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Author Contributions: X.Z. and D.N. conceived and designed the experiments; X.Z. performed the experiments; R.O. and C.W. collected the data and assisted in the experiment; D.L., N.C. and D.N. assisted in the result analysis and provided overall guidance; X.Z. and D.N. wrote the paper; All authors reviewed and edited the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

McWilliams et al. found that the largest yield reduction occurred with water-stress at silking, and the total reduction was 50% [49]; for the stage before and after silking, the total reduction was 25% respectively, which meant silking stage was most sensitive to the stress, and then the stage before and after silking. Therefore, water-stress coefficients of 0.25, 0.50, and 0.25 were used in this study to represent degree of the corn response to drought condition. The similar result appears in Denmead and Shaw, which pointed out that moisture stress prior to silking reduced grain yield by 25%, moisture stress at silking reduced grain yield by 50% and moisture stress after silking reduced grain yield by 21% [58]. Many commons are that the most sensitive period for drought stress in corn is during the period between silk emergence and the blister stage (one stage before Milk). Therefore, based on the above research, we divided the corn period to three stages, and defined their sensitivity coefficients shown in the Table 2.

The exactly starting date of period 1, 2 could be acquired from the Crop Progress data in USDA NASS [42]. According to the USDA, an acre would be considered in or beyond a phenological stage when 50 percent or more of the plants in that acre are in or beyond that stage. Therefore, we can know when 50% or more of the corn develop to stage 1 (planted) and stage 2 (silking) to determine the start dates of each of them, respectively. For the start date of stage 3, according to McWilliams et al. [24], it was defined by "20 days after silking". But we only have the statistics of the next stage: Dough. And it is defined as "26 days after silking". Therefore, we define "the date when 50% or more of the plants in that acre are in or beyond Dough stage, minus 6 days "as the start date of stage 3. For the end of each stage, we use one date before new stage start. And the end of stage 3 is the time when 50% or more of the corn develop to stage maturity.

Appendix B

Based on the drought evolution process (i.e., onset and development phases) obtained by EPMC, PADI assesses the agricultural drought impacts by integrating it with crop phenology [20]. In particular, PADI combined the different water-deficit sensitivities during different crop growth stages with drought evolutions. The concept of PADI is defined as the crop accumulated drought severity from its growth. The calculation of PADI begins when both crop growth and agricultural drought exist. Its formula is proposed as below:

$$\mathrm{PADI}_t = \mathrm{PADI}_{t-1} + \frac{\sum_{i=1}^{n} [(T \cap s_i \cap p_2) * \lambda_i * (1 - SMCI_t) + (T \cap s_i \cap p_3) * (1 - VCI_t)]}{\mathrm{PADI}_{\max}} \quad \text{(A1)}$$

where PADI_t is the PADI value in the time t, and T is the time interval for each PADI value. Here T is 7 days, as PADI will be refreshed weekly. s_i represents different crop growth stages in the study area, and n is the total number of growth stages. This data was obtained from USDA NASS in 2012 as described in Appendix A. p_2 and p_3 are the durations of the onset phase and development phase, respectively. $T \cap s_i \cap p_2$ represents the duration of the intersection between this calculation week, growth stage i, and the onset phase, which is similar to $T \cap s_i \cap p_3$. λ_i is the water-deficit sensitivity coefficient in the growth stage i, which describes the degree of soil water stress impacts on the crops. $SMCI_t$ and VCI_t are the SMCI and VCI values during the period of $T \cap s_i \cap p_2$ and $T \cap s_i \cap p_3$, respectively. Using these two univariate drought indices (SMCI and VCI) in PADI ensures anomalies in root zone soil moisture and vegetation can be directly represented. By adding the previous PADI value (PADI_{t-1}), a higher PADI indicates increased accumulated impacts over the crop areas. The most severe agricultural drought occurs when crop growth is affected by extreme environmental conditions. In this case, PADI reaches up to the maximum value, $\mathrm{PADI}_{\max} = \sum_{i=1}^{n} [(s_i \cap p_2) * 1 + (s_i \cap p_3) * 1]$, which is the denominator.

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