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Exceedance Probability of the Standardized Precipitation-Evapotranspiration Index in the Texas High Plains

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Abstract

Drought is a common occurrence in many arid and semi-arid regions that can have large negative impacts on water resources and agricultural production. Since agricultural drought is affected by both water supply and demand (precipitation and evapotranspiration), it is beneficial to include both in agricultural drought monitoring. The Standardized Precipitation-Evapotranspiration Index (SPEI) was found to be a suitable drought index for monitoring agricultural drought. In this study, the SPEI calculated from agro-meteorological weather stations was used to determine exceedance probabilities at five levels in the Texas High Plains. In addition, the kriging method was used to interpolate between the stations to generate spatial maps for the exceedance probabilities. No significant differences were found between stations, indicating any station should be suitable to represent the Texas High Plains. Results showed drought conditions occurred at all five probability levels during the summer growing season for this region. Although differences were not significantly different, the interpolated maps showed a trend where minor differences in the SPEI values were associated with the West-East precipitation gradient. However, there was no trend associated with the North-South air temperature gradient. A risk analysis showed that the SPEI probability values can provide policy and decision makers with additional information for better water management in the Texas High Plains.

Keywords

Drought, Semi-Arid Region, Water Management, Irrigation

1. Introduction

Drought is a common occurrence in most arid and semi-arid climates that can have drastic economic consequences, especially for agriculture. Drought is a complex phenomenon, which causes difficulty in creating a singular definition [1]. Location and climate influence the definition and relative severity of drought. For instance, in tropical climates, a drought will be defined differently than in an arid climate. The definition of drought will also vary based on the field of the study or use of the definition. For hydrology, droughts are characterized by periods of below normal stream flow and depleted reservoir storage. In meteorology, drought may be defined as extended periods of below normal precipitation. In agriculture, the main concern may be with periods of below-normal soil water that affect crop growth, which vary among the respective growing seasons. Economists are concerned with low water supply and the effects on society's productive and consumptive activities [1]. Although drought impacts most aspects of life, the greatest impact is observed in agriculture.

In areas such as the Texas High Plains, which is largely an agricultural region, drought can cause severe economic losses due to reduced crop yields or reduced cattle gains, or in extreme cases, crop failure or livestock death. In irrigated crop production, losses to drought can be somewhat mitigated; however, the increased irrigation requirements due to decreased/erratic precipitation put additional strain on already limited water resources. In the Texas High Plains, water resources are becoming scarce [2] [3], which has caused physical and political limitations on water use. In many areas, well capacities have decreased due to the lowering water table of the Ogallala Aquifer [4]. The reduced water availability also has caused local groundwater conservation districts to impose regulatory limits on the amount of irrigation water that can be withdrawn annually by producers [5] [6] [7].

Drought management strategies may be useful for maintaining profitable agricultural production and optimal policy decision making. Understanding drought conditions, or more importantly, the probability of drought occurrence and severity, can be beneficial for managing water resources. For monitoring agricultural drought, Moorhead *et al.* [8] found the Standardized Precipitation-Evapotranspiration Index (SPEI-[9]) to be the most suitable drought index. The SPEI accounts for precipitation and evapotranspiration (ET), which are two of the main components of the water balance. Moorhead *et al.* [10] revised the SPEI by replacing reference ET with potential ET of specific crops to make it more suitable for its application in irrigated regions. They reported statistical regression models for major irrigated crops in the Texas High Plains. These regression models offer a simplified method for determining irrigation water demand based on current drought conditions in the Texas High Plains.

The usefulness of the SPEI demonstrates that management decisions can benefit from a greater understanding of current or possible drought conditions. Although forecasting drought can be rather difficult, exceedance probability methods offer useful information for future water management purposes. The exceedance probability indicates likelihood that a certain value, or level of drought, will occur based on historical data. For example, a 50% exceedance probability indicates a 50% chance of up to a certain level or severity of drought occurring, or such a level of drought could be expected to occur "on average" one out of two years. The probability can then be used as an assumed level of risk [11], where assuming a 20% risk level would indicate using the 80% exceedance probability. Exceedance probability analyses have been used in a wide array of applications, from climate change research [12] to natural disaster risk assessment [13] to solar energy analysis [14].

Drought forecasting and risk assessment studies have been performed using a variety of methods. Drought forecasting typically attempts to predict future conditions based on historical precipitation patterns and other data. Forecasting drought using the Standardized Precipitation Index (SPI) has been investigated using Gamma Highest Probability [15], Markov chains [16], and other methods. Although forecasting may be beneficial for water management decision making, it also can be advantageous to have an analysis of probability occurrence with certain potential scenarios. Probability-based decision making can allow various stakeholders to assume any desired (acceptable) level of risk. The probabilities also make risk analysis and various projection scenarios possible. Probability exceedance-based decision metrics do have an inherently higher risk over small time periods. Therefore they are no guarantee that in any one given year that the results will fall in line with the probabilities. As such, these approaches are more appropriate in assessing risk as part of a longer term management plan.

Shahid and Behrawan [17] performed a drought risk assessment for Bangladesh using SPI. They noted that Bangladesh has high population density and poverty rates, making it vulnerable to drought-based disasters. To assess the vulnerability, the SPI and several socio-economic and physical factors were used to develop a drought risk index. Using geographical information systems (GIS), they then created drought risk maps for three month and six month time steps. Shahid and Behrawan [17] hoped that the maps will aid in disaster risk reduction and intervention in Bangladesh in the future.

Carbone and Dow [18] produced drought probability forecasts for South Carolina using the Palmer Drought Severity Index (PDSI). They noted that several stakeholders at local and state levels were interested in knowing various states of probabilities of drought to anticipate potential water restrictions. They developed a matrix using precipitation and temperature data and used terciles to categorize each month as compared to normal conditions. Then, a probability anomaly value was estimated using Gaussian and gamma distributions. Carbone and Dow [18] noted that forecasts reflected the historical data from which they were derived more than the probability of occurrence; therefore, users can benefit from probabilities without forecasts.

Torres *et al.* [19] evaluated drought probability based on soil water deficit.

They developed probabilities for each day of year for eight meteorological stations in Oklahoma. They calculated the drought probability as the number of times the soil water deficit exceeded a set threshold, divided by the number of observations. This procedure provided the probability of a given soil water deficit status for each day of the year.

Understanding the potential for drought conditions and associated probabilities can be beneficial for water management by stakeholders and policy makers in areas such as the Texas High Plains. Although several studies have investigated risk assessment or forecasting of drought, few have used the exceedance probability approach. Exceedance probability should provide indications to likely drought scenarios and allow for the selection of a desired (acceptable) level of risk in decision making. In addition, having spatial representation of drought probability can demonstrate the variability of drought conditions and lead to more local, specialized water management strategies. Therefore, the objectives of this study were to evaluate the variability of the SPEI based on historical climate data and to develop spatially representative maps of drought exceedance probabilities using SPEI.

Study Area

The Texas High Plains, comprising the Texas Panhandle, constitutes a major portion of the Southern High Plains in the Ogallala Aquifer region. In the Texas High Plains, agriculture accounts for a large portion of the land use, while irrigated land accounts for the majority of the agricultural crop production. Irrigation in this region accounts for 89% of the total fresh water use, in contrast to 60% for the entire state of Texas [20]. The Texas High Plains is a major wheat, corn, and cotton producing region. Corn production in the Texas High Plains is largely dependent on irrigation, while wheat and cotton may be grown under fully irrigated, deficit irrigated, or dryland conditions. The vast majority of irrigation water for regional crop production is withdrawn from the Ogallala Aquifer. Limited rainfall (400 to 600 $mm \cdot yr^{-1}$ or 16 to 24 in. yr^{-1}, on average across the region), provides little recharge in this region of the Ogallala Aquifer [2], which results in the aquifer being effectively a finite resource. Consequently, water conservation is an integral part of the regional water management plan [21]. The northern and southern parts of the Texas High Plains (see **Figure 1**) are similar in size; however, the northern Texas High Plains irrigates over 1.1 million ha (2.7 million ac) while the southern Texas High Plains irrigates about 760,000 ha [4]. In both northern and southern regions, irrigated crop yields generally are at least twice the yields obtained under dryland (rainfed) conditions.

2. Methodology

The SPEI was chosen as the drought index based on the findings of Moorhead *et al.* [8]. They investigated several drought indices for suitability of agricultural

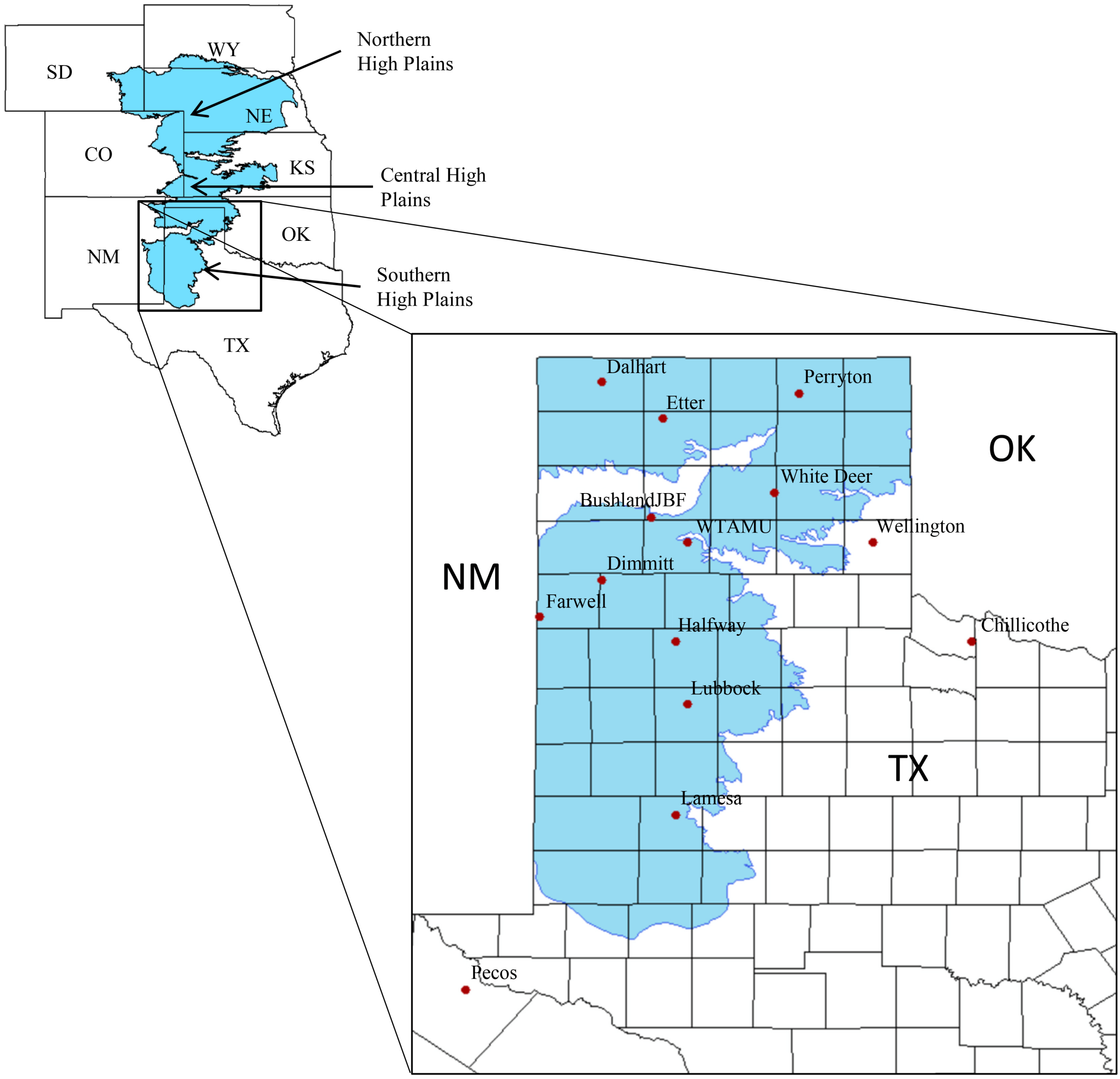

Figure 1. Locations of the selected TXHPET network stations throughout the Texas high plains.

drought monitoring. They determined the SPEI to be suitable for agricultural drought, since it accounts for both water input as precipitation and water loss as ET. The SPEI determines relative wet or dry conditions, based on the difference between precipitation and ET. The calculation methodology of the SPEI is detailed in Vicente-Serrano *et al.* [9]. Data for SPEI calculations were obtained from the Texas High Plains ET (TXHPET) Network [22], which consisted of 19 agro-meteorological stations throughout the Texas High Plains (**Figure 1**) during the period of 1991-2014. The TXHPET network was selected for the data source since all stations were sited and maintained for the purpose of estimating ET, following specifications in the 2005 ASCE Standardized Reference ET Equation Manual [23]. Proper station siting, design, and maintenance should provide the most accurate ET data for SPEI calculation. A study by Porter *et al*. [24] showed that errors in weather measurements can have large effects on reference ET calculations.

The TXHPET network recorded weather at 6 s intervals and data were averaged or summed for hourly intervals. Measured weather parameters included precipitation, wind speed, air temperature, relative humidity, and solar radiation (irradiance). These hourly measurements were used to calculate hourly grass and alfalfa reference ET (ET_{os} and ET_{rs}, respectively) using the 2005 ASCE Standardized ET Equation [23] which are then summed to provide daily ET values. Prior to distribution, the data underwent quality control assessment to identify and correct any errors or missing data. This quality control procedure involved ensuring each measurement fell within realistic upper and lower limits as well as cumulative comparisons with weather stations within close proximity. Even though data was subjected to TXHPET quality control, each dataset was additionally visually inspected for incorrect or missing data.

Precipitation and ET_{os} data collected from TXHPET stations were used to calculate the SPEI at a monthly time step in this study. The monthly time step was chosen, as it is short enough to be useful in agricultural applications, but long enough to help account for the variability in precipitation and ET_{os}. Daily precipitation and ET_{os} data from the TXHPET Network were summed to monthly values. The difference between monthly precipitation and ET_{os} was then used to calculate the SPEI. Calculation of SPEI was performed in the same manner as described by Vicente-Serrano *et al*. [9] and the same log-logistic distribution was used to allow for commonality in calculation methodology. The log-logistic distribution was also used for the TXHPET data by Moorhead *et al*. [10] and Moorhead *et al*. [8]. Although Moorhead *et al*. [8] found that using crop-specific ET (ET_c) to calculate SPEI differed from using ET_{os}, and may be more beneficial in some cases, the purpose of this study was to determine the probability of relative drought conditions. Therefore, ET_{os} was used to calculate SPEI, as ET_{os} represents the atmospheric demand for water, based on micrometeorological parameters and associated water requirements of a standardized, short grass reference crop.

The monthly SPEI was calculated for all TXHPET stations with a data record longer than 10 years, which consisted of 15 stations with a data record of at least 13 years (**Table 1**). Although a much longer data record is desired for exceedance probability calculations, agro-meteorological stations with continuous, highly accurate ET data are uncommon and have not been in existence as long as other, less agriculturally representative weather station networks. To calculate the exceedance probabilities for each network station, monthly SPEI values were calculated and ranked by month, from largest to smallest. The probabilities were then calculated by dividing the rank by the number of observations per month plus one (n + 1). This method of calculating exceedance probability has been

Table 1. Location and data record of selected TXHPET stations.

Station	Latitude (degrees)	Longitude (degrees)	Data Record
Bushland	35.20	−102.10	1991-2014
Chillicothe	34.20	−99.50	1999-2014
Dalhart	36.30	−102.50	1995-2010
Dimmitt	34.70	−102.50	1995-2010
Etter	36.00	−102.00	1995-2014
Farwell	34.40	−103.00	1997-2010
Halfway	34.20	−101.90	1998-2014
JBF	35.20	−102.10	1995-2014
Lamesa	32.80	−101.90	1998-2014
Lubbock	33.70	−101.80	1998-2014
Pecos	31.40	−103.60	1995-2014
Perryton	36.20	−100.90	1997-2010
Wellington	35.00	−100.30	1996-2010
White Deer	35.40	−101.10	1995-2010
WTAMU	35.00	−101.80	2002-2014

used in other water monitoring and management applications such as streamflow analysis [25], groundwater contamination analysis [26], precipitation analysis [27], and in other areas of water and risk management. In this study, five probability levels were selected for analysis: 25%, 50%, 60%, 75%, and 85%. These probability levels provide the quartiles as well as a value slightly above the median and a value of high likelihood.

In the Texas High Plains (and the rest of the Ogallala Aquifer region), gradients exist for some weather parameters. In general, air temperature decreases from North to South and precipitation increases from West to East [28]. The variation in temperature and precipitation may lead to differences in drought conditions. As precipitation and ET data are often not normally distributed, the Shapiro-Wilk test was performed to test for normality. Based on the Shapiro-Wilk outcome, an analysis of variance (ANOVA) or the Kruskal-Wallis test was performed to test for significant differences between stations for average monthly SPEI and for each exceedance probability level. To provide a visual representation of any spatial variation in the exceedance probabilities, maps were created using spatial interpolation. The GIS software ArcMap (ESRI, Redlands, CA) was used to create shapefiles containing the SPEI exceedance probabilities. The ordinary kriging procedure was used with the shapefiles to generate the exceedance probability maps.

The availability of drought maps can be more beneficial than using point-based data for a variety of planning and policy applications. For on-farm decision making, it can be difficult to determine which station is closest, or best represents a specific field. With a map, a value for any specific location can be selected. In addition, maps can be used for larger scale decision making, such as on a county or regional level. The spatial representation allows for determining what portion of a region may experience a certain level of drought.

The drought probability values were used to perform a risk assessment comparing drought probability levels and associated effects on crop yields and irrigation water requirements. First, a regression equation was established between the SPEI and precipitation to allow for the SPEI to be used as a predictor of potential rainfall. Then, to assess effects on irrigation requirements, monthly SPEI values from the mean, as well as 25%, 50%, 60%, 75%, and 85% probability levels were used to estimate potential monthly precipitation amounts. These precipitation amounts were used to determine how much irrigation would be required to achieve total seasonal crop water use of 750 mm (30 in.) for grain corn, which would result in maximum yield based on regional production functions [29]. The Texas A&M-Amarillo (TAMA) regional water demand model [20] was used to determine average monthly soil moisture depletion and fraction of irrigation and precipitation that occurs each month of the growing season. This analysis allowed for determining how the various drought scenarios would affect irrigation requirements to maintain maximum crop production.

In the Texas High Plains and many other areas, irrigation may be limited through regulation (established pumping limits, often on a per acre basis), or in many cases, physical hydrologic limitation (water availability, saturated thickness, etc.) of the irrigation wells. In the Texas High Plains, the capacity of many irrigation wells has decreased to the point that producers struggle to supply enough water to crops to attain maximum production; in fact many cannot meet full crop water demand due to low well capacities. Whether physical or regulatory limitations, achieving a desired water amount may not be possible. To determine the effects of drought on these situations, yield was calculated based on the crop production function of a common grain corn variety grown in the Texas High Plains [29]; however, rather than meeting a total water threshold, the seasonal irrigation amount was held constant at 400 mm (16 in.), which is a targeted regulatory limit desired by several groundwater conservation districts in the Texas High Plains [6] [7]. In this scenario, irrigation water was held constant and yield fluctuated based on the precipitation calculated from the drought probability levels. This allowed for an analysis of how various drought levels would affect yield.

3. Results and Discussion

The SPEI was calculated at a monthly time step from 15 TXHPET network stations across the Texas High Plains. Drought conditions are frequent in the region, as indicated by the average monthly SPEI value for each station. For all stations, the average monthly SPEI was below zero (indicating drought conditions) for the months between April and September, with the lone exception being the Farwell station for August (**Figure 2**). (While located in the southwest area of

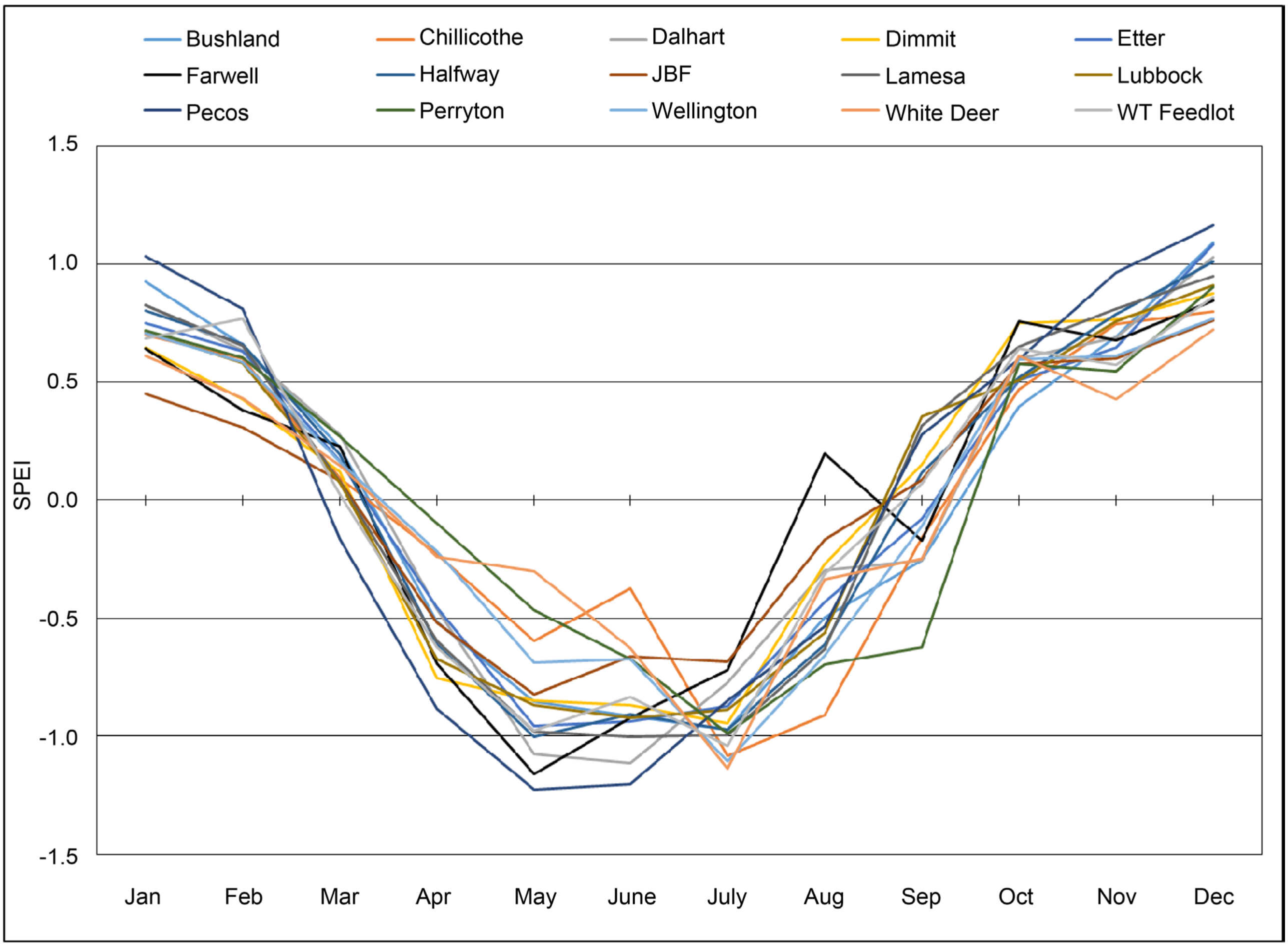

Figure 2. Monthly average SPEI values for each TXHPET Network station.

the network, the Farwell location has a comparative high altitude, and ET_{os} is lower as compared to other surrounding stations). Although numerical differences existed between the average monthly SPEI values, as indicated by **Figure 2**, the differences were not found to be statistically significant. Therefore, drought conditions could be effectively monitored by any one of the stations for the Texas High Plains, based upon the data set evaluated.

Based on the SPEI, the months typically exhibiting drought correspond to the summer growing season when most crops are grown in the Texas High Plains. This illustrates why irrigation is so prevalent in the region. The precipitation events occurring during the summer do not satisfy the demand for water adequately. In addition to the growing season, the summer months also coincide with the period of highest temperatures. Although the SPEI in this study was calculated using ET_{os}, Moorhead *et al.* [8] showed similar results are seen when using crop specific ET.

Exceedance probabilities for SPEI in the Texas High Plains were calculated for the monthly SPEI at five probability levels. The results of the Shapiro-Wilk test for normality showed that the SPEI data were not normally distributed, so the

Kruskal-Wallis test was used to test for differences among the TXHPET stations. The Kruskal-Wallis results showed that differences between the stations were not statistically significant, with all p-values being greater than 0.99. Since there were no significant differences between stations, the SPEI values for each exceedance probability level were averaged for all stations (see **Figure 3**). The data show a pattern where the SPEI values for any particular month become smaller (indicating greater drought conditions) as the exceedance probability increases. This is because the exceedance probability indicates the likelihood of a particular value being exceeded, so a more extreme value should have a higher likelihood of being exceeded.

Figure 3 illustrates how using probabilities can be different than using the average values. All but the 25% probability level indicate drier conditions than using the average. Therefore, using the average SPEI value for a particular month may indicate the expected drought conditions are less than what is more probable. This illustrates how using the average value for decision making can be misleading as to what conditions may be more likely or probabilistic. The numerical values of **Figure 3** are presented in **Table 2**.

Although differences were not significant between the THXPET stations, the SPEI exceedance probabilities were mapped to illustrate the existence of potential

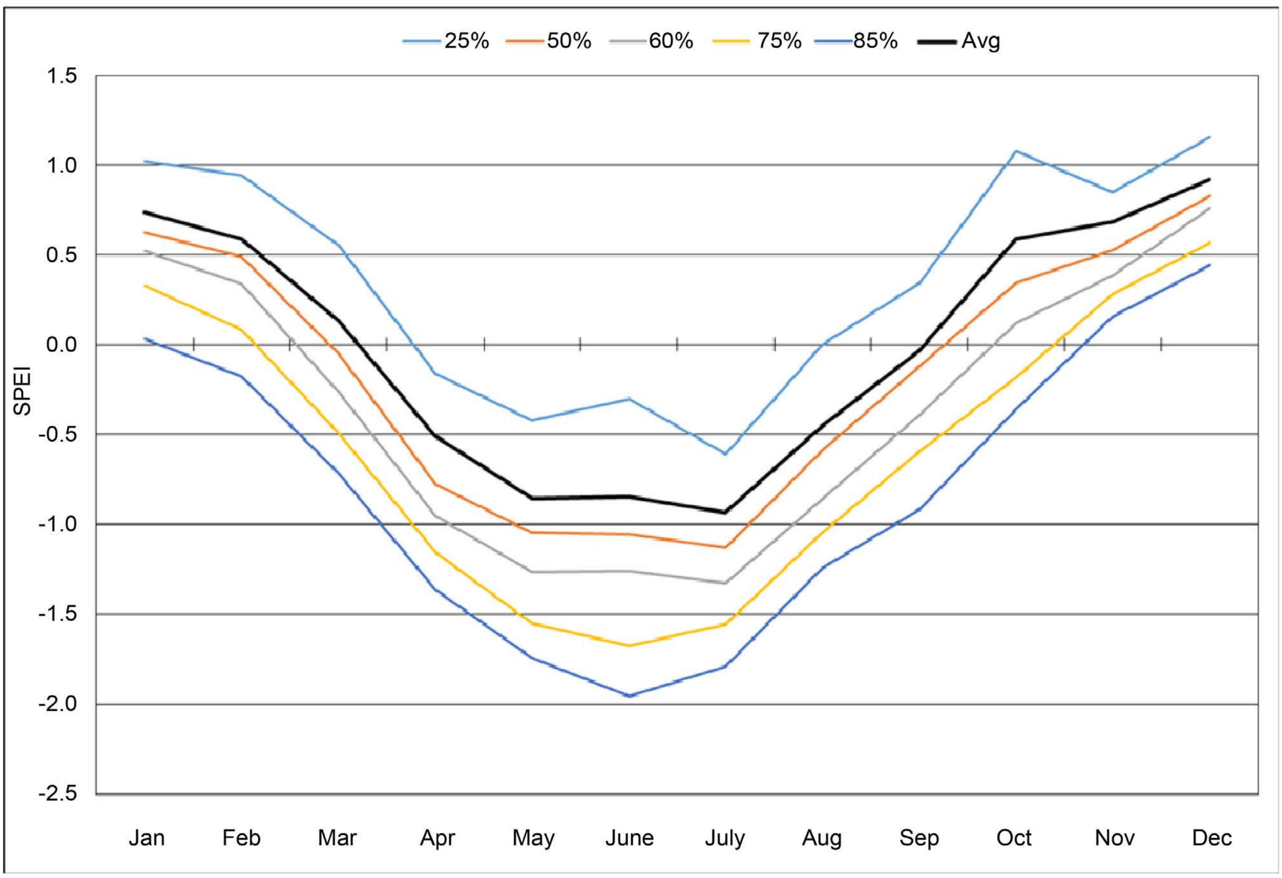

Figure 3. SPEI exceedance probabilities averaged across all TXHPET stations.

Table 2. Monthly average and exceedance probability level SPEI values.

Month	Average	25%	50%	60%	75%	85%
January	0.74	1.02	0.62	0.52	0.33	0.03
February	0.58	0.94	0.49	0.34	0.08	−0.18
March	0.13	0.55	−0.05	−0.27	−0.49	−0.72
April	−0.50	−0.16	−0.77	−0.95	−1.15	−1.36
May	−0.85	−0.42	−1.04	−1.26	−1.55	−1.74
June	−0.84	−0.30	−1.06	−1.26	−1.68	−1.95
July	−0.93	−0.61	−1.13	−1.32	−1.56	−1.79
August	−0.45	0.00	−0.59	−0.86	−1.05	−1.24
September	−0.04	0.34	−0.12	−0.39	−0.59	−0.91
October	0.58	1.07	0.34	0.12	−0.18	−0.36
November	0.69	0.85	0.52	0.38	0.28	0.16
December	0.92	1.15	0.83	0.76	0.57	0.44

gradients in SPEI. The months of June, July, and August had the driest conditions and are therefore presented in Figures 4-6. The figures show trends where differences tend to occur from East to West, which corresponds with the precipitation gradient. For most of the maps, much less variation is seen in the North-South directions, which may indicate that the air temperature gradient does not have as large of an impact on drought conditions as the precipitation gradient.

Figure 7 presents the regression analysis that was used to predict potential precipitation from the SPEI exceedance probabilities. The expected yields based on precipitation calculated from the equation in Figure 7 and 400 mm (16 in.) of irrigation are presented in Figure 8. Using the SPEI probability values at the 85% level, and assuming 400 mm (16 in.) of irrigation, resulted in an estimated grain corn yield of 10.8 $Mg \cdot ha^{-1}$ (172 bu ac^{-1}); whereas using the 50% level resulted in a yield of 13.5 $Mg \cdot ha^{-1}$ (215 bu ac^{-1}). This illustrates how the SPEI probability can be used to assist management decisions. If a producer is expecting a normal year, near the 50% probability level, and actual conditions move towards the 85% level, the producer can manage inputs accordingly to try to minimize expenses knowing yield will likely be decreased. For example, to achieve a grain corn yield goal of 13.2 $Mg \cdot ha^{-1}$ (210 bu ac^{-1}), 302 $kg \cdot ha^{-1}$ (270 lb. ac^{-1}) of nitrogen (N) would be required [30]. Adjusting the yield goal to 10.7 $Mg \cdot ha^{-1}$ (170 bu ac^{-1}) would reduce the N requirement to 224.2 $kg \cdot ha^{-1}$ (200 lb. ac^{-1}). This 78.5 $kg \cdot ha^{-1}$ (70 lb. ac^{-1}) reduction in fertilizer would reduce the producer's input costs and potentially increase profits. Likewise, if a producer expects dry conditions, such as the 75% probability level, and actual conditions become more favorable and more precipitation occurs, inputs can be increased to take advantage of the higher potential yield. In addition, the ability to quantify the

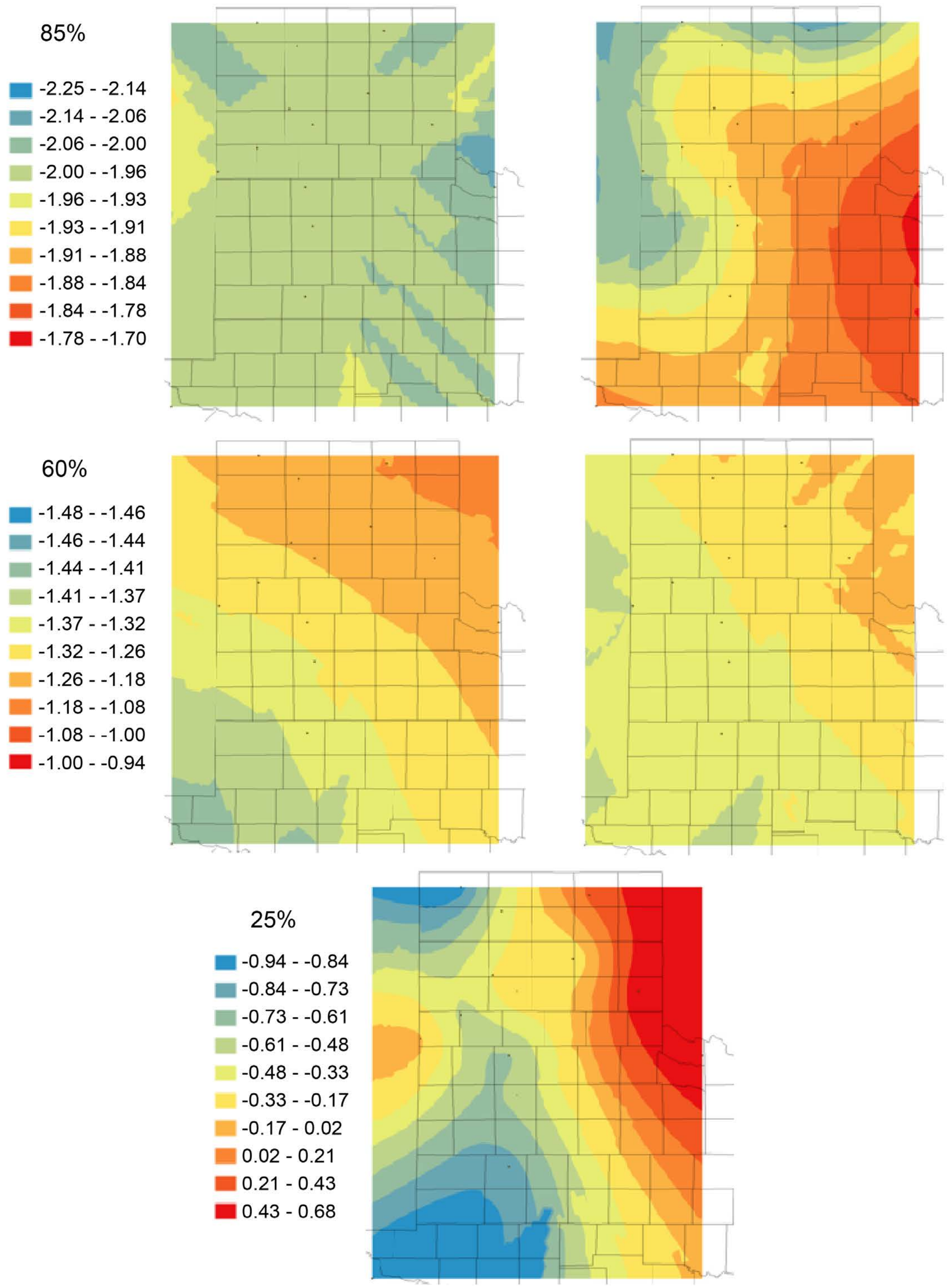

Figure 4. Exceedance probability maps for June.

change in yield based on the SPEI can allow a producer to manage inputs to a specific yield goal.

For maximum grain corn production, a total water of 750 mm (30 in.) is required based on the production functions presented by Hao *et al.* [29]. To illu-

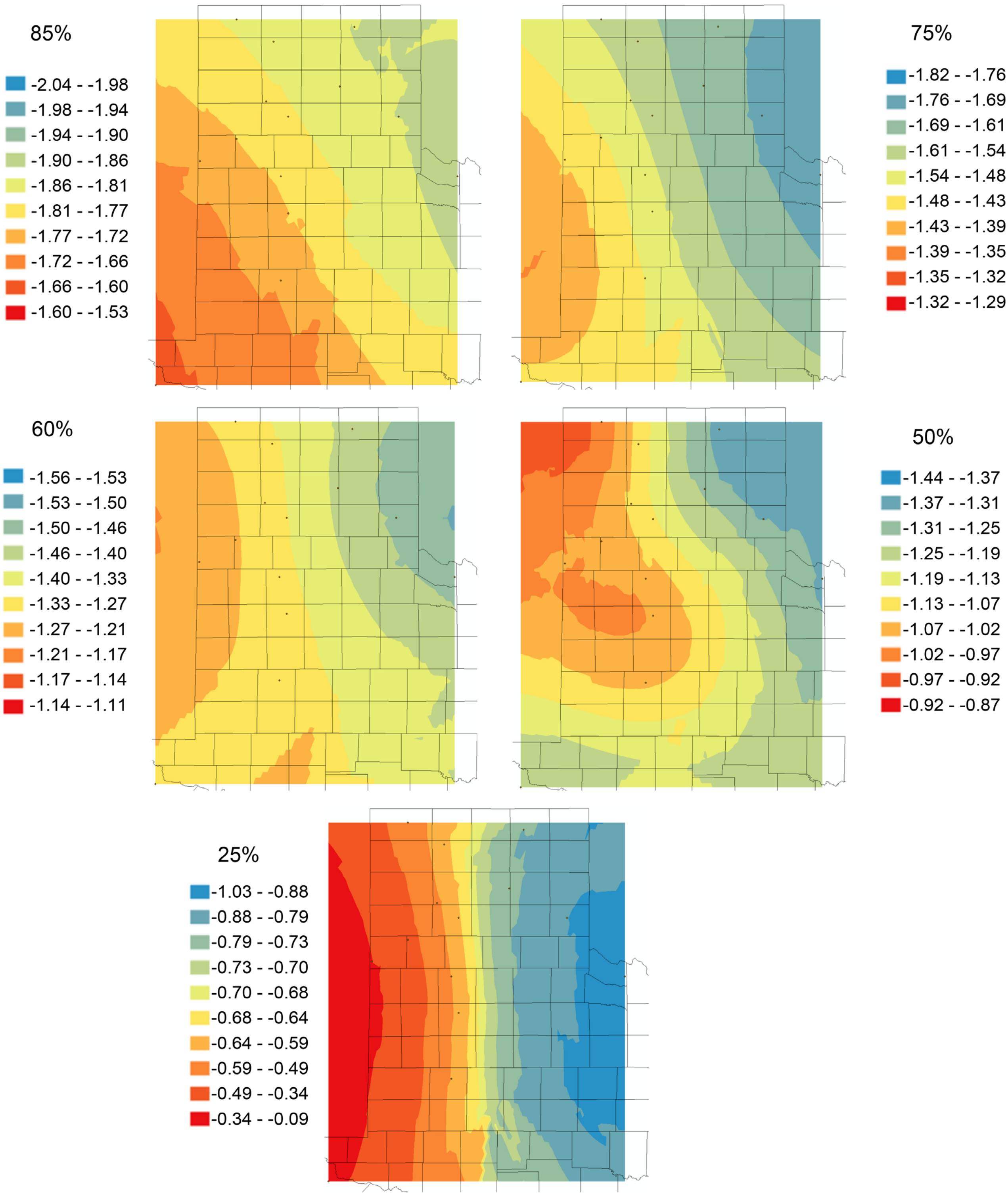

Figure 5. Exceedance probability maps for July.

strate the benefits of SPEI probability values in a different way, the probability levels can be used to determine how much irrigation will be required to achieve the targeted total water. The irrigation requirement for each probability level is

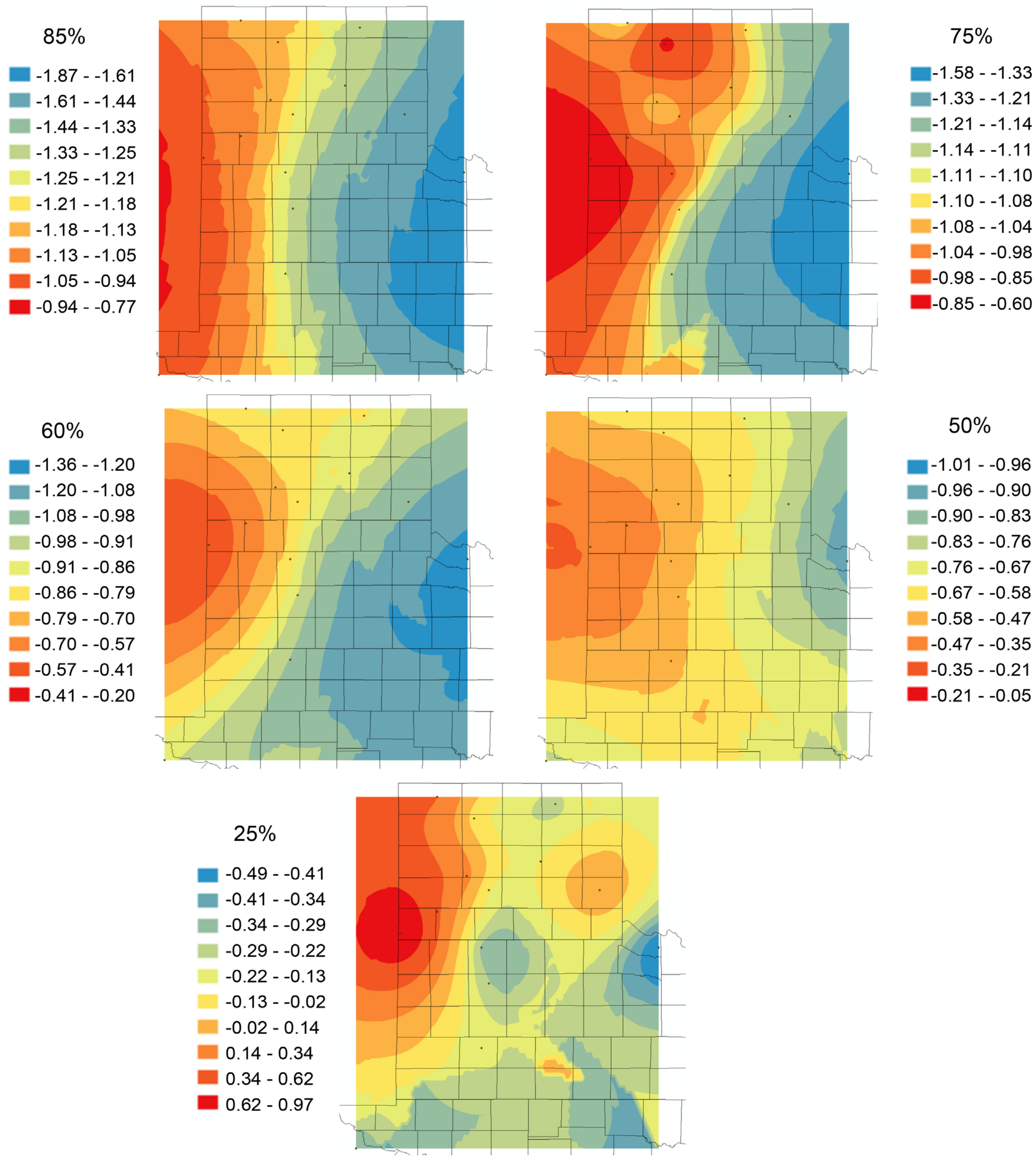

Figure 6. Exceedance probability maps for August.

presented in **Figure 9**. For conditions representing the 75% probability level, the irrigation required for total water of 750 mm would be 550 mm, whereas only 480 mm are needed at the 50% probability level. This type of relationship can assist decision making not only for producers, but also for groundwater management districts that place regulations on groundwater withdrawal. These data can

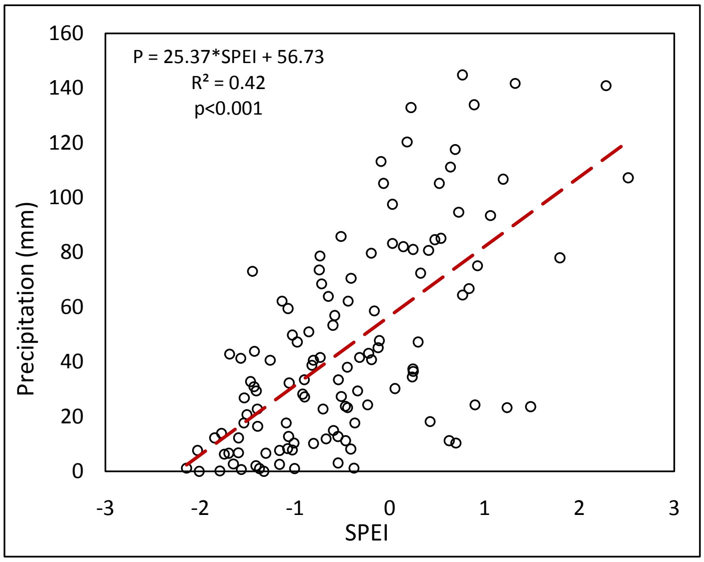

Figure 7. Regression using SPEI as a predictor for precipitation.

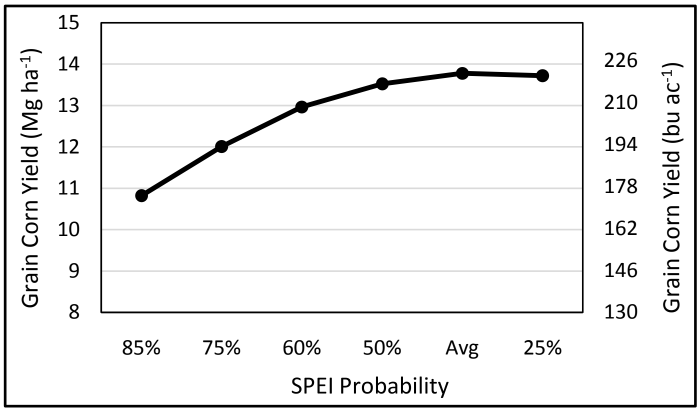

Figure 8. Grain corn yield estimated from SPEI exceedance probability, assuming 400 mm irrigation capacity.

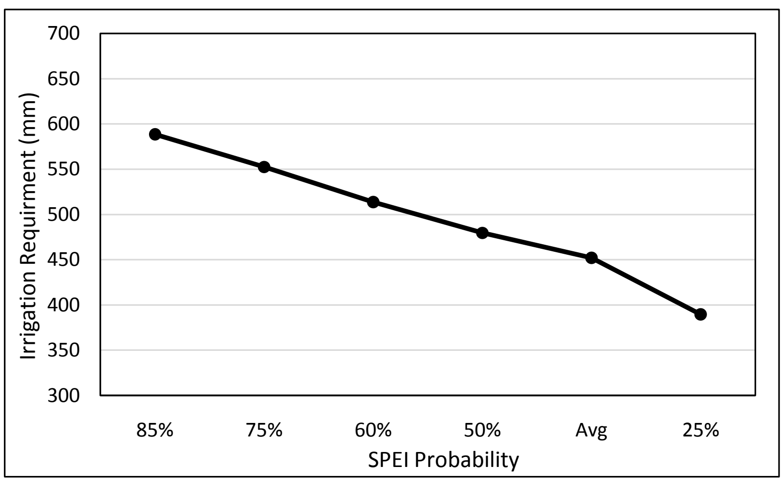

Figure 9. Irrigation requirement to achieve 750 mm (30 in.) total seasonal water for each SPEI probability level.

illustrate how in extremely dry conditions or extremely wet conditions, withdrawal regulations can be temporarily altered to allow producers to maintain profitable production or increase water conservation. To illustrate an example, setting a yield goal could be the basis for determining irrigation withdrawal limits. With a yield goal of 12.6 $Mg \cdot ha^{-1}$ (200 bu. ac^{-1}) at the 50% probability level, 375 mm (15 in.) of irrigation would be required. At the 75% level, the withdrawal limit could be increased to 450 mm (18 in.) to achieve 12.6 $Mg \cdot ha^{-1}$ (200 bu. ac^{-1}); however, in a wet period corresponding to the 25% probability level, the withdrawal limit (or recommendation) could be decreased to 288 mm (11.5 in.) to achieve the same 12.6 $Mg \cdot ha^{-1}$ (200 bu. ac^{-1}).

4. Conclusion

Managing water resources in arid and semi-arid regions can be most challenging. With water resources becoming ever increasingly limited, new management tools and information can be beneficial to policy and decision makers. In arid and semi-arid areas, such as the Texas High Plains where drought conditions are common, characterizing the potential level of drought for a given time period can aid in decision making regarding irrigation and water management. In this study, exceedance probabilities were calculated based on 25%, 50%, 60%, 75%, and 85% probability levels for the SPEI calculated from weather data from 15 TXHPET network weather stations. The results showed that all stations indicated drought conditions at each probability level during the months that coincide with the summer growing season. The Kruskal-Wallis test indicated that there were no significant differences between the stations at any of the probability levels, which indicates that data from any one station could be used for the Texas High Plains. The exceedance probabilities were interpolated using kriging to produce spatial maps for each probability level. The interpolated maps showed that even though differences were not significantly different, there was a trend of SPEI values becoming lesser from West to East, which corresponds to a precipitation gradient where precipitation increases from West to East. An analysis of drought effects on yield and irrigation requirements showed that the exceedance probability of the SPEI can provide a useful tool for management decisions for producers as well as agricultural and water policymakers.

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