Journal of the Arkansas Academy of Science

Volume 70 Article 24

2016

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Running Title: Impact of Climate Variations in Eastern Arkansas: 1960-2014

Abstract

Climate is the major factor affecting crop production; therefore, various agro-meteorological indicators have been frequently used to evaluate the impact of climate on crop production. In this study, we examined the temporal variations of agro-meteorological indicators (growing degree days, total precipitation, dry spells and drought indices) during 1960-2014 and their impact on soybean yields in East Arkansas. Results show an increasing trend in growing degree days (GDDs) and dry spells, though the total precipitation during the soybean growing season remained nearly unchanged during the study period. Generally, GDDs and dry spells show a strong correlation with yields. We also evaluated drought variability based on different drought indices, including the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI). The drought indices are all negatively correlated to soybean yields. Overall, the one month SPEI showed the strongest impact on yields. After regression analysis, Dry spells and Total precipitation were the only significant factors in the General Linear Model (GLM).

Key words: Climate change, Agro-indicators, Drought indices

Introduction

Urbanization, salinization, climate change and water scarcity all pose renewed challenges to agriculture (Fedoroff et al. 2010). Increases in crop yields are required to meet both domestic and commercial demands for food, but climate change and diminishing returns from technological advancements will limit potential success (Lobell and Asner 2003). Temperatures above 30°C tend to diminish yields of most crops because of the photosynthetic threshold temperature. These elevated temperatures accelerate crop reproductive development thereby reducing accumulation of carbohydrates, fats and proteins that are major components of grains and fruits (Fedoroff et al. 2010). In fact, studies project 17% decreases in both corn and soybean yields for each degree rise in growing season temperature in the South East United States (Lobell and Asner 2003).

There is a general trend of early onset of spring and increasing growing degree days in the United States (Feng and Hu 2004, Schwartz and Reiter 2000). Previous satellite and climatological studies agree that there are shifts in timing and length of the growing season (Tucker et al. 2001). Increasing growing season length provides opportunities for earlier planting, ensuring maturation and possibilities of multiple cropping. However, higher temperatures could speed development and reduce time to accumulate dry mater, which in turn could cause slight decreases in yields (A.C.I. 2004, Linderholm 2006, Stocker et al. 2013). Additionally, variation in crop yields is more influenced by regional weather and climate rather than large scale climate dynamics. Therefore, it is more important to develop agro-meteorological indicators at the regional level to study their relationship with individual crop yields (Mishra and Cherkauer 2010).

The long term average, frequency and extremes of several weather variables are the chief determinant of the general climate of a region (Patel et al. 2007). To evaluate the impact of climate on agriculture, multiple agro-meteorological indicators are used. Agro-meteorological indicators are constructed from climatic variables that have an impact on plant life. They are used to assess site suitability for crop growth, geographical limits of crop land use and to establish estimates of weather anomalies or trends (Confalonieri et al. 2010). The study of both temperature and precipitation based indicators has never been more critical because varying climate has and will continue to alter agricultural environment and affect crop productions (Feng and Hu 2004).

There is a consensus that climate change will alter the frequency, timing and intensity of extreme events such as drought (Greenough et al. 2001). In fact, climate model simulations indicate that the interiors of northern continents will become drier during summer over the next century (Wetherald and Manabe 2002). Socio-economic and environmental effects of droughts are costly due to their spatial and temporal extent (Wilhite 2000). Thus, increased severity and frequency of droughts is a major concern to many stakeholders, increasing the need to measure and study drought impacts on crop yields (Sheffield and Wood 2008, Wang 2005).

Drought is the least understood yet most complex of all natural hazards (Patel et al. 2007). Most elements of drought (onset, duration, intensity and end) are determined by moisture deficits (Kogan 1997, Vicente-Serrano et al. 2010). Due to dependence on water resources and soil moisture for crop growth, agriculture is often the first sector to be affected by onset of drought, making reductions in crop yields a good indicator for the impact of drought on agriculture (Kogan 1997, Narasimhan and Srinivasan 2005). The costliest droughts occur during the grain filling period of most crops. Corn and soybean, for example, are most severely affected when drought occurs during the grain filling period (Mishra and Cherkauer 2010). Nonetheless, lack of a universal drought monitoring framework makes it impossible to assess drought impacts across ecosystems and different countries' economies (Kogan 1997).

Monitoring, early warning and assessment of consequences of drought are the most common tools used in drought mitigation. Most countries' drought watch systems are based on analysis of weather anomalies or domestic indices, which are formulated by integrating temperature, rainfall and evapotranspiration (Kogan 1997, Patel et al. 2007). Drought indices must be associated with specific timescales to be useful for monitoring different types of drought (Patel et al. 2007, Vicente-Serrano et al. 2010). According to Vicente-Serrano et al (2009), PDSI was found to explain variability in production and activity of natural vegetation better than SPI. Patel et al (2007) also found that 3-month SPI could help assess in advance the decline in food and grain production caused by droughts in India (Gujarat State). In this paper, we considered three drought indices i.e. Palmer Drought Index (PDSI), Standardized Precipitation Index (SPI) and Standardized Precipitation and Evapotranspiration Index (SPEI).

Our study focuses on East Arkansas, where the majority of agricultural activity in the state occurs. Arkansas is a major agricultural producer and the largest producer of rice in the nation, with other major crops including soybean, corn, wheat and cotton (Nickerson et al. 2011). Arkansas's agriculture is heavily irrigated and is the fourth largest user of groundwater for irrigation in the nation (Holland 2007, Schaible and Aillery 2012). The climate of Arkansas is humid sub-tropical, with average temperatures of about 15.8°C (Feng et al. 2014). The major rainy seasons in Arkansas occurs from March to May and then from October to December. Climate change may affect Arkansas' agriculture both directly through its effect on crop growth and indirectly through its effect on irrigation water supply. This study will explore the relationship between, Agro-meteorological indicators and crop yields in East Arkansas. We will also examine the performance of various indices to draw conclusions for policymakers and stakeholders.

Methods

Study Region

The study sites encompass 3 eight-digit hydrological unit code watersheds (L'anguille, Big, and the Lower White), within the farming region of the Arkansas Delta where the Mississippi alluvial aquifer is most depleted. The study area consists of 11 counties located in East Arkansas (Figure 1). It lies within latitudes 35.99 and 33.95 degrees North and longitudes 90.29 and 91.34 degrees West. The area is geographically homogenous: a predominantly flat alluvial plain in the Mississippi River Valley in Eastern Arkansas. This region is the most agriculturally productive region in Arkansas, producing rice, soybean, corn, wheat and cotton.

Data

The daily temperature (minimum, maximum and mean) and precipitation from the 11 counties in the study regions from 1960 to 2014 were obtained from National oceanic and Atmospheric administration (NOAA) (DeGaetano et al, 2015). Soybean was chosen for the study due to ease of non-irrigated soybean data availability. The LOESS regression method was used to remove trends in soybean crop yield arising from genetic and management improvements (Mishra and Cherkauer 2010).

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DOI: 10.54119/jaas.2016.7016

Temperature Based Indicators

Growth events of crops such as flowering and maturity depend on the accumulation of specific quantities of heat or thermal time (Miller et al. 2001). Growing Degree Days (GDDs) is therefore a measure of heat accumulation necessary for maturity (Feng and Hu 2004, Hassan et al. 2007).

The calculation of thermal time (TT) in the unit of GDD is given by the following equation:-

$$TT = \sum_{Pb}^{Pe} \frac{(T_{max} + T_{min})}{2} - T_b$$

where T_{max} and T_{min} are the daily maximum and minimum surface air temperature; P_b and P_e are the beginning and ending dates of the growth season (Feng and Hu 2004). The base temperature (T_b) for growth was set as 10˚C for soybean (Feng and Hu 2004, Sarma et al. 2008). The threshold temperatures T_{min} and T_{max} was set as 10˚C and 30˚C respectively. The growing season (June, July, August, September & part of October/JJASO) for soybean was set between June 1st (P_b) and October 16th (P_e) from University of Arkansas Division of Agriculture Cooperative Extension Services (http://www.uaex.edu/).

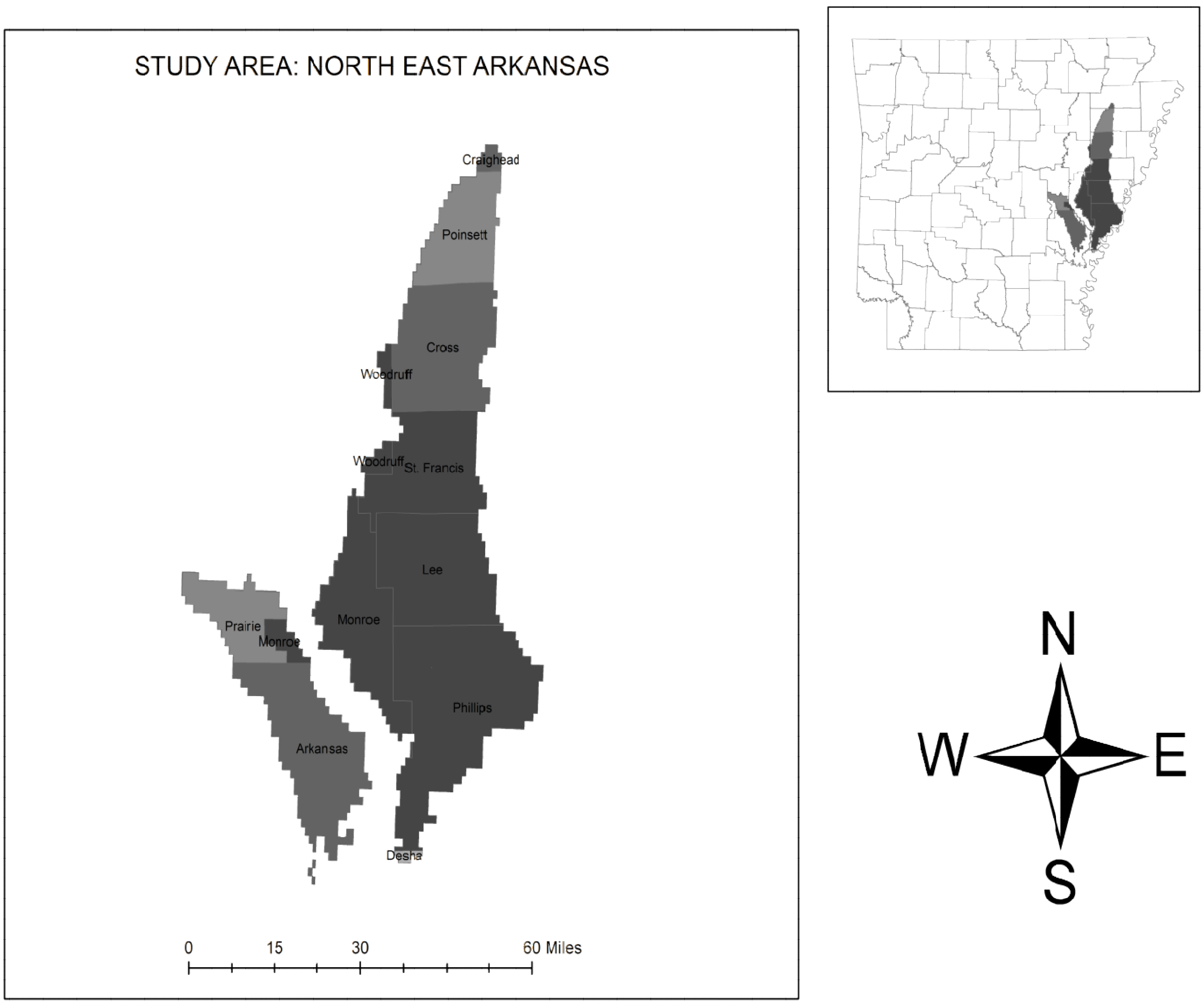

Figure 1. Study area in East Arkansas

Precipitation Indicators

Growing season total precipitation was calculated from daily precipitation data representing cumulative rainfall totals for the growing season (Kunkel et al. 1999). Dry spells during the growing season were defined as consecutive dry days without precipitation or when precipitation is below 1mm (Piani et al., 2010). Dryness and wetness are relative to historical average rather than absolute total of precipitation for given areas (Patel et al. 2007).

Drought indices

Different drought indices were used to evaluate the impact of the drought on crop yields (Heim Jr 2002). The three frequently used drought indices are the Palmer Drought Severity Index (Alley, 1984; Wells et al. 2004), the Standardized Precipitation Index (McKee et al. 1993, Patel et al. 2007) and the Standardized Precipitation-Evapotranspiration Index (Begueria et al. 2014).

The PDSI is the most common meteorological index used in USA. It is a standardized measure, ranging from -10(dry) to + 10(wet)(Dai et al. 2004). Since PDSI has a time span of 9 months or longer, it does not allow detection of droughts over different periods at multiple time scales and differentiation among different drought types (Hayes et al. 1999, Vicente-Serrano et al. 2010). For these reasons, PDSI responds slowly to drought and can retain values reflecting drought even after climatological recovery from drought has occurred (Hayes et al. 1999).

SPI is produced by standardizing the probability of observed precipitation for a given duration. Moreover, SPI is designed to detect drought over different periods at multiple time scales (1, 3 & 6 months) in this study. Positive values of SPI indicate greater mean precipitation while negative values indicate less than the mean precipitation (Patel et al. 2007). The main undoing of SPI is that it only uses precipitation in its formulation. Therefore, It does not consider other variables that can influence droughts like temperature, evapotranspiration, wind speed and soil water holding capacity (Vicente-Serrano et al. 2010).

On the other hand, SPEI (1, 3 & 6 months) is based on precipitation and potential evapotranspiration (PET). SPEI combines sensitivity of PDSI to changes in evaporation demand (caused by temperature variations and trends) with the simplicity of calculation and the multi-temporal nature of the SPI. Therefore, use of drought indices that include temperature data in the formulation is preferable. SPEI is particularly well suited for detecting, monitoring and exploring the consequences of global warming on drought conditions (Vicente-Serrano et al. 2010). Based on daily temperature and precipitation, the monthly mean temperature and monthly precipitation totals in individual counties were computed and then used to calculate the PDSI, SPI and SPEI for Soybean growing season in this study.

Data analysis

The response variable, soybean yield, and all the other predictor variables i.e. Growing Degree Days (GDDs), Dry spell and SPEI-1 were screened for possible outliers to confirm the normality of data distribution (Royston 1992). Correlation analysis was done to assess individual agro-climatic indicators performance against soybean yields for individual counties and the entire study area. Pearson Correlation analysis was also done for all three drought indices to establish their relationship with soybean yield during the growing season for each county and study area. Finally, Multiple Linear Regression (MLR) was used to fit General Linear Models (GLM) for individual counties and the study area using JMP Pro 12 (Preacher et al. 2006).

Results and Discussion

Agro-climatic indicators and yield anomalies

Soybean yields for the study area (Figure 2a) have increased steadily from the 1960s to 2014. These increases in yields have been attributed to scientific improvement through breeding and improved scientific management (Feng and Hu 2004, Mishra and Cherkauer 2010). Figure 2 shows agro-indicator anomalies for the study area. Results reveal that the soybean yields are negatively correlated to dry spells during the 1980s late 1990s and 2000s. GDDs were highly correlated with dry spells, with longer dry spells corresponding to longer GDDs (Figure 3). In addition, total precipitation was positively correlated with yields. Higher yields were observed when there was a considerable increase in total precipitation. Similar studies by Feng and Hu (2004) also revealed that dry and wet spells had the largest effect on dry-land corn yield in Nebraska.

The correlation between agro-indicators and soybean yields is shown in Table 1. Growing season GDDs and Dry spells are negatively correlated with yields while total precipitation and SPEI-1 are positively correlated. These results show that both precipitation and temperature indicators have significant effect on soybean yields. Accordingly, the

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DOI: 10.54119/jaas.2016.7016

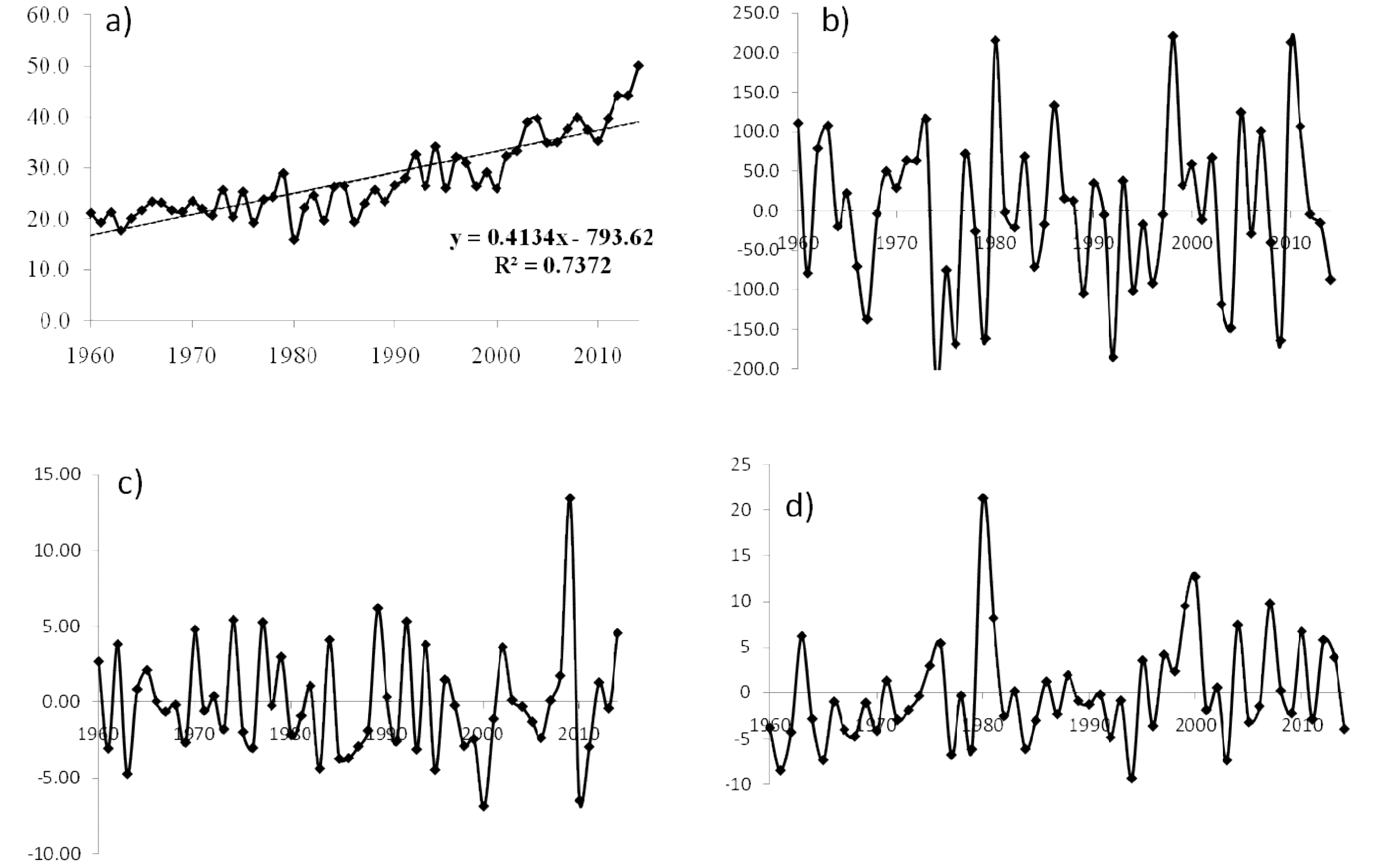

Figure 2: a) JJASO Soybean yields for study area (1960-2014), b) JJASO GDD anomalies (1960-2014), c) JJASO Total precipitation anomaly (1960-2014), and d) JJASO Dry spell anomalies (1960-2014) for East Arkansas.

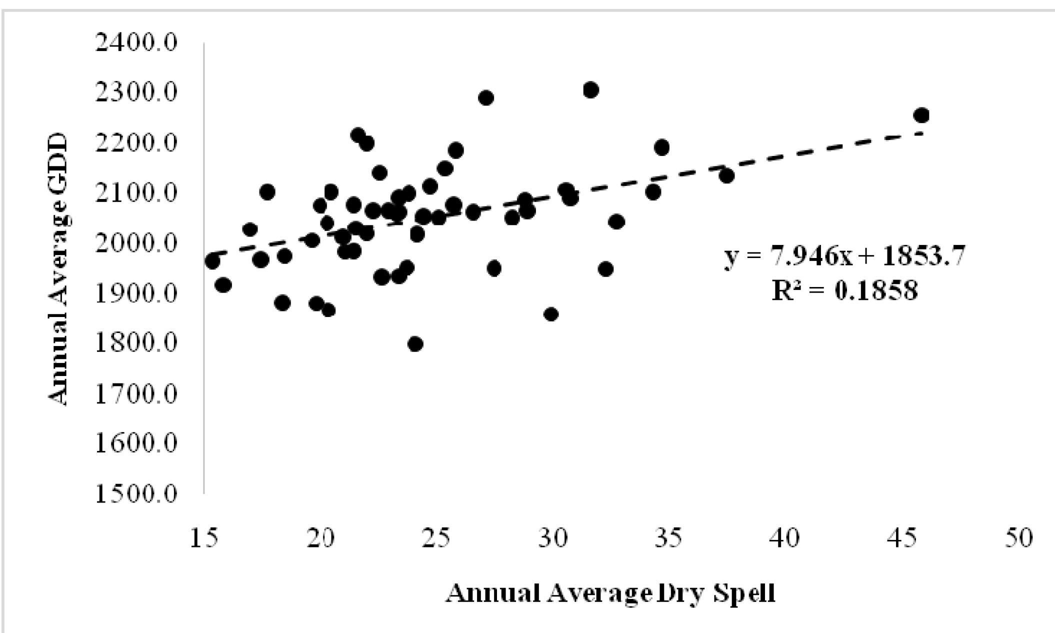

Figure 3: Correlation between GDD and Dry spell for the study area (1960-2014)

Table 1: Correlation between (JJASO) Agro-climatic indicators and Soybean yields (1960-2014)

County	GDD	Total precipi-tation	Dry spells	SPEI-1
Arkansas	**-0.197***	0.119	-0.044	**0.588*****
Craighead	-0.180	**0.328****	-0.033	**0.26****
Cross	-0.085	0.126	**-0.328*****	**0.201***
Desha	**-0.51*****	**0.210***	**-0.344*****	**0.412*****
Lee	**-0.211***	0.154	**-0.198***	**0.247***
Monroe	**-0.430*****	0.23	-0.075	**0.235***
Phillips	**-0.550*****	**0.314****	**-0.252***	**0.484*****
Poinsett	**-0.200***	**0.212***	**-0.283****	**0.313****
Prairie	-0.180	0.156	-0.188	**0.294****
St Francis	**-0.470*****	0.094	-0.086	0.121
Woodruff	-0.120	0.188	**-0.246****	**0.203***
Study area	**-0.311****	0.135	**-0.282****	**0.302****

*** indicates 99% confidence, ** indicates 95% Confidence and * indicates 90% confidence.

increase in dry spells resulting in accumulation of GDDs during the growing season is the factor most responsible for reduction in soybean yields in East Arkansas. Based on these results, it is very likely that global climate change will have great impact on agriculture through changes in precipitation and temperature.

Drought Indices and yield anomalies

Figure 4 shows PDSI and the 1-, 3- and 6- month SPEI and SPI for East Arkansas between 1960 and 2014. PDSI reveals major drought episodes in the 1960s, 1980s, mid- 1990s, and late 2005 and 2010. Although strongly correlated, SPEI and SPI also indicated drought during these time periods. These results reveal that, in circumstances where low variability of temperature occurs, both SPEI and SPI indices respond mainly to precipitation. These results are similar to those of Vicente-Serrano et al. (2010).

The JJASO drought indices were correlated with corresponding yield anomalies for each county (Table 2) of the soybean growing season for 1960-2014. The results showed significant positive correlation between these indices and de-trended Soybean anomalies for 8 of the 11 counties in the study area. Craighead county particularly had very high correlations (r >0.5) for all the three indices (PDSI, SPEI-1 and SPI-1). Differences in soybean planting dates during the crop growing season may explain the difference in correlations between the counties in the study area (Narasimhan and Srinivasan 2005). The results also reveal that drought indices may be a valuable instrument for forecasting soybean grain yield loss resulting from meteorological drought.

PDSI performed well in this study; it was positively correlated with seven instances of departures in soybean yields—six at the 99% confidence level and once at the 95% confidence level. SPEI-1, and was closely correlated to the yields for eight of the counties studied. Six of the counties were correlated at the 99% confidence level and while two were correlated at the 95% confidence level. SPEI-3 was also correlated with eight counties, but at lower confidence levels.

Table 2: Correlation between JJASO Drought indicators and de-trended Soybean yield anomaly (1960-2014)

County	PDSI	SPEI-1 month	SPEI-3 months	SPEI-6 Months	SPI-1 month	SPI-3 months	SPI-6 months
Arkansas	0.022	**0.232***	0.141	0.047	0.160	0.077	0.054
Craighead	**0.512*****	**0.501*****	**0.459*****	**0.368*****	**0.537*****	**0.468*****	**0.368*****
Cross	**0.531*****	**0.444*****	**0.371*****	**0.261****	**0.397*****	**0.338****	**0.237***
Desha	0.078	0.154	0.061	0.097	0.165	0.073	0.085
Lee	**0.332*****	**0.469*****	**0.505*****	**0.434*****	**0.410*****	**0.446*****	**0.395*****
Monroe	**0.320*****	**0.508*****	**0.426*****	**0.303****	**0.463*****	**0.402****	**0.278***
Phillips	0.071	**0.282****	**0.238***	0.141	**0.226***	0.176	0.081
Poinsett	**0.317****	**0.408*****	**0.345*****	**0.312****	**0.397*****	**0.311****	**0.270****
Prairie	**0.445*****	**0.433*****	**0.463*****	**0.326****	**0.392*****	**0.424****	**0.306****
St Francis	0.061	0.203	0.078	0.068	0.154	0.009	0.023
Woodruff	**0.267****	**0.282****	**0.238***	0.202	0.195	0.030	0.004
Study area	**0.367*****	**0.393*****	**0.345*****	**0.261****	**0.414*****	**0.334*****	**0.221***

***indicates 99% confidence, ** indicates 95% Confidence and * indicates 90% confidence

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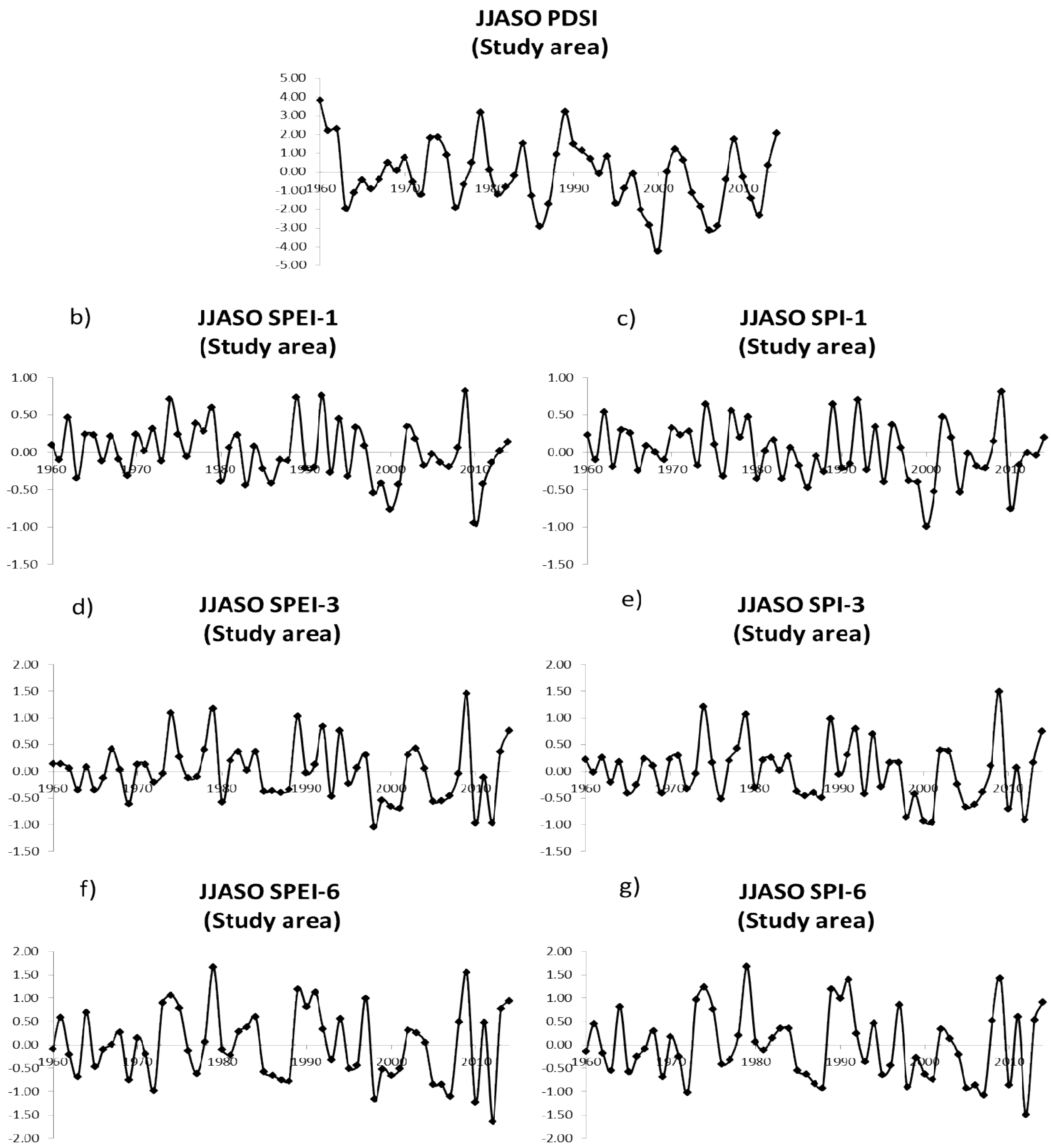

Figure 4: a) JJASO PDSI (1960-2014), b) JJASO SPEI-1month (1960-2014), c) JJASO SPI-1month (1960-2014), d) JJASO SPEI-3months (1960-2014), e) JJASO SPI-3 months (1960-2014), f) JJASO SPEI-6 months (1960-2014) and g) JJASO SPI-6 months (1960-2014).

Performance of the SPEI-6 was only significantly correlated to yields in 6 counties. These results reveal that SPEI based indices did better than PDSI save for SPEI-6. It is also important to note that the explanatory power of the SPEI diminishes as the time frame increases. For SPI, SPI-1 performed better with strong correlation in seven cases, six at the 99% confidence level. The explanatory power of the SPI indices also diminished as the time frame increased.In summary, SPEI indices outperformed PDSI and SPI. PDSI performed better than SPI, probably due to the inclusion of temperature in its computation. Short-term agricultural drought is best correlated to SPEI-1 and SPI-1. There are cases when drought indices do not exhibit meaningful correlation, as illustrated by their failure to indicate significant drought impact on yields in three of the 11 counties in the study area, where soybean was likely irrigated to mitigate drought impact. The absence of significant correlation for these counties may also result from low data quality of local weather stations.

Multiple Linear Regression

Multiple linear regression was performed with three agro-meteorological indicators (GDD, total precipitation and dry spell) to establish a GLM for each county and study area. Regression results for the counties and study area are shown in Table 3. Total precipitation and dry spell were the only factors explaining yield departures of soybean at 90% the confidence level in the final model for study area (Figure 5). The final model is shown below:-

$$Soybean\ Yield = b_0 - b_1 Dry\ Spell * + b_2 GDD - b_3 PRECIPITATION *$$

Where, b_0 is the intercept, b_1, $b_{2,}$ and b_3 are the parameters of Dry spell, GDD, and Total precipitation respectively. Figure 5 shows that the total precipitation is significant at α = 0.056 and total precipitation significant at α = 0.027. The parameter estimates suggests, b_0 = 49.78, b_1 = -0.60, b_2 = 0.006 and b_3 = -0.125.

Conclusion

This study was carried out to explore the relationship between, Agro-meteorological indicators, drought indices and crop yields in East Arkansas. There was positive correlation between total precipitation and yields. Furthermore, GDDs and dry spells were negatively correlated with the yields. Dry spell and Total precipitation were the only factors explaining yield departures of soybean from the normal values in our multi-linear regression model developed for the study area. The increases in GDDS and dry spell during the crop growing season will serve to lower yields and increase the cost of doing agriculture in the study area. Coupled with global change, increased costs due to irrigation demands will hurt farmers by putting pressure on ground water.

Table 3: General Linear Models for individual counties and study area (JJASO)

County	Intercept	GDD	Total Precipitation	Dry Spell
Arkansas	-10	**0.02***	0.022	0.002
Craighead	47.62	-0.018	**0.11***	0.042
Cross	30	0.07	0.042	**0.28****
Desha	-44	**0.028*****	**0.07****	**0.21***
Lee	12.81	0.02	0.044	0.091
Monroe	-21.38	**0.076***	0.07	0.51
Phillips	-5.61	**0.04***	0.04	0.022
Poinsett	28.89	0.006	0.038	**0.207***
Prairie	30.69	0.008	**0.105****	0.044
St Francis	-18.51	**0.02***	0.07	0.018
Woodruff	19.22	0.002	0.06	**0.105***
Study area	49.78	0.006	**-0.125***	**-0.60***

***indicates 99% confidence, ** indicates 95% Confidence and * indicates 90% confidence

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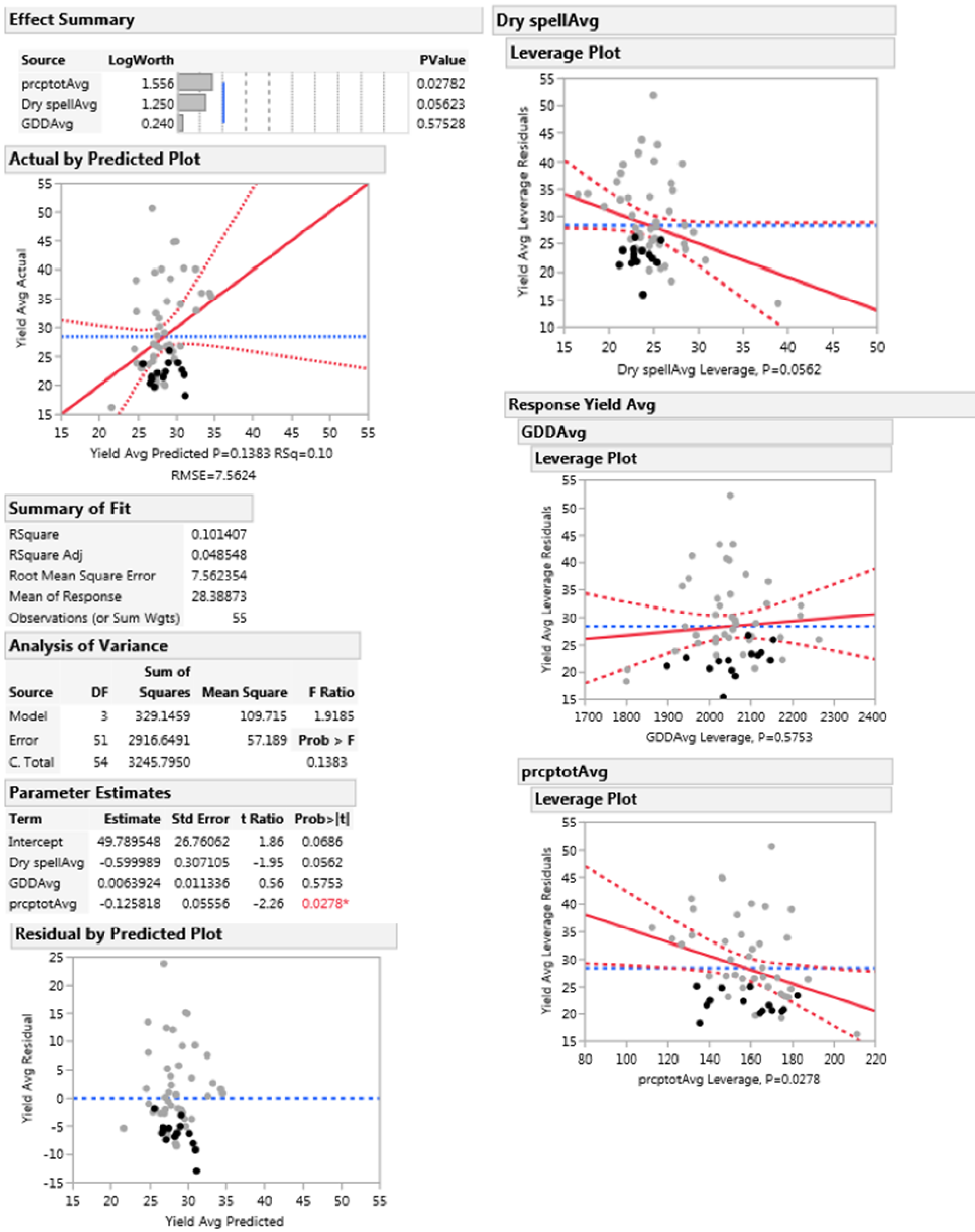

Figure 5: General Linear Model for soybean yields (1960-2014) for East Arkansas (JJASO)

While PDSI's efficacy was restricted to explanation of long-run drought impacts, it performed better than SPI indices. SPEI indices out performed both SPI and PDSI indices. SPEI and SPI indices, especially the one and three month indices, were closely correlated. PDSI was closely correlated to the SPEI-6 and SPI-6 indices. Importantly, short-term agricultural drought is best explained by SPEI-1 and SPI-1.

In cases where temperature trends are not apparent (relatively uniform), there was little difference in values obtained by precipitation indices like SPI or those formulated by potential evapotranspiration like SPEI. It is fair to conclude that in similar cases, precipitation data could be used to compute agricultural drought. SPI and SPEI-6 were strongly correlated to PDSI suggesting that precipitation was the most dominant factor in long term drought conditions. Due to negative effects of drought on agriculture and environment, agro meteorological indicators will play a critical role in long term studies for policy makers.

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