Drought Tolerance of Soybean Crops in Missouri

Joseph L. Parcell
Associate Professor
Department of Agricultural & Applied Economics
University of Missouri
143 Mumford Hall
Columbia, MO 65211
Phone: (573) 882-0870
Email: parcellj@missouri.edu

Jewelwayne Cain
Research Assistant
Department of Agricultural & Applied Economics
University of Missouri
143-C Mumford Hall
Columbia, MO 65211
Email: jscain@mail.missouri.edu
[Presenting Author]

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Joseph L. Parcell and Jewelwayne Cain
University of Missouri-Columbia

Abstract

Constant research efforts have been undertaken to create and adopt soybean varieties and farming practices that would lead to more drought-tolerant crops. Given that drought-tolerant crops are more stable in terms of price and supply, private genetic companies invest in those genetic materials with the biggest market opportunities. This begs the question: has there been any indication of improvements in drought-tolerance of crops? In this study, we focus on analyzing three soybean distinct relative maturity zones in the state of Missouri and determine if and in what direction is the drought tolerance of these crops changing over time.

Keywords: soybeans, drought tolerance, Missouri
JEL Classification: C23, C43, Q51, Q54

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Introduction

Soybean crops are an important source of oil and protein. Apart from being a popular substitute for meat, it is widely used in industrial and pharmaceutical application because of its known health-promoting properties (Gepts et al., 2005; Duranti, 2006; Chema et al., 2006; O'Brian and Vance, 2007; Tran and Mochida, 2010). It's more recent industrial application includes production of biodiesel (Hill et al., 2006; Tao and Aden, 2009; Pradhan et al., 2011; Yusuf et al., 2011).

According to data from the American Soybean Association, the United States is the world's largest producer of soybeans, producing 33% of world soybean production in 2011. The United States is also the second largest exporter of soybeans, exporting 37% of world soybean exports in 2011. Major growing areas of soybeans include Illinois and Iowa, with minor growing areas encompassing the surrounding states including Missouri. In the year 2010, 77.4 million acres (31.3 million hectares) of land were in soybean production yielding crop value of approximately $38.9 billion.

However, soybean farmers continue to face a number of challenges, among which is the constant environmental threat brought about by prolonged periods of drought. Drought is a situation where there is either less than average precipitation in the air or less amount of moisture in the soil. Among the immediate consequences is a diminished crop growth or yield production.

The United States has experienced several major periods of drought since the early 1900s. The worst recent drought was during the summer of 1988 where 35 states were affected and rainfall totals were up to 85% below normal. These periods of extreme drought have also witnessed low soybean crop production. Midwest states were affected heavily. For example, Saline, one of the central counties of Missouri, experienced sharp decline in soybean crop yields in 1978, 1980, 1984, and 1988 that were associated with high levels of drought conditions[1] (see Figure 1).

Towards the end of 2011, the United States again began experiencing drought. The drought persists into 2013. Throughout Midwest, soybean farms are producing far smaller yields (Taylor, 2012).

While correct farm management practices that minimize the environmental stress due to drought are constantly being advocated and adopted (McWilliams et al., 1999), increasing focus is being given to create and develop soybean varieties that are more drought-tolerant (Tran and Mochida, 2010). Plant breeding programs have offered better alternative to appropriate farm management practices that minimize adverse drought effects (Manavalan et al., 2009). Furthermore, there has already been arguments made that crops genetically modified for other purposes have the unintended

[1] Drought conditions as measured by the drought index proposed by Yu and Babcock (2010). See next section for a discussion on how the index is calculated.

additional benefit of making these crops able to withstand drought conditions as well (Yu and Babcock, 2010). While these arguments come from studies that look at corn varieties, soybeans genetically modified for a different purpose might acquire the same unintended additional trait of becoming more tolerant to droughts. This is particularly interesting especially given the fact that after a decade of introduction, 87 percent of total U.S. soybean production in 2005 are genetically modified (Chema et al., 2006).[2]

This begs the question, has there been any indication of improvements in drought-tolerant soybean crops? We explore the answer to this question by focusing on the state of Missouri.

There are already many studies that analyze the effects of extreme weather conditions on crop levels and yield variability using either simulation models (for example: Terjung et al., 1984; Mearns et al., 1996; Eitzinger et al., 2003; Schlenker and Roberts, 2009) or regression techniques (for example: Thompson, 1986; Mendelsohn et al., 1994; Isik and Devadoss, 2006; Lobell et al., 2007; Almaraz et al., 2008).[3] Regression techniques, however, provide more accurate estimates of the effects of climate factors on crops (Sarker et al, 2012). Most studies are on agronomic crops, especially corn. Regression-based studies that look at the effects of weather on soybean crops in particular include Chen et al. (2004), Prasad et al. (2006), McCarl et al. (2008), and Yu and Babcock (2010). Of these, Yu and Babcock (2010) is one of the few studies that

[2] The Roundup Ready Soybean is a herbicide immune crop introduced in the U.S. market in 1996.
[3] Also see McKeown et al. (2006) and Schlenker and Roberts (2009) for excellent reviews of some methods.

further analyze the changes in drought tolerance of soybean crops over time. Their data sample, however, only includes counties from Iowa, Illinois, and Indiana.

In this paper, we took a similar approach as that of Yu and Babcock (2010) in identifying if there are any improvements in drought tolerance of soybean crops in Missouri over time using county-level data on soybean yield and climate. In contrast to other studies, we distinguish three periods at which extreme drought incidents have occurred. These three periods combined cover the annual life cycle of a soybean plant. In addition, we consider geographic sensitivity of the effect of drought by dividing our sample into three regions. These two novelties help identify temporal and spatial heterogeneity in the drought effects.

Empirical Model

We analyze drought tolerance over time using a multivariate panel data regression model. We use a modified version of the yield-drought model specification of Yu and Babcock (2010):

$$
\begin{aligned}
Y_{i,t} = \alpha_i &+ \sum_{m=1}^{3} \beta_m (REGION_m \times TREND) + \sum_{m=1}^{3} \gamma_m \left(REGION_m \times DI_{i,t}\right) \\
&+ \sum_{m=1}^{3} \delta_m \left(REGION_m \times DI_{i,t} \times TREND\right) \\
&+ \sum_{m=1}^{3} \vartheta_m \left(REGION_m \times DI_{i,t}^2\right) + \epsilon_{i,t}
\end{aligned}
\tag{1}
$$

Subscripts t, i, and m denote time, county, and geographic region (northern counties, central counties, and southern counties), respectively. Y denotes natural log of soybean yield. *TREND* is a time trend variable with a starting value of 1 for year 1970 and 41 for year 2010. *DI* is a measure of drought index, which is also adopted from Yu and Babcock (2010):

$$(2) \qquad DI_{i,t} = \left[-max\left(0, CLDD_{i,t}^{stand}\right)\right] \times \left[min\left(0, TPCP_{i,t}^{stand}\right)\right],$$

where CLDD refers to cooling degree days and TPCP refers to total monthly precipitation. Both are standardized by subtracting county averages (across years) from each observation and then dividing the result by the county-level standard deviations (also across years). The Yu-Babcock drought index is a composite measure that has the advantage of capturing not only hot conditions, but dry conditions as well. Higher values of the index mean either the temperature measure is above average, the rainfall measure is below average, or both. We calculate aggregate drought indices separately for three periods encompassing the life cycle of a soybean plant: April to June total, June to August total, and August to October total. The drought indices are aggregated by summing CLDD and TPCP over each of these periods and then using the formula in (2) to calculate the final value.

The last variable is the quadratic form of *DI*. The quadratic form of *DI* is included to capture the possibility that the rate of marginal effect of drought on yield could be increasing or decreasing at higher levels of drought.

Equation (1) consists of a deterministic trend yield, $\alpha_i + \sum_1^3 \beta_m (REGION_m \times TREND)$, the drought-driven deviations from the trend, $\sum_1^3 \gamma_m \left(REGION_m \times DI_{i,t}\right) + \sum_1^3 \delta_m \left(REGION_m \times DI_{i,t} \times TREND\right) + \sum_1^3 \vartheta_m \left(REGION_m \times DI_{i,t}^2\right)$, and the residual, $\epsilon_{i,t}$. The deterministic trend yield contains a time-invariant county-specific intercept term, α_i, that will also serve to capture heterogeneity across panels, such as soil type and quality (Schlenker and Roberts, 2009). The second term of the deterministic trend yield is a region-specific slope. We assume that the yield over time is similar among counties in the same region.

We are most particularly interested in the drought-driven deviations. We also assume that the deviations are region-specific. Soybean yield from counties in one region experience the same effects from drought. If we differentiate equation (1) with respect to the drought index for a particular region m, we have the effect of drought on soybean yield:

(3) $$\frac{\partial Y_{i,t}}{\partial DI} = \gamma_m + \delta_m \times TREND + 2\vartheta_m \times DI_{i,t} \quad < 0$$

Since it is widely acknowledged that one primary consequence of drought is diminished yield production, we should expect the marginal effect as defined above to be negative. This is primarily seen through the value of γ_m. If $\gamma_m < 0$, drought has an adverse effect on soybean yield. Still, there could be a possibility that soybean crops benefit from high levels of drought, in which case we should see $\gamma_m > 0$. ϑ_m simply indicates the rate of change of the marginal effect of drought on yield, while δ_m specifies how this marginal effect changes over time.

Most important in our analysis is the sign of δ_m. In particular, differentiating equation (3) with respect to time, $TREND$, we capture the change in the effects of drought on yield over time for any given region m:

$$(4) \qquad \frac{\partial Y_{i,t}}{\partial DI \partial T} = \delta_m \quad \begin{cases} > 0\,, & indicates\ soybean\ is\ more\ drought-tolerant\ over\ time \\ < 0\,, & indicates\ soybean\ is\ less\ drought-tolerant\ over\ time \end{cases}$$

If δ_m is positive for any given region m, this means that soybean crops of this region are generally becoming more drought-tolerant over time. If instead the coefficient is negative, then soybean crops are becoming less tolerant to droughts over time. Finally, if the coefficient turns out to be not significant, then there is not enough evidence to suggest any changes in the soybean's drought tolerance over time.

Data

Data on soybean yield are available from the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA), while data on cooling degree days (CLDD) and total monthly precipitation (TPCP) are from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). Out of 80 counties with complete 1970 to 2010 soybean yield data, 9 have complete climate data from one weather station. Missing climate data from 11 other counties are imputed as follows: first, one station for each county with more complete climate data are identified and used as the primary source; second, missing values are generated using the Gaussian normal regression imputation method, with data from the primary station used as the dependent variable and data from another station as the independent variable. We implement the imputations in a Monte Carlo set-up of 1,000 iterations with the final value aggregated as the average of all results. The results are averaged and then used as the final value.

The same method was also used to impute missing climate data of an additional 10 counties, this time using climate data from stations of adjacent counties. To ensure that unique information are preserved for the main regression analysis, two conditions have to be met: (i) counties with which climate data will be imputed should have at most six missing observations (no more than 15% of the total 41 observations per county); and, (ii) adjacent counties have to be those that will not be included in the final analysis. The last condition is met by choosing among counties that have incomplete soybean data. In identifying and matching two counties, the distances between their respective weather stations have to be no longer than 50 road miles apart and the correlation coefficients of available climate data between the two counties be no less than 0.75. Once the match is made, the same Gaussian normal regression imputation method is implemented using climate data from the adjacent county as the independent variable.

The 30 counties are broken into three geographic regions: 8 northern counties, 13 central counties, and 9 southern counties. Each county has 41 observations; each observation corresponding to each year in the sample (1970 to 2010). A summary of descriptive statistics on the variables used in the regression analysis is presented in Table 1.

Preliminary Tests

Before identifying the correct regression estimation method to use, we conduct several preliminary tests to check if there is a need to transform the data or use a different regression method other than ordinary least squares. We first perform unit root tests to verify that the variables natural log of soybean yield and the calculated indices are each stationary. This is particularly important given that we are using a trend variable. Thome (1996) cautions that there might be some consequences of using a time trend when the series actually contain some unit roots. Among the consequences are spurious coefficient of determination (R-square) and biased estimators.[4] We

[4] This refers to the so-called situation of "spurious detrending."

specifically use four panel data stationary tests. The first two, the Levin-Li-Chu test (Levin et al., 2002) and the Hadri test (Hadri, 2000), assume that the autoregressive parameter is the same across all panels. While the null hypothesis of the Levin-Li-Chu test is that all panel data are stationary, the null hypothesis of the Hadri test is that all panel data have unit roots. In a way, these two tests complement each other. Running both tests can clearly establish if (i) all panel data are stationary, (ii) all panel data have unit roots, or (iii) some panel data are stationary while others have unit roots. If we were only to run one test, the Levin-Li-Chu test for example, rejection of the null hypothesis can either mean some panel data have unit roots, or all panel data have unit roots. If we additionally run the Hadri test, we can narrow down which of the two is likely the case. For example, if we additionally fail to reject the null hypothesis of the Hadri test, then we have strong evidence that all panel data contain unit roots.

One obvious weakness to the Levin-Li-Chu test and the Hadri test is the restrictive assumption of common autoregressive parameter. Certain factors, especially geographic features, may make such assumption unrealistic. So we employ two other panel data stationary tests that relax this assumption: the Im-Pesaran-Shin test (Im et al., 2003) and a Fisher-type meta-analysis of the results from implementing augmented Dickey-Fuller tests on each panel data (Fisher, 1932; Maddala and Wu, 1999). The Im-Pesaran-Shin test and the Fisher-ADF test have the same null hypothesis: all panel data contain unit roots.

In order to minimize complications that would arise due to cross-sectional dependence when implementing the stationary tests, the cross-sectional averages are subtracted from each panel data. Furthermore, we include only one-period county-specific lags in all tests. We determined that including only one-period lagged term is sufficient given that the appropriate number of lags chosen by three information criterion (Akaike, Bayesian, and Hannan-Quinn) averaged between 0.03 to 0.90 across all panels.

The results of the stationary tests are reported in Table 2. All tests strongly reject the null hypothesis of the existence of unit roots in all panel data. In particular, the results of both the Levin-Li-Chu tests and the Hadri tests provide strong evidence that the drought index for each period in each county is stationary. In summary, these results suggest that we do not need to transform the data to address any potential nonstationarity issues in the time series.

We also ran tests on the error structure of the model to check for cross-sectional dependence (contemporaneous correlation of errors across panels), serial correlation, and cross-panel heteroskedasticity. The results of all these tests are shown in Table 3.

Significant cross-sectional dependence in errors may cause either inefficient estimators (if the dependence is caused by unobserved common factors not correlated with any of the regressors) or biased and inconsistent estimators (if such unobserved factors are correlated with the regressors). Three tests of cross-sectional dependence were employed: the Pesaran CD test (Pesaran, 2004), the Friedman R test (Friedman, 1937), and the Frees average R test (Frees, 1995, 2004).[5] All tests have no cross-sectional dependence as the null hypothesis. Given the test results shown in Table 3, there is strong evidence suggesting that cross-sectional units are not independent.

Next we test for serial correlation within each panel using the method suggested by Wooldridge (2002). Drukker (2003) showed that the Wooldridge test is very attractive because it is less restrictive than other tests and it is easy to implement.[6] As shown in Table 3, the null hypothesis of no serial correlation is not rejected.

Finally, using least squares method on panel data regression requires that variances should not differ within cross-sectional units as well as across units (Baum, 2001). So we also test cross-panel heteroskedasticity using a method proposed by Greene (2000). The Greene test calculates a modified Wald test statistic from the residuals of a fixed-effect regression model. The p-value of the modified Wald test statistic shown in Table 3 indicates that the null hypothesis of no cross-panel heteroskedasticity is strongly rejected. This means that there is strong evidence the variance differs across panels.

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[5] A more common test in the literature is the LM test of Breusch and Pagan (1980). We did not include this test since the Breusch-Pagan test cannot be implemented for non-linear specifications. As De Hoyos and Sarafides (2006) stated, all four tests can still be considered as complimentary to each other.

[6] The Baltagi-Li test, for instance, makes certain specific assumptions about individual effects, whereas the Wooldridge test requires only a few assumptions (Baltagi and Li, 1995; Drukker, 2003).

Based on these preliminary findings, we run equation (1) using feasible generalized least squares method that includes a heteroskedastic error structure with cross-panel correlation. This method will take into account the presence of cross-sectional correlation and heteroskedasticity across panels.

Estimation Results

We estimate equation (1) separately for each of the three time periods of drought data: April to June, June to August, and August to October. We also made a fourth estimation, where we simultaneously include drought episodes from all three periods.

Column (1) of Table 4 shows the estimation results of the specification that uses drought data only from April to June. Contrary to expectations, the positive and significant coefficients on drought index for northern and central regions indicate that drought seems to have a positive effect on yields for soybeans planted in counties within these two regions. However surprising this result may be, at least for counties in the northern region, we find that this positive marginal effect of drought on yield gets smaller as the level of drought increases. This is evident from the significant and negative coefficient of the drought index quadratic term. For counties in the southern region, the coefficient of drought index is not significant, which imply that drought has no effect on soybean yield at all.

Despite these differences across regions, the drought-trend interaction terms are the same for all regions. They are negative and significant, showing that the positive effect of drought on yield, if any, is decreasing over time. This means that soybean crops are becoming less tolerant to droughts that occur between April and June.

Looking next at results of the specification that include only drought incidents between June and August, as shown in column (2) of Table 4, we now find that the drought index is negative and significant for all regions. Matching our expectations, drought occurring in this period has caused lower soybean crop yield. The result that soybean crops are adversely affected by extreme drought incidents from this period and not from the period between April and June coincides with studies that find flowering stages of the soybean plant to be most critical with regards to drought stress (Meckel et al., 1984, and Wrather et al., 2003). The soybean's flowering stages primarily occur early during the June-August period.

The drought-trend interaction term continue to be negative and significant for northern and central regions. This means that soybean crops in counties within these two regions are also becoming less tolerant to drought incidents occurring in the months of June to August. For the southern region, however, the interaction term is positive and significant for the southern region. This is evidence that soybean crops planted in counties within the southern region have actually become more tolerant over time to drought incidents happening during this period.

Drought incidents occurring between August and October continue to adversely affect the annual soybean yield of all regions, as shown from the results of the third model specification in column (3) of Table 4. The coefficients of all drought indices are negative and significant. This time, however, crops in all regions exhibit increasing tolerance over time to droughts occurring in this period. This is evidenced from the drought-trend interaction terms, which are positive and significant for all regions.

For the final model specification in column (4) of Table 4, we now include drought indices from all three periods. We see some robustness in the results from the previous three specifications. In particular, crops from all regions are still becoming less tolerant over time to droughts occurring between April and June (as seen from the negative and significant coefficients of the drought-trend interaction terms). The only difference from the previous specification is that all regions, including the southern region this time, are shown to be positively affected by drought occurring in this period.

For drought incidents occurring between June and August, we find qualitatively similar results: drought adversely affect annual soybean yield in all regions; and, only soybean planted in counties within the southern region are exhibiting increasing drought tolerance over time. Counties from the rest of the other regions are shown to still have decreasing tolerance to drought over time.

Finally, for August to October drought occurrences, only soybeans planted in the northern region have qualitatively similar results as that of the previous specifications.

The findings that drought adversely affect annual soybean yield and that soybeans are nevertheless becoming increasingly drought tolerant over time, is robust only for counties in the northern region.

For counties in the central region, extreme droughts happening between August and October still adversely affect soybean yield. This time, however, the drought-trend interaction term is not significant. This means that in contrast to the previous specifications, the effect of drought on soybean crops in the central region is not changing over time.

For the southern region, we find a completely different result. The coefficient of the drought index is now positive and significant, while the coefficient of the drought-trend interaction term is negative and significant. This means that contrary to the findings of the previous specifications, drought between August and October positively affects annual soybean yield in counties within the southern region, and that this positive effect is declining over time (i.e., decreasing drought tolerance).

Conclusion

This paper attempts to analyze the effects of drought on soybean yield over time, focusing on the state of Missouri. We employ a regression-based approach, using generalized least squares estimation on county-level data to account for cross-panel correlation and heteroskedasticity. Drought data aggregated in three periods over the life cycle of a soybean plant are analyzed for 30 counties divided into three geographic regions.

The regression results can be summarized as follows:

1. Drought occurrences between April and June seem to have positive effect on soybean crop yield, but that this positive effect is decreasing over time.
2. Soybean crops are adversely affected by drought incidents that occur only between June and October.
3. Soybean crops planted in northern and central counties show increasing tolerance only against droughts occurring between August and October.
4. For soybean crops planted in southern counties, they only exhibit increasing tolerance over time against droughts occurring between June and August.

All these suggest that there is heterogeneity in the effects of drought on soybean crop yield for the state of Missouri depending on (i) geographic location and (ii) period in the soybean plant's life cycle. Such differences may be due to soil quality and various farming practices. It could even be simply down to differences in physiological traits of soybean crops planted across different regions. However, analysis of which of these factors come into play is beyond the scope of this paper and should be the subject of future research.

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Tables and Figures

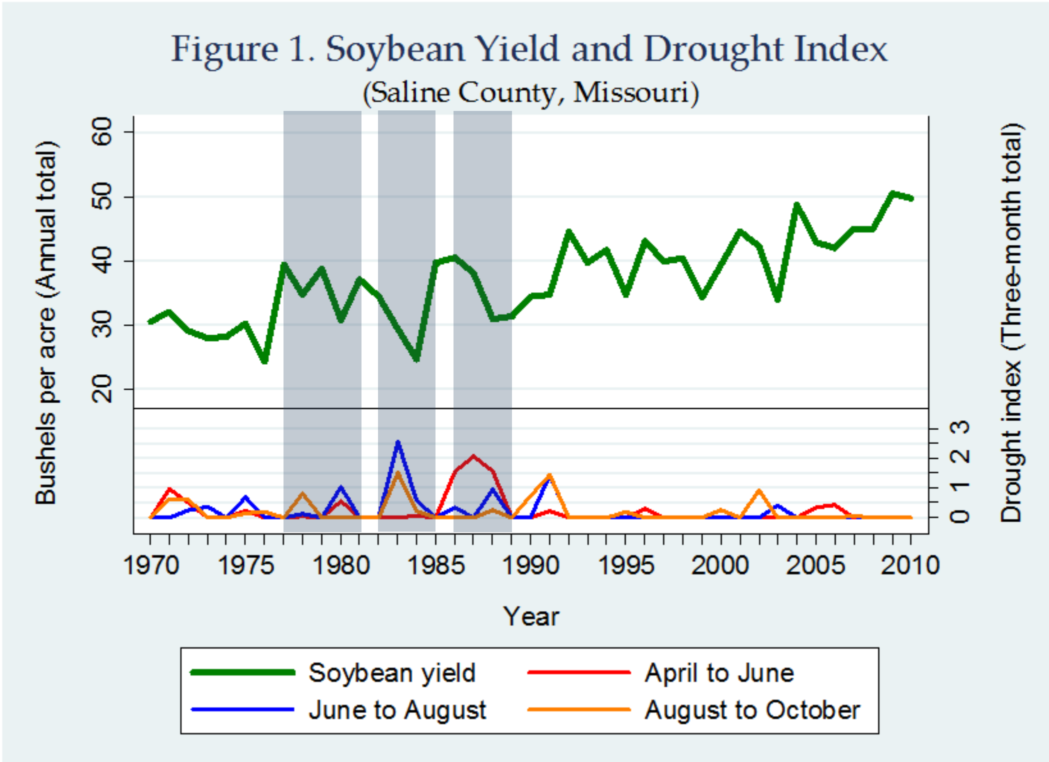

Table 1. Descriptive Statistics of Data Number of observations: 1,230				
Variables	Mean	Standard Deviation	Minimum	Maximum
Soybean yield (bushels per acre)	30.4509	7.8832	6.8000	50.8000
Natural log of soybean yield	3.3779	0.2895	1.9169	3.9279
Drought index (April to June)	0.2159	0.5505	0.0000	5.9189
Drought index (June to August)	0.2430	0.6870	0.0000	7.3993
Drought index (August to October)	0.1932	0.4831	0.0000	4.7434

Table 2. Unit Root Tests for Panel Data				
	Common Autoregressive Parameter		Panel-specific Autoregressive Parameter	
Variable	Levin-Li-Chu (Adjusted t) *H_0: Unit root*	Hadri (Z) *H_0: No unit root*	Im-Pesaran-Shin ($W_{t\text{-bar}}$) *H_0: Unit root*	Fisher – ADF (Inverse normal Z) *H_0: Unit root*
Natural Log of Soybean yield	– 15.1075 (0.0000)	2.4716 (0.0067)	– 18.8042 (0.0000)	– 17.9155 (0.0000)
Drought Index (April to June)	– 14.8954 (0.0000)	0.9692 (0.1662)	– 16.6167 (0.0000)	– 17.7446 (0.0000)
Drought Index (June to August)	– 12.4403 (0.0000)	1.0671 (0.1430)	– 15.3297 (0.0000)	– 16.4718 (0.0000)
Drought Index (August to October)	– 14.8488 (0.0000)	1.2249 (0.1103)	– 16.6774 (0.0000)	– 17.8080 (0.0000)
Note: Each test uses one-period lagged term. P-values in parentheses.				

Table 3. Analysis of the Error Structure	
Test for cross-sectional dependence *(H_0: No dependence)*	
Pesaran CD test	78.554 (0.0000)
Friedman R_{ave} test	683.089 (0.0000)
Frees R_{ave}^2 test	9.139 (0.0000)
Test for serial correlation *(H_0: No serial correlation)*	
Wooldridge Wald test	0.527 (0.4736)
Test for cross-panel heteroskedasticity *(H_0: No heteroskedasticity)*	
Greene modified Wald test	113.82 (0.0000)
Note: P-values in parenthesis	

Table 4. Generalized Least Squares Estimation Results with Quadratic Term for Drought Index Dependent variable: Natural log of soybean yield					
Region	Variables	(1)	(2)	(3)	(4)
April to June Drought					
North	Drought index	0.1583 ***			0.1511 ***
	Drought index * Trend	– 0.0041 ***			– 0.0025 ***
	Drought index squared	– 0.0272 ***			– 0.0228 ***
Central	Drought index	0.0353 **			0.1301 ***
	Drought index * Trend	– 0.0036 ***			– 0.0031 ***
	Drought index squared	0.0045			– 0.0089 *
South	Drought index	0.0038			0.1077 ***
	Drought index * Trend	– 0.0033 ***			– 0.0055 ***
	Drought index squared	0.0094 **			0.0039
June to August Drought					
North	Drought index		– 0.1019 ***		– 0.0484 **
	Drought index * Trend		– 0.0023 ***		– 0.0040 ***
	Drought index squared		0.0061		0.0042
Central	Drought index		– 0.0993 ***		– 0.1270 ***
	Drought index * Trend		– 0.00445 ***		– 0.0025 ***
	Drought index squared		0.0012		0.0011
South	Drought index		– 0.2396 ***		– 0.2539 ***
	Drought index * Trend		0.0042 ***		0.0051 ***
	Drought index squared		0.0106 ***		0.0157 ***
August to October Drought					
North	Drought index			– 0.3531 ***	– 0.2105 ***
	Drought index * Trend			0.0053 ***	0.0045 ***
	Drought index squared			0.0433 ***	0.0250 ***
Central	Drought index			– 0.3136 ***	– 0.1078 ***
	Drought index * Trend			0.0043 ***	– 0.0009
	Drought index squared			0.0183 ***	0.0268 ***
South	Drought index			– 0.1541 ***	0.0585 **
	Drought index * Trend			0.0018 **	– 0.0042 ***
	Drought index squared			– 0.0217 ***	– 0.0285 ***
Northern county dummy * Trend		0.0130 ***	0.0119 ***	0.0119 ***	0.0119 ***
Central county dummy * Trend		0.0138 ***	0.0129 ***	0.0129 ***	0.0133 ***
Southern county dummy * Trend		0.0138 ***	0.0124 ***	0.0133 ***	0.0140 ***
Notes: Number of panels: 30; number of periods: 41; total number of observations: 1,230. Also included but not reported in the estimation above are time-invariant county-specific dummy variables. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.					