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CLIMATIC VARIABILITY AND CROP PRICE TRENDS IN WEST TENNESSEE: A BIVARIATE GRANGER CAUSALITY ANALYSIS

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Abstract

Weather aberrations like drought and extremely high temperatures have been associated with adverse impacts on crop yields particularly in agricultural production areas that extensively rely on rainfall. Extremely dry weather accompanied with low or negligible precipitation often leads to crop failure, resulting in decline of supplies and increasing crop prices. Among the recent climatic events of importance, U.S agriculture as a whole experienced one of its worst droughts in mid-year 2012 over a three decade horizon. The 2012 drought had serious implications particularly in the major production areas of Midwest and Southeast U.S damaging vast portions of field crops like corn and soybeans subsequently leading to increase in farm prices. The objective of this study is to conduct a bivariate granger causality analysis for climatic indicators causing soybean price changes over a study period from 1975-2013. The results indicate that a significant causality was detected for precipitation impacting commodity price movements for soybeans. No significant evidence was obtained for the presence of Granger causality between temperature related indicators (maximum, minimum, and average) and soybeans prices. The outcome of this study provides an initial insight into the causality between climatic indicators and commodity price movements for soybeans in the study region, and emphasizes the existence of causality for commodity prices by precipitation changes as compared to changes in temperature, especially in the absence of irrigation based production in the region.

Keywords: Climatic variability, Granger causality, Precipitation, Soybean prices, Temperature, West Tennessee

Introduction

Weather aberrations like drought and extremely high temperatures have been associated with adverse impacts on crop yields particularly in agricultural production areas that extensively rely on rainfall. Changes in crop yields impact crop prices which influence the regional production systems and the overall agricultural economy. Extremely dry weather accompanied with low or negligible precipitation often leads to crop failure, resulting in decline of supplies and increasing crop prices. This is also crucial to consumers because higher crop prices typically lead to higher retail prices. Among the recent climatic events of importance, U.S agriculture experienced one of its worst droughts in mid-year 2012 over a three decade horizon. According to the U.S. Department of Agriculture [7] 80 percent of agricultural land in the United States experienced drought conditions in 2012, with the month of July being the warmest throughout the country in the last hundred and thirty years. The 2012 drought had serious implications for major field crops damaging major portions of crops in the Midwest and Southeast particularly field corn and soybeans [7]. This subsequently led to increase in the farm prices of corn, soybeans, and other farm commodities. The above information highlights the fact that climatic aberrations can influence the market prices of commodities in areas of significant production. In Southeast U.S, particularly in the state of Tennessee, soybeans production is of significant economic importance among row crops due to high planted acreages. The crop accounts for the largest planted row crop acres in Tennessee, with over one million acres grown annually, and ranks in the top three for cash receipts for row crops [18]. The average statewide yields for soybeans range from 2200-2800 kilograms per hectare. Most soybeans are grown in Western and middle Tennessee counties under rainfed conditions and over 80% are grown in a no-till or conservation tillage system with yields being heavily dependent on rainfall [18].

Numerous agronomic studies have been conducted in the past to determine the response of soybean crop to water and temperature stresses [19]. Soil moisture stress throughout the growing season results in reduced leaf area, leaf duration, crop growth rate, shoot dry matter [21], number of pods per square meter, and number of seeds per pod [20]. Number of pods has been found to be the most sensitive component to drought stress [22], while seed weight is least affected by drought. It has also been found that moisture stress impacts on soybean yields differ from one variety to the other [19], and absolute yield reductions can vary from 1.0 megagram per hectare (Mg/ha) in the most sensitive varieties to 0.2 Mg/ha (3.0 bu/ac) in the least sensitive varieties [23]. Adequate water is imperative after full bloom and during the pod fill stage for maximum yields in soybeans [27]. It has also been found that with rise in air temperature, the rate of development increases, which may in turn result in shorter durations of various stages, such as seed fill and impact yields negatively. Further, night temperatures also impact seed growth, and specific studies reveal that temperatures less than 10°C [24] and greater than 28°C lead to a reduction in seed growth. Also, the effects of low night temperatures on soybean pod set were not offset by high daytime temperatures [25].

Given the above argument about the influence of climatic variability on crop production which in turn impacts crop prices, it becomes imperative to understand the causality between the two, particularly for high soybeans production areas in the state of Tennessee. This investigation becomes inevitable given the limited literature and regional studies for the state of Tennessee that address climatic influence on agricultural production of row crops. However, it is important to note that crop prices are not just a function of production parameters, and are influenced by other exogenous factors like farm programs, and crop insurance programs. Programs like direct payments and crop insurance subsidies are government tools to stabilize food prices for consumers while protecting farmers from weather-related losses. Recent statistics reveal that the Federal crop program insured $117 billion worth of crops for the year 2012, including almost all the corn, soybeans, cotton and wheat grown in the U.S, and made a record $14 billion worth of payouts and subsidies in 2012 [26]. This is a heavy price to pay on behalf of the taxpayers, even if the instruments are intended to stabilize crop prices. These situations further emphasize the uncertainty that agricultural production brings along with the economic costs involved. Understanding the influence of climatic parameters especially in areas of rainfed production could be an initial step towards exploring the contribution of weather related uncertainty on crop price fluctuations. Therefore, this study starts with an initial exploration into the movement of historical crop prices with weather parameters, in West Tennessee as the study region. In the past, broader studies have been conducted for the Southeastern U.S including the state of Tennessee as part of the national climate assessment [4] and this study attempts to enhance the currently available literature in the area of climatic variability assessment on agricultural production of economically important row crops like soybeans for the specific study region of West Tennessee.

According to the recently released Third National Climate Assessment for the Southeast U.S and the Caribbean [4], the agricultural sector is likely to experience uneven impacts on account of future climatic variability throughout the country including the state of Tennessee. This report also indicates that increasing temperatures will eventually nullify the initial economic gains derived from altered growing conditions, and events like regional droughts, water shortages, excess precipitation, as well as pest and disease incidences will negatively impact agriculture in most regions. Although, the report suggests that crop production may likely be increased for crops like soybeans due to an increase in three major climatic variables - temperature, precipitation, and carbon dioxide levels, extreme events such as heat waves, droughts, and floods, which are highly unpredictable bring forth a large amount of uncertainty for future agricultural productivity in the state of Tennessee. For instance, an early study by [6] revealed that climate variability can severely impact the overall profit margin in the Midwest states. The results indicated that an increase of 10-25 percent in the variability of temperature and precipitation would lead to increased agricultural losses in the range of 150 percent and above, even when holding average temperature and total precipitation increases constant. This could also lead to increased crop pests incidences, due to rising temperatures primarily resulting in higher wintertime lows which eventually would make the winters in the future incapable of killing off pest generations [16]. Furthermore, in a study by [17] it was found that lengthening of the warm season will allow greater numbers of pest generations to coexist. It has not been found yet how climate change will affect cotton and soybean crop pests, but a general conclusion is that crop pests incidences will become more prevalent with climate change [4]. From the point of view of the capacity of agricultural producers to adapt to these climatic changes, there are studies that bring to light the consideration that effects of climate change are likely to appear both in gradual terms and in episodic crises such as outbreaks of new pests and in the onset of severe droughts [28]. This study further suggests that historical records provide evidence in the favor of farmers being able to develop technologies to expand production into areas that were considered unsuitable on account of unfavorable climatic conditions. Also, while it is expected that technological advances will be able to counter some problems brought about by global warming, the ability of farmers to deal with events like episodic pest occurrences is still under question.

In light of the above information and past studies, it is evident that specific climatic information of regional emphasis in areas of high agricultural production in the state of Tennessee may be a starting point for understanding future climate variability and subsequent impacts in these areas. This study utilizes a bivariate granger causality approach to create a basis for future predictive studies which may be extremely useful for evaluating how future climate variability could impact agricultural production in West Tennessee. The specific objective of this study is to explore the granger causality between climatic indicators (like temperature and precipitation) and soybean crop prices, using West Tennessee as the study region. This becomes extremely important given the future projections of increasing temperatures and declining precipitation for most agricultural production regions in the country including the study area [12].

Experimental Section

Study area

The specific area chosen for this study is West Tennessee (Figure 1). Climatic data was gathered for the outlined counties (Figure 1: Weakley, Henry, Gibson, and Carroll) to derive representative observations for the study area.

Data

Observations for daily maximum, minimum, and average temperature and precipitation for individual weather stations in the study area are obtained from the GHCN daily legend (Global Historical Climatology Network) of the National Climate Data center [15]. Further, observations from different weather stations for the climatic variables of interest are averaged to represent a local climate for the study region. Monthly data for commodity prices for soybeans (historical prices received by U.S producers by marketing year) are obtained from the National Agricultural Statistics Service [14]. We use the study region's consumer price index (July 2013) to adjust the prices for inflation [3]. A descriptive statistics of climatic variables and soybeans prices in West Tennessee used in the study is provided in Table 1.

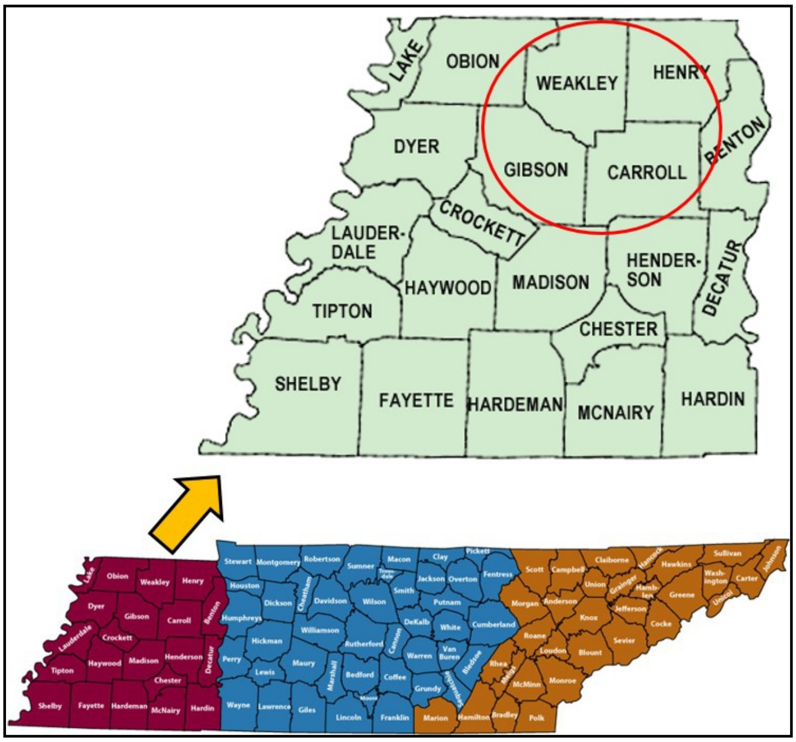

Figure 1. Study area depicting West Tennessee counties used for climatic analysis

Table 1. Descriptive statistics of climatic variables and soybeans prices in West Tennessee (1975-2013)

	Precipitation (mm)	Max temp (^{0}C)	Min temp (^{0}C)	Avg. annual temp (^{0}C)	Soybeans price ($/bu, 1 bu=27 kg)
Mean	111.82	21.64	9.45	15.55	6.81
Standard Error	2.85	0.15	0.12	0.13	0.37
Median	111.38	21.65	9.49	15.56	5.98
Std. Deviation	17.59	0.92	0.75	0.79	2.25
Range	68.63	5.60	4.47	4.70	10.02
Minimum	80.02	17.73	6.43	12.07	4.38
Maximum	148.65	23.33	10.90	16.77	14.40
Observations	38	38	38	38	38

Granger causality

The primary tool used in our analysis is the notion of Granger causality between two time series [9]. The Granger causality approach has been applied to climatic time series in several studies in various fields of interest. However, the literature on causality between climatic indicators and agricultural commodity prices is scarce. Some studies have utilized the concept of granger causality to evaluate agricultural market integration and performance as impacted by climatic shocks [1] [13]. The most relevant study to this analysis that utilized a similar framework was conducted by [2], where they used granger causality to evaluate the trend changes in climatic parameters and agricultural production in Nigeria, as well as the dimension and linkage between the same. The results revealed that changes in rainfall positively affected agricultural production in Nigeria, while temperature, on the other hand, remained relatively constant and did not affect agricultural output. The Granger Causality test, according to [8], involved the estimation of the following pairs:

$$W_t = \sum_{t=1}^{n} \alpha_1 \; Z_{t-1} + \sum_{j=1}^{n} \beta_1 \; W_{t-1} + U_{1t} \quad (1)$$

$$W_t = \sum_{t=1}^{n} \alpha_1 \; Z_{t-1} + \sum_{j=1}^{n} \delta_1 \; W_{t-1} + U_{2t} \quad (2)$$

where U1t and U2t is a disturbance term; Wt represents climatic element at time t; Zt represents soybeans prices at time t; and t-1 represent lag variables. By this model, a variable that causes the order is identified. This leads to a regression model with a lag variable, which is given as:

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_{t-1} + \beta_3 Y_{t-1} + U_t \quad (3)$$

where Yt is a dependent variable estimated by the Granger model (Wt or Zt); Yt-1, X t-1 are lagged dependent and independent variables; Ut is an error term. Before testing for causality, it is important to go through the process of testing for stationarity of a time series data, which can strongly influence its behaviour and properties. If the variables in the regression model are not stationary, then the standard assumptions for asymptotic analysis do not hold (like the t-distribution for the t-ratios) and the mean or variance is not constant as we go over progressive units in time. On the other hand, when a process is stationary, the distribution does not depend on time t. Thus the data is i.i.d (identically and independently distributed). The test for stationarity is carried out in terms of the unit root using a Dickey Fuller test [5]. The basic objective of the Dickey Fuller test is to test the null hypothesis that $\varphi=1$ in: $Yt= \varphi Yt\text{-}1+ ut$

H0: $\varphi = 1$ ($\varphi (z) = 0$ has a unit root)

H1: Series is stationary

If we fail to reject the null hypothesis of unit root for the time series in question, we conclude that the series is non-stationary and take differences to transform it into a stationary series. Subjecting the data to the Augmented Dickey Fuller (ADF) test, we fail to reject the null hypothesis of unit root for the climatic indicators as well as soybean crops prices and conclude that the series is non-stationary. We further take first differences of each of the climatic variables as well as crop prices to transform the data and again apply the ADF test. The first differenced values show stationarity and we go ahead and proceed with the analysis.

The plots for the climatic indicators and prices as well as their first differenced values are provided in Figures 2, 3, 4, and 5.

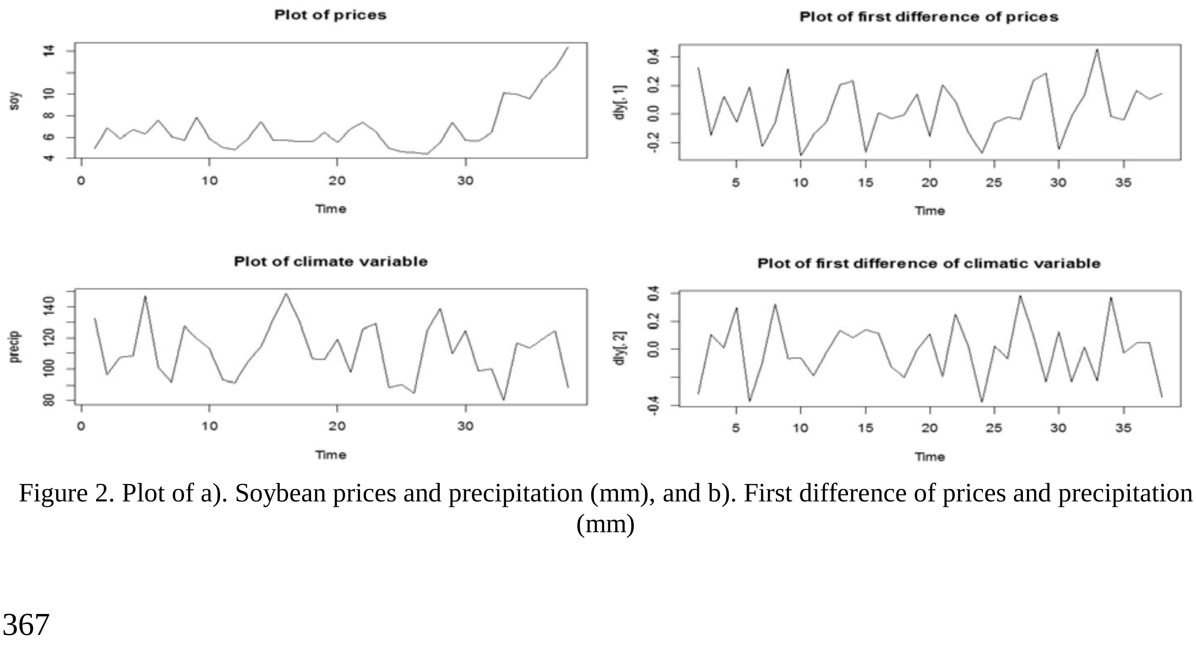

Figure 2. Plot of a). Soybean prices and precipitation (mm), and b). First difference of prices and precipitation (mm)

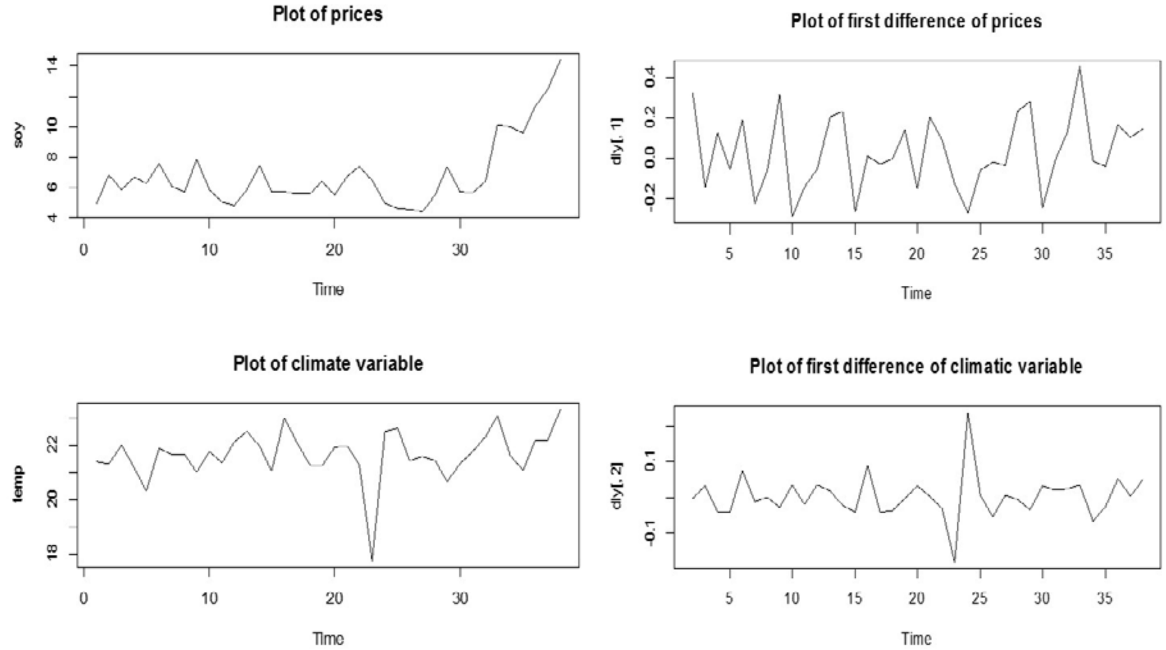

Figure 3. Plot of a). Soybean prices and maximum temperature (0C), and b). First difference of prices and maximum temperature (0C)

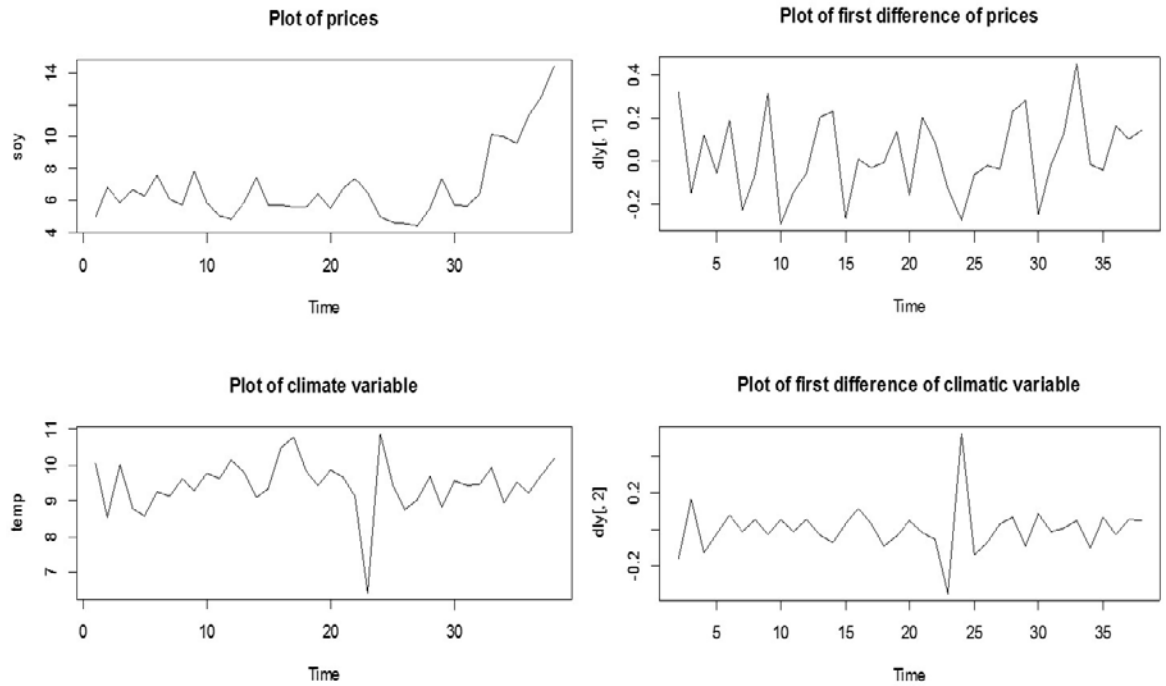

Figure 4. Plot of a). Soybean prices and minimum temperature (0C), and b). First difference of prices and minimum temperature (0C)

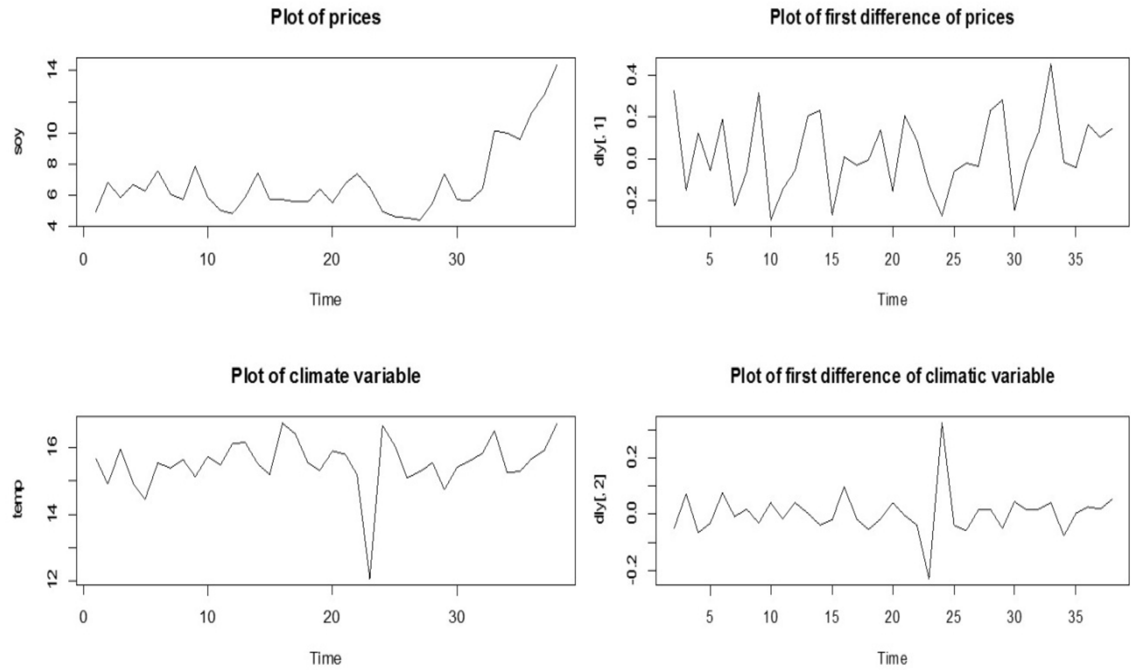

Figure 5. Plot of a). Soybean prices and average annual temperature (0C), and b). First difference of prices and average annual temperature (0C)

In this study, it is relevant to test if there is causality between soybean prices and each of the climate variables during the study period. Generally stating, an X variable Granger causes Y if Y can be better predicted using the histories of both X and Y (lagged values) than it can using the history of Y alone. The analysis is done using a bivariate VAR (Vector Autoregression) for soybean crop prices and climatic indicators. The general null hypothesis to be tested for each of the climatic variables (precipitation, Tmax, Tmin, and Taverage) and crop prices for soybeans is given as following:

H_0 : Climate variable does not Granger cause soybean prices

H_1 : Climate variable Granger causes soybean prices

VAR specification

Vector autoregression (VAR) is an econometric technique used to capture the evolution and interdependencies between multiple time series, generalizing the univariate AR models [10]. In a VAR model, all variables are treated symmetrically by the use of each variable as an equation that details its evolution based on its own lags and the lags of all the other variables in the model [10]. A VAR model describes the evolution of a set of k variables over the same sample period (t = 1, ...,T) as a linear function of only their past evolution. The variables are collected in a k × 1 vector y_t, which has as the i-th element $y_{i,t}$, the time t observation of variable y_i [11]. For instance, if the i-th variable is precipitation, then $y_{i,t}$ is the value of precipitation at t.

A (reduced) p-th order VAR, denoted VAR (p), is:

$$y_t = c + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \quad (4)$$

where c is a k × 1 vector of constants (intercept), Φ_i is a k × k matrix (for every i = 1, ..., p) and ε_t is a k × 1 vector of error terms. The i-periods back observation y_{t-i} is called the i-th lag of y. In this manner, a p-th-order VAR is also called a VAR with p lags.

Results and Discussion

Results of VAR Lag Order Selection

The lag order selection is considered an important preliminary step in model building and further conducting a causality analysis. In this study we use some commonly used lag-order selection criteria to choose the lag order, such as AIC (Akaike Information Criterion), HQ (Hannan-Quinn), and SC (Schwartz Criterion). Using the "VARselect" in R, the lag length selection under different criterion for individual analyses of climatic indicators and soybean crop prices was calculated. The results are provided in Tables 2, 3, 4 and 5.

Table 2. Precipitation and Prices: lag length selection in VAR model: AIC (Akaike Information Criterion) - SC (Schwarz Criterion) and HQ (Hannan–Quinn information criterion). The minimum for each criterion is provided in bold type-face.

Lag (m)	AIC	SC	HQ
1	-6.6301	-6.4469	-6.5694
2	-6.7019	-6.3354	-6.5804
3	-6.4935	-5.9439	-6.3113
4	-6.5218	-5.789	-6.2789
5	-6.5562	-5.6402	-6.2526

Table 3. Maximum temperature and prices: lag length selection in VAR model: AIC (Akaike Information Criterion) - SC (Schwarz Criterion) and HQ (Hannan–Quinn information criterion). The minimum for each criterion is provided in bold type-face.

Lag (m)	AIC	SC	HQ
1	-8.9318	-8.7486	-8.8711
2	-8.9696	-8.6032	-8.8482
3	-8.91	-8.3603	-8.7278
4	-8.774	-8.0411	-8.5311
5	-8.8947	-7.9786	-8.5911

Table 4. Minimum temperature and Prices: lag length selection in VAR model: AIC (Akaike Information Criterion) - SC (Schwarz Criterion) and HQ (Hannan–Quinn information criterion). The minimum for each criterion is provided in bold type-face.

Lag (m)	AIC	SC	HQ
1	-7.7059	-7.5226	-7.6451
2	-7.7289	-7.3625	-7.6074
3	-7.6591	-7.1095	-7.4769
4	-7.4417	-6.7088	-7.1988
5	-7.5701	-6.654	-7.2665

Table 5. Average annual temperature and prices: lag length selection in VAR model: AIC (Akaike Information Criterion) - SC (Schwarz Criterion) and HQ (Hannan–Quinn information criterion). The minimum for each criterion is provided in bold type-face.

Lag (m)	AIC	SC	HQ
1	-8.5397	-8.3565	-8.479
2	-8.5825	-8.216	-8.461
3	-8.5352	-7.9855	-8.353
4	-8.3642	-7.6313	-8.1212
5	-8.5212	-7.6051	-8.2175

Results of Granger analysis

Given the results for the lag order selection for the VAR model above, the lag orders chosen for conducting the Granger analysis are both VAR (1) and VAR (2) (under different criteria – AIC, SC, and HQ) for the various combinations of climatic indicators and soybeans prices. The results of Granger test for causality analysis between each climatic indicator and soybeans prices are provided in Table 6. It was observed that significant results at 5% were obtained for precipitation granger causing prices for both lag lengths under different criteria (2, 1). Further, no significant causality was detected for maximum, minimum, and average annual temperatures granger causing soybean prices, under both lag orders of the VAR model. The results from this analysis clearly support the existing literature discussed earlier in this study and reinstate the importance of precipitation variability as a significant factor in rainfall based agricultural production thereby impacting commodity prices in the markets. It is not clear why the temperature values did not show significance in the granger tests for prices. The lack of significance for temperature causing future prices could be related to the discussion mentioned early in this study, that suggest specific night temperatures may lead to reduction in seed growth, which may impact yields. The drawback of this explanation however, comes from the climatic data in hand being available for average daily values, and not for specific night or daytime temperatures (to which the soybean yields are sensitive). A more extensive climate dataset may be needed to address these points in future studies of relevance.

Table 6. Results of Granger causality test with lag lengths m=1 and m=2 for climatic variables. Here A/→B stands for "A fails to Granger cause B"; the null hypothesis is that the past values of A do not help in predicting future values of B.

Null Hypothesis	Lag length (m)	P-value
Precipitation /→ Soybean prices	1	0.0304*
Precipitation /→ Soybean prices	2	0.0219*
Maximum Temp /→ Soybean prices	1	0.3304
Maximum Temp /→ Soybean prices	2	0.7311
Minimum Temp /→ Soybean prices	1	0.1607
Minimum Temp /→ Soybean prices	2	0.4941
Avg. Annual Temp /→ Soybean prices	1	0.2229
Avg. Annual Temp /→ Soybean prices	2	0.6158

*significant at 5%

Further, based on the IRF’s for VAR(1) and VAR (2), in Figures 6 and 7 respectively, we conclude that a shock to the precipitation levels increases the soybean price levels in the initial 2-3 time periods to a peak and then takes a dip in the next few time periods. However, the impulse responses of soybean prices on account of precipitation shocks stays longer as forecasted by the VAR (2) model relative to VAR (1) where the curve dies out relatively earlier.

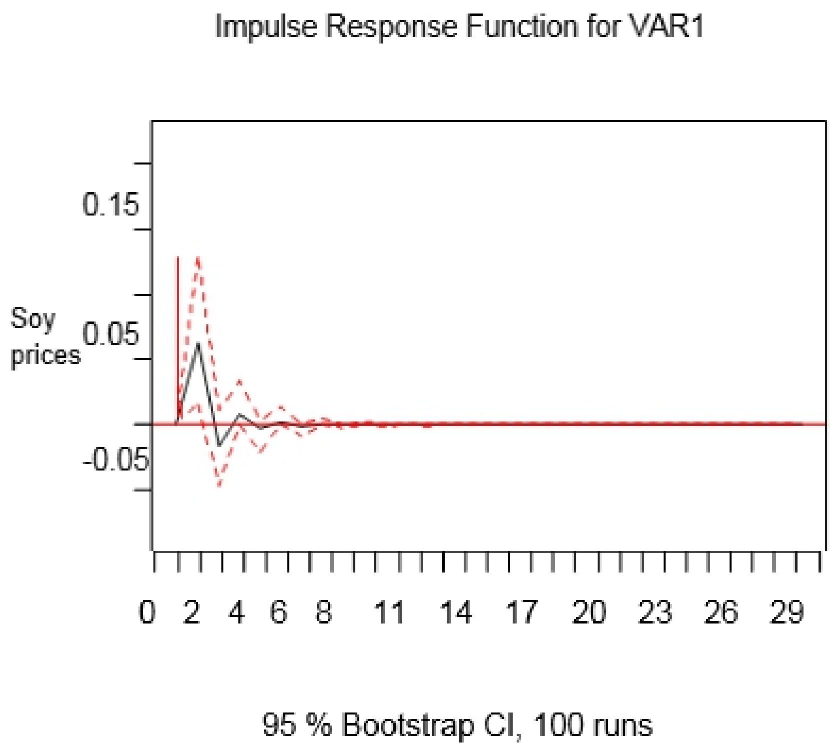

Figure 6. Impulse response function for VAR (1) depicting the response of soy-prices to a shock in precipitation with significant granger causality (Precipitation /→ Soybean prices)

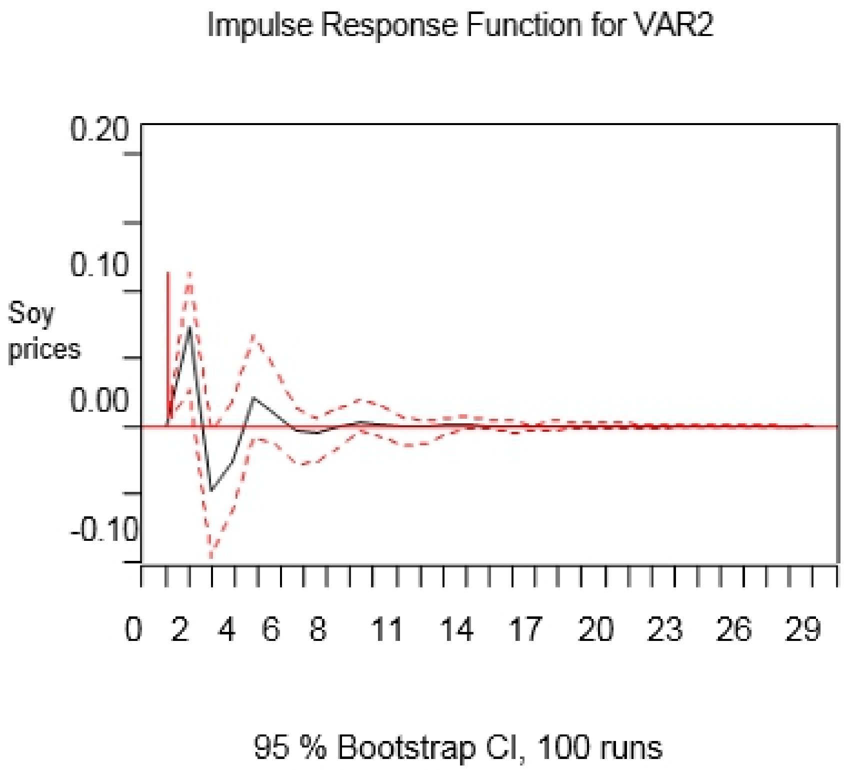

Figure 7. Impulse response function for VAR (2) depicting the response of soy-prices to a shock in precipitation with significant granger causality (Precipitation /→ Soybean prices)

Conclusion

This study evaluated the causality between climatic indicators and commodity price movements of soybeans in the West Tennessee region. A Granger causality test was applied to understand the relationship between climatic indicators and commodity price movements for soybeans. The results indicate that a significant causality was detected for precipitation impacting commodity price movements for soybeans. No significant evidence was obtained for the presence of Granger causality between temperature related indicators (maximum, minimum, and average) and soybean prices. These results concur with the agronomic framework mentioned earlier in this study, that moisture stress is a significant factor affecting soybeans yields. A major limitation of this study was the availability pf climate data. Currently, no specific climatic data sets, or Mesonet exist for West Tennessee. The results from this study intend to draw attention, and promote the thought among research agencies and organizations in the region about this impending need. The outcome of this study provides an initial insight into the causality between climatic indicators and commodity price movements for soybeans in the study region, and emphasizes that commodity prices are more influenced by precipitation changes as compared to changes in temperature, especially in the absence of irrigation based production in the region. This information can be used to highlight the impact of climatic variables like rainfall on commodity prices and to forecast price fluctuations in the regional markets for commodities given future climatic projections. It will serve as an initial framework for developing economic studies that will incorporate multiple secondary climatic indicators besides temperature and precipitation, that impact plant growth and yields at critical stages of production and ultimately the crop prices for various crops of importance.

References:

Aker, J. (2010) Rainfall Shocks, Markets and Food Crises: The Effect of Drought on Grain Markets in Niger, Revue d'Economie de Développement. 1(3), 71-108.

Ayinde ,O.E., Ajewole, O. O., Ogunlade, I. and Adewumi, M.O. (2010). Empirical analysis of agricultural production and climate change: A case study of Nigeria. Journal of Sustainable Development in Africa, 12(6), 345-253.

Bureau of Labor Statistics, 2013. U.S Department of Labor. Midwest region consumer price index.

Carter, L. M., Jones, J. W., Berry, L., Burkett,V., Murley, J. F., Obeysekera, J., Schramm, P. J., and Wear, D. (2014) Ch. 17: Southeast and the Caribbean. Climate Change Impacts in the United States: The Third National Climate Assessment, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, 396-417.doi:10.7930/J0NP22CB.

Dickey, D. A. and Fuller, W. A. 1979. Distribution of the Estimation for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74: 427-431.

Dixon, B. L. and Segerson, K.. (1999) Impacts of Increased Climate Variability on the Profitability of Midwest Agriculture. Journal of Agricultural and Applied Economics, 31, 3. December, 1999. p. 537-549.

Economic Research service, USDA. 2013. U.S. Drought 2012: Farm and Food Impacts. http://www.ers.usda.gov/topics/in-the-news/us-drought-2012-farm-and-food-impacts.aspx#.UjYbXfMo42x.

Granger, C.W.J. 1969. Investigating causal relation by econometrics and cross-sectional method. Econometrica, 37: 424-438.

Granger, C. W. J. and Lee, T. H. (1989), Investigation of production, sales and inventory relationships using multicointegration and non-symmetric error correction models. Journal of Applied Econometrics, 4: S145–S159. doi: 10.1002/jae.3950040508

Gujarati, D.N. and Porter, D.C. (2009). Vector Autoregression (VAR). Basic Econometrics (Fifth international ed.). New York: McGraw-Hill. pp. 784–790. ISBN 978-007-127625-2.
Hengqing, T., Kumar, K.T., and Huang, Y. (2011), Developing Econometrics. West Sussex, UK: John Wiley & Sons, Ltd., 486 pages. ISBN: 978-0470681770.
Karl, R.T., Melillo, J.M. and Peterson, T.C. (2009) (eds.), Global Climate Change Impacts in the United States, Cambridge University Press. 2009.
Mukhtar, T. and Javed, M.T. (2007) Price Integration in Wholesale Maize Markets in Pakistan The Pakistan Development Review, 46 (4) Part II (Winter 2007), 1075–1084
National Agricultural Statistics Service (2013). Monthly and annual farm prices received by marketing year. Agricultural Prices, published by USDA's National Agricultural Statistics Service.
http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1002
National Oceanic and Atmospheric Administration, "National Climatic Data Center," 2014.
Patterson, D.T., Westbrook, J.K., Joyce, R.J.V., Lingren, P.D., and Rogasik, J., (1999). Weeds, insects, and diseases. Climatic Change. 43, 711-727.
Porter, J.H., Parry, M.L., and Carter, T.R., (1991), The potential effects of climatic change on agricultural insect pests Agricultural and Forest Meteorology, 57, 221-240.
The University of Tennessee Institute for Agriculture (2014) http://www.utcrops.com/Soybean/
[19] Hollinger, S.E., and Changnon, S.A., (1993). Response of Corn and Soybean Yields to Precipitation Augmentation, and Implications for Weather Modification in Illinois, Illinois State Water Survey, Champaign, Bulletin 73.
Pandey, R.K., W.A.T. Herrera, and J.W. Pendleton. 1984a. Drought Response of Grain Legumes Under Irrigation Gradient, I: Yield and Yield Components. Agron. J. 76:549-553.
Pandey,R.K.,W.A.T.Herrera,A.N.Villegas,and J.W. Pendleton. 1984b. Drought Response of Grain Legumes under Irrigation Gradient, III: Plant Growth. Agron. J. 76:557-560.
Cox, W.J., and G.D. Jolliff. 1986. Growth and Yield of Sunflower and Soybean under Soil Water Deficit. Agron. J. 78:226-230.
Mederski, H.J., and D.L. Jeffers. 1973. Yield Response of Soybean Varieties Grown at Two Soil Moisture Stress Levels. Agron. J. 65:410-412.
Seddigh, M., and G.D. Jolliff. 1984. Night Temperature Effects on Morphology, Phenology, Yield and Yield Components of Indeterminate Field-Grown Soybean. Agron. J. 76:824-828.
Lawn, R.J., and DJ. Hume. 1985. Response of Tropical and Temperate Soybean Geonotypes to Temperature during Early Reproductive Growth. Crop Sci. 25:137-142.
Sciammacco, S. 2013 Federal Crop Insurance Over-Compensates Farmers And Insurance Companies. Environmental Working Group report. http://www.ewg.org/release/new-report-highlights-ways-cut-waste-federal-crop-insurance-program
Doss, B.D.,R.W. Pearson, and H.T. Rogers. 1974. Effect of Soil Water Stress at Various Growth Stages on Soybean Yield. Agron. J. 66:297-299.
[28] Olmstead, A.L and P.W. Rhode, "Responding to climatic challenges: lessons from US agricultural development," in "The Economics of Climate Change: Adaptations Past and Present" 2011, pp. 169–194.