International Journal of Food and Agricultural Economics
ISSN 2147-8988, E-ISSN: 2149-3766
Vol. 4 No. 2, 2016, pp. 1-10

CLIMATE CHANGE AND ITS IMPACT ON WHEAT PRODUCTION IN KANSAS

Joshua C. Howard
Department of Economics, University of New Haven, West Haven, CT 06516, USA

Esin Cakan
Department of Economics, University of New Haven, West Haven, CT 06516, USA

Kamal P. Upadhyaya
Department of Economics, University of New Haven, West Haven, CT 06516, USA
E-mail: Kupadhyaya@newhaven.edu

Abstract

This paper studies the effect of climate change on wheat production in Kansas using annual time series data from 1949 to 2014. For the study, an error correction model is developed in which the price of wheat, the price of oats (substitute good), average annual temperature and average annual precipitation are used as explanatory variables with total output of wheat being the dependent variable. Time series properties of the data series are diagnosed using unit root and cointegration tests. The estimated results suggest that Kansas farmers are supply responsive to both wheat as well as its substitute (oat) prices in the short run as well as in the long run. Climate variables; temperature has a positive effect on wheat output in the short run but an insignificant effect in the long run. Precipitation has a positive effect in the short run but a negative effect in the long run.
Keywords*: Kansas, climate change, wheat production, supply response, error correction model*
JEL Codes: *Q11, Q50, Q54*

1. Introduction

Global warming and its effects on climate change have been considered important issues that can have long term economic implications. There are different schools of thought on its causes as well as consequences, but there is evidence that the solar system goes through different cycles causing rises in global temperature for long spans of time. It also goes through cooling phases during which average temperature falls below normal levels for relatively long periods (e.g. the mini ice age that began in 1645 and lasted until 1715). A careful perusal of the data reveals that the global temperature has more or less fluctuated approximately every twenty years on average. For example, there was a cooling phase from the early 1950's to the late 1970's, from 1980 to the late 1990's the temperature was warming, and after that a cooling period again started (Easterbrook, 2008). Even though it has been observed that there is a fluctuation in global temperature every 15 or 20 years, it is possible that there is a long-run trend in temperature, precipitation, and other climate related variables (see Hansen et al., 2010). The short run as well as long-run fluctuations in temperature alter the climate, and this, in turn, can affect agricultural production.

There are ample studies regarding the effect of climate change on agricultural production. The findings, however, are mixed. For example, Rosenzweig and Parry (1994) conducted a global assessment of the potential impact of climate change on world food supply. Their findings from the assessment suggest that doubling of the atmospheric carbon dioxide concentration will lead to only a small decrease in global crop production, and developing countries are likely to bear the brunt of the problem. Dakhawa and Campbell (1998) studied the effect on crop production of differential day-night warming created by global climate change. From their findings, they suggest that the potential crop damage caused by global warming may be less severe due to the existence of asymmetric day-night warming rather than equal day-night warming. Tol (2002) estimates the potential impacts of climate change including the impact on agriculture. According to his findings, a 1° C increase in the global mean surface air temperature is likely to have a net positive effect on China, the Middle East, and member nations of the Organization for Economic Co-operation and Development (OECD). However, it will have a negative effect on other countries.

Parry et al. (2004) estimates the potential impact of climate change under climate change scenarios developed from a model in the Intergovernmental Panel on Climate Change's Special Report on Emission Scenarios (SRES). They calculate the projected changes in yield using transfer functions derived from crop model simulations with observed climate data and projected climate change scenarios. They further use the basic linked system (BLS) to evaluate the consequent changes in global cereal production, cereal prices, and the number of people at risk from hunger. Their findings from the simulation experiments conclude that the world, for the most part, would be able to continue to feed itself for the rest of the century under the SRES scenarios. However, one interesting point in their findings is that the balance is achieved through an increase in production in developed countries, which mostly benefit from climate change that compensates for the decline in developing countries.

Kang, Khan, and Ma (2009) provide a comprehensive review of literature related to the assessment of the impacts of climate change on crop yield, crop water productivity, and food as well as water security. Based on the literature review, they project that because of climate change, there will be an increase in water availability in some parts of the world. This increase will have an effect on water use efficiency and allocation. They further argue that this can lead to an increase in crop production, though irrigation expansion can cause environmental degradation. The effect of climate change on crop production will differ by location depending on irrigation and latitude; some areas will increase production while others will experience a decrease. In conclusion, they suggest that expanding irrigated areas will increase total crop production, but the food and environmental quality may degrade.

Tack et al. (2015) used a unique data set that cobines Kansas wheat variety field trial outcomes for 1985 – 2013 with locational weather data to analyze the effect of weather on wheat yield using regression analysis. They find that the largest drivers of yield loss are freezing temperatures in the fall and extreme heat events in the spring. Lobell et al. (2011) examine the climate trends and global crop production since 1980 and suggest that in the cropping regions and growing seasons of most countries, global maize and wheat production has declined by 3.8% and 5.5%, respectively, relative to an absence of climate trends. One caveat in their study is that the United States is an exception to their findings.

Deschenes and Greenstone (2011) used a new method to study the impact of climate change on the US agricultural sector. Their method involves the exploitation of the random year-to-year variation in temperature and precipitation to estimate their effect on agricultural profits using county level panel data. From the estimated results, they conclude that the overall effect of climate change on profits is small with heterogeneous effects across the states. Their analysis further indicates that the predicted increases in temperature and precipitation will have virtually no effect on yields among the most important crops such as corn and soybeans.

Most of the studies on this issue, including those mentioned above, use forecasting based on some sort of simulation with a variety of assumptions. An empirical study based on quantifiable statistical analysis seems lacking. Given this shortcoming, the purpose of this paper is to estimate the effect of climate change on agricultural crop production in the United States. Specifically, the objective of this study is to estimate the impact of temperature and precipitation on wheat production in Kansas. The state of Kansas is selected for the study because it is one of the major wheat producers in the U.S. It is expected that the findings of this study will shed more light on the relationship between climate change and wheat production in the U.S as well as the rest of the world.

The remainder of the paper is organized as follows: The theoretical background and methodology are presented in sections II and III respectively. Section IV reports the empirical findings and analysis. Section V includes the summary and conclusion.

2. Theoretical Background

Nerlove (1956, 1958) developed a supply response model based on time series data to describe the output of an agricultural product. According to his model, the supply can be estimated by a partial adjustment model, dynamic by nature, with a loss minimization function of the form

$$L_t = c_1(Y_t - Y^*_t)^2 + c_2 (Y_t - Y_{t-1})^2 \quad (1)$$

where L_t is the loss incurred by the producer in period *t* in the supply of the crop. Y^*_t is the desired long-run equilibrium level of some variable Y_t, and it is defined according to stationary expectations of some conditioning variables towards which adjustments are made in the long run. Loss minimization (L_t) with respect to some output level (Y_t) gives the partial adjustment model

$$\Delta Y_t = Y_t - Y_{t-1} = c\,(Y_t^* - Y_t) \quad (2)$$

where c (= c_1/c_2) is the long-run response of output with respect to price. In other words, the change in output between the current and previous periods is only a proportion of the difference between the optimum level and last year's output. The parameter c is the adjustment coefficient, and its value lies between zero and one. ΔY_t is the actual change, $Y_t^* - Y_t$ is the desired change, and Δ is the first difference operator. Y_t can be either expected product or input prices. The assumption is that there is a long-run equilibrium towards which producers are moving. It is also assumed that the future values of the exogenous variables remain unchanged and that, because of optimization of the behavior of producers, Y_t adjusts towards the fixed target Y_t^* in the long run.

In the past, Nerlove's partial adjustment model has been widely used. One major limitation of this model is that it assumes a fixed target. This is unrealistic, because farmers face different conditions while they optimize their decision. To overcome this issue, many researchers have been using error correction modeling in order to analyze the supply response of agricultural products (Nickell, 1985; Hallam & Zanoli, 1993; Weliwita & Govindasamy, 1997). The error correction model is superior to the traditional supply response model, since the error correction model captures both the short-run dynamics as well as the adjustment towards the long-run equilibrium.

3. Methodology and Data

Before developing the model, we reviewed the average yearly temperatures in Kansas and the continental United States in order to find out if there is indeed a trend of rising temperature (Figure 1). The fitted line in Figure 1 clearly indicates that there is a trend of rising temperature in both Kansas as well as the continental USA from 1949 to 2014. Next, we looked at the annual precipitation data in Kansas and fitted a trend line which showed an upward increase in precipitation during the same period (Figure 2).

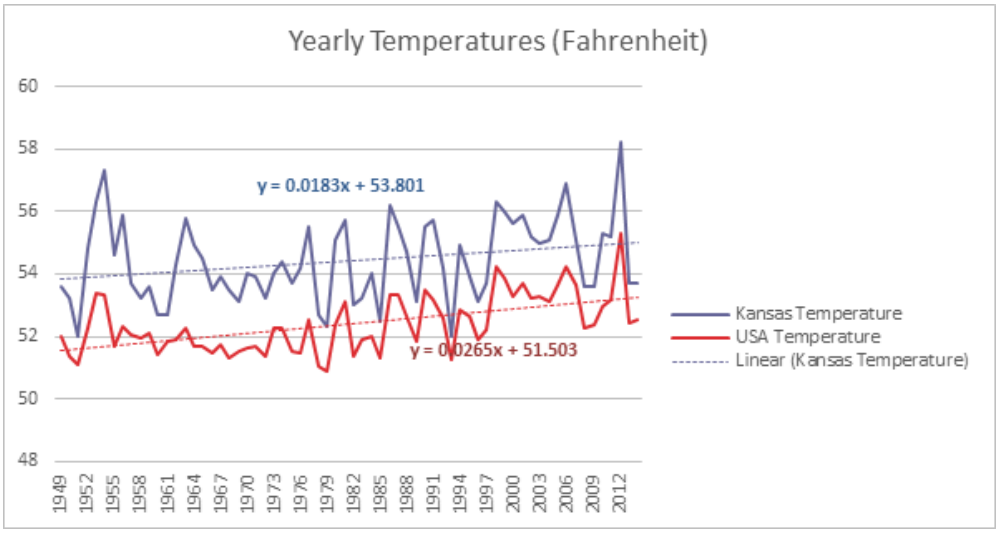

Figure 1. Yearly Average Temperatures in Kansas and the Continental United States

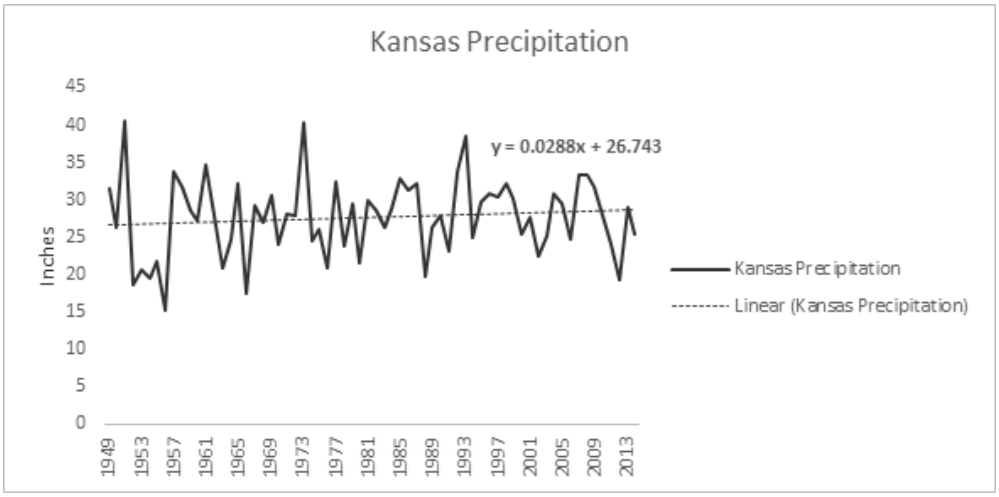

Figure 2. Kansas Precipitation Levels

As mentioned in the previous section, we developed an error correction model which starts with the following functional form equation.

$$PROD = f(PWHEAT, POAT, TEMP, PRECP) \quad (3)$$

where,
PROD = Total output of wheat production
PWHEAT = Price of wheat in real terms
POAT = Price of oats in real terms
TEMP = Average yearly temperature
PRECP = Average yearly precipitation

In equation (3), the coefficient of *PWHEAT* is expected to be positive, as an increase in the price of wheat encourages farmers to produce more wheat by switching production from other crops to wheat, *ceteris paribus.* The coefficient of *POAT*, however, is expected to be negative, as a rise in the price of oats (substitute crop) incentivizes the farmers to switch from wheat production to oat production. As indicated above, *TEMP* and *PRECP* are climate change variables, and their coefficients are the focus of this study. If the coefficient of *TEMP* is negative and statistically significant, we will argue that global warming has a negative effect on wheat production. If it is positive and statistically significant, it can be argued that global warming has a positive effect on wheat production. Likewise, if the coefficient of *PRECP* is negative and significant, it can be said that increasing precipitation overtime has decreased wheat production. If it is positive and statistically significant, it can be argued that increases in precipitation have raised total wheat production.

Converting all the variables into log form, equation (3) can be written in the following statistical form.

$$logPROD_t = a_0 + a_1 logPWHEAT_{t-1} + a_2 logPWHEAT_{t-2} + a_3 logPOAT_{t-1} + a_4 logPOAT_{t-2} + a_5 logTEMP_t + a_6 \Delta logPRECP_t + \varepsilon_t \quad (4)$$

In equation (4), *e* is the random error term. Since farmers respond in the future to any changes in the current price of the crop, we have used lagged variables of both wheat price (*logPWHEAT*) as well as its substitute crop (oat) price (*logPOAT*).

Annual time series data from 1949 to 2014 is used. *PWHEAT* and *POAT* are in 1985 constant prices. Wheat and oat production (in bushels) as well as their data for prices are derived from the National Agricultural Statistics Service. Temperature (in Fahrenheit) and precipitation (in inches) data are derived from the National Climatic Data Center.

4. Estimation and Empirical Findings

Before carrying out the estimation of equation (4), it is important to test the stationarity of the data series to avoid spurious results. Following Nelson and Plosser (1982), an augmented Dickey-Fuller test is conducted on the data series to ensure the stationarity of the data. This involves estimating the following regression and carrying out unit root tests:

$$\Delta X_t = \alpha + \rho t + \beta X_{t-1} + \sum_{i=1}^{n} \lambda_i \Delta X_{t-i} + \varepsilon_t \quad (5)$$

In equation (5), X is the variable under consideration, Δ is the first difference operator, t is a time trend, and ε is a stationary random error term. If the null hypothesis, that $\beta = 0$, is not rejected, the variable series contains a unit root and is non-stationary. The optimal lag length in the above equation is identified by ensuring that the error term is white noise.

In addition to the augmented Dickey-Fuller (1979) test, a Phillips-Perron test (Phillips 1987; Phillips & Perron, 1988) is conducted to ensure the stationarity of the data series. The Phillips-Perron test uses non-parametric corrections to deal with any correlation in the error terms. The test results are reported in Table 1. As the results in Table 1 point out, both the Dickey-Fuller test and the Phillips-Perron test indicate that all the data series are non-stationary in level form. Therefore, the same tests are performed for first-differences. The test results (see Table 1) indicate that all of the series are stationary in first-difference form.

Table 1. Unit Root Test Results

	Level		First Difference	
Variable	ADF	P-P	ADF	P-P
logPROD	-2.67	0.27	-6.94***	-13.32***
logPWHEAT	-2.66	-2.88	-5.91***	-9.01***
logPOAT	-2.39	-2.85	-6.55***	-7.38***
logTEMP	-2.51	-0.07	-5.18***	-10.85***
logPRECP	-0.36	-0.29	-7.83***	-17.56***

Note: ADF = augmented Dickey-Fuller Test, P-P = Phillip–Perron Test
*** denotes significant at the 1% critical level.

Having established the stationarity of the data, the Johansen (1988) as well as Johansen and Juselius (1990) approaches are explored to test for a long-run equilibrium relationship among the variables. This involves testing the cointegrating vectors. Consider a p dimensional vector autoregression,

$$X_t = \sum_{i=1}^{k} \pi_i X_{t-i} + c + \varepsilon_t \tag{6}$$

which can be written as,

$$\Delta X_t = \sum_{i=1}^{k} \Gamma_i X_{t-i} - \pi X_{t-k} + c + \varepsilon_t \tag{7}$$

where,

$$\Gamma_i = -\mathrm{I} + \pi_1 + \pi_2 + \cdots \ldots + \pi_t \tag{8}$$

$i = 1, 2,\ldots\ldots, k\text{-}1$ and

$$\pi = I - \pi_1 - \pi_2 - \cdots \ldots \ldots \pi_k \tag{9}$$

where p is the number of variables under consideration. The matrix π captures the long-run relationship between p variables, and this can be decomposed into two matrices, A and B, such that $\pi = AB'$. A is interpreted as the vector error correction parameter and B as cointegrating vectors. This procedure is used to test the existence of a long-run relationship between the variables in equation (3).

Table 2. Cointegration Test Results

H_0	*Trace Stat.*	*Max Eigenvalue Stat.*
r = 0	90.23**	41.65**
r ≤ 1	48.58**	24.73
r ≤ 2	23.85	16.63
r ≤ 3	7.21	6.58
r ≤ 4	0.63	0.63

Note: ** denotes significant at the 5% critical level.

Johansen's cointegration test result is reported in Table 2. Table 3 reports cointegrated vectors, normalized on *logPROD*, which essentially are the estimates of the long-run elasticity of wheat production in Kansas with respect to wheat price, oat price (substitute good), temperature, and precipitation. Both the trace statistics and the maximum Eigenvalue statistics in Table 2 reject the null hypothesis of no cointegration. Thus, following Engle and Granger (1987), we developed the following error correction model.

$$\Delta logPROD_t = a_0 + a_1\Delta logPWHEAT_{t-1} + a_2\Delta logPWHEAT_{t-2} + a_3\Delta logPOAT_{t-1} + a_4\Delta logPOAT_{t-2} + a_5\Delta logTEMP_t + a_6\Delta logPRECP_t + a_7E_{t-1} + v_t \quad (10)$$

Table 3. Cointegrated Vector Normalized on *LogPROD*

Variable	*Coefficient*
logPWHEAT	0.51 (1.96)*
logPOAT	-0.69 (2.98)***
logTEMP	1.86 (0.61)
logPRECP	-2.61 (61.74)***

Note*:* Figures in the parentheses are t-values for the corresponding coefficients. *** and * denote statistically significant at the 1% and 10% critical levels respectively.

In equation (10), Δ is the first difference operator, *v* is the random error term, and E_{t-1} is the error correction term which is the lag of the estimated error term from equation (3). The estimated result of equation (10) is reported in Table 4.

Several interesting findings emerge from our empirical estimates. First, as indicated above, Table 3 presents the long-run elasticities of wheat production with respect to different variables in the model. The positive and statistically significant coefficient of Δ*logPWHEAT* suggests that the farmers do respond to the change in wheat price by changing the output of wheat production (cultivated area) in the long run. Likewise, the negative and statistically significant coefficient of Δ*logPOAT* indicates that when the price of oats is increased over a period of time, farmers switch from wheat production to oat production and vice versa, *ceteris paribus.*

Table 4. Estimation of the Error Correction Model

Variable	*Coefficient*
Constant	0.04 (0.50)
$\Delta logPWHEAT_{t-1}$	0.49 (2.77)***
$\Delta logPWHEAT_{t-2}$	0.30 (1.85)*
$\Delta logPOAT_{t-1}$	-0.81 (5.23)***
$\Delta logPOAT_{t-2}$	-0.29 (1.28)
$\Delta logTEMP_t$	2.25 (2.91)***
$\Delta logPRECP_t$	0.20 (2.72)***
E_{t-1}	-1.36 (12.24)***
AR(1)	0.62 (4.45)***
Adj R^2	0.41
F – Stat	6.28***
D. W.	1.90
n	62

Note*:* Figures in the parentheses are t-values for the corresponding coefficients. ***and * denote statistically significant at the 1% and 10% critical levels respectively.

The focus of this study is the climate change which is represented by changes in temperature as well as precipitation. Interestingly, the long-run elasticity of wheat production in respect to the temperature change during the period from 1949 to 2014 is statistically insignificant. It suggests that the rise in temperature during this time has not had any significant positive or negative effect on wheat production in Kansas. The coefficient of $\Delta logPRECP$, however, is negative and statistically significant as well. This suggests that the continuous increase in precipitation has reduced the total output of wheat in Kansas during the period from 1949 to 2014.

Table 4 reports the estimated results of equation (10) in which each variable's respective coefficient represents the short-run elasticity of wheat production. Since the initial regression estimations suffered from a first-order autocorrelation problem, the model is estimated with an AR(1) term. The coefficient of $\Delta logPWHEAT$ is positive and statistically significant for both one year as well as two-year lags. It indicates that Kansas farmers are supply responsive with respect to changes in wheat price in not only the long run but in the short run as well. The coefficient of $\Delta logPOAT$ is negative and statistically significant for one-year lag, but barely significant for two-year lag. It suggests that for Kansas farmers, wheat and oats are substitutes and any time the price of one crop is increased, farmers respond by switching to that particular crop. The coefficients of $\Delta logTEMP$ and $\Delta logPRECP$ are both positive and statistically significant. This suggests that climate change, in terms of rising temperature and increasing precipitation, has a positive effect on wheat production in Kansas. Finally, as is usual, the coefficient of the error correction term, E_{t-1}, is negative and statistically significant, thus indicating that wheat production adjusts to the equilibrium given any changes in price, substitute (oat) price, or climatic conditions.

5. Summary and Conclusion

The impacts on global food production created by climate change effects, including rising global temperatures and continuous changes in precipitation, has become an important issue. To further this debate, this paper studies the impact of climate change on wheat production in the state of Kansas, USA.

For the analysis, an error correction model is developed which is based on Nerlove's (1956, 1958) supply response model. In the model, total yearly output of wheat is the dependent variable while explanatory variables include real price of wheat with lags, real price of oats (substitute good) with lags, average yearly temperature, and average yearly precipitation. Time series data from 1949 to 2014 is used. Before estimating the model, the time series properties of all the series are diagnosed using unit root tests and Johansen's cointegration tests. The test results suggest that all series are integrated of order one (stationary at the first-difference level), and the hypothesis of no cointegration is rejected. Therefore, an error correction model is developed and estimated.

The estimated results suggest that Kansas farmers are supply responsive to changes in the price of wheat as well as its substitute, oats, in both the short run as well as the long run. A rise in temperature has a positive effect on wheat production in the short run, but it has neither positive nor negative effect in the long run. Increasing precipitation has a positive effect in the short run but a negative long-run effect on wheat production.

In sum, the findings from the literature survey and this empirical study suggest that the overall effect of climate change on crop production in developed countries is positive. However, the impact of climate change on agricultural production in developing countries does not seem to be encouraging. This is likely because of its negative impact on soil conditions and agro-water management. In order for developing countries to mitigate the negative impact of climate change on food production, they need to better manage their irrigation systems and follow the steps of developed countries in order to improve soil quality.

References

Dakhawa, G. B. & C. L. Campbell (1998). "Potential Effects of Differential Day-Night Warming in Global Climate Change on Crop Production", *Climatic Change*, 40(3-4) 647-667.

Deschenes, O. & Greenstone, M. (2011). "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, 3(4), pp. 152-185.

Dickey, A. D. & Fuller, W. (1979). "Distribution of the Estimators for Autoregressive Time Series with a Unit root." *Journal of the American Statistical Association* 74.366a, 427-431.

Easterbrook, D. J. (2008). "Global Cooling is Here", *Global Research Newsletter*, Western Washington University and Global Research, No page number.

Engle, R.F., & Granger, C.W.J. (1987). "Cointegration and Error—Correction: Representation, Estimation, and Testing", *Econometrica*, 55 (2): 251—276.

Hallam, D., & Zanoli, R. (1993). "Error Correction Models and Agricultural Supply Response", *European Review of Agricultural Economics*, 20(2), 151-166.

Hansen, J., Ruedy, R., Sato, M., & Lo, K. (2010). "Global Surface Temperature Change". *Reviews of Geophysics*, *48*(4), *doi:10.1029/2010RG000345*.

Johansen, S., (1988). "Statistical Analysis of Cointegration Vectors". *Journal of Economic Dynamics and Control*, *12*(2), 231-254.

Johansen, S., & K. Juselius (1990). "Maximum Likelihood Estimation and Inference on Cointegration—with Applications to the Demand for Money." *Oxford Bulletin of Economics Statistics*, 52(2), 169-210.

Kang, Y., Khan, S., & Ma, X. (2009). "Climate Change Impacts on Crop Yield, Crop water Productivity and Food Security - A Review" *Progress in Natural Science,* 19(12), 1665-1674.

Lobell, D. B., Schlenker, W., & Costa- Roberts, J. (2011). "Climate Trends and Global Crop Production since 1980" *Science*, 333(6042), 616-620.

Nelson, C. R., & C. I. Plosser (1982). "Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications" *Journal of Monetary Economics,* 10(2), 139-162.

Nerlove, M. (1956). "Estimates of Supply of Selected Agricultural Commodities" *Journal of Farm Economics,* 38(2), 495-509.

Nerlove, M. (1958). *The Dynamics of Supply: Estimation of Farmers' Response to Prices,* Baltimore, Johns Hopkins University Press.

Nickell, S. (1985). "Error Correction, Partial Adjustment and All that: An Expository Note" *Oxford Bulletin of Economics and Statistics*, 47(2), 119- 129.

Parry, M., Rosenzweig, A., Iglesias, A., Livermore, M. & Fischer, G. (2004). "Effects of Climate Change on Global Food Production under SRES Emission and Socio-economic Scenarios" *Global Environmental Change*, 14(1), 53-67.

Phillips, P. C. (1987). "Time Series Regression with a Unit Root." *Econometrica: Journal of the Econometric Society*, 55(2), 277-301.

Phillips, P. & Perron, P. (1988). "Testing for a unit root in time series regression." *Biometrika* 75(2), 335-346.

Tack, J., Barkley, A., & Nalley, L. L. (2015). "Effect of Warming Temperatures on US Wheat Yield" *Proceeding of the National Academy of Sciences,* 112(22), 6931 – 6936.

Tol, R. (2002). "Estimates of the Damage Costs of Climate Change" *Environmental and Resource Economics,* 21(1), 47-73.

Rosenzweig, A., & Parry M. (1994), "Potential Impact of Climate Change on World Food Supply" *Nature*, 367 (13 January), pp. 133-84.

Weliwita, A., & Govindasamy, R. (1997). "Supply Response in Northeastern Fresh Tomato Market: Cointegration and Error Correction Analysis" *Agricultural and Resource Economics Review*, 26(2), 247 – 255.