THE IMPACT OF A SORGHUM-BASED ETHANOL PLANT ON LOCAL COTTON ACREAGE: A SPATIAL APPROACH

B. Liu
D. Hudson
M. Farmer
Department of Agricultural and Applied Economics
Texas Tech University
Lubbock, TX

Abstract

Over the past decade, construction of starch-based ethanol plants has expanded rapidly across the United States to meet growing (largely policy-induced) ethanol consumption. On the one hand, locating an ethanol plant in a small rural city potentially benefits a local economy significantly in terms of increased job opportunities and tax revenue. In the Texas High Plains, however, there are growing concerns that the introduction of a new demand source for sorghum as feedstock is likely to affect farmers' cropping decisions in the area around the ethanol plant. Thus, it is important to quantify how the opening of an ethanol plant causes farmers to alter their planting decisions. This study models the cotton acreage response from 2002 to 2014, using county-level panel data collected from Hockley County, Texas, that currently has a 40 million gallon per year sorghum-based ethanol plant in operation. Spatial econometric models are employed to account for any spatial dependence and other factors are used to control for prices, water availability, and other production decision variables. The spatial tests results show that cotton area planted around Hockley County is highly clustered. But after controlling for spatial autocorrelation and dependence, the model results suggest that the existence of the ethanol plant has no effect on the surrounding cotton acreage.

Introduction

Over the past decade, construction of starch-based ethanol plants has expanded rapidly across the United States to meet the growing energy consumption generated by the Renewable Fuel Standard (RFS). As of January 2015, the Renewable Fuels Association (RFA) has listed 213 operational ethanol plants with the capacity totaling over 15 billion gallons per year (RFA 2015). From 2005 to 2015, the ethanol production capacity of the U.S. increased from 3.6 to 15 billion gallons per year. The rise in the U.S. ethanol production is primarily policy-induced: high energy costs, increased national energy security to reduce dependence on foreign oil, and the demand for cleaner burning fuels to alleviating global warming are the stated reasons for market interaction.

Most of the recent developments in ethanol production have focused on rural areas. On the one hand, locating an ethanol plant in a small rural city is expected to potentially benefit a local economy significantly in terms of increased job opportunities, enhanced farmer income through purchases of local farm production to be used as feedstock, and improved community infrastructure for future potential growth. In places like Iowa, increased demand for corn for ethanol may have only minimal effects on farmers cropping decisions as they largely grow corn already. In the Texas High Plains, however, there are growing concerns that the introduction of a new demand source for sorghum as feedstock is likely to affect farmers' cropping decisions in the area around the ethanol plant. That is to say, higher prices provide an incentive for local farmers to convert more land to sorghum production, the major feedstock being used in Texas ethanol plants, at the expense of other crops, mainly cotton, where a large local infrastructure exists. Thus, a policy-induced shift in acreage could actually negatively affect local infrastructure devoted to the cotton industry and regional economic activity.

Texas is the leading producer of cotton in the U.S. Texas farmers planted about 6.22 million acres of cotton, and produced more than 6 million bales in 2014, accounting for over one-third of total U.S. production (NASS, 2015). Cotton is a major industry and contributor to the economy of Hockley County and its surrounding region (the Texas High Plains). And, it is the most important crop in the region in terms of both acreage and crop value. Approximately 280,000 acres of cotton were planted in Hockley County in 2014, accounting for about 85 percent of the county's total cropland acreage (NASS, 2015).

This study focuses on Hockley County and surrounding area because its economy has experienced significant changes since the establishment of Levelland-Hockley County Ethanol plant. Since the operation of the ethanol plant began in 2008, it currently produces 40 million gallons of ethanol per year using only sorghum as a feedstock obtained from local producers. Assuming operating at full production capacity, the plant requires approximately 15 million bushels of sorghum per year (Guerrero, et al. 2011). Given the recent average state yield of 58 bushels per acre (NASS, 2015), that is equivalent to approximately 260,000 acres of sorghum, or 12 percent of the 2.25 million acres of sorghum harvested in the state in 2014. The region is known for cotton production, while sorghum is considered primarily as a second crop planted behind failed cotton or in a planned rotation. Because ethanol production increases the demand for sorghum and is expected to increase the local sorghum price, it allows local farmers to incorporate sorghum into their crop rotation with cotton to maximize their revenues. Rapid shifts in crop production are occurring in neighboring communities due to increasing demand of sorghum for ethanol production. To the extent that ethanol production affects farmers' cropping decisions, it is important to quantify how the opening of an ethanol plant causes farmers to alter their planting decisions to provide more information in expected changes to regional infrastructure.

This study aims to examine the cotton acreage changes in Hockley County and surrounding areas as a result of introducing a sorghum-based ethanol plant to the High Plains of Texas. To achieve this objective, this study models the cotton acreage percentage response from 2002 to 2014, using county-level panel data collected from Hockley and surrounding counties, that currently have a 40 million gallon per year sorghum-based ethanol plant in operation. Due to the spatial pattern of cropland around an ethanol plant, the presence of a positive spatial autocorrelation is expected. Two alternative regression models: a spatial lag model and a spatial error model, are employed to account for any spatial dependence and other factors are used to control for prices, water availability, and other production decision variables.

The following section provides an overview of previous studies examining the effect of ethanol plants on cropland uses. Section 3 discusses the specific models used in the present study in more detail and details regarding the data. The estimation results are presented in section 4, together with diagnostic tests for spatial effects, and section 5 offers conclusions and the implications of this research.

Literature Review

Several studies have examined the community impacts of ethanol plants. Most of these studies focus on the effects of ethanol plants on local grain prices (McNew and Griffith, 2005; Behnke and Fortenbery, 2011; Katchova, 2009), and effects on both residential land and cropland values (Hodge, 2011; Henderson and Gloy, 2009; Blomendahl, Perrin and Johnson, 2011). However, few of them have directly addressed the impacts of ethanol plants on the cropland acreage changes. More relevant to the current study is the impact of ethanol production on local agricultural land use.

In an effort to provide a more complete understanding of the local impacts experienced by communities hosting ethanol plants, Turnquist et al. (2008) examined the effects of corn ethanol production on local land use and residential land values using data from 2000 to 2006 in Wisconsin. Their analysis considered whether agricultural land use trends are different in areas where agricultural production contributes to an ethanol plants' feedstock source compared to areas that are outside the purchase range of an ethanol plant. Their results showed that the agricultural land conversion was not affected by ethanol plants in their proximity. And they found no change in residential land values resulting from the ethanol plants. While there are increases and decreases in value, on average, any significant positive or negative effects of ethanol plants on residential land values are offset at the municipal-level.

Secchi *et al.* (2011) examined the impact of the biofuels industry in Iowa on both the current cropland and on land in the Conservation Reserve Program (CRP), and its environmental consequences. In their analysis of land use change associated with the expansion of biofuels over the period from 2002 to 2006, the authors found that as corn prices increase, more cropland is planted with continuous corn because corn becomes relatively more profitable than soybeans. They concluded that substantial shifts in rotations favoring continuous corn rotations are likely if high corn prices are sustained.

Using a logit land share model, Miao (2011) estimated the local land-use change effect of ethanol plants in Iowa between 1997 and 2009. The author considered the effects of ethanol plants both locally owned and non-locally owned, the effects of competing crop (soybeans) and the input prices. The Arellano-Bond difference estimation was applied to address the inherent econometric issues like autocorrelation, endogeneity and unobserved time-constant variables. Regression results implied that the existence of ethanol plants has a significant effect on land-use change in counties where the plants are located. Moreover, locally owned ethanol plants have slightly higher effects than non-locally owned ethanol plants. And, the land-use change effect is larger in counties with medium corn share than in counties with either low or high corn shares.

Most of these studies have focused on crops such as corn and soybeans, not cotton. And the findings of these studies seem to indicate that the land use change near ethanol plants can be quite variable based on the ethanol plant size and location. In contrast with studies examining aggregate agricultural land use change, we focus on the impact of an ethanol plant on the cotton acreage response while controlling for the effects of prices, irrigation conditions, and other production factors. In particular, this article adds another dimension to this literature by explicitly considering spatial effects. Given the important role played by the cotton production in Texas High Plains and the limited literature available, a comprehensive analysis of ethanol plants impacts on cropland changes would be useful in providing accurate information for policy makers, stakeholders and local farmers.

Empirical Model and Data

The OLS Model

In the context of this paper, the dependent variable is the cotton acreage percentage in each county from 2002 to 2014. Data on cotton acres planted, crop total acres, cotton production and state level prices were obtained from National Agricultural Statistic Service (NASS) of the U.S. Department of Agriculture (USDA). Irrigation water level data for the observation wells in each county were obtained from High Plains Underground Water Conservation District No. 1 (HPWD).

The following linear function is specified to represent the cotton acreage percentage of county *i* at period *t*:

$$(Cotton\ Acreage\ Percentage)_{i,t} = \alpha_0 + \alpha_1*(CP)_{i,t-1} + \alpha_2*(WL)_{i,t} + \alpha_3*(CS)_{i,t-1} + \alpha_4*(OS)_{i,t-2} + \alpha_5*(DT)_i + \alpha_6*(IT)_i + \varepsilon_{i,t} \quad (1)$$

where $i = 1 \ldots N$, $t = 1 \ldots T$. The variable $(CP)_{i,t-1}$ is the state average cotton price ($/lb.) for county *i* in year $t-1$; $(WL)_{i,t}$ is the irrigation water (ft.) available for county *i* in year *t*; $(CS)_{i,t-1}$ is the cotton production (480 lb. bales) for county *i* in year $t-1$; $(OS)_{i,t-2}$ is the cotton production (480 lb. bales) of neighboring counties for county *i* in year $t-2$; $(DT)_i$ is the respective driving time (min.) from each county seat of neighboring counties to the Levelland Hockley County Ethanol plant; $(IT)_i$ is an interaction term between the driving time and dummy variable for the period of 2008 to 2014, which is the time period in which the ethanol plant was in operation; and $\varepsilon_{i,t}$ is assumed to be a vector of independent and identically distributed (i.i.d.) error terms.

Note that cotton production (*CS*) and prices (*CP*) are one-year lagged values. This is due to the fact that farmers making their planting decisions in year *t* are affected by cotton prices and cotton production from previous year (in year $t-1$). Two-year lagged cotton production (*OS*) from contiguous counties (having common borders) are included to capture their aggregate effects (regional tendencies)on cotton area planted in county *i*. Irrigation water level (*WL*) data for the observation wells at different locations are included as a measure of irrigation water availability. A high level of irrigation water available is expected to decrease the acreage planted to cotton, as farmers convert to alternative crops which bring more profit per acre inch of water, such as corn. Drive time (*DT*) from the respective county seat of neighboring counties to the ethanol plant facility is included as a measurement of accessibility, which is expected to be negatively related to cotton acreage in each county. Variables that are expected to capture influences of recent ethanol production on cotton acreage changes include a dummy variable for the period of 2008 to 2014 and the interaction term (*IT*) between the dummy variable and drive time. The dummy variable is specified to reflect the impact of the establishment of an ethanol plant on cotton acreage relative to the base period of 2002 to 2007.

The cotton acreage observation in a region is likely to be affected by other explanatory variables observed at neighboring regions, which is due to the spatial dependence commonly detected in such estimations. As such, use of conventional estimation methods that omit the presence of spatial effects, like Ordinary Least Squares (OLS), may not only affect the magnitudes of the estimates, but also their significance (Anselin, 1988). Therefore, to account for any potential spatial dependence present among observations, two alternative econometric models that incorporate spatial effects are considered: a spatial lag model and a spatial error model.

The Spatial Regression Models

The spatial autoregressive model (SAR), or the spatial lag model, assumes that dependencies exist directly among the levels of the dependent variable y. That is, the acreage planted to cotton at location i is more likely to be influenced by the cotton acreage planted at neighboring locations. Thus, by including a spatially lagged dependent variable as an additional predictor, it takes the form:

$$y = \rho W_y + X\beta + u \tag{2}$$

where y is a $n\times 1$ vector representing the dependent variables, ρ is the spatial autocorrelation coefficient which equals to 0 if y does not depend on lagged neighboring y values, W_y is the spatially lagged dependent variables for weights matrix W, X represents the $n\times k$ data matrix containing explanatory variables, and u is a vector of error terms which follows the normal assumptions.

Although equation 2 captures the relationship where the dependent variable y is influenced directly by the values of y among neighbors, the potential problem of spatial autocorrelation in the disturbances remains; that is, the error term u is also correlated over space. One reason for this might be that there are some spatially clustered factors that influence the dependent variable y but is omitted from the specification. To this end, an alternative model with spatially correlated errors is proposed. This model is commonly referred to as the spatial error model (SEM), where disturbances exhibit spatial dependence. Then the following model is developed by incorporating spatial effects through error term:

$$y=X\beta+u$$
$$u=\lambda W_u+\varepsilon \tag{3}$$

where W is the spatial weight matrix that specifies the neighborhood set for each location, λ is the spatial autoregressive coefficient on the spatially correlated errors, β reflects the influence of the explanatory variables on variation in the dependent variable y, and ε is assumed to be a vector of i.i.d. errors.

While both spatial models are quite similar mathematically, the economic interpretation underlying is different for each model. The SAR implicitly assumes that the spatially weighted sum of cotton acreages in neighboring counties affects the cotton acreage in each county (indirect effects), in addition to the standard explanatory variables and neighborhood characteristics (direct effects). In contrast, the SEM accounts for only direct effects, and spatial autocorrelation is assumed to arise from omitted variables that exhibit a spatial pattern. Therefore, the SEM is particularly appropriate in cases where neighborhood spillover effects exist.

The spatial weight matrix $W =(w_{ij}: i, j = 1, \ldots n)$ defines neighbors, as well as the spatial relationships that exist among n geographic units. Thus, it is employed to reflect the structure of potential spatial interaction. It is a positive matrix, and each spatial weight, w_{ij}, is defined to reflect the spatial influence of location j on location i. Typically, the definition of neighbors used in the weights matrix is based on a notion of distance decay or contiguity. By convention, the diagonal elements of the weights matrix are set to zero, $w_{ij} = 0 \ \forall\, i = j$, and row elements are standardized such that they sum to one. There are numerous ways to construct a weight matrix, but there is no direct method of choosing one over another (Anselin, 2002). For this study, W is weighted by inverse distance weight $1/d$, where d is the distance between two units. This approach assumes that geographically closer factors would be weighted stronger than more distant factors. The distances between two counties are calculated using the latitude and longtitude of all counties centroids. The weights are row-standardized so that all the elements of each row sum to one, that is, $w_{ij}^s = w_{ij} / (\sum_j w_{ij})$.

Results

Spatial Autocorrelation

At first, a global Moran's I test was used to test for spatial autocorrelation. First introduced by Moran (1950), Moran's I statistic is the most commonly used measure of spatial autocorrelation, which is calculated as:

$$I = \frac{n}{S_0}\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{4}$$

where n is the number of locations, $\bar{x}$ is the mean of the x variable, w_{ij} are the elements of the weight matrix, and S_0 is the sum of the elements of the weight matrix: $S_0 = \sum_i \sum_j w_{ij}$. The statistic varies from -1 to +1. A positive I value indicates that there is clustering of similar values across geographic space, while negative I value indicates that neighboring values are more dissimilar.

Table 1 displays the results from the Moran's *I* test for the dependent variable to be estimated. The Moran's *I* statistic (0.05) is statistically significant; thus, the H_0 of no spatial dependence is rejected for cotton acreage percentage. For further illustration purpose, Figure 1 depicts the Moran's scatter plots, which describes an observation's values in relation to its neighbors. The slope of the scatter plots corresponds to the value of Moran's *I*. As shown in Figure 1, counties with more cropland planted to cotton are likely to be close to other counties with high cotton acreage, while counties with fewer cotton planted acres are likely to be surrounded by other similar neighbors.

Table 1. Moran' *I* Test Results for Cotton Acreage Percentage

Variable	*I*	*E(I)*	*Sd(I)*	*Z*	*p-value*
Cotton Acreage	0.05	-0.01	0.01	8.69	0.00

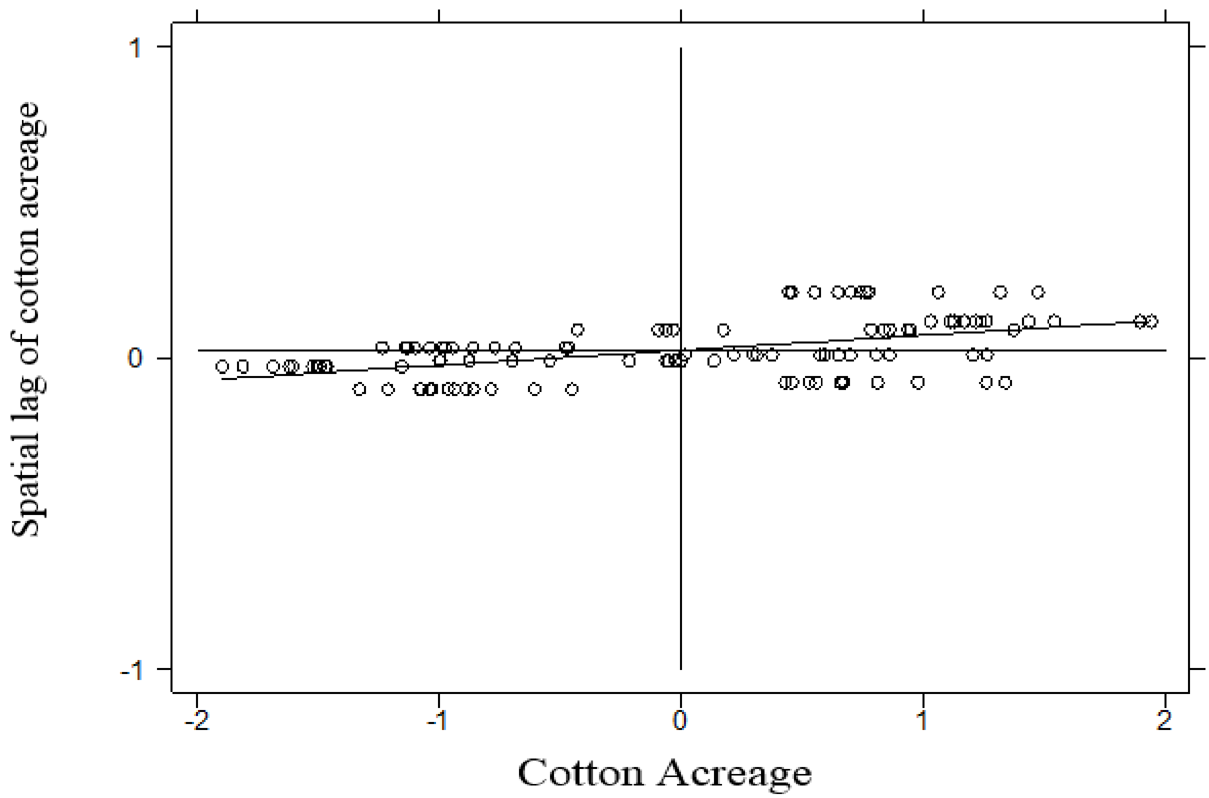

Figure 1. Moran's Scatterplot for the Cotton Acreage Percentage

Model Results and Selection

Table 2 summarizes the estimation results from the OLS regression, the spatial lag model (SAR) and the spatial error model (SEM), respectively. Both spatial models were estimated with the maximum likelihoood method using STATA. First, we use the OLS regression results to estimate the determinants of the cotton acreage changes. Overall, the model achieves a reasonable goodness of fit (adjusted R^2 of 0.54) and all estimated coefficients have the expected signs. Then based on the OLS estimations, a series of further tests are carried out to assess the specific form of spatial autocorrelation. The results of spatial diagnostic tests are summarized in Table 3. However, as indicated by the Moran's *I* statistic (0.82 with a *p*-value of 0.41), it fails to reject the H_0 of no spatial autocorrelation. To decide whether a spatial error or a spatial lag specification is more appropriate, the Lagrange Multiplier (LM) tests are further applied. As indicated by the robust form of these LM statistics, the spatial lag model (SAR) is the preferred specification. Hence, we concetrate on the interpretation of the spatial lag model results.

Table 2. Models Estimation Results of Cotton Acreage Percentage

	OLS	Spatial Lag	Spatial Error
Intercept	0.03	-0.04	0.03
Standard Error	*(0.02)*	*(0.03)*	*(0.02)*
Lagged Cotton Prices	0.08***	0.07***	0.07***
	(0.02)	*(0.02)*	*(0.02)*
Water Level	-2.19E-4***	-2.05E-4***	-2.29E-4***
	(0.77E-4)	*(0.84E-4)*	*(1.01E-4)*
Lagged Cotton Production	1.67E-7***	1.58E-7***	1.70E-7***
	(2.17E-8)	*(1.91E-8)*	*(2.22E-8)*
Lagged Cotton Production of Neighboring Counties	2.69E-8***	2.50E-8***	2.79E-8***
	(6.56E-9)	*(5.17E-9)*	(*6.79E-9*)
Drive Time	-1.12E-4	-1.75E-4	-1.09E-4
	(1.50E-4)	*(1.43E-4)*	*(1.54E-4)*
Interaction Term	-0.46E-4	-0.48E-4	-0.46E-4
	(1.31E-4)	*(1.35E-4)*	*(1.37E-4)*
ρ		0.76***	
		(0.23)	
λ			-0.31
			(1.19)
R-squared	0.56		
Adj. R-squared	0.54		
LM Test (ρ=0)		5.47**	
Wald Test (ρ=0)		10.55***	
LM Test (λ=0)			0.06
Wald Test (λ=0)			0.07

*Notes significance at $\rho \leq 0.10$
**Notes significance at $\rho \leq 0.05$
***Notes significance at $\rho \leq 0.01$

Table 3. Diagnostic Tests for Spatial Dependence in OLS Regression

		Statistic	*p*-value
Spatial Error:			
	Moran's *I*	0.82	0.41
	LM	0.06	0.81
	Robust LM	59.85	0.00
Spatial Lag:			
	LM	5.47	0.02
	Robust LM	65.26	0.00

Due to the nature of the spatial lag model, regression coefficients in a spatial lag model cannot be interpreted and compared directly with coefficients obtained from the OLS model without a spatial lag. The coefficient estimates have different interpretations, as the spatial lag model is an autoregressive specification. An implication of this is that a change in the dependent variable for an observation can potentially affect the dependent variables in all other observations. For example, the coefficient of lagged local cotton production is $1.58E^{-7}$, which only accounts for the short-run impact of a change in the production. However, an increase in the cotton production and the subsequent increase in cotton planting area in region *i* will also affect cotton planting area in all neighboring regions through the spatial lag, and, consequently feeds back to the cotton land in region *i*. This feedback is commonly referred as the direct effect as discussed in LeSage and Pace (2009). Thus, this direct effects give the average (over all regions) of the impact of changing one explanatory variable in one region. With appropriate spatial filters, the degree to which other factors affect the cotton acreage can be estimated consistently. The spatial lag coefficient ρ is estimated to be 0.76, which implies that cotton acreages planted in area *i* covaries with the cotton acreage among its neighbors. Specifically, the coefficient indicates that cotton acreage percentage in area *i* increases by about 0.76% when cotton acreage percentage increases by 1% in surrounding areas.

Beyond the spatial terms, the estimation results suggest that lagged cotton production, prices, and irrigation water levels contribute significantly to the changes in the cotton area planted around an ethanol plant. Sorghum price was included to account for the effect of competing crop on cotton acreage, but dropped from the estimation due to high positive correlation associated with cotton price (a correlation coefficient of 0.74 in our sample). As expected, the effect of last year's cotton production and price on cotton acreage is positive and significant. The estimate of water level indicates a strong and negative relationship between irrigation conditions and cotton area planted. That is to say, in areas with adequate amount of irrigation water available, farmers are more likely to switch to alternative crops which bring more profit but require large quantities of water, such as corn.

The coefficient of the drive time variable is negative, which is used as a proxy for accessibility to the ethanol plant. In a spatial estimation context, the drive time variable represents a circle of equal driving time around the ethanol plant, rather than a spatial point on the map. Thus, the negative sign indicates that fewer cotton acres are expected to be planted for every minute of driving away from the ethanol plant facility. Likewise, the coefficient of the interaction term is negative, which is the product of the dummy variable and drive time as defined earlier. However, both of the coefficients are statistically insignificant. This basically means that these two variables have no effect on cotton acreage planted around the ethanol plant. The reasons are: first, sorghum is considered a rotation crop or a second crop planted after failed cotton. Second, as Hockley county is considered highly concentrated on cotton production, cropland near the ethanol plant is intensively devoted to growing cotton. As a result, the cotton area planted is naturally declining for cropland located further away. At last, the Levelland-Hockley County Ethanol plant is a small plant, which only produces 40 million gallons of ethanol per year. Its demand of sorghum for feedstock is not large enough to have an impact on cotton acreage.

Conclusions and Implications

The purpose of this study is to examine impacts on local cotton acreage from a locally owned 40 million gallon sorghum-based ethanol plant, located in Hockley, Texas, over the period from 2002 to 2014. Moran's *I* tests provided evidence of the existence of spatial dependence in cotton acreage percentage. Further spatial tests were performed to determine the appropriate regression model.

In the case of cotton acreage percentage estimation, the spatial lag model performs significantly better than the OLS. Our results indicates that cotton production both from locally and neighboring counties, cotton prices and irrigation water availability are factors contributed significantly to the changes in the cotton area planted around an ethanol plant. Additionally, the spatial lag coefficient ρ (0.76) implies that if cotton acreage percentage increases by 1% in neighboring counties, cotton acreage percentage around an ethanol plant increases by about 0.76%. Although the drive time and the interaction term variable have the expected signs, they are statistically insignificant. This indicates that the Levelland-Hockley County Ethanol plant has no impact on surrounding cotton acreage.

Our method provides an alternative approach that is complementary to existing spatial techniques and contributes to expanding the research related to the spatial effect of ethanol industry on the cropland changes. The model could be extended to include all ethanol plants within a state, which allows for a comprehensive study of the impacts of ethanol production on a state level. Data used in the model could be continually updated to see the long-term effect on the cropland use changes. Future research could also apply this model to other states to estimate the impact of ethanol production and make comparisons.

References

Anselin, L. 1988. Spatial econometrics: Methods and models. Dordrecht Boston: Kluwer Academic Publishers.

Anselin, L. 2002. "Under the hood: Issues in the specification and interpretation of spatial regression models." Agricultural Economics 247–267.

Behnke, K., and T.R. Fortenbery. 2011. "The Impact of Ethanol Production on Local Corn Basis." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.: [http://www.farmdoc.illinois.edu/nccc134].

Blomendahl, B.H., R.K. Perrin, and B.B. Johnson. 2011. "The impact of ethanol plants on surrounding farmland values: A case study." Land Economics 87(2), 223-232.

Guerrero, B., J. Johnson, S. Amosson, P. Johnson, E. Segarra, and J. Surles. 2011. "Ethanol Production in the Southern High Plains of Texas: Impacts on the Economy and Scarce Water Resources." Journal of Regional Analysis and Policy 41(1), 22Á32.

Henderson, J., and B.A. Gloy. 2009. "The impact of ethanol plants on cropland values in the great plains." Agricultural Finance Review 69(1), 36-48.

High Plains Water District No. 1. 2015. Accessed April 2015. http://www.hpwd.org/reports.

Hodge, T.R. 2011. "The Effect of Ethanol Plants on Residential Property Values: Evidence from Michigan." Journal of Regional Analysis and Policy 41(2), 148-167.

Katchova, A.L. 2009. "The Spatial Effect of Ethanol Biorefinery Locations on Local Corn Prices." Agricultural & Applied Economics Association's 2009 AAEA &ACCI Joint Annual Meeting. Milwaukee, WI.

LeSage, J., and R. K. Pace. 2009. Introduction to Spatial Econometrics. Boca Raton: Taylor & Francis Group.

Lewis, K.E., and G.T. Tonsor. 2011. "The Impact of Ethanol Production on Spatial Grain Market Relationships." International Food and Agribusiness Management Review Volume 14, Issue 4.

McNew, K., and D. Griffith. 2005. "Measuring the Impact of Ethanol Plants on Local Grain Prices." Review of Agricultural Economics 164-80.

Miao, R. 2011. The Land-use change effect of ethanol plants in Iowa: 1997–2009. Working paper. Ames, Iowa: Iowa State University.

Moran, P.A.P. 1950. "Notes on continuous stochastic phenomena." Biometrika 37:17.

NASS. 2015. National Agricultural Statistics Service. http://quickstats.nass.usda.gov/.

NASS. 2015. National Agricultural Statistics Service, USDA. July. Accessed 2015. http://www.nass.usda.gov/Statistics_by_State/Texas/Publications/County_Estimates/index.asp.

Olson, A., N. Klein, and G. Taylor. 2007. "The Impact of Increased Ethanol Production on Corn Basis in South Dakota." American Agricultural Economics Association Annual Meeting. Portland, Oregon.

PSD, Production, Supply and Distribution. 2015. Foreign Agricultural Service's Production, Supply and Distribution (PSD) online database. https://apps.fas.usda.gov/psdonline/psdQuery.aspx.

RFA. 2015. Statistics. Accessed June 2015. http://www.ethanolrfa.org/pages/statistics.

Secchi, S., L. Kurkalova, P.W. Gassman, and C. Hart. 2011. "Land use change in a biofuels hotspot: the case of Iowa, USA." Biomass and Bioenergy 35(6), 2391-2400.

Turnquist, A., T.R. Fortenbery, and J. Foltz. 2008. "Progress or devastation? The effects of ethanol plant location on local land use." American Agricultural Economics Association Annual Meeting. Orlando, FL. 27-29.