A Spatial Analysis on Corn Production: Implication for Ethanol Sustainability

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1 Introduction

Over the last few decades, the expansion of ethanol production has been encouraged by the U.S. government to meet domestic energy needs and reduce greenhouse gas emissions. While federal tax credits supported the ethanol market at the early stage of ethanol usage under the Energy Tax Act of 1978, the Renewable Fuel Standard (RFS) program facilitated a substantial growth in the ethanol market through the mandatory usage of ethanol under the Energy Policy Act of 2005 (Schnepf and Yacobucci, 2013). The tax incentives expired, but the Energy Independence and Security Act of 2007 expanded the mandate to renewable fuel, advanced biofuel, cellulosic biofuel, and biomass-based diesel. Due to the governmental support, ethanol production has increased dramatically. According to the U.S. Bioenergy Statistics (USDA-ERS, 2017), ethanol production increased from about 83 million gallons in 1981 to about 15 billion gallons in 2016, which amounts to over 99% of domestic ethanol consumption.

While the U.S. produced about 15 billion bushels of corn in 2016, about 34% of total corn production was used for ethanol production: about 5 billion bushels of corn. Since corn is a main feedstock for ethanol production, the productivity of corn is considered an important factor to sustain the supply of ethanol to the energy market. However, corn production is at risk because climate change in the future is expected to have negative effects on corn yields. The risk of changing corn yields has been emphasized under future climate change scenarios, showing that increasing drought under global warming and extreme weather events would threaten corn yields (Adams et al., 1990). In particular, changes in temperature and precipitation are considered to affect negatively corn yields with variations in regions (Southworth et al., 2000; Priya and Shibasaki, 2001; Schlenker and Roberts, 2006; Almaraz et al., 2008; Schlenker and Roberts, 2009; Neumann et al., 2010; Tack and Holt, 2016).

Most previous studies used reduced-form regression or crop simulation models to investigate the linkage between weather variables and corn yields. They focused on a specific region or a time-period to found how corn yields responded directly to changes in weather conditions. However, corn yields and local weather conditions in a region are correlated with those of other neighboring regions. While changes in local temperature and precipitation affect corn yields directly in a region, corn yields are spatially correlated with those of neighboring regions because neighboring regions face similar weather conditions. Due to the importance of spatial correlations in predicting corn yields, some studies emphasized the spatial variability in crop productivity (Priya and Shibasaki, 2001; Neumann et al., 2010), and others considered the spatial correlations in crop yields explicitly to forecast yield changes in response to weather events (McCullagh and C., 2006; Zhu et al., 2009; Tack and Holt, 2016).

If climate change negatively affects corn yields, the productivity of corn will be a critical concern of ethanol producers for the sustainable supply of ethanol to the energy market. In particular, if there are spatial correlations in corn yields, the spatial estimation is needed for obtaining correct estimates under weather conditions, which will eventually determine the productivity of ethanol. Moreover, the U.S. Environmental Protection Agency (EPA) will need correct estimates about corn yields to determine the mandatory usage level of ethanol appropriately. Thus, the specific objective of this study is twofold. First, this study estimates corn yields using a spatial panel analysis. With a focus on the Mid-western regions that grow mainly corn in the United States, this study performs the spatial panel analysis to predict corn yields in response to changes in fertilizer, temperature, and precipitation. Second, this study simulates the amount of ethanol produced from the expected corn availability. From the estimates of the standard and spatial panel models, this study offers valuable insights into the prediction of ethanol yields under climate change.

The rest of this paper is structured as follows. Section 2 introduces the spatial panel models and discusses its applicability to the analysis of estimating corn yields, and Section 3 provides data descriptions and empirical results. The potential ethanol availability is also simulated by using the predicted corn yields in this section. Finally, a summary and discussion are provided in Section 4.

2 Methodology

This section follows Burnett et al. (2013)'s methodology to describe the panel data analysis with spatial correlations. Consider a regression model with individual i for $i = 1, \cdots, N$ in time period t for $t = 1, \cdots, T$. The standard specification for panel data is

$$y = X\beta + (\iota_T \otimes I_N)\,\gamma + (I_T \otimes \iota_N)\,\delta + \varepsilon \tag{1}$$

where y is the $NT \times 1$ vector of a dependent variable, X is the $NT \times K$ matrix of independent variables, ι_T is the $T \times 1$ vector of unity, ι_N is $N \times 1$ vector of unity, I_N is the $N \times N$ identity matrix, I_T is the $T \times T$ identity matrix, and ε is the error term that follows the normal distribution. While $\otimes$ is the Kronecker product, β, γ, and δ denote the coefficients for explanatory variables, the coefficients for individual effects, and the coefficients for time effects, respectively. The standard approach to panel data is based on the fixed-effect and random-effect models. The fixed-effect model reflects that individual effects are correlated with independent variables, and the random-effect model assumes that individual effects are uncorrelated with independent variables. In Equation

(1), the fixed-effect model considers that γ is fixed across individuals over time, but the random-effect model assumes that γ is not fixed but rather unobserved random variables. The Hausman specification test determines which model is appropriate for the data; the test statistic is asymptotically distributed as χ^2_K where K is the number of independent variables (Hausman, 1978).

From the standard panel models, spatial correlations are reflected to address their potential effects on neighbors. According to Anselin (1988) and Anselin and Bera (1998), value i is influenced by value j for $i \neq j$ when the characteristics and activities of an individual have an impact on neighboring individuals. Considering economic distances, a spatial weighting matrix W_N is constructed to introduce the spatial effects to the panel models. The weighting matrix is expressed by

$$W_{NT} = I_T \otimes W_N \tag{2}$$

which is the $N \times N$ positive matrix where an element in the matrix (w_{ij}) represents the interaction between individuals i and j. When the weighting matrix is applied to the panel model, there exist three types of spatial panel models: the spatial autoregressive, spatial error, and spatial Durbin models. The spatial autoregressive model (SAR) is written as

$$y = \theta W_{NT} y + X\beta + (\iota_T \otimes I_N)\gamma + (I_T \otimes \iota_N)\delta + \varepsilon \tag{3}$$

where θ is the spatial autoregressive coefficient. The spatial error model (SEM) is written as

$$\begin{aligned} y &= X\beta + (\iota_T \otimes I_N)\gamma + (I_T \otimes \iota_N)\delta + \varepsilon \\ \varepsilon &= \rho W_{NT}\varepsilon + u \end{aligned} \tag{4}$$

where ρ is the spatial autocorrelation coefficient for the error term. The final form is the spatial Durbin model (SDM) which is written as

$$y = \theta W_{NT} y + X\beta + \phi W_{NT} X + (\iota_T \otimes I_N)\,\gamma + (I_T \otimes \iota_N)\,\delta + \varepsilon \tag{5}$$

where ϕ is the spatial autocorrelation coefficient. The spatial Durbin model nests the spatial autoregressive and spatial error models because it reflects the dependence in the error term and the dependent variable (LeSage and Pace, 2009). The estimated coefficients in the spatial Durbin model can be used to determine whether the spatial Durbin model is simplified to the spatial autoregressive or spatial error model. The spatial Durbin model can be reduced to the spatial autocorrelation model if we reject the null hypothesis of $\phi = 0$, whereas it can be reduced to the spatial error model if we reject the null hypothesis of $\phi + \theta\beta = 0$ (LeSage and Pace, 2009). The spatial Durbin model will be used if both null hypotheses are rejected.

3 Empirical Analysis

3.1 Data and Estimation

Study areas cover major states producing corn in the Midwestern United States; 10 states such as Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin. With a focus on corn yields determined by pursuing the intensive margin, the data such as corn yields and fertilizers are obtained from the National Agricultural Statistics Service of the U.S. Department of Agriculture (USDA-NASS). Corn yields are measured in bushels per acre, while fertilizers incorporating nitrogen, phosphorus, and potash are measure in lb. per acre. To consider climatic factors, the historically observed weather data such as average temperature and precipitation are obtained from the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration (NOAA). The annual average temperature is measured in Fahrenheit scale, while the annual average precipitation is measured in inches. All variables in the data are used to construct a panel dataset with 10 states for the period between 1990 and 2014.

Figure 1 shows the average values of corn yields, fertilizers, temperature, and precipitation in the study areas. All the variables vary across the states. While the average value of corn yields of 10 states is 131.65 bushels per acre, Iowa has the greatest corn yields (143.59), but South Dakota has the least corn yields (102.65). The use of fertilizer is proportional mainly to corn yields, and the average value is 255.94 lb. per acre. The amount of fertilizers used for corn production is the most in Illinois (346.88) but the least in South Dakota (157.47). For climate factors, the average temperature is 49.35° F: the highest in Kansas (54.82) but the lowest in Minnesota (41.49). The average precipitation is 33.37 inches but varies across states. The highest level of precipitation is in Missouri (42.48) but the lowest is in South Dakota (20.88).

On the basis of the data, the empirical model is constructed as

$$
\begin{aligned}
y_{it} = \beta_0 + \beta_1 F_{it} + \beta_2 C_{it} + \beta_3 R_{it} + \frac{1}{2}\big[&\beta_4 F_{it}^2 + \beta_5 C_{it}^2 + \beta_6 R_{it}^2 \\
&+ 2\beta_7 F_{it} C_{it} + 2\beta_8 F_{it} R_{it} + 2\beta_8 C_{it} R_{it}\,\big] + \gamma_i + \delta_t + \varepsilon_{it}
\end{aligned}
\tag{6}
$$

for $i = 1, \cdots, N$ and $t = 1, \cdots, T$. In Equation (6), y_{it} is corn yields, F_{it} is the amount of fertilizers used for corn, C_{it} is temperature, and R_{it} is precipitation, respectively. In addition, γ_i denotes state-specific effects, and δ_t denotes time-period effects. Based on this specification, non-spatial and spatial panel models are estimated.

3.2 Estimation Results

The estimation results for the standard panel models are presented in Table 1. The results of both fixed- and random-effect models represent that fertilizer use, temperature, and precipitation are associated with corn yields. The Hausman test is conducted to determine which model best fits for the data. The test statistic is 18.32, indicating the fixed-effect model is more appropriate for the data used in this study. The results of the fixed-effect model show that the estimates of the fertilizer and temperature variables are positive and statistically significant. While there is no statistical significance in the estimate of the quadratic term of the fertilizer variable, that of the temperature variable is negative and statistically significant, which is consistent with the inverted U-shaped relationship between temperature and corn yields. In addition, the estimate of the quadratic term of the precipitation variable is negative and statistically significant.

Table 2 reveals the estimation results of the spatial panel models. We construct a distance-based weighting matrix, which is obtained by calculating distances between centroids of states. Using the weighting matrix, we apply the spatial Durbin panel model to both random- and fixed-effect models and determine which model fits for the data well by employing the Hausman test. Regarding the spatial Durbin models with the fixed and random effects, the Hausman test indicates that the fixed-effect model is preferred to the random-effect model; the test static is 20.10. Moreover, since the spatial Durbin model nests the spatial autoregressive and spatial error models, the likelihood-ratio tests are conducted to determine whether the spatial Durbin model is simplified to the spatial autoregressive or spatial error model. The test results indicate that the first hypothesis ($\phi = 0$) is rejected at 1% level; the test statistic is 81.83. This implies that the spatial Durbin model is preferred to the spatial autoregressive model. The test statistic for the second hypothesis ($\phi + \theta\beta = 0$) is 82.78, which rejects the null hypothesis at 1% level. This shows that the spatial error model is not appropriate for the panel dataset. The results of the diagnostic tests reveal that the spatial Durbin model with fixed effects is the best fits for the data.

In Table 2, the estimation results of the SDM model with fixed effects represent that the estimated spatial autoregressive coefficient is 0.52 and statistically significant at the 1% level. This implies that corn yields in a state have positive effects on those in neighboring states. The main estimates indicate that only temperature affects corn yields. From the estimates, Table 3 reveals the direct, indirect, and total effects of the variables in the spatial Durbin models. Regarding the direct effects of the SDM model with fixed effects, the estimates are different from the point estimates reported in Table 2. The differences are due to the presence of spatial correlations between states. In particular, the results show that the estimates of both fertilizer and temperature variables have the inverted U-shaped relationships with corn yields, respectively. Moreover, the indirect effects reported in Table 3 represent the extent to which the explanatory variables influence neighboring states' corn yields. The results indicate that there exist spillover effects of fertilizer use, temperature and precipitation in a state on corn yields in neighboring states. Finally, the total effects incorporate the indirect effects into the direct effects, which show the robust estimates reflecting the spatial correlations.

Based on the estimates, we simulate how much ethanol will be produced from the expected corn availability. The predicted values of corn yields are calculated by using the estimates of the standard fixed model and the spatial Durbin model with fixed effects. The potential amount of ethanol produced is projected by assuming that 2.8 gallons of ethanol are produced by one bushel of corn (de Gorter and Just, 2009a,b). Table 4 reports the predicted value of ethanol yield measured in gallons per acre. Compared with the predicted values obtained by the standard fixed-effect model, the estimates obtained by the spatial Durbin model with fixed effects are closer to the real average values. The standard fixed-effect model yields the minimum difference of 4.15 and the maximum difference of 109.68, whereas the spatial model yields the differences ranging only from

1.49 to 18.53. The root-mean-square error (RMSE) also indicate that the predicted values of the spatial Durbin model (1.01) have more predictive power than those of the standard panel model (1.99). The results imply that the spatial correlations have to be reflected in predicting ethanol yields correctly. Without considering spatial effects, the potential availability of ethanol may be overestimated or underestimated, which can provide policy makers with incorrect information about corn availability. As the EPA determines the mandated level of ethanol, it is important for the EPA to predict ethanol availability based on the spatial effects of corn yields.

4 Conclusions

Corn is a major input for ethanol production, but most producers are expected to face uncertainty to manage and control corn production due to unpredictable characteristics of climate change. Since the sustainability of ethanol is completely dependent on the availability of corn, the extent to which climate change affects corn production will be a great concern of ethanol producers. Due to the importance of potential corn availability for ethanol production, this study estimates corn yields with a focus on fertilizers and weather variables. In particular, corn yields, fertilizers, and weather variables in a state are spatially correlated with those of neighboring states. Considering their spatial effects, this study uses a spatial panel model to obtain robust estimates for corn yields. Based on the estimates, the potential ethanol availability is projected by using the fact that 2.8 gallons of ethanol are produced by on bushel of corn.

The estimation results reveal that the spatial correlations are an important factor to forecast corn yields correctly. The findings reveal that a spatial analysis on corn yields is necessary for the EPA to predict the potential amount of ethanol correctly. When considering spatial spillover effects of weather conditions on corn yields, ethanol yields are also dependent on the spatial correlations between states. The consideration of spatial relationships will provide policy makers with correct information about future corn availability, which will guarantee the sustainable supply of ethanol to the energy market. The findings will be of interest of the EPA setting the blending requirements of ethanol with gasoline based on the availability of corn for ethanol production.

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Table 1: Estimation Results of Standard Panel Models

	Fixed Effect	Random Effect
Fertilizer	2.301***	2.261***
	(0.561)	(0.427)
Temperature	35.437***	26.939***
	(9.189)	(6.880)
Precipitation	-3.963	2.622
	(3.770)	(2.871)
Fertilizer^2	-0.003	-0.004
	(0.003)	(0.003)
Temperature^2	-1.229***	-0.763**
	(0.423)	(0.311)
Precipitation^2	-0.343***	-0.294***
	(0.104)	(0.112)
Fertilizer × Temperature	-0.039***	-0.038***
	(0.011)	(0.011)
Fertilizer × Precipitation	0.013*	0.009
	(0.007)	(0.007)
Temperature × Precipitation	0.131	-0.006
	(0.083)	(0.071)
Constant	-1003.473***	-827.739***
	(228.544)	(178.375)

Note: Standard errors are in parentheses.
***Denotes statistical significance at the 1% level.
**Denotes statistical significance at the 5% level.
*Denotes statistical significance at the 10% level.

Table 2: Estimation Results of Spatial Durbin Models

	Fixed Effect	Random Effect
Spatial Autoregressive Coefficients (θ)	0.517***	0.506***
	(0.049)	(0.043)
Main Coefficients (β)		
Fertilizer	-1.584	1.041
	(1.073)	(0.911)
Temperature	41.709**	30.427**
	(18.178)	(15.299)
Precipitation	-6.418	0.392
	(7.432)	(5.925)
Fertilizer^2	0.002	-0.011*
	(0.006)	(0.006)
Temperature^2	-2.535***	-1.506**
	(0.875)	(0.701)
Precipitation^2	0.100	-0.225
	(0.214)	(0.231)
Fertilizer $\times$ Temperature	0.035	0.006
	(0.022)	(0.023)
Fertilizer $\times$ Precipitation	-0.014	0.004
	(0.015)	(0.015)
Temperature $\times$ Precipitation	0.175	0.065
	(0.163)	(0.140)
Spatial Autocorrelation Coefficients (ϕ)		
Fertilizer	-1.290***	-1.556***
	(0.342)	(0.256)
Temperature	-20.247***	2.760**
	(5.317)	(1.144)
Precipitation	0.575	3.790*
	(1.801)	(1.793)
Fertilizer^2	0.004*	0.004**
	(0.002)	(0.002)
Temperature^2	0.721***	-0.229**
	(0.228)	(0.106)
Precipitation^2	0.142**	0.113*
	(0.058)	(0.062)
Fertilizer $\times$ Temperature	0.017***	0.024***
	(0.006)	(0.006)
Fertilizer $\times$ Precipitation	-0.006*	-0.006
	(0.004)	(0.004)
Temperature $\times$ Precipitation	-0.030	-0.078*
	(0.039)	(0.041)
Log-likelihood	-725.900	-751.243

Note: Standard errors are in parentheses.
***Denotes statistical significance at the 1% level.
**Denotes statistical significance at the 5% level.
*Denotes statistical significance at the 10% level.

Table 3: Direct, Indirect, and Total Effects from Spatial Durbin Models

	Direct Effect	Indirect Effect	Total Effect
SDM with Fixed Effect			
Fertilizer	2.533***	2.592***	5.125***
	(0.608)	(0.727)	(1.146)
Temperature	39.001***	-1.715	37.286*
	(10.149)	(14.122)	(21.762)
Precipitation	-1.052	3.222	2.170
	(3.784)	(5.557)	(8.550)
Fertilizer^2	-0.007*	-0.005	-0.012
	(0.004)	(0.005)	(0.008)
Temperature^2	-1.369***	0.726	-0.643
	(0.447)	(0.656)	(0.973)
Precipitation^2	-0.271**	-0.229*	-0.500***
	(0.107)	(0.136)	(0.192)
Fertilizer × Temperature	-0.034***	-0.044***	-0.078***
	(0.011)	(0.014)	(0.021)
Fertilizer × Precipitation	0.012*	0.017*	0.029**
	(0.007)	(0.009)	(0.013)
Temperature × Precipitation	0.054	-0.073	-0.019
	(0.084)	(0.125)	(0.193)
SDM with Random Effect			
Fertilizer	3.127***	1.337**	4.464***
	(0.488)	(0.661)	(1.006)
Temperature	-6.460*	-23.276**	-29.736**
	(3.561)	(10.543)	(12.715)
Precipitation	-7.746**	-5.297	-13.043*
	(3.699)	(4.651)	(7.641)
Fertilizer^2	-0.007**	0.002	-0.005
	(0.004)	(0.004)	(0.007)
Temperature^2	0.508**	1.269**	1.777**
	(0.257)	(0.519)	(0.703)
Precipitation^2	-0.216*	0.009	-0.206
	(0.116)	(0.148)	(0.208)
Fertilizer × Temperature	-0.049***	-0.035**	-0.084***
	(0.012)	(0.016)	(0.024)
Fertilizer × Precipitation	0.011	0.004	0.016
	(0.007)	(0.010)	(0.015)
Temperature × Precipitation	0.157	0.073	0.220
	(0.085)	(0.108)	(0.174)

Note: Standard errors are in parentheses.
***Denotes statistical significance at the 1% level.
**Denotes statistical significance at the 5% level.
*Denotes statistical significance at the 10% level.

Table 4: Predicted Values of Ethanol Yields (Gallons Per Acre)

	Ethanol Yield (E)	Predicted Yield (FE)	E-EF	Predicted Yield (SDM)	E-SDM
Illinois	400.235	482.419	-82.183	393.994	6.241
	(59.310)	(30.817)		(19.051)	
Indiana	385.247	475.818	90.571	366.721	18.526
	(60.005)	(28.491)		(21.121)	
Iowa	402.047	406.197	-4.150	392.199	9.848
	(65.405)	(38.562)		(50.498)	
Kansas	374.871	336.334	38.536	378.889	-4.018
	(33.305)	(24.260)		(26.096)	
Minnesota	384.424	328.508	55.916	382.936	1.487
	(71.185)	(51.847)		(32.062)	
Missouri	332.047	385.395	-53.348	322.408	9.639
	(64.431)	(35.437)		(47.962)	
Nebraska	386.894	311.963	74.932	373.009	13.885
	(51.136)	(18.262)		(27.254)	
Ohio	370.753	477.750	-106.998	388.825	-18.072
	(63.389)	(21.693)		(33.173)	
South Dakota	287.412	229.225	58.187	304.002	-16.590
	(62.836)	(53.399)		(50.234)	
Wisconsin	362.353	252.674	109.679	360.736	1.617
	(51.449)	(37.160)		(47.385)	

Note: All estimates are statistically significant at the 1% level.

Figure 1: Average Values of Corn Yield, Fertilizer Use, Temperature, and Precipitation