Estimating the Effects of Weather Variations on Corn Yields using Geographically Weighted Panel Regression

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Abstract: Through a geographically weighted panel regression analysis, we demonstrate the spatially varying relationship between weather and corn yields. A balanced panel data of 958 U.S. corn production counties for the period 2002-2006 is used. The results indicate that the relationship between weather and corn yield has large spatial variability. In specific, temperature tends to have negative marginal effects on corn yield in warmer regions, and positive effects in cooler regions. The spatial pattern of precipitation effects is more complicated since it is expected to be largely affected by local irrigation systems.

Key words: Geographically weighted panel regression, Climate change, Corn yields

Introduction

Global climate models (GCMs) such as the CSIRO 3.5, CGCM 3.1, and MIROC 3.2 models predict that average temperature will keep rising and precipitation will change moderately in the continental U.S. for the rest of the century based on the IPCC A1B emission scenario (Coulson et al., 2010). These weather variations are expected to have large impacts on crop yields. These impacts are also expected to be spatially varying due to regional environmental characteristics such as soil quality. In addition to global impacts of climate on crop yields, regional difference in these impacts could have some side effects. For example, people may want to migrate from a region with negative climate change impacts to a region with mild or positive climate change impacts, and the resulting population redistribution could raise socio-economic issues. A study of regional differences could provide policy makers with information on the local impacts of weather variations. While a large body of literature has examined the linkage between climate and crop yields, relatively little research has attempted to compare the impacts of climate change on crop yields across regions (Tao et al., 2006; Kucharik and Serbin, 2008; Schlenker and Roberts, 2009; Butterworth et al., 2010). Using the data from stations located in various climate zones in China, Tao et al. (2006) demonstrated that temperature was negatively correlated with crop yields at all stations except the one in northeastern China. Kucharik and Serbin (2008) found that spatial variability in climate trends at the county level in Wisconsin has contributed to variable trends of soybean and corn yields. Schlenker and Roberts (2009) explored how the temperature-yield relationship varies across different U.S. regions and found that southern crops have lower sensitivity to extreme heat. Butterworth et al. (2010) demonstrated that climate change increases the productivity of oilseed rape in the U.K., with greater benefits in Scotland than England.

In this study, we use a relatively new method - Geographically Weighted Panel Regression (GWPR) to test the hypothesis of spatially varying climate change impacts on crop yields. We demonstrate spatially varying local relationships between corn yield and weather variations for continental U.S. counties.

Literature review

Two major approaches have been used to study the relationship between climate change and crop yields: crop simulation models and empirical regression models. Crop simulation models are useful in simulating how environmental characteristics affect crop growth (Hoogenboom, 2000; Jones et al., 2003). However, crop simulation models are not suitable for testing our hypothesis, since they are site-specific, requiring local time-invariant information such as soil properties, which has already incorporated regional differences. Besides, crop simulation models usually require extensive information, making it difficult to apply them to analysis with large spatial scale. Empirical regression models have been intensively used to study the impacts of climate change on crop yields (Thompson, 1988; Kandiannan et al., 2002; Lobell, Cahill, and Field, 2007; Tannura, Irwin, and Good, 2008; Schlenker and Roberts, 2009). Kandiannan et al. (2002) used multiple regression models to study the effects of weather on turmeric yield based on a 20-year dataset. Tannura, Irwin, and Good (2008) used a modified multiple regression model, first developed by Thompson (1988), to study the relationship between corn and soybean yields, monthly weather condition during 1960-2006 for Illinois, Indiana, and Iowa. Using a regression model, Lobell, Cahill, and Field (2007) analyzed the relationship between crop yield and three climatic variables (minimum temperature, maximum temperature, and precipitation) for 12 major Californian crops during 1980-2003.

Most of these regression models are cross-sectional analysis. Compared to cross-sectional data, panel data has several advantages. Panel data allows us to control for unobserved heterogeneity using fixed or random effects model. We can also improve estimation efficiency by conducting panel data analysis (Wooldridge, 2002). Deschenes and Greenstone (2007) found that growing degree days has negative effects on corn and soybean yields using a fixed effects model with state by year dummies based on U.S. county-level data. Using panel data at the U.S. state-level, McCarl et al. (2008) demonstrated positive effects of temperature on soybean yield by estimating a fixed effects model with time trend. Using county-level data during 1950-2005, Schlenker and Roberts (2009) estimated a fixed effects model with state-specific quadratic time trend, and demonstrated the nonlinear temperature effects on corn, soybeans, and cotton yields.

Both conventional Ordinary Least Square (OLS) regression models and fixed or random effects models assume that coefficient estimates are spatially invariant; therefore, spatial heterogeneity of the relationship between weather and crop yields is ignored. Furthermore, regression residuals from spatial data are often spatially dependent, violating the basic assumption of independent distributed errors. That means even we are only interested in the global mean of the relationship, the conventional regression estimation of spatial data is still problematic. Spatial models such as the spatial lag model and spatial error model have been developed to control for the spatial dependence, however, they only generate globally constant estimates and spatial heterogeneity is still not studied.

Geographically weighted regression (GWR) is a local spatial statistical technique using neighboring observations near certain locations to generate local regression estimates which are allowed to vary across the space (Brunsdon et al., 1996; Fotheringham et al., 2002), therefore spatially heterogeneity could be detected. GWR model is developed based on the assumption that nearby observations are more related than distant observations. Using a distance decay function in local regression models, observations near local regression points are assigned with the higher weights than the distant observations. GWR could be used to detect the spatially varying relationships between climate change and crop yields. Furthermore, by applying GWR to investigate the relationship between vegetation and climate, Propastin et al. (2007) found that, although constructed differently from spatial lag or error models, GWR also helps reduce the magnitude of spatially autocorrelation. Olgun and Erdogan (2009) modeled wheat yield potential on certain climatic conditions using GWR. They demonstrated that the relationship between the level of wheat potential and various climatic factors exhibited considerable spatial variability. Sharma (2011) used GWR to study the relationship between crop yield and precipitation for 93 counties in Nebraska, and found that the performance of GWR model is significantly better than the performance of OLS model.

For the conventional GWR model, local models are linear regression models estimated by OLS. The studies that use GWR to analyze panel data are still rare. As a pioneer work, Yu (2010) combined GWR and panel regression model to study the regional development of great Beijing area. In this study, we follow Yu (2010) to apply a panel data version of GWR, named geographically weighted panel regression (GWPR), to study the spatially varying relationship between climate change and crop yields in the continental U.S. at the county level. In the current study, instead of using an OLS regression model, we use a fixed effects model for GWR local regression. We expect that GWPR could take advantage of panel data and generate more thorough results compared to GWR.

Methodology

In this study, we use a panel data of 958 U.S. corn production counties for the period 2002-2006. A fixed effects model with time trend can be written as:

$$\mathbf{y}_{(lat,long)t} = \mathbf{X}_{(lat,long)t}\boldsymbol{\beta} + \alpha_{(lat,long)} + t + \mathbf{u}_{(lat,long)t} \tag{1}$$

where subscript $(\boldsymbol{lat}, \boldsymbol{long})$ denotes latitude and longitude coordinates, and subscript t indicates year. $\mathbf{y}_{(lat,long)t}$ denotes corn yield for county located at certain coordinate at year t. $\mathbf{X}_{(lat,long)t}$ denotes weather condition at certain coordinate at year t. $\boldsymbol{\beta}$ is a global coefficient. $\alpha_{(lat,long)}$ denotes time-invariant fixed effects such as local soil quality which does not change over time, t is a linear time trend to remove the effects of agricultural technological improvements over time. $\mathbf{u}_{(lat,long)t}$ is the error term.

Following Yu (2010), we use GWPR to study the relationship between weather and crop yields for U.S. corn production counties. Our GWPR model has local fixed effects model with a time trend and can be written as:

$$\mathbf{y}_{(lat,long)t} = \mathbf{X}_{(lat,long)t}\boldsymbol{\beta}_{(lat,long)} + \alpha_{(lat,long)} + t + \mathbf{u}_{(lat,long)t} \tag{2}$$

Equation (2) has two differences compared to equation (1). First, equation (2) is for local regression only, therefore including fewer observations compared to a global regression. Second, the value of $\boldsymbol{\beta}$ now varies across the space, which could be mapped to illustrate the spatially varying relationship between $\mathbf{y}_{(lat,long)t}$ and $\mathbf{X}_{(lat,long)t}$.

We do not estimate random effects model here. We expect that county fixed effects $\alpha_{(lat,long)}$ are correlated with weather conditions $\mathbf{X}_{(lat,long)t}$, which violates the assumption of random effects model. For example, a county with more or less precipitation $\mathbf{X}_{(lat,long)t}$ may have better irrigation system $\alpha_{(lat,long)}$. We confirm this with several statistical tests which help determine the appropriate panel regression model. Based on the results from those tests, a two-way fixed effects model (a fixed effects model with time fixed effects) is preferred. However, we use a fixed effects model with time trend for GWPR due to the following considerations. First, it should be noted that above tests are conducted to choose the best panel model based on the global panel data, while a GWPR model uses a local panel models which has many fewer observations compared to the global panel model. We also suspect that time dummies could absorb large portion of variations which are useful for estimating the relationship between crop yields and climate models for local panel models, which we will explain in the Results section.

Bandwidth determines the number of observations included in a GWR local regression model. There are two spatial kernels for bandwidths. Fixed kernel includes observations within a fixed distance around a regression point. However, this approach could generate local models with different sample sizes if observations are not evenly distributed across the space, such as states or counties. Therefore, we use adaptive kernel which includes specific number of observations near the regression point in the local model. Bandwidth could be optimized using corrected Akaike Information Criterion (AICc) or cross validation (CV) criterion. Compared to cross-sectional data, the selection of bandwidth is more complicated in panel data. Optimization of bandwidth based on different cross sections will generate different bandwidths. To simplify our analysis, we assume that bandwidths are time-invariant. Besides, using different bandwidths for different cross sections could generate unbalanced local model since there will be some counties which don't have values for all the years. After selection of bandwidth, each observation in the local model is weighted based on a geographical weighting function using the bi-square scheme. Nearby observations nearer to the regression point are assigned with more weight to represents larger impacts.

We use the "spgwr" package in R for GWR estimation. We use the "gwr.sel" function to optimize bandwidth and the "gwr" function to estimate local GWPR coefficients. Since "gwr" and "gwr.sel" functions are designed for cross-sectional data, we estimate local models of demeaned values for yield and weather using OLS.

Data

As a major crop in the U.S., corn is used in our study so that a large spatial analysis can be conducted. In the U.S., corn is mostly grown in the Corn Belt states. Corn yield data for 958 U.S. counties from 2002 to 2006 were collected from the U.S. Department of Agriculture's National Agricultural Statistics Service (USDA-NASS). We use 2002-2006 data in order to avoid the effects from policy changes. We use a balanced panel to simply the GWPR analysis[1].

We incorporate monthly temperature and precipitation data during growing season, collected from the National Climatic Data Center (NCDC) based on weather stations.[2] These weather data are converted from station level into county level before analysis.

Results and Discussion

The spatial distributions of temperature, precipitation, and corn yields for 958 counties during 2002-2006 are presented in Figures 1-3, respectively. Large spatial variations could be observed. In general, temperature decreases from south to north, while precipitation decreases from south

[1] A balanced panel data for 2001-2010 would only include 453 counties compared to 958 counties for 2002-2006, since many counties has missing yield data during 2008-2010. We also exclude all the western coast counties which are far away from the rest of counties.

[2] Each county generally has different corn growing season lengths. We assume that growing season for corn is from April to October for all the counties.

to north and from east to west. Most counties with high corn yields are located in the Corn Belt region. Table 1 shows summary statistics of corn yields and weather data used in this study.

We start with a GWR analysis of cross-sectional data. We construct a cross section which is the average value of weather and crop yields over the period 2002-2006. The results from the global OLS regression model show that corn yields are negatively related to both precipitation and temperature (Table 2). As mentioned earlier, applying OLS to spatial data may induce inefficient results due to possible spatial dependence. To test the existence of the spatial autocorrelation in our data, we apply Moran's I to the residuals of the global OLS regression model. As shown in Table 2, Moran's I is 0.79, indicating strong positive spatial autocorrelation between neighboring counties. Therefore, a global linear regression model estimated by OLS is not appropriate for analyzing our spatial data.

We use spatial lag and spatial error models to account for spatial dependence. Compared to Moran's I of the global OLS model, we find that Moran's I is now reduced to -0.0095 for spatial lag model and -0.0065 for spatial error model, indicating that the issue of spatial autocorrelation has been addressed by spatial regression models (Table 2). However, spatial models do not present spatial heterogeneity.

Now we apply a GWR model to this average cross section. The AICc of GWR model is 8125.293, lower than 9241.7 for OLS model, 8643.5 for spatial lag model, and 8652.2 for spatial error model, indicating that GWR model is an improvement compared to global OLS model and spatial regression models in this study. Towards GWR coefficients, the mean growing season temperature coefficient is positive, and the mean growing season precipitation coefficient is negative. These values are different from the coefficients based on global OLS model and global spatial regression models, for which growing season temperature and precipitation coefficients are both negative. Temperature coefficients vary from -1.17109 to 1.2896, and precipitation coefficients vary from -3.25049 to 2.8302, indicating spatial variability of both GWR coefficients. The adjusted R-squared of GWR results indicates that local models have varied explanatory power across the space. It is noted that Moran's I for GWR residuals is lower than that of OLS model but higher than that of spatial regression models, indicating that GWR helps partially address the spatial dependence, but does not work as well as spatial regressions. Figures 4-7 illustrate the spatial distributions of estimated GWR coefficients for temperature and precipitation. However, the number of counties with GWR coefficients that are pseudo-significant at 5% significance level is limited. We suspect that large portion of variations representing the response of corn yield to weather over time has been removed by use the average value over five years[3].

Above results are based on a conventional GWR analysis on cross-sectional data. In this study, we attempt to take advantage of panel data. We conduct both global panel model and GWPR analysis. Our panel data consists of 958 U.S. corn production counties during the period 2002-2006. We conduct several statistical tests, and determine that a preferred panel model for our data is a fixed effects model with time dummies[4]. For literature of weather-crop yield, it is common to include a time trend as an explanatory variable in order to remove the effects of technological improvements over time. Therefore, we also estimate a fixed effects model with a linear time trend. As shown in Table 3, global fixed effects models with time dummies or time trend generate similar coefficient estimates, that corn yields are negatively related to growing

[3] Using one year data as cross-section shows more pseudo-significant GWR coefficients compared to an average cross-sectional data. However, we are focusing on a GWPR model in this study, those GWR results using one year data are not presented here.

[4] These tests include Hausman test to compare random effects model and fixed effects model, LM test to compare random effects model and OLS model, and an F test to determine if time-fixed effect is needed.

season temperature, while positively related to growing season precipitation. This is consistent with the work of Schlenker and Roberts (2009) that the estimated temperature effects are very similar if year dummies are used rather than state-specific quadratic time trends.

The above global fixed effects models do not account for spatial dependence and do not demonstrate spatial heterogeneity. Thus we estimate a GWPR model with local fixed effects models and time trend to extract spatially varying relationships. Based on a GWR analysis conducted earlier, we also expect that GWPR model could help partially address the spatial dependence issue. A GWPR bandwidth is optimized by CV criterion, which results in about 156 observations in each local regression model. Each local regression is thus a fixed effects model based on a local panel data of about 31 counties for five years. The mean value of GWPR coefficient estimates for both precipitation and temperature are similar to the estimates from two global fixed effects models in both sign and magnitude (Table 3). We also find that GWPR coefficient estimates show large spatial variability, ranging from -0.230 to 0.271 for precipitation, and from -3.047 to 1.564 for temperature. Compared to the earlier GWR analysis on the average cross section, we have more pseudo-significant coefficients in GWPR analysis, about 53.1% for precipitation and 64.6% for temperature (Figures 9 and 11). We find that corn yields in most counties in the north and northeast are positively related to temperature, while negative relationships are presented in other regions, consistent with existing literature that temperature tends to have positive impacts on crop yields in cold regions. This spatial pattern could be explained by the fact that in the southern Corn Belt and other southern states, the average temperature is higher than the optimal corn growth temperature; therefore, temperature variations tend to have negative marginal effects. In northern U.S., the average temperature is lower than the optimal corn growth temperature; therefore, temperature variations tend to have positive marginal effects. Corn yields are negatively related to precipitation in some Indiana and Nebraska counties. Compared to temperature coefficients, the number of precipitation coefficients with positive effects is more. About 76.8% of counties have positive precipitation coefficients, compared to 28.0% of counties with positive temperature coefficients. It indicates that an increase in precipitation is more favorable than an increase in temperature for corn production in most U.S. counties. Positive precipitation effects also indicate that the average precipitation is below the optimal precipitation for most U.S. corn production counties. This observation supports Good (2011) in that the most favorable precipitation in July in the heart of the Corn Belt should be about 25 percent above average. Compared to a simple spatial pattern of temperature coefficients, the spatial pattern of precipitation coefficients is more complicated. The yield response to precipitation is expected to be largely affected by local irrigation system. In Figure 12, it is observed that some heavily irrigated land tends to have insignificant or negatively significant precipitation effects, such as Nebraska and Mississippi river. Sharma (2011) also indicated that regions with better irrigation systems, crop yield could be less related to temperature and precipitation.

Although two fixed effects models with time dummies or time trend have been estimated for global model, we focus on a fixed effects model with time trend for GWPR model. We argue that time dummies for local GWPR model may absorb too much of the useful variations of corn yields and weather. The global fixed effects model with time dummies or time trends generate similar results, since global variations of county averages should be smaller than local variations of county averages and therefore time dummies would not absorb too much useful variations. Due to the fact that the GWPR model estimates local models with small sample size, we prefer to use a fixed effects model with time trend. We also conduct a GWPR analysis with a fixed effects model with time dummies and observe that only about 18.6% of counties have significant GWPR precipitation coefficients, and only about 16.1% of counties have significant GWPR temperature coefficient. This result supports our hypothesis that using time dummies in GWPR could absorb too much useful variations. Similarly, a GWR analysis of an average cross section conducted earlier generates significant coefficients in a limited number of counties. While avoiding using time dummies keeps useful variations for estimation, it also keeps other unrelated variations which could have been removed by using time dummies, such as policy changes or technological improvements. Therefore, we use a linear time trend to help remove technological improvements and use the data for the period 2002-2006 to avoid the effect of policy changes[5].

Conclusion

In this study, we conduct a GWPR analysis to demonstrate the spatial variability of climate-crop yields relationship for the continental U.S. counties. Our GWPR results show that the relationship between corn yields and weather varies across geographic space. In specific, temperature tends to have negative effects on corn yields in warmer regions, and positive effects in cooler regions, as expected. The spatial pattern of precipitation effects is more complicated. The sign and significance of precipitation effects in some regions are believed to be affected by local irrigation systems. Future research using only rainfed yield could help explain the effects of irrigation systems.

Our model and results are expected to provide agricultural producers with spatially-explicit guidance for future planting decisions under uncertain future climate conditions. The results also provide federal and state governments with information about the regional differences of climate effects on U.S. corn productions.

[5] Farm bill 2002 expired in 2007.

As one of the first studies using GWPR, our analysis does have certain limitations. For example, it is assumed that there is no CO_2 fertilization effect which is expected to enhance crop yields. We used weather data collected from weather stations that are not necessarily in the same location as the associated farms; this could reduce the spatial relevance of the climate conditions used. Future studies should use spatially interpolated weather data to improve the correspondence. We also notice that total precipitation only partially captures extreme precipitation events. In addition to total precipitation or extremity of precipitation events, the timing of precipitation also matters. Two months with the same amount of precipitation but different daily distributions could have dissimilar impacts on corn yields. A month with more evenly distributed rainfall is expected to result in higher yields than the month with several extreme precipitation events. Due to the availability of climate variables in climate projections we used, we did not include the effects of drought or flood in the model. In future studies when adequate climate change data becomes available, we recommend considering the intensity and timing of extreme precipitation events in the model. Irrigated and rainfed yields are not specified due to data limitation. Future research could specify these yields and compare their GWPR results.

Reference

Brunsdon, C., Fotheringham, S., & Charlton, M. (1996). “Geographically Weighted Regression: a Method for Exploring Spatial Nonstationarity.” *Geographical Analysis* 28:281–298.

Coulson, D.P., L.A. Joyce, D.T. Price, D.W. McKenney, R. Siltanen, P. Papadopol, and K. Lawrence. “Climate Scenarios for the Conterminous United States at the County Spatial Scale Using SRES Scenarios A1B and A2 and Prism Climatology.” U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO, 2010. Internet site: http://www.fs.fed.us/rm/data_archive/dataaccess/US_ClimateScenarios_ county_A1B_A2 _PRISM.shtml (Accessed October 20, 2011).

Deschenes, O., and M. Greenstone. 2007. “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather.” *American Economic Review* 97:354–85.

Fotheringham, S., C. Brunsdon, M. Charlton. 2002. *Geographically Weighted Regression: the analysis of spatially varying relationships.* John Wiley & Sons, UK.

Good, D. 2011. “How much risk to the corn crop?” University of Illinois Extention.

Hoogenboom, G. “Contribution of Agrometeorology to the Simulation of Crop Production and its Applications.” *Agricultural and Forest Meteorology* 103(2000):137-57.

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. “The DSSAT Cropping System Model.” *European Journal of Agronomy* 18(2003):235-65.

Kandiannan, K., K.K. Chandaragiri, N. Sankaran, T.N. Balasubramanian, and C. Kailasam. 2002. “Crop-Weather Model for Turmeric Yield Forecasting for Coimbatore District, Tamil Nadu, India." *Agricultural and Forest Meteorology* 112:133-37.

Kucharik, C.J., S.P. Serbin. 2008. “Impacts of Recent Climate Change on Wisconsin Corn and Soybean Yield Trends.” *Environmental Research Letters* 3, doi:10.1088/1748-9326/3/3/034003.

Lobell, D.B., K.N. Cahill, and C.B. Field. 2007. “Historical Effects of Temperature and Precipitation on California Crop Yields.” *Climatic Change* 81**:**187-203.

McCarl, B.A., X. Villavicencio, and X. Wu. 2008. “Climate Change and Future Analysis: Is Stationary Dying?” *American Journal of Agricultural Economics* 90: 1241-1247.

Olgun, M. and S. Erdogan. 2009. “Modeling Crop Yield Potential of Eastern Anatolia by Using Geographically Weighted Regression.” *Archives of Agronomy and Soil Science* 55:255-263.

Propastin, P., M. Kappas, S. Erasmi. 2008. “Application of Geographically Weighted Regression to Investigate the Impact of Scale on Prediction Uncertainty by Modelling Relationships between Vegetation and Climate.” *International Journal of Spatial Data Infrastructure* 3:73-94.

Sharma, V. 2011. “Quantification on Net Irrigation Requairement and Application of GIS and Geographically Weighted Regression to Evaluate the Spatial Non-Stationarity between Precipitations vs Irrigated and Rainfed Maize and Soybean Yields across Nebraska.” *Biological Systems Engineering--Dissertations, Theses, and Student Research* Paper 18. University of Nebraska-Lincoln.

Schlenker, W., and M.J. Roberts. 2009. “Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change.” *Proceedings of the National Academy of Sciences* 106:15594-98.

Tannura, M. A., S. H. Irwin, and D. L. Good. 2008. “Weather, Technology, and Corn and Soybean Yields in the U.S. Corn Belt.” Marketing and Outlook Res. Rep. No. 2008-01, Dept. of Agr. Econ., University of Illinois at Urbana-Champaign.

Thompson, L.M. 1988. “Effects of Changes in Climate and Weather Variability On the Yields of Corn and Soybeans.” *Journal of Production Agriculture* 1:20-27.

U.S. Department of Agriculture, National Agricultural Statistics Service. Quick Stats - The National Agricultural Statistics Service Interactive, Online Statistical Database. Internet site: http://quickstats.nass.usda.gov/ (Accessed May 2nd, 2012.)

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: The MIT Press.

Yu, D. 2010. “Exploring Spatiotemporally Varying Regressed Relationships: The Geographically Weighted Panel Regression Analysis. *Joint International Conference on Theory, Data Handling and Modelling in GeoSpatial Information Science.* Hong Kong.

Table 1. Estimation results for the OLS, Spatial lag model, Spatial error model, and GWR of an average cross section

	Mean	**Median**	**Standard deviation**	**Minimum**	**Maximum**
Corn yields (Bu/Acre)	125.7	128.2	37.8	0	229.4
Growing season precipitation (Inch)	3.6	3.7	1.2	0.5	9.1
Growing season temperature (degrees Fahrenheit)	65.4	65.2	5.3	53.4	83.6

Table 2. Estimation results for the OLS, Spatial lag model, Spatial error model, and GWR of an average cross section

Dependent variable: Corn Yields	**OLS model**		**Spatial lag model**		**Spatial error model**		**GWR**		
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Min Coef**	**Mean Coef.**	**Max Coef.**
Growing season precipitation	-0.0498***	(0.0107)	-0.0201	(0.0070)	-0.0375	(0.0134)	-1.1711	0.0187	1.2896
Growing season temperature	-0.1380***	(0.0193)	-0.0536	(0.0126)	-0.1011	(0.0256)	-3.2505	0.0680	2.8302
Number of obs:	958		958		958				958
AIC	9241.7		8643.5		8652.2				8125.3
Moran's I	0.7912		-0.0095		-0.0065				0.1140
F-statistic:	22.94								
p-value	2.8E-10								
Adjusted R-squared	0.0500								0.8665
LR test			600.12		591.42				
Log likelihood	-29396.5		-4316.8		-4321.1				
λ					0.571				
ρ			0.573						

***, **, * stand for 1%, 5%, and 10% significance level, respectively.

Table 3. Estimation results for the fixed effects models and GWPR model

Dependent variable: Corn Yields	fixed effects (1)		fixed effects (2)		GWPR		
	Coef.	Std. Err.	Coef.	Std. Err.	Min Coef	Mean Coef.	Max Coef
Growing season precipitation	0.0546***	(0.0044)	0.0581***	(0)	-0.2303	0.05081	0.2707
Growing season temperature	-0.4685***	(0.0399)	-0.5393***	(0.04)	-3.0466	-0.6127	1.5641
Time dummies	Yes		No			No	
Time trend	No		Yes			Yes	
Number of observations:	4790		4790			4790.000	
n	958		958			958.000	
T	5		5			5.000	
F-statistic:	291.739		386.259				
p-value	< 2.22e-16		< 2.22e-16				
Adjusted R-squared	0.25073		0.18571			0.5071001	

***, **, * stand for 1%, 5%, and 10% significance level, respectively.

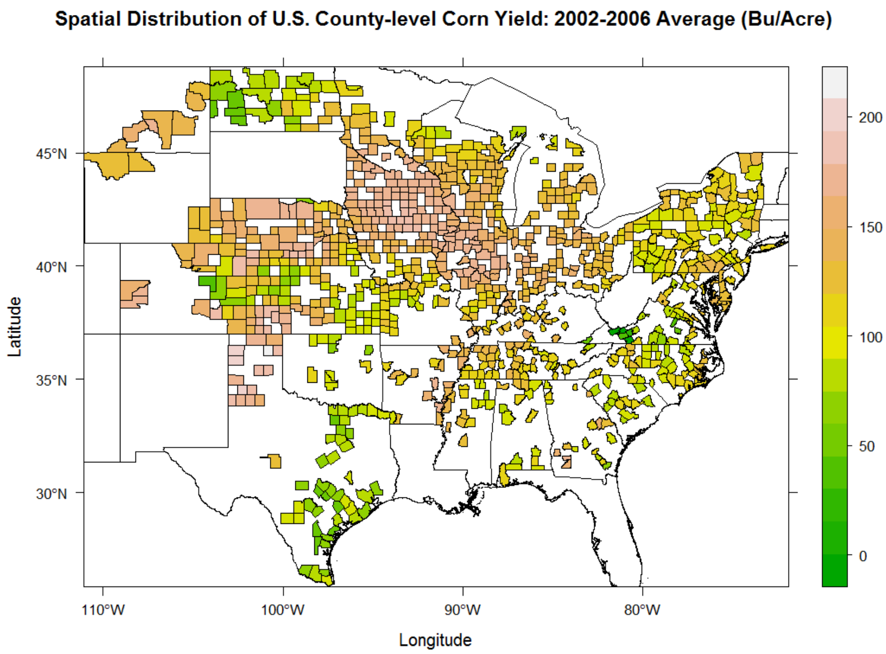

Figure 1. Spatial distribution of the average U.S. county-level corn yield during 2002-2006

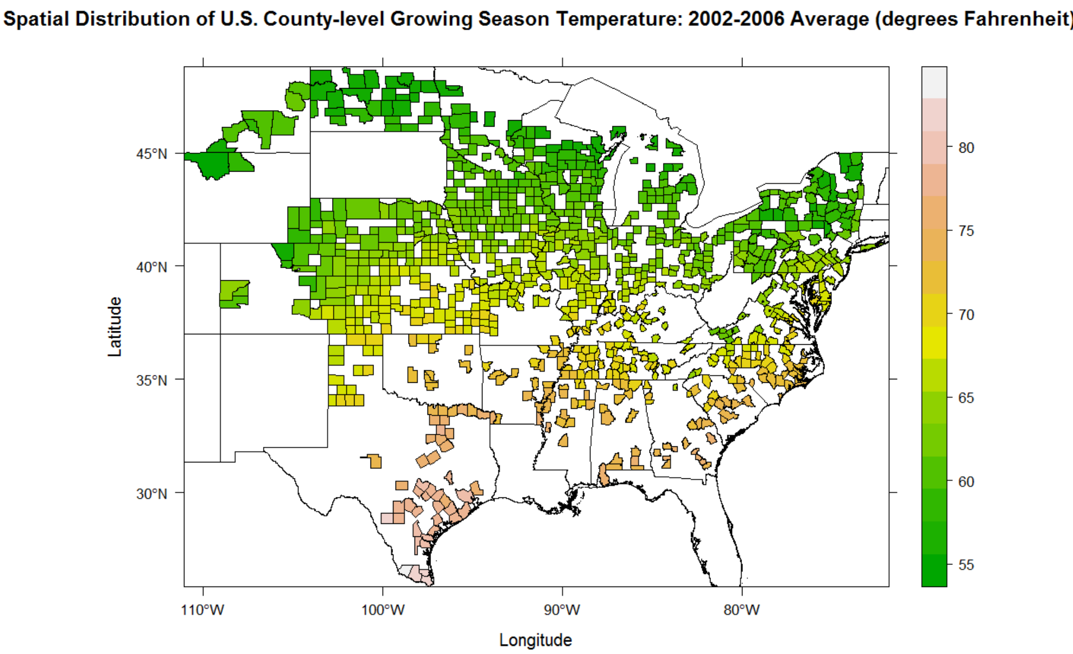

Figure 2. Spatial distribution of the average of U.S. county-level temperature during 2002-2006

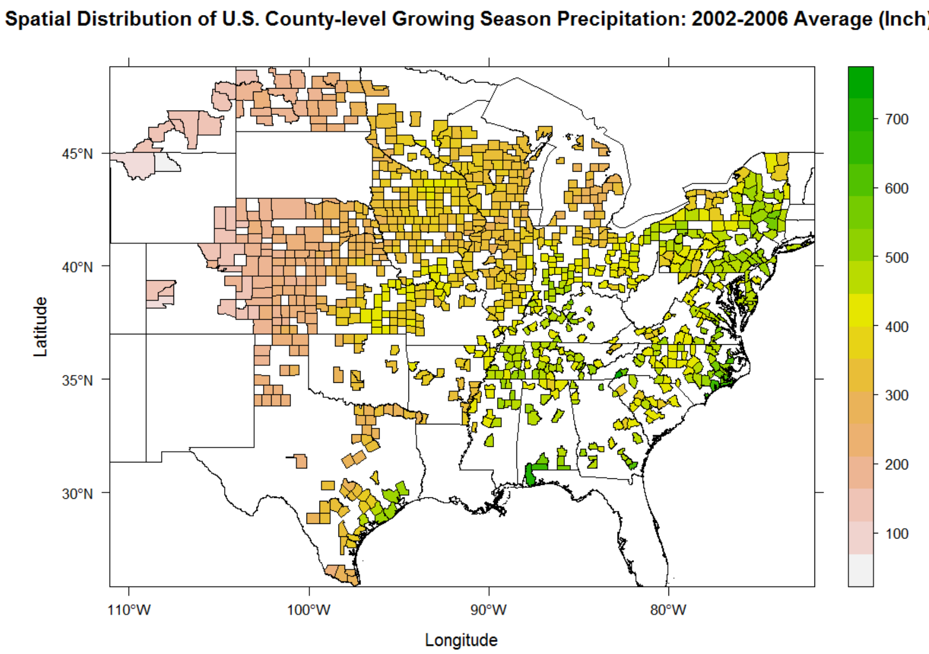

Figure 3. Spatial distribution of the average U.S. county-level precipitation during 2002-2006

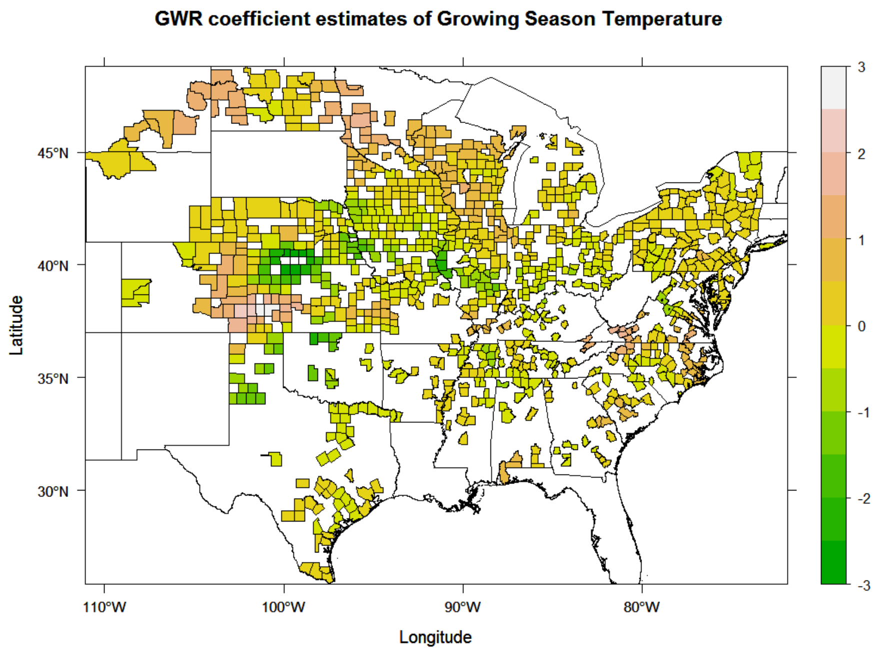

Figure 4. Spatial distribution of the GWR coefficients of growing season temperature. This is a GWR analysis based a cross section for 958 counties with the average of 2002-2006.

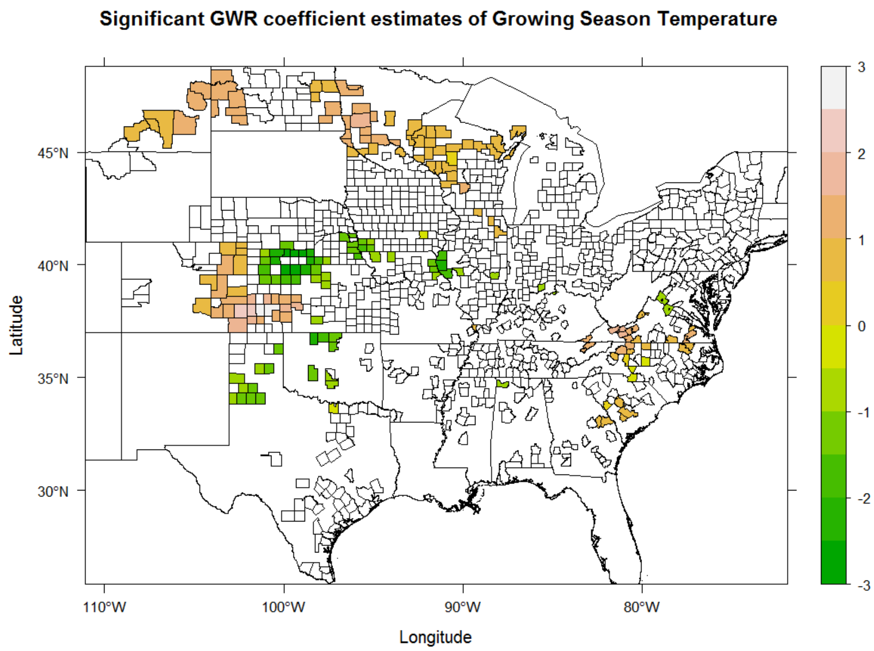

Figure 5. Spatial distribution of the GWR coefficients of growing season temperature. Only pseudo-significant counties are mapped. This is a GWR analysis based a cross section for 958 counties with the average of 2002-2006.

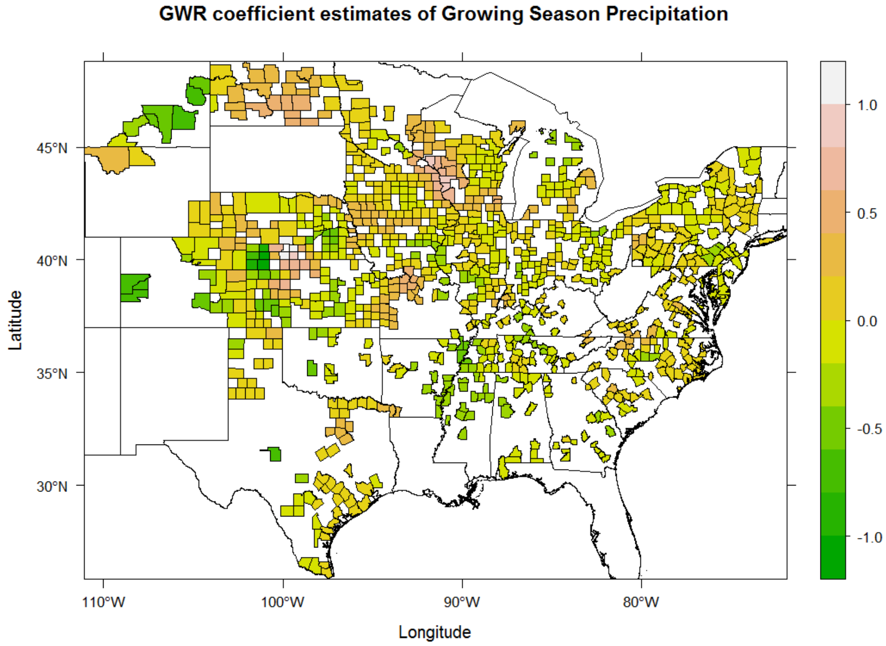

Figure 6. Spatial distribution of the GWR coefficients of growing season precipitation. This is a GWR analysis based a cross section for 958 counties with the average of 2002-2006.

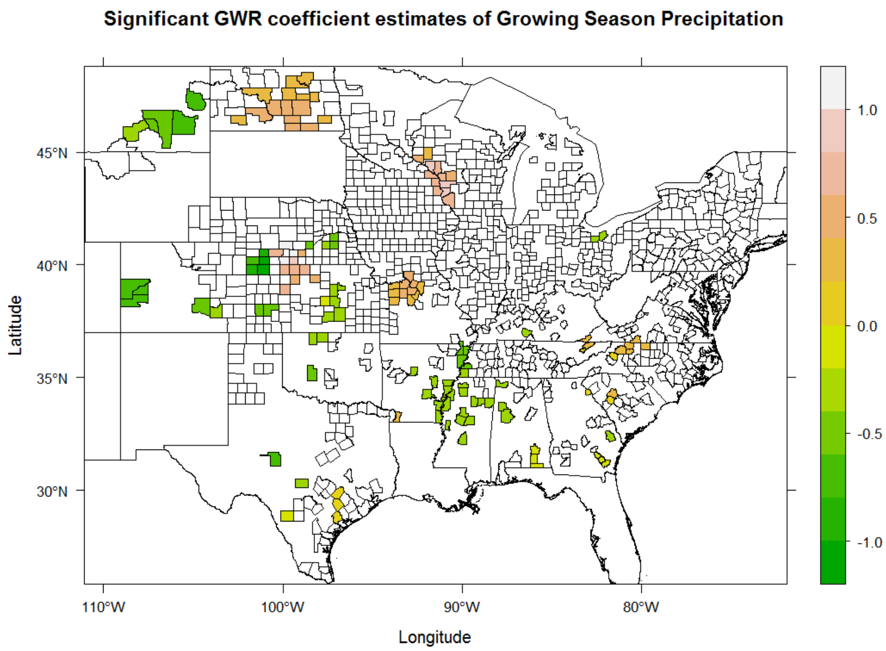

Figure 7. Spatial distribution of the GWR coefficients of growing season precipitation. Only pseudo-significant counties are mapped. This is a GWR analysis based a cross section for 958 counties with the average of 2002-2006.

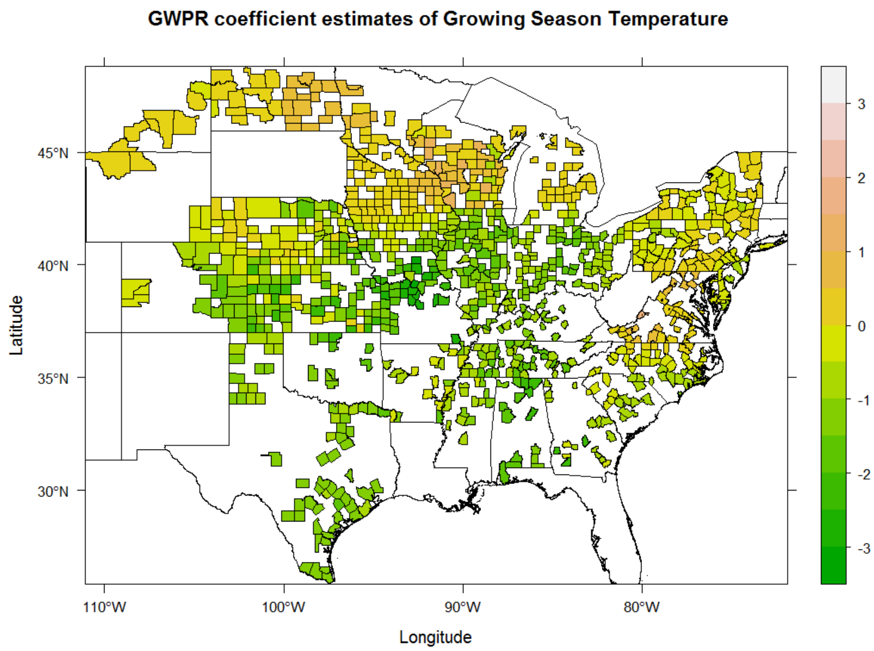

Figure 8. Spatial distribution of the GWPR coefficients of growing season temperature. This is a GWPR analysis based a panel data of 958 counties during 2002-2006.

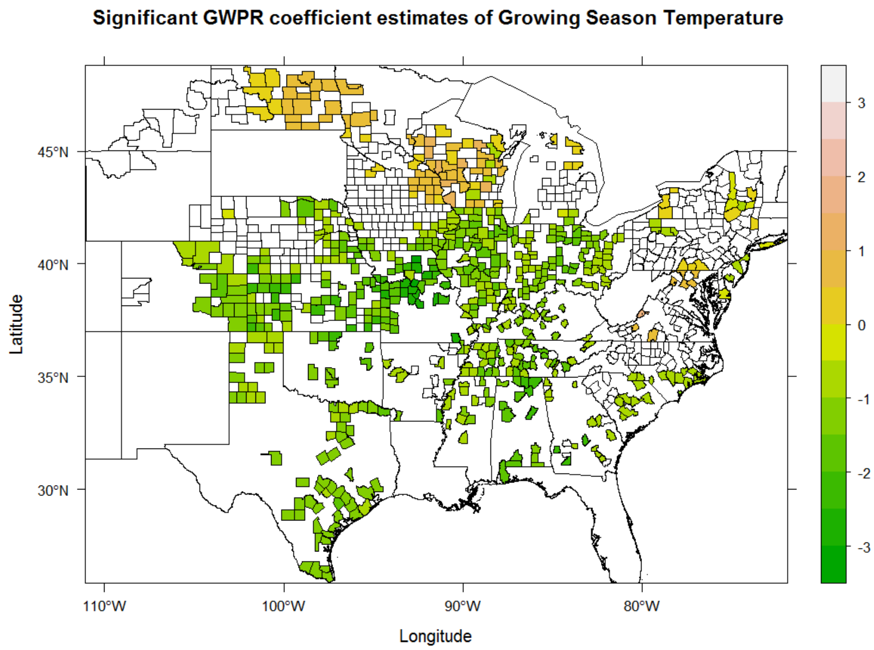

Figure 9. Spatial distribution of the GWPR coefficients of growing season temperature. Only pseudo-significant counties are mapped. This is a GWPR analysis based a panel data of 958 counties during 2002-2006.

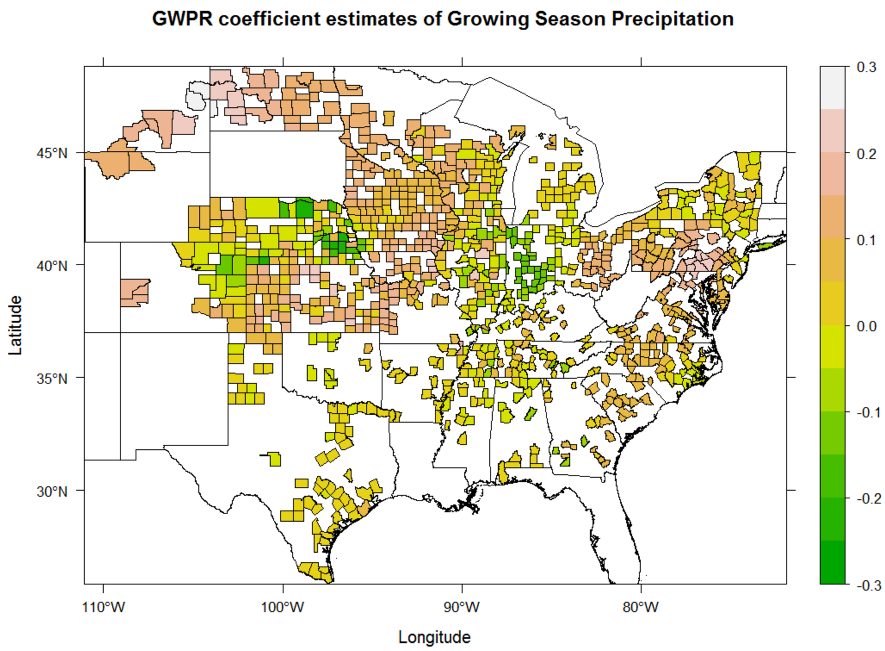

Figure 10. Spatial distribution of the GWPR coefficients of growing season precipitation. This is a GWPR analysis based a panel data of 958 counties during 2002-2006.

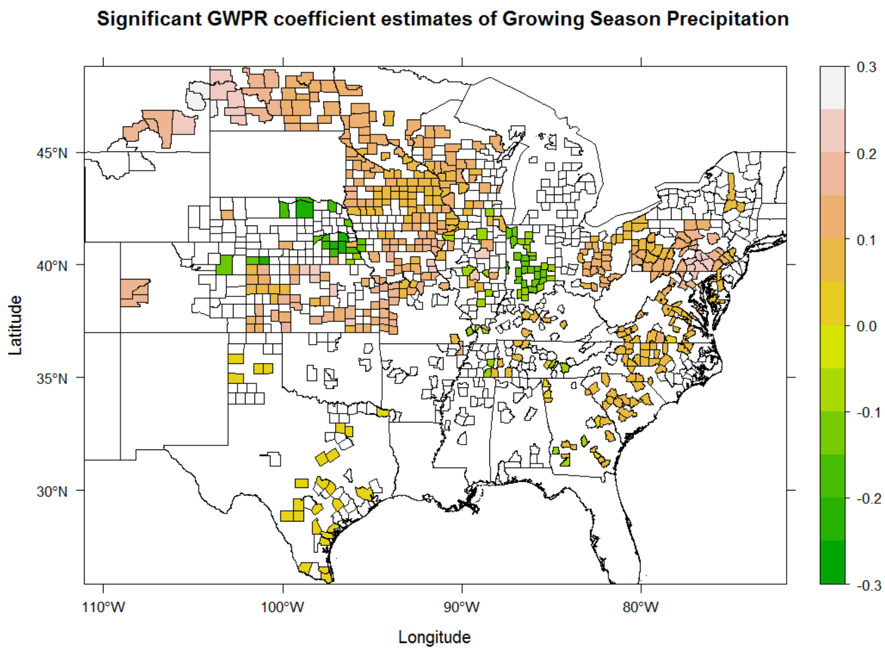

Figure 11. Spatial distribution of the GWPR coefficients of growing season precipitation. Only pseudo-significant counties are mapped. This is a GWPR analysis based a panel data of 958 counties during 2002-2006.

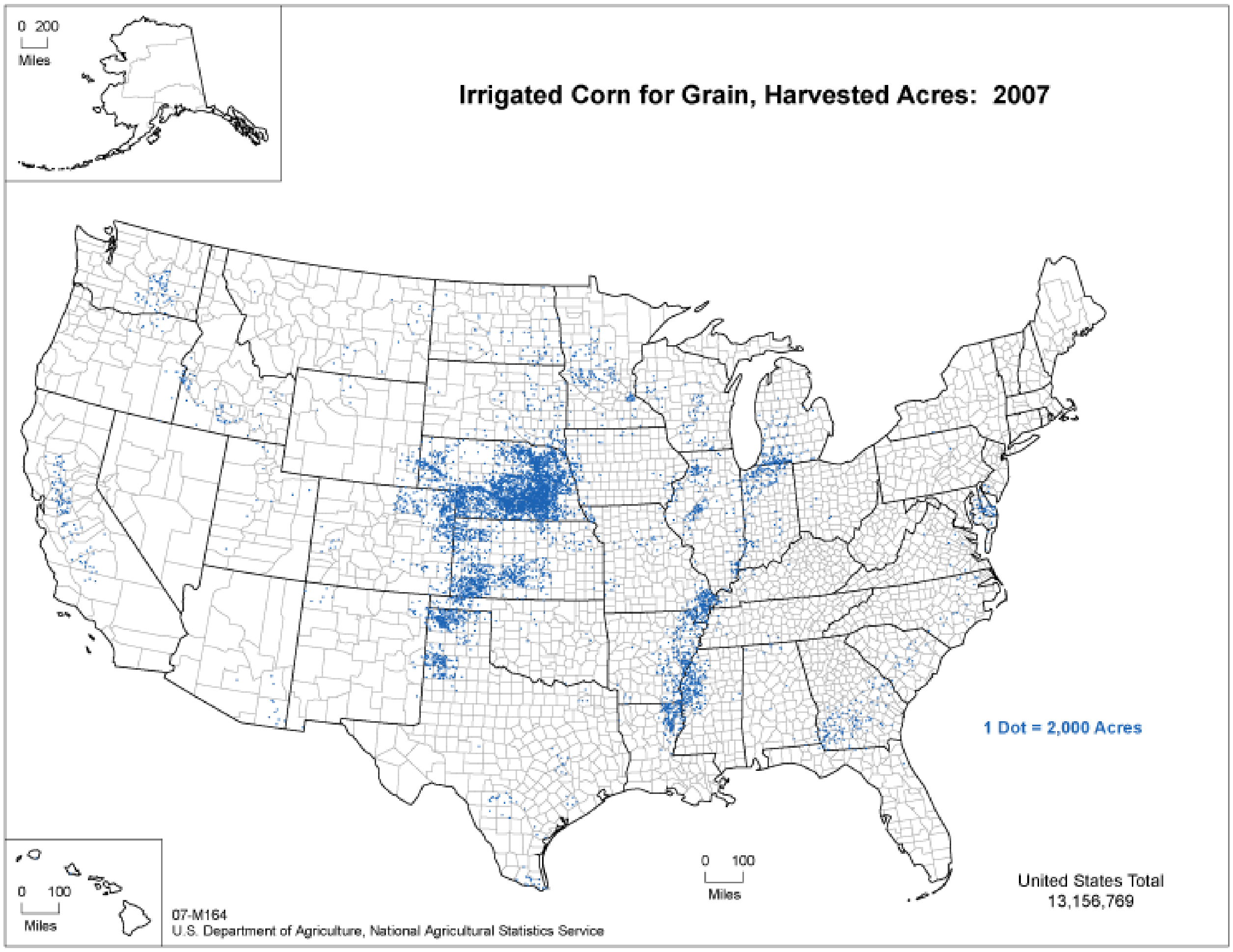

Figure 12. Irrigated Corn for Grain, Harvested Acres in 2007.