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# Estimating Spatial Heterogeneity in Hay Yield Responses to Weather Variations in Oklahoma

**Kwideok Han and Brian E. Whitacre***

## Abstract

Hay is an important field crop in the U.S., with over 54 million harvested acres in 2015. In many southern states, hay is an important input for cattle production, and reducing forage costs is crucial for improving the profitability of livestock operations. It is well known that crop yields and quality are significantly influenced by weather variations, which can have different impacts across geographical regions and over years. This study quantifies possible heterogeneous impacts in hay yield responses to weather variations in Oklahoma hay yields. The paper uses panel data on hay yields for Oklahoma's 77 counties from 1977 to 2007. The weather variables include temperature and precipitation. A geographically weighted regression (GWR) approach is used to estimate the local effects of weather variations on hay yields in geographic regions. The GWR allows the relationships between hay yields and weather variations to vary across geographic regions. Results suggest that geographic variation does exist in hay's response to weather. Accordingly, it is important to model hay production within a framework that allows weather response parameters to vary. Hay producers can reduce their production risk by incorporating models that permit geographical variation in how the local climate impacts yields.

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## Introduction

Hay is an important field crop in the U.S. with a gross value of $16.8 billion and total harvested acres of 54.4 million in 2015(USDA-NASS, 2015). Alfalfa is known to be the most valuable variety of hay. Hay is an important forage crop in Oklahoma as well. In addition to the leguminous alfalfa, there are other leguminous (such as cowpeas, clover, and soybeans) and non-leguminous (such as ryegrass, bermudagrass, fescue, lovegrass, orchardgrass, and wheat hay/straw) forage/pasture crops grown in Oklahoma (Arnall et al., 2017). Oklahoma Agricultural Statistics (issued by Oklahoma Department of Agriculture, Food and Forestry and USDA-NASS) indicate that as an aggregate crop grouping, hay ranks in the top five crops of Oklahoma in terms of annual dollar value of production in most years. Oklahoma is one of the top producers of non-alfalfa hay varieties.

Hay plays an important role as input in cattle production, and profitability of livestock operations can be improved by reducing the input costs associated with forage production and feeding (Redfearn, 2003). Better forage conditions help Oklahoma cattle producers to implement more aggressive cattle production and marketing plans; decisions to expand cattle production depends greatly on realistic forage production estimates (Peel, 2005). Many popular cattle market information sources such as cattlenetwork.com frequently carry news about hay inventories, weather impacts, and their implications for cattle producers. Given this spillover effects of hay production into cattle market, there is a need to better understand the characteristics of yield and prices of the hay crop.

Hay production is known to be sensitive to weather conditions. For example, total hay production in Oklahoma dropped from 5.9 million tons in 2010 to 2.3 million tons in 2011 due to the extreme drought conditions (USDA-NASS, 2013). In addition to quantity, the quality of hay is influenced by temperature and rainfall during the crop season. Adverse temperature fluctuations during the season leads to mixed pasture or hay; growth of hay slows down if rainfall is insufficient and subsoil moisture is inadequate (Redfearn, 2013). Rainfall in Oklahoma is characterized by a steep decline from eastern part of the state to the west (MESONET, 2017). Inconsistent Oklahoma rainfall impacts nitrogen availability to hay crops, creating conditions in which moisture is more limited than nitrogen (Arnall et al., 2017). In addition to inherent regional characteristics such as soil quality and irrigation systems associated with a farm, these weather variables influence crop yields. Hence, spatial attributes and weather variables are critical in determining crop yield. There have been numerous studies that predict crop yield conditional on climatic information, using agricultural simulation models, such as the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1984), as well as a variety of multiple regression models. Though many studies have analyzed the effect of climate and climate change on crop yield fluctuations, there have been not many attempts to model fluctuations in hay production.

Finding ways to improve hay yield predictions has become even more important after the introduction of the pilot Rainfall Index - Annual Forage Insurance Plan (RI-AF) by the USDA Risk Management Agency (USDA-RMA, 2013) in Oklahoma and other selected states starting in May 2013. Crop insurance aids growers in risk management; a higher subsidy premium applies in areas with higher risks and riskier crops (Goodwin, 2001). In general, there is a systemic risk associated with crop yields, with risks being correlated systematically across individual policy owners. Spatial correlation of yield, caused by spatially correlated weather patterns, is closely associated with such systemic risks. The correlation between price and yield, and the spatial dimension associated with this correlation must be taken into account while estimating risk in insurance (Goodwin, 2001). Given that rainfall is a critical factor in hay production, the RI-AF plan insures growers against rainfall shortages below the long-term average rainfall levels[1]. Therefore, an accurate estimate of the relationship between yield and weather and spatial variables helps in determining an accurate appropriate premium rate.

There can be two types of spatial relationships associated with crop yield distribution. One is spatial *dependence*, which refers to the fact that one observation in a cross sectional sample is dependent on one or more neighboring observations (Anselin, 1988). Spatial dependence can serve as a surrogate for unobserved covariates that vary smoothly over the entire region of interest (Cessie, 1993). Measures of spatial dependence can be either "local" or "global", with global meaning that one parameter is taken to describe the dependence across the whole study area. The other type of spatial relationship is *heterogeneity* in observed variables across space. Here, the mean and variance of the observed variable are not stationary across space. If this heterogeneity in parameters is attributable to spatially varying characteristics (such as physical geography and cultural practices etc.), then allowing those parameters to vary across space is optimal modeling of such heterogeneity (Smit et al., 2015). Cai, Yu, and Oppenheimer (2014) note that research on spatial heterogeneity in crop yields is limited. However, given the importance of spatial variability of crop yields in determining insurance premiums, a global measure of spatial dependence is inappropriate. Moreover, a more detailed accounting of regional differences in crop yields and climate impacts would be useful to develop more appropriate policy measures, or responses to those measures. Therefore, our study models both spatial dependence and spatial heterogeneity in hay yields in Oklahoma. For measuring spatial dependence, we first use the Moran's *I* statistic and test its statistical significance; and then to model both spatial dependence and spatial heterogeneity in hay yield we make use of three alternative specifications, i.e., a non-spatial

[1] This insurance is available for pasture, rangeland, and forage used for haying or grazing on perennial grasses. The RIFAP is structured so that producers can insure a productivity factor based on the county average.

fixed-effects model, a spatial fixed-effects model, and geographically weighted regression (GWR).

## Econometric Modeling of Oklahoma Hay Yield Pattern

To measure spatial dependence in hay yield, we calculate Moran's $I$ for each year in the panel to determine any patterns in spatial dependence over the years. Moran's $I$ is a global indicator[2] of spatial autocorrelation, and the statistic can be used to test the hypothesis that the spatial process promoting the pattern of observations is due to random chance. If the statistic is positive and statistically significant, it implies that similar values of hay yields have spatially clustered pattern compared to a spatial process with random distribution. In contrast, a negative and statistically significant Moran's $I$ -statistic indicates clustering of dissimilar hay yields. Neighboring units can be defined in a variety of ways, including distance-based or contiguity. The Moran's $I$ is calculated as follows (Cliff and Ord, 1981):

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} {z_i}^2} \tag{1}$$

where $n$ is the number of observations, $w_{ij}$ is the spatial weight between locations $i$ and $j$, $S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$ is the aggregate of all spatial weight, and $z_i = (y_i - \bar{y})$ is the deviation of observed yield $y$ from its mean. Variance of $I$ is given by (Cliff and Ord, 1981):

$$Var_N(I) = \frac{1}{(n-1)(n+1)\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right)^2} \left[ n^2 S_1 - nS_2 + 3\left( \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \right)^2 \right] - \frac{1}{(n-1)^2}$$

where $S_1 = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(w_{ij} + w_{ji}\right)^2, S_2 = \sum_{i=1}^{n} (w_i + w_i)^2$. The expected value of $I$ is given by $E_N(I) = -(n-1)^{-1}$ and the statistical significance of $I$ is given the $Z$-socre

[2] Spatial dependence measures that are based on simultaneous measurements from many locations are called global spatial statistics (Cliff and Ord, 1981).

computed as $Z = \frac{I-E(I)}{\sqrt{Var(I)}}$.

The basic econometric model used is a linear regression model (the "pooled" model) estimated using ordinary least-squares (OLS), ignoring any spatial and temporal effects on hay yield. The pooled model is given as:

$$y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 t + \epsilon_{it} \tag{2}$$

where $y_{it}$ is the hay yield in county $i$ at time $t$, $X_{it}$ is a vector of weather variables (average temperature and precipitation) in county $i$ at time $t$, $t$ is a linear time trend that accounts for technological changes over time, $\beta_0$, $\beta_1$, and $\beta_2$ are parameters to be estimated, and $\epsilon_{it}$ is the disturbance term[3].

The next model takes advantage of the panel structure of the data to estimate a fixed-effects regression model as follows:

$$y_{it} = \beta_{0i} + \beta_1 X_{it} + \beta_2 t + \epsilon_{it} \tag{3}$$

where $\beta_{0i}$ are coefficients of time-invariant fixed-effects on the geographical units estimated using the least-squares dummy variables (LSDV) estimator. In equation (3), it is possible to include time-specific fixed effects[4]. Since we have information about the geospatial location of the hay yield data, it is possible to improve model (3) by incorporating this spatial information. Therefore, a spatial fixed-effects model that includes both a spatial lag and a spatial error term is estimated as follows:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_0 + \beta_{0i} + \beta_1 X_{it} + \beta_2 t + \epsilon_{it} \tag{4a}$$

[3] A first-differenced version of (2) can be used to estimate the time-invariant unobserved effects of individual components.

[4] Random-effects model is not suitable in this case due to the violation of the orthogonality condition of the spatial variables with the weather variables (Cai, Yu, and Oppenheimer, 2014).

(4b) $$\epsilon_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, \epsilon_{jt} + u_{it}$$

where $w_{ij}$ is an element in the spatial weight matrix $W$, and $\rho$ and $\lambda$ are the spatial autoregressive and autocorrelation coefficients, respectively. The spatial weight matrix[5] is created from the latitude and longitude information of individual counties based on distance-based measures. All counties are considered neighbors but closer ones are given more weight.

We can then test to find out which model is a better fit. The OLS model is estimated and tested for whether the spatial lag model or the spatial error model is more appropriate to explain the data (i.e. $H_0\colon \rho = 0$ or $\lambda = 0$). We use the classic LM-tests and the robust LM-tests (Anselin, 1988; Anselin et al., 1996). Both the tests are implemented based on the residuals of the OLS model and follow a Chi-squared distribution with one degree of freedom.

The log-likelihood function of (4a) is given as:

(5) $$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) + Tlog|I_N - \rho W| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij}y_{jt} - \beta_0 - \beta_{0i} - \beta_1 X_{it} - \beta_2 t\right)^2$$

where the second term on the right hand side is the Jacobian term of the transformation from $\epsilon_{it}$ to $y_{it}$ taking into account the endogeneity of $\sum_{j=1}^{N} w_{ij}y_{jt}$ (Anslin, 1988, P. 63). The partial derivatives of the log-likelihood with respect to $\beta_{0i}$ are:

(6) $$\frac{\partial LogL}{\partial \beta_{0i}} = \frac{1}{\sigma^2}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij}y_{jt} - \beta_0 - \beta_{0i} - \beta_1 X_{it} - \beta_2 t\right) = 0, i = 1, \dots, N$$

whose solution is given by:

[5] Alternatively, the spatial weight matrix will be defined using contiguity-based measures to check the robustness of model. The spatial weighted matrix used can vary from contiguity-based measures to distance-based ones.

$$(7) \qquad \beta_{0i} = \frac{1}{T}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij}y_{jt} - \beta_0 - \beta_1 X_{it} - \beta_2 t\right) = 0, i = 1, \ldots, N$$

Substituting the solution of $\beta_{0i}$ from (7) into the log-likelihood function and rearranging the terms, the concentrated log-likelihood function is:

$$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) + Tlog|I_N - \rho W|$$

$$(8) \qquad -\frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}{}^{*} - \rho\left[\sum_{j=1}^{N} w_{ij}y_{jt}\right]^{*} - \beta_0 - \beta_1 X_{it}{}^{*} - \beta_2 t\right)^2$$

where the asterisk denotes demeaned variables, i.e., for a variable $x_{it}$, $\left(x_{it}{}^{*} - \sum_{t=1}^{T}\frac{x_{it}}{T}\right)$. Details of estimation of (4a) or (4b) are provided in Elhorst (2014, p. 37-93). The maximum likelihood estimates of $\rho$ and $(\beta, \sigma^2)$ are computed sequentially by fitting in the OLS estimates and residuals into the concentrated log-likelihood function[6].

Regular spatial models such as the spatial lag model or spatial error model assume that coefficients are constant over space. As an alternative, we use the GWR, which is a special case of locally weighted regression, as a flexible model of spatial heterogeneity in crop yield response. In a locally weighted regression, the conditional mean equation is given by $y = XB(z)$ where X can be any variables and $z$ are the variables that enter non-parametrically. In GWR, the $z$ variables are coordinates of the geographical unit (McMillen, 2013). Econometric specification of GWR is as follows:

$$(9) \qquad y_{it} = \beta_{0i} + \beta_{1i}X_{it} + \beta_{2i}t + \epsilon_{it}$$

The $i$ component is defined by the latitude and longitude of the respective county. The

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[6] We used different packages available in the open-source software *R* (R Core Team, 2017) for data preparation and analysis. The packages used are “ggmap” (Kahle and Wickham, 2013); “plm” (Croissant and Millo, 2008); “sp” (Pebesma and Bivand, 2005; Bivand, Pebesma, and Gomez-Rubio, 2013); “pgirmess” (Giraudoux, 2017); “spdep” (Bivand and Piras, 2015); and “splm” (Millo and Piras, 2012).

difference between (9) and (3) is that the former allows the $X_{it}$ variables to have spatially varying impact on crop yield response as denoted by $\beta_{1i}$. In the locally weighted regression, coefficients are calibrated by assigning weights to data points at locations according to their spatial proximity to location $i$. These weights allow the nearer spatial points to have greater influence on the yield response than the farther ones. Parameters of (9) are obtained by minimizing a weighted residual sum of squares. If $(u, v)$ represents the latitude and longitude of spatial unit $i$, the regression coefficients (say $\hat{\beta}$) are given by:

$$\hat{\beta}(u, v) = (X^T W(u, v) X)^{-1} X^T W(u, v) y$$

where

$$W(u, v) = \begin{bmatrix} w_1(u, v) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_n(u, v) \end{bmatrix}$$

with the elements of the $W(u, v)$ calculated by kernels. A Gaussian kernel shape is given by

$$w_i(u, v) = e^{-0.5\left(\frac{d_i(u,v)}{h}\right)^2}$$

where $d_i(u, v)$ is the Euclidean distance between location $(u, v)$ and observation $i$, and $h$ is the bandwidth (a quantity expressed in the same coordinate units as used in the data). Other types of kernel shapes may be used to define the $W(u, v)$ matrix. Even though the type of kernel shape does not influence the results of regression, the choice of bandwidth may be of critical importance. For larger values of $h$, the weights $w_i(u, v)$ tend to one and the estimation results would be similar to those using OLS. When the sample is regularly spaced in the study area, a kernel with fixed bandwidth is recommended. If this is not the case, an adaptive bandwidth may be the solution. In the adaptive form, a minimum number of observations or a maximum distance are fixed in order to calculate the weights (Suarez-Vega et al, 2013, p. 195-212).

## Data

We pooled county level hay production data from the annual reports of Oklahoma Agricultural Statistics for the period of 1977-2007[7]. These reports contain estimates of acreage, production quantity, and yield for hay crops. Data on hay are available on three different levels of crop aggregation: only alfalfa, non-alfalfa (grouped together as "other" hay), and all hay (sum of alfalfa and the "other"). The data on all hay production has a balanced panel structure comprising of 77 counties (belonging to nine geographical districts) and 31 years[8].

Daily weather data were obtained from Schlenker (2017). The data is available at www.wolfram-schlenker.com/dailyData.html. The data contains daily precipitation, and daily minimum and maximum temperatures on a 2.5 x 2.5 mile grid for the contiguous Oklahoma state. First, we created daily average temperature by taking the average of minimum and maximum temperatures. We then converted daily average temperature and precipitation on 2.5 x 2.5 mile grids to county-level data by taking the average of all grid observations corresponding to each county. Finally, we converted daily county-level data to monthly county-level data by taking the average of daily observations for each month in a county. Seasonal average temperature and precipitation are calculated by taking the average of monthly observations for each season in a county. S1 is the average of the winter months' observations from January to March, S2 is the average of the spring months from April to June, S3 is the average of the summer months from July to September, and S4 represents the average of the fall months from October to December, respectively. We hypothesize that the

[7] These reports provide information on the rank of hay crops within the crop portfolio of Oklahoma, and also the rank of Oklahoma hay production in the U.S. The reports also provide a snapshot of weather for the year of reporting and how those weather conditions affected different crops.

[8] Hay yields data used in this study were limited to the period of 1977-2007 in order to include all counties in Oklahoma while maintaining a balanced panel. During 2008-2015, some counties did not publish any data, or were combined with a smaller county.

spring and summer seasons are the most important for hay production. The summary statistics for all hay yields, seasonal monthly mean temperatures, and seasonal monthly total precipitations are presented in Table 1. The average of all hay yields of all counties in Oklahoma over the period of 1997-2007 is 1.92 bushels per acre. Temperature and precipitation have significant fluctuations by county, but on average the hottest season is the summer (S3), and the wettest is the spring (S2) (as expected).

## Preliminary Results

We first implement the local Moran's *I* statistic to see if spatial autocorrelation of all hay yields is present among a subset of counties in Oklahoma. The results from the local Moran's *I* statistics and the corresponding *p*-values for the statistics are illustrated in Figures 4 and 5, respectively. We see that there are several counties which show significant local autocorrelation in hay production, most of which occur on the Oklahoma panhandle and on the north and south west parts of Oklahoma with high production, while the east central part shows significant correlation with low production.

The results from the global fixed effects and spatial fixed effects models with a linear time trend using panel data, and the GWR model using the 31-year averaged data are presented in Table 3. The estimation results from the global fixed effects model show negative impacts associated with temperature and positive impacts for precipitation in each of the 4 seasons. After controlling for these variables, there are significant positive (and negative) county fixed effects, and a negative time trend. The coefficient estimates for the county fixed effects are presented in Table 4 and the spatial distribution of their coefficients is illustrated in Figure 6. The results also find that hay yields are negatively associated with seasonal monthly mean temperatures while positively associated with seasonal monthly total precipitations. We implement the Moran's $I$ test on the residuals of the non-spatial fixed effects model for the potential autocorrelation and find that the Moran's $I$ statistic is -0.028 and the $p$-value of the statistic is 0.997, suggesting that no spatial autocorrelation exists between neighboring counties. This was expected, given that the county-level fixed effects parameters are capturing most of the geographical variation in the data.

In the spatial fixed effects models, significant spatial lag and error effects at the 5% level were found in hay production. In particular, the spatial lag and error coefficient estimates are 0.425 and 0.435, respectively, suggesting not only that hay yield does depend on neighboring counties' hay yields, but also that there is spatial correlation between the errors. The results show that the spatial lag model has results in no significant county fixed effects (reinforcing our finding from the Moran's I of the residuals for the non-spatial model), while the spatial error model has only about 26% of counties with significant fixed effects. The coefficient estimates for the county fixed effects from both models are presented in Table 4 and the spatial distributions of their coefficients are illustrated in Figures 7 and 8, respectively. The results from the spatial fixed effects error model find that hay yields are negatively related to mean temperatures while positively related to total precipitations with the exception of winter season.

To examine spatial heterogeneity in hay yield responses to weather variations, the GWR model is estimated. The optimized bandwidth selected by a Cross Validation (CV) criterion with adaptive bandwidths is used for the GWR local model and for each local model is estimated with 46 observations. The coefficient estimates of the GWR model show certain spatial variability in hay yields in Oklahoma (Table 3). In particular, hay yields are positively associated with spring season temperature on the central and southcentral parts of Oklahoma, while the negative relationships are found on other parts of Oklahoma (Figure 9b). In terms of summer season total precipitation, hay yields are negatively associated with precipitation on the southcentral and east central parts of Oklahoma, while positively associated on other parts of Oklahoma (Figure 10c). The coefficients for spring season mean temperature range from a minimum value of -0.128 (1 ºC increase in temperature resulting in a drop in average hay yield by 0.128 bushels per acre) to 0.109 (1 ºC increase in temperature resulting in an increase in average hay yield by 0.109 bushels per acre). The coefficient estimates for summer season total temperature range from -0.071 to 0.198. The estimation results from the GWR model found some evidence of spatial varying relationship between weather and hay yields, suggesting that the weather impacts on hay yields vary across geographic regions in Oklahoma.

## Conclusion

The GWR approach was used in order to capture spatial heterogeneity in hay yield responses to weather variations by integrating spatial information in the weighing scheme. However, further investigation is needed in order to test its improved performance in determining the impacts of climate changes on hay yields. Future versions of this manuscript will evaluate which model is the best to predict hay yields conditional on weather variations among three alternative models (i.e., the non-spatial fixed-effects model, spatial fixed-effects model, and GWR model).

**Table 1. Summary Statistics of All Hay Yields, and Seasonal Average Temperatures and Total Precipitations**

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| AllHayYield (bu/ac) | 2387 | 1.92 | 0.51 | 0.50 | 4.97 |
| Avg.Temperature_S1 (ºC) | 2387 | 6.18 | 1.99 | -0.40 | 10.95 |
| Avg.Temperature_S2 (ºC) | 2387 | 20.21 | 1.26 | 14.21 | 23.37 |
| Avg.Temperature_S3 (ºC) | 2387 | 26.00 | 1.25 | 21.61 | 29.78 |
| Avg.Temperature_S4 (ºC) | 2387 | 10.17 | 1.47 | 5.35 | 13.81 |
| Tot.Precipitation_S1 (mm) | 2387 | 1.95 | 0.94 | 0.17 | 6.25 |
| Tot.Precipitation_S2 (mm) | 2387 | 3.67 | 1.21 | 0.65 | 7.96 |
| Tot.Precipitation_S3 (mm) | 2387 | 2.58 | 1.05 | 0.38 | 6.53 |
| Tot.Precipitation_S4 (mm) | 2387 | 2.37 | 1.28 | 0.15 | 7.60 |

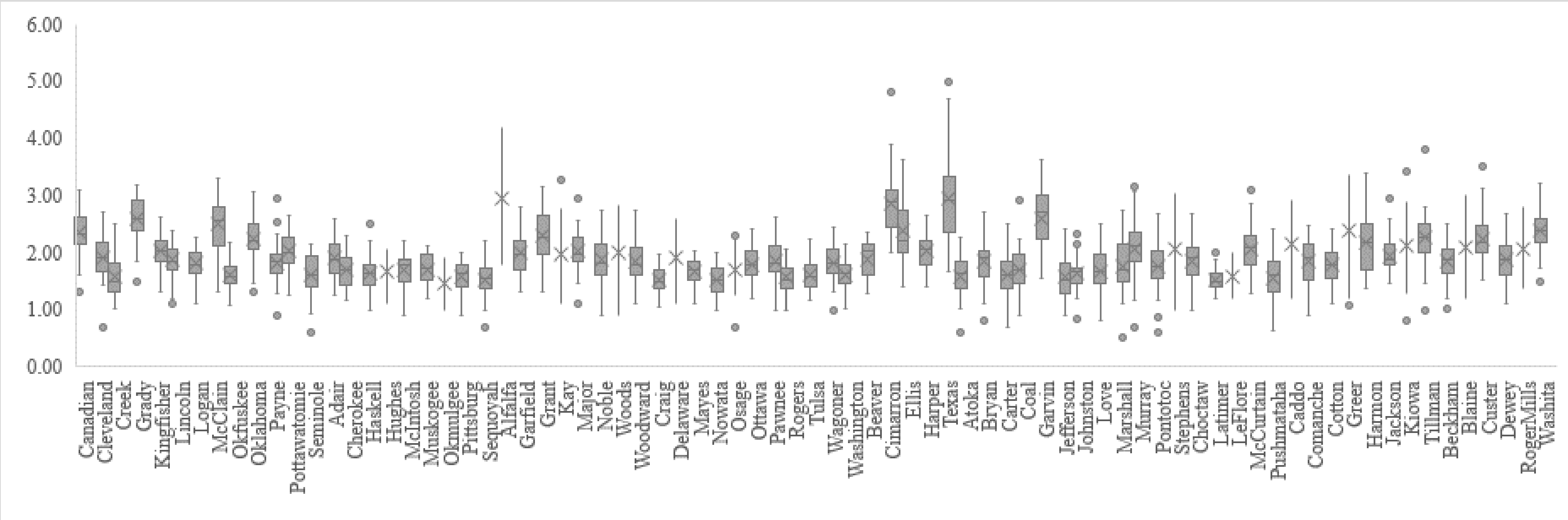


**Figure 1. Distributions of county all hay yields (bu/ac) in Oklahoma, 1977-2007**

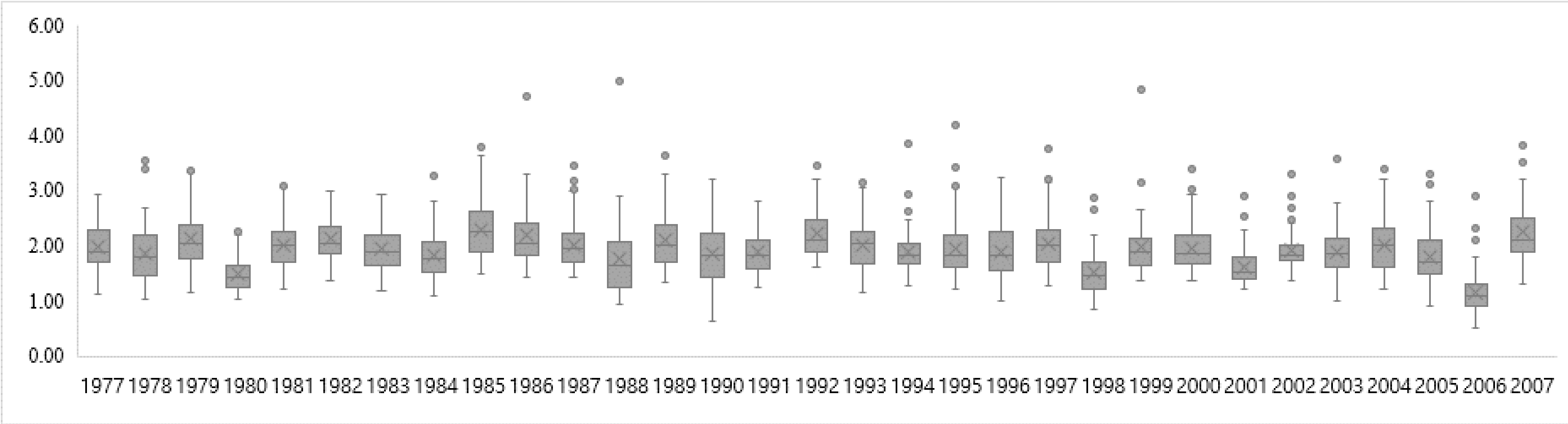


**Figure 2. Distributions of yearly all hay yields (bu/ac) in Oklahoma, 1977-2007**

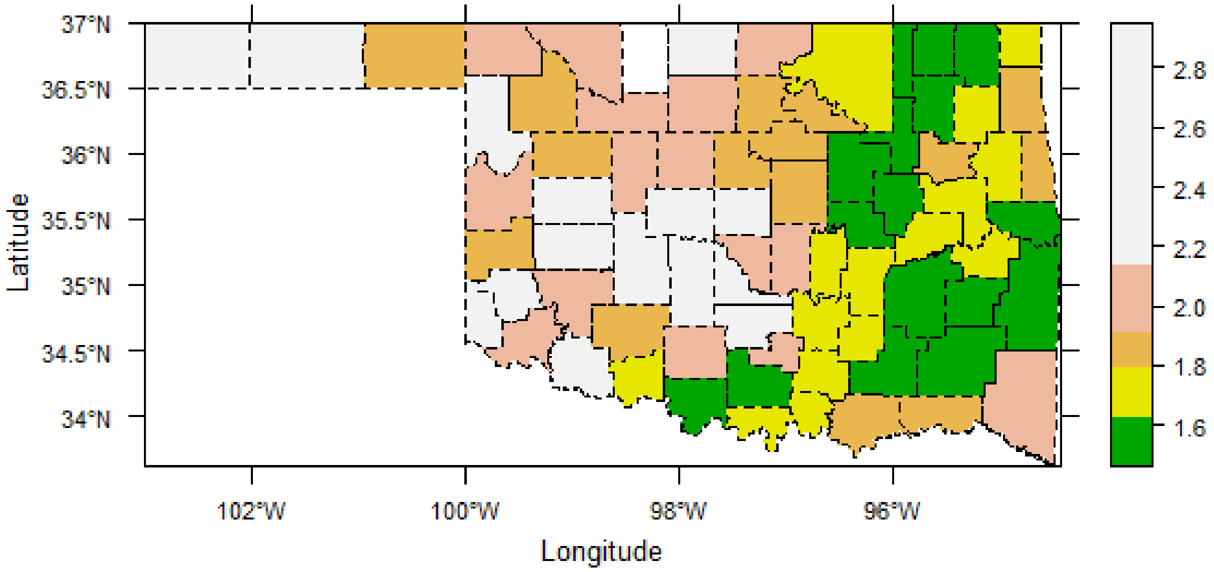


**Figure 3. Spatial distribution of average Oklahoma county all hay yields (bu/ac), 1977-2007**

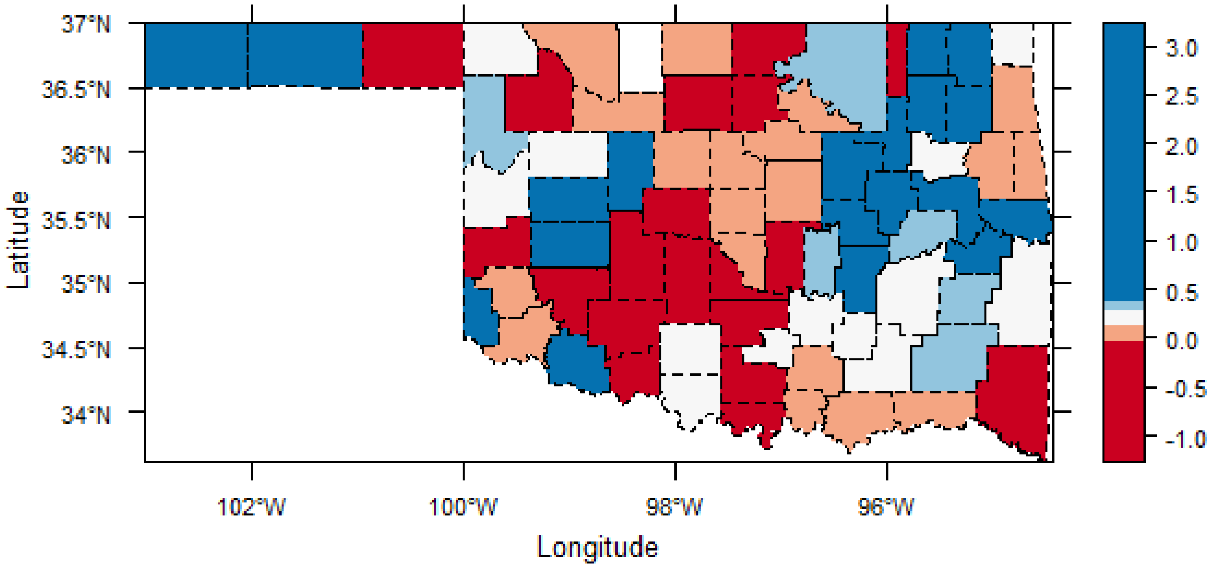


**Figure 4. Spatial distribution of the local Moran's *I* statistics of average all hay yields**

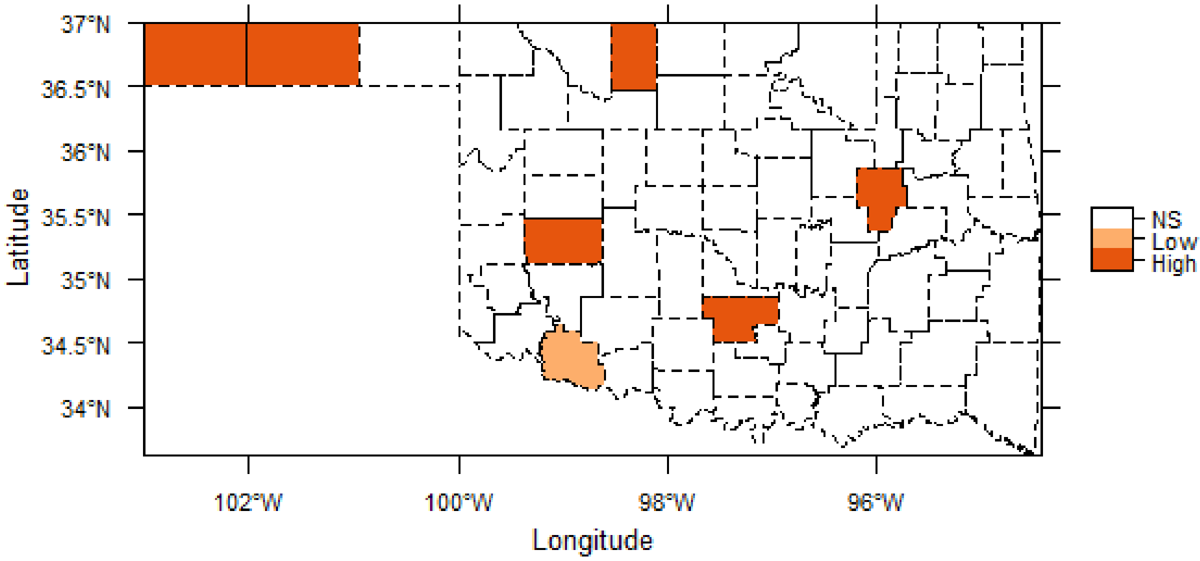


**Figure 5. Spatial distribution of the significant local clusters of average all hay yields**

**Table 2. Moran's *I* of Oklahoma All Hay Yields, 1977-2007**

| Year | Average Yield (bu/ac) | Moran's *I* | p-value |
|---|---|---|---|
| 1977 | 1.903 | 0.216 | 0.004*** |
| 1978 | 2.950 | 0.226 | 0.002*** |
| 1979 | 1.581 | 0.124 | 0.054** |
| 1980 | 1.881 | 0.326 | 0.000*** |
| 1981 | 1.847 | 0.083 | 0.129 |
| 1982 | 2.097 | 0.178 | 0.013** |
| 1983 | 1.852 | 0.042 | 0.258 |
| 1984 | 2.145 | 0.139 | 0.035** |
| 1985 | 2.360 | 0.323 | 0.000*** |
| 1986 | 1.616 | 0.145 | 0.028** |
| 1987 | 1.699 | 0.165 | 0.017** |
| 1988 | 1.851 | 0.354 | 0.000*** |
| 1989 | 2.843 | 0.265 | 0.001*** |
| 1990 | 1.918 | 0.281 | 0.000*** |
| 1991 | 1.689 | 0.120 | 0.060* |
| 1992 | 1.856 | 0.120 | 0.059* |
| 1993 | 1.779 | 0.295 | 0.000*** |
| 1994 | 1.517 | 0.093 | 0.094* |
| 1995 | 1.592 | 0.157 | 0.021** |
| 1996 | 2.239 | 0.368 | 0.000*** |
| 1997 | 1.893 | 0.252 | 0.001*** |
| 1998 | 1.868 | 0.278 | 0.000*** |
| 1999 | 2.368 | 0.242 | 0.001*** |
| 2000 | 1.990 | 0.115 | 0.065* |
| 2001 | 2.580 | 0.233 | 0.002*** |
| 2002 | 2.587 | 0.093 | 0.101 |
| 2003 | 2.287 | -0.035 | 0.603 |
| 2004 | 2.378 | 0.208 | 0.005*** |
| 2005 | 2.172 | 0.206 | 0.005*** |
| 2006 | 2.034 | 0.333 | 0.000*** |
| 2007 | 1.636 | -0.029 | 0.574 |

*Notes*: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

**Table 3. Estimation Results for the Fixed Effects, Spatial Fixed Effects Models, and The GWR Model in Oklahoma Counties, 1977-2007**

| **Dependent Variable** | | **Spatial Fixed Effects Model** | | **GWR** | | | | |
|---|---|---|---|---|---|---|---|---|
| **Hay Yields** | **Fixed Effects Model** | **Spatial Fixed Effects Lag Model** | **Spatial Fixed Effects Error Model** | **Min** | **1st Qu.** | **Median** | **3rd Qu.** | **Max** |
| Constant | | 2.708** | 5.178*** | -2.327 | 3.927 | 4.539 | 5.840 | 8.671 |
| | | (1.336) | (0.241) | | | | | |
| Avg.Temperature_S1 | -0.016*** | -0.013 | -0.012 | -0.087 | -0.038 | -0.023 | -0.004 | 0.086 |
| | (0.005) | (0.026) | (0.008) | | | | | |
| Avg.Temperature_S2 | -0.051*** | -0.032 | -0.059*** | -0.128 | -0.059 | -0.027 | 0.019 | 0.109 |
| | (0.008) | (0.043) | (0.012) | | | | | |
| Avg.Temperature_S3 | -0.076*** | -0.040 | -0.078*** | -0.155 | -0.113 | -0.069 | -0.048 | 0.018 |
| | (0.008) | (0.042) | (0.012) | | | | | |
| Avg.Temperature_S4 | -0.032*** | -0.017 | -0.029** | -0.193 | -0.094 | -0.053 | -0.011 | 0.113 |
| | (0.008) | (0.039) | (0.012) | | | | | |
| Tot.Precipitation_S1 | 0.020** | 0.012 | 0.006 | -0.157 | -0.060 | -0.018 | 0.031 | 0.185 |
| | (0.010) | (0.049) | (0.013) | | | | | |
| Tot.Precipitation_S2 | 0.090*** | 0.056 | 0.068*** | -0.098 | 0.047 | 0.085 | 0.114 | 0.194 |
| | (0.007) | (0.037) | (0.009) | | | | | |
| Tot.Precipitation_S3 | 0.065*** | 0.049 | 0.062*** | -0.071 | -0.012 | 0.025 | 0.058 | 0.198 |
| | (0.009) | (0.046) | (0.011) | | | | | |
| Tot.Precipitation_S4 | 0.034*** | 0.026 | 0.023** | -0.107 | -0.021 | -0.003 | 0.028 | 0.110 |
| | (0.007) | (0.037) | (0.009) | | | | | |
| $\boldsymbol{t}$ | -0.008*** | -0.005 | -0.009*** | | | | | |
| | (0.001) | (0.004) | (0.001) | | | | | |
| $\boldsymbol{\rho}$ | | 0.425*** | | | | | | |
| | | (0.025) | | | | | | |
| $\boldsymbol{\lambda}$ | | | 0.435*** | | | | | |
| | | | (0.025) | | | | | |
| N | 2387 | 2387 | 2387 | | | | | |
| Number of Counties | 77 | 77 | 77 | | | | | |
| Number of Years | 31 | 31 | 31 | | | | | |
| Adj. $R^2$ | 0.25 | | | | | 0.52 | | |

*Notes*: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis.

**Table 4. Estimation Results for the Fixed Effects and Spatial Fixed Effects Models in Oklahoma Counties, 1977-2007**

| Depend. Var. | Fixed Effects Model | | Spatial Fixed Effects Lag Model | | Spatial Fixed Effects Error Model | |
|---|---|---|---|---|---|---|
| **Hay Yields** | **Estimate** | **P-value** | **Estimate** | **P-value** | **Estimate** | **P-value** |
| Adair | 4.583*** | 0.000 | -0.041 | 0.976 | -0.245 | 0.316 |
| Alfalfa | 5.864*** | 0.000 | 0.858 | 0.523 | 0.992*** | 0.000 |
| Atoka | 4.555*** | 0.000 | -0.301 | 0.832 | -0.274 | 0.286 |
| Beaver | 4.722*** | 0.000 | -0.238 | 0.850 | -0.191 | 0.397 |
| Beckham | 4.853*** | 0.000 | -0.085 | 0.949 | -0.039 | 0.872 |
| Blaine | 5.056*** | 0.000 | 0.047 | 0.972 | 0.179 | 0.459 |
| Bryan | 4.892*** | 0.000 | -0.002 | 0.999 | 0.057 | 0.823 |
| Caddo | 5.147*** | 0.000 | 0.317 | 0.816 | 0.277 | 0.260 |
| Canadian | 5.306*** | 0.000 | 0.542 | 0.690 | 0.439* | 0.072 |
| Carter | 4.738*** | 0.000 | -0.280 | 0.843 | -0.119 | 0.640 |
| Cherokee | 4.474*** | 0.000 | -0.348 | 0.801 | -0.356 | 0.150 |
| Choctaw | 4.851*** | 0.000 | -0.052 | 0.971 | 0.025 | 0.923 |
| Cimarron | 5.543*** | 0.000 | 0.650 | 0.577 | 0.595*** | 0.005 |
| Cleveland | 4.886*** | 0.000 | 0.088 | 0.949 | 0.032 | 0.897 |
| Coal | 4.670*** | 0.000 | -0.195 | 0.891 | -0.165 | 0.518 |
| Comanche | 4.961*** | 0.000 | -0.115 | 0.934 | 0.090 | 0.718 |
| Cotton | 5.025*** | 0.000 | -0.095 | 0.947 | 0.154 | 0.546 |
| Craig | 4.211*** | 0.000 | -0.499 | 0.712 | -0.626*** | 0.010 |
| Creek | 4.496*** | 0.000 | -0.255 | 0.854 | -0.350 | 0.160 |
| Custer | 5.210*** | 0.000 | 0.238 | 0.859 | 0.329 | 0.172 |
| Delaware | 4.601*** | 0.000 | -0.049 | 0.971 | -0.236 | 0.332 |
| Dewey | 4.774*** | 0.000 | 0.054 | 0.967 | -0.111 | 0.639 |
| Ellis | 5.229*** | 0.000 | 0.374 | 0.769 | 0.327 | 0.153 |
| Garfield | 4.901*** | 0.000 | 0.107 | 0.938 | 0.037 | 0.879 |
| Garvin | 5.579*** | 0.000 | 0.775 | 0.577 | 0.727*** | 0.004 |
| Grady | 5.615*** | 0.000 | 0.726 | 0.600 | 0.753*** | 0.002 |
| Grant | 5.157*** | 0.000 | 0.304 | 0.822 | 0.294 | 0.227 |
| Greer | 5.498*** | 0.000 | 0.555 | 0.684 | 0.612** | 0.013 |
| Harmon | 5.372*** | 0.000 | 0.329 | 0.811 | 0.48* | 0.052 |
| Harper | 4.965*** | 0.000 | 0.057 | 0.965 | 0.065 | 0.781 |
| Haskell | 4.549*** | 0.000 | -0.211 | 0.882 | -0.276 | 0.280 |
| Hughes | 4.594*** | 0.000 | -0.215 | 0.878 | -0.248 | 0.325 |
| Jackson | 5.139*** | 0.000 | 0.124 | 0.929 | 0.256 | 0.306 |
| Jefferson | 4.790*** | 0.000 | -0.151 | 0.915 | -0.076 | 0.765 |
| Johnston | 4.666*** | 0.000 | -0.238 | 0.866 | -0.176 | 0.491 |
| Kay | 4.800*** | 0.000 | 0.018 | 0.990 | -0.056 | 0.821 |
| Kingfisher | 4.956*** | 0.000 | 0.065 | 0.962 | 0.088 | 0.719 |
| Kiowa | 5.207*** | 0.000 | 0.347 | 0.801 | 0.329 | 0.183 |
| Latimer | 4.353*** | 0.000 | -0.452 | 0.750 | -0.462* | 0.070 |
| LeFlore | 4.365*** | 0.000 | -0.418 | 0.765 | -0.448* | 0.075 |
| Lincoln | 4.820*** | 0.000 | 0.004 | 0.998 | -0.032 | 0.899 |
| Logan | 4.776*** | 0.000 | -0.113 | 0.935 | -0.081 | 0.746 |
| Love | 4.857*** | 0.000 | -0.161 | 0.910 | -0.001 | 0.996 |
| Major | 5.005*** | 0.000 | 0.111 | 0.934 | 0.126 | 0.602 |
| Marshall | 4.858*** | 0.000 | -0.053 | 0.970 | 0.015 | 0.954 |
| Mayes | 4.482*** | 0.000 | -0.253 | 0.854 | -0.357 | 0.148 |
| McClain | 5.465*** | 0.000 | 0.581 | 0.675 | 0.611** | 0.014 |
| McCurtain | 4.903*** | 0.000 | 0.117 | 0.934 | 0.089 | 0.727 |
| McIntosh | 4.616*** | 0.000 | -0.180 | 0.898 | -0.216 | 0.396 |
| Murray | 5.069*** | 0.000 | 0.124 | 0.929 | 0.220 | 0.383 |
| Muskogee | 4.577*** | 0.000 | -0.162 | 0.908 | -0.254 | 0.313 |
| Noble | 4.763*** | 0.000 | -0.143 | 0.917 | -0.093 | 0.707 |
| Nowata | 4.268*** | 0.000 | -0.458 | 0.736 | -0.571** | 0.019 |
| Okfuskee | 4.526*** | 0.000 | -0.220 | 0.875 | -0.313 | 0.214 |
| Oklahoma | 5.187*** | 0.000 | 0.304 | 0.825 | 0.329 | 0.185 |
| Okmulgee | 4.324*** | 0.000 | -0.398 | 0.773 | -0.517** | 0.038 |
| Osage | 4.501*** | 0.000 | -0.250 | 0.855 | -0.342 | 0.165 |
| Ottawa | 4.412*** | 0.000 | -0.249 | 0.852 | -0.425* | 0.078 |
| Pawnee | 4.748*** | 0.000 | -0.056 | 0.968 | -0.100 | 0.688 |
| Payne | 4.740*** | 0.000 | -0.083 | 0.952 | -0.112 | 0.651 |
| Pittsburg | 4.503*** | 0.000 | -0.346 | 0.807 | -0.326 | 0.201 |
| Pontotoc | 4.701*** | 0.000 | -0.094 | 0.946 | -0.146 | 0.558 |
| Pottawatomie | 4.971*** | 0.000 | 0.159 | 0.909 | 0.122 | 0.627 |
| Pushmataha | 4.399*** | 0.000 | -0.399 | 0.778 | -0.416 | 0.102 |

**Table 4. Continued.**

| Depend. Var. | Fixed Effects Model | | Spatial Fixed Effects Lag Model | | Spatial Fixed Effects Error Model | |
|---|---|---|---|---|---|---|
| **Hay Yields** | **Estimate** | **P-value** | **Estimate** | **P-value** | **Estimate** | **P-value** |
| RogerMills | 4.994*** | 0.000 | 0.079 | 0.952 | 0.098 | 0.674 |
| Rogers | 4.374*** | 0.000 | -0.359 | 0.794 | -0.467* | 0.059 |
| Seminole | 4.579*** | 0.000 | -0.248 | 0.859 | -0.267 | 0.289 |
| Sequoyah | 4.382*** | 0.000 | -0.374 | 0.788 | -0.446* | 0.075 |
| Stephens | 5.140*** | 0.000 | 0.150 | 0.915 | 0.280 | 0.266 |
| Texas | 5.763*** | 0.000 | 0.821 | 0.500 | 0.829*** | 0.000 |
| Tillman | 5.506*** | 0.000 | 0.362 | 0.798 | 0.629** | 0.013 |
| Tulsa | 4.480*** | 0.000 | -0.236 | 0.864 | -0.363 | 0.145 |
| Wagoner | 4.686*** | 0.000 | -0.069 | 0.961 | -0.150 | 0.549 |
| Washington | 4.374*** | 0.000 | -0.504 | 0.710 | -0.469* | 0.055 |
| Washita | 5.415*** | 0.000 | 0.390 | 0.774 | 0.537** | 0.028 |
| Woods | 4.922*** | 0.000 | 0.054 | 0.967 | 0.037 | 0.875 |
| Woodward | 4.744*** | 0.000 | -0.181 | 0.889 | -0.149 | 0.522 |

*Notes*: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

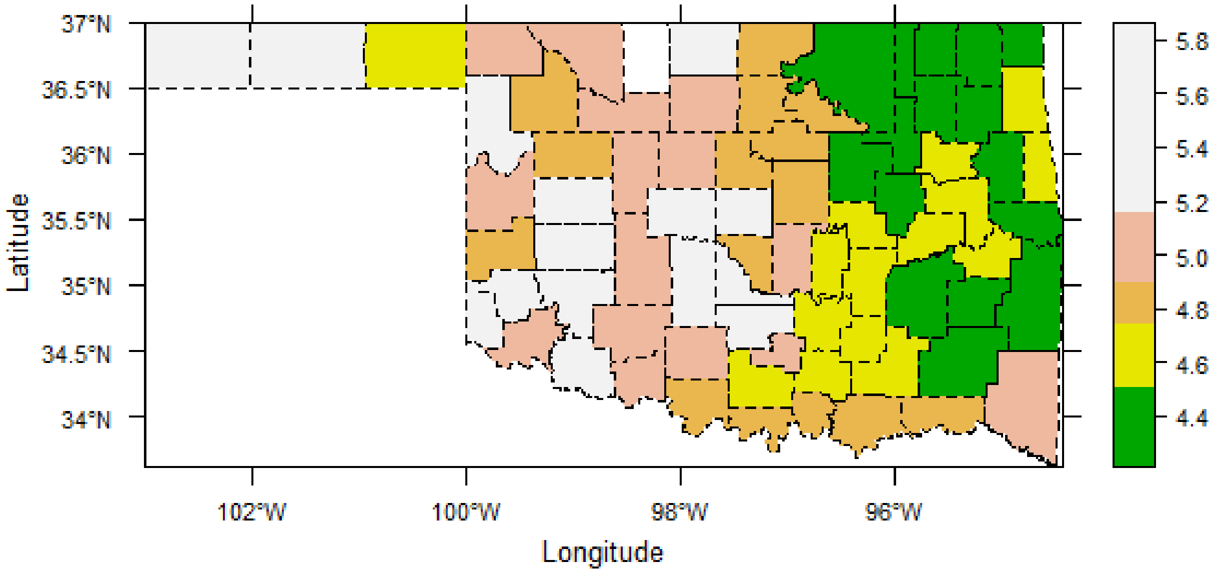


**Figure 6. Spatial distribution of county fixed effect coefficients from the fixed effects model**

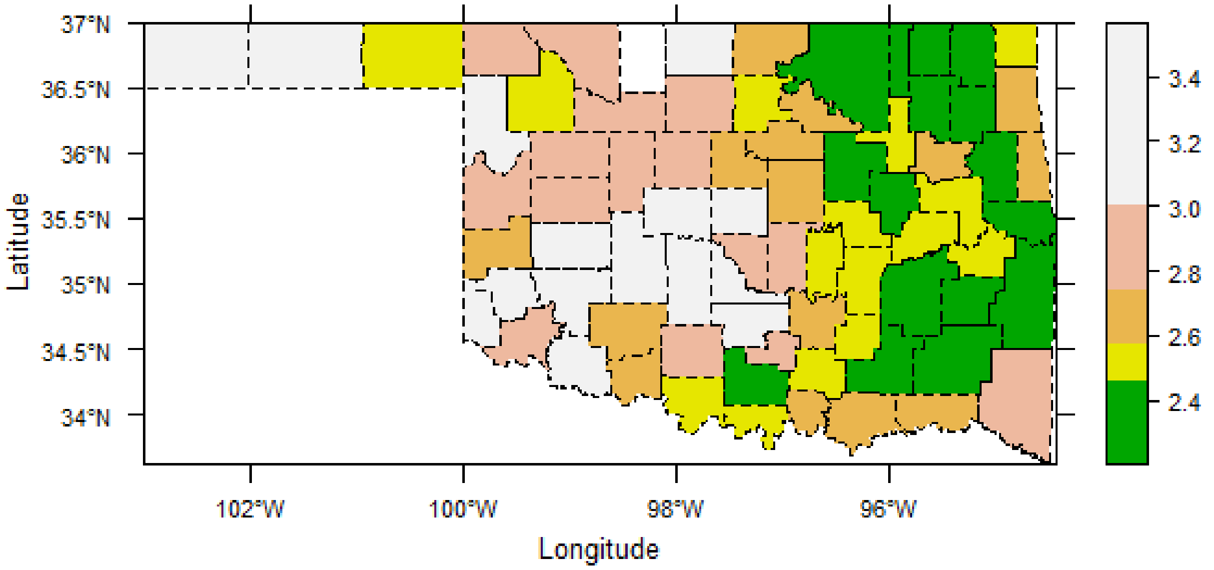


**Figure 7. Spatial distribution of county fixed effect coefficients from the spatial fixed effects lag model**

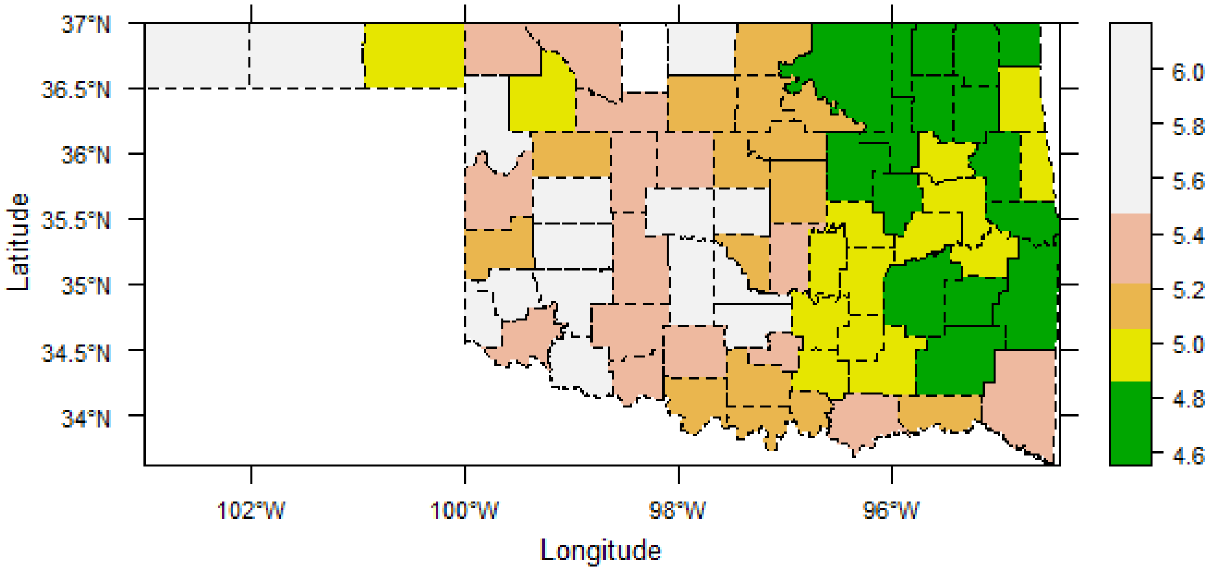


**Figure 8. Spatial distribution of county fixed effect coefficients from the spatial fixed effects error model**

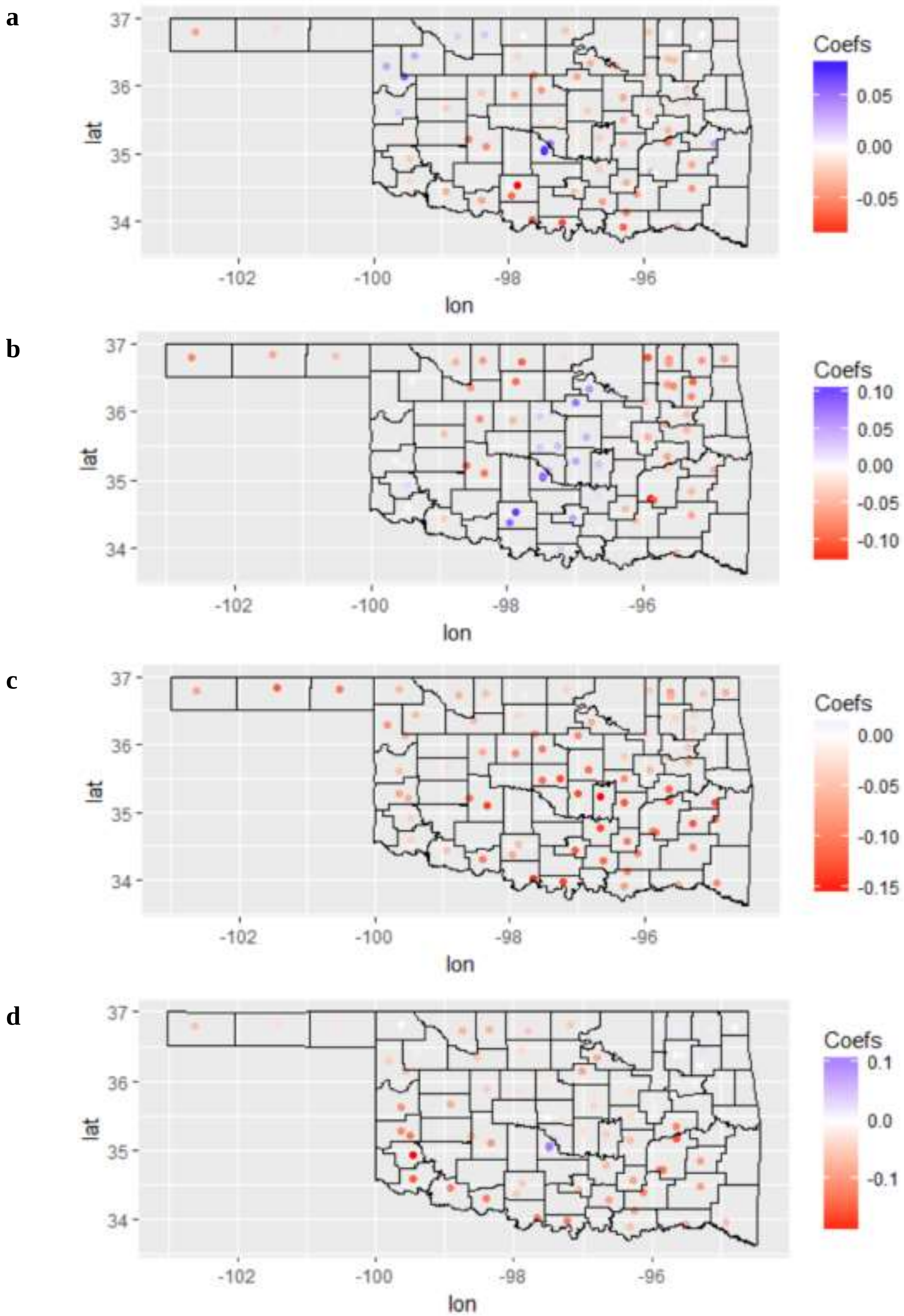


**Figure 9. Spatial distribution of GWR coefficients of seasonal mean temperature effects**

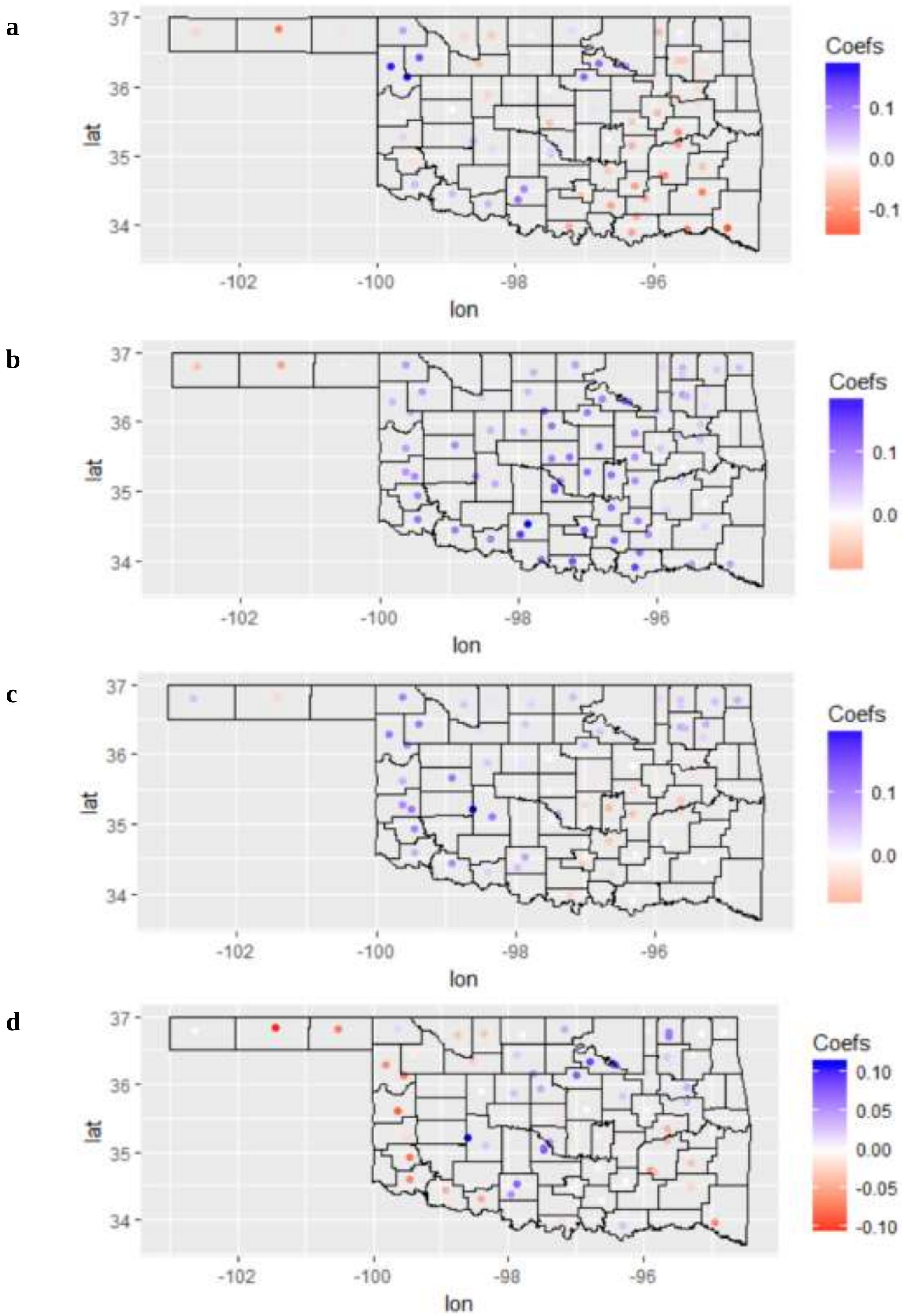


**Figure 10. Spatial distribution of GWR coefficients of seasonal total precipitation effects**

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