Spatial Heterogeneity in U.S. Agricultural Productivity

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# Abstract

This study uses U.S. county-level agricultural data for 2017 to estimate a spatially explicit production function and analyze the impact of spatial heterogeneity on the corresponding input-output relationships. This is an important consideration given that traditional analyses are often temporal. Results indicate that significant spatial heterogeneity is present, the effects of which are presented via quantile map. Clustering is apparent, with high productivity areas concentrated in the Midwest and Southeast, with low productivity areas scattered though parts of the southwest, Appalachia, and parts of the Northeast. Spillover effects are quantified and presented. Spatial heterogeneity is a predominant factor in determining agricultural productivity and this paper quantifies its impact for policy makers, researchers, and agricultural producers.

*Keywords:* agricultural productivity, spatial heterogeneity, spillover effects.

*JEL: C21, Q10, Q18*

# Introduction

The U.S. is one of the largest agricultural producers in the world and has more arable land than any other nation (World Bank, 2022). The global agricultural system is complex, and the business of agriculture is characterized by high startup costs and a commodity output with low per-unit value. Regardless, the 2017 Census of Agriculture showed that the market value of U.S. agricultural products sold was ~$388.5 billion.

Agricultural producers have long been subject to uncertainty and price fluctuations, and the market has generated a number of mechanisms for risk mitigation. Over the 20th century, inflation had a quantifiable impact on the agricultural markets as well. The EPA notes that using 1910-1914 as a base, prices received by today’s farmers have increased at least 6x, while the costs of production have increased at least 16x (EPA, 2015a).

A historically low per-unit value of produced goods and ever changing price conditions have led to a push for increased efficiency in agricultural production. This resulted in a shift toward large-scale operations that produce in high volume. Small farms, while high in numbers, now comprise a small percentage of overall farmland. Farms in the highest economic sales class are much smaller in number, but use the largest amount of farmland (EPA, 2015b).

U.S. agricultural productivity is growing faster than domestic food and fiber demand. Thus, U.S. farmers rely heavily on export markets to sustain income. According to USDA data, monthly U.S. agricultural imports have exceeded exports only 36 times (about 6% of months in the last 46 years). Torgerson and Shane (2014) show that the overall value added to GDP by agriculture and related industries is approximately 5% of GDP ($776 billion).

As a result of an increased push for productivity and the concentration of agricultural production into larger mega-producers, understanding the impact of spatial heterogeneity on agricultural productivity is paramount. This provides the motivation for our study, which adapts the framework set forth by Yu et al. (2014), in which the authors evaluate the impact of spatial heterogeneity on the variation of input-output relationships in Turkey.

In the U.S., different regions are characterized by different conditions important for agricultural production, including rainfall, soil, sunlight, temperature, etc. This variation can have significant impacts on productivity. For example, Lkupitiya et al. (2012) find substantial spatial and temporal variation in organic matter stocks in U.S. croplands.

Agricultural activity in the U.S. is also affected by policy. The primary agricultural policy tool of the U.S. government is the Farm Bill, which is renewed and revised every five years. The most recent update is the 2018 Farm Bill, which largely continues the farm and nutrition policy of prior years. Farm Bills are highly impactful to the agricultural sector and involve a number of programs including direct payments, crop insurance, risk management, and SNAP (Stabenow, 2014). Agricultural policies also exist at the state-level and may address local or regional concerns (Hamilton, 2013). Given that local agricultural policy factors are not captured, variations in local agricultural policy are one potential source of heterogeneity in the “returns” obtained from standard agricultural inputs across space.

This study aims to provide evidence of the effects of spatial heterogeneity on agricultural productivity across the mainland counties of the United States. Such information may be useful for agricultural producers, policy makers, and other market actors concerned with the productivity of agricultural activities in the U.S. Combined with other research, we help to paint a more complete picture of the U.S. agricultural sector and the factors that influence it.

Section 2 provides a detailed review of the existing literature, beginning with a discussion of agricultural production economics and moving toward an exposition of agricultural productivity, production function estimation, and spatial heterogeneity. Sections 3 and 4 describe the empirical methods used to quantify spatial heterogeneity. Section 5 is an overview of the data and transformations. Sections 6 and 7 present results, conclusions, and recommendations for future research.

# Background

The last century resulted in major progress in agricultural economics and farm management strategies. Debertin (2012) describes agriculture as the closest real-world example of a purely competitive market. There are clearly some caveats, as subsidies, risk programs, and other publicly funded or mandated actions impact the agricultural sector at many levels. However, the purely competitive model appears to represent farming better than any other existing model of economic behavior.

Chavas et al. (2010) provide a “reflection on the path taken by production economics and farm management over the past century.” The authors identify 16 major contributes in production analysis, agricultural productivity, risk management, and dynamics. Some relevant findings include the identification of the role of diminishing returns in agricultural production and an assessment of economies of scale in agriculture (Spillman, 1923; 1924; 1933; Spillman and Lang, 1924).

Lyson and Welsh (1993) compare the current agricultural system to that of the mass production model of manufacturing in which efficiency and profit maximization is the ultimate aim. The level of U.S. farm output and input use from 1948-2011 grew at an average rate of 1.49 and 0.07 %, respectively. The significant difference between these numbers implies serious growth in productivity over time. Despite this, state-level analyses show considerable variation in growth rates across space (Ball et al., 2014). This variation in space provides additional motivation for the examination of spatial heterogeneity in agricultural production.

Many studies exist regarding the estimation of production functions, and that discussion could be a paper in and of itself. Rather, this review focuses on production function estimation with a spatial component. Shaik (2014) shows that traditional measures of return to scale and technology are under- and over-estimated in states at the upper and lower quantiles of the distribution, respectively. Weiss (1996) provides an overview of the emerging role of spatial analysis in agricultural economics and defines the core opportunity of economists as the need to quantify the costs and benefits of detecting and exploring spatial variation. Yu et al. (2014) refer to multiple other studies examining the role of space in production functions (Anselin et al., 1997; Cavailhes and Wavresky, 2003; Fingleton and Mccombie, 2006; Lambert and Cho, 2008; Vaya et al., 2004). Despite a fairly wide application of the more general methods of “spatial analysis”, the use of spatial econometrics in agricultural production function modeling to date is limited.

Cho et al. (2007) estimate an agricultural production function using Chinese county-level data and geographically weighted regression (GWR). They also compute county-specific input-output elasticities and create a visual representation using GIS. Their results are obtained by comparing GWR and OLS estimates to confirm that allowing for spatial variation in the regression paradigm significantly improves model performance.

Yu et al. (2014) provide an evaluation of the spatial variation that exists in the Turkish agricultural sector and how it impacts input-output elasticities across the country. Their results indicate that disparities in agricultural activities and geographic conditions affected the return from input factors, and that policy makers should consider this regional heterogeneity and potential comparative advantage when creating new legislation. The authors break this process down into four steps: [1] identifying spatial dependence; [2] generalizing a spatial production function; [3] comparing and selecting appropriate models; and [4] estimation and results. These four steps provide the generalized framework for this study. Additional papers of interest include Bille et al. (2015), Pedersen et al. (2017), Koc et al. (2017), Xu et al. (2020), and Ma et al. (2021).

# Identifying Spatial Dependence

Before considering the use of a spatial econometric model, it is important to explore the concept of spatial dependence. Generally, spatial dependence is “a situation in which values observed at one location depend on the values observed at nearby locations” (LeSage and Pace, 2009). Whether or not a location is nearby can be determined through the use of a various mathematical criteria, e.g. Euclidean distance, connected borders, etc. The authors provide the generalized example for which observations and represent neighbors as defined by some criteria. Thus, the data generating process with spatial correlation takes the following form:

where

For , we have that and . This is a general system of spatial dependence where the actions undertaken in county impact the outcomes in neighboring counties , and vice versa.

The idea of spatial autocorrelation is similar to that of the continuous Pearson correlation of traditional statistics. Its value lies in [-1, +1], with *positive spatial autocorrelation* defined as the situation in which nearby observations are likely to be similar to one another; *negative spatial autocorrelation* defined as the situation in which nearby observations are likely to be opposite one another; and values near 0 implying a lack of spatial autocorrelation.

In most any dataset with a spatial component, everything is related to everything else. However, things that are closer together are “more” related than those that are farther away (Tobler, 1970). Yu at al. (2014) cite a number of other examples that have been discussed in the spatial econometrics literature (Anselin, 1995; Can, 1990; Can, 1992; Cliff and Ord, 1973; Dubin, 1992; Kilkenny and Thisse, 1999; LeSage, 1997; Leung et al., 2000; McMillen, 1992; McMillen, 2003).

In testing for the presence of spatial autocorrelation, the Moran’s I statistic is a generally accepted starting point. Moran’s I is a global value that provides an indication of the presence (or lack) of a pattern of spatial dependence that is true for the entire dataset (Anselin, 1996). The Moran’s I is defined as follows, with as the number of spatial units, as the variable of interest, as the mean of , and as the spatial weights matrix (Moran, 1948):

While it is important to consider the values of Moran’s I, given its global nature, it is not without flaws. When datasets become large, the degree of spatial autocorrelation between observations becomes more likely to show instability in the form of nonstationarity at the local level, spatial regimes, or spatial drift (Anselin, 1996). As a potential solution, Anselin (1995) proposed a general class of “local indicators of spatial association (LISA)” which allow for the decomposition of global indicators such as Moran’s I into the contribution of each observation. This technique lends itself readily to visualization and can provide insight into the spatial distribution of spatially associated effects. We apply both the Moran’s I and LISA procedures to our data to ensure that spatial autocorrelation is detectable.

# Empirical Model

The framework employed in this paper draws heavily from Yu et al. (2014), but differs in its method of model selection, estimation, and interpretation. We begin with a Cobb-Douglas functional form, a tool widely used in agricultural studies since 1928 (Debertin, 2012). The generalized form is represented below, in which represents net agricultural income for county , is total factor productivity (TFP), is input for state , and is the return of each input to output.

If production is assumed to be stochastic, a random shock can be incorporated, also referred to as a Solow residual.

The Solow residual is the regional variation in technological efficiency (LeSage and Pace, 2009). This is the productivity of input factors by county not included in the aggregated total factor productivity (TFP) (). This provides a clear window to the degree of spatial heterogeneity that may exist in U.S. agricultural production. To linearize the relationship, the natural log of both sides can be taken and converted to matrix form.

We consider multiple spatial econometric models for updating the production function. The most common spatial models are the Spatial Autoregressive Model (SAR), Spatial Durbin Model (SDM), and the Spatial Error Model (SEM) (LeSage and Pace, 2009). The SAR model’s only deviation from our formulation above is its inclusion of a spatial lag on the dependent variable. The SAR model is stated below, in which is the spatial lag coefficient value and is the weighted average of the dependent variable values of the surrounding counties:

It is important to consider the choice of a spatial weights matrix. There has been much debate in the econometrics literature regarding the specification of weights matrices, with concern that various specifications may produce varying or biased estimates. LeSage and Pace (2014) find no theoretical basis for this belief and conclude that weight-matrix specification is not likely to significantly impact results.

The Spatial Durbin Model (SDM) expands the framework further by including spatial lags of explanatory variables as well as the dependent variable.

Finally, the Spatial Error Model (SEM) uses lags to reflect dependence in the error process.

where .

Various specifications of these three models are considered through a rigorous model selection process. The use of OLS in spatial models can lead to inconsistent estimates, incorrect standard errors, and more. Maximum Likelihood, however, is consistent for spatial models and provides a reliable estimation method (LeSage and Pace, 2009). It should be noted that the interpretation of estimation results in spatial models is not as straightforward as that of a linear process. E.g., in the simple linear regression model, the interpretation of is that for a one-unit increase in X, y should increase by . This does not hold true for models such as the SAR or SDM.

This discrepancy comes as a result of the functional form, whereas the partial derivative is not simply equal to as a result of the spatially lagged dependent variable. A change in an explanatory variable in one region will affect the region itself (direct effect) and potentially all other regions (indirect effects). These effects are combined to yield the “total effect” of a marginal change. To determine the value of the derivative for an equation with a spatially lagged dependent variable, the equation must be algebraically manipulated (i.e. the model must be written in reduced form) (LeSage and Pace, 2009).

In the estimation of such models, the ideal data transformation is that of a log-log specification because of the scaling effect that occurs and also because coefficients of this type of model can be interpreted as the input-output elasticity for the given variable. Given that this data includes various negative net income values which yield complex numbers when logged, the data is transformed via the use of studentization. This process consists of subtracting the mean from each observation and dividing by the standard deviation. Coefficients (in the case of models with spatially lagged dependent variables, effects estimates) should then be interpreted as changes in standard deviation.

Model specification is assessed using the procedure defined by Elhorst (2010) in an article that provides a broad perspective on some key issues regarding the 2009 LeSage and Pace text. Elhorst begins with the testing procedure defined by Florax et al. (2003), which allows for testing the significance of the spatially lagged dependent variable and spatially lagged error term. Using this as a starting point, he proposes a generalized testing procedure that can help the econometrician determine the best model specification given the data.

The main problem with the procedure provided by Florax is that it provides only a limited model space in which we have . However, this does not allow for the consideration of the alternative specifications . The Spatial Lag of X (SLX) model is simply a standard normal linear model with an additional term consisting of spatially lagged independent variables. In this model, OLS can be used and coefficient interpretation is straightforward.

The Spatial Durbin Error Model (SDEM) augments the SEM model with a spatial lag of the explanatory variables.

where . By implementing a likelihood-ratio test and Wald test, Elhorst is able to develop a procedure that expands the model space to , providing expanded possibilities for global, local, and OLS models. A step-by-step overview of the Elhorst testing procedure can be found in Appendix 2. For a more thorough review, see the Elhorst (2010) article.

# Data

Data for this analysis is derived from the USDA NASS Quick Stats 2.0 web portal and the USDA Census of Agriculture for 3,079 counties in 2017. Net income ($) serves as a proxy for output. Input variables include labor expense ($), fertilizer expense ($), fuel expense ($), acres of land harvested, machinery asset value ($), and inventory of tractors and trucks. Many studies are fairly limited in their choice of input variables for the agricultural production function. The inclusion of this wide array of variables allows a vast overview of relationships and spatial dependence. Descriptive statistics are provided in Table 1.

Table 1: Descriptive Statistics

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable** | **Avg** | **SD** | **Min** | **Max** |
| Net Income ($M) | 28.9 | 55.8 | -46.4 | 1,162.9 |
| Fertilizer ($M) | 7.7 | 12.8 | 0.001 | 269.8 |
| Fuel ($M) | 4.4 | 7.3 | 0.001 | 210.3 |
| Labor ($M) | 10.4 | 32.5 | 0.003 | 648.3 |
| Land (Acres, thousands) | 129.5 | 151.7 | 0.007 | 1,309.7 |
| Machinery ($M) | 88.7 | 83.7 | 0.024 | 1,120.9 |
| Tractors (Inventory, hundreds) | 13.2 | 10.6 | 0.04 | 145.2 |
| Trucks (Inventory, hundreds) | 10.9 | 8.2 | 0.04 | 103.4 |

The dataset includes missing values in a small number of instances (~2.5% of counties have at least one missing value). When this occurs for variable , we impute the average value of variable for all other counties in state . Prior to regression modeling, variables are scaled to adjust for differences in the units of measurement. Monetary values (net income, fertilizer, fuel, labor, and machinery) are converted to millions of dollars. Land is scaled by 1e5, or hundreds of thousands of acres. Tractors and trucks are not scaled.

# Results

The Moran’s I statistic is displayed in Table 2 for our target (net income) and input variables. Results are computed in GeoDa using a rook contiguity matrix with value if county and share a common border, and otherwise. The degree of spatial autocorrelation is positive and relatively high for all variables, ranging from approximately 0.455 to 0.726. This provides sufficient justification for further exploration of the impact of space on agricultural production.

Table 2: Univariate Moran's I Results

|  |  |
| --- | --- |
| **Variable** | **Moran’s I** |
| Net Income | 0.474 |
| Labor | 0.534 |
| Land | 0.726 |
| Machinery | 0.579 |
| Fertilizer | 0.517 |
| Fuel | 0.455 |
| Tractors | 0.513 |
| Trucks | 0.474 |

To examine local spatial autocorrelation, we use the LISA method (Figure 1), mapping results across 3,079 mainland counties for each variable. This creates a visual overview of the presence of local spatial association in the dataset. Within each section, shading represents significance of at least 95%. Darker portions represent higher significance. It’s clear that significant clustering exists, with the location of that clustering varying depending on input variable. Given that this represents positive spatial autocorrelation, counties that are highly significant tend to be surrounded by other similarly valued counties.

Figure 1: Local Indicators of Spatial Association (LISA)

A picture containing background pattern

Description automatically generated

We follow the Elhorst (2010) procedure for model specification, the results of which are listed in Table 3. The embedded Florax et al. (2003) process indicates a rejection of the null hypothesis that in the generalized test, but fails to reject in the robust variety. The null hypothesis that is rejected in both the generalized and robust cases. Using the steps laid out in the process defined by Elhorst, we are pointed toward the SDM model. Moving forward with the LR test to determine whether the SDM can be reduced to the SAR results in a rejection of SAR. The same is true for the restricted SEM. The results in Table 3 provide empirical support for the use of a spatial model and imply that spatially lagged variables are likely to play an important role in the underlying data generating process.

Table 3: Elhorst (2010) Specification Testing

|  |  |  |
| --- | --- | --- |
|  | **Marginal Probability** | **Result** |
| LM Lag | 0.0000 | Reject the null that rho = 0. |
| LM Error | 0.0000 | Reject the null that lambda = 0. |
| LM Lag Robust | 0.7473 | Fail to reject the null that rho = 0. |
| LM Error Robust | 0.0000 | Reject the null that lambda = 0. |
| LR (SDM vs. SAR) | 0.0000 | Reject the restricted (SAR) model. |
| LR (SDM vs. SEM) | 0.0000 | Reject the restricted (SEM) model. |
| Wald (SLX vs. OLS) | n/a | Testing points to SDM model. |

Table 4 presents the results of our estimated Spatial Durbin Model for U.S. mainland counties in 2017. The model is built in 3,069 observations using a rook contiguity matrix and yields and of 0.7929. Most notably, is significant at the 99% level and suggests a high degree of positive spatial autocorrelation. In other words, counties with high agricultural net income are likely surrounding by counties with the same.

Table 4: Spatial Durbin Model Results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable** | **Coefficient** | **Direct** | **Indirect** | **Total** |
| Constant | 0.557\*\*\* |  |  |  |
| Fertilizer | -0.170 | -0.232\*\* | -0.930\*\* | -1.162\*\* |
| Fuel | 3.314\*\*\* | 3.578\*\*\* | 4.176\*\*\* | 7.754\*\*\* |
| Labor | 0.430\*\* | 0.401\*\*\* | -0.484\*\*\* | -0.082 |
| Land | -0.438\*\*\* | -0.943 | -7.825\*\*\* | -8.768\*\*\* |
| Machinery | 0.331 | 0.341\*\*\* | 0.152\* | 0.493\*\*\* |
| Tractors | -0.0002 | -0.0001 | -0.010\*\* | -0.012\*\* |
| Trucks | -0.012\*\*\* | -0.012\*\*\* | -0.002 | -0.014\*\*\* |
| W-Fertilizer | -0.227\*\*\* |  | | |
| W-Fuel | -0.615\*\*\* |
| W-Labor | -0.458 |
| W-Land | -2.654\*\*\* |
| W-Machinery | -0.158 |
| W-Tractors | -0.004 |
| W-Trucks | 0.007\*\*\* |
| Rho | 0.649\*\*\* |

\*, \*\*, and \*\*\* indicate significance at 90, 95, and 99%, respectively.

It is important to note that when interpreting output from a regression model with a spatially lagged dependent variable, attention must be paid to effects estimates rather than raw coefficients. Effects estimates of an independent variable in county can be interpreted such that a one standard deviation increase (decrease) in the variable increases (decreases) the target variable by standard deviations.

Results indicate that fuel, labor, and machinery have a positive impact on net income, with directs effects estimates of 3.578, 0.401, and 0.341, respectively. Fertilizer, land, tractors, and trucks have a negative effect on net income, which may be explained by the hypothesis that (with the exception of fertilizer), these are largely assets held by the owner that may or may not directly add to the net income, and may involve debt service that takes away from net income.

In considering spillover effects, the indirect effect estimate is the change in standard deviations of net income for county that can be attributed to a one standard deviation change in a given independent variable for a weighted average of neighboring counties. Spillover effects are observed, but vary in their directionality. These results conflict with those found by Yu et al. (2014), which observed insignificant indirect effects for agricultural production.

Recall that our primary indicator of spatial heterogeneity is the derived Solow Residual . The represents regional variation in the productivity of input factors by county not included in the TFP (). Given a Solow Residual defined as:

,

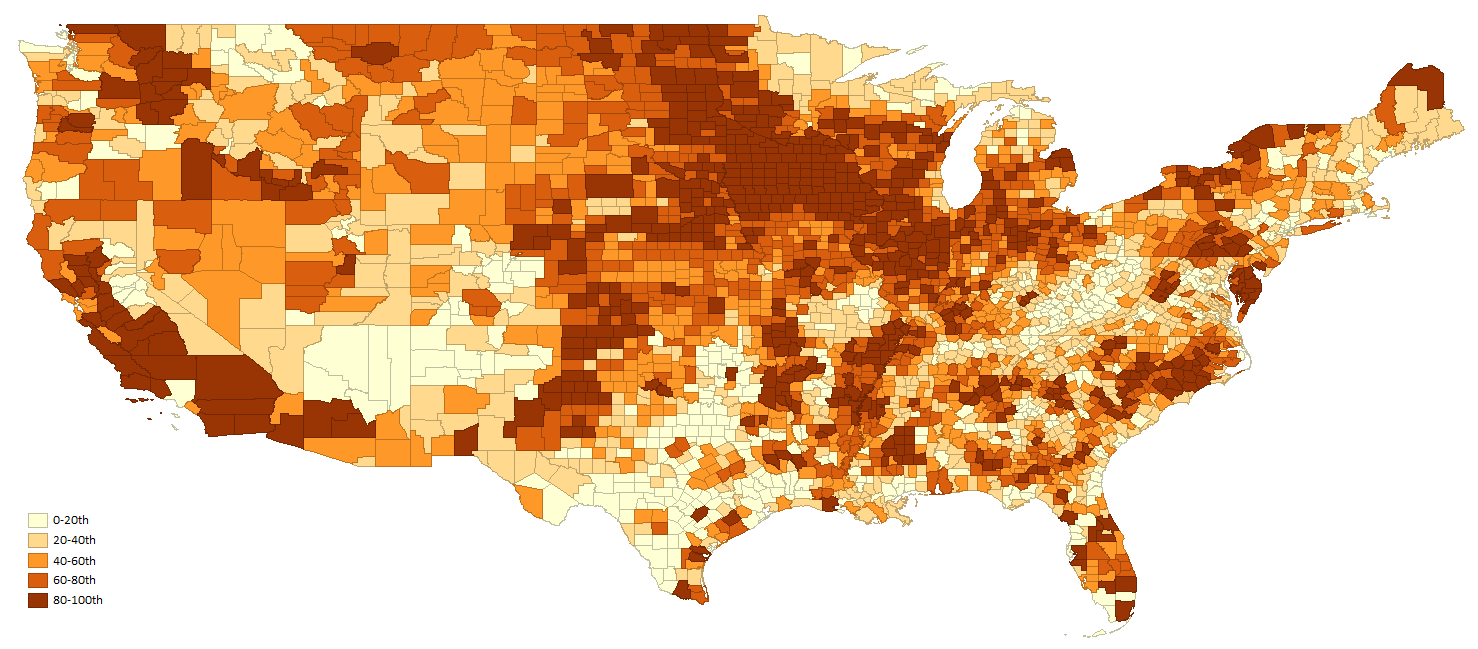
we interpret results as follows. If , this means that , or that the derived production function predicts that higher-than-observed production should occur in county based on the input factors . For reasons attributed to spatial heterogeneity, the county underproduces compared to expectations given input consumption. If , so actual production exceeds the expectations of the derived production function given the consumed inputs . This means that areas with experience higher-than-average (lower-than-average) productivity that we attribute to spatial heterogeneity.

Figure 2 presents estimated Solow Residuals () by county for 2017. Clusters of high productivity occur in the Midwest and Southeast. Particularly low productivity regions are scattered throughout the Southwest, Appalachia, and the Northeast. This reveals significant impacts of spatial heterogeneity on the input-output relationships in U.S. agricultural production.

Our findings are intuitive, as states in the Midwest and Southeast have historically exhibited favorable conditions for agricultural production and production is usually focused on crops that perform well in the conditions of the local environment. One important factor is water availability. While irrigation systems exist to mitigate risk, they do not entirely offset water concerns in dry areas such as the Southwest. The plains of the Midwest lend themselves readily to production of fields of crops and the utilization of large machinery which significantly increases productivity. In addition, land in the Northeast is highly forested and this extends to agricultural parcels. Comparing this to a highly productive region such as the Midwest reveals that highly productive regions are typically less forested and more conducive to mass-scale row crops and animal agriculture.

Results reveal some significance in total effects and these values are worth noting. The total effect is the combination of direct + indirect effects and represents the effect of a marginal change in input use on agricultural net income across the country. Total effects are significant and worth noting. E.g., a marginal increase in the use of fertilizer in county leads to an increase in net income not only in county , but also in surrounding counties .

Figure 2: Solow Residuals by County



# Conclusion

This study used U.S. county-level agricultural data for 2017 to estimate a spatially explicit production function for U.S. agriculture. This allows for an expanded understanding of the traditionally non-spatial and largely temporal framework of estimation. Results indicate that significant spatial heterogeneity is present and impacts productivity substantially by reducing the degree of return to inputs in certain areas. Significant clustering is apparent, with high productivity areas concentrated in the Midwest and Southeast, and low productivity areas in the Southwest and Northeast. This is likely a result of a combination of various factors including land use, geography, water availability, and local policy actions.

The use of this spatial econometric estimation technique provides value by allowing for the separation of the effects of generalized productivity increases and those derived from spatial heterogeneity, which has been clearly demonstrated using a Solow Residual. Spillovers are observed and the presence of a spatial lag is significant regarding net income. The meaning of this finding is not well-defined, as it’s possible that counties are similar to those around them with regard to economics, geographic characteristics, and climate, resulting in similar activity under similar conditions.

Policymakers should consider the costs and benefits of subsidizing agricultural activity in low-productivity areas, as a more efficient scenario likely exists. This may result in more fragmented policies that encourage agricultural activity in productive areas and discourage it in less productive areas. Alternatively, policymakers could focus on ways to improve productivity in low-productivity zones.

# Appendix: Elhorst Testing Procedure

The Elhorst (2010) testing procedure is summarized as follows. Consider a model space , which is a set containing the following possible models: {OLS, SAR, SEM, SDM, SLX, SDEM}. includes three global spatial models, two local spatial models, and the simple OLS specification. The procedure is outlined as follows:

1. Estimate the model via OLS and use the various LM tests to determine the proper model (e.g., use the Florax et al. procedure).
2. If OLS is rejected in favor of SAR, SEM, or both, estimate the SDM.
3. Use the LR test to examine the following hypotheses:
   1. H0: tests whether SDM can be reduced to SAR.
   2. H0: tests whether SDM can be reduced to SEM.
4. If H0(a) can’t be rejected, use SAR as long as robust LM test statistics point to SAR.
5. If H0(b) can’t be rejected, use SEM as long as the LM test points to SEM.
6. If one of the conditions in 4 and 5 are not satisfied, use the SDM.
7. If OLS is estimated and not rejected in favor of both SAR and SEM, the OLS should be re-estimated with spatially lagged explanatory variables and the hypothesis H0: tested.
8. If H0: can’t be rejected, use OLS.
9. If H0: is rejected, the SDM model should be estimated and H0: should be tested.
10. If H0: is rejected, use SDM. Else, use SLX.

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